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INCORPORATING PATIENT DETERIORATION WHEN SIMULATING UTILIZATION OF A CARDIOVASCULAR INTENSIVE CARE UNIT

Ziqi Wang
Ambika Agrawal
Imani Carson
Luke Liu
Harini Pennathur
Hadi Saab
Amy Cohn

Industrial & Operations Engineering
University of Michigan
1205 Beal Ave
Ann Arbor, MI 48105, USA

Amanda Moreno-Hernandez

William Davidson Institute
724 E University Ave,
Ann Arbor, MI 48105, USA
William Davidson Institute

Hitinder Gurm

Department of Internal Medicine
University of Michigan
2215 Fuller Road, Primary Care
Ann Arbor, MI 48105, USA

ABSTRACT

Patients undergoing many forms of cardiovascular surgery typically enter the cardiac intensive care unit (CICU) after surgery, transfer to a step down (SDn) unit, and then are ultimately either discharged or bounce back to the CICU because of deterioration. Randomness and unpredictability exist in these processes, especially the bounce back process. Underestimation of bounce back rates will result in a lack of bed capacity for patients and patient deferrals. Adding beds, however, will lead to an increase in cost. Therefore, trade-offs must be carefully considered between decreasing patients denied versus potential system costs when bounce back is introduced to the system. We present a discrete-event simulation model to assess how bounce back will impact assessment of bed capacity in the CICU and SDn and other major metrics of the system. We present analyses utilizing data from our collaborators at the Samuel and Jean Frankel Cardiovascular Center at Michigan Medicine.

1 INTRODUCTION

Randomness and unpredictability are hallmarks of the healthcare system. These include the length of stay for patients requiring immediate treatment and the frequency of patients arriving into the system. Hospital bed management, or capacity management, entails the allocation of units and affiliated services that go with being treated by the medical facility. Abrupt arrival of emergency patients combined with scheduled elective operations and patient discharge delays produce significant pressure on hospital systems. Effective bed management optimizes patient flow by reducing the risk of delays in patient accommodation and treatment by ensuring the required resources are available and accessible. Simulation modeling has been utilized by many researchers involved in capacity management as it can illustrate a multivariable dynamic

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environment capable of handling the complexity of patient placement found in real-world settings (Bae et al. 2017).

This study primarily focuses on capacity management in the Cardiovascular Surgical Intensive Care Unit (CICU) and the Step-Down Unit (SDn), the downstream unit to the CICU. The CICU unit provides advanced surgical critical care for patients following heart surgery. With our aging population and our procedures becoming more sophisticated, cardiac surgery is more frequently being conducted on older and more complicated patients. Thus, post-operative care is also becoming more intricate, forcing hospitals to set aside specific rooms to care for these surgery patients. Cardiovascular diseases (CVD), which include heart disease, vascular disease, stroke, and arrhythmia, among other conditions, are the leading cause of death internationally; the Centers for Disease Control and Prevention estimates that CVD is the cause of death for 647,000 Americans each year, approximately 1 in every 4 deaths (Mc Namara et al. 2019).

SDn beds provide a lower level of care for patients transitioning out of the CICU once they are assessed to have recovered to a threshold established by their physicians and it is no longer necessary for them to remain in the CICU. A transfer to the SDn is seen as a path towards being discharged from the hospital. The transfer of patients from the CICU to SDn is not unidirectional, as individual patient health can rapidly deteriorate and require an immediate transfer back, i.e bounce back, into the CICU, adding an extra layer of complexity in simulation modeling. Bounce back is further explained in Section 2.3. Additionally, a lack of capacity in the CICU may necessitate the canceling of elective or less urgent surgeries. The focus of this study is to better understand the flow of patients between the CICU and SDn in order to make the patient flow process more efficient. Our study inspects the percentage of patients denied when adjusting SDn beds relative to ICU beds and altering bounce back rates in the CICU at the Samuel and Jean Frankel Cardiovascular Center within Michigan Medicine, a wholly-owned academic medical center of the University of Michigan in Ann Arbor, Michigan. The scope of our study is not to propose specific bed management strategies, but to determine the effects of bounce back on the bed capacity which can aid clinicians and engineers in developing policies to address the problem.

