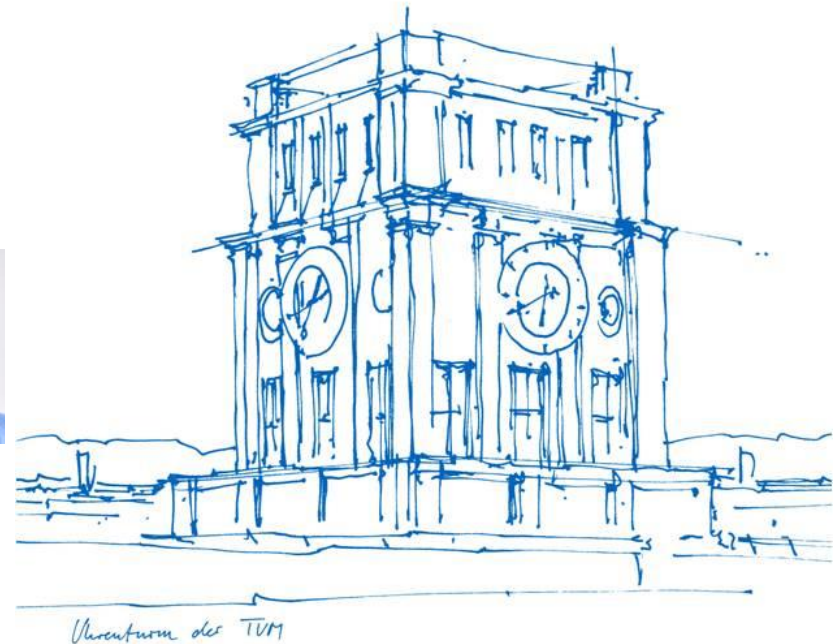


Simulation-based network capacity allocation optimization for traffic resilience via enhanced mixed stochastic approximation

Conference in Emerging Technologies in Transportation Systems (TRC-30)

Qinglong Lu, Yunping Huang, Wenzhe Sun,
Jan-Dirk Schmöcker, Constantinos Antoniou



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Outline

1. Introduction
2. Traffic resilience definition
3. Network capacity allocation
4. Case study
5. Conclusions



Introduction

Higher capacity means less congestion?

❑ Increase network capacity:

- Widening existing roads
- Building new corridors

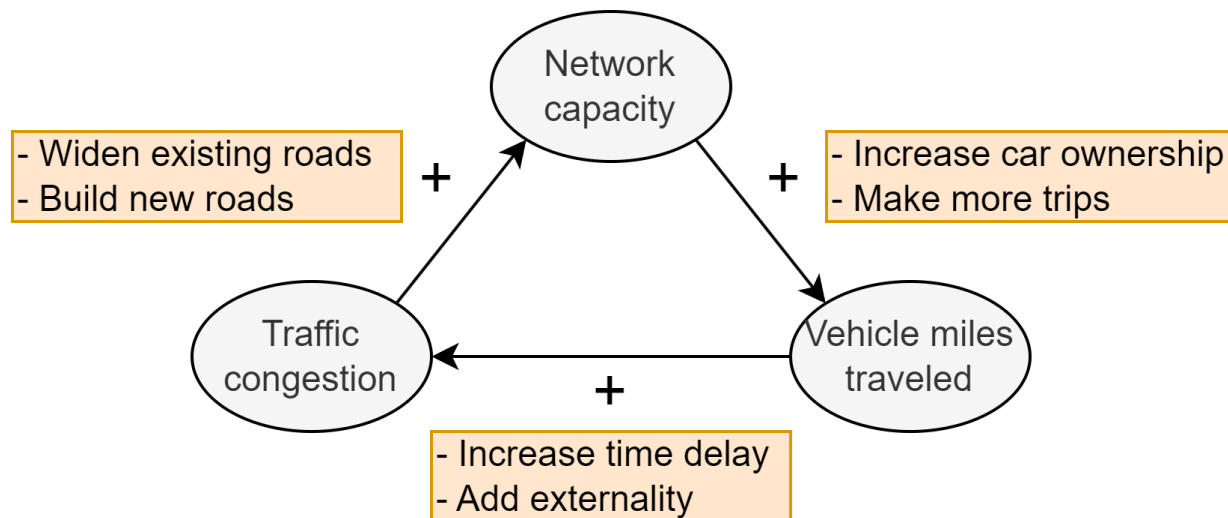
Ewing, R., Tian, G., & Lyons, T. (2018). Does compact development increase or reduce traffic congestion?. *Cities*, 72, 94-101.

