A Simulation Approach to Exploring Whole Hospital System Operational Performance and Efficiencies

Raymond L. Smith III and Stephen D. Roberts
Edward P. Fitts Department of Industrial and Systems Engineering
North Carolina State University
Raleigh, North Carolina USA

Abstract

This research presents a system dynamics whole hospital simulation model for the purpose of exploring how interacting unit capacities influence overall efficiency and performance. Many research studies have sought to reduce congestion, improve performance or increase patient throughput in select individual units of a hospital. Unfortunately, the restrictive focus to an isolated unit or department often overlooks important factors related to the relationship and policies among hospital departments. Our research considers the following key question: What important factors significantly contribute to the overall performance and efficiency of the hospital enterprise? Using a system dynamics model based on a medium size, semi-urban, acute care community hospital, our research applies the sequential bifurcation technique to identify these important factors. These findings reveal interesting factors and could subsequently be studied further using sensitivity analysis and optimization methods.

Keywords
Healthcare Modeling, Hospital Model, System Dynamics, Factor Screening, Sequential Bifurcation

1 Introduction

In recent decades, hospitals throughout the United States have wrestled with the challenge to achieve financial performance, maintain access to health care, expand patient services, improve quality of care delivered, and increase patient experience satisfaction. At the same time, congestion in the emergency department and hospital has become a never ending trend, especially in urban areas of particular regions of the country. Numerous external issues contribute to this congestion: for example, insufficient access to primary care, lack of preventive care, neighboring hospital and emergency department closures, continued inpatient bed capacity reductions, dwindling reimbursement rates, certificate of need restrictions, and catchment area demographics. Numerous internal issues also contribute to this congestion. Poorly planned facilities, inadequate capacity, insufficient staffing, inefficient processes, over utilization of resources, improper scheduling, and management imposed boundaries are a few possible contributors.

Countless research studies and simulation models have sought to examine performance issues within select units of the hospital. Regrettably, the outcome usually results in making an improvement for the unit of study, often neglecting the consequences to upstream or downstream processes. More often, these studies conclude without any improvement since the area of needed focus falls outside the scope of study: for instance, many emergency department studies frequently conclude with the discovery that insufficient inpatient bed space results in blocking and reduced throughput as patients wait in the emergency department to be boarded.

Our efforts explore the unaddressed concern for the whole hospital. Specifically, we seek to understand the dynamic behavior inherent within the hospital enterprise and identify areas for potential improvement and efficiency gain. In this study, we develop a system dynamics model based on a medium sized, semi-urban, acute care community hospital that provides a broad range of health care offerings and services in its catchment area. The large scale and system complexity of a whole hospital model make it difficult to determine the most important factors influencing operational performance. While a number of operational metrics may be used to characterize a hospital’s performance, our objective in this study is to identify the important factors that specifically influence patient throughput volume and achievement of associated service time targets. To accomplish this goal, we employ and
demonstrate a technique known as Sequential Bifurcation (SB) to screen the numerous factors present in the model and determine the most important factors. Once identified subsequent procedures, such as sensitivity analysis and optimization methods, may be performed to help determine system efficiency improvements or develop policy heuristics.

2 Hospital Models
The literature related to the modeling of whole hospitals is sparse. The limited number of examples and related work focus predominantly on health policy concerns related to wait list management under capacity restrictions in the United Kingdom, or the disaster preparedness for emergency demand surge in the United States. While these models have captured a substantial portion of hospital behavior and produced insightful outcomes relevant to their intended purposes, the analyses have often been limited to comparing predefined 'what-if' scenarios rather than employing more rigorous techniques to identify the important factors that influence operational performance.

Lane, Monefeldt [1] formulated and calibrated a system dynamics model to explore the performance interactions of demand pattern, Accident & Emergency (A&E) department resource deployment, generalized hospital processes and bed numbers. They illustrated under the British National Health Service (NHS) that reductions in hospital bed numbers would not increase waiting times for emergency admissions as feared by the public; however, they did demonstrate such a reduction would have an adverse effect with a significant number of elective surgery cancellations, thereby increasing wait list times. While beneficial to dispel a momentary public concern, the work falls short by limiting consideration only to a predetermined set of policy alternatives rather than exploring optimum policies using more rigorous techniques.