2 PROBLEM DESCRIPTION

2.1 General Cardiac Patient Flow

The Cardiovascular ICU at Michigan Medicine receives patients from four major avenues: from Michigan Medicine's Emergency Department, from a Michigan Medicine inpatient unit, transfer from an external hospital's Emergency Department, and transfer from an external hospital's inpatient unit. Adequate resources must be available in order for a patient to be transferred. These resources include an available physician, operating room, and a CICU bed; the CICU bed is often the limiting factor in the acceptance of a patient. If a CICU bed is unavailable at the time of a patient's requested transfer, they may be denied entry and surgery from Michigan's Cardiovascular Center.

Once assigned to a CICU bed, a patient will stay for a period of time. During their stay, physicians will assess their health and recommend/prescribe treatments daily; this process is known as 'rounding'. When the physician determines that the patient no longer requires care in the CICU, they will be discharged to the SDn, the downstream unit of the CICU. From there, they will again be provided care until they are deemed fit to be discharged from the hospital entirely.

There is always a risk that a patient who is transferred to the SDn may deteriorate in condition and need to revisit the CICU. For the purposes of our research, this phenomenon is referred to as a "bounce back". Bounce backs are important to consider as they are now the fifth stream into the CICU and can present additional challenges in accommodating all patients who require care in the CICU.

2.2 CICU vs SDn Utilization and Cost

A key limitation to guaranteeing an adequate number of CICU rooms under all possible circumstances is the high cost of this resource. One estimate of the cost of an ICU bed is $4,300/day (Halpern et al. 2016). They estimate that a SDn bed costs less than half of that at $1,909/day (Halpern et al. 2016). This difference is largely because an ICU bed requires the availability of more staff in order to provide care at a higher intensity. Additionally, the upkeep and management of more sophisticated medical equipment in the ICU room trigger the daily cost to heighten further.

In many cases, the number of beds in the ICU can be a limiting factor in accommodating new patients. An additional limiting factor may be the number of SDn beds. If a patient is determined to no longer require CICU care (we will refer to these patients as "SDn Status") but a SDn bed is unavailable, the patient will continue to utilize the CICU bed in place of a more critically ill patient. In turn, a SDn Status patient occupying a CICU bed incurs a higher cost for the hospital than if a SDn bed was available for them. Thus, it is crucial to optimize the ratio of CICU and SDn beds to maximize the number of patients admitted to the CICU and minimize the number of SDn Status patients housed in the CICU.

2.3 Bounce Back

Bounce back rates between the CICU and SDn have previously been studied in the literature as ICU beds are a significant driver of hospital costs (Fakhry et al. 2013; Lissauer et al. 2013). Although we focus our simulation on Michigan Medicine data, bounce back is a concern nationally as well. Bounce back can slow the efficiency and reduce capacity management of the ICU. 13.4 % of all hospital costs and 4.1 % of all national healthcare spending in the United States are related to ICU care (Lissauer et al. 2013). Being a problem across CICUs nationally, bounce back is important to address in capacity management simulation models. Here, we focus on bounce back patients returning to the CICU as a significant portion of all bounce back patients return specifically to the CICU. It has been estimated that 10.22% out of all bounce back patients returning to ICU's return to specifically the CICU (Fakhry et al. 2013).

Various studies define bounce back differently. Some studies define it to include patients who have been discharged from the hospital and readmitted. Others place a cap on the number of days (e.g. 7 days) in between initial ICU release and readmission to be considered a bounce back (Fakhry et al. 2013). Here, we define bounce back as patients who return to the CICU because of health deterioration within the same hospital visit. We do not set an upper bound on the number of days that a patient resides in the SDn before bouncing back and do not include patients that died in the SDn. Our simulation focuses on the extent to which bounce back patients affect CICU bed availability as bounce back patients can be treated as another source of admission to the CICU.

