Modeling and Optimizing Emergency Department Workflow

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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

ED 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?

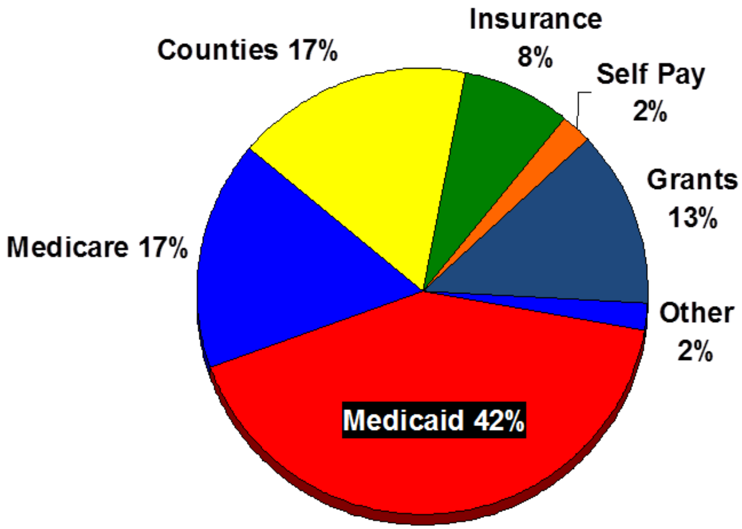
Remarkable Scope of Services

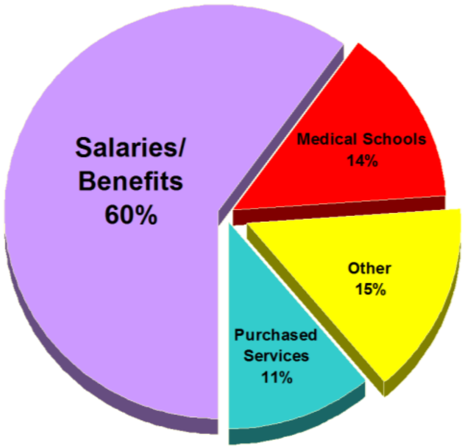
- Region's Largest Level I Trauma Center
- Nation's Largest Hospital Based 911 Ambulance Service
- Regional Coordinating Hospital for All Disasters (natural or man-made)
- One of the Nation's Busiest ERs
- Georgia's Only Poison Center
- One of the Nation's Largest Burn Units (only two in the state)
- 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

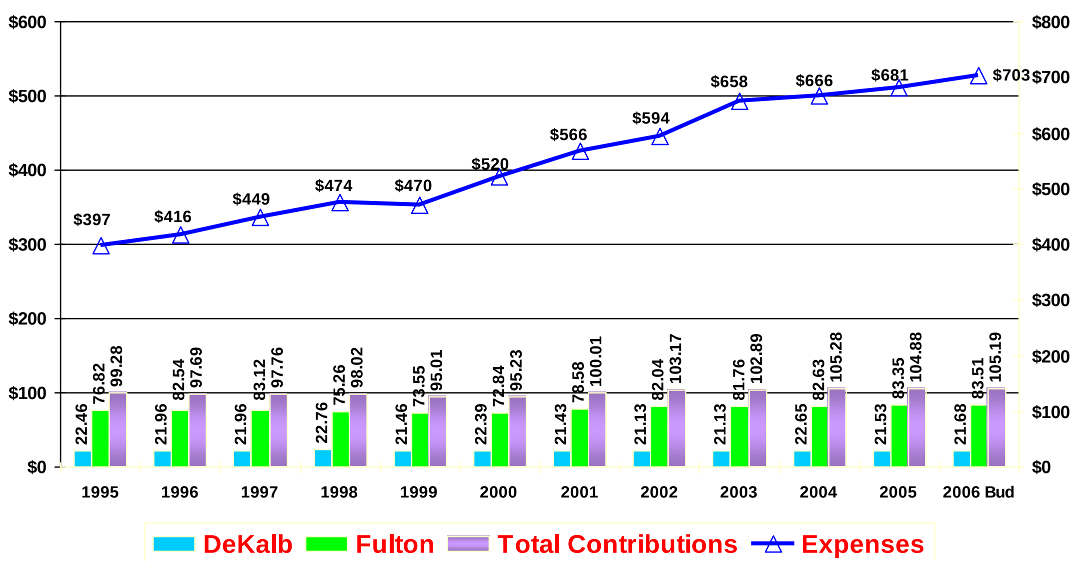
Safety Net Role

- 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







<u>Other = 15%</u>

Supplies/Drugs	.05%
Contract labor	1.32%
Insurance	2.27%
Depreciation/ Amortization	7.00%
Additional	4.36%

