# Optimal Communications Systems and Network Design for Cargo Monitoring

Daniel T. Fokum

Ph.D. dissertation oral defense

Department of Electrical Engineering & Computer Science

University of Kansas

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# Outline

- Acknowledgements
- Introduction
- Modeling
- System Trade-offs
- Heuristic
- Conclusion
- Questions?

# Motivation

- Cargo theft is a major problem.
  - Indirect costs of cargo theft can be two to five times the direct losses
- Cargo theft affects originators, shippers, and receivers.
- Need to monitor cargo shipments along the supply chain, e.g., between a port and an inland intermodal shipping terminal.
  - Lack of visibility, accountability, efficiency and security in cargo shipments
- Deployment of sensors, networks, and information technology offer potential to address these issues.

# Objectives

- Design the sensing, networks, and associated information technology systems to provide cost-effective visibility into shipments.

- Test viability of a transportation security sensor network for cargo monitoring

- Develop models to find the "best" system design including:

  - Communications network design

  - Locations for sensors in a rail-based sensor network.

- Determine system trade-offs when monitoring cargo in motion.

- Guide the design of future cargo monitoring systems.

# New Definition of Visibility

- Define visibility space as the set of system costs such that customer requirements for probability of detection, probability of false alarm and reporting deadline are met.
  - Visibility is a binary function of $t, \tau, \mathrm{TR}_j, P_\varepsilon, E_j, P_\alpha, F_j$
    - A load is visible if:
      - $P_\varepsilon > E_j$ AND $\mathrm{Pr}(t \leq \tau) \geq \mathrm{TR}_j$ AND $P_\alpha < F_j$
    - Mathematically we may state:

$$\nu(j, t, \tau, \mathrm{TR}_j, P_\epsilon, E_j, P_\alpha, F_j) = \begin{cases} 1 & \text{if } (\mathrm{Pr}(t \leq \tau) \geq \mathrm{TR}_j \text{ AND } P_\epsilon \geq E_j \text{ AND } P_\alpha \leq F_j) \\ 0 & \text{Otherwise} \end{cases}$$

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# Problem Statement

- Given a collection of containers and a collection of end-to-end information subsystems (including sensors, seals, readers, and networks); how do we design an end-to-end system that meets the visibility constraints for all containers while minimizing overall system cost?
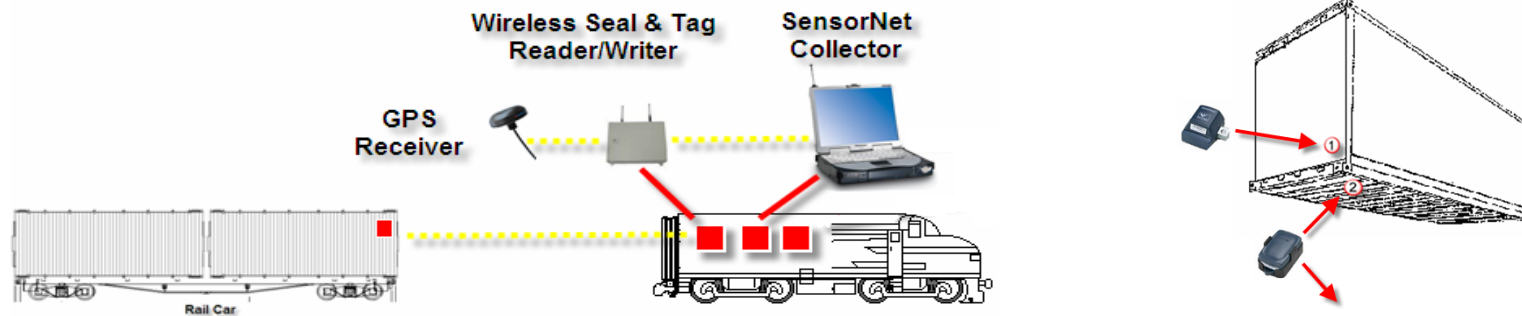
# Problem Statement

- For rail scenario we may restate the problem as follows:
  1. How to map (analyze) a "system" description of containers on railcars, train scenario and associated communications infrastructure into the visibility space? Thus, an appropriate system model needs to be developed.
  2. How to assign a cost to every position in the visibility space?
  3. Use 1. and 2. to find minimum "cost" systems for providing visibility into a rail shipment.
  4. Use 1. and 2. to determine important system trade-offs when seeking visibility into rail shipments.

# Contributions

- Analysis of data from a field trail of a cargo monitoring system to show that commercial-off-the shelf devices can be used for timely notification.

- Formal definition of visibility for cargo monitoring systems.

- Development of mechanisms that lead to cost-effective system design for cargo monitoring.

- Study of trade-offs when designing systems for monitoring cargo in motion, thereby guiding future system design.

- A heuristic to aid in design of systems of realistic scale for monitoring cargo in motion.

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# Object Identification and Location

- Identify each container with a unique integer, $j$.
  - Container attributes can be retrieved by using functions that take $j$ as input.
- Each unit is uniquely identified by an integer, $k$, that starts off at 1.
  - Value $k=0$ is reserved for identifying the locomotive.
- Units have at most two layers for holding loads.
  - Within each layer one or more slots are available for holding loads.
    - Slots are identified by an integer, $q$

$$j=2, q=1, y_{211}=1$$

$$j=1, q=0, y_{101}=1$$

$$k=1$$

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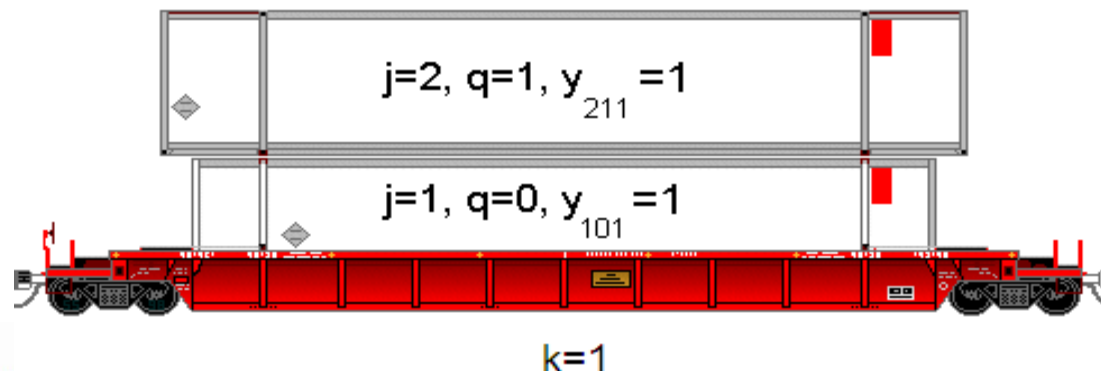
# Model Descriptions

- Problem can be split into two main cases:
  - Train-mounted deployment
    - Containers assigned to fixed slots on the train
    - Sensors are on train
    - Backhaul communications device is on train
  - Trackside deployment
    - Containers assigned to fixed slots on the train
    - Sensors are on train
    - Sensor readers are at trackside at regular intervals
  - Objective in each case is to place sensors and communications systems to minimize the operational cost of monitoring cargo in motion.

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# Train-mounted Deployment Model

- Objective function sums the cost of false alarms over a rail journey, cost of sensors missing event detection, the cost of a sensor failing to communicate in a timely manner, the cost of communications across a rail journey, the material and installation costs of sensors, readers, and a backhaul communications device , respectively

Backhaul Communications

Sensors

k=0

k=1

k=2
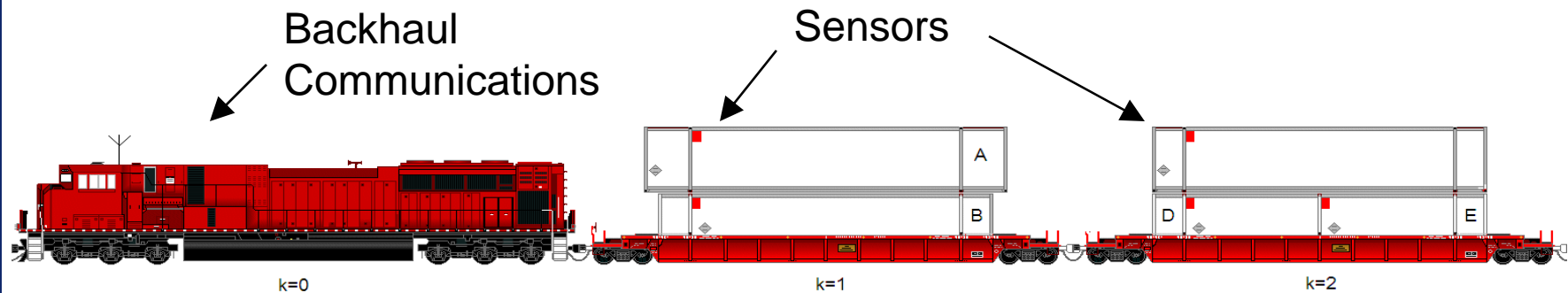
# Trackside Deployment Model

- No backhaul communications system on train; readers at trackside.
  - Objective function sums the cost of false alarms over a rail journey, cost of missing a detection at a given container, the cost of a sensor failing to communicate with a trackside reader, the cost of communications across a rail journey, the material and installation costs of sensors and readers, respectively
  - Reader separation is done to minimize system cost metric subject to reporting deadlines.

k=0          k=1          k=2

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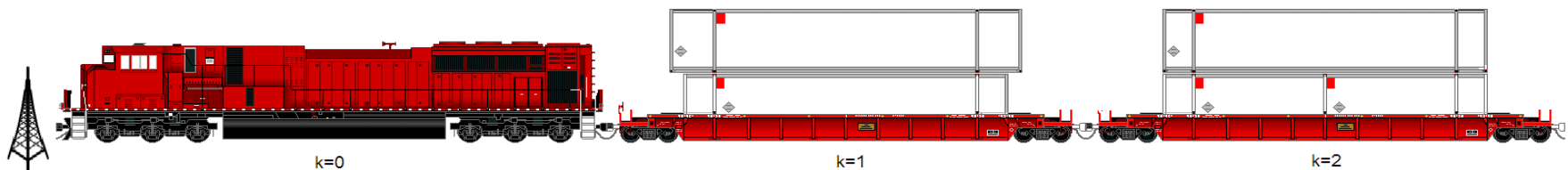
# Parameters

- Values need to be given to system designer to solve the problem.
- Container placement parameters
  - Include:
    - The set of units (railcars) to be used in the problem with each unit's characteristics, i.e., weight limits and length limits for the different layers in the unit
    - Container values and savings resulting from detecting events at containers
- Information system placement parameters
  - Include:
    - A set of sensors to be assigned
    - Message generation rates for sensors

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# Variables

- Goal is to have optimization solver determine appropriate variable values.

- Examples of variables:

    - A binary variable indicating sensor placement on a container, slot, and unit.

