

Boat Allocations, Football Inspections, Cargo Handling, and Nuclear Detection with Taxis: Examples of Model Validation

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“Changing the Culture”

- Sometimes modeling tools lead to policy recommendations that require changing the way we are used to doing things.
- **“Changing the culture”**
- But how can we be sure that our model’s recommendations are valid?



CHANGING THE CULTURE

Changing the Culture

- We give four examples of use of models in applications to homeland security
- In each case, policy analytics (data-driven modeling and simulation) led to changes in policy that required changes in the “usual way of operating”: Changes in behavior, attitudes, or other aspects of public policy: ***Changes in the Culture.***

CCICADA Center

- CCICADA is the Command, Control, and Interoperability Center for Advanced Data Analysis
- Founded by US Dept. of Homeland Security as a “university center of excellence”
- Based at Rutgers University, but with 17 partner institutions



Four Examples from Work at CCICADA

- Allocation of USCG Boats to Boat Stations
- Sports Stadium Security
- Container Inspection at Ports
- Nuclear Detection with Taxis



Example I: Coast Guard Boat Allocation Problem

- We have worked with the US Coast Guard on a variety of projects involving information-based modeling and simulation and other advanced data analysis tools



Rutgers group touring
Port of Philadelphia with
Coast Guard Sector
Delaware Bay



Boat Allocation Module (BAM)

- The US Coast Guard has boat stations all around the country
- Each station has different areas of responsibility (missions)
 - Search and rescue
 - Drug interdiction
 - Enforcement of Fisheries Regulations
- There are many types of boats
- Some boats are better at some types of “missions”
- For each station, we have historical data on number of hours required for each type of mission
- Problem: Assign boats to boat stations so number of mission hours required is achieved, but do so “efficiently”

BAM Model

- So, we have:
 - Missions
 - Boat types
 - Capabilities of each boat type for different missions



Missions (M)	
$m \in M$	Name
1	SAR
2	PWCS
3	LMR
4	CD
5	AMIO
6	ELT
7	RBS
8	Marine Safety
9	MEP
10	ATON
11	Training
12	Cmd Flexibility/Discretion

Boat Types (T)	
$t \in T$	Name
1	MLB
2	SPC-NLB
3	SPC-HWX
4	RB-M
5	RB-S
6	RBS-AUX
7	SPC-LE
8	SPC-SW
9	SPC-AIR
10	SPC-ICE
11	SPC-SKF

Capabilities (C)		
$c \in C$	Name	$\{t \in T \mid G_{tc} = 1\}$
1	AUXOPS	{5, 6}
2	FLOOD	{11}
3	HWX	{1, 2, 3, 4}
4	LH-ICE	{9}
5	PURSUIT	{4, 7}
6	SH-ICE	{10}
7	SHALLOW	{2, 8, 11}
8	SURF	{1, 2, 3}
9	TACTICAL	{1, 4, 5, 6, 7}
10	TRAILER	{5, 6, 8, 11}
11	BIG	{1, 2, 3, 4}

Boat Allocation Module Project

- Overall Project Goal:
 - Design and implement a software package:
 - To be used solely and independently by USCG analysts
 - To serve as a decision-making tool when faced with questions related to re-allocation of boats among USCG stations
- Project sought to create a mathematical model that could produce “good assignments” of boats to boat stations so all station requirements are met.



Boat Allocation Module Project

- What Makes One Boat Allocation Better than Another?
 - **Minimize Budget:** Total cost (of hourly use, personnel training, routine maintenance) is as small as possible, while still allowing all tasks to be completed
 - **Minimize “Unmet Hours”:** Include limiting budget as a constraint and try to minimize the “unmet” task demand.
 - We formalized both ideas, but our tool is designed around the latter. It can, however, be used to do “what if” experiments to address the former.



BAM: Technical Model

- ***UnMet Hours***: Minimize the deviation under the desired number of hours for each mission at each boat station
- ***Precise formulation of the objective function and the constraints was a long-term collaborative effort. CCICADA & USCG people worked closely to formulate and test the model***
- It required:
 - Back and forth with experts on boat allocation
 - Computer experimentation with different versions to make sure constraints were formulated as we intended them to be.

BAM: Technical Model

- We formulated this as a mixed integer programming problem
- Known to be computationally “hard” in theory
- Moderately-sized applications can typically be solved close to optimality in a reasonable amount of time.
- ***Our solution employs a powerful heuristic technique: Branch and Bound***
- We encode our problem in a leading commercial optimization package, ***Xpress-MP***.
- This includes a “state of the art” Branch and Bound method.

BAM: Technical Model

- Model was subjected to extensive and precise testing at all stages of development
- Our software was tested on USCGC computers by USCGC users
- Our software was delivered to the Coast Guard along with a detailed User Guide
- ***It then went through a rigorous, well-defined USCGC “verification, validation & accreditation process” with independent testers before being cleared to use on USCGC computers.***



BAM Model (Unmet Hours)

$$\text{minimize } \sum_{s \in S} \sum_{m \in M} W_{sm} x_{sm} + \alpha \sum_{t \in T} u_t + \beta \sum_{s \in S} v_s \quad (1)$$

$$\text{subject to } \sum_{t \in T} G_{tc} b_{ts} \geq R_{sc} \quad \forall c \in C, s \in S \quad (2)$$

$$\sum_{t \in T} G_{tc} y_{ts} \leq R'_{sc} \quad \forall c \in C, s \in S \quad (3)$$

$$\sum_{s \in S} b_{ts} \leq B_t + u_t \quad \forall t \in T \quad (4)$$

$$\sum_{t \in T} b_{ts} \leq P_s + v_s \quad \forall s \in S \quad (5)$$

$$b_{ts} \leq B'_t y_{ts} \quad \forall t \in T, s \in S \quad (6)$$

$$\gamma \cdot y_{ts} \leq b_{ts} \quad \forall t \in T, s \in S \quad (7)$$

$$h_{tsm} = 0 \quad \forall t \in T, s \in S, m \in M : \lambda_{tm} = 1 \quad (8)$$

$$\sum_{m \in M} h_{tsm} \geq A'_t b_{ts} \quad \forall t \in T, s \in S \quad (9)$$

$$\sum_{m \in M} h_{tsm} \leq (A_t + E_t) b_{ts} \quad \forall t \in T, s \in S \quad (10)$$

$$\sum_{s \in S} \sum_{m \in M} h_{tsm} \leq (A_t + L_t E_t) \sum_{s \in S} b_{ts} \quad \forall t \in T \quad (11)$$

$$h_{t,s,11} \geq U_t y_{ts} \quad \forall t \in T, s \in S \quad (12)$$

BAM Model (Unmet Hours)

$$\sum_{s \in S} \left(\sum_{t \in T} (F_t b_{ts} + V_t \sum_{m \in M} h_{tsm}) + \sum_{i \in I} J_i z_{si} \right) \leq D \quad (13)$$

$$z_{si} \geq \sum_{t \in T} y_{ts} - i \quad \forall s \in S, i \in I \quad (14)$$

$$z_{si} \geq 0 \quad \forall s \in S, i \in I \quad (15)$$

$$x_{sm} \geq H_{sm} - \sum_{t \in T} h_{tsm} \quad \forall s \in S, m \in M \quad (16)$$

$$x_{sm} \geq 0 \quad \forall s \in S, m \in M \quad (17)$$

$$q_{tk} = \sum_{s \in S} Q_{sk} b_{ts} \quad \forall t \in T, k \in K \quad (18)$$

$$q_{tk} \in \{0, 1, 2, \dots\} \quad \forall t \in T, k \in K \quad (19)$$

$$y_{ts} \in \{0, 1\} \quad \forall t \in T, s \in S \quad (20)$$

$$u_t \in \{0, 1, 2, \dots\} \quad \forall t \in T \quad (21)$$

$$v_s \in \{0, 1, 2, \dots\} \quad \forall s \in S \quad (22)$$

$$h_{tsm} \geq 0 \quad \forall t \in T, s \in S, m \in M \quad (23)$$

$$b_{ts} \geq 0 \quad \forall t \in T, s \in S \quad (24)$$

BAM Model – Input Parameters

Input Parameters		
Type	Notation	Description
Set	<i>C</i>	Set of capabilities
	<i>I</i>	Index set $\{1, 2, \dots, T - 1\}$
	<i>M</i>	Set of missions
	<i>T</i>	Set of boat types
	<i>Dis</i>	Set of districts
	<i>Sec</i>	Set of sectors
	<i>S</i>	Set of stations
	<i>K</i>	Set of nil, districts, sectors or individual stations ($K \in \{\emptyset, Dis, Sec, S\}$)

