Optimizing Information Values in Smart Mobility

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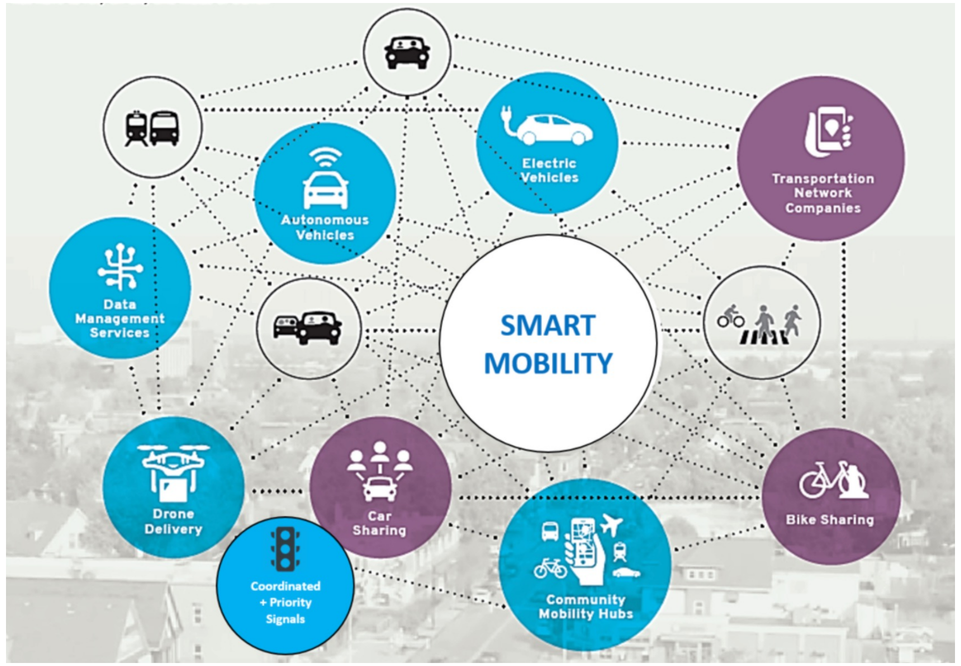
Outline

- Chapter 1: Introduction
- Chapter 2: System-level impacts of en-route information sharing considering adaptive routing
- Chapter 3: Optimal speed limit control for network mobility and safety: A twin-delayed deep deterministic policy gradient approach
- Chapter 4: Spatial pricing of ride-sourcing services in a congested transportation network
- Chapter 5: Conclusions

Chapter 1 : Introduction

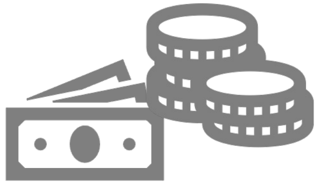
Background

- Smart mobility integrates advanced technologies, data analytics, and innovative solutions to revolutionize transportation systems.
- Smart mobility addresses the challenges of enhancing mobility and safety in transportation systems.



54 hours of traffic delay yearly per commuter

Fatalities: 36,500
Injuries: 4.5 million



Congestion cost: $210 billion
Accident cost: $340 billion

Source: [1],[2]

Background

- Real-time information sharing plays crucial role in smart mobility
- Real-time information sharing
  - Collection, analysis, and dissemination of up-to-date information
  - Example: Traffic updates, road closures, parking availability

Background

- Benefits of information sharing:
  - Improved decision-making and routing behavior [3],[4].
  - Increased road capacity and travel-time savings [5-8].
- Information sharing may not always be beneficial for transportation network
  - "information paradox" : sharing additional information may worsen system performance [9],[10].
  - Impact of additional information on network performance varies based on network characteristics and specific conditions of information provision [11].

Challenges

Lack of Unified Modeling Frameworks

- Difficulty in capturing decentralized multi-agent interaction in transportation Systems
- Heterogeneity in diverse decision-makers

Computational Challenges

- Non-convexity and high dimensionality of problems
- Need for scalable and efficient computational techniques

Research Gap:

1. Limited research on unified modeling frameworks incorporating decentralized multi-agent interaction.
2. Lack of scalable solution approaches to address the computational challenges

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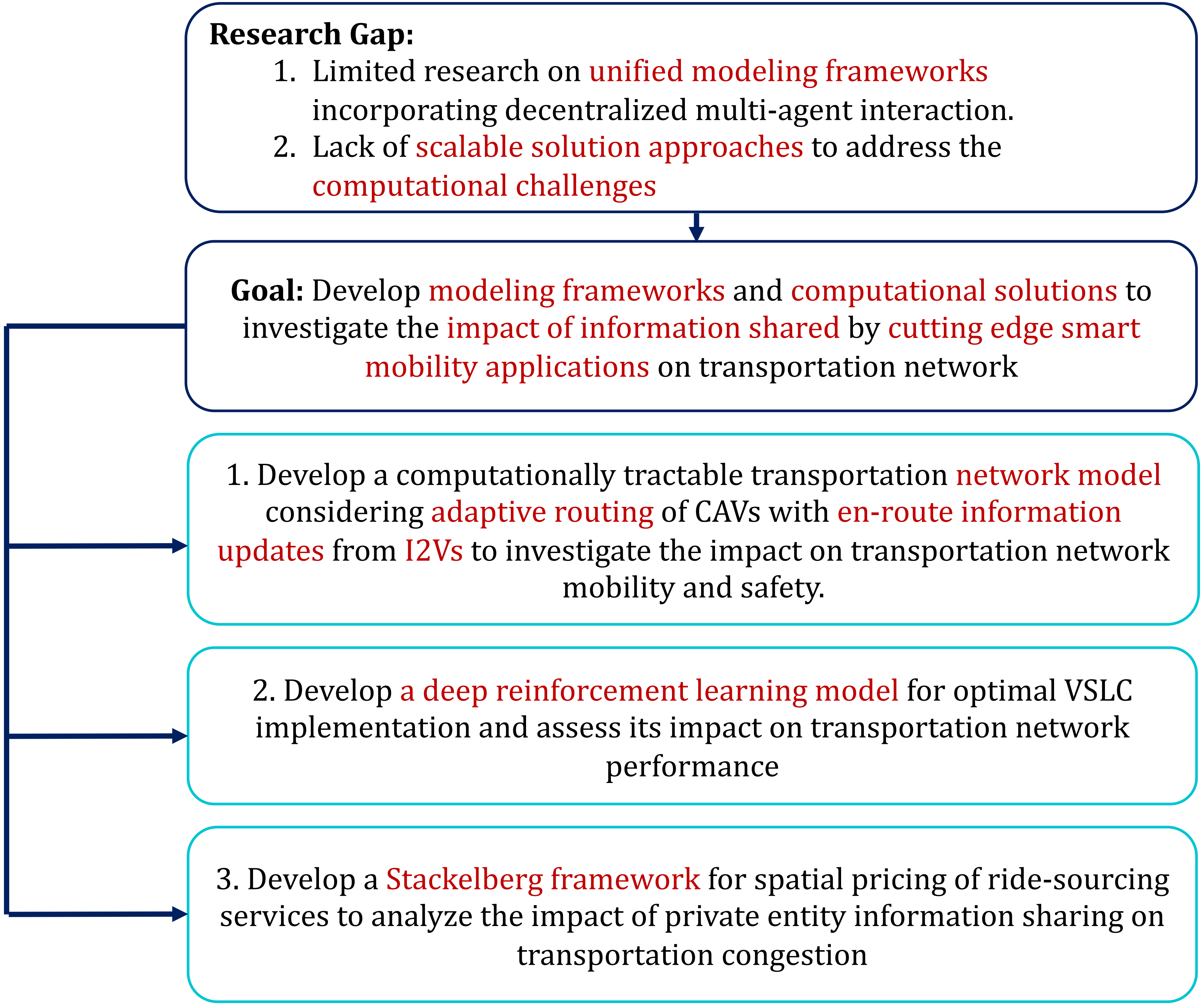
Goal: Develop modeling frameworks and computational solutions to investigate the impact of information shared by cutting edge smart mobility applications on transportation network

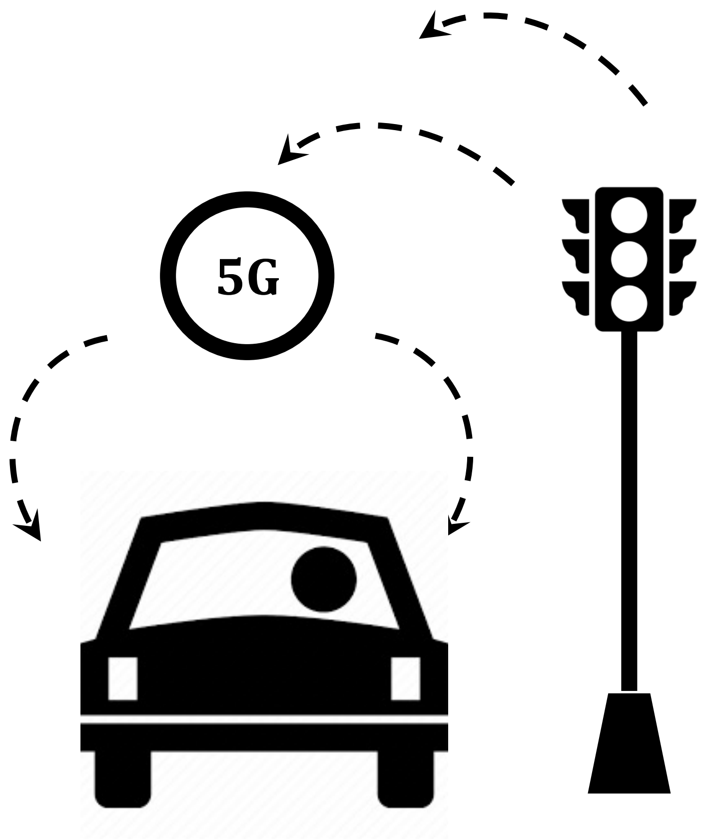

Research Gap:
1. Limited research on unified modeling frameworks incorporating decentralized multi-agent interaction.
2. Lack of scalable solution approaches to address the computational challenges
Goal: Develop modeling frameworks and computational solutions to investigate the impact of information shared by cutting edge smart mobility applications on transportation network
1. Develop a computationally tractable transportation network model considering adaptive routing of CAVs with en-route information updates from I2Vs to investigate the impact on transportation network mobility and safety.
2. Develop a deep reinforcement learning model for optimal VSLC implementation and assess its impact on transportation network performance
3. Develop a Stackelberg framework for spatial pricing of ride-sourcing services to analyze the impact of private entity information sharing on transportation congestion

Chapter 2: System-level impacts of en-route information sharing considering adaptive routing

Afifah, F., Guo, Z., & Abdel-Aty, M. (2023). System-level impacts of en-route information sharing considering adaptive routing. *Transportation Research Part C: Emerging Technologies*, *149*, 104075.

