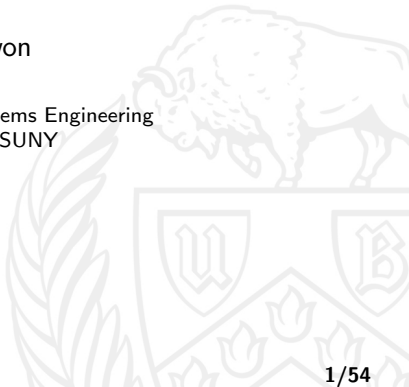


Uncertainty in Hazardous Materials Transportation

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Department of Industrial & Systems Engineering
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May 7, 2015



Outline

- 1 Introduction
- 2 Risk Measures
- 3 Data Uncertainty
- 4 Behavioral Uncertainty



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Hazardous Materials

Hazardous Materials (hazmat), Dangerous Goods

Class 1: Explosives

Divisions: 1.1, 1.2, 1.3, 1.4, 1.5, 1.6



Class 6: Poison (Toxic) and Poison Inhalation Hazard

Class 2: Gases

Divisions: 2.1, 2.2, 2.3



Class 7: Radioactive

Class 3: Flammable Liquid and Combustible Liquid



Class 8: Corrosive

Class 4: Flammable Solid, Spontaneously Combustible, and Dangerous When Wet

Divisions 4.1, 4.2, 4.3



Class 9: Miscellaneous

Class 5: Oxidizer and Organic Peroxide

Divisions 5.1, 5.2



Dangerous

Introduction

Hazmat transportation

- Number of accidents is small compared to the number of shipments
- Consequence is very severe in terms of fatalities, injuries, large-scale evacuation and environmental damage



Introduction

Table: 2014 Hazmat Summary by Transportation Phase ¹

Transportation Phase	Incidents	Hospitalized	Non-Hospitalized	Fatalities	Damages
In Transit	4,190	2	53	5	\$63,686,925
In Transit Storage	614	1	1	0	\$1,629,889
Loading	3,262	3	20	0	\$1,021,289
Unloading	8,149	5	47	1	\$3,848,737
Unreported	1	0	0	0	\$0

¹Hazmat Intelligence Portal, US Department of Transportation.

Introduction

Table: Hazmat Shipment Tonnage Shares by Mode in 2007²

Mode of Transportation	Percentage of Tons
Truck	53.9%
Pipeline	28.2%
Water	6.7%
Rail	5.8%
Multiple modes	5.0%
Other and unknown modes	0.4%

²Research and Innovative Technology Administration and US Census Bureau, *2007 Commodity Flow Survey, Hazardous Materials*

Three Types of Uncertainty

- 1 Where will be the accident location?
 - Probabilistic nature of traffic accident
 - 2 How large will be the accident consequence?
 - Data uncertainty
 - 3 How do hazmat carriers determine routes?
 - Behavioral uncertainty
- (1), (2): Risk Measures
 - (2), (3): Robustness



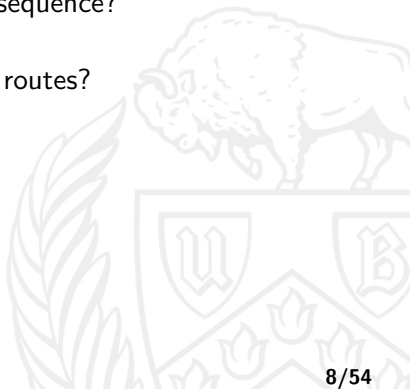
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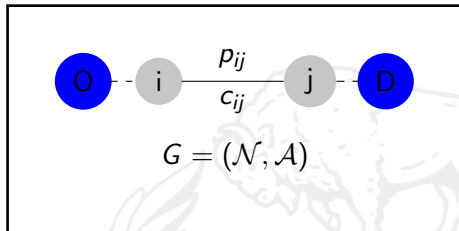
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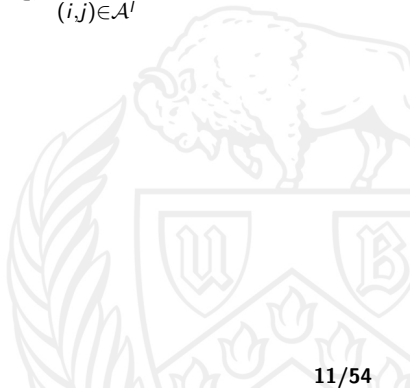
Hazmat Transportation Network

- $G = (\mathcal{N}, \mathcal{A})$ – a road network
- \mathcal{N} is the node set and \mathcal{A} is the arc set.
- p_{ij} – accident probability on arc $(i, j) \in \mathcal{A}$.
- c_{ij} – accident consequence of traveling on arc $(i, j) \in \mathcal{A}$.



