Simulating Access And Patient Flow For A Cardiovascular ICU

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CHEPS

INNOVATING HEALTHCARE DELIVERY

FOSTERING LEARNING

BUILDING COMMUNITY

POSITIVE IMPACT THROUGH...
Research
Education
Implementation
Outreach
Dissemination
OUTLINE

• Background
• Simulation Framework
• Analyses
• Future Research
BACKGROUND
HOW SIMULATION CAN HELP

Test Policies to Increase Patients’ Access to High Quality Care

Current State

Build Simulation Tool

Future State

Educate Clinical Partners About Uncertainty
Patient Arrives

Open ICU Bed?

ICU-first Patients

ICU

Open SDn Bed?

Bounce Back

Assumptions
• OR, surgeon and staff are always available
• Any patient can be denied

Ready for Transfer?

Step Down (SDn)

Ready for Discharge?

Discharged

NO

NO

NO

YES

YES

YES
Fixed input:
• Bed count per unit
• Time horizon: 1 year
• Number of replications: 1000
• Bounce back probability: determined value calculated from electronic health record data

Variable input:
• Arrival rate: exponential distribution
• LOS in ICU and SDn: geometric distribution
**SIMULATION - INPUT**

**Arrival rate:** depends on day of week (different days of the week have different arrival rates)

**LOS in ICU and SDn (ICU-first Patients):**
- For patient $X_i$, we set $ICULOS_i^j$ to represent his LOS of $j$ th ICU visit
- We set $SDLOS_i^j$ to represent his LOS of $j$ th SDn visit
- Since the patient starts from ICU, whether he bounces back or not, he will visit ICU and SDn the same number of times
- $N$ represents the number of patients
- $M_i$ represents how many times patient $i$ visits ICU/SDn.
- Then, we calculate:

\[
ICULOS_1 = \frac{1}{N} \sum_{j=1}^{N} ICULOS_i^1,\ ICULOS_2 = \frac{1}{N \times (\sum M_i)} \sum_{j=1}^{N} \sum_{i=2}^{M_i} ICULOS_i^j
\]

\[
SDLOS_1 = \frac{1}{N} \sum_{j=1}^{N} SDLOS_i^1,\ SDLOS_2 = \frac{1}{N \times (\sum M_i)} \sum_{j=1}^{N} \sum_{i=2}^{M_i} SDLOS_i^j
\]

- This means we separate patients’ first ICU/SDn stay and the all remaining ICU/SDn stays
**SIMULATION - INPUT**

**Bounce Back Probability**

- 2 patient groups
  - LOS longer than median
  - LOS shorter than median
- Bounce Back probability used depends on LOS of the most recent ICU stay
  - $BounceBack_1$ for patients whose LOS of their most recent ICU visit is longer than the median
  - $BounceBack_2$ for patients whose LOS of their most recent ICU visit is below the median

\[ BounceBack_1 > BounceBack_2 \]
LOS in SDn: (SDn-first patients)

For their first SDn visit, they have different LOS $LOS_{SD}$ and bounce back probability $BounceBack_{SD}$. 

**Diagram:**
- **Patient Arrives**
  - **YES**
    - **Ready for Discharge?**
      - **YES**
        - Discharged
      - **NO**
        - **Ready for Transfer?**
          - **YES**
            - **Open SDn Bed?**
              - **YES**
                - **Step Down**
              - **NO**
                - **Bounce Back**
          - **NO**
            - **ICU**

  - **NO**
    - **Bounce Back**
## Simulation - Metrics

<table>
<thead>
<tr>
<th>Number of…</th>
<th>ICU</th>
<th>Step Down (SDn)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Patient Arrivals</td>
<td>• Patient LOS</td>
<td>• Patient LOS</td>
</tr>
<tr>
<td></td>
<td>• Unnecessary days in an ICU bed (SDn status)</td>
<td>• Unnecessary days in a SDn bed (ICU status)</td>
</tr>
<tr>
<td></td>
<td>• Bed Utilization</td>
<td>• Bed Utilization</td>
</tr>
<tr>
<td>Accepted Patients</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Denied Patients</td>
<td></td>
<td></td>
</tr>
</tbody>
</table>
ANALYSES

Analysis 1
How many beds we need in ICU

Analysis 2
How many beds we need in SDn

Analysis 3
How bounce back influences the denial rate
BASE CASE PARAMETERS

• 1 Patient Type
• Arrival Rate vs. Day of Week

<table>
<thead>
<tr>
<th>Day of Week</th>
<th>Monday</th>
<th>Tuesday</th>
<th>Wednesday</th>
<th>Thursday</th>
<th>Friday</th>
<th>Saturday</th>
<th>Sunday</th>
</tr>
</thead>
<tbody>
<tr>
<td>Arrival Rate (patients/hour)</td>
<td>0.237</td>
<td>0.281</td>
<td>0.245</td>
<td>0.231</td>
<td>0.243</td>
<td>0.090</td>
<td>0.080</td>
</tr>
</tbody>
</table>

• Time Horizon: 1 year
• Replications of simulation: 1000
• ICU-first patients (72.3%)

<table>
<thead>
<tr>
<th>Parameters</th>
<th>$ICULOS_1$</th>
<th>$ICULOS_2$</th>
<th>$SDLOS_1$</th>
<th>$SDLOS_2$</th>
<th>$BounceBack_1$</th>
<th>$BounceBack_2$</th>
</tr>
</thead>
<tbody>
<tr>
<td>Value</td>
<td>3.64 days</td>
<td>6.29 days</td>
<td>4.29 days</td>
<td>5.33 days</td>
<td>15.2%</td>
<td>10.8%</td>
</tr>
</tbody>
</table>

• SD-first patients (27.7%)

<table>
<thead>
<tr>
<th>Parameters</th>
<th>$LOS_{SD}$</th>
<th>$BounceBack_{SD}$</th>
</tr>
</thead>
<tbody>
<tr>
<td>Value</td>
<td>3.45 days</td>
<td>12.4%</td>
</tr>
</tbody>
</table>
Set 1000 SDn beds to avoid bottleneck from ICU to SDn.