Problem Statement

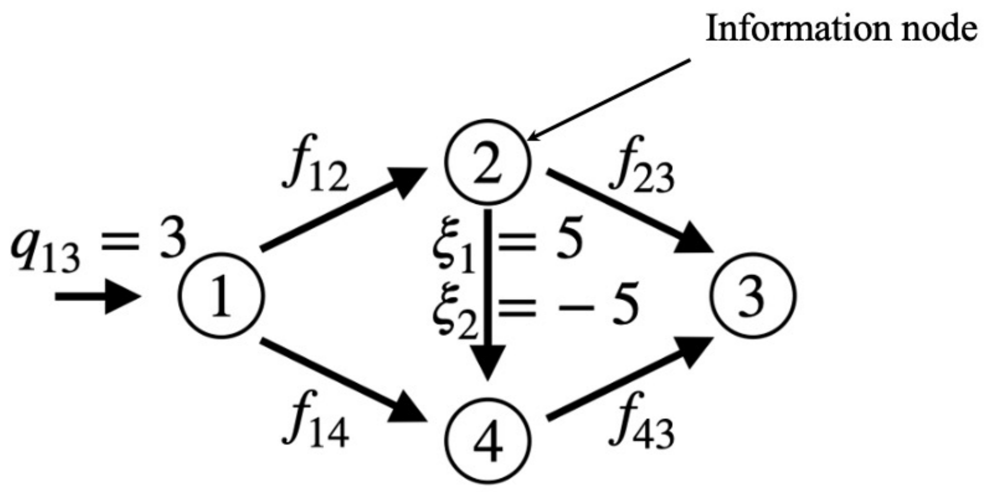
- Infrastructure-to-vehicle (I2V) technologies enable connected and automated vehicles (CAVs) to make informed decisions, adapt behavior, and optimize routes.
- **Motivation**
  - The influence of information sharing on network mobility and safety remains uncertain and requires further investigation.
- **Research Questions**
  - Does local-level traffic change due to en-route information impacts the system-level performance?
  - Is more information beneficial for improving network performance?



Problem Statement

- **Research gap**
  - **Research on adaptive decision making with information updates**
    - Roundabout/signalized intersection/link/zone safety [13-18].
    - Simulation-based dynamic traffic assignment (DTA) [19,20,21]. However, calibration for large network is difficult.
    - Equilibrium routing decision [22] and user equilibrium with recourse [23]. These studies consider information implicitly in routing policies and the number of routing policies grows exponentially.
- **Objective of this study**
  - Propose a novel and computationally tractable transportation network model to describe the traffic equilibrium patterns considering the adaptive routing of CAVs with en-route information updates.

Network Modeling



(a) Four-node network with stochastic link cost

Path	Flow		Travel Costs			
	ξ_1	ξ_2	ξ_1	ξ_2	Exp.	Var.
p_1	7/3	0	14/3	-	2.5	9.4
p_2	0	7/3	-	1/3		
p_3	2/3	2/3	4/3	11/3	2.5	2.7

(b) Equilibrium solution with risk-neutral adaptive behaviors

Definition: Two-stage Stochastic User Equilibrium (two-stage SUE)

- The expected travel time on all Hyperpaths used in the first stage are equal and less than any unused path.
- The expected travel time on all paths used in the second stage are equal and less than any unused path.

- Path: $p_1 = \{1,2,3\}$; $p_2 = \{1,2,3,4\}$; $p_3 = \{1,4,3\}$
- Hyperpath: $\mathcal{P}_1^{rs} = \{p_1, p_2\}$ and $\mathcal{P}_2^{rs} = \{p_3\}$

Two-stage Stochastic Network Model

- Objective:

$$\min_{x_p(\xi)\geq 0, \forall p,\xi} \mathbb{E}\left(\sum_{a\in A}\int_0^{v_a(\xi)} t_a(u,\xi)\mathrm{d}u\right)$$

- Constraints:
  - Flow conservation constraints

$$v_a(\xi) = \sum_{rs\in\mathcal{RS}}\sum_{p\in\mathcal{P}^{rs}} \delta_{ap}\, x_p(\xi), \forall a \in \mathcal{A}, \xi \in \Xi$$

$$(\gamma^{rs}(\xi)) \sum_{p\in\mathcal{P}^{rs}} x_p(\xi) = q^{rs}$$

  - Non-anticipativity constraint

$$(\lambda_{a,k}^{rs}(\xi)) \quad \sum_{p\in\mathcal{P}_k^{rs}} \delta_{ap}^{+} x_p(\xi) = x_{a,k}^{rs} \quad \forall rs \in RS, a \in \mathcal{A}, \xi \in \Xi$$

Theorem

The traffic flow pattern is following two-stage-SUE principles if and only if it is the optimal solution to the two-stage stochastic network model

Proof.

Strategy: KKT conditions of the two-stage stochastic network model and the two-stage SUE principles are identical.

Orlando Network

- Data Collection
  - Traffic Data: Regional Integrated Transportation Information System (RITIS)
  - Crash Data: Florida Highway Safety and Motor Vehicles (FLHSMV)
- Base Case
  - Incident links: 14-17, 17-14, 3-5, and 5-3
  - Information shared at node 10
- Scenarios
  - Normal Scenario
  - Incident Scenario

