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Performance analysis of organizations as complex systems.

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PERFORMANCE ANALYSIS OF ORGANIZATIONS AS COMPLEX SYSTEMS

By

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DEDICATION

This dissertation is dedicated to my wife

Krista Lynn Harrington

whom I love with all my heart.

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ABSTRACT

PERFORMANCE ANALYSIS OF ORGANIZATIONS AS COMPLEX SYSTEMS

William C. Harrington, Jr.

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This dissertation provides a method for evaluating the difference in performance after an organization makes a change while considering the stochastic nature in which it operates. A procedure that uses simulation to estimate outcomes by adjusting controllable parameters and leaving uncontrolled parameters unadjusted is proposed. As healthcare organizations are considered as highly complex systems, a case study involving a scheduling tactic change in the mother-baby service line of a hospital is used to demonstrate application of this procedure.

The goal in the case study was to reduce delays in transitioning care of mother patients from the labor and delivery unit to the postpartum care unit. The Holds Rate metric measured delays as the number of mothers deemed to be unintentionally delayed from transferring to the postpartum care unit to the total number of deliveries. While the scheduling tactic change did not yield the anticipated result, the proposed procedure was used to show that performance would have been worse had the change not been made. Hospital leadership chose to keep the solution and target performance was later surpassed. Ultimately, hospital leaders heralded the project as a great success.

The proposed procedure was applied with two different simulation methods. A Monte Carlo simulation model was used to measure Holds Rate and a discrete-event simulation model to measure the average delay time experienced by patients waiting to be placed in a postpartum bed following delivery. The results of the procedure with both models led to the same conclusion that the scheduling tactic change indeed reduced delays in the transitions of care between the two hospital units.

The case study demonstrated the validity and applicability of the proposed procedure and organizations may benefit from its use as leaders may be more prone to act since analysis with the procedure isolates the effects of uncontrolled parameters. Isolating these effects to better understand those of controlled parameters can promote an organization's sustainability by advancing knowledge of cause-and-effect relationships. Future research with this topic can include application with other simulation methods, investigating the impacts of technology advancements, and considering a method of analysis using Bayesian inference.

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CHAPTER 1

INTRODUCTION

1.1 Background

Between 2012 and 2013, I led a project for my employer, Norton Healthcare (NHC), which involved reducing delays in care transitions for mothers who recently delivered in the labor and delivery (L&D) unit. The amount of time a patient was delayed from transferring to the postpartum (PP) care unit was a key factor in determining a patient to be unintentionally held. This project was relevant to patient satisfaction, which was measured in the Hospital Consumer Assessment of Healthcare Providers and Systems (HCAHPS) surveys. Any patient rating for the hospital less than a 9 on a 0-10 scale is considered unfavorable. An internal study revealed that patients who were held from the PP care unit were 57% more likely to rate the hospital unfavorably than other patients. This result was found to be significant by means of a Two-Proportions Test ($p = 0.037$).

While improving patient satisfaction was the impetus for the project, there are other factors apart from considering patients to be held that impact patient satisfaction. For example, how physicians and staff interact with the patients is one such factor. Therefore, the scope of the project was to reduce the frequency of patients being held from the PP care unit as it was not to directly improve patient satisfaction scores.

The targeted goal in reducing delays was not initially achieved after implementing process improvements. However, I suspected that factors outside the control of the project team contributed to this performance gap. The challenge was how to quantify what the performance would have been had these conditions been similar to those at the start of the project. I was familiar with Monte Carlo simulation (MCS) and I had applied this technique earlier in the project to demonstrate the anticipated impact various parameter changes would have on delays. I used a less-refined version of the method discussed in Chapter 3 to demonstrate to hospital leadership that the post-implementation performance would have been better if conditions outside the control of the project team had not changed. The analysis allowed leaders to continue their support of the initial interventions, which eventually led to the goal being exceeded.

This experience inspired me to pursue this dissertation topic as I see opportunity to use the proposed method to enhance the evaluation of performance in organizations and thereby promote more appropriate responses in the presence of environmental variability. I am further hopeful that growth in the availability of electronic data and the capability of computing will allow the work of this dissertation to be leveraged for practical use.

1.2 Problem Statement

Organizations are complex systems operating in dynamic environments, often with limited control. For example, a manufacturer may have minimal influence over the cost and availability of its resources as well as the price and demand for its end products. At the same time, the manufacturer could directly change the design of its products,

production methods, marketing tactics, and other aspects that impact how value is created and delivered. Therefore, it may be difficult to determine if a change in performance was due to the actions of leadership or due to market forces beyond the firm's direct control.

The objective of this dissertation is to provide a method for evaluating the difference in performance after an organization makes a change while considering the stochastic nature of the environment in which it operates. There are two possible questions that such an organization would want answered:

> **Question #1:** If the post-change approach existed in the baseline, how would the baseline (pre-change) performance have differed?
>
> **Question #2:** If the baseline approach still existed, how would the post-change performance have differed?

While the first question may be limiting since the past cannot be altered, it is still insightful to know should similar conditions present themselves in the future. The second question, however, is directly actionable as it addresses the current state conditions.

There are at least two primary benefits for utilizing this type of analysis. The first benefit is to provide a better gauge of performance shift (i.e., the difference in performance between two values of interest) between the post-change environment and the baseline environment to prevent irrational reaction. One such irrational reaction could be reverting to a prior process even though the new process actually prevented performance from further deterioration (referred to as the *unfortunate loser* condition). Another irrational reaction is applauding a new approach while external forces have been the primary cause for success and results would have been even better with the prior method (referred to as the *undeserving winner* condition).

The second benefit is to challenge the extent to which market forces are deemed uncontrollable. In modeling a real world environment, variables are either deterministic or stochastic. With each stochastic variable, there may be parameters that an organization controls. The sustainability of a firm can be strengthened by identifying such parameters and leveraging them to mitigate performance headwinds created by the associated stochastic variables. A key example of this is when a business unit deploys scheduling tactics to manage demand. While the overall level of demand may not be directly controlled, although marketing strategies may have some impact, the variation in daily demand can be regulated.

The hypothesis of this research is that organizations can use simulation to evaluate the efficacy of a change that has already been made, and that doing so is more insightful than simply comparing pre-change and post-change performance. To validate this hypothesis, an actual case study is used.

1.3 Dissertation Organization

After the introduction provided in Chapter 1, a literature review is provided in Chapter 2. Topics central to this dissertation are discussed, which include understanding organizations as complex systems and simulation modeling to assess system performance. Special attention is given to reviewing the presence of complexity and the use of simulation in healthcare due to the nature of the case study presented. In Chapter 3, the proposed analysis method is detailed. A step-by-step procedure is provided for answering both questions posed in Section 1.2 above. Both the validity and the applicability of this procedure are demonstrated in Chapters 4–6. To demonstrate

validity, an actual case study in hospital operations involving a baseline and two improvement periods is discussed in Chapter 4. To prove the breadth of applicability with the procedure, analysis was conducted with MCS in Chapter 5 and discrete-event simulation (DES) in Chapter 6. However, the analysis was restricted in Chapter 6 to only answering Question #2 for the comparison between the baseline and second improvement period, and this was due to limitations with the availability of data in the baseline and first improvement period. Implications of this topic are discussed in Chapter 7. While the case study illustrates a particular application, the potential for using the proposed analysis method and subsequent ramifications go well beyond hospital operations and healthcare.

1.4 Software

Microsoft Excel was used to calculate parameters detailed in Chapter 4 for both modeling approaches and to create and run the MCS trials in Chapter 5. Microsoft Excel was also used to calculate values in both Chapters 5 and 6 for Steps 1.7–1.9 and Steps 2.7–2.9 of the proposed procedure outlined in Chapter 3. Minitab was used for all statistical hypothesis tests ($\alpha = 0.05$), distribution identification, and regression analyses. Arena was used to create and run simulations for the DES approach in Chapter 6.

CHAPTER 2

LITERATURE REVIEW

This chapter provides a summary of the literature review performed. In addition to the relevant sections of books, papers reviewed include journal articles and conference proceedings accessed from various search engines and databases including Google Scholar, Ei Compendex, PubMed, and MEDLINE. These works cover topics on organizational science, complex systems, and simulation modeling with application of these topics in healthcare. Conclusions on current applications of simulation modeling, especially those pertaining to healthcare, are made in the final section of this chapter.

2.1 Understanding Organizations as Complex Systems

Dooley (2002) found that organizations are viewed as complex systems whose complexity is a function of its external environment, internal environment, and institutional environment. The author defined organizational complexity to be "the amount of differentiation that exists within different elements constituting the organization." An organization's complexity is driven by various factors including its structure, authority and locus of control, attributes of personnel, products, and technologies.

Sterman (2001) argued that organizational leaders must be knowledgeable of dynamic complexity in order to "understand the sources of policy resistance, and design more effective policies." Dynamic complexity is the "often counterintuitive behavior of complex systems" generated by interactions between agents. This is contrasted with combinatorial complexity, which is the number of components a system possesses or the number of options to consider in decision making. Also, policy resistance is the tendency for a system to respond to an intervention in a manner that defeats the aim of the intervention. The author claimed the heuristics humans use to determine cause-and-effect relationships "systematically lead to cognitive maps that ignore feedbacks, nonlinearities, time delays, and other elements of dynamic complexity." Thus, tools are needed to understand the workings of dynamic complexity in a system.

Chu et al. (2003) clarified six generators of complexity for any system, which are internal inhomogeneity, adaptivity, nonlinearity, net-like causality, radical openness, and contextuality. With radical openness, the interaction between system and ambience is unbound. Furthermore, there may be more generators of complexity than the six discussed. Therefore, the authors argued that achievement of a unified Theory of Complexity is unrealistic.

Kinsner (2008) reached a similar conclusion by identifying that the degree of complexity in a system "appears to be context sensitive, and cannot be defined universally, once and for all." Various contexts for understanding and defining complexity include the system's structure, dynamics, function, organizational depth, and design in its creation. Also, the authors pointed out that the bounds of system stability

change when a perestroika occurs, which is defined as a "phase transition induced by changing control parameters or operating conditions of the system."

Halley and Winkler (2008) postulated the existence of self-organization in a system is the critical factor in determining emergence to be complex rather than simple, and a system becomes complex when "complex emergence properties come into being." Self-organization is defined as "a dissipative non-equilibrium order at macroscopic levels, due to collective, nonlinear interactions between multiple microscopic components." In other words, a system self-organizes when its agent interactions, which may vary disproportionately in scale, result in the system dynamically adapting to its environment. Emergence is "typically described as a property of a system that is not reducible to, nor readily predictable from the properties of individual system components" and it ranges on a continuum of simple to complex. To provide examples, the authors claimed the emergent properties of an ideal gas as "described by a simple gas law equation" are simple while those of an ecosystem are complex. The authors stated that "as systems become more complex" they "have multiple hierarchical levels of self-organization."

Hafez (2010) proposed that the Shannon Communication Model defined in Shannon and Weaver (1949) can be applied to quantify the system-environment interaction process. Accordingly, interaction between a system and its environment is analogous to communication. Under this paradigm, the sensors collecting information from the environment are synonymous to a communication source, the controller that determines actions based on the inputs and desired goals functions as a communication channel, and the effectors implementing the actions are similar to a communication

destination. The ability of a complex system to interact with its environment is dependent on the amount, quality, and relevance of the information it receives, the availability of dependent responses, and its capacity to process information and determine responses.

In continuing this work, Hafez (2012) posited that system complexity can be measured by application of the Shannon Communication Model. The degree of complexity present in a system is based on the size of input and output event sets, considered to be the available communication resources, and the level of dependency between inputs and outputs, known as I/O dependency. A system is considered to approach perfect communication efficiency as its I/O dependency makes increasing use of the available communication resources. However, perfect efficiency is not achieved as systems continuously become more complex.

Spear (2009) acknowledged that organizations have become more complex as technological capabilities have advanced over time. The author offered the healthcare industry as an example where technological growth has resulted in more specialties, marking an increase in inhomogeneity, which has raised the level of organizational complexity. Corroboration is provided by Dooley (2002), which stated that "a hospital would be considered to have quite great complexity," and Chu et al. (2003), which indicated that the field of medicine imports "the concepts of and insights from the study of complex systems."

2.2 Complexity in Healthcare

In 2001, *British Medical Journal* published a series of four articles on the topic of complexity science and its relationship to healthcare. Plsek and Greenhalgh (2001) presented the first article, which showed how a healthcare system can be viewed as a complex adaptive system (CAS). The authors defined a CAS as "a collection of individual agents with freedom to act in ways that are not always totally predictable, and whose actions are interconnected so that one agent's actions changes the context for other agents." Also, ways in which healthcare systems fit the characteristics of a CAS were discussed. Two examples are clinical or administrative staff having personal obligations that may conflict with a change in practice hours, thereby creating fuzzy boundaries of the system, and care providers having different internal rules for how they choose to accommodate patient needs. These examples respectively exemplify the concepts of contextuality and internal inhomogeneity presented by Chu et al. (2003).

In the second article, Wilson and Holt (2001) demonstrated how complexity science applies to the diagnosis and treatment of patients as well as the promotion of healthy lifestyles. Clinical diagnoses are not always certain and there can be disagreement between clinicians, which are conditions that embody the characteristics of non-linearity and internal inhomogeneity from Chu et al. (2003). Also, patients have the autonomy of whether or not to follow a treatment plan, which the authors argued demands the need for clinicians to understand what attracts patients to healthy or unhealthy behaviors. These interactions between patients and clinicians align with definition of self-organization from Halley and Winkler (2008).

The third article is that of Plsek and Wilson (2001), who demonstrated how complexity thinking applies to the organization and management of healthcare systems. The authors promoted the development of system-level targets and pooled budgets to encourage the creativity needed to maximize value in care delivery, as opposed to specifying individual targets and budgets for each agency in the continuum of care. They proposed that leadership should set a system framework based on minimum specifications that have directional goals, set boundaries, identified resources, and established permissions. The authors suggested, "Leadership inspired by complexity theory recognizes that change occurs naturally within the system and that individuals engage in this effort for a variety of reasons." These prescriptions for healthcare system leadership respect the concepts of adaptivity from Chu et al. (2003) and self-organization from self-organization from Halley and Winkler (2008).

The four-article series concluded with Fraser and Greenhalgh (2001), who discussed the need for clinical education to include the development of capability in addition to competence. Capability entails adapting, learning, and improving, which the authors argued is essential in healthcare, especially when dealing with atypical patient presentations. The authors claimed that an education process providing concurrent performance feedback enhances capability. They offered an example in the "Norwegian continuing medical education system, where doctors in a peer group state learning needs, discuss ways forward, take action, and then report back on the feedback from the action." This learning process is described as one where "individuals can achieve more than the sum of the parts (non-linear effects in a complex system)" and the authors propose that "both content learning and non-linear learning methods are needed."

Shiell et al. (2008) argued that complex health interventions differ from interventions made in complex systems, which may require evaluation approaches to account for the dynamic characteristics of complex systems when they are significant. Complex interventions, while considered to be complicated by having many components, do not alone fit the definitions of system complexity. Alternatively, complex systems are presented as those having properties like interconnectedness and non-linearity. Interconnectedness can result in spin-off effects and the potential for stakeholders' concepts of value to change, while non-linearity can be seen in small intermediate changes being realized before a phase transition occurs. The authors provided evidence for these concepts in health policy evaluation by citing Siahpush and Scollo (2001), which documented the increase in support of public smoking bans after policy implementation. The authors concluded that when the effects of complexity stretch beyond the capabilities of existing valuation methods, new approaches become necessary. They proposed such approaches should involve data collection that is inclusive of potential spin-off effects and modeling techniques that account for non-linear effects and extended impacts.

2.3 Simulation Modeling to Assess System Performance

Kelton et al. (2015) indicated that simulation "involves systems and models of them" that are used to mimic real system behavior. Models "serve as a stand-in for studying" systems. The authors pointed out that systems, including their respective models, are often studied to measure performance, improve operation, or even evaluate a potential design.

Chu et al. (2003) stated a complex system can be modeled provided that (1) radical openness, or the interactions with an ambient environment, and (2) contextuality, or the sharing of elements with other systems that take part in other causal processes, are reducible. Furthermore, it is possible to represent some systems with more than one type of model.

Casti (1999) documented that a CAS has agents each making decisions based on deterministic functions of available information, yet the aggregate effect may appear to be random. A CAS can be modeled at the agent level provided that the following three conditions are true. First, there are a medium number of agents that is not too large for intuition and hand-calculation, and is not too small for statistical aggregation to sufficiently answer the study's questions. Second, the agents are intelligent and adapt their behavior by changing their rules, including generating new rules, on the basis of new information. Third, each agent gets only local information from a relatively small portion of the other agents and uses this information to reach a decision on the next action.

Barbati et al. (2012) provided a thorough review to evaluate the impact of agent-based models (ABMs) as they are presented in operational research and management science literature. Similar to the models discussed in Casti (1999), ABMs "consist of a set of elements (agents) characterized by some attributes, which interact with each other through the definition of appropriate rules in a given environment." The authors argued that an ABM provides a useful heuristic-based solution approach when the problem is of large size, has modularity in its domain (i.e., agents make decisions), and when the domain changes frequently (i.e., agents constantly modify or adapt their decision rules).

Regarding decision paradigms, an ABM consists of either a cooperative or a competitive paradigm. Cooperation-based interaction entails use of planning approaches to manage resource constraints so global goals are achieved, while competition-based interaction entails negotiation among self-interested agents, thereby hindering the opportunity for global optimization. Common uses of ABMs for optimization include scheduling, transportation / logistics, and supply chain planning.

In the event that statistical aggregation can sufficiently answer the study's questions, it is possible to use modeling approaches other than an ABM. Kelton et al. (2015) provided three dimensions to classify a simulation model. First, the model can be static or dynamic, where dynamic models are time dependent as they have trials whose results are a function of previous trials, while the trials of static models are independent from each other. Second, the elements of the model can be either continuous or discrete, where continuous elements are not bound by events that can only occur at separated points in time as is the case for discrete elements. Models can be purely continuous, purely discrete, or mixed. Third, the model can be either deterministic or stochastic, where a deterministic model does not have any random inputs like those present in a stochastic model. When statistical aggregation is suitable, stochastic models can be applied. In particular, the authors presented DES as a dynamic and discrete stochastic modeling approach that is useful for understanding business operations.

Anderson et al. (2006) acknowledged that MCS is historically understood to be a static simulation approach while many individuals today take the term to mean any form of a stochastic simulation. The authors presented a hypothetical example of modeling the operation of a computer manufacturer using the historical approach for MCS. In the

example, direct labor cost, parts cost, and first-year demand were all randomly generated to compute profits in a stochastic model that was static and continuous. While the example could have also been modeled using DES (e.g., order intake fluctuation requiring inventory, part expedites, and overtime costs), it demonstrated the ability to also use MCS for this type of problem.

Another modeling approach is system dynamic (SD) simulation. Sterman (2001) stated that SD modeling and simulation are tools to "design and evaluate new policies before implementing them in the real world." SD models account for the elements of dynamic complexity by incorporating feedback loops and stock and flow structures, which can both be shown on causal loop diagrams (CLDs). Feedback loops can be positive (i.e., self-reinforcing) and "amplify whatever is happening in the system" or they can be negative (i.e., self-correcting) and oppose changes in the system. A set of interacting model equations is derived from a CLD, with probability factors included for elements that have uncertainty and may dynamically change. The model equations can then be used in dynamic simulation to show time delays and nonlinear behavior of the system.

Halley and Winkler (2008) clarified that modeling a relationship at a system level with state variables (e.g., MCS and SD models) may be just as effective at predicting system behavior as a component-level model with individual events (e.g., ABMs and DES models). When a system-level model is reasonably as effective at prediction as a component-level model, the state variables of the system-level model are identified as "real emergent properties." The authors pointed out that the PV = nRT relationship of modeling the thermodynamic properties associated with a gas is at the system-level and,

while possible, component-level models that make the same predictions based on molecular dynamics would add negligible value to the analysis of gases in closed vessels.

Mustafee et al. (2010) included an overview of when each of these four simulation techniques is typically applied. DES was found to be popular for modeling queuing systems. MCS is typically applied when computation of an exact value for a response variable is "impossible or infeasible" using fixed values of input variables or by using deterministic algorithms. SD is used to analyze the "behavior of complex systems over time" with the core assumption that changing one part of a system "will impact all other parts of an interrelated system." Finally, agent-based simulation (ABS) is well-suited for modeling when assumptions at an agent interaction level do not infer obvious results at a system level.

2.4 Simulation Modeling in Healthcare: An Overview

There exists a multitude of examples where simulation has been applied to better understand healthcare, which affirms the previous comments on complexity in this field. Five literature review articles are discussed in this section. The following three sections (i.e., 2.5–2.7) contain a sample of articles from journals and conference proceedings that cover a diverse range of topics pertaining to simulation in healthcare. These papers are directly associated with the operations of healthcare facilities or supporting tools such as clinical science and economic evaluation, which may impact the decisions made within healthcare operations. Also, Section 2.8 discusses barriers to implementing recommendations from simulation models in healthcare given that such implementation

is rarely documented, which is a topic discussed in four of the five literature review articles in this section.

Jun et al. (1999) provided a literature review focused primarily on works published between the mid-1970's and 1997 of simulation applied to the operational needs of health care clinics. Topics addressed included patient flow, resource allocation, and other future opportunities for improvement. The authors found patient flow is addressed through scheduling and patient routing, and resource allocation has covered sizing and planning of beds, rooms, and staff. While the authors identified that use of DES in healthcare grew over the time period reviewed, there was little evidence of recommendations from simulations being successfully implemented. Future opportunities presented by the authors included complex multi-facility studies, leveraging optimization techniques with simulation, more user-friendly simulation software, and addressing implementation issues. Finally, an observation of this journal article is that it is referenced by all four of the other literature review articles showcased.

Fone et al. (2003) reviewed 182 papers published between 1980 and 1999 covering topics relating to computer simulation of stochastic systems with individuals in a population health or health service delivery setting. The authors used an appraisal method adopted from a prior published format that first screened each paper, then assessed its validity, and finally evaluated its overall results and findings. Papers were categorized into five topic groups. Articles related to hospital scheduling were found to be the most prevalent, but tend to be of poorer quality as compared to those for screening patients. A key deficit of hospital scheduling articles is that "very few papers reported that models had been implemented." In fact, the authors were "unable to reach any

conclusion on the value of modeling in health care because the evidence of implementation was so scant." However, an increasing trend in the "numbers of quality papers published in medical or health services research journals" was found. Regarding simulation methodology, the authors reveal that DES was the most commonly used modeling approach, while MCS prevails in cancer screening studies.

Brailsford et al. (2009) searched roughly 10,000 articles and methodically identified 342 articles for full review that pertain to simulation and modeling in healthcare contexts. These articles were published between 1952 and 2007 and are categorized by nine different attributes with subsequent analysis. This effort supported a broader aim of developing a user guide to suggest appropriate modeling methods relative to problem type in healthcare. While forms of modeling beyond simulation were considered, simulation was noted as "dominant in planning and system / resource utilization." Despite a growing trend with almost 50% of all modeling articles and over 60% of simulation articles published between 2000 and 2007, fewer than 10% of studies had their findings implemented regardless of modeling method. However, a significant number of studies' findings have been discussed with client organizations. Furthermore, the authors found evidence of unpublished modeling work in healthcare performed by business consultants and employed analysts based on commercial and promotional literature. Regarding funding of published studies, academia was the dominant source under any modeling method while commercial funding sources were primarily restricted to simulation studies.

Mustafee et al. (2010) queried papers published between 1970 and 2007 listed in the ISI Web of Science® database with simulation in the healthcare context. After initial

screening, 201 papers published between 1988 and 2007 were reviewed for categorization by simulation technique and topic, profiling of key attributes (e.g., authors, publication year, etc.), and strategic importance of papers and authors. Strategic importance was determined via a five-stage co-citation analysis. The authors found MCS to be the most commonly used simulation method followed by DES, SD, and ABS. Regarding applications, MCS was mainly used for health economics and evaluation of health interventions, DES was often applied for problems concerned with patient flow and resource scarcity, and SD was used for broad scale modeling of health systems and policy. The authors could not comment on the application trends for ABS as only two of the papers used this method, which were both published in 2006. The use of simulation in healthcare was observed as a growing trend due to the steady increase in publications between 2000 and 2007. Regarding key significant publications, the authors identified five turning point articles, three of which are included in this Chapter 2 with Jun et al. (1999) being one and the other two being discussed in the following pages.

Günal and Pidd (2010) provided a review of articles published between 1965 and 2009 that discussed DES modeling in healthcare with a focus on patient flows through hospitals and their departments. Articles were classified by hospital area of application and accident and emergency (A&E) units were the most popular application for DES, with a variety of modeling objectives mentioned. Inpatient units and outpatient clinics were other popular areas for modeling. Inpatient models tended to focus on "patient flows to hospital beds, bed occupancy, and length of stay (LOS)" while outpatient models were mostly concerned with scheduling and capacity planning. Despite other areas like operating rooms and critical care units having been modeled, there were very few

examples of whole hospital DES models and most studies were unit specific, which the authors found to potentially neglect interactions with other units. The authors also identified long project cycle times, project cost, and determining the appropriate model accuracy as factors that continue to serve as "barriers to the successful implementation of simulation." While generic modeling software exists, the vast majority of articles focus on models developed for very specific applications, and the authors conclude this lack of genericity has resulted in case studies that seldom lead to common insights or general theory.

2.5 Simulation Modeling in Healthcare: DES Models for Operations

This section provides an assortment of papers demonstrating the use of DES to model healthcare operations. Applications have included a variety of surgical, inpatient, and ambulatory care environments. Five papers discuss models developed and a sixth article relates to the use of modeling software designed for the healthcare industry.

