Improving ICU Patient Flow through Discrete-Event Simulation

by

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B.S. Mechanical Engineering
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Submitted to the MIT Sloan School of Management and the Engineering Systems Division in Partial Fulfillment of the Requirements for the Degrees of

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Master of Science in Engineering Systems

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Abstract

Massachusetts General Hospital (MGH), the largest hospital in New England and a national leader in care delivery, teaching, and research, operates ten Intensive Care Units (ICUs), including the 20-bed Ellison 4 Surgical Intensive Care Unit (SICU), a versatile unit which has a major role in perioperative and emergency care. 90% of SICU patients are eventually transferred to another unit in the hospital. Frequent and sometimes lengthy non-clinical delays in this transfer process can be primarily attributed to congestion in downstream units. Multivariable regression analysis demonstrates that additional non-clinical SICU time yields negligible downstream time savings, while consuming an average of 2.4 SICU beds per day, or 12% of total SICU capacity. In addition to exacerbating the delays of patients requiring admission to the SICU, these non-clinical SICU exit delays are responsible for a yearly attributable annual cost in excess of $2.5M. Possible ameliorating approaches include prioritizing SICU transfers, or modifying the care of delayed SICU patients to begin preparing for discharge from the hospital.

Any such choices affecting capacity and resource allocation in the ICU environment involve high cost as well as potentially high risks related to quality of care. To evaluate the impact of potential operational changes, the SICU and its six primary downstream units are modeled in a highly detailed discrete event simulation. Patients are divided into ~2,700 procedural and diagnostic types. Entries (admissions) for each patient type are characterized as inhomogeneous Poisson processes, with lengths of stay drawn from probability distributions. Transfer practices and priorities are encoded in simulation logic. A simulation of twenty replication periods, each one year long, allows for calibration and validation by detailed comparison with historical data. Simulated average hourly census values are within 1% of historical averages and RMSE is below 4% for each of the five modeled areas, indicating high accuracy and low bias.

The validated simulation is applied to evaluate the impact of several possible operational adjustments, including changes to discharge timing, transfer priorities, and resource allocation. Two approaches prove most promising: 1) Transferring patients as soon as possible after medical clearance, eliminating the current practice of waiting to see if other patients might need downstream beds. 2) Implementing a 24-hour rolling medical clearance process in the SICU. These interventions are predicted to lower average and peak SICU utilization by ~6%, cut SICU entrance delays by ~35%, and decrease SICU exit delays by ~50%, with relatively little impact on downstream floors and no additional capital expenditures. These relatively simple policy changes can save ~$1M in non-reimbursed expenditures while reducing overcrowding. If capital expenditures are approved, the simulation indicates that adding beds to downstream units would be more beneficial to the system than adding the same number of intensive care beds (at a much higher cost). Similar results are likely to be applicable to other ICUs at MGH, multiplying the potential impact of these findings several times over.

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1 Introduction

This thesis applies multiple tools of Operations Management within the framework of an IRB-approved study[1] at MGH to elucidate the effect of patient transfer delays on ICU overcrowding and on the hospital system as a whole, and identifies potential approaches to address the root causes of these significant systemic issues.

1.1 Background

Critical care costs exceed 10% of hospital costs and 0.5% of U.S. gross domestic product.[1] Tertiary care centers such as MGH face critical care costs that are higher than average as a percentage of total inpatient costs. In addition, many ICUs at MGH already operate very near to operational capacity, and as the U.S. population ages, demand for intensive care is expected to increase substantially.[2]

1.2 Literature Review

The core focus of this thesis is the impact of delays in transferring intensive care unit patients to a general unit. While a large body of research has been published on delays in transferring into the ICU (see, for example, [3], [4]), relatively little has been written about the effects of delays in transferring *out* of critical care units (a term generally used interchangeable with "intensive care units"). One research group recorded and analyzed delays in transferring out of a 22-bed ICU over a 6-month period, finding that 27% of patients were delayed at least 8 hours; 81% of those delays were due to unavailable ward beds.[5] Members of the same group published a new analysis of the same system eight years later, finding that the percentage of delayed patients had

[1] MGH Protocol # 2011-P-001124/1, "MGH-MIT Collaboration: Surgical Inpatient Flow." Principal Investigator: Peter Dunn, MD. While the MGH work as a whole is governed by this MGH IRB approval, the author's contributions fall under the auspices of MIT COUHES approval.

increased to 31%. This statistically significant increase suggesting that initial efforts to address the delay problem had proven fruitless thus far.[6]

Several efforts have been made and reported in the literature to improve this transfer process. Some investigators have considered the perspective of the patient, whose experience is certainly influenced by unnecessary transfer delays.[7] Another group suggested that a smooth transfer process depends highly on the approach taken by downstream nursing staff members who receive these high-intensity patients into general units.[8] One recent report investigated the impact of controlled improvements to communication between intensive and general care units in the transfer-out process, finding that a highly targeted intervention to improve inter-unit nursing communication significantly reduced transfer delays for patients exiting the ICU.[9]

With respect to the methods of this thesis, principles of Operations Management have been frequently effectively applied to address capacity constraints in critical care, as has been extensively demonstrated in the literature (see, for example, [10]). Many detailed references are presented later in this thesis within the context of discussing each individual method. Multiple additional references are also cited throughout this work within the context of each considered topic.

1.3 Massachusetts General Hospital

The Massachusetts General Hospital, founded in 1811, is one of the largest hospitals in the United States. The tertiary/quaternary center hosts over 900 licensed inpatient beds which serve 47,000 inpatients per year. In addition, MGH surgeons perform approximately 38,000 operations yearly, while the Emergency Department (ED) records 88,000 visits. In addition to this high volume of patient care, MGH conducts the largest hospital-based research program in the country, with an annual budget near $550M, and serves as the original and largest teaching hospital of Harvard Medical School, which also provides faculty appointments to nearly all MGH staff physicians.[11]

As a tertiary/quaternary care center, MGH places a high priority on critical care. Including the recent (December 2011) addition of the Blake 12 unit, MGH hosts ten separate intensive care units.[12] Each of these ten units is specialized for a particular target patient population, and each follows slightly different modes of operation. However, all work within the same hospital system with a common goal of returning the sickest of patients to a stable condition as quickly and safely as possible; as a result of this commonality, several of our findings will be applicable in many or all MGH intensive care units.

1.4 The Surgical Intensive Care Unit

This project focuses on the 20-bed Ellison 4 Surgical Intensive Care Unit (SICU), a versatile unit which has a major role in perioperative (including pre-surgical and post-surgical) and emergency care. Although the SICU contains a relatively small proportion of MGH's inpatient beds, it plays an outsize role in terms of operations, quality and safety, and financial metrics. Operationally, the SICU serves as a hub, and therefore a potential bottleneck, for several major patient pathways, in particular those involving high-intensity patients from the perioperative system. SICU availability is critical for optimal quality and safety of care of the most severely ill patients along these pathways. Financially, the SICU's high operating costs, high cost of capital expansion, and high impact on revenue-generating OR capacity merit close attention. This is particularly true at a time when Partners HealthCare, the major Boston-area care network of which MGH is a founding partner, has established a goal to save $300M over three years.[13]

1.5 Overview of the patient transfer process at MGH

Transferring patients from one unit to the other involves coordination between several different areas of the hospital. Understanding this process is a key first step to approaching the issue of patient delays – and to identifying possible ameliorating solutions. Within the context of an ICU at MGH, the most common steps are as follows:

1. Patients are declared "ready for transfer" by the attending physician and his or her team. This most frequently happens during morning rounds, typically before 8:00 AM. Patients can also be cleared at other times of day, although this is an exception to the morning rounds rule.
2. The number and names of these ICU "movers" are communicated to the Nursing Supervisors (also known as the "triage nurses;" typically three of these are available on a 24-hour, 7-day basis). This is done by a variety of methods, depending in part on the custom of a particular unit. The primary mode of communication is face-to-face at the daily morning "beds meeting," which follows decisions made during morning physician rounds. Additional requests may also be made by telephone.
3. Patient move requests are entered into CBEDS (MGH's custom bed management software system). This step theoretically parallels the informal requests made in person at the bed meeting or by telephone. However, the many different units in MGH have a variety of approaches to dealing with CBEDS. In theory, bed requests made in CBEDS should be placed for patients who are truly ready to move to another floor. However, some units have been encouraged to enter in all patients whose probability of moving is greater than 50%. Because of these varying approaches, CBEDS appears to be viewed as more of a helpful resource than as a definitive authority.

4. Nursing Supervisors review OR schedule to determine how many admissions to expect from the OR into the ICU that day (a number which theoretically is self-reported by the surgeons, but not all comply; the Nursing Supervisors use their experience and judgment to extrapolate missing data). The Nursing Supervisors will also regularly keep in touch with the "floor walker" for the OR area, an anesthesiologist who takes the role of monitoring surgeries and potential ICU needs for the day. Ideally, the Nursing Supervisors are alerted one hour before planned surgery end for a patient requiring an ICU bed, providing sufficient time to ensure that bed is available as planned.
5. Based on all of this data, patient transfer decisions are made on a rolling basis through communication between the Nursing Supervisors, Admitting personnel, and unit nurses. Admitting's decision role is typically lesser in the ICU context than that of the Nursing Supervisors, although Admitting will routinely take the lead in activities such as decompressing the SICU to make way for incoming operations.

This process is both highly complex and also depends heavily on informal processes and procedures which vary significantly from unit to unit. What is immediately clear is that those making transfer decisions – primarily the Nursing Supervisors, in the case of ICU patients, with significant input and boundaries from Admitting – have a high level of discretion in choosing between different transfer candidates under the (very common) condition of constrained downstream resources. These highly-experienced personnel are very skilled at what they do, and very adept at performing their fundamental assigned duty: making sure everyone who needs a bed has a bed. If given a choice, then, between moving a SICU patient to a surgical floor, or giving that same open bed to a patient waiting in the ED, the open bed will almost always go to the ED patient, all else being equal (and with no immediate constraints on SICU capacity). This is a logical and reasonable choice. Taken to its extreme, however, we will see that this informal policy of deprioritizing transfers of ICU patients to the floor has serious consequences for the entire inpatient system.

1.6 Overview of SICU patient flow

Figure 1 depicts the major pathways of patients entering and exiting the SICU, with percentages indicating proportions of patients entering particular areas along different pathways. The figure highlights critical pathways which are good candidates for close inspection: patients entering the SICU from the OR, and patients exiting the SICU to downstream floors, particular to designated surgical floors. Concurrent work by colleagues at MIT and MGH is focusing on the effect of OR scheduling on capacity management of other floors. This project focuses on the next link in the chain, from the SICU point of view: patients transferring from intensive care into non-intensive units of the hospital, commonly known as "the floor."

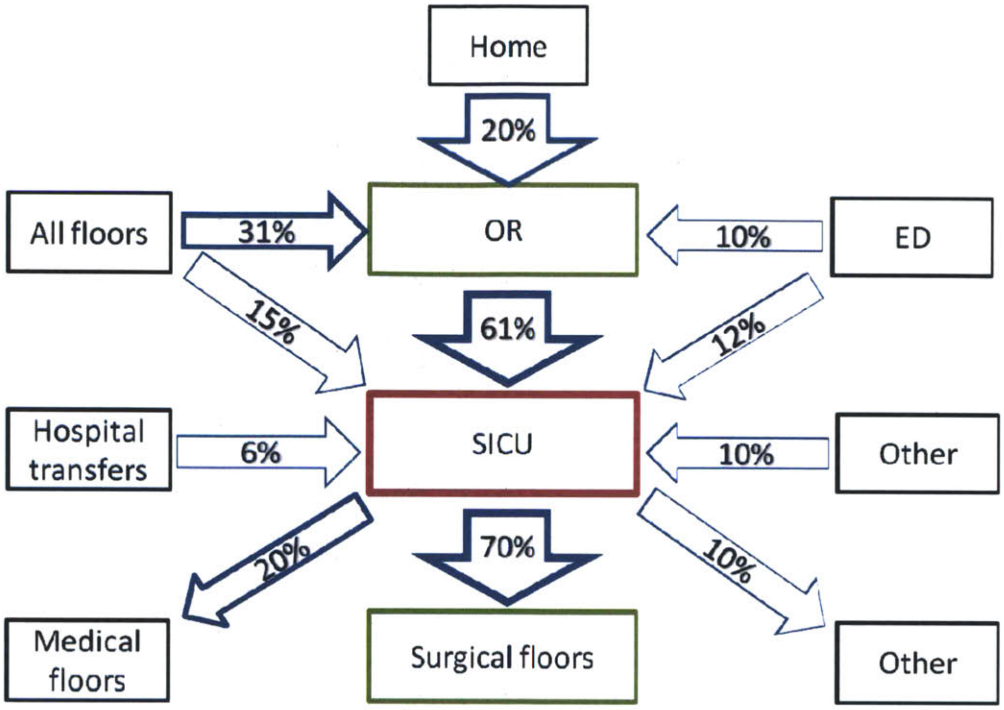

Figure 1: Major SICU patient pathways

As depicted above, approximately 90% of SICU patients are transferred to another MGH unit. Frequent and sometimes lengthy non-clinical delays in this transfer process can be primarily attributed to congestion in these downstream units.

1.7 Project Overview

While touching on safety and financial issues, this project focuses on the operational impact of operating the SICU – or, indeed, any similarly highly-connected unit – at a utilization level very close to operational capacity. In the case of the SICU, demand exceeding available capacity leads to upstream delays in patients moving from the Emergency Department (ED), as well as delays in patients exiting the operating rooms (OR). A cascading effect then leads to difficulties for patients attempting to enter upstream areas, such as the ED or OR.[14] In such circumstances, expedited transfers may be performed from the SICU to downstream units (regular hospital floors), leading to difficult and potentially dangerous transitions to downstream units under rushed conditions, as well as an increased risk of "bouncebacks," or unplanned readmission to the SICU.[15]

This project aims to discover the root causes of some of these negative effects of congestion, and to ameliorate those effects by developing targeted solutions aimed at maximizing value-added resource utilization. Specific objectives include:

- Characterize ICU patient flow patterns
- Identify sources of variability (random and artificial)
- Build a quantitative model of ICU patient flow
- Identify bottlenecks
- Build a simulation tool to enable testing the potential impacts of various changes and interventions
- Recommend actions to increase functional capacity and reduce delays

A successful outcome will include recommendations aimed not only at ameliorating current difficulties, but also designed to illustrate a path to survive and thrive under the pressures to be expected from the increase in volume which will accompany an aging population.

1.8 Summary of Results

This project was conducted in two phases. The first phase focused on characterizing the impact of non-clinical patient delays on subsequent length of stay (LOS) in the hospital. The results of this first phase demonstrate that additional non-clinical SICU time yields negligible downstream time savings, while consuming an average of 2.4 SICU beds per day, or 12% of total SICU capacity, at a yearly attributable annual cost in excess of $2.5M.

The second phase turns to a highly detailed discrete event simulation in order to evaluate the impact of potential operational changes targeted to address the root causes of capacity constraint in the SICU. Two approaches prove most promising: 1) Transferring patients as soon as possible after medical clearance, eliminating the current practice of waiting to see if other patients might need downstream beds. 2) Implementing a 24-hour rolling medical clearance process in the SICU. These interventions are predicted to lower average and peak SICU utilization by ~6%, cut SICU entrance delays by ~35%, and decrease SICU exit delays by ~50%, with relatively little impact on downstream floors and no capital expenditures. These relatively simple policy changes can also save ~$1M in non-reimbursed expenditures while reducing overcrowding.

If capital expenditures are approved, the simulation indicates that adding beds to downstream units would be more beneficial to the system than adding the same number of intensive care beds (at a much higher cost).

1.9 Thesis Outline

This thesis will initially approach each of these two project phases separately, addressing characterization of SICU transfer delays before integrating those findings into a larger simulation framework. It will close with conclusions and a discussion of the meaning of this work beyond the limited framework of its direct origin, including applications both inside and outside the field of healthcare delivery.

2 Characterization of SICU Transfer Delays

2.1 Introduction

This portion of the project has its roots in a study performed by Daniel Johnson together with Edward Bittner, Ulrich Schmidt, and Richard Pino, all affiliated with MGH. In an IRB-approved prospective observational study performed over more than six months in 2010, Dr. Johnson demonstrated that 22% of all patients transferring from the SICU to another MGH unit were delayed by at least one extra day. 89% of these significantly delayed patients were kept behind due to lack of an appropriate bed in the target unit. Some patients were delayed for several days – as long as six full days in the study sample population.[16]

These striking figures led Dr. Schmidt, medical director of the SICU, to raise a very meaningful question: if these patients were delayed from transferring, did the time of delay contribute to their process of preparing for eventual successful discharge from the hospital, or was it merely wasted time? In other words, would the subsequent hospital length of stay (LOS) of a delayed patient by longer than that of a non-delayed patient, if the clock for both were started at the time they were medically cleared to transfer to another unit? This question forms the basis of this first phase of the project. We hypothesized that delayed transfer from the SICU significantly impacts subsequent hospital length of stay (subsequent LOS) after medical readiness for transfer as well as total patient costs to the hospital over the same time period (subsequent costs).

2.2 Methods

A multivariate regression is presented to investigate the contributions of non-clinical delay in exiting the SICU to subsequent LOS and subsequent costs.

2.2.1 Data Collection

As mentioned previously, Dr. Daniel Johnson collected non-medical transfer delay data for 731 consecutive patients transferred from a 20-bed SICU over a 27-week period.[16] This study was then further filtered to patients with a single SICU visit whose post-SICU location was another floor in the hospital, leaving 567 samples[2]. The primary factors of interest as dependent variables for later analysis were subsequent LOS and subsequent costs. Subsequent LOS was defined as days spent (including fractions thereof) in any area of the hospital after clinical readiness for transfer to a general care unit ("the floor"). During the 27-week observation period, data were collected on all patients who were delayed overnight for non-clinical reasons. After the 27-week observation period, separate data collection was instituted to record the times at which patients were clinically ready to leave the SICU; this data was obtained by clinical assistants recording the time at which the physician team declared particular patients as ready to transfer in a previously existing SICU patient transfer database, which was modified to enable this new data entry. Nine months of data (March 2011 through December 2011) revealed that on average, patients were declared clinically ready to leave the SICU at approximately 8:30 AM. Subsequent LOS was therefore defined as the total time patients spend in the SICU after 8:30 AM on the day they are clinically ready for departure. The average non-clinical transfer delay for the 567 patients in the study was approximately 15 hours.

Significant adjustments needed to be made to the timestamps of patients admitted to the SICU after surgery. The timestamps recorded in PATCOM, the official database of patient admissions, discharges, and transfers maintained by Admitting, showed admissions from the OR peaking at 6 AM – an observation which correlated very poorly with both the team's observations and the

[2] One confounding variable – patient age – could not be identified for one patient in this study. For some analyses, then, the actual number of samples is 566, not 567. While the appropriate number was used in all calculations, for the sake of simplicity, this thesis will continue to cite the total number of samples as 567.

separately maintained SICU database, which suggested a peak time around 5 PM. Further investigation revealed that Admitting typically keyed in patients as “admitted” to the SICU as much as several hours before a surgery expected to require a SICU stay had even begun, and on average 11 hours before the patient actually first occupied the SICU bed. This practice of early admission recording essentially serves as a method of reserving a bed for the expected incoming OR patient. However, it made accurate determination of SICU patient flow very difficult. To correct for these discrepancies, SICU admission timestamps for patients arriving from the OR (directly or via the PACU) were overwritten for the sake of later analyses with the OR/PACU exit timestamp.

Subsequent cost was determined using Transition Systems Inc (TSI) methodology (Eclipsys Corporation; Atlanta, GA), which is accepted in the literature as “useful for estimating in-hospital costs of treatment.”[17] These cost figures include direct care costs (based on acuity and hours of care) in addition to room and various overhead costs, as proportioned out to individual patients for internal accounting purposes, and as such can be considered a meaningful estimate of total resource use apportionable to each patient. As another MGH-based study concluded, the TSI methodology “is superior to using charge or reimbursement data” [18]. In the context of this study, commonly used charge or reimbursement approaches would not only underestimate costs, but would also fail to distinguish between similar patients with drastically different non-charged, non-reimbursed costs of care – a particularly relevant point when considering delays of a non-clinical nature.

Note that all reported costs, and savings, are total, not solely variable – an approach which has been opposed by some as unrealistic.[19] However, inasmuch as the purpose of fixed costs is to manage variable patients, we believe that for the type of long-term, forward-looking proposals suggested in this work, total costs are a more relevant metric. In the long term, there are no truly fixed costs; everything from labor to facilities to utilities must be variable as patient loads change. In addition, under the aforementioned expectation of increasing volume with an aging population, savings attributable to reduced census are very real, as they will reduce the need to construct, staff, and manage additional units.

To determine subsequent cost, actual costs are summed for each patient beginning at 8:30 AM on the day of clinical readiness for transfer out of the SICU until final discharge from the hospital. Costs of partial days are pro-rated according to the number of hours a patient was present in each relevant unit. If a patient was delayed from transferring out of the SICU for non-medical reasons, subsequent costs for the patient include costs for the total amount of time spent in the SICU after medical readiness for transfer, in addition to the total costs of all days in other units after transfer, until the patient is discharged from the hospital.

Some factors associated with a higher chance of non-clinical delay, such as infectious precautions in a patient, are also associated with a longer subsequent LOS. A multivariate regression analysis is therefore indicated in order to isolate the effect of the delay itself, independent of other confounding factors. Towards this aim, a large number of additional variables were collected for each patient in addition to the core subsequent LOS and subsequent cost dependent variables. Together with the primary factor of non-clinical delay until transferring out of the SICU, these variables form the basis of a robust multivariate regression, controlling for a wide range of potential confounding variables. Additional data collected for all patients includes:

- Major diagnosis group

- LOS before entering the SICU
- SICU LOS before medical clearance for transfer
- Acuity (as used at MGH, primarily a measure of nursing workload) on last day in the SICU
- Age
- Service
- SICU admission source (ED, OR, Other)
- Infectious precautions
- Mean diagnosis LOS (discussed in more detail below)
- American Society of Anesthesiologists (ASA) score (discussed in more detail below)

These potential factors are depicted in Figure 2, which represents the hypothesized factors affecting subsequent LOS.

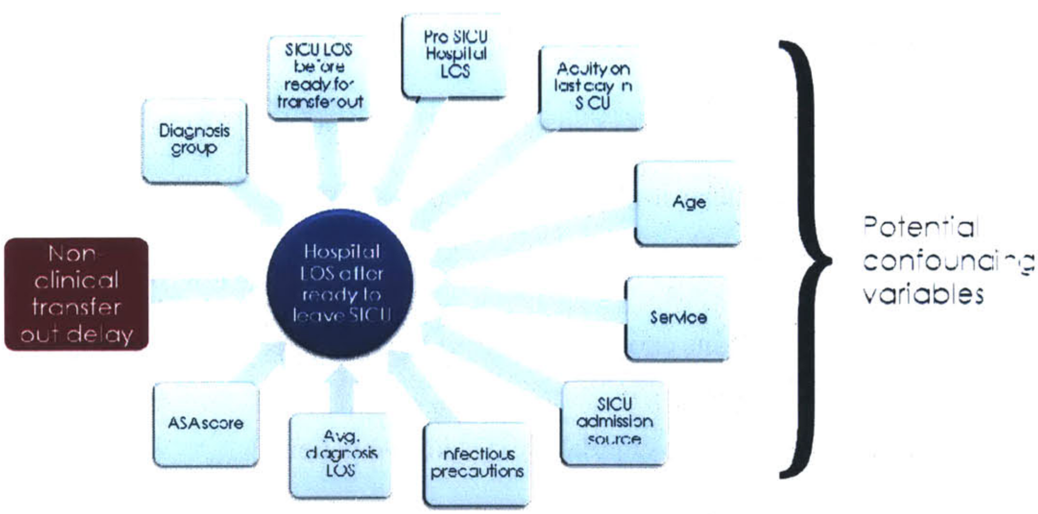

Figure 2: Variables considered as possible factors affecting subsequent LOS (depicted) or subsequent costs

2.2.1.1 Diagnosis variables

Diagnosis information for all 2009-2010 SICU patients was obtained via TSI in the following forms:

- MS-DRG (Medicare) codes – coded for non-Medicare patients as well
- AP-DRG ("All Patient") version 21 codes
- ICD-9 principal diagnosis codes
- ICD-9 principal procedure codes

The 567 patients in the study were coded into 111 different AP-DRG categories (as not all patients in this study were Medicare patients, AP-DRG codes were used when possible). Since applying DRG directly as a regression factor would therefore add 111 explanatory variables to the regression analysis, two indirect methods are instead used to account for diagnosis factors.