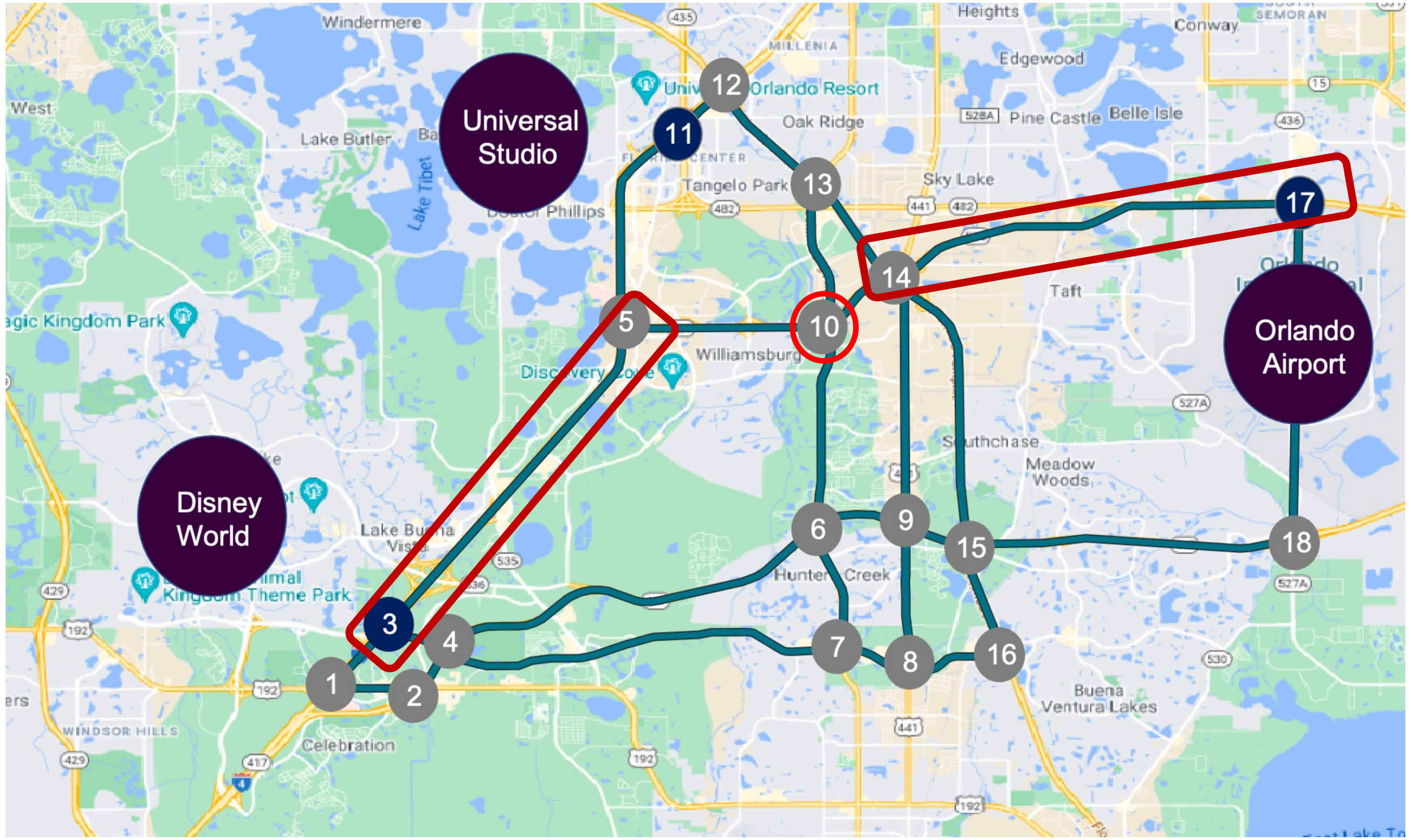


Figure: Orlando Transportation Network

Sensitivity of Information Sharing Strategies

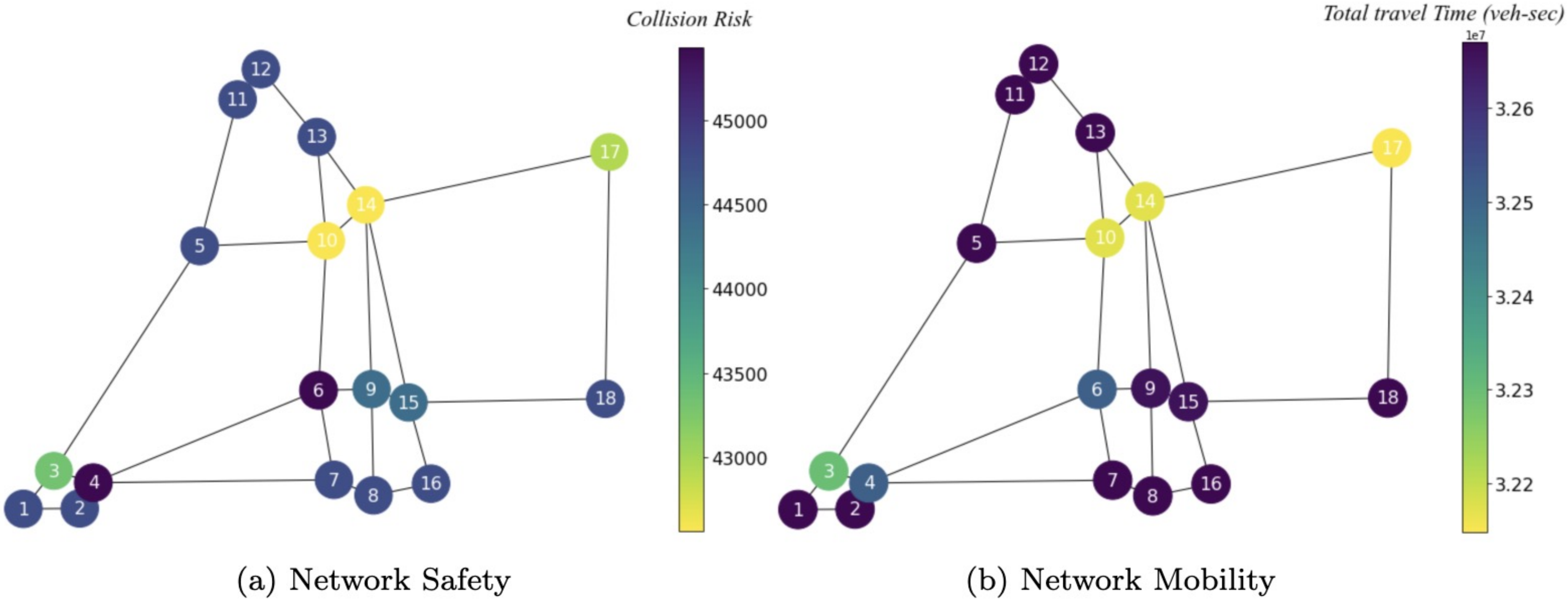
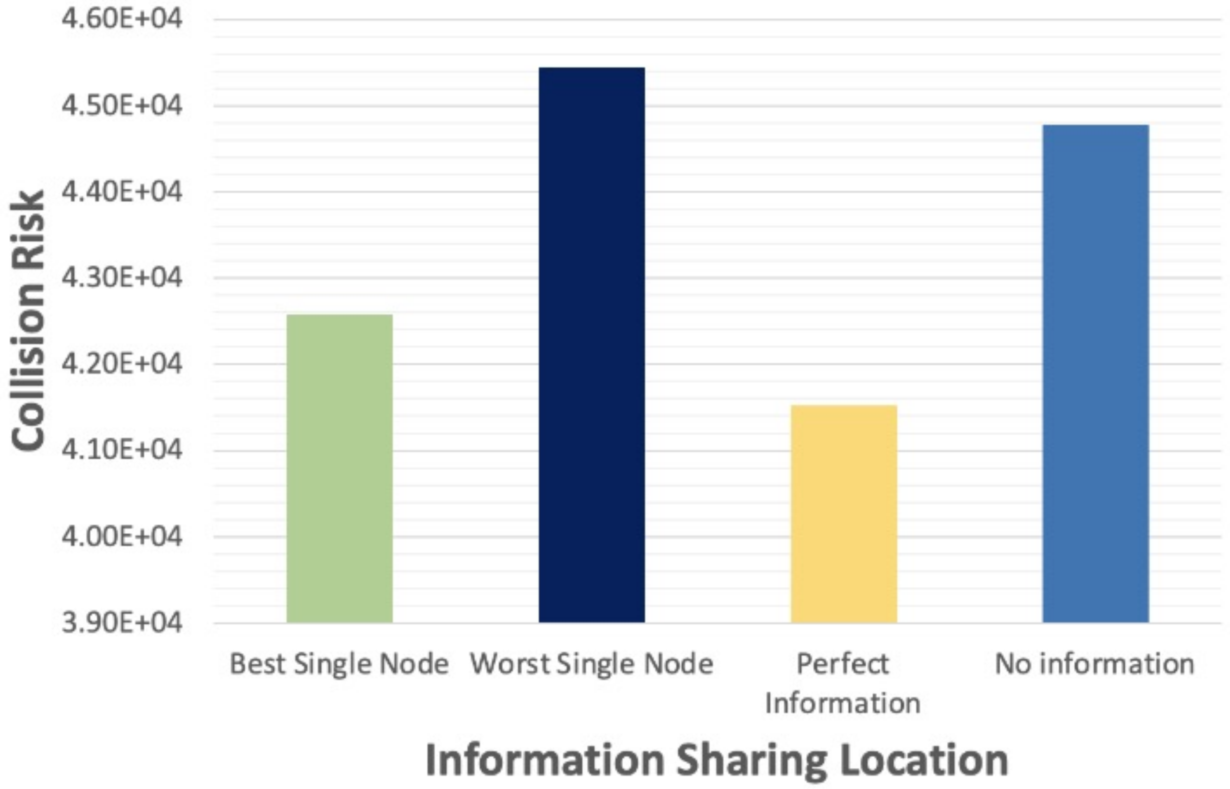
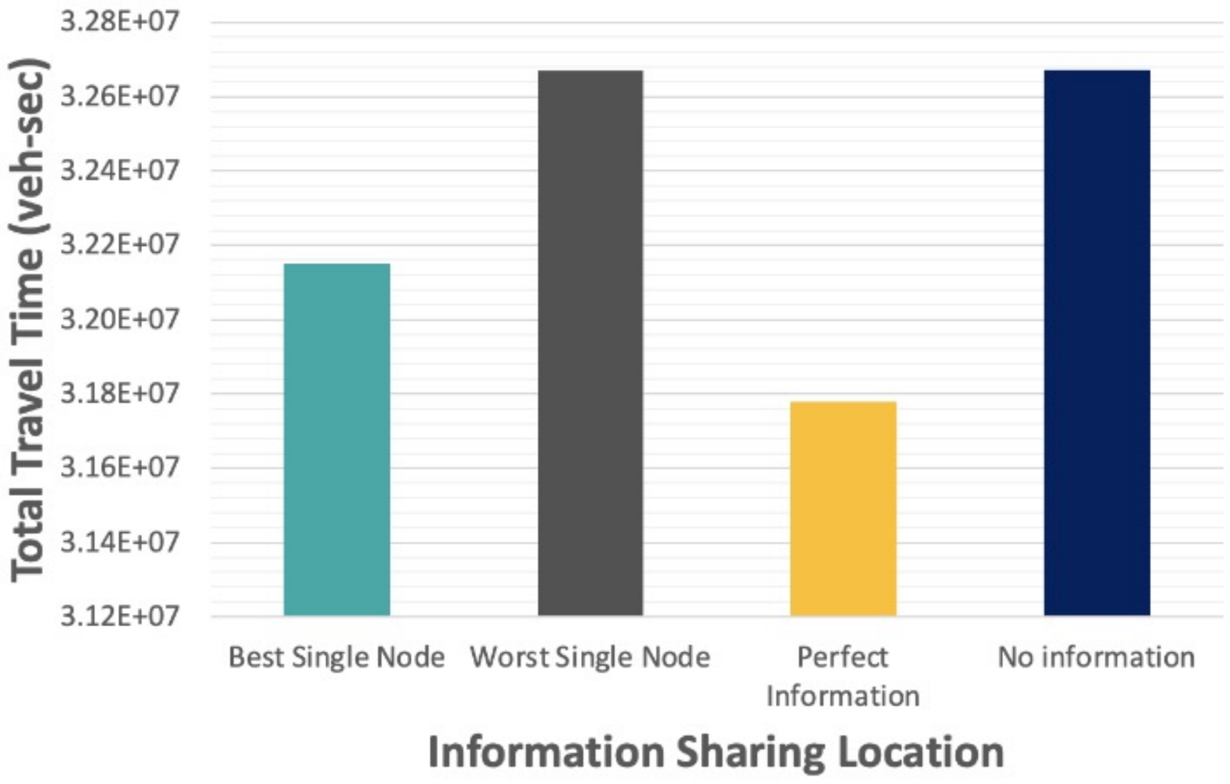