❑ Increased capacity ➡ additional travel

- Mode shifts, route shifts
- Redistribution of trips, new trips

Noland, R. B. (2001). Relationships between highway capacity and induced vehicle travel. *Transportation Research Part A: Policy and Practice*, 35(1), 47-72.

➡ Improve network capacity allocation



Urban transportation disruptions

- ❑ Triggers: natural disasters, special events, etc.
- ❑ Impacts of disruptions
 - Reducing traffic efficiency
 - Increasing travel risk
 - Cascading to other urban subsystems



Significant social and economic losses!



Reuter

Research question

How to optimize network capacity allocation plan to improve traffic resilience?

⇒ **Strategic network design**

Farahani, R. Z., Miandoabchi, E., Szeto, W. Y., & Rashidi, H. (2013). A review of urban transportation network design problems. *European Journal of Operational Research*, 229(2), 281–302.

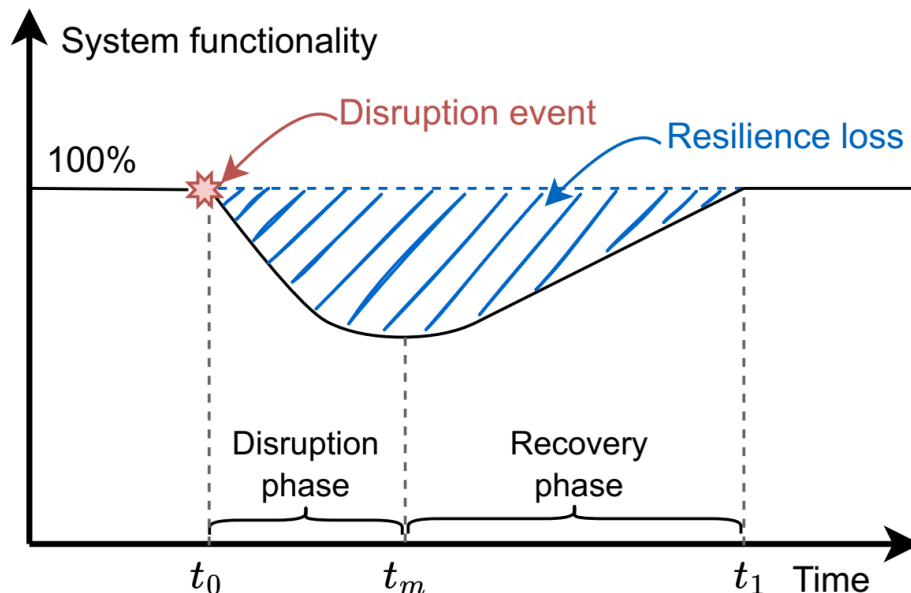
Traffic resilience definition

What is system resilience?

“Resilience represents the ability to prepare for changing conditions and withstand, respond to, and recover rapidly from disruptions.”

— Federal Highway Administration (FHWA) of the US

- ❑ Different aspects compared to other concepts (e.g., vulnerability, robustness)
 - New equilibrium state
 - Recovery speed



“Resilience Triangle”

$$R = \int_{t_0}^{t_1} (100 - Q(t)) dt$$

Bruneau, M., Chang, S. E., Eguchi, R. T., Lee, G. C., O'Rourke, T. D., Reinhorn, A. M., Shinozuka, M., Tierney, K., Wallace, W. A., & Von Winterfeldt, D. (2003). A framework to quantitatively assess and enhance the seismic resilience of communities. *Earthquake Spectra*, 19(4), 733–752.

