Advancing Public Health and Medical Preparedness with Operations Research

Centers for Disease Control and Prevention Team

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Emergency Response and Medical Preparedness: The Role of Operations Research

Greg Burel, Director
Division of Strategic National Stockpile
Today’s Strategic National Stockpile
Supporting National Health Security
*It’s more than stuff!*

- Acquire and manage countermeasures and medical devices to meet requirements to assure regulatory compliance, viability and safe effective use
- Develop and support federal/state/local and private sector partners to effectively use SNS material
- Create guidance and policy for safe and effective implementation of a countermeasure response
  - Scientific research
  - Clinical guidance and support
  - Regulatory management
- Provide subject matter expertise to create and manage alternate/surge supply chains
- Scored SLTT reviews that show return on preparedness investment
Today’s Strategic National Stockpile Operation
Supporting National Health Security

- Manages a supply of life-saving medical materiel designed to supplement and re-supply state and local public health agencies in the event of an emergency
- Supports the nation to increase ability to rapidly and correctly dispense medical assets in an emergency
- Integrates with state developed plans to receive and distribute countermeasures as quickly as possible
- Responds to requests for federal assistance for CDC in medical countermeasure response working with public health to determine what support is needed
- Deploys support teams to assist during a public health emergency
- Refines guidance and requirements through sound application of science
- Delivers unique countermeasures available from no other source
Whole of Community Response

“Our national preparedness is the shared responsibility of all levels of government, the private and nonprofit sectors, and individual citizens. Everyone can contribute to safeguarding the Nation from harm”.

Presidential Policy Directive 8
March 30, 2011
Dispensing Challenges Present Partnership Opportunities to Create Community Resilience

- Dispensing is primarily conducted through Points of Dispensing (POD)
  - POD Staffing requirements are beyond the capacity of many jurisdictions
  - Limited Health Department staffing at state and local levels dedicated to countermeasure dispensing planning

- Declining state tax base and decreased federal public health preparedness funding
  - Eroding public health infrastructure
  - State and local government staff furloughs and lay-offs
  - Inability to maintain staffs to sustain planning and preparedness efforts

- Difficulty in measuring the capacity to achieve the 48 hour “challenge”
The Benchmark Challenge
Reduce Catastrophic Loss of Lives
in an Aerosolized Anthrax Event

Percent We Save with Oral Antibiotics
Non-specific flu-like symptoms

% of ill population saved
0 20 40 60 80 100
0 1 2 3 4 5 6 7 8
Time after Attack (days)

Detect  Decide  Distribute  Dispense

8%
**CDC Historical Approach**

- **CDC Maxi-Vac**: a system designed via Arena-Optquest linking simulation and optimization to determine optimal staffing.
  - Even for 25 workers, required more than 10 hours to run, returned a solution far from “optimal”.
- **Arlington, Virginia smallpox exercise highlighted the importance of a real-time system**
  - develop operational plans based on their regional needs
  - analyze trade-offs
  - perform dynamic changes as an event unfolds (on staffing assignments, floor-plan reconfiguration, etc.)
Richard Besser, M.D.

- Director, Coordinating Office for Terrorism Preparedness and Emergency Response
- Previous CDC Acting Director
Goals

• Prevent illness, save as many lives as possible utilizing limited resources (time, labor, finance)
  – Mass dispensing of medical countermeasures to minimize the number of deaths and illnesses, and to limit the extent of a potential epidemic

• Best use of local resources

• Setting gold standards for operations performance

• Informed decision-making (for CDC and local leaders)
Operations Research Offers:

- Fast and robust optimization of scarce resources
- Efficient operations and optimized throughput for maximum population coverage
- Scenario-base training and planning
- Rapid reconfiguration in response to evolving on-the-ground situation
- Strategic and operational planning
- Informed operations and decision-making
- Rapid and objective training of emergency workforce
- Portable knowledge across sites
RealOpt-POD©

- Integrates simulation and optimization technology into a unified software framework for realistic modeling of large-scale real-world applications with human cognitive and behavioral elements.
- Rapidly optimizes overall resource allocation, system performance, processes, and operations.
OR Technological Advances

