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Performance-Based Risk Assessment For Large-Scale Transportation Networks

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Risk of Transportation Networks

Indirect Risk in terms of reduction in performance

Risk = Probability x Consequences

Probability = likelihood of the occurrence of an adverse event

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

Why should we care?

Develop a quantitative method for assessing benefits and costs of risk mitigation.

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

Risk Assessment of Large-scale Systems

Gaps and Challenge

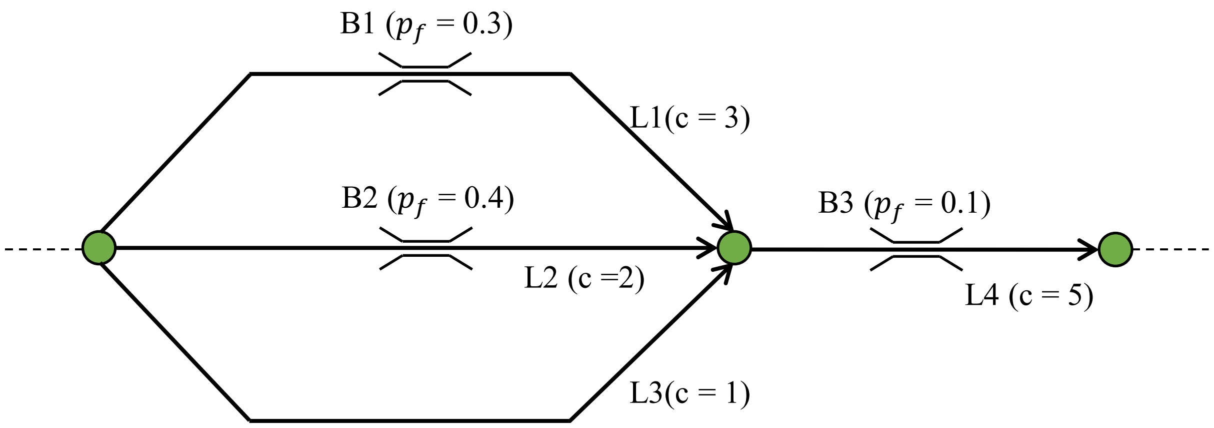
Interdependency between assets hinders isolated analyses of individual assets (network effect) = risk should be assessed at system level

Assessment is computationally challenging for large-scale systems (curse of dimensionality) = sampling or special methods must be used

Low probability, high consequence events may dominate the indirect risk ("grey swan" events) = conventional methods are ineffective

Network Effect and Grey Swan Events

Illustration



(Image: Authors)

Network Risk

$$\rho_{NET} = \sum_{\mathbf{s}} p(\mathbf{s}) \cdot \left| C_{NET,0} - C_{NET}(\mathbf{s}) \right|$$

where $\boldsymbol{s}$ = a vector of damages states; $p(\text{s})$ = probability of the system state; $C_{NET}(\boldsymbol{s})$ and $C_{NET,0}$ = network capacity given $\boldsymbol{s}$ and that without any damage

- ✓ Reduction in the flow capacity due to failures of Bridges B1 and B3 is 5 (precise consequence)
- ✓ The sum of flow capacities of Bridges B1 and B3 is 8 (Indirect total consequence)
- ✓ Reduction in network capacity analyzed separately is 7 (additive indirect consequence)

- ✓ Sampling all 8 system states gives 32% risk
- ✓ Failing to sample B3 failure will underestimate the risk to 22.4%

Proposed method of risk assessment

Adaptation of Transitional Markov Chain Monte Carlo (TMCMC)

- Baye's theorem

$$f(\boldsymbol{\theta}|D) = \frac{f(D|\boldsymbol{\theta}) \cdot f(\boldsymbol{\theta})}{\int_{\theta} f(D|\boldsymbol{\theta}) \cdot f(\boldsymbol{\theta}) d(\theta)}$$

where $f(\boldsymbol{\theta})$ = prior probability density function (PDF) of model parameters $\boldsymbol{\theta}$; $f(D|\boldsymbol{\theta})$ = likelihood associated with the observation D of model output, which equals the conditional PDF of D given model parameters $\boldsymbol{\theta}$