Both AP-DRG and MS-DRG codes are divided into one of 25 nearly identical Master Diagnosis Categories (MDCs). The U.S. Government's Center for Medicare and Medicaid Services (CMS) publishes a crosswalk linking MS-DRG codes to MDC category.[20] This crosswalk was used to categorize each patient's diagnosis into an MDC; study patients were found in 20 of the 25 possible MDCs. However, over 70% of patients could be categorized into one of 6 MDC categories, each of which contains enough patients to be considered as a regressor:

- Diseases and disorders of the circulatory system (96 patients)
- Diseases and disorders of the digestive system (83 patients)
- Diseases and disorders of the musculoskeletal system and connective tissue (82 patients)
- Diseases and disorders of the respiratory system (74 patients)

- Multiple significant trauma (36 patients)
- No MDC (includes transplants and other highly complex cases) (38 patients)

In addition, to account more directly for the capacity impact of individual diagnoses, information from Massachusetts' Office of Health and Human Services [21] is used to map individual AP-DRG codes to the mean statewide hospital LOS for patients receiving that diagnosis. A more useful form of this variable is created by subtracting each individual patient's actual LOS until departure from the SICU from the expected mean LOS. This created a single explanatory variable indicating a rough average expected remaining LOS for similar patients in the state of Massachusetts – obviously not a perfect variable, but one that proves very useful for the analysis and highly significant as a regressor ($p < 0.0001$ for both analyses); in essence, it stands in as an additional metric of average clinical acuity for a given group of patients.

Diagnosis data in the form of All-Patient DRG codes (Version 21) are correlated with average length of stay reported by all hospitals statewide and publicly available from the Massachusetts Executive Office of Health and Human Services[21]. Subtracting prior LOS from the total LOS expected for each DRG code resulted in a measure of expected remaining LOS for each patient. This method provided an additional metric of clinical acuity.

2.2.1.2 ASA score variables

The ASA physical status classification system was created by the American Society of Anesthesiologists as a means of assessing and recording a rough measure of the physical condition of patients prior to surgery. All surgical patients are classified into one of six types:

1 - A normal healthy patient

2 - A patient with mild systemic disease

3 - A patient with severe systemic disease

4 - A patient with severe systemic disease that is a constant threat to life

5 - A moribund patient who is not expected to survive without the operation

6 - A declared brain-dead patient whose organs are being removed for donor purposes [22]

377 out of the 567 study patients had surgery within one day prior to entering the ICU. All but 16 of these 377 patients were classified into ASA class 2, 3, or 4. Binary variables were therefore created for each of these classes and added to the regression analysis as an additional measure of physical condition for surgical patients. All three variables proved to be significant regressors in the analysis.

2.2.2 Regression design

This investigation aims to identify to what degree non-clinical delays in transferring out of the SICU affect patient length of stay in the hospital after clinical readiness for transfer out of intensive care, as well as costs associated with extended length of stay. The model considers the individual effects of 26 potential confounding variables for each patient, in addition to the primary variable of interest, non-clinical delay time ("Time delayed"). A list of all individua variables with explanatory notes is reproduced in Table 11 in the Appendix. Second-degree interactions were also generated between all considered variables except for non-clinical delay time (as interactions for that variable would have masked the primary effect of interest) and included as factors in the analysis. A full list of all independent variables and considered interactions is found in **Table 12** in the Appendix. The resulting very high number of potential regressors (257, compared to a sample size of 567) makes model selection an important question.

For this analysis, we turned to the statistical technique of information criterion minimization to select an optimal model. Information criteria are additional factors added to a model selection process to penalize the addition of large numbers of regressors. In essence, these methods attempt to find an ideal balance of information, or regressors – just enough, but not too many. Regressors are typically added and removed from the model one by one, similar to the mixed stepwise approach described above. However, the addition of an information criterion typically leads to the selection of smaller models than standard stepwise approaches, as the model attempts to minimize not only the sum of squared errors, but also the information criterion sum – the penalty for having many regressors. The Bayesian Information Criterion (BIC) is an approach in this category which has seen increasing usage in medical journal regression methods in recent years (see, for example, [23], [24], and [25]). By minimizing the BIC metric, this algorithm tends to select substantially fewer regressors than the historically more common Akaike's Information Criterion (AIC); some research indicates that these sparser BIC models may reflect reality better than many other methods.[26]

All regression analyses, including BIC model selection, were performed with JMP 9.[27] The robustness of the chosen model selection method was confirmed by comparing several different model selection approaches: backward stepwise, forward stepwise, mixed stepwise, minimum AIC, and minimum BIC. The primary regression coefficient of interest was within a narrow 6% range for four of the five investigated methods, including the chosen BIC approach. This robust finding using several different approaches suggests that we may proceed to results with full confidence in our statistical methods.

2.3 Results

858 yearly SICU bed-days are occupied by patients waiting for delayed transfers, leading to an average SICU capacity loss of 2.4 beds (12%). The regression analysis demonstrates that each day of transfer delay correlates with a 0.95-day increase in subsequent LOS ($p < 0.0001$; 95% CI = 0.63 to 1.26), meaning that non-clinical delay adds almost completely to total LOS; only 1/20th

of a day downstream is saved by delaying a patient unnecessarily in the SICU for one full day. The long-term downstream bed savings attributable to these delays in leaving the SICU therefore accumulate to only about 0.1 of a bed, on average. In other words, saving one bed-day in a downstream area through transfer delays requires consuming 20 bed-days in the SICU – a staggering operational and financial cost.

Regression on cost factors demonstrates a \$3,126 increase in subsequent costs ($p<0.0001$; 95% CI = \$2,610 to \$3,642) for each day of non-clinical delay in the SICU. Over a full year under current conditions, these costs accumulate to an approximate loss of \$2.7M for MGH.[3] These costs accumulate because delay time spent in the SICU after a patient is clinically ready to transfer to a general unit leads to no significant reduction in subsequent LOS, and so costs incurred while in the SICU are almost pure additions to those incurred by similar patients who do not experience such non-clinical delays. The regression results consider only direct costs and allocated overhead; the actual financial impact in terms of opportunity costs and indirect costs could be significantly higher. Detailed regression model results for both analyses (as selected through the Bayes Information Criterion) are listed in the Appendix, Table 13 and Table 14.

2.4 Discussion

Transfer delays out of the SICU lead to a significant increase in subsequent LOS. This is correlated with a decrease in operational capacity of the SICU as well as significant cost increases. Two general mitigation approaches are suggested when reviewing these results: (i) redesign of patient flow and bed capacity allocation to ensure timely flow of patients from the

[3] An additional analysis added estimated non-clinical delay costs for patients discharged home, estimating the hourly cost at the 10th percentile level of average hourly costs of SICU stays. However, this additional factor proved insignificant at the given rounding level (making no change to the \$2.7M figure), and is therefore best ignored for clarity of analysis.

ICU to the floors, and (ii) tailoring the care of delayed ICU patient transfers with the intent of decreasing subsequent floor LOS.

As an example of the first mitigation approach, if SICU patients delayed overnight for non-clinical reasons would instead have been transferred downstream by 8:00 PM on the day of clinical readiness, average SICU capacity would increase by at least 1.1 beds (5%) and delay-associated costs would decrease by at least $1.2M. These figures emerge from artificially adjusting the transfer times of all patients who were delayed at least one day to have instead been transferred on their day of readiness at 8:00 PM. More elaborate changes to patient flow and bed capacity allocation will be discussed in the following section discussing simulation approaches.

To consider the second mitigation approach of tailoring the care of patients with delayed transfers, we should consider some of the *why* questions suggested by this analysis. Why does it take essentially just as long for a patient to be ready for discharge from a regular unit, regardless of extra time spent in the ICU? Interviews with multiple MGH personnel who are involved with different levels of this process identify two primary issues. First, Critical Care nurses are not trained or expected to think about discharge readiness; that simply isn't their mission. Second, the fact that a patient has spent extra time in critical care and may be more progressed than the average patient with a similar condition being transferred to the floor is not systematically communicated to general unit care teams, who therefore assume that this patient can be expected to follow a typical, rather than abbreviated, path to final discharge. These findings suggest two strategies for improving the care of these patients: first, provide training to support Critical Care nurses in preparing stabilized patients for discharge readiness if they are delayed in transferring to the floor. Second, create a formalized communication format associated with transfer to a general unit to be sure that patients are effectively given as much "credit" as possible for additional time spent in the ICU which was not, strictly speaking, medically necessary at the critical care level.

There are also potentially counterproductive incentives in place which may affect the likelihood of delaying patients longer than is clinically necessary. As previously noted, the primary cause of such delays is insufficient bed capacity in downstream units. However, when beds do become open, several complicated factors interact to determine which patient moves next to occupy that bed. It may be meaningful that the incentives for ICU nursing directors arguably encourage them to hold on to patients longer than necessary. As communicated in interviews, the yearly budgeting process depends on capacity utilization of a unit over the previous year. This means that there is an incentive for nursing directors to effectively struggle against a high level of utilization, in order to obtain an increased budget for the following year – and allowing clinically ready patients to stay longer than necessary can be one means of increasing utilization, particularly during slower periods. As acknowledged by one ICU nursing director, these "floor boarders," as they are sometimes known, do act as a double-edged sword; along with raising census, they also lower overall acuity. However, the net effect would be generally beneficial to an ICU nursing director's efforts to demonstrate need for increased budget in the following year. While it is certainly not clear that all nursing directors consider this approach, it is also clear that some do, and that this incentive system may merit a closer look. While the nursing directors do not make transfer decisions, their opinion certainly matters – and if a patient already has a bed and the nursing director of that unit is happy to keep that patient, a harried nursing supervisor (triage nurse) will likely be inclined to allow that patient to stay an extra day.

3 Evaluating Options through Simulation

3.1 Introduction

The previous analysis suggests redesigning patient flow and bed capacity allocation to ensure timely flow of patients from the ICU to the floors. Much of hospital capacity planning is based on relatively simple deterministic models – in short, averages – combined with a healthy dose of long-term experience. Without the experience factor, which often leads practitioners to add significant buffers to calculated capacity expectations, deterministic models are completely inadequate for the task of capacity planning in such a highly variable system. [28]

Even the most experienced professional, however, will still have major difficulty in predicting the capacity effects of significant changes to the structure, policies or resources which affect more than a limited subsector of the hospital. Such failures arise not out of any inadequacy in personnel involved, but simply due to the extraordinary complexity and interconnectedness of admission, discharge, and transfer patterns within and between hospital units, as well as external sources and destinations. An appropriately designed simulation can work through these complexities at literally superhuman speeds in order to provide valuable insight into the core operational issues.

The goal of this phase of the project is to identify viable options for ameliorating capacity constraints and related patient flow issues. The chosen approach to achieving this goal is to develop, validate, and apply a realistic simulation of SICU patient flow which will allow for a flexible, realistic representation of varying resources, practices, and policies. The modeled changes, or scenarios, include:

- Add SICU beds

- Add general beds (to downstream units)
- Transfer when ready: Eliminate unnecessary transfer delay when a bed is available downstream
- Transfer when ready, with SICU priority: As above, but also giving SICU patients priority over other patients when more than one type of patient needs to enter the same downstream bed
- 24-hour rolling transfer readiness: Instead of determining clinical readiness only once each day (during morning rounds), make transfer readiness decisions on a rolling basis around the clock
- 24-hour rolling transfer readiness, with SICU priority: As above, but also giving SICU patients priority over other patients when more than one type of patient needs to enter the same downstream bed

Each of these scenarios is investigated in detail later in this thesis.

3.2 Methods

3.2.1 Introduction to Discrete Event Simulation

While a basic analytic queuing model can provide substantive insight into system behavior, simulation-based methodologies have significant advantages. These include the ability to "handle both individual arrival and service data, and … permit us to experiment with, and evaluate, various … policies." [29] Within the field of simulation, a variety of modeling approaches is available. Discrete event simulation (DES) combines patient-level detail and institution-level policy encoding, while tracing each simulated patient individually through a realistically modeled hospital system. Within the context of a complex hospital system, DES provides an ideal tool to evaluate the effects of potential interventions, as has been well-recognized in a rich foundation of relevant literature.[30] [28][31]

This simulation was constructed and evaluated using ProModel Corporation's MedModel discrete event simulation software, which is by far the dominant player in the realm of hospital operations simulation.[32] Due to its well-suited feature set, MedModel is commonly used as a basis for peer-reviewed publications in this field.[33]

3.2.2 SICU simulation overview

A high-level overview of the presented SICU simulation will be helpful in navigating the subsequent sections, which provide a highly detailed description of the simulation structure and design. The simulation provides a detailed representation of Ellison 4, abbreviated as SICU or, occasionally, E04I, as well as the following six units arranged into four "downstream" areas:

- Ellison 6 and White 6, combined and abbreviated as E06 & W06 or E06W06
- Ellison 7 and White 7, combined and abbreviated as E07 & W07 or E07W07
- Ellison 19, abbreviated as E19
- Bigelow 14, abbreviated as G14

Patients identified by various diagnosis or procedure types attempt to enter these areas according to historical patterns and distributions. Patients also transfer from the SICU to downstream areas according to historical patterns and distributions. When space is not available in a downstream unit, patients wait until a bed opens up, depending on patient priority levels.

When patients complete their allotted stay within the modeled hospital system, they are transferred to a Discharge area and removed from the simulation. One notable simplification of this model is no direct modeling of "bouncebacks" – patients who are transferred from an intensive care unit to a downstream unit, but who subsequently return to a critical state and must return to the ICU. Although this dynamic is not captured directly in the simulation, its effects are modeled accurately, since "bouncebacks" entering the SICU are included in arrival and LOS distributions used to generate incoming patients. The simplification lies in the simulation's assumption that these are new patients, rather than previous patients seen for a second time.[4]

The simulation records hourly census values in each modeled area, as well as key delay times in entering and exiting units. Multiple replications are performed, and representative statistics are compared to historical values for validation purposes. Once the baseline model is validated, several scenarios are evaluated in order to consider the effects of proposed approaches to improving SICU patient flow.

Summaries of simulation inputs and outputs are listed below in Table 1 and Table 2, respectively.

Table 1: Summary of simulation inputs

Simulation inputs	Source of input
Patients' arrival timestamps in modeled units	Admission and transfer-in records, as well as OR transfer-out records
Patients' SICU exit delays	Dan Johnson study and SICU database entries
Patients' length of stay in modeled units	Transfer-out records compared to arrival times and adjusted to remove recorded delay time
Patients' ICD-9 procedure/diagnosis codes	Internal MGH database (TSI)

[4] If structural or policy changes focused on the bounceback rate were to be modeled and studied in detail, the bounceback process would need to be directly modeled and tracked. Such analysis is out of the scope of the current project.

Table 2: Summary of simulation outputs

Simulation outputs	Purpose of output
Hourly census counts for each location, with separate counts for each replication, as well as averages, standard deviations, and 95% confidence intervals	Compare simulated to historical values, as well as different scenarios to baseline, including 95% confidence intervals.
Average time simulated patients spent in pre-unit waiting areas, including standard deviations	Compare delay time for new patients entering units, including 95% confidence intervals.
Average and 95% confidence intervals of logged SICU exit delays	Compare average delay time experienced when exiting the SICU, including 95% confidence intervals.
Failed arrivals (due to lack of capacity in pre-unit waitin areas)	Measure diversions required by extreme overcapacity situations. Used to adjust census statistics in order to be able to compare different scenarios on an equal footing.

3.2.3 Data preparation

3.2.3.1 Patient transfers

The first step in creating simulation is to assemble historical data as a basis for simulated patient attributes and movements. Processed data include timestamps for admissions, transfers, and discharges, OR/PACU transfer timestamps for surgical patients, and principal procedure/diagnosis information for all considered patients. Each of these datasets is filtered according to patient source and destination – e.g., an ED patient arriving in the SICU would be filtered into a different dataset than an OR patient arriving in a downstream unit. A subset of "ready to transfer" timestamps was also recorded for the SICU.

Data is compiled for all patients spending at least part of CY10 (i.e., January – December, 2010) in any of the five modeled areas: SICU, E06 & W06, E07 & W07, E19, and G14. Each of these areas received at least 10% of SICU patients as incoming transfers in CY10; no other units or logical unit combinations met that threshold, so all other patient transfers, including deaths and discharges, were classified as "Other." The four modeled downstream areas received a total of 67% of all patients exiting the SICU. As shown below in Table 3, the distribution of destinations for patients exiting the SICU varied only slightly according to pre-SICU patient source. However, since other attributes did vary substantially according to patient source, the simulation structure continues to take previous location into account in determining factors such as LOS in a downstream unit.

Table 3: Destination distributions for patients exiting the SICU

Pre-SICU	Percent of SICU patients transferring to these areas				
patient source	E06 & W06	E07 & W07	G14	E19	Other
ED	10%	27%	14%	16%	33%
OR	10%	26%	13%	15%	36%
Other	10%	25%	16%	16%	33%

3.2.3.2 Diagnosis and procedure codes

All patients are distinguished by their 4-digit ICD-9 Principal Procedure codes (for patients entering a unit from the OR or PACU) or their 5-digit ICD-9 Principal Diagnosis code (for all other patients). Multiple different schemes of placing individual ICD-9 codes into larger groups in order to simplify modeling were attempted; however, none were found to provide sufficient sensitivity to match historical data, so each represented code in the data forms its own group. However, one concession to modeling feasibility was made; all represented 4-digit principal procedure codes (975 of which were represented in the data) were mapped to a PatientType variable between 1 and 975, while all represented 5-digit principal diagnosis codes (1757 of which were represented in the data) were mapped to a PatientType variable between 1001 and

2757. Any errors or missing codes (which were few) were mapped to a PatientType variable of 999 for Diagnosis or 2999 for Procedure in order to prevent mixing with correctly mapped codes.

These PatientType variables form the basis of nearly all data input into the simulation. As will be described, patients enter units, stay in units, and transfer to other units in patterns defined separately for each PatientType group.

3.2.4 Simulation design

3.2.4.1 Structure overview

Discrete event simulation entails generating a large number of simulated *entities*, in this case patients, and moving those patients through a series of appropriate *locations*, in this case primarily beds within defined areas. Figure 3 outlines a framework for patient flow through the SICU simulation.

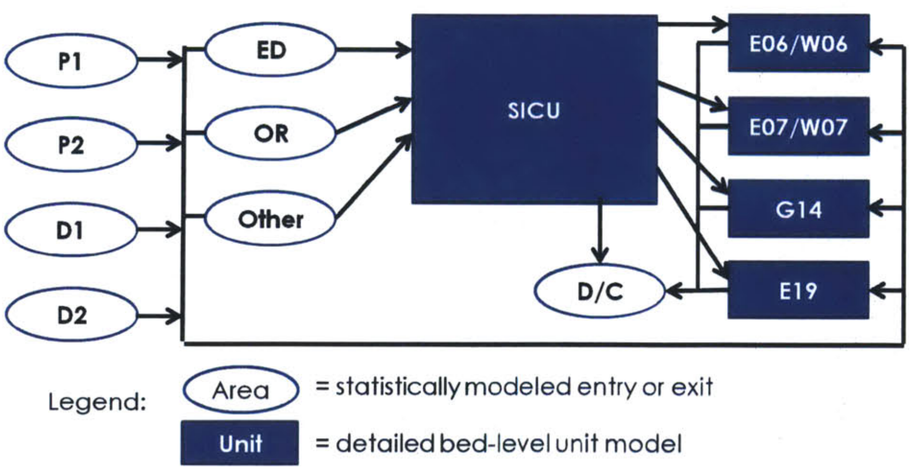

Figure 3: Schematic of simulated patient flows

On the far left side of the diagram, four circles represent the ~2700 ICD-9 principal procedure and principal diagnosis groups represented in the data – the previously described PatientType identifier. Patients from each PatientType arrive, via a holding area, in one of the five defined areas (represented by solid blue boxes). Each of these patients is also associated with one of three "patient source" areas: the ED, the OR, or "Other." To prevent additional diagram complexity, these areas are depicted only entering the SICU; in fact, the same source distinctions exist entering each of the five defined areas.

Once patients arrive in one of the five defined areas, a length of stay (LOS) is assigned. Both the arrival process and LOS process are discussed in more detail in upcoming sections. In the SICU, patients completing their assigned LOS are defined as clinically ready to transfer, and will do so as soon as a bed in their assigned subsequent unit is available – a process which will also be discussed in more detail in a following section. When patients in one of the four downstream areas complete their assigned LOS, or when a SICU patient is directed to transfer outside of one of the modeled downstream areas, they depart from the modeled system.[5]

3.2.4.2 Arrivals

Patients "arrive," meaning that they are created within the simulation, in holding areas which feed into each of the five modeled areas. Arrivals are defined as nonhomogeneous Poisson processes, with each patient type/source/location combination having a uniquely defined process. Interarrival times are generated for each nonhomogeneous Poisson process through a random sampling approach, typically known as "thinning."[34] Within the context of this simulation, the nonhomogeneous Poisson thinning algorithm may be briefly described as follows:

[5] As previously noted, in reality, some patients return, or "bounce back," to the SICU, either directly or via other paths.

1. Choose an hourly arrival rate λ^* which is greater than or equal to all recorded hourly arrival rates $\lambda(t)$ for the given patient type/source/location combination
2. Set initial time to next arrival to 0 hours
3. Generate a random number y from the uniform distribution between 0 and 1: U(0,1)
4. Set $t = t - \frac{1}{\lambda}\ln y$
5. Generate another random number z from U(0,1)
6. If $z \leq \lambda(t)/\lambda^*$, set next arrival for the given patient type/source/location combination t hours ahead
7. Else, return to step 3 (algorithm description adapted from [35])

Poisson process parameters for each type/source/location combination are passed into the simulation through a series of "arrival files," which consist of single-sheet Microsoft Excel-formatted (*.xls) spreadsheet files. An arrival file is created for all patients arriving from a given area (e.g. OR or SICU) to another area (e.g. E06W06), making for 19 total arrival files, representing 19 possible pathways these patients could follow to enter modeled units.

Each of these arrival files contains approximately 2700 rows of data. Each row encodes the probability that a patient with a given diagnosis or procedure code will arrive at various times of the week along the pathway represented by that file. Each row is broken up into 168 (24 hours/day * 7 days) 1-hour blocks. Each of these blocks contains the probability that a patient of that type will arrive in that hour of that weekday. For example, a probability of 0.1 on Monday in the 10:00 – 11:00 AM block means that there is a 10% probability that a patient of this type will arrive between 10:00 and 11:00 AM on any simulated Monday. Note that through the thinning algorithm, simulated patient arrival probabilities are uniformly distributed across each one-hour interval; patients do not arrive in batches on the hour.

These probabilities are drawn directly from historical data by taking the total number of relevant patient arrivals in a particular weekday/hour combination and dividing that number by the number of times that weekday occurred in 2010 (53 for Friday, 52 for all other weekdays). The standard unit of time in this simulation is a 24-hour day, so the final probabilities are produced after an additional multiplication by 24 to convert from arrivals/hour to arrivals/day.

Each file also contains the reference λ^* value, which is chosen by multiplying the maximum lambda encountered in a given arrival file by 1.1 and placing the product in the [3000,1] spot of the relevant Excel arrivals file. This process ensures that λ^* will be greater than any individual $\lambda(t)$ encountered in a particular thinning algorithm run.

3.2.4.3 Holding areas

Holding areas are attached to each of the five modeled areas. These areas serve as queues for newly generated simulated patients who are waiting to enter an area, and reflect the reality that new patients often do have to wait to enter an area.