The earliest healthcare operations simulation paper reviewed is Schmitz and Kwak (1972). The authors used DES to determine how many new operating rooms (OR) and recovery rooms (RR) were needed to accommodate an expected increase in surgical volume. Also, a method was detailed for forecasting the volume increase, which was based on a 144 bed expansion of the medical-surgical (M/S) unit. The forecast assumed that expansion of the M/S unit would result in full bed utilization and that increased surgical demand would have the same case mix as the prior year. Simulation was then used to determine the number of OR's and RR's needed such that delays would not occur once surgery began. The only stochastic variable in the model was the type of surgery

performed, which was determined based upon generating a single random exponential number (REN) from a single uniform random number (URN) for each event. Surgical duration, whether or not a RR is used, and time spent in the RR were all based on the REN and were unique values for each surgical case type. Other variables like transfer time from an OR to an RR, and make-ready times for OR's and RR's are all constant values regardless of case type. Additional daily surgical volumes were fixed at 27 cases per day, "which was the predicted new surgical load due to the increased bed compliment." Despite the limited amount of simulated values, the authors claimed that the method applied was "extremely accurate" once actual observation of the constructed department was possible.

Dexter et al. (1999) discussed use of DES to derive an OR scheduling strategy that maximizes OR utilization. Simulating OR suites allowed the research team to gather a substantial amount of data and generate statistically meaningful findings, as decades or more of real world samples would have been required due to the presence of auto-correlation in successive OR utilization measurements. The model included five input parameters that required 216 combinations of discrete values to determine significant factors, and the average delay in patients being scheduled for surgery was found to have the greatest impact on OR utilization in an inverse relationship. Eleven questions addressing the concerns of key stakeholders (i.e., patients, surgeons, anesthesiologists, OR managers, etc.) were formulated to evaluate alternative strategies for managing varying objectives that may have conflicted with one another. For example, a key concern for patients was extensive delays to having surgery, while OR utilization was a substantial concern for hospital leaders due to high staffing costs that were relatively

fixed. The authors proposed a three-part scheduling strategy that first allocated block times (i.e., specified time windows for surgery) to surgeons based on the expected time needed for elective cases. Second, patients were scheduled into the first available open block provided it fell within four weeks of the request. Third, patients who were not assigned to an open block within four weeks of the request were then scheduled in an overflow time outside of a block. The proposed strategy involved shifting the locus of control for scheduling "from the surgeon and patient to the OR suite," which presented a barrier to implementation.

Swisher and Jacobson (2002) shared a DES model developed to recommend operational parameter settings for a two-physician family practice healthcare clinic based on the results of simulation optimization to maximize clinic effectiveness (CE). CE is a multi-attribute variable "constructed on a monetary scale" that considers clinic profit, patient satisfaction, and staff satisfaction. A two-physician clinic was selected for the study "due to their prevalence, especially among those clinics that do not have an existing network or hospital affiliation." A fractional factorial experimental design was applied to identify four significant parameters out of the six considered. Afterward, the authors applied a two-stage optimization technique in the model, which first eliminated any statistically non-optimal solutions and then presented optimal solution alternatives that maximized CE for further evaluation. Clinical decision-maker(s) were involved in the study presented, but there was no evidence presented of the model being used to make operational decisions.

Ahmed and Alkhamis (2009) proposed a method using system simulation combined with optimization to maximize throughput in an emergency department (ED)

by considering different staffing distributions across functional roles (e.g., doctors, nurses, etc.). A DES model was nested in the optimization model to quantify average throughput and delays. The optimization model used a two-phase approach where Phase I identified feasible and near-feasible solution alternatives to be evaluated in Phase II, which identified the optimal solution from the alternatives. The optimization model had a mix of stochastic and deterministic functions between the objective and constraints with patient arrival rates and process service times as the stochastic variables. Despite the model finding an optimal solution that improved service performance while not exceeding current costs, hospital management had concerns over the impact to staffing distribution efficiency and overall individual waiting time. Unfortunately, there was no evidence of any recommendations being implemented.

The final paper reviewed that documents a healthcare operations study using DES is Thorwarth et al. (2009), which showed how DES was used to validate an analytical model for assessing utilization in the flexible workload environment of an ED. The workload was flexible since nurses managed a variety of separate tasks for a several patients during the same timeframe. The analytical model could be used to predict utilization based on patient interarrival time, service time, the number of staff, and the number of tasks, where utilization was the product of activity utilization and staff utilization. The results of the analytical model were compared to those of the simulation model and differences were "ultimately due to the variability caused by random arrival rates." The authors determined that system instability, which was represented in high utilization and ever growing wait times, occurred when the longest service rate was greater than the arrival rate and when the number of staff was less than the number of

tasks. While there was no evidence that the model had been used by operational decision makers, the authors proposed that it could have been used to vary staffing levels such that utilization would not exceed 85% as studies were cited to show the costs of excessively high utilization. These costs included occupational burnout, absenteeism, higher error rates, and increased patient mortality risk. The model was limited due to its simplification of only considering nursing staff and that it did not account for service rate variation, however the authors contended that decision makers could "still use the model to achieve a greater transparency" of conditions critical to system operation.

Regarding software for modeling operations with DES, Harrell and Lange (2001) showcased MedModel, a simulation software specifically designed for healthcare operations. The authors argued that specialized simulation software was necessary for the healthcare industry due to its unique issues. Process flows in healthcare operations were described as complex due to variable pathways, multiple tasks that may be repeated, and other forms of operational variety. For example, the software employs patient identity numbers to match split entities (e.g., when a lab is processed while a patient flows to radiology for a test). MedModel also allows for a number of queue management rules and representative logic allows for resources to be preempted, given that both of these functions are important in healthcare as priorities are often based on patient acuity. Program logic also supports resources being used for a wide variety of tasks or situations, flexible shift patterns, and both bidirectional and unidirectional pathways. Finally, MedModel was designed so model code could be programmed in a menu-driven logic builder with a user-friendly interface. Despite such efforts to make the software

functional and user-centered in its design, the authors did not provide any real world applications of the software.

2.6 Simulation Modeling in Healthcare: Other Models for Operations

This section reviews papers on the use of simulation methods for modeling healthcare operations other than DES alone. These include MCS and SD modeling, which can also be used in conjunction with DES. Two papers covered modeling applications and another two discussed modeling approaches.

Harrison et al. (2005) shared the development of a simulation model to calculate bed occupancy of a hospital's medical division while accounting for variability in admissions and transitions of care between three stages that may all exist in the same unit. In their review, Günal and Pidd (2010) classified this model as a "Monte Carlo model rather than a DES model," while detailed inspection revealed that the model was dynamic and system state variables were simulated rather than event-level variables. The authors found that the model had at least five areas of application for hospital administrators. The areas of application included identifying abnormal bed demand levels and contributing factors, determining target occupancy rates, assessing the impact of growth or expansion, understanding the impact of short-term vs. long-term occupancy, and evaluating tactics to smooth variability. Regarding its breadth of application, the model was formulated in a way that produced generic equations for any hospital to use, thereby contributing knowledge that is broadly applicable in healthcare. Regarding the model's validity, admission and transition parameters for stochastic input variables were derived and validated using actual hospital data along with the final model output

showing “no statistically significant difference” when compared to actual occupancy data. The authors concluded that understanding the “variability in the number of beds occupied is essential to improving the management and increasing the efficiency of hospitals” and that “smoothing out the variation in discharge rates may be more effective than smoothing the variations in admission” based on the various model results. However, no evidence of the model being used or key findings being implemented was provided.

Brailsford et al. (2004) discussed the creation of an SD model consisting of both qualitative and quantitative phases to simulate the flow of admissions to hospital wards from various pathways and identify bottlenecks in the broader healthcare system of Nottingham, England. SD modeling was applied due to the size of the system being modeled and computational efficiency concerns associated with large scale DES models, whereas a DES model was used to investigate patient routing options within the A&E unit. The SD model was validated by having the key stakeholders of the project’s Steering Group be engaged with its qualitative structure and by having its quantitative output for bed occupancies compared to actual data that was not part of the model’s construction. Data in the model consisted of patient encounter information and arrival rates through two sources channeled to seven sectors before inpatient admission, however the “quality and level of data were variable.” Stakeholders benefited from the qualitative phase by gaining a complete view of the system and gathering insights on system interactions impacting their respective components. The quantitative phase yielded value by demonstrating the impacts and effectiveness of different interventions aimed at improving flows by reducing emergency admissions and the Steering Group was “keen to

suggest alternative scenarios for testing." The study had been conducted jointly "with a health and social care community" that valued the system-level approach to development. The authors claimed that both the "process and findings of this independent inquiry" appeared to have favorably impacted local efforts to solve emergency care access problems.

Regarding the use of SD, Taylor and Lane (1998) contrasted the value of SD simulation to understanding and solving problems in healthcare with that of traditional simulation approaches. A detailed comparison between SD and DES is provided to highlight these differences. While the authors acknowledged that the stages of developing an SD model are similar in their respective scopes and challenges as other modeling approaches, SD models provide some advantages. Specifically, SD adds unique value in its ability to model both the physical and information delays associated with dynamic complexity and to capture organizational complexity "through the explicit representation of intangibles and the distinction between perceived and actual values." However, the authors stated that SD is limited in considering detailed complexities, whereas "DES primarily concentrates on detail complexity." A hypothetical example of addressing waiting times for coronary heart disease (CHD) treatment was provided where both DES and SD are used for different purposes. The DES model focused on changes to treatment strategies and localized decisions to impact queues within hospital, while the SD model was concerned with the "feedback processes underlying changes to waiting" including treatment effectiveness. The authors concluded that "no single modeling approach can offer a panacea to management problems" and "it is important to acknowledge the limitations of a method and to understand its scope."

Regarding the use of SD and DES together, Chahal and Eldabi (2008) argued that both detailed operations and environmental interactions need to be understood to make effective and sustainable decisions in healthcare systems, which were viewed as complex and adaptive. The authors proposed using a hybrid approach that applies both discrete-event simulation (DES) and system dynamics (SD) for each mode of governance presented. In a top-down mode where leadership at the strategic level set targets and passes them down to operational management, a hierarchical method can be used. This starts with strategic level decisions represented in an SD model that are then passed to a DES model to validate operational feasibility via a cycle of output from one model being used as input to another. In a network partnership mode where pathways for patient care span a network of independent service providers, a process–environment method can be used. This functions similar to the hierarchical method, but starts with process changes being represented in a DES model. Finally, in a quasi-market mode where strategic leadership and operational providers are bound by contracts, an integrated method can be used with elements represented in either model. Similar to Taylor and Lane (1998), the authors found that DES is effective for modeling detailed operations, while SD is effective for capturing dynamic complexities from interaction between system components, so the two modeling methods can complement each other.

2.7 Simulation Modeling in Healthcare: Models beyond Operations

In this section, seven papers are reviewed that discussed modeling a variety of topics in the fields of clinical science, health economics, and healthcare accreditation. These papers provide examples of DES, MCS, and SD models. Three papers that used

DES are presented first, followed by two papers that used MCS and then another two papers that used SD modeling.

Barth-Jones et al. (2000) demonstrated the use of DES to validate that retrospective partner trial (RPT) study designs are accurate and have significant statistical power in estimating human immunodeficiency virus (HIV) vaccine effectiveness parameters provided sufficiently large sample sizes are used. Standard vaccine trial design is only capable of detecting Vaccine Effects on Susceptibility (VE_S), where susceptibility is the risk of becoming infected. However, RPT and DES designs can additionally evaluate Vaccine Effects on Infectiousness (VE_I), where infectiousness is the ability of an infected individual to transmit the disease to other individuals. Both VE_S and VE_I are important for reducing transmissibility and the study showed a >90% chance that an RPT design would have found a vaccine that reduces transmissibility by 81.25% to be efficacious. However, a standard vaccine trial design would have a ~50% chance of rejecting the same vaccine due to its low VE_S value. DES was used to find that HIV infection risk varies among individuals due to epidemic transmission dynamics as it provides perfect information with all events being known. RPT study design, however, has incomplete information as partners may not be remembered or may not be contacted. Despite this concern with RPT design, the authors found that it has sufficient statistical power when partner data is randomly missing based on comparisons with DES study results.

Cooper et al. (2002) detailed the development of a model depicting the treatment and subsequent disease states and interventions for coronary heart disease (CHD) patients who have had a coronary event. The model used DES to simulate the next event type

(i.e., disease state or intervention) and time following the current event. Past surveys and studies were used to define model data used for time-to-event parameters and event type probabilities with assumptions and extrapolations having been made when desired prognostic factors were not "broken down sufficiently." The main difficulties the authors encountered in gathering model data were discrepancies between studies using different approaches to acquire data, patient and other factor or result categories being excluded from studies, complete absence of desired data, and diagnostic coding errors or limitations jeopardizing the quality of data. Patient Oriented Simulation Technique (POST) software, which allows for more than one future event to be prescribed to patient entities with the possibility of events taking place in parallel, was used to write simulation code. The simulation showed a 50% increase in angiogram referrals and doubling bypass grafts and angioplasties had negligible effect on rates for myocardial infarctions and CHD-related deaths. The authors planned to continue model development through refinement of the parameters and they concluded that initial results pointed to higher volumes of revascularizations having minimal impact on myocardial infarction and death rates.

Babad and Sanderson (2002) is the second turning point article from Mustafee et al. (2010) featured in this chapter. In their work, the authors described the process of developing the primary prevention strategy component of a model for assessing the economic impacts of various Coronary Heart Disease (CHD) management approaches. The model, which was still under development during publication, used DES to simulate the time between events that trigger "changes in risk factors and/or changes in disease status" for "individual members of populations" serving as model entities. The model

data used to define time-to-event parameters were based on past surveys and studies. While some desired data elements were not available, the authors planned to include such data in future versions of the model. Other parameters defining probabilities of patient behavior in response to prescribed treatment and treatment effectiveness were based on estimates gathered from literature review. Regarding model setup, it was designed for users to specify or confirm parameters prior to running the model, which allowed for various intervention strategies to be evaluated. To run the model, simulation routines established "specifically for modelling healthcare systems" were applied and flags were set when non-fatal disease events occur, which triggered the treatment model component described in Cooper et al. (2002). Regarding validation, the authors mentioned a forthcoming paper that would provide details on testing for technical accuracy and consistencies in the model pertaining to "the feasible range of parameter values" and the "model's results with observed data."

Zenios et al. (1999) investigated alternative methods for allocating cadaveric kidneys with the aim of identifying the method that best balances efficient allocation and equitable allocation, especially in terms of racial equity. Four alternatives were evaluated against two efficiency measures, which were patient survival and quality-adjusted life expectancy, and two equity measures, which were waiting time and likelihood of transplantation. The current allocation strategy at the time, which was the point system used by the United Network of Organ Sharing (UNOS), was considered along with three other allocation methods. These were a first-come first-transplant (FCFT) system, an efficiency-based algorithm, and a distributive efficiency algorithm, which mimicked the efficiency-based algorithm except that race was not considered in prioritization. The

authors described using an MCS model to simulate the "operations of a single organ procurement organization" and generate results from a 10-year simulation run length, which was found to be sufficient from the sensitivity analysis performed. The model contained five internal models, which simulated arrival rates for candidates and donors, patient outcomes while waiting for transplantation and following such treatment, and the decision-making for organ allocation. Data for model parameters were gathered from UNOS and United States Renal Data System (USRDS) reports and sensitivity analysis of model parameters did not change qualitative findings. The distributive efficiency algorithm was found to provide the greatest benefits overall without penalizing African-Americans. Thus, the authors concluded the development of "evidence-based policies that simultaneously improve health outcomes for all patients with end-stage renal disease" is possible.

Kahn et al. (2007) described how cohort data from a clinical database was used in an MCS study to analyze changes in the Standardized Mortality Ratio (SMR) from increasing the out-of-hospital transfer rate. SMR compares the hospital's mortality rate to an expected value based on severity of illness and case mix with any value over one indicating an elevated mortality rate. The study was performed using a final cohort of 85 Intensive Care Units (ICUs) and the data gathered contain seven discharge locations, including dead, with two being considered as transfers to other care centers. The MCS model applied an algorithm that adds a uniformly distributed random number to each patient's scaled risk of hospital death score in order to identify upper percentile patients for transfer. Simulations were performed at transfer increases of 2% and 6% above baseline, where all patients who were not originally transferred but selected by the

algorithm were recoded as a living transfer discharge, including those who were originally coded as dead. Subsequently, "SMR was recalculated" along with transfer bias, which is defined as "the difference between the mean simulated SMR and the original SMR." The study found that increasing out-of-hospital transfers causes "a significant downward bias in the SMR at both 2% and 6% above baseline" and an ICU could significantly improve its SMR rank. The authors argued in their conclusion that the "transfer bias presents an important limitation to the SMR" and "uncritical use of the SMR to benchmark ICU performance is likely to misinform rather than provide meaningful information about ICU quality."

Banz et al. (2003) discussed a study to evaluate three vaccination strategies for varicella (or chickenpox) in Germany against the current strategy at the time, which only administered vaccines to high risk groups and was also known as a "no vaccination" strategy. The study used a model, referred to as economic varicella vaccination tool for analysis (EVITA), to assess the economic impacts of each vaccination strategy from both societal and payer perspectives. While not explicitly identified as such, EVITA could be classified as an SD model based on its structure and operation. The authors described EVITA as being an "age-structured deterministic model based on a set of differential equations" where "probabilities at each chance node determine the flow of patients through the simulation tool." In the model, the population was "divided into 1-year age cohorts" from age 0 to 70 and a time-step d*t* of one year was used for a simulation length of 30 years. Probabilities of infection, or annual attack rates, were set for five age categories and probabilities were also set for other factors including vaccination coverage, vaccine efficacy, and clinical outcomes. In addition to a base case, best and

worst case scenarios were developed by simultaneously varying parameters that had "considerable uncertainty and high sensitivity" with vaccination coverage and various costs. The various cost discount rates were identified as having the highest sensitivity. The key finding of the study was that a strategy to vaccinate children between 12 and 18 months of age or another strategy that also vaccinates adolescents between 11 and 12 years of age are both substantially more effective that the current strategy or one that only vaccinates adolescents. However, this finding assumed vaccination coverage rates of 75% or more and the authors also concluded coverage rates below 50% could cause the average age of infection to increase, which results in worse outcomes and higher costs.

The third and final turning point article from Mustafee et al. (2010) presented in this chapter is Hammerschmidt et al. (2003). In the paper, the authors presented the efforts to validate the EVITA model proposed in Banz et al. (2003) as "the acceptance of models is highly dependent on their validity." Five validation methods were discussed and the authors were able to apply four of the five methods, which the authors used to collectively validate the model. EVITA was said to meet descriptive validity as Module 1, which was "an age-structured, deterministic model" leading up to the point of infection, was "based on an established and peer-reviewed model." Module 2 of EVITA, which "describes the course of varicella and its potential complications as well as the associated health-care resource utilization," was found to meet descriptive validity. The authors held this claim since the "data and development" were "reviewed by a German expert panel and deemed to provide an adequate picture of the course of varicella and its clinical management in Germany." Technical validity was proven by applying extreme values to generate outcomes that would have been expected and face validity was shown

as the model produced a result similar to that of prior literature for vaccination coverage levels required to eliminate varicella when the same assumptions were made. Convergent validity was demonstrated by "comparing the results of other models with the result of the EVITA model" and finding similar results when accounting for parameter differences. However, the authors could not assess predictive validity since "no data are available on the effects of universal varicella vaccination in Germany."

2.8 Simulation Modeling in Healthcare: Barriers to Implementation

As previously mentioned, four of the five literature review articles presented in Section 2.5 indicated that recommendations from simulation models in healthcare are rarely documented as being implemented. The next three papers have discussed barriers to such implementation.

Sanchez et al. (2000) provided a compilation of submitted statements from the authors for a panel discussion at the 2000 Winter Simulation Conference. The intent of the discussion was to identify key issues that need to be addressed for simulation to be effective in healthcare, and the authors represented the healthcare industry, consulting, and academia. Many of statements made were shared amongst the authors and they acknowledged that simulation can help healthcare leaders understand processes so that realistic financial performance targets can be set with operational plans to achieve them. However, healthcare models often have conflicting objectives when "the opinions of hospital managers clash with those of medical personnel." Other barriers to effective modeling include lack of available data and the extensive time often required to observe healthcare processes in developing a representative model. Data availability and integrity

is of critical concern as "small variations in some distribution parameters, or (worse) a change in the distribution itself, usually leads to significant changes in model results" and possibly different conclusions. The authors recommended that both operational and clinical leadership be engaged in projects for these barriers to be addressed and for key model recommendations to be supported for implementation.

Eldabi and Paul (2001) argued that traditional simulation modeling approaches do not focus on problem formulation and structuring, which are key to understanding problems, and that problem definition is paramount to modeling healthcare problems. The authors proposed a modeling approach that demands iterative communication between various stakeholders and the model itself during model development, which helps to ensure that objectives and constraints are properly expressed. The approach is referred to as a Modeling Approach that is Participatory Iterative for Understanding (MAPIU) and it consists of an initialization stage and a processing stage. Initialization classifies stakeholders as problem owners, experts, and actual users in order to "ease the process of collecting the right information based on the needs of the problem owners for a given problem." The processing stage entails modeling, communication, and deriving information, which are parallel components that evolve during the modeling process. An example of using MAPIU to model the decision making process for liver transplant allocation is provided with stakeholders being health economists, who are classified as problem owners and actual users, and clinicians, as experts. These stakeholders have differing views regarding the method for liver allocation, which drives iteration through the processing stage components to reach a final model. The authors concluded that MAPIU features of stakeholder participation and iterative processing aim to address the

challenges associated with "lack of understanding of the healthcare process by the concerned people," conflicting objectives, and intercommunication difficulties.

Brailsford (2005) discussed the obstacles to successfully implementing recommendations from simulation models in healthcare environments and offered insight to why these obstacles exist. The author presented an example of a successful implementation effort, which addressed meeting demand for emergency care in Nottingham, England as documented in Brailsford et al. (2004), which was reviewed in Section 2.6. Factors for success with the example are identified as "impetus for the project" coming from the client, a "charismatic and enthusiastic local sponsor" chairing a Steering Group that was involved in model development, a multi-disciplinary research team, and a high priority on data collection. Regarding barriers to implementing recommendations from any project, the author defined such challenges pertaining to culture, cost, data, incentives, and the level of specificity required. Recommendations were made for academia and practitioners, modeling software developers, and healthcare providers. Academia and practitioners were advised to address problems critical to hospitals and patients, identify "enthusiastic and powerful" project sponsors, create multi-disciplinary teams, and balance "user-friendliness with scientific rigor and validity" in models. Developing models that can be easily tailored for various hospitals by identifying the "basic components of all patient flow systems" was an additional challenge that was also extended to software developers and MedModel is cited as such an attempt, which was presented in Section 2.5 with Harrell and Lange (2001). Finally, the author encouraged healthcare providers to pool resources with partners and work

together, overcome "cultural issues and resistance to change," and implement "robust, practical data collection systems."

2.9 Observations of Existing Literature

The literature shared in this chapter has put forth a number of concepts relevant to this dissertation. First, organizations can be viewed as complex systems and their complexities can be defined in a myriad of contexts. Also, healthcare organizations are recognized as having great complexity.

Regarding simulation, a system can be modeled as long as its complexity is reducible, and there are multiple approaches to system modeling and simulation. The literature focuses on models used to evaluate potential system designs and how performance would differ from the current state. There does not appear to be use of simulation to evaluate current or past performance or the effectiveness of a new system design that is already implemented. In healthcare, such use is even less likely due to the lack of implementation associated with simulation study recommendations. In fact, in gathering papers for the literature review, a search in Google Scholar used the phrases "simulation performance analysis organizations" and "model performance analysis organizations" to see if any papers address the two questions posed in Chapter 1. Google Scholar was used due to the breadth of its search capabilities, but none of the papers sampled had titles or abstracts covering this interest.

Regarding performance analysis, current health economic valuation approaches do not utilize modeling techniques that account for non-linear effects and extended impacts from interconnected system components. Therefore, problems may exist in some

models that prevent them from being used for assessing effectiveness of changes made. Also, metrics may be chosen as performance indicators without consideration of all the influencing factors, and this may be especially true for healthcare quality measures. Given that healthcare organizations are identified as being highly complex and that their performance metrics may have many influencing factors, a case study in healthcare operations seems appropriate in validating an approach to answering the two questions posed in Chapter 1. Chapter 3 presents the methodology proposed to answer these two questions.

CHAPTER 3

METHODOLOGY

The proposed method seeks to answer the two questions posed in Chapter 1 using simulation. These questions, which are restated below, are graphically depicted in Figures 1 and 2.

> **Question #1:** If the post-change approach existed in the baseline, how would the baseline (pre-change) performance have differed?
>
> **Question #2:** If the baseline approach still existed, how would the post-change performance have differed?

The solid line in Figure 1 shows the actual performance between time T_0 and T_1, while the dashed line indicates performance between T_0 and T_1 if the post change approach were in place during T_0. The estimated value for $Y_{0'}$ is better than Y_0, which indicates that performance would have been improved in T_0 had the change been in place. Conversely, in Figure 2, the dashed line demonstrates performance between T_0 and T_1 if the change had not been in place during T_1, while the solid line is the same as that of Figure 1. Y_1 is better than the estimated value for $Y_{1'}$, which indicates that performance in T_1 would have been worse had the change not been in place. While this example shows that actual performance has benefited from the change, this will not always be the case.