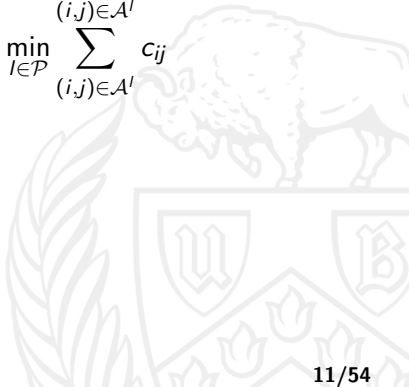
Comparison of Risk Measures

Model	Risk Measure	Function
TR	Expected Risk	$\min_{I \in \mathcal{P}} \sum_{(i,j) \in A^I} p_{ij} c_{ij}$



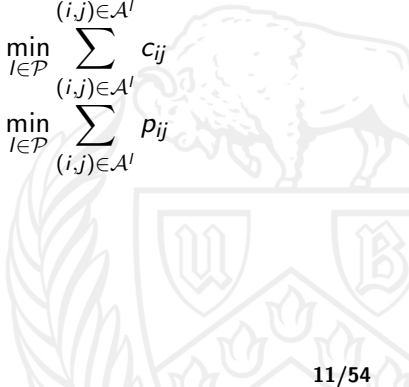
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IP	Incident Probability	$\min_{l \in \mathcal{P}} \sum_{(i,j) \in \mathcal{A}^l} p_{ij}$
PR	Perceived Risk	$\min_{l \in \mathcal{P}} \sum_{(i,j) \in \mathcal{A}^l} p_{ij} (c_{ij})^q$

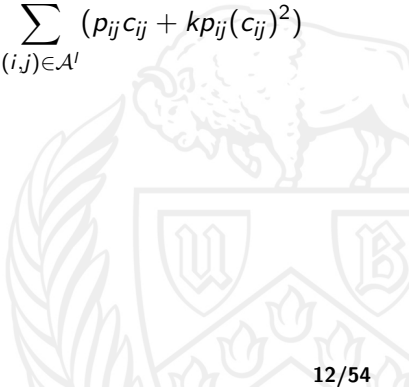
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DU	Disutility	$\min_{I \in \mathcal{P}} \sum_{(i,j) \in A^I} p_{ij} (\exp(k c_{ij}) - 1)$
CR	Conditional Probability	$\min_{I \in \mathcal{P}} \left(\frac{\sum_{(i,j) \in A^I} p_{ij} c_{ij}}{\sum_{(i,j) \in A^I} p_{ij}} \right)$

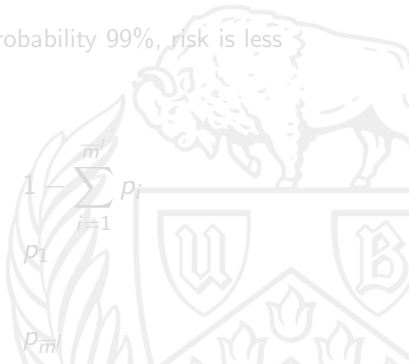
Value-at-Risk (VaR) in Hazmat Problem³

- Cutoff Risk β_α^l for path l such that
 - the probability of a shipment experiencing a greater risk than β_α^l is less than confidence level α

$$VaR_\alpha^l = \min\{\beta : \Pr(R^l > \beta) \leq 1 - \alpha\}$$

- $VaR = 100$ at $\alpha = 99\%$: With probability 99%, risk is less than 100.
- Risk of a path l :

$$R^l = \begin{cases} 0, & \text{w.p. } 1 - \sum_{i=1}^{\bar{m}^l} p_i \\ C_1, & \text{w.p. } p_1 \\ \vdots \\ C_{\bar{m}^l}, & \text{w.p. } p_{\bar{m}^l} \end{cases}$$



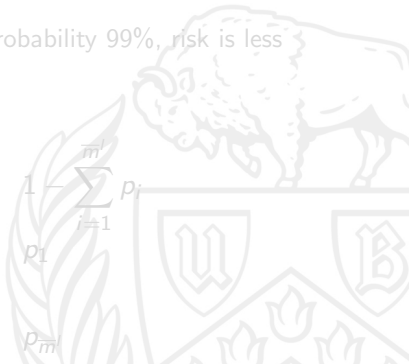
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Risk Preference with VaR

Confidence Level α	0	→	1
Risk Attitude	Risk Indifferent	→	Risk Averse
Equivalent Model	-		Min-Max Model $\min_{I \in \mathcal{P}} \max_{(i,j) \in \mathcal{P}^I} C_{(i,j)}$

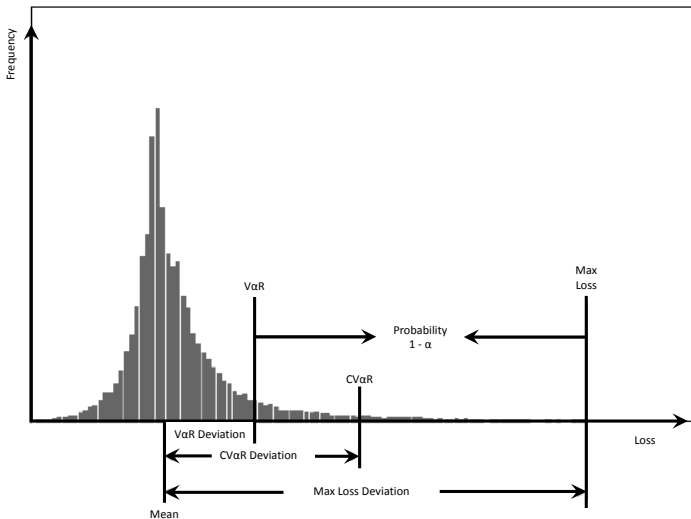
Sufficiently small α can be as large as 0.999977 in hazmat routing.