RealOpt-Regional©

- Attacks NP-hard facility location problems with real-time socio-spatial interfaces.
- Solves large-scale instances (in the order of 10 million variables) to near-optimality (within 8%) within seconds.
- Enables a tactical and strategic tool for regional planning and actual execution.
RealOpt© suite

- Offers a powerful cognitive – analytic integration, where input from users translates “automatically” into back-end sophisticated mathematical models for optimization and simulation.
Road Map of Our Work

• OR-based decision support for population flow planning, medication flow planning, and real-time resource allocation within dispensing facilities.
• Operational and strategic planning, optimal setup of regional PODs and its regional stockpile/distribution planning.
• Real-time dynamic reconfiguration
• Disease propagation modeling and mitigation strategies
• Responses to other hazards
Actual Point-of-Dispensing Design

Smallpox walk-in open POD, 2003

Full-scale anthrax drill walk-in open POD, 2007

Hepatitis B drive-through open POD, 2008

Flu vaccine closed POD, 2009
I. RealOpt-Regional©
Facilitates Strategic Planning

• Given a regional population, determine where and how many PODs are needed for optimal operations
• How to direct residents to these locations?
• Multiple Objectives: minimize average distance/time to the closest dispensing location, as well as minimize facility set-up cost.
Large-Scale Dispensing Population Flow

• Given a regional population, determine where and how many PODs are needed for optimal operations
• Determine optimal assignment of individuals to various PODs
• Determine optimal staffing/resources needed at each POD for required throughput
Large-Scale Dispensing Population Flow

• Given a regional population, determine where and how many PODs are needed for optimal operations
• Determine optimal assignment of individuals to various PODs
• Determine optimal staffing/resources needed at each POD for required throughput
The 11 districts and the number of households
Task for RealOpt-Regional©: Model and study the impact of the number of dispensing locations on the average travel distance. Model has many variations.

Facility Location Model:
- Minimize average distance travelled or travel time
- Constraints
  - Each household is assigned to 1 POD (satisfying local constraints)
  - Maximum capability of each POD (space, fire code, parking, etc)
  - Maximum number of PODs
- Solution
  - Optimal # and placement of PODs
  - Routing of each household

Computational Challenges: require sophisticated and rapid algorithms
2-stage Mixed Integer Programming approach

Let $K = \{1, \ldots, k\}$ be the number of districts
- $G_i$ = set of grids in district $i$
- $d(r,l)$ = distance between grids $r$ and $l$
- $d_{\text{max}}$ = maximum allowed travel distance
- $c_l$ = the capacity of the facility at grid $l$.
- $P_r$ = population of grid $r$

Decision variables
- $y_l = 1$ if facility site at grid $l$ is selected for setting up a dispensing facility, 0 otherwise
- $x_{rl} = 1$ if the population in grid $r$ is served by the facility at grid $l$, and 0 otherwise
Facility Location Model

Minimize $\sum \sum y_i$

Subject to

$\sum_{l \in G_i} y_i \geq 2$

$d(r,l)x_{rl} \leq d_{\text{max}} y_i$

$\sum_{l \in G_i} x_{rl} = 1$

$\sum_{r \in G_i} x_{rl} p_r \leq c_l$

$x_{rl}, y_i \in \{0,1\}$

Minimize total distance/time travelled

Minimize $\sum \sum \sum x_{rl} d(r,l) p_r$

Subject to

$\sum_{l \in G_i} y_i = n_i$

$d(r,l)x_{rl} \leq d_{\text{max}} y_i$

$\sum_{l \in G_i} x_{rl} = 1$

$\sum_{r \in G_i} x_{rl} p_r \leq c_l$

$x_{rl}, y_i \in \{0,1\}$

Minimize # of facilities needed
### Benchmarking on CPLEX V12

A small instance: approx. ~300,000 0/1 variables

<table>
<thead>
<tr>
<th>Elapsed Time CPU seconds</th>
<th>Best IP obj.</th>
<th>Best LP obj.</th>
<th>Branch-and-bound nodes searched</th>
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</thead>
<tbody>
<tr>
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<td>48</td>
<td>4.0000</td>
<td>10, 56 cuts</td>
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<td>4.0000</td>
<td>60</td>
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<td>711531.85</td>
<td>11</td>
<td>4.0000</td>
<td>49000</td>
</tr>
</tbody>
</table>
Challenges

