TREC Friday Seminar Series

Transportation Research and Education Center (TREC)

11-4-2022

System-level Risk Management of Transportation Structures and Networks

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System-level Risk Management of Transportation Structures and Networks

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TRANSPORTATION RESEARCH and EDUCATION CENTER

Portland State UNIVERSITY

Risk of Transportation Structures and Networks

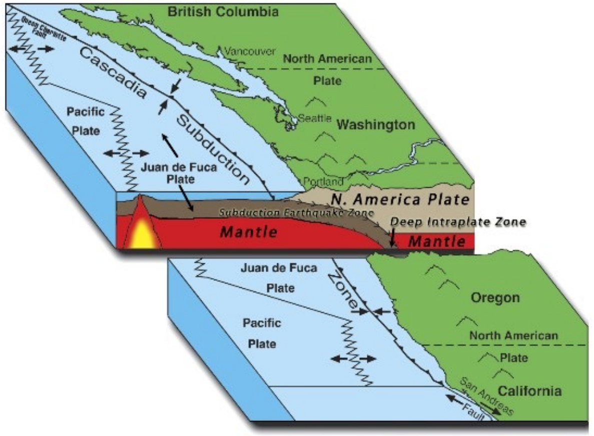
Risk definition

Risk = Probability x Consequences

Probability = likelihood of the occurrence of an adverse event and its exposure

Consequence = Extent of impacts (economic, social, and environmental)

Cascadia Subduction Zone Earthquake
Source: Oregon OEM
https://www.oregon.gov/oem/hazardsprep/Pages/Cascadia-Subduction-Zone.aspx



Failure/disruption during normal conditions due to e.g., extensive corrosion and deterioration

2022 Taiwan earthquake
https://www.rte.ie/news/newslens/2022/0919/1324288-bridge-taiwan/

Bridge in PA collapsed due to lack of repair
Replacement estimated at $25.3 mil
https://www.cnn.com/2022/02/04/us/pennsylvania-bridge-repair/index.html

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Risk of Transportation Structures and Networks

Gaps in the practice of risk assessment

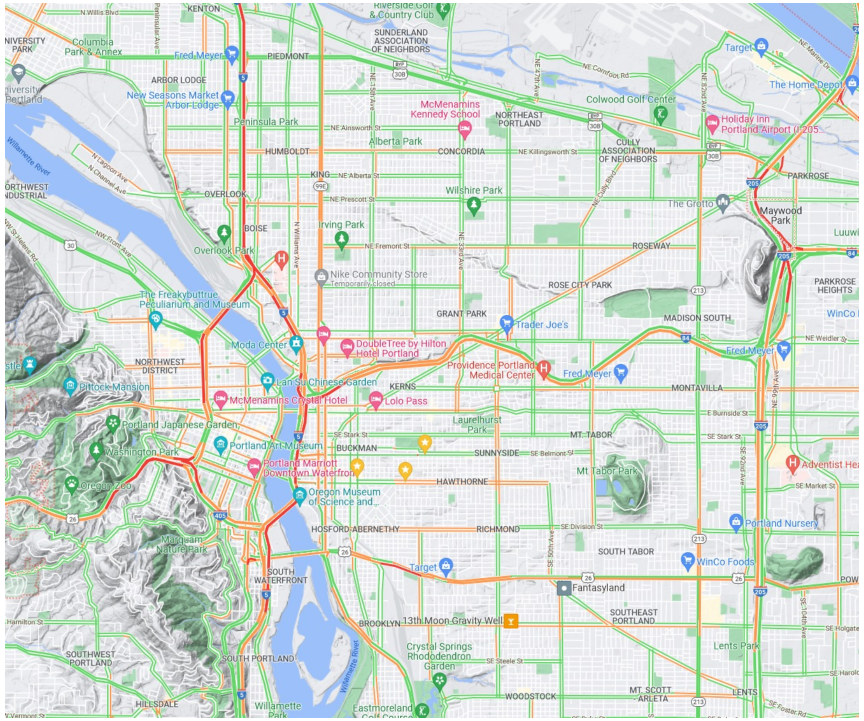
Risk = Probability x Consequences

Probability = likelihood of the occurrence of an adverse event

Consequence = Extent of impacts (economic, social, and environmental)

Impact at key infrastructure assets can spread quickly to the entire system

https://en.wikipedia.org/wiki/List_of_crossings_of_the_Willamette_River

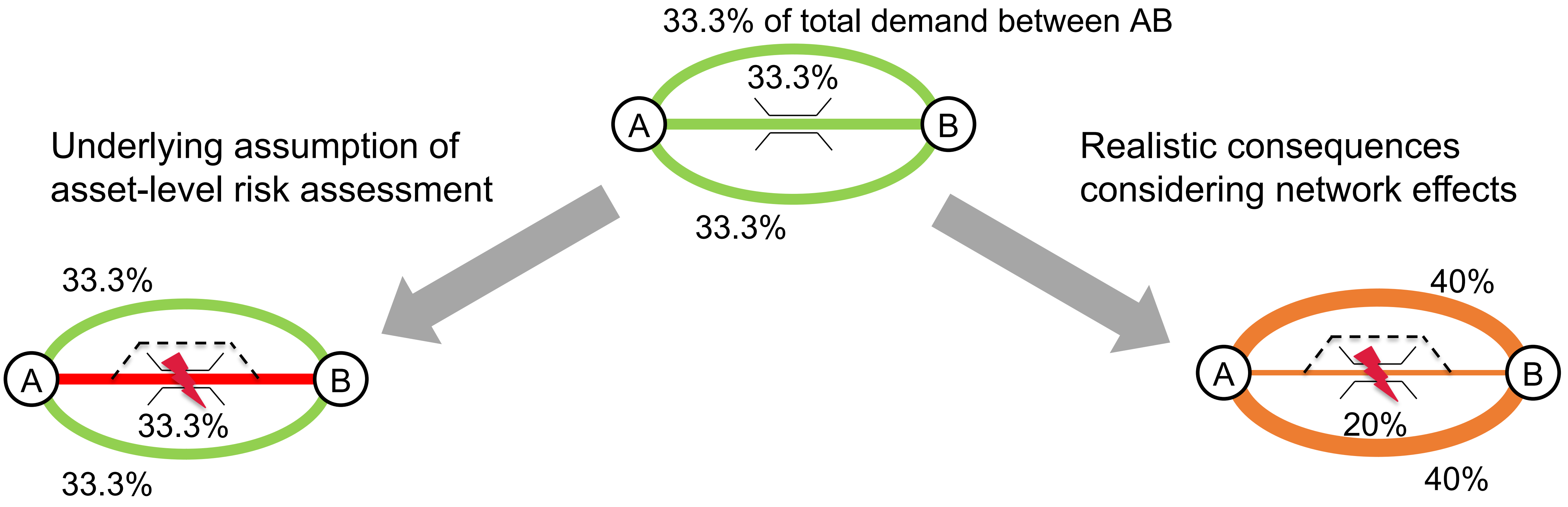


Google Maps: Typical traffic, Monday 5:10pm

Risk of Transportation Structures and Networks

Gaps in the practice of risk assessment

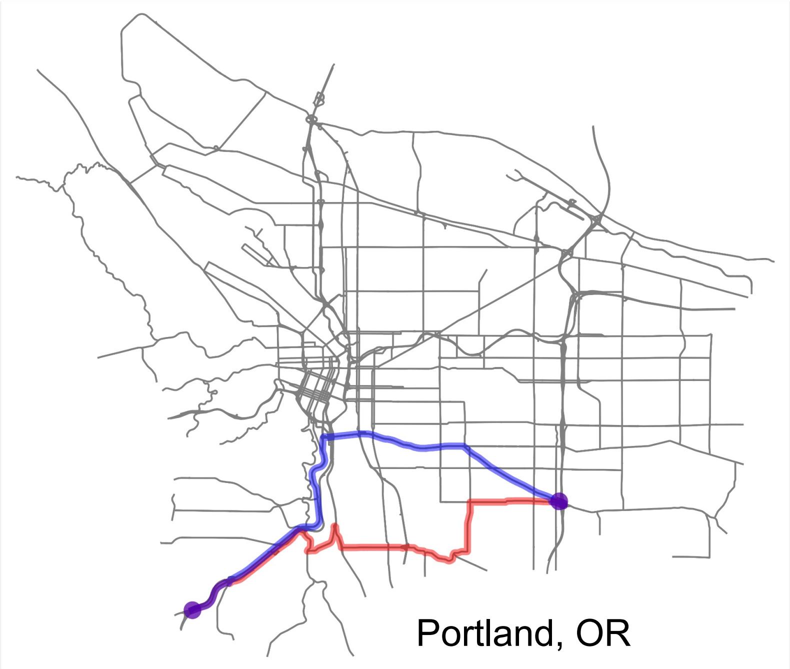
- Traditionally, risk assessment has been carried out at the asset level
  - Network performance is approximated by aggregating asset performance
- However, transportation assets are interconnected, and the impact of structural failure may propagate to other routes in the network



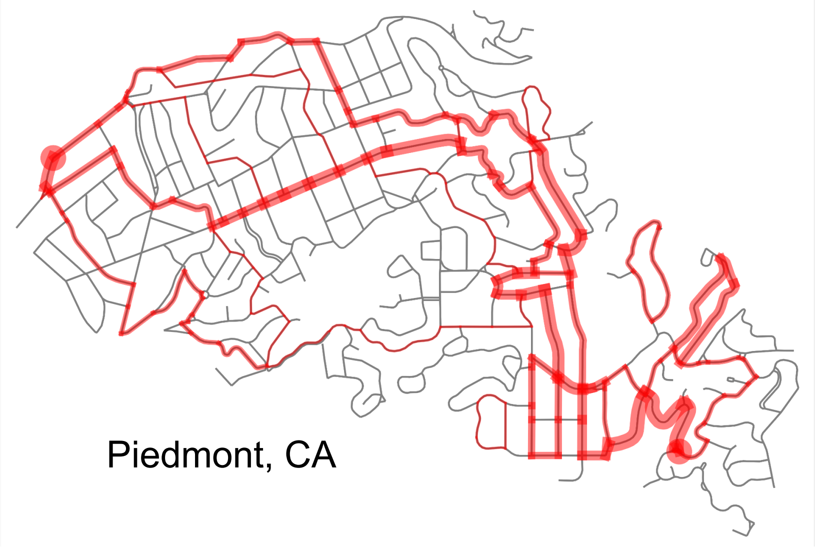
System-level Impacts of Transportation Networks

System-level functionality indicators

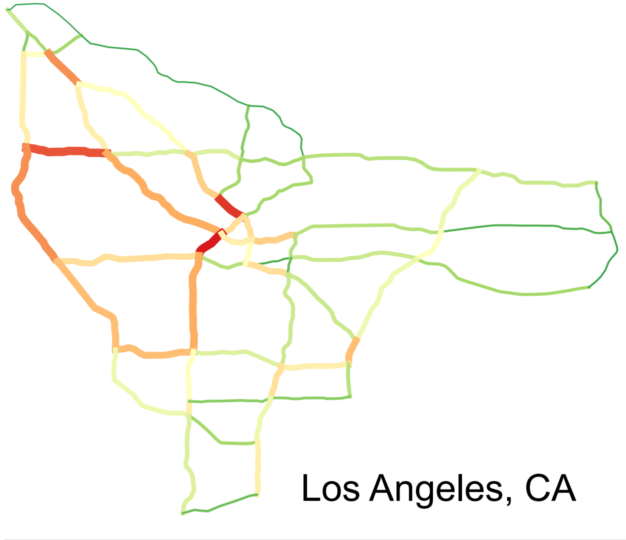
Connectivity



Maximum flow
(network capacity)



Travel time and distance
(traffic assignment)



Computational complexity

Low → High

System-level Impacts of Transportation Networks

Why it matters?

- Risk assessment forms the basis for risk management
  - Accurate risk assessment is essential to gauging the benefit of management actions
  - The risk-informed cost-benefit analysis can be directly used for infrastructure management

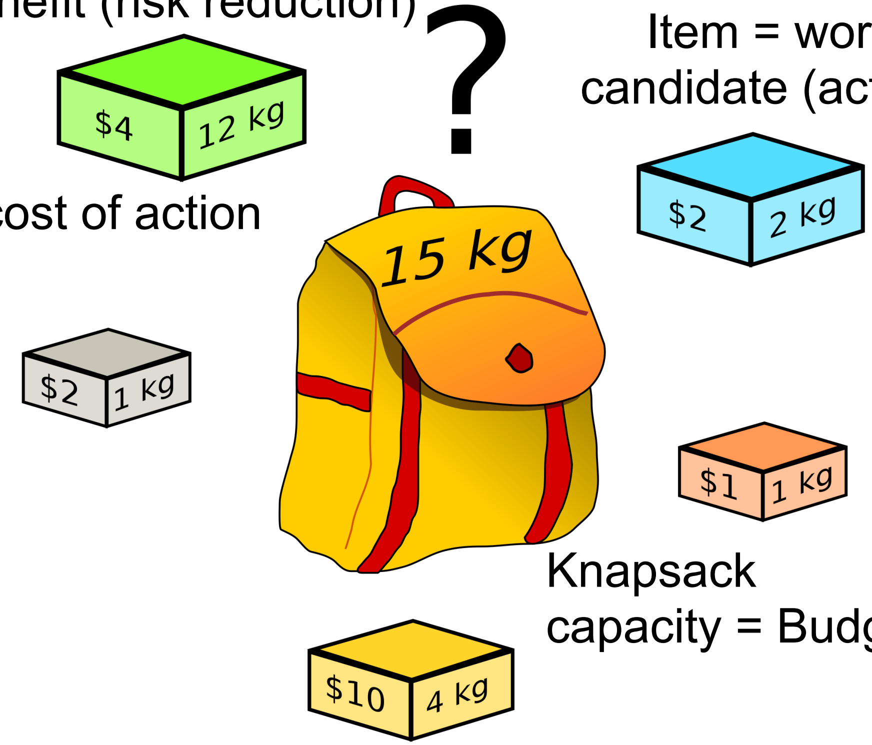
Optimization problem of risk management
Maximize: Total benefit in risk reduction (from a pool of work candidates)
Subject to: Budget constraint

Equivalent prioritization (ranking) problem
Knapsack problem: solved by ranking the projects in decreasing order of benefit/cost ratio, and select and cut off the sorted work candidates when the budget is exhausted

Value = benefit (risk reduction)

Item = work candidate (action)

Weight = cost of action



Knapsack capacity = Budget

https://commons.wikimedia.org/wiki/File:Knapsack.svg

System-level Impacts of Transportation Networks

Why it matters?