Figure: Network impacts of information sharing at individual nodes

Sensitivity of Information Sharing Strategies



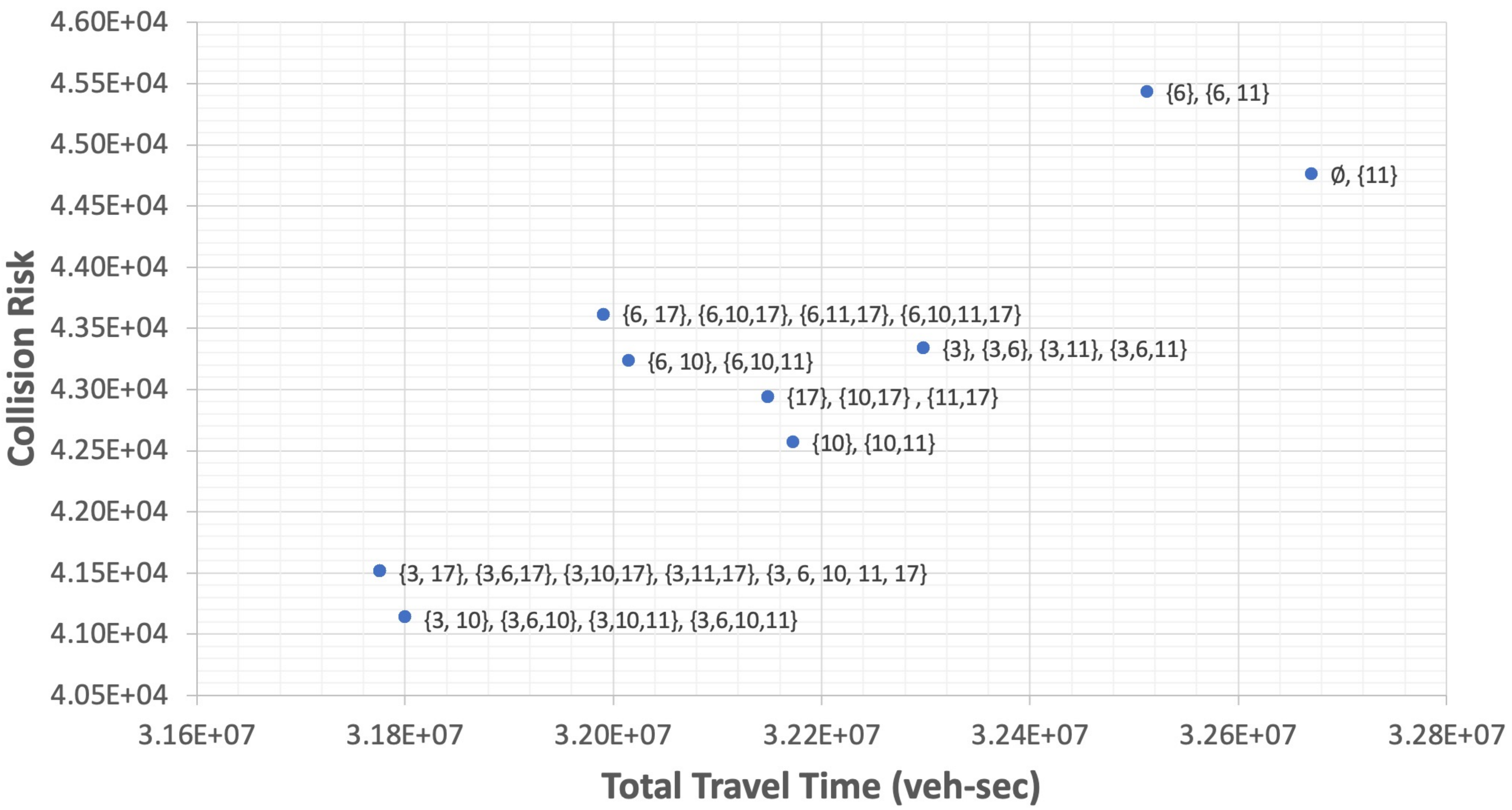
(a) Network Safety



(b) Network Mobility

Figure: Comparison of different information sharing strategies

Sensitivity of Information Sharing Strategies



Discussion

Contributions:

- We proposed a transportation network modeling framework to model the adaptive routing behavior of CAVs with information updates. The proposed model is structured as a convex stochastic optimization problem, thereby facilitating scalability by leveraging efficient stochastic programming algorithms.
- We explored strategies to share information to improve network mobility and safety.

Findings:

- The optimal information sharing strategies depend on specific network configuration.
- More/less information is not always better/worse for the network mobility and safety.
- Locational information sharing encourages the traffic on travel through information nodes to make informed rerouting decision.
- Potential extension: heterogeneous information? Mixed traffic?

Chapter 3: Optimal speed limit control for network mobility and safety: A twin-delayed deep deterministic policy gradient approach

Problem Statement

- Variable speed limit control(VSLC) dynamically adjusts speed limits in response to traffic conditions and regulate traffic flow and reduce congestion.
- **Motivation**
  - Optimal control over the speed limit of a route using VSLC and its impact on network mobility and safety has hardly been explored.
- **Research Questions**
  - How does VSLC implementation affect the traffic behavior?
  - What rewards can be provided to VSLC system to incentivize the provision of speed limits that enhance network mobility and safety?

Figure: Variable speed limit

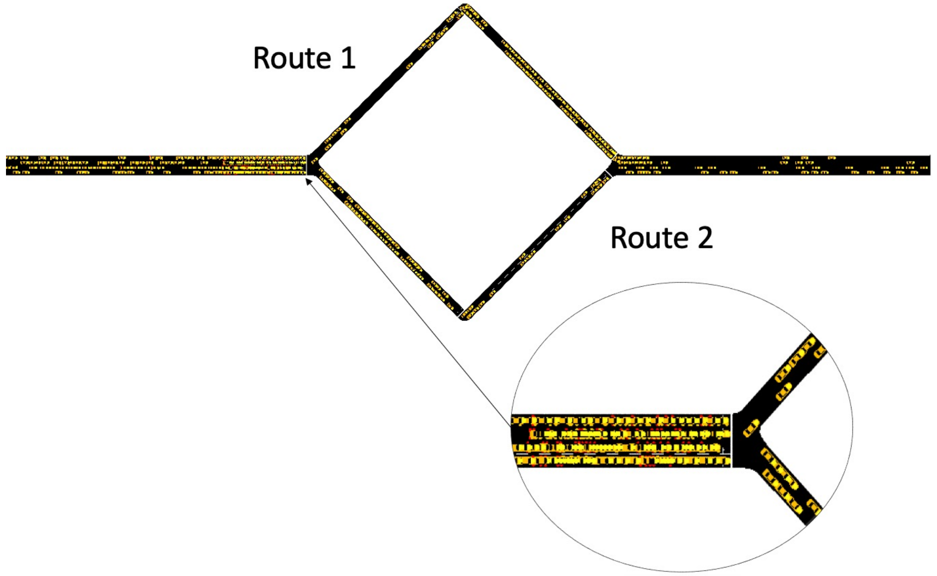


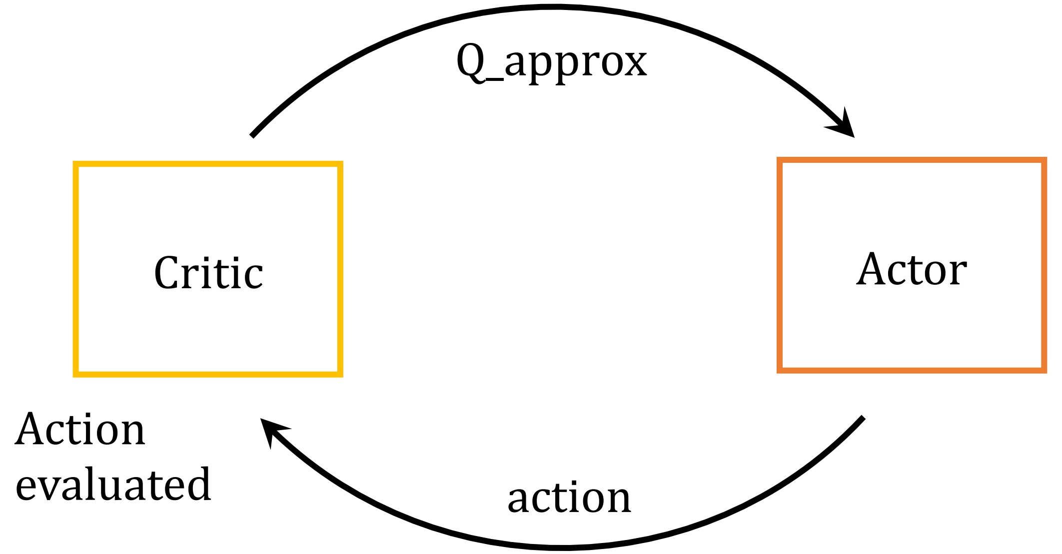
Figure: Network-level impact of VSLC

Problem Statement

- **Research Gaps**
  - Physical-model based approach [24,25,26]. However, it requires accurate model of the system and faces computational difficulties.
  - Reinforcement-learning based approach freeway bottleneck [27], ramp metering [28], work zone operation [29]. However, mostly used for small-scale problems.
- **Objective of the study**
  - Propose a deep reinforcement learning (DRL) model to implement VSLC in a network to improve overall network mobility and safety considering rerouting behavior of vehicles.
  - Propose suitable rewards for the DRL model to improve mobility and safety of a network.