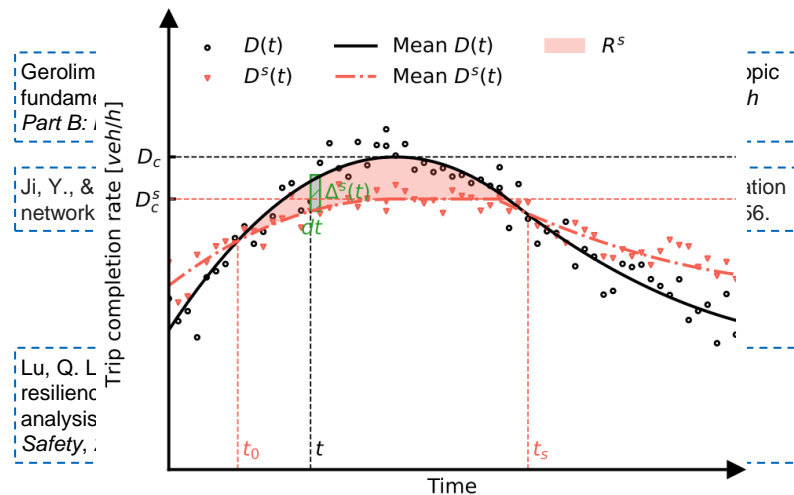
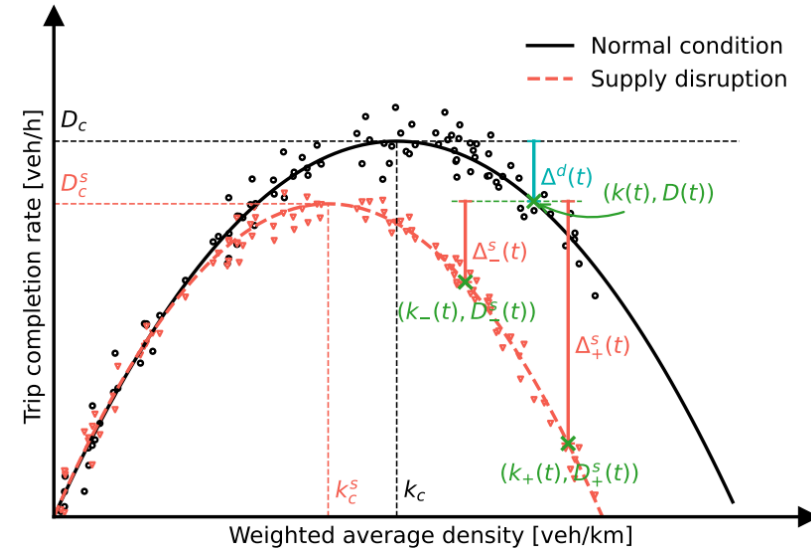
MFD-based resilience indicators

Macroscopic fundamental diagram (MFD)

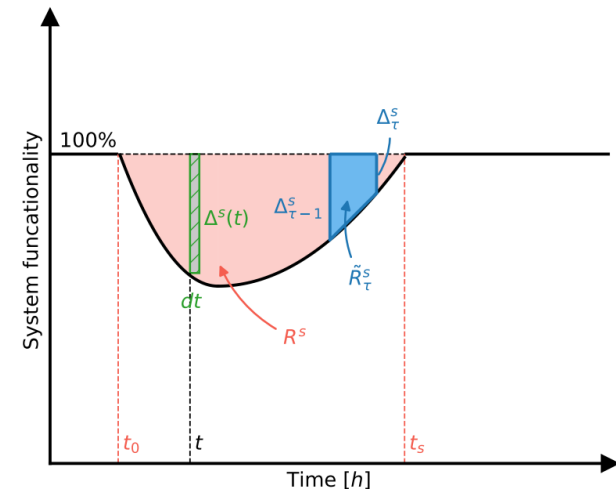
- x -axis: Weighted average density (or Accumulation)
- y -axis: Trip completion rate (or weighted space-mean flow)