BAM Model – Input Parameters

Array	α	Penalty term per assigned boat of type $t \in T$ exceeding inventory (B_t)
	β	Penalty term per assigned boat exceeding capacity at station $s \in S$
	A_t	Preferred number of hours to be spent on any assigned boat of type $t \in T$
	A'_t	Minimum number of hours to be spent on any assigned boat of type $t \in T$
	B_t	Maximum number of boats of type $t \in T$ available to be assigned
	B'_t	Maximum number of boats of type $t \in T$ allowed at a station
	D	Total budget in U.S. Dollars
	E_t	Maximum number of extra hours allowed for each boat of type $t \in T$
	F_t	Cost of assigning a single boat of type $t \in T$ to a station
	γ	A fraction in $[0, 1]$, denoting the minimum a fractional boat assignment value can take (<i>i.e.</i> b_{ts} is either zero-valued or “not too close” to zero when it is positive)
	G_{tc}	Binary entry denoting if a boat of type $t \in T$ is within capability $c \in C$
	H_{sm}	Preferred number of hours to be spent on missions of type $m \in M$ at $s \in S$
	J_i	Incremental cost of having $i + 1$ boat types assigned, $i \in I$
	λ_{tm}	Binary entry denoting whether a boat of type $t \in T$ is forbidden to perform missions of type $m \in M$ (1) or not (0)
	L_t	Maximum fraction of total extra hours for all boats of type $t \in T$
	P_s	Maximum number of boats allowed at station $s \in S$
	Q_{sk}	Binary value denoting if a station $s \in S$ belongs to unit $k \in K$ (1) or not (0)
	R_{sc}	Minimum number of boats required from the subset of boat types with capability $c \in C$, at stations $s \in S$
	R'_{sc}	Maximum number of boat types allowed at station $s \in S$ to satisfy $c \in C$
	U_t	Minimum number of training hours a station requires when at least one boat of type $t \in T$ is assigned
V_t	Cost per hour of using a single boat of type $t \in T$	
W_{sm}	Weight of importance assigned to missions of type $m \in M$ at station $s \in S$	

BAM Model – Decision Variables

Decision Variables		
Binary	y_{ts}	A value of 1 corresponds to assigning at least one boat of type $t \in T$ to station $s \in S$, 0 otherwise
Integer	q_{tk}	A non-negative integer denotes the number of boats of type $t \in T$ assigned to each unit $k \in K$
	u_t	A non-negative integer denotes how many extra boats of type $t \in T$ are needed in order to ensure feasibility of our problem
	v_s	A non-negative integer denotes how many extra boats of any type are needed at station $s \in S$ in order to ensure feasibility
Continuous	b_{ts}	A non-negative value denotes the (fractional) number of boats of type $t \in T$ assigned to station $s \in S$
	h_{tsm}	A non-negative value denotes the (fractional) number of hours assigned to all boats of type $t \in T$ at station $s \in S$ for missions of type $m \in M$
	z_{si}	A non-negative value denotes the total number of boat types above $i \in I$, at station $s \in S$
	x_{sm}	A non-negative value denotes the total number of hours under the preferred H_{sm} for $s \in S$, $m \in M$

BAM Model (Unmet Hours) Constraint Explanations

- (1) is our objective function, which asks to minimize the total number of hours under the maximum a station $s \in S$ has spent on missions of type $m \in M$, which is typically written as:

$$\text{minimize } \sum_{s \in S} \sum_{m \in M} W_{sm} \left(H_{sm} - \sum_{t \in T} h_{tsm} \right)^+,$$

once the smallest increase in total inventory ($\sum_t u_t$) as well as total pier space ($\sum_s v_s$) have been found (assuming α and β are large enough, *e.g.* 1,000,000);

- (2) guarantees that the minimum number of boats (R_{sc}) is selected from over the feasible set $\{t \in T | G_{tc} = 1\}$ which in turn satisfies the capability requirement of $c \in C$, for each station $s \in S$ (NOTE: we only need to include such constraints when $R_{sc} > 0$ since our variables and parameters are nonnegative);
- (3) guarantees that the maximum number of boat types satisfying the capability requirements (R_{sc}), is not more than that allowed (R'_{sc}) (NOTE: if there is no restriction or $\sum_t G_{tc} \leq R'_{sc}$, then we do not encode such a constraint, and signify as such $R'_{sc} := 0$);
- (4) guarantees that we do not schedule more than the total number of boats (B_t) of type $t \in T$ available to all stations if possible, else u_t will give us a positive number denoting the minimum increase B_t needs for a feasible assignment to exist;
- (5) guarantees that we do not assign more boats in total ($\sum_{t \in T} b_{ts}$) than the maximum number allowed at station $s \in S$ (P_s), else v_s will give a positive number denoting the minimum increase P_s needs for a feasible assignment to exist;
- (6) guarantees that the number of boats of type $t \in T$ at station $s \in S$ (b_{ts}) is not more than that allowed at any station (B'_t , which is equal to B_t if no restriction is to be imposed), and $b_{ts} = 0$ if $y_{ts} = 0$;

BAM Model (Unmet Hours)

Constraint Explanations

- (7) guarantees that we do not assign a fraction of boats (b_{ts}) less than γ percent to any station, and $y_{ts} = 0$ if $b_{ts} = 0$;
- (8) guarantees that if a boat type $t \in T$ cannot satisfy a mission of type $m \in M$, then it is not assigned any hours ($h_{tsm} = 0$), for every station $s \in S$ (NOTE: this can be encoded as a single constraint $\sum_{t,s,m} \lambda_{tm} h_{tsm}$, since $h_{tsm} \geq 0$ and $\lambda_{tm} \geq 0$);
- (9) guarantees that each boat of type $t \in T$ assigned to a station $s \in S$ is given a minimum number of total hours A'_t ;
- (10) guarantees that the total number of hours spent on any mission on boats of type $t \in T$ at station $s \in S$ ($\sum_{m \in M} h_{tsm}$) is at most the total number of preferred hours for all boats of this type ($A_t b_{ts}$) plus the amount of overtime allowed on such boats ($E_t b_{ts}$), otherwise $\sum_m h_{tsm} = 0$ (implying $h_{tsm} = 0$ for each $m \in M$) whenever b_{ts} ;
- (11) guarantees that the total number of hours spent on all boats of type $t \in T$ (over all missions and all stations, $\sum_{s \in S} \sum_{m \in M} h_{tsm}$) is at most the total number of hours preferred for all assigned boats of this type ($A_t \sum_{s \in S} b_{ts}$) plus some fraction of the available amount of overtime ($L_t E_t \sum_{s \in S} b_{ts}$);
- (12) guarantees that if a boat of type $t \in T$ is assigned to station $s \in S$, then that station requires at least U_t hours of training;
- (13) guarantees that the total cost of assigned boats ($\sum_{s \in S} \sum_{t \in T} F_t b_{ts}$), plus the total cost of assigning hours to each boat in use ($\sum_{s \in S} \sum_{t \in T} V_t h_{ts}$), plus the cost of having excess distinct boat types assigned ($\sum_{i \in I} C_i z_{si}$), does not exceed the budget (D);

BAM Model (Unmet Hours) Constraint Explanations

- (14) and (15) linearly encode the terms $z_{si} = \max\{\sum_{t \in T} y_{ts} - i, 0\}$ (also written as $(\sum_{t \in T} y_{ts} - i)^+$), which penalize incrementally any solution using $i + 1$ distinct boat types;
- (16) and (17) linearly encode the terms $x_{sm} = (H_{sm} - \sum_{t \in T} h_{tsm})^+$, which appear in our objective function as the number of “unmet hours”;
- (18) and (19) guarantee that although a fractional number of boats of type $t \in T$ may be allowed at any single station $s \in S$ (b_{ts} , when $K = S$), we still have an integral number assigned to each unit $k \in K$ ($\sum_{s \in S} Q_{sk} b_{ts}$) (NOTE: if $K = S$, then $q_{tk} = b_{ts}$ with $k = s$, so we can drop the variables q and just let b be integral; and we let $K =$ denote that we at least want a whole number of boats assigned to the entire instance of stations);
- (20) guarantees that our decision variable y_{ts} is binary;
- (21) and (22) guarantee that our variables are integral (NOTE: each u_t will be integral since $\sum_s b_{ts} = \sum_{s,k} Q_{tk} b_{ts}$ is integral, and v_s will be integral if $K = S$, so we may encode by relaxing the integrality of such variables to non-negativity);
- (23) and (24) guarantee that our variables will never be negative-valued;

Using our Tool

- Tool can give you allocation of boats to stations given inputs such as:
 - Total budget
 - Requested hours per mission at each station
 - Number hours a particular kind of boat can be used before maintenance
 - Maximum number of boats of a given type allowed at a station
 - Weight of importance assigned to missions of a given type at a given station



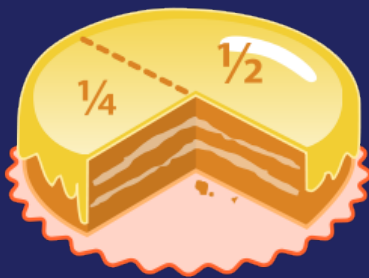
Using our Tool

- Tool can be used to do “what if” tests:
 - If we cut the budget by 5%, how can we change some of the requirements to make the new budget achievable without unmet mission hours?
 - Is across the board 5% cut in mission hours required the way to go?
 - Should we cut mission hours for certain missions?
 - Can we loosen requirements on hours before maintenance?
 - Can we loosen restriction on number of boats at a given station?