    - Sensor transmission range

    - Trackside reader separation

# Train-mounted Model

*minimize*

$$C_\alpha \sum_{\forall i,j,q,k} \alpha S_{ijqk} y_{jqk} + \zeta \left( \sum_{\forall j,q,k} \sigma_j y_{jqk} - \sum_{\forall i,j,q,k} \epsilon \sigma_j S_{ijqk} y_{jqk} \right)$$

$$+\zeta \left( \sum_{\forall j,q,k} \sigma_j y_{jqk} - \sum_{\forall i,j,q,k} \varphi \sigma_j S_{ijqk} y_{jqk} \right) + D(\Pr(H)C_c + \Pr(I)(1-\Pr(H))C_s)l \sum_{\forall i,j,q,k} \lambda_i S_{ijqk} y_{jqk}$$

$$\sum_{\forall i,j,q,k} (C_H + C_{HL}) S_{ijqk} y_{jqk} + \sum_{\forall q,k} (C_A + C_{\mathrm{AL}}) A_{qk}$$

$$+ \left( \frac{C_{\mathrm{BC}}}{t_L \times \mathrm{LT}_c} + \frac{C_{\mathrm{BS}}}{t_L \times \mathrm{LT}_s} \right) \sum_{\forall q,k} B_{qk}$$

# Trackside Model

$minimize$

$$C_\alpha \sum_{\forall\, i,j,q,k} \alpha S_{ijqk} y_{jqk} + \zeta\left( \sum_{\forall\, j,q,k} \sigma_j y_{jqk} - \sum_{\forall\, i,j,q,k} \epsilon \sigma_j S_{ijqk} y_{jqk} \right)$$

$$+ \zeta\left( \sum_{\forall\, j,q,k} \sigma_j y_{jqk} - \sum_{\forall\, i,j,q,k} \rho \sigma_j S_{ijqk} y_{jqk} \right) + \left(\frac{d_T}{\dot{x}}\right) C_c l \sum_{\forall\, i,j,q,k} \lambda_i S_{ijqk} y_{jqk}$$

$$+ \sum_{\forall\, i,j,q,k} (C_H + C_{HL}) S_{ijqk} y_{jqk} + \left( \left( \frac{C_A + C_{\mathrm{AD}}}{t_f \times \mathrm{LT}_A} + \frac{C_{\mathrm{BC}} + C_{\mathrm{BD}}}{t_f \times \mathrm{LT}_c} \right) \times \left\lfloor \frac{d_T}{d_A} \right\rfloor \right)$$

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# Constraints

- Constraints for all models include:
    - Requirement that all visibility conditions are satisfied
    - Requirement that no more than one sensor is assigned to a container
    - Requirement that a sensor is used exactly once
- In addition for trackside model we require that:
    - A sensor must be read within the time interval that a sensor is within range of a reader.
    - The train must cover the distance between two trackside readers within the deadline for decision maker notification.

# Solution Methodologies

- Mixed Integer Nonlinear Program (MINLP) is optimization problem with some integer-constrained and continuous variables as well as nonlinear constraints and/or objective function
  - If all the variables are continuous, then we have a nonlinear program
  - If all the functions are linear, then we have a mixed integer linear program
- MINLP are NP-Hard.
- Convex MINLP can be solved with the following techniques:
  - Branch-and-bound
  - Extended cutting plane
  - Outer approximation
  - Generalized Benders decomposition
  - LP/NLP-based branch-and-bound
  - Branch-and-cut

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# Solution Methodologies

- Models have been solved using the Bonmin solver running on the Network-Enabled Optimization System (NEOS) server
  - NEOS server handed off problems to solvers hosted at Lehigh University
  - Solver machines were Pentium 4 computers with clock speed of at least 2.0 GHz and at least 500 MB of RAM
- Bonmin used the outer approximation method to solve the optimization problems
- Solving optimization problem yields sensor mappings, i.e., sensor locations, and determines appropriate values for all other variables

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# Validation of Models

- Model validation seeks to determine if a given mathematical abstraction matches a real system

- "Validated" the train-mounted and trackside models by studying trends in the behavior of the optimization models at the boundaries of the visibility space.

  - Aim was to see if model displayed correct behavior, e.g.,
    - Does system cost increase as probability of critical event increases?
    - Does the system cost metric decrease as train goes faster?
    - Does sensor transmission range increase with train speed?

# Validation for Train-mounted Model
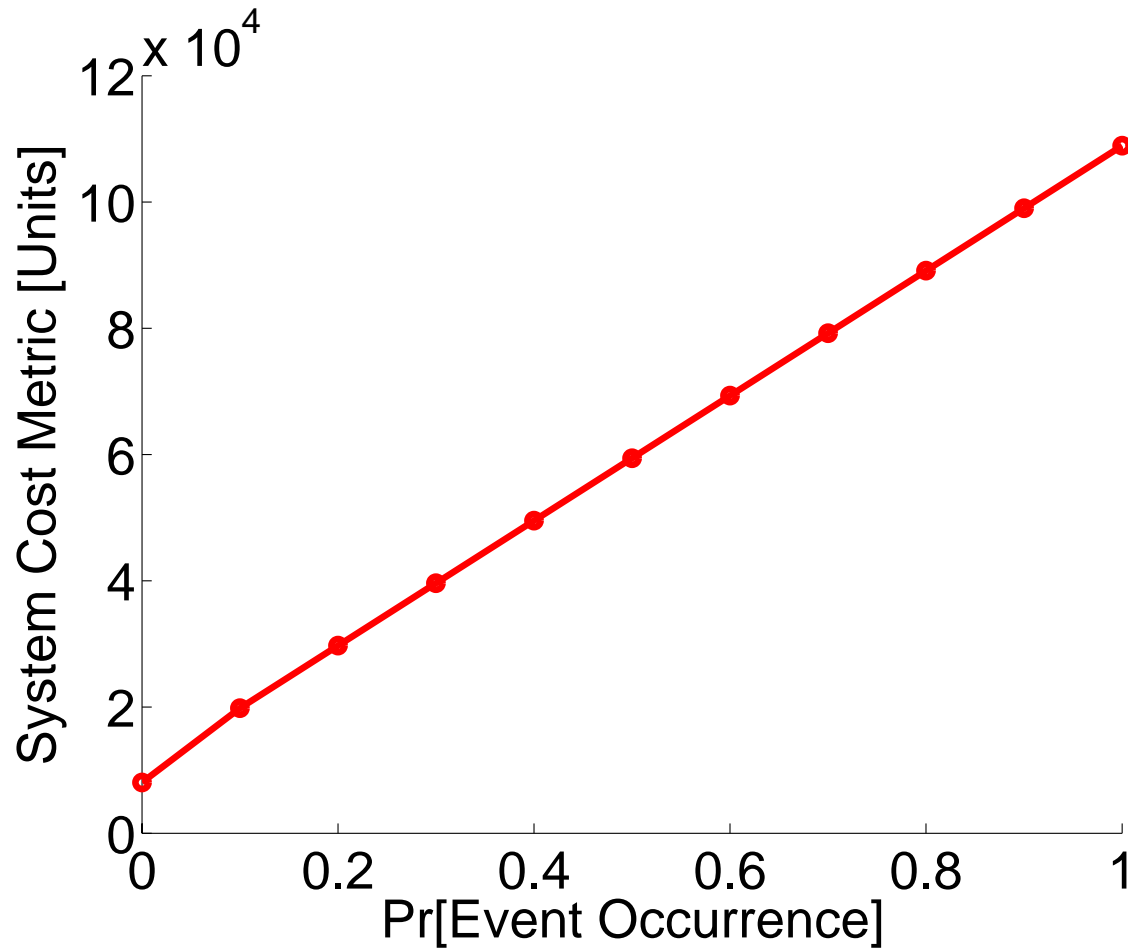
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# System Trade-offs : Introduction

- Models were developed and applied to determine system trade-offs when seeking visibility into cargo shipments.

- Objectives:
  - Study trade-offs when monitoring cargo in motion and to identify the important factors that system architects must consider when choosing to implement either a train-mounted or trackside deployment system
  - Provide tools for designers of cargo monitoring systems that balance performance and cost
  - Highlight the power of the models developed

- Studied system trade-offs when two different sensor cost models were available:
  - Linear cost model
  - Nonlinear cost model

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# System Trade-offs : Introduction

- Due to computational limits on solver, system trade-offs were studied on train with:
  - 15 units (railcars)
  - 33 containers
  - Up to 33 sensors
- Other train details:
  - Average train speed was 25 km/h
  - Length of the rail trip was 1984 km, which is the distance from Laredo to Kansas City
  - Cost of each false alarm was 20,000 units
  - Other parameters in dissertation

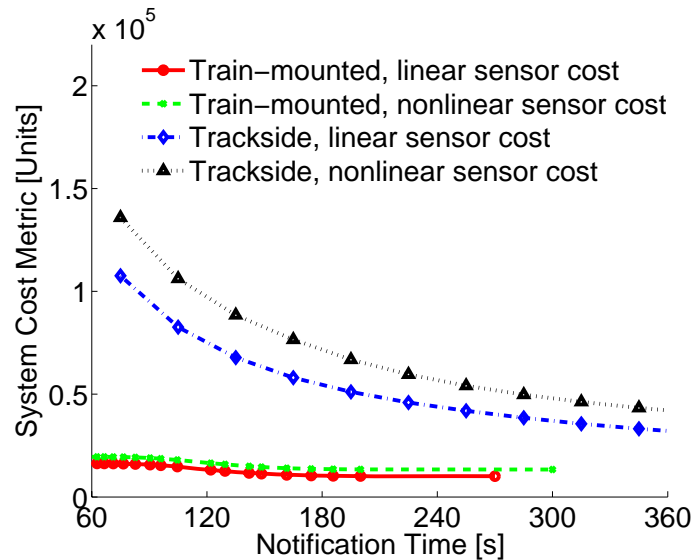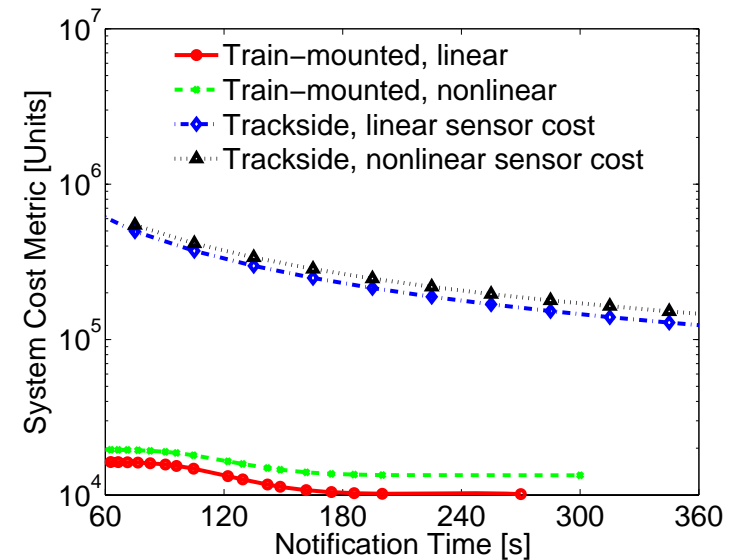# Train-Mounted System Deployment: Trade-offs with Prob. Of Detection
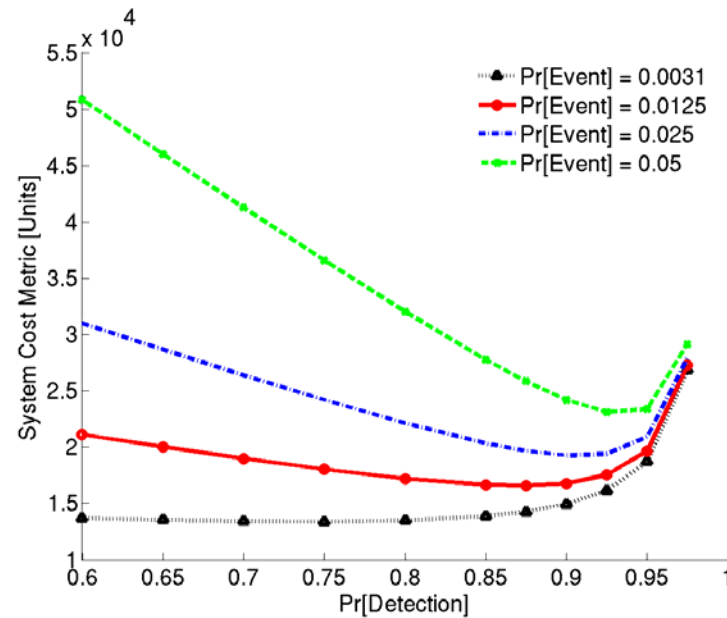


- What is the effect of changes in the probability of detection on the system cost metric?