Occasionally, a sequence of events will severely overburden a particular unit. Under such circumstances, MGH would act to relieve pressure on the system, such as expediting some transfers out of the unit or boarding patients in a different unit. Such advanced logic is outside the scope of this simulation, but the problem must still be addressed in order to prevent a unit from occasionally experiencing unrealistically long entry queues. To simulate a "pressure valve," each holding unit has a maximum capacity. Through trial and error during the validation process (to be discussed later), a capacity equal to 3 average days' worth of entries was found to produce the most accurate unit census behavior. If patients attempt to enter a holding area when it is already at capacity (a very rare event for most units), those patients are "diverted" out of the system. These diversions are recorded and later used for adjusting census statistics in order to be able to compare different scenarios on equal footing.[6]

3.2.4.4 Length of stay

A clinically necessary length of stay (LOS) is assigned as soon as a patient enters one of the five primary modeled areas. The system first generates the expected number of nights the patient will spend in the unit by drawing a number from the appropriate patient type row of the relevant LOS file. Similar to the previously described arrival files, LOS files are created for each of the 19 possible patient entry pathways. Again, each file contains ~2700 rows, representing each of the diagnosis/procedure types for each pathway. Each row of each arrival file contains the historical distribution of the number of nights patients of that type along that pathway spent in that unit until ready to transfer. Since only actual transfer data, not transfer readiness data, is recorded in central hospital systems, data from Dan Johnson's transfer readiness study[16] is incorporated into these LOS distributions for patients entering the SICU. This SICU transfer readiness study was limited to about six months, as opposed to the full calendar year of data on which the simulation is based, and so transfer readiness distributions cannot be found for every patient type (i.e., procedure or diagnosis). For missing patient types, nights until transfer readiness is approximated by creating a distribution of nights until actual transfer, and then, after a number is drawn from that distribution, subtracting a "days delayed" variable drawn from a single SICU

[6] Simulated census values are divided by the percentage of patients *not* diverted (1 - % diverted). The 95% confidence interval is also scaled accordingly (symmetrically about the mean).

distribution created from the Johnson study data. Since only 22% of patients were delayed overnight in this study, this "days delayed" variable will equal 0 approximately 78% of the time.

Each of these distributions is discretized into 5-percentile gradations. Standard spreadsheet percentile formulae are avoided, as they would yield interpolated results which are less compatible with later exit time calculations. Instead, non-interpolated percentiles are calculated based on a rank order of all relevant number-of-nights LOS figures for each relevant group. Percentiles are derived from the ordinal rank $n = p * N + 0.5$, which has been shown to produce more accurate results than other common percentile techniques.[36] Note that the 100th percentile is defined to be the largest value, to prevent problems with the rank turning out to be greater than the number of values in the original list. Also note that since percentiles are defined every 5% between 0% and 100%, the 0th and 100^{th} percentiles only cover 2.5% of the viable range each, while all other percentiles cover 5%. These lowest and highest percentiles are therefore weighted by half when drawing from the distribution.

This initial LOS figure contains only the number of nights the patient will stay until readiness for departure. The *time* of day at which the patient will be ready is decoupled to reflect the lack of substantive correlation between time of day of patient arrival and time of day of patient exit from the unit, several days later. This is logical, since patients are medically cleared for transfer on a set schedule, which does not vary according to the time of day of arrival. Of course, under extreme circumstances (e.g. arriving at 11:30 PM), a significant correlation exists between the time of day of arrival and the number of *days* a patient stays; these circumstances, however, are rare.

The time of day of readiness for departure needs, then, to be drawn from historical data. A complication arises, however, due to an informal practice of delaying SICU transfers, even when a bed is available downstream. As seen in the data and confirmed through interviews, Nursing Supervisors and Admitting are slow to move a SICU patient to a downstream unit even once the move is approved and space is available. The patient already has a bed, after all, and there could always be an unexpected request for the available downstream bed. In practice, then, patients are typically transferred from the SICU to another unit later in the day, often towards early- to mid-afternoon when the bed status for the day is more certain. In order to simulate current practice, then, it becomes necessary to use actual exit times as a basis for distributions of "effective" readiness times. This also allows for creation of a meaningful test scenario in which this artificial delay is not imposed.

An initial LOS is obtained by adding the generated number of nights, or full days, to the subsequently generated exit time (subtracting the time of day at entry to prevent exit time distortion). This generated LOS value may be considered a minimum value. Once this minimum LOS is complete, the patient attempts to move on. If the patient is in a downstream unit (i.e., not the SICU), the patient exits the system with no further delay. For patients staying in the SICU, the final simulated LOS may vary substantially, and often does, as downstream bed availability may constrain further movement. If the patient's next location is already at capacity, the patient will stay in the current SICU bed until called for transfer. In all cases, an absolute minimum LOS of two hours is imposed, to prevent unrealistically short stays.[7]

[7] A unit length of stay as short as two hours is very rare, but has been observed in the data.

As demonstrated in the first phase of this project, delay for non-clinical reasons in transferring out of the SICU conveys no significant benefit to reducing the patient's subsequent stay in a downstream unit. The simulation emulates this behavior by making no change to a patient's downstream LOS, regardless of how long that patient was delayed for capacity-constraint reasons when attempting to exit the SICU.

One further detail should be mentioned in connection with LOS assignment. Because just one abnormally long LOS can severely impact a unit's long-term census, and this is very difficult to capture in a necessarily roughly discretized probability distribution (due to the massive number of patient type/source/location combinations), the LOS variables required some calibration to match historical data. The average LOS for SICU patients, for example, was increased by 2.5% by shifting the discretized LOS probability distribution to match the equivalent metric in the historical data. So as not to disturb the exit time distribution, this calibration is accomplished by adding full additional days (or, equivalently, additional nights) to randomly selected patients on a probabilistic basis weighted by expected length of stay. In the SICU LOS example cited above, a patient with an expected LOS of four full days would have a 10% chance (4*2.5%) of staying one additional day. Because these small calibration factors effectively stretch out the probability distribution, rather than adding directly to the top percentiles, the correction effect is not exact. However, no exact method is possible within reasonable computation limits while maintaining the requested diagnosis- and procedure-based approach, which imposes a 2700x multiplier on most additional calculations. Thankfully, this relatively simple calibration approach does, as will be extensively demonstrated in the validation section, allow for a high level of accuracy and precision at the decision scale considered in this project.

3.2.4.5 Transfers

Modeled patients may undergo several transfers from one area to another in the course of their simulated MGH encounter. The first transfer for a newly created patient is from a holding area to an available bed in the attached destination area. The modeled SICU area has a more detailed holding structure than the four downstream areas. Patients pass through (and possibly wait in) separate holding areas depending on their original source: the OR, the ED, or another area. Based on interviews and observation, all else being equal, priority is given to patients attempting to access the SICU from some area other than the OR or ED, since these patients are more likely to have degenerated quickly and unexpectedly in some other area of the hospital and to be in need of immediate care. Patients from the ED are next in the priority list, while the OR is last, under the presumption that the PACU overnight area (or the new Blake 12 ICU, once it is fully operational) may be able to absorb overflow.

A SICU patient's next location is determined probabilistically according to a unique distribution for each patient type. Based on historical data, each of the 2700 possible types of patients in the SICU (i.e., procedure or diagnosis groups) will have separately defined probabilities of moving to one of five locations after exiting the SICU: E06 & W06, E07 & W07, G14, E19, or Other/Discharge. In the last case, the patient will move and exit the system directly. In the first four cases, as previously noted, the SICU patient will not move to the new unit until a bed is available. However, bed availability is not necessarily as simple as a bed opening up in the target unit.

For example, a SICU patient may be waiting for a bed in G14 (Bigelow 14). However, under particularly overcrowded conditions which develop from time to time, several other patients may be waiting in the pre-G14 holding area for that same bed. If more than one patient is attempting to access an overcrowded location, the baseline simulation policy follows interview findings in allocating scarce bed resources to patients moving from the units with the *least available capacity*. For example, if the pre-G14 holding area has an open bed, while the SICU has none, the SICU patient will take priority in moving to G14 – even if the pre-G14 patient has been waiting longer. The opposite is, of course, also true; non-SICU patients can take priority over SICU patients if their own holding areas of patients arriving from other areas are more backed up than the SICU itself. While not an exact replica of the complex decision-making process which is played out on an hour-by-hour basis by the Nursing Supervisors and Admitting, this simulated policy is a reasonable approximation of hospital behavior under bed-constrained circumstances.

3.2.4.6 Bed closings

One more waiting period applies between bed occupancies by two different patients. To emulate actual bed closings due to cleaning, all beds are closed for a "setup time" drawn from a normal distribution with a mean of one hour and standard deviation of 0.25 hour, or N(1,0.25), an approximate distribution derived from interviews with nursing staff familiar with the process.

In addition, MGH beds have historically been closed for one of several other reasons. The primary two reasons are infectious precautions and insufficient staff. Infectious precautions come into play when a patient under precautions for an infectious condition (such as MRSA or VRE) is placed in a double room, requiring closure of the other bed. Required staffing levels vary with the "acuity," or nursing workload intensity, of patients. When the workload exceeds the number of available nursing staff for the unit, some beds may be marked as closed to indicate that, although some reserve capacity exists in the unit, it is not actually able to accommodate any more patients. While SICU bed closings are quite rare, other units are significantly affected, as demonstrated by collected bed closure data for CY2010. For example, average bed closures in the E07 & W07 area exceed two beds at any given time, out of a total of 63, representing over 3% of capacity – a significant amount in a capacity-constrained system. For the purposes of this simulation, we lump bed closures for all causes (other than environmental services between patients) together into a single metric. This closed bed metric, however, is divided by area and day of week; for example, staffing closures tend to be significantly higher on weekends than weekdays, a logical pattern reflecting patient loads. Beds are then closed in each unit in varying ratios – some for entire days, some for partial days – so as to match the historical average closed bed metrics for the given area on a particular day of the week to a high level of fidelity. As with all described simulation details, the effects of this method cannot be measured directly, as they interact with so many other factors; we will therefore turn to validation to ensure that the system is reacting in a manner reasonably similar to its historical patterns.

3.2.4.7 Simulation run parameters

Each reported simulation run was performed as 20 replications of a 1-year long simulation period, with a 1-year warm-up period prior to each simulated year. These twenty independent observations are used to report mean statistics as well as confidence intervals for various metrics.

3.3 Results

To consider simulation results in a meaningful manner, we must first establish the validity of the baseline simulation. Following validation, we may examine the performance of the system under various potential future scenarios.

3.3.1 Baseline Validation

The validation process focuses on comparing historical and simulated census metrics. Several metrics, such as entry and length of stay patterns, could be considered in evaluating the validity of the simulation. A detailed analysis of census is a good choice for two primary reasons. First, historical data is reasonably accessible and robust. Second, detailed census metrics arguably incorporate all other relevant measures of validity; if, for example, either length of stay or entry patterns were substantively skewed, an associated skew would be clearly visible in the simulation data.

Because census is typically only recorded once or twice a day in formal MGH records, a surrogate continuous census was created by correlating CY2010 admission and discharge records. For completeness of record, this surrogate census also took into account prior admissions and subsequent discharges of patients who spent at least part of 2010 in one of the modeled areas. The following charts (Figure 4, Figure 5, Figure 6, Figure 7, Figure 8, and Figure 9) compare historical and simulated average census values by day of week for each of the primary modeled areas, as well as the sum of these areas.

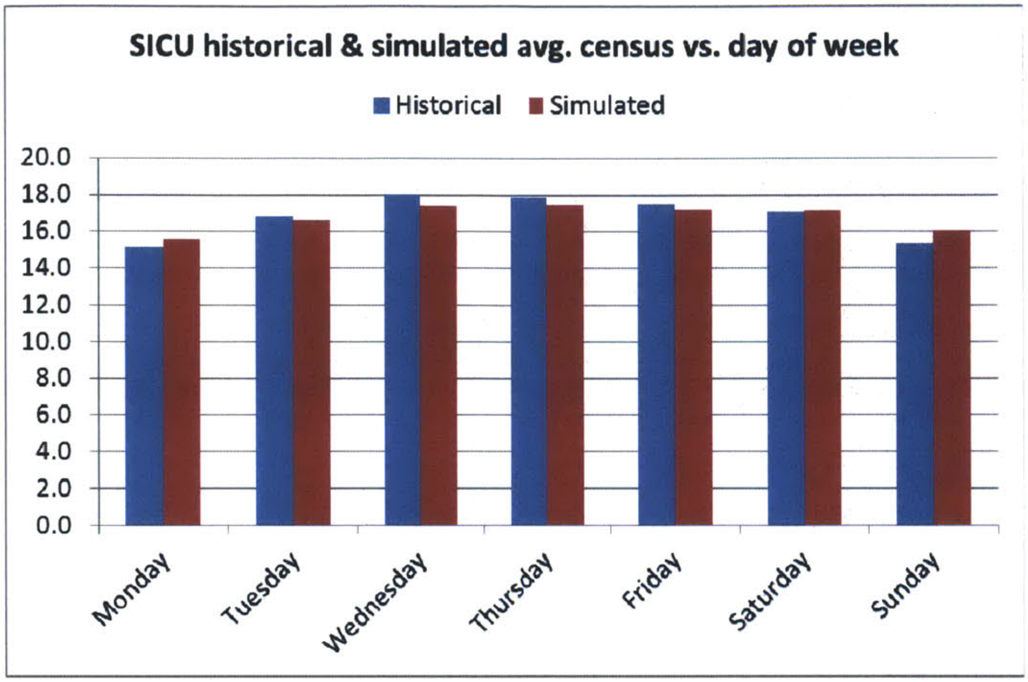

Figure 4: SICU historical and simulated average census vs. day of week

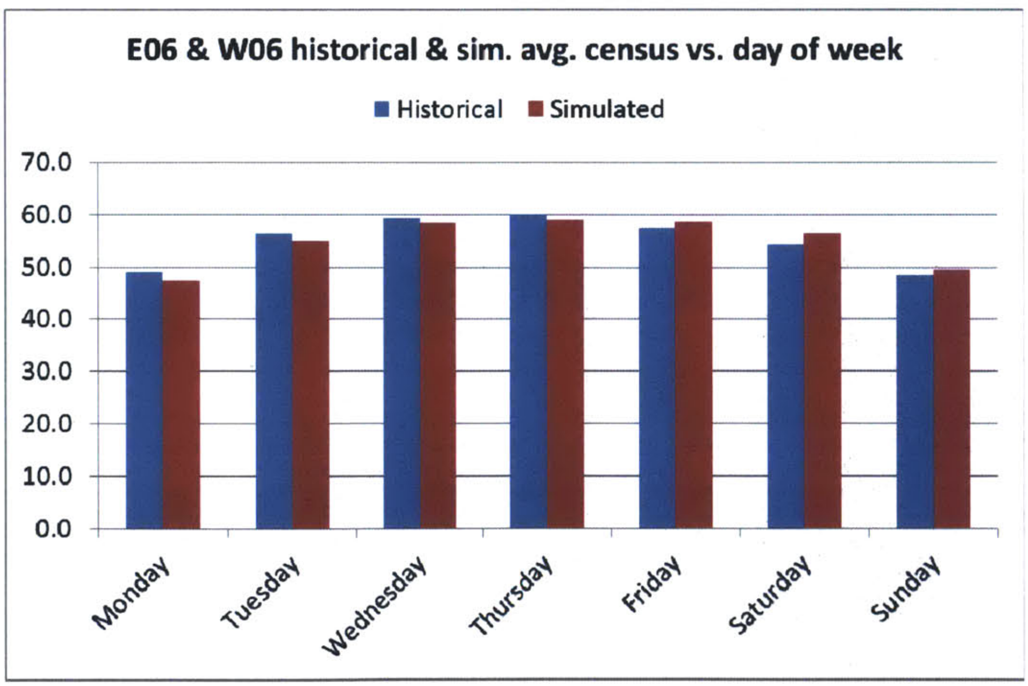

Figure 5: E06 & W06 historical and simulated average census vs. day of week

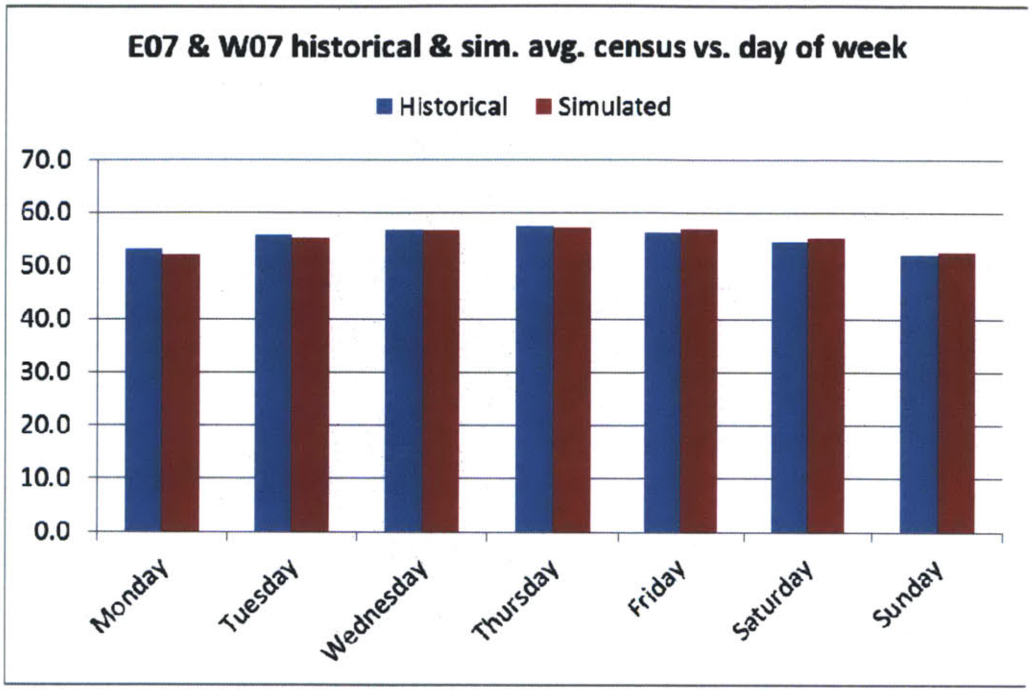

Figure 6: E07 & W07 historical and simulated average census vs. day of week

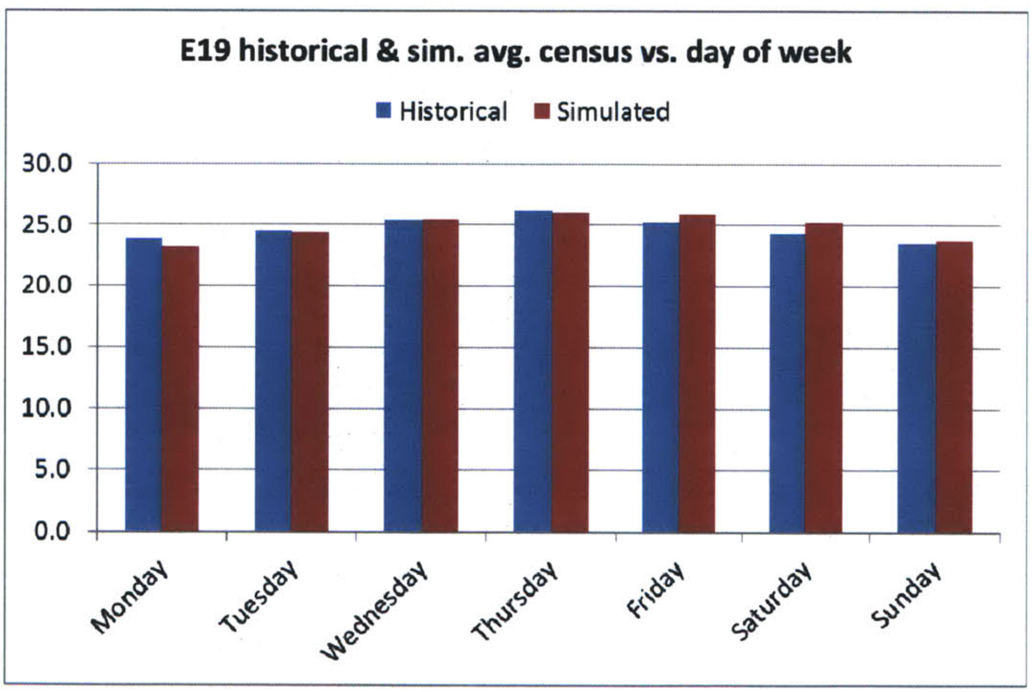

Figure 7: E19 historical and simulated average census vs. day of week

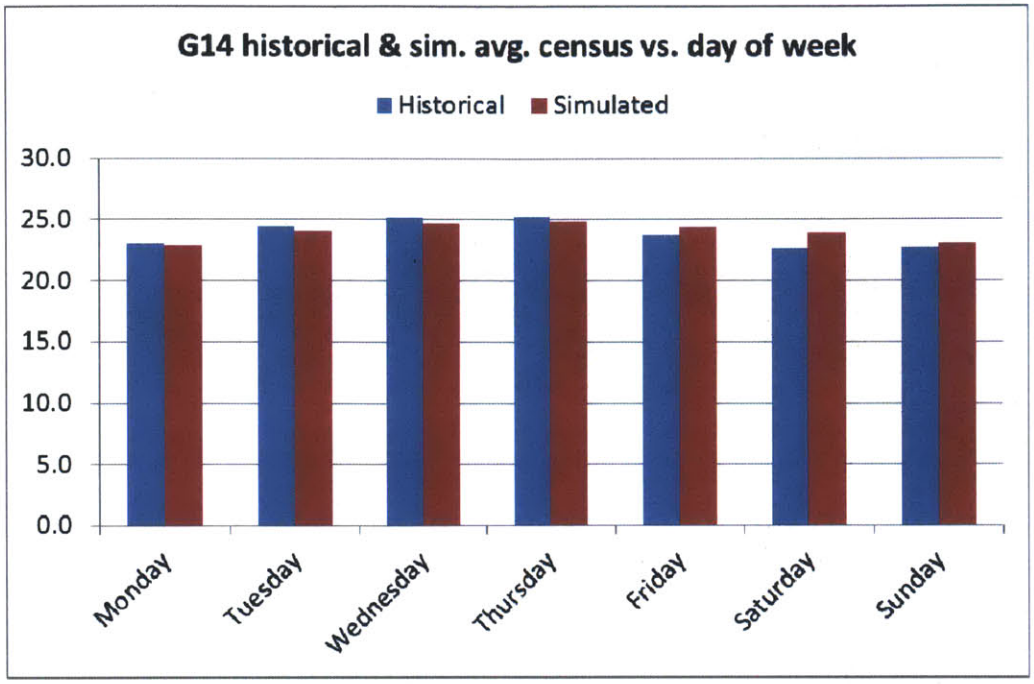

Figure 8: G14 historical and simulated average census vs. day of week

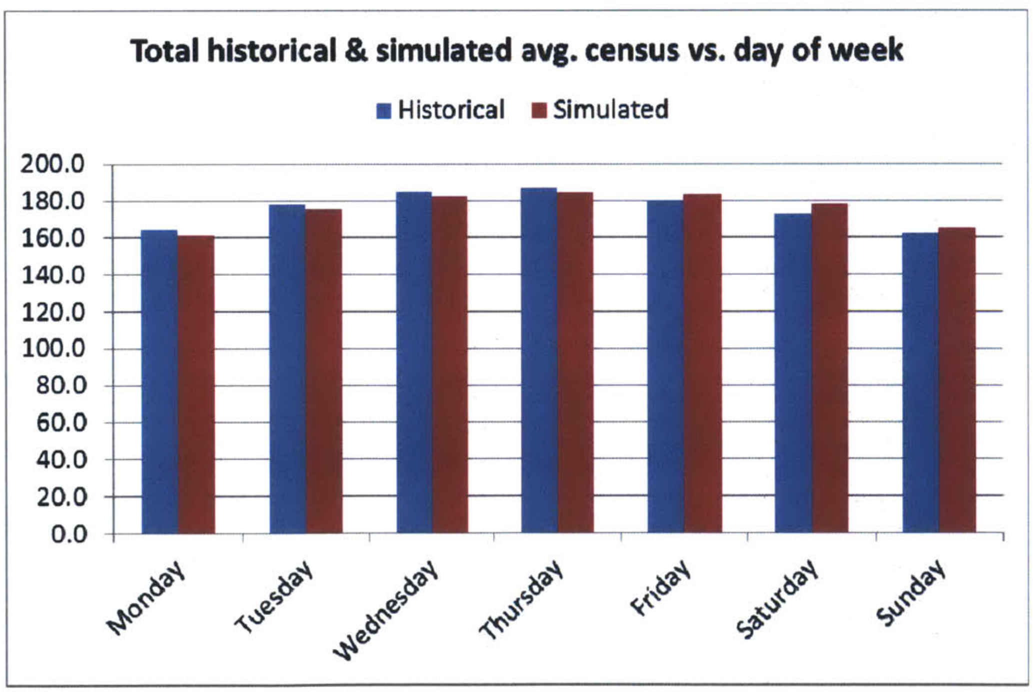

Figure 9: Total (of all considered areas) historical and simulated average census vs. day of week

A summary of the preceding six charts is displayed in Table 4 below. Like many of the following tables, this table is color-coded to allow for rapid visual comparison with similar tables. In this case, Table 4 should be compared with Table 5, which indicates the same metrics as produced by the simulation. The color scheme is consistent for each unit across these two tables. The median value for the census of a single unit – E06W06, for example – is the same shade of yellow in both Table 4 and Table 5. The highest daily census average seen in this unit between *either* actual or simulated values is fully red, while the lowest is fully green. This consistent color scheme for each unit allows for direct visual comparison of historical (actual) and simulated unit performance.