Massive repository
Of deficient structures

ASCE Report Card (2021)
7.5% of the surveyed bridges as structurally deficient

ICE Report (2014)
1/3 of the local transportation systems need urgent attention for maintenance

Scarce resources
For maintenance

McKinsey Report (2013)
60% shortage for investment in infrastructure globally

ASCE Report Card (2021)
$123 billion in need to clear the backlog of bridge repair needs

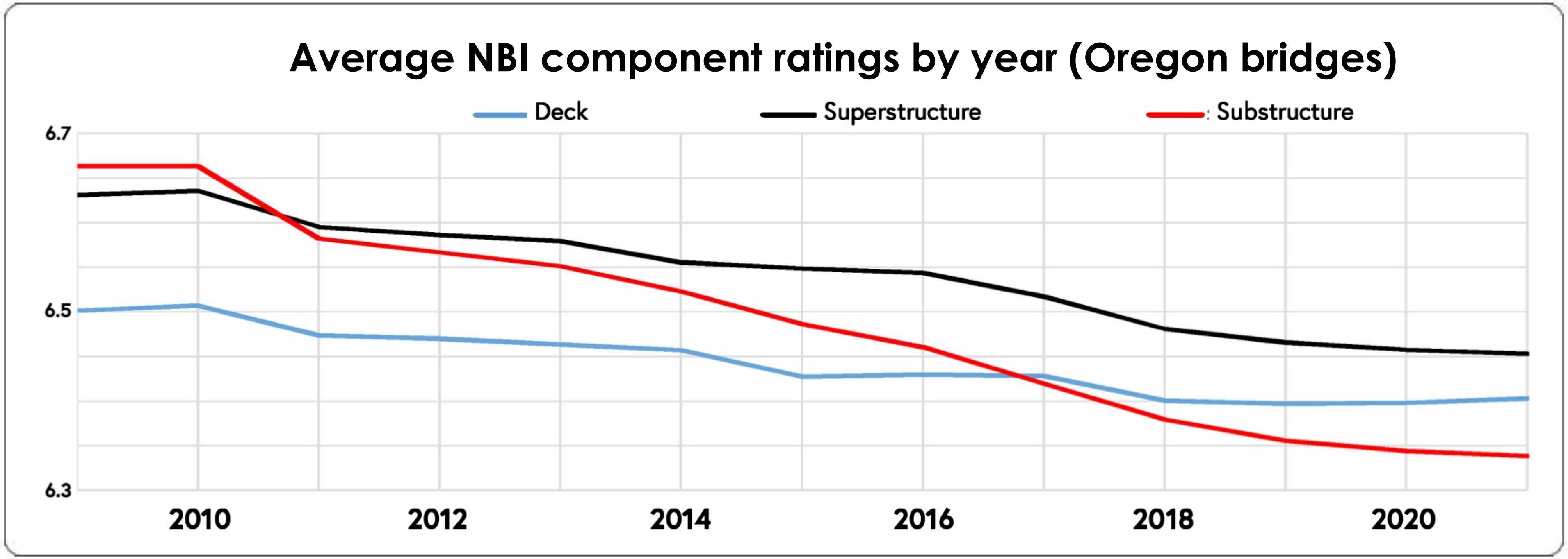
Lack of Strategic Management

FHWA Questionnaire (2010)
Most states in the U.S. do not have a systematic strategy for funding allocation; Worst-first approach, based on either condition or qualitative risk score, is still being widely used.

SYSTEM-LEVEL IMPACTS OF TRANSPORTATION NETWORKS

Why it matters?

- State DOTs continue to lose ground in bridge management efforts
  - At the current funding rate for bridge replacement, an Oregon bridge will need to stay in service for over 900 years (ODOT 2021 Bridge Condition Report)



Source: ODOT 2021 Bridge Condition Report

Risk-informed Bridge Ranking at Project and Network Levels

Yang, D. Y., & Frangopol, D. M. (2018). *ASCE Journal of Infrastructure Systems*, 24(3), 04018018

Overview of Methodology

Proposed vs existing methods

Markov chain deterioration model

- ✓ Transition matrix based on historical evidence
- ✓ From Markovian states to reliability indices

Risk assessment in practice

- ✓ Rebuilding and repair costs
- ✓ Asset-level failure impacts

Existing ranking methods

- ✓ Safety rating (condition-based)
- ✓ Sufficiency rating (qualitative risk)

Network function for risk assessment

- ✓ Traffic flow re-assignment given bridge failure
- ✓ Spatial correlation of bridge failures
- ✓ Risk assessment at network level

MARKOV DETERIORATION MODEL

Definition and quantification

- Bridge conditions are commonly represented by condition ratings derived from regular inspection reports
- Deterioration, represented by the reduction in condition ratings, can be modeled as a (descending) Markov chain

$$\begin{bmatrix} s_1 \\ s_2 \\ s_3 \\ \vdots \\ s_7 \end{bmatrix}^{(t+1)} = \begin{bmatrix} \tau_{11} & \tau_{12} & 0 & \cdots & 0 \\ 0 & \tau_{22} & \tau_{23} & \cdots & 0 \\ 0 & 0 & \tau_{33} & \cdots & 0 \\ \vdots & \vdots & \vdots & \ddots & \vdots \\ 0 & 0 & 0 & \cdots & \tau_{77} = 1 \end{bmatrix}^{\mathrm{T}} \begin{bmatrix} s_1 \\ s_2 \\ s_3 \\ \vdots \\ s_7 \end{bmatrix}^{(t)}$$

$$\mathbf{s}(t+1) = \mathbf{T}^{\mathrm{T}} \cdot \mathbf{s}(t)$$

TABLE. Condition rating and Markov state
Source: Adapted from FHWA (1995)

Code	Description	Markov state
N	N/A	N/A
9	Excellent condition	MS 1
8	Very good condition—no problems noted	—
7	Good condition—some minor problems	MS 2
6	Satisfactory condition—structural elements show some minor deterioration	MS 3
5	Fair condition—all primary structural elements are sound but may have minor section loss, cracking, spalling or scour	MS 4
4	Poor condition—advanced section loss, deterioration, spalling or scour	MS 5
3	Serious condition—loss of section, deterioration of primary structural elements. Fatigue cracks in steel or shear cracks in concrete may be present	MS 6
2	Critical condition—advanced deterioration of primary structural elements. Fatigue cracks in steel or shear cracks in concrete may be present or scour may have removed substructure support. Unless closely monitored it may be necessary to close the bridge until corrective action is taken	MS 7
1	Imminent failure condition—major deterioration or section loss present in critical structural components or obvious vertical or horizontal movement affecting structure stability. Bridge is closed to traffic but corrective action may put it back in light service	—
0	Failed condition—out of service; beyond corrective action	—

Markov Deterioration Model

Derivation of transition probabilities

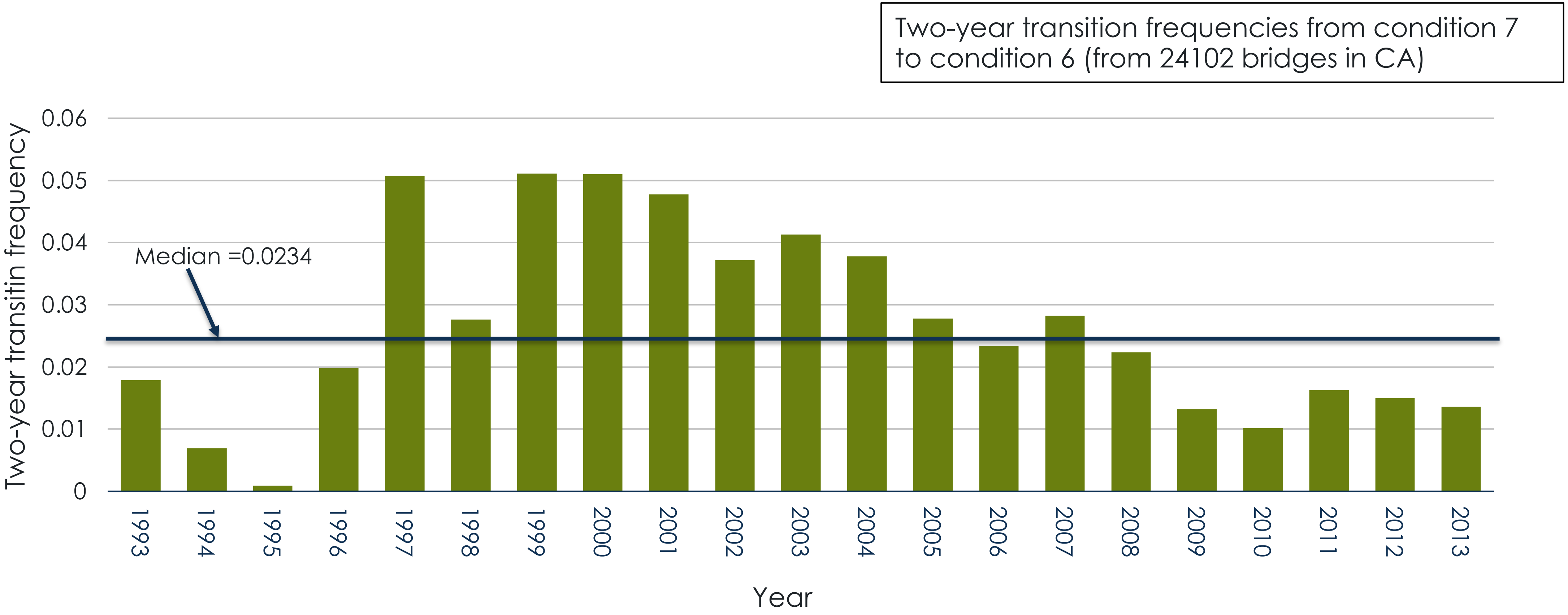


FIGURE. Two-year transition frequencies from NBI data
Used to derive annual transition probabilities due to deterioration

Markov Deterioration Model

Simulated deterioration

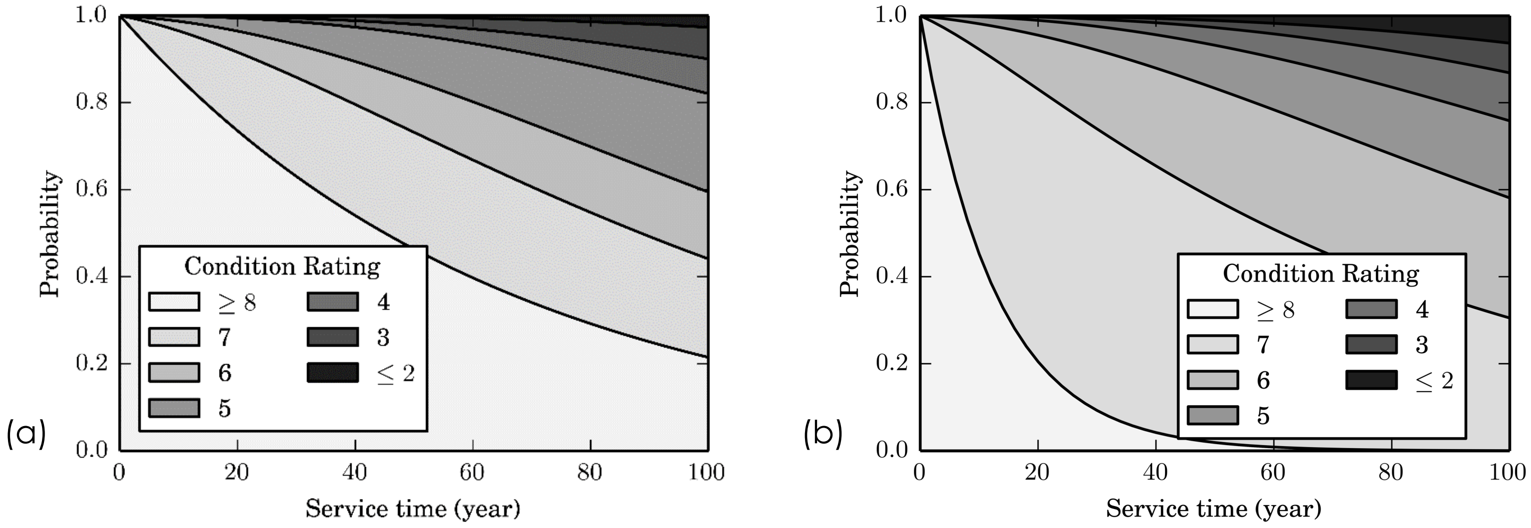


FIGURE. Markovian deterioration of bridge super- and substructures

(a) Superstructure

(b) Substructure

Markov state → Central safety factor → Structural reliability index

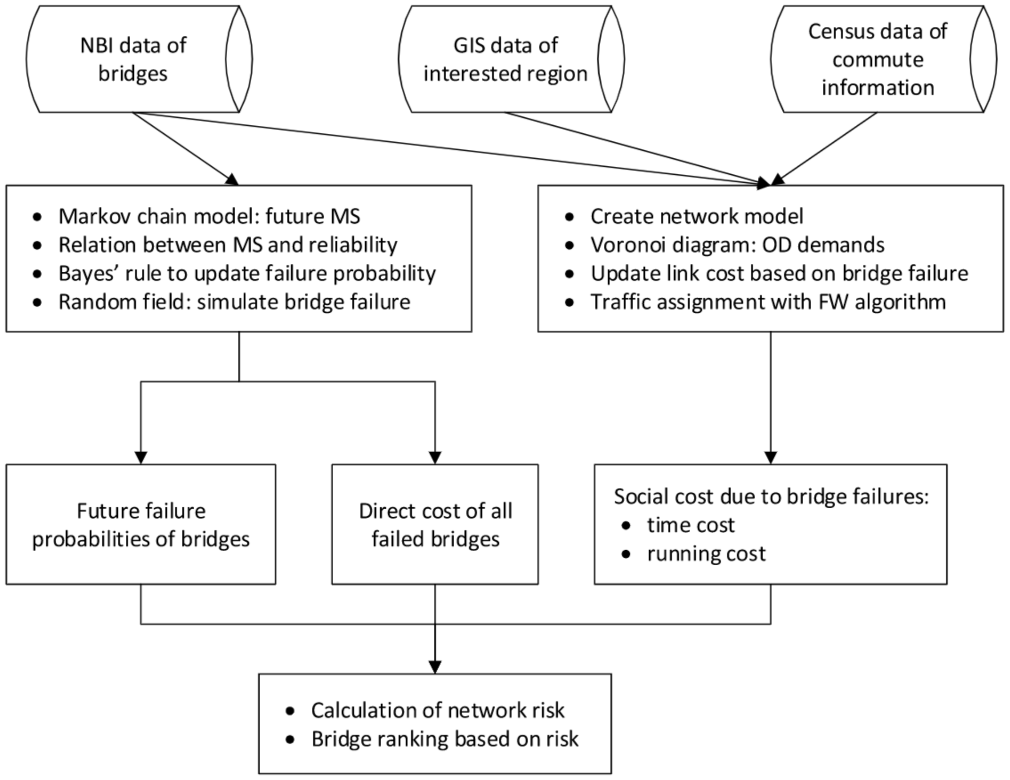
$$\theta(s) = \frac{\theta_7 - \theta_1}{7 - 1}(s - 7) + \theta_7$$