A Key Observation

- Our tools are estimated to save the Coast Guard \$120 million over a period of 20 years.
- Our first formulation of the problem was as an integer programming problem.
- ***But: we observed that if we allow fractional solutions, the solutions are more efficient (cheaper) and faster.***
- But what does a fractional solution mean?



Credit: en.wikipedia.org



A Key Observation

- Fractional solution corresponds to *sharing boats* between boat stations.
- *This goes completely against “the culture” of the Coast Guard.*
- They have never done it and at first it made them very uncomfortable

Credit: Wikiipedia.org



A Key Observation

- Admiral Daniel Abel: “When was the last time you rented a car and washed and waxed it before returning it?”



Credit:groupon.com

FR and Admiral
Daniel Abel,
Coast Guard
District 1



Advantages of Sharing

- What does sharing get you?
- Small example: three stations, 300 boat hours required per station per quarter, maximum hours per boat per year = 1000

	Qtr 1	Qtr 2	Qtr 3	Qtr 4
Station 1	300	300	300	300
Station 2	300	300	300	300
Station 3	300	300	300	300

- Conclusion: ***If no sharing, need two boats per station, or 6 boats in all.***



Advantages of Sharing

- What does sharing get you?
- Small example: three stations, 300 boat hours required per station per quarter, maximum hours per boat per year = 1000

	Qtr 1	Qtr 2	Qtr 3	Qtr 4
Station 1	300 Boat 1	300 Boat 2	300 Boat 2	300 Boat 2
Station 2	300 Boat 3	300 Boat 1	300 Boat 3	300 Boat 3
Station 3	300 Boat 4	300 Boat 4	300 Boat 1	300 Boat 4

- Conclusion: ***This solution shows you can get away with 4 boats if you allow sharing of Boat 1.***



A Key Observation

- We presented the results to Admiral Mark Butt at Coast Guard HQ in Washington, DC.
- With the help of our Coast Guard research partners, we convinced the Coast Guard leadership that boat sharing was worth exploring.
- The Coast Guard is now working with us on a practical implementation of boat sharing. ***The culture is changing.***

Delivering Report on Boat
Allocation Module to Admiral
Butt



Phase II: BAM

- Boat Sharing Phase II initial approach:
 - Think about restrictions:
 - Geographic
 - Costs
 - Frequency of boat switches
 - Limit number of stations sharing a boat
 - Part A: Boats can be allocated to stations with variety of time frames allowed for switching
 - Simulate this to determine potential savings with sharing
 - Part B: model that only allows switching boat between stations a limited number of times



Phase II: BAM

- BAM II in final stages of completion.
- Briefed Admiral Paul Zukunft, Commandant of the Coast Guard.
- He said in his Coast Guard, the culture would have to change.



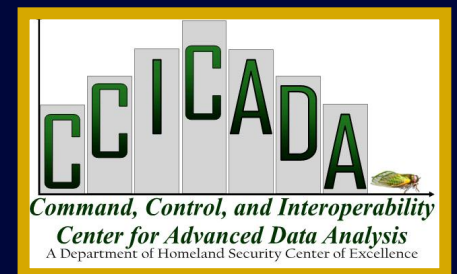
Phase II: Aviation

- Next steps for the project: Aviation Problem posed by Coast Guard
 - Similar problem for Coast Guard aircraft
 - Complication: aircraft heavily used for search and rescue operations, but these are distributed over space and time
 - Complication: aircraft break down and breakdowns are distributed over time in a stochastic way
- Software delivered to USCG and currently undergoing USCG V, V & A.



Example II: Inspections at Sports Stadiums & Large Gathering Places

- Earlier work: modeling and simulation of sports stadium evacuation led us to close collaborations with National Football League (NFL) security and stadium operators.
 - Worked with 6 NFL stadiums and Indianapolis SuperBowl
 - Work applied during lightning storm at MetLife Stadium in NJ



Stadium Security

- This has led us to work with all major sports leagues (NFL, National Basketball Assn (NBA), National Hockey League (NHL), Major League Baseball, Major League Soccer, US Lawn Tennis Assn, NASCAR auto racing) + college football & basketball + minor league baseball & hockey, etc.



Stadium Inspection

- NFL asked all stadium security operators to perform 100% wanding of patrons.
- This didn't always work. Close to game start time, lines got too long.
- They stopped wanding when lines got too long and did less thorough inspection: “pat down”
- Met with NFL Security
- Began analysis of security procedures at one stadium



Security at NFL Stadiums

- In practice: Started by looking at three types of inspection:

- *Wanding*

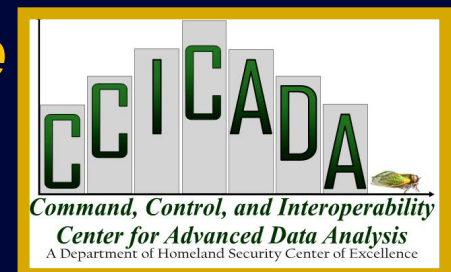
- *Pat-down*

- *Bag inspection*



- Observed stadium inspections and gathered data about each type of inspection, in particular length of time it takes.

- ***Data shows statistically significant differences depending on inspector, inspection method, time before game start, gate, type of event, etc.***

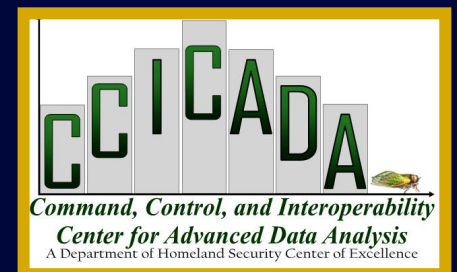


Walkthrough Metal Detectors

- After Boston Marathon attack, National Football League decided it needed to be more strict about inspections.
- It established “outer perimeters” and new bag rules
- It began to investigate use of airport-style walkthrough metal detectors (WTMDs) (magnetometers)

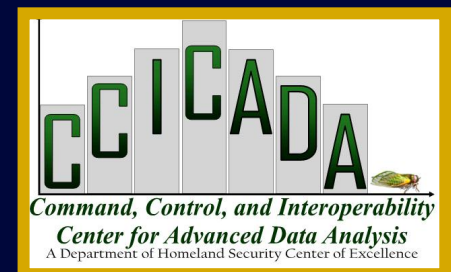


CCredit kitv.com



WTMDs

- We developed models for analyzing the strategy of going to 100% WTMD use
- WTMD Issues:
 - ✓ How many WTMDs needed?
 - ✓ How many screeners needed?
 - ✓ What is the “throughput”?
 - ✓ Performance in bad weather?
 - ✓ Training
- Observed experimental magnetometer use at an NFL stadium in December 2012
- Repeated same type of analysis we did for wandering
- ***Preliminary conclusion: Small # of WTMDs unlikely to get everyone through quickly enough.***



Patron Screening Modeling Tool

- More generally, designed research project to ***develop a patron screening modeling tool:***
 - ✓ Variety of inspection methods
 - ✓ Know for each the “throughput,” the arrival rates at different times, the error rates, etc.
 - ✓ Have goals such as:
 - Getting everyone in by certain time
 - Not letting queues get too long – this produces vulnerabilities (and patron dissatisfaction)
 - Keeping maximum wait time low
 - ✓ Can you model which inspection process to use when and for how long?



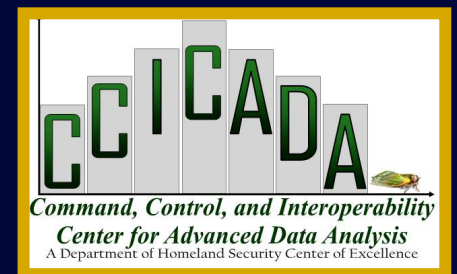
Information from the Stadium Feeds Model

- Ticket scan (“throughput”) data for 14 home games
- Time at which each ticket was scanned (and which gate)
 - ✓ Note: No data on patron arrival rates
- Estimated average screening times per patron
 - ✓ Analysis of ticket data
 - ✓ Observations using stopwatches and clipboards – following up on Stage I work
- Discussions with stadium security personnel
 - ✓ Confirming assumptions and estimates
 - ✓ Feedback on the model and its output
 - ✓ ***This was crucial at all steps of the modeling and was part of the model “validation”***



Screening Rates

- Based on throughput data and site observations, we estimated:
 - ✓ Wandings took between 12 and 15 seconds
 - ✓ Patdowns took between 6 and 8 seconds
- Preliminary assumptions and simplifications:
 - ✓ WTMDs would take between 5 and 7 seconds
 - ✓ For each patron, the time to screen them will be generated from a uniform distribution: equally likely to take any number of seconds between highest and lowest.
- Other venues have obtained different numbers.
- ***Key point: Model allows you to use any numbers that make sense for your arena.***
- ***Key point: Data & assumptions compared to security director experience***