Table 4: Historical census averages, CY2010

Actual averages (across entire day)						
	E06W06	E07W07	E19	G14	E04I	Total
Monday	49.0	53.0	23.8	23.1	15.1	164.1
Tuesday	56.4	55.8	24.5	24.4	16.9	177.9
Wednesday	59.5	56.7	25.4	25.1	18.0	184.7
Thursday	60.0	57.5	26.1	25.3	17.9	186.8
Friday	57.4	56.2	25.3	23.7	17.5	180.1
Saturday	54.3	54.4	24.3	22.6	17.1	172.7
Sunday	48.5	52.1	23.6	22.8	15.4	162.2
Average	55.0	55.1	24.7	23.9	16.8	175.5

Table 5: Simulated census averages

	Simulated averages (across entire day)					
	E06 & W06	E07 & W07	E19	G14	E04I	Total
Monday	47.4	52.2	23.1	22.9	15.6	161.2
Tuesday	54.9	55.3	24.4	24.1	16.6	175.3
Wednesday	58.2	56.7	25.5	24.7	17.4	182.5
Thursday	59.1	57.2	26.0	24.8	17.4	184.5
Friday	58.5	56.9	25.9	24.4	17.2	182.8
Saturday	56.4	55.4	25.2	23.9	17.1	178.1
Sunday	49.4	52.5	23.7	23.0	16.0	164.8
Average	54.9	55.2	24.8	24.0	16.8	175.6

The following table, Table 6, provides an even more direct comparison. In this case, the simulation discrepancy, obtained by subtracting historical average census values from equivalent simulated census values, are displayed as percentages of the historical values. On the right side, we see discrepancies across all units for individual days of the week; on the bottom, discrepancies across all days of the week for individual units. Color coding is consistent across the entire table; a discrepancy of 0% has no shading, while simulated values higher than expected yield an increasing red shade; simulated values below their historical equivalents are shaded blue. As we will see, this table allows us to begin drawing meaningful conclusions about the behavior of the simulation.

Table 6: Average census discrepancy (simulated minus historical) on a unit-by-unit basis

	Average census discrepancy					
	E06 & W06	E07 & W07	E19	G14	E04I	Total
Monday	-3%	-2%	-3%	-1%	3%	-2%
Tuesday	-3%	-1%	0%	-2%	-2%	-1%
Wednesday	-2%	0%	0%	-2%	-3%	-1%
Thursday	-2%	0%	-1%	-2%	-3%	-1%
Friday	2%	1%	2%	3%	-2%	2%
Saturday	4%	2%	4%	6%	0%	3%
Sunday	2%	1%	1%	1%	4%	2%
Total	-0.3%	0.2%	0.5%	0.4%	-0.5%	$\boxed{0.1\%}$

We first notice along the bottom row that the overall performance of each unit matched historical values with a remarkable degree of fidelity. Averaged across days of the week, all units displayed a mean absolute census deviation of 0.5% or lower; the overall deviation was only 0.1%. Individual days of the week did not fare quite as well, as a trend emerged of the simulation slightly underestimating midweek peaks, and slightly overestimating weekend troughs. Still, the maximum overall absolute weekday deviation of 3% on Saturdays falls well within the bounds of meaningful accuracy for a model of such an extraordinarily complex system.

We next focus in for a much more detailed look at a similar set of metrics. Table 7 effectively serves as an expansion of the SICU/E04I column from Table 4, with the average historical census now broken out into time of day on an hourly basis, in addition to days of the week. The color-coding is again consistent with its matching pair from simulation data,

Table 8; a single color scheme is used for the entirety of both tables. An initial observation indicates that the general pattern of census highs and lows is very consistent between historical and simulated data. However, some discrepancies exist, as historical data has both higher peaks and lower troughs in average census than its simulated equivalent.

Table 7: Historical CY2010 SICU (E04I) census vs. day of week and time of day

	E04I	**Actual**						
	Monday	Tuesday	Wednesday	Thursday	Friday	Saturday	Sunday	**Average**
0:00	14.4	16.3	18.0	17.8	17.6	17.2	15.7	**16.7**
1:00	14.5	16.4	18.0	18.0	17.6	17.4	15.7	**16.8**
2:00	14.6	16.4	18.1	18.0	17.7	17.6	15.8	**16.9**
3:00	14.7	16.4	18.1	18.0	17.7	17.6	15.8	**16.9**
4:00	14.7	16.5	18.1	18.0	17.8	17.7	15.8	**16.9**
5:00	14.7	16.5	18.2	18.1	17.7	17.7	15.9	**17.0**
6:00	14.8	16.6	18.2	18.1	17.7	17.7	16.0	**17.0**
7:00	14.9	16.7	18.3	18.2	17.8	17.8	15.9	**17.1**
8:00	15.0	16.8	18.2	18.3	17.9	17.8	16.0	**17.1**
9:00	15.1	16.8	18.3	18.3	17.9	17.9	16.0	**17.2**
10:00	15.2	16.9	18.5	18.3	18.0	17.9	16.0	**17.3**
11:00	15.3	17.0	18.5	18.5	18.0	18.0	16.0	**17.3**
12:00	15.2	17.0	18.3	18.4	18.0	17.9	15.9	**17.2**
13:00	15.2	17.1	18.3	18.3	17.9	18.1	15.8	**17.2**
14:00	15.3	17.1	18.3	18.3	17.9	18.0	15.7	**17.2**
15:00	15.3	16.8	18.0	18.0	17.5	17.5	15.3	**16.9**
16:00	15.3	16.7	17.6	17.8	17.4	17.2	15.1	**16.7**
17:00	15.0	16.7	17.4	17.2	16.9	16.4	14.6	**16.3**
18:00	15.2	16.7	17.2	17.0	16.5	15.8	14.3	**16.1**
19:00	15.4	16.9	17.3	17.1	16.5	15.4	14.3	**16.2**
20:00	15.7	17.4	17.7	17.5	17.0	15.6	14.3	**16.4**
21:00	15.9	17.6	17.6	17.5	17.1	15.5	14.2	**16.5**
22:00	15.9	17.8	17.7	17.5	17.1	15.6	14.3	**16.6**
23:00	16.2	17.9	17.8	17.5	17.1	15.6	14.3	**16.6**
Average	**15.1**	**16.9**	**18.0**	**17.9**	**17.5**	**17.1**	**15.4**	**16.84**

Table 8: Simulated SICU (E04I) census vs. day of week and time of day

E04I	Simulated							
	Monday	Tuesday	Wednesday	Thursday	Friday	Saturday	Sunday	**Average**
0:00	15.1	16.3	17.3	17.5	17.2	17.3	16.4	**16.7**
1:00	15.1	16.3	17.4	17.5	17.2	17.4	16.4	**16.8**
2:00	15.2	16.3	17.4	17.6	17.2	17.5	16.4	**16.8**
3:00	15.2	16.3	17.4	17.6	17.2	17.5	16.5	**16.8**
4:00	15.2	16.4	17.4	17.6	17.2	17.5	16.5	**16.8**
5:00	15.3	16.4	17.5	17.6	17.2	17.5	16.5	**16.9**
6:00	15.4	16.5	17.5	17.7	17.3	17.5	16.5	**16.9**
7:00	15.5	16.5	17.5	17.7	17.3	17.6	16.5	**16.9**
8:00	15.5	16.5	17.5	17.7	17.4	17.6	16.6	**17.0**
9:00	15.6	16.5	17.6	17.8	17.4	17.6	16.6	**17.0**
10:00	15.7	16.6	17.6	17.8	17.4	17.7	16.6	**17.0**
11:00	15.7	16.6	17.6	17.8	17.4	17.7	16.5	**17.0**
12:00	15.7	16.6	17.6	17.7	17.3	17.6	16.5	**17.0**
13:00	15.7	16.7	17.6	17.7	17.3	17.6	16.4	**17.0**
14:00	15.7	16.6	17.5	17.6	17.2	17.4	16.2	**16.9**
15:00	15.6	16.5	17.3	17.4	17.0	17.1	16.0	**16.7**
16:00	15.6	16.4	17.2	17.2	16.9	16.8	15.7	**16.5**
17:00	15.4	16.4	17.1	16.9	16.8	16.5	15.3	**16.4**
18:00	15.5	16.5	17.1	16.9	16.8	16.3	15.2	**16.3**
19:00	15.7	16.7	17.3	17.0	17.0	16.2	15.2	**16.4**
20:00	15.9	16.9	17.3	17.1	17.2	16.3	15.1	**16.5**
21:00	16.0	17.1	17.4	17.1	17.2	16.2	15.0	**16.6**
22:00	16.1	17.2	17.4	17.1	17.2	16.2	15.0	**16.6**
23:00	16.2	17.3	17.4	17.2	17.3	16.3	15.1	**16.7**
Average	**15.6**	**16.6**	**17.4**	**17.4**	**17.2**	**17.1**	**16.0**	**16.76**

While these color scales are instructive, the discrepancies between historical and actual census figures merit a closer look. Table 9 provides this detail; similar to the previously discussed Table 6, the difference, or discrepancy, between actual and simulated data is displayed as a percentage of historical values. These discrepancies are obtained by subtracting historical average census values from the equivalent simulated census values, and then converting these differences into percentages of the historical values. As before, time blocks in which the simulated census is higher than the equivalent historical value are shaded red, while lower values are shaded blue.

Table 9: Discrepancy between historical and simulated SICU (E04I) census vs. day of week and time of day

	E04I	**Discrepancy**						
	Monday	Tuesday	Wednesday	Thursday	Friday	Saturday	Sunday	**Average**
0:00	5%	0%	-4%	-2%	-2%	1%	4%	**0%**
1:00	5%	-1%	-4%	-2%	-2%	0%	4%	**0%**
2:00	4%	-1%	-4%	-2%	-3%	-1%	4%	**0%**
3:00	3%	-1%	-4%	-2%	-3%	-1%	4%	**0%**
4:00	4%	-1%	-4%	-2%	-3%	-1%	4%	**0%**
5:00	4%	-1%	-4%	-2%	-3%	-1%	4%	**0%**
6:00	4%	-1%	-4%	-2%	-3%	-1%	4%	**-1%**
7:00	4%	-1%	-4%	-3%	-3%	-1%	4%	**-1%**
8:00	3%	-1%	-4%	-3%	-3%	-1%	4%	**-1%**
9:00	3%	-2%	-4%	-3%	-3%	-1%	4%	**-1%**
10:00	3%	-2%	-4%	-3%	-3%	-1%	4%	**-1%**
11:00	2%	-2%	-5%	-4%	-3%	-2%	3%	**-1%**
12:00	3%	-2%	-4%	-4%	-4%	-2%	4%	**-1%**
13:00	3%	-2%	-4%	-3%	-4%	-3%	4%	**-1%**
14:00	3%	-3%	-5%	-4%	-4%	-3%	4%	**-2%**
15:00	2%	-1%	-4%	-4%	-3%	-2%	4%	**-1%**
16:00	1%	-1%	-2%	-3%	-3%	-2%	4%	**-1%**
17:00	3%	-2%	-2%	-1%	-1%	0%	5%	**0%**
18:00	2%	-1%	0%	-1%	2%	3%	6%	**2%**
19:00	2%	-1%	-1%	-1%	3%	5%	6%	**2%**
20:00	1%	-2%	-2%	-2%	1%	4%	5%	**1%**
21:00	1%	-3%	-1%	-2%	1%	5%	6%	**1%**
22:00	1%	-4%	-2%	-2%	1%	4%	5%	**0%**
23:00	0%	-3%	-2%	-2%	1%	5%	5%	**0%**
Average	**3%**	**-2%**	**-3%**	**-3%**	**-2%**	**0%**	**4%**	**-0.3%**
							RMSE:	**3.1%**

While the correlation between historical and simulated values is not perfect, we see little in the way of discrepancies beyond what was already evident in Table 6. For the scale and scope of this investigation, these mostly low-single-digit discrepancies do not pose a significant issue, in particular as there is no significant overall bias.

It is notable that the primary focus of this project – the SICU, or E04I – consistently has greater discrepancies than other units. This pattern remains true for almost all metrics considered. This is logical and arguably inevitable, given the structure of the simulation. Discrepancies in the downstream units directly affect the census of the SICU by slightly altering the pattern of transfers from the SICU; as previously noted, a significant majority of SICU patients do transfer to one of these modeled units, and so these discrepancies can accumulate. The converse is not as true for downstream units; SICU patients comprise only a small minority of patients entering any one of the modeled areas, and so relatively small inherent discrepancies in the SICU transfer pattern do not substantively affect downstream census values.

One further type of validation merits consideration. Thus far, we have only examined various forms of averages. The distribution of values which make up those averages reveals an additional facet of system behavior; two identical averages, for example, could be formed by wildly different distributions of values, with accordingly different system behavior. We therefore consider the distribution of census values within individual areas, comparing historical (actual) to simulated figures as always. These figures are largely self-explanatory; we will display graphs for each individual area (Figure 10, Figure 11, Figure 12, Figure 13, and Figure 14), followed by a similar distribution graph for the system as a whole in Figure 15. Discussion will follow.