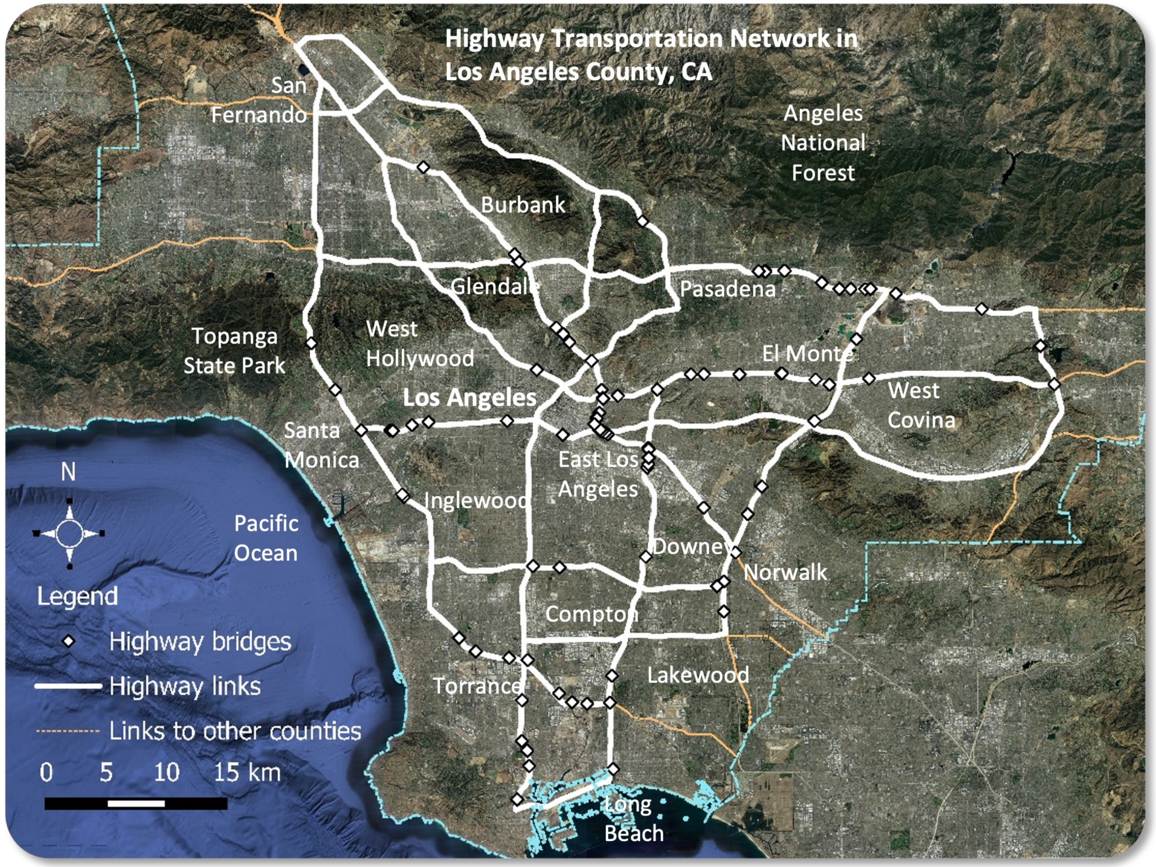
$$\beta(s) = \frac{\mu_R - \mu_S}{\sqrt{\mu_R^2\delta_R^2 + \mu_S^2\delta_S^2}} = \frac{\theta(s) - 1}{\sqrt{\theta(s)^2\delta_R^2 + \delta_S^2}} = -\Phi^{-1}\left[p_f(s)\right]$$

ILLUSTRATIVE EXAMPLE

Highway bridges in LA county, CA

- Cost to transportation users from **extra travel time and distance** is used for network-level risk assessment and risk-based ranking
  - The highway bridge network include 91 highway bridges on 66 links





ILLUSTRATIVE EXAMPLE

Highway bridges in LA county, CA

- Comparison of different bridge performance indicators for ranking
  - Structural adequacy and safety
    - ✓ Condition and load rating of key bridge components
  - Sufficiency rating
    - ✓ Qualitative indicator combining structural adequacy and safety, serviceability, and essentiality for public use
  - Project-level quantitative risk
    - ✓ Quantitative risk assessment at the asset level
  - Network-level quantitative risk
    - ✓ Quantitative risk assessment at the system level

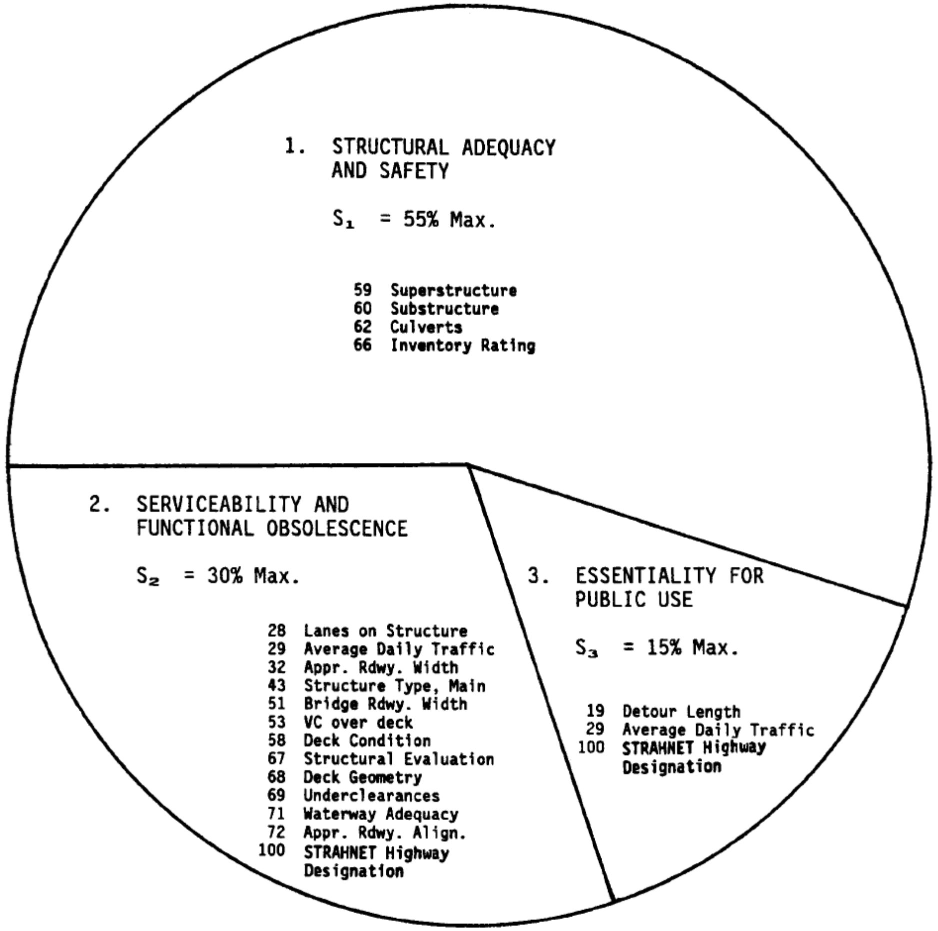


FIGURE. Sufficiency rating composition

Source: FHWA (1995)

ILLUSTRATIVE EXAMPLE

Highway bridges in LA county, CA

Traffic assignment was first carried out to derive baseline travel time and travel distance of all users

Traffic fills the 110 during rush hour in downtown L.A.