- Denominator is a constant (evidence)
- Distribution will gradually transition from $f(\boldsymbol{\theta})$ to $f(\boldsymbol{\theta}|D)$
- TMCMC introduces transitional exponent and efficiently samples the posterior distribution
- The denominator term is obtained as a by-product of the sampling process
- Network risk is formulated as multivariate normal distribution with hidden variable
- Network capacity is used as performance indicator

Method Verification

Case I: Increasing number of assets

(a) 5 assets (precise risk = 2.205)

Method	Average risk	Standard deviation	Max	Min
TMCMC	2.217	0.011	2.235	2.209
MC	2.202	0.003	2.205	2.198
Bound	2.205	0.000	2.205	2.205

(b) 10 assets (precise risk = 7.527)

Method	Average risk	Standard deviation	Max	Min
TMCMC	7.506	0.093	7.606	7.371
MC	7.531	0.009	7.540	7.520
Bound	7.527	0.000	7.527	7.527

(c) 30 assets (precise risk = 39.45)

Method	Average risk	Standard deviation	Max	Min
TMCMC	39.47	0.47	39.98	38.78
MC	39.45	0.08	39.54	39.34
Bound	16.67	0.00	16.67	16.67

(d) 50 assets (precise risk = 91.41)

Method	Average risk	Standard deviation	Max	Min
TMCMC	91.75	0.51	92.37	90.98
MC	91.35	0.12	91.45	91.18
Bound	0.71	0.00	0.71	0.71

Method Verification

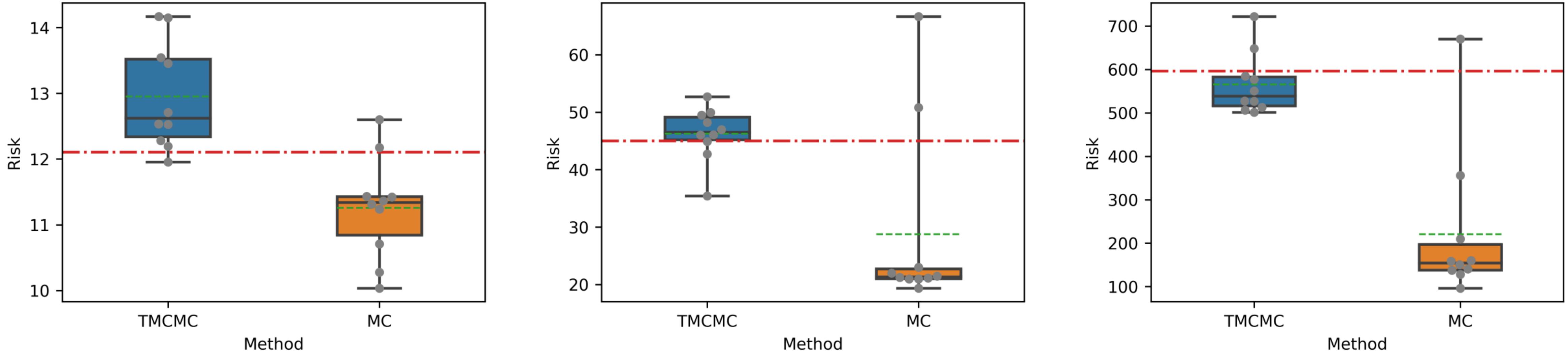
Case II: Risk involving Network Effects and Grey Swan Events

$$\rho II = \sum_{k \in Q} p_{f,k} \cdot C(\boldsymbol{s}_k)$$

$$C(\boldsymbol{s}) = \prod_{i \in u} c_i^{s_i}$$

$$c_i = \begin{cases} 10^{\frac{(r-1)\beta_i}{n_s - 1}} & \text{if asset i is relevant} \\ 0 & \text{otherwise} \end{cases}$$

