The Hospital Patient Flow Model: A Simulation Decision Support Tool

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Abstract

Hospital overcrowding is a serious condition that threatens patient quality and a health system’s bottom line. Discrete-event simulation (DES), due to its ability to accurately predict outcomes in complex systems in both manufacturing and service industry design and improvement, is a well-matched choice for studying organizations with elevated variation. The objective of this study was to, through DES, establish a method by which one could forecast a range of possible Y-variables such as hospital-wide census and census on individual nursing units when a host of different X-variables might be changed (i.e. ward capacity, length of stay, admission volume) through various process improvement initiatives. The DES allowed incorporation of multifaceted variation found in a hospital into the model through the use of probability distributions (PDs) which determined patient attributes and the actions of patients flowing through the system. Scenarios were designed to determine the impact of closing or opening beds and changing flow policy on the output variables of average daily census and percent of beds filled for the hospital and sections within the hospital. The results of the experimentation informed leaders on how their decisions might impact the system as a whole and the far reaching consequences of policy changes. The Hospital Patient Flow Model was successful in allowing experimentation a virtual environment, and thus mitigating the risk of investing resources in non-value added policy.

Background

Hospital overcrowding, brought on by a heightened demand for services, is a serious issue that, in light of Affordable Care Act tenets which expand the insured base, health care leaders must continue to acknowledge. The lack of inpatient beds is the most significant reason for emergency department (ED) overcrowding [1,2], and the ill-effects of ED overcrowding are well documented. Crowding has many detrimental effects including adverse events, extended pain and suffering and poor outcomes brought on by treatment delays, medical errors and unsafe practices. In addition to reduced quality, increased chance of ambulance diversions and negligence claims threaten a hospital’s financial well being [3,4,5]. The harmful effects of hospital congestion prompted The Joint Commission to revise standards (effective Jan. 1st, 2013) that increase emphasis on the importance of patient flow throughout the hospital [6]. With all the incentives, both positive and negative, to improve patient flow within hospitals, it is no wonder that CapSite, a subsidiary of Healthcare Information and Management Systems Society (HIMSS), determined in their “2012 U.S. Patient Flow Study,” that some 31 percent of U.S. hospitals plan to purchase patient flow solutions to improve overcrowding [7].

One strategy hospitals have used to combat overcrowding is investment in new construction and additional staffing. Another strategy that offers a potential for greater return on investment is incremental process improvement through the use of predictive analytics. However, the high rate of variation within a hospital may cause static and deterministic methods to inadequately reflect the system under study. For example, significant variation exists in patients’ day-to-day and hour-to-hour patient arrival rates, length of stay, acuity level, and pathway among nursing units throughout an inpatient encounter. Furthermore, actions taken in one section of a hospital system may have far-reaching and unpredictable affects on elements in another section.

Discrete-event simulation (DES), due to its ability to accurately predict outcomes in complex systems in both manufacturing and service industry design and improvement, is a well-matched choice for studying organizations with elevated variation [8]. A significant value of DES in healthcare is that it allows one to evaluate a problem in terms of whole-systems thinking, as it accounts for how actions in one part of a patient’s pathway might impact other parts of that pathway and other patients’ care [9].

The objective of this study was to, through DES, establish a method by which one could forecast Y-variables such as hospital-wide census and census on individual nursing units when X-variables might be changed through various process improvement initiatives. This decision support system, based on “what if” analysis, would test the impact of hospital operational modifications such as raising or lowering the number beds on a specific nursing unit, closing or opening a nursing unit, reducing the time required to discharge a
patient, or raising or lowering arrival volume by specific patient type.

Methods

This study was conducted at the Carilion Clinic’s tertiary care hospital in Roanoke, VA. The focus components of the simulation were all non-obstetrics and non-pediatrics nursing units in the hospital. This included 426 patient beds spread throughout 26 nursing wards and comprising intensive care units (ICUs), progressive care units (PCUs) and medical surgical units (M/S). The average daily census for the beds under study was 368. The software MedModel (ProModel Corp., Orem, UT) allowed for the application of the comprehensive set of input variables necessary to power the model.