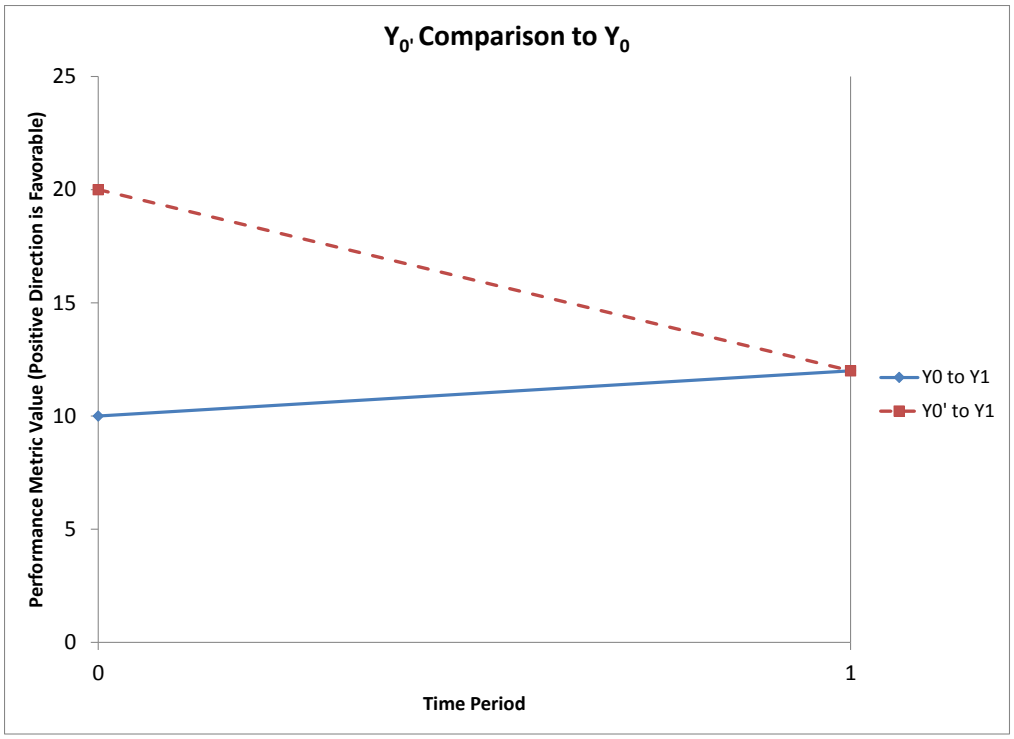

Figure 1: Graphical depiction of answer to Question #1

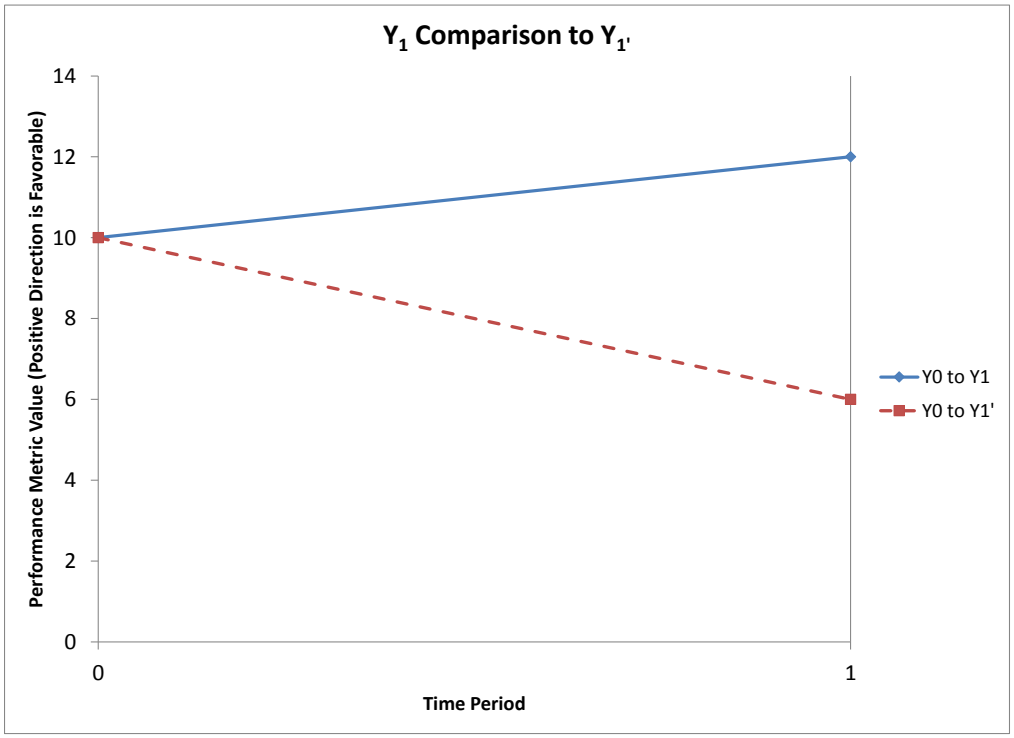

Figure 2: Graphical depiction of answer to Question #2

In order to answer these questions, a procedure is developed as the central focus of this research. This procedure involves using a modeling approach that applies factor values that are derived from statistical aggregation in simulations to develop statistical distributions of comparison values that are then analyzed. This procedure first begins with an analysis of the baseline as described in Step 0.1 below:

Step 0.1 Identify a representative model linking the performance metric (response variable) to the input variables (factors), of which at least one needs to be stochastic in nature.

Question #1 above can be answered with the approach outlined as follows:

Step 1.1 Use simulation to develop a distribution of the response variable based on the model.

Step 1.1.1 Identify distributions of factors in the baseline data.

Step 1.1.2 Use simulation to develop a distribution of the response using the model from Step 0.1 and the factor distributions from Step 1.1.1.

Step 1.2 Determine the probability of the baseline performance observation along with the cumulative distribution function (CDF) for the distribution found in Step 1.1.2. Record this as the baseline CDF probability.

Step 1.3 If necessary, repeat Step 0.1 to identify any new relationship between the response and the factors following the change made. If the model from Step 0.1 is still valid, continue using that model.

Step 1.4 Use simulation to develop a distribution of the response using the model from Step 1.3 and factor values from Step 1.4.1 and Step 1.4.2. Record these as $T_{0'}$ factor values.

Step 1.4.1 For factors that have been influenced by the change, identify the new values or distributions from the post-change data. Apply these to the simulation as this is necessary to reflect the new method.

Step 1.4.2 For factors that have not been influence by the change, leave values or distributions as they were in the baseline.

Step 1.5 Determine the simulated baseline value ($Y_{0'}$) based on the baseline CDF probability from Step 1.2 and the distribution found in Step 1.4.

Step 1.6 Compare the simulated baseline ($Y_{0'}$) from Step 1.5 to the actual baseline performance observed (Y_0). Express the performance shift ($\Delta_{0'/0}$) in % $Y_{0'}$ improved over Y_0 performance terms based on the desired direction of $\Delta_{0'/0}$ as defined in Equation (1).

$$\Delta_{0'/0} = \begin{cases} (Y_0 - Y_{0'})/Y_0 \,, if\ the\ desired\ direction\ is\ to\ lower\ Y \\ (Y_{0'} - Y_0)/Y_0 \,, if\ the\ desired\ direction\ is\ to\ raise\ Y \end{cases} \quad (1)$$

Step 1.7 Repeat Steps 1.1–1.6 to develop a distribution of comparison values.

Step 1.8 If a targeted performance shift was set, determine the probability of the targeted performance shift along with the CDF for the distribution found in Step 1.7. Record this as the baseline performance shift CDF probability. If a targeted performance shift was not established, review the distribution of comparison values from Step 1.7 and analyze the results.

Step 1.9 Estimate the probability that the targeted performance shift would have been achieved in the baseline by subtracting the baseline performance shift CDF probability from one.

A process flow diagram of the procedure to answer Question #1 is shown in Figure 3.

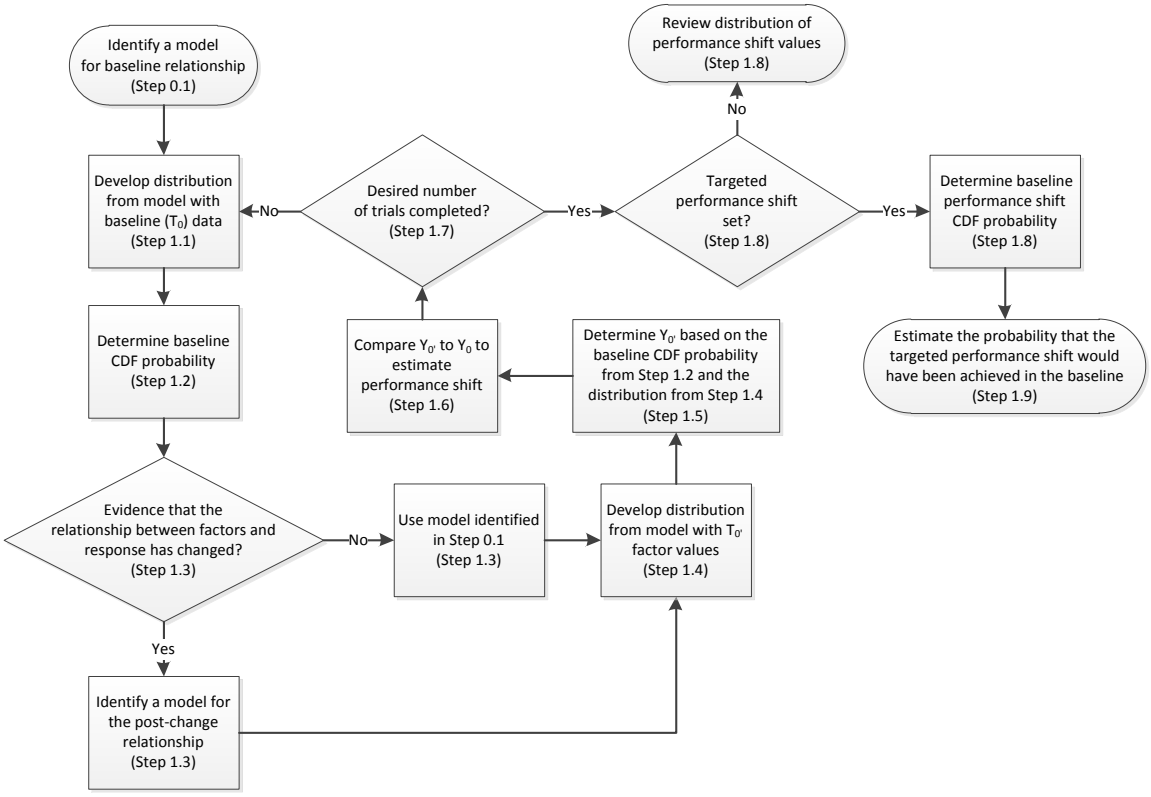

Figure 3: Process flow diagram of the procedure to answer Question #1

Question #2 above can be answered with the approach outlined as follows:

Step 2.1 If necessary, repeat Step 0.1 to identify any new relationship between the response and the factors following the change made. If the model from Step 0.1 is still valid, continue using that model.

Step 2.2 Repeat Step 1.1 with the post-change data.

Step 2.2.1 Identify distributions of factors in the post-change data.

Step 2.2.2 Use simulation to develop a distribution of the response variable using the model from Step 2.1 and the factor distributions from Step 2.2.1.

Step 2.3 Determine the probability of the post-change performance observation along with the CDF for the distribution found in Step 2.2.2. Record this as the post-change CDF probability.

Step 2.4 Use simulation to develop a distribution of the response using the model from Step 0.1 and factor values from Step 2.4.1 and Step 2.4.2. Record these as $T_{1'}$ factor values.

Step 2.4.1 For factors that have been influenced by the change, leave values or distributions as they were in the baseline.

Step 2.4.2 For factors that have not been influenced by the change, identify the new values or distributions from the post-change data. Apply these to the simulation as this is necessary to reflect the post-change environment.

Step 2.5 Determine the simulated post-change value ($Y_{1'}$) based on the post-change CDF probability from Step 2.3 and the distribution found in Step 2.4.

Step 2.6 Compare the actual post-change performance observed (Y_1) to the simulated post-change ($Y_{1'}$) from Step 2.5. Express the performance shift ($\Delta_{1/1'}$) in % Y_1 improved over $Y_{1'}$ terms based on the desired direction of $\Delta_{1/1'}$ as defined in Equation (2).

$$\Delta_{1/1'} = \begin{cases} (Y_{1'} - Y_1)/Y_{1'}, & \textit{if the desired direction is to lower } Y \\ (Y_1 - Y_{1'})/Y_{1'}, & \textit{if the desired direction is to raise } Y \end{cases} \quad (2)$$

Step 2.7 Repeat Steps 2.1–2.6 to develop a distribution of comparison values.

Step 2.8 If a targeted performance shift was set, determine the probability of the targeted performance shift along with the CDF for the distribution found in Step 2.7. Record this as the post-change performance shift CDF probability. If a targeted performance shift was not established, review the distribution of comparison values from Step 2.7 and analyze the results.

Step 2.9 Estimate the probability that the targeted performance shift would have been achieved in the post-change environment by subtracting the post-change performance shift CDF probability from one.

A process flow diagram of the procedure to answer Question #2 is shown in Figure 4.

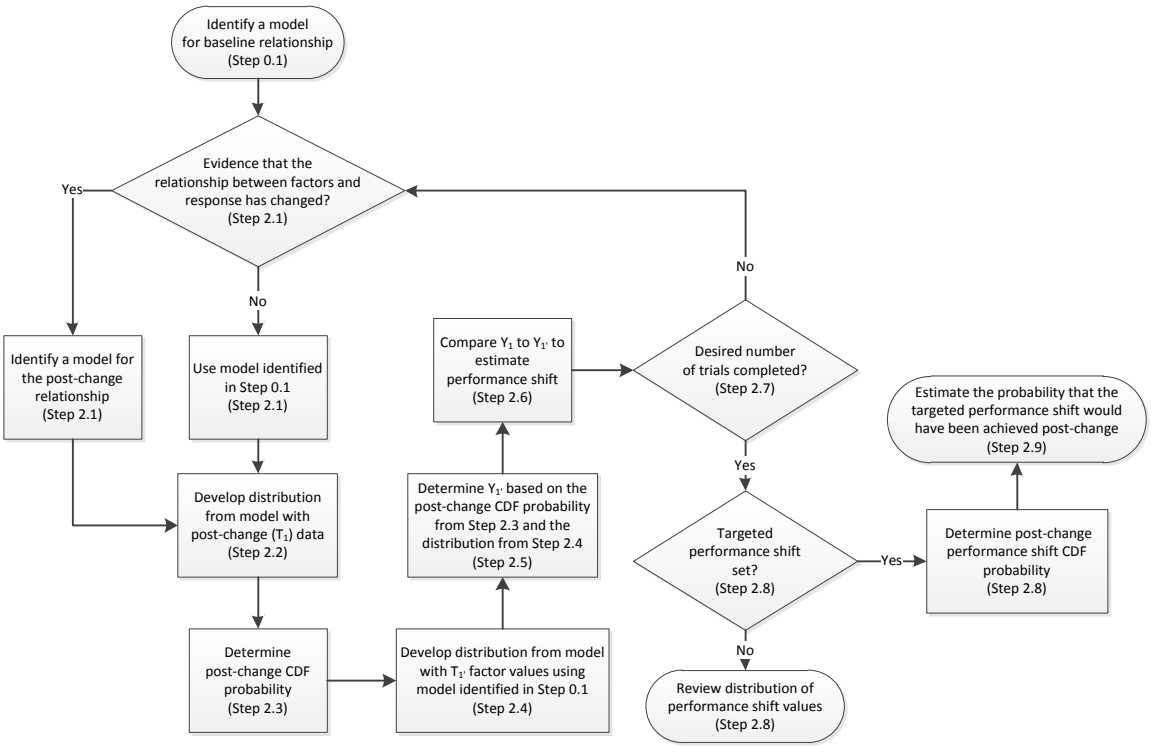

Figure 4: Process flow diagram of the procedure to answer Question #2

The application of this procedure is demonstrated in Chapters 5 and 6. Detailed explanation of each procedural step is provided in these chapters to illustrate the underlying logic of the procedure. However, the following paragraphs include some general comments on the procedure.

Selecting the modeling approach is paramount in Step 0.1. As Kelton et al. (2015) stated, the type of model chosen will depend on how the system can be described. As shown in the case study presented and analyzed in Chapters 4–6, there may be more than one way to describe, and thereby model, the system.

The possibility of needing to develop a new model is raised in Steps 1.3 and 2.1. Such a need depends on the modeling approach and the changes made. In a regression-based model, factor values beyond the range observed in the baseline would require new model formulation according to the assumptions associated with the use of regression models as stated by Montgomery (2013). Regarding a DES model, a structural change in the system would require a new model to be developed. For example, if two process steps are coupled into one step, then a queue is eliminated.

The term CDF probability is used in several of the procedure's steps. As Devore (1995) indicated, CDF probability is the location of a particular value in the outcome distribution, a figure that is measured from zero to one. The CDF probability can also be thought of as the chance that the particular value of interest is greater than a randomly selected value in the outcome distribution.

In Step 1.2, the baseline CDF probability is calculated using the distribution of possible performance values given the distributions of the inputs during T_0 and the actual performance metric value of T_0 (Y_0). The baseline CDF probability is used in Step 1.5 to estimate the value of the performance metric in T_0 if the input parameters affected by the change were in place during T_0 while considering the same CDF probability associated with Y_0. This metric is referred to as $Y_{0'}$ and the altered state of T_0 is referred to as $T_{0'}$.

In Step 2.3, the post-change CDF probability is calculated using the distribution of possible performance values given the distributions of the inputs during T_1 and the actual performance metric value of T_1 (Y_1). The post-change CDF probability is used in Step 2.5 to estimate the value of the performance metric in T_1 if the input parameters affected by the change were not in place during T_1 while considering the same CDF

probability associated with Y_1. This metric is referred to as $Y_{1'}$ and the altered state of T_1 is referred to as $T_{1'}$.

In Step 1.8, the baseline performance shift CDF probability is calculated using the distribution of comparison values found in Step 1.7 and the targeted performance shift value if one was established. A targeted performance shift is defined as the minimal amount of improvement required in the performance metric value for the change implemented to be considered a success. In Step 1.9, the baseline performance shift CDF probability is subtracted from one to estimate the probability that the targeted performance shift would have been achieved in the baseline.

In Step 2.8, the post-change performance shift CDF probability is calculated using the distribution of comparison values found in Step 2.7 and the targeted performance shift value if one was established. In Step 2.9, the post-change performance shift CDF probability is subtracted from one to estimate the probability that the targeted performance shift would have been achieved in the post-change environment.

Chapter 4 details the case study that Chapters 5 and 6 both use to demonstrate the analysis procedure outlined in this Chapter 3. Chapters 5 and 6 also reveal that this procedure can be applied using different simulation methods to model the same environment and reach similar conclusions.

CHAPTER 4

CASE STUDY:

MOTHER-BABY THROUGHPUT IMPROVEMENT PROJECT

The case study presented involves an improvement project in the mother-baby service line at then-named Norton Suburban Hospital (NSH) in Louisville, KY. The project's key metric was the Holds Rate, which is defined as the ratio of mothers considered to be unintentionally delayed (i.e., held) from transferring to the postpartum (PP) care unit to the total number of deliveries (i.e., births). The project goal was to reduce the Holds Rate by 15% as holding patients was correlated to lower satisfaction scores. Figure 5 shows the typical patient flow from delivery to discharge.

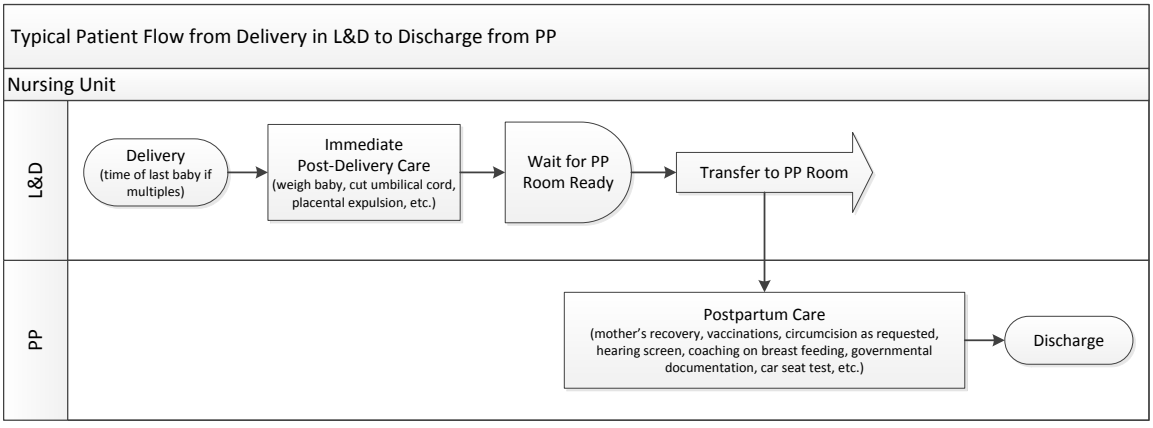

Figure 5: Typical patient flow from delivery in L&D to discharge from PP

The mother-baby service line is itself an organization within the hospital. There are many different agents including administrators, nurses, obstetricians, pediatricians, anesthesiologists, and environmental services staff all working together to serve the mother and infant patients and their families. The mother-baby service line has properties matching the six generators of complexity identified by Chu et al. (2003) as shown in Table 1.

Table 1: Chu et al. (2003) Complexity Generators Mapped to Mother-Baby Service Line Properties

Complexity Generator	Property of a Mother-Baby Service Line
Internal inhomogeneity	Different classes of autonomous agents are present (e.g., obstetricians, pediatricians, L&D nurses, PP nurses, staff, leadership, etc.).
Adaptivity	Agents of the care delivery system can adapt to dynamics (e.g., physicians protect interests of only their patients).
Nonlinearity	Interactions of scheduling with Holds Rate are nonlinear as utilization has a nonlinear impact on queue time.
Net-like causality	When a delivered mother is held from a PP unit, the PP care is delivered in another place that is not designed for PP care. This is not ideal for patient care and other risks may propagate.
Radical openness	Changes in system can impact other business decisions or patient preferences, but this is reducible as a relatively stable environment existed in the time periods observed.
Contextuality	Obstetricians and pediatricians working have office practice hours away from the hospital, but this is reducible as the LOS in PP (PP LOS) is fairly predictable.

Another aspect that illustrates the complexity present in the mother-baby service line is the presence of self-organization as defined by Halley and Winkler (2008). This can be evidenced by interactions between physicians and patients being nonlinear due to emotions, which can be overwhelming in nature. For example, there may be disagreement between an obstetrician and the laboring patient on when cesarean delivery is needed during a prolonged attempt at vaginal delivery.

Data was collected and analyzed over four separate time periods, as defined in Table 2. The time periods are not adjacent and the specific reasons supporting this approach are discussed in the following paragraphs.

Table 2: Time Period Definitions

Name	Duration	Considerations
Regression Study (RS)	115 consecutive days between 1Q 2012 and 2Q 2012	None
Baseline (BL)	63 consecutive days between 1Q 2012 and 2Q 2012	A portion of the regression study selected to be same length as IP2
Improvement Period 1 (IP1)	63 consecutive days between 4Q 2012 and 1Q 2013	L&D scheduling tactic change was implemented and selected to be same length as IP2
Improvement Period 2 (IP2)	63 consecutive days between 2Q 2013 and 3Q 2013	New EHR implementation complete and ends with start of construction work

The first time period, Regression Study (RS), was a period of time longer than the others as this data was used to establish the regression equation to estimate daily Holds Rate values in the MCS model. Routine data collection mostly consisted of counting the daily numbers of deliveries and holds. All other data collection for the project was ad hoc and sometimes cumbersome. The project team used the data for RS to develop a causal model to predict Holds Rate via regression as understanding cause and effect was the focus of project work during the early phases of the project.

Baseline (BL) is a portion of RS that was selected to be the same length as Improvement Period 2 (IP2), which was nine full weeks (i.e., Sunday through Saturday). Improvement Period 1 (IP1) was also the same length as IP2, as keeping all time periods used in the comparative analysis the same length reduced the impact of sample size on standard deviation, and this was a key parameter in the analysis. Devore (1995) detailed the relationship between sample size and standard deviation.

IP1 began with the implementation of a scheduling tactic change in L&D, which is viewed as a perestroika event and ended with the implementation of a new electronic health record (EHR) system. Implementing the new EHR system was disruptive and it took users some time to adjust. Also, data was not captured for time stamps needed to determine PP LOS in IP1. This was due to the difficulty of retrieving the time stamp data and administrative resources were preoccupied with preparation for conversion to the new EHR system. PP LOS and all related metrics for IP1 are estimated for purposes of the analyses in Chapter 5.

IP2 began following a period for users to adjust to the new EHR system and ended with the start of a new construction project, which temporarily reduced the number of rooms for PP. IP2 also included the on-boarding of a new PP nurse manager who, with the assistance of her staff, refined the checklist used to coordinate events leading up to patient discharge. While nurses routinely used the checklist to more effectively manage shift hand-off communication, this checklist did not impact PP LOS or its variation.

A major benefit with the new EHR system used in IP2 was the enhanced reporting capabilities. The new system not only made it possible to capture PP LOS for IP2, but also enabled the team to study the time it takes to clean and prepare a PP room for the next patient following a discharge. Another advantage was that the delay between delivery and transfer to the PP room could be calculated.

In IP1, the project goal of reducing the Holds Rate by 15% was not achieved while the goal was exceeded in IP2. Chapter 5 details how the procedure was applied to assess Holds Rate performance by answering Questions #1 and #2 for both improvement

periods using an MCS model. Regression was used to develop the simulation equation for MCS. This approach was necessary due to the judgment involved in determining the hold status of a patient, which is discussed below and is viewed as difficult to define entirely by a deterministic algorithm.

Chapter 6 shows how the procedure was used with a DES model to assess transfer delay performance by answering Question #2 for IP2 since this was the only comparison with sufficient data to support the analysis. Since the system involved a queue between L&D and PP, DES was applied as a simulation technique to validate that the scheduling tactic change indeed reduced delays in the care transitions.

The two modeling approaches, MCS and DES, were applied to demonstrate the generality of the procedure. The observations from Mustafee et al. (2010) on MCS and DES applications support both approaches as being acceptable simulation techniques.