Goal: *Fast* and *good* solutions

- Two approaches
  - **Exact algorithms**: so we can determine optimal solutions
  - **Fast heuristics**: so it is practical and we can compare how well they do against the optimal solutions
Consider the IP:
\[
\text{minimize } c^T x, \ A x \leq b, \ x \geq 0, \ x \text{ binary}
\]

Conflict Hypergraph H:

\[V = x, \ E = \text{knapscack covers (i.e., these variables cannot be simultaneously chosen in a feasible solution.)}\]

**Theory:** Hyper-cliques, (anti) odd holes, (anti) wheels, (anti) webs, (multi) stars, and other structures

**Computational advances**
Adaptive Genetic Algorithm

Evaluation (decoding)

Potential served sets are selected in the sequence of indexes on chromosome until all the grids are covered.

Identify and delete redundant potential served set

Chromosome Representation

Corresponding population grids

Population grids are then assigned to their closest open facility.
Local Improvement

- Insertion and switch can improve solution only when open facilities are relocated first.
- Switch is computationally intensive and hence only applied to the best solution in each generation.
Computational Significance

Of the over 2900+ MIP instances (for metro Atlanta)

- **Exact algorithm**
  - solves all except 5 to proven-optimal within 1800 CPU seconds
  - Within 900 CPU seconds, a feasible solution is returned within 5% to optimality.

- **Heuristic algorithm**
  - Within 10-50 CPU seconds, solutions returned are within 8% to optimality in many instances
  - A few instances take about 2 minutes.

*Real-time is very critical for planners.*
Optimal vs Heuristics

Tradeoffs – no. of facilities vs distance traveled vs facility hourly capacity
Realistic & Cost-Effective Dispensing –
Public Health + Private Sector

Heterogeneous mixed of
dispensing modalities:

Public PODs:
- Drive-through (brown)
- Walk-through (blue)

Private/Closed PODs:
- University/college campus
- Assisted living facilities
- Prisons/Jails
- Large corporation Offices
- Airport

Mobile PODs:
- Deliver to special need population (disabled, home-bound, etc)
Zoom in: Most Cost-effective Public PODs

Heterogeneous mode of dispensing, Variation of throughput
RealOpt-Regional©: Basic planning steps
Large-Scale Dispensing Population Flow

• Given a regional population, determine where and how many PODs are needed for optimal operations
• Determine optimal assignment of individuals to various PODs
• Determine optimal staffing/resources needed at each POD for required throughput
II. RealOpt-POD©
Multiple Resource Allocation
Operational/Tactical Planning

• Objectives:
  – minimize resources (given required throughput)
  – maximize throughput (given available resources)

• Constraints:
  – maximum limits on wait time and queue length
  – range of utilization desired at each station
  – assignability and availability, for each resource group, of resource types at each station
  – maximum limit on the cycle time of the individual.
Nonlinear Mixed Integer Program

Parameters:

- $R$: the set of resource groups.
- $T_r$: the set of resource types in resource group $r$, $r \in R$;
- $S$: the set of services in the process flow;
- $S_{ir} \subseteq S$: the set of services in which resource type $i$ in resource group $r$ can be assigned. This models the assignability of the resource (e.g., based on skills of workers);
- $k_{ijr}$: the cost of assigning a resource of type $i$ in resource group $r$ to station $j$. $r \in R$, $i \in T_r$, $j \in S_{ir}$;
- $\underline{m_{ijr}}$ and $\overline{m_{ijr}}$: the maximum and minimum number of resources of type $i$ in resource group $r$ that may be assigned to station $j$. $r \in R$, $i \in T_r$, $j \in S_{ir}$;
- $n_{ir}$: the number of available resources of type $i$ in resource group $r$. $r \in R$, $i \in T_r$;
- $w_{j}, q_j$, and $u_j$: the average wait time, average queue length, and average utilization rate, respectively, at station $j$. $j \in S$;
- $C$: the average cycle time (i.e., the length of time a customer spends in the system); and
- $\theta$: the average throughput (number of customers served in a specified period).
Decision Variables

- $x_{ijr}$: the number of resources of type $i$ in resource group $r$ assigned to station $j$. $r \in R$, $i \in T_r$, $j \in S_{ir}$