Gunal and Pidd [2] developed a discrete-event simulation framework of a generic hospital, known as the DGHPSim suite, using a performance management framework to simulate a particular hospital by employing data appropriate to that hospital from available data sets. The DGHPSim suite incorporates a novel way of simulating the multitasking behavior of clinicians and uses transition matrices, extracted from standardized datasets, to represent the states through which patients pass in the care pathways. The DGHPSim suite was tailored specifically to the performance management framework, data sets and policies for Britain’s NHS. While the authors explore how policy changes may improve health care delivery for a specific hospital, they do not examine or identify the underlying factors inhibiting performance.

Manley et al. [3] [4] and Hoard et al. [5] introduce frameworks using a system dynamics model to help hospitals assess their ability to handle rural disaster preparedness and planning. They examined the response to policies for increasing nursing resource in the either the emergency department or patient wards to investigate hospital performance and recovery when confronted with four different types of capacity surge scenarios. The authors explore alternative policies for the allocation of nursing resource to facilitate timely patient treatment and hospital surge recovery. While the authors employ a sophisticated model, they do not explore important factors outside varying the nursing capacity applied in the emergency department or wards in predefined policies. Furthermore, the authors fail to employ a structured sensitivity analysis and optimization methods which could be used to determine decision making heuristics for applying or reallocating nursing resource between the two units considered.

3 Model Development
This paper proposes a methodology using a two-stage approach that incorporates system dynamics modeling and a factor screening technique to identify a subset of factors that are most important to explaining desired hospital performance. The modeling and analysis methodology presented in this paper can be summarized as follows:

1. Modeling patient and ancillary request flow within the hospital as a system of stocks and flows
2. Identifying and modeling potential pressure points and policies to improve rates of flow
3. Verifying and validating the model
4. Analyzing the behavior dynamics, and
5. Identifying most important factors influencing efficiency using the Sequential Bifurcation technique

While the description above implies that each stage is investigated serially, there was considerable iteration between stages as new information became available and discoveries were made. Furthermore, the reference base hospital
R. Smith and S. Roberts

administration and other similar facilities along with literature was used throughout the model construction both to capture the whole hospital behavior and to insure the validity of the final results.

3.1 Model Conceptualization
The objective of this research is to identify in a whole hospital model the important factors that specifically influence patient throughputs and achievement of associated service time targets. For this purpose we can conceptualize the whole hospital system in terms of two areas: the community (or catchment population), and the hospital. The relevant functions of the hospital are sub-divided into several groups: (1) the Emergency Department (ED); (2) the diagnostics imaging services and laboratory services; (3) the surgical department (ambulatory same day services excluded); and (4) the surgical and medical inpatient wards, where bed types are organized by critical care unit (CCU), progressive care unit (PCU), and acute care unit (ACU). The conceptualization for our whole hospital model can be characterized as follows:

3.1.1 The Community – Catchment Population
Patients flow into the hospital from the surrounding community, receive treatment, and are subsequently discharged back into the community. Three main patient groups arriving to the hospital are considered: emergency patients (walk-in or ambulance delivered), direct medical admission patients (referred by hospital affiliated physician), and scheduled surgery patients (elective surgery). The rate for emergency patients arriving to the emergency department depends on many characteristics and demographics of the community. The patient arrival rates were treated as exogenous inputs, which have been represented using historical time-series data. The rate at which patients are discharged back into the community is related to the treatment length-of-stay (LOS), which in turn influences hospital occupancy. Various factors affecting the length-of-time patients stay in the hospital are delineated by the patient type, surgical or medical, and the initial admission placement by bed type (patient acuity).

3.1.2 The Hospital – Emergency Department
Many elements make up the time which elapses between a patient arriving in the ED and, if necessary, being admitted to the medical or surgical wards. Patients follow different pathways through the emergency department before they are eventually admitted to the hospital, retained for observation, or discharged home. Patients arriving in the ED are registered and triaged and then wait for an initial consultation with an ED physician. The number of ED physicians staffed varies throughout the day. Patients may be treated and discharged, or may be the subject of further clinical evaluation and testing prior to diagnosis, treatment and discharge. In more severe circumstances, patients may be referred to a consulting specialty physician that maybe called to the ED from elsewhere in the hospital. These severe cases may undergo further test procedures and then be treated and discharged, or admitted and treated.