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

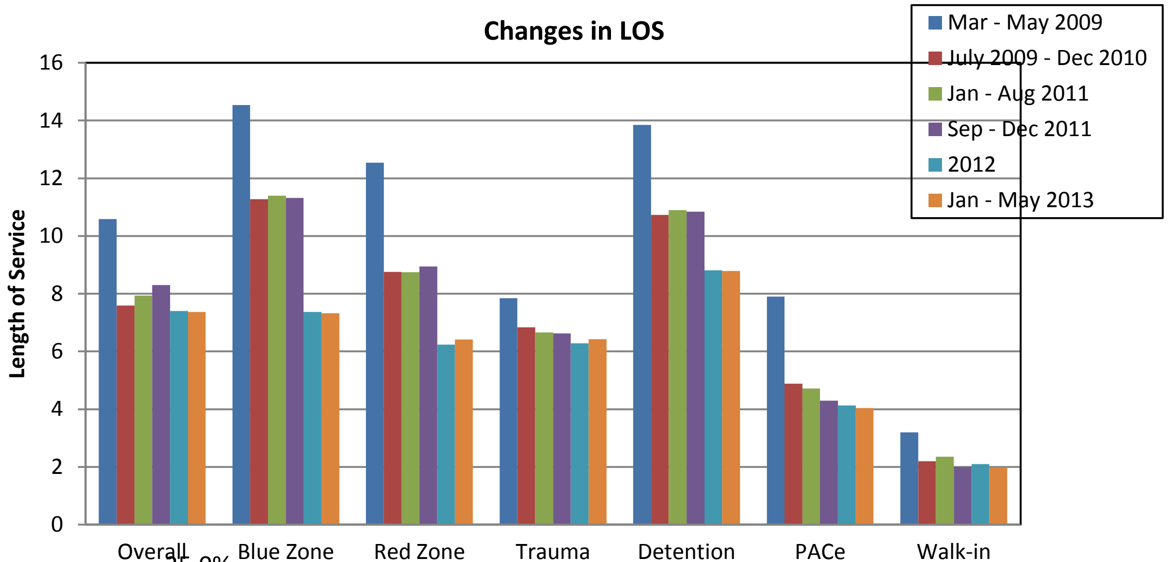
- Improve ED patient flow
- Reduce LOS
  - 14 hrs – 2005
  - 10.6 hrs – 2008
  - 6.97 hrs – 2012
  - 7.3 hrs – 2013 (May)
- Reduce LWBS (increase throughput)
- Reduce non-value added activities (reduce waste)
- Reduce/re-direct non-urgent patients
- Analyze/Predict revisit patterns and intervene to improve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