Transportation systems:

- Service rate \leftrightarrow Trip completion rate
- \Rightarrow MFD-based traffic resilience indicators



(a) Trip completion rate deviation



(b) System functionality

Network capacity allocation

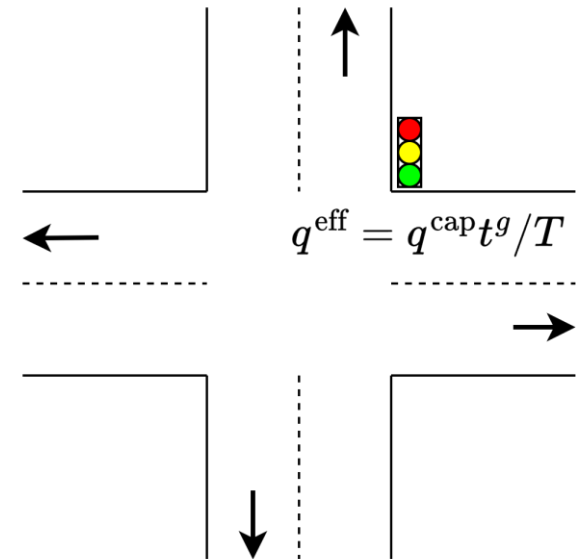
Network capacity allocation problem

□ Calculation example:

- Effective capacity of a lane i : $q_i^{\text{eff}} = \frac{q_i^{\text{cap}} t_i^g}{T}$
- Effective capacity of a link l : $q_l = \sum_{i=1}^{n_l} q_i^{\text{eff}}$

□ Network capacity allocation:

- Lane allocation (**discrete**)
 - Traffic signal timing (**continuous**)
- ⇒ **Mixed** network design problem



Multi-objective optimization

- Objective function:

- Disruption probability
- Economic losses

} Risk assessment

-
- ```
graph LR; Start((Start)) --> Init[Initialization]; Init --> CAP[Capacity allocation plan]; CAP -- Input --> TS[Traffic simulator]; Dis[Disruption scenarios] -.-> TS; Pset["{ps} s in S"] -.-> TS; TS -- Output --> TD[Traffic data]; TD -- Input --> TRE[Traffic resilience evaluation]; TRE -- Inform --> Opt[Optimizer]; Opt --> Conv{Converged?}; Conv -- Yes --> End([End]); Conv -- No --> Update[Update]; Update --> CAP;
```
- The flowchart illustrates the iterative process of traffic resilience evaluation. It begins with a 'Start' node leading to 'Initialization'. The 'Capacity allocation plan' receives input from 'Initialization' and provides 'Input' to the 'Traffic simulator'. The 'Traffic simulator' also receives inputs from 'Disruption scenarios' and a set of probabilities  $\{p_s\}_{s \in \mathbb{S}}$ . The output of the simulator is 'Traffic data', which is used as 'Input' for 'Traffic resilience evaluation'. This module informs the 'Optimizer', which checks if the system has 'Converged?'. If 'Yes', it leads to 'End'. If 'No', it triggers an 'Update' of the 'Capacity allocation plan', looping back to the start of the iteration.