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VaR vs Conditional Value-at-Risk (CVaR)



Risk Preference with CVaR

Confidence Level α	0	→	1
Risk Attitude	Risk Neutral	→	Risk Averse
Equivalent Model	Traditional Risk Model $\min_{I \in \mathcal{P}} \mathbb{E}[R^I]$		Min-Max Model $\min_{I \in \mathcal{P}} \max_{(i,j) \in \mathcal{P}^I} c_{ij}$

CVaR Defined

- For a path $l \in \mathcal{P}$ at the confidence level α , the CVaR is defined as:

$$\text{CVaR}_\alpha^l = \lambda_\alpha^l \text{VaR}_\alpha^l + (1 - \lambda_\alpha^l) \mathbb{E}[R^l : R^l > \text{VaR}_\alpha^l]$$

where $\lambda_\alpha^l = \left(\Pr[R^l \leq \text{VaR}_\alpha^l] - \alpha \right) / (1 - \alpha)$.

- Hard to be considered in an optimization problem format mainly due to conditioning.

Auxiliary Form

- Following Rockafellar and Uraysev (2000), we consider the following function:

$$\begin{aligned}
 \Phi_{\alpha}^l(v) &= v + \frac{1}{1-\alpha} \mathbb{E}[R^l - v]^+ \\
 &\approx v + \frac{1}{1-\alpha} \sum_{(i,j) \in \mathcal{A}^l} p_{ij} [c_{ij} - v]^+
 \end{aligned}$$

where we denote $[x]^+ = \max(x, 0)$.

- Then, we can show that the CVaR minimization is equivalent to minimize Φ_{α}^l by choosing a path $l \in \mathcal{P}$ at the confidence level α . That is,

$$\min_{l \in \mathcal{P}} \text{CVaR}_{\alpha}^l = \min_{l \in \mathcal{P}, v \in \mathbb{R}^+} \Phi_{\alpha}^l(v)$$

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A Computational Method for CVaR Minimization

- $v^* \in \{0\} \cup \{c_{ij} : (i,j) \in \mathcal{A}\}$
- A shortest-path algorithm (like Dijkstra's) for solving the sub-problem.
- $|\mathcal{A}| + 1$ number of shortest-path problems.
- C. Kwon (2011), "Conditional Value-at-Risk Model for Hazardous Materials Transportation", in *Proceedings of the 2011 Winter Simulation Conference*, S. Jain, R. R. Creasey, J. Himmelspach, K. P. White, and M. Fu, eds. pp. 1708-1714
- Toumazis, I., C. Kwon, and R. Batta (2013), "Value-at-Risk and Conditional Value-at-Risk Minimization for Hazardous Materials Routing", in *Handbook of OR/MS Models in Hazardous Materials Transportation* (Eds.:R. Batta and C. Kwon), Springer
- Toumazis, I. and C. Kwon (2013), "Routing Hazardous Materials on Time-Dependent Networks using Conditional Value-at-Risk", *Transportation Research Part C: Emerging Technologies*, 37, 7392.

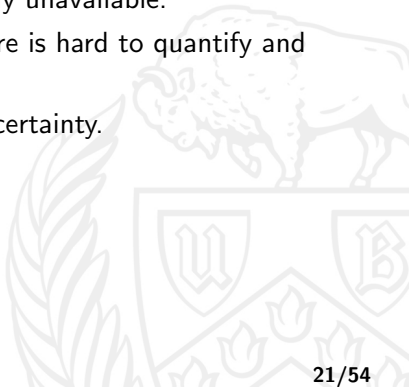
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A Challenge for Hazmat Routing

- Accident Probability: data is usually unavailable.
- Accident Consequence: any measure is hard to quantify and subject to uncertainty.
- Need a robust method for data uncertainty.



Shortest Path Problem

For a graph $G(\mathcal{N}, \mathcal{A})$, to find a path with the least path cost.

$$\min_{x \in \Omega} \sum_{(i,j) \in \mathcal{A}} c_{ij} x_{ij}$$

where

$$\Omega \equiv \left\{ x : \sum_{(i,j) \in \mathcal{A}} x_{ij} - \sum_{(j,i) \in \mathcal{A}} x_{ji} = b_i \quad \forall i \in \mathcal{N}, \right. \\ \left. \text{and } x_{ij} \in \{0, 1\} \quad \forall (i,j) \in \mathcal{A} \right\}$$

Dijkstra's Algorithm $O(|\mathcal{N}|^2)$

Robust Shortest Path Problem

The cost coefficient c may be subject to some uncertainty.

$$\min_{x \in \Omega} \sum_{(i,j) \in \mathcal{A}} \tilde{c}_{ij} x_{ij}$$

The uncertain \tilde{c} belongs to an uncertain set C .

$$\min_{x \in \Omega} \max_{\tilde{c} \in C} \sum_{(i,j) \in \mathcal{A}} \tilde{c}_{ij} x_{ij}$$

The robust shortest path problem is to find a path that minimizes the worst-case path cost.

