

Framework and Methods for Infrastructure Management

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Outline

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2. Flowchart for IM Systems
3. Issues in infrastructure deterioration models
4. Issues in M&R decision-making
5. Focus: Model uncertainty
6. Adaptive MDP formulations
7. Parametric analyses
8. An alternate approach: Robust optimization
9. Results

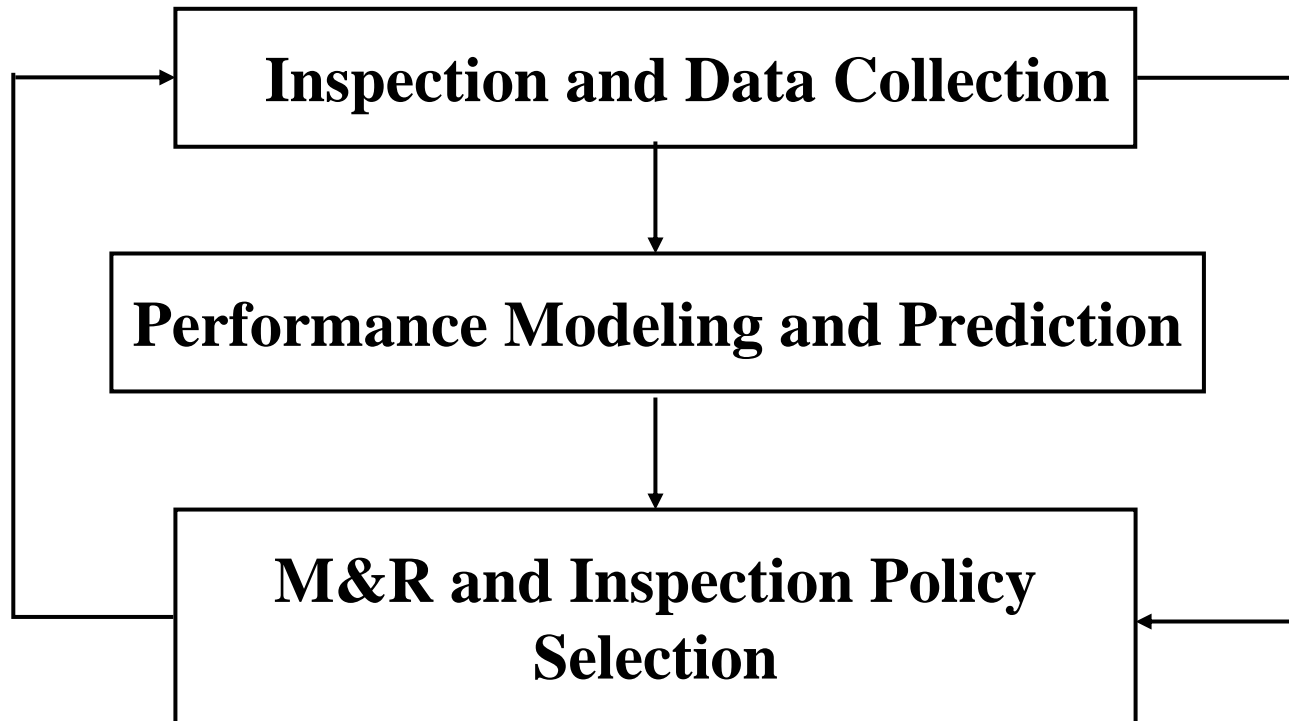
Infrastructure Management

- Infrastructure Management
 - Concerned with the selection of cost-effective policies to monitor, maintain and repair (M&R) deteriorating facilities in Infrastructure Systems
- Examples of IM Systems
 - Arizona's Pavement Management System
 - PONTIS: FHWA Bridge Management System

Deterioration and M&R actions

- Facilities deteriorate under the influence of traffic and environmental factors
- User costs increase as condition worsens
- To mitigate/reverse deterioration, agencies apply maintenance and repair (M&R) actions
- Range of M&R policies available: frequent low-cost maintenance vs. infrequent high-cost rehabilitation
- Allocation of resources among facilities in network

Flowchart for IM Systems



Infrastructure deterioration models

- Dependent variable: future condition of a facility
- Explanatory variables: usage, structure, environmental conditions, past deterioration, history of M&R actions
- Forms: continuous or discrete condition states
- Example: stochastic models (Markov processes, semi-Markov processes, etc).

Issues in deterioration modeling

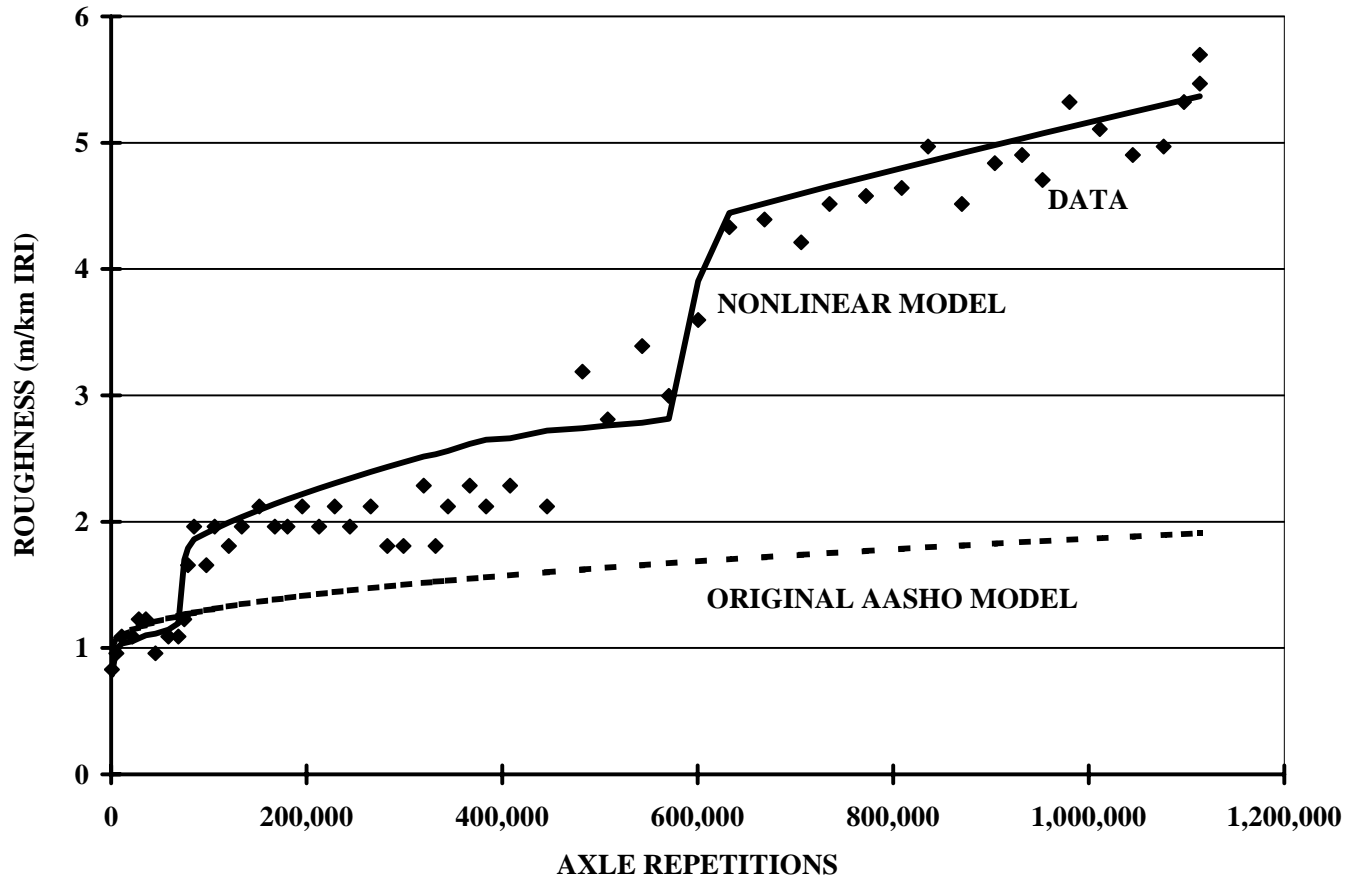
1. Data source used: experimental data vs. field data
 - Experimental data may not represent the true process of deterioration in the field (e.g., accelerated pavement testing) and may suffer from censoring (unobserved failure times due to limited duration of experiments)
 - Field data suffer from large measurement errors, endogeneity of observed design variables (pavement sections designed on the basis of predicted traffic) and selectivity bias (e.g., maintenance activity is selected based on observed deterioration)
2. Discrete indicators of performance
 - Interest is in the duration of some process (time to failure, time to condition transition)
 - What is the appropriate probability model?