Proposed Algorithm

- We propose using **Twin-delayed deep deterministic policy gradient (TD3)**
- Deep deterministic policy gradient (DDPG) suffers from [30]:
  - Overestimation Bias



  - Accumulation Error

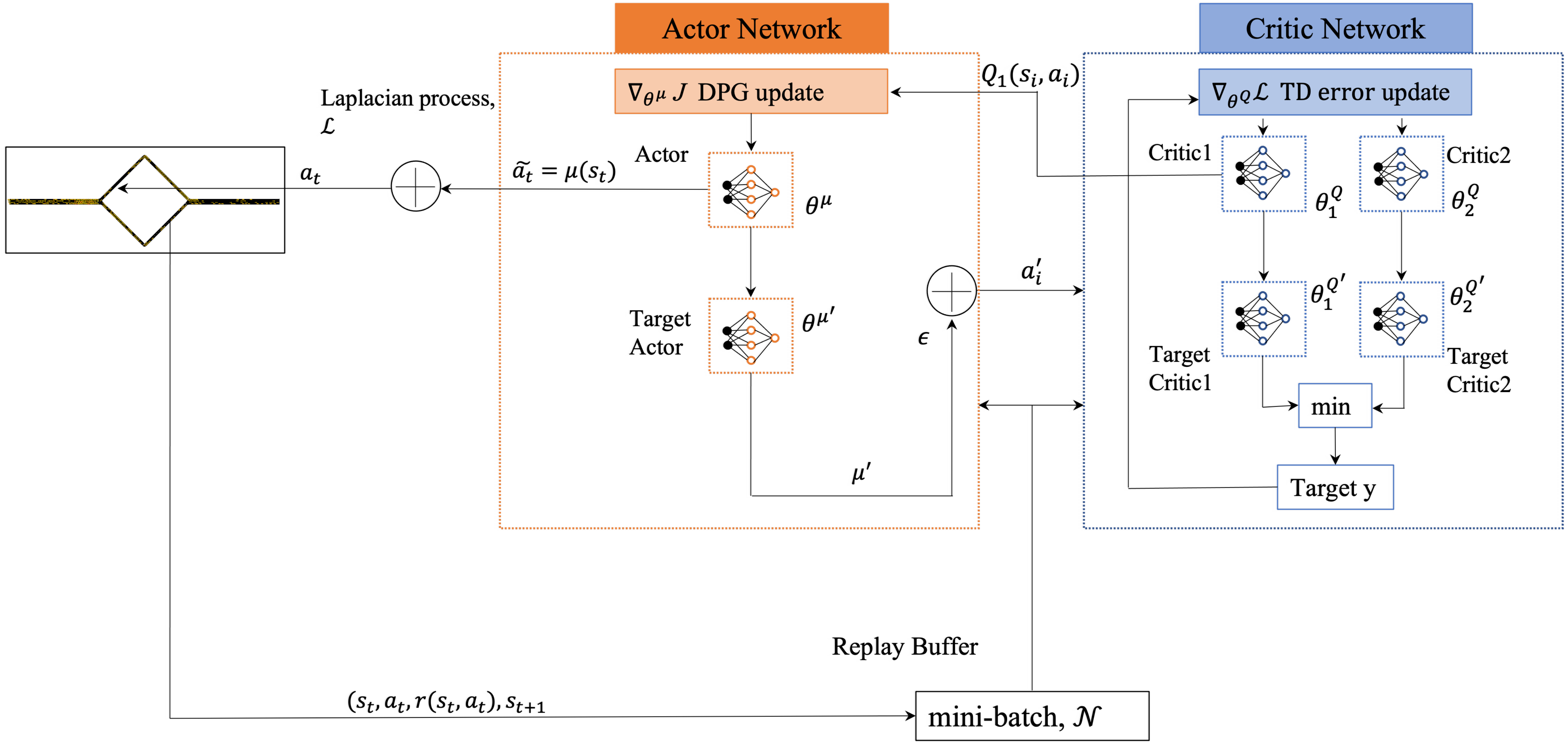
$$\delta = r_t + \gamma\, Q\left(s_{\{t+1\}}, a_{\{t+1\}}\right) - Q(s_t, a_t)$$

TD error

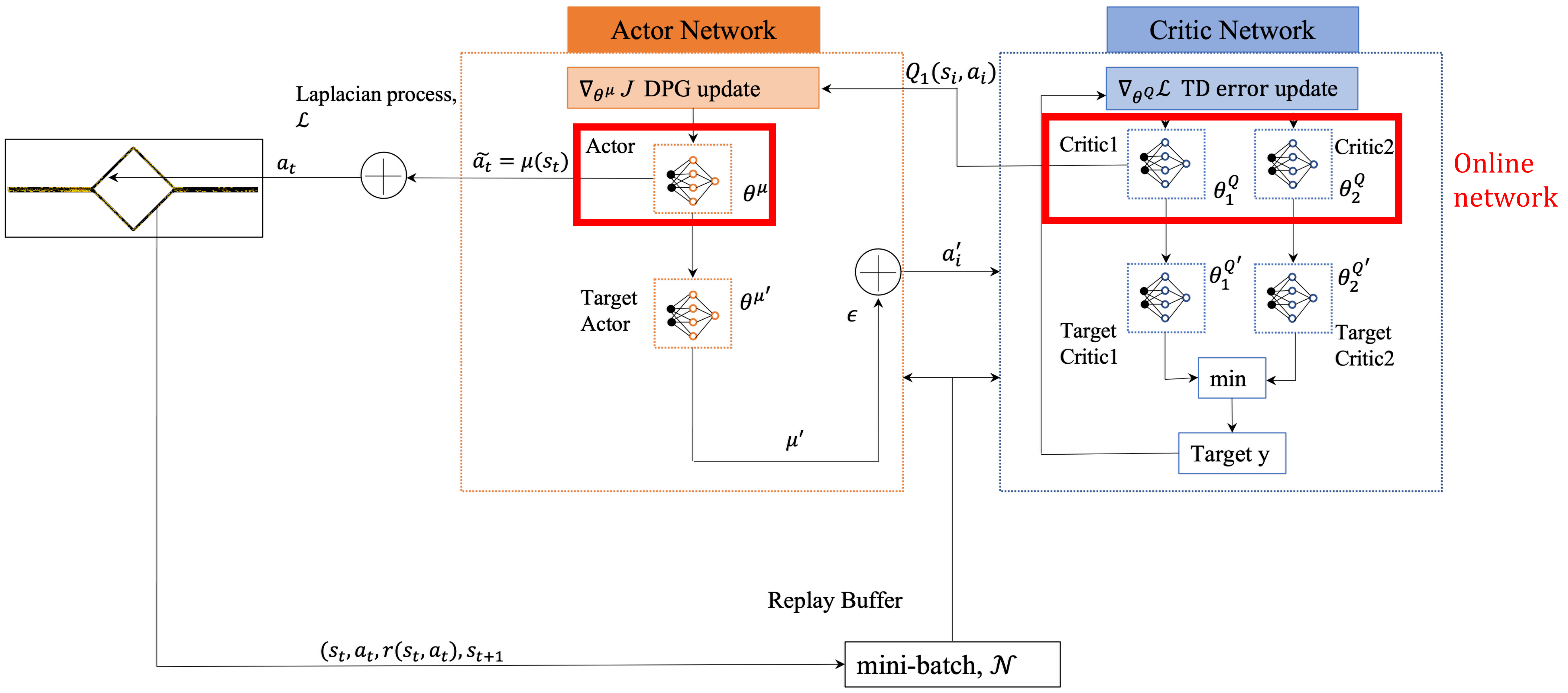
$$Q(s_t, a_t) = Q(s_t, a_t) + \alpha * \delta$$

Q-value estimate at the current step

Twin-delayed deep deterministic policy gradient (TD3)



Twin-delayed deep deterministic policy gradient (TD3)