# Solution algorithm

## □ Problem characteristics:

- High-dimensional
- Stochastic
- Expensive-to-evaluate objective
- Mixed network design

⇒ Enhanced mixed simultaneous perturbation stochastic approximation (SPSA)

$$\begin{aligned}
 (\text{SOCA}) \min_{\mathbf{z}, \mathbf{x}} \quad & \mathbb{E}_{\xi} = [y(\mathbf{z}, \mathbf{x}, \xi)] \\
 \text{s.t.} \quad & \mathbb{E}_{\xi} = [g(\mathbf{z}, \mathbf{x}, \xi)] \leq 0 \\
 & \mathbf{z} + \mathbf{z}^{\text{opp}} = \mathbf{n} \\
 & \mathbf{B}\mathbf{x} = \mathbf{T} \\
 & \mathbf{z}_l \leq \mathbf{z} \leq \mathbf{z}_u \\
 & \mathbf{x}_l \leq \mathbf{x} \leq \mathbf{x}_u \\
 & \mathbf{z} \in \mathbb{Z}^d, \mathbf{x} \in \mathbb{R}^{p-d}
 \end{aligned}$$

SPSA ⇒ { Second-order SPSA (2SPSA)  
Mixed SPSA (MSPSA) } ⇒ Second-order mixed SPSA (2MSPSA)

$$\hat{\theta}_{k+1} = \hat{\theta}_k - a_k \bar{\bar{\mathbf{H}}}_k^{-1}(\hat{\theta}_k) \mathbf{G}_k(\hat{\theta}_k)$$

Spall, J. C. (2009). Feedback and Weighting Mechanisms for Improving Jacobian Estimates in the Adaptive Simultaneous Perturbation Algorithm. *IEEE Transactions on Automatic Control*, 54(6), 1216–1229.

Wang, L., Zhu, J., & Spall, J. C. (2018). Mixed Simultaneous Perturbation Stochastic Approximation for Gradient-Free Optimization with Noisy Measurements. *2018 Annual American Control Conference (ACC)*, 3774–3779.

# 2MSPSA algorithm

$$\hat{\theta}_{k+1} = \hat{\theta}_k - a_k \boxed{G_k(\hat{\theta}_k)}$$

$$G_k(\hat{\theta}_k) = \frac{y(\hat{\theta}_k^{(+)}) - y(\hat{\theta}_k^{(-)})}{2C_k \circ \Delta_k}$$

$$\bar{\bar{H}}_k = f_k(\bar{H}_k)$$

$$\bar{H}_k = (1 - w_k)\bar{H}_{k-1} + w_k(\hat{H}_k - \hat{\Psi}_k)$$

$$\hat{H}_k = \frac{1}{2} \left[ \frac{\delta G_k}{2} (C_k \circ \Delta_k)^{-\top} + \left( \frac{\delta G_k}{2} (C_k \circ \Delta_k)^{-\top} \right)^{\top} \right]$$

$$\delta G_k = G_k^{(1)}(\hat{\theta}_k^{(+)}) - G_k^{(1)}(\hat{\theta}_k^{(-)})$$

$$G_k^{(1)}(\hat{\theta}_k^{(\pm)}) = \frac{y(\hat{\theta}_k^{(\pm)} + \tilde{C}_k \circ \tilde{\Delta}_k) - y(\hat{\theta}_k^{(\pm)})}{\tilde{C}_k \circ \tilde{\Delta}_k}$$

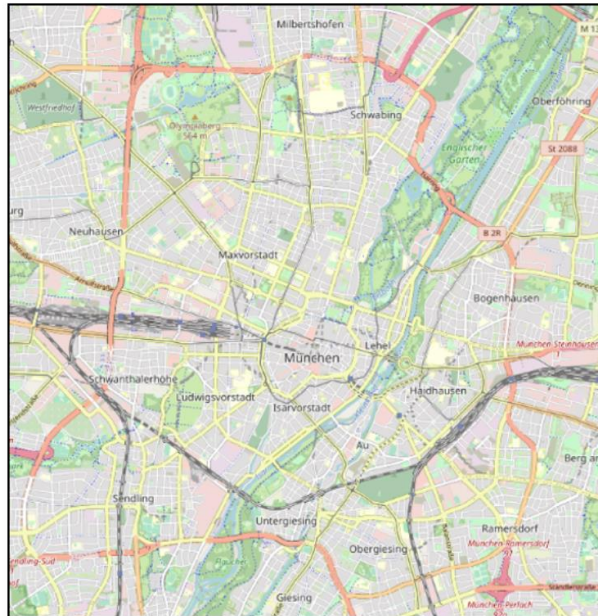
$$C_k = \underbrace{(0.5, \dots, 0.5)}_{d \text{ elements}}, \underbrace{(c_k, \dots, c_k)}_{p-d \text{ elements}})^{\top}$$