Issue 1. Deterioration modeling by combining experimental and field data

- Specifications based on physical understanding of facility behavior and structured statistical estimation methods for parameter calibration
- Joint estimation with experimental and field data sets
- Examples:
 - Nonlinear models of pavement rutting progression (Archilla and Madanat 2000, 2001)
 - Nonlinear models of pavement roughness progression (Prozzi and Madanat 2003, 2004)

Prediction tests with nonlinear model

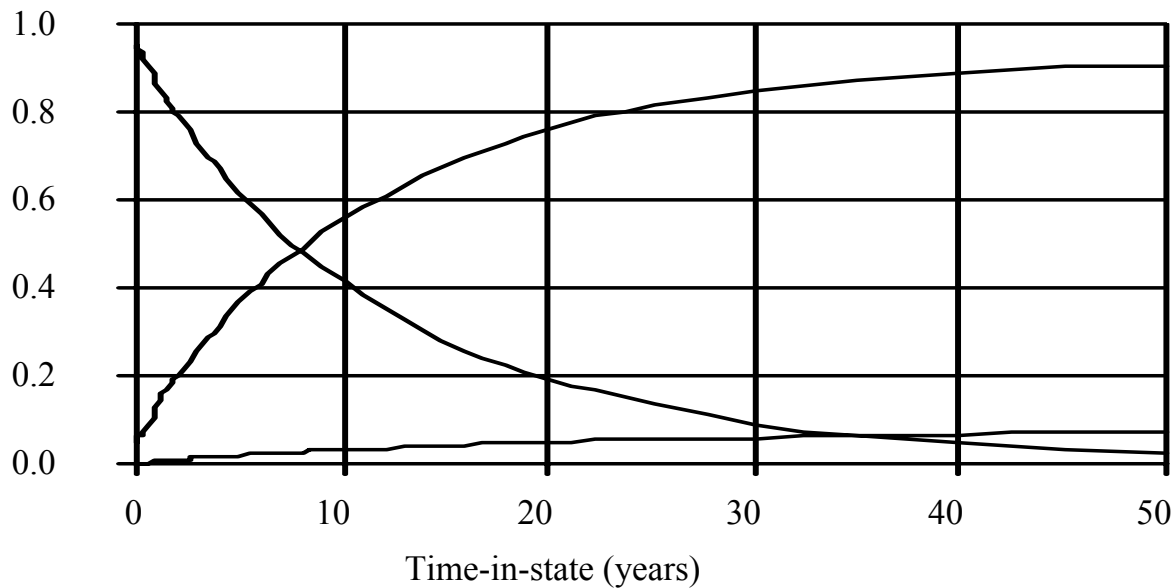
(Prozzi and Madanat 2003)



Issue 2. Stochastic deterioration models of facility state transitions

- Some facilities have monotonic failure rate, and parametric methods (e.g. Weibull) are appropriate; examples:
 - Models of state transition probabilities for bridge decks (Mishalani and Madanat 2002)
 - Models of pavement crack initiation (Shin and Madanat 2003)
- For others, failure rate cannot be represented by known probability models: semi-parametric methods more appropriate; example:
 - Models of overlay crack initiation for in-service pavements (Nakat and Madanat 2005)

Estimated transition probabilities (Mishalani and Madanat 2002)



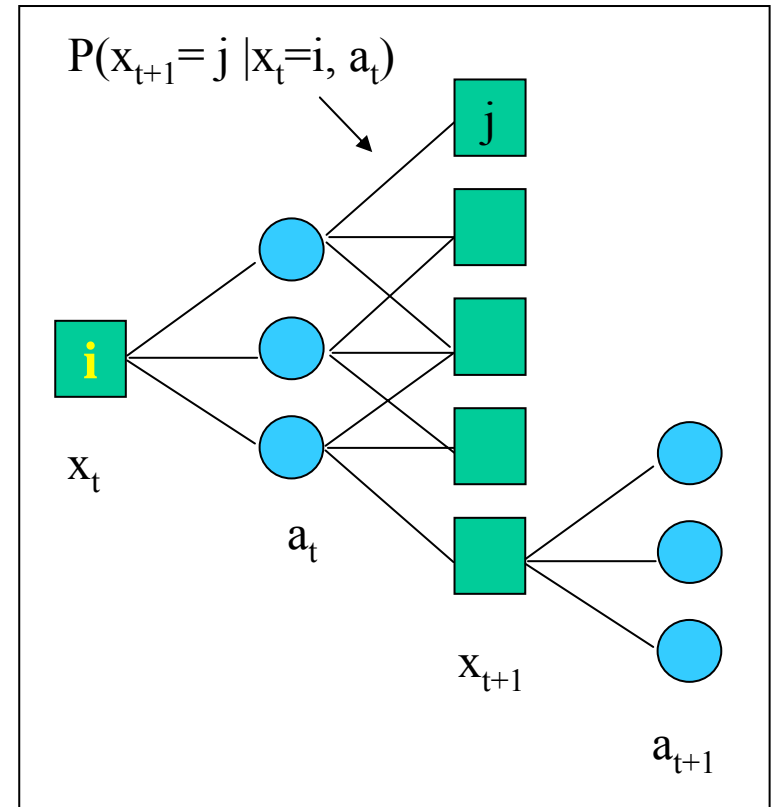
Corrosion-induced bridge deck deterioration; condition state 8