As mentioned in the CICU vs SDn cost section (2.2), patients may be housed in the CICU waiting for a SDn bed; in our model, we refer to these patients as "SDn status in CICU". SDn patients who would bounce back if there was a CICU bed available, but cannot due to lack of beds, are referred to as "CICU status in SDn". In the real world, these patients may be moved out to another ICU which will incur additional costs. Additionally, if a patient needs emergency surgery, but a bed was reserved for an elective surgery patient, elective surgeries may be canceled or delayed. This puts future strain on the system, creating a backlog of surgeries, and delaying care for patients.

3 SIMULATION FRAMEWORK

3.1 Use of the Simulation Model

It is clear that a health system bears innumerable uncertainties at almost every step of a patient's journey. Therefore, it is important to determine which effective strategies a health system can focus on in order to save lives as well as contain costs and preserve hospital resources. This is where data-driven simulation becomes imperative to cost-effectively foresee how several parameters can affect healthcare delivery.

3.2 Data Acquisition

We acquired data through DataDirect, the University of Michigan Health System's historical patient database. DataDirect provides information on Michigan patients by extracting data from MiChart, the University of Michigan's electronic health record (EHR). We established a cohort of adult patients over a one-year time frame from December 1st, 2018 to December 1st, 2019. Patients must have been seen in one of the CICU units to be included in our dataset. With these filters, we identified 2,375 patients. An example output of our data is summarized below in Table 1. No real patient data or unit location data is shown.

Table 1: Example DataDirect output sheet.

Patient ID	Encounter ID	Arrival Time	Transfer Time	Unit	Room	Bed	Room Type
1	4	6/01/19 03:01	6/05/19 09:31	CICU	3000	4	ICU
3	2	8/14/19 17:43	8/17/19 13:45	CSDn	1000	10	SDn
14	2	9/21/19 12:16	9/21/19 19:34	OR	OR	1	OR

As shown in Table 1 above, each patient is identified by a Patient ID that is unique to them and is used for any visit a patient has within Michigan Medicine. A patient's visit is encapsulated by the Encounter ID. This ID is assigned to a patient at the time of first admittance and used until the patient is discharged from the hospital. In a future visit, they will receive a new Encounter ID. There is also an Arrival Time and Transfer Time associated with each transfer between locations. Using a reference list of rooms provided by Michigan Medicine, we assigned room numbers on our spreadsheet to general locations. Examples of these locations included "ICU" (Intensive Care Unit), "SDn" (Step Down), "OR" (Operating Room).

3.3 Patient Arrival Rate to CICU Parameter Calculation

In order to model patients within the hospital, we had to determine the frequency at which patients enter the system. In this framework, patients arrive directly to the CICU. We refer to this as the patient "arrival rate". To make the model more realistic, we calculate the arrival rate for different days of the week. These calculated intervals were analyzed through R using the readxl, dplr, fitdistplus, and MASS packages. Our results show that the arrival rate of every day of the week can be fit by an exponential distribution with the rate as shown in Table 2, determined by a Goodness of Fit (Akaike's Information Criterion and Bayesian Information Criterion) test. Of note, a new parameter need not be calculated for the SDn since patients do not arrive directly to that location and admittance to the SDn is a function of arrivals into the CICU.

Table 2: Arrival rate based on day of week.

Sunday	Monday	Tuesday	Wednesday	Thursday	Friday	Saturday
Exp (0.136)	Exp (0.317)	Exp (0.333)	Exp (0.307)	Exp (0.282)	Exp (0.309)	Exp (0.155)

3.4 Patient Length of Stay by Unit Parameter Calculation

It is also critical to parametrize the amount of time a patient occupies their bed within both the CICU and SDn. We refer to this constant as a patient's "length of stay" or "LOS". These distributions determine the utilization of each location which ultimately affects the new patient admittance rate into the Cardiovascular Center. We calculated the difference between arrival and transfer times and plotted their distribution through R using the readxl, dplr, fitdistplus, and MASS packages. We determined the overall LOS in the

CICU to follow a Geometric (0.198) distribution. The same procedure was followed for the length of stay in the SDn; this was determined to follow a Geometric (0.209) distribution. Moreover, we found that patients will have longer LOS in CICU after they bounce back from SDn compared with LOS of their first visit in CICU. Following the same procedure, we determined the LOS of their first visit in the CICU to follow a Geometric (0.213) distribution and the LOS of the CICU visits after bounce back to follow a Geometric (0.128) distribution.