Dependent variables for the MCS model were the number of holds (Holds) and Holds Rate. Holds were tabulated on a daily basis as the number of patients considered to be held from the PP care unit based on a nurse's judgment, which included assessing factors related to clinical care and patient-family satisfaction. For instance, a study IP2 data revealed that 21.5% of patients who waited over three hours to be transferred to a PP room were logged as a hold, which implies factors other than queue time influenced this judgment. However, delay in transferring the patient still had a substantial influence on nurses' judgment as only 1.7% of patients who waited three hours or less for transfer to the PP room were logged as a hold.

Holds Rate is defined as the ratio of Holds to Daily Deliveries, with Daily Deliveries being the number of newborns delivered in a day. The regression model,

which was a component of the MCS model, was used to directly calculate Holds Rate and then Holds was calculated by multiplying Holds Rate by Daily Deliveries. Holds Rate was also calculated over a 63 day simulation run length and the 63 Day Holds Rate was the output of each simulation run.

The DES model was used to calculate the time each patient spent waiting to be transferred to her bed in the PP care unit following delivery (Delay Time). Delay Times were averaged over a 63 day simulation replication length following a 7-day warm-up period and the 63 Day Average Delay Time (ADT) was the output of each replication.

Several key independent variables were considered in each model. For the regression model, Daily Deliveries and the PP LOS associated with the PP discharges for each day (Days D-C PP LOS) are considered. These variables were also measured over a two-day interval. For the DES model, independent variables existed at a more granular level than the regression model and were used to describe patient deliveries, patient stays, or the hospital. Patient delivery variables included the Hourly Rate of Deliveries (HRD), Delivery Type (i.e., vaginal or cesarean), and whether a delivery was Single Birth or Lastborn Twin as all multiple deliveries were twins in IP2. Patient stay variables included time required to care for a mother immediately after delivery (L&D Post-Delivery Care Time), the time to transport a patient from L&D to PP (Patient Transport Time), and time for a PP room to be cleaned following the stay (D-C to Room Clean Time). The Number of PP Rooms was the only hospital variable and it reflected the hospital's ability to accommodate patient care in the PP care unit. Table 3 summarizes the key variables considered in each model.

Table 3: Listing of Key Variables (2 Days are day and prior day)

Variable Name (regression code)	Variable Type	Model(s)
Holds Rate	Dependent	MCS Model
Holds	Dependent	MCS Model
Delay Time	Dependent	DES Model
Daily Deliveries (A)	Independent / Stochastic	Regression (for MCS)
Days D-C PP LOS (B)	Independent / Stochastic	Regression (for MCS)
2 Days Deliveries (C)	Independent / Stochastic	Regression (for MCS)
2 Days D-C PP LOS (D)	Independent / Stochastic	Regression (for MCS)
Hourly Rate of Deliveries	Independent / Stochastic	DES Model
Delivery Type	Independent / Stochastic	DES Model
Single Birth or Lastborn Twin	Independent / Stochastic	DES Model
L&D Post-Delivery Care Time	Independent / Stochastic	DES Model
PP LOS	Independent / Stochastic	DES Model
Patient Transport Time	Independent / Stochastic	DES Model
D-C to Room Clean Time	Independent / Stochastic	DES Model
Number of PP Rooms	Independent / Deterministic	DES Model

Table 4 provides data by time period for the regression model. Analysis to develop the model revealed that the interaction term of Days D-C PP LOS (B) and 2 Days Deliveries (C), or C*B, was the only significant term. Chapter 5 provides a detailed discussion of the regression analysis completed for Step 0.1.

Table 4: Summary of Data Provided for Regression Model Used for the MCS Model

Time Period (days)	Total No. of Holds	Total No. of Deliveries	Overall Holds Rate	Daily Deliveries μ / σ	Distribution of Daily Deliveries	Daily Discharges μ / σ	Distribution of Daily Discharges	Daily Average PP LOS (days) μ / σ	Distribution of Daily Average PP LOS	Daily Days D-C PP LOS μ / σ	Distribution of Daily Days D-C PP LOS
RS (115)	88	1560	5.64%	13.57 / 4.84	Normal p = 0.127	Not used in regression analysis				34.58 / 11.99	Normal p = 0.388
BL (63)	46	849	5.42%	13.48 / 5.17	Normal p = 0.173	13.78 / 4.89 *3.65 / 0.67*	Normal Transformed (Box-Cox λ = 0.5) p = 0.289	2.54 / 0.24 *0.93 / 0.10*	Normal Transformed (Box-Cox λ = 0) p = 0.794	34.90 / 12.28	Normal p = 0.612
IP1 (63)	45	851	5.29%	13.51 / 4.94	Normal p = 0.346	13.29 / 4.27 *3.57 / 0.60*	Normal Transformed (Box-Cox λ = 0.5) p = 0.504	2.53 / 0.27 *0.92 / 0.11*	Normal Transformed (Box-Cox λ = 0) p = 0.896	33.16 / 11.15	Normal p = 0.392
IP2 (63)	28	854	3.28%	13.56 / 4.74	Normal p = 0.050	13.52 / 4.25 *3.63 / 0.59*	Normal Transformed (Box-Cox λ = 0.5) p = 0.593	2.56 / 0.27 *0.93 / 0.10*	Normal Transformed (Box-Cox λ = 0) p = 0.158	34.61 / 11.22	Normal p = 0.127

α = 0.05

Values after transformation (distributions selected to be most appropriate fit over all 3 time periods for comparative analysis)

Per Two-Sample t Test, Daily Avg PP LOS for BL and IP2 found to be same

Note: Shaded area contains simulated data for IP1, which was generated using data from BL and IP2

As indicated in Table 4, data was not captured for Daily Average PP LOS during IP1. However, data for this figure was captured in both BL and IP2. Furthermore, Daily Average PP LOS was tested for stability between these time periods. Figure 6 shows the spread of the normal transformed data (Box-Cox $\lambda = 0$), and this type of distribution is also known as a lognormal distribution. In Figure 6, the vertical lines represent the first and fourth quartiles, the shaded rectangles represent the second and third quartiles, and asterisks signify outlier data points.

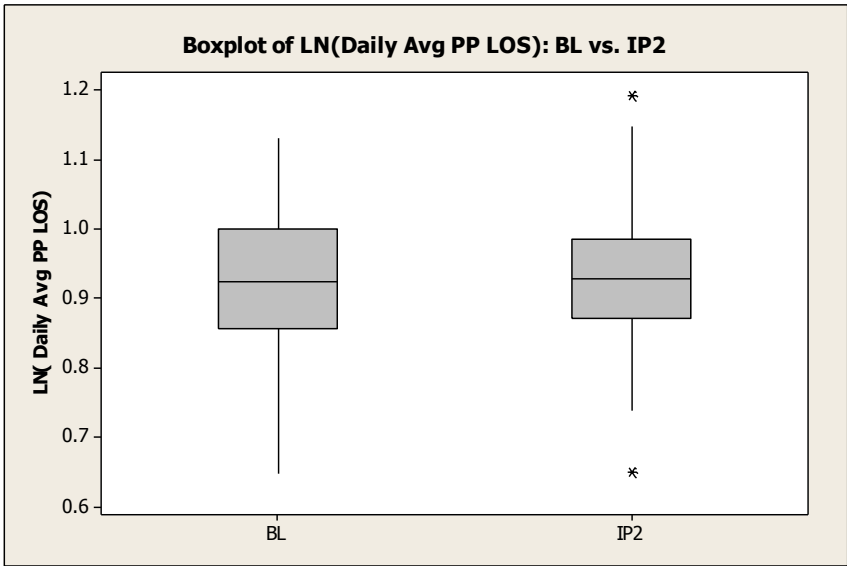

Figure 6: Boxplot with Two-Sample t Test for Daily Average PP LOS (LN = Box-Cox λ = 0)

A Two Sample t-Test was used to compare the mean value of the normal transformed data for BL to that of IP2. Also, equal variances were assumed as an F-Test showed no significant difference ($p = 0.666$). The Two-Sample t-Test found that the BL mean did not significantly differ from the IP2 mean ($p = 0.747$), so stability between the time periods was demonstrated with these results. Therefore, IP1 is assumed to have the same distribution as the other two time periods, which was normal transformed (Box-Cox $\lambda = 0$) with transformed mean of 0.93 and standard deviation of 0.10.

Daily Average PP LOS data was simulated for IP1 in order to include it in the analysis. Values for the natural log of Daily Average PP LOS were randomly generated using the mean and standard deviation parameters, 0.93 and 0.10, respectively, for a lognormal distribution. The simulated data had a mean of 0.92 and standard deviation of 0.11. Daily Average PP LOS values were attained by converting each simulated value, and this permitted Daily Days D-C PP LOS (measured in patient days) to be assessed.

In the DES model, each newborn baby enters the system as an entity upon delivery. If the baby is from a single birth or if the baby is the lastborn of a multiple birth, then the entity converts to a mother and enters the queue for being transferred to a PP room. Based on the delivery type and weekday of delivery, the mother's PP LOS is determined and she exits the system upon discharge. However, the PP room is technically occupied until it is clean and available for the next patient. Therefore, the DES model has a single resource type, the PP room, which is seized by the entity, the patient encounter, until the PP room is clean.

While other factors could have been incorporated in the DES model, they are not necessary due to statistical aggregation. For instance, human resources like nurses, physicians, and room cleaning staff are not included. This is due to the fact that the distributions of PP LOS and D-C to Room Clean Time inherently account for the availability of these resources. Chapter 6 provides a detailed discussion of the DES model developed for Step 0.1.

Table 5 provides data by time period for the DES model. As shown, data is not provided for IP1. This is due to the absence of delivery time stamp data needed for calculating the HRD values required by the DES model. Also, data was not available for

other elements of the DES model in BL due to the limitations of the EHR used during that time period. Table 5 indicates the data not available for BL in the sections shaded in gray. As a result, analysis with the DES model was limited to Question #2 for the IP2 vs. BL comparison.

Table 5: Summary of Data Provided for the DES Model

Time Period (days)	Avg. Delay Time (hours)	Hourly Rate of Deliveries	Delivery Type Prob.: Vaginal / Cesarean	Multiple Births Prob. (ε) / % Twins	Prob. of Single Born or Lastborn Twin (ψ)	L&D Post-Delivery Care Time (hours)	Distribution of L&D Post-Delivery Care Time	Patient Transport Time (hours)	Distribution of Patient Transport Time	PP LOS (hours) μ / σ	D-C to Room Clean Time (hours) μ / σ	Distribution of D-C to Room Clean Time	No. of PP Rms.
BL (63)		Varies by day and shift (See Table 6)	Varies by day and shift (See Table 7)			Min: 0.67 Mode: 1.5 Max: 2.0	Triangular based on estimates	Min: 0.33 Mode: 0.33 Max: 0.50	Triangular based on estimates	Varies by delivery type and weekday (See Table 7)			47
IP2 (63)	2.64	Varies by day and shift (See Table 6)	Varies by day and shift (See Table 7)	3.28% / 100%	98.36% (See Eqn. (3))	Min: 0.67 Mode: 1.5 Max: 2.0	Triangular based on estimates	Min: 0.33 Mode: 0.33 Max: 0.50	Triangular based on estimates	Varies by delivery type and weekday (See Table 7)	1.73 / 1.27 *0.34 / 0.64*	Lognormal (See Fig. 9)	47

α = 0.05

Values after transformation

Data only available in IP2 due to enhanced data collection capability of new EHR, so analysis limited to Question #2

The rate of deliveries in each time period followed a non-homogenous Poisson process (NHPP). As Hopp and Spearman (2008) indicated, a Poisson distribution is often found to reasonably approximate counts of entity arrivals per unit of time. HRD data in BL and IP2 are provided in Table 6.

Table 6: HRD Values by Weekday and Time Window for the DES Model

Time Period	Time Window	SUN		MON		TUE		WED		THU		FRI		SAT	
		$\bar{E}$	S^2	$\bar{E}$	S^2	$\bar{E}$	S^2	$\bar{E}$	S^2	$\bar{E}$	S^2	$\bar{E}$	S^2	$\bar{E}$	S^2
BL	1	0.167	0.143	0.250	0.250	0.194	0.161	0.472	0.542	0.361	0.466	0.361	0.409	0.444	0.425
	2	0.278	0.263	0.361	0.294	0.194	0.161	0.500	0.486	0.556	0.425	0.472	0.485	0.250	0.250
	3	0.333	0.286	0.972	0.885	0.833	0.943	0.889	1.016	1.000	0.571	0.722	0.549	0.472	0.485
	4	0.333	0.286	0.722	0.606	0.667	0.571	0.861	0.809	1.139	1.094	0.861	0.809	0.583	0.364
	5	0.417	0.421	0.611	0.644	0.694	0.675	0.750	0.821	0.806	0.904	0.611	0.473	0.500	0.543
	6	0.389	0.359	0.500	0.486	0.861	0.637	0.528	0.599	0.694	0.675	0.667	0.686	0.306	0.218
IP2	1	0.278	0.263	0.278	0.263	0.389	0.359	0.250	0.193	0.639	0.694	0.306	0.275	0.278	0.378
	2	0.250	0.250	0.556	0.540	0.472	0.371	0.500	0.486	0.472	0.485	0.611	0.473	0.389	0.302
	3	0.306	0.390	0.833	0.600	1.083	0.993	0.722	0.492	0.889	0.444	0.694	0.504	0.417	0.364
	4	0.583	0.650	0.694	0.561	0.639	0.637	0.667	0.686	0.806	0.618	1.139	0.694	0.556	0.540
	5	0.361	0.352	0.611	0.644	0.667	0.857	0.639	0.523	0.833	0.771	1.083	1.050	0.472	0.599
	6	0.194	0.275	0.444	0.368	0.500	0.600	0.639	0.466	0.556	0.597	0.528	0.656	0.500	0.371

Values approximate to a Poisson Distribution

Devore (1995) stated that a property of a Poisson distribution is that variance (σ^2) and mean (μ) are equivalent, and this condition was not exactly met with the data in Table 6 for values of sample variance (S^2) and those of sample mean ($\bar{E}$). Regression equations with y-intercepts of zero were developed for time window mean HRD values to predict variance values, and none of the assumptions for regression analysis defined in Montgomery (2013) were violated. The slope in the regression equation for BL was 0.9339 with an R^2_{adj} value of 0.9710, and the slope for IP2 was 0.8808 with an R^2_{adj} value of 0.9520. Since the slopes and R^2_{adj} values were each close to one, mean was found to be a significant predictor of variance in both time periods.

The Poisson assumption for HRD values in IP2 was further tested by comparing the simulated daily delivery values of the DES model created for IP2 to the to those actually observed. Due to the limitation of data available for BL, such a model was not created for BL. Figure 7 shows the spread of both data sets where the vertical lines represent the first and fourth quartiles, the shaded rectangles represent the second and third quartiles, and asterisks signify outlier data points.

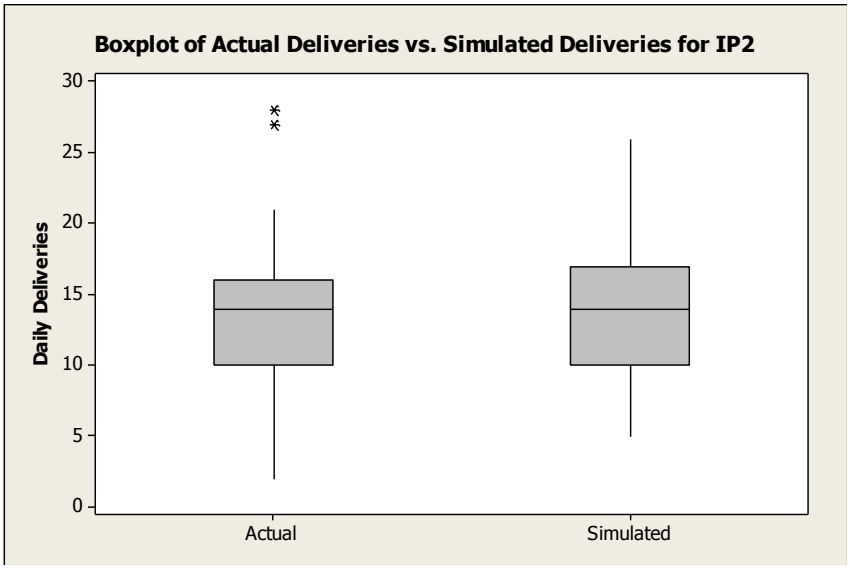

Figure 7: Boxplot of actual daily deliveries vs. simulated daily deliveries from the DES model for IP2

A Two Sample t-Test was used to compare the mean value of the simulation to that value of the actual IP2 data since both data sets were normally distributed. Also, equal variances were assumed as an F-Test showed no significant difference (p = 0.459). The Two-Sample t-Test found that the simulation mean value of 13.57 did not significantly differ from the actual mean value of 13.56 (p = 0.986), so HRD values were determined to reasonability fit Poisson distributions.

Multiple Births Probabilities were documented in Table 5 since it is the mother who is delayed from receiving a PP room. Multiple Births Probabilities were not captured in BL as the data set did not include patient identifiers for mothers as did the data set for IP2. Since all multiple births in IP2 were twins, Multiple Births Probability (ε) for IP2 is the probability that the newborn is a twin. The calculation for the probability that a newborn is a single born or a lastborn twin (ψ) can be calculated using Equation (3).

$$\psi_k = (1 - \varepsilon_k) + \varepsilon_k/2 \tag{3}$$

Where:

k: Index for time period

ψ_k: Probability that a newborn is a single born or lastborn twin

ε_k: Probability that a newborn is a twin

As stated in Table 5, parameter values for L&D Post-Delivery Care Time and Patient Transport Time were based on estimates, which were provided by nursing leaders as data were not available. Also, Kelton et al. (2015) recommended use of a triangular distribution when practitioner estimates become necessary due to lack of data.

Table 7 provides information on the delivery type probabilities by weekday and PP LOS parameters by delivery type and weekday of delivery. These parameters were

assessed by weekday due to the scheduling tactic change, which limited scheduled deliveries by delivery type on a daily basis as part of reducing the overall scheduled deliveries allowed per day.

Table 7: Delivery Type and PP LOS Data by Weekday for the DES Model

Time Period	Day	Vaginal						Cesarean					
		PP LOS (Hours): $\bar{E}$	PP LOS (Hours): S	p-value Fit with LN Dist.	% Vaginal	% of Week's Vaginal Deliveries	Number Vaginal Deliveries	PP LOS (Hours): $\bar{E}$	PP LOS (Hours): S	p-value Fit with LN Dist.	% Cesarean	% of Week's Cesarean Deliveries	Number Cesarean Deliveries
BL	SUN	50.47	16.17	< 0.005	68.12%	8.74%	47	83.67	17.99	0.054	31.88%	7.07%	22
	MON	50.28	12.35	< 0.005	57.72%	13.20%	71	75.29	14.33	0.083	42.28%	16.72%	52
	TUE	48.61	8.04	0.005	58.87%	13.57%	73	81.44	18.19	0.121	41.13%	16.40%	51
	WED	50.12	8.53	0.248	66.67%	17.84%	96	79.50	14.03	0.147	33.33%	15.43%	48
	THU	49.69	10.27	< 0.005	62.20%	18.96%	102	77.37	15.11	< 0.005	37.80%	19.94%	62
	FRI	49.16	8.61	0.084	60.90%	15.06%	81	79.51	15.28	0.031	39.10%	16.72%	52
	SAT	49.64	9.59	< 0.005	73.91%	12.64%	68	86.78	19.12	0.986	26.09%	7.72%	24
	Total	49.68	10.32	< 0.005	63.37%	100.00%	538	79.55	16.10	< 0.005	36.63%	100.00%	311
IP2	SUN	49.97	7.99	0.367	70.42%	9.16%	50	84.87	16.49	0.122	29.58%	6.93%	21
	MON	51.13	9.08	0.032	62.60%	14.10%	77	80.70	26.43	< 0.005	37.40%	15.18%	46
	TUE	50.08	13.15	< 0.005	60.74%	15.02%	82	82.09	21.61	0.010	39.26%	17.49%	53
	WED	48.37	8.32	0.078	68.03%	15.20%	83	77.41	21.79	0.075	31.97%	12.87%	39
	THU	50.40	9.35	0.139	62.84%	17.03%	93	82.13	17.18	0.018	37.16%	18.15%	55
	FRI	49.44	8.21	0.392	60.26%	17.22%	94	78.72	20.23	< 0.005	39.74%	20.46%	62
	SAT	53.98	14.37	0.006	71.28%	12.27%	67	85.38	24.95	0.098	28.72%	8.91%	27
	Total	50.38	10.35	< 0.005	64.31%	100.00%	546	81.08	21.38	< 0.005	35.69%	100.00%	303

$\alpha = 0.05$

Note: Data for delivery type was missing from the EHR report on five deliveries in IP2

A lognormal distribution was applied in the DES model to simulate PP LOS values as only positive values are present in a lognormal distribution and PP LOS must be positive. Half of delivery type and weekday combinations had PP LOS data that fit a lognormal distribution as indicated in the columns titled "p-value Fit with LN Dist." in Table 7. Also, lognormal distribution probability plots of the combinations that did not show statistical fit still demonstrated graphical fit with lognormal distributions.

The lognormal assumption for PP LOS was further tested in the DES model for IP2 by comparing the distribution from the same simulation replication used for Figure 7 to the distribution of the actual data. Figure 8 shows the spread of both data sets where the vertical lines represent the first and fourth quartiles, the shaded rectangles represent the second and third quartiles, and asterisks signify outlier data points.

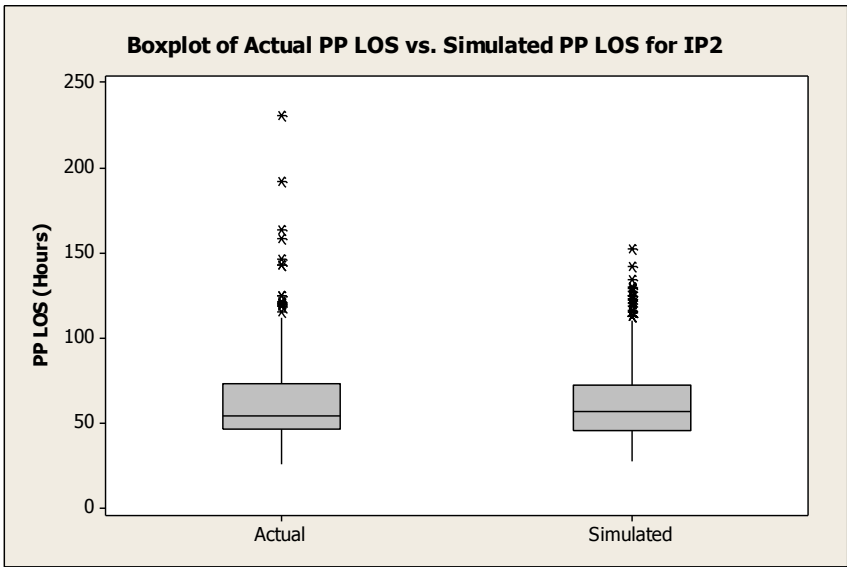

Figure 8: Boxplot of actual PP LOS vs. simulated PP LOS from the DES model for IP2

A Mood's Median Test was used to compare the median PP LOS values of both data sets since they were not normally distributed and contained outliers. The simulated median value of 57.16 hours did not significantly differ from the actual median value of 54.83 hours ($p = 0.058$) and the spread of the data in Figure 8 was considered to be similar, so the lognormal assumption for PP LOS was accepted.

Figure 9 shows the data for D-C to Room Clean Time graphically fit a lognormal distribution between the 1^{st} and 99^{th} percentiles (i.e., CDF probabilities) of the IP2 distribution. Additional testing was not performed to further validate the lognormal assumption due to the relatively small impact of D-C to Room Clean Time in the DES model.

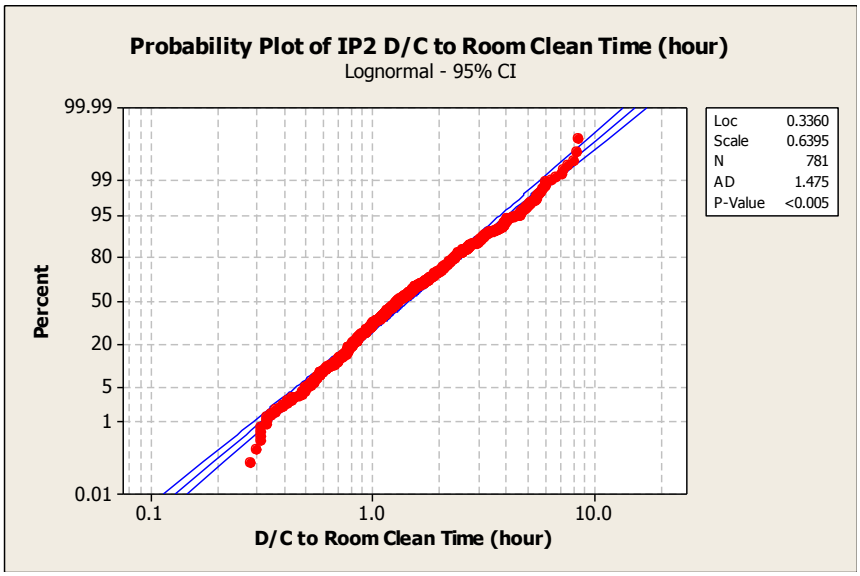

Figure 9: Lognormal probability plot of D/C to Room Clean Time in IP2

CHAPTER 5

MONTE CARLO SIMULATION MODEL

This Chapter 5 showcases use of the procedure proposed in Chapter 3 using Monte Carlo simulation as defined by Anderson et al. (2006). Questions #1 and #2 were addressed to determine the impact on Holds Rate for the case study detailed in Chapter 4.