Issues in M&R Decision-Making

1. Accounting for stochastic facility deterioration in M&R decision-making
2. Accounting for budget constraints (system level vs. facility level problems)
3. Accounting for measurement errors in inspection
4. Accounting for model uncertainty:
 - Successive reduction of model uncertainty through parameter updating, using latest inspection data
 - Accepting model uncertainty as a fact of life and avoiding worst-case scenarios

Issue 1. Markov Decision Process (MDP)

- Markov assumption: facility deterioration is a function only of current state and current action
- Deterioration model: Markovian transition probabilities
- Finite horizon problems: solve by Dynamic Programming
- Infinite horizon problems: solve by successive approximation or policy iteration



Partial Decision Tree for Markov Decision Process

Issue 2. System-level MDP

- Use randomized policies: solve for optimal fractions of facilities in state i to which action a is applied
- Formulate as a linear program
- Infinite planning horizon problems: minimize expected cost per year
- Finite planning horizon problems: minimize expected discounted total cost for planning horizon

System-level MDP formulation

(for finite horizon problem)

Math Program

$$\text{Min}_f \sum_{t=0}^T \alpha^t [\sum_{i \in I} \sum_{a \in A} tc(i, a) f(i, a, t) N]$$

$$\text{s.t. } \sum_{a \in A} f(i, a, 0) = \text{init}(i) \quad \forall i \in I \quad (1)$$

$$f(i, a, t) \geq 0 \quad \forall i \in I, a \in A, t \in \{1, 2, \dots, T\} \quad (2)$$

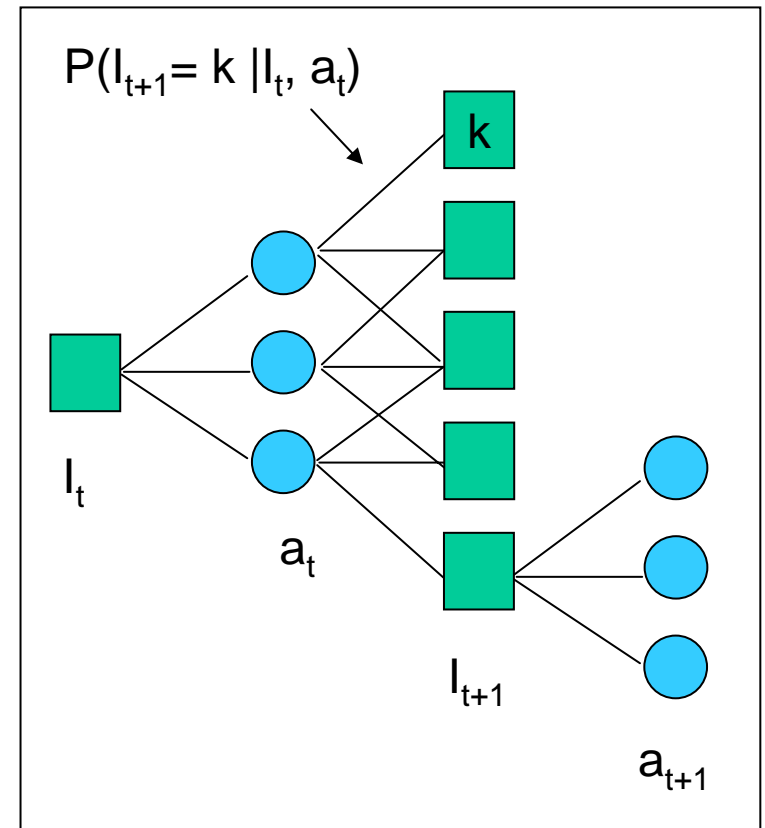
$$f(i, a, t) = 0 \quad \forall i \in X, a \in A, t \in \{1, 2, \dots, T\} \quad (3)$$

$$\sum_{i \in I} \sum_{a \in A} f(i, a, t-1) p(j|i, a) = \sum_{b \in A} f(j, b, t) \quad \forall j \in I, t \in \{1, 2, \dots, T\} \quad (4)$$

$$\sum_{i \in I} \sum_{a \in A} ac(i, a) f(i, a, t) N \leq b(t) \quad \forall t \in \{0, 1, 2, \dots, T\} \quad (5)$$

Issue 3. The Latent MDP

- Measurement uncertainty: condition state imperfectly observed
- State of system given by the information state
- Evolution of information state is Markovian
- Apply Dynamic Programming to solve finite horizon problem