Two Multiplicative Cost Coefficients⁴

Nominal Problem

$$\min_{x \in \Omega} \sum_{(i,j) \in \mathcal{A}} p_{ij} c_{ij} x_{ij}$$

Uncertain Problem

$$\min_{x \in \Omega} \sum_{(i,j) \in \mathcal{A}} \tilde{p}_{ij} \tilde{c}_{ij} x_{ij}$$

Robust Problem

$$\min_{x \in \Omega} \max_{\tilde{p}, \tilde{c}} \sum_{(i,j) \in \mathcal{A}} \tilde{p}_{ij} \tilde{c}_{ij} x_{ij}$$

⁴Kwon, C., T. Lee, P. G. Berglund (2013), "Robust Shortest Path Problems with Two Uncertain Multiplicative Cost Coefficients", *Naval Research Logistics*, 60(5), 375394

Robust Shortest Path Problems with Two Uncertain Multiplicative Cost Coefficients

$$\min_{x \in \Omega} \max_{u \in U, v \in V} \sum_{(i,j) \in \mathcal{A}} (p_{ij} + q_{ij}u_{ij})(c_{ij} + d_{ij}v_{ij})x_{ij}$$

where

$$U = \left\{ u : 0 \leq u_{ij} \leq 1 \quad \forall (i,j), \quad \sum_{(i,j)} u_{ij} \leq \Gamma_u \right\}$$

$$V = \left\{ v : 0 \leq v_{ij} \leq 1 \quad \forall (i,j), \quad \sum_{(i,j)} v_{ij} \leq \Gamma_v \right\}$$

and Γ_u and Γ_v are positive integers.

The objective function can be written as follows:

$$\min_{x \in \Omega} \left[p_{ij}c_{ij}x_{ij} + \max_{u \in U, v \in V} (q_{ij}c_{ij}x_{ij}u_{ij} + p_{ij}d_{ij}x_{ij}v_{ij} + q_{ij}d_{ij}x_{ij}u_{ij}v_{ij}) \right]$$

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Mixed Integer Linear Program

$$\min p_{ij}c_{ij}x_{ij} + \Gamma_u\theta_u + \Gamma_v\theta_v + \sum_{(i,j)}(\rho_{ij} + \mu_{ij})$$

subject to

$$x \in \Omega$$

$$\rho_{ij} - \eta_{ij} + \theta_u \geq q_{ij}c_{ij}x_{ij}$$

$$\mu_{ij} - \pi_{ij} + \theta_v \geq p_{ij}d_{ij}x_{ij}$$

$$\eta_{ij} + \pi_{ij} \geq q_{ij}d_{ij}x_{ij}$$

$$\rho_{ij}, \mu_{ij}, \eta_{ij}, \pi_{ij}, \theta_u, \theta_v \geq 0$$

Solution of the Dual Problem

A solution to the dual problem for any given x is:

$$\begin{aligned}
 \rho_{ij} &= \max(q_{ij}c_{ij}x_{ij} - \theta_u + \eta_{ij}, 0) \\
 &= \max(q_{ij}c_{ij}x_{ij} + q_{ij}d_{ij}x_{ij} - \min(q_{ij}d_{ij}x_{ij}, \max(\theta_v - p_{ij}d_{ij}x_{ij}, 0)) \\
 &\quad - \theta_u, 0)
 \end{aligned}$$

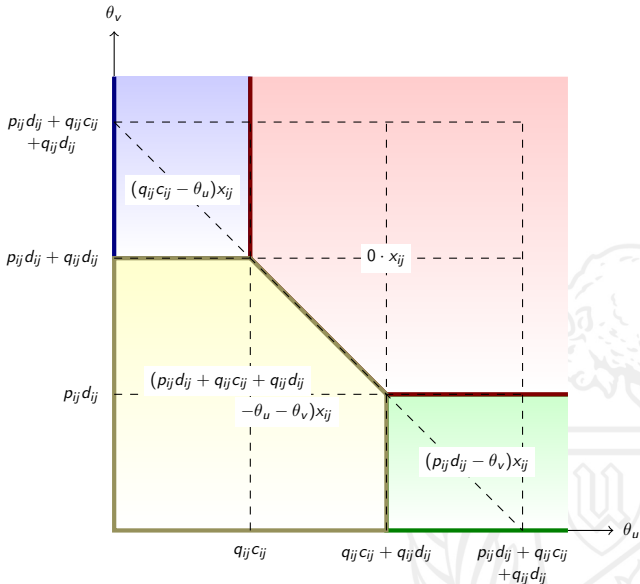
$$\begin{aligned}
 \mu_{ij} &= \max(p_{ij}d_{ij}x_{ij} - \theta_v + \pi_{ij}, 0) \\
 &= \max(p_{ij}d_{ij}x_{ij} + \min(q_{ij}d_{ij}x_{ij}, \max(\theta_v - p_{ij}d_{ij}x_{ij}, 0)) - \theta_v, 0)
 \end{aligned}$$

Lemma

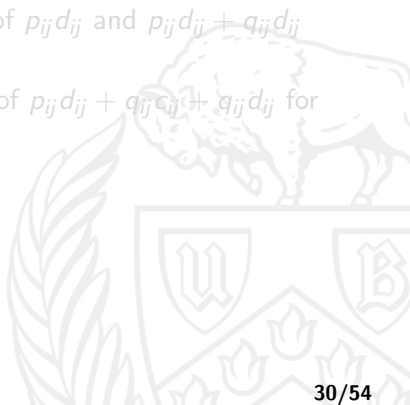
The sum $\rho_{ij} + \mu_{ij}$ can be expressed as follows:

$$\rho_{ij} + \mu_{ij} = \begin{cases} 0 \cdot x_{ij} & \text{if } \theta_u \geq q_{ij}c_{ij}, \theta_v \geq p_{ij}d_{ij} + q_{ij}d_{ij} \\ & \text{or } p_{ij}d_{ij} \leq \theta_v \leq p_{ij}d_{ij} + q_{ij}d_{ij}, \theta_u + \theta_v \geq p_{ij}d_{ij} + q_{ij}c_{ij} + q_{ij}d_{ij} \\ (q_{ij}c_{ij} - \theta_u)x_{ij} & \text{if } \theta_u \leq q_{ij}c_{ij}, \theta_v \geq p_{ij}d_{ij} + q_{ij}d_{ij} \\ (p_{ij}d_{ij} + q_{ij}c_{ij} + q_{ij}d_{ij} - \theta_u - \theta_v)x_{ij} & \text{if } p_{ij}d_{ij} \leq \theta_v \leq p_{ij}d_{ij} + q_{ij}d_{ij}, \theta_u + \theta_v \leq p_{ij}d_{ij} + q_{ij}c_{ij} + q_{ij}d_{ij} \\ & \text{or } \theta_u \leq q_{ij}c_{ij} + q_{ij}d_{ij}, \theta_v \leq p_{ij}d_{ij} \\ (p_{ij}d_{ij} - \theta_v)x_{ij} & \text{if } \theta_u \geq q_{ij}c_{ij} + q_{ij}d_{ij}, \theta_v \leq p_{ij}d_{ij} \end{cases}$$

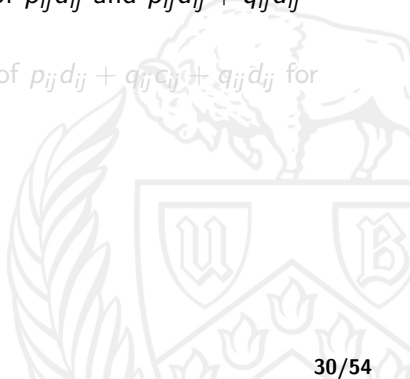
for each $(i, j) \in \mathcal{A}$ and all $\theta_u \geq 0$ and $\theta_v \geq 0$.



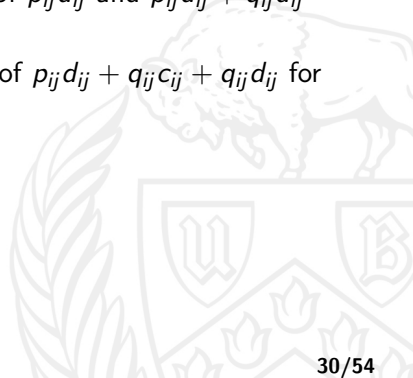
- Let $\{a_k\}$ be the ordered sequence of $q_{ij}c_{ij} + q_{ij}d_{ij}$ and $q_{ij}c_{ij}$ for all $(i, j) \in \mathcal{A}$ and 0.
- Let $\{b_l\}$ be the ordered sequence of $p_{ij}d_{ij}$ and $p_{ij}d_{ij} + q_{ij}d_{ij}$ for all $(i, j) \in \mathcal{A}$ and 0.
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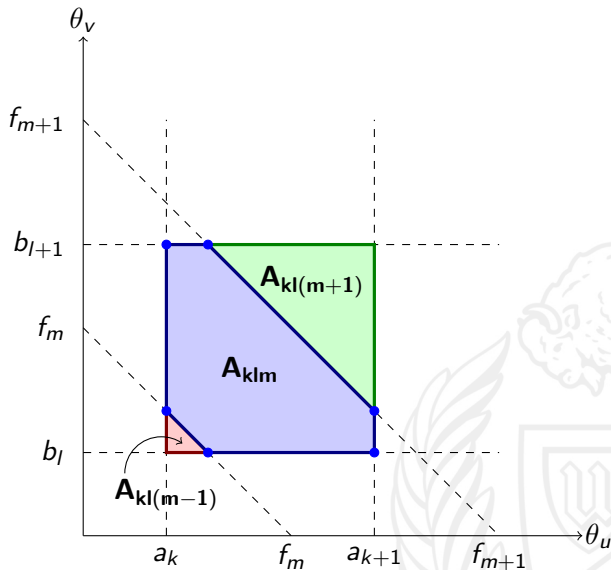


We consider the following problem, defined over a sub-area of the entire (θ_u, θ_v) -space:

$$Z_{klm} = \min_{x, \theta_u, \theta_v} \Gamma_u \theta_u + \Gamma_v \theta_v + \sum_{(i,j)} (p_{ij} c_{ij} x_{ij} + \rho_{ij} + \mu_{ij})$$

subject to

$$\begin{aligned}
 &x \in \Omega \\
 &a_k \leq \theta_u \leq a_{k+1} \\
 &b_l \leq \theta_v \leq b_{l+1} \\
 &f_m \leq \theta_u + \theta_v \quad \text{if } f_m \in [a_k + b_l, a_{k+1} + b_{l+1}] \\
 &f_{m+1} \geq \theta_u + \theta_v \quad \text{if } f_{m+1} \in [a_k + b_l, a_{k+1} + b_{l+1}]
 \end{aligned}$$



Robust Problem

Theorem

Let us define the following problem with an arbitrary constraint set Θ :

$$Z(\Theta) = \min_{x \in \Omega, (\theta_u, \theta_v) \in \Theta} \Gamma_u \theta_u + \Gamma_v \theta_v + \sum_{(i,j)} (p_{ij} c_{ij} x_{ij} + \rho_{ij} + \mu_{ij}) \quad (1)$$

Then the robust shortest path problem is equivalent to the following problem:

$$Z^* = \min_{k,l,m} Z(\Theta_{klm}) \quad (2)$$

Some reduction in the search space is possible! ⁵

⁵Kwon, C., T. Lee, P. G. Berglund (2013), "Robust Shortest Path Problems with Two Uncertain Multiplicative Cost Coefficients", *Naval Research Logistics*, 60(5), 375394