# Train-Mounted System Deployment: Trade-offs with Prob. Of False Alarm
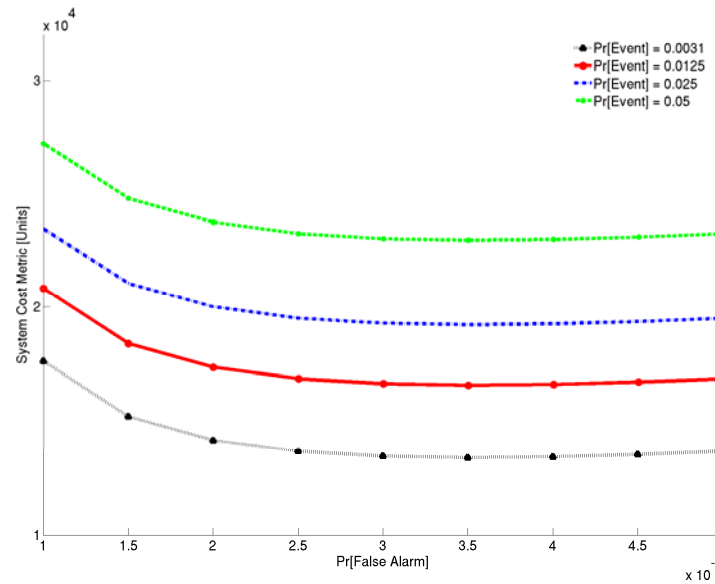


- What is the effect of changes in the probability of false alarm on the system cost metric?

# Train-Mounted System Deployment: Effects of Changes in Prob. Of Event Occurrence
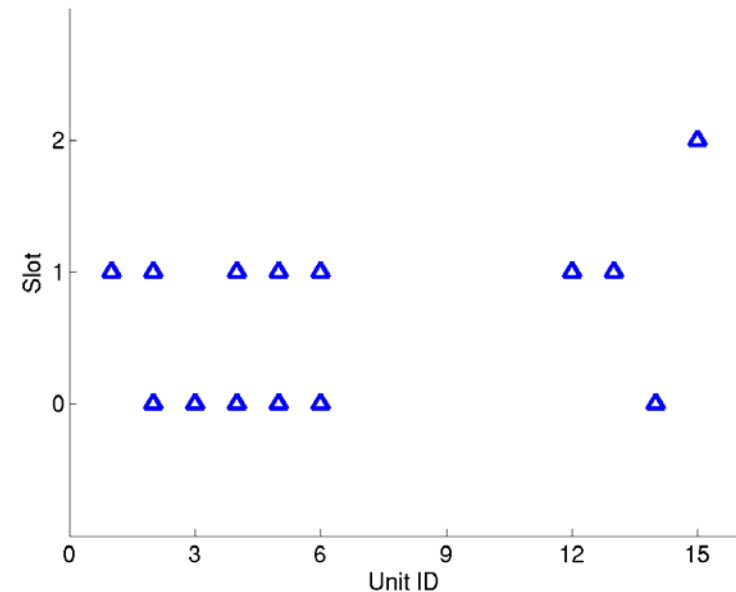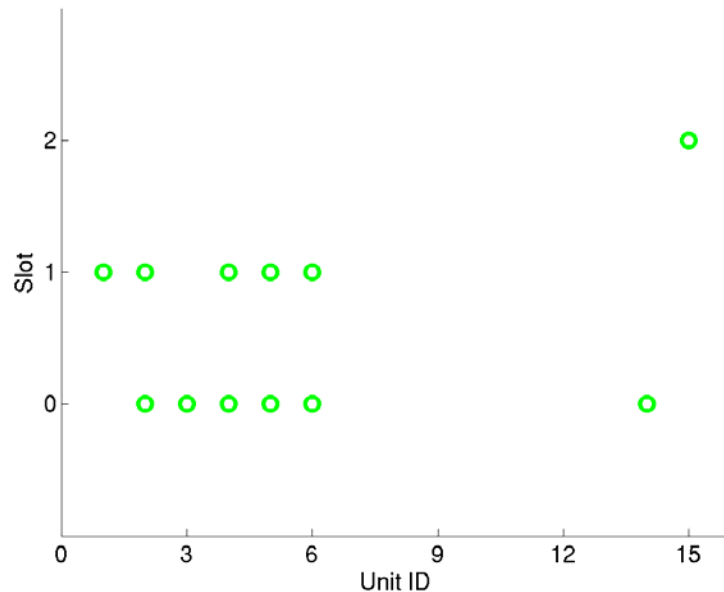


Critical Event Probability = 0.0031          Critical Event Probability = 0.0062

- How is the optimal number of sensors for a given train configuration affected by changes in the probability of event occurrence?

# Train-Mounted System Deployment: Effects of Variations in Probability of Detection
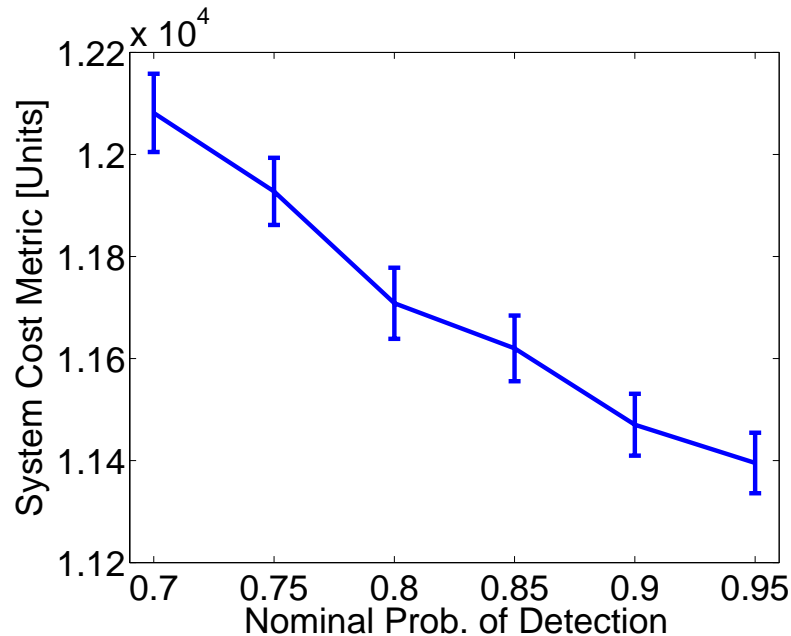


a) Linear sensor cost model
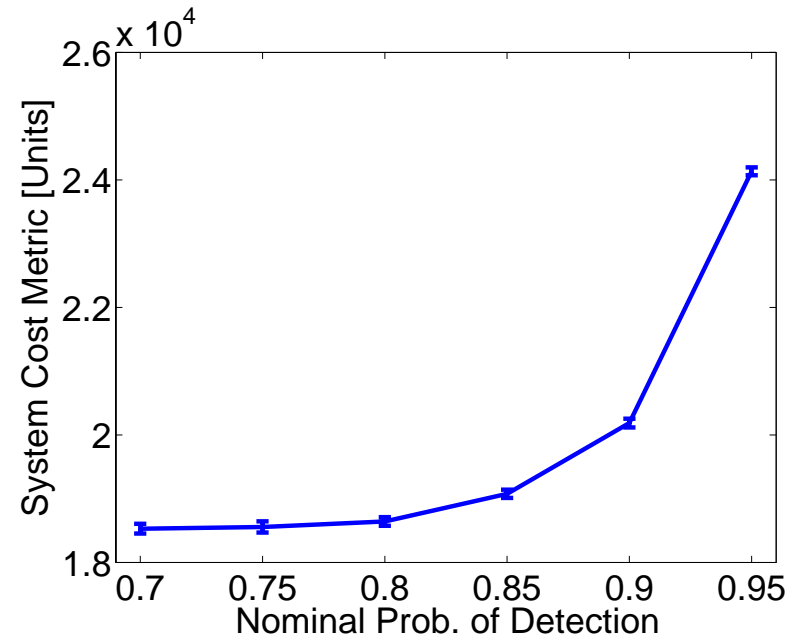


b) Nonlinear sensor cost model

- What is the effect of variations in the probability of detection on the system cost metric?

# Trackside System Deployment: Trade-offs with Prob. Of Successful Communications
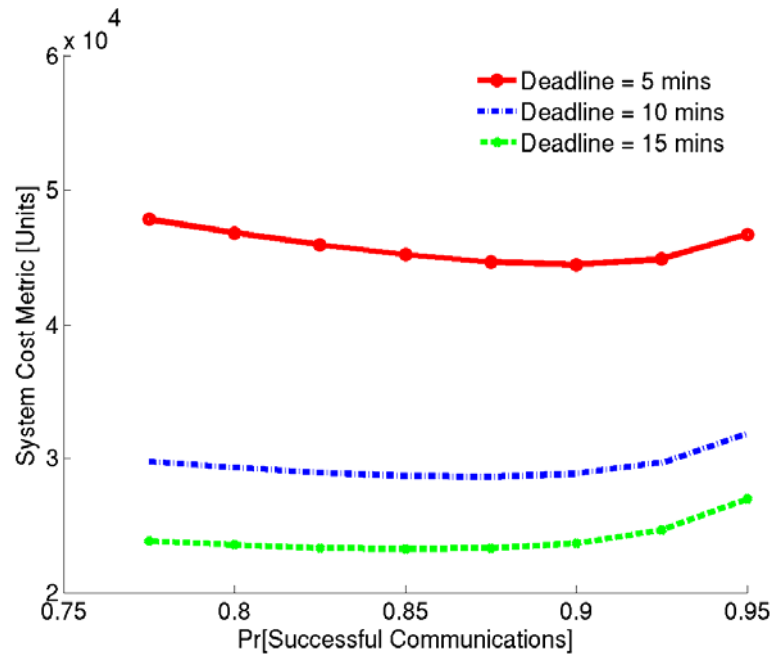


- What is the effect of changes in the probability of successful communications on the system cost metric?