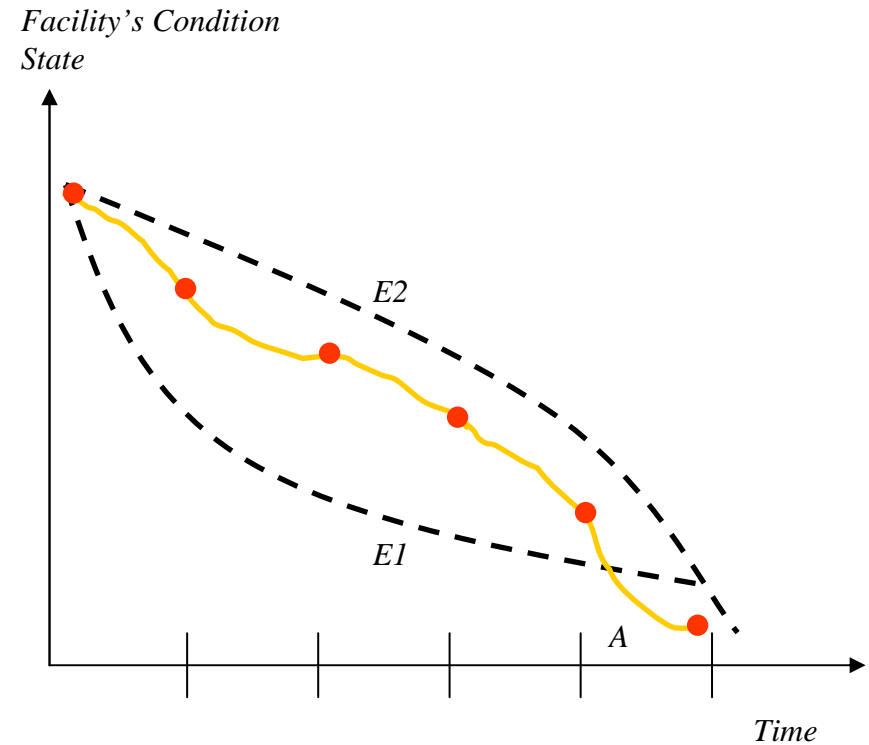
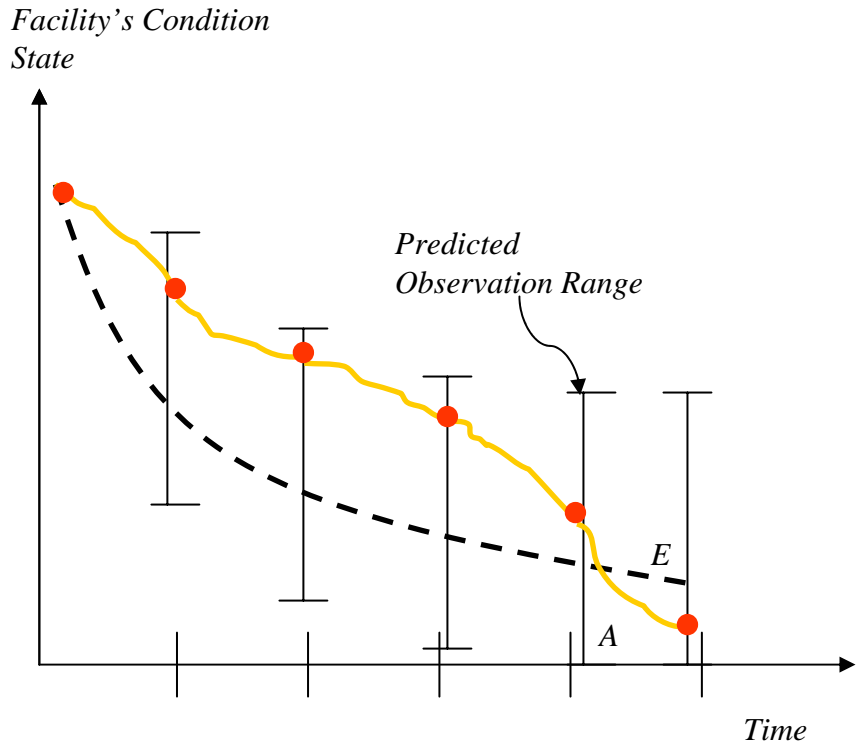


Partial Decision Tree for Latent Markov Decision Process

Issue 4: Model Uncertainty

- Model uncertainty is due to incomplete knowledge of facility deterioration processes
- Reasons:
 - partial information about facility structure or materials
 - uncertainty about construction quality
 - material behavior poorly understood
 - differences between laboratory and field deterioration
- Epistemic uncertainty, as opposed to statistical uncertainty (represented by stochastic model or random error)