A flow diagram was developed to understand the process whereby patients moved throughout the hospital and among the nursing units under study. The simulated process (Figure 1) starts with the assignment of patient attributes to include ED patient vs. direct admit patient and the service line of the patient’s admitting physician.

An additional patient attribute assigned is the acuity level of the patient (does the patient’s condition require the highest level of care delivered on an ICU, a mid-level level of care from a PCU, or a lower level of care offered on a M/S ward?). Based on these attributes, a patient moves either to the ED or to a nursing unit as a direct admit. An ED patient will be treated and then transferred to a unit. All patients will receive a nursing unit assignment based on their service line and acuity level. Once a patient arrives on a ward, his length of stay (LOS) is dependent on his service line, acuity level and how many times he has moved between units at that moment. Most patients move at least once, and some move several times between units prior to being discharged because their acuity level changes. A screen shot of a section of the animated model is presented here (Figure 2).

The DES allowed incorporation of multifaceted variation found in a hospital into the model. Probability distributions (PDs) accounted for this variation and were used to determine patient attributes and the actions of patients flowing through the model. Two years of admissions data were analyzed to build the logic that drove the simulation, and the model simulated 365 days of hospital operations. Data was also collected from interviews with transfer center and ED leadership subject matter experts. Patients arrived in the model in daily quantities that changed by day of week. The change in variation in arrival quantity by hour of day was determined by PDs. Probability also determined which patients entered the hospital through the ED, as well as what acuity level (ICU, PCU, or M/S) the patient was assigned. A PD also determined the patient’s admitting physician’s service line. Each patient was categorized into one of 12 service line types based on his admitting physician’s specialty. Some smaller categories (i.e. neurosurgery) were collapsed into other like categories. The service lines were: hospitalist, primary care, cardiology, general surgery, orthopedics, trauma critical care surgery, vascular surgery, stroke, cardiac surgery, oncology, critical care and cardiothoracic surgery.

Length of stay on each nursing unit was determined by theoretical distributions fitted against empirical data. The attributes of service line, acuity level and the patient’s transfer status (how many times he had been moved between units) were used to create 109 possible LOS distributions. Once a patient completed his LOS on a specific unit, a PD was used to determine whether the patient would go up, down, lateral or out (UDLO). “Up” meant that a patient’s condition was declining and required a higher level of acuity as when a M/S ward patient transfers to a PCU. “Down” indicated a patient was moving to a unit serving lower acuity patients (i.e. ICU to PCU). If a patient received a “Lateral” attribute, he would stay the same acuity, but move between units as when a M/S patient in one ward was transferred to another.
M/S ward. “Out” indicated a patient was selected for discharge. The UDLO PDs were assigned according to a patient’s service line and number of previous moves.

The decisions of the hospital transfer center when deciding which nursing unit to send patients were replicated with simulation logic. Multiple routing sequences were developed based on service line and acuity level. Each routing sequence reflected service line physicians’ 1st, 2nd, 3rd, etc choice for nursing unit. If the first choice unit was full, the patient was routed to the 2nd choice, and so on. Because the input data reflect true-life variation, the randomness of the variables results in one simulation replication representing only one of several possible outcomes [10]. Therefore the 7-day hospital week was expanded to a 365-day operational model which was run with 40 iterations thus simulating 40 years.

Scenarios were designed which altered input. X-variables, to accommodate the measurement of specific output, Y-variables, relevant to achievement of three project goals. It was the objective of the team charged with throughput optimization to study the impact of changing capacity among locations where bottlenecks were most prevalent: PCU units. In addition to altering capacity, the team wanted to know what would happen if PCU-level observation patients were sent exclusively to an “observation unit,” as opposed to normal routing. Observation patients were unique in that they were typically admitted for a shorter LOS and infrequently moved between units. Thus, the three goals of the study were defined as: (1) Determine the impact of closing 10 PCU beds (five on two separate wards) and simultaneously opening a new eight-bed PCU on the average daily census and percent of beds filled for the hospital, overall PCU unit total and individual PCU units; (2) In addition to goal one’s changes, determine the affect of opening an additional new 8-bed PCU on the average daily census and percent of beds filled for the hospital, overall PCU unit total and individual PCU units; and (3) Determine how setting aside one of the PCU units exclusively for observation patients would impact average daily census and percent of beds filled for the hospital, overall PCU unit total and individual PCU units.