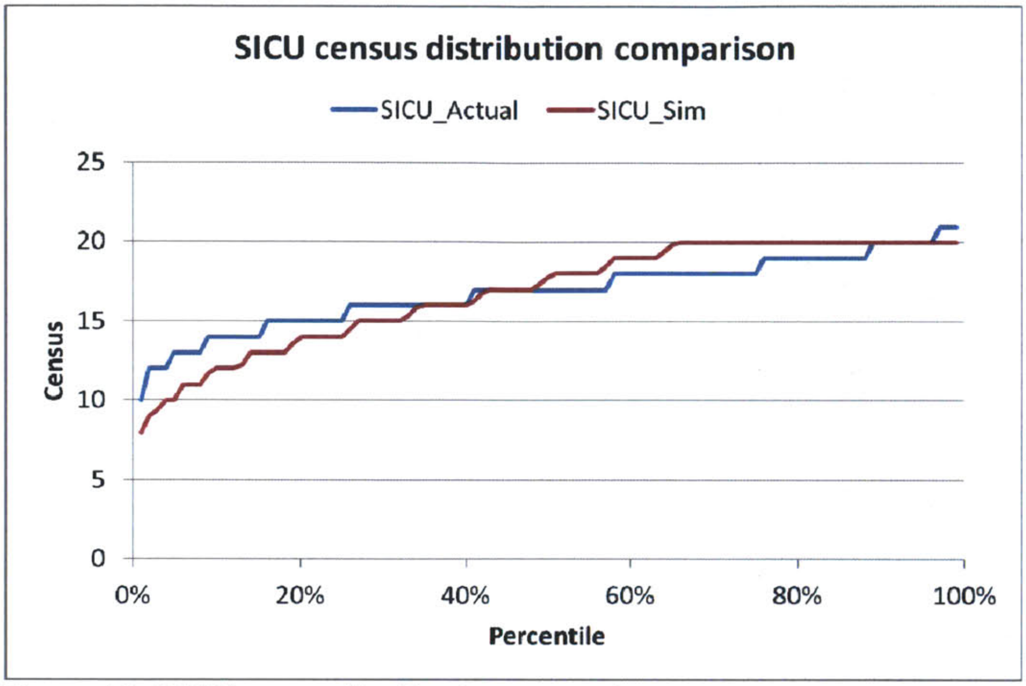

Figure 10: SICU census distribution comparison

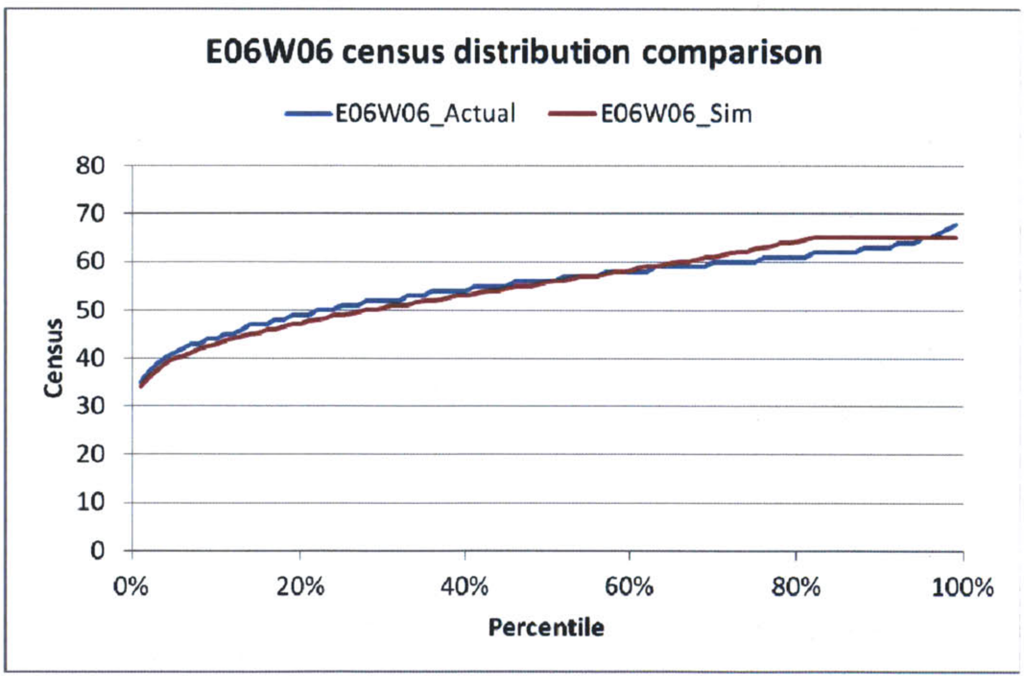

Figure 11: E06W06 census distribution comparison

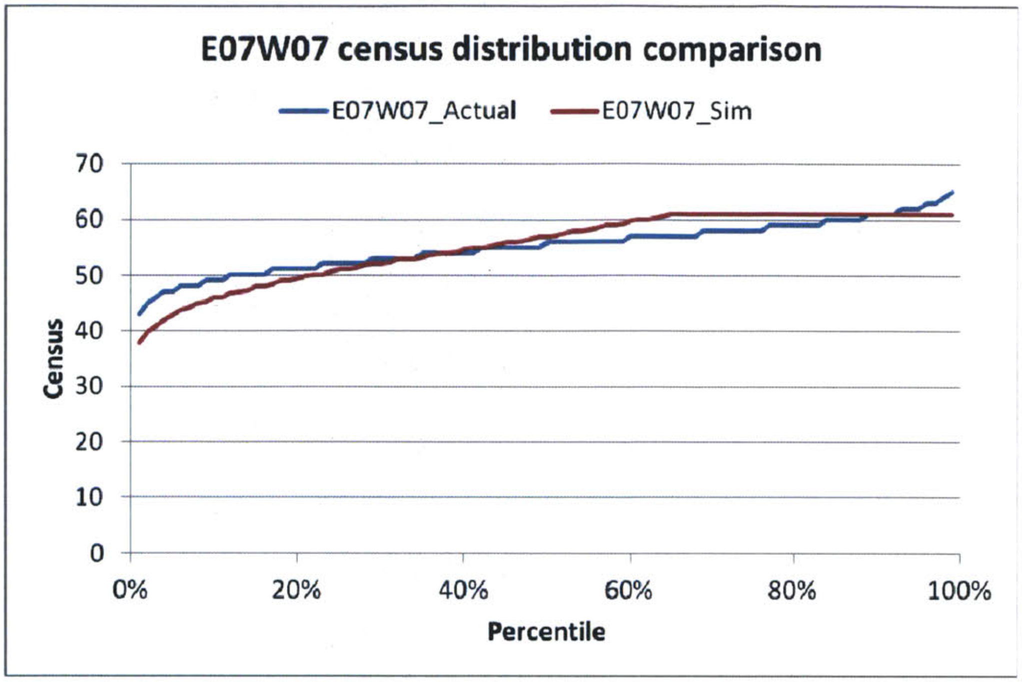

Figure 12: E07W07 census distribution comparison

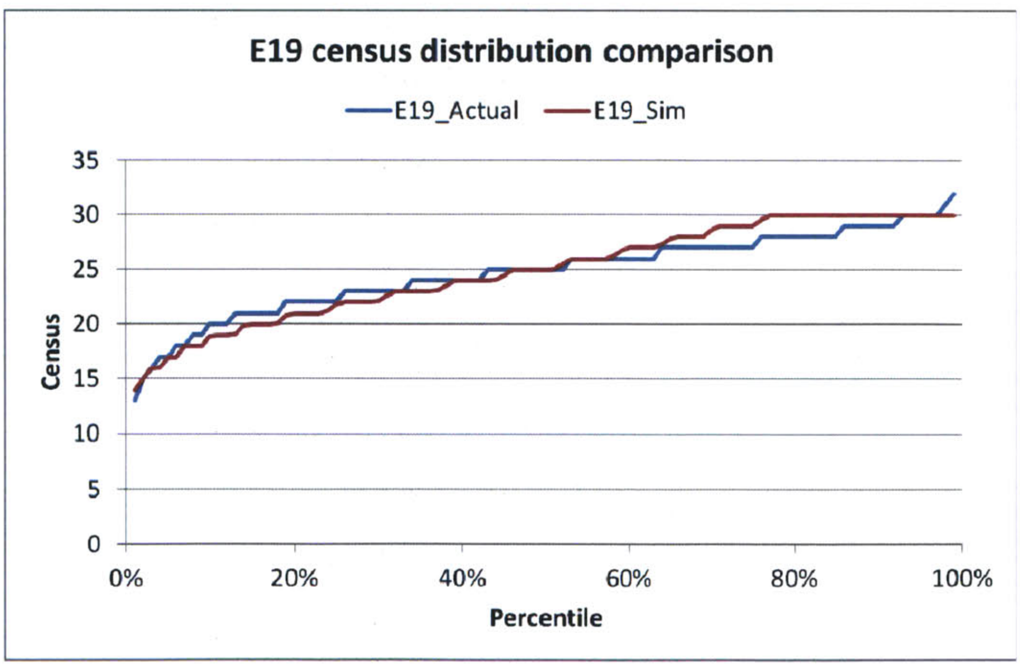

Figure 13: E19 census distribution comparison

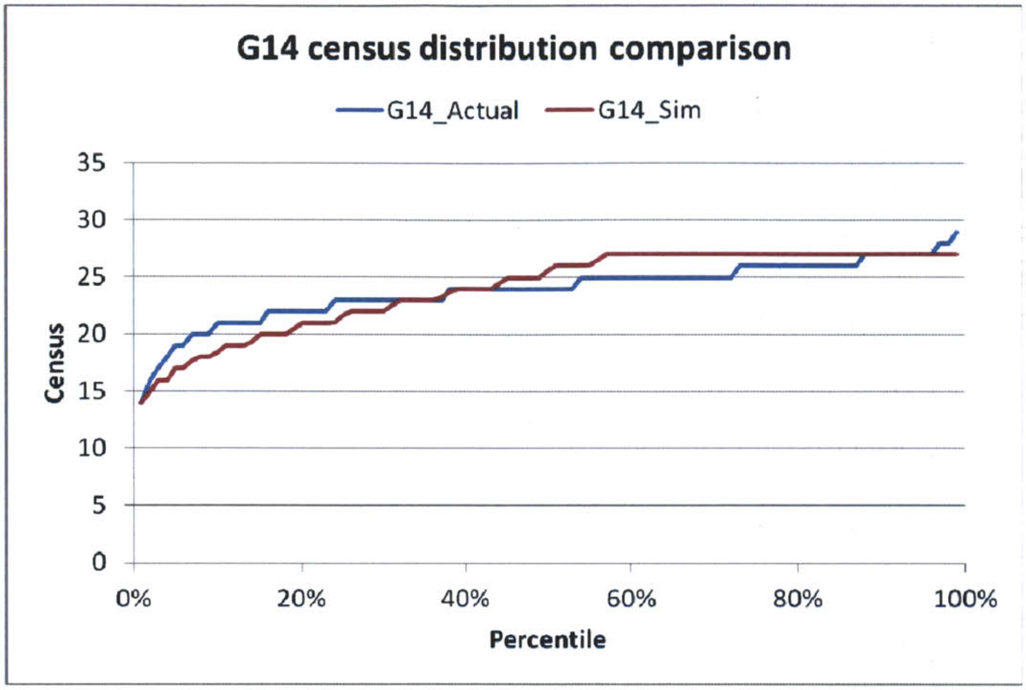

Figure 14: G14 census distribution comparison

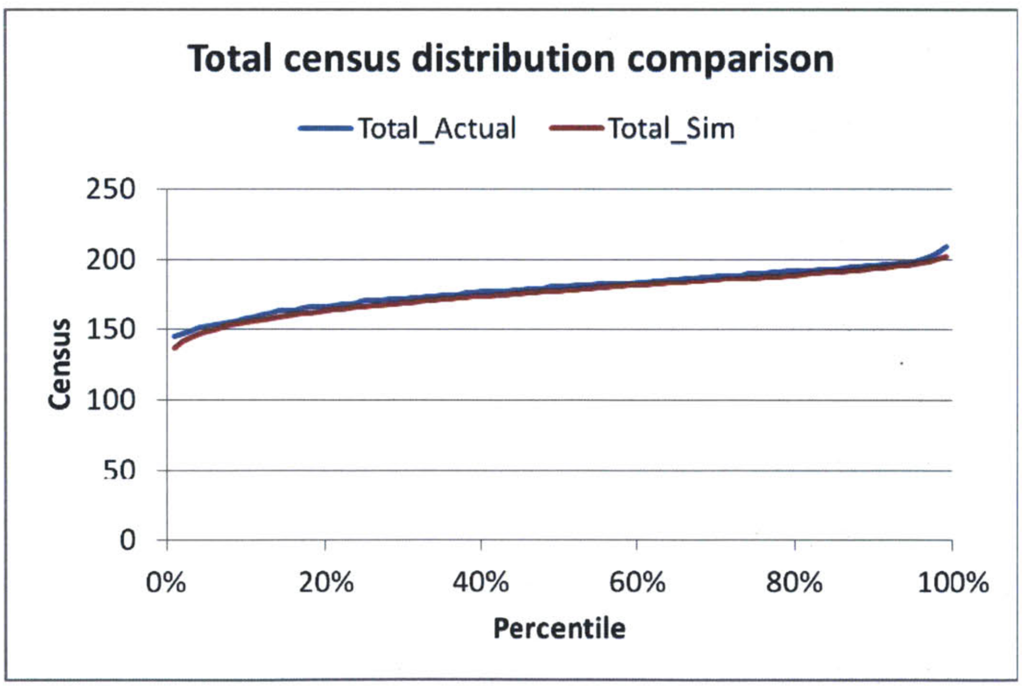

Figure 15: Census distribution comparison for all considered units

A summary version of these data is tabulated in Table 27 in the Appendix. As seen in the graphs above, comparisons between actual and simulated percentiles are generally very encouraging. While the model is certainly not a perfect mirror of reality, the distributions emerging from the described simulation structure do show remarkably close resemblances to historical distributions.

One notable observation is that the very highest percentiles of each area tend to exceed those of the simulated distributions. This effect, which is typically only visible above the 95th percentile mark, is an artifact of the simulation's methodology for simulating the closed beds process; the method used introduces a slight probability that the historical hospital census will exceed simulated values at the highest levels, as observed in the above figures. The plateaus observed in simulated data at high levels indicate that all additional beds were closed in the simulation. The net effect is the same under both historical and simulated conditions: no beds are available for patients attempting to transfer into the unit at that point.

To circumvent this artifact, operational utilization could have been used instead of raw bed occupancy. However, this presents a significant obstacle of interpretation: the "occupancy" of most importance to MGH is relative to time-varying staffing levels, which are not readily available for analysis. Initial attempts to discuss results in terms of occupancy raised more concerns than were readily resolvable without substantial additional resources, and so raw census figures – adjusted for bed closures in all cases – remain the source of choice for most meaningful metrics for the foreseeable future. Utilization figures are referred to occasionally as an additional point of reference.

One additional item of validation can be considered outside of census figures. From the previously described transfer delay study, we know that SICU patients experience an average delay of 14.6 hours between medical clearance for transfer and the actual move. This figure was also tracked in simulation; the baseline case showed an average delay of 14.3 hours, with a 95% confidence interval of 13.71 – 14.91 hours. In this case, the simulated value matches historical observations very closely.

While there are issues with some metrics, the weight of evidence suggests that the SICU patient flow simulation recreates the actual status quo with a high level of fidelity, and may reasonably be used to predict the system's response to various potential future scenarios. We therefore turn our attention to these scenarios.

3.3.2 Scenarios

Most simulations have utility only inasmuch as they provide insight into possible future conditions, thereby allowing managers to practice possible interventions in a simulated world with zero long-term consequences before committing any changes to the actual system in question. We therefore consider several possible scenarios, or approaches, with the goal of ameliorating current SICU system difficulties, as well as preparing for an uncertain future. We will first describe the scenarios in question, and then present the results of simulating the describe courses of action.

3.3.2.1 Baseline

This scenario has been the subject of all discussion in this thesis to this point. As the name suggests, the Baseline scenario closely emulates the current status quo.

3.3.2.2 Add SICU beds

This scenario simulates system behavior if SICU beds were increased by four, from 20 to 24 total. It is assumed that commensurate staff increases are also made in order to ensure operational capacity matches physical capacity. All other parameters remain identical to the baseline.

3.3.2.3 Add general beds

This scenario simulates system behavior if general (downstream) beds were increased by four Additional bed allocations were made to downstream units on the basis of high baseline utilization and frequency of SICU patients transferring into the unit. These criteria resulted in adding two beds to the E07 & W07 area (increasing capacity to 65 beds), one bed to E19 (increasing capacity to 31 beds), and one bed to G14 (increasing capacity to 28 beds). As above, commensurate staffing increases are assumed.

3.3.2.4 Transfer when ready

As previously noted, an artificial delay is habitually added to SICU patients' length of stay; even if beds are available downstream, a SICU patient who is ready for transfer in the morning will most likely not be moved until later in the day, often not before early afternoon. This scenario, abbreviated as TWR, simulates system behavior if this artificial delay is removed. If a bed is available to a clinically ready SICU patient, and no other patient (e.g. in a holding area) has precedence over the SICU patient, the patient will transfer immediately. For the sake of realism, "immediately" does incorporate a two-hour delay to account for additional nursing and logistical tasks which must typically be performed before a patient is truly available for transfer. This estimate was obtained through interviews with nursing staff responsible for preparing patients for the move.

3.3.2.5 Transfer when ready, with SICU priority

This scenario takes the previous TWR system as a foundation, but adds an additional level of SICU patient prioritization. In this case, a clinically ready SICU patient will always transfer to the first available bed in the designated downstream location, regardless of the state of any holding area in which patients may also be waiting for a bed in that same location. If multiple SICU patients are waiting, the longest-waiting patient will be selected from that group, and all patients from this highest-priority group will be served before any patients from any other group.

Full SICU priority would be very difficult to implement in practice because of strong competing priorities from the ED (with the added pressure of the Department of Public Health) and the OR, which is key to revenue generation. However, this approach is still worth examining to understand what the boundary conditions would be if SICU priority were to be increased.

3.3.2.6 24-hour rolling transfer readiness

This scenario derives from an interesting question which was raised by both Dr. Schmidt and Dr. Dunn: what if patients were declared "ready to transfer" by the physician team on a rolling, around-the-clock basis, rather than primarily in one big batch in the morning? According to both physicians, the practice of one-time rounding dates back to times in which attending physicians were not continuously available to oversee and approve the evaluations of residents and fellows. However, the SICU now has continuous attending coverage, and so continuous transfer readiness evaluation is theoretically feasible.

Simulation of this scenario is feasible because ready-for-exit times are decoupled from expected number of nights stayed in the unit. First, this scenario assumes patients will transfer as soon as they are ready, as long as a bed is available and no higher-priority patients are in line ahead of them (as in the "Transfer when ready" scenario). The actual readiness time is determined by assuming that patients who were declared ready to transfer at a particular time in the historical data actually achieved clinical readiness at some time in the previous 24 hours – i.e., after their last opportunity to meet transfer criteria. A uniform distribution is assumed for patients' readiness over this preceding 24-hour period. Simulated patients under this scenario are declared ready to transfer according to the exit time drawn from this distribution; the actual transfer, as with the TWR scenario, still depends on the condition of the target downstream floor, as well as its holding area.

Dr. Schmidt has raised one potential concern with this approach: most general units have less coverage (in terms of MDs and nursing) during the night hours, and may not be fully prepared to regularly receive multiple patient transfers during this relative downtime. Further investigation is warranted before implementing this recommendation; in addition, implementation should be very carefully monitored and established on a gradual basis.

3.3.2.7 24-hour rolling transfer readiness, with SICU priority

This scenario adds SICU patient prioritization, as explained in section 3.3.2.5 above, to the previously described 24-hour rolling transfer readiness scenario. It is the most aggressive of the policy-focused scenarios under consideration in this project.

3.3.3 Comparison of Scenarios

A number of key metrics were chosen as comparison factors between the various considered scenarios. Since the focus of this project was the SICU itself, that area also formed the focus of comparison metrics. All other areas were combined into a single "downstream units" section. In addition to the average census metric, three peak census values were compared between each scenario: the maximum among the day of week averages in the considered area, the maximum of the hour of day averages in the considered area, and the overall maximum among all day-of-week/hour-of-day combinations for the considered area.

The analysis also considers patient delay statistics – a key factor not only for operational efficiency, but also for optimal patient health, as well as perceived patient satisfaction. Average delays are measured for patients entering both the SICU as well as downstream areas. Patient exit delays – the subject of the first phase of this project – have meaning only for the SICU in this simulation, since patients exiting downstream areas leave the system boundaries immediately. As such, only the SICU reports this measurement.

In addition to averages, 95% confidence intervals were reported for the overall average census figures as well as all delay metrics. Such confidence intervals are possible because the simulation is run as a series of 20 independent one-year replications, each of which follows an equally independent one-year warm-up period. Obtaining confidence intervals for these metrics requires a standard deviation for the distribution of the metric in question. For the census, this is a straightforward square root of the summed variances for each individual area. Several of the delay characteristics require more complex calculations; for example, patients enter the SICU from three separate holding areas, and so a meaningful confidence interval requires determining the standard deviation of a *weighted* average entry delay time according to the following equation.

$$\sigma(\bar{x}) = \sqrt{\sum_{i=1}^{n} w_i^2 \sigma_i^2}$$

The w_i factors in this equation weight individual variances according to total number of patients entering the SICU through that area. Note also that since the number of replications (20) is relatively small for a statistical sample, Student's T-distribution is applied to generate conservative confidence intervals, rather than the more common normal (Z-) distribution.

With these notes as preface, we open our scenario comparison with Table 10, which summarizes the results of all six previously described approaches, in addition to the baseline simulation. Note that all census values in this table have been adjusted to account for diverted patients, as described in section 3.2.4.3, and so the average baseline census values do not necessarily agree exactly with those presented in the validation section. Baseline figures are listed in the first column. With the exception of confidence intervals, all subsequent columns report *differences* from the baseline scenario, color-coded to indicate red for higher values and green for lower values. 95% confidence intervals are reported as absolute figures in order to allow for direct C.I. range comparison.

Table 10: Scenario metric comparison

Key Metrics	Baseline simulation	Add 4 SICU beds	Add 4 general beds	Transfer when ready	Transfer when ready, SICU priority	24-hr transfers	24-hr transfers, SICU priority
		Difference from baseline for each scenario					
SICU							
Avg. SICU census	**17.2**	**0.1**	**0.0**	**-0.7**	**-1.1**	**-2.5**	**-3.2**
95% confidence interval (absolute)	16.98 - 17.45	16.94 - 17.61	16.93 - 17.53	16.28 - 16.75	15.8 - 16.37	14.43 - 15.06	13.65 - 14.42
Max. avg. day of week SICU census	17.9	0.3	0.0	-0.7	-1.2	-2.4	-3.2
Max. avg. hour of day SICU census	17.5	0.2	0.0	-0.4	-0.7	-2.4	-3.1
Max. avg. overall peak SICU census	18.3	0.4	-0.1	-0.5	-0.9	-2.4	-3.1
Avg. delay entering SICU	**7.2**	**-5.8**	**0.2**	**-1.3**	**-2.4**	**-5.0**	**-5.7**
95% confidence interval (absolute)	6.48 - 7.98	1.08 - 1.79	6.31 - 8.59	4.97 - 6.8	4.07 - 5.49	1.8 - 2.56	1.06 - 1.89
Avg. delay leaving SICU	**14.3**	**0.5**	**-1.8**	**-5.3**	**-9.8**	**-4.0**	**-9.2**
95% confidence interval (absolute)	13.71 - 14.91	14.06 - 15.56	11.89 - 13.2	8.31 - 9.66	4.42 - 4.67	9.74 - 10.87	4.96 - 5.28
All downstream units (D.U.)							
Avg. total D.U. census	**159.4**	**0.2**	**0.2**	**0.1**	**1.1**	**0.4**	**0.2**
95% confidence interval (absolute)	158.52 - 160.18	158.55 - 160.46	158.7 - 160.48	158.6 - 160.3	159.56 - 161.34	158.9 - 160.68	158.5 - 160.53
Sum of max. avg. day of week D.U. censuses	167.6	0.2	0.6	0.1	0.9	0.4	-0.1
Sum of max. avg. hour of day D.U. censuses	163.2	0.1	0.5	0.9	1.8	0.7	0.5
Sum of max. avg. overall peak D.U. censuses	171.7	0.1	0.9	0.5	1.3	0.5	0.1
Avg. delay for new patients entering D.U.	**4.9**	**0.4**	**-1.3**	**0.1**	**0.7**	**0.5**	**0.2**
95% confidence interval (absolute)	4.45 - 5.35	4.74 - 5.91	3.11 - 4.09	4.49 - 5.48	4.9 - 6.29	4.82 - 5.89	4.52 - 5.64

While several observations are immediately possible, a graphical depiction of key metrics is beneficial before entering into such a discussion. The following five figures (Figure 16, Figure 17, Figure 18, Figure 19, and Figure 20) portray average SICU census, average SICU entry delay, average SICU exit delay, average downstream census, and average downstream entry delay, respectively. Each graph provides insight into the effects, both intended and unintended, of each scenario's plan of action. Each will be discussed in turn.

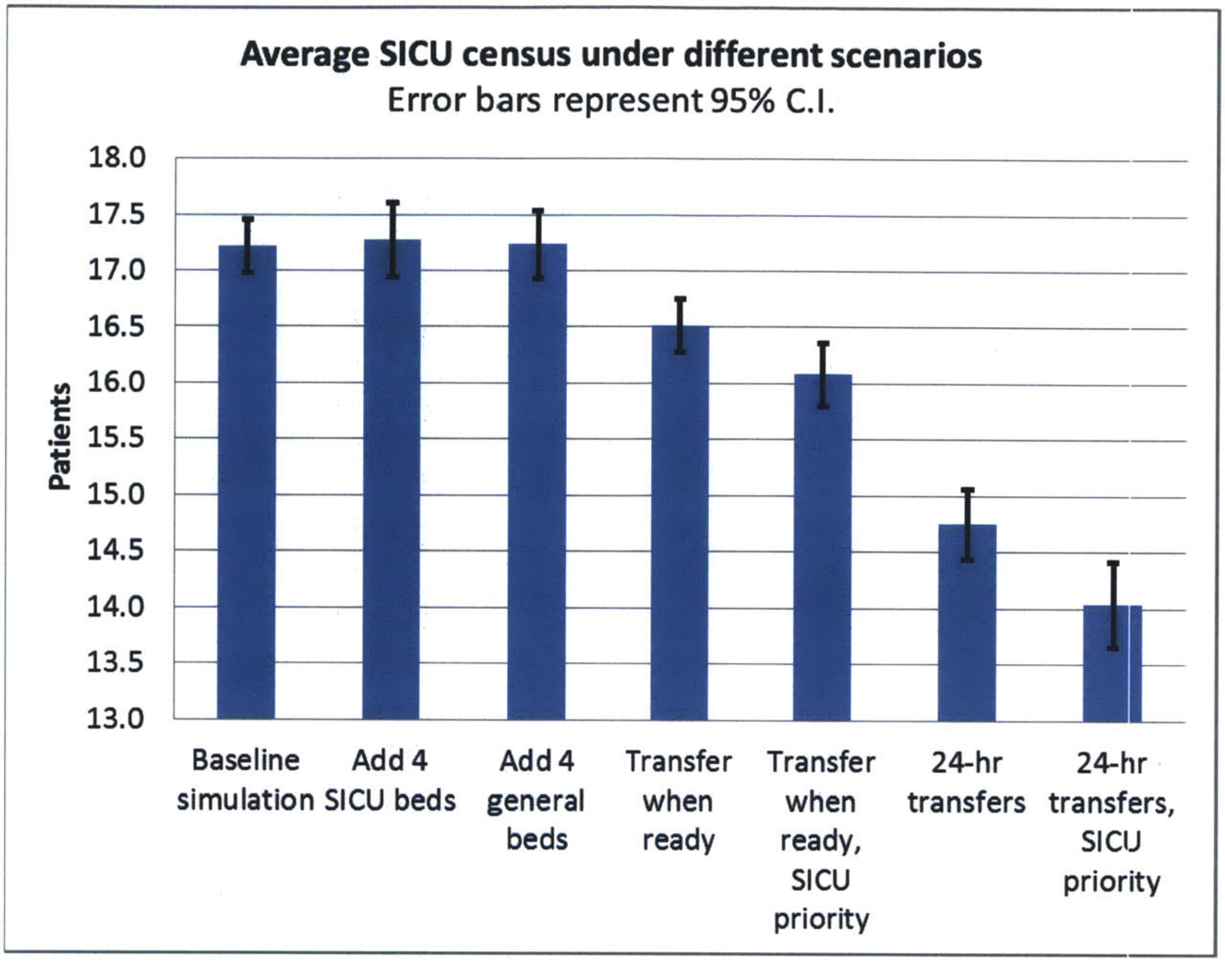

Figure 16: Average SICU census under different scenarios

Because the SICU already runs into capacity constraints, and increased volume may be expected in the future, reducing average SICU census is a key goal deserving careful evaluation. We see in Figure 16 that adding beds to either the SICU or downstream areas does not significantly change the expected census (although adding beds to the SICU with no increased volume does, of course, decrease operational utilization). Implementing the TWR policy, on the other hand, does provide a significant and substantive increase in available capacity. Implementing rolling 24-hour transfer readiness has an even greater effect. In both cases, giving priority to SICU transfers magnifies the effect – but, as we will see later, at a cost.

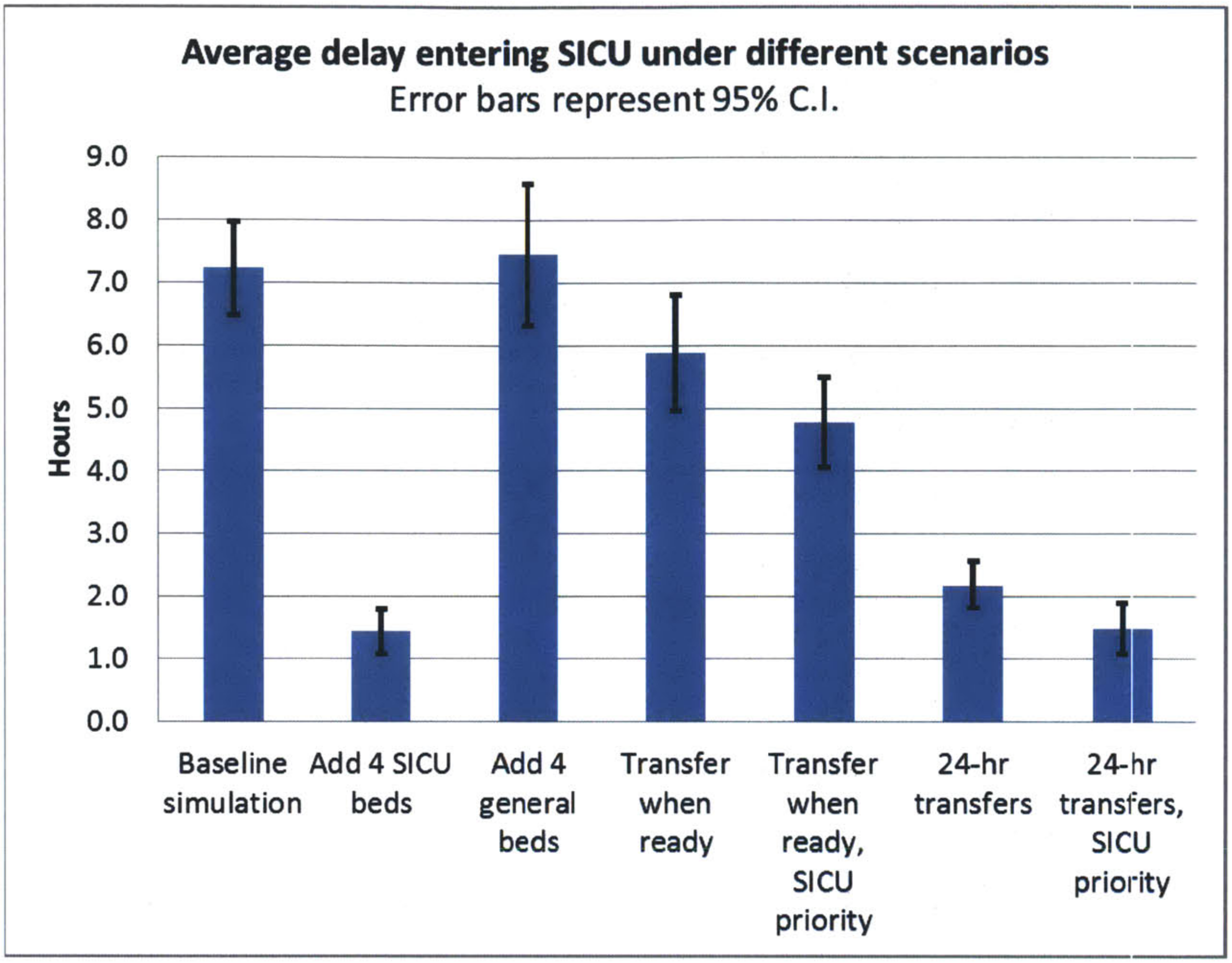

Figure 17: Average delay entering SICU under different scenarios

As expected, Figure 17 demonstrates a dramatic reduction in SICU entry delays if more SICU beds are added. Otherwise, this metric logically tracks the SICU census; transfer delays of any type are of course very highly correlated to utilization of the target area. Interestingly, we see in Figure 18 below that adding SICU beds actually increases the delays patients experience in exiting the SICU, although the effect is not clearly significant.