# Trackside vs. Train-Mounted System Deployments



a) Reader cost = 3,000

b) Reader cost = 15,000

- How is the system cost metric affected by changes in the event notification time?

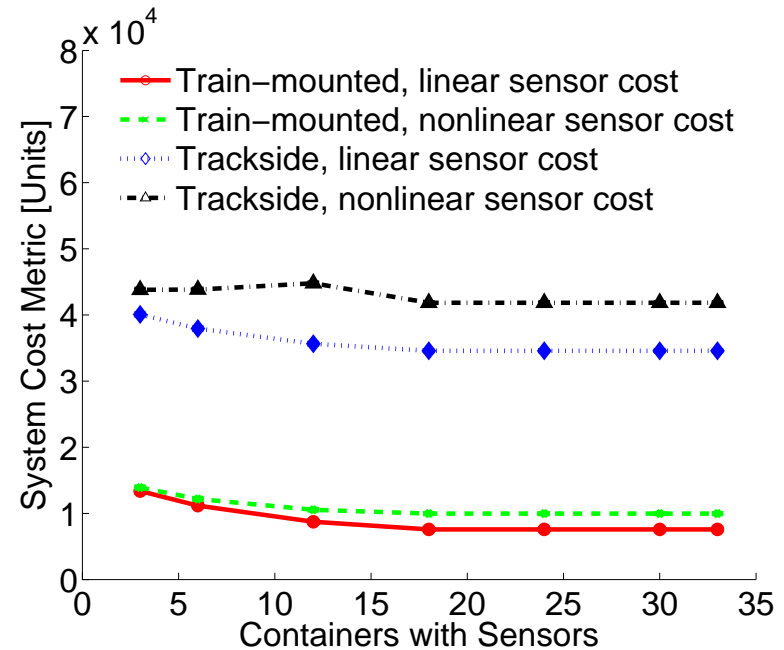# Trackside vs. Train-Mounted System Deployments
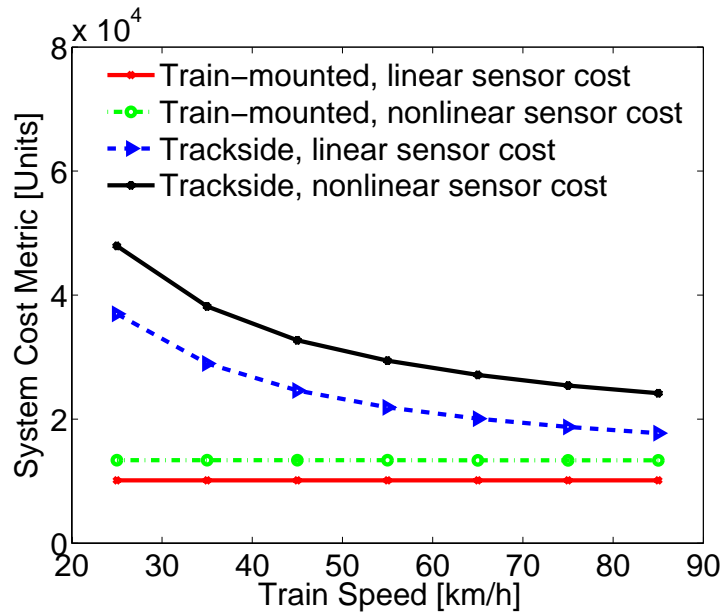


a) Reader cost = 3,000
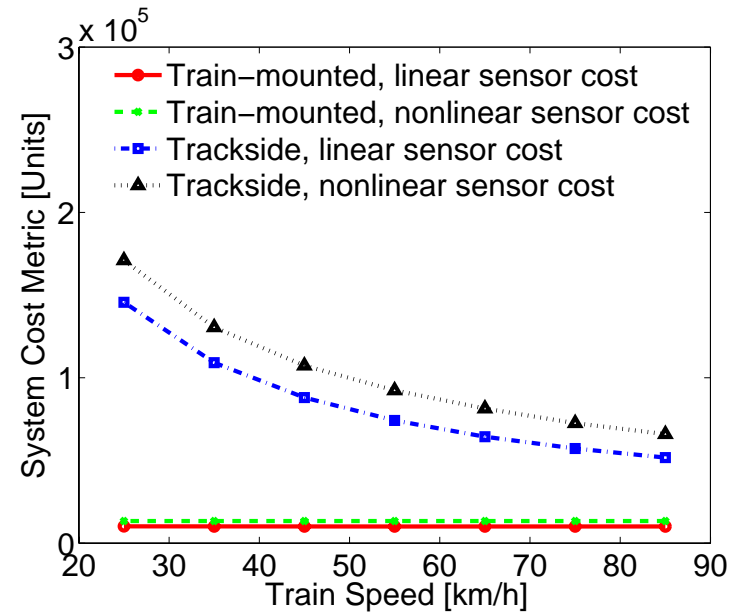
b) Reader cost = 15,000

- What are the effects of changes in train speed on the system cost metric?

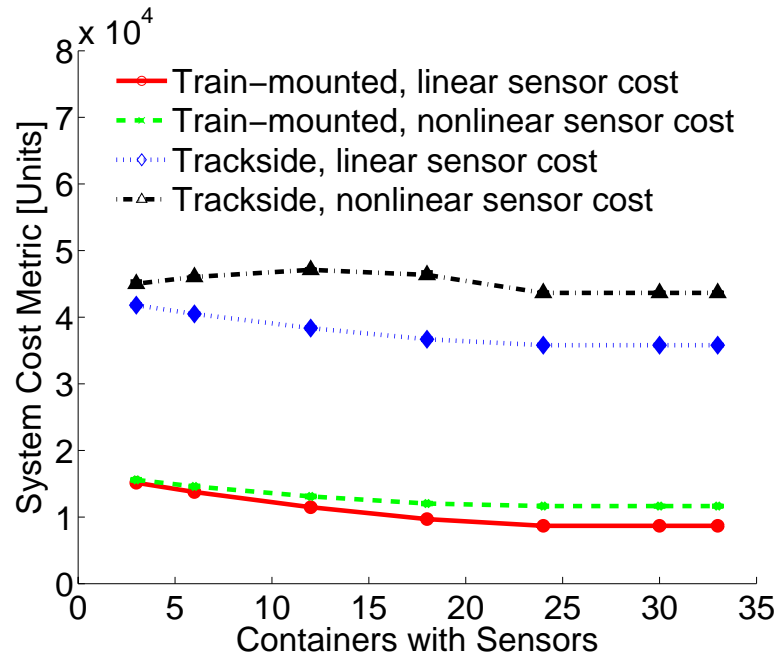# Trackside vs. Train-Mounted System Deployments
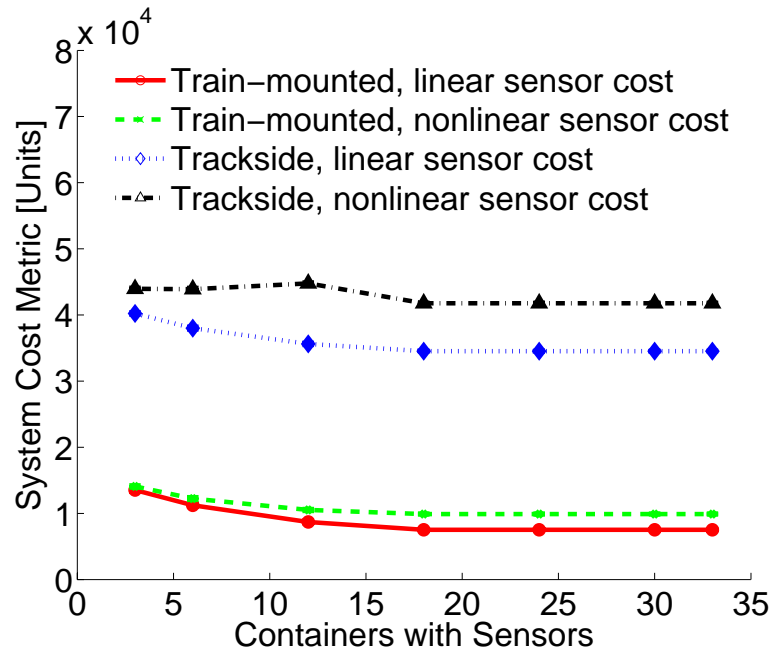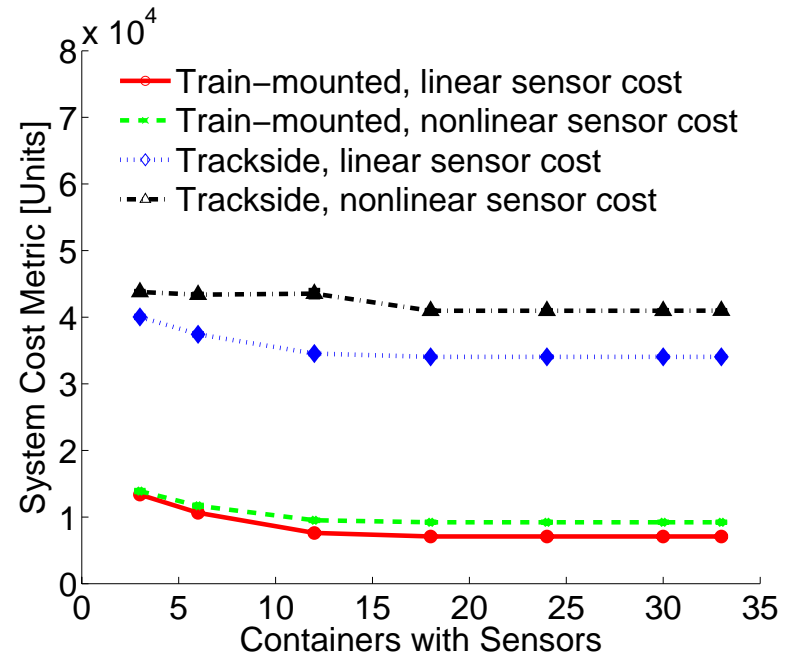


a) High value containers dominate

b) Approx. equal number of low and high value containers

- How does the system cost metric vary for different container savings distributions?

# Trackside vs. Train-Mounted System Deployments



c) Mostly medium value containers

d) Mostly low value containers

- How does the system cost metric vary for different container savings distributions?