3.5 Bounce Back Rate Parameter Calculation

Due to its nature, the Encounter ID is useful to track events that occur in a singular visit. For our bounce back study, we utilized this ID to count the number of transfers into the CICU within one visit; this tells us the number of bounce backs.

After filtering for records with a CICU Room Type, we created a flag named "Number of CICU Stays" that incremented if a patient had multiple records of a CICU stay within the same encounter. Additionally, these stays had to be non-consecutive, meaning the patient had to have changed the level of care between CICU stays, in order to be counted. Using the historical data, we can see that a total of 216 patients had more than one CICU stay within the same encounter out of a total patient cohort of 1,977. This suggests a 10.93% probability for a patient to bounce back.

To make it more specific, we found that patients' bounce back rate also varies with the LOS of their first visit to the CICU. Following the same procedure, we determined the bounce back rate of patients whose LOS of their first visit in CICU longer than the median is 10.8% and 15.2% for patients whose LOS of their first visit in CICU below the median.

3.6 Model Input Parameters

We used the data from Data Direct and parameters calculated above as inputs for our model; these values are summarized below in Table 3.

Table 3: Input distribution and parameters used in the simulation model.

Arrival Interval	LOS in CICU	LOS in SDn	Bounce Back Probability	Bed Count in CICU	Bed Count in SD
Table 2	Geometric(0.198)	Geometric(0.209)	10.93%	36	32

3.7 Assumptions and Conditions

In our model, we assume that patients can enter the CICU any time and that the distribution of patients' arrival rates is specific to the day of week, but the rate remains the same over the course of a day. It is worth noting that the model naturally does allow for multiple patient types with each patient type having their own randomly generated arrival rates, LOS, and bounce back rates. However, this simulation only considers a single patient type, as our model's main focus is on the impact of bounce back. Furthermore, we assume that the CICU patients are rounded on at 9 a.m. and SDn patients are rounded on at 8 a.m. At these times, we decide whether CICU patients will transfer to SDn, if SDn patients will bounce back to CICU, or if SDn patients will be discharged using our previously defined distributions. Moreover, for patients bouncing back to the CICU, we adopt the memoryless property and treat them as new patients who will experience the same distribution of LOS in the CICU and probability of another bounce back.

3.8 Number of Replications for Simulation

Here we determine the number of replications for our simulation. For each simulation, we set the number of replications to be 1,000 according to the rule of thumb. Then, we calculate the mean of the number of patients' arrival for different number of replications for five times. Then we found values stabilize when the number of simulations is greater than 800. This indicates that we should choose a replication number greater than 800 (Robinson 1994).

According to our experiments, we found that there is no significant difference in time cost between 800 replications and 1,000 replications. Therefore, we set the number of replications to be 1,000 and the corresponding running time is about 80 seconds.

4 SIMULATION LOGIC

Patients arrive into the system through an exponential interarrival process that varies with the day of the week as described in section 3.2. Once a patient arrives, we check if there is an ICU bed available in the system. If there is not one available, then the patient is denied. If there is an ICU bed available, then the patient is placed in the ICU bed until further rounding. Once the patient's health is assessed in the ICU, then two criteria will be checked before the patient can move to SDn. The first is if the patient is ready to be transferred, i.e. is the patient healthy enough to move to SDn. This will be determined by a Bernoulli probability based on the historical LOS. As an example, if the average LOS in the CICU was 4.52 days, then to calculate a Bernoulli probability it would be 22.1%. So, the patient will have a 22.1% chance of being deemed as healthy enough to move on. The second criterion is if there is a SDn bed available. If both of these criteria are met - the patient is deemed healthy enough from the Bernoulli probability and there is a SDn bed available - then the patient will be moved to a SDn bed. If the patient is not healthy enough and/or there is not a SDn bed available, then they stay in the ICU bed. Once the patient moves on to SDn, the final check is to see if the patient is healthy enough to leave the system/hospital. This is done with a Bernoulli probability based on the historical LOS of patients in SDn beds. If the patient is healthy enough, then they exit the system. Otherwise, the patient stays in the SDn bed.