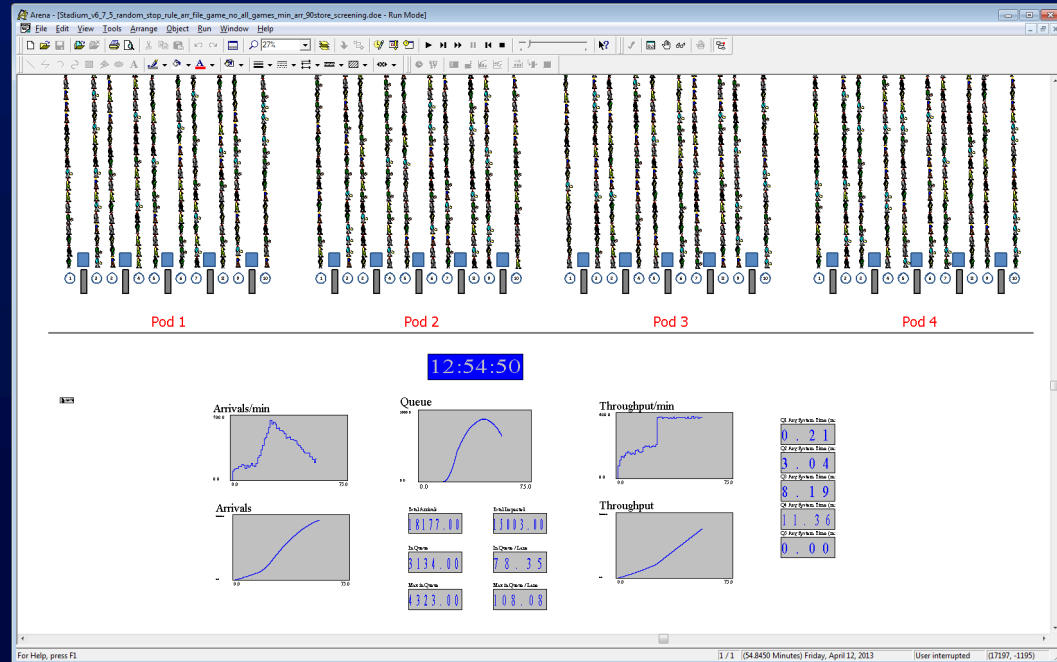
The Simulation Model



Most of the **parameters** can be obtained by **choosing a representative game**

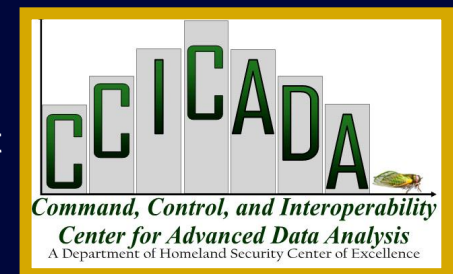
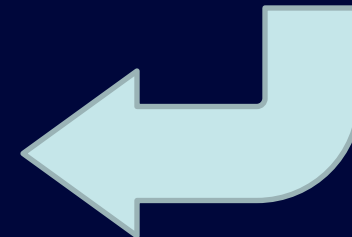
- **Parameters**
 - Arrival rates
 - Number of lanes
 - Wandering times
 - Pat-down times
 - Magnetometer times

- **Screening Strategy**
 - Switching inspection type (Y/N)
 - Number of patrons in queue to switch the process, or
 - Time of switch
 - Does phase 2 include randomization? (Y/N)
 - Ratio of patrons in each type of inspection in the randomization



The model **output** file includes:

- Total Arrivals
- Total Arrivals @ kickoff
- Maximum number in Queue
- **In Queue @ kickoff**
- **Queue clearance time**
- Screening switch time
- Number of patrons inspected by different procedures
- **Max Waiting Time per patron**



WTMDs

- The model was first used in 2013 to determine if the stadium could switch to WTMDs for screening patrons.
- A switch to WTMDs would involve a serious investment, so it was important to make the determination BEFORE purchasing the WTMDs.
- Goal: get patrons in by 5 minutes after kickoff; other goals can be modeled
- Compared new procedures to the “*base case*”: wand patrons until queue gets too long, then switch to pat-downs.
- We compared queue clearance times with various numbers of WTMDs to the base case.
- Model clock starts at 0 at 60 minutes before kickoff, so *goal is to clear queue by 65 minutes*



WTMD Scenarios (Queue Clearance)

No	Game Time	Queue Clearance Times as function of Number of Lanes					
		Base Case (Wanding & switch to Patdown)	Magnetometer Scenarios (Number of Lanes)				
			40	20	25	30	35
1	9/16/12 1:00 PM	64.65	97.76	83.57	72.18	63.19	56.57
2	10/7/12 1:00 PM	72.79	113.38	95.87	81.07	72.39	64.66
3	10/21/12 1:00 PM	68.67	108.49	92.53	82.13	71.48	65.03
4	11/4/12 4:25 PM	66.80	114.18	94.48	79.75	71.21	61.03
5	11/25/12 8:20 PM	72.40	111.95	94.56	82.52	74.22	65.96
6	12/9/12 4:25 PM	75.40	118.88	99.42	85.81	76.06	67.32
7	12/30/12 1:00 PM	82.67	128.82	108.36	95.27	85.81	76.99
8	9/9/12 1:00 PM	65.46	108.92	89.23	77.64	67.33	58.04
9	9/30/12 1:00 PM	71.33	111.08	94.26	83.39	74.11	65.91
10	10/8/12 8:30 PM	60.80	94.76	76.65	58.19	55.00	55.00
11	10/14/12 1:00 PM	66.50	109.20	91.91	79.01	65.45	55.00
12	10/28/12 1:00 PM	70.82	112.12	93.47	81.09	69.53	61.86
13	11/22/12 8:20 PM	65.94	93.41	79.52	55.12	55.00	55.00
14	12/2/12 1:00 PM	64.45	105.51	91.92	77.06	55.00	55.00

44



Worse than the Base and does not meet the goal

Similar to Base or better, but does not meet the goal

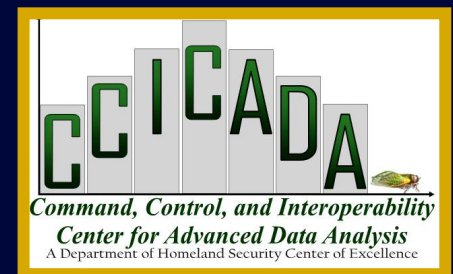
Meets the goal



Goal: Queue clears by 65 minutes

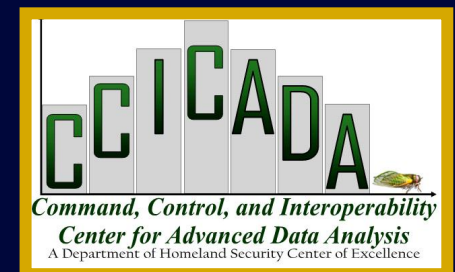
Conclusion from Data Analysis and Modeling

- If you want to do more rigorous inspection of all the patrons, you need to get more of them to arrive early and enter the stadium.
- You have to ***“change the culture”***



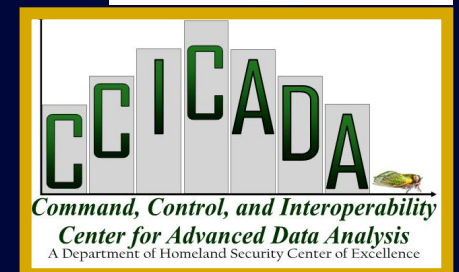
Data Analysis

- “Changing the culture” requires changing the way people behave – through policy changes.
- Create incentives for people to arrive early
- *1/2 price beer 2 hours before kickoff*



Data Analysis

- “Changing the culture” requires changing the way people behave – through policy changes.
- Create incentives for people to arrive early
- ***Allow patrons to walk on the field if arrive early***

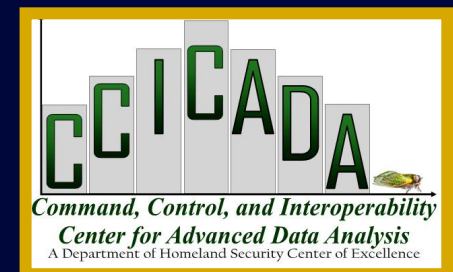


Data Analysis

- “Changing the culture” requires changing the way people behave – through policy changes.
- Create incentives for people to arrive early
- ***Allow early-arriving patrons to enter a lottery for special prizes***

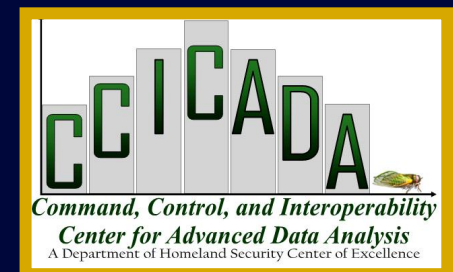


Credit:
washingtoncitypaper.com



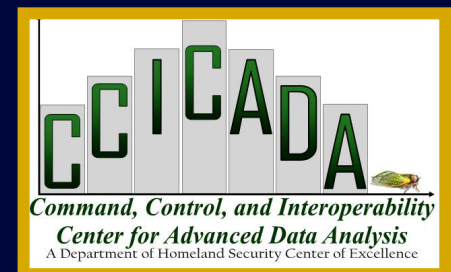
Data Analysis

- “Changing the culture” requires changing the way people behave – through policy changes.
- Create incentives for people to arrive early
- This worked in Oakland, California at the Oakland Coliseum
- Changed the culture



Was the Model Accepted?