Quality, Efficiency, Effectiveness

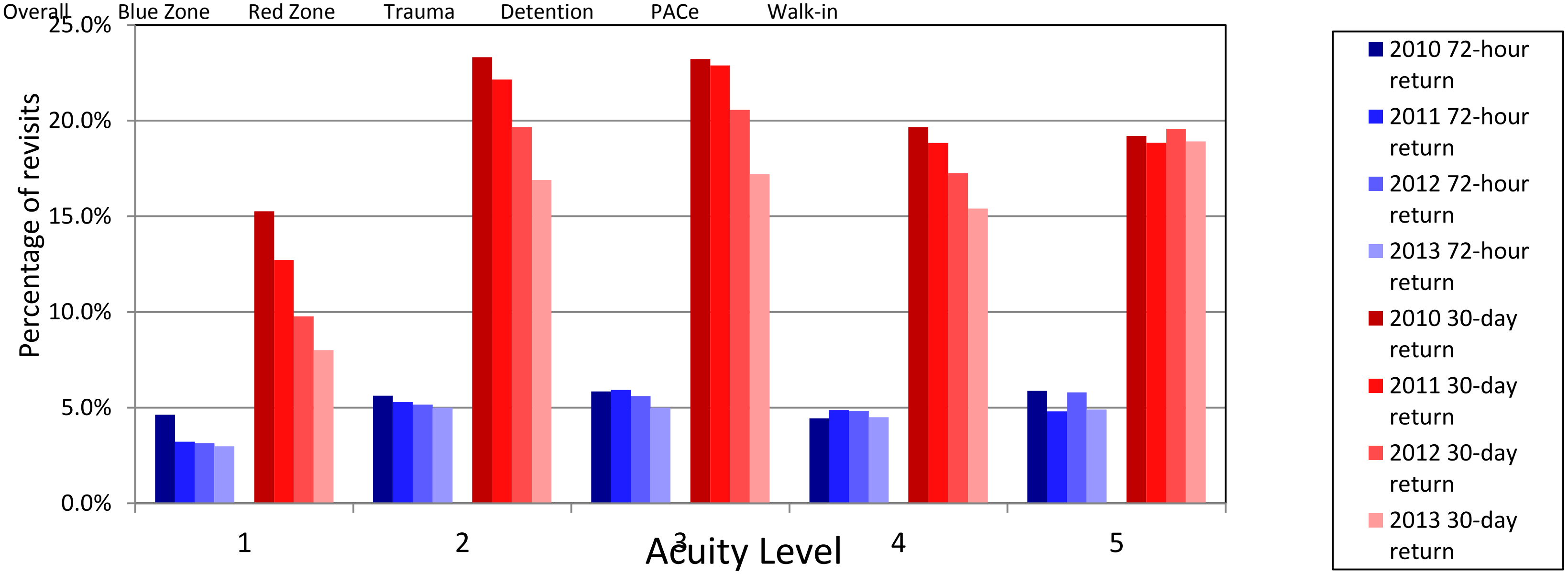
Benefits to Patients

- 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



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

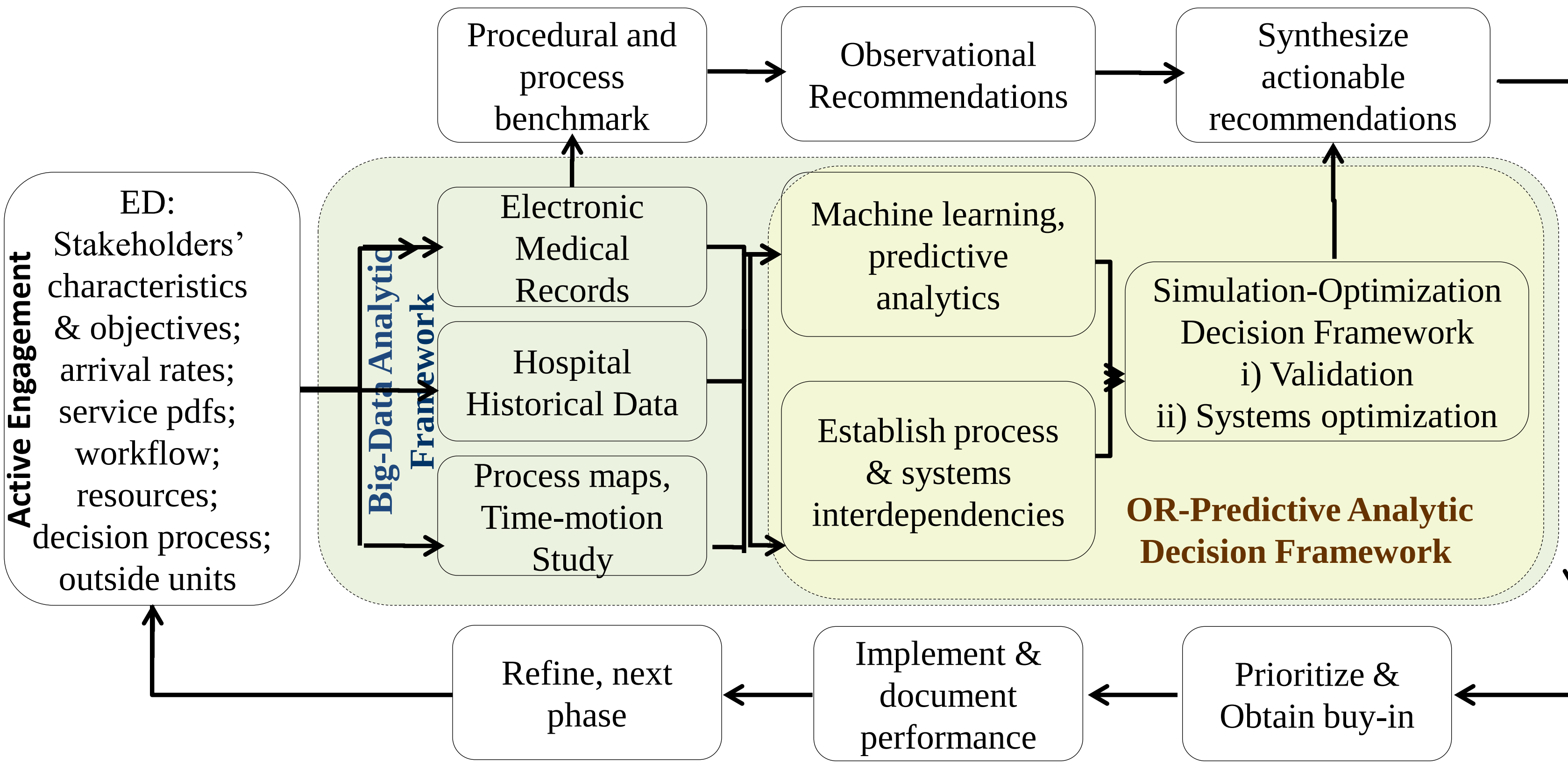


OR Advances

- 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



Data Collection and Time-Motion Study

Parameter & Training Data	Phase I Aug 2008 – Feb 2009	Phase II Oct 2010 – Dec 2010
Inter-arrival rate	poisson (3.48)	% by acuity, % by means of arrival
Service Time		
Walk-in registration	Triangular (1.13,4.53,14.73)	normal (2.332, 3.088)
Walk-in triage	3.55 + 1.18e+003 * beta (1.05, 2.37)	1+expo (4.431)
Ambulance triage	normal (6.43, 3.17)	1.12+expo (10.886)
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.)	mean: triangular (22.18, 45.23, 136.38)	0.65+expo (71.42) # of rounds of lab orders by acuity level
X-ray turnaround	mean: uniform (77.29)	mean: uniform (61.72)
PA treatment (PACe, Walk-in)	1.4 + expo (6.43)	1.2+exp (6.30)
Zone discharge	uniform (3.5, 44.5)	normal (8.133, 6.226)
Waiting time for Admittance	N/A	normal (131.64, 15.72)
Length of stay	10.6 hours	7.59 hours
Percentage of re-visits	5.90%, 20.66%	5.20%, 19.80%