Model scenarios were designed to answer the research questions by allowing “what if” experimentation that compared three scenarios against a base case (status quo). “Scenario One”, the base case scenario was used to validate the model and establish output to compare subsequent cases to. “Scenario Two” opened location 7 Mountain PCU 2, an 8-bed ward and simultaneously reduced existing capacity by closing five beds on location 7 South PCU and five beds on location 8 South PCU. “Scenario 3” kept the changes from Scenario 2 and opened location 7 West PCU, a new eight-bed ward. “Scenario Four” added to the previous two scenarios by retaining location 7 East PCU, a 12-bed ward, for observation patients.

Figure 2 – Screen Shot of Model Running in Animation Mode
Results

Two methods were used to validate the model: face validation and a comparison of means. Face validity was achieved by allowing subject matter experts to observe the model in animation mode, and answer the questions, “Does this model resemble reality?” and “How can we improve the model?” Additionally, the means of empirical data sets were compared to the means of model-generated data sets. When comparing overall hospital LOS, the means varied by only 2.0%, and when comparing average daily hospital census, the variance was only 0.7%. The LOS means comparison validation was then extended to each service line, and it was found that means varied between 0.1% and 7.3%. Additionally, the average daily census validation was extended to all individual nursing units, where we found model-generated average daily census for 23 out of 24 units was within a 2.0 plus or minus spread from empirical census.

The results from 40 repetitions were averaged, and scenario data were compared to the base case. In answering the first research goal, both overall hospital and PCU total average daily census remained unchanged at 370 patients and 187 patients respectively (Figure 3). Overall hospital percent of beds filled also held steady at 87%, but overall PCU unit total rose from 88% to 89% (Figure 4). On individual units, the second scenario increased occupancy rate from 85.4% to 90.1% and from 92.0% to 93.6% on 7 South PCU and 8 South PCU respectively. The new ward, 7 Mountain PCU 2, was occupied at a 96.9% rate (Figure 5).

The second goal explored the effect of opening an additional eight-bed PCU ward and compared “Scenario 2” to “Scenario 3.” Average daily hospital census remained unchanged, and PCU census rose by one patient to 188 patients in “Scenario 3.” Hospital percent of beds filled dropped from 87% to 86% in the new scenario, while overall PCU unit total percent filled dropped from 89% to 86%. On the unit affected, the newly established 7 West PCU, occupancy averaged 88.2%. Another interesting outcome from this scenario was a small but noticeable decrease in “M/S” ward total census by 0.81 patients, which demonstrated the interrelationship between PCU and M/S units. This was explained by hospital policy and model-embedded routing logic that allowed some M/S patients to flow to PCU beds if M/S beds were full.

The third goal of determining whether to set aside 7 East PCU for PCU observation patients was then studied by comparing “Scenario 3” to “Scenario 4.” Hospital-wide average daily census remained unchanged, but overall PCU unit total average daily census dropped from 188 patients in the previous scenario to 185 patients. Hospital percent of beds filled stayed the same, and PCU-wide total beds dropped from 86% to 85%. The occupancy rate on 7 East PCU dropped from 93.0% to 25.8% as a result of “Scenario 4.” However, the scenario triggered increased occupancy rates in the other PCUs as patients flowed to other wards to compensate for the latest access void. For example, 7 West PCU and 7 South PCU went from occupancy rates of 88.2% to 94.7% and 87.5% to 89.4% respectively. Results indicated the proposal to set aside 7 East PCU for observations patients reduced access for non-observation PCU patients. The M/S units were also impacted by this scenario in that total M/S census rose by 2.84 patients.
Discussion

Discrete-event simulation continues to demonstrate success as a decision support tool in hospital settings due to its ability to predict outcomes in complex, dynamic and stochastic healthcare systems, and there is documented success in improving patient flow on both the ED and inpatient wards. Paul et al. demonstrated how 43 simulation studies were published on improving ED overcrowding, although central to the findings was the point that interactions between ED and the rest of the hospital were not modeled in most studies [11]. The random arrival rate of emergency room admissions, and the corresponding effect on downstream bed capacity and ED patient risk was studied, however, using DES [12].