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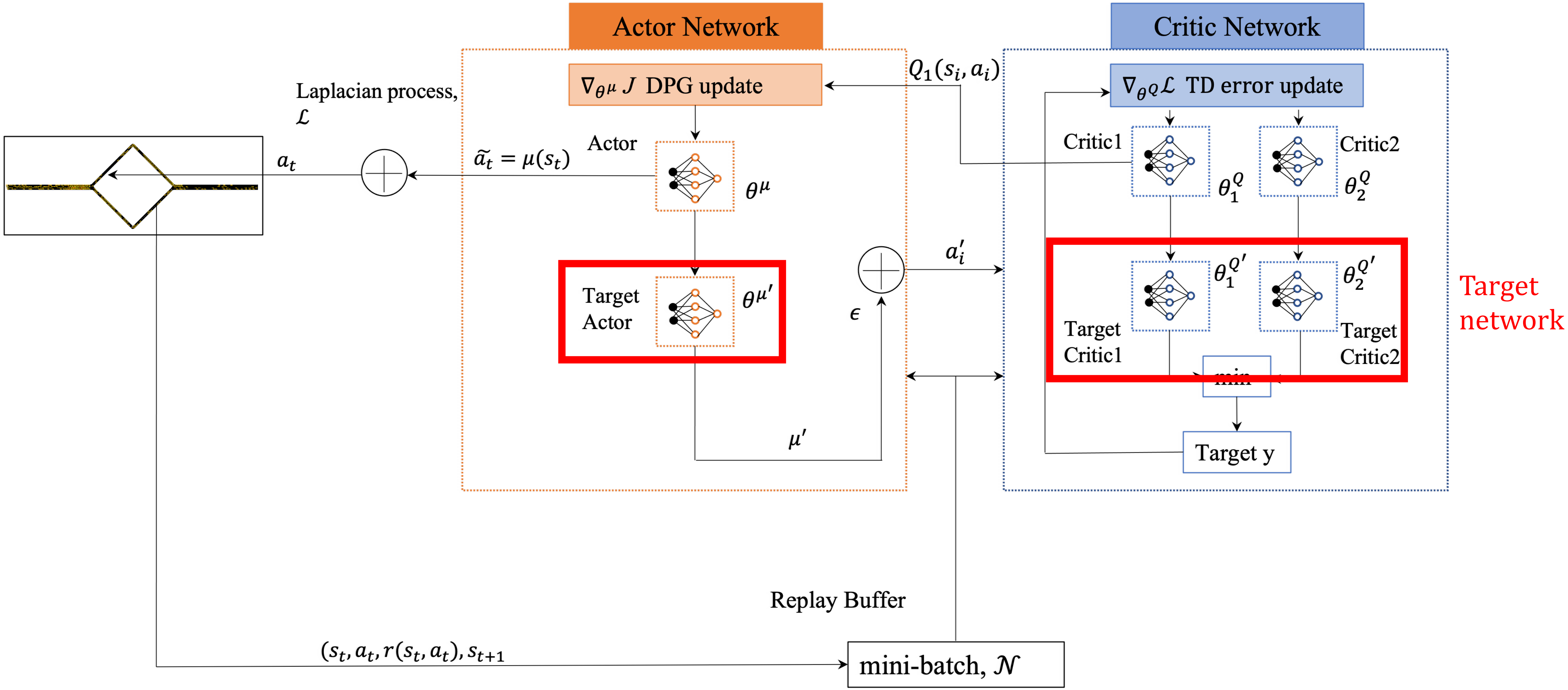
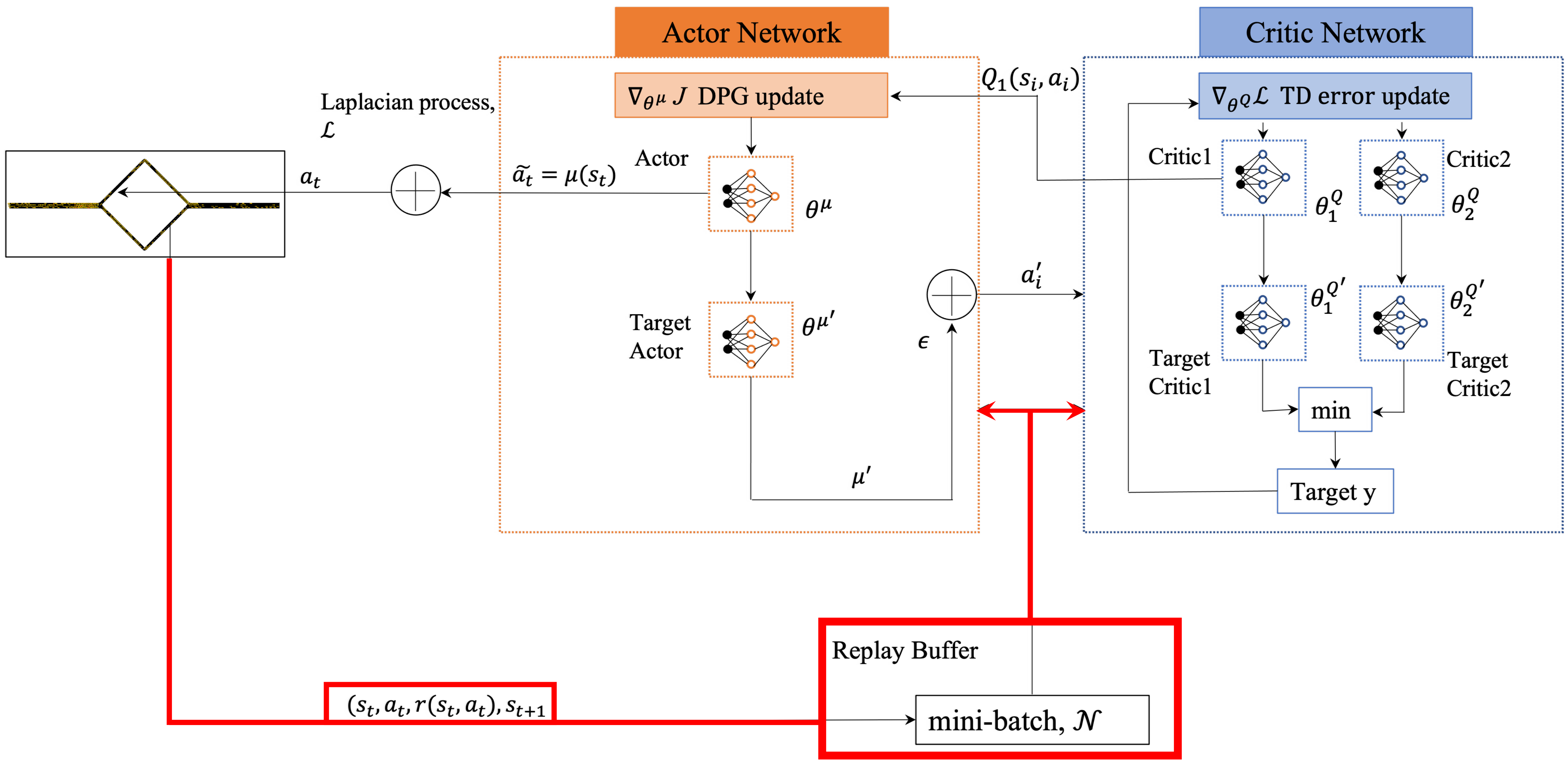


Twin-delayed deep deterministic policy gradient (TD3)



Twin-delayed deep deterministic policy gradient (TD3)

- Target critic

$$a_i' = \mu'\left(s_{i+1};\ \theta^{\mu'}\right) + \epsilon \rightarrow \text{Target action}$$

$$\epsilon \sim clip(\mathcal{N}(0,\sigma), a_{min}, a_{max})$$

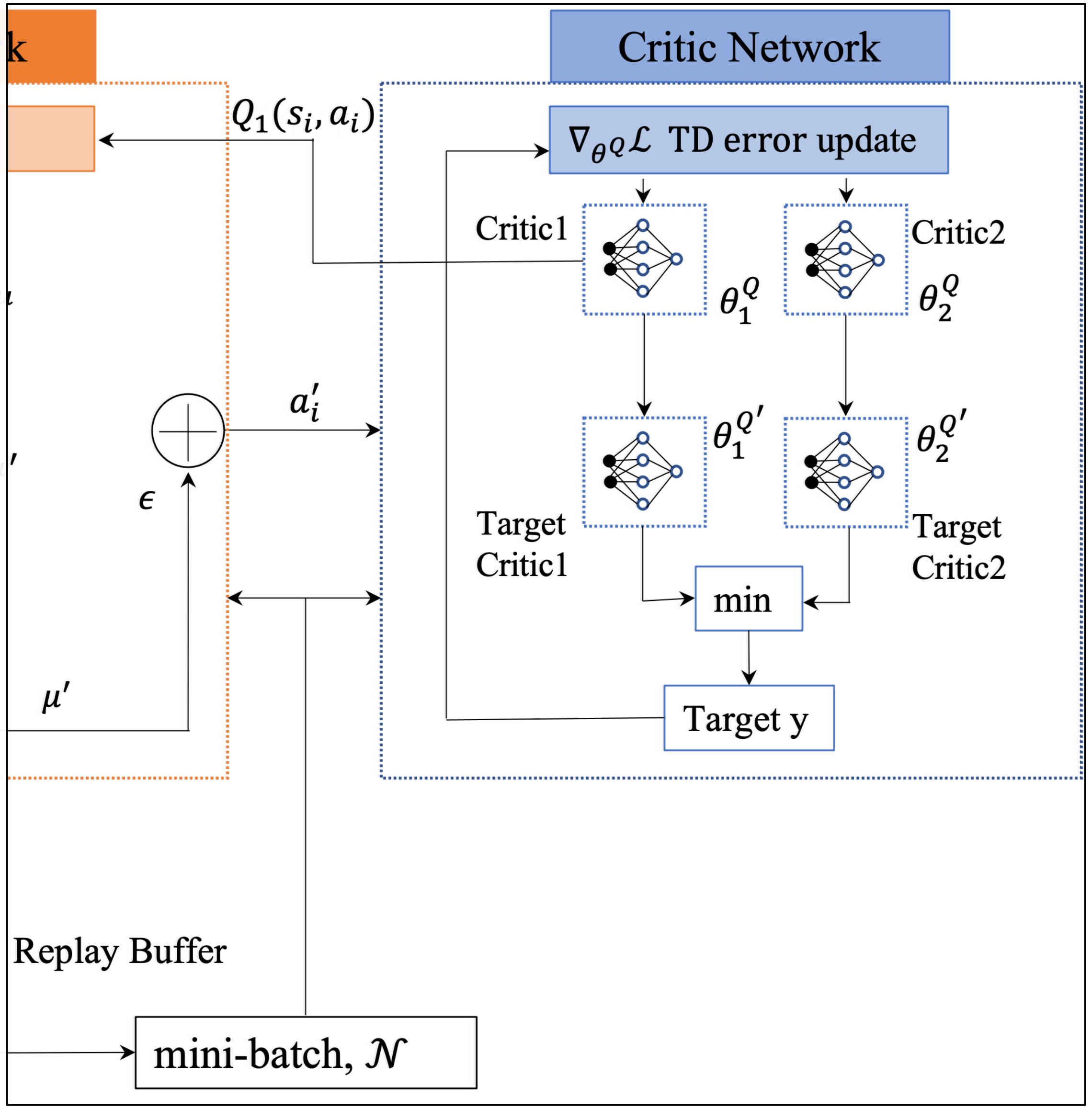
$$Q_j'(s_{i+1}, a_i');\ \theta_j^{Q'}), \forall\, j = 1,2$$

- Target y

$$y_i = r_i + \gamma \min_{j=1,2} Q_j'(s_{i+1}, a_i');\ \theta_j^{Q'})$$

- Online critic network update

$$\nabla_{\theta_j^Q}\mathcal{L}\left(\theta_j^Q\right) = \frac{1}{N}\sum_i \nabla_{\theta_j^Q}(y_i - Q_j\left(s_i, a_i; \theta_j^Q\right))^2$$