Robust Problem

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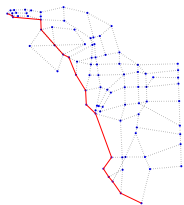
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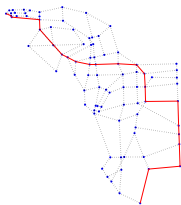
⁵Kwon, C., T. Lee, P. G. Berglund (2013), "Robust Shortest Path Problems with Two Uncertain Multiplicative Cost Coefficients", *Naval Research Logistics*, 60(5), 375394

Worst-Case Conditional Value-at-Risk (WCVaR) ⁶

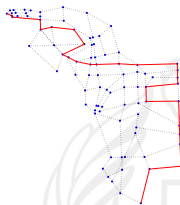
We can also consider the worst-case of the CVaR risk measure. Computing the best WCVaR route requires solving a series of robust shortest-path problems.



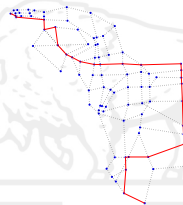
$\alpha = 0$



$\alpha = 0.999965$



$\alpha = 0.999973$



$\alpha = 0.999990$

⁶Toumazis, I. and C. Kwon, "Worst-case Conditional Value-at-Risk Minimization for Hazardous Materials Transportation", submitted to *Transportation Science*, in Revision

Outline

- 1 Introduction
- 2 Risk Measures
- 3 Data Uncertainty
- 4 Behavioral Uncertainty**



Hazmat Network Design

- To design a safe road network, considering drivers' reaction to the design change.

$$\min_y \text{Risk}(x(y))$$

where $x(y)$ describes the drivers' reaction to the design variable y .

- y is a binary variable to close a certain link or not.
- Uncertainty in the risk measure can be considered.⁷
- Most papers assume drivers take the shortest path, i.e., $x(y)$ is a solution to the shortest-path problem.

⁷Sun, L., M. Karwan, and C. Kwon, "Robust Hazmat Network Design Problems Considering Risk Uncertainty", submitted to *Transportation Science*, in Revision

Behavioral Uncertainty

- Zhu and Levinson (2010): Most commuters do not choose the shortest path
- Nakayama et al. (2001): drivers are not fully rational
- How do hazmat drivers choose routes? Travel time? Highway vs local roads? Number of turns?
- We want some robustness in hazmat network design against behavioral uncertainty of drivers.

Example: two groups of people

- Betty Rogerson (BR): Doesn't care about the shortest path, as long as her path is within 5 minute difference.
- Peter Edison (PE): Cares about the shortest path, but based on his own perception of link travel costs.

Bounded Rationality in Transportation

- Simon (1955): “A Behavioral Model of Rational Choice”
- Drivers choose a route if its length is no longer than the shortest-path length + a certain threshold
- Mahmassani and Chang (1987): “A **boundedly rational user equilibrium (BRUE)** is achieved in a transportation system when all users are satisfied with their current travel choices.”
- Han et al. (2014): dynamic BRUE
- Lou et al. (2010): robust congestion pricing with BR
- This presentation: **perception error model** to generalize BR in the context of hazmat transportation (on-going research)

Bounded Rationality

Definition (Additive Bounded Rationality)

A path is called a **boundedly rational shortest path** within an **additive** indifference band, if the path can be represented by a vector $x \in X$ such that

$$(A-BR) \quad \sum_{(i,j) \in \mathcal{A}} c_{ij} x_{ij} \leq c^0 + E \quad (3)$$

where E is a positive constant for the additive indifference band.

Definition (Multiplicative Bounded Rationality)

A path is called a **boundedly rational shortest path** within a **multiplicative** indifference band, if the path can be represented by a vector $x \in X$ such that

$$(M-BR) \quad \sum_{(i,j) \in \mathcal{A}} c_{ij} x_{ij} \leq (1 + \kappa) c^0 \quad (4)$$

where $\kappa \in (0, 1)$ is a constant for the multiplicative indifference band.

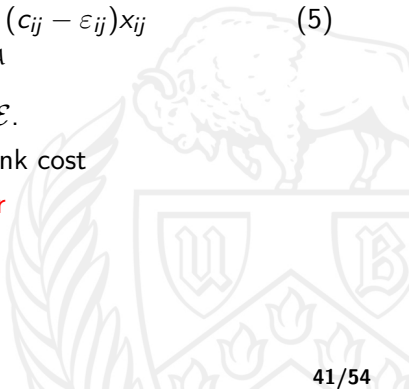
Perception Error

- The Perception Error (PE) model:

$$(PE) \quad \min_{x \in X} \sum_{(i,j) \in \mathcal{A}} (c_{ij} - \varepsilon_{ij}) x_{ij} \quad (5)$$

for some constant cost vector $\varepsilon \in \mathcal{E}$.