Bounce back can occur when the patient is in the SDn bed. There is a probability of bounce back (set by the user) that the patient deteriorates in health and will require an ICU bed. This probability of bounce back occurs every day for patients in the SDn. If there is not an ICU bed available at the time the patient deteriorates, then the patient stays in the SDn bed. The whole patient flow process is replicated for the full time horizon (time horizon and number of replications are defined by the user) and metrics are collected at the end. The full patient flow our model applies is illustrated in Figure 1 below.

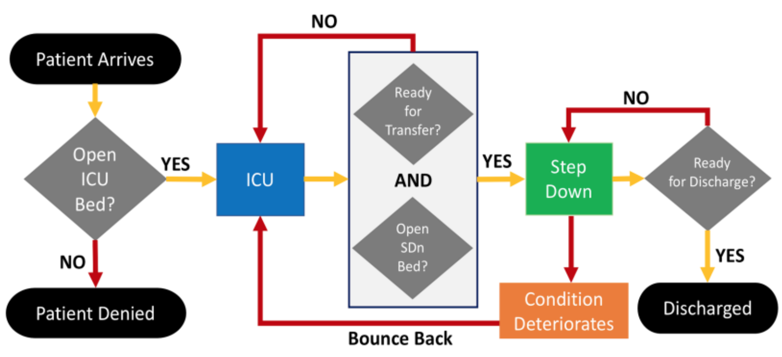

Figure 1: Cardiac patient flow diagram.

5 ANALYSIS

We construct four experiments to demonstrate how our simulation tool could be used to assess the impact of bounce back on CICU and SDn bed utilization. Rather than using the actual number of beds, we want to ensure that in the later experiments, when we add in the bounce back rate, that it is bounce back affecting LOS and patients denied and not the number of beds. We mainly focus on the percentage of patients denied, CICU status LOS in SDn, and unit utilization to estimate the model and compare the results. These three metrics represent the number of patients accepted, blockage of patient flow from SDn to CICU, and waste of unit beds correspondingly which depict model performance from three different aspects. In addition, we can compare the metrics with input parameters from clinic data to validate our model. For example, the total number of arrival patients calculated from the arrival rate should be close to the corresponding metrics from the simulation. For each experiment, we simulate a year (365 days) of patient flow in the CICU. Each year is simulated 1,000 times to ensure the accuracy of the results.

5.1 Experiment 1: Examining Number of CICU Beds

Since the CICU is the first unit of the patient flow and also has a higher cost than the SDn, we first construct the experiment to assess the number of CICU beds that can accept all arriving patients without considering bounce back. To achieve this goal, we set the number of SDn beds to a large number (1,000) which can eliminate its influence on patients denied. The number of CICU beds begins at 30 and increases by 2 for each simulation until the main performance metric (percentage of patients denied entrance to the CICU) decreases to 5%. Table 4 shows that 36 CICU beds is the minimal number of CICU beds which gives us an acceptable percentage of patients denied established by the institutional data. Moreover, since there are 1,000 beds in the SDn which can receive all patients from the CICU, then there is no SDn status stay in the CICU, allowing us to assess the number of beds without bounce back.

Table 4: Metrics of experiment 1.

# CICU bed	30	32	34	**36**
# SDn bed	1,000	1,000	1,000	1,000
# Patients arrival	2,299	2,299	2,299	2,299
# Patients accepted	1,969	2,051	2,125	2,181
# Patients denied	330 (14.35%)	248 (10.79%)	174 (7.57%)	**118 (5.13%)**
Avg SDn status LOS in CICU	0.00	0.00	0.00	0.00
Avg CICU status LOS in SDn	0.00	0.00	0.00	0.00
CICU utilization	83.96%	81.93%	79.54%	77.07%
SDn utilization	2.52%	2.62%	2.72%	2.79%

5.2 Experiment 2: Examining Number of SDn Beds

In the second scenario, we want to assess the number of SDn beds based on the number of CICU beds we get in the first scenario. Similar to the first experiment, we set the number of CICU beds to 36 and let the SDn beds count start at 32 and increase by 2 for each simulation until the percentage of patients denied entry to the CICU decreases to the same level as the first experiment (5%). Additionally, we note that the marginal benefits of the SDn beds plateaus after 36 beds and the percentage of patients denied won't reduce by a significant percentage as shown in Table 5 which indicates the CICU is the bottleneck under this scenario.