Cost functions

- Cost at each station = $g_j(k_{ijr}x_{ijr}, w_j, q_j, u_j)$
- Total cost = $\sum_j (g_j, c, t \text{ het } a)$
- Not a closed form
NMIP: Mathematical Formulation

\[
\begin{align*}
\text{min} & \quad z = f \left( \sum_{j \in S} g_j, c, \theta \right) \quad (0) \\
\text{s.t.} & \quad m_{ijr} \leq x_{ijr} \leq m_{ijr}, \quad \forall r \in R, i \in T_r, j \in S_{tr} \quad (1) \\
& \quad \sum_{j \in S_{tr}} x_{ijr} \leq n_{ir}, \quad \forall r \in R, i \in T_r \quad (2) \\
& \quad w(x)_j \leq w_{\text{max}} \\
& \quad q(x)_j \leq q_{\text{max}} \quad \forall j \in S \quad (3) \\
& \quad u_{\text{min}} \leq u(x)_j \leq u_{\text{max}} \\
& \quad \theta(x) \geq \theta_{\text{max}} \\
& \quad c(x) \leq c_{\text{max}} \quad (4) \\
& \quad x_{ijr} \in \mathbb{Z}_+ \quad \forall r \in R, i \in T_r, j \in S_{tr} \quad (5)
\end{align*}
\]

Cost at each station = \( g_j \left( k_{ijr} x_{ijr}, w_j, q_j, u_j \right) \)
Computational Strategies

1. **Input Model**
2. **Create Internal Flowchart & mathematical models**
3. **Determine worker-requirement**
4. **Simulate system performance**
5. **Generate Report & Graphs**
6. **Simulate System**
7. **Min-cost network to determine worker assignment**
8. **Report**
Initialize the number of workers at each Process block

Compute average total service and delay time

**Simulate** flows and waiting times

Identify Process blocks that are among the longest total waiting time

**Optimize** the number of workers at these Process blocks

Identify Process blocks with violated average waiting time

**Optimize** the number of workers at these Process blocks

**Simulate** flows and waiting times

Simulation extension and system flow time feasible?

Yes

No

Average wait time at each Process block feasible?

Yes

No

Waiting time based local search via Discrete Event Simulation
Resource Allocation –

Minimizing total number of critical personnel required to man the public PODs for each 12-hour shift
III. Disease Propagation
Novel Model of Disease Propagation

SEPAIR: Susceptible, exposed, infectious, asymptomatic, symptomatic, recovered.

Use default or user input: Incoming rates, dwell time, force of infection
Novel Model of Disease Propagation

Select: SEIR, SEPAIR

User-input: own compartmental models

Outside POD

\[
\frac{d}{dt} S_0 = -r_a \frac{S_0}{N_0} - \beta (r_0 + A_0 + I_0) \frac{S_0}{N_0} \\
\frac{d}{dt} E_0 = -r_a \frac{E_0}{N_0} - \mu E_0 + \beta (r_0 + A_0 + I_0) \frac{S_0}{N_0} \\
\frac{d}{dt} R_0 = -r_a \frac{R_0}{N_0} + (1 - p_e) (\mu A_0 + \mu I_0) \\
\frac{d}{dt} A_0 = -r_a \frac{A_0}{N_0} - \mu A_0 + (1 - p_e) \mu E_0 \\
\frac{d}{dt} P_0 = 0
\]