- ε : a vector of **perception error** of link cost
- \mathcal{E} : **set of uncertain perception error**



Equivalence of BR and PE

$$(PE) \quad \min_{x \in X} \sum_{(i,j) \in \mathcal{A}} (c_{ij} - \varepsilon_{ij}) x_{ij} \tag{6}$$

$$\mathcal{E}_A = \left\{ \varepsilon : \sum_{(i,j) \in \mathcal{A}} \varepsilon_{ij} \leq E, \quad \varepsilon_{ij} \geq 0 \quad \forall (i,j) \in \mathcal{A} \right\} \tag{7}$$

$$\mathcal{E}_M = \left\{ \varepsilon : \sum_{(i,j) \in \mathcal{A}} \varepsilon_{ij} \leq \kappa c^0, \quad \varepsilon_{ij} \geq 0 \quad \forall (i,j) \in \mathcal{A} \right\} \tag{8}$$

Theorem

- $PE + \mathcal{E}_A \iff A\text{-BR}$
- $PE + \mathcal{E}_M \iff M\text{-BR}$

Sub-path Multiplicative Bounded Rationality (SM-BR)

Definition

A path is called a *subpath multiplicative bounded-rationality shortest-path*, or *SM-BR path* with the multiplicative indifference band κ , if **any subpath of the path is an M-BR path** with the same multiplicative indifference band κ between the corresponding origin and destination nodes.

$$\mathcal{E}_L = \left\{ \varepsilon : 0 \leq \varepsilon_{ij} \leq \frac{\kappa}{1 + \kappa} c_{ij} \quad \forall (i, j) \in \mathcal{A} \right\} \quad (9)$$

Theorem

$$\text{PE} + \mathcal{E}_L \iff \text{SM-BR}$$

Some Other Examples of the Perception Error Set \mathcal{E}

$$\mathcal{E}_H = \left\{ \varepsilon : \sum_{(i,j) \in \mathcal{A}} \varepsilon_{ij} \leq E, \sum_{(i,j) \in \mathcal{A}} \varepsilon_{ij} \leq (1 + \kappa)c^0 \quad \forall (i,j) \in \mathcal{A} \right\} \tag{10}$$

$$\mathcal{E}_B = \left\{ \varepsilon : l_{ij} \leq \varepsilon_{ij} \leq u_{ij} \leq c_{ij} \quad \forall (i,j) \in \mathcal{A} \right\} \tag{11}$$

Ellipsoidal Set

$$\mathcal{E}_E = \left\{ \varepsilon : \|Q^{-1/2}\varepsilon\|_2 \leq \xi \right\}$$

Theorem

Let \bar{x} be an optimal solution to (6) for some $\varepsilon \in \mathcal{E}_E$. Then,

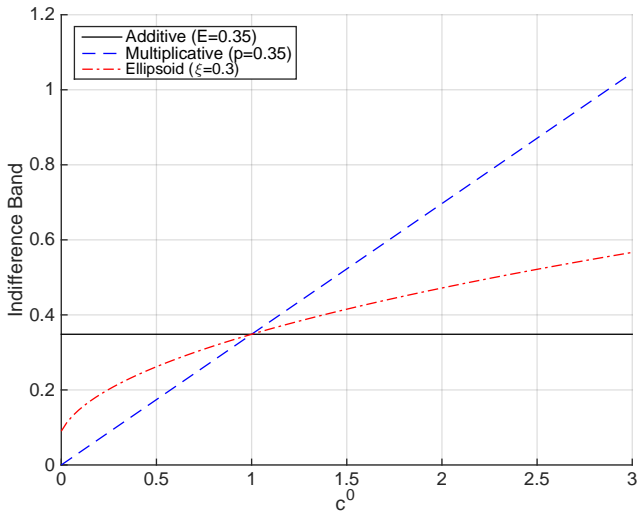
$$\sum_{(i,j) \in \mathcal{A}} c_{ij} \bar{x}_{ij} \leq c^0 + \xi \sqrt{\bar{x}^T Q \bar{x}} \tag{12}$$

Furthermore, the following bound holds

$$\sum_{(i,j) \in \mathcal{A}} c_{ij} \bar{x}_{ij} \leq c^0 + \frac{\xi^2}{2} + \xi \sqrt{c^0 + \frac{\xi^2}{4}} \tag{13}$$

in a special case when $Q = \text{diag}(\dots, c_{ij}, \dots)$.

Ellipsoidal Set



Generalized Bounded Rationality

- BR is a special case of PE.
- With PE, modelers have flexibility with link-specific preferences/perception of drivers.
- Link-based modeling (PE) is usually preferred to path-based modeling (BR).

Definition

A network user possesses **generalized bounded rationality**, if the user's route-choice decision-making can be justified by the perception error model for some closed and bounded set \mathcal{E} .

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Definition

A network user possesses **generalized bounded rationality**, if the user's route-choice decision-making can be justified by the perception error model for some closed and bounded set \mathcal{E} .

Robust Network Design with PE

$$\min_y \max_{x, \varepsilon} \sum_{(i,j) \in \mathcal{A}} \sum_{s \in \mathcal{S}} r_{ij}^s x_{ij}^s \quad (14)$$

subject to

$$y_{ij} \in \{0, 1\} \quad \forall (i, j) \in \mathcal{A} \quad (15)$$

$$\varepsilon^s \in \mathcal{E}^s \quad \forall s \in \mathcal{S} \quad (16)$$

$$x^s = \arg \min_x \sum_{(i,j) \in \mathcal{A}} (c_{ij} - \varepsilon_{ij}^s) x_{ij}^s \quad (17)$$

$$\text{subject to} \quad - \sum_{(i,j) \in \mathcal{A}} x_{ij}^s + \sum_{(j,i) \in \mathcal{A}} x_{ji}^s = -b_i^s \quad \forall i \in \mathcal{N} \quad (18)$$

$$x_{ij}^s \leq y_{ij} \quad \forall (i, j) \in \mathcal{A}, s \in \mathcal{S} \quad (19)$$

$$x_{ij}^s \in \{0, 1\} \quad \forall (i, j) \in \mathcal{A}, s \in \mathcal{S} \quad (20)$$