Model uncertainty vs. random error



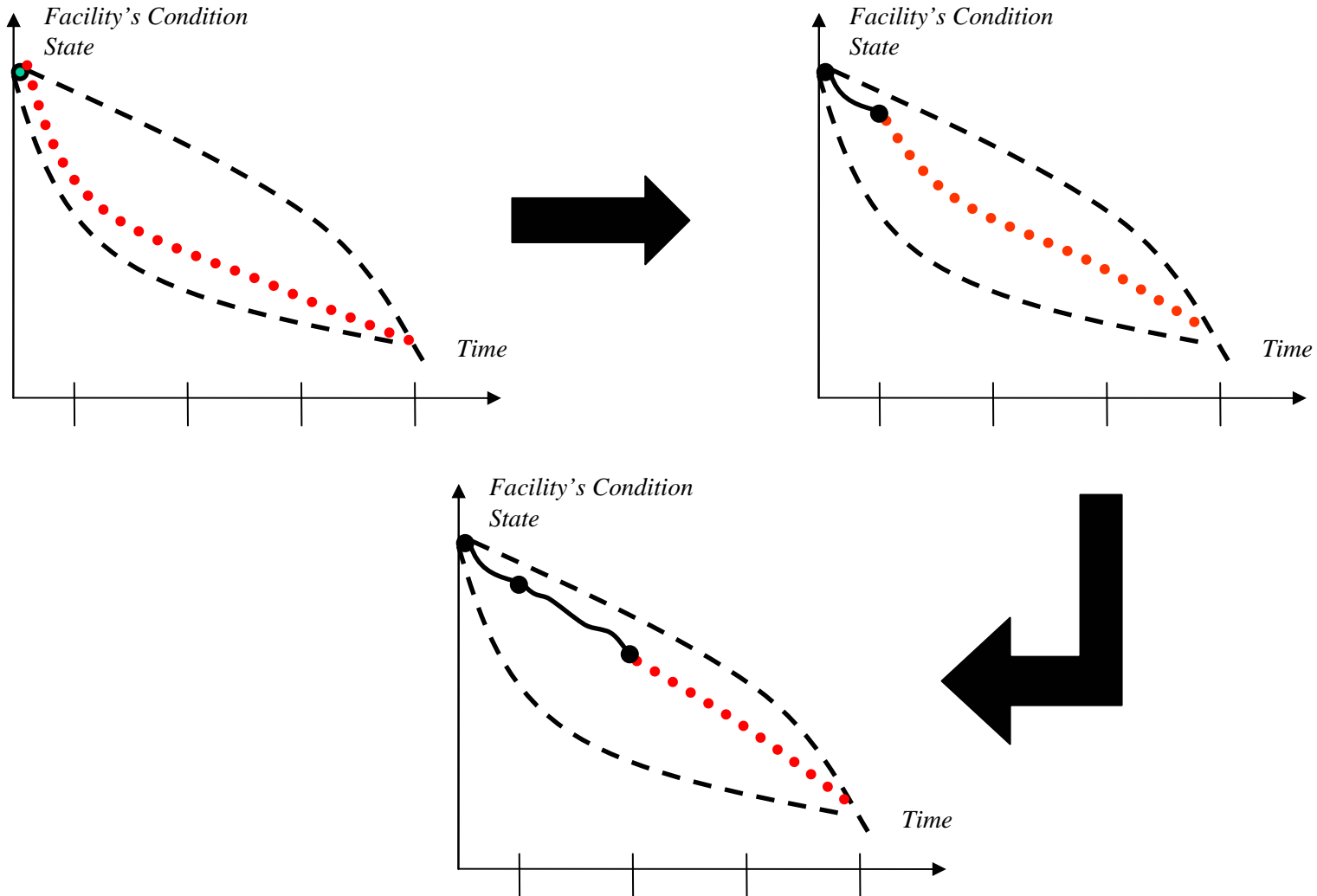
E: Expected deterioration process

A: Actual/Observed deterioration process

Accounting for model uncertainty

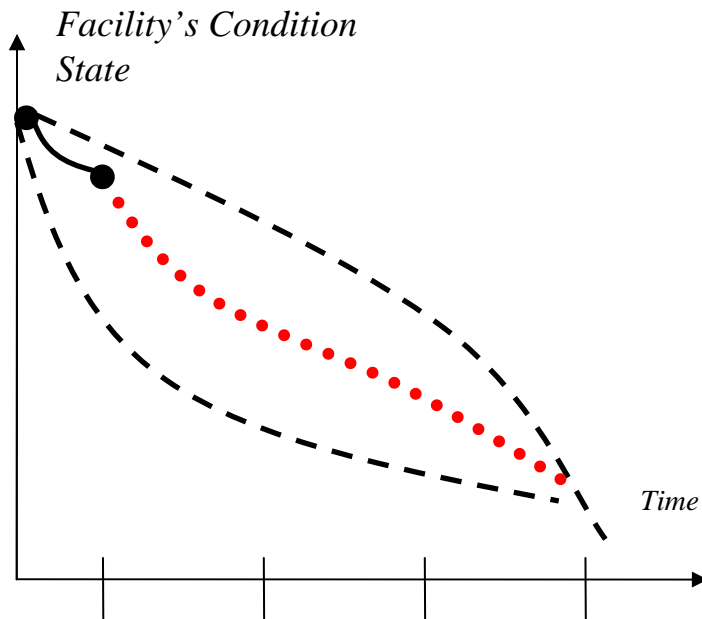
- Adaptive MDP (Durango and Madanat 2002)
 - Characterizes more than one possible deterioration model
 - Represents model uncertainty through decision-maker beliefs
 - Uses Bayes' Law to update beliefs
 - Updated beliefs used to determine M&R policies for subsequent time periods

Bayesian updating of beliefs

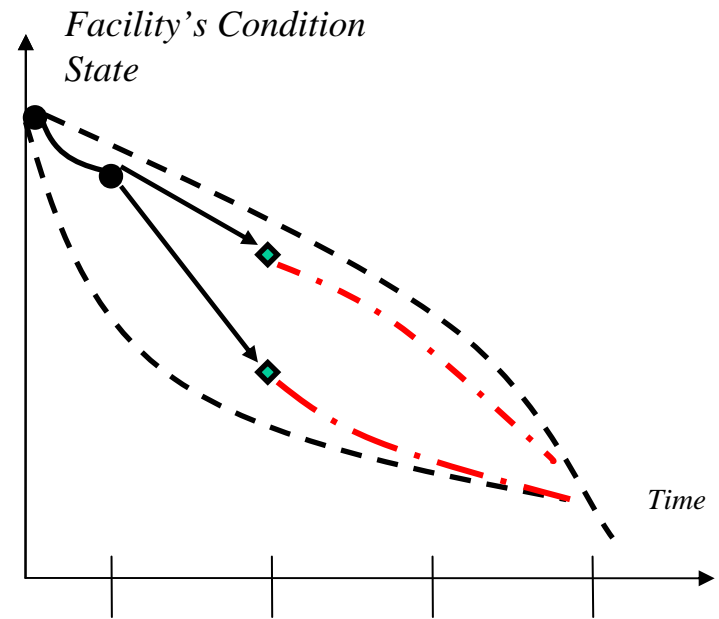


Open-loop feedback vs. Closed-loop Control

Open-loop feedback

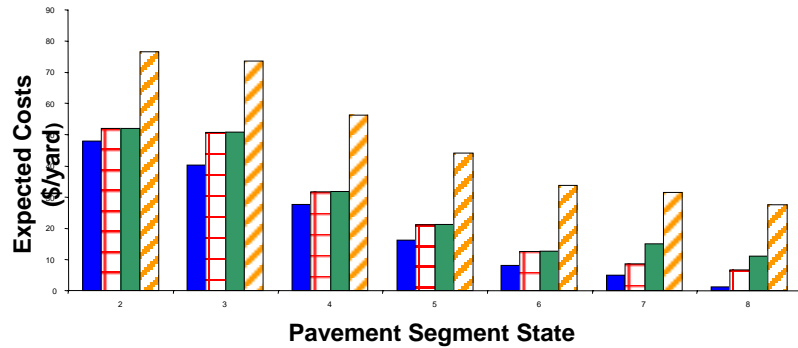


Closed-loop

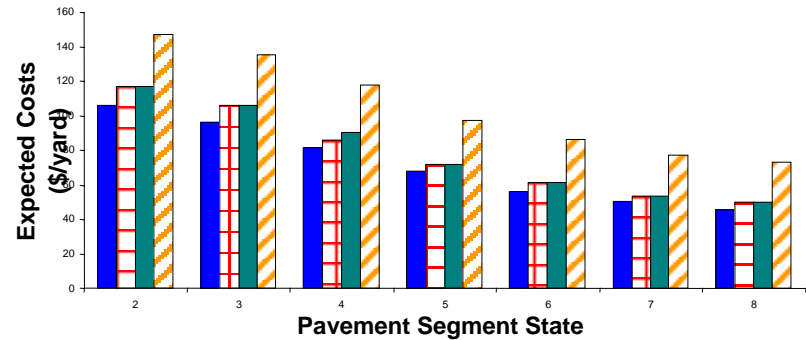


Results: value of updating

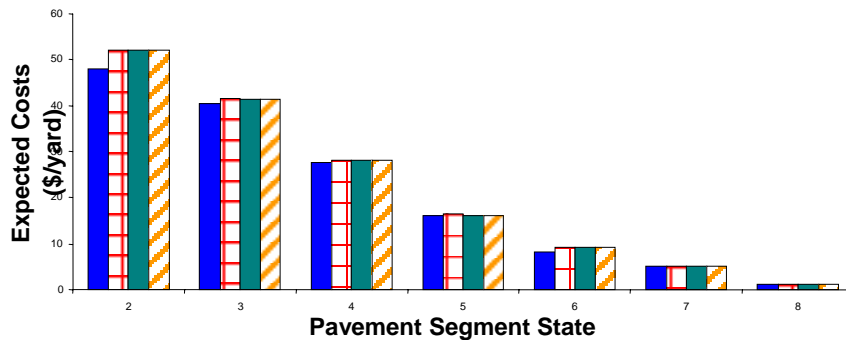
Actual Deterioration Rate: Slow
Prior Beliefs: (0.05, 0.05, 0.90)