# Case study

## Case studies: Study areas and disruptions

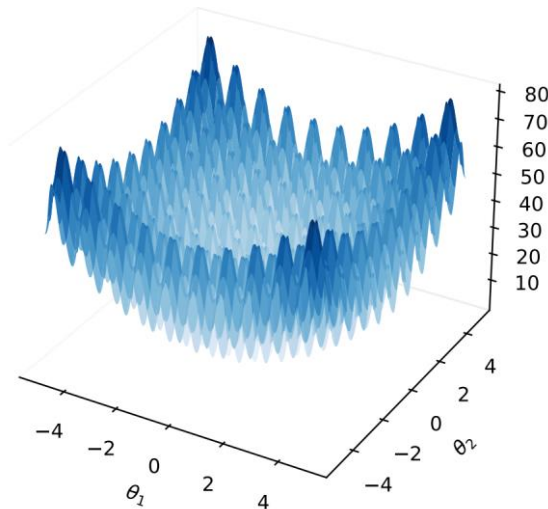
- ❑ Munich city center, Germany: 100 km<sup>2</sup>, 2605 links
  - ❑ Simulator: SUMO
  - ❑ Disruption scenarios
    - Daily operation ( $w^n$ )
    - Hyper-congestion ( $w^d$ )
    - Flooding ( $w_1^s$ )
- $y(\mathbf{z}, \mathbf{x}, \boldsymbol{\xi}) = -w^n D_c - w^d R^d$

$$y(\mathbf{z}, \mathbf{x}, \xi) = -w^n D_c - w^d R^d(\mathbf{z}, \mathbf{x}, \xi) - \sum_{\phi \in \mathbb{S}} w_\phi^s R^s(\mathbf{z}, \mathbf{x}, \xi, \phi)$$



# Algorithm evaluation

## 2MSPSA vs MSPSA



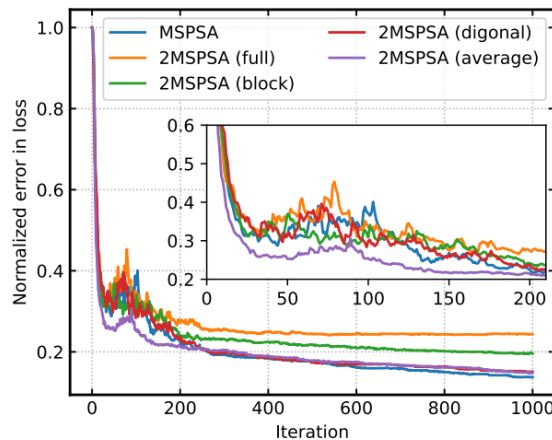
Rastrigin function:

$$L(\boldsymbol{\theta}) = 10p + \sum_{i=1}^p [\theta_i - 10\cos(2\pi\theta_i)]$$

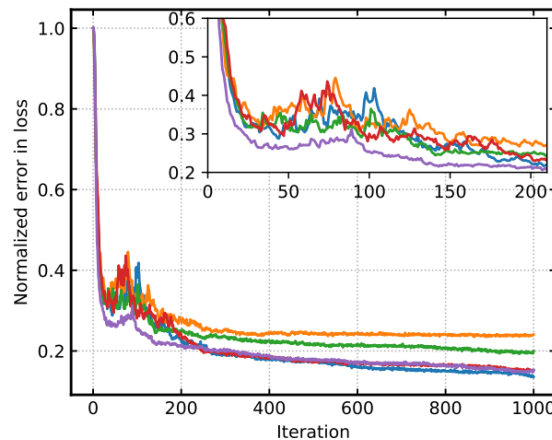
$$y(\boldsymbol{\theta}) = L(\boldsymbol{\theta}) + \varepsilon$$

Where  $p$  is the number of parameters, among which  $d$  variables are discrete,  $\varepsilon \sim N(0, \sigma)$ .