Bed Assignment	N/A	triangular (4, 7, 10)

Machine Learning for Predicting Re-visit Patterns (DAMIP)

$$
\begin{array}{lrcll}
\text{maximize} & & & \displaystyle\sum_{g\in G}\sum_{j\in N_g} u_{ggj} & \\
\text{subject to} & & & & \\
& L_{hgj} & = & \pi_h f_h(x^{gj}) - \displaystyle\sum_{i\in G,\ i\neq h} f_i(x^{gj})\lambda_{ih} & g,h\in G,\ j\in N_g \\
& y_{gj} - L_{hgj} & \leq & M(1-u_{hgj}) & g,h\in G,\ j\in N_g \\
& y_{gj} & \leq & M(1-u_{0gj}) & g\in G,\ j\in N_g \\
& y_{gj} & \geq & \epsilon u_{hgj} & g,h\in G,\ j\in N_g \\
& y_{gj} - L_{hgj} & \geq & \epsilon(1-u_{hgj}) & \in N_g \\
& \displaystyle\sum_{0,h\in G} u_{hgj} & = & 1 & N_g \\
& \displaystyle\sum_{j\in N_g} u_{hgj} & \leq & \lfloor \alpha_{hg} n_g \rfloor & h,g\in G,\ h\neq g \\
& \multicolumn{4}{c}{-\infty < L_{hgj} < \infty,\ \ y_{gj}\geq 0,\ \ \lambda_{ih}\geq 0,\ \ u_{hgj}\in\{0,1\}}
\end{array}
$$

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

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

Simulation-Optimization for Modeling ED Workflow

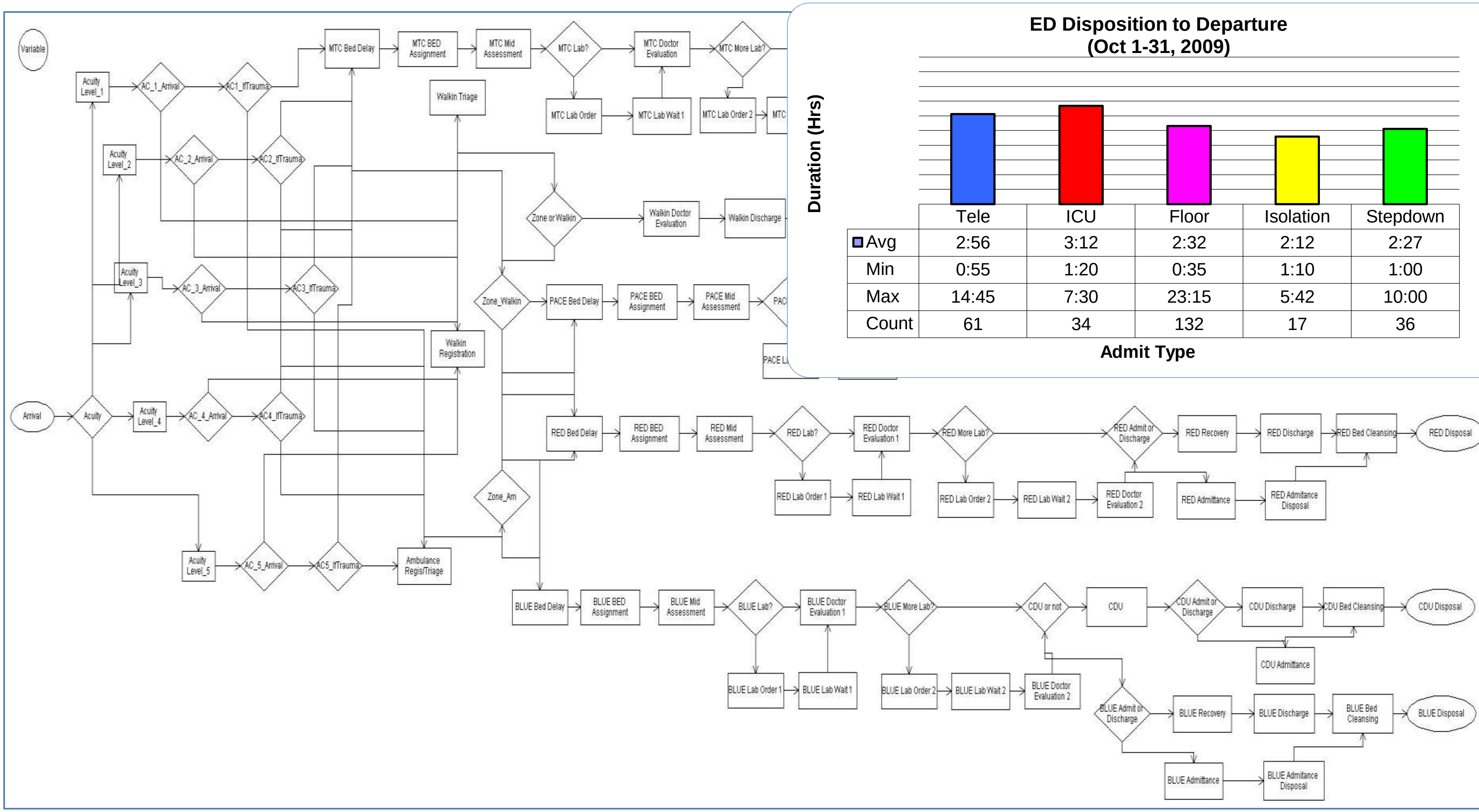
- Large-scale and fast simulator
- *Intractable, non-closed form* nonlinear mixed integer programming resource allocation