3.1.3 The Hospital – Diagnostics: Imaging and Laboratory Services
Physicians frequently order diagnostic testing for patients that arrive to the ED, the surgical department, and patients being treated in the medical and surgical wards. Demand fluctuations and urgent requests may place considerable workload on these services, which may result in further delay and patient blocking. Diagnostic testing in a medical hospital occurs in two forms: (1) radiology and medical imaging to examine underlying physical human structure; and (2) laboratory services to perform clinical pathology generally on bodily fluids from specimens. Radiology and medical imaging generally requires that the patient be transported to a fixed piece of equipment, such as a Computer Tomography (CT) scanner or Magnetic Resonance Imaging (MRI) scanner. In a high demand environment the radiology and medical imaging resources may impose a significant constraint. Laboratory service requests originate with a specimen obtained from the patient which is then submitted to the laboratory for analysis. Specimens are processed and results returned to the point of request for physician evaluation. In most medium sized, community hospitals laboratory services are centralized. Larger, urban medical centers may have unit specific laboratories.

3.1.4 The Hospital – Surgical Department
Patients requiring surgery arrive either as a scheduled elective surgery patient or through the ED. The scheduled elective surgery patients receive pre-operative and post-operative care planning, which includes diagnostic testing, which are performed prior to the day of surgery. Patients that arrive in the ED requiring emergency surgery will require diagnostic testing and rapid preparation for surgery. The surgical department consists of pre-operative care where patients are prepared for surgery, intra-operative care where patients undergo surgery, and post-operative care where patients are overseen in a post anesthesia care unit (PACU). Each area of care has capacity limitations that
may restrict the patient flow and influence delay times. Patients remain in the PACU until they are ready to be moved into an available bed in the surgical ward.

3.1.5 The Hospital – Inpatient Medical and Surgical Wards

Patients admitted to the hospital will be assigned to either a medical ward or a surgical ward determined by the nature of their admission. Medical admission arrivals are sourced through the ED or through a direct admission process by a hospital affiliated physician. Surgical admissions are sourced through the ED or through the scheduled elective surgery process by a hospital affiliated surgeon. Wards are organized into three types of units: (1) a Critical Care Unit (CCU) which provides the highest level of care (intensive care); (2) a Progressive Care Unit (PCU) provides a “step-down” level of care (intermediate care); and, (3) Acute Care Unit (ACU) provides a standard care. Patients may transition from the highest level of care to the lowest level of care prior to being discharged. It is possible that patients may be discharged from any level of care directly, although unlikely from the highest level of care.

3.2 Model Formulation: Use of System Dynamics

In most studies, health care delivery tends to gravitate toward the experience of individual patients as they proceed through various treatment pathways. As a result, most simulation studies employ discrete-event simulation (DES) to generate detailed results for a specific unit or isolated portion of the hospital. With DES models the details often become too great a modeling burden to consider producing a whole hospital model. A once determined client would either exhaust all their funds or available time before such a model could be realized. By comparison, system dynamics (SD) allows one to investigate the strategic decisions and system behavior at a much higher level; however, SD results in the loss of interesting stochastic properties and queuing behavior is not accommodated.

3.2.1 The Dynamic Hypothesis

Although no two hospitals will have the exact same problems, capacity configuration or community demographics, many interactions among the hospital departments which patients flow through have well defined relationships. In our model there are three main routes which patients may enter the hospital: (1) the ED patient arrival; (2) the scheduled elective surgery patient arrival; and, (3) the direct medical admission patient arrival. These patients compete for resources in the ED treatment area, the surgical operative area, and, for those admitted, the medical or surgical inpatient wards. The principle interactions, related specifically to patient flow, are shown in Figure 1 as a casual loop diagram. The main feedback loops in our model are all observed to be balancing loops. We describe below the loops illustrated in Figure 1.

Loops in B1 work to drain the number of emergency patients occupying the ED: loop B1a discharges patients from the ED that have been treated and require no further attendance; loop B1b admits patients from the ED into the medical ward for additional treatment or recovery; and, loop B1c admits patients from the ED that requiring immediate surgery.

Loops in B2 work both to fill and to drain the number of patients occupying the medical wards: loop B2a receives admission patients originating from the ED; loop B2b receives admission patients originating from the direct medical admissions process; and, loop B2c discharges medical patients when they have fulfilled their length-of-stay and capacity to discharge them is available.

Loops in B3 work to fill and drain the patients occupying the operative unit (surgical department): loop B3a receives emergency surgery patients from the ED; loop B3b works to drain patients occupying the operative unit when they have fulfilled their length-of-stay. Loops in B4 work to fill and to drain the number of patients occupying the surgical wards; loop B4a receives surgical patients originating from the surgical department; and, loop B4b works to drain patients from occupying the surgical wards when they have fulfilled their length-of-stay and capacity to discharge them is available.

