Modeling and Optimizing Emergency Department Workflow

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Distinguished Scholar, Health System Institute, Emory / Georgia Tech
Professor, School of Industrial and Systems Engineering, Georgia Tech
Emergency Department (ED) Challenges

• Overcrowding, growing volume
• Unnecessarily long length-of-stay, long wait times
• Presence of patients with non-urgent medical conditions (~40%)
• Return after 72 hours (5%), 30 days (20%)
• Decreased quality of care and patient satisfaction
• Shrinking rates of reimbursement (Medicare, Medicaid, Commercial)
• Federal and State Regulations (COBRA, HCFA, etc)
Grady’s ED Challenges

• Premier Level I Trauma Center for the region
• Internationally recognized teaching Hospital (Emory, Morehouse)
• 120,000 ED patients per year
  – Approximately 3500 acute trauma patient admissions
  – Approximately 350 patients daily
• Safety net
• Only 8% privately insured, 36% Medicaid/Medicare, 55% self-pay
  – Nationally 50% insured
• Growing ED demand
• Limited healthcare access for the un/underinsured
EDI Patients and Workflow

- Emergency Severity Index (ESI) – Triage evaluation of patient acuity
  - 1 (immediate)
  - 2 (emergent)
  - 3 (urgent)
  - 4 (less urgent)
  - 5 (non-urgent)

- Blue Zone - Major/Medical

- Red Zone - Low acuity/Mental health

- PACe (fast track) – low acuity

- Detention Treatment Area

- Trauma Treatment Area
Some Definitions

• **Length of Stay (LOS):** the time when a patient arrives to the ED to the time s/he departs from the ED

• **Avoidable Revisit:** revisit resulting from an adverse event that occurred during the initial visit or from inappropriate care coordination following discharge
  – Major burden to US health system
  – Over $20 billion in Medicare spending (2005)

• **LWBS:** Left without being seen
  – Patient arrived in the ED but left before being seen by a qualified medical provider
What Sets Grady Apart?

Remarkable Scope of Services

- Region’s Largest Level I Trauma Center
- Nation’s Largest Hospital Based 911 Ambulance Service
- Regional Coordinating Hospital for All Disasters (natural or man-made)
- One of the Nation’s Busiest ERs
- Georgia’s Only Poison Center
- One of the Nation’s Largest Burn Units (only two in the state)
- Georgia Cancer Center for Excellence
- Regional Perinatal Center & Neonatal ICU
- One of the Nation’s Top Infectious Disease Programs
- World Renowned Diabetes & Comprehensive Sickle Cell Centers
- Certified Primary Stroke Center
- Largest Nursing Home in Georgia
- 9 Neighborhood Health Centers
Safety Net Role

- Bridge collapse at the Atlanta Botanical Gardens
- Olympic Park bombing
- Fulton County courthouse shooting
- Bluffton baseball team bus crash
- International TB scare
- ASA plane crash
- Designated hospital for visiting dignitaries, including the president of the U.S.
Grady Annual Revenue & Expenses

- Medicaid: 42%
- Medicare: 17%
- Counties: 17%
- Insurance: 8%
- Self Pay: 2%
- Grants: 13%
- Other: 2%
- Other: 15%
- Supplies/Drugs: .05%
- Contract labor: 1.32%
- Insurance: 2.27%
- Depreciation/Amortization: 7.00%
- Additional: 4.36%

Total Contributions

1995: $2196
1996: $2196
1997: $2196
1998: $2196
1999: $2196
2000: $2196
2001: $2196
2002: $2196
2003: $2196
2004: $2196
2005: $2196
2006: $2196

Expenses

1995: $2196
1996: $2196
1997: $2196
1998: $2196
1999: $2196
2000: $2196
2001: $2196
2002: $2196
2003: $2196
2004: $2196
2005: $2196
2006: $2196

Bud

DeKalb
Fulton
Total Contributions
Expenses
Grady’s Annual Economic Impact

- Positive Economic Impact of $1.5 Billion
  - $252 million in direct expenditures
  - $46 million in local/state tax revenues
  - 5,000+ employees
  - $238 million in wages and salaries
  - 12,435 area jobs created/sustained
Georgia Tech – Grady Collaboration