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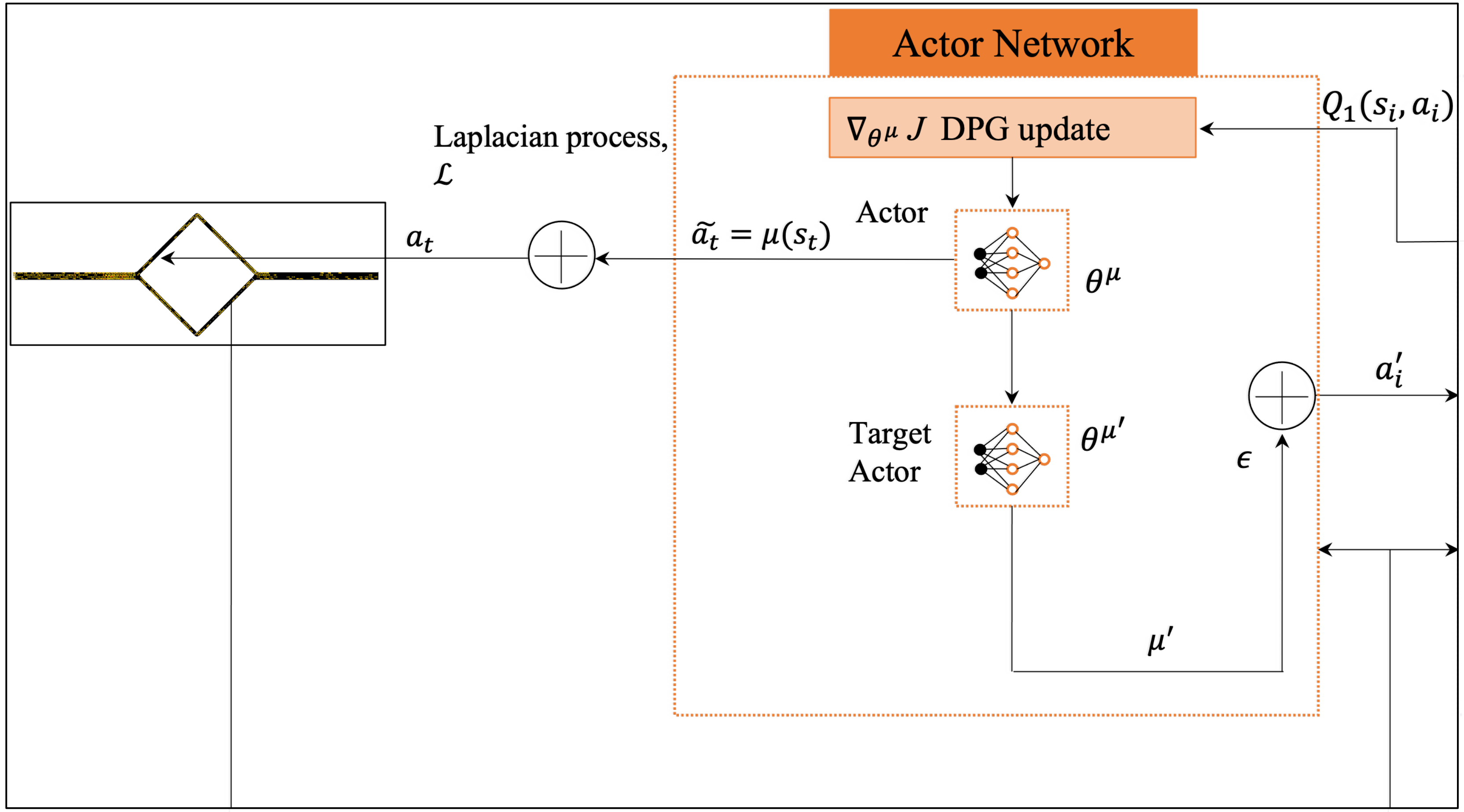


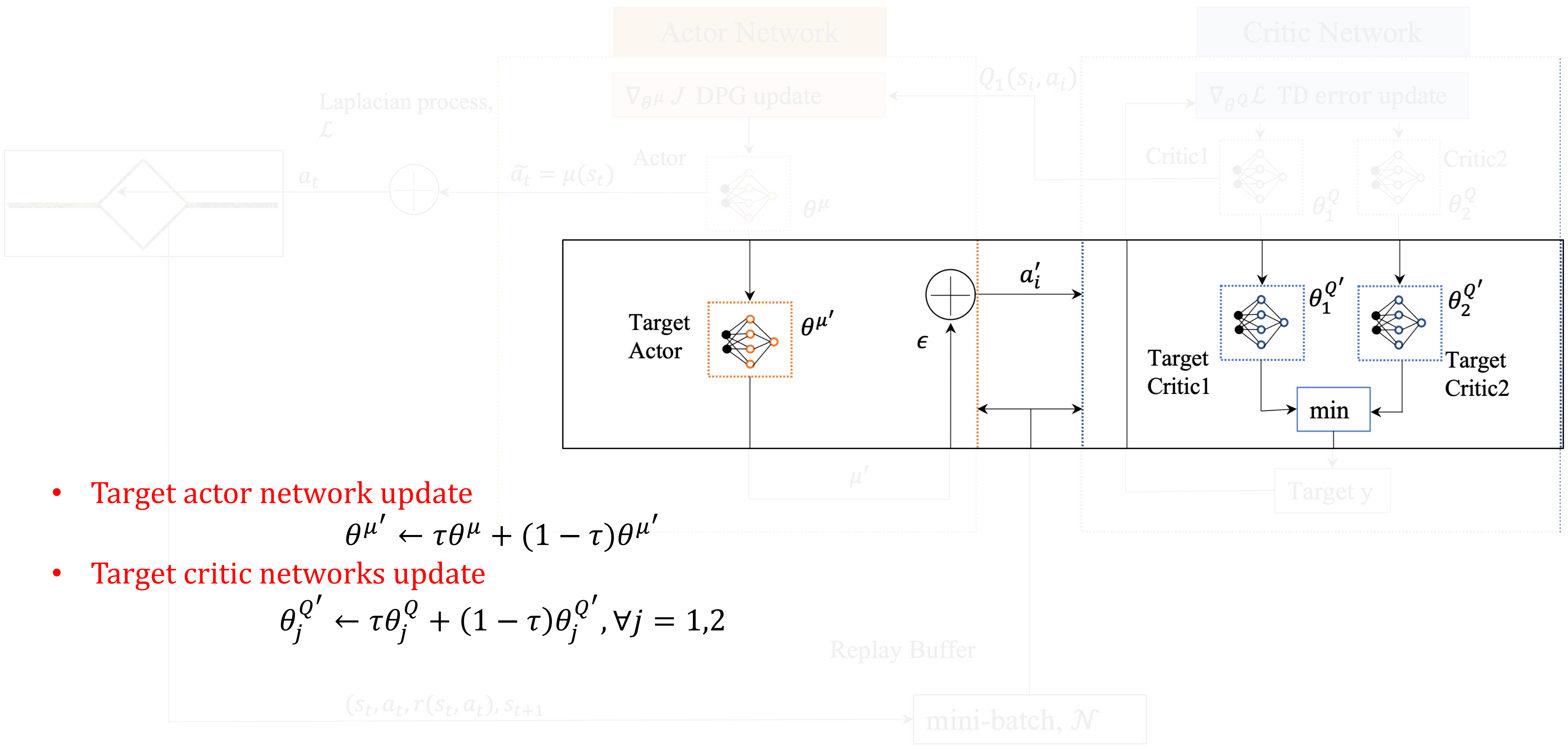
$a_i = \mu(s_i)$

- Online actor network update

$$\nabla_{\theta^\mu} J = \frac{1}{N} \sum_i [\nabla_a Q_1(s_i, a_i; \theta_1^Q)\ \nabla_{\theta^\mu} \mu(s_i; \theta^\mu)]$$

- The actor network is updated less frequently than the critic network

Twin-delayed deep deterministic policy gradient (TD3)