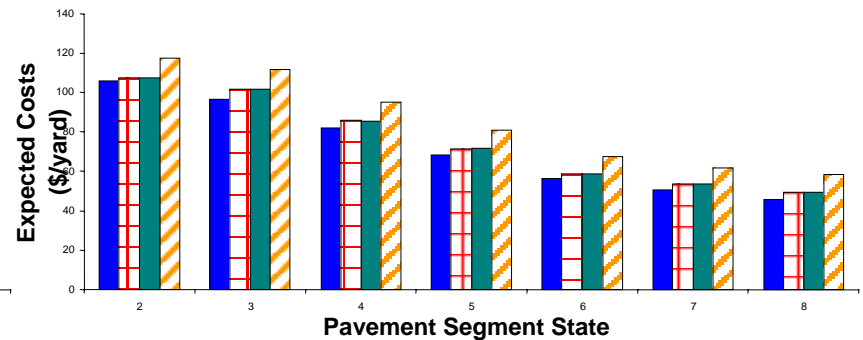
Actual Deterioration Rate: Fast
Prior Beliefs: (0.90, 0.05, 0.05)



Actual Deterioration Rate: Slow
Prior Beliefs: (0.33, 0.34, 0.33)



Actual Deterioration Rate: Fast
Prior Beliefs: (0.33, 0.34, 0.33)

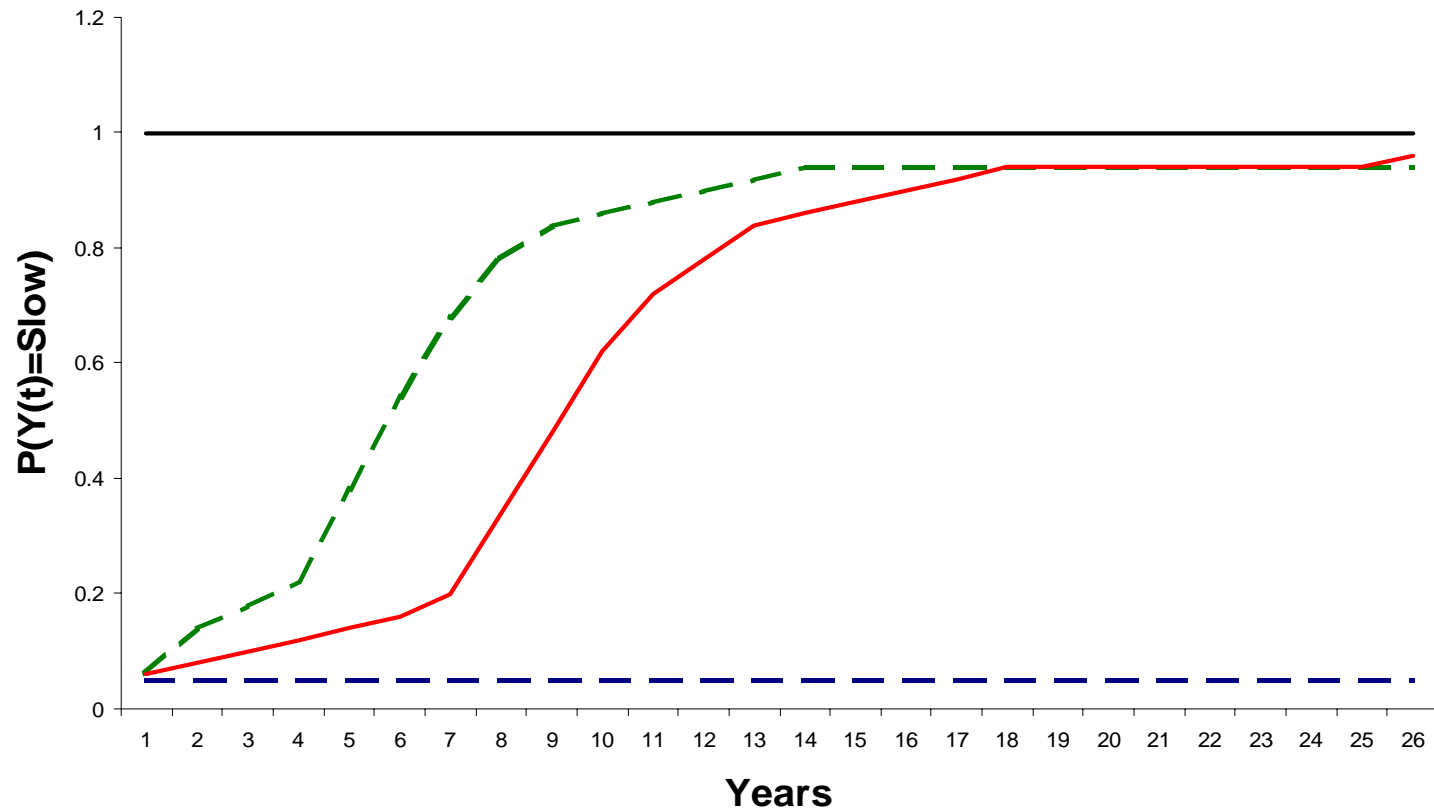


Results: CLC vs. OLFC

Actual Deterioration Rate: Slow

Prior Beliefs: (0.05, 0.05, 0.90)

Initial State: New



Problems with Adaptive Control methods

- CLC methods not practical for system-level decision-making and OLFC methods may not converge to true model
- To guarantee convergence, OLFC methods require costly “probing”
- Both CLC and OLFC require large amounts of data to reduce deterioration model uncertainty, but condition survey data accumulates slowly

Alternate approach: Robust optimization

- Work in progress (Kuhn and Madanat 2005)
- does not assume full knowledge of model parameters, only assume parameters belong to defined “uncertainty sets”
- seek solutions that are not overly sensitive to any realization of uncertainty within set
- Range of possible criteria: MAXIMIN, MAXIMAX, Hurwicz

System-level MAXIMIN MDP formulation

Robust Math Program

$$\text{Min}_f \text{Max}_p \sum_{t=0}^T \alpha^t [\sum_{i \in I} \sum_{a \in A} tc(i, a) f(i, a, t) N]$$

$$\text{s.t. } \sum_{a \in A} f(i, a, 0) = \text{init}(i) \quad \forall i \in I \quad (1)$$

$$f(i, a, t) \geq 0 \quad \forall i \in I, a \in A, t \in \{1, 2, \dots, T\} \quad (2)$$