- ***Sometimes “validation” of a model means it was accepted by the policy maker/decision maker.***
- In this case:
 - NFL Security liked it and I was invited to give a plenary presentation to the annual NFL Security Seminar in 2014.
 - Our stadium partner asked for more applications of the model
 - The director of the NFL stadium we worked with testified before a Congressional committee on how useful the modeling has been
- We now use the tool at an NBA Arena and a MLB stadium
- Why it worked: share data, discuss assumptions, test model under variety of conditions, given access to stadium events to observe model predictions, ***model agrees with security director’s practical experience***



Example III: Container Inspection at Ports



Container Inspection at Ports

- A large and expensive job
- Critical that it be carried out effectively and efficiently.
- 95% of goods coming into the US come on ships
- In the 21st century, the marine transportation system has become a complex, just-in-time operation.
- Keeping ports operational and moving cargo is of central importance to the world economy and in keeping the supply chain moving.



Data Credit: Forbes Business 10/25/11; Wikipedia

Container Inspection at Ports

- US Customs and Border Protection (CBP) is responsible for inspection at ports and borders.
- At container ports, we use VACIS machines
- VACIS = Vehicle and Cargo Inspection System



VACIS Inspection Processes at APM Terminal

- Phase I Project Goal: study the VACIS operation at the APM terminal in Port Elizabeth, NJ using ***simulation modeling and analysis to improve VACIS operational efficiency and throughput.***
- A simulation model was built to capture
 - vessel arrivals
 - container storage at the yard
 - presentation of containers to CBP officers
 - and the actual inspection processes.
- A number of scenarios were analyzed to understand the capabilities of the inspection process under various surge conditions

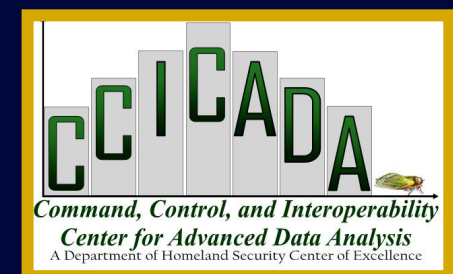
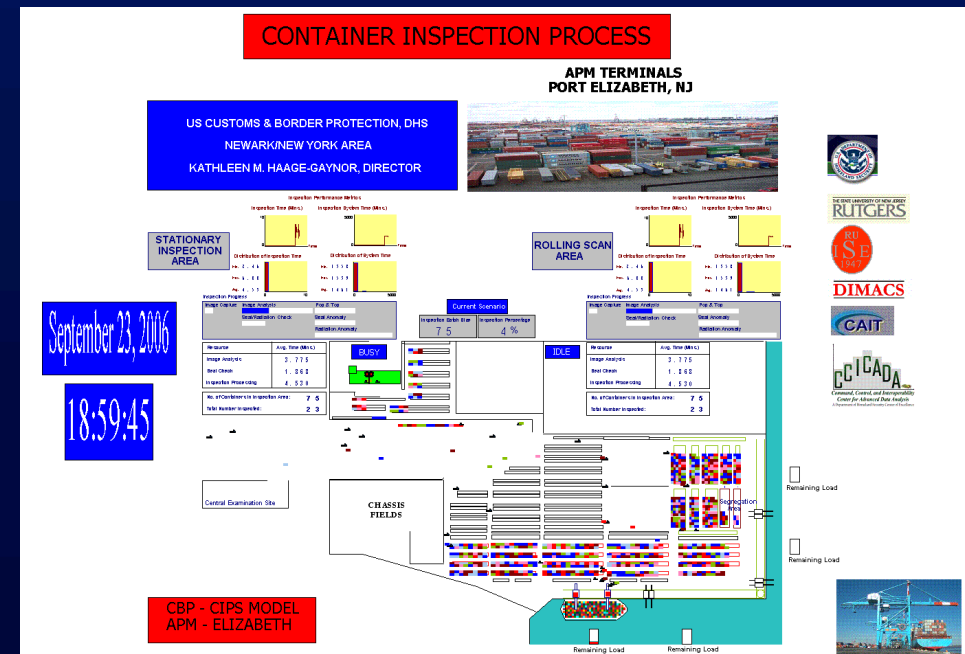


The Simulation Model

Use Discrete Event Simulation with ARENA software

The animation displays:

- The incoming workload with ship arrivals and departures
- Loading and unloading of containers by cranes
- Shuttling of containers to storage areas
- Transfer of CBP-specified containers to the inspection area
- Container inspection processes
 - Stationary Scan
 - Moving Scan



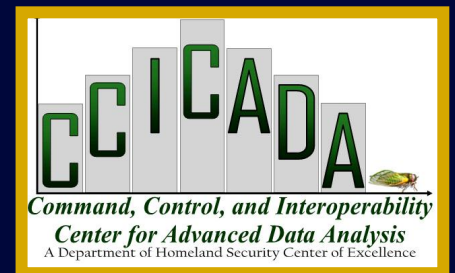
Performance Metrics

- The simulation model produces statistical results for the inspection performance metrics as well as the port performance metrics.
- **Inspection statistics** metrics:
 - Inspection processing time per container
 - # containers inspected in 48 hours in a designated batch
 - % containers inspected in 48 hours in a designated batch
 - Time to complete a batch of designated quantity
- **Port statistics** metrics:
 - Port time per inspected container (from vessel arrival to inspection completion)
 - Time elapsed from vessel arrival to segregation area
 - Time spent in segregation area
 - Delay in inspection area
 - Inspection time



Container Inspection at Ports

- ***Impact: A revision was proposed in the way the hourly throughput is calculated in CBP's inspection operations to better reflect CBP operational metrics.***
- Why did this model work?
 - Lots of data made available to us
 - Detailed observations made at ports; access to observe port operations
 - Input not only from CBP but from port operators and shipping companies
- ***“Validation”*: Was the model accepted by user and did user ask for more?**
- Model accepted by CBP as useful because its output gave them new ideas that turned out to be useful



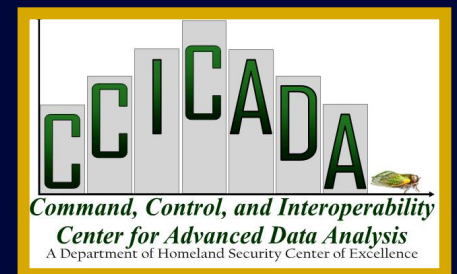
Container Inspection at Ports: Phase II

- Traditionally, we bring the inspectors to the ports.
- There is often a delay in waiting for an inspector to come to a port to inspect the containers that are lined up waiting there.
- The modeling work that we and others did led CBP to ask: ***Is it better to bring the inspectors to the containers or to bring the containers to the inspectors?***
- This would require a ***change in the culture.***
- It is not what we were used to doing
- There was a lot of skepticism about it.



Container Inspection at Ports

- Still: CBP decided to try something different: Set up warehouses away from the ports, keep inspectors there, and bring containers to the warehouses to have them inspected.
- CBP of New York/Newark approached CCICADA to help with new initiative.
- CBP experimented with the new approaches
- Questions: Does this make inspection more efficient (faster throughput)? Does it make it less costly?
- CCICADA project: modeling and analysis of new approaches



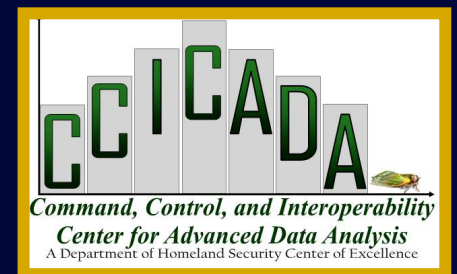
Model Performance Comparisons

- By 2012, the inspection process had moved **off-site** and occurred in privately owned central examination stations
- CCICADA ***examined and compared 2012 inspection cycle times with those of prior years and before off-site inspection.***
- A breakdown of container cycle times (from arrival of container until CBP release) was obtained for each inspection process.
- Offsite inspection facility performances were compared for 2012



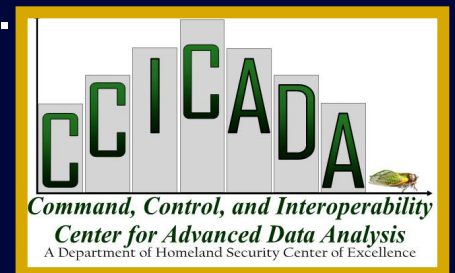
But there Were Problems

- A key part of the analysis was to compare “costs” to shippers of the old inspection model vs. the new model
- The problem was that “costs” were not easy to determine.
- Bills of lading and invoices were “all over the place” in format.
- It wasn’t clear what charges resulted from inspection and what charges resulted from other factors.
- It was impossible to do the analysis.