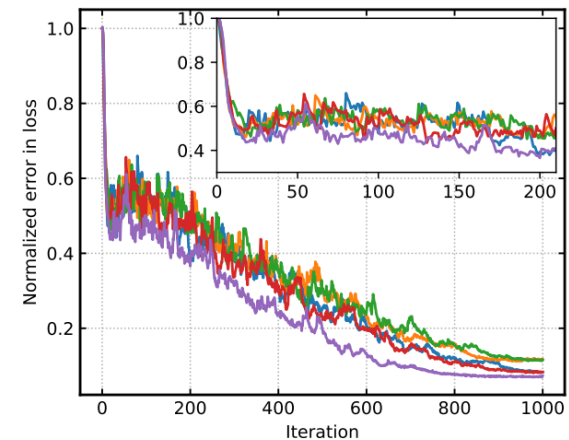
$$\hat{\boldsymbol{\theta}}_{k+1} = \hat{\boldsymbol{\theta}}_k - a_k \bar{\bar{\mathbf{H}}}_k^{-1}(\hat{\boldsymbol{\theta}}_k) \mathbf{G}_k(\hat{\boldsymbol{\theta}}_k)$$



(a)  $\sigma = 0.1, d = 50$



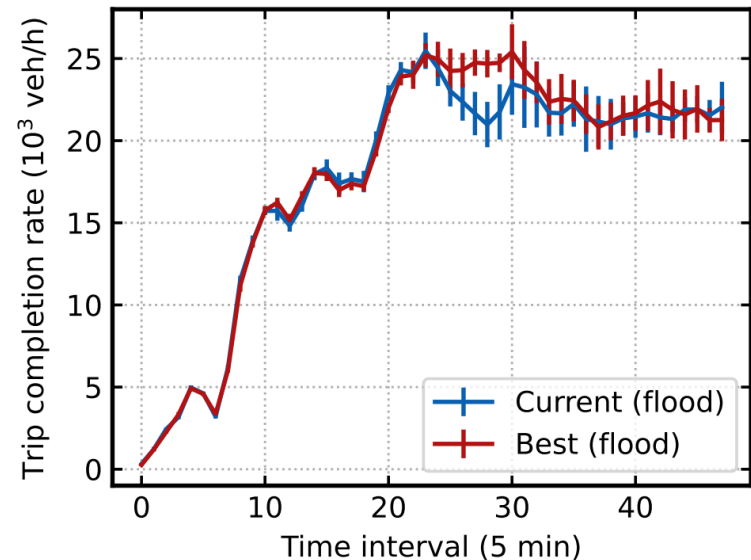
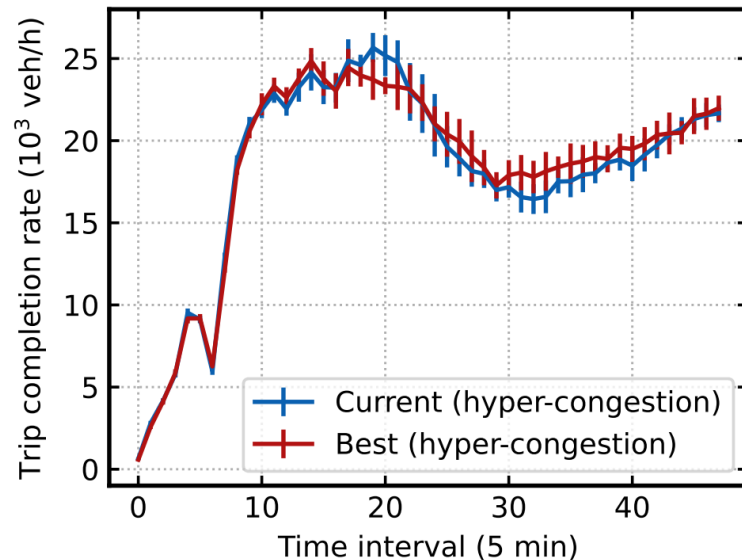
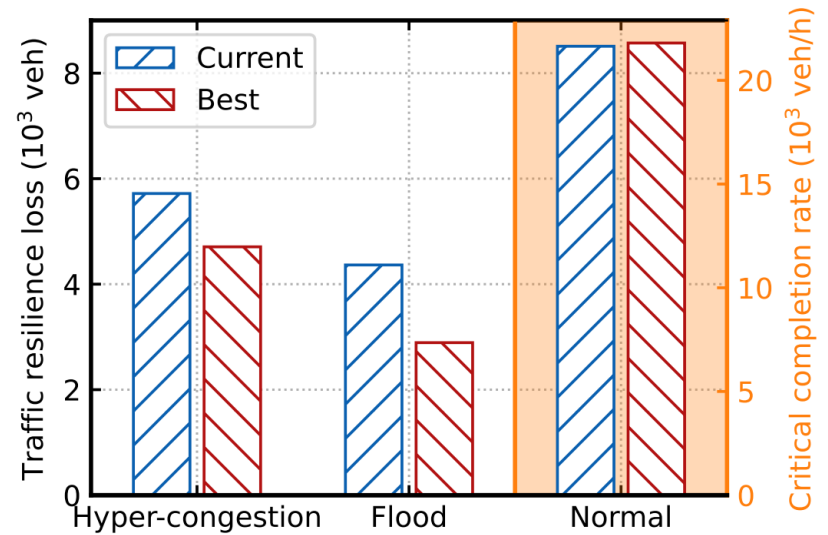
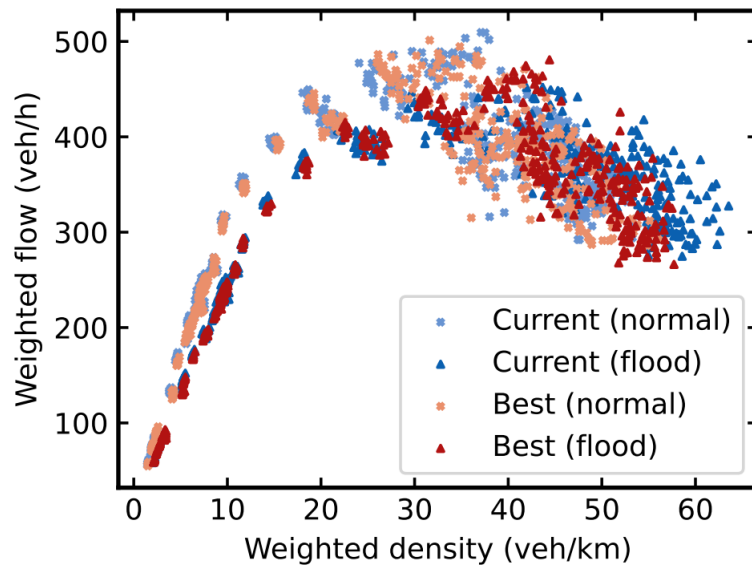
(b)  $\sigma = 1, d = 50$



(c)  $\sigma = 1, d = 10$



# Traffic dynamics and resilience comparisons



# Conclusions

# Conclusions

- ❑ Formulated the simulation-based network capacity allocation optimization problem
- ❑ Developed the second-order mixed SPSA (2MSPSA) algorithm
- ❑ Evaluated the 2MSPSA algorithm
- ❑ Evaluated the resilient network capacity allocation plan
  
- ❑ Future research:
  - Other disruption scenarios, e.g., cyberattacks
  - Dynamic resilient capacity allocation control

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# Questions?



Contact: Qinglong Lu  
Email: [qinglong.lu@tum.de](mailto:qinglong.lu@tum.de)

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