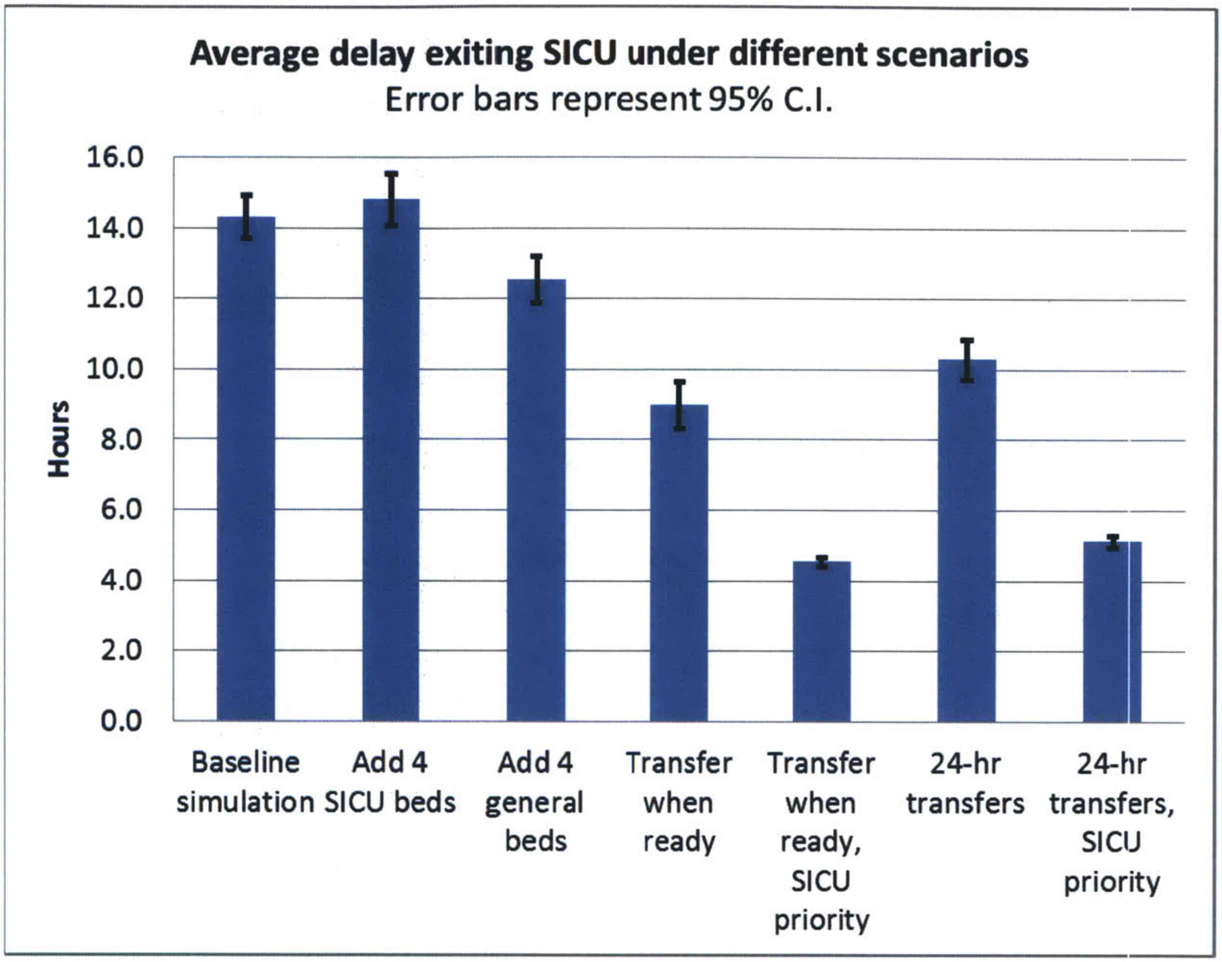

Figure 18: Average delay exiting SICU under different scenarios

All other considered interventions significantly decrease this delay time, which was the subject of the first phase of this project. One item of note is the relatively higher delays under the 24-hour transfer scenario as opposed to the TWR scenario. This phenomenon may be a result of the downstream units' own discharge schedule, which is a mostly batched format in relative sync of TWR patients' transfer requests, as opposed to the continuous requests of the 24-hour scenario. We also note that, again, adding SICU priority to either policy significantly magnifies the positive effect on this metric.

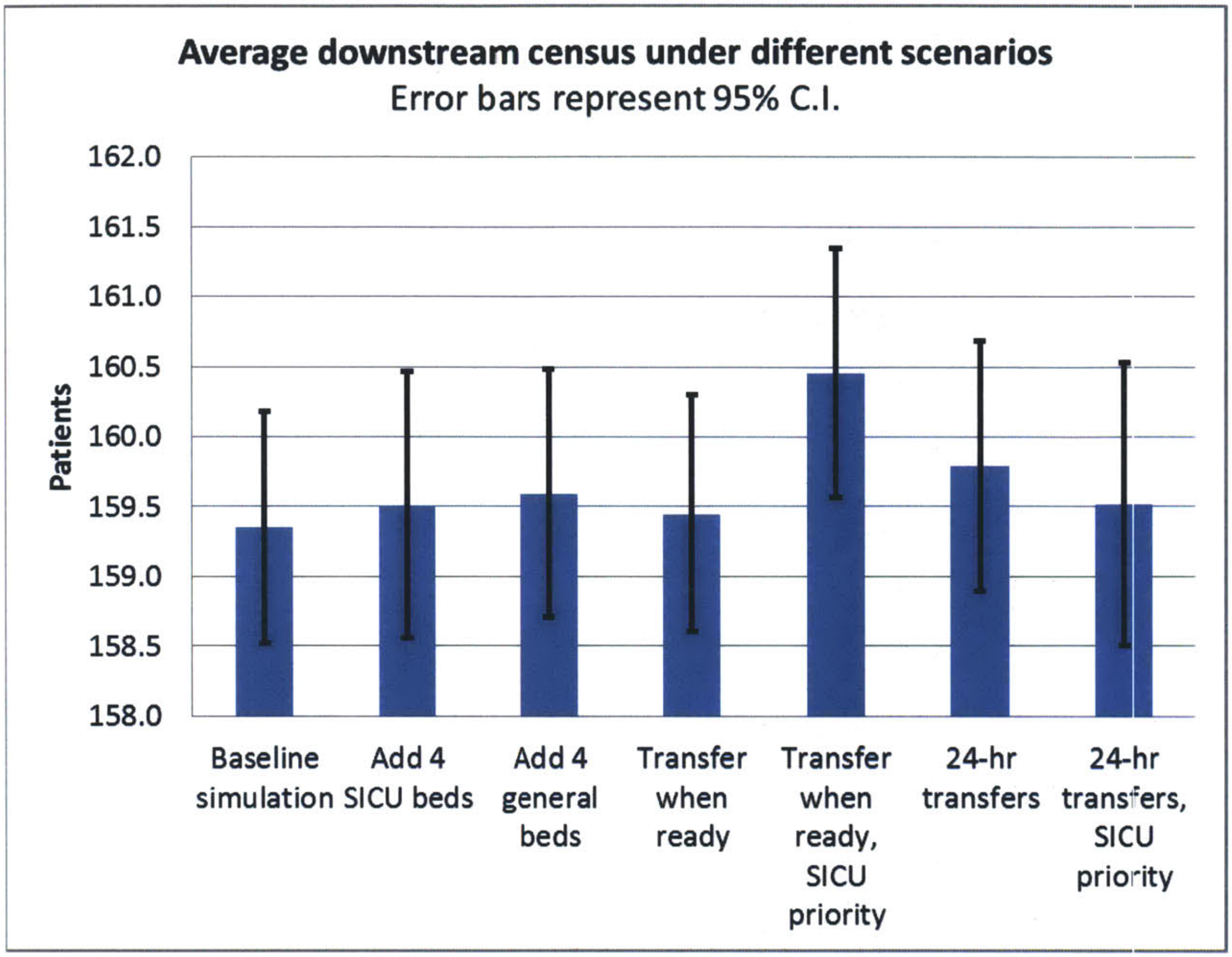

Figure 19: Average downstream census under different scenarios

We first notice the breadth of confidence intervals in Figure 19. On closer inspection, as a percentage of the mean values, these intervals are in fact very tight. However, since the mean values themselves are very large – and very close together in all cases – these larger scaled confidence intervals make it difficult to make major conclusions from this metric. We may note that the TWR policy appears to have more of an increasing effect on downstream area censuses than any other – a fact perhaps explained by the observation that TWR patients tend to arrive downstream earlier in the day, but due to the downstream units' own batched discharged processes, are not necessarily likely to *leave* the downstream area any earlier in the day on their eventual day of discharge.

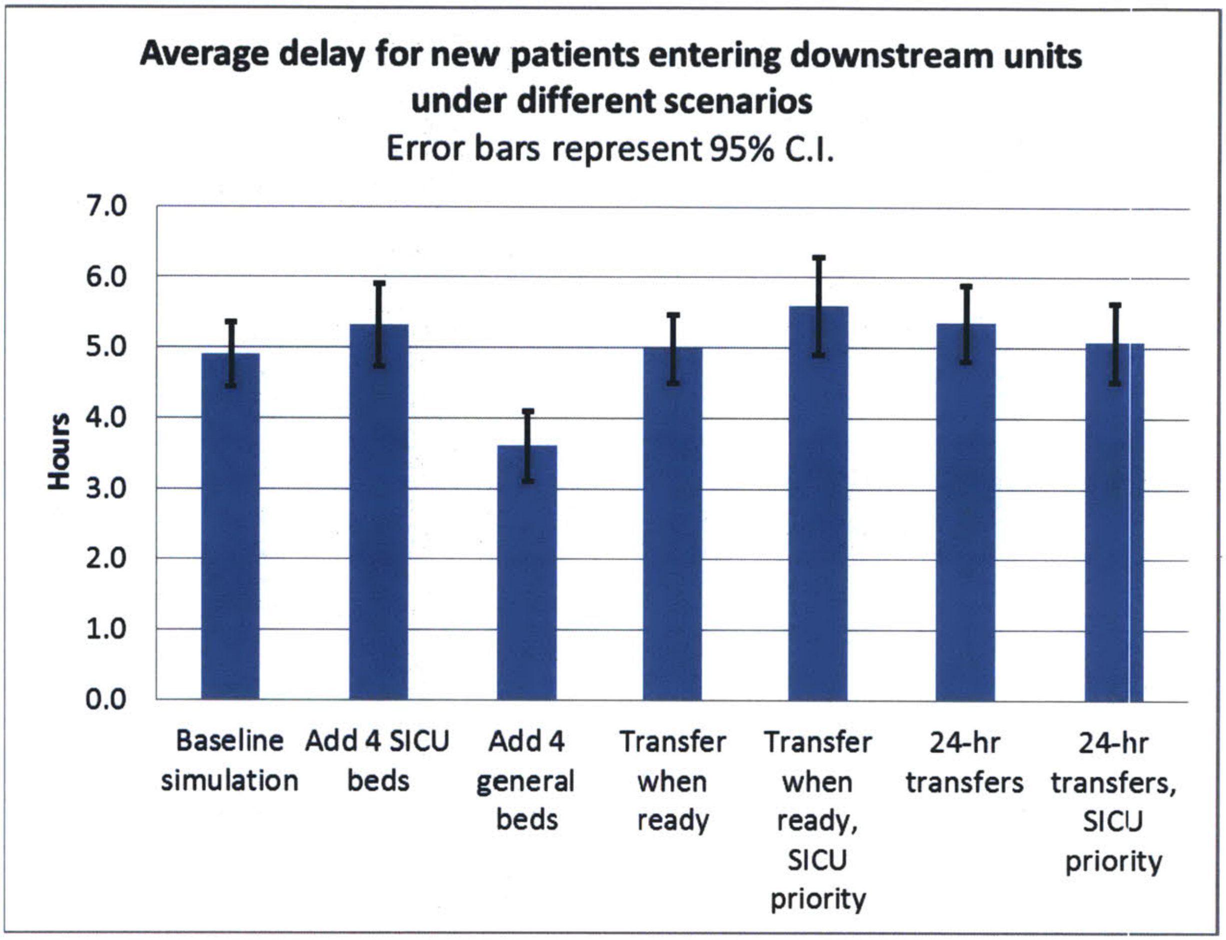

Figure 20: Average delay for new patients entering downstream units under different scenarios

Our final detailed metric, downstream area entry delays, is depicted above in Figure 20. This metric presents one clear winner: adding general beds significantly decreases the time that new patients entering downstream areas must wait before being served. While the effect may be slight, multiplying the impact by the thousands of patients which enter these units on a yearly basis suggests that this unexpected collateral benefit is more substantive than it may initially appear.

3.4 Discussion

The initial crisis reaction of most large organizations is to add resources to the area where the most painful symptoms are observed: more equipment, more staff, and more overtime. A potential MGH analogy to this common issue is in a common response to SICU patient flow difficulties: more SICU beds.

This analysis demonstrates that while this approach has its merits, it is by no means ideal. The single major contribution of adding SICU beds is to substantially decrease the average delay time for patients attempting to enter the unit. This is definitely helpful; however, is it the best use of the hospital's resources?

For example, significantly fewer resources would be required to add the same number of general unit beds, which have as little as half the start-up and operation costs of critical care beds. This option would lead to significantly lower entry delays to downstream units, as well as a lower exit delay from the SICU – which is an express purpose of this project, and a goal of the hospital. Given the framework of this project, adding general beds would appear to be a wiser use of necessarily constrained resources. On a day-to-day basis, MGH does not truly need more ICU beds. MGH *does* need more general beds – and the scenario results demonstrate why, with decreased delays affecting 100% of the included population, rather than a small subset.

But, first we should ask if any new beds are necessary at all! Two of the evaluated scenarios require no new capital equipment and no new staff – and yet achieve results comparable or even better than bed additions. Transferring when ready and implementing a 24-hour discharge are essentially different flavors of the same basic approach: simply change the timing of patients' transfers to the floor. Both approaches yield substantive drops in the SICU census, major drops in SICU entry delays (the 24-hour approach nearly matches adding four physical beds!), major improvements in SICU exit delays, and no significant negative impacts to downstream units. In fact, either of these policy changes could save on the order of $1M annually simply from reducing SICU exit delays – a figure which does not include additional benefits to other units or opportunity costs. These effects are magnified in both scenarios if we introduce SICU priority.

4 Conclusions

The primary outputs of this project are a few key figures and recommendations. First, we find that additional non-clinical SICU time yields negligible downstream time savings, while consuming an average of 2.4 SICU beds per day, or 12% of total SICU capacity, at a yearly attributable annual cost in excess of $2.5M. Second, we identify two promising approaches for ameliorating the root causes of these delays: 1) Transferring patients as soon as possible after medical clearance, eliminating the current practice of waiting to see if other patients might need downstream beds, and 2) Implementing a 24-hour rolling medical clearance process in the SICU. These interventions are predicted to lower average and peak SICU utilization by ~6%, cut SICU entrance delays by ~35%, and decrease SICU exit delays by ~50%, potentially saving ~$1M in non-reimbursed expenditures while reducing overcrowding. If capital expenditures are approved, the simulation results suggest increasing the capacity of downstream general units before addressing SICU constraints directly.

While these recommendations are highly customized to MGH's current condition, the general circumstances surrounding this project are far from unique. Delays in transferring clinically ready patients out of the ICU due to downstream capacity constraints are common in many hospitals. Indeed, patient flow issues in the necessarily unpredictable ICU are also very common. What can we draw from this project that will apply not only within the walls of MGH, but also throughout the medical community? Might some of the lessons learned even prove relevant to the operations of entirely different industries?

First, well before throwing more resources at a problem, consider several possible alternative approaches to addressing the root causes of the issue. Although adding beds to MGH certainly does alleviate some symptoms of overcrowding, it does so at great capital and operational expense. The most obvious solution, adding beds to the SICU itself, does not address the root of the problem, which is insufficient capacity downstream. In this case, as in many others, equivalent or better results – and certainly more sustainable results – could be obtained simply by changing the current operating procedures, such as allowing clinically ready ICU patients to move to a general unit more quickly. While the implementation challenge of changing ingrained behavior presents a significant short-term barrier, long-term operational benefits to the hospital merit providing sufficient high-level attention to such changes to overcome such natural, and understandable, obstacles.

Second, a similar lesson can be learned in examining the incentives which drive much decision-making behavior, whether conscious or unconscious. We previously reviewed how nursing directors are inadvertently incentivized to encourage non-critical care patients to stay beyond necessity in critical care units. For another example, many patients (who may be delirious, etc.) are delayed from transferring to another floor because of the lack of a "sitter" in that unit to watch over them. As Dr. Schmidt pointed out, the "sitter" position is an inexpensive one to fill, but since it's paid out of the budget of the receiving unit, there is no incentive to hire more than the absolute minimum. In the meanwhile, each patient waiting for an inexpensive "sitter" assistant costs the hospital thousands of dollars every day. Incentives are evidently misaligned in both of these examples. Such incentive systems are typically within the purview of top management, and MGH executives would be well-advised to thoroughly review the formal and informal incentive systems which govern much of the system behavior, giving careful consideration to both intended and unintended consequences.

Third, share best practices. If revised transfer practices are successful in the SICU, why not share with other units of the hospital? For example, could the downstream discharge practice benefit from some measure of similar unbatching? Unfortunately, decision-making at MGH, as at most large institutions, is often hampered by highly local vision. Currently, nursing supervisors' triage function largely optimizes patient flow around a single day, with little longitudinal visibility into forecasts for upcoming days. Individual units optimize their own unit flow, although in some cases their decisions may be detrimental to the system as a whole. Surgeons optimize for their own patients and their own schedule.

Such local optimization is natural and expected, and is consequentially pervasive throughout any large, complex organization. As the academic medical center has appropriately been called "one of the most complex organizational settings imaginable," the challenges presented by local optimization can present significant obstacles to the implementation of any substantive policy change.[37] The consequences of missteps can be organizationally catastrophic. Very careful attention and continuing research are therefore highly recommended as the findings of this thesis are put into practice. Encouragingly, one substantial proposal has already been implemented at a high level. Following the first phase of this project, a recommendation was made to begin tracking patients who are ready to be transferred from an ICU, but who cannot obtain a floor bed.

This reporting is now in place, and is influencing the decision-making process of those who manage bed capacity at MGH.

Beyond monitoring existing recommendations, the results of this project suggest several possible directions for future research. Expansions of scale and scope are clear avenues for elucidation of overall system effects. The simulation is structured such that it can be reasonably applied to virtually any other area of MGH with reasonably similar patient flow and accessible data – criteria which likely include all nine of the other ICUs at MGH, among other areas. In addition, MGH needs to significantly improve tracking of various types of delays. Transfer delays are particularly symptomatic of larger operational issues, and thus merit serious attention. Finally, because the simulation's structure is based on a very detailed foundation of diagnoses and procedures, very detailed questions and scenarios may be addressed with reasonable fidelity. What, for example, might be the impact of an initiative to shorten a common procedure's subsequent hospital length of stay, or to shift the care pathway for patients with a particular diagnosis? In aggregate, the intelligence gained through many such detailed analyses can contribute significantly to the quality and sustainability of care at MGH.

Thankfully, MGH is blessed with an extraordinary reservoir of talent and energy to make such improvements. Employees, students, volunteers, and patients work together every day to deliver a high standard of care. There is, of course, room for further improvement; as demonstrated in this thesis, inexpensive transfer practices bear promise of substantial performance gains with little long-term downside. With the right analysis, careful alignment of incentives, and thorough shepherding of the change process, MGH can turn ICU patient flow issues into opportunities for systemwide patient flow improvement.

5 Appendix

Table 11: Regression variables with explanatory notes

Regression variables	Notes
Time delayed (days)	Nonclinical delay transferring out of SICU
SICU LOS until transfer readiness	
Hospital LOS until SICU admission	
Acuity on day ready to transfer from SICU	A measure of expected nursing workload
Age	Age at time of service
AP rem. LOS	Expected remaining hospital LOS after transfer according to statewide averages based on AP-21 DRG codes
Precautions	Presence of infectious precautions (yes/no)
OR	Patient arrived in the SICU from this area
ED	
Floor/Other	
THORACIC SURG	Responsible service for the patient in the SICU (yes/no)
VASCULAR SURG	
ORTHOPEDICS PRIVATE	
SURGERY - GEN. or PRIV.	
E07 / W07	Patient was transferred to this area after leaving the SICU (yes/no)
E06 / W06	
G14	
E19	
CIRCULATORY	Patient was assigned to this Major Diagnostic Category (MDC) according to MS-DRG (Medicare) coding
DIGESTIVE	
MUSCULOSKELETAL	
RESPIRATORY	
NO MDC	
TRAUMA	
ASA II	Patient was assigned to this American Society of Anesthesiologists physical classification score, indicating pre-surgical condition severity (yes/no)
ASA III	
ASA IV	
Hospital LOS after ready to leave SICU (days)	Dependent variable for the first regression analysis
Costs incurred after 8:30 AM on day ready to leave SICU	Dependent variable for the second regression analysis

Table 12: Complete list of independent variables and interactions for regression analysis [8]

#	Variables and Interactions
1	Time delayed (days)
2	SICU LOS until transfer readiness
3	Hospital LOS until SICU admission
4	Acuity on day ready to transfer from SICU
5	Age
6	AP rem. LOS
7	Precautions
8	OR
9	ED
10	Floor/Other
11	THORACIC SURG
12	VASCULAR SURG
13	ORTHOPEDICS PRIVATE
14	SURGERY - GEN. or PRIV.
15	E07 / W07
16	E06 / W06
17	G14
18	E19
19	CIRCULATORY
20	DIGESTIVE
21	MUSCULOSKELETAL
22	RESPIRATORY
23	NO MDC
24	TRAUMA
25	ASA II
26	ASA III
27	ASA IV
28	(SICU LOS until transfer readiness-2.84187)*(Hospital LOS until SICU admission-1.8131)
29	(SICU LOS until transfer readiness-2.84187)*(Acuity on day ready to transfer from SICU-4.80919)
30	(SICU LOS until transfer readiness-2.84187)*(Age-60.4265)
31	(SICU LOS until transfer readiness-2.84187)*(AP rem. LOS-4.73183)
32	(SICU LOS until transfer readiness-2.84187)*(Precautions-0.12191)
33	(SICU LOS until transfer readiness-2.84187)*(OR-0.59894)
34	(SICU LOS until transfer readiness-2.84187)*(ED-0.11307)
35	(SICU LOS until transfer readiness-2.84187)*(Floor/Other-0.15194)

[8] In order to reduce collinearity when crossing two continuous variables, JMP first subtracts the mean value of each variable before multiplying the factors. All variables in this analysis were defined as continuous numeric values. For yes/no variables, "yes" was defined as 1 and "no" as 0. If 20% of values for a particular variable were defined as "yes," the mean for that variable would be 0.2. This mean would be subtracted from the variable before crossing with another variable, as seen in interaction listings below.