The regression equation used by the MCS model was derived first to complete Step 0.1. Next, a detailed explanation of Steps 1.1–1.6 is provided to demonstrate how a single performance shift value was calculated. Subsequently, Steps 1.7–1.9 were completed to develop distributions of performance shift values and estimate the probability that target performance would have been achieved in the baseline to answer Question #1. This process was repeated for Steps 2.1–2.6 and for Steps 2.7–2.9 to answer Question #2. Results are provided for all time periods and this Chapter 5 ends with a discussion of the analysis. Questions #1 and #2 are restated below.

> **Question #1:** If the scheduling rules of the IP1 and IP2 time periods existed in the BL time period, how would the Holds Rate have differed in the BL time period?
>
> **Question #2:** If the scheduling rules of the BL time period still existed in the IP1 and IP2 time periods, how would the Holds Rate have differed in the IP1 and IP2 time periods?

5.1 Model Description for BL, IP1, and IP2

The regression equation was derived using the daily values of data summarized in Table 4 for the RS time period. As shown in Table 3 and discussed in Chapter 4, four variables were considered, but only the interaction term between B and C was found to be significant. Variables A and C represented incoming demand to the PP unit, while B and D were indicators of PP room utilization. These variables were considered for the regression modeling process as both incoming demand and utilization of capacity are generally known to be drivers of queue length and time spent in queue. Figure 10 provides the best subsets analysis that was performed to start the regression modeling process.

Response is Holds Rate

														A	A	C	C	
														*	*	*	*	
										A	A	C	C	B	D	B	D	
			Mallows							*	*	*	*	^	^	^	^	
Vars	R-Sq	R-Sq(adj)	Cp	S	A	B	C	D	B	D	B	D	2	2	2	2	
1	55.9	55.5	69.6	0.10468											X		
1	42.9	42.4	122.8	0.11909												X	
2	65.6	65.0	31.8	0.092837							X				X		
2	62.6	61.9	44.1	0.096818					X						X		
3	69.3	68.5	18.7	0.088109							X		X		X		
3	67.3	66.5	26.7	0.090881					X		X				X		
4	71.5	70.5	11.7	0.085290							X			X	X	X	
4	71.4	70.4	12.1	0.085426							X		X		X	X	
5	73.5	72.3	5.5	0.082626					X		X			X	X	X	
5	73.3	72.0	6.5	0.082985						X	X			X	X	X	
6	74.5	73.1	3.3	0.081383					X		X		X	X	X	X	
6	74.5	73.1	3.5	0.081433					X	X	X	X	X		X		
7	74.7	73.0	4.8	0.081536					X	X	X	X	X		X	X	
7	74.6	73.0	4.9	0.081580					X	X	X		X	X	X	X	
8	74.8	72.9	6.1	0.081676	X		X		X	X	X	X	X		X		
8	74.7	72.8	6.5	0.081818	X			X	X	X	X		X		X	X	
9	75.0	72.9	7.2	0.081695	X		X		X	X	X	X	X		X	X	
9	75.0	72.9	7.3	0.081715	X		X		X	X	X	X	X	X	X		
10	75.0	72.7	9.1	0.082057	X	X	X		X	X	X	X	X		X	X	
10	75.0	72.6	9.2	0.082058	X		X		X	X	X	X	X	X	X	X	
11	75.1	72.4	11.1	0.082416	X	X	X	X	X	X	X	X	X	X	X		
11	75.1	72.4	11.1	0.082422	X	X	X	X	X	X	X	X	X		X	X	
12	75.1	72.2	13.0	0.082797	X	X	X	X	X	X	X	X	X	X	X	X	

Figure 10: Best subsets analysis for regression using all values of RS data

As shown in Figure 10 with the red arrow, the subset chosen for further analysis was the model using C*B and $(C*B)^2$ as terms. These terms were chosen due to the high adjusted R^2 value with fewer variable terms as compared with other model subset options. Figure 11 plots the fitted line of the regression model initially considered.

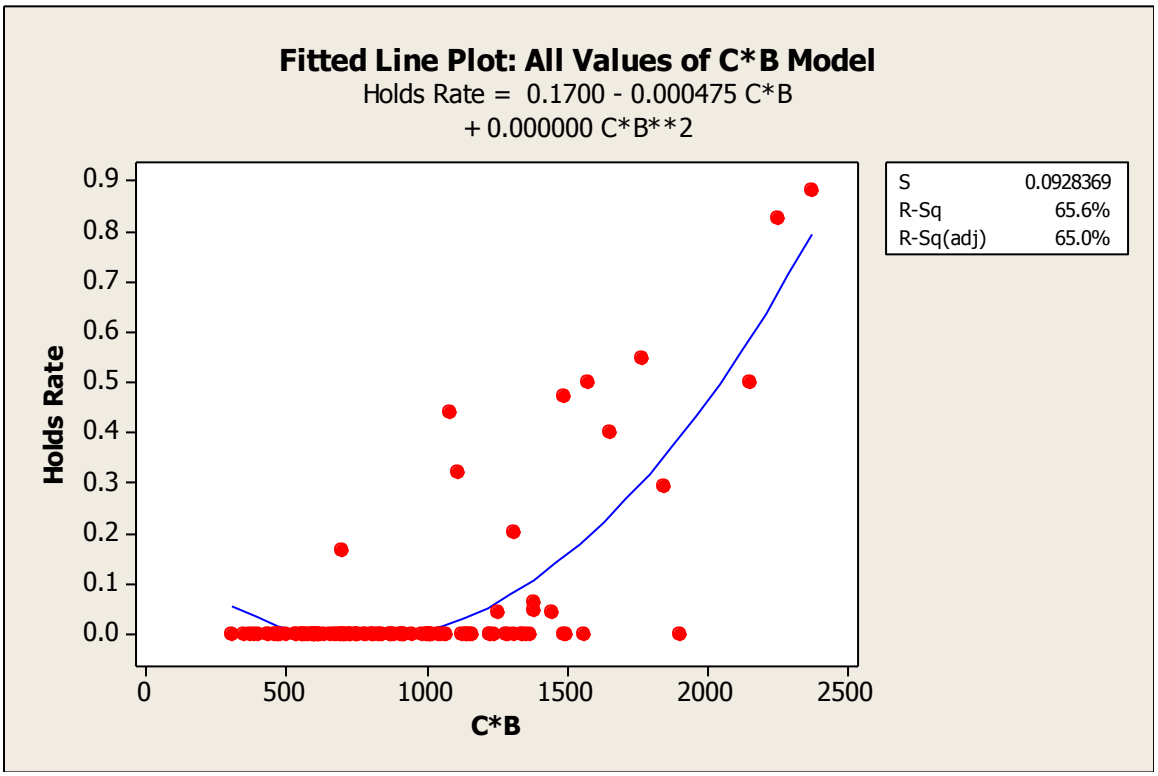

Figure 11: Two term regression model to fit all values of RS data

However, this model was found to be inadequate as indicated by the residual plots shown in Figure 12. A model's adequacy must be supported by normally distributed residuals that are independent in time order and have constant variance at fitted values as indicated by Montgomery (2013). While the residuals appeared to adhere to the independence assumption in the residual vs. order plot, this model violated the normality assumption as illustrated by the normal probability plot and the histogram. Regarding variance of the residuals, the residual values appeared to be positively skewed in the residual vs. fit plot indicating that variance was not constant.

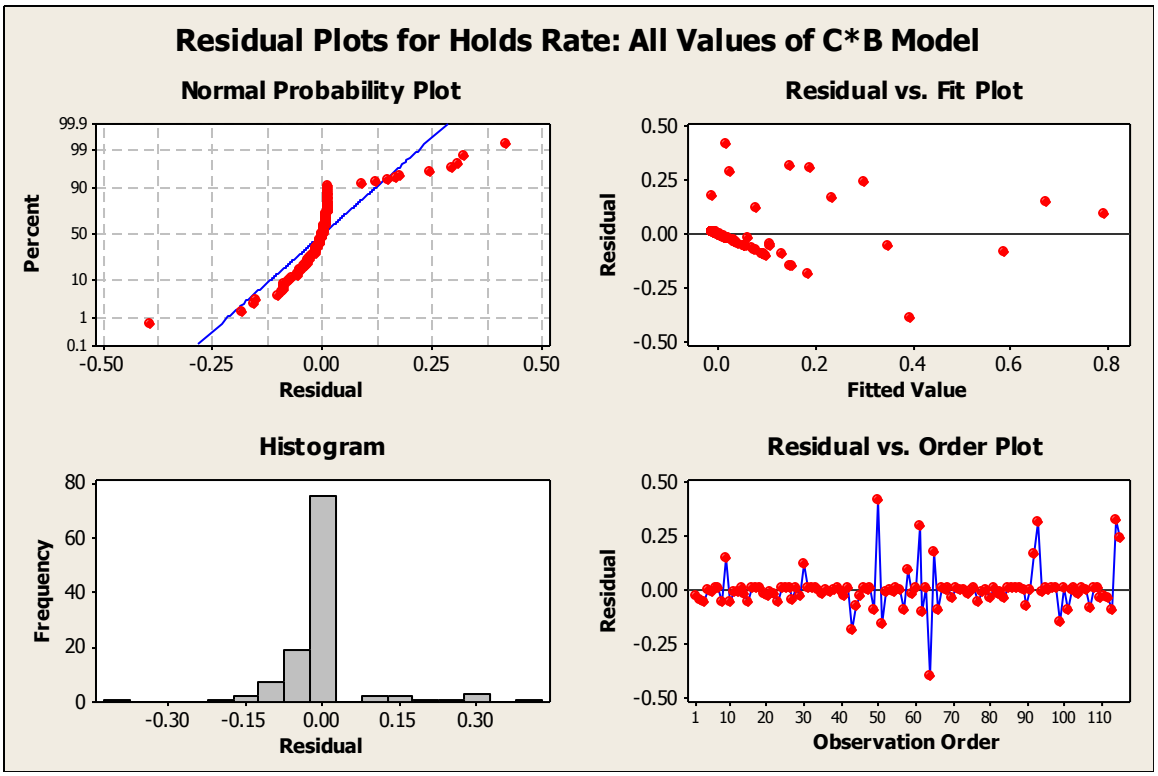

Figure 12: Residual plots of two term regression model to fit all values of RS data

Upon further evaluation of Figure 11, the curved nature of the fitted regression line appeared to be inappropriate as Holds Rate values tended to be zero with lower C*B values. Figure 13 displays only three data points below 1200 in C*B value had a non-zero Holds Rate, where the vertical dashed line demarks 1200 in C*B value. Furthermore, values of C*B above 1200 appeared to be positively correlated with higher Holds Rate values as shown in Figure 13.

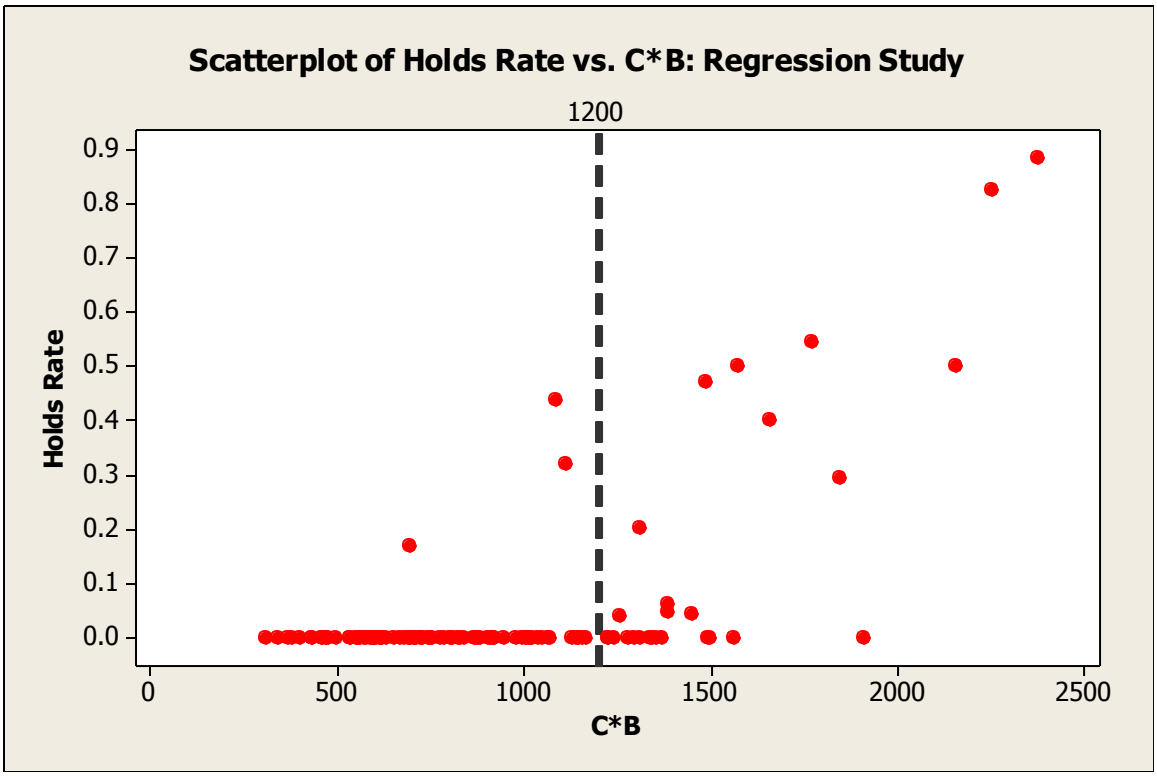

Figure 13: Scatterplot of Holds Rate vs. C*B for RS data

The best subsets analysis was repeated for the BL data using only C*B values greater than 1200. In Figure 14, the red arrow points to the model selected for further evaluation. This model was selected as it is linear and the non-linear alternatives each violated the normality assumption associated with the distribution of the residuals.

Response is Holds Rate

Vars	R-Sq	R-Sq(adj)	Mallows Cp	S	C * B	C * C * B ^ 2
1	67.5	66.2	1.1	0.15770		X
1	66.5	65.2	1.8	0.16016	X	
2	67.6	65.0	3.0	0.16069	X	X

Figure 14: Best subsets analysis for regression using RS data with C*B values >1200

Figure 15 shows the fit of the regression line among the BL data with C*B values greater than 1200. The linear model was the best fit found over this range of data with

the C*B term being statistically significant as p = 0.000 for the regression term in the associated Analysis of Variance (ANOVA).

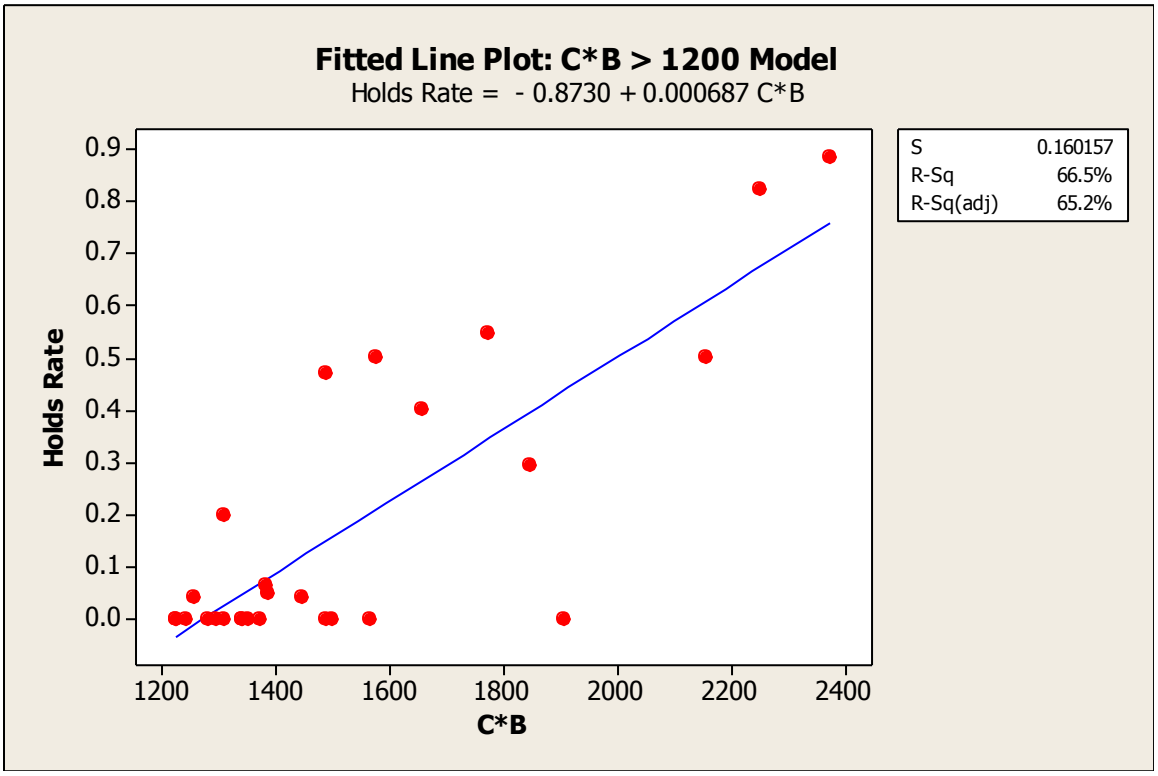

Figure 15: Selected regression model to fit C*B values >1200 of RS data

Figure 16 confirms the model's adequacy as none of the assumptions defined in Montgomery (2013) were violated since normal distribution, time ordered independence, and constant variance of the residuals were all supported. Figure 17 further validates the normality assumption associated with the distribution of the residuals as p = 0.251 for the normality test. Figure 17 plots the residuals for the 27 C*B values above 1200 in the RS data (N = 27), with the X-axis being residual value and the Y-axis being CDF probability. The middle line, which is straight, is the plot of a normal distribution and the curved lines represent the upper and lower confidence intervals. As shown, all but one residual value fell within the confidence intervals.

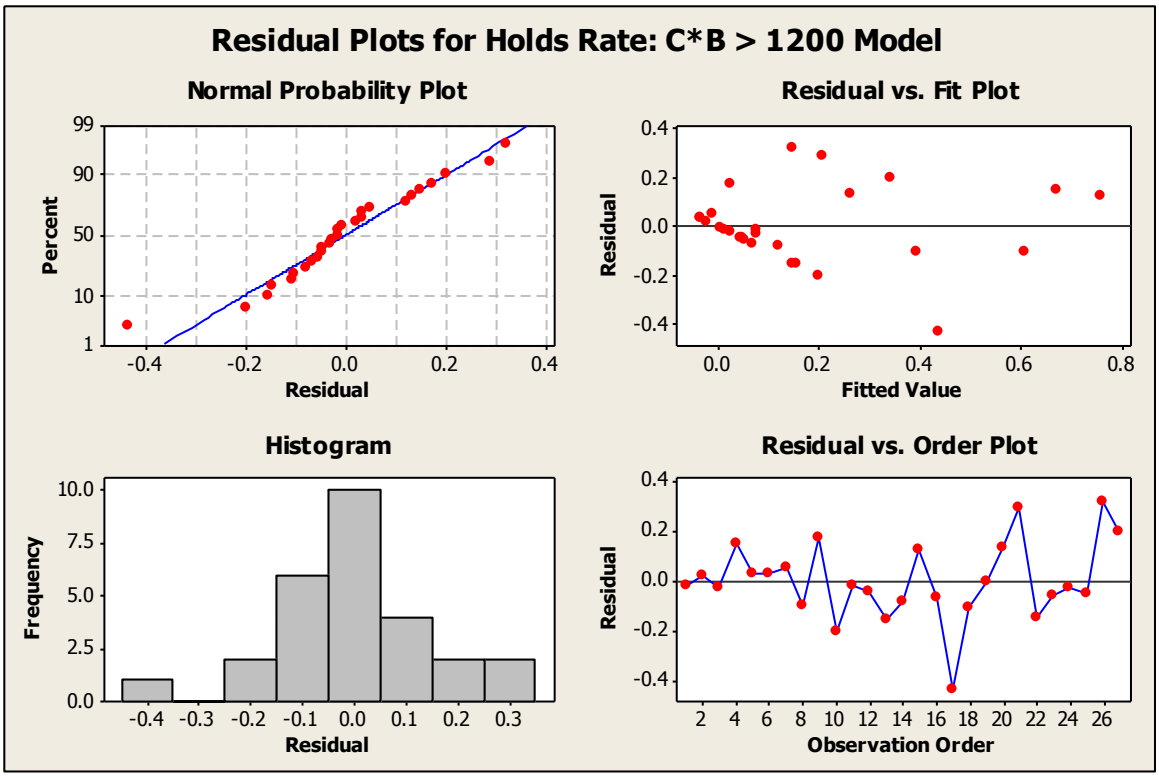

Figure 16: Residual plots of selected regression model

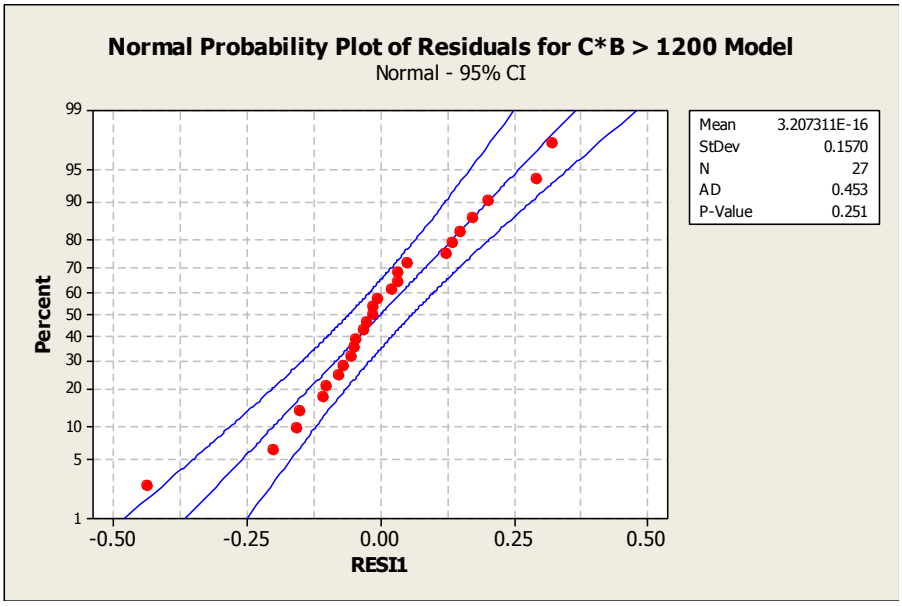

Figure 17: Normal probability plot of residuals for selected regression model

Based on the regression analysis, a two-stage MCS model was developed. C*B values were used by determining 2 Days Deliveries (C) and Days D-C PP LOS (B), where 2 Days Deliveries (C) was the summation of Daily Deliveries (A) for the subject day and one day prior. This model is expressed in Equations (4) – (7).

Notations:

i: Index for days

j: Index for time periods

q_i: Holds Rate for day i

C_i: 2 Days Deliveries for day i

B_i: Days D-C PP LOS for day i

A_i: Daily Deliveries for day i

h_i: Holds for day i (rounded to the nearest integer)

Q_j: 63 Day Holds Rate for 63 day period j

I_j: The subset of days contained in 63 day period j, where periods are non-overlapping

Regression Model:

$$q_i = \begin{cases} 0 \ , \forall \ C_i * B_i < 1271, i \geq 2 \\ -0.8730 + 0.000687(C_i * B_i) \ , \forall \ C_i * B_i \geq 1271, i \geq 2 \end{cases} \quad (4)$$

$$C_i = \ A_i + A_{i-1} \ \ , \forall \ i \geq 2 \quad (5)$$

$$h_i = q_i * A_i \ , \forall \ i \geq 2 \quad (6)$$

$$Q_j = \sum_{i \in I_j} h_i / \sum_{i \in I_j} A_i \ \ , \forall \ i \geq 2, j \geq 1 \quad (7)$$

In Equation (4), the Holds Rate (q_i) is calculated for each day based on the regression equation, which yields positive q_i values for any C*B value that is at least 1,271. Therefore, q_i is forced to zero for any C*B value below 1,271. B_i values are the total time that all patients (mothers) discharged on day i stayed in the hospital following delivery. For example, if 20 patients discharged with an average PP LOS of 3.5 days per

patient, then the B_i value for that day would be 70 Days D-C PP LOS. C_i values are the summation of the number of deliveries for day i (A_i) and the prior day's value (A_{i-1}) as defined by Equation (5). Equation (6) is used to calculate the total number of Holds (h_i) for each day by multiplying that day's q_i value by its A_i value and rounding the output value to the nearest integer. In order to determine the 63 Day Holds Rate (Q_j) for each 63 day period j, the summation of h_i for days $i \in I_j$ is divided by the summation of A_i for days $i \in I_j$ as defined by Equation (7).

As shown in Figure 18, Days D-C PP LOS (B) and 2 Days Deliveries (C) were independent of one another due to a weak correlation coefficient that is statistically insignificant. The Pearson correlation coefficient is also referred to as the correlation coefficient and an absolute value below 0.5 is considered to be weak according to Devore (1995). Also, C_i values were derived by adding successive A_i values from Equation (5), so the data was investigated for autocorrelation. Autocorrelation between successive A_i values is defined by Equation (8), which was derived from the formula for sample correlation coefficient as documented in Devore (1995).

$$r_{A_{i-1},A_i} = \frac{n\sum_i(A_{i-1}*A_i)-(\sum_i A_{i-1})(\sum_i A_i)}{\sqrt{n\sum_i A_{i-1}^2-(\sum_i A_{i-1})^2}\sqrt{n\sum_i A_i^2-(\sum_i A_i)^2}} \quad ,\forall\, 2 \le i \le n+1 \tag{8}$$

Where:

r_{A_{i-1},A_i}: Sample correlation coefficient between A_{i-1} and A_i

n: Sample size of days in RS (115)

Correlation was weak and statistically insignificant between successive A_i values as displayed in Figure 19. Furthermore, there is no graphical evidence of any nonlinear relationship in Figure 18 or Figure 19. Therefore, C_i and B_i values could be independently created for simulation by randomly generating values for A_i and B_i.