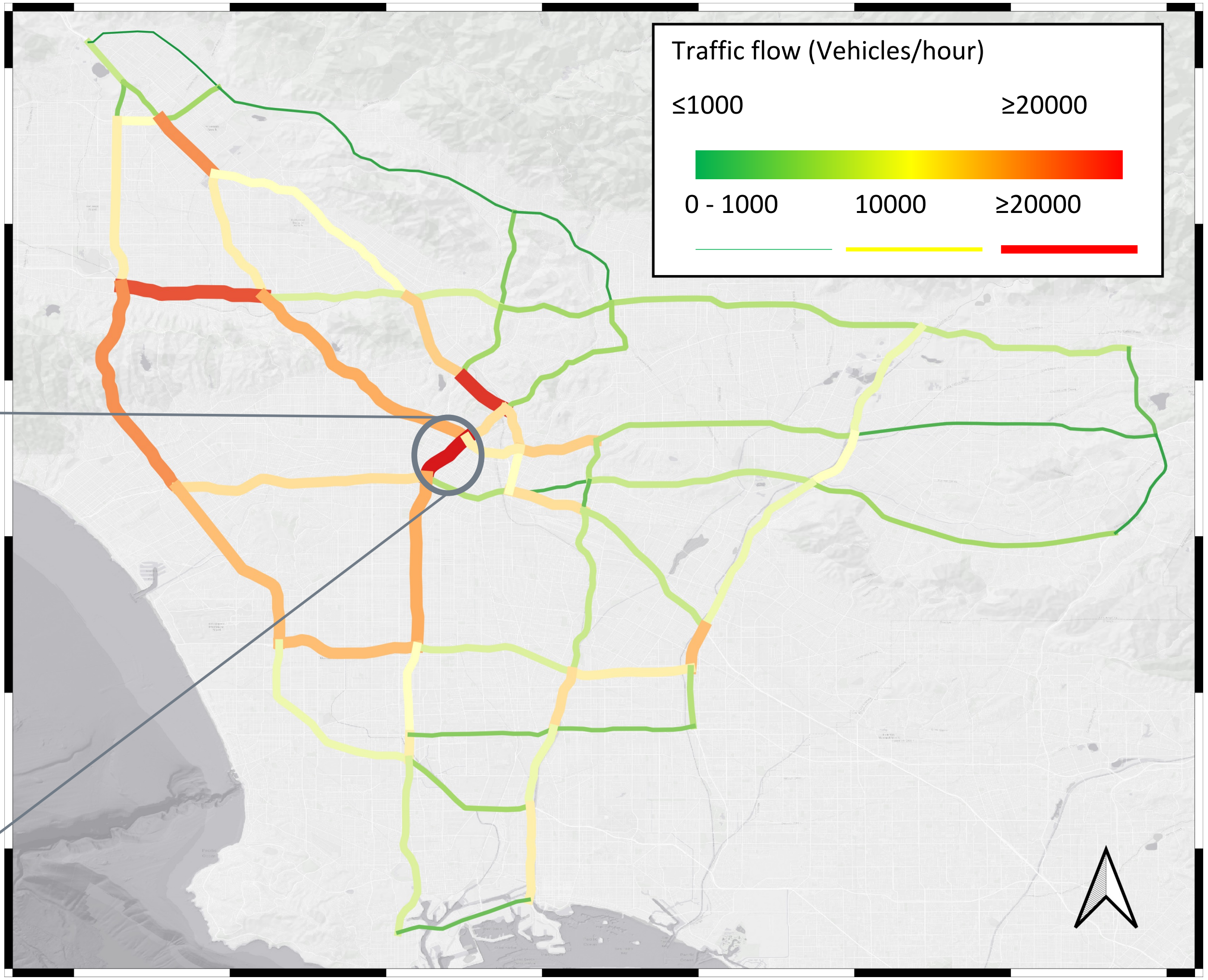


FIGURE. Traffic flow estimation from traffic assignment

Illustrative Example

Bridge ranking: network risk vs safety/sufficiency ratings

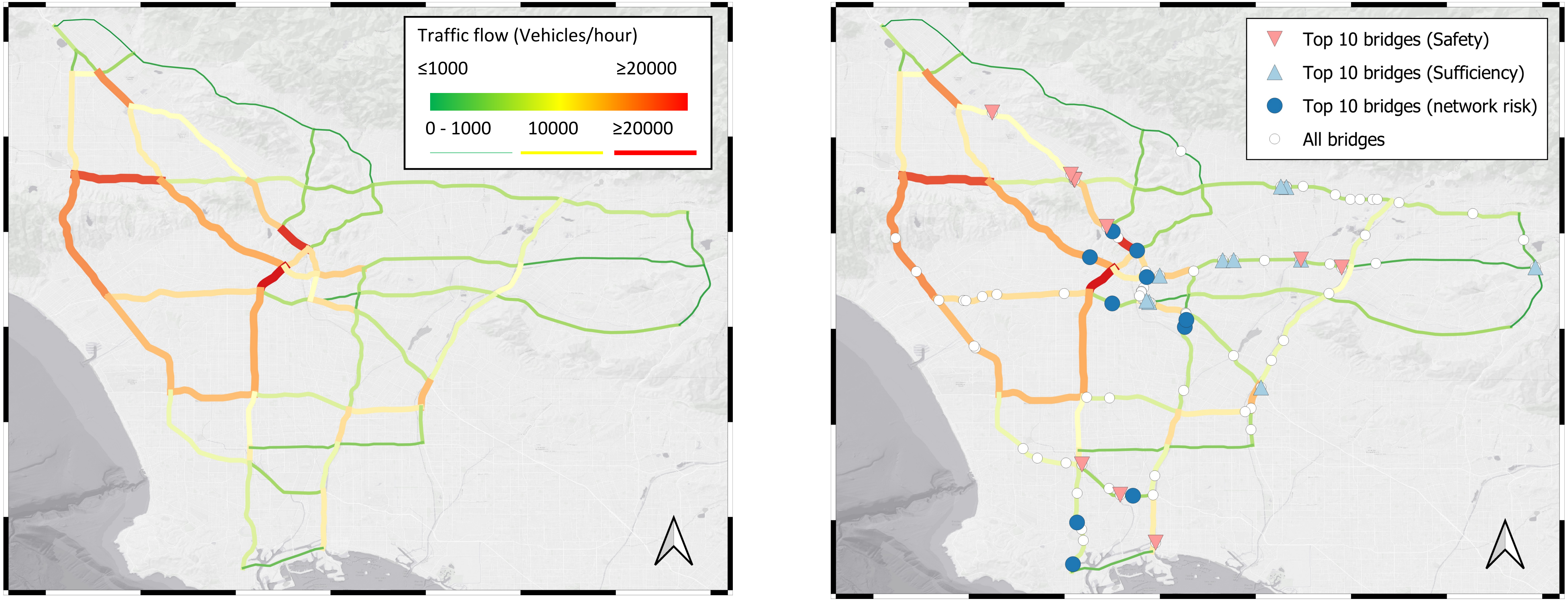


FIGURE. Locations of top-ranked bridges

Illustrative Example

Bridge ranking: network risk vs project risk

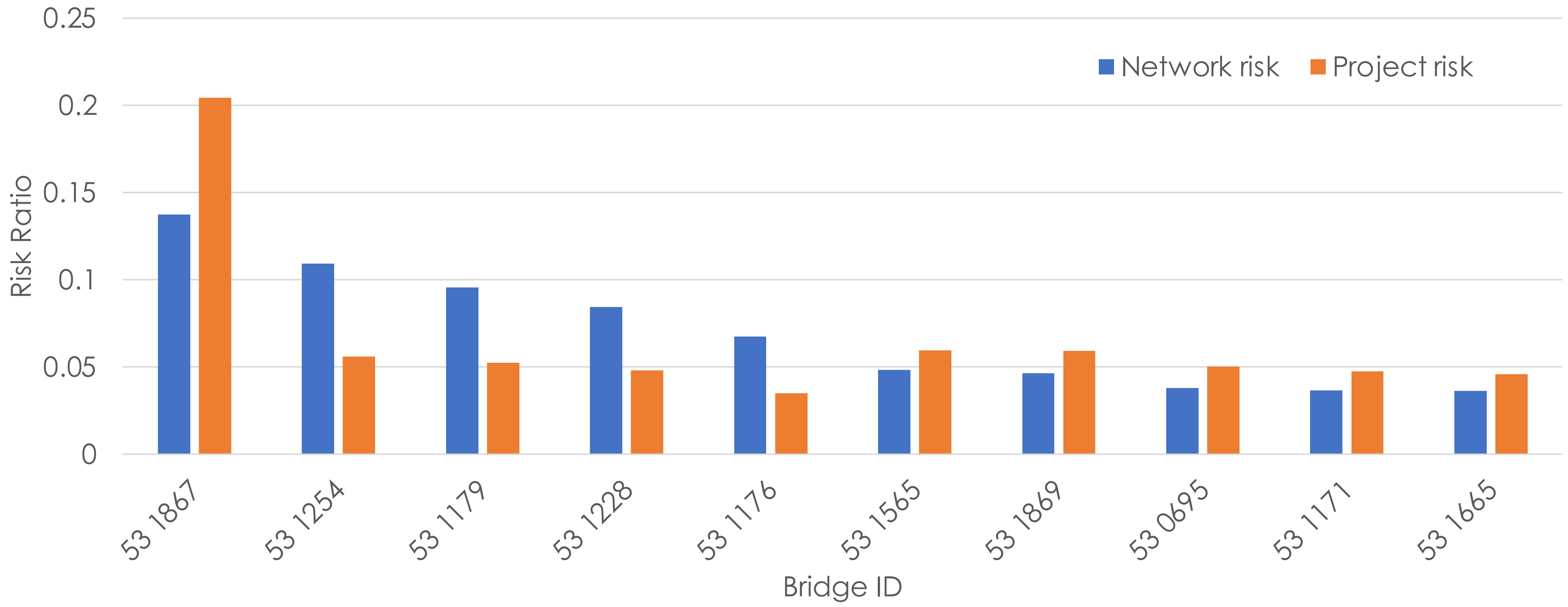


FIGURE. Risk ratio and bridge ranking (top 10) based on network- and project-level risks

Network-Level Asset Management Enabled by Deep Reinforcement Learning

Yang, D. Y. (2022). *ASCE Journal of Infrastructure Systems*, 28(3), 04022023

Yang, D. Y. (2022). *ASCE Journal of Engineering Mechanics*, 148(1), 04021126

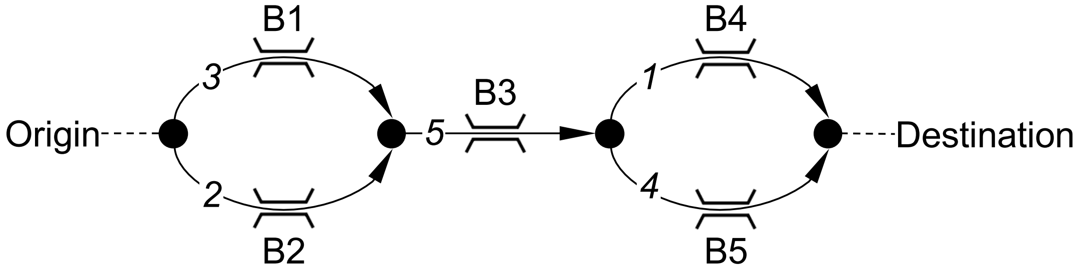
RISK OF DETERIORATING BRIDGE NETWORKS

Network risk based on transportation functionality

- Network risk due to bridge deterioration can be formulated based on
  - Network connectivity
  - Travel time and travel distance of network users
  - **Traffic flow capacity** (maximum flow between all origin-destination pairs)
- Network risk based on flow capacity is defined as follows

$$R_{NET}(\mathbf{s}) = \sum_{\mathbf{c}} p(\mathbf{c}|\mathbf{s})[F_0 - F(\mathbf{c})]$$

$\mathbf{c}$ = binary vector denoting bridge failures in a network (i.e., config. of a damaged network)
F_0 = flow capacity in an intact network
$F(\mathbf{c})$ = flow capacity given config. $\mathbf{c}$
$p(\mathbf{c}|\mathbf{s})$ = prob. of config. $\mathbf{c}$ given bridge states $\mathbf{s}$
$R_{NET}(\mathbf{s})$ = network risk given bridge states $\mathbf{s}$



$F_0 = 5$ when all bridges are safe

If bridge B1 failed,

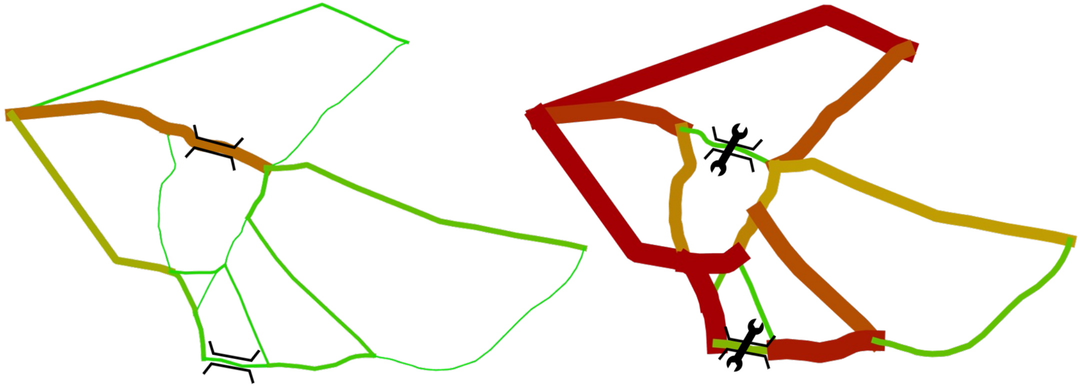
$$\mathbf{c} = [1, 0, 0, 0, 0] \text{ and } F(\mathbf{c}) = 2$$

LIFE-CYCLE RISK MANAGEMENT AND REINFORCEMENT LEARNING

Formulation of reinforcement learning (RL) problem

- Risk management in structural life-cycle as a sequential decision-making problem

Bridge performance
given adopted action



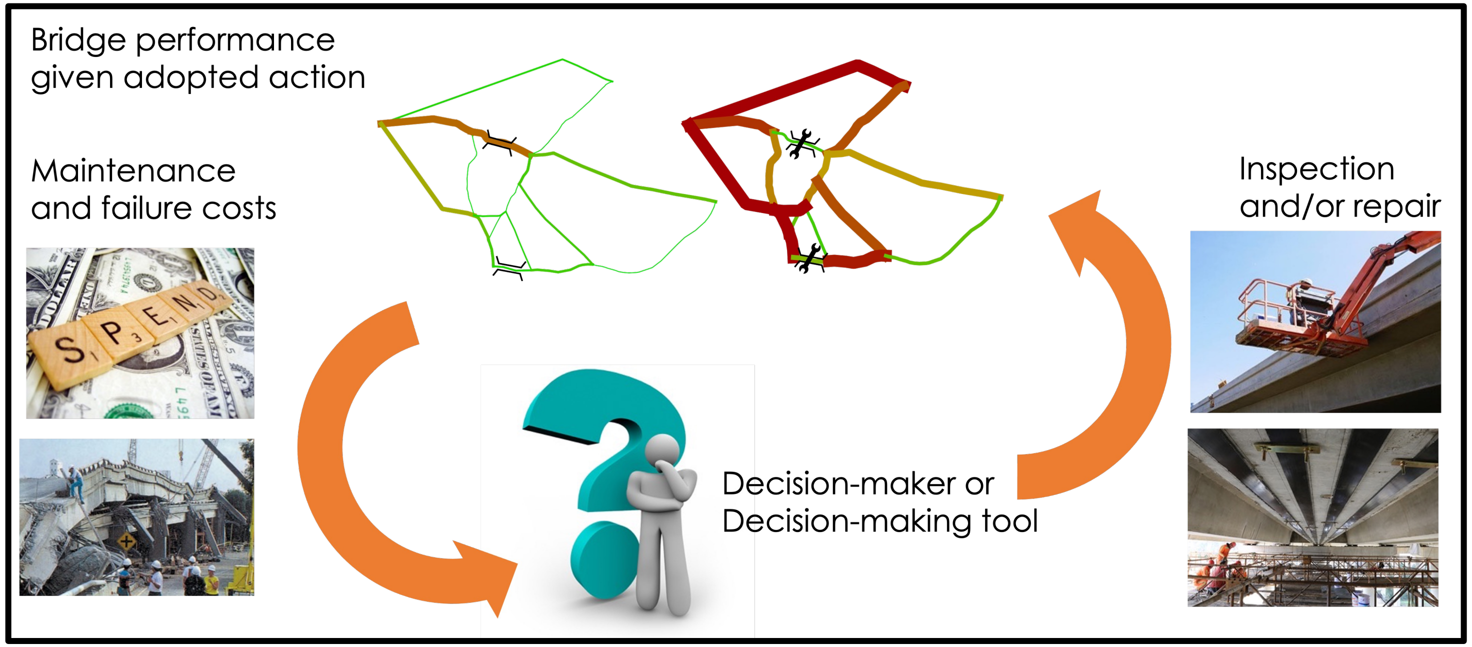
Maintenance
and failure costs

Inspection
and/or repair

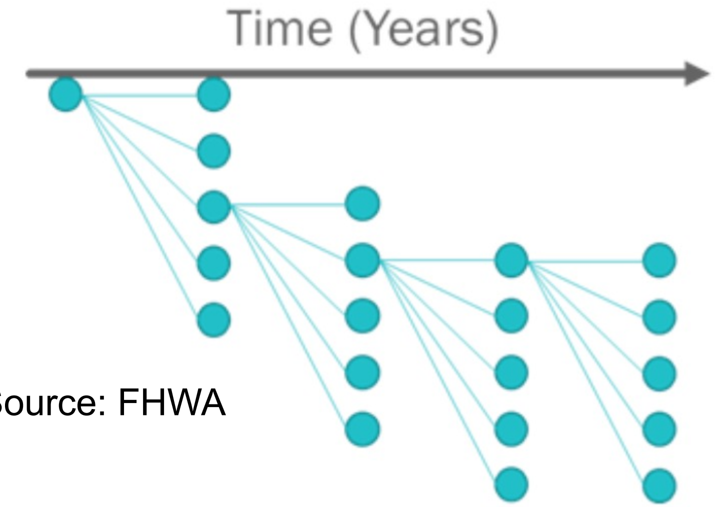
Decision-maker or
Decision-making tool

Life-cycle Risk Management and Reinforcement Learning

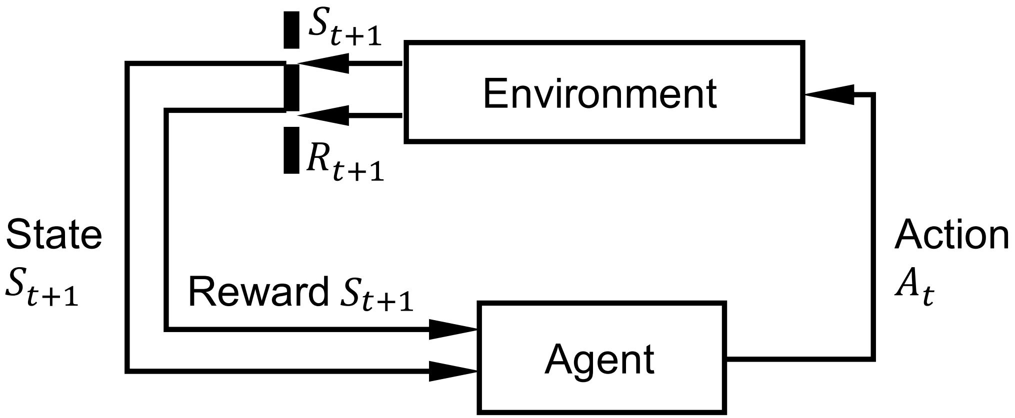
Formulation of reinforcement learning (RL) problem



5 action per bridge in a 10-year decision-horizon across 100 bridges = $9{,}765{,}625^{100}$ potential policy paths



Source: FHWA



One episode = One service life
One time-step = One year

Source: Sutton and Barto (2018)

Life-cycle Risk Management and Reinforcement Learning

Formulation of reinforcement learning (RL) problem

- The condition preservation effort in bridge management systems can be formulated as a problem of risk-informed value maximization:

Find a policy from state $\mathbf{s}$ to action $\mathbf{a}$: $\pi(\mathbf{a}|\mathbf{s}) = \Pr[\mathbf{a}|\mathbf{s}]\,, \forall \mathbf{a} \in \mathcal{A}, \mathbf{s} \in \mathcal{S}$

to maximize the following recursive value function:

$$V_{k+1}^{\pi}(\mathbf{s}) = \mathbb{E}_{\pi}[R(\mathbf{s},\mathbf{a},\mathbf{s}') + \gamma V_k^{\pi}(\mathbf{s})]$$

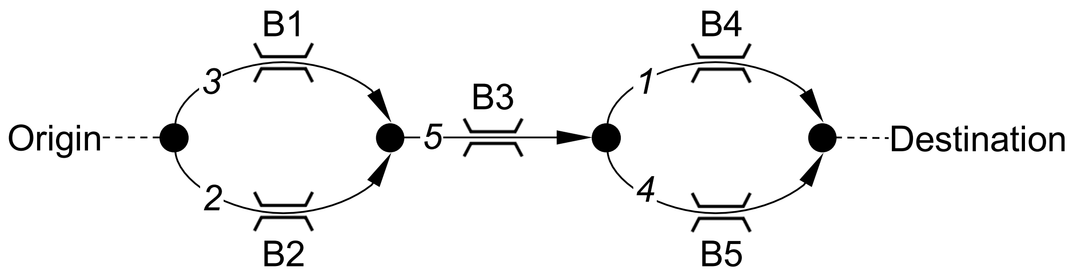
where the risk-informed reward is defined as

$$R(\mathbf{s},\mathbf{a},\mathbf{s}') = -\left[\frac{C(\mathbf{s},\mathbf{a},\mathbf{s}') + R_{AST}(\mathbf{s})}{\lambda_{ECON}} + w_{NET} \cdot \frac{R_{NET}(\mathbf{s})}{\lambda_{FLOW}}\right]$$

LIFE-CYCLE RISK MANAGEMENT AND REINFORCEMENT LEARNING

Formulation of reinforcement learning (RL) problem

- When network risk is ignored ($w_{NET} = 0$), the optimization can be carried out at the asset level
  - Bridges are considered homogeneous assets in a large inventory
  - The optimal policy is scaled based on the number of bridges in the inventory
- However, since the network consequences are non-additive, the policy considering network risk must be analyzed at the network level



Consider the damaged network with two failed bridges, B1 and B3.