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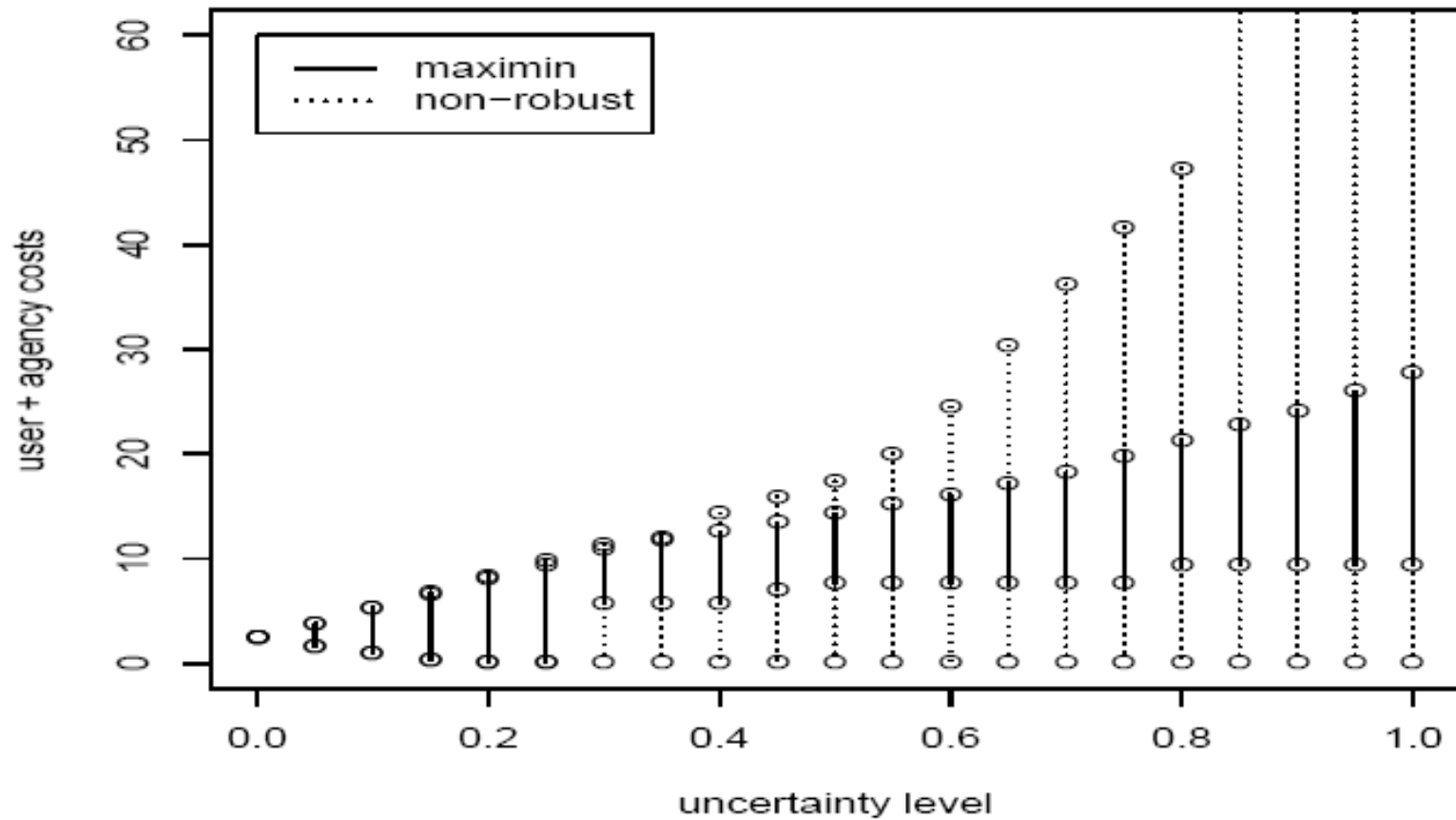
$$\sum_{i \in I} \sum_{a \in A} ac(i, a) f(i, a, t) N \leq b(t) \quad \forall t \in \{0, 1, 2, \dots, T\} \quad (5)$$

$$|p(j|i, a) - q(j|i, a)| \leq \delta \quad \forall i \in I, j \in I, a \in A \quad (6)$$