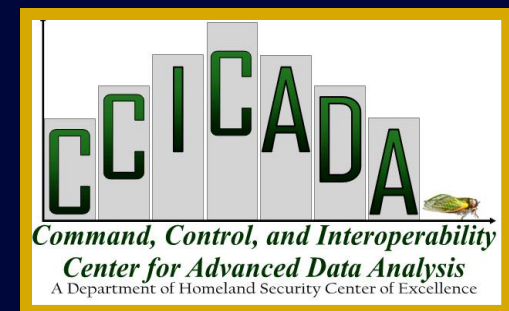
But there Were Problems

- In the end:
 - We found that inspection times were basically improved
 - But we could not begin to develop the model far enough to have confidence in comparing costs
 - ***There was just not enough data in usable form to validate the model***
 - CBP seems committed to continuing the experiment with offsite inspections at warehouses.
 - There does seem to be a “***change in the culture***”
 - Our first modeling effort helped get to this point.
 - But validation of the idea did not work well.
 - Phase II modeling ran afoul of poor data.



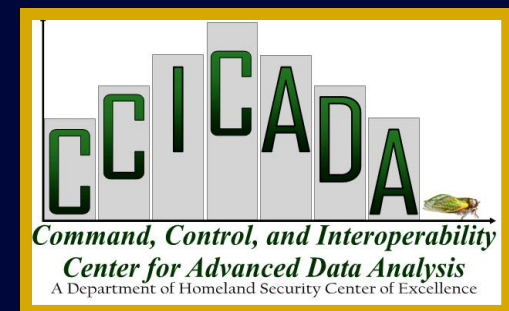
Example IV: Nuclear Detection in a City

- Big city police departments have experimented with putting nuclear detectors in police cars.
- We wanted to see if there were enough police cars to give “adequate” coverage to have a high probability of finding a nuclear device.



Nuclear Detection Using Vehicles

- Distribute GPS tracking and nuclear detection devices to police cars in a metropolitan area.
 - Feasibility: New technologies are making devices portable, powerful, and cheaper.
 - ***Some police departments are already experimenting with nuclear detectors.***
- Send out signals if the vehicles are getting close to nuclear sources.
- Analyze the information (both locations and nuclear signals) to detect potential location of a source.
- A cluster of alarms suggests there is a source.



Nuclear Detection using Police Cars



GPS tracking
device

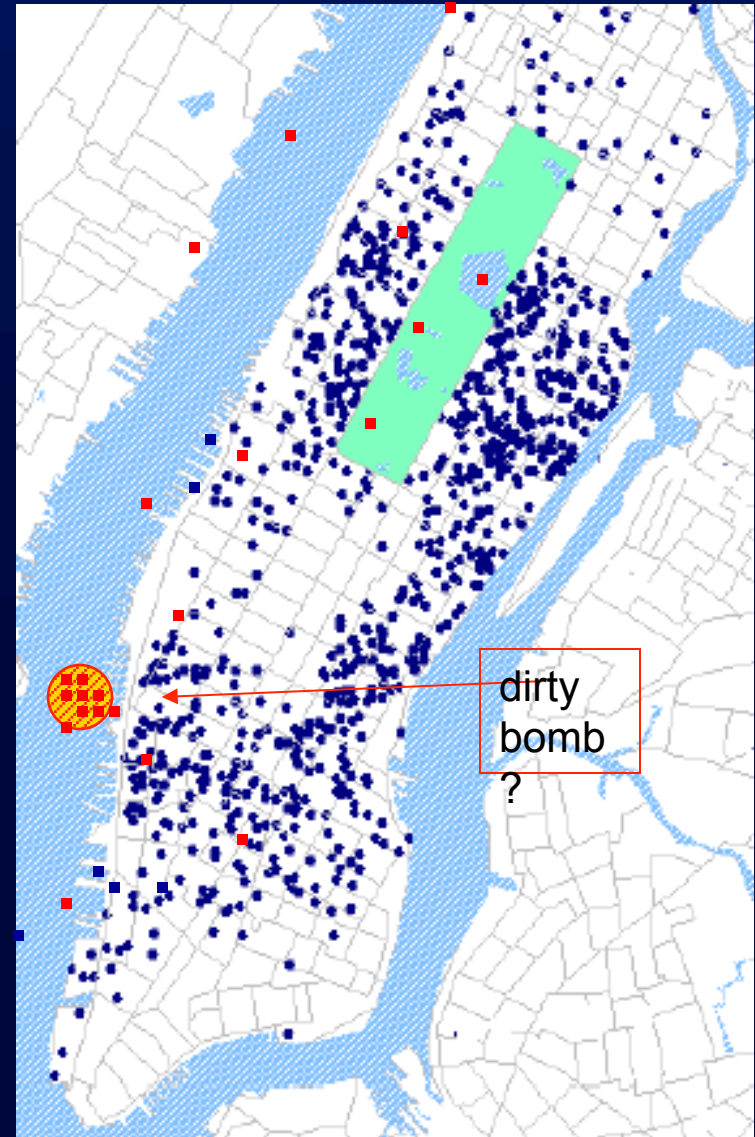
+



Nuclear sensor
device

A cluster of alarms suggests there is a
source

Manhattan, New York City
A simulation of police car locations
at morning rush hour



Detectors in Vehicles – Model Components

- In our early work, we did not have a specific model of vehicle movement.
- We assumed that vehicles are randomly moved to new locations in the region being monitored each time period.
- If there are many vehicles with sufficiently random movements, this is a reasonable first approximation.



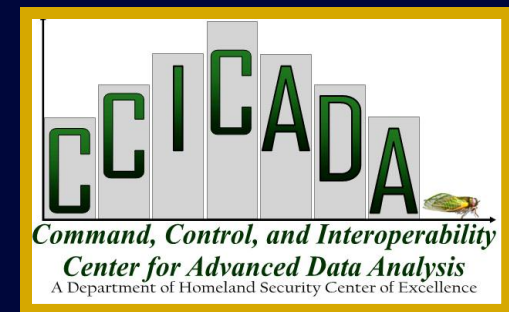
Vehicles - Simulation

- First stage of work
- Generated data in Manhattan and did a simulation – applying the clustering approach with success
- Used spatclus package in R: software package to detect clusters
- In the simulations, we have considered both moving and stationary sources.



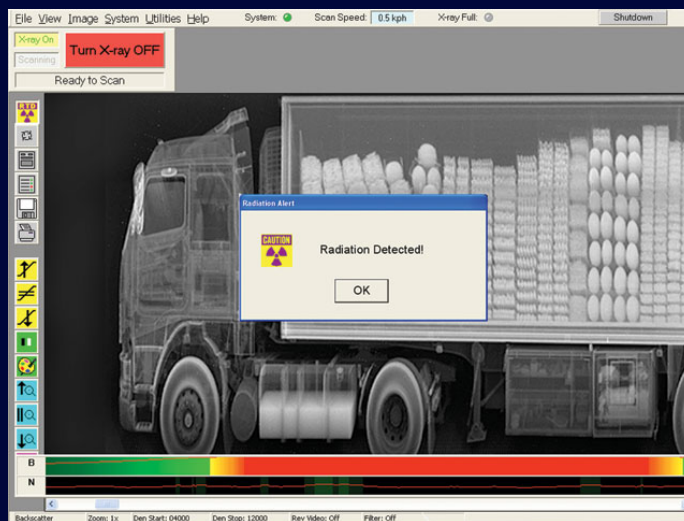
Number of Vehicles Needed

- The required number of vehicles in the surveillance network can be determined by **statistical power analysis** (determination of probability of detection)
 - The larger # of vehicles, the higher power of detection
- An illustrative example:
 - A surveillance network covers area 4000 ft. by 10000 ft.
 - Roughly equal to the area of the roads and sidewalks of Mid/Downtown Manhattan
 - Vehicles are randomly moving around in the area



Number of Vehicles Needed

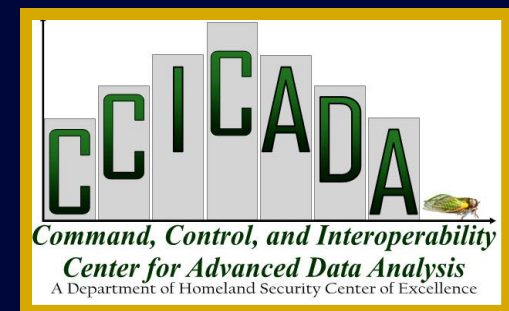
- Fix key parameters
 - Effective range of a working detector
 - False positive & false negative rates for detectors
 - ***The ranges and rates we used are not realistic, but we wanted to test general methods, & not be tied to today's technology***
- A fixed nuclear source randomly placed in the area