min	$z = f\left(\sum_{j \in \mathbf{S}} g_j, c, \theta\right)$		(0)
s.t.	$\underline{m_{ijr}} \le x_{ijr} \le \overline{m_{ijr}},$	$\forall\, r \in \mathbf{R}, i \in \mathbf{T}_r,\ j \in \mathbf{S}_{ir}$	(1)
	$\sum_{j \in \mathbf{S}_{ir}} x_{ijr} \le n_{ir},$	$\forall\, r \in \mathbf{R}, i \in \mathbf{T}_r$	(2)
	$w(x)_j \le w_{max}$ $q(x)_j \le q_{max}$ $u_{min} \le u(x)_j \le u_{max}$	$\forall\, j \in \mathbf{S}$	(3)
	$\theta(x) \ge \theta_{max}$ $c(x) \le c_{max}$		(4)
	$x_{ijr} \in \mathbf{Z}_+$	$\forall\, r \in \mathbf{R}, i \in \mathbf{T}_r,\ j \in \mathbf{S}_{ir}$	(5)

- 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)

	Tele	ICU	Floor	Isolation	Stepdown
Avg	2:56	3:12	2:32	2:12	2:27
Min	0:55	1:20	0:35	1:10	1:00
Max	14:45	7:30	23:15	5:42	10:00
Count	61	34	132	17	36

Admit Type

Model Validation

ED Zone	Phase I: Train Aug 2008 – Feb 2009 Validate: Mar – May 2009					Phase II: Train Oct – Dec 2010 Validate: Jan – Mar 2011			
	Hospital Statistics		Simulated			Hospital Statistics		Simulated	
	LOS	Patient Volume	LOS	Patient Volume		LOS	Patient Volume	LOS	Patient Volume
Overall	10.59 h	8274*	10.49 h	8446		7.97 h	8421	8.02 h	8398
Blue zone	14.54 h	2141	13.90 h	2137		11.40 h	2107	11.78 h	2126
Red zone	12.54 h	2097	11.96 h	2140		8.98 h	2083	8.37 h	2133
Trauma	7.85 h	271	7.98 h	251		6.80 h	268	6.86 h	259
Detention	13.85 h	437	12.93 h	407		10.90 h	441	10.53 h	432
PACe	7.90 h	2037	8.60 h	1983		5.10 h	1920	5.60 h	1983
Walk-in	3.20 h	990	3.30 h	992		2.50 h	950	2.88 h	940
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.								