• Long history of partnership – Georgia Tech team and Grady leaders have long been working on quality improvement

• In 2008 – Grady signs on to become a leader of the NSF Center for Health Organization Transformation
  – Rapid development and test of change
  – Patients demand change
  – Economy demands change
  – US Healthcare behind industry in terms of process improvement and change management
Grady-Georgia Tech Collaboration

Healthcare Delivery Transformation

• Improve ED patient flow
• Reduce LOS
  – 14 hrs – 2005
  – 10.6 hrs – 2008
  – 6.97 hrs – 2012
  – 7.3 hrs – 2013 (May)
• Reduce LWBS (increase throughput)
• Reduce non-value added activities (reduce waste)
• Reduce/re-direct non-urgent patients
• Analyze/Predict revisit patterns and intervene to improve care
• Reduce revisits (by 25%)
• Improve quality of care and patient satisfaction

Quality, Efficiency, Effectiveness
Benefits to Patients

- Substantial improvements (2008-now):
  - reduce LOS -30%
    - reduce wait-time -70%
  - reduce LWBS -30%
  - increase throughput +19%
  - reduce non-urgent admissions -32%
- Realized without extra financial investment or labor
- Repurposed existing resource: clinical decision unit
  - Reduce revisit -28%
- Helped Grady acquire external sponsorships/donations, permitting additional ED advances:
  - Alternative-care facility opens a new business model
  - Expansion of trauma care: 4 beds to 15 beds; increase trauma throughput (3 fold)
Grady Global ED System Transformation

Changes in LOS

Blue/Red/Pace: -50%
Trauma: -18%
Detention: -36%
OR Advances

- Optimize within simulation, global system optimization
  - Non-closed form intractable nonlinear mixed integer program
- Machine learning theory and computation
  - General N-group classifier, effective for imbalanced data, high-dimension noise reduction, new complexity theory.
- Integrate machine learning, simulation and optimization into a predictive analytic decision framework
- Big data analytics
  - Model ED operations and system dynamics
  - Model dynamic patient characteristics and treatment patterns
  - Model ED revisits: demographics, socio-economic status, clinical information, hospital operations, and disease/behavioral patterns.
  - Model system inter-dependencies (including in-out of ED)

Challenges: Mathematical Theory and Computation
Methods: Technical Approaches

ED: Stakeholders’ characteristics & objectives; arrival rates; service pdfs; workflow; resources; decision process; outside units

Active Engagement

Big-DATA Analytic Framework

- Procedural and process benchmark
- Electronic Medical Records
- Hospital Historical Data
- Process maps, Time-motion Study

Observational Recommendations

- Machine learning, predictive analytics
- Establish process & systems interdependencies

Synthesize actionable recommendations

Simulation-Optimization Decision Framework

i) Validation
ii) Systems optimization

OR-Predictive Analytic Decision Framework

- Refine, next phase
- Implement & document performance
- Prioritize & Obtain buy-in

Simulate; Benchmark; Predict; Validate; Optimize; Synthesize; Prioritize; Implement & Document; Obtain Buy-in
## Data Collection and Time-Motion Study