Number of Vehicles Needed

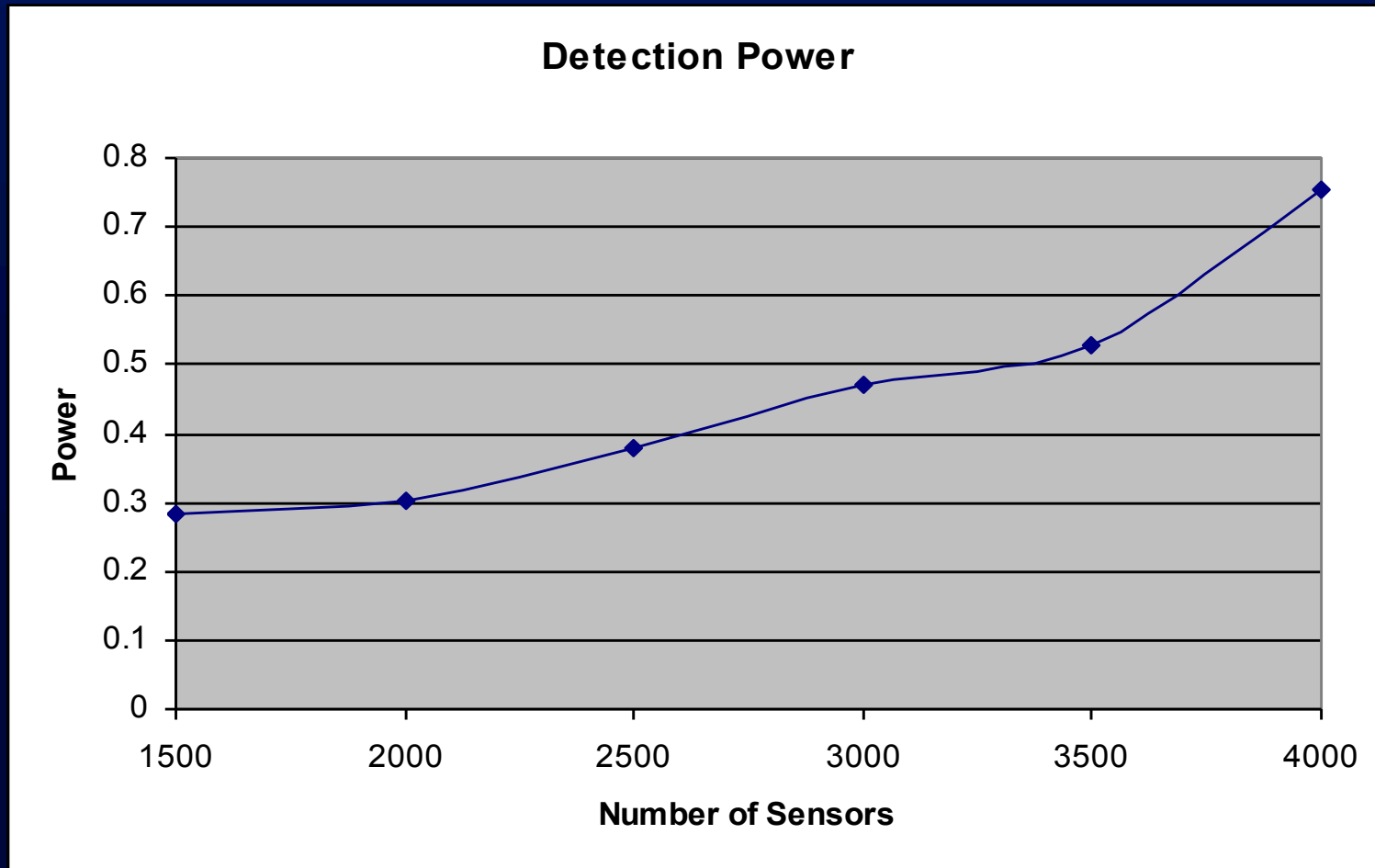
First Model

- Effective range of detector: 150 ft.
- False positive rate 2%
- False negative rate 5%
- Varied number of vehicles (= number of sensors) and ran at least 50 simulations for each number of vehicles.
- For each, measure the **power** = $P(D=1/S=1)$ = probability of detection of a source.



Number of Vehicles (Sensors) Needed

Sensor range=150 feet, false positive=2%, false negative=5%.



Conclusion: Need 4000 vehicles to even get 75% power.

Number of Vehicles Needed

- NYPD has 3000+ vehicles in 76 precincts in 5 boroughs. Perhaps 500 to 750 are in streets of Mid/Downtown Manhattan at one time.
- ***Preliminary conclusion: The number of police cars in Manhattan would not be sufficient to even give 30% power.***

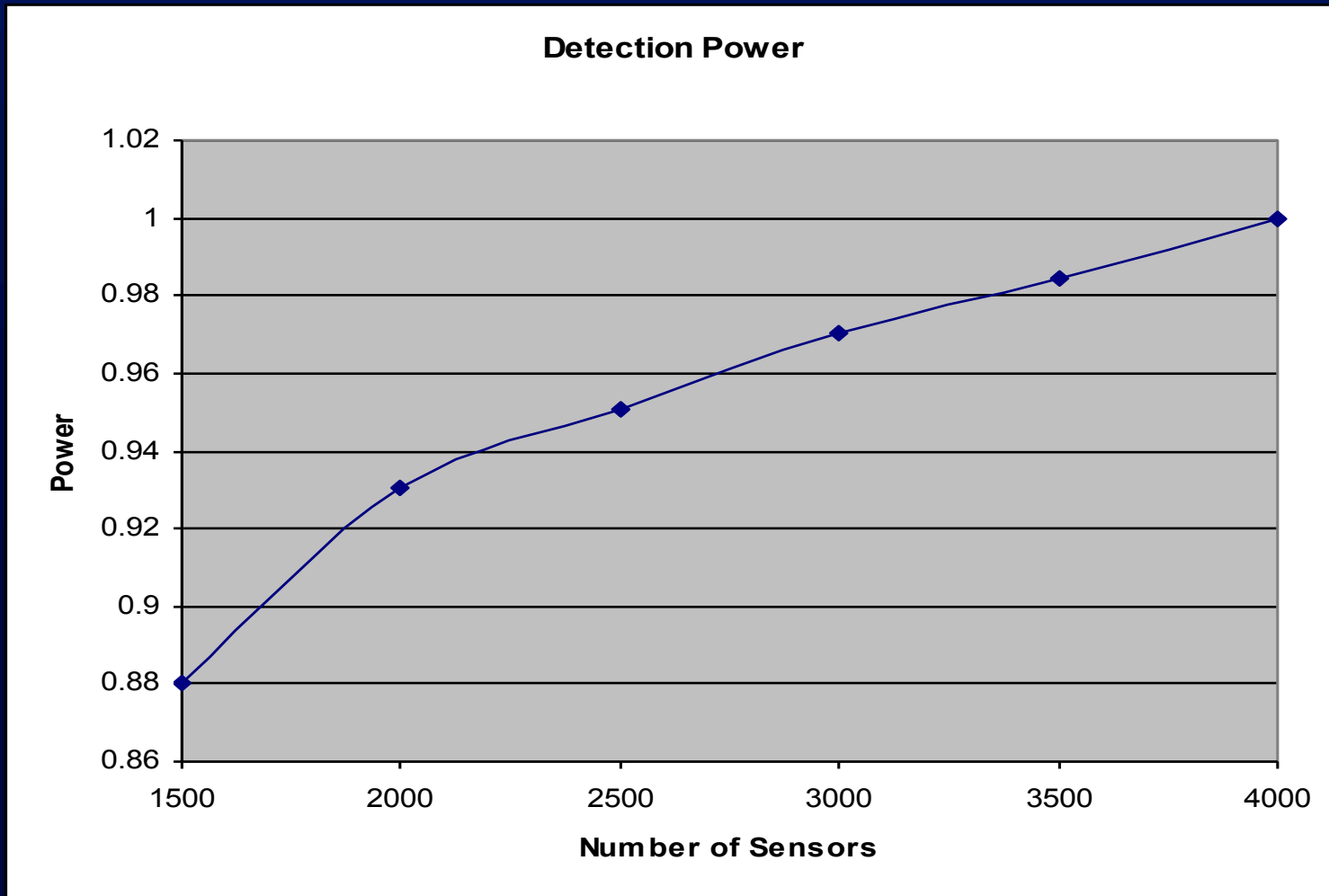
Modified Model

- What if we have a better detector, say with effective range of 250 ft.?
- Don't change assumptions about false positive & false negative rates.



Number of Vehicles (Sensors) Needed

Sensor range=250 feet, false positive=2%, false negative=5%.