In the study of patient flow post surgery, DES was used to achieve optimized bed capacity and patient flow on an ICU and in a large surgical center by more efficient scheduling procedures [13,14]. Optimal levels of critical care (ICU) beds were also the focus of a DES study that observed patients arrival from both ED and surgery [15]. Other studies have continued to confirm the value in applying DES to optimize bed allocation in hospitals [16,17,18]. In a thorough review of the literature, no studies were identified that demonstrated the value of DES by offering operational decision makers a decision support tool that accounted for patient flow across all levels of acuity wards while accounting for physician’s bed assignment choices and UDLO in order to render a versatile set of Y-variable answers to multiple X-variable questions.

The Hospital Patient Flow Model was successful in achieving all three research goals, and the resulting data informed decision-makers who ultimately altered policy accordingly. The model demonstrated that changing the number of beds on a unit impacted census both negatively and positively. The model was built to offer operators maximum flexibility in conducting “what if” analysis. New research goals involving changing X-variables such as specific nursing unit capacity, explicit patient-type LOS, or specific service line admission volume were easily incorporated into the model and output data promptly displayed.

In the writing of this paper, a conscious effort was made to discuss only actual, current applications of our Hospital Patient Flow Model, as opposed to hypothetical problems, as many published works entail. The model continues to be used by decision-makers charged with improving patient flow in their evaluation of proposed solutions. Hypothetical experimentation would have offered the reader more robust scenario comparison graphics. However, it is important to note that often it is the smaller, incremental but “continuous” process improvement steps that achieve the most significant impact on hospitals’ quality improvement and cost containment strategies.

Other capabilities were built into our model, that offer exciting hypothetical results, but which have not been placed into real-world practice as of this writing. One such feature is the ability of the model to predict the prevalence of physicians’ first choice of nursing unit bed assignment for their patients. Output could tell decision-makers, under assorted scenarios, what percent of patients, for each service line, were placed in the correct bed according to physicians’ preference. Another unexploited feature of the model is the revenue generator which predicts how changes to the model impact gross
charges. To build this capability, two years of charges per All Patient Defined Diagnosis Related Group (APR-DRG) were studied, and probability distributions were calculated in order to assign each virtual patient an APR-DRG and subsequent charge. Thus, if any change in an X-variable produced a statistically significant change in the Y-variable Revenue, the model subsequently informs decision-makers.

In spite of the strengths of DES, there were some limitations. First, output data, and conclusions drawn from them, are only as good as the data inputs. Electronic health record-generated admissions data consist of numerous “time stamps,” the accuracy of which relies on human input. To help offset this limitation, the data collection period was extended to two years, and data point outliers that defied reality were omitted. Furthermore, model validation was expanded beyond macro-level hospital census and LOS to unit and service line specific data. Another limitation with DES is that it is time intensive. Although simulation produces a superior analytical product, there is a considerable effort that goes into data collection, model development, validation and experimentation. Knowing in advance the complexity of the model, the team enlisted the consulting services of a simulation software firm; the resulting model is presumably transferrable to other hospitals.

Conclusion

In this atmosphere of hospital overcrowding and changing dynamics, it is imperative that healthcare leaders have proper analytical tools to help them make decisions that will ultimately increase quality and revenues while reducing costs and liability. Discrete-event simulation has a proven track record of adding revenues while reducing costs and liability. Discrete-decisions that will ultimately increase quality and leaders have proper analytical tools to help them make decisions prior to full implementation. Experimenting with patient flow in a virtual environment also served to mitigate the risk of investing resources in a non-value added policy.

References


Authors’ Biographies

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