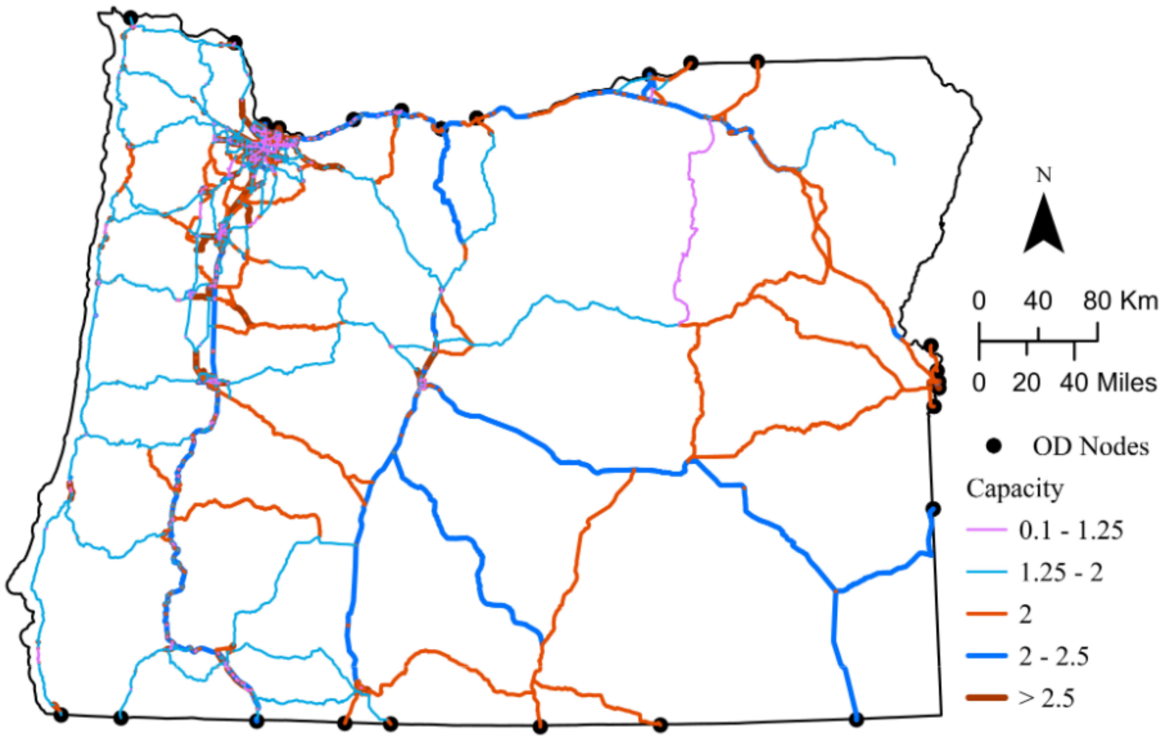
where β_i= reliability index of asset i; r = rank in the ordered asset list; n_s = total number of assets (i.e., n_s = 30); s_i = state of asset i; c_i = consequence associated with failure of asset i; $p_{f,k}$ and$C(\boldsymbol{s}_k)$= failure probability and consequence associated with system state k; Q = the set of system states involving relevant assets and ρII = precise system risk



Case Study on Oregon Highway Network

Setup

- Network contains 6,437 nodes and 10,637 links
- 1,938 links carry bridges that may fail due to deterioration/extreme events
- failure probability is based on assume reliability indices