Acuity Level	72-hour return		30-day return	
	10-fold cross validation	Blind prediction accuracy	10-fold cross validation	Blind prediction accuracy
1: Immediate	0.839	0.827	0.783	0.754
2: Emergent	0.7	0.7	0.797	0.79
3: Urgent	0.701	0.705	0.785	0.785
4: Less urgent	0.711	0.701	0.802	0.8
5: Non-urgent	0.705	0.705	0.77	0.785
None – missing	0.753	0.747	0.898	0.911
Overall	0.71	0.711	0.793	0.787
Payment Type				
INSURANCE	0.865	0.859	0.847	0.848
SELF-PAY	0.671	0.673	0.769	0.766
MEDICARE	0.701	0.709	0.775	0.779
MEDICAID	0.661	0.674	0.765	0.767

Phase I Recommendations

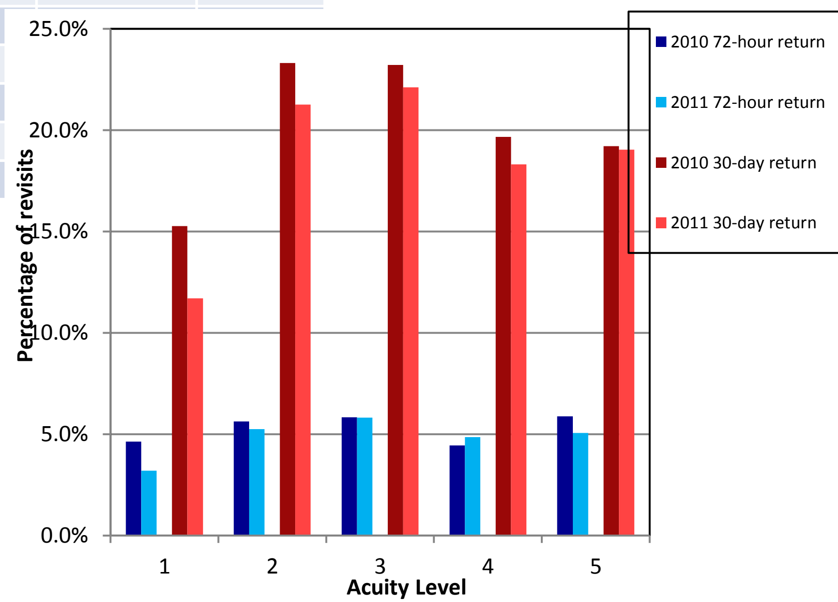
	Actual Hospital Operations	Simulation Systems Performance						
	Mar - May 2009		Systems Improvement					
	Actual Hospital Statistics	Simulation Output (using Aug – Dec 2008 observed data for training)	System Solution (Options 1-4)	Option 1. Combine registration & triage	Option 2. Reduce lab X-ray turnaround (-15 min)	Option 3. Optimize staffing in Blue & Red zones	Option 4. Optimize staffing in triage, walk-in & PACe	Option 5. Combine Blue &Red zones with optimized staffing
Overall LOS	10.59 h	10.49 h	7.33 h	10.02 h	9.22 h	9.84 h	9.49 h	7.68 h
Overall Ave wait time	4.51 h	4.34 h	1.39 h	3.95 h	2.50 h	3.87 h	3.64 h	1.76 h
Blue Zone LOS	14.54 h	13.9 h	11.08 h	12.89 h	11.83 h	13.38 h	14.00 h	8.70 h
Red Zone LOS	12.54 h	11.96 h	8.64 h	11.34 h	10.34	10.62 h	12.01 h	See above
Trauma LOS	7.85 h	7.98 h	6.94 h	7.51 h	7.49 h	7.74 h	7.98 h	7.70 h
Detention LOS	13.85 h	12.93 h	10.17 h	13.95 h	11.36 h	12.46 h	13.95 h	9.16 h
PACe LOS	7.90 h	8.60 h	3.64 h	8.60 h	7.95 h	7.74 h	4.03 h	6.63 h
Walk-in LOS	3.20 h	3.30 h	1.9 h	3.31 h	2.86	3.2 h	2.49 h	2.94 h

Phase I Implementation Results

ED Zone	Phase I: Comparison of ED Performance (Actual Hospital Monthly Statistics)							
	Original		Implementation of Recommendations					
			Options 1-4, 7, 8		Options 1-4, 7, 8, 9 (clinical decision unit for observation)		Options 1-4, 7, 8, 9, 10 (redirect non-urgent visits to alternative care)	
	Mar – May 2009		July 2009 – Dec 2010		Jan – Aug 2011		Sep 2011 – Dec 2011	
	Length of Stay (l*)	Patient Volume	Reduction in LOS (l – l*)	Patient Volume	Reduction in LOS (l-l*)	Patient Volume	Reduction in LOS (l-l*)	Patient Volume
Overall	10.59 h	8274	-3.00 h	8315	-2.66 h	8421	-2.29 h	7664
Blue zone	14.54 h	2141	-3.26 h	2525	-3.14 h	2317	-3.22 h	2503
Red zone	12.54 h	2097	-3.78 h	2109	-3.80 h	2230		
Trauma center	7.85 h	271	-1.01 h	252	-1.19 h	283		
Detention	13.85 h	437	-3.12 h	420	-2.95 h	446		
PACe	7.90 h	2037	-3.02 h	2104	-3.18 h	2098		
Walk-in	3.20 h	990	-1.0 h	945	-0.85 h	970		