The capacity reduction is 5, which is not the sum (8) of

the capacity reductions due to only bridge B1 (3) and only bridge B3 (5)

Deep Reinforcement Learning for Risk management

Algorithm development

- The necessity of network-level analysis drastically increases the size of state and action spaces.
- Therefore, a distributed PPO algorithm was developed to handle large state and action spaces

Distributed actors based on system state:

$$\pi_\theta(\mathbf{a}|\mathbf{s}) = \prod_b \pi_{\theta_b}(a_b|\mathbf{s})$$

Proximal policy optimization (PPO) algorithm:

$$L^{CLIP}(\theta) = \widehat{\mathbb{E}}_t\left[\min\left(r_t(\theta)A_t, r_{t,clip}(\theta,\epsilon)A_t\right)\right]$$

$$r_t(\theta) = \frac{\pi_\theta(\mathbf{a}_t|\mathbf{s}_t)}{\pi_{\theta_{old}}(\mathbf{a}_t|\mathbf{s}_t)}$$

$\pi_\theta(\mathbf{a}|\mathbf{s})$ = parameterized policy (neural network)
A_t = advantage of the action in time step t

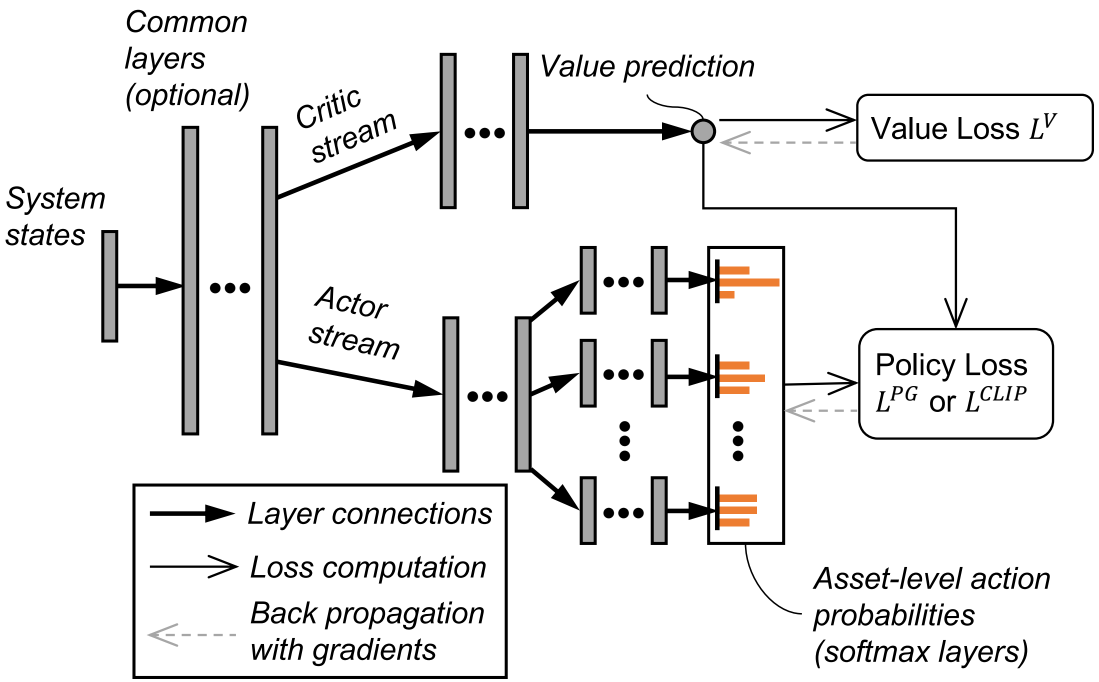
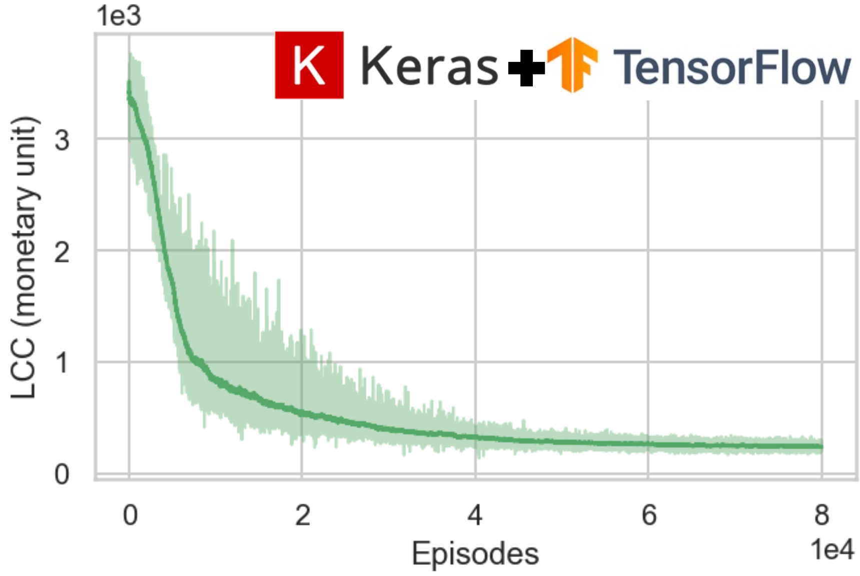
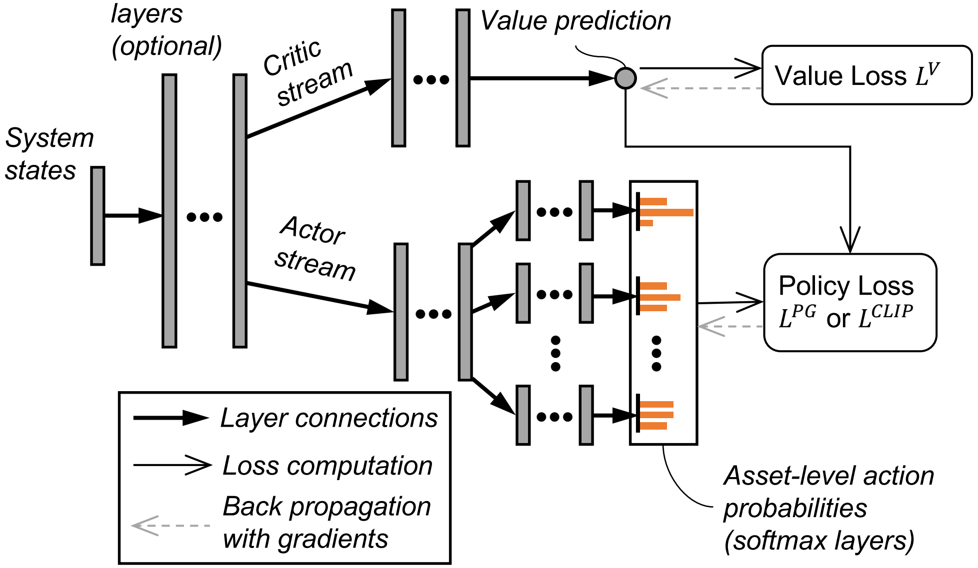


FIGURE. DRL architecture and neural network training

Deep Reinforcement Learning for Risk management

Algorithm development





Input: Algorithm hyperparameters
Output: Actor and critic networks after training
Initialize π_θ, V_ϕ, and data buffer for storing experiences

for *until maximum number of iterations M* **do**

Gain Experience

`// generate` N `episodes based on` π_θ `(parallel processing):`
for *each* $i \in [1, N]$ **do**
  store episodic experiences: $\{(\mathbf{s}_t, \mathbf{a}_t, R_t)\}$
  calculate returns $G_t \leftarrow R_t + \gamma G_{t+1}$ for $t = T-1, T-2, \ldots, 0$
end

`// assemble training datasets`
$\mathcal{S}_{train} \leftarrow \{s_{i,t} \quad , \forall i \in [1, N], t \in [0, T]\}$
$\mathcal{A}_{train} \leftarrow \{a_{i,t} \quad , \forall i \in [1, N], t \in [0, T]\}$
$\mathcal{G}_{train} \leftarrow \{G_{i,t} \quad , \forall i \in [1, N], t \in [0, T]\}$

`// train actor and critic networks for` K `steps`
$\pi_{\theta_{old}} \leftarrow \pi_\theta$

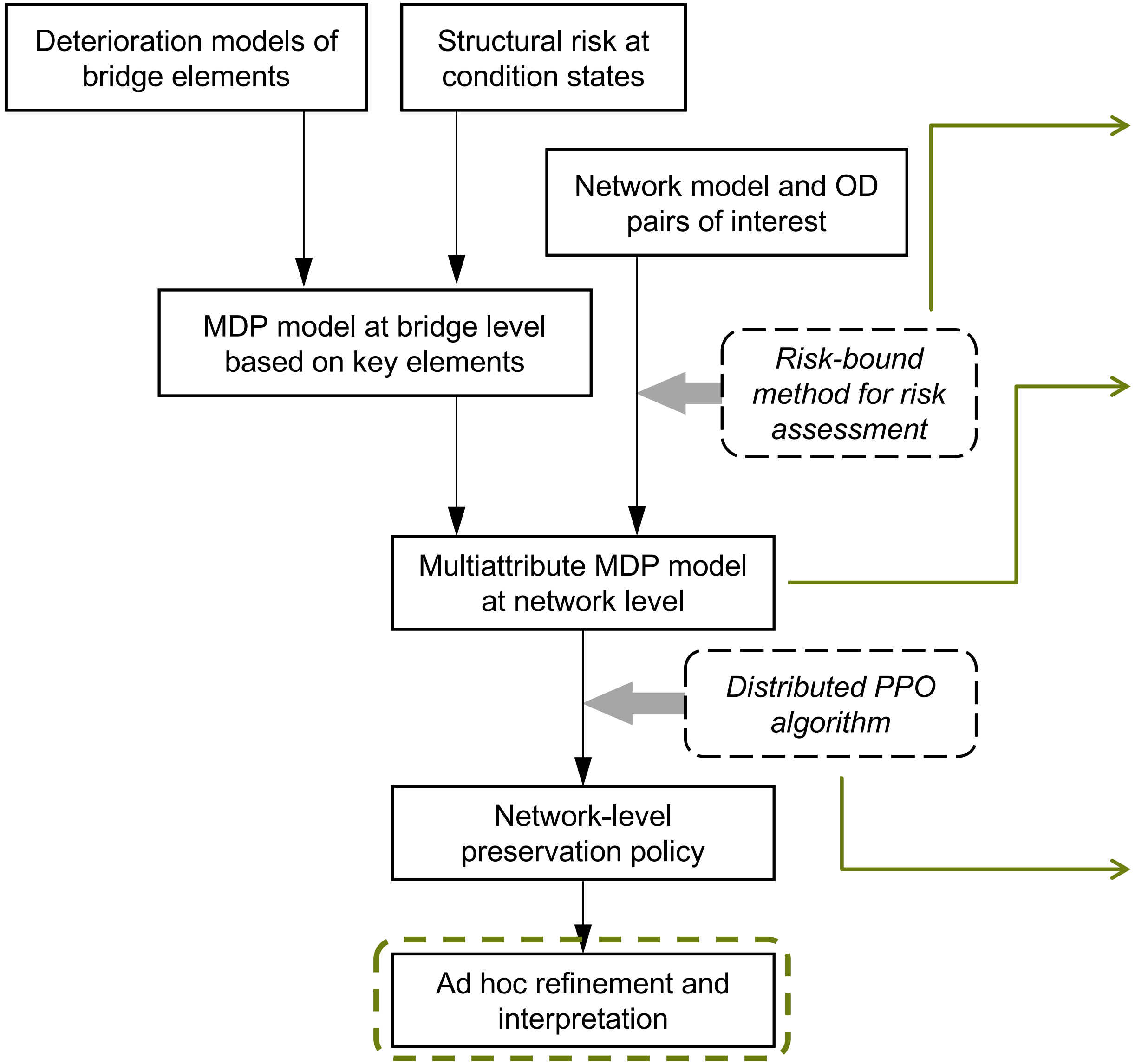
Learn policy

for $k \leftarrow 1, 2, \cdots, K$ **do**
  calculate value function loss $L^V(\phi)$ based on Eq. 11 using the experiences in $\mathcal{G}_{train}$ and $\mathcal{S}_{train}$
  calculate clipped surrogate loss $L^{CLIP}(\theta)$ based on Eq. 12 using the experiences in $\mathcal{G}_{train}$, $\mathcal{A}_{train}$, and $\mathcal{S}_{train}$
  `// conduct one step of gradient descent following an optimizer`
  if *actor and critic networks share common hidden layers* **then**
    $L^{TOTAL} \leftarrow L^{CLIP}(\theta) + \eta L^V(\phi)$
    $\{\theta, \phi\} \leftarrow \{\theta, \phi\} + \alpha \nabla_{\theta,\phi} L^{TOTAL}$
    (η = hyperparameter combining loss; α = learning rate)
  else
    $\theta \leftarrow \theta + \alpha_\theta \nabla_\theta L^{CLIP}(\theta)$
    $\phi \leftarrow \phi + \alpha_\phi \nabla_\phi L^V(\phi)$
    (α_θ and α_ϕ = learning rates for actor and critic networks respectively)
  end
end
clear data buffer $\mathcal{S}_{train}$, $\mathcal{A}_{train}$, and $\mathcal{G}_{train}$

end

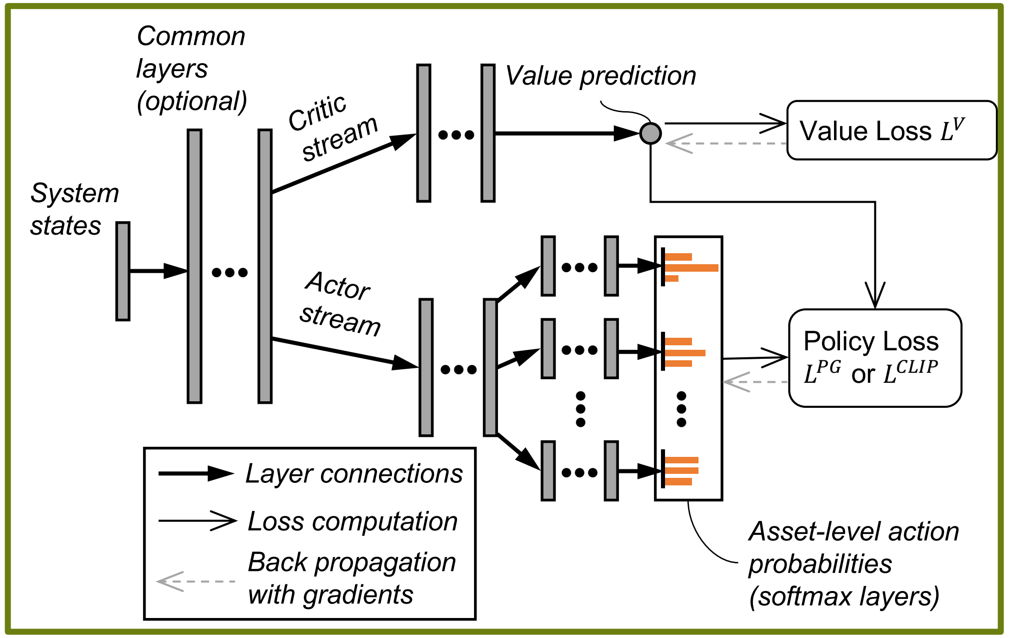
Methodology Overview

DRL-based risk management of transportation networks



Yang, D.Y. & Frangopol, D.M., 2020. Life-cycle management of deteriorating bridge networks with network-level risk bounds and system reliability analysis. *Structural Safety*, 83: 101911.