Intra POD

\[
\frac{d}{dt} S_i = \psi r_a \frac{S_i}{N_0} + \sum_{j \neq i} \phi_a \min \left( \frac{A_j}{N_j}, \frac{I_j}{N_j} \right) - \mu S_i - \beta_i \sum \min \left( \frac{A_j}{N_j}, \frac{I_j}{N_j} \right) - \mu E_i + \beta_i \sum \min \left( \frac{A_j}{N_j}, \frac{I_j}{N_j} \right) \\
\frac{d}{dt} E_i = \psi r_a \frac{E_i}{N_0} + \sum_{j \neq i} \phi_a \min \left( \frac{A_j}{N_j}, \frac{I_j}{N_j} \right) - \mu E_i \\
\frac{d}{dt} A_i = \psi r_a \frac{A_i}{N_0} + \sum_{j \neq i} \phi_a \min \left( \frac{A_j}{N_j}, \frac{I_j}{N_j} \right) - \mu A_i - \mu A_i + (1 - p_a) \mu E_i \\
\frac{d}{dt} I_i = \psi r_a \frac{I_i}{N_0} + \sum_{j \neq i} \phi_a \min \left( \frac{A_j}{N_j}, \frac{I_j}{N_j} \right) - \mu I_i + p_a \mu E_i \\
\frac{d}{dt} R_i = \psi r_a \frac{R_i}{N_0} + \sum_{j \neq i} \phi_a \min \left( \frac{A_j}{N_j}, \frac{I_j}{N_j} \right) - \mu R_i + (1 - p_e) (\mu A_i + \mu I_i) \\
\frac{d}{dt} P_i = p_D (\mu A_i + \mu I_i)
\]
Novel Model of Disease Propagation

• Facilitates decision-making regarding triage (symptoms vs no symptoms)
  – Scale of outbreaks
  – Ease of infectivity

• Allows modeling of re-infection; infectivity between vaccinees and workers

• Facilitates POD design: *operations versus disease propagation*
IV. Cognitive Analytics
Automatic Translation

Modeling and optimizing systems performance:

- Translate to backend simulation and optimization models
- Can change/draw layout with a mouse click and keystrokes.

Powerful and novel modeling framework for epidemiologists:

- Translate flowcharts to discrete event simulation \textit{and} ODE systems
- Enable easy comparisons of the two modeling approaches epidemiologists typically use.

Combines planning with disease propagation mitigation
### Population served

<table>
<thead>
<tr>
<th>Population served</th>
<th># of Nurses</th>
<th># of Health Technicians</th>
<th># of Volunteers/Traffic Controllers</th>
<th># of Security Personnel for intra-POD security</th>
<th># of Interpreters</th>
</tr>
</thead>
<tbody>
<tr>
<td>8,057,135 (96.3% of NY City Population)</td>
<td>2041</td>
<td>1311</td>
<td>606</td>
<td>2670</td>
<td>1293</td>
</tr>
</tbody>
</table>
Significance to Users

Bernard Hicks

- Emergency Response Manager
- DeKalb County Board of Health, Georgia

- Co-Chair, Cities Readiness Initiative Planning Committee.

Written letters of usage
With RealOpt: Less Labor, More Throughput

<table>
<thead>
<tr>
<th>Site</th>
<th>Population</th>
<th>Type of Medical Countermeasures</th>
<th>Labor usage After / Before</th>
<th>Throughput After / Before</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>698129</td>
<td>H1N1 vaccine</td>
<td>0.285</td>
<td>4.66</td>
</tr>
<tr>
<td>2</td>
<td>127932</td>
<td>H1N1 vaccine</td>
<td>0.378</td>
<td>3.14</td>
</tr>
<tr>
<td>3</td>
<td>1464202</td>
<td>Flu vaccine</td>
<td>0.594</td>
<td>1.80</td>
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<tr>
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<td>1420239</td>
<td>Flu vaccine</td>
<td>0.555</td>
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<td>410443</td>
<td>Flu vaccine</td>
<td>0.641</td>
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<td>6</td>
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<td>Flu vaccine</td>
<td>0.684</td>
<td>2.60</td>
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<tr>
<td>7</td>
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<td>Oral antibiotics</td>
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<td>0.350</td>
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<td>0.145</td>
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<td>Oral antibiotics</td>
<td>0.197</td>
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</tr>
</tbody>
</table>
RealOpt Can Decrease Morbidity and Mortality

Aerosolized Anthrax Scenario

- No prophylaxis
- Local staff assignment
- RealOpt assignment

Prophylaxis campaign executed in 5 days via RealOpt staffing
Detection and decision-making take no more than 2 days
Adopted Beyond U.S. Public Health Community

- All-hazard Evacuations (First Responders)
- Crowd Control (Public Venues)
- International
  - Protecting US military personnel overseas
  - Tanzania optimizing scarce healthcare resources
  - Israeli Ministry of Health
  - Qatar Red Crescent Society
  - Haiti earthquake (food, water/supply distribution)
  - Japan Fukushima disasters (radiological screening, shelters, supplies)
OR Technological Advances

I. Powerful simulation-optimization system with complex modeling and rapid computation

• integrated simulation and optimization technology into a unified software framework for realistic modeling of large-scale real-world applications with human cognitive and behavioral elements.
• created a more seamless and more powerful ‘decision support’ environment. The software assists in optimizing overall systems performance, processes, and operations.
II. Large-scale optimization and computation

• Attacks NP-hard facility location problems with real-time socio-spatial interfaces.