36	(SICU LOS until transfer readiness-2.84187)*(THORACIC SURG-0.20495)
37	(SICU LOS until transfer readiness-2.84187)*(VASCULAR SURG-0.19611)
38	(SICU LOS until transfer readiness-2.84187)*(ORTHOPEDICS PRIVATE-0.10601)
39	(SICU LOS until transfer readiness-2.84187)*(SURGERY - GEN. or PRIV.-0.33746)
40	(SICU LOS until transfer readiness-2.84187)*(E07 / W07-0.28975)
41	(SICU LOS until transfer readiness-2.84187)*(E06 / W06-0.12191)
42	(SICU LOS until transfer readiness-2.84187)*(G14-0.18728)
43	(SICU LOS until transfer readiness-2.84187)*(E19-0.19258)
44	(SICU LOS until transfer readiness-2.84187)*(CIRCULATORY-0.16961)
45	(SICU LOS until transfer readiness-2.84187)*(DIGESTIVE-0.14664)
46	(SICU LOS until transfer readiness-2.84187)*(MUSCULOSKELETAL-0.14488)
47	(SICU LOS until transfer readiness-2.84187)*(RESPIRATORY-0.13074)
48	(SICU LOS until transfer readiness-2.84187)*(NO MDC-0.06714)
49	(SICU LOS until transfer readiness-2.84187)*(TRAUMA-0.0636)
50	(SICU LOS until transfer readiness-2.84187)*(ASA II-0.20318)
51	(SICU LOS until transfer readiness-2.84187)*(ASA III-0.34982)
52	(SICU LOS until transfer readiness-2.84187)*(ASA IV-0.08481)
53	(Hospital LOS until SICU admission-1.8131)*(Acuity on day ready to transfer from SICU-4.80919)
54	(Hospital LOS until SICU admission-1.8131)*(Age-60.4265)
55	(Hospital LOS until SICU admission-1.8131)*(AP rem. LOS-4.73183)
56	(Hospital LOS until SICU admission-1.8131)*(Precautions-0.12191)
57	(Hospital LOS until SICU admission-1.8131)*(OR-0.59894)
58	(Hospital LOS until SICU admission-1.8131)*(ED-0.11307)
59	(Hospital LOS until SICU admission-1.8131)*(Floor/Other-0.15194)
60	(Hospital LOS until SICU admission-1.8131)*(THORACIC SURG-0.20495)
61	(Hospital LOS until SICU admission-1.8131)*(VASCULAR SURG-0.19611)
62	(Hospital LOS until SICU admission-1.8131)*(ORTHOPEDICS PRIVATE-0.10601)
63	(Hospital LOS until SICU admission-1.8131)*(SURGERY - GEN. or PRIV.-0.33746)
64	(Hospital LOS until SICU admission-1.8131)*(E07 / W07-0.28975)
65	(Hospital LOS until SICU admission-1.8131)*(E06 / W06-0.12191)
66	(Hospital LOS until SICU admission-1.8131)*(G14-0.18728)
67	(Hospital LOS until SICU admission-1.8131)*(E19-0.19258)
68	(Hospital LOS until SICU admission-1.8131)*(CIRCULATORY-0.16961)
69	(Hospital LOS until SICU admission-1.8131)*(DIGESTIVE-0.14664)
70	(Hospital LOS until SICU admission-1.8131)*(MUSCULOSKELETAL-0.14488)
71	(Hospital LOS until SICU admission-1.8131)*(RESPIRATORY-0.13074)
72	(Hospital LOS until SICU admission-1.8131)*(NO MDC-0.06714)
73	(Hospital LOS until SICU admission-1.8131)*(TRAUMA-0.0636)
74	(Hospital LOS until SICU admission-1.8131)*(ASA II-0.20318)
75	(Hospital LOS until SICU admission-1.8131)*(ASA III-0.34982)
76	(Hospital LOS until SICU admission-1.8131)*(ASA IV-0.08481)

77	(Acuity on day ready to transfer from SICU-4.80919)*(Age-60.4265)
78	(Acuity on day ready to transfer from SICU-4.80919)*(AP rem. LOS-4.73183)
79	(Acuity on day ready to transfer from SICU-4.80919)*(Precautions-0.12191)
80	(Acuity on day ready to transfer from SICU-4.80919)*(OR-0.59894)
81	(Acuity on day ready to transfer from SICU-4.80919)*(ED-0.11307)
82	(Acuity on day ready to transfer from SICU-4.80919)*(Floor/Other-0.15194)
83	(Acuity on day ready to transfer from SICU-4.80919)*(THORACIC SURG-0.20495)
84	(Acuity on day ready to transfer from SICU-4.80919)*(VASCULAR SURG-0.19611)
85	(Acuity on day ready to transfer from SICU-4.80919)*(ORTHOPEDICS PRIVATE-0.10601)
86	(Acuity on day ready to transfer from SICU-4.80919)*(SURGERY - GEN. or PRIV.-0.33746)
87	(Acuity on day ready to transfer from SICU-4.80919)*(E07 / W07-0.28975)
88	(Acuity on day ready to transfer from SICU-4.80919)*(E06 / W06-0.12191)
89	(Acuity on day ready to transfer from SICU-4.80919)*(G14-0.18728)
90	(Acuity on day ready to transfer from SICU-4.80919)*(E19-0.19258)
91	(Acuity on day ready to transfer from SICU-4.80919)*(CIRCULATORY-0.16961)
92	(Acuity on day ready to transfer from SICU-4.80919)*(DIGESTIVE-0.14664)
93	(Acuity on day ready to transfer from SICU-4.80919)*(MUSCULOSKELETAL-0.14488)
94	(Acuity on day ready to transfer from SICU-4.80919)*(RESPIRATORY-0.13074)
95	(Acuity on day ready to transfer from SICU-4.80919)*(NO MDC-0.06714)
96	(Acuity on day ready to transfer from SICU-4.80919)*(TRAUMA-0.0636)
97	(Acuity on day ready to transfer from SICU-4.80919)*(ASA II-0.20318)
98	(Acuity on day ready to transfer from SICU-4.80919)*(ASA III-0.34982)
99	(Acuity on day ready to transfer from SICU-4.80919)*(ASA IV-0.08481)
100	(Age-60.4265)*(AP rem. LOS-4.73183)
101	(Age-60.4265)*(Precautions-0.12191)
102	(Age-60.4265)*(OR-0.59894)
103	(Age-60.4265)*(ED-0.11307)
104	(Age-60.4265)*(Floor/Other-0.15194)
105	(Age-60.4265)*(THORACIC SURG-0.20495)
106	(Age-60.4265)*(VASCULAR SURG-0.19611)
107	(Age-60.4265)*(ORTHOPEDICS PRIVATE-0.10601)
108	(Age-60.4265)*(SURGERY - GEN. or PRIV.-0.33746)
109	(Age-60.4265)*(E07 / W07-0.28975)
110	(Age-60.4265)*(E06 / W06-0.12191)
111	(Age-60.4265)*(G14-0.18728)
112	(Age-60.4265)*(E19-0.19258)
113	(Age-60.4265)*(CIRCULATORY-0.16961)
114	(Age-60.4265)*(DIGESTIVE-0.14664)
115	(Age-60.4265)*(MUSCULOSKELETAL-0.14488)
116	(Age-60.4265)*(RESPIRATORY-0.13074)
117	(Age-60.4265)*(NO MDC-0.06714)

118	(Age-60.4265)*(TRAUMA-0.0636)
119	(Age-60.4265)*(ASA II-0.20318)
120	(Age-60.4265)*(ASA III-0.34982)
121	(Age-60.4265)*(ASA IV-0.08481)
122	(AP rem. LOS-4.73183)*(Precautions-0.12191)
123	(AP rem. LOS-4.73183)*(OR-0.59894)
124	(AP rem. LOS-4.73183)*(ED-0.11307)
125	(AP rem. LOS-4.73183)*(Floor/Other-0.15194)
126	(AP rem. LOS-4.73183)*(THORACIC SURG-0.20495)
127	(AP rem. LOS-4.73183)*(VASCULAR SURG-0.19611)
128	(AP rem. LOS-4.73183)*(ORTHOPEDICS PRIVATE-0.10601)
129	(AP rem. LOS-4.73183)*(SURGERY - GEN. or PRIV.-0.33746)
130	(AP rem. LOS-4.73183)*(E07 / W07-0.28975)
131	(AP rem. LOS-4.73183)*(E06 / W06-0.12191)
132	(AP rem. LOS-4.73183)*(E19-0.19258)
133	(AP rem. LOS-4.73183)*(CIRCULATORY-0.16961)
134	(AP rem. LOS-4.73183)*(DIGESTIVE-0.14664)
135	(AP rem. LOS-4.73183)*(MUSCULOSKELETAL-0.14488)
136	(AP rem. LOS-4.73183)*(RESPIRATORY-0.13074)
137	(AP rem. LOS-4.73183)*(NO MDC-0.06714)
138	(AP rem. LOS-4.73183)*(TRAUMA-0.0636)
139	(AP rem. LOS-4.73183)*(ASA II-0.20318)
140	(AP rem. LOS-4.73183)*(ASA III-0.34982)
141	(AP rem. LOS-4.73183)*(ASA IV-0.08481)
142	(Precautions-0.12191)*(OR-0.59894)
143	(Precautions-0.12191)*(ED-0.11307)
144	(Precautions-0.12191)*(Floor/Other-0.15194)
145	(Precautions-0.12191)*(THORACIC SURG-0.20495)
146	(Precautions-0.12191)*(VASCULAR SURG-0.19611)
147	(Precautions-0.12191)*(ORTHOPEDICS PRIVATE-0.10601)
148	(Precautions-0.12191)*(SURGERY - GEN. or PRIV.-0.33746)
149	(Precautions-0.12191)*(E07 / W07-0.28975)
150	(Precautions-0.12191)*(E19-0.19258)
151	(Precautions-0.12191)*(CIRCULATORY-0.16961)
152	(Precautions-0.12191)*(DIGESTIVE-0.14664)
153	(Precautions-0.12191)*(MUSCULOSKELETAL-0.14488)
154	(Precautions-0.12191)*(RESPIRATORY-0.13074)
155	(Precautions-0.12191)*(NO MDC-0.06714)
156	(Precautions-0.12191)*(TRAUMA-0.0636)
157	(Precautions-0.12191)*(ASA II-0.20318)
158	(Precautions-0.12191)*(ASA III-0.34982)

159	(Precautions-0.12191)*(ASA IV-0.08481)
160	(OR-0.59894)*(THORACIC SURG-0.20495)
161	(OR-0.59894)*(VASCULAR SURG-0.19611)
162	(OR-0.59894)*(ORTHOPEDICS PRIVATE-0.10601)
163	(OR-0.59894)*(SURGERY - GEN. or PRIV.-0.33746)
164	(OR-0.59894)*(E07 / W07-0.28975)
165	(OR-0.59894)*(E06 / W06-0.12191)
166	(OR-0.59894)*(CIRCULATORY-0.16961)
167	(OR-0.59894)*(DIGESTIVE-0.14664)
168	(OR-0.59894)*(MUSCULOSKELETAL-0.14488)
169	(OR-0.59894)*(RESPIRATORY-0.13074)
170	(OR-0.59894)*(NO MDC-0.06714)
171	(OR-0.59894)*(TRAUMA-0.0636)
172	(OR-0.59894)*(ASA II-0.20318)
173	(OR-0.59894)*(ASA III-0.34982)
174	(OR-0.59894)*(ASA IV-0.08481)
175	(ED-0.11307)*(THORACIC SURG-0.20495)
176	(ED-0.11307)*(VASCULAR SURG-0.19611)
177	(ED-0.11307)*(SURGERY - GEN. or PRIV.-0.33746)
178	(ED-0.11307)*(E07 / W07-0.28975)
179	(ED-0.11307)*(CIRCULATORY-0.16961)
180	(ED-0.11307)*(DIGESTIVE-0.14664)
181	(ED-0.11307)*(MUSCULOSKELETAL-0.14488)
182	(ED-0.11307)*(RESPIRATORY-0.13074)
183	(ED-0.11307)*(NO MDC-0.06714)
184	(ED-0.11307)*(TRAUMA-0.0636)
185	(ED-0.11307)*(ASA II-0.20318)
186	(ED-0.11307)*(ASA III-0.34982)
187	(ED-0.11307)*(ASA IV-0.08481)
188	(Floor/Other-0.15194)*(THORACIC SURG-0.20495)
189	(Floor/Other-0.15194)*(VASCULAR SURG-0.19611)
190	(Floor/Other-0.15194)*(ORTHOPEDICS PRIVATE-0.10601)
191	(Floor/Other-0.15194)*(SURGERY - GEN. or PRIV.-0.33746)
192	(Floor/Other-0.15194)*(E07 / W07-0.28975)
193	(Floor/Other-0.15194)*(E06 / W06-0.12191)
194	(Floor/Other-0.15194)*(CIRCULATORY-0.16961)
195	(Floor/Other-0.15194)*(DIGESTIVE-0.14664)
196	(Floor/Other-0.15194)*(MUSCULOSKELETAL-0.14488)
197	(Floor/Other-0.15194)*(RESPIRATORY-0.13074)
198	(Floor/Other-0.15194)*(NO MDC-0.06714)
199	(Floor/Other-0.15194)*(TRAUMA-0.0636)

200	(Floor/Other-0.15194)*(ASA II-0.20318)
201	(Floor/Other-0.15194)*(ASA III-0.34982)
202	(Floor/Other-0.15194)*(ASA IV-0.08481)
203	(THORACIC SURG-0.20495)*(DIGESTIVE-0.14664)
204	(THORACIC SURG-0.20495)*(MUSCULOSKELETAL-0.14488)
205	(THORACIC SURG-0.20495)*(RESPIRATORY-0.13074)
206	(THORACIC SURG-0.20495)*(NO MDC-0.06714)
207	(THORACIC SURG-0.20495)*(ASA II-0.20318)
208	(THORACIC SURG-0.20495)*(ASA III-0.34982)
209	(VASCULAR SURG-0.19611)*(CIRCULATORY-0.16961)
210	(VASCULAR SURG-0.19611)*(DIGESTIVE-0.14664)
211	(VASCULAR SURG-0.19611)*(MUSCULOSKELETAL-0.14488)
212	(VASCULAR SURG-0.19611)*(RESPIRATORY-0.13074)
213	(VASCULAR SURG-0.19611)*(ASA II-0.20318)
214	(VASCULAR SURG-0.19611)*(ASA III-0.34982)
215	(VASCULAR SURG-0.19611)*(ASA IV-0.08481)
216	(ORTHOPEDICS PRIVATE-0.10601)*(E07 / W07-0.28975)
217	(ORTHOPEDICS PRIVATE-0.10601)*(E06 / W06-0.12191)
218	(ORTHOPEDICS PRIVATE-0.10601)*(MUSCULOSKELETAL-0.14488)
219	(ORTHOPEDICS PRIVATE-0.10601)*(NO MDC-0.06714)
220	(ORTHOPEDICS PRIVATE-0.10601)*(ASA II-0.20318)
221	(ORTHOPEDICS PRIVATE-0.10601)*(ASA III-0.34982)
222	(ORTHOPEDICS PRIVATE-0.10601)*(ASA IV-0.08481)
223	(SURGERY - GEN. or PRIV.-0.33746)*(E07 / W07-0.28975)
224	(SURGERY - GEN. or PRIV.-0.33746)*(DIGESTIVE-0.14664)
225	(SURGERY - GEN. or PRIV.-0.33746)*(MUSCULOSKELETAL-0.14488)
226	(SURGERY - GEN. or PRIV.-0.33746)*(RESPIRATORY-0.13074)
227	(SURGERY - GEN. or PRIV.-0.33746)*(NO MDC-0.06714)
228	(SURGERY - GEN. or PRIV.-0.33746)*(TRAUMA-0.0636)
229	(SURGERY - GEN. or PRIV.-0.33746)*(ASA II-0.20318)
230	(SURGERY - GEN. or PRIV.-0.33746)*(ASA III-0.34982)
231	(SURGERY - GEN. or PRIV.-0.33746)*(ASA IV-0.08481)
232	(E07 / W07-0.28975)*(DIGESTIVE-0.14664)
233	(E07 / W07-0.28975)*(MUSCULOSKELETAL-0.14488)
234	(E07 / W07-0.28975)*(NO MDC-0.06714)
235	(E07 / W07-0.28975)*(ASA II-0.20318)
236	(E07 / W07-0.28975)*(ASA III-0.34982)
237	(E07 / W07-0.28975)*(ASA IV-0.08481)
238	(E06 / W06-0.12191)*(ASA II-0.20318)
239	(E06 / W06-0.12191)*(ASA III-0.34982)
240	(CIRCULATORY-0.16961)*(ASA II-0.20318)

241	(CIRCULATORY-0.16961)*(ASA III-0.34982)
242	(CIRCULATORY-0.16961)*(ASA IV-0.08481)
243	(DIGESTIVE-0.14664)*(ASA II-0.20318)
244	(DIGESTIVE-0.14664)*(ASA III-0.34982)
245	(DIGESTIVE-0.14664)*(ASA IV-0.08481)
246	(MUSCULOSKELETAL-0.14488)*(ASA II-0.20318)
247	(MUSCULOSKELETAL-0.14488)*(ASA III-0.34982)
248	(MUSCULOSKELETAL-0.14488)*(ASA IV-0.08481)
249	(RESPIRATORY-0.13074)*(ASA II-0.20318)
250	(RESPIRATORY-0.13074)*(ASA III-0.34982)
251	(RESPIRATORY-0.13074)*(ASA IV-0.08481)
252	(NO MDC-0.06714)*(ASA II-0.20318)
253	(NO MDC-0.06714)*(ASA III-0.34982)
254	(NO MDC-0.06714)*(ASA IV-0.08481)
255	(TRAUMA-0.0636)*(ASA II-0.20318)
256	(TRAUMA-0.0636)*(ASA III-0.34982)
257	(TRAUMA-0.0636)*(ASA IV-0.08481)

Table 13: Subsequent LOS regression results

Response Hospital LOS after ready to leave SICU (days)

Parameter Estimates

Term	Estimate	Prob>|t|	Lower 95%	Upper 95%
Intercept	3.5354029	<.0001*	3.0746818	3.996124
Time delayed (days)	0.9459211	<.0001*	0.6270863	1.2647558
SICU LOS until transfer readiness	0.232195	<.0001*	0.1646416	0.2997484
Hospital LOS until SICU admission	0.1684143	<.0001*	0.091053	0.2457755
AP rem. LOS	0.1847341	<.0001*	0.1301068	0.2393614
Precautions	1.0142089	0.0088*	0.2560052	1.7724127

Table 14: Subsequent costs regression results

Response Costs incurred after 8:30 AM on day ready to leave SICU

Parameter Estimates

Term	Estimate	Prob>|t|	Lower 95%	Upper 95%
Intercept	3045.1575	<.0001*	1957.7202	4132.5947
Time delayed (days)	3125.8024	<.0001*	2609.9944	3641.6103
SICU LOS until transfer readiness	471.15002	<.0001*	329.02283	613.27722
Hospital LOS until SICU admission	327.76228	<.0001*	205.266	450.25856
AP rem. LOS	255.09894	<.0001*	134.7142	375.48367
OR	791.42567	0.0605	-34.89934	1617.7507
SURGERY - GEN. or PRIV.	1157.6927	0.0165*	212.16215	2103.2232
E19	-184.8195	0.7326	-1246.988	877.34936
NO MDC	5818.8388	<.0001*	3375.0555	8262.6221
(SICU LOS until transfer readiness-2.83841)*(SURGERY - GEN. or PRIV.-0.33862)	-327.9503	0.0053*	-558.0409	-97.85967
(OR-0.59788)*(NO MDC-0.06702)	5107.8414	0.0021*	1866.0659	8349.617
(E19-0.19224)*(NO MDC-0.06702)	-8278.893	0.0001*	-12469.71	-4088.074

Table 15: Historical CY2010 E06W06 census vs. day of week and time of day

	E06W06	Actual						
	Monday	Tuesday	Wednesday	Thursday	Friday	Saturday	Sunday	Average
0:00	46.9	55.4	60.3	61.9	59.4	57.8	49.7	55.9
1:00	47.1	55.8	60.5	62.1	59.7	58.2	50.2	56.2
2:00	47.4	56.2	60.6	62.2	59.8	58.3	50.3	56.4
3:00	47.6	56.3	60.7	62.3	60.0	58.4	50.4	56.5
4:00	47.8	56.5	60.8	62.3	60.0	58.4	50.5	56.6
5:00	47.9	56.6	60.8	62.4	60.1	58.5	50.7	56.7
6:00	48.0	56.7	61.1	62.4	60.1	58.7	50.7	56.8
7:00	48.2	56.9	61.2	62.5	60.2	58.8	50.9	57.0
8:00	48.3	57.0	61.4	62.8	60.2	58.8	51.2	57.1
9:00	48.4	57.3	61.5	63.1	60.3	58.9	51.3	57.3
10:00	48.8	57.6	61.5	63.4	60.2	59.1	51.3	57.4
11:00	48.9	57.4	61.1	63.3	59.9	58.2	51.1	57.1
12:00	48.6	56.7	59.8	61.9	58.3	56.4	49.6	55.9
13:00	48.4	56.1	58.8	60.6	57.2	54.5	48.6	54.9
14:00	47.6	54.9	57.6	58.5	54.7	52.0	46.9	53.2
15:00	47.4	53.8	56.5	56.2	53.3	49.6	45.7	51.8
16:00	47.5	53.1	55.6	54.9	52.3	48.3	44.9	50.9
17:00	48.0	53.6	55.5	54.5	52.5	47.7	44.9	51.0
18:00	48.8	54.5	55.8	55.1	52.7	48.0	45.2	51.4
19:00	50.0	55.6	56.6	55.7	53.4	48.2	45.3	52.1
20:00	51.5	56.4	57.6	56.3	54.2	48.2	45.5	52.8
21:00	52.9	58.5	59.6	57.8	55.6	48.6	45.8	54.1
22:00	54.3	59.7	60.7	59.1	56.7	49.1	46.2	55.1
23:00	55.0	60.2	61.5	59.6	57.3	49.4	46.5	55.6
Average	49.0	56.4	59.5	60.0	57.4	54.3	48.5	55.00

Table 16: Simulated E06W06 census vs. day of week and time of day

	E06W06 Monday	**Simulated** Tuesday	Wednesday	Thursday	Friday	Saturday	Sunday	**Average**
0:00	45.5	53.7	58.9	60.4	59.5	59.7	52.1	**55.7**
1:00	45.7	54.1	59.0	60.5	59.6	59.9	52.3	**55.9**
2:00	45.9	54.3	59.1	60.5	59.7	59.9	52.5	**56.0**
3:00	46.1	54.4	59.1	60.6	59.8	60.0	52.6	**56.1**
4:00	46.2	54.5	59.2	60.6	59.8	60.0	52.7	**56.1**
5:00	46.3	54.6	59.3	60.6	59.8	60.1	52.8	**56.2**
6:00	46.5	54.8	59.4	60.7	59.9	60.2	52.9	**56.3**
7:00	46.6	55.0	59.5	60.8	59.9	60.2	53.1	**56.4**
8:00	46.8	55.1	59.6	60.9	59.9	60.3	53.2	**56.5**
9:00	47.0	55.4	59.6	61.1	60.0	60.3	53.3	**56.7**
10:00	47.2	55.5	59.6	61.1	59.9	60.2	53.1	**56.7**
11:00	46.9	55.1	58.9	60.6	59.3	59.5	52.3	**56.1**
12:00	46.3	54.5	57.9	59.7	58.5	58.5	51.2	**55.2**
13:00	45.9	53.9	56.8	58.5	57.4	57.0	49.9	**54.2**
14:00	45.5	53.1	55.7	56.9	56.2	55.1	48.0	**52.9**
15:00	45.5	52.7	55.1	55.8	55.5	53.3	46.5	**52.1**
16:00	45.8	52.8	54.9	55.3	55.3	51.9	45.3	**51.6**
17:00	46.7	53.5	55.3	55.5	55.6	51.2	44.7	**51.8**
18:00	47.8	54.5	56.1	56.1	56.2	50.9	44.4	**52.3**
19:00	49.1	55.4	56.9	56.6	56.8	50.7	44.2	**52.8**
20:00	50.6	56.6	58.1	57.5	57.7	50.8	44.3	**53.7**
21:00	52.0	57.9	59.3	58.6	58.7	51.2	44.6	**54.6**
22:00	52.9	58.5	59.9	59.1	59.2	51.5	44.9	**55.2**
23:00	53.4	58.7	60.3	59.4	59.5	51.8	45.2	**55.5**
Average	**47.4**	**54.9**	**58.2**	**59.1**	**58.5**	**56.4**	**49.4**	**54.85**

Table 17: Discrepancy between historical and simulated E06W06 census vs. day of week and time of day