$$R(\mathbf{s},\mathbf{a},\mathbf{s}') = -\left[\frac{C(\mathbf{s},\mathbf{a},\mathbf{s}') + R_{AST}(\mathbf{s})}{\lambda_{ECON}} + w_{NET}\cdot\frac{R_{NET}(\mathbf{s})}{\lambda_{FLOW}}\right]$$



Bridge Network Example

Sioux Falls network, South Dakota

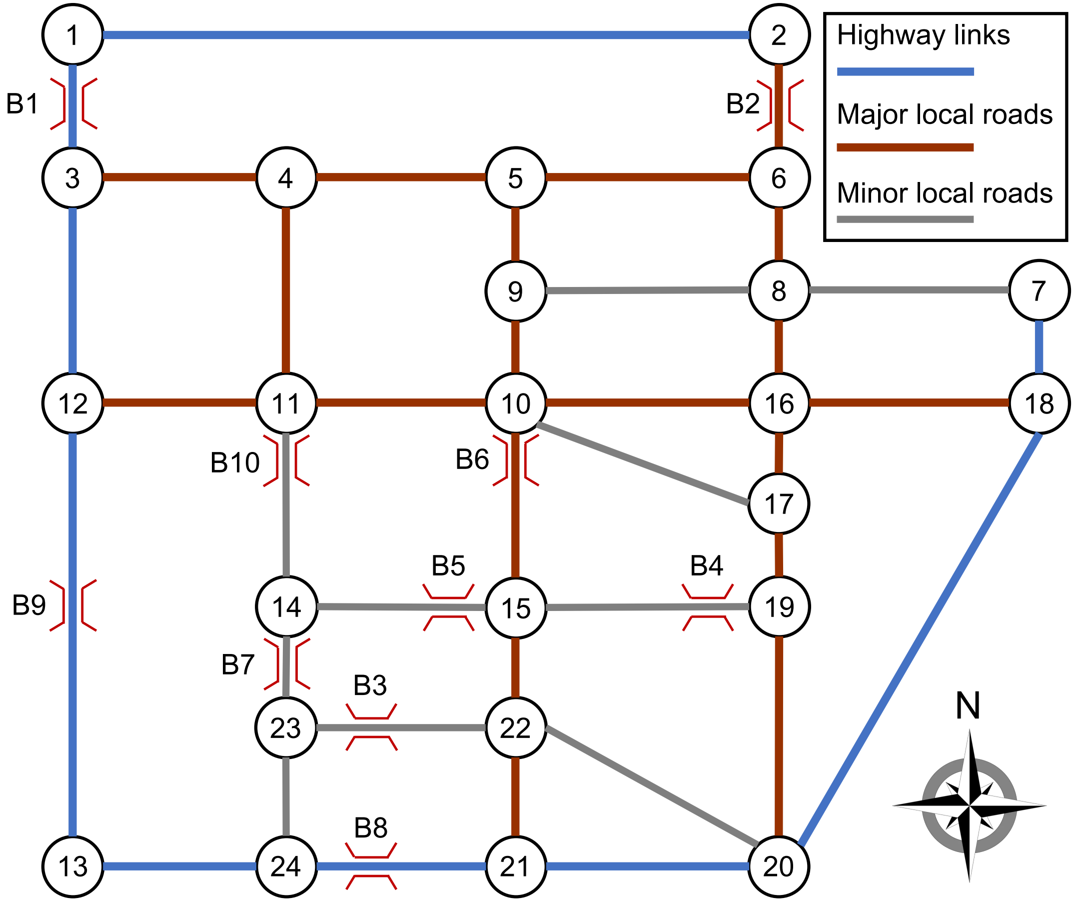


FIGURE. Idealized bridge network in the City of Sioux Falls, South Dakota

- Sioux Falls network with 10 bridges was analyzed using the proposed method
- Assumptions:
  - All steel girder bridges with different numbers of girder elements, inferred from bridge dimension
  - Structural safety controlled by the condition state of girder elements
  - Five generic actions: do-nothing, maintenance, repair, rehabilitation, replacement
- Policy optimization is conducted with 3,000 episodes (one ep. = 75 yr)
  - Collectively, 225,000 years of experience

UNDERSTANDING DRL-BASED POLICY WITH SIOUX FALLS NETWORK

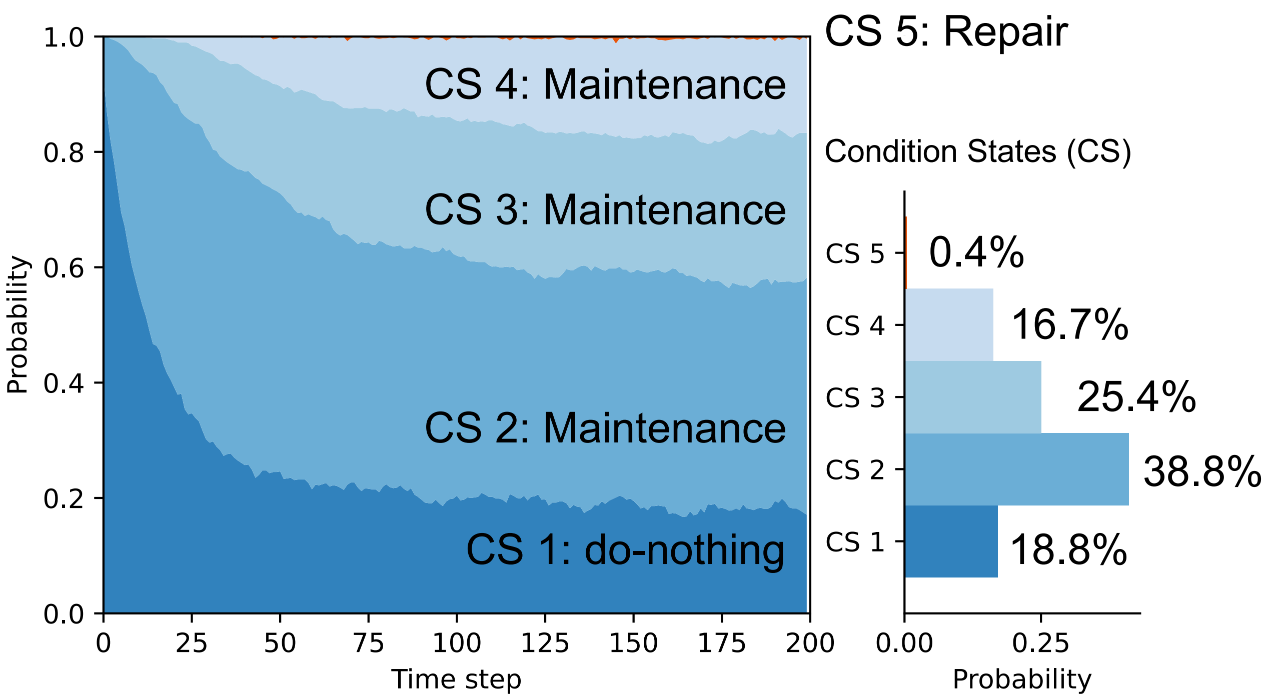
Benchmark results from asset-level analysis (w_{NET} = 0)

Condition state	Action	Transition probability					Cost (USD per element)	Reliability index
CS1	do-nothing	0.9381	0.0619	0	0	0	0	4.2
	mainte-nance	0.9900	0.0100	0	0	0	40	
CS2	do-nothing	0.8888	0.1112	0	0	0	0	3.5
	mainte-nance	0.0300	0.9500	0.0200	0	0	40	
	repair	0.5000	0.4500	0.0500	0	0	320	
CS3	do-nothing	0.8712	0.1288	0	0	0	0	3.0
	mainte-nance	0	0.0300	0.9500	0.0200	0	40	
	repair	0	0.5000	0.4500	0.0500	0	320	
	rehabili-tation	0.5000	0.3000	0.2000	0	0	1280	
CS4	do-nothing	0	0	0	0.8888	0.1112	0	2.5
	mainte-nance	0	0	0.0300	0.9500	0.0200	40	
	repair	0	0	0.5000	0.4500	0.0500	640	
	rehabili-tation	0.4000	0.3000	0.2000	0.1000	0	2560	
CS5	do-nothing	0	0	0	0	1	0	1.0
	repair	0	0	0	0.9000	0.1000	160	
	rehabili-tation	0.4000	0.3000	0.2000	0.1000	0	2560	
	replace-ment	1	0	0	0	0	5120	
Failure	-	-					10240	-

TABLE. Transition probabilities of Markov Decision Process

The optimal policy can be determined with exact dynamic programming algorithms (value iteration used herein)

- Normalized long-term costs: **0.1971±0.0372**
- Policy and steady-state distribution:



UNDERSTANDING DRL-BASED POLICY WITH SIOUX FALLS NETWORK

Results from network-level analysis based on DRL

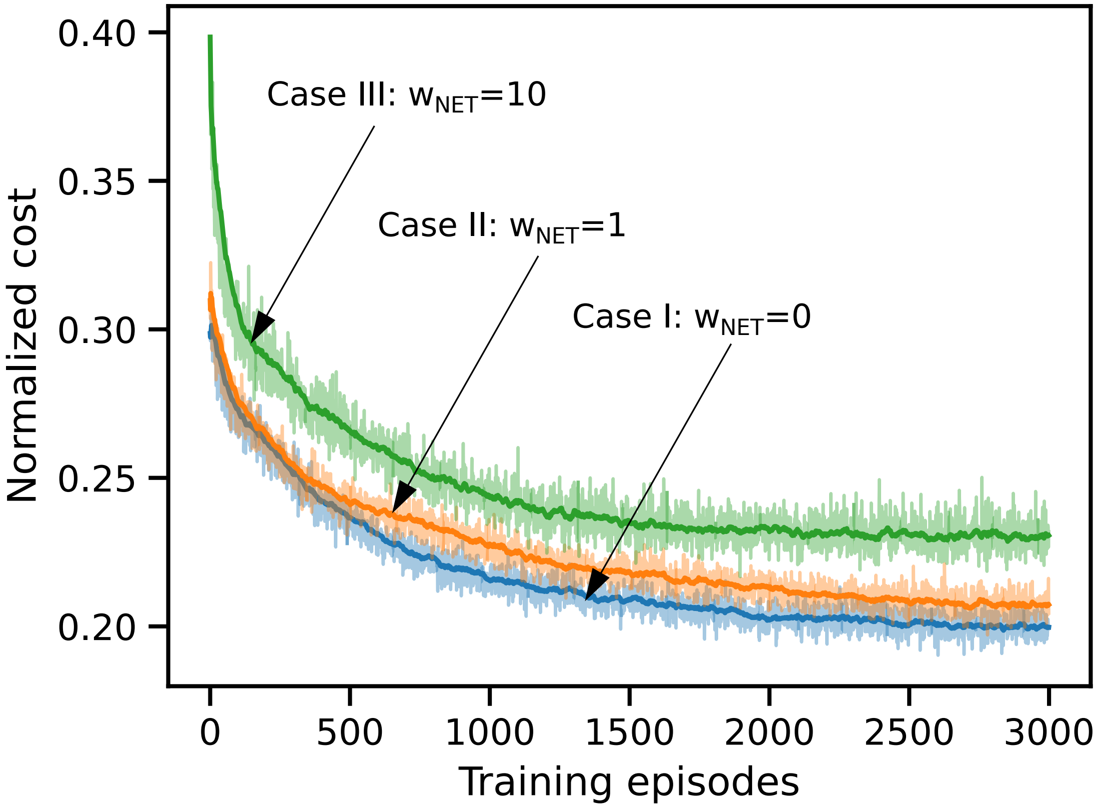
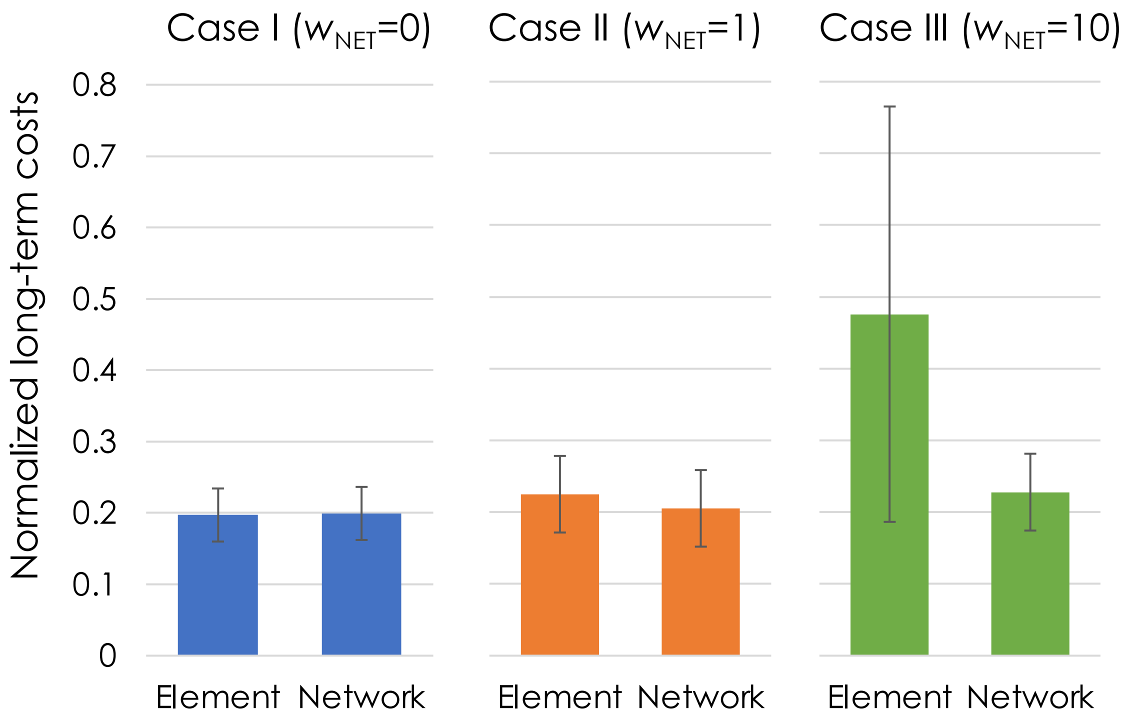