<table>
<thead>
<tr>
<th></th>
<th></th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Inter-arrival rate</strong></td>
<td>poisson (3.48)</td>
<td>% by acuity, % by means of arrival</td>
</tr>
<tr>
<td><strong>Service Time</strong></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Walk-in registration</td>
<td>Triangular (1.13,4.53,14.73)</td>
<td>normal (2.332, 3.088)</td>
</tr>
<tr>
<td>Walk-in triage</td>
<td>3.55 + 1.18e+003 * beta (1.05, 2.37)</td>
<td>1+expo (4.431)</td>
</tr>
<tr>
<td>Ambulance triage</td>
<td>normal (6.43, 3.17)</td>
<td>1.12+expo (10.886)</td>
</tr>
<tr>
<td>Labs turnaround (hospital data includes individual service time for labs: CHEM, GAS, HEME, COAG, UA, Radiology test, Stat X-ray, Emergent X-ray, CT w/wo Contrast.)</td>
<td>mean: triangular (22.18, 45.23, 136.38)</td>
<td>0.65+expo (71.42) # of rounds of lab orders by acuity level</td>
</tr>
<tr>
<td>X-ray turnaround</td>
<td>mean: uniform (77.29)</td>
<td>mean: uniform (61.72)</td>
</tr>
<tr>
<td>PA treatment (PACe, Walk-in)</td>
<td>1.4 + expo (6.43)</td>
<td>1.2+exp (6.30)</td>
</tr>
<tr>
<td>Zone discharge</td>
<td>uniform (3.5, 44.5)</td>
<td>normal (8.133, 6.226)</td>
</tr>
<tr>
<td>Waiting time for Admittance</td>
<td>N/A</td>
<td>normal (131.64, 15.72)</td>
</tr>
<tr>
<td>Length of stay</td>
<td>10.6 hours</td>
<td>7.59 hours</td>
</tr>
<tr>
<td>Percentage of re-visits</td>
<td>5.90%, 20.66%</td>
<td>5.20%, 19.80%</td>
</tr>
<tr>
<td>Bed Assignment</td>
<td>N/A</td>
<td>triangular (4, 7, 10)</td>
</tr>
</tbody>
</table>
Machine Learning for Predicting Re-visit Patterns (DAMIP)

\[
\begin{align*}
\text{maximize} & \quad \sum_{g \in G} \sum_{j \in N_g} u_{g_{hj}} \\
\text{subject to} & \quad L_{h_{gj}} = \pi_h f_h(x^{g_{hj}}) - \sum_{i \in G, \ i \neq h} f_i(x^{g_{ij}}) \lambda_{ih} \quad g, h \in G, \ j \in N_g \\
& \quad y_{gj} - L_{h_{gj}} \leq M(1 - u_{h_{gj}}) \quad g, h \in G, \ j \in N_g \\
& \quad y_{gj} \leq M(1 - u_{0_{gj}}) \quad g \in G, \ j \in N_g \\
& \quad y_{gj} \geq \epsilon u_{h_{gj}} \quad g, h \in G, \ j \in N_g \\
& \quad y_{gj} - L_{h_{gj}} \geq \epsilon(1 - u_{h_{gj}}) \quad g, h \in G, \ j \in N_g \\
& \quad \sum_{0, h \in G} u_{h_{gj}} = 1 \\
& \quad \sum_{j \in N_g} u_{h_{gj}} \leq \lfloor \alpha_{hg} n_g \rfloor \\
& \quad -\infty < L_{h_{gj}} < \infty, \ y_{gj} \geq 0, \ \lambda_{ih} \geq 0, \ u_{h_{gj}} \in \{0, 1\}
\end{align*}
\]

Maximizing total correct classification

Constrain the total percentage of mis-classifications in each group.
Model Characteristics & Novelty

- **Constrained discriminant rule with a single reserved judgment region (for multi-stage analysis)**
  - First efficient computational model which allows for classification of *any number of groups*
  - Nonlinear transformation to manage curse-of-dimensionality
  - Allows constraints on misclassification rates
  - Provides a reserved judgment region for entities that are fuzzy
  - Allows for objective development of predictive rule (not over-trained), and continued multi-stage classification
Theoretical Complexity

- **Theory**
  - *NP-Complete (for G > 2)*
  - DAMIP is a *universally strongly consistent* method for classification

- **Solution Characteristics**
  - The predictive power of a DAMIP rule is independent of sample size, the proportions of training observations from each group, and the probability distribution functions of the groups.
  - A DAMIP rule is insensitive to the choice of prior probabilities.
  - A DAMIP rule is capable of maintaining low misclassification rates when the number of training observations from each group varies significantly.
Quality of Solutions