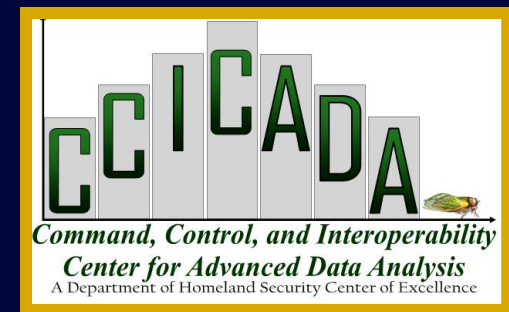


Conclusion: 2000 vehicles already give 93% power.



Number of Vehicles Needed

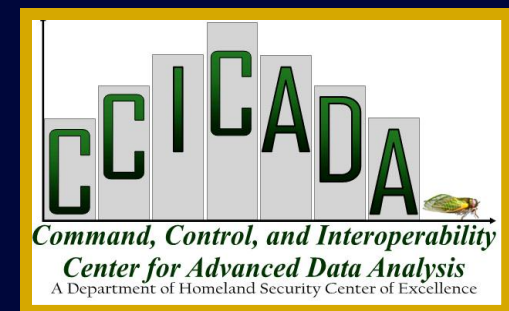
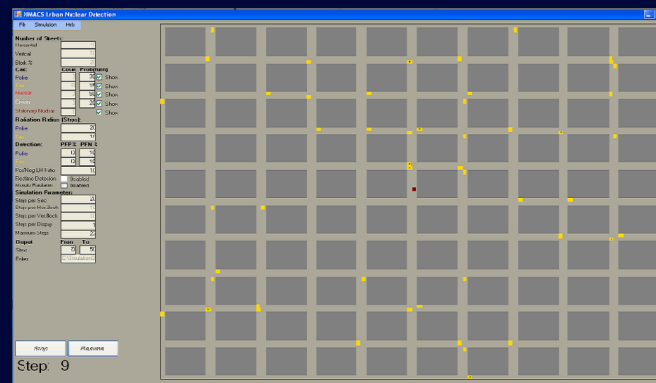
- ***There are not enough police cars to accomplish this kind of coverage.***
- There are other problems with our model as it relates to police cars:
 - Police cars tend to remain in their own region/precinct.
 - Police cars don't move around very randomly and randomness is needed else an adversary can anticipate inspections



Next Step: Add a Random Movement Model

- Adding a movement model makes the analysis more realistic.
- We take a street network.
- We assume that vehicles move along until they hit an intersection.
- At each intersection, they continue straight or turn left or right according to a random process.
- Again conclude not enough police cars

Simulation uses
ARENA software



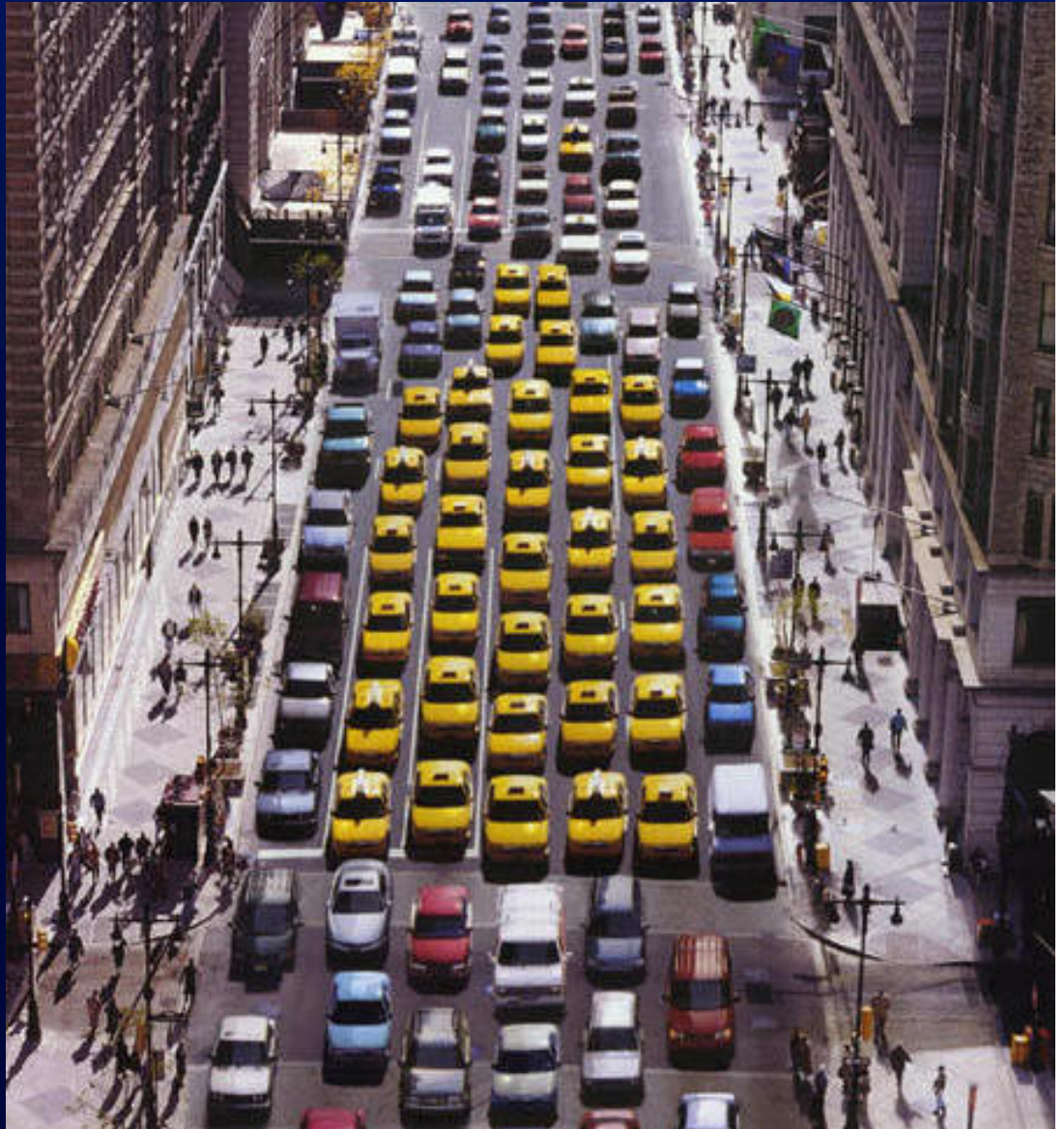
Number of Vehicles Needed

- ***But maybe there are enough taxis***
- There are other problems with our model as it relates to police cars:
 - Police cars tend to remain in their own region/precinct.
 - Taxis don't
 - Police cars don't move around very randomly
 - Taxis do move more randomly



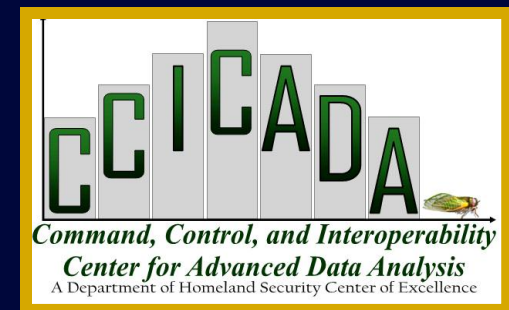
Number of Vehicles Needed

- *Are there enough taxis to achieve a high enough detection power?*
- *Our models show that there are – at least under our simplifying assumptions*



Nuclear Detection Using Taxicabs

- ***But are we comfortable using the model?***
- ***The model was hard to validate:***
 - Too many simplifying assumptions (and some unrealistic)
 - Hard to actually test the model: discomfort with putting detectors into cabs – as we will note
- ***Some models are not designed to be validated.***
- This model was designed to generate concepts and ideas for further analysis
- In this sense, not every model needs to be “validated” to be useful



Nuclear Detection Using Taxicabs

- What is needed to implement the solution of putting nuclear detectors in taxicabs?
- Or at least experiment with it?
- Unfortunately, the police departments in large cities in the US such as New York do not like to depend on the private sector for a substantial role in law enforcement.
- It would require a **“change in the culture”** for them to trust taxis:
 - Educate” the police to the advantages of using taxicabs.
 - Create new and better communication and interrelationships between police security and taxicab drivers



Closing Comments

- Modeling to influence policy needs different kinds of validation in different contexts
- Close collaboration with practitioners early and often is necessary
- Good data is essential
- Sometimes, implementation requires a change in the culture



CHANGING THE CULTURE

Thanks

- **Coast Guard Boat Allocation:** Jake Baron, Endre Boros, Bobby DeMarco, Paul Kantor, Christie Nelson, Matt Oster, Yao Wang, Jim Wojtowicz
- **Stadium Security:** Alper Almaz, Jonathan Bullinger, Bobby DeMarco, Cindy Hui, Paul Kantor, Alisa Matlin, Ryan Whytlaw, Jim Wojtowicz
- **CBP Container Inspection:** Alper Almaz
- **Nuclear Detection with Taxis:** Rong Chen, Jerry Cheng, Minge Xie