FIGURE. DRL training process under different weights of network risk (Case I was used to fine-tune hyperparameters)

TABLE. Normalized long-term costs under different policies

	Case I		Case II		Case III	
	Element[1]	Network[2]	Element	Network	Element	Network
Mean	0.1971	0.1993	0.2250	0.2053	0.4758	0.2279
STD	0.0372	0.0372	0.0534	0.0399	0.2896	0.0536

Monte Carlo results based on (1) element- and (2) network-level policies



UNDERSTANDING DRL-BASED POLICY WITH SIOUX FALLS NETWORK

Interpretation of the network-level policies

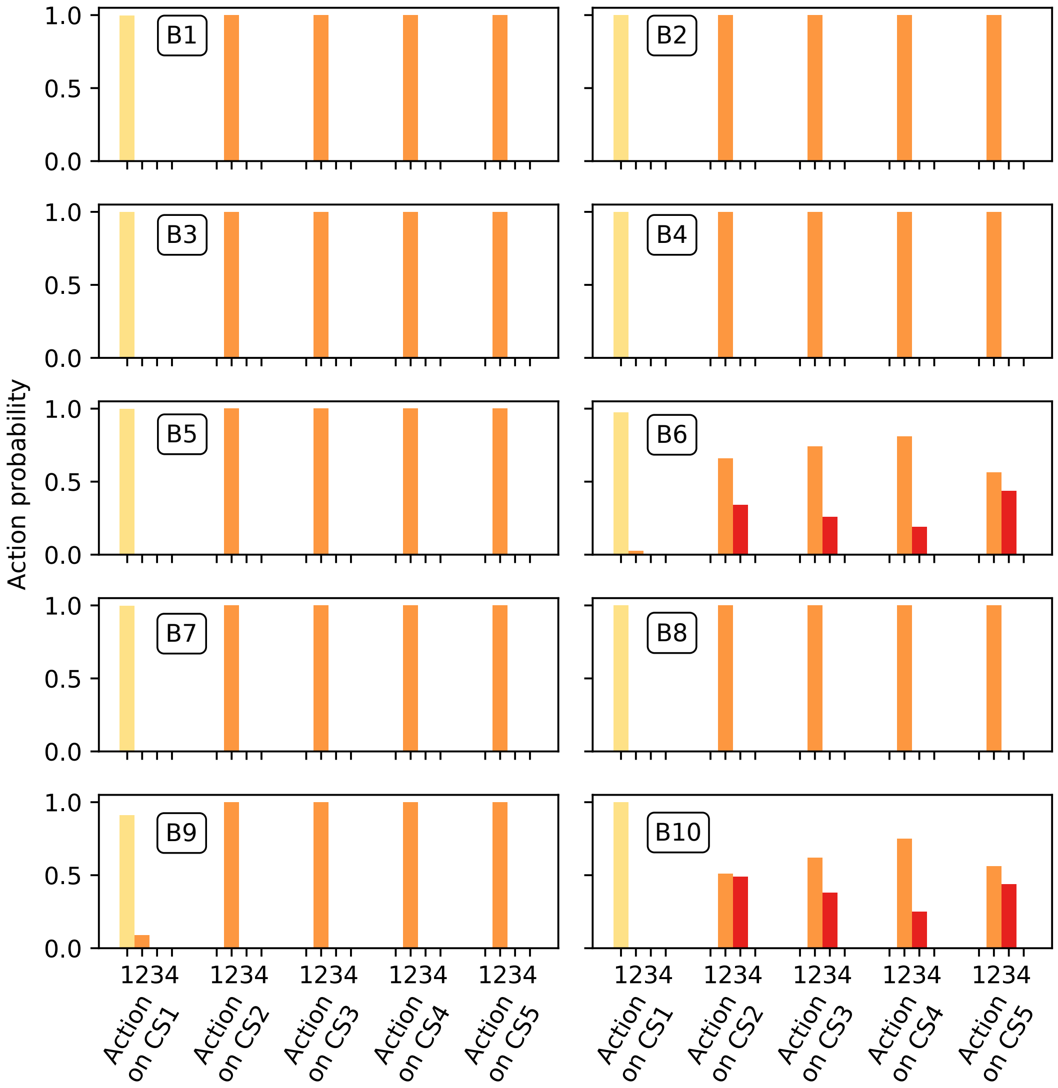


FIGURE. Condition-action pairs at the bridge level (w_{NET} = 0)

Probabilities of taking different actions given CS:
Action 1 Action 2 Action 3 Action 4

Monte Carlo simulation with 6,400 episodes is used for interpretation

- When w_{NET} = 0, DRL delivers similar policies compared to the element-level results
- The long-term costs under element- and network-level policies are almost identical: 0.1993 vs 0.1971
- This similarity verified the effectiveness of the DRL algorithm in finding near-optimal policies

UNDERSTANDING DRL-BASED POLICY WITH SIOUX FALLS NETWORK

Interpretation of the network-level policies

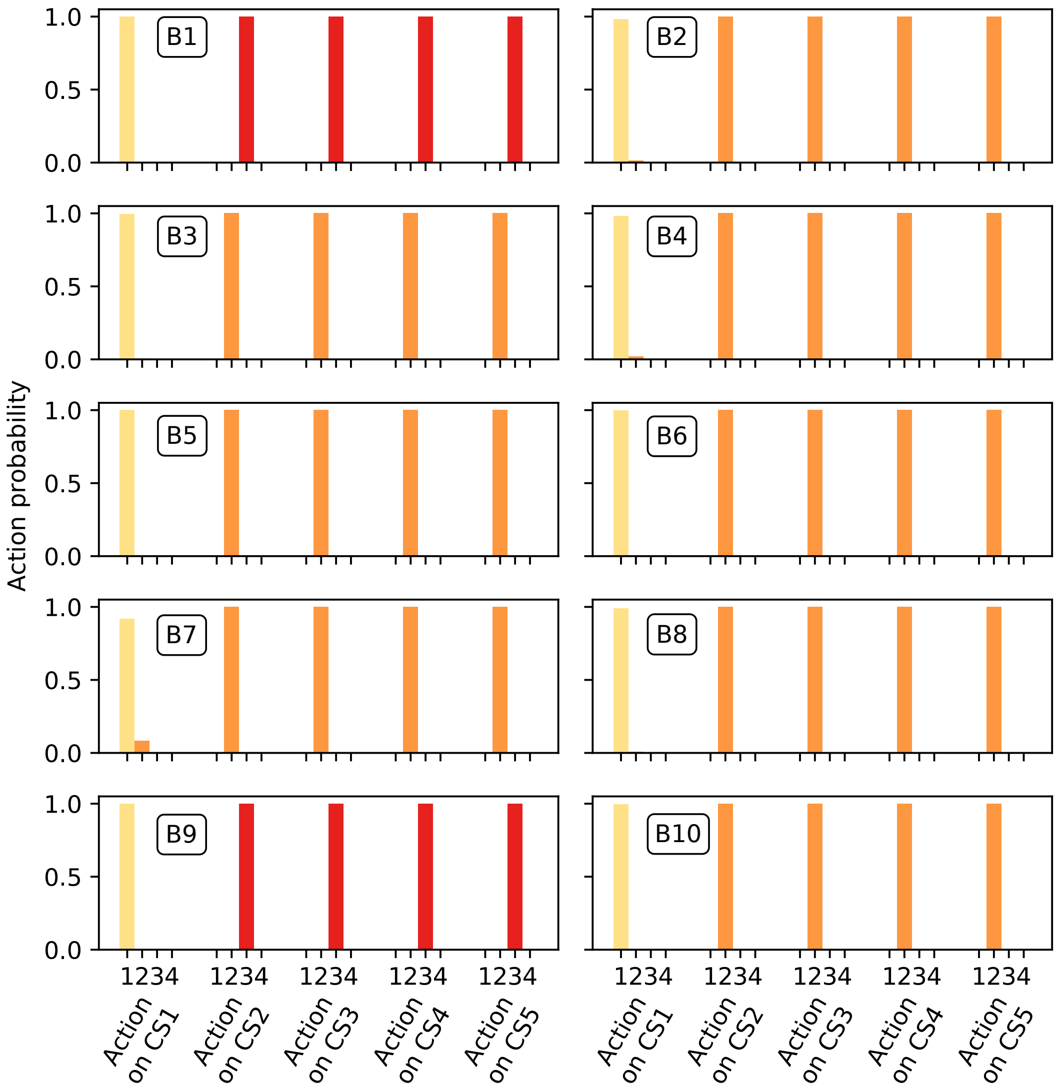


FIGURE. Condition-action pairs at the bridge level (w_{NET} = 1)

- As network risk is considered, different bridges start to have different optimal policies, reflecting their importance to the flow capacity
  - Bridge B1 and bridge B9 should take a more aggressive maintenance strategy
- For Sioux Falls network, decisions can be made at the bridge level
  - Given a condition state, a bridge overwhelmingly favors one action regardless of the states of other bridges

UNDERSTANDING DRL-BASED POLICY WITH SIOUX FALLS NETWORK

Interpretation of the network-level policies

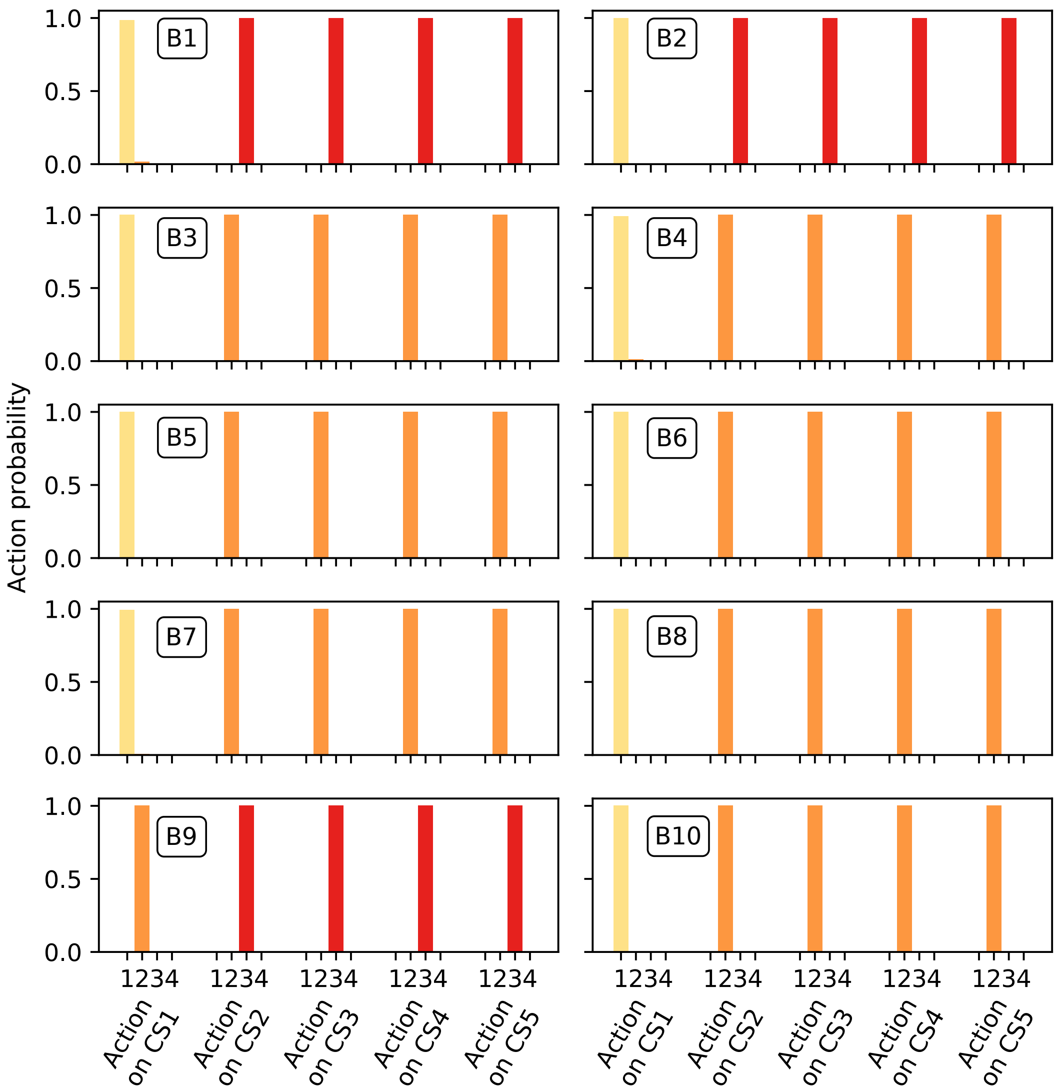


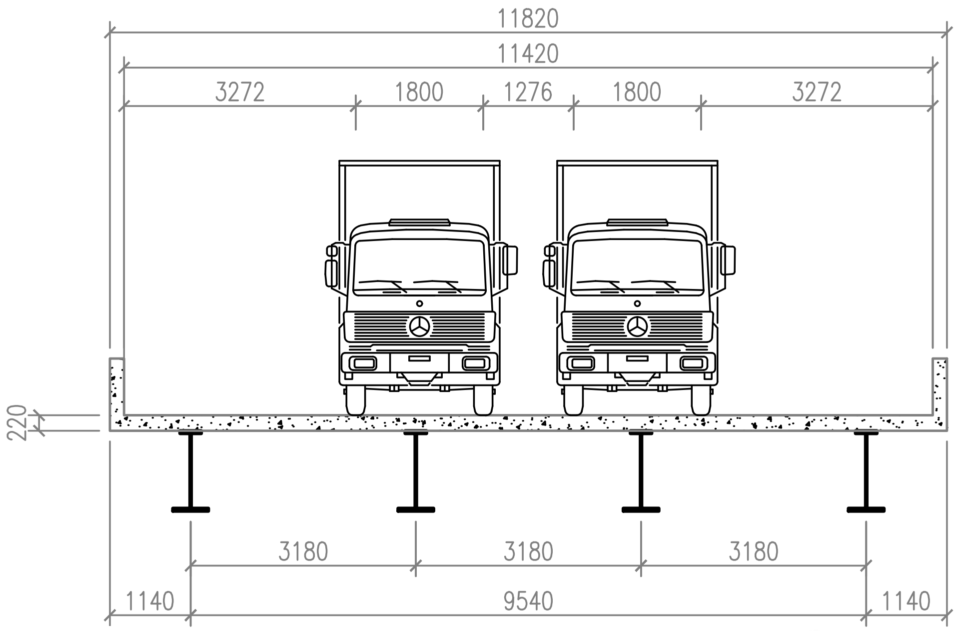
FIGURE. Condition-action pairs at the bridge level (w_{NET} = 10)