<table>
<thead>
<tr>
<th>Classification Method</th>
<th>Overall</th>
<th>Non-return</th>
<th>Return</th>
<th>Overall</th>
<th>Non-return</th>
<th>Return</th>
</tr>
</thead>
<tbody>
<tr>
<td>72-hour return</td>
<td>Training Set: 15,000</td>
<td>Blind Prediction Set: 12,534</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>10-fold Cross Validation</td>
<td>Accuracy</td>
<td>Blind Prediction Accuracy</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Linear Discriminant Analysis</td>
<td>96.3%</td>
<td>99.6%</td>
<td>5.5%</td>
<td>96.1%</td>
<td>99.6%</td>
<td>5.3%</td>
</tr>
<tr>
<td>Naïve Bayesian</td>
<td>51.6%</td>
<td>50.3%</td>
<td>87.0%</td>
<td>51.7%</td>
<td>50.2%</td>
<td>89.2%</td>
</tr>
<tr>
<td>State-of-the-art SVM</td>
<td>96.5%</td>
<td>100.0%</td>
<td>0.0%</td>
<td>96.2%</td>
<td>100.0%</td>
<td>0.0%</td>
</tr>
<tr>
<td>Logistic Regression</td>
<td>96.5%</td>
<td>99.8%</td>
<td>5.9%</td>
<td>96.3%</td>
<td>99.8%</td>
<td>8.3%</td>
</tr>
<tr>
<td>Classification Tree</td>
<td>96.6%</td>
<td>99.9%</td>
<td>4.4%</td>
<td>96.3%</td>
<td>100.0%</td>
<td>3.0%</td>
</tr>
<tr>
<td>Random Forest</td>
<td>96.6%</td>
<td>100.0%</td>
<td>1.5%</td>
<td>96.3%</td>
<td>100.0%</td>
<td>1.9%</td>
</tr>
<tr>
<td>Nearest Shrunken Centroid</td>
<td>62.7%</td>
<td>62.9%</td>
<td>50.0%</td>
<td>48.7%</td>
<td>48.2%</td>
<td>64.7%</td>
</tr>
<tr>
<td><strong>DAMIP/PSO</strong></td>
<td><strong>71.1%</strong></td>
<td><strong>71.0%</strong></td>
<td><strong>71.1%</strong></td>
<td><strong>72.2%</strong></td>
<td><strong>72.3%</strong></td>
<td><strong>73.7%</strong></td>
</tr>
</tbody>
</table>
Simulation-Optimization for Modeling ED Workflow

- Large-scale and fast simulator
- *Intractable, non-closed form* nonlinear mixed integer programming resource allocation

```
\begin{align*}
\min & \quad z = f(\sum_{j \in S} g_j, c, \theta) \\
\text{s.t.} & \quad m_{ijr} \leq x_{ijr} \leq M_{ijr}, \quad \forall r \in R, i \in T_r, j \in S_{ir} \quad (1) \\
& \quad \sum_{j \in S_{ir}} x_{ijr} \leq n_{ir}, \quad \forall r \in R, i \in T_r \quad (2) \\
& \quad w(x)_j \leq w_{\max} \\
& \quad q(x)_j \leq q_{\max} \quad \forall j \in S \quad (3) \\
& \quad u_{\min} \leq u(x)_j \leq u_{\max} \\
& \quad \theta(x) \geq \theta_{\max} \\
& \quad c(x) \leq c_{\max} \quad (4) \\
& \quad x_{ijr} \in Z_+ \quad \forall r \in R, i \in T_r, j \in S_{ir} \quad (5)
\end{align*}
```

- Fast optimization engine intertwined with simulation
- Incorporate machine learning patient/treatment characteristics
A Simplified ED Model

Systems inter-dependencies

ED Disposition to Departure
(Oct 1-31, 2009)