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# System Trade-offs Observations

- For the cases studied:
    - Trackside system has a higher cost metric that train-mounted system
    - Trackside system is more sensitive to train speed than train-mounted system.
    - Can trade-off event notification deadline with system cost
    - The optimal number of sensors is dependent on the container savings distribution and the probability of critical event occurrence
    - The optimal probability of false alarm is independent of the probability of critical event occurrence and event reporting deadline.
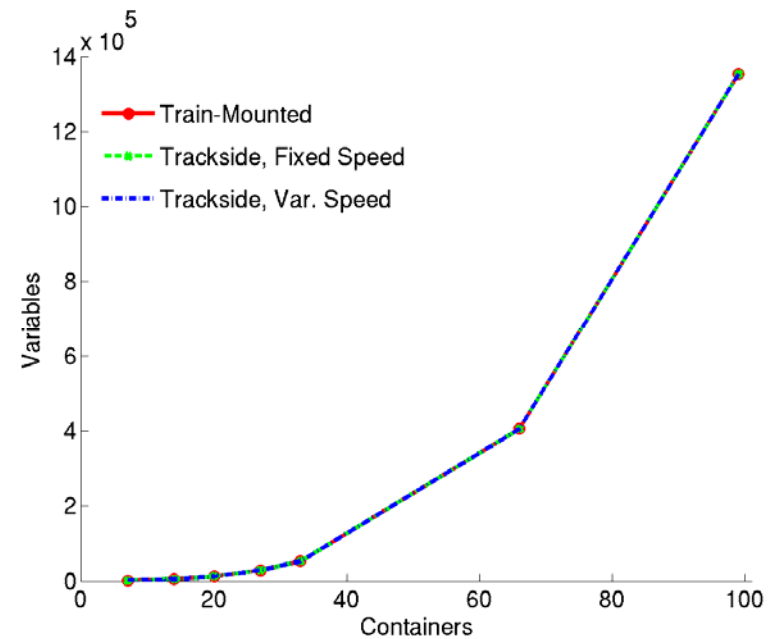
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# Model Growth
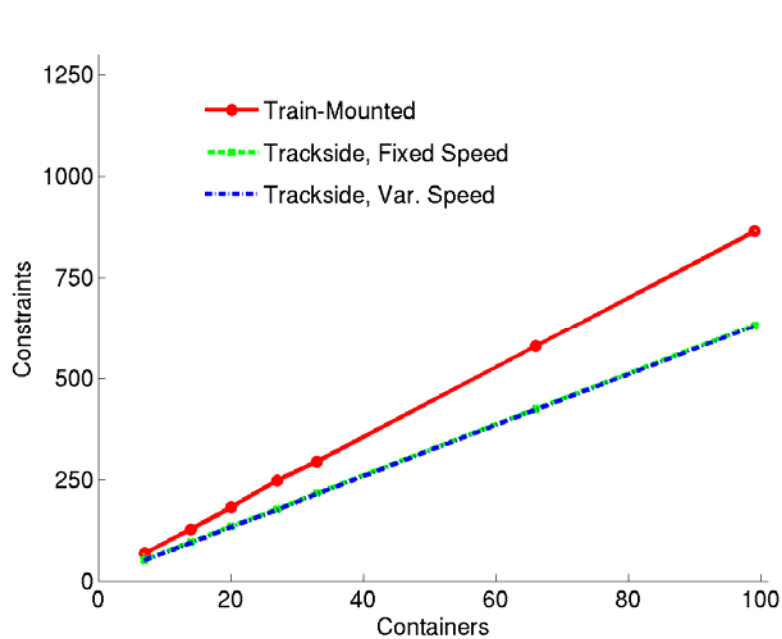


a) Constraints                      b) Variables

- How quickly do the number of constraints and variables grow for the models?

# Heuristic Motivation

- MINLP can be used to optimally assign sensors to containers on a train.

- MINLP approach was only used on a train with 15 units and 33 containers.

- Typical international intermodal stack train can have up to 104 units and 224 containers.

- Heuristic needed to place sensors on typically-sized trains.

## Assumptions for Heuristic

- Finite number of sensors

- A valid sensor placement solution exists

- Unit cost of each sensor is related to the sensor capabilities using either a linear or nonlinear cost model

- Transmission range of the sensors can be modified so that all the sensors are connected in a cargo monitoring network.

- A visibility weight is associated with each container

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# Heuristic Description

- Heuristic stores the number of sensors available to be used on the train and the total savings for all the containers on the train.

- Computes the visibility weight for each container and stores the visibility weights in descending order.

- Computes the probabilities of detection and false alarm for each sensor.

- Assigns sensors to containers in order of descending visibility weight as long as there are sensors available.

- Check that each sensor can communicate with its neighbors.

- Compute cargo monitoring cost and terminate.

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# Heuristic Validation

- Heuristic was implemented in Java and run over trains of different sizes with the linear and nonlinear sensor cost models
- Train configuration:
  - Some details identical to those used for system trade-off studies
  - One train had 33 containers and 15 units; the next train had 20 containers and 9 units; and the last train had 14 containers and 6 units
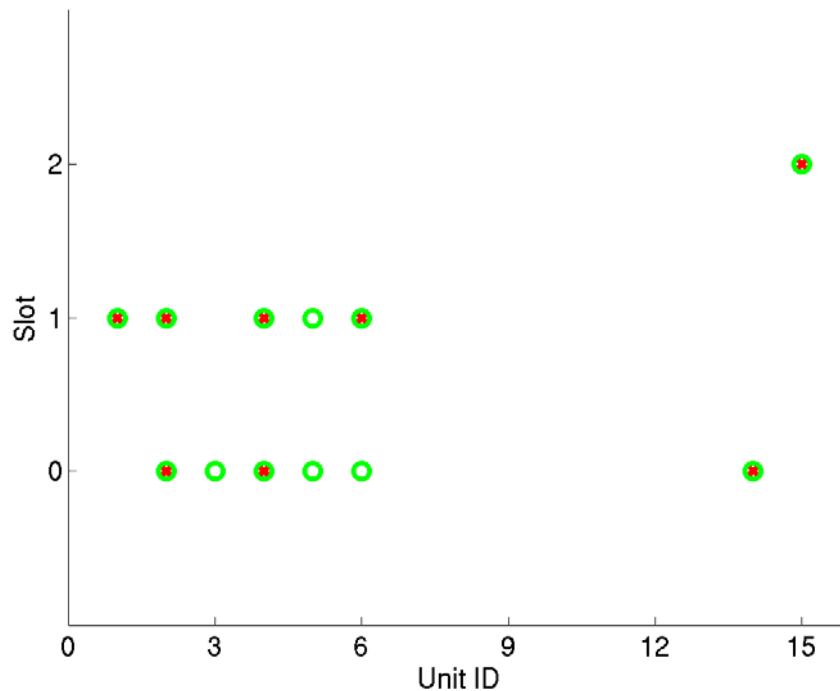
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# Heuristic Validation
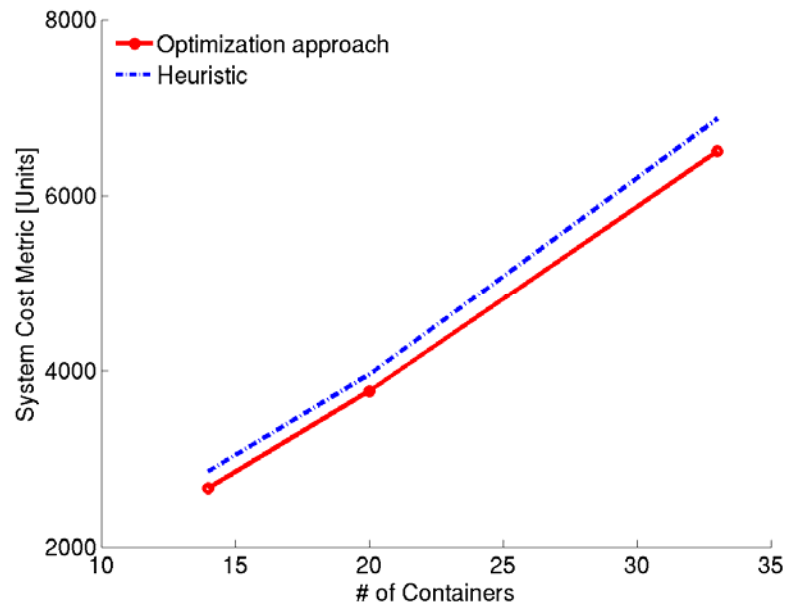


a) Linear sensor cost model,
Prob. of critical event = 0.0031
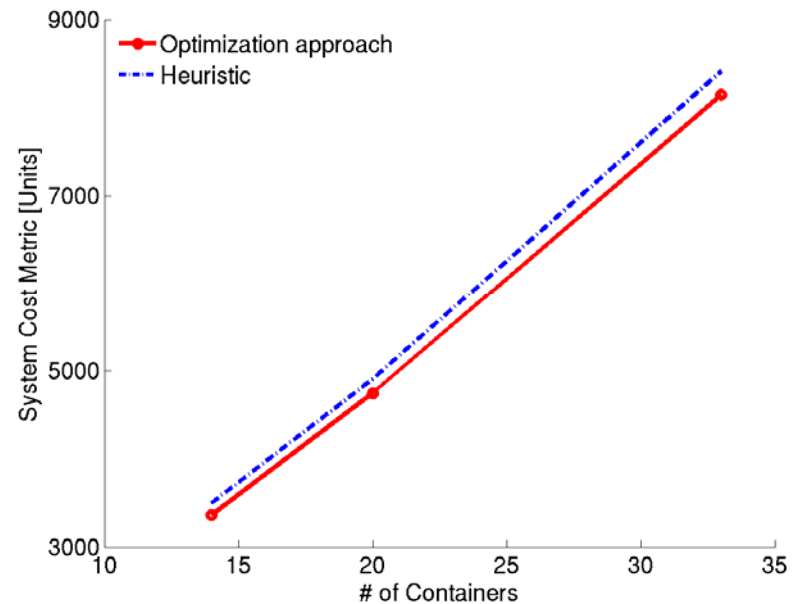
b) Nonlinear sensor cost model,
Prob. of critical event = 0.0031

- How do the optimization and heuristic approaches compare for trains with different sizes?

# Heuristic Output: Sensor Locations



- How do the heuristic-determined sensor locations compare with those found by the optimization procedure for a train with 33 containers?

# Application of Heuristic

- Heuristic applied to train using the following assumptions:
  - The average train speed was 25 km/h
  - The length of the rail trip was 1984 km, which is the distance from Laredo to Kansas City
  - There were 105 units and 225 containers on the train, with 30 20-feet, 186 40-feet, and 9 45-feet containers.
  - 150 containers had a mean value of 20,000 units, 50 containers had a mean value of 100,000 units, and 25 containers had a mean value of 200,000 units.
  - Containers were placed in slots on the train using only the train company's loading rules
  - The probability of a critical event, such as a container seal being opened, closed, or tampered with, occurring at each container was varied across the runs.