- As network risk becomes more important (w_{NET} = 10), more bridges (bridge B2) require more aggressive maintenance
- Maintenance requirement for bridge B9 becomes even more stringent
- It is still possible to make decisions at the bridge level, while network risk can be considered by taking different policies for different bridges
  - This could be network dependent

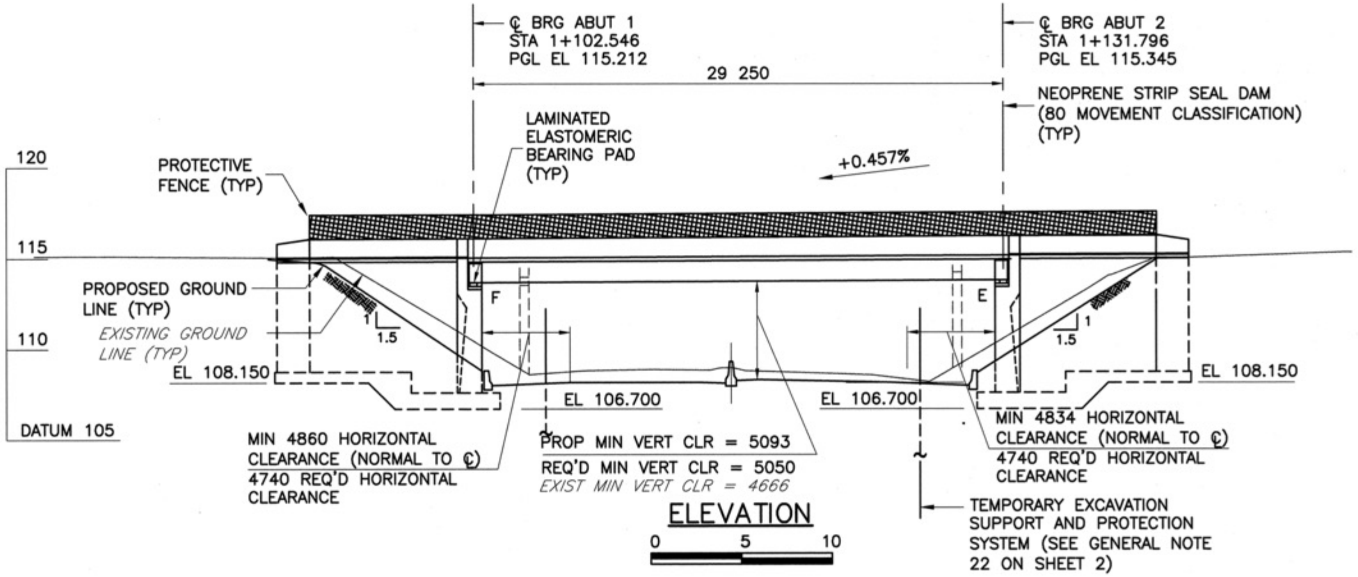
Example of Structural Systems

Montgomery bridge, PA

- Composite steel girder bridge
- Constructed in 2005
- Load case:
  - Dead load
  - Two HS20 truck loads side-by-side

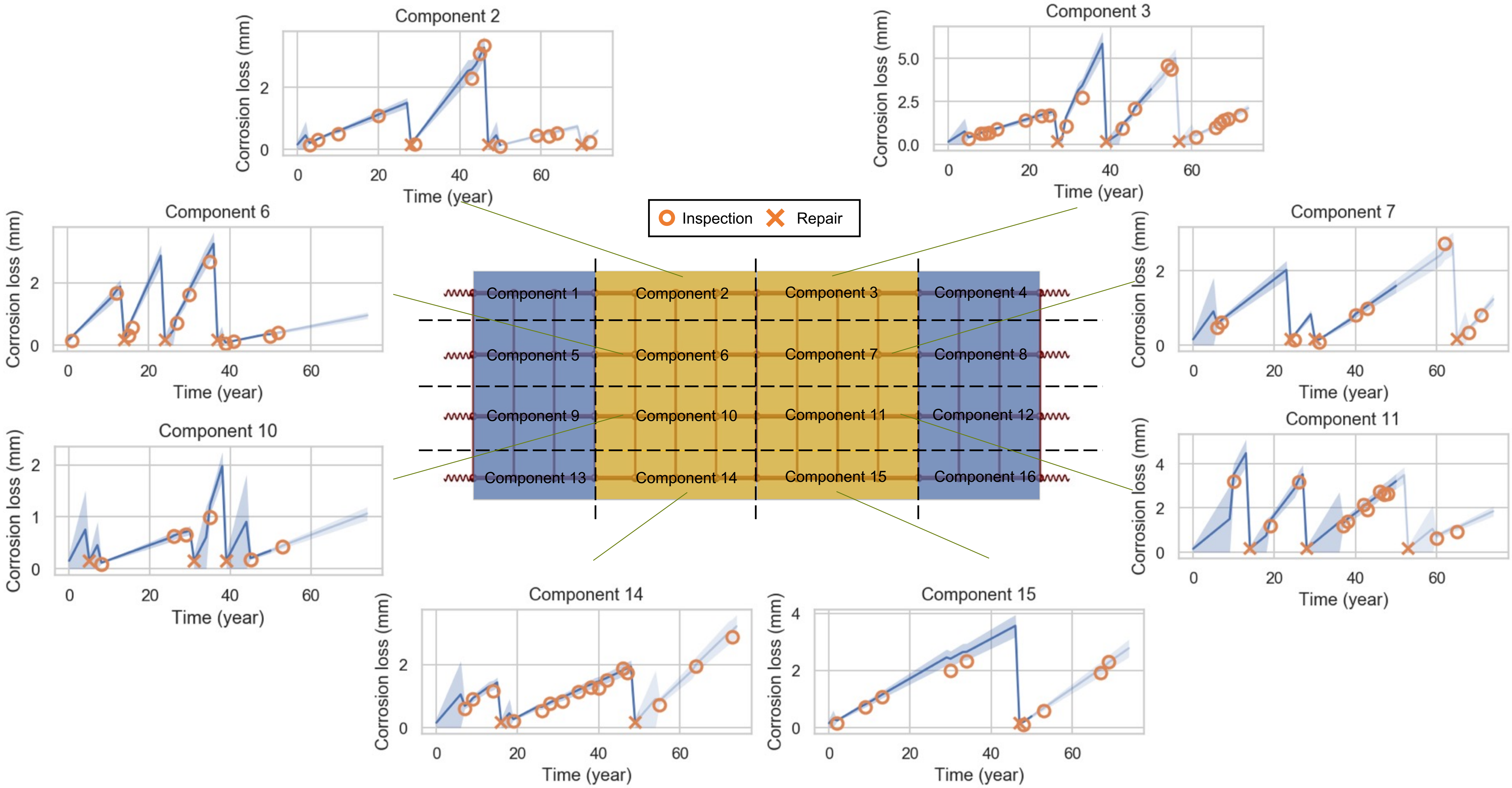


Bridge drawings: PennDOT



EXAMPLE OF STRUCTURAL SYSTEMS

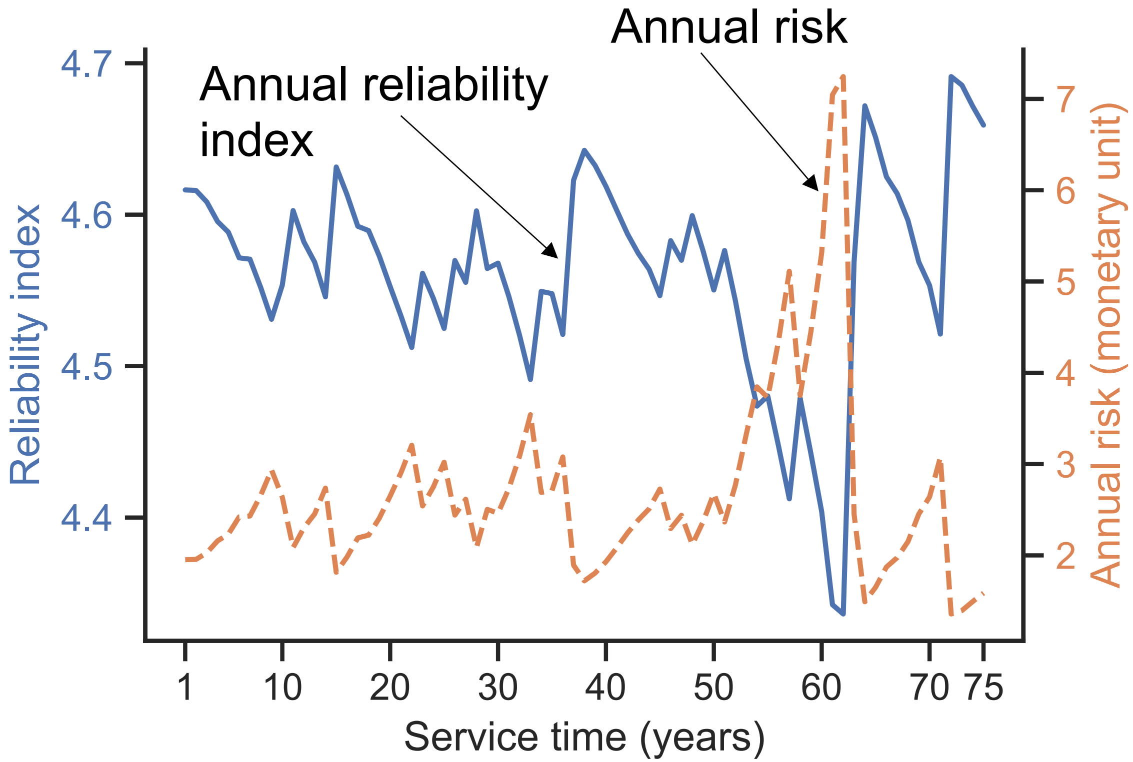
Montgomery bridge, PA

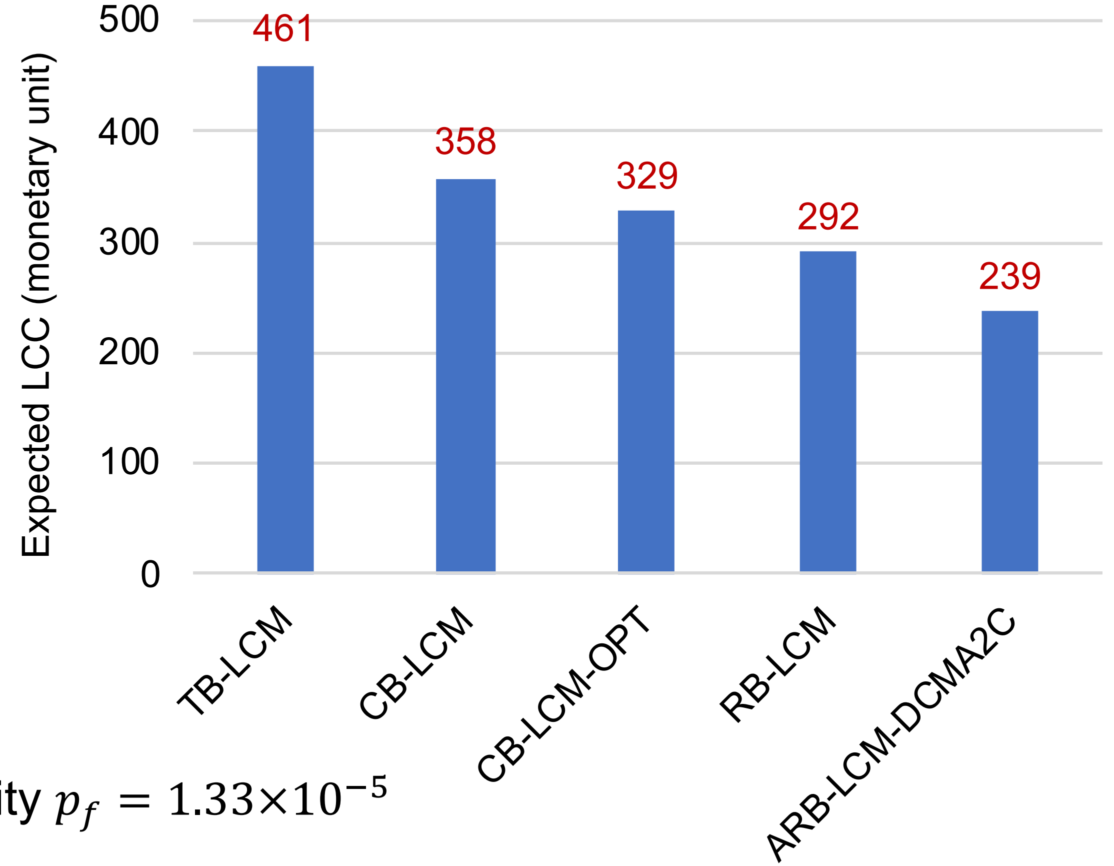


Example of Structural Systems

Montgomery bridge, PA

- Risk management using DRL can
  - reduce LCC by **half** compared to time-based LCM
  - reduce LCC by **around 20%** compared to conventional risk-based LCM





$p_f = \Phi(-\beta)$, e.g. reliability index $\beta = 4.2$, failure probability $p_f = 1.33\times10^{-5}$

Conclusions

- Why to assess system-level risk:
  - Transportation assets are interconnected, and the impact of structural failure may propagate to other routes in the network
  - Failure to capture the interdependence may lead to inaccurate estimation of social risk and consequently mislead the allocation of usually limited resources
  - Conventional preservation policies based solely on minimizing long-term agency cost cannot always yield satisfactory network performance
- How to manage system-level risk:
  - Deep reinforcement learning can achieve objective network-level policy optimization for multi-attribute, risk-informed infrastructure management
  - The proposed policy interpretation method can simultaneously identify critical assets and formulate optimal policies reflecting asset importance to network performance
- Risk of transportation structures and networks should and could be managed at the system level!

THANK YOU

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