<table>
<thead>
<tr>
<th></th>
<th>Tele</th>
<th>ICU</th>
<th>Floor</th>
<th>Isolation</th>
<th>Stepdown</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Avg</strong></td>
<td>2:56</td>
<td>3:12</td>
<td>2:32</td>
<td>2:12</td>
<td>2:27</td>
</tr>
<tr>
<td><strong>Min</strong></td>
<td>0:55</td>
<td>1:20</td>
<td>0:35</td>
<td>1:10</td>
<td>1:00</td>
</tr>
<tr>
<td><strong>Max</strong></td>
<td>14:45</td>
<td>7:30</td>
<td>23:15</td>
<td>5:42</td>
<td>10:00</td>
</tr>
<tr>
<td><strong>Count</strong></td>
<td>61</td>
<td>34</td>
<td>132</td>
<td>17</td>
<td>36</td>
</tr>
</tbody>
</table>

Admit Type
## Model Validation

### Phase I: Train Aug 2008 – Feb 2009
**Validate: Mar – May 2009**

<table>
<thead>
<tr>
<th>ED Zone</th>
<th>Hospital Statistics</th>
<th>Simulated</th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>LOS</td>
<td>Patient Volume</td>
<td>LOS</td>
</tr>
<tr>
<td>Overall</td>
<td>10.59 h</td>
<td>8274*</td>
<td>10.49 h</td>
</tr>
<tr>
<td>Blue zone</td>
<td>14.54 h</td>
<td>2141</td>
<td>13.90 h</td>
</tr>
<tr>
<td>Red zone</td>
<td>12.54 h</td>
<td>2097</td>
<td>11.96 h</td>
</tr>
<tr>
<td>Trauma</td>
<td>7.85 h</td>
<td>271</td>
<td>7.98 h</td>
</tr>
<tr>
<td>Detention</td>
<td>13.85 h</td>
<td>437</td>
<td>12.93 h</td>
</tr>
<tr>
<td>PACe</td>
<td>7.90 h</td>
<td>2037</td>
<td>8.60 h</td>
</tr>
<tr>
<td>Walk-in</td>
<td>3.20 h</td>
<td>990</td>
<td>3.30 h</td>
</tr>
</tbody>
</table>

**Remainder patients**

*8274-2141-2097-271-437-2037-990 = 301 these patients include those who left before service, transferred to other facility, or no information provided.

### Phase II: Train Oct – Dec 2010
**Validate: Jan – Mar 2011**

<table>
<thead>
<tr>
<th>ED Zone</th>
<th>Hospital Statistics</th>
<th>Simulated</th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>LOS</td>
<td>Patient Volume</td>
<td>LOS</td>
</tr>
<tr>
<td>Overall</td>
<td>7.97 h</td>
<td>8421</td>
<td>8.02 h</td>
</tr>
<tr>
<td>Blue zone</td>
<td>11.40 h</td>
<td>2107</td>
<td>11.78 h</td>
</tr>
<tr>
<td>Red zone</td>
<td>8.98 h</td>
<td>2083</td>
<td>8.37 h</td>
</tr>
<tr>
<td>Trauma</td>
<td>6.80 h</td>
<td>268</td>
<td>6.86 h</td>
</tr>
<tr>
<td>Detention</td>
<td>10.90 h</td>
<td>441</td>
<td>10.53 h</td>
</tr>
<tr>
<td>PACe</td>
<td>5.10 h</td>
<td>1920</td>
<td>5.60 h</td>
</tr>
<tr>
<td>Walk-in</td>
<td>2.50 h</td>
<td>950</td>
<td>2.88 h</td>
</tr>
</tbody>
</table>

### Acuity Level

<table>
<thead>
<tr>
<th>Acuity Level</th>
<th>72-hour return</th>
<th>30-day return</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>10-fold cross validation</td>
<td>Blind prediction accuracy</td>
</tr>
<tr>
<td>1: Immediate</td>
<td>0.839</td>
<td>0.827</td>
</tr>
<tr>
<td>2: Emergent</td>
<td>0.7</td>
<td>0.7</td>
</tr>
<tr>
<td>3: Urgent</td>
<td>0.701</td>
<td>0.705</td>
</tr>
<tr>
<td>4: Less urgent</td>
<td>0.711</td>
<td>0.701</td>
</tr>
<tr>
<td>5: Non-urgent</td>
<td>0.705</td>
<td>0.705</td>
</tr>
<tr>
<td>None – missing</td>
<td>0.753</td>
<td>0.747</td>
</tr>
<tr>
<td>Overall</td>
<td>0.71</td>
<td>0.711</td>
</tr>
</tbody>
</table>