• Large-scale instances (~10 million variables) can be solved to near-optimality (within 8%) within seconds, enabling a tactical and strategic tool for regional planning and actual execution.

• Designs a powerful simulation-guided algorithm for finding ‘good’ feasible solutions for resource allocation instances with the simulation-optimization environment for real-time decisions.
III. Powerful cognitive – analytic integration

- Developed techniques for automatically interpreting human computer-rendered drawings of processes/tasks in our design panel into system process maps for simulation and optimization. As complex visualization and graphical user interfaces become ubiquitous in decision analysis, automatic translation from mouse clicks and keystrokes to analytic workflow models become essential in human-computer interface.

- Translates epidemiology human-input block model to
  - **Ordinary differential equation systems**
  - **Discrete event simulation**
  *These are new capabilities in epidemiology*

- Exploits multiple automatic translations that offer seamless user-interfaces as well as powerful cognitive – analytic integration.
IV. New polyhedral theory

- Motivates/influences the development of new polyhedral theory related to hypergraphic structures (high-dimensional lattices containing multiple sets of nodes that cannot be simultaneously feasible).
- Facilitates development of exact algorithms for solving many intractable facility location problems.
CDC Nationwide Broadcast on Mass Antibiotic Dispensing

• Taking the Guesswork Out of the POD Design
• A short excerpt of Dr. Neff’s comments, and response to questions sent in by audience.
  – Linda Neff, Ph.D., Senior Science Officer, Epidemiologist, Division of Strategic National Stockpile, CDC
Primary Benefits: Prevent Illness, Save Lives

- More people receive treatment within the same resource constraints
  - For the 12 sites analyzed
    - Throughput increases ranged from 175% to 1000%.
    - Conservative estimate (using 175%): dispense to 5.25 million more people.
    - Translates to prevent illness or death of 1.3 million people (assuming a 25% exposure rate).
  - Other sites reported
    - Uniformly report improvement in throughput and reduce staff usage
    - Facilities planning/training
Benefits: Widespread Adoption

• **User base**: 4000+ user sites
• **Emergency drills and dispensing events**:
  – Used in hundreds of dispensing drills and vaccination events (anthrax drills, actual seasonal flu, H1N1, Hepatitis B)
  – Careful before/after studies were conducted in a sample of twelve sites, which served populations ranging from 128,000 to 4,023,000
Benefits: Qualitative Impacts

- National security and emergency response capability:
  - establishes decision-makers’ reliance on analytically based strategic/tactical decision and policy making (budget, resource, assessment, training)
  - improves mass dispensing capability and efficiency
  - lessens the subsequent disease cost, care burden, mortality, and economic impact
  - supports effective & dynamic operational planning and execution
  - establishes knowledge databank for accurate prediction, dissemination, collaborative competition
Benefits: Quality Assurance and Training

- Removes operator-dependent planning
- Establishes “standard” quality assurance guidelines
- Provides better overall coordination
  - Simultaneous reduced staffing needs, drastically increased throughput, and decreased operator-dependency
- Facilitates rapid training, enables alternative administrative leaders
- Encourages collaborative competition that benefits the nation’s preparedness.

Critical to major catastrophic events
Benefits:
Quality of service and worker morale

- Reduces wait-time and cycle time
  - Improved quality of service
  - better control of crowds
  - better infection mitigation strategies
- Maintains rather even utilization among workers (improve performance, morale)
Concluding Remarks

• Through application of operations research and decision analytics, CDC and Georgia Tech are providing a critical resource to national, state and local responders

• This tool has been widely adopted, with greater than 4,000 user sites across the country

• The gains made through the use of the RealOpt tool are real and lasting – improving preparedness to protect the nation’s health security