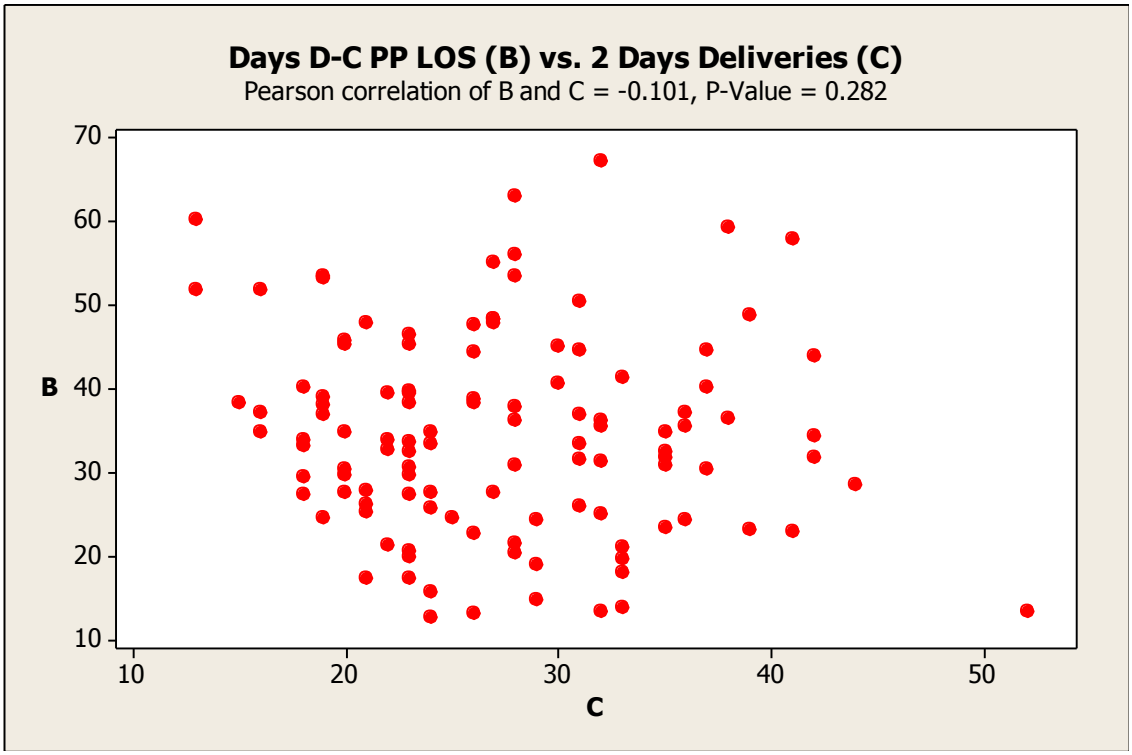

Figure 18: Scatterplot of B vs. C for RS data

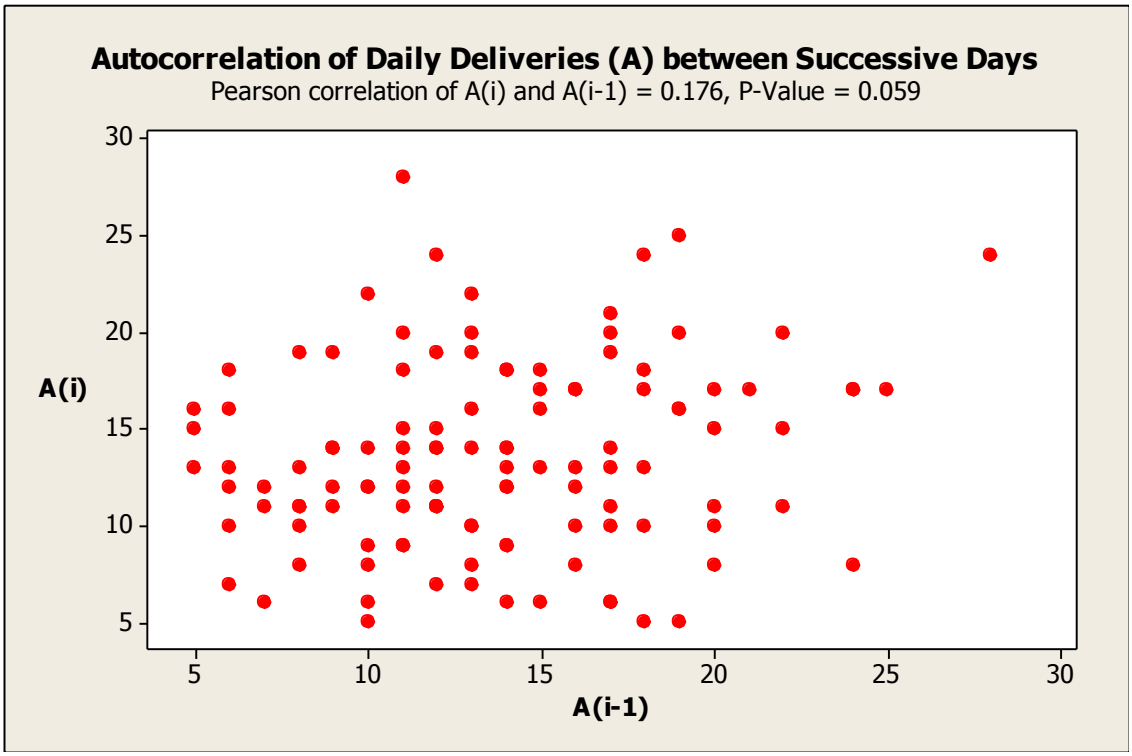

Figure 19: Scatterplot of A_i vs. A_{i-1} for RS data

5.2 Question #1: Experimental Design Demonstrated for IP1 vs. BL

The proposed analysis procedure for answering Question #1 begins with Step 1.1, thus a simulation of Q_j values was conducted using BL parameters as defined in Table 4. The distribution of Q_j values for T_0 from the simulation is depicted in Figure 20, with the red line marking the BL Overall Holds Rate (Y_0).

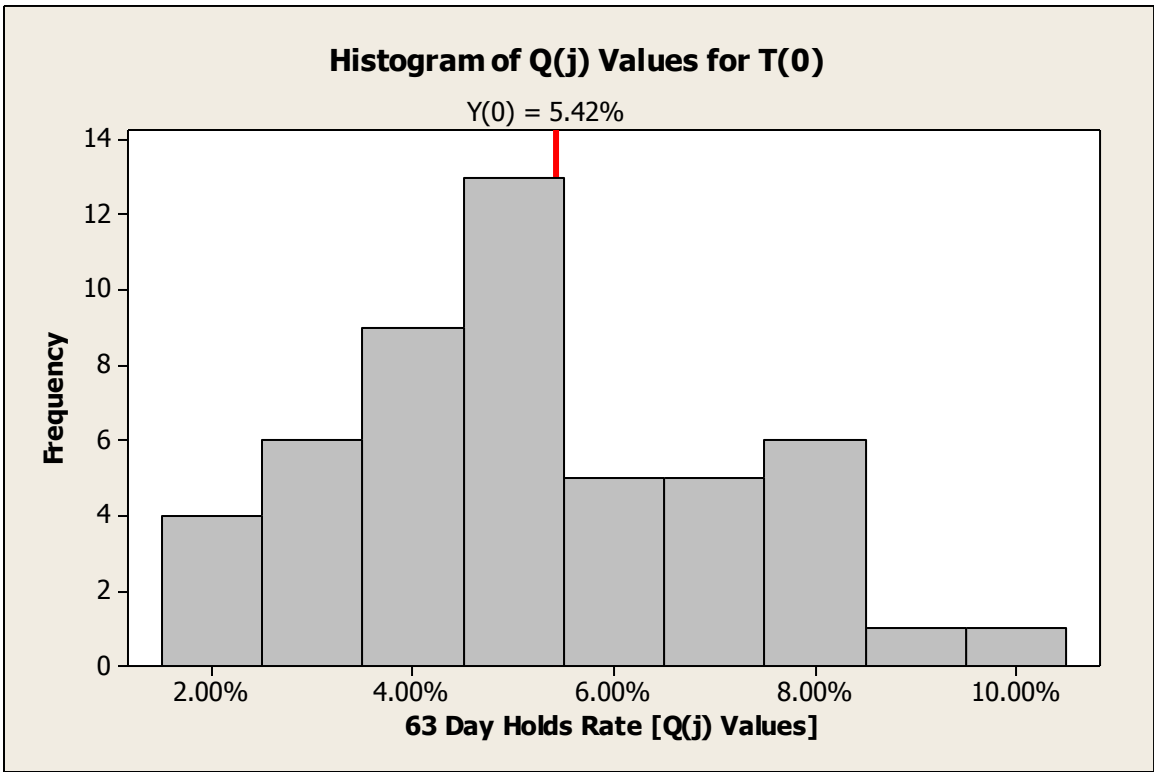

Figure 20: Simulation output compared to BL Overall Holds Rate (Y_0)

A normal transformed (Box-Cox $\lambda = 0.5$) was found to adequately represent the distribution of 50 simulated Q_j values for T_0 with a very strong fit ($p = 0.855$). As seen in Figure 20, the observed result was located near the center of the simulation distribution, which was 58.48% of the cumulative normal transformed distribution in Step 1.2. Therefore, the baseline CDF probability associated with BL was 0.5848.

Figure 21 shows that the factor values of C*B in IP1 fell within the range used to develop Equation (4). Thus, identifying a new relationship for Step 1.3 was unnecessary.

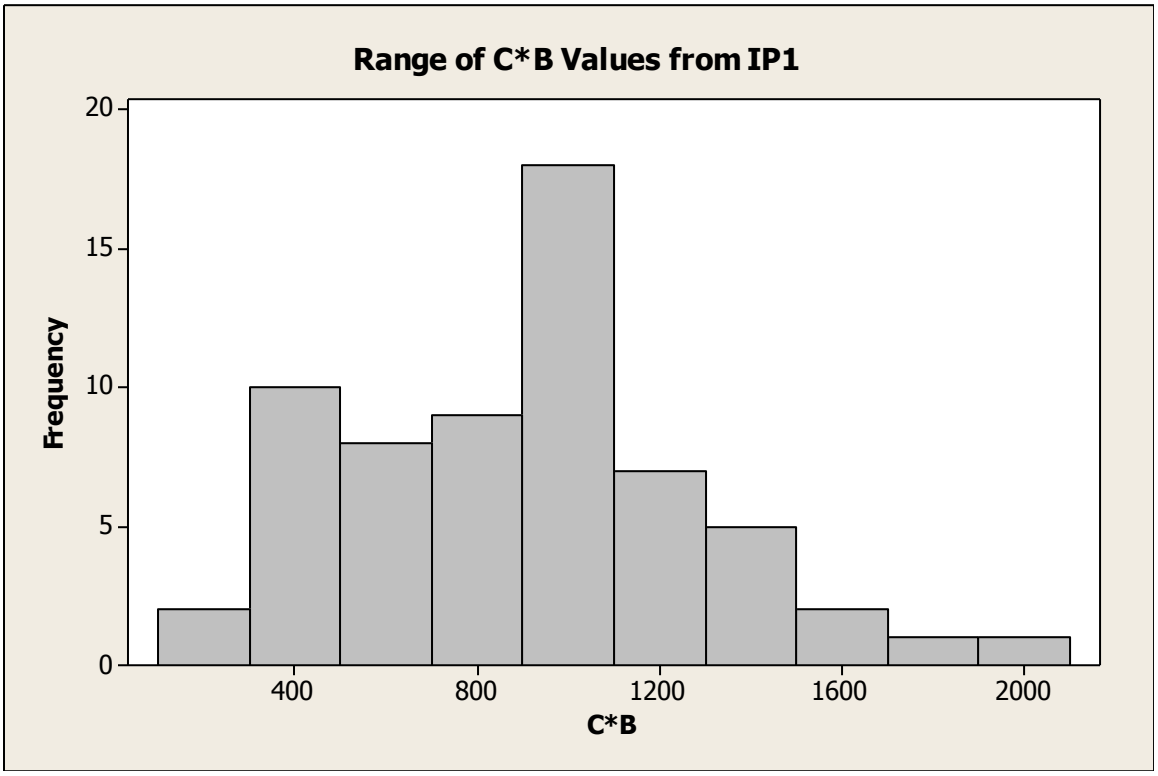

Figure 21: Histogram of C*B values for IP1 data

Step 1.4 was accomplished using 50 simulation replications to generate Q_j values by applying Equations (4) – (7) and randomly generating values for B_i and A_i. As shown in Table 2, the scheduling rules changed in IP1. Subsequently, the variability of volumes in the L&D and PP units was reduced in IP1. This impact was measured by each variable's coefficient of variation (CV), which is defined as the standard deviation divided by the mean value of a random variable as documented by Hopp and Spearman (2008). Table 8 shows the CV's for variables A and B in both the BL (T_0) and IP1 (T_1) time periods.

Table 8: CV Calculation for BL (T_0) and IP1 (T_1)

Parameter	Value	Distribution / Comments
T_0 Mean Daily Total Deliveries (A)	13.48	Normal (See Table 4 for BL)
T_0 Stdev Daily Total Deliveries (A)	5.17	Normal (See Table 4 for BL)
T_0 CV (A)	0.3839	Mean / Stdev
T_0 Mean Days D-C PP LOS (B)	34.89	Normal (See Table 4 for BL)
T_0 Stdev Days D-C PP LOS (B)	12.28	Normal (See Table 4 for BL)
T_0 CV (B)	0.3520	Mean / Stdev
T_1 Mean Daily Total Deliveries (A)	13.51	Normal (See Table 4 for IP1)
T_1 Stdev Daily Total Deliveries (A)	4.94	Normal (See Table 4 for IP1)
T_1 CV (A)	0.3658	Mean / Stdev
T_1 Mean Days D-C PP LOS (B)	33.16	Normal (See Table 4 for IP1)
T_1 Stdev Days D-C PP LOS (B)	11.15	Normal (See Table 4 for IP1)
T_1 CV (B)	0.3364	Mean / Stdev

Since the scheduling rules introduced in IP1 were intended to reduce the variability of volumes in the L&D and PP units, the respective CV's associated with A and B were determined to be factors influenced by the change (i.e., controlled parameters). However, overall delivery volumes and subsequent demand for PP care were not controlled by scheduling. Therefore, standard deviation values of A and B were deemed to be affected by the scheduling tactic change, whereas mean values of A and B were not. Table 9 outlines the parameter values for $T_{0'}$.

Table 9: $T_{0'}$ Parameter Values for the MCS Model

Parameter	Value	Distribution / Comments
$T_{0'}$ Mean Daily Total Deliveries (A)	13.48	Normal (uncontrolled, same as BL)
$T_{0'}$ Stdev Daily Total Deliveries (A)	4.93	Normal (calculated as CV is controlled parameter)
$T_{0'}$ CV (A)	0.3658	Controlled in IP1
$T_{0'}$ Mean Days D-C PP LOS (B)	34.89	Normal (uncontrolled, same as BL)
$T_{0'}$ Std Dev Days D-C PP LOS (B)	11.74	Normal (calculated as CV is controlled parameter)
$T_{0'}$ CV (B)	0.3364	Controlled in IP1

The parameter values in Table 9 were used in the 50 simulation replications to generate Q_j values that were used along with the baseline CDF probability to determine $Y_{0'}$. The distribution of simulated Q_j values for $T_{0'}$ was found to be normal transformed (Box-Cox $\lambda = 0.5$) with a strong fit ($p = 0.576$). The baseline CDF probability and the inverse of the CDF for the normal transformed distribution were used together to calculate a transformed $Y_{0'}$ value ($Y_{0'}^t$). The transformed $Y_{0'}$ value was squared to find $Y_{0'}$ in Step 1.5. Subsequently, Y_0 was compared to Y_0 in Step 1.6 of the analysis. Table 10 details the values pertinent to the calculations for Steps 1.5 and 1.6.

Table 10: Calculation of $Y_{0'}$ and % $Y_{0'}$ Improved over Y_0 for Holds Rate

Variable	Value
BL CDF Probability	0.5848
Mean Q_j^t for $T_{0'}$	20.92%
Stdev Q_j^t for $T_{0'}$	3.92%
$Y_{0'}^t$ Using BL CDF Probability	21.76%
Step 1.5 $Y_{0'}$ Using BL CDF Probability	4.73%
BL Holds Rate (Y_0)	5.42%
Step 1.6 % $Y_{0'}$ Improved over Y_0	12.6%

A distribution of 50 comparison values was developed in Step 1.7 by repeating Steps 1.1–1.6. Also, each simulation applied common random numbers (CRN) as part of a variance reduction technique shared in Kelton et al. (2015). This distribution was found to be normal ($p = 0.392$). As shown in Figure 22, the baseline performance shift CDF probability was one, or 100% of the cumulative normal distribution, in Step 1.8. The targeted performance shift of 15% is represented by the lower specification limit (LSL) since the targeted performance shift represents the minimal amount of improvement required. Any value below the LSL is counted to the parts per million (PPM) total, where

PPM is a measure of how many trials (parts) are expected to be non-conforming out of one million trials.

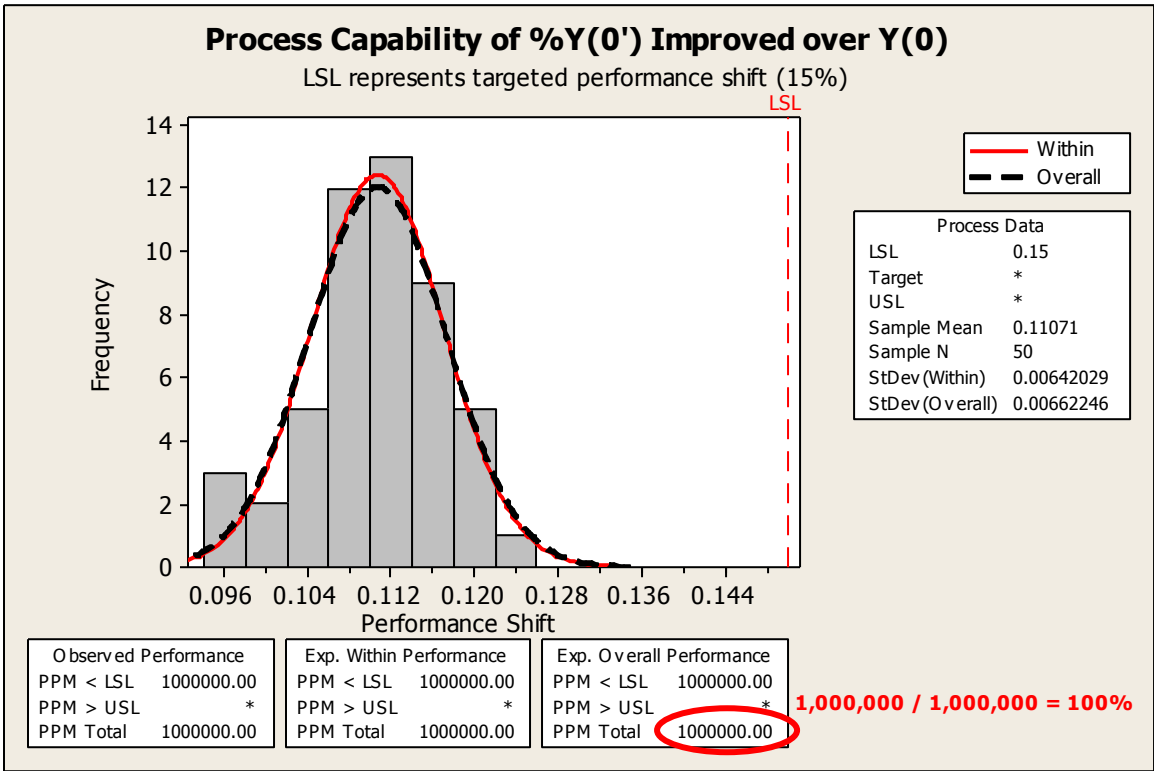

Figure 22: Baseline performance shift CDF probability for Holds Rate

In order to complete Step 1.9, the result of Step 1.8 was subtracted from one. Thus, there is a probability of zero that the actual Holds Rate performance observed during BL (Y_0) could have been at least 15% lower had the L&D schedule been managed in BL as it was in IP1 ($Y_{0'}$). However, further review of the information presented in Figure 22 indicated that Holds Rate performance could have been at least 9% lower in BL had the L&D scheduled been managed as it was in IP1. These statements provided the answer to Question #1 and it was substantiated by the distribution found in Step 1.7, which is shown in Figure 22.

5.3 Question #2: Experimental Design Demonstrated for IP1 vs. BL

The proposed analysis procedure for answering Question #2 begins with Step 2.1, which is identical to Step 1.3. As shown in Figure 21 and discussed in Section 5.2, the factor values of C*B in IP1 fell within the range used to develop Equation (4). Thus, identifying a new relationship for Step 2.1 was unnecessary.

To complete Step 2.2, a simulation of Q_j values was conducted using IP1 parameters as defined in Table 4. The distribution of Q_j values for T_1 from the simulation is depicted in Figure 23, with the red line marking the IP1 Overall Holds Rate (Y_1).

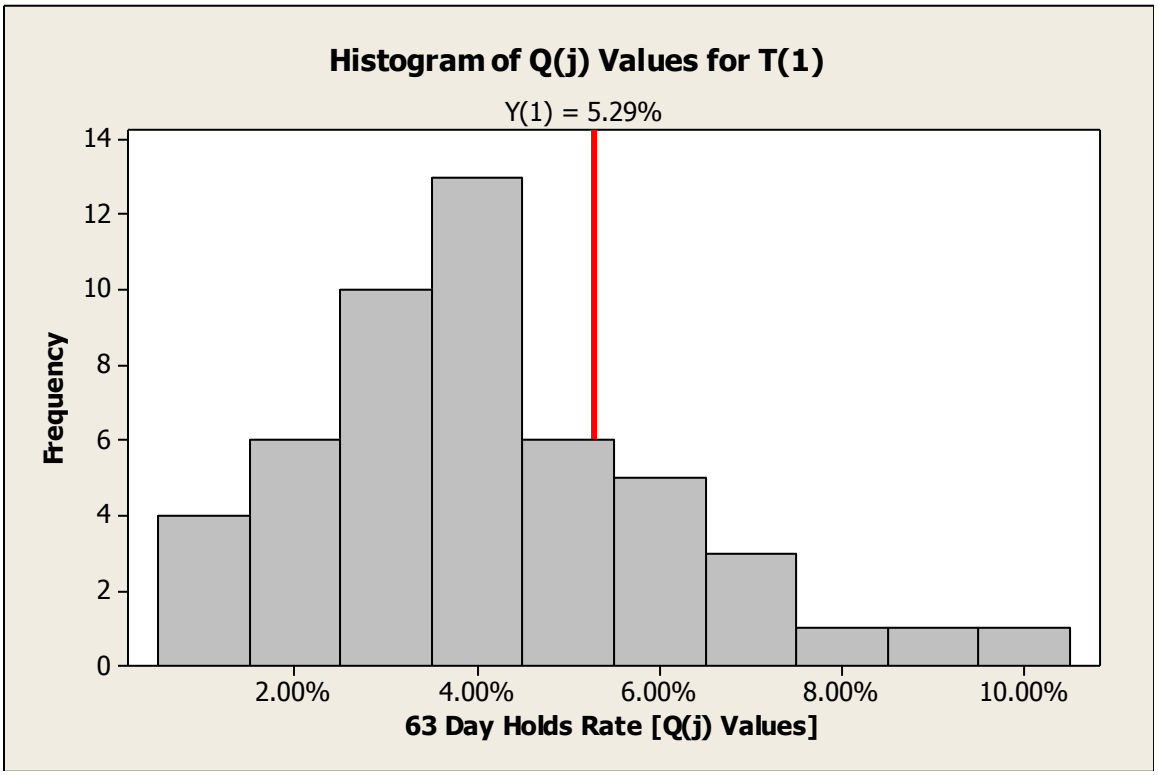

Figure 23: Simulation output compared to IP1 Overall Holds Rate (Y_1)

A normal transformed (Box-Cox $\lambda = 0.5$) was found to adequately represent the distribution of 50 simulated Q_j values for T_1 with a very strong fit ($p = 0.896$). As seen in Figure 23, the observed result was located near the mode of the simulation distribution,

and was 74.44% of the cumulative normal transformed distribution in Step 2.3. Therefore, the post-change CDF probability associated with IP1 was 0.7444.

Step 2.4 was accomplished using 50 simulation replications (Q_j values) applying Equations (4) – (7) and randomly generating values for B_i and A_i. As discussed in Section 5.2, the scheduling rules changed in IP1 and the variability of volumes in the L&D and PP units was reduced as intended. Accordingly, the respective CV's for A and B were determined to be factors influenced by the change (i.e., controlled parameters), while overall delivery volumes and subsequent demand for PP care were not controlled by scheduling. Therefore, standard deviation values of A and B were to be affected by the scheduling tactic change, while mean values of A and B were not. Table 11 outlines the parameter values for $T_{1'}$.

Table 11: $T_{1'}$ Parameter Values for the MCS Model

Parameter	Value	Distribution / Comments
$T_{1'}$ Mean Daily Total Deliveries (A)	13.51	Normal (uncontrolled, same as IP1)
$T_{1'}$ Stdev Daily Total Deliveries (A)	5.19	Normal (calculated as CV is controlled parameter)
$T_{1'}$ CV (A)	0.3839	Controlled in BL
$T_{1'}$ Mean Days D-C PP LOS (B)	33.16	Normal (uncontrolled, same as IP1)
$T_{1'}$ Std Dev Days D-C PP LOS (B)	11.67	Normal (calculated as CV is controlled parameter)
$T_{1'}$ CV (B)	0.3520	Controlled in BL

The parameter values in Table 11 were used in the 50 simulation replications to generate Q_j values used along with the post-change CDF probability to determine $Y_{1'}$. The distribution of simulated Q_j values for $T_{1'}$ was found to be normal transformed (Box-Cox $\lambda = 0.5$) with a strong fit ($p = 0.651$). The post-change CDF probability and the inverse of the CDF for the normal transformed distribution were used together to calculate a transformed $Y_{1'}$ value ($Y_{1'}^{t}$). The transformed $Y_{1'}$ value was squared to find

$Y_{1'}$ in Step 2.5. Subsequently, Y_1 was compared to $Y_{1'}$ in Step 2.6 of the analysis. Table 12 details the values pertinent to the calculations for Steps 2.5 and 2.6.