In the first two experiments, we find that CICU status LOS in SDn always shows 0 in different scenarios which is consistent with the no bounce back condition. Moreover, CICU and SDn utilization decrease when we add in more beds which decreases the number of patients denied but results in increased cost. When choosing the ideal number of CICU and SDn beds, we get around 77% utilization of CICU and SDn.

Compared with the average national CICU occupancy rate (66%) in 2010, our result is in a reasonable range which indicates 36 CICU beds don't lead to an unacceptable cost (Halpern et al. 2015).

Table 5: Metrics of experiment 2.

# CICU bed	36	36	36	36
#SDn bed	32	34	**36**	38
# Patients arrival	2,299	2,298	2,299	2,300
# Patients accepted	2,156	2,172	2,178	2,181
# Patients denied	134 (5.83%)	126 (5.48%)	**121 (5.26%)**	119 (5.17%)
Avg SDn status LOS in CICU	0.10	0.05	0.02	0.00
Avg CICU status LOS in SDn	0.00	0.00	0.00	0.00
CICU utilization	78.14%	77.63%	77.36%	77.16%
SDn utilization	84.69%	80.77%	76.94%	73.22%

5.3 Experiment 3: Examining the Influence of Bounce Back

As stated in the problem description, we aim to figure out the impact of bounce back on system performance in the third experiment. In this scenario, patients will have a longer LOS in the ICU after they bounce back from SDn (7.83 days) than the LOS of the first visit to the CICU (4.70 days). We set the number of beds in the CICU and the SDn to 36 and decremented the bounce back rate from the actual value (10.93%) to 2% as shown in Table 6. We find that the percentage of patients denied grows more rapidly than the bounce back rate which indicates that small rates of bounce back will have a strong impact on the patient flow and system performance. Moreover, the average CICU status LOS in SDn also grows quickly when increasing the bounce back rate which represents blockage of bouncing back patients.

Next, we use the same method as in previous experiments to assess the number of CICU and SDn beds when factoring in the effects of bounce back. As shown in Table 7, bed counts in CICU and SDn have similar increasing trends as bounce back rate. However, when we consider the actual bounce back rate (10.93%), the ideal number of CICU beds is 43 and the ideal number of SDn beds is 45, a 34% increase compared to the original count.

In summary, a small increase in bounce back rate will have a significant impact on the system and lead to more blockage of patient flow from SDn back to the CICU. This confirms our previous statement and also shows that more attention should be paid to bounce back, for example, whether longer LOS in the CICU reduces bounce back rate.

Table 6: Metrics of experiment 3.

#CICU bed	36	36	36	36	36
# SDn bed	36	36	36	36	36
Bounce back rate	**10.93%**	**8.00%**	**6.00%**	**4.00%**	**2.00%**
# Patients arrival	2,302	2,301	2,303	2,300	2,300

# Patients accepted	1,720	1,867	1,958	2,054	2,148
# Patients denied	**582 (25.3%)**	**434 (18.9%)**	**345 (14.9%)**	**246 (10.7%)**	**152 (6.6%)**
Avg CICU status LOS in CICU	5.19	4.92	4.76	4.16	4.34
Avg SDn status LOS in CICU	**0.86**	**0.48**	**0.30**	**0.17**	**0.09**
Avg SDn status LOS in SDn	5.83	5.64	5.43	5.14	4.85
Avg CICU status LOS in SDn	**0.88**	**0.53**	**0.31**	**0.14**	**0.04**
CICU utilization	90.12%	87.97%	86.03%	83.12%	78.97%
SDn utilization	91.85%	87.55%	84.34%	81.47%	79.70%

Table 7: Number of CICU and SDn beds with different bounce back rates.