	E06W06 Monday	**Discrepancy** Tuesday	Wednesday	Thursday	Friday	Saturday	Sunday	**Average**
0:00	-3%	-3%	-2%	-2%	0%	3%	5%	**0%**
1:00	-3%	-3%	-3%	-3%	0%	3%	4%	**-1%**
2:00	-3%	-3%	-3%	-3%	0%	3%	4%	**-1%**
3:00	-3%	-3%	-3%	-3%	0%	3%	4%	**-1%**
4:00	-3%	-3%	-3%	-3%	0%	3%	4%	**-1%**
5:00	-3%	-3%	-3%	-3%	0%	3%	4%	**-1%**
6:00	-3%	-3%	-3%	-3%	0%	2%	4%	**-1%**
7:00	-3%	-3%	-3%	-3%	0%	2%	4%	**-1%**
8:00	-3%	-3%	-3%	-3%	0%	2%	4%	**-1%**
9:00	-3%	-3%	-3%	-3%	-1%	2%	4%	**-1%**
10:00	-3%	-4%	-3%	-4%	-1%	2%	3%	**-1%**
11:00	-4%	-4%	-4%	-4%	-1%	2%	2%	**-2%**
12:00	-5%	-4%	-3%	-3%	0%	4%	3%	**-1%**
13:00	-5%	-4%	-3%	-4%	0%	5%	3%	**-1%**
14:00	-4%	-3%	-3%	-3%	3%	6%	2%	**0%**
15:00	-4%	-2%	-3%	-1%	4%	8%	2%	**1%**
16:00	-4%	-1%	-1%	1%	6%	8%	1%	**1%**
17:00	-3%	0%	0%	2%	6%	7%	0%	**2%**
18:00	-2%	0%	0%	2%	7%	6%	-2%	**2%**
19:00	-2%	0%	0%	2%	6%	5%	-2%	**1%**
20:00	-2%	0%	1%	2%	7%	6%	-3%	**2%**
21:00	-2%	-1%	-1%	1%	6%	5%	-3%	**1%**
22:00	-3%	-2%	-1%	0%	4%	5%	-3%	**0%**
23:00	-3%	-2%	-2%	0%	4%	5%	-3%	**0%**
Average	**-3%**	**-3%**	**-2%**	**-2%**	**2%**	**4%**	**2%**	**-0.2%**
							RMSE:	**3.3%**

Table 18: Historical CY2010 E07W07 census vs. day of week and time of day

	E07W07 Monday	**Actual** Tuesday	Wednesday	Thursday	Friday	Saturday	Sunday	**Average**
0:00	51.8	56.2	56.9	58.2	57.2	55.8	52.0	**55.4**
1:00	52.2	56.5	57.2	58.4	57.5	56.1	52.3	**55.8**
2:00	52.3	56.6	57.5	58.7	57.9	56.2	52.4	**55.9**
3:00	52.5	56.8	57.6	58.8	58.0	56.3	52.7	**56.1**
4:00	52.6	56.8	57.6	58.9	58.2	56.5	52.8	**56.2**
5:00	52.8	57.0	57.7	59.1	58.3	56.5	52.9	**56.3**
6:00	53.1	57.3	57.8	59.3	58.4	56.6	53.0	**56.5**
7:00	53.3	57.5	58.1	59.5	58.6	56.8	53.2	**56.7**
8:00	53.3	57.7	58.3	59.8	58.7	56.9	53.4	**56.9**
9:00	53.5	57.7	58.4	60.0	58.8	57.0	53.6	**57.0**
10:00	53.7	57.7	58.5	60.1	58.9	57.0	53.7	**57.1**
11:00	53.7	57.1	58.2	59.9	58.2	56.7	53.5	**56.8**
12:00	53.4	56.2	57.4	58.8	57.2	56.1	52.9	**56.0**
13:00	53.0	55.0	56.2	57.7	56.0	54.9	52.3	**55.0**
14:00	52.4	54.4	55.3	56.6	55.0	53.3	51.6	**54.1**
15:00	51.7	53.4	54.8	55.2	53.5	52.2	50.9	**53.1**
16:00	51.6	52.9	54.3	54.4	52.9	51.4	50.3	**52.5**
17:00	52.2	53.1	54.1	53.9	52.5	51.1	50.3	**52.5**
18:00	52.3	53.3	54.2	53.8	52.8	51.4	50.6	**52.6**
19:00	52.8	53.9	54.5	54.3	52.8	51.2	50.6	**52.9**
20:00	53.1	54.4	55.0	54.6	53.1	51.4	50.7	**53.2**
21:00	54.4	55.4	56.2	55.8	53.8	51.4	51.0	**54.0**
22:00	55.4	56.2	57.0	56.4	54.7	51.7	51.3	**54.7**
23:00	55.8	56.7	57.8	57.1	55.2	51.8	51.5	**55.1**
Average	**53.0**	**55.8**	**56.7**	**57.5**	**56.2**	**54.4**	**52.1**	**55.10**

Table 19: Simulated E07W07 census vs. day of week and time of day

	E07W07 Monday	Simulated Tuesday	Wednesday	Thursday	Friday	Saturday	Sunday	Average
0:00	51.2	55.0	56.8	57.5	57.5	56.7	53.3	55.4
1:00	51.5	55.2	56.9	57.7	57.6	56.9	53.4	55.6
2:00	51.6	55.3	57.0	57.8	57.7	56.9	53.6	55.7
3:00	51.7	55.3	57.1	57.8	57.8	57.0	53.8	55.8
4:00	51.8	55.4	57.1	57.9	57.8	57.0	53.8	55.8
5:00	52.0	55.6	57.2	58.0	57.9	57.1	53.9	55.9
6:00	52.2	55.7	57.3	58.1	57.9	57.1	54.0	56.1
7:00	52.3	55.8	57.4	58.2	58.0	57.2	54.1	56.2
8:00	52.4	55.9	57.5	58.3	58.1	57.2	54.3	56.2
9:00	52.6	56.0	57.6	58.4	58.1	57.3	54.4	56.3
10:00	52.6	56.0	57.6	58.4	58.1	57.2	54.3	56.3
11:00	52.4	55.6	57.4	58.1	57.7	56.8	54.0	56.0
12:00	52.0	55.2	56.9	57.6	57.2	56.4	53.4	55.5
13:00	51.6	54.7	56.5	57.1	56.6	55.7	52.8	55.0
14:00	51.1	54.2	55.9	56.4	55.9	54.8	52.0	54.3
15:00	51.0	54.0	55.5	55.9	55.4	54.2	51.3	53.9
16:00	51.3	54.0	55.3	55.6	55.1	53.7	50.8	53.7
17:00	51.7	54.3	55.3	55.6	55.1	53.4	50.5	53.7
18:00	52.0	54.6	55.5	55.8	55.1	53.2	50.4	53.8
19:00	52.5	55.0	55.7	56.0	55.3	53.0	50.3	54.0
20:00	53.1	55.5	56.2	56.3	55.6	52.9	50.4	54.3
21:00	54.0	56.0	56.8	56.8	56.0	53.0	50.5	54.7
22:00	54.5	56.4	57.2	57.1	56.3	53.1	50.7	55.0
23:00	54.8	56.6	57.4	57.3	56.6	53.1	50.9	55.2
Average	52.2	55.3	56.7	57.2	56.9	55.4	52.5	55.19

Table 20: Discrepancy between historical and simulated E07W07 census vs. day of week and time of day

	E07W07	**Discrepancy**						
	Monday	Tuesday	Wednesday	Thursday	Friday	Saturday	Sunday	**Average**
0:00	-1%	-2%	0%	-1%	0%	2%	3%	**0%**
1:00	-1%	-2%	-1%	-1%	0%	1%	2%	**0%**
2:00	-1%	-2%	-1%	-2%	0%	1%	2%	**0%**
3:00	-2%	-3%	-1%	-2%	0%	1%	2%	**-1%**
4:00	-1%	-3%	-1%	-2%	-1%	1%	2%	**-1%**
5:00	-2%	-3%	-1%	-2%	-1%	1%	2%	**-1%**
6:00	-2%	-3%	-1%	-2%	-1%	1%	2%	**-1%**
7:00	-2%	-3%	-1%	-2%	-1%	1%	2%	**-1%**
8:00	-2%	-3%	-1%	-3%	-1%	1%	2%	**-1%**
9:00	-2%	-3%	-1%	-3%	-1%	0%	1%	**-1%**
10:00	-2%	-3%	-2%	-3%	-1%	0%	1%	**-1%**
11:00	-2%	-3%	-1%	-3%	-1%	0%	1%	**-1%**
12:00	-3%	-2%	-1%	-2%	0%	0%	1%	**-1%**
13:00	-3%	-1%	1%	-1%	1%	1%	1%	**0%**
14:00	-2%	0%	1%	0%	2%	3%	1%	**0%**
15:00	-1%	1%	1%	1%	4%	4%	1%	**2%**
16:00	-1%	2%	2%	2%	4%	4%	1%	**2%**
17:00	-1%	2%	2%	3%	5%	4%	0%	**2%**
18:00	-1%	2%	2%	4%	4%	3%	0%	**2%**
19:00	-1%	2%	2%	3%	5%	3%	-1%	**2%**
20:00	0%	2%	2%	3%	5%	3%	-1%	**2%**
21:00	-1%	1%	1%	2%	4%	3%	-1%	**1%**
22:00	-2%	0%	0%	1%	3%	3%	-1%	**1%**
23:00	-2%	0%	-1%	0%	2%	3%	-1%	**0%**
Average	**-2%**	**-1%**	**0%**	**0%**	**1%**	**2%**	**1%**	**0.2%**
							RMSE:	**2.0%**

Table 21: Historical CY2010 E19 census vs. day of week and time of day

	E19 Monday	Actual Tuesday	Wednesday	Thursday	Friday	Saturday	Sunday	Average
0:00	23.3	24.3	24.7	26.0	25.7	24.5	23.9	**24.6**
1:00	23.3	24.4	24.7	26.2	25.8	24.6	23.9	**24.7**
2:00	23.3	24.4	24.9	26.3	25.9	24.6	23.9	**24.8**
3:00	23.4	24.4	24.9	26.3	25.9	24.6	23.9	**24.8**
4:00	23.4	24.5	24.9	26.3	25.9	24.6	24.0	**24.8**
5:00	23.4	24.5	24.9	26.4	26.0	24.6	24.0	**24.8**
6:00	23.6	24.6	25.0	26.3	26.0	24.7	24.0	**24.9**
7:00	23.8	24.7	25.2	26.4	26.1	24.7	24.0	**25.0**
8:00	24.0	24.7	25.2	26.6	26.2	24.7	24.1	**25.1**
9:00	24.2	24.8	25.3	26.8	26.3	24.8	24.2	**25.2**
10:00	24.5	24.8	25.3	26.8	26.3	24.7	24.2	**25.2**
11:00	24.8	25.1	25.6	27.0	26.5	24.9	23.9	**25.4**
12:00	24.7	25.0	25.9	26.8	26.2	24.8	24.0	**25.3**
13:00	24.3	24.7	25.8	26.7	25.7	24.4	23.7	**25.0**
14:00	24.0	24.4	25.5	26.0	25.2	24.1	23.2	**24.6**
15:00	23.9	24.0	25.4	25.8	24.7	23.8	22.9	**24.4**
16:00	23.8	24.0	25.4	25.6	24.2	23.7	22.8	**24.2**
17:00	23.7	24.0	25.7	25.6	24.1	23.6	22.8	**24.2**
18:00	23.5	24.1	25.7	25.7	23.8	23.6	22.8	**24.2**
19:00	23.5	24.1	25.6	25.5	23.9	23.8	22.9	**24.2**
20:00	23.6	24.1	25.6	25.4	23.9	23.7	23.0	**24.2**
21:00	23.9	24.2	25.8	25.6	24.0	23.8	23.1	**24.3**
22:00	24.1	24.5	25.9	25.7	24.2	23.8	23.1	**24.5**
23:00	24.3	24.6	26.0	25.8	24.3	23.9	23.2	**24.6**
Average	**23.8**	**24.5**	**25.4**	**26.1**	**25.3**	**24.3**	**23.6**	**24.71**

Table 22: Simulated E19 census vs. day of week and time of day

	E19 Monday	Simulated Tuesday	Wednesday	Thursday	Friday	Saturday	Sunday	Average
0:00	22.5	24.0	24.9	25.9	25.9	25.6	24.5	**24.7**
1:00	22.5	24.0	25.0	25.9	26.0	25.7	24.5	**24.8**
2:00	22.5	24.0	25.0	26.0	26.1	25.7	24.5	**24.8**
3:00	22.5	24.0	25.1	26.0	26.1	25.7	24.5	**24.8**
4:00	22.5	24.1	25.1	26.0	26.1	25.7	24.5	**24.9**
5:00	22.6	24.1	25.2	26.0	26.1	25.7	24.5	**24.9**
6:00	22.8	24.2	25.2	26.0	26.2	25.7	24.5	**25.0**
7:00	22.9	24.2	25.3	26.1	26.2	25.7	24.6	**25.0**
8:00	23.1	24.3	25.4	26.2	26.3	25.8	24.7	**25.1**
9:00	23.3	24.3	25.5	26.3	26.3	25.8	24.7	**25.2**
10:00	23.5	24.5	25.6	26.3	26.4	25.8	24.6	**25.3**
11:00	23.5	24.7	25.8	26.4	26.4	25.8	24.5	**25.3**
12:00	23.5	24.7	25.9	26.3	26.2	25.6	24.3	**25.2**
13:00	23.3	24.5	25.8	26.1	26.0	25.3	23.9	**25.0**
14:00	23.3	24.3	25.6	25.9	25.7	25.1	23.4	**24.8**
15:00	23.3	24.4	25.6	25.9	25.6	24.9	23.0	**24.7**
16:00	23.2	24.4	25.6	25.9	25.5	24.8	22.9	**24.6**
17:00	23.2	24.5	25.7	25.9	25.4	24.7	22.7	**24.6**
18:00	23.3	24.6	25.6	25.8	25.4	24.6	22.6	**24.6**
19:00	23.4	24.6	25.6	25.7	25.4	24.5	22.4	**24.5**
20:00	23.5	24.6	25.6	25.7	25.5	24.4	22.3	**24.5**
21:00	23.7	24.8	25.7	25.8	25.6	24.5	22.3	**24.6**
22:00	23.9	24.9	25.7	25.8	25.6	24.5	22.3	**24.7**
23:00	23.9	24.9	25.8	25.9	25.6	24.5	22.4	**24.7**
Average	**23.1**	**24.4**	**25.5**	**26.0**	**25.9**	**25.2**	**23.7**	**24.84**

Table 23: Discrepancy between historical and simulated E19 census vs. day of week and time of day

	E19 Monday	**Discrepancy** Tuesday	Wednesday	Thursday	Friday	Saturday	Sunday	**Average**
0:00	-4%	-1%	1%	0%	1%	5%	2%	**1%**
1:00	-4%	-2%	1%	-1%	1%	4%	2%	**0%**
2:00	-4%	-2%	1%	-1%	1%	4%	2%	**0%**
3:00	-4%	-1%	1%	-1%	1%	4%	3%	**0%**
4:00	-4%	-2%	1%	-1%	1%	4%	2%	**0%**
5:00	-3%	-2%	1%	-1%	1%	4%	2%	**0%**
6:00	-3%	-2%	1%	-1%	1%	4%	2%	**0%**
7:00	-4%	-2%	1%	-1%	1%	4%	2%	**0%**
8:00	-4%	-2%	1%	-1%	0%	4%	2%	**0%**
9:00	-4%	-2%	1%	-2%	0%	4%	2%	**0%**
10:00	-4%	-1%	1%	-2%	0%	4%	2%	**0%**
11:00	-5%	-2%	1%	-2%	0%	4%	2%	**0%**
12:00	-5%	-1%	0%	-2%	0%	3%	1%	**-1%**
13:00	-4%	-1%	0%	-2%	1%	4%	1%	**0%**
14:00	-3%	0%	0%	0%	2%	4%	1%	**1%**
15:00	-3%	2%	1%	0%	4%	5%	1%	**1%**
16:00	-2%	2%	1%	1%	6%	5%	0%	**2%**
17:00	-2%	2%	0%	1%	6%	5%	0%	**2%**
18:00	-1%	2%	0%	1%	6%	4%	-1%	**2%**
19:00	-1%	2%	0%	1%	6%	3%	-2%	**1%**
20:00	-1%	2%	0%	1%	6%	3%	-3%	**1%**
21:00	-1%	2%	0%	1%	6%	3%	-3%	**1%**
22:00	-1%	2%	-1%	0%	6%	3%	-3%	**1%**
23:00	-1%	1%	-1%	0%	5%	2%	-3%	**1%**
Average	**-3%**	**0%**	**0%**	**-1%**	**3%**	**4%**	**1%**	**0.5%**
							RMSE:	**2.6%**

Table 24: Historical CY2010 G14 census vs. day of week and time of day

	G14 Monday	Actual Tuesday	Wednesday	Thursday	Friday	Saturday	Sunday	Average
0:00	22.5	23.8	25.0	25.5	24.4	22.9	22.5	**23.8**
1:00	22.6	24.1	25.2	25.6	24.5	23.0	22.6	**23.9**
2:00	22.6	24.3	25.2	25.7	24.5	23.1	22.6	**24.0**
3:00	22.7	24.3	25.3	25.8	24.5	23.2	22.7	**24.0**
4:00	22.7	24.4	25.3	25.8	24.6	23.2	22.8	**24.1**
5:00	22.7	24.4	25.4	25.8	24.6	23.3	22.8	**24.1**
6:00	22.7	24.5	25.4	25.8	24.7	23.3	22.8	**24.2**
7:00	22.8	24.6	25.5	25.9	24.7	23.3	22.9	**24.2**
8:00	23.0	24.9	25.7	26.1	24.8	23.3	23.3	**24.4**
9:00	23.3	25.1	25.7	26.3	24.9	23.3	23.8	**24.6**
10:00	23.6	25.0	25.7	26.5	25.0	23.4	23.8	**24.7**
11:00	23.8	24.8	25.8	26.6	24.6	23.2	23.7	**24.6**
12:00	23.8	24.9	25.4	26.3	24.1	22.8	23.3	**24.4**
13:00	23.7	24.6	25.2	25.8	23.8	22.3	23.0	**24.1**
14:00	23.4	24.4	24.9	25.2	23.2	21.9	22.7	**23.7**
15:00	23.0	24.1	24.5	24.7	22.5	21.5	22.4	**23.2**
16:00	22.8	23.9	24.2	24.3	22.0	21.4	22.3	**23.0**
17:00	22.8	23.8	24.4	24.1	22.1	21.6	22.4	**23.0**
18:00	22.9	24.1	24.5	24.0	22.2	21.8	22.3	**23.1**
19:00	23.0	24.2	24.8	24.0	22.4	21.9	22.2	**23.2**
20:00	23.1	24.3	24.8	23.9	22.3	22.1	22.1	**23.2**
21:00	23.3	24.6	25.0	24.2	22.7	22.2	22.3	**23.5**
22:00	23.4	24.8	25.2	24.4	22.8	22.3	22.4	**23.6**
23:00	23.7	25.0	25.4	24.5	22.9	22.4	22.4	**23.8**
Average	**23.1**	**24.4**	**25.1**	**25.3**	**23.7**	**22.6**	**22.8**	**23.86**

Table 25: Simulated G14 census vs. day of week and time of day

	G14 Monday	Simulated Tuesday	Wednesday	Thursday	Friday	Saturday	Sunday	Average
0:00	22.3	23.6	24.5	24.9	24.6	24.3	23.3	**23.9**
1:00	22.4	23.7	24.5	25.0	24.6	24.4	23.3	**24.0**
2:00	22.4	23.8	24.5	25.0	24.6	24.4	23.3	**24.0**
3:00	22.4	23.9	24.6	25.0	24.6	24.4	23.4	**24.0**
4:00	22.4	23.9	24.6	25.0	24.6	24.4	23.4	**24.1**
5:00	22.4	23.9	24.6	25.0	24.6	24.4	23.4	**24.1**
6:00	22.5	24.0	24.6	25.0	24.7	24.5	23.5	**24.1**
7:00	22.6	24.1	24.7	25.1	24.7	24.5	23.6	**24.2**
8:00	22.8	24.2	24.7	25.2	24.7	24.5	23.8	**24.3**
9:00	23.0	24.3	24.8	25.3	24.8	24.5	23.9	**24.4**
10:00	23.1	24.4	24.9	25.3	24.8	24.4	23.8	**24.4**
11:00	23.1	24.4	24.9	25.2	24.6	24.2	23.7	**24.3**
12:00	23.0	24.2	24.9	25.1	24.5	24.0	23.5	**24.2**
13:00	23.0	24.1	24.8	24.9	24.3	23.9	23.3	**24.0**
14:00	22.9	24.0	24.6	24.7	24.1	23.6	22.9	**23.8**
15:00	22.9	23.9	24.5	24.5	23.9	23.4	22.7	**23.7**
16:00	22.9	24.0	24.5	24.4	23.9	23.3	22.5	**23.6**
17:00	23.0	24.0	24.6	24.4	23.9	23.2	22.4	**23.6**
18:00	23.1	24.1	24.6	24.3	24.0	23.2	22.3	**23.7**
19:00	23.1	24.1	24.6	24.3	24.0	23.1	22.2	**23.6**
20:00	23.2	24.2	24.7	24.3	24.1	23.1	22.2	**23.7**
21:00	23.3	24.3	24.8	24.5	24.2	23.1	22.2	**23.8**
22:00	23.4	24.4	24.9	24.5	24.3	23.2	22.3	**23.9**
23:00	23.5	24.4	24.9	24.6	24.3	23.2	22.3	**23.9**
Average	**22.9**	**24.1**	**24.7**	**24.8**	**24.4**	**23.9**	**23.0**	**23.96**

Table 26: Discrepancy between historical and simulated G14 census vs. day of week and time of day

G14	Discrepancy							
	Monday	Tuesday	Wednesday	Thursday	Friday	Saturday	Sunday	**Average**
0:00	-1%	-1%	-2%	-2%	1%	6%	3%	**1%**
1:00	-1%	-1%	-3%	-2%	0%	6%	3%	**0%**
2:00	-1%	-2%	-3%	-3%	0%	5%	3%	**0%**
3:00	-1%	-2%	-3%	-3%	0%	5%	3%	**0%**
4:00	-1%	-2%	-3%	-3%	0%	5%	3%	**0%**
5:00	-1%	-2%	-3%	-3%	0%	5%	3%	**0%**
6:00	-1%	-2%	-3%	-3%	0%	5%	3%	**0%**
7:00	-1%	-2%	-3%	-3%	0%	5%	3%	**0%**
8:00	-1%	-3%	-4%	-3%	0%	5%	2%	**-1%**
9:00	-1%	-3%	-3%	-4%	-1%	5%	1%	**-1%**
10:00	-2%	-2%	-3%	-5%	-1%	4%	0%	**-1%**
11:00	-3%	-2%	-3%	-5%	0%	4%	0%	**-1%**
12:00	-3%	-2%	-2%	-5%	2%	5%	1%	**-1%**
13:00	-3%	-2%	-2%	-3%	2%	7%	1%	**0%**
14:00	-2%	-2%	-1%	-2%	4%	8%	1%	**1%**
15:00	-1%	-1%	0%	-1%	6%	9%	1%	**2%**
16:00	0%	0%	1%	0%	9%	9%	1%	**3%**
17:00	1%	1%	1%	1%	8%	7%	0%	**3%**
18:00	1%	0%	1%	1%	8%	6%	0%	**2%**
19:00	1%	0%	-1%	1%	7%	5%	0%	**2%**
20:00	1%	0%	0%	2%	8%	5%	0%	**2%**
21:00	0%	-1%	-1%	1%	7%	4%	0%	**1%**
22:00	0%	-2%	-1%	0%	6%	4%	-1%	**1%**
23:00	0%	-2%	-2%	0%	6%	4%	-1%	**1%**
Average	**-1%**	**-1%**	**-2%**	**-2%**	**3%**	**6%**	**1%**	**0.6%**
							RMSE:	**3.3%**

Table 27: Census percentile discrepancies

	Census percentile discrepancy					
Percentile	E06W06	E07W07	E19	G14	E04I	Total
5%	-3%	-9%	0%	-11%	-23%	-2%
10%	-2%	-6%	-6%	-12%	-14%	-2%
15%	-4%	-4%	-5%	-5%	-7%	-2%
20%	-4%	-3%	-5%	-5%	-7%	-2%
25%	-4%	-2%	-1%	-6%	-7%	-2%
30%	-3%	-2%	-4%	-4%	-6%	-2%
35%	-2%	-1%	-4%	0%	0%	-2%
40%	-2%	1%	0%	0%	0%	-2%
45%	-1%	2%	-2%	4%	0%	-2%
50%	0%	2%	0%	6%	5%	-2%
55%	0%	4%	0%	4%	6%	-2%
60%	0%	5%	4%	8%	6%	-2%
65%	2%	7%	3%	8%	10%	-2%
70%	2%	5%	6%	8%	11%	-2%
75%	5%	5%	7%	4%	11%	-2%
80%	5%	3%	7%	4%	5%	-2%
85%	5%	2%	7%	4%	5%	-1%
90%	3%	0%	3%	0%	0%	-1%
95%	0%	-2%	0%	0%	0%	-1%

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