### Payment Type

<table>
<thead>
<tr>
<th>Payment Type</th>
<th>72-hour return</th>
<th>30-day return</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>10-fold cross validation</td>
<td>Blind prediction accuracy</td>
</tr>
<tr>
<td>INSURANCE</td>
<td>0.865</td>
<td>0.859</td>
</tr>
<tr>
<td>SELF-PAY</td>
<td>0.671</td>
<td>0.673</td>
</tr>
<tr>
<td>MEDICARE</td>
<td>0.701</td>
<td>0.709</td>
</tr>
<tr>
<td>MEDICAID</td>
<td>0.661</td>
<td>0.674</td>
</tr>
</tbody>
</table>
# Phase I Recommendations

<table>
<thead>
<tr>
<th>Actual Hospital Operations</th>
<th>Simulation Systems Performance</th>
</tr>
</thead>
<tbody>
<tr>
<td>Mar - May 2009</td>
<td>Systems Improvement</td>
</tr>
<tr>
<td>Option 2. Reduce lab X-ray turnaround (-15 min)</td>
<td>Option 3. Optimize staffing in Blue &amp; Red zones</td>
</tr>
<tr>
<td>Option 4. Optimize staffing in triage, walk-in &amp; PACe</td>
<td></td>
</tr>
<tr>
<td>Option 5. Combine Blue &amp; Red zones with optimized staffing</td>
<td></td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Actual Hospital Statistics</th>
<th>Overall LOS</th>
<th>Overall Ave wait time</th>
<th>Blue Zone LOS</th>
<th>Red Zone LOS</th>
<th>Trauma LOS</th>
<th>Detention LOS</th>
<th>PACe LOS</th>
<th>Walk-in LOS</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>10.59 h</td>
<td>4.51 h</td>
<td>14.54 h</td>
<td>12.54 h</td>
<td>7.85 h</td>
<td>13.85 h</td>
<td>7.90 h</td>
<td>3.20 h</td>
</tr>
<tr>
<td></td>
<td>10.49 h</td>
<td>4.34 h</td>
<td>13.9 h</td>
<td>11.96 h</td>
<td>7.98 h</td>
<td>12.93 h</td>
<td>8.60 h</td>
<td>3.30 h</td>
</tr>
<tr>
<td></td>
<td>7.33 h</td>
<td>1.39 h</td>
<td>11.08 h</td>
<td>8.64 h</td>
<td>6.94 h</td>
<td>10.17 h</td>
<td>3.64 h</td>
<td>1.9 h</td>
</tr>
<tr>
<td></td>
<td>10.02 h</td>
<td>3.95 h</td>
<td>12.89 h</td>
<td>11.34 h</td>
<td>7.51 h</td>
<td>13.95 h</td>
<td>8.60 h</td>
<td>3.31 h</td>
</tr>
<tr>
<td></td>
<td>9.22 h</td>
<td>2.50 h</td>
<td>11.83 h</td>
<td>10.34 h</td>
<td>7.49 h</td>
<td>11.36 h</td>
<td>7.95 h</td>
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<td></td>
<td>9.84 h</td>
<td>3.87 h</td>
<td>13.38 h</td>
<td>10.62 h</td>
<td>7.74 h</td>
<td>12.46 h</td>
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<td>9.49 h</td>
<td>3.64 h</td>
<td>14.00 h</td>
<td>12.01 h</td>
<td>7.98 h</td>
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<td>4.03 h</td>
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<td></td>
<td>7.68 h</td>
<td>1.76 h</td>
<td>8.70 h</td>
<td>See above</td>
<td>7.70 h</td>
<td>9.16 h</td>
<td>6.63 h</td>
<td>2.94 h</td>
</tr>
</tbody>
</table>

Overall LOS: 10.59 h
Overall Average wait time: 4.51 h
Blue Zone LOS: 14.54 h
Red Zone LOS: 12.54 h
Trauma LOS: 7.85 h
Detention LOS: 13.85 h
PACe LOS: 7.90 h
Walk-in LOS: 3.20 h
Phase I Implementation Results

The new trauma center was opened in November, 2011.