#CICU bed	43	40	38	36	34
# SDn bed	45	40	38	36	34
Bounce back rate	**10.93%**	**8.00%**	**6.00%**	**4.00%**	**2.00%**
# Patients arrival	2,302	2,300	2,300	2,302	2,301
# Patients accepted	2,178	2,179	2,180	2,179	2,175
# Patients denied	**124 (5.3%)**	**121(5.3%)**	**120 (5.2%)**	**123 (5.3%)**	**126 (5.4%)**

5.4 Experiment 4: Evaluating System Performance with Different Levels of Bounce Back Rate

To make the model more realistic, we conduct experiment 4 to evaluate the system performance with different levels of bounce back. Instead of assuming every patient has the same bounce back probability, we observe in our historical data that there is a significant difference in the bounce back rate of patients whose LOS in CICU is longer than the median and patients whose LOS in CICU is below the median, which is 15.2% and 10.8% respectively. Meanwhile, similar to experiment 3, patients will have a longer LOS in CICU after they bounce back from SDn than the LOS of the first visit of CICU.

As shown in Table 8, the percentage of patients denied is 35.33% which is even greater than the scenario which considers all the patients to have the same bounce back rate. Therefore, this more realistic model strengthens the impact of bounce back on the percentage of patients denied.

Table 8: Metrics of experiment 4.

Bounce back rate	# CICU beds	# SDn beds	# Patients arrival	# Patients accepted	# Patients denied
10.80% 15.20%	36	36	2,301	1,488	813 (35.33%)

Avg CICU status LOS in CICU	Avg SDn status LOS in CICU	Avg SDn status LOS in SDn	Avg CICU status LOS in SDn	CICU utilization	SDn utilization
5.80	1.50	5.84	1.32	92.58%	96.10%

6 RESULTS AND DISCUSSION

The simulations are conducted to assess how bounce back might affect patient access to care. In order to apply the results to the clinical environment, we present a few key takeaways based on the aforementioned experiments.

6.1 Experiment 1 & 2

Experiments 1 and 2 show us that the benefits of adding CICU/SDn beds will plateau after a certain point as after this threshold, the marginal benefits of lowering the percentage of patients denied will be outweighed by the drawbacks of low bed utilization. We see that the number of patients denied decreases with additional beds added throughout our simulation. However, after the inclusion of 36 CICU and 36 SDn beds, additional beds may not be worth the trade-off of the low utilization that accompanies it. A higher number of CICU and SDn beds naturally creates more available beds for patients and thus lowers the number of patients denied. But, many of these newly staffed beds will go unused more frequently, increasing the costs of upholding empty beds while incurring no added revenue from them. Our results from Experiments 1 and 2 illustrated that 36 SDn and CICU beds each keeps the percentage of patients denied relatively low (5.26%) while still conserving above a 70% bed utilization in both the SDn and CICU; these experiments assumed no bounce-backs. There is no standard ideal combination of beds that will work in all situations, but this simulation tool will help clinicians make more educated decisions about the ideal bed numbers for their given circumstances.

6.2 Experiment 3 & 4

Experiment 3 illustrated that even a small amount of uncertainty in the hospital system has a significant impact on patient flow. A 2% bounce back rate affects the system by increasing the patient denials by almost 26% when compared to no bounce back as seen from Tables 5 and 6 (from 121 to 152 patients). As we increase bounce back rates all the way to 10.93% (from Table 6), the percentage of patients denied rises to 25.3%. This is nearly 1 in every 4 patients denied. A rate of 10.93% is not unrealistically high as we found this in our data set, which raises the point that additional CICU and SDn beds are required when accounting for bounce back. Moreover, experiment 4 which is a more realistic model considering the different patients will have different bounce back rates illustrated that a much higher percentage of patients denied (35.33%).