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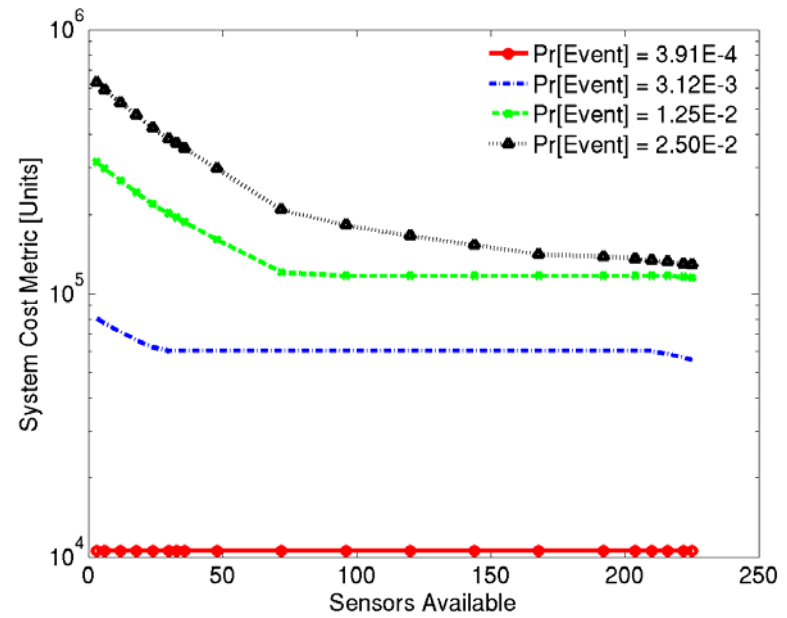# Heuristic Output
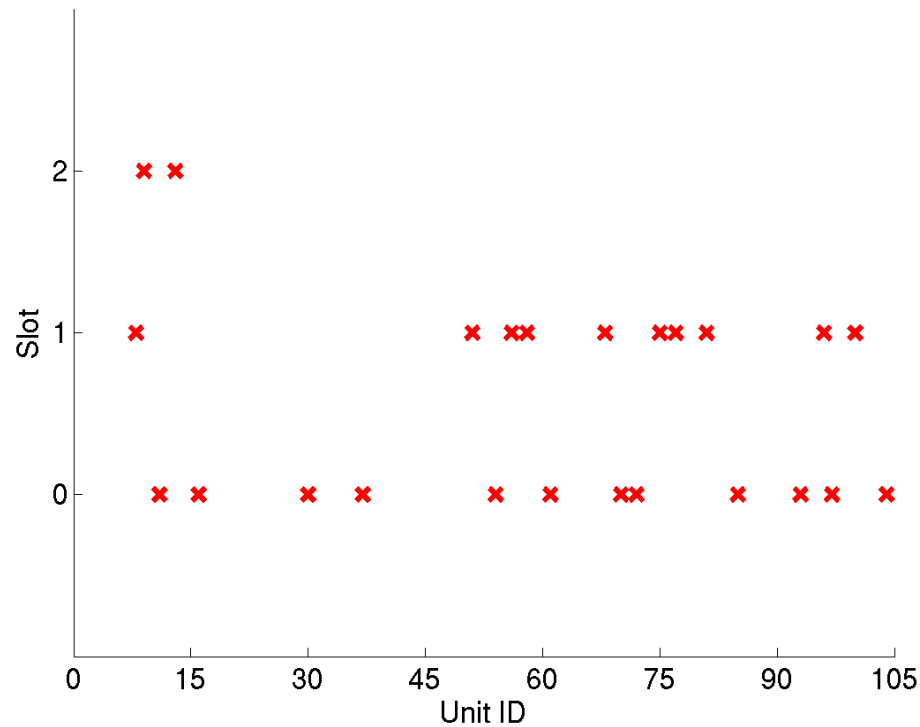


- Where does the heuristic assign sensors in the case of the 225 container train?

# Application of Heuristic
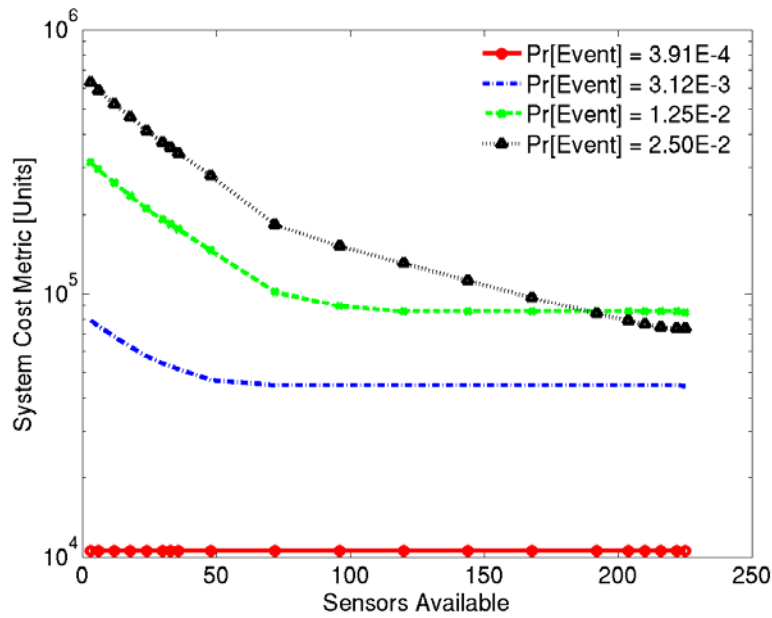


a) Linear Sensor Cost Model                    b) Nonlinear Sensor Cost Model

- How does the heuristic perform when applied to a 225 container train with different probabilities of critical event occurrence?

# Heuristic Findings

- Heuristic is able to determine appropriate sensor assignments and sensor characteristics for near to optimal system performance.

- Depending on the probability of critical event occurrence it may be necessary to use fewer sensors than the total number of containers, if the cost of an event exceeds the unit sensor cost.

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# Contributions Summary

- Developed and applied a new definition for container visibility.

- Developed a mechanism for container location and identification on trains: indexing scheme.

- Produced models that find the optimal assignment of sensors to containers on a train

- Studied system trade-offs between:

  - Train-mounted and trackside deployment of readers.

  - System cost and time needed to report events.

- Developed a heuristic for deploying sensors to trains of realistic size.

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# Future Work

- Investigate methods of validating the models more rigorously
- Improve the sensor cost models such that they incorporate a standard deviation in sensor characteristics
  - The more a sensor deviates from the optimum value, the cheaper it is.
- Improve the calculation for the system cost metric such that it incorporates a small loss to the system operator if there is an event, unlike the current situation
- Literature review indicates that cargo is most at risk when it is stationary.
  - Thus, the probability of a critical event needs to be related to train speed.
- Investigate the maximum sized train that can be handled by the heuristic

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Questions?

Back-up Slides

# Experiences from a Transportation Security Sensor Network Field Trial

- Cargo theft estimated to cost the US economy $15–$30 billion
  - Cargo theft affects originators, shippers, and receivers.
- Most non-bulk cargo travels in shipping containers.
  - Container transport is characterized by complex interactions.
- Deficiencies in container transport chain expose the system to attacks such as:
  - Trojan Horse
  - Hijack or theft of goods
- Insufficiencies in these areas can be overcome by creating secure trade lanes, especially at intermodal points.
- Transportation Security Sensor Network (TSSN) has been developed for monitoring integrity of cargo shipments.
- TSSN has been implemented and a field trial conducted to evaluate its effectiveness and performance.

# TSSN System Architecture
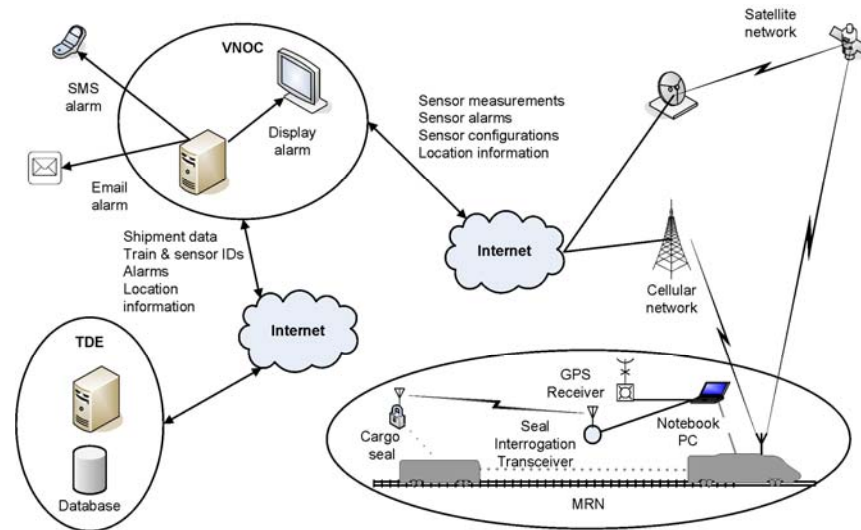


- TSSN is composed of Trade Data Exchange (TDE), Virtual Network Operations Center (VNOC), and Mobile Rail Network (MRN).

- Using commercial off-the-shelf hardware and networks combined with middleware developed in-house the TSSN is able to detect events and report those relevant to shippers and other decision makers.

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# Short-haul trial Experiment

- Field trail carried out on train making a ~35 km trip from intermodal facility to rail yard.

- Field trail objectives:
  - Determine performance of TSSN system when detecting events on intermodal containers in a rail environment.
  - Investigate if decision makers could be informed of events in a timely manner using SMS messages and email.
  - Collect data that will be used in a model to investigate system trade-offs for monitoring rail-borne cargo.

- During experiment events were created by breaking and closing a seal kept in the locomotive.