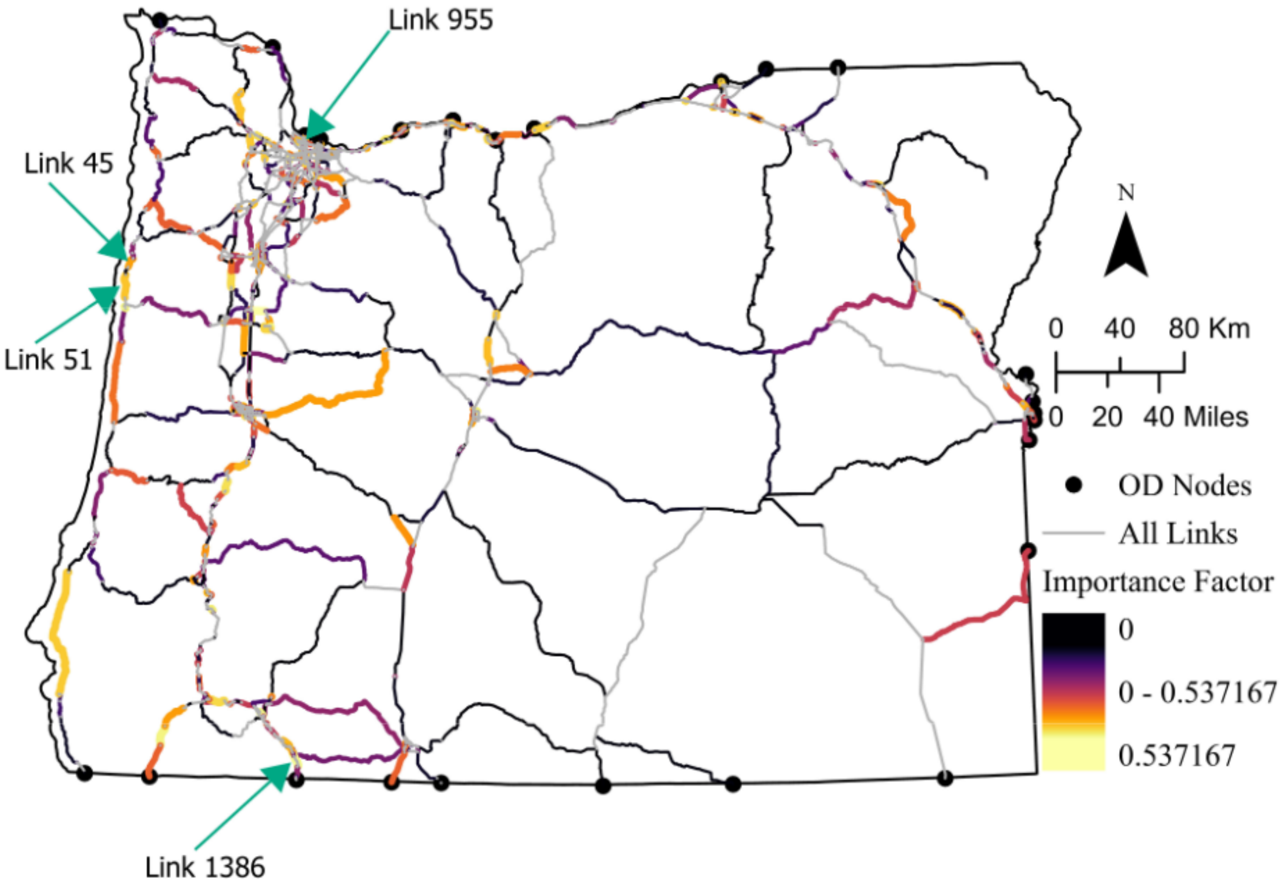


(Image: Authors)

Case Study on Oregon Highway Network

Results

- Successfully sampled 44,123 unique system states out of approximately 2.19×10^{583} possible states.
- Estimated network risk is 0.3262, suggesting a 32.62% expected reduction in throughput due to bridge link failure probabilities.
- Computation time on a stack server with 4 Intel Xeon Gold 6230 CPUs and 160 logical processors was 23.41 hours.



(Image: Authors)