A significant number of non-urgent ED patients were redirected to the alternative care facility since August 19, 2011, thus resulting in a significant drop in Walk-in patients.

<table>
<thead>
<tr>
<th>ED Zone</th>
<th>Original</th>
<th>Implementation of Recommendations</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td></td>
<td>Options 1-4, 7, 8</td>
</tr>
<tr>
<td></td>
<td></td>
<td>Options 1-4, 7, 8, 9 (clinical decision unit for observation)</td>
</tr>
<tr>
<td></td>
<td></td>
<td>Options 1-4, 7, 8, 9, 10 (redirect non-urgent visits to alternative care)</td>
</tr>
<tr>
<td>Length of Stay (l*)</td>
<td>Patient Volume</td>
<td>Reduction in LOS (l-l*)</td>
</tr>
<tr>
<td>Overall</td>
<td>10.59 h</td>
<td>8274</td>
</tr>
<tr>
<td>Blue zone</td>
<td>14.54 h</td>
<td>2141</td>
</tr>
<tr>
<td>Red zone</td>
<td>12.54 h</td>
<td>2097</td>
</tr>
<tr>
<td>Trauma center</td>
<td>7.85 h</td>
<td>271</td>
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<tr>
<td>Detention</td>
<td>13.85 h</td>
<td>437</td>
</tr>
<tr>
<td>PACe</td>
<td>7.90 h</td>
<td>2037</td>
</tr>
<tr>
<td>Walk-in</td>
<td>3.20 h</td>
<td>990</td>
</tr>
</tbody>
</table>

**Option 7**: Eliminate batch patients from walk-in to zone or PACe

**Option 8**: Eliminate batch discharges

**Option 9**: Create an observation area clinical decision unit

**Option 10**: Alternative Care
## Phase II Implementation Results

### Simulation Systems Performance

<table>
<thead>
<tr>
<th></th>
<th></th>
<th></th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td>Overall</td>
<td>8.30 h</td>
<td>6.79 h (-1.51 h)</td>
<td>7.21 h (-1.09 h)</td>
</tr>
<tr>
<td></td>
<td>Blue zone</td>
<td>11.32 h</td>
<td>6.24 h (-5.08 h)</td>
</tr>
<tr>
<td></td>
<td>Red zone</td>
<td>8.94 h</td>
<td>6.24 h (-2.70 h)</td>
</tr>
<tr>
<td></td>
<td>Trauma center</td>
<td>6.63 h</td>
<td>6.46 h (-0.17 h)</td>
</tr>
</tbody>
</table>

### Phase II: Comparison of ED Performance (Actual Hospital Monthly Statistics)

<table>
<thead>
<tr>
<th>ED Zone</th>
<th>Original (from Phase I improvement)</th>
<th>Implementation of Recommendations</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Length of Stay (l**)</td>
<td>Reduction in LOS (l - l**)</td>
</tr>
<tr>
<td></td>
<td>Sep 2011 – Dec 2011</td>
<td>Option 11 (optimizing overall ED staffing)</td>
</tr>
<tr>
<td></td>
<td></td>
<td>2012</td>
</tr>
<tr>
<td>Overall</td>
<td>8.30 h</td>
<td>-0.90 h</td>
</tr>
<tr>
<td>Blue zone</td>
<td>11.32 h</td>
<td>-3.95 h</td>
</tr>
<tr>
<td>Red zone</td>
<td>8.94 h</td>
<td>-2.75 h</td>
</tr>
<tr>
<td>Trauma center</td>
<td>6.64 h</td>
<td>-0.35 h</td>
</tr>
</tbody>
</table>

### Percentage of revisits

- 2011 72-hour return
- 2012 72-hour return
- 2011 30-day return
- 2012 30-day return