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

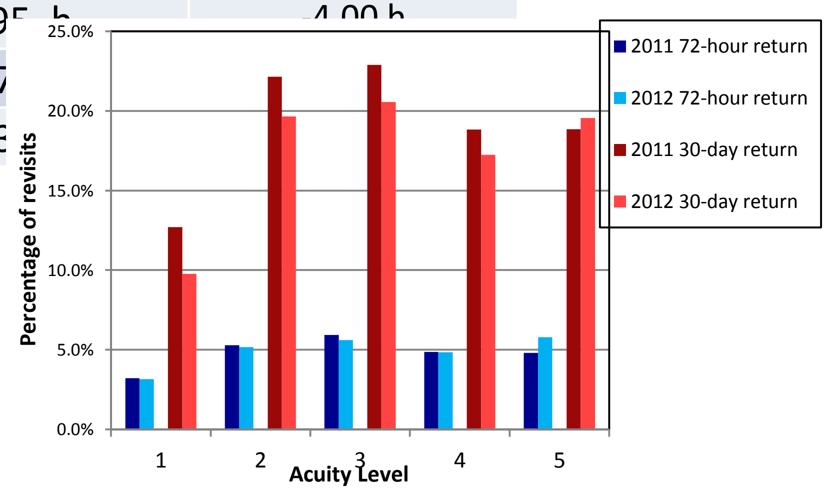
* The new trauma center was opened in November, 2011.
# A significant number of non-urgent ED patients were redirected to the alternative care facility since August 19, 2011, thus resulting in a significant drop in Walk-in patients.



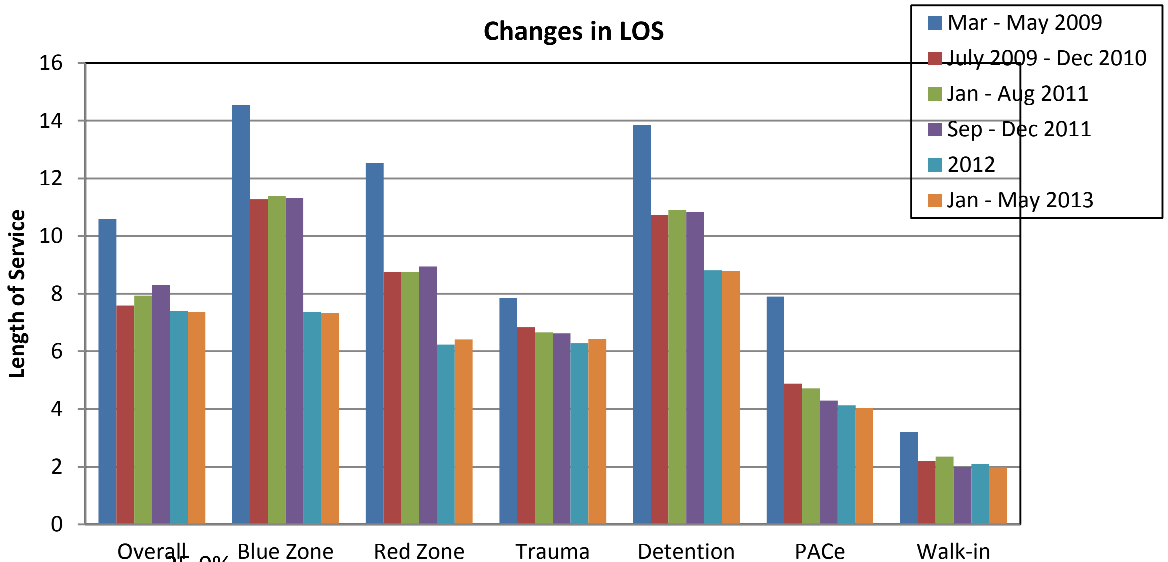
Phase II Implementation Results

	Actual Hospital Operations Aug – Dec 2011	Simulation Systems Performance		
		Global Strategy: System optimization (resource + layout)	Option 11: Optimize worker allocation	Option 12: Combine Blue and Red zones
Overall	8.30 h	6.79 h (-1.51 h)	7.21 h (-1.09 h)	6.94 h (-1.36 h)
Blue zone	11.32 h	6.24 h (-5.08 h)	6.66 h (-4.66 h)	6.61 h (-4.71 h)
Red zone	8.94 h	6.24 h (-2.70 h)	6.19 h (-2.75 h)	6.61 h (-2.33 h)
Trauma center	6.63 h	6.46 h (-0.17 h)	6.16 h (-0.47 h)	6.47 h (-0.16 h)

ED Zone	Phase II: Comparison of ED Performance (Actual Hospital Monthly Statistics)		
	Original (from Phase I improvement)	**Implementation of Recommendations**	
		Option 11 (optimizing overall ED staffing)	
	Sep 2011 – Dec 2011	2012	Jan – May 2013
	Length of Stay (l**)	Reduction in LOS (l - l**)	Reduction in LOS (l-l**)
Overall	8.30 h	-0.90 h	-0.93 h
Blue zone	11.32 h	-3.9	-4.00 h
Red zone	8.94 h	-2.7	[illegible]
Trauma center	6.64 h	-0.3	[illegible]