The flow of test orders originating from the various department units for diagnostic imaging and laboratory services is not shown in Figure 1 for clarity purposes. These flows would form an additional layer of balancing feedback loops. Backlogs for test completion causes time delay, which can retard discharge, admission and completion rates.
3.2.2 Model Structure Formulation

This section outlines the key elements of the model formulation. Detailed sub-models are used to represent the ED, the diagnostic imaging services unit and laboratory services unit, surgical unit, and separate medical and surgical inpatient wards. This formulation represents the processes previously illustrated in Figure 1 with the causal loop diagram. The model incorporates the handling of scheduled elective surgery patients and direct admission medical patients, where Figure 2 provides a simplified high-level stock and flow representation.

Patients that have been scheduled for elective surgery are modeled as flowing into the surgical department the day of the scheduled procedure. Cancellation of a scheduled elective surgery patient may occur the day of arrival if
insufficient bed space is expected on the surgical patient ward, or if the surgical process sustains significant delay. Ambulatory same-day surgery was enabled during the study of this model. Patients that have been referred by a hospital affiliated physician for direct admission arrive with little advance notice. These arriving patients may be required to wait until an available space can be found for them in the medical patient ward.

The system dynamics model was realized using the Vensim software by Ventana Systems Incorporated on a Windows-Intel based personal computer. The model utilized 36 stocks and 215 other variables to perform the core hospital processes, and utilized an additional 24 stocks and 24 other variables in order to calculate the performance measures.

4 Model Calibration, Analysis, and Validation
This section reviews the model calibration, analysis and validation using output from a base case simulation run.

4.1 Base Case output generation, performance measures and preliminary analysis
The calibration of patient arrival rates was determined based on historical time series data with comparison among several data sources from U.S. based hospitals. This time series data produces a 24 hour cycle of arrivals specific for each day of the week. On average, 168 patients per day arrive at the ED in the model. Similarly, patient length-of-stay is based on historical data obtained from U.S. based hospitals fitted to a lognormal distribution for critical and noncritical care. Subsequently, Erlang distributions were used to approximate the lognormal distributions since they are better represented in the Vensim modeling environment.

The simulation model starts initially “empty-and-idle” to all the stock levels. In order to remove any initial bias, a warm-up simulation period of five weeks is performed in order to obtain a well-conditioned system. Subsequently, a simulation run of ten weeks was then performed. The output of the base case simulation was used to analyze the functioning of the ED and hospital in detail.

Figure 3 and Figure 4 illustrate the base case results for the both the ED and medical wards, respectively. These figures align with Figure 2, the high level stock and flow diagram; however, the surgical wards were omitted due to space limitations. Figure 3 and Figure 4 illustrate the 24 hour period for day 37 (starting at midnight hour 864 and ending at midnight hour 888).

We observe in Figure 3: (1) the varied rate of emergency patient arrivals, (2) the rate of patients leaving without being seen (LWBS) departures due to congestion and delay they may have encountered in the waiting room; (3) the rate of decision to admit emergency patients for either medical or surgical treatment; (4) the rate of patients that have completed treatment being discharged to home; and, (5) the overall utilization of the ED treatment capacity.
Not illustrated are the fluctuating stock levels where patients may be held waiting to be seen, receiving treatment or awaiting resources, such as diagnostic testing results to proceed or allocation of an available ward bed.

We observe in Figure 4: (1) the rate of ED medical admissions placing patients into ward beds, which may have been delayed in the ED pending availability; (2) the rate of direct medical admission patients placed into ward beds, which may have been delayed pending availability; (3) the rate of patients that have completed treatment being discharged to home, which occurs during the hours from 10am to 6pm. This subsequently makes bed space available, after cleaning, to those patients waiting on ward bed availability elsewhere in the hospital. This is observed with the increased afternoon emergency and direct patient admissions; (4) the rate of medical ward patients transferring beds from the higher levels of care to the lower levels of care, as appropriate for their acuity level; (5) the medical ward occupancy level for PCU level of care; and (6) the medical ward occupancy level for ACU level of care.

4.2 Model Validation
Model validation tests specific to system dynamics focus on (1) correctness in model structure, and (2) obtaining the referenced simulated behavior. Structured-based validation tests are concerned with the formulation and ensure that the model is suitable for its purpose and is consistent with the real world system. Efforts were made to evaluate the suitability of the model through careful examination of internal matters, which included checking for dimensional consistency and range testing formulations for the proper handling of extreme values.