Case Study on Oregon Highway Network

Beyond Risk Estimation

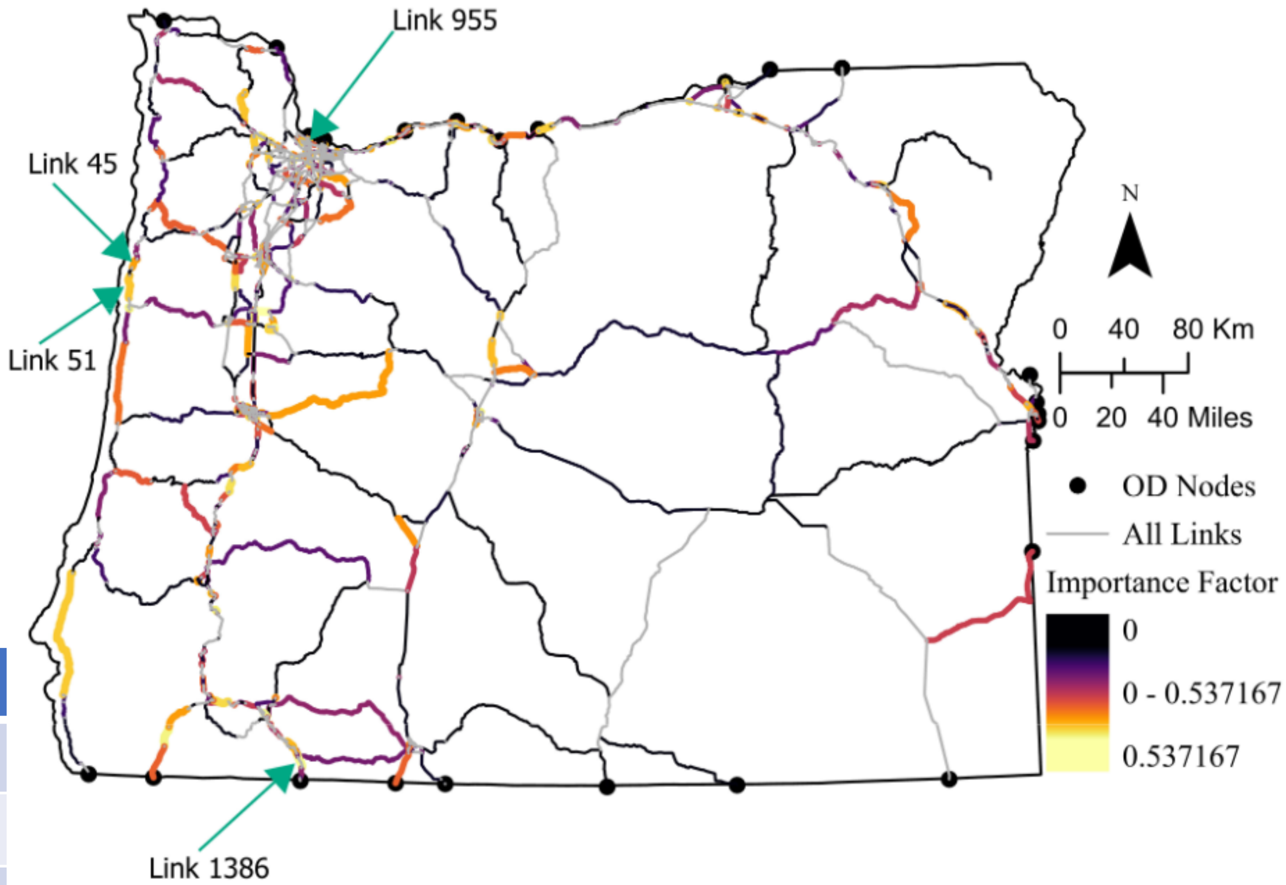
- Importance factor

$$\alpha_i = \frac{\sum_{k=1}^{N} s_i^{(k)}}{N}$$

where α_i= importance factor for asset i; N = total number of samples; $s_i^{(k)}$ = state of asset i in the k^{th} sample, which equals 1 if asset i failed in sample k, and 0 otherwise

  - ✓ Equivalent with posterior failure probability
  - ✓ Influenced by prior failure probability, contribution to network performance or both

Link	β	α
45	0.378	0.423
51	0.477	0.464
955	0.48	0.43
1386	0.469	0.524



(Image: Authors)

PERFORMANCE-BASED RISK ASSESSMENT METHOD FOR LARGE-SCALE TRANSPORTATION NETWORKS

Summary and Conclusion

- Proposed a new method for risk assessment focusing on system performance under adverse events.
- Reformulated system risk as Bayesian updating problem using TMCMC method for efficient estimation.
- Tested effectiveness of the new approach with varying asset numbers.
- Compared with conventional MC methods and non-simulation-based approaches.
- Showed that conventional MC method may underestimate system risk due to grey swan events, while proposed method accurately estimates risk.
- Assessed risk in terms of network capacity drop for a large-scale network.
- Demonstrated scalability of the new approach.
- Derived risk-informed importance factors for assets, providing valuable insight for transportation asset management.

THANK YOU

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