Table 12: Calculation of $Y_{1'}$ and % Y_1 Improved over $Y_{1'}$ for Holds Rate

Variable	Value
IP1 CDF Probability	0.7444
Mean Q_j^t for $T_{1'}$	21.01%
Stdev Q_j^t for $T_{1'}$	5.27%
$Y_{1'}^t$ Using IP1 CDF Probability	24.47%
Step 2.5 $Y_{1'}$ Using IP1 CDF Probability	5.99%
IP1 Holds Rate (Y_1)	5.29%
Step 2.6 % Y_1 Improved over $Y_{1'}$	11.7%

A distribution of comparison values was developed in Step 2.7 with 50 repetitions of Steps 2.1–2.6. Also, each simulation applied common random numbers (CRN) as part of a variance reduction technique shared in Kelton et al. (2015). This distribution was found to be normal with a very strong fit ($p = 0.988$). As shown in Figure 24, the post-change performance shift CDF probability was 0.9999, or 99.99% of the cumulative normal distribution, in Step 2.8. The targeted performance shift of 15% is represented by the lower specification limit (LSL) since the targeted performance shift represents the minimal amount of improvement required. Any value below the LSL is counted to the parts per million (PPM) total, where PPM is a measure of how many trials (parts) are expected to be non-conforming out of one million trials.

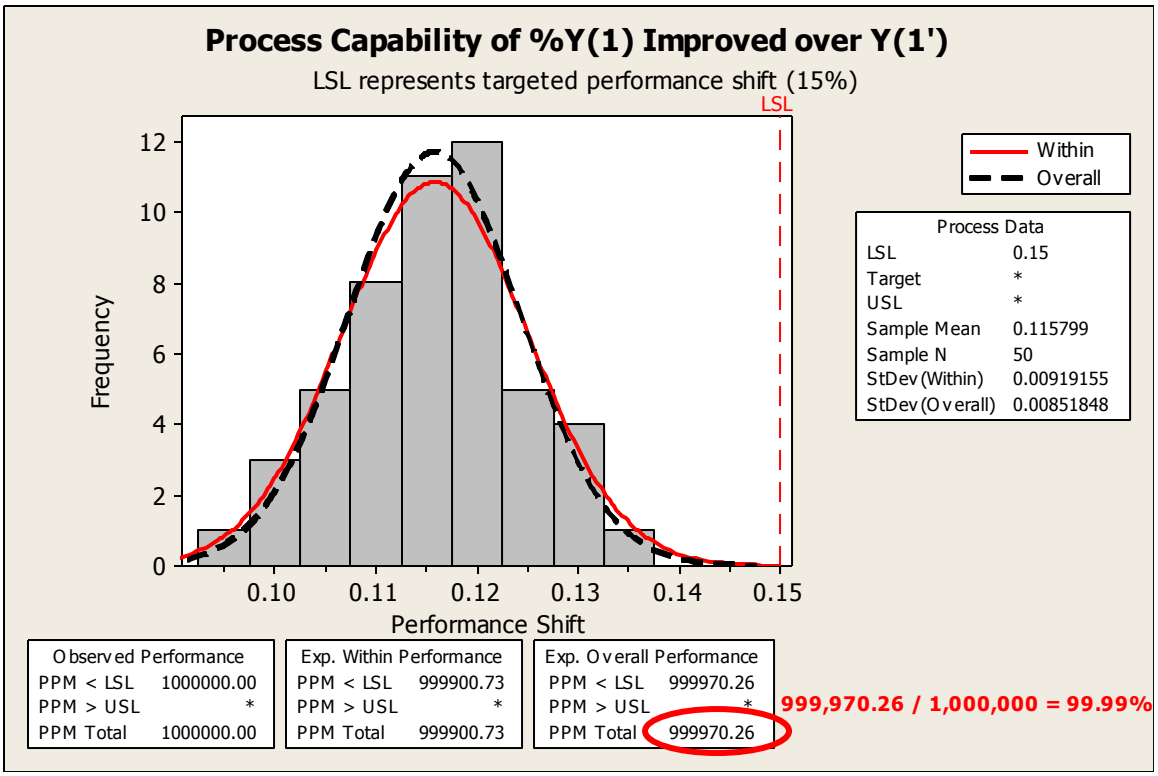

Figure 24: Post-change performance shift CDF probability for Holds Rate

In order to complete Step 2.9, the result of Step 2.8 was subtracted from one. Thus, there is a probability of 0.0001 that the actual Holds Rate performance observed during IP1 (Y_1) could have been at least 15% lower than it would have been had the L&D schedule been managed in IP1 as it was in BL ($Y_{1'}$). However, further review of the information presented in Figure 24 indicated that Holds Rate performance could have been at least 9% lower in IP1 than if the L&D scheduled had been managed as it was in BL. These statements provided the answer to Question #2 and it was substantiated by the distribution found in Step 2.7, which is shown in Figure 24.

5.4 Results for IP1 vs. BL and IP2 vs. BL

The analyses detailed in Sections 5.2 and 5.3 were replicated to compare the performance of IP2 to that of BL. Figure 25 shows that the factor values of C*B in IP2

fell within the range used to develop Equation (4). Thus, identifying a new relationship for Steps 1.3 and 2.1 was unnecessary.

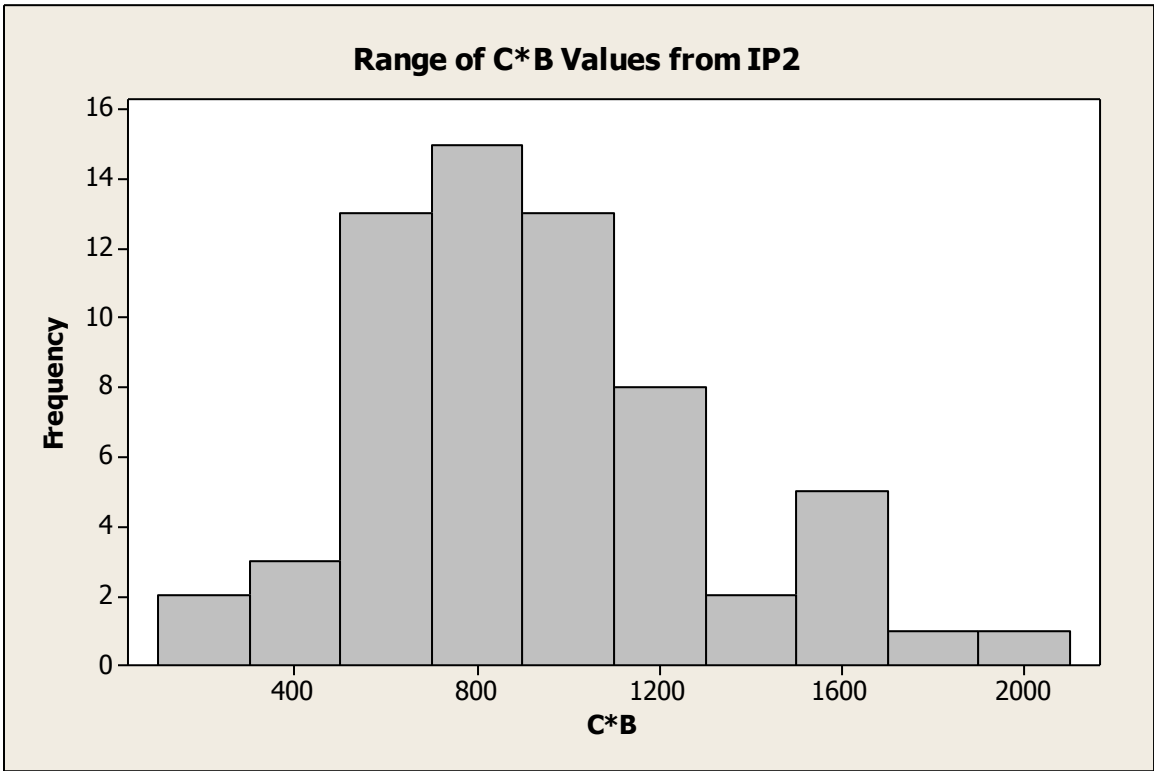

Figure 25: Histogram of C*B values for IP2 data

In IP2, the Overall Holds Rate (Y_1) was only 3.28%, which marked a 39.48% improvement over the BL Overall Holds Rate (Y_0). However, as shown in Figure 26, the observed result was located to the left of the simulation distribution's center, with a post-change CDF probability of 0.3166. The baseline CDF probability associated with BL was 0.5348, so the amount that the IP2 Overall Holds Rate (Y_1) improved over the BL Overall Holds Rate (Y_0) appeared to be caused by more than the scheduling tactic change alone. As will be shown, the proposed procedure addressed this concern by using the baseline CDF probability to answer Question #1 and by using the post-change CDF probability to answer Question #2. As stated in Chapter 3, a CDF probability is a

measure of chance, and using these CDF probabilities isolates the chance associated with each time period under analysis.

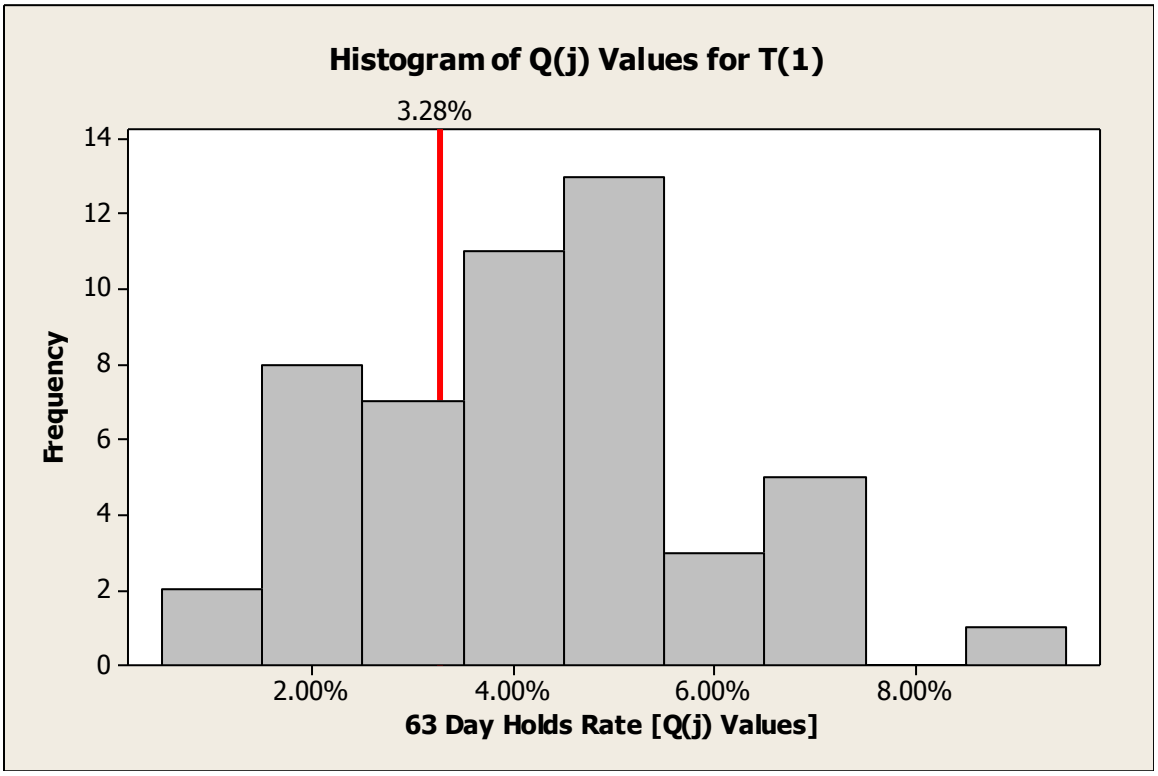

Figure 26: Simulation output compared to IP2 Overall Holds Rate (Y_1)

Table 13 details the observed Holds Rate improvement versus those values determined by following the proposed procedure. As shown, the difference in performance shift from BL to IP1 compared to that from BL to IP2 was much smaller using the results from the proposed procedure as compared to the observed results. These results indicated that uncontrolled factors influencing the Holds Rate in IP1, including those attributed to chance, contributed a negative effect. Conversely, the uncontrolled factors in IP2 made a positive impact. However, the difference in performance caused by the controllable factors, which are variation in Daily Deliveries and the PP LOS associated with the PP discharges for each day (Days D-C PP LOS), had a more consistent and positive impact between IP1 and IP2.

Table 13: Observed Holds Rate Improvement Values Compared to Procedure-Derived Values

Time Period Comparison	Y_0 (Observed)	Y_1 (Observed)	$\%Y_1$ Improved over Y_0 (Observed Performance Shift)	$\%Y_{0'}$ Improved over Y_0 (Procedure for Question #1)	$\%Y_1$ Improved over $Y_{1'}$ (Procedure for Question #2)
				$\bar{E}$ = 11.07%	$\bar{E}$ = 11.58%
				S = 0.66%	S = 0.85%
				n = 50 comparisons	n = 50 comparisons
IP1 vs. BL	5.42%	5.29%	2.40%	Prob. Target Achieved = 0.0000	Prob. Target Achieved = 0.0000
				$\bar{E}$ = 20.12%	$\bar{E}$ = 21.09%
				S = 0.59%	S = 0.98%
				n = 50 comparisons	n = 50 comparisons
IP2 vs. BL	5.42%	3.28%	39.48%	Prob. Target Achieved = 1.0000	Prob. Target Achieved = 1.0000

α = 0.05, Power = 1.00 (β = 0.00)

H_a for One-Sample t Test is μ > 15% (targeted performance shift)

As shown in Table 13, 50 sample comparisons were made from the proposed procedure to assess $\%Y_{0'}$ Improved over Y_0 and to assess $\%Y_1$ Improved over $Y_{1'}$ for both time period comparisons. This yielded a statistical power of 1.00 for each One-Sample t Test performed when seeking to detect a difference in the mean value for performance shift of 1%. This 1% value was chosen since the sample mean values of each time period comparison were more than two percentage points different than the targeted performance shift of 15%. Thus, there was a probability of one to conclude that the mean was greater than 15% (i.e., reject H_0) when indeed the mean was greater than 15% (i.e., H_0 is false). In the IP2 vs. BL comparison, the p-value of each One-Sample t Test was 0.000, thereby indicating a probability of zero to conclude that mean performance shift was greater than 15% (i.e., reject H_0) when indeed it was no different than 15% (i.e., H_0 is true). However, in the IP1 vs. BL comparison, the p-value of each One-Sample t Test was 1.000, thereby indicating a probability of one to conclude that the mean performance shift was greater than 15% (i.e., reject H_0) when indeed it was no different than 15% (i.e., H_0 is true). These observations, combined with the Probability Target Achieved values in Table 13, led to the conclusion that target performance for

Holds Rate was not achieved in the IP1 vs. BL comparison and it was exceeded in the IP2 vs. BL comparison.

A sample size of 50 comparisons was used for each time period analysis though a smaller sample size could have been used. Also, each simulation run consisted of 50 replications, while fewer replications would have been sufficient. While a sample size (n) requirement is determined by the statistical power achieved, estimating the error of the simulation sample mean relative to the population mean (γ) is an objective approach to determining the number of replications (m) needed in each simulation run. Law (2007) provided mathematical relationships for the method of estimating γ to determine the required value of m as expressed in Equations (9) – (12).

$$\gamma = \frac{|\bar{E}(m)-\mu|}{|\mu|} \tag{9}$$

$$\delta(m,\alpha) = t_{m-1,1-\alpha/2}\sqrt{\frac{S^2(m)}{m}} \tag{10}$$

$$\delta(m,\alpha)/|\bar{E}(m)| \leq \gamma',\ \gamma' = \frac{\gamma}{(1+\gamma)} \tag{11}$$

$$I(\alpha,\gamma) = [\bar{E}(m) - \delta(m,\alpha), \bar{E}(m) + \delta(m,\alpha)] \tag{12}$$

Where:

γ: Actual error of the simulation sample mean relative to the population mean

μ: Population mean

m: Number of replications in each simulation run

$\bar{E}(m)$: Simulation sample mean based on m replications

γ': "Adjusted" relative error needed to get an actual relative error of γ

$\delta(m,\alpha)$: Confidence interval half-length for μ based on m simulation replications and α

$S^2(m)$: Simulation sample variance based on m replications

$I(\alpha,\gamma)$: Confidence interval for μ based on α and γ

In Equation (9), the population mean (μ) is unknown despite the simulation sample mean based on m replications being known, which is denoted as $\bar{E}(m)$. Therefore, γ cannot be directly calculated in Equation (9), so Equations (10) and (11) are necessary. In Equation (10), $\delta(m, \alpha)$ is the confidence interval half-length for μ based on m replications and α, and Equations (5) and (6) are used together in an iterative process to determine the required m to achieve an adjusted relative error (γ') that results in a sufficient γ. A larger m results in longer simulation run times, but also yields a smaller γ and a tighter confidence interval, which is denoted in Equation (12) as $I(\alpha, \gamma)$.

To demonstrate the impact of m and n on γ', γ, and statistical power, values of m and n were varied in an analysis of $\%Y_1$ Improved over $Y_{1'}$ for IP2 vs. BL as documented in Table 14. Case I is the same comparison made for IP2 vs. BL and Question #2 in Table 13. Min γ' is the minimal value of γ' required to satisfy Equation (11) for all comparisons with simulations of replication length m and sample size n listed. Min γ was calculated by algebraic conversion of Equation (11).

Table 14: Results of IP2 vs. BL for Holds Rate Using Different Replication Lengths and Sample Sizes

Case	Replications (m)	Samples (n)	Min γ'	Min γ	$\%Y_1$ Improved over $Y_{1'}$ (Procedure for Question #2)
Case I	50	50	0.1428	0.1666	$\bar{E}$ = 21.09% S = 0.98% Actual Power = 1.0000
Case II	30	30	0.2116	0.2683	$\bar{E}$ = 21.43% S = 1.45% Actual Power = 0.9794
Case III	25	30	0.2238	0.2883	$\bar{E}$ = 21.23% S = 1.19% Actual Power = 0.9978
Case IV	20	30	0.2920	0.4125	$\bar{E}$ = 21.50% S = 1.35% Actual Power = 0.9897
Case V	20	20	0.2506	0.3344	$\bar{E}$ = 21.24% S = 1.30% Actual Power = 0.9932

α = 0.05, Target Power = 0.95 (β = 0.05)

H_a for One-Sample t Test is μ > 15% (targeted performance shift)

The probability that the target was achieved was one for each case in Table 6. Also the actual statistical power of the One-Sample t-Test performed in each case was approximately one while the p-value of each One-Sample t-Test was zero. Therefore, there was near certainty in correctly concluding that the mean value for performance shift was greater than 15% in each case. Fairly large values of Min γ were obtained without sacrificing the actual statistical power associated with the comparison made in Step 2.9, and this was attributed to the relatively small standard deviation associated with the comparison values as a result of using the CRN variance reduction technique.

In Table 6, the five cases presented show that varying m and n impact Min γ (γ'). Cases II–IV have n fixed at 30, and the values of Min γ (γ') are inversely related to m, which was expected based on Equations (10) and (11) since $\delta(m,\alpha)$ increases as m decreases when all other parameters are held constant. Also, n impacts Min γ (γ') as shown in Cases IV and V, and this is due a larger sample size allowing for a broader range of γ (γ') values.

5.5 Discussion

As mentioned in Section 5.4, uncontrolled factors influencing the Holds Rate in IP1 contributed a negative effect, while those in IP2 made a positive impact. Though not indicative of the targeted performance shift of 15% being achieved, the results of the proposed procedure for the IP1 vs. BL comparison were nearly five times greater than the observed performance shift of IP1 vs. BL. Thus, the scheduling tactic change was more effective than the observed performance showed. As stated in Section 1.1, a less-refined version of the proposed procedure demonstrated to hospital leadership that the change

was more effective than what was observed in the Holds Rate data. This analysis allowed leaders to continue their support of the scheduling tactic change. Thus, the proposed procedure can allow organizations to quantitatively assess the effectiveness of a change while accounting for unfavorable influence from the uncontrolled environment.

Alternatively, the results in Table 13 for IP2 vs. BL show that the observed performance far exceeded the targeted performance shift of 15%. However, the proposed procedure yielded results much closer to that goal. Therefore, the proposed procedure can allow organizations to quantitatively assess the effectiveness of a change while accounting for favorable influence from the uncontrolled environment.

The new scheduling rules reduced the CV's of Daily Deliveries and Days D-C PP LOS by up to 5% in IP1 and 8% in IP2. This reduction allowed the flow of patients into the system to be smoothed. Patients were less likely to be held as indicated by the results of the analysis with the proposed procedure, and this correlates to higher patient satisfaction. Nurses and physicians were burdened less than they were in BL on peak days of volume in L&D and PP due to the smoothed patient flow. In fact, both the hospital's chief administrative officer (CAO) and the System Vice President (SVP) of Women's Services at NHC have heralded this project as successful.

CHAPTER 6

DISCRETE-EVENT SIMULATION MODEL

This Chapter 6 provides an example of the procedure proposed in Chapter 3 being applied using discrete-event simulation. Only Question #2 was addressed to determine the impact on ADT for the case study detailed in Chapter 4, and this was due to the limitations of data available prior to the new EHR being implemented.

A DES model was developed to complete Step 0.1. Next, a detailed explanation of Steps 2.1–2.6 is provided to demonstrate how a single performance shift value was calculated. Subsequently, Steps 2.7–2.8 were completed to develop a distribution of performance shift values and estimate the mean change in performance. Step 2.9 was not performed since no targeted performance shift was set. Results are provided for the IP2 vs. BL comparison made in Step 2.8 and this Chapter 6 ends with a discussion of the analysis. Question #2 is restated below.

> **Question #2:** If the scheduling rules of the BL time period still existed in the IP2 time period, how would ADT have differed in the IP2 time period?

6.1 Model Description for BL and IP2

Figure 27 depicts the basic structure of patient flow for BL and IP2, and a DES model was implemented using Arena. In the model, entities flowed through the model such that PP bed assignment and duration of PP bed seizure were accurately captured.

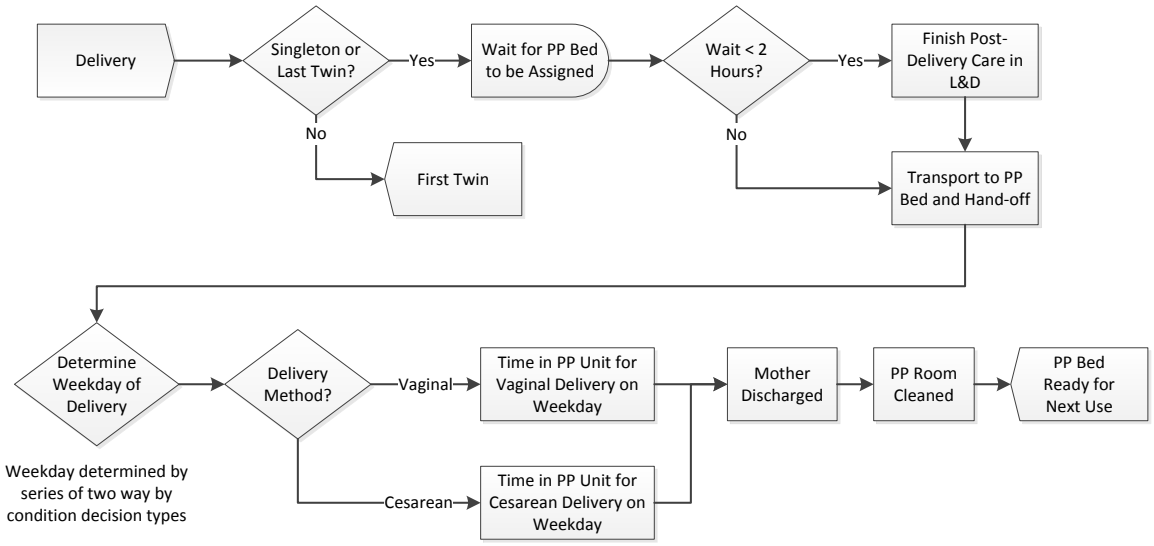

Figure 27: Basic structure of the DES model

- First, entities arrive in the model as newborn deliveries. Since the mother is assigned a PP bed, the newborn entity is represented as a mother patient. This is accomplished immediately following the Delivery step as the probability of the newborn being a singleton (i.e., single birth) or lastborn twin is applied in the subsequent decision point. The entity exits the model if it is a firstborn twin so as to only allow the mother to move forward since she is associated by proxy with the lastborn twin. Following delivery, each mother waits to have a PP bed assigned to her. The mother entity then seizes the PP bed resource when departing this queue despite not yet being transported to the PP unit. The PP bed is seized before transport as each mother patient has claim to her assigned PP bed at this point.

- If a mother happens to wait less than two hours to seize a PP bed, then more time is added to the delay so post-delivery care is finished before transporting the patient since such care can take from 40 minutes to two hours. Post-delivery care includes activities such as weighing the baby, cutting the umbilical cord, and placental expulsion. It is possible for a mother entity to wait just under two hours and then incur an additional two hours of post-delivery care, but the impact of this on the results was negligible. However, each mother entity is delayed at least 40 minutes from being transported to her PP bed in the model, and this reflects the actual process. Transporting each mother to her PP bed includes conducting a nursing hand-off.
- Once the mother arrives to her PP bed, her weekday of delivery and method of delivery are determined due to their impacts on PP LOS. The probability of vaginal delivery is based on the weekday of delivery. The duration of time in the PP unit is measured by subtracting the entity's time between delivery and being transported to the PP bed from the entity's PP LOS. Time in the PP unit accounts for various clinical and non-clinical activities, which include the mother's recovery, vaccinations, circumcision as requested, hearing screens, lactation consults, governmental documentation, and a car seat test.
- After completion of her time in the PP unit, the mother is discharged and the entity turns into a room cleaning need. The time to clean the PP room includes the response time of environmental services staff to the cleaning request in addition to the time spent cleaning the room. Upon the PP room being cleaned, the PP bed is released for a future use in the model.