Behavior-based validation tests are concerned with exploring the validity of the model construction. In creating the whole hospital model we encountered problems with obtaining representative data, either due to the lack of existence or proprietary nature, making it challenging to validate all aspects of the system behavior. In the absence of this data, we relied on examining various dimensions that included: judging the behavior subjectively; by qualitative analysis of time series analysis; and, objective quantitative summary data. Graphs of the base case results prove to be helpful, but further exploration is required using a range of input parameters to examine the system behavior.

5 Identifying Important Factors
For models of large complex systems, there are usually too many factors to be simultaneously considered. As a result such large models cannot be easily used to interpret system behavior and anticipate performance, especially as changes are contemplated. Therefore, it is important to try to reduce the complexity of a large model by determining the important factors that influence system behavior and performance. Researchers and simulation analysts have sometimes relied on group screening techniques to identify such important factors. These techniques, which vary
greatly in their efficiency, generally combine individual factors into groups and experiment with these groups as if they were individual factors. Few published applications of these techniques can be found in the literature.

Bettonvil and Kleijnen [6] introduced a novel technique known as Sequential Bifurcation (SB) used for screening for important factors in simulation models with many factors. Compared with other group screening methods, SB has been demonstrated to be more efficient than many competing group screening techniques. The authors present the application of SB to a complicated deterministic simulation model of the ‘greenhouse’ phenomenon. Kleijnen [7] presents an additional application of SB to a complex supply chain stochastic simulation model at Ericsson. In order to identify the important factors our system dynamics hospital model we applied the SB technique.

5.1 The Hospital – Factors of Importance
A formal description of sequential bifurcation can be found in Bettonvil [8], or summarized by Bettonvil and Kleijnen [6]. The procedure follows a sequence of steps. It begins by placing all factors into a single group, ordered by perceived importance, and testing whether the group of factors has an important effect. If it does, the group is split into two subgroups and each of these is then tested for importance. The procedure continues in this way, discarding unimportant groups and splitting important groups into smaller groups. Eventually, all factors that are not in groups labelled as unimportant are tested individually.

The goal of the present simulation study is to quantify the relationships between the inputs, or factors, and the simulation outputs. For this case study, the outputs are the patients that arrive to the hospital through the emergency department, scheduled surgery, or direct medical admission, that receive satisfactory and timely service, while completing their health care treatment. The inputs are factors such as treatment capacity in the emergency department, operative care capacity in the surgical department, bed capacity by type in both the medical and surgical inpatient wards, and capacity of ancillary supporting units like diagnostic imaging and laboratory services. The objective is to find robust solutions to address a complex system. To this end, we distinguish between two types of factors:

1. Factors that are controllable by the hospital enterprise: for example, the hospital can change the processing capacity in the diagnostic unit by adding imaging equipment or by upgrading laboratory equipment to increase throughput. These may represent strategic, long-term structural changes.
2. Factors which are uncontrollable and determined by the environment, or as in our case the population: for example, the number of arriving patients to the emergency department, or the number of patients referred by a physician for direct medical admission. These may represent short-term fluctuations.

Our model of the hospital has 93 factors to be examined: 6 factors are identified as environment factors related to properties of patient arrivals: 10 factors are identified as physical capacity factors for the number of beds, or rooms; and the remaining 77 factors are related to capacity, management, scheduling, time delay, and dwell times.

5.2 The Implementation – Factors of Importance
We conduct our sequential bifurcation via Microsoft Excel, using the Visual Basic Application (VBA) Dynamic Link Library (DLL) resource to execute simulation runs in Vensim. We store and manage input and output data in Excel worksheets. This greatly helps facilitate the management of input factor levels and the analysis of the resulting simulation output. Using the Excel worksheets, we first conduct a 5 week warm-up model conditioning followed by a 10 week simulation run.

Following Bettonvil and Kleijnen’s guidance, we divide the group of 93 factors into two subgroups. Into one group we place all the 77 factors related to capacity, management, scheduling, time delay, and dwell times; and into the other group, we place the 6 environmental factors for patient arrivals and the 10 factors for physical capacity - which were perceived to be of higher importance. We perform the associated simulation run, recording the results as outlined in Figure 5. The process of sequential bifurcation is repeated until the important factors have been revealed or the allotment of simulation time has been exhausted. For this study, sequential bifurcation stops after 31 steps. The main effect of any remaining individual factor is then reduced to 219.
The list of the 11 most important factors is given in Table 1. The ordered table reveals that factor 88 is the most important with an estimated main effect of 7,339. In addition, factors 57 (main effect of 7,186), 62 (6,611), and 33 (1,292) are recognized as important, indicating that timely completion of laboratory requests is a restrictive process to patient throughput in this particular hospital setting. The remaining identified important factors relate to the timely management of patients in both the medical and surgery wards, and through their discharge process.