$$\sum_{j \in I} p(j|i, a) = 1 \quad \forall i \in I, a \in A \quad (7)$$

$$p(j|i, a) \geq 0 \quad \forall i \in I, j \in I, a \in A \quad (8)$$

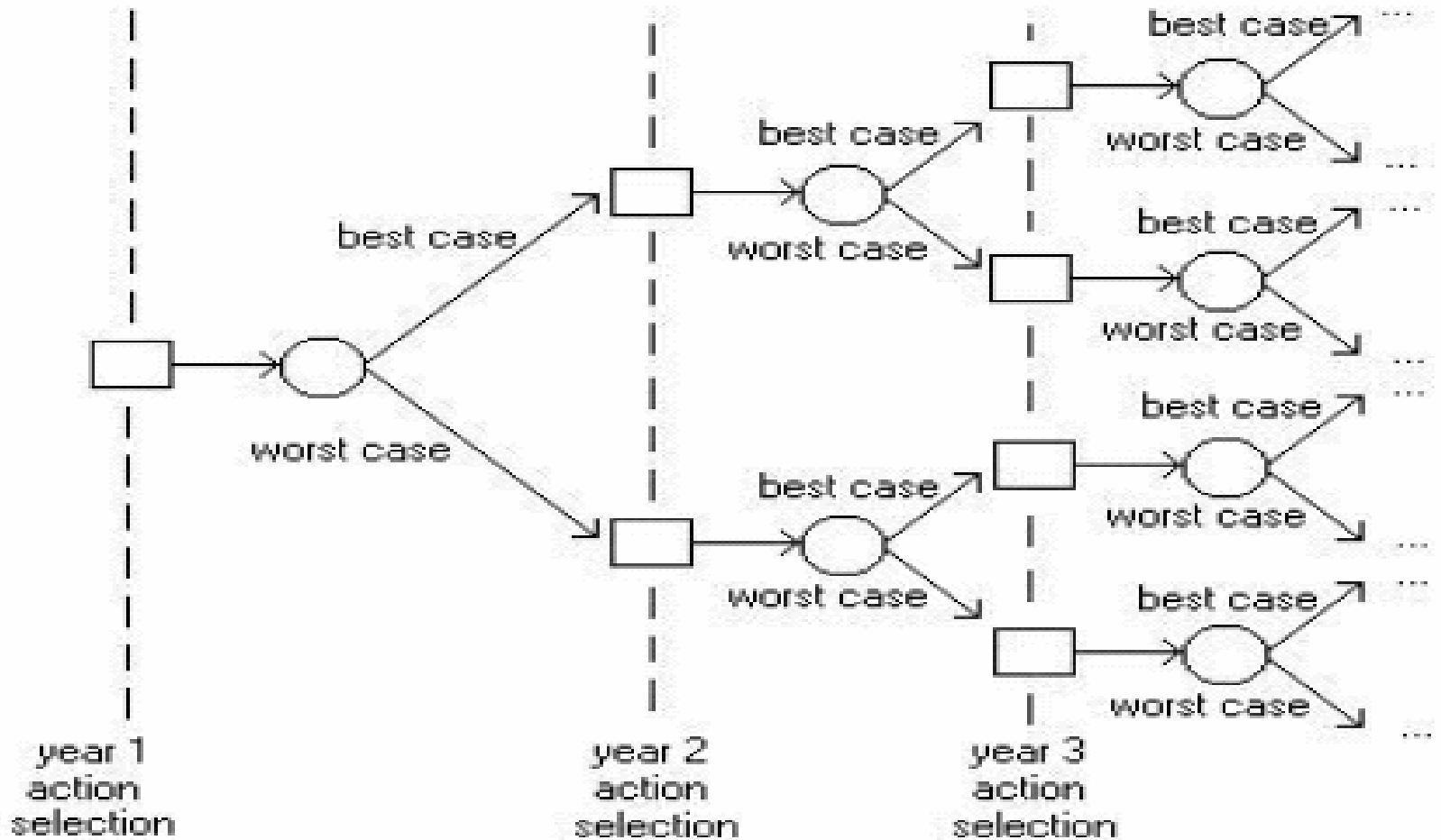
System-level MDP: cost ranges



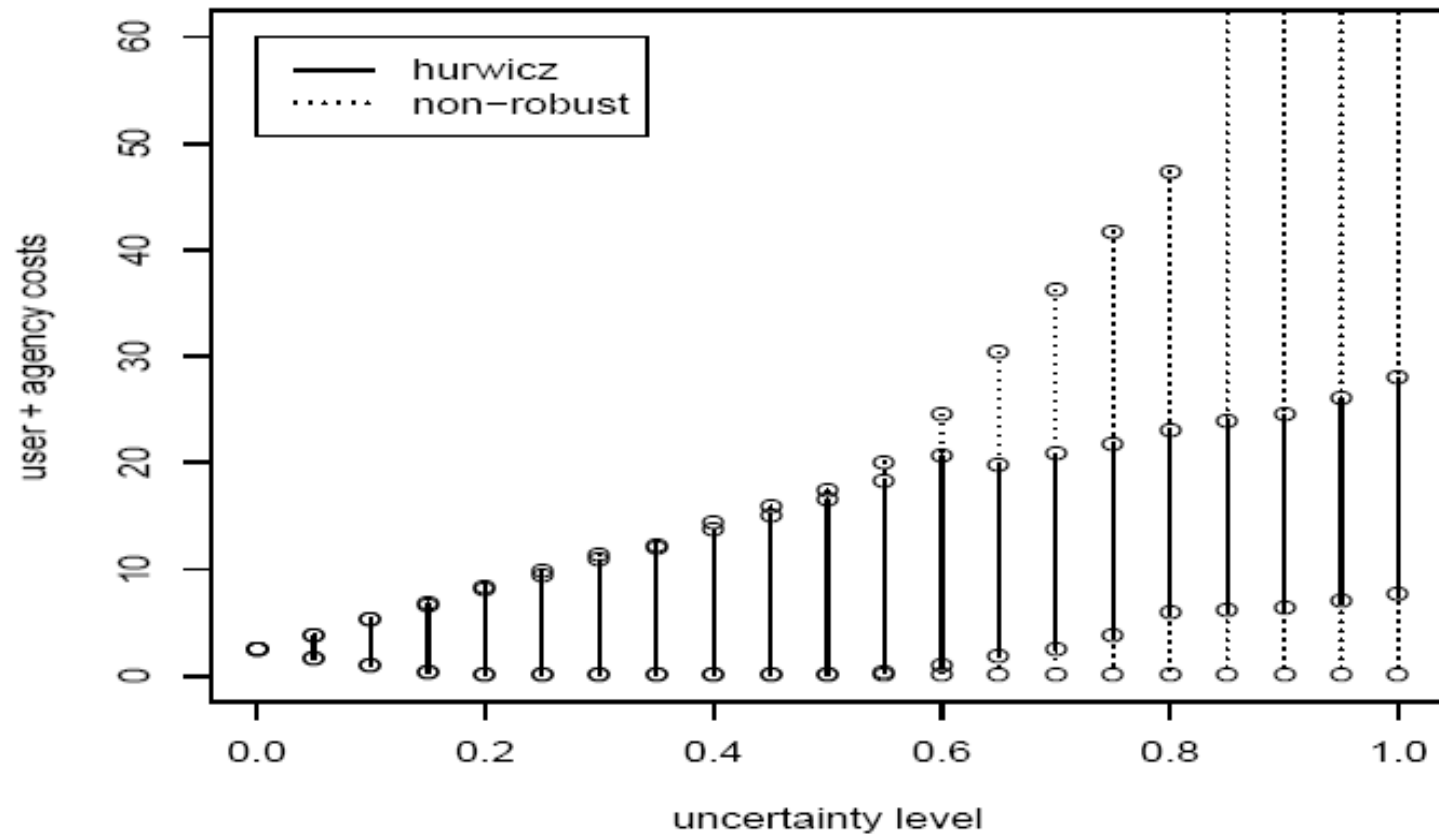
Alternatives to MAXIMIN

- MAXIMAX
 - assume nature is benevolent
- Hurwicz criterion
 - define an optimism level β in $[0,1]$
 - then let $1 - \beta$ be the pessimism level
 - maximize the sum of the optimism level times the best possible outcome and the pessimism level times the worst possible outcome

System-level Hurwicz MDP formulation



System-level MDP: cost ranges



Conclusions

- Model uncertainty has important cost implications if not accounted for in M&R decision-making
- Adaptive optimization methods can reduce the impacts of model uncertainty but require large amounts of data or long time horizons
- Robust optimization is a practical alternative to adaptive optimization methods
- Robust optimization saves more under worst case conditions than it costs under expected or best case conditions