### Acuity Level

- 1
- 2
- 3
- 4
- 5
Grady Global ED System Transformation

Changes in LOS

- Blue/Red/PACe: -50%
- Trauma: -18%
- Detention: -36%

Percentage of revisits

Acuity Level

2010 72-hour return
2011 72-hour return
2012 72-hour return
2013 72-hour return
2010 30-day return
2011 30-day return
2012 30-day return
2013 30-day return
Significant Benefits

• Quality of care:
  – Reduce LOS (-30%), reduce wait-time (-70%)
  – Reduce revisits (-28%)
  – Reduce LWBS (-30%)
  – Timeliness of care: saving lives (trauma/blue patients)

• Efficiency and effectiveness:
  – Increase ED throughput (+19%)
  – Reduce/redirect non-urgent patients (-32%)

• New business for alternative care

• Expand trauma care
  – Increased throughput
  – 90 minute reduction in treatment time (saving lives)

• Sustained improvement
Realized Annual Financial Implication

• Increase throughput
  – ~$41.8 million

• Reduce revisits
  – ~$7.5 million (plus much more from reduced side-effects)

• New business (non-urgent alternative care):
  – ~$4.6 million

• Expansion in trauma care
  – ~$9.1 million

• Timeliness of care
  – Reduction in disability and improved outcomes
    • Tens/hundreds of millions of dollars for trauma patients and critical care/stroke patients.
How to Make it Work?

• Challenges
  – Over 1,100 physicians on active medical staff from Emory & Morehouse
  – Over 800 residents/fellows trained annually
  – Over 300 medical students educated at Grady annually
  – Very diverse teams of providers and leaders
  – “The only constant is change”

• Driving force to change
  – Safety net – strong desire to improve patient care, regardless of $,
    maintain commitment to the underserved
  – Survival and needs (hospital and patients)
  – Financial hardship – reduced reimbursement, increased penalties
  – Premier public hospital in the US

• Culture of change
  – Continuous change and demand alignment

• Strong appreciation of mathematics, OR and analytics
Continued Challenges

• Growing demand (w/o Healthcare Bill)

• Facility layout re-design
• Strategic planning
• Regulatory compliance
• Superutilizers
  – Top 20 utilizers of the ED on a monthly basis
    • Up to 33 visits in a 30 day month
  – Case management
  – Mental health treatment
OR Advances

• Optimize within simulation, global system optimization
  – Non-closed form intractable nonlinear mixed integer program
• Machine learning theory and computation
  – General N-group classifier, effective for imbalanced data, high-dimension noise reduction, new complexity theory.
• Integrate machine learning, simulation and optimization into a predictive analytic decision framework
• Big data analytics
  – Model ED operations and system dynamics
  – Model dynamic patient characteristics and treatment patterns
  – Model ED revisits: demographics, socio-economic status, clinical information, hospital operations, and disease/behavioral patterns.
  – Model system inter-dependencies (including in-out of ED)

Challenges: Mathematical Theory and Computation
Values Added

• Can be used for other hospital units and environment: ICU, OR, hospital acquired condition, surgical site infection, etc. All are active projects now with exciting results!!

• Have been applied to other ED sites with successes

• Generalizable technology, beyond healthcare
The Team

Grady Health System
• Hany Atallah, MD, Chief of Emergency Medicine
• Leon L. Haley, MD, Executive Associate Dean, Emory University
• Daniel Wu, MD, CMIO
• Michael Wright, former SVP operations
• Michelle Wallace, Exec Dir ED & Trauma
• Ellie Post, former SVP ED
• Calvin Thomas, former SVP operations
• Deborah Western
• Mr Manuel
• Ms Nadia
• Jill Cuestas
• All the nurses, and providers

Georgia Tech
• Eva K Lee
• Fan Yuan
• Ruilin Zhou
• Saloua Lablou

Time-motion study:
• Colby Allen, Cory Girard, Doug Meagh, Jeff Phillips, Amanda Widmaier, Hanzhen Zhang
Thank you