Aside from the model's structure, the model involved steady-state simulation since the mother baby service line continuously operated. Thus, prior to completing Steps 0.1 and 2.1, a warm-up period needed to be established with a duration that allowed for stabilization to occur as indicated by Kelton et al. (2015). Both the number of occupied PP beds and the average delay time between delivery of a singleton or last born twin and the mother being placed into a PP bed (ADT) were examined to determine the appropriate number of days in the simulation needed for the warm-up period. Only IP2 data was used for this assessment since not all required data points were available to make such an assessment for BL.

The number of occupied PP beds was counted at every midnight in the simulation following the start, which is consistent with the method for measuring census level at Norton Healthcare. Daily delivery volumes fluctuated by weekday, as did census levels routinely throughout each week. Therefore, census level values needed to be compared by weekday in order to assess when steady-state was reached in the simulation. The difference between each day's census and the average census for that weekday over the weeks remaining in each simulation replication was measured to identify stability. Mean differences across 50 replications were plotted over simulation days in Figure 28, and the results indicated mean differences approached zero.

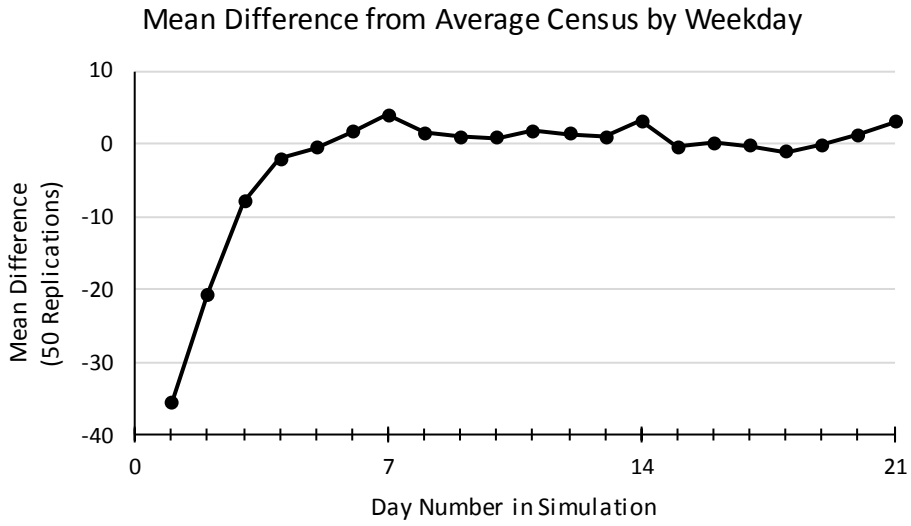

Figure 28: Plot of mean difference from average census by weekday in IP2 simulation

Mean ADT values were calculated over 50 replications to measure delays between mother's delivery and her placement in a PP bed. Due to delivery volumes fluctuating by weekday, mean ADT values were also analyzed by weekday as shown in Table 15. The mean ADT value for only Sunday of Week 1 was identified to be lower than all of those values of the remaining weeks.

Table 15: Mean ADT Values by Weekday in IP2 Simulation

Week #	SUN	MON	TUE	WED	THU	FRI	SAT
1	1.73	1.80	1.83	2.19	2.33	3.30	3.20
2	2.33	1.78	1.82	2.02	2.44	3.43	3.64
3	2.18	1.78	1.86	2.23	2.17	2.72	2.93
4	2.06	1.79	1.76	1.85	2.10	3.05	2.98
5	2.04	1.79	1.81	2.13	2.49	3.20	3.20
6	1.85	1.77	1.80	2.36	2.02	2.89	2.69
7	2.44	1.80	1.91	2.22	2.48	3.07	2.84
8	2.23	1.83	1.97	2.13	2.20	2.57	2.90
9	2.51	1.76	1.79	1.81	2.04	3.36	3.47
10	2.61	1.77	1.78	2.31	2.64	3.36	3.58

Based on the trends observed in Figure 28 and Table 15, a warm-up period of seven days was determined to be sufficient for stability to be achieved in the model. While a shorter warm-up period of four or five days could have been considered, seven

days allowed for additional assurance that individual replications would achieve steady-state prior to output data being reported.

6.2 Question #2: Experimental Design Demonstrated for IP2 vs. BL

After having developed a suitable model for both BL and IP2 to fulfill the requirements of Steps 0.1 and 2.1, the proposed analysis procedure for answering Question #2 advanced to Step 2.2. To complete Step 2.2, a simulation of ADT values was conducted using IP2 parameters as defined in Tables 5–7. The distribution of ADT values for T_1 from the simulation is depicted in Figure 29, with the red line marking the IP2 ADT value (Y_1).

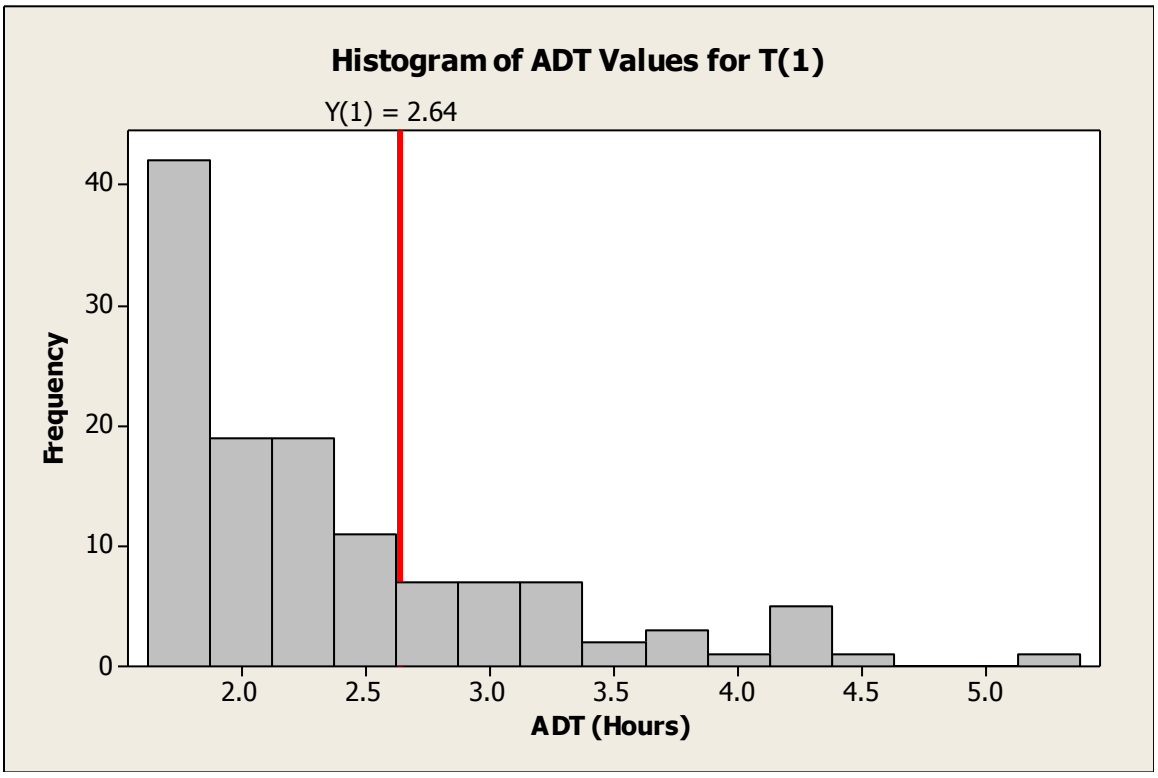

Figure 29: Simulation output compared to IP2 ADT value (Y_1)

A normal transformed distribution which used Equation (13) in the Johnson transformation (JT) method was found to adequately represent the distribution of 125

simulated ADT values for T_1 with acceptable fit (p = 0.083). The number of simulation replications (m = 125) was determined using Equations (9) – (12) and a relative error γ equal to 0.10. This target value of γ was selected since a One Sample t-Test and statistical power calculation were not practical as a targeted performance shift was not specified for ADT. Also, the lack of a targeted performance shift for ADT resulted in the analysis being terminated at Step 2.8. The value of m was incremented by 25 until an acceptable value was found for all simulation samples used in the analysis to answer Question #2. Min γ at 125 replications was 0.0845, so the target γ of 0.10 was achieved. As seen in Figure 29, the observed result was 74.83% of the cumulative normal transformed distribution in Step 2.3. Therefore, the post-change CDF probability associated with IP2 was 0.7483.

$$\upsilon = 1 + 0.5 \times \mathrm{LN}\left(\frac{\varphi - 0.01 - \eta}{\chi + 0.30 - \varphi}\right) \tag{13}$$

Where:

υ: JT value of ADT

φ: ADT value to be transformed

η: Minimum value of ADT across all replications

χ: Maximum value of ADT across all replications

In Step 2.4, 125 simulation replications (ADT values) were used and all parameters of the DES model had the same values as those of IP2 with the exception of HRD values and weekday delivery type probabilities. The scheduling tactic change limited scheduled deliveries by delivery type on a daily basis as part of reducing the overall scheduled deliveries allowed per day. Thus, HRD values and probabilities of vaginal delivery by weekday were considered as factors influenced by the change (i.e., controlled parameters), while other parameters were not.

Equation (14) was used to estimate HRD parameters for $T_{1'}$ that reflected the volume variability of BL in an NHPP since volume variability was controlled by the scheduling tactic change. Also, the process needed to have a value for overall mean daily deliveries equal to that of IP2 as overall delivery volume was deemed to be an uncontrolled parameter.

$$\bar{E}_{g,h} = \frac{\mu * \tau * \theta_h * \omega_{g,h}}{\rho} \quad (14)$$

Where:

g: Index for time window

h: Index for weekday

$\bar{E}_{g,h}$: HRD parameter for use in time window g on weekday h in $T_{1'}$

μ: Mean of daily deliveries for IP2

θ_h: Proportion of deliveries occurring on weekday h in BL

$\omega_{g,h}$: Proportion of deliveries in time window g on weekday h in BL

τ: Scaling factor for weekdays per week (7)

ρ: Number of hours per time window (4)

In Equation (14), the mean daily deliveries for IP2 (μ = 13.56) were multiplied by a scaling factor (τ = 7) to determine the mean volume of weekly deliveries in IP2. The mean volume of weekly deliveries in IP2 was multiplied by the proportion of deliveries that occurred on weekday h (θ_h) in BL to estimate the mean daily deliveries for weekday h in $T_{1'}$. The estimate of mean daily deliveries for weekday h was multiplied by the proportion of deliveries for weekday h that occurred during time window g on weekday h in BL ($\omega_{g,h}$) to estimate the mean amount of deliveries that occurred during time window g on weekday h in $T_{1'}$. Finally, the estimate of the mean amount of deliveries that occurred during time window g on weekday h was divided by the number of hours per

time window (ρ = 4) to estimate the HRD parameter for use in time window g on weekday h in $T_{1'}$ ($\bar{E}_{g,h}$). Values of θ_h are shown in Figure 30 and values of $\omega_{g,h}$ are shown in Table 16. Table 17 provides the $\bar{E}_{g,h}$ values calculated using Equation (14).

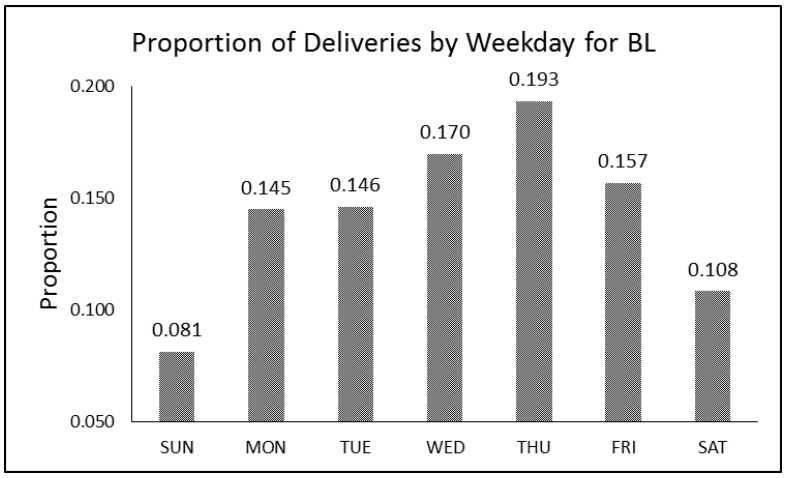

Figure 30: Bar graph of θ_h values

Table 16: Table of $\omega_{g,h}$ Values

Time Window	SUN	MON	TUE	WED	THU	FRI	SAT
1	0.087	0.073	0.056	0.118	0.079	0.098	0.174
2	0.145	0.106	0.056	0.125	0.122	0.128	0.098
3	0.174	0.285	0.242	0.222	0.220	0.195	0.185
4	0.174	0.211	0.194	0.215	0.250	0.233	0.228
5	0.217	0.179	0.202	0.188	0.177	0.165	0.196
6	0.203	0.146	0.250	0.132	0.152	0.180	0.120

Table 17: Table of $\bar{E}_{g,h}$ Values

Time	$\bar{E}$						
Window	SUN	MON	TUE	WED	THU	FRI	SAT
1	0.168	0.252	0.196	0.475	0.363	0.363	0.447
2	0.280	0.363	0.196	0.503	0.559	0.475	0.252
3	0.335	0.978	0.839	0.894	1.006	0.727	0.475
4	0.335	0.727	0.671	0.866	1.146	0.866	0.587
5	0.419	0.615	0.699	0.755	0.811	0.615	0.503
6	0.391	0.503	0.866	0.531	0.699	0.671	0.307

Probabilities of vaginal delivery by weekday for $T_{1'}$ were estimated with data from Table 7. First, the total Number of Vaginal Deliveries in IP2 was multiplied by the % of Week's Vaginal Deliveries for each weekday in BL and rounded to the nearest integer to estimate the Number of Vaginal Deliveries for each weekday in $T_{1'}$. This operation was done since the scheduling tactic change affected the distribution of deliveries across weekdays for each delivery type. This estimate for each weekday was then divided by the summation of the total Number of Vaginal Deliveries in IP2 and the total Number of Cesarean Deliveries in IP2 to calculate the Estimated Probability of Vaginal Delivery by weekday for $T_{1'}$. Table 18 provides the Estimated Probability of Vaginal Delivery by weekday for $T_{1'}$.

Table 18: Estimated Probability of Vaginal Delivery by Weekday for $T_{1'}$

Day	Estimated Prob. of Vaginal Delivery	Estimated Vaginal Deliveries	Estimated Cesarean Deliveries
SUN	69.57%	48	21
MON	58.54%	72	51
TUE	59.68%	74	50
WED	67.36%	97	47
THU	63.41%	104	60
FRI	61.65%	82	51
SAT	75.00%	69	23
Total	64.31%	546	303

The parameter values in Tables 17 and 18 were used with all other parameter values from IP2 to generate ADT values for $T_{1'}$. The ADT values for $T_{1'}$ were found to be normal transformed using Equation (13) with acceptable fit ($p = 0.061$), and this distribution was used along with the post-change CDF probability to determine $Y_{1'}$. The post-change CDF probability and the inverse of the CDF for the normal transformed distribution were used together to calculate a transformed $Y_{1'}$ value (JT Value of $Y_{1'}$). The transformed $Y_{1'}$ value was used in a routine using Excel Solver to calculate $Y_{1'}$ in

Step 2.5. Subsequently, Y_1 was compared to $Y_{1'}$ in Step 2.6 of the analysis. Table 19 details the values pertinent to the calculations for Steps 2.5 and 2.6.

Table 19: Calculation of $Y_{1'}$ and % Y_1 Improved over $Y_{1'}$ for ADT

Variable	Value
IP2 CDF Probability	0.7483
Mean JT Value of ADT for $T_{1'}$	-0.2330
Stdev JT Value of ADT for $T_{1'}$	0.8750
JT Value of $Y_{1'}$ Using IP2 CDF Probability	0.3526
Step 2.5 $Y_{1'}$ Using IP2 CDF Probability	2.88
IP2 ADT (Y_1)	2.64
Step 2.6 % Y_1 Improved over $Y_{1'}$	8.2%

A distribution of comparison values ($\Delta_{1/1'}$ values) was developed in Step 2.7 with 32 repetitions of Steps 2.1–2.6 to generate 32 sample observations. Samples were increased in the increment of 16 as simulation runs in Arena were made with 2,000 replications each to generate 16 samples of 125 replications each. A target γ of 0.10 was selected for the mean value of $\Delta_{1/1'}$, and Equations (9) – (12) were applied by substituting *n* in place of *m* in the equations. The target γ was achieved after generating 32 samples, which resulted in a γ value of 0.0759.

Each simulation applied common random numbers (CRN) as part of a variance reduction technique shared in Kelton et al. (2015). This distribution was found to be normal with a very strong fit (p = 0.754). As shown in Figure 31, the mean value of $\Delta_{1/1'}$ was 10.742%, with a 95% confidence interval of (9.984%, 11.499%). Also, the comparison values from the simulation ranged between 6.691% and 15.917%, and this indicates that the scheduling tactic change reduced ADT from what it would have been if the scheduling tactics from BL were still in use in IP2. These statements provided the

answer to Question #2 and it was substantiated by the distribution of Step 2.7 as shown in Figure 31.

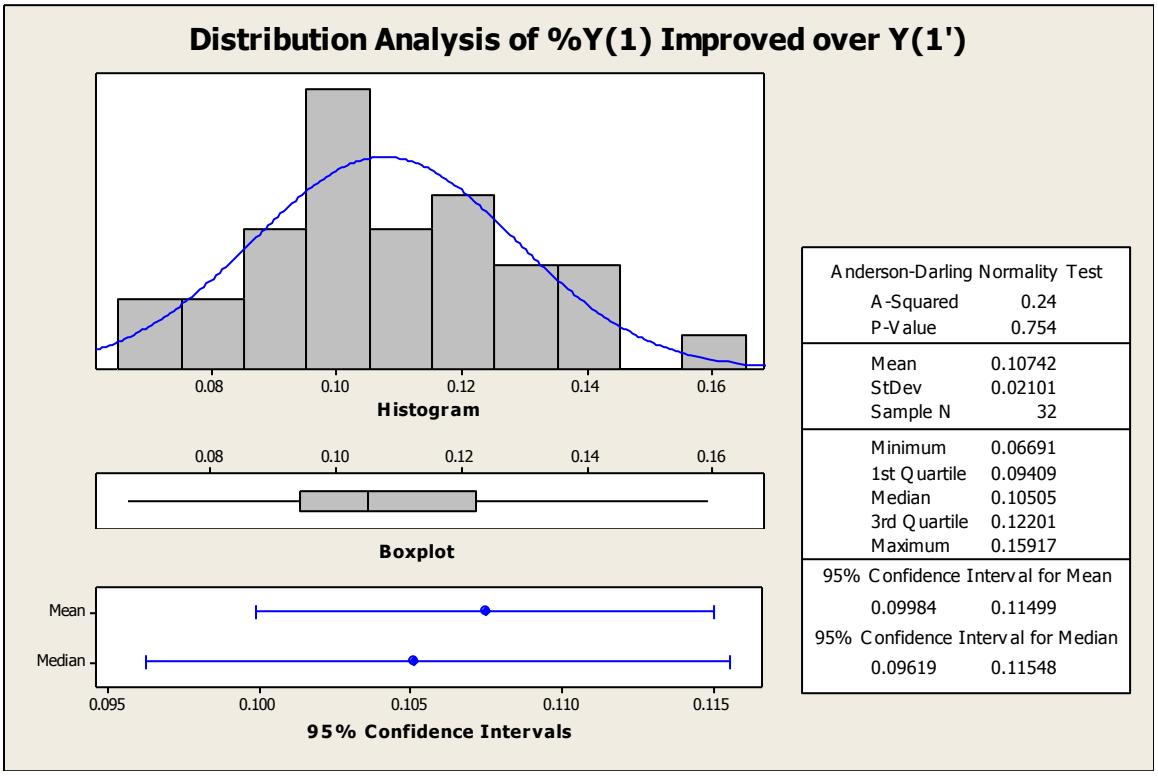

Figure 31: Distribution of post-change performance shift values for ADT

6.3 Discussion

The analysis presented in this Chapter 6 demonstrates that the scheduling tactic change was effective in reducing delays in the transitions of care between L&D and PP. This conclusion corroborates with the conclusion in Chapter 5 that the scheduling tactic change successfully reduced the Holds Rate in IP2 as compared to BL given the definition of Holds Rate provided in Chapter 4, which validates both findings between the MCS model and DES model. This observation confirms that this procedure can allow similar conclusions to be reached using different methodologies to analyze the same environment.

CHAPTER 7

CONCLUSIONS

The objective of this dissertation is to provide a method for evaluating the difference in performance after an organization makes a change while considering the stochastic nature of the environment in which it operates. The literature review of Chapter 2 identified that simulation is an effective approach to analyze systems with stochastic variables and that organizations can be viewed as complex systems. Furthermore, models discussed in literature have been used to evaluate potential system designs and there does not appear to be use of simulation to evaluate current or past performance or the effectiveness of a new system design that is already implemented. The procedure proposed in Chapter 3 was developed as a means for meeting the objective of this dissertation and it contributes an understanding of how simulation can be used to analyze the performance of organizations as complex systems. Specifically, this dissertation work advances the ability to assess the impact a change has made on the performance of an organization with a quantitative approach that uses simulation to account for the influence of stochastic variables and uncontrolled parameters.

The validity of the procedure was demonstrated in Chapters 5 and 6 with the case study introduced in Chapter 4. In Chapter 5, the scheduling tactic change of the case study was assessed to be more effective than the observed performance shift of

IP1 vs. BL based on the results of the procedure. The uncontrolled environment of the mother-baby service line, which included nursing judgment on factors related to clinical care and patient-family satisfaction, presented unfavorable influence on the Holds Rate in the IP1 vs. BL comparison. Conversely, the procedure was used to show that this uncontrolled environment provided favorable influence in the IP2 vs. BL comparison since the scheduling tactic change was assessed to be less effective than the observed performance shift of IP2 vs. BL indicated. However, the results of the procedure in both comparisons led to the conclusion that the scheduling tactic change had a reducing effect on the Holds Rate.

In Chapter 6, the analysis using the procedure demonstrated that the scheduling tactic change was effective in reducing delays in the transitions of care between L&D and PP. This conclusion indicated that convergent validity was achieved between the DES models and MCS models in using the procedure since determining a patient to be held involves judging the transition of care to be unintentionally delayed.

Regarding applicability of the procedure, Chapter 5 demonstrated that the procedure can allow organizations to quantitatively assess the effectiveness of a change while accounting for unfavorable or favorable influence from the uncontrolled environment. In addition, Chapters 5 and 6 together showed that the procedure can be used with different simulation methods to reach similar conclusions. Furthermore, the case study demonstrated that using this procedure can enable leadership to better understand the efficacy of a change, which can allow leaders to remain patient with a change when uncontrolled conditions are unfavorable. In the case study, insights gained

from use of the procedure promoted the key understanding leaders had of the project's success relative to the dynamics of its environment.

It is also possible that meeting the objective with this procedure may yield additional advantages with risk taking and achievement. Reeve (1997) stated that situations involving the opportunity for achievement occur when a person knows that the performance attributed to him or her will lead to an evaluation, favorable or unfavorable, that may serve as the basis for assessing personal competency. Furthermore, Atkinson (1957, 1964) asserted that achievement behaviors are guided by both a tendency to approach success and a tendency to avoid failure. In this assertion, the perception of the probability of success is paramount to taking a risk, aside from intrinsic motives and extrinsic incentives associated with that risk. Also, Burger (1985) posited that one's desire to establish control influenced the degree of persistence with confronting a difficult task (i.e., a situation that involves a lower probability of success). Thus, in complex environments where organizations have limited control, the probability of success may be perceived as being low, especially by decision-makers with low desire for control, and this may lead to performance stagnation due to inaction. However, use of the proposed procedure allows for performance to be assessed independent of uncontrollable parameters and this form of assessment may favorably affect the perception decision-makers have of the probability of success. This benefit, along with an accurate understanding of risk associated with a proposed change in deciding whether to implement it, would serve to promote performance growth.

The case study presented in this dissertation applied the proposed procedure using an MCS model and a DES model. As stated in Chapter 2, other simulation methods

exist. Applying this procedure using other simulation models may advance research related to the objective of this dissertation. For example, an ABS model may be used to further understand how dynamic complexity in the broader environment affects uncontrollable parameters of agents' decision-making behaviors.

Another opportunity for future research is to study the impact of technology in addressing Questions #1 and #2. For instance, parameters once considered to be uncontrollable may later be viewed as being controllable with the advent of new technology. Also, the ability to measure and study more parameters may improve as new means of data technology emerge.

While there may be other opportunities for future research in this topic, a final proposal for research is to investigate other means of addressing Questions #1 and #2. For example, the proposed procedure in Chapter 3 and the case study analyses of Chapters 5 and 6 applied frequentist inference while an approach using Bayesian inference could be explored.

Aside from further research, opportunities exist in the application of the proposed procedure. As mentioned in Chapter 1, irrational reaction to observed performance can take place when uncontrolled external forces overshadow the impact of the change being assessed in either the form of the *unfortunate loser* condition or the *undeserving winner* condition. The ability of the proposed procedure to provide an assessment of performance that isolates the impacts of these external forces can potentially enable an organization to better understand the cause-and-effect relationships of its actions and thereby leverage this knowledge to become more sustainable.

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