7 CONCLUSIONS

Using discrete event simulation, we evaluated the impact of bounce back on patient flow from CICU to SDn. We estimated parameters of arrival rate, LOS in CICU and SDn, bounce back rate from Data Direct that applied as simulation input. These experiments collected metrics such as the percentage of denied patients, CICU status, and LOS in SDn to evaluate the model in different scenarios which demonstrate that simulation is a technique that can be used in other similar situations. The discussed model gives us a clear result that a small increase in bounce back rate will lead to a significant increase in patient denials, thus creating a blockage in the patient flow between CICU and SDn. As a result, more beds in the CICU and SDn are necessary to reduce the influence created by patients bouncing back. This work provides an invaluable tool to both clinicians and engineers working to eliminate bottlenecks of patient flow in the CICU.

This version of the simulation is a first phase. In order to increase the accuracy of the model to simulate the real world, we plan future expansions in the functionality of the model. One factor is bounce back variability based on how many times one has bounced back. Readmission to CICU has been shown to be correlated with a twofold longer hospital length of stay (Rosenberg and Charles 2000). In addition, bounce back is associated with increased morbidity and mortality, with odds of death being six to seven times higher independent of other factors (Magruder et al. 2015; Fakhry et al. 2013). LOS can also be impacted by whether the hospital stay is a bounce back, which indicates bounce back patients might not be treated as new patients. We also plan to integrate our model with the urgent and elective surgery schedule in relation to patient arrival time into CICU. Finally, instead of choosing the ideal number of CICU and SDn beds directly, we plan to create an optional scenario where CICU or SDn care can be provided to the patients in the same room, which introduces a flexible CICU or SDn bed. These future steps will ultimately make our simulation model more realistic and useful. The hope is to then apply our simulation model to other types of hospital rooms such as CCUs (Coronary Care Unit) and CCMUs (Critical Care Medicine Unit) where bounce back also has an impact.

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AUTHOR BIOGRAPHIES

ZIQI WANG is an M.S.E student in Industrial and Operations Engineering at the University of Michigan. Ziqi has been working for the Center for Healthcare and Patient Safety (CHEPS) at Michigan since September of 2019. Her email address is ziwang@umich.edu.

AMBIKA AGRAWAL is an undergraduate student studying Computer Science and Biomolecular Science at the University of Michigan. Her email address is agra@umich.edu.

IMANI CARSON is an undergraduate student at the University of Michigan studying Industrial and Operations Engineering. Her email address is icarson@umich.edu.

LUKE LIU is a senior studying Industrial and Operations Engineering at the University of Michigan and plans to graduate in May 2020. He will be finding work in Ann Arbor after graduation. His email address is hubliu@umich.edu.

HARINI PENNATHUR is an undergraduate student in the College of Engineering at the University of Michigan. She is studying Industrial and Operations Engineering and plans to graduate in May 2021. Harini has been working for the Center for Healthcare and Patient Safety (CHEPS) at Michigan since May of 2019. Her email address is hpennath@umich.edu.

HADI SAAB is a junior undergraduate student at the University of Michigan studying Biopsychology, Cognition, and Neuroscience with plans to attend medical school after graduation. His email address is hhsaab@umich.edu.

AMY COHN is an Alfred F. Thurnau Professor in the Department of Industrial and Operations Engineering at the University of Michigan, where she also holds an appointment in the Department of Health Management and Policy in the School of Public Health. Dr. Cohn is the Associate Director of the Center for Healthcare Engineering and Patient Safety. Her email address is amycohn@med.umich.edu.

AMANDA MORENO-HERNANDEZ is a Research Associate in the William Davidson Institute Healthcare sector. Moreno-Hernandez earned a B.S. degree in Industrial Engineering at the University of Puerto Rico and an M.S.E. in Industrial and Operations Engineering at the University of Michigan. Her email address is admh@umich.edu.

HITINDER GURM is an Associate Chief Clinical Officer at the University of Michigan. He is a Professor of Internal Medicine, and is widely recognized for his work in improving safety and quality of cardiovascular procedures. He is the recipient of the Michigan Health & Hospital Association's Patient Safety & Quality Leadership Award for 2016 and has been elected to the American Society for Clinical Investigation. His email address is hgurm@med.umich.edu.