Cutting Plane Algorithm

Step 1. Solve the **master network design problem** to obtain x^k and y^k .

$$\min_y \sum_{(i,j) \in \mathcal{A}} \sum_{s \in \mathcal{S}} r_{ij}^s x_{ij}^s$$

$$\text{s.t. } y_{ij} \in \{0, 1\} \quad \forall (i,j) \in \mathcal{A}$$

$$\varepsilon^s \in \mathcal{E}^s \quad \forall s \in \mathcal{S}$$

$$\min_x \sum_{(i,j) \in \mathcal{A}} (c_{ij} - \varepsilon_{ij}^s) x_{ij}^s$$

$$\text{s.t. } - \sum_{(i,j) \in \mathcal{A}} x_{ij}^s + \sum_{(j,i) \in \mathcal{A}} x_{ji}^s = -b_i^s \quad \forall i \in \mathcal{N}$$

$$x_{ij}^s \leq y_{ij} \quad \forall (i,j) \in \mathcal{A}, s \in \mathcal{S}$$

$$x_{ij}^s \in \{0, 1\} \quad \forall (i,j) \in \mathcal{A}, s \in \mathcal{S}$$

Cutting Plane Algorithm

Step 2. Given y^k , solve the **worst-risk route-choice problem** and obtain \hat{x}^k :

$$\max_{x, \varepsilon} \sum_{(i,j) \in \mathcal{A}} \sum_{s \in \mathcal{S}} r_{ij}^s x_{ij}^s$$

$$\text{s.t. } \varepsilon^s \in \mathcal{E}^s \quad \forall s \in \mathcal{S}$$

$$\min_x \sum_{(i,j) \in \mathcal{A}} (c_{ij} - \varepsilon_{ij}^s) x_{ij}^s$$

$$\text{s.t. } - \sum_{(i,j) \in \mathcal{A}} x_{ij}^s + \sum_{(j,i) \in \mathcal{A}} x_{ji}^s = -b_i^s \quad \forall i \in \mathcal{N}$$

$$x_{ij}^s \leq y_{ij}^k \quad \forall (i,j) \in \mathcal{A}, s \in \mathcal{S}$$

$$x_{ij}^s \in \{0, 1\} \quad \forall (i,j) \in \mathcal{A}, s \in \mathcal{S}$$

Cutting Plane Algorithm

Step 3. If \hat{x}^k is identical to x^k , stop. Otherwise add cuts to the master network design problem and go to Step 1.

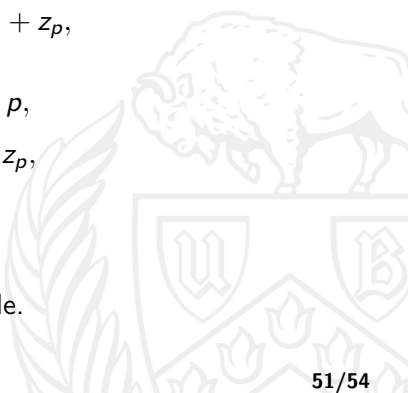
$$\sum_{(i,j) \in p} x_{ij}^s \leq |p| - 1 + z_p,$$

$$z_p \leq x_{ij}^s \quad \forall (i,j) \in p,$$

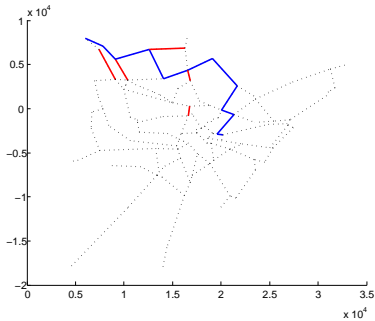
$$\sum_{(i,j) \in p'} y_{ij} \leq |p'| - z_p,$$

$$z_p \in \{0, 1\}$$

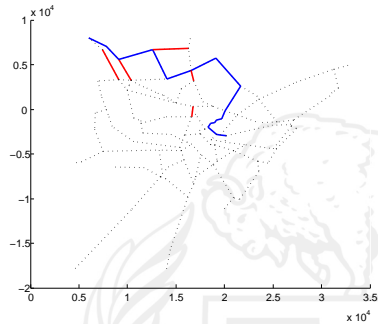
These cuts make the path \hat{x}^k unavailable.



Solution without considering uncertain behavior

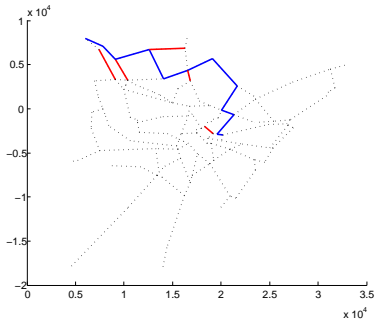


Nominal design

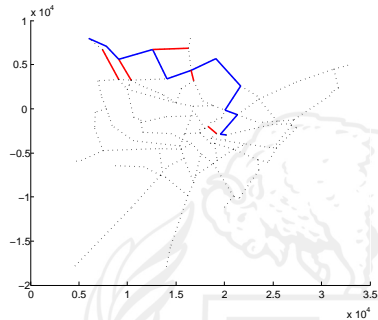


Worst-case

Robust solution considering uncertain behavior



Robust design



Worst-case

Question???



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