Table 1: Important factors identified by the Sequential Bifurcation technique

<table>
<thead>
<tr>
<th>Factor</th>
<th>Main Effect</th>
<th>Range</th>
<th>Factor Description</th>
</tr>
</thead>
<tbody>
<tr>
<td>88</td>
<td>7339</td>
<td>143</td>
<td>193</td>
</tr>
<tr>
<td>57</td>
<td>7186</td>
<td>0.48</td>
<td>0.28</td>
</tr>
<tr>
<td>62</td>
<td>6611</td>
<td>0.45</td>
<td>0.26</td>
</tr>
<tr>
<td>92</td>
<td>1591</td>
<td>29</td>
<td>39</td>
</tr>
<tr>
<td>33</td>
<td>1292</td>
<td>70</td>
<td>75</td>
</tr>
<tr>
<td>64</td>
<td>1142</td>
<td>10</td>
<td>2</td>
</tr>
<tr>
<td>90</td>
<td>1050</td>
<td>0.85</td>
<td>1.15</td>
</tr>
<tr>
<td>93</td>
<td>1006</td>
<td>0.501</td>
<td>0.167</td>
</tr>
<tr>
<td>68</td>
<td>763</td>
<td>6</td>
<td>2</td>
</tr>
<tr>
<td>70</td>
<td>262</td>
<td>24</td>
<td>18</td>
</tr>
<tr>
<td>71</td>
<td>252</td>
<td>52</td>
<td>44</td>
</tr>
</tbody>
</table>

We view the application of the SB technique to a whole hospital system dynamic model as being helpful in identifying the important factors. Our key findings from this study pertaining to the hospital modeled include:

1. SB efficiently in 31 steps identified the 11 most important factors influencing the hospital performance.
2. SB revealed that the external environmental factors, such as the volume of patients arriving to the emergency department, the timely scheduling of surgery patients, and high variability of direct medical admission patients, all influence overall performance of the hospital.
3. SB revealed that ancillary services, such as the laboratory capacity throughput, contribute significantly to the overall efficiency and responsiveness of the hospital.
4. SB revealed that capacity management around the timely flow of both surgical and medical patients contributes significantly to the efficiency of the hospital.
5. Surprisingly, SB did not indicate that capacity expansion was needed for additional beds, treatment areas, or operative care areas.

6 Conclusions and Future Research
In this study, we proposed examining the dynamic behavior of a complex system framed as the hospital enterprise with the objective to understand the important factors influencing performance and efficiency. Developing a system dynamics model to represent the whole hospital provided a reasonable representation of the dynamic behavior. Applying the technique of sequential bifurcation to the system dynamics model proved to be very helpful in determining the most important factors, where many factors were present. While the objective is to identify the most important factors, outcomes of an SB study may provide the simulation analyst with information on where they may want to budget additional efforts to improve data analysis and refinement, or model robustness and fidelity.

In this study, we modeled a representative medium sized, semi-urban, acute care community hospital at the enterprise level. Using the SB technique we discovered that among the identified important factors that laboratory services capacity had a significant effect in both medical and surgery wards, as well as, impacting the emergency department throughput. The use of traditional approaches to identify problems at the department level would probably have not identified the wide spread impacts related to this capacity issue. More importantly, the identification of the broader issues allows decision makers to appropriately address the capacity issue rather than move the problem around to afflict other parts of the hospital. We also observed that several identified important factors were directly related to hospital capacity management with the need for moving patients along various care pathways in a timely manner. While it was somewhat expected that capacity expansion for beds and treatment areas to ease congestion would be among the top important factors list - they were not. Instead, systems dynamics identified several other improvement opportunities could be found throughout the enterprise.

While SB techniques may demonstrate the ability to identify important factors in a large and complex systems which would have otherwise being overlooked, it is important reflect on the fact that this knowledge can serve as a future starting point. Using these important factor findings, future research may be conducted using sensitivity analysis and optimization methods to investigate more deeply possible performance and efficiency improvements.

Acknowledgements
The authors would like to thank Kristen Hassmiller Lich, Ph.D. and Jackie Ring, RN, FACHE, CNAA for contributing their expertise toward this research in the related fields of health policy and management, and hospital administration.

References