### ANALYSIS 1 – HOW MANY BEDS IN ICU

<table>
<thead>
<tr>
<th>Allocated ICU Beds</th>
<th>28</th>
<th>30</th>
<th>32</th>
<th>34</th>
</tr>
</thead>
<tbody>
<tr>
<td>Annual Patient Arrival</td>
<td>1784</td>
<td>1784</td>
<td>1785</td>
<td>1783</td>
</tr>
<tr>
<td>Patients Denied</td>
<td>8.67%</td>
<td>7.12%</td>
<td>5.92%</td>
<td>4.91%</td>
</tr>
<tr>
<td>ICU Average LOS ICU Status</td>
<td>3.94</td>
<td>4.02</td>
<td>3.98</td>
<td>4.01</td>
</tr>
<tr>
<td>ICU Average LOS SDn Status</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
</tr>
<tr>
<td>SDn Average LOS</td>
<td>6.03</td>
<td>6.05</td>
<td>6.02</td>
<td>5.99</td>
</tr>
<tr>
<td>ICU Beds Utilization</td>
<td>81.93%</td>
<td>80.92%</td>
<td>79.92%</td>
<td>78.81%</td>
</tr>
</tbody>
</table>

Acceptable level of patients denied: 5%
Acceptable level of ICU beds utilization: 75%
ANALYSIS 2 – HOW MANY BEDS IN SDn

Set 34 ICU beds to avoid bottleneck from ICU to SDn.

<table>
<thead>
<tr>
<th>Allocated SDn Beds</th>
<th>34</th>
<th>42</th>
<th>50</th>
<th>58</th>
<th>62</th>
</tr>
</thead>
<tbody>
<tr>
<td>Annual Patient Arrival</td>
<td>1785</td>
<td>1781</td>
<td>1784</td>
<td>1786</td>
<td>1784</td>
</tr>
<tr>
<td>Patients Denied</td>
<td>11.91%</td>
<td>8.54%</td>
<td>5.77%</td>
<td>5.13%</td>
<td>5.00%</td>
</tr>
<tr>
<td>ICU Average LOS ICU Status</td>
<td>4.34</td>
<td>4.27</td>
<td>4.21</td>
<td>4.20</td>
<td>4.20</td>
</tr>
<tr>
<td>ICU Average LOS SDn Status</td>
<td>0.54</td>
<td>0.44</td>
<td>0.37</td>
<td>0.36</td>
<td>0.36</td>
</tr>
<tr>
<td>SDn Average LOS</td>
<td>5.81</td>
<td>5.93</td>
<td>5.98</td>
<td>5.99</td>
<td>6.00</td>
</tr>
<tr>
<td>SDn Beds Utilization</td>
<td>79.84</td>
<td>73.08</td>
<td>61.73%</td>
<td>53.88%</td>
<td>50.56%</td>
</tr>
</tbody>
</table>

Acceptable level of patients denied: 5%
ANALYSIS 3 – INFLUENCE OF BB

Set 34 ICU beds and 50 SDn beds.

<table>
<thead>
<tr>
<th></th>
<th>10.8%</th>
<th>12.8%</th>
<th>14.8%</th>
<th>16.8%</th>
</tr>
</thead>
<tbody>
<tr>
<td>BounceBack Probability 1</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>BounceBack Probability 2</td>
<td>15.2%</td>
<td>17.2%</td>
<td>19.2%</td>
<td>21.2%</td>
</tr>
<tr>
<td>Annual Patient Arrival</td>
<td>1784</td>
<td>1784</td>
<td>1785</td>
<td>1786</td>
</tr>
<tr>
<td>Patients Denied</td>
<td>5.69%</td>
<td>7.48%</td>
<td>9.93%</td>
<td>13.41%</td>
</tr>
<tr>
<td>ICU Average LOS ICU Status</td>
<td>4.21</td>
<td>4.26</td>
<td>4.31</td>
<td>4.39</td>
</tr>
<tr>
<td>ICU Average LOS SDn Status</td>
<td>0.37</td>
<td>0.42</td>
<td>0.48</td>
<td>0.59</td>
</tr>
<tr>
<td>SDn Average LOS</td>
<td>5.99</td>
<td>6.25</td>
<td>6.52</td>
<td>6.78</td>
</tr>
<tr>
<td>ICU Beds Utilization</td>
<td>78.77%</td>
<td>79.92%</td>
<td>80.76%</td>
<td>81.44%</td>
</tr>
<tr>
<td>SDn Beds Utilization</td>
<td>61.77%</td>
<td>66.87%</td>
<td>72.69%</td>
<td>78.45%</td>
</tr>
</tbody>
</table>
TAKEAWAYS

1. The benefits of adding ICU/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.

2. Even a small amount of uncertainty (change of bounce back probability) in the hospital system has a significant impact on patient flow.
FUTURE RESEARCH

1. Add elective surgery process to the model which may influence the arrival rate

2. Use the simulation to help make better decisions about accepting transfers and arranging elective surgeries
ACKNOWLEDGEMENTS

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