# Short-haul Trial Configuration
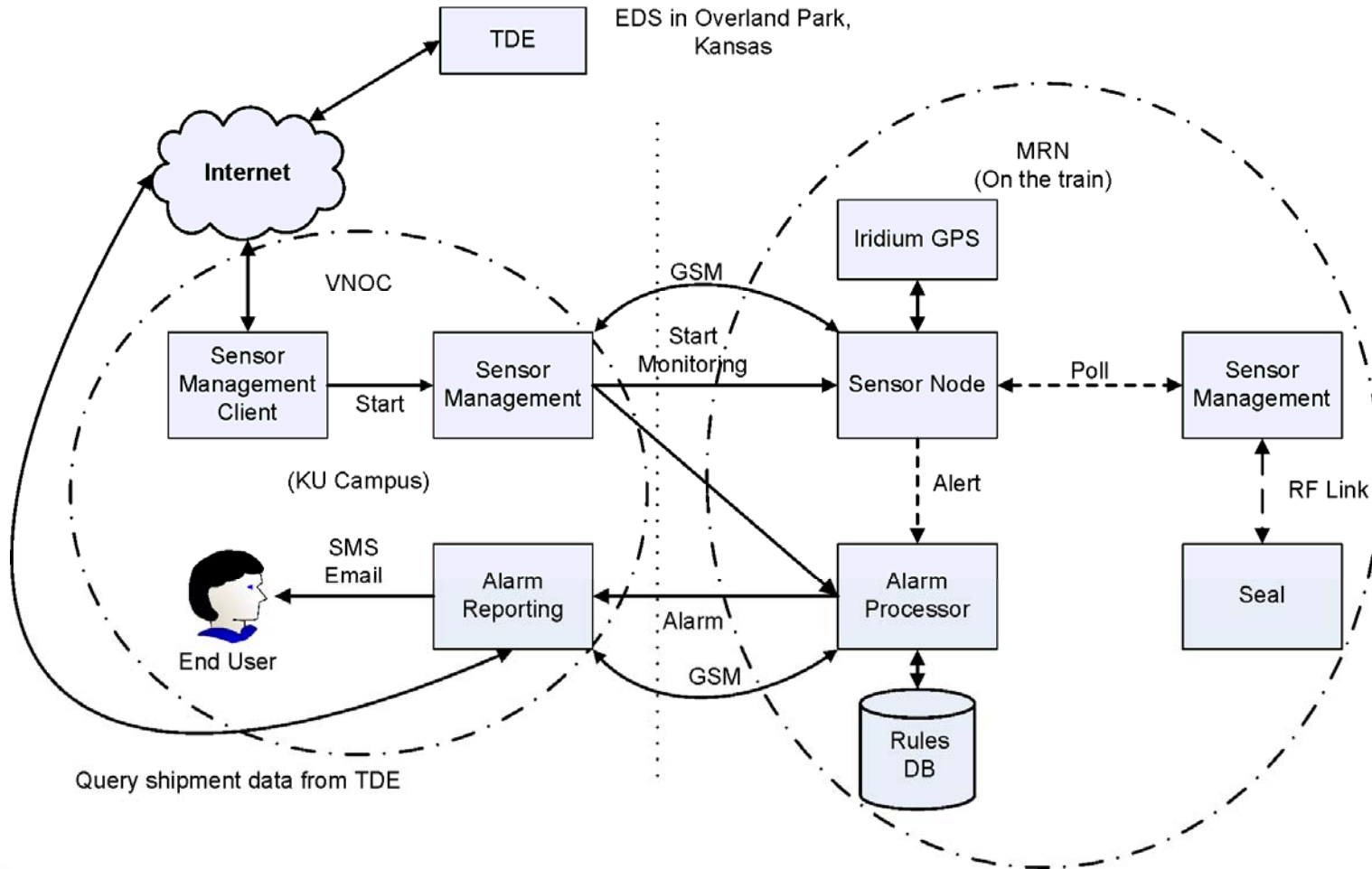
# Short-haul trial decision maker notification
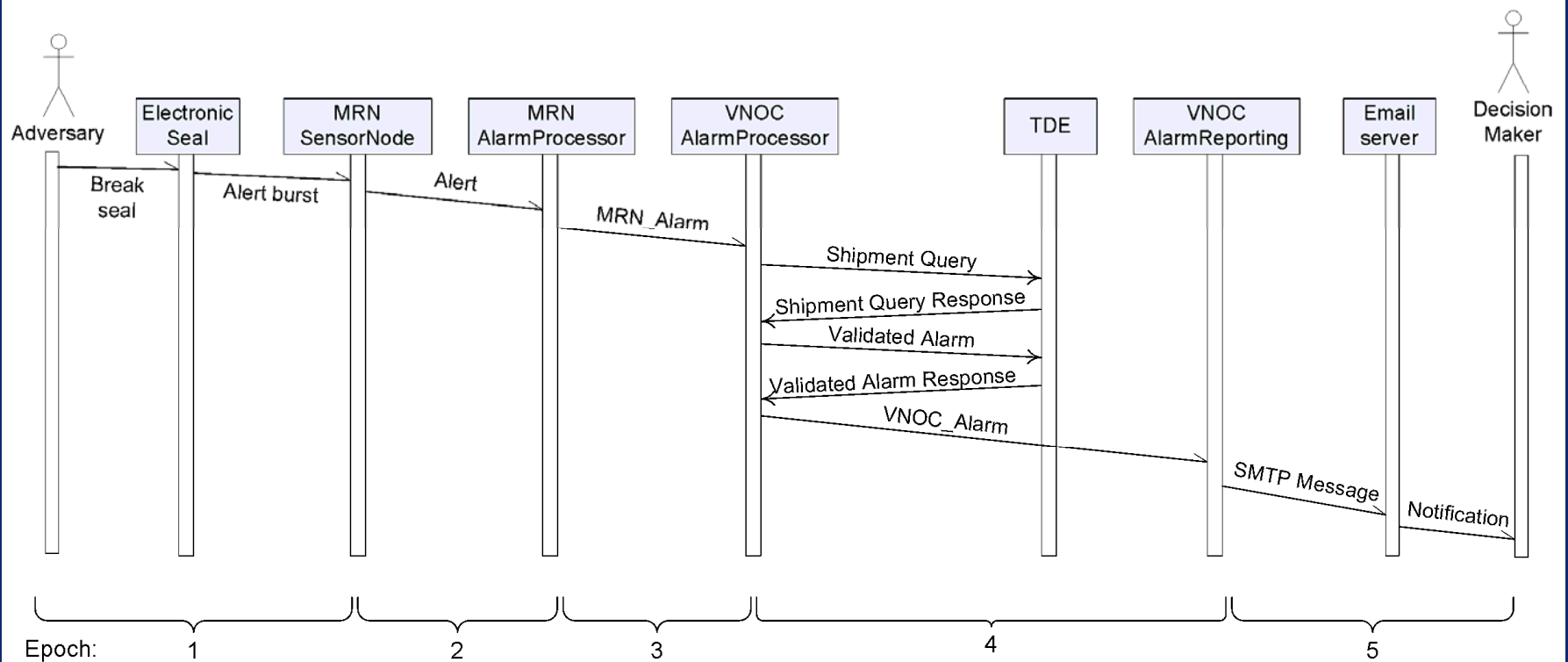
# TSSN Short-haul Trial Results

| Epoch | Description | Median/s | Max/s |
|-------|-------------|----------|-------|
| 1 | Event occurrence to alert generation | 2.13 | 8.75 |
| 2 | Alert generation to MRN AlarmProcessor service | 0.01 | 0.08 |
| 3 | One-way delay from MRN AlarmProcessor to VNOC AlarmProcessor service | 1.94 | 2.90 |
| 4 | MRN_Alarm arrival at VNOC to AlarmReporting service | 0.05 | 3.01 |
| 5 | Elapsed time from VNOC AlarmReporting service to decision maker's phone | 9.80 | 58.7 |

# TSSN Refinements and Conclusions

- Refinements:
  - Redesign MRN hardware for TSSN collector node to have redundant backhaul communications capabilities.
  - Enhanced sensor capabilities to enable whole-train monitoring.
- Conclusions
  - Based on our experiments and evaluations TSSN is viable for monitoring rail-borne cargo.
  - Based on experimental results it can take just over one minute to notify decision makers of events.
  - We have successfully demonstrated that events can be detected and decision makers notified within decision maker threshold.
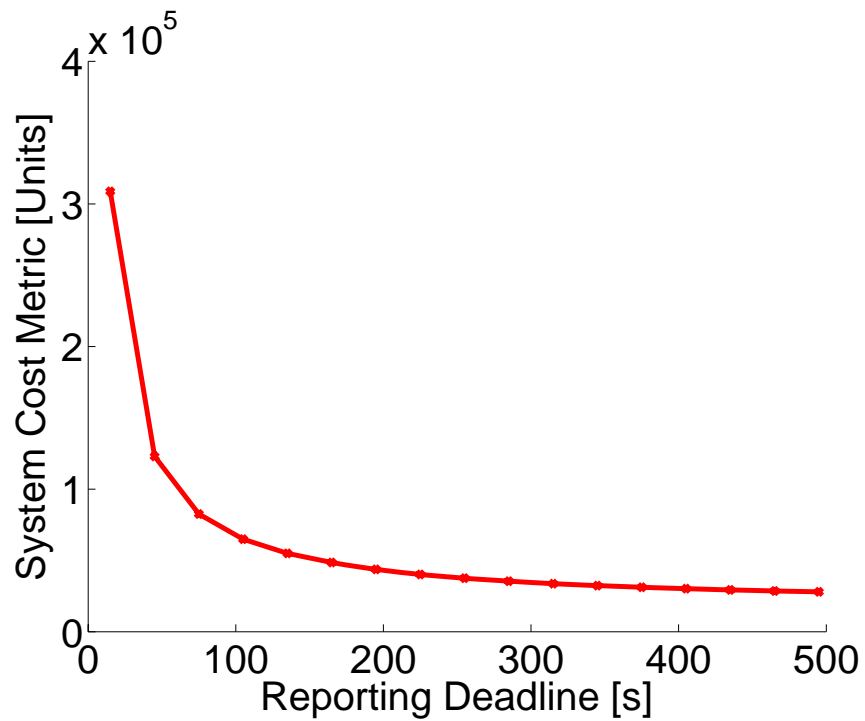
# Validation for Train-mounted Model
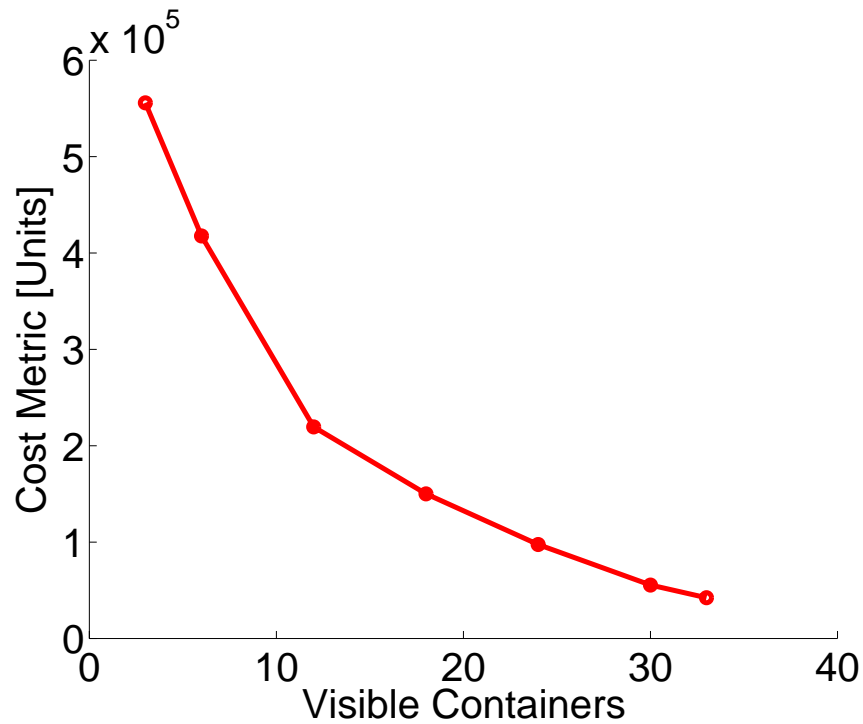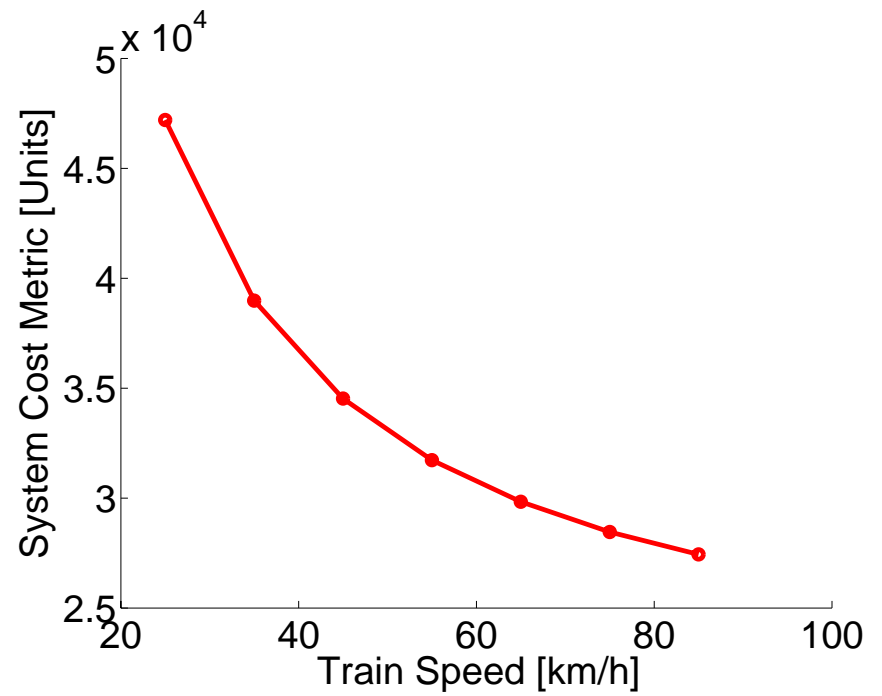