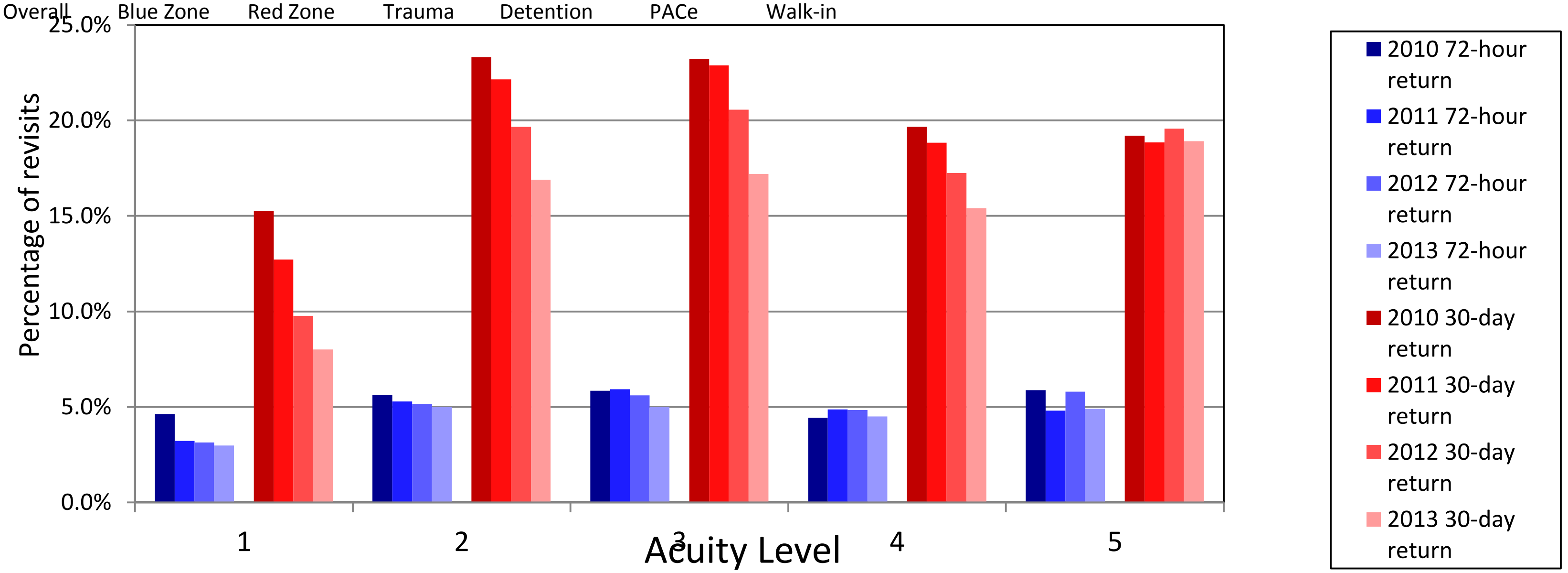
Grady Global ED System Transformation



Blue/Red/PACe: -50%

Trauma: -18%

Detention: -36%



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

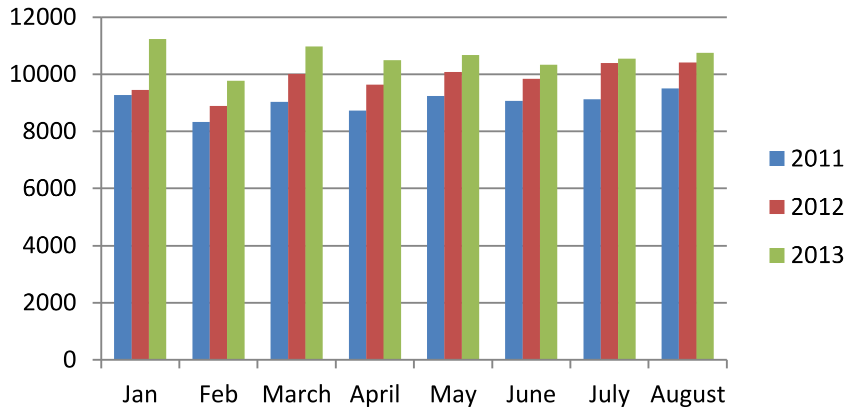
- Increase throughput
  - ~$41.8 million
- Reduce revisits
  - ~$7.5 million (plus much more from reduced side-effects)
- New business (non-urgent alternative care):
  - ~$4.6 million
- Expansion in trauma care
  - ~$9.1 million
- Timeliness of care
  - Reduction in disability and improved outcomes
    - 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