a) Cost Metric vs. Number of Visible Containers
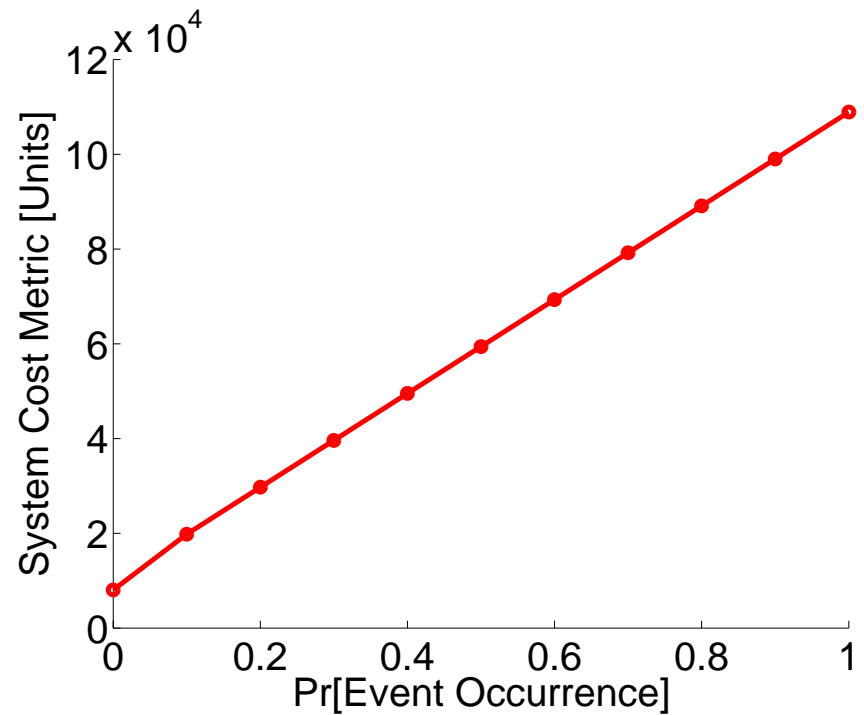
b) Cost Metric vs. Prob. Of Event Occurrence

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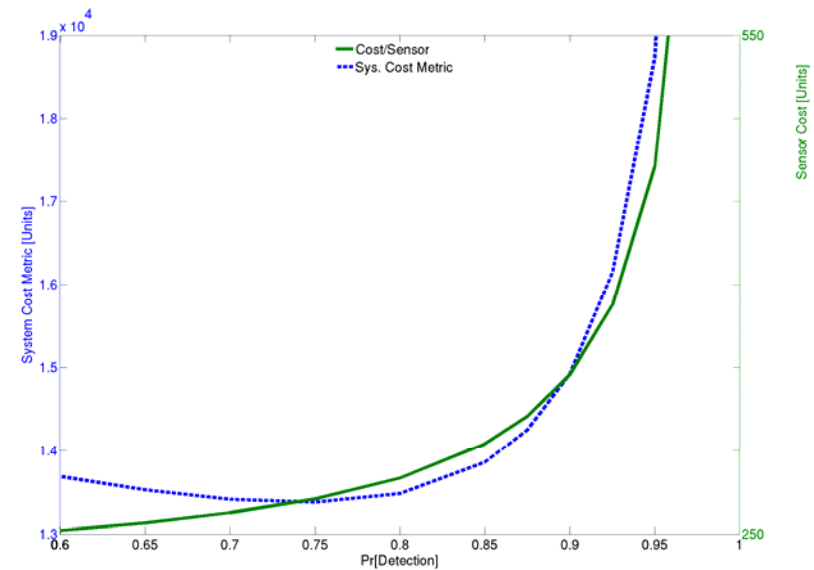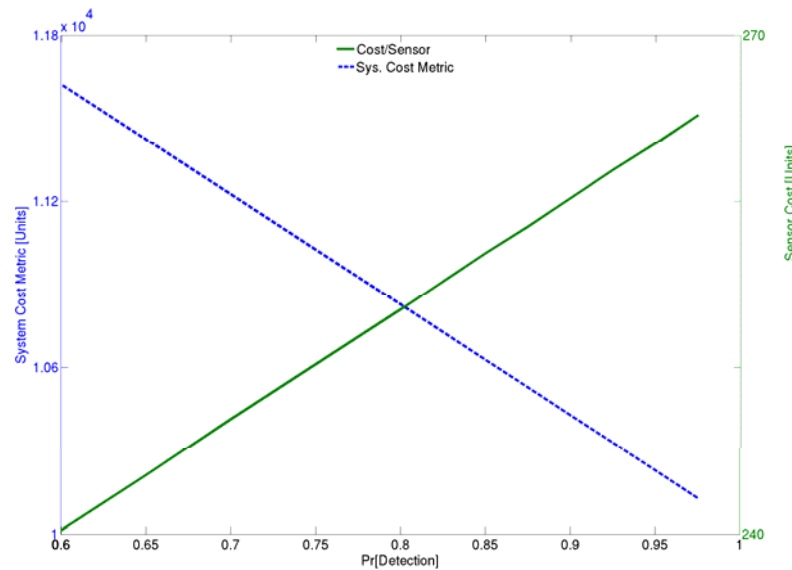
# Validation for Trackside Model



a) Reporting Deadline vs. Cost Metric

b) Train Speed vs. Cost Metric

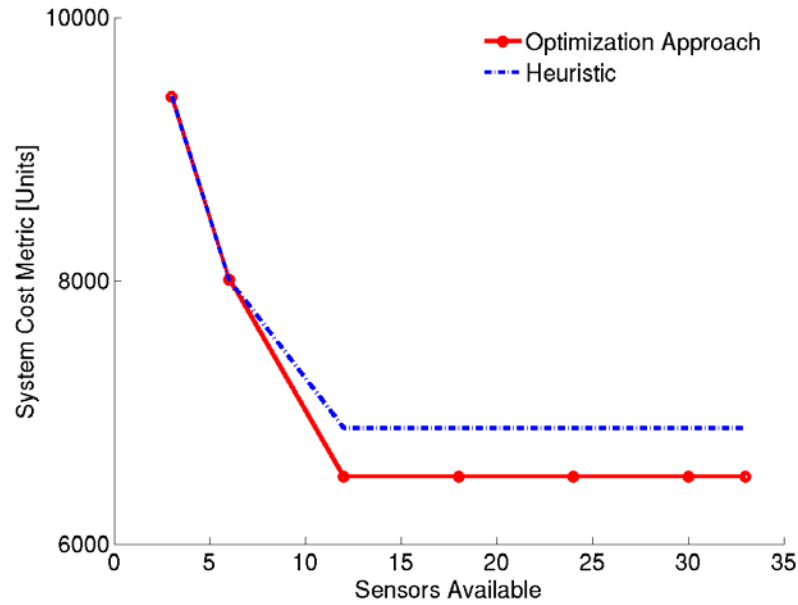# Train-Mounted System Deployment: Trade-offs with Prob. Of Detection
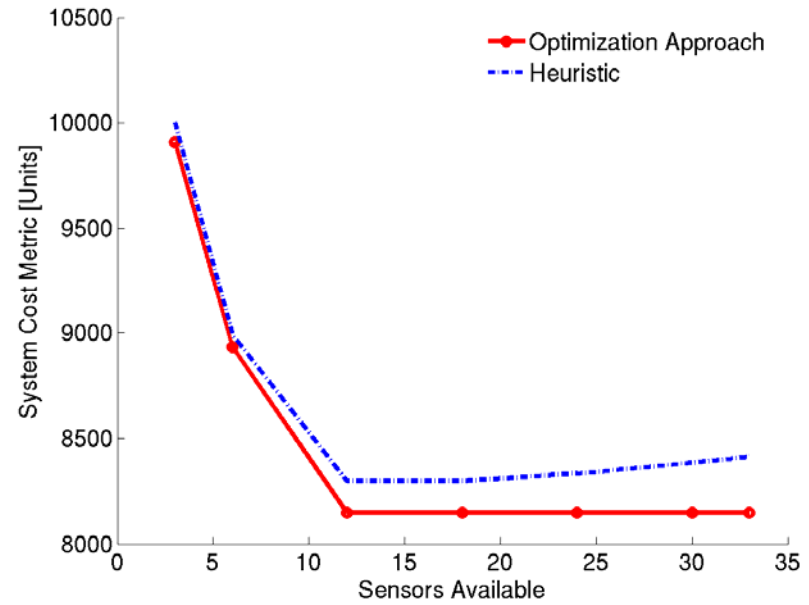


a) Linear sensor cost model

b) Nonlinear sensor cost model

- What is the effect of changes in the probability of detection on the system cost metric?

# Heuristic Validation



a) Linear sensor cost model, 15 unit train with 33 containers

b) Nonlinear sensor cost model, 15 unit train with 33 containers

- How do the optimization and heuristic approaches compare for a train with 15 units and 33 containers?

# Conclusions

- An open system transportation security sensor network can be used to provide decision makers with timely notification of events on a train.

- Two mechanisms have been developed to determine sensor placements and system trade-offs when seeking visibility into cargo shipments.

  - Models show that it is cost-effective to use sensor networks for cargo monitoring.

# Conclusions

- System trade-off studies showed that:
  - Optimal number of sensors is dependent on the container savings distribution and the probability of critical event occurrence
  - For nonlinear sensor cost model the optimal probability of detection is dependent on the probability of critical event occurrence
  - For the linear sensor cost model the optimal probability of detection is independent of the probability of critical event occurrence
  - Optimal probability of false alarm is independent of the probability of critical event occurrence and event reporting deadline.
  - System deployment cost is inversely related to the deadline for decision maker notification.
- Developed a heuristic for deploying sensors to a train
  - Heuristic performance is reasonable when compared to optimization approach.