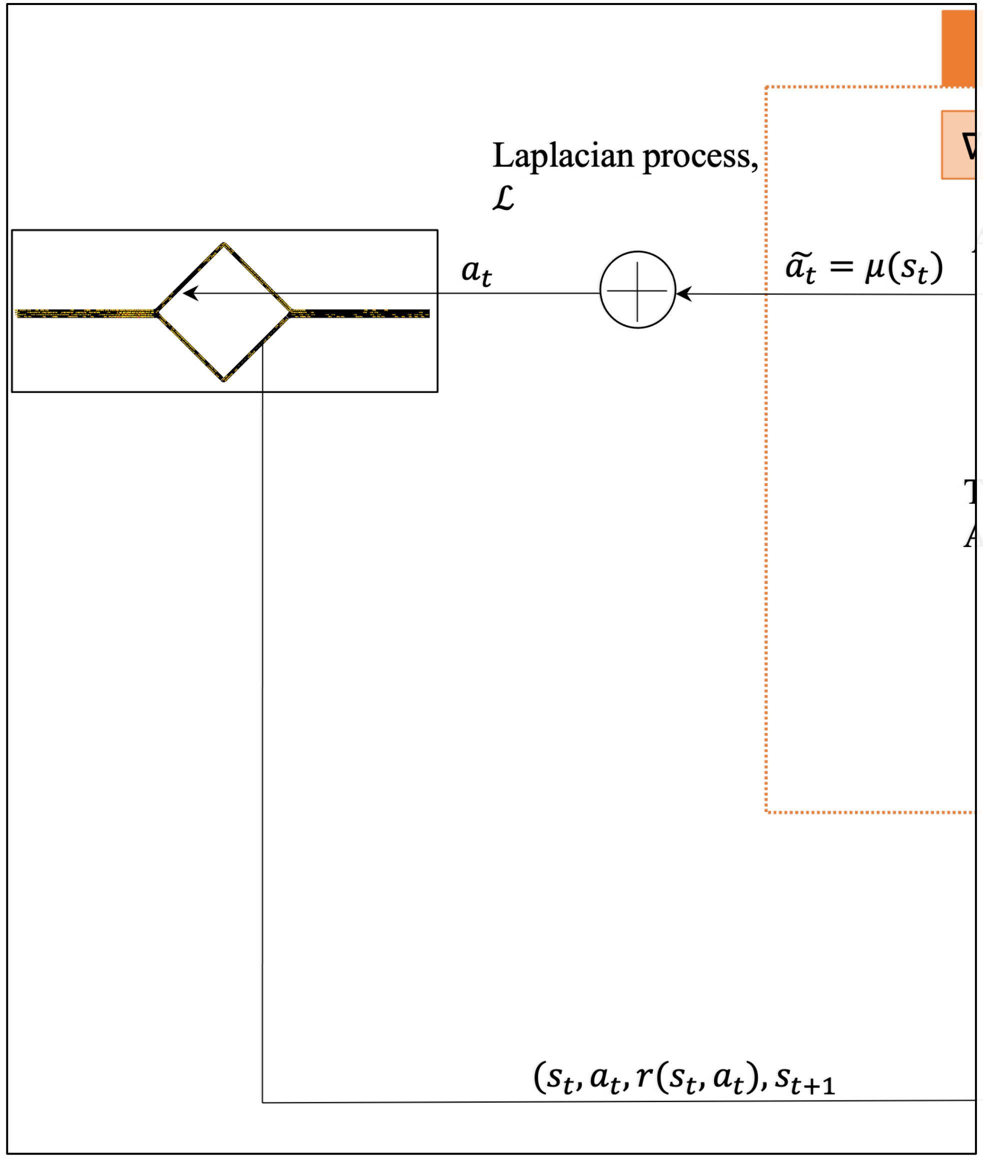
- Target actor network update

$$\theta^{\mu'} \leftarrow \tau\theta^{\mu} + (1-\tau)\theta^{\mu'}$$

- Target critic networks update

$$\theta_j^{Q'} \leftarrow \tau\theta_j^{Q} + (1-\tau)\theta_j^{Q'}, \forall j = 1,2$$

Twin-delayed deep deterministic policy gradient (TD3)



- Exploration Method

$$\tilde{a}_t = \mu(s_t)$$

- Laplacian process

$$\mathcal{L}(\tilde{a}_t | b_t) \sim \frac{1}{2b_t} \exp\left(-\frac{\tilde{a}_t}{b_t}\right)$$

$$a_t = clip(\mathcal{L}(\tilde{a}_t | b_t), a_{min}, a_{max})$$

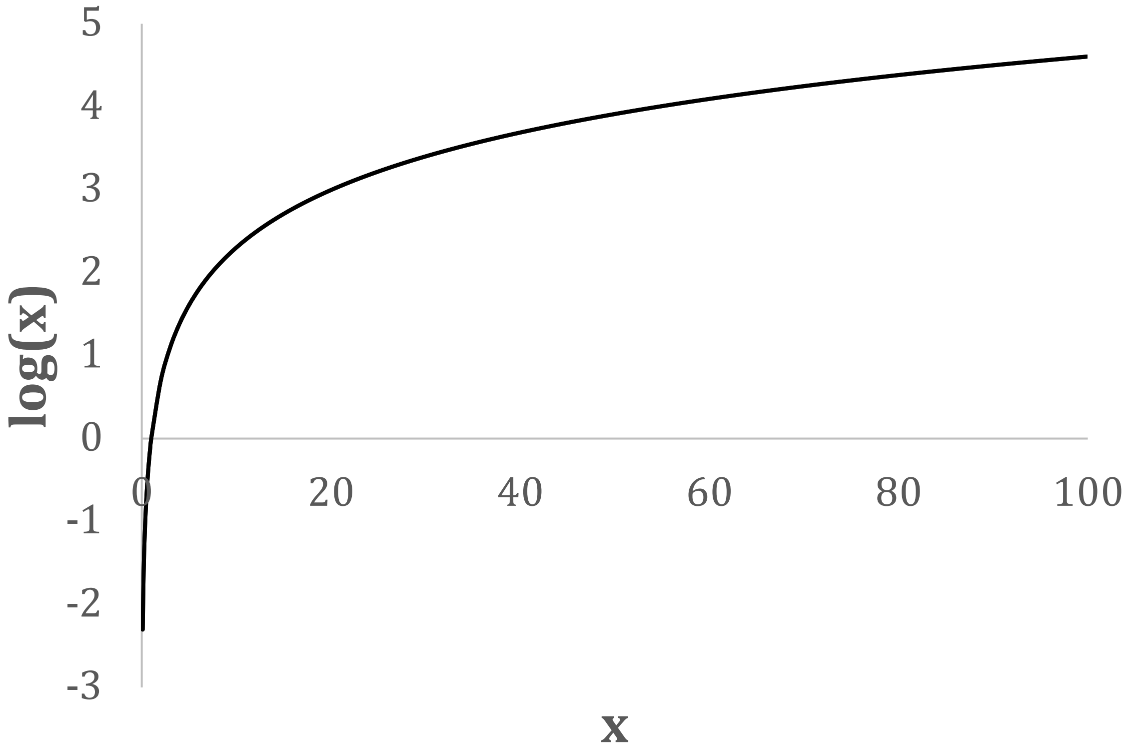
States, action, reward

- State : Occupancy
- Action: {30,35,40,45,50,55,60,65}mph
- Reward
  - *Improving safety*:

$$Safety\ Measure = log(TTC)$$

where

TTC: time-to-collsion. It is defined as the estimated time it will take for two vehicles to collide if they maintain their current trajectory and speed



States, action, reward

- Reward
  - *Improving mobility:*

$$TTT = \sum_{a \in A} Current_{TTT_a} \times N_a$$

where
TTT: total travel time at a step
$Current_{TTT_a}$: current travel time on an edge a
N_a: number of vehicles on the edge a

  - *Traffic oscillation dampening*:

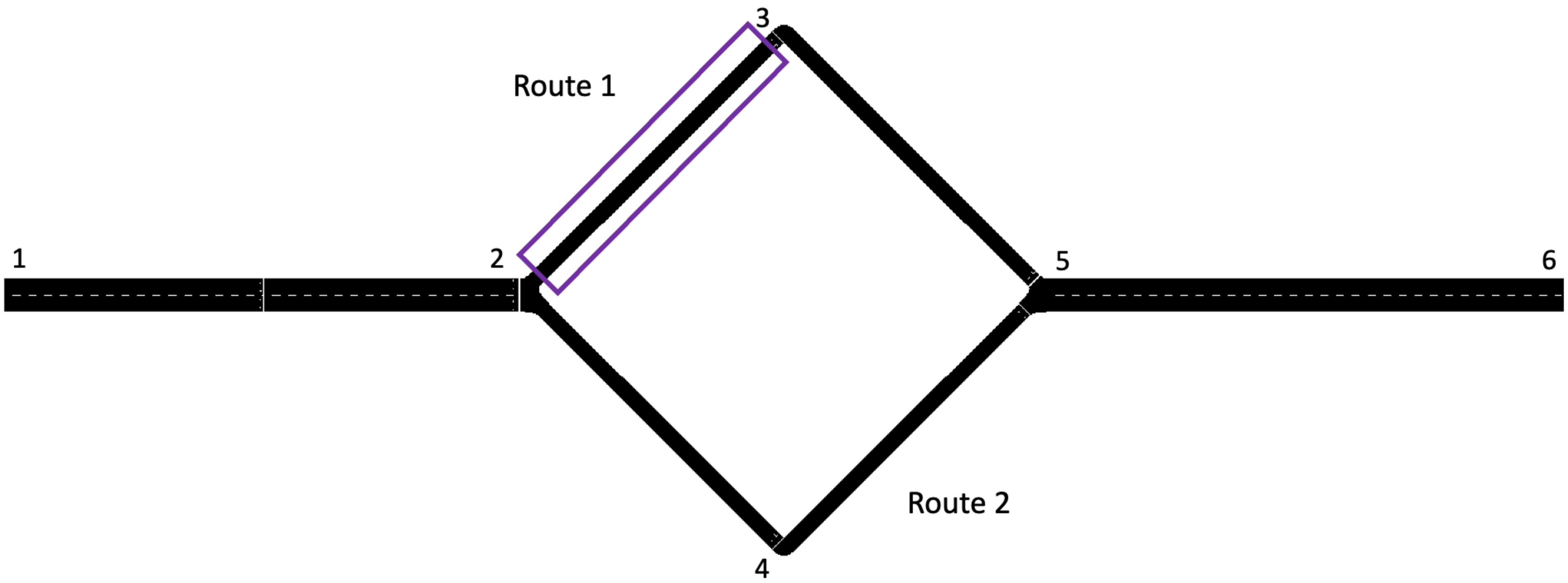
$$\Delta NumVeh = (NumVeh_{route_1} - NumVeh_{route_2})$$

where
$\Delta NumVeh$: relative difference in the number of vehicles in different routes.

SUMO Configuration

- Simulation of Urban MObility (SUMO)
- Traffic Control Interface (TraCI)
- Rerouting of vehicles:
  - *traci.vehicle.rerouteTraveltime(vehID, currentTravelTimes = True)*
- "speedFactor" : *norm(1,0.1,.2,2)*
- "lcspeedGain”: *1*

Experimental Results



Comparison with other methods

Method	Network safety (units: seconds)	Network mobility (unit: seconds)
No VSLC	9.5262e+05	9.1878e+07
VSLC-DQL	8.8534e+05	1.1302e+08
VSLC-SAC	9.2121e+05	8.4903e+07
VSLC-DDPG	**9.9546e+05**	7.2324e+07
VSLC-TD3	9.8919e+05	**6.1384e+07**

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VSLC-DDPG	**9.9546e+05**	4.50% higher	7.2324e+07
VSLC-TD3	9.8919e+05		**6.1384e+07**

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VSLC-SAC	9.2121e+05		8.4903e+07
VSLC-DDPG	**9.9546e+05**		7.2324e+07
VSLC-TD3	$\boxed{9.8919e+05}$	**3.84% higher**	**6.1384e+07**

Comparison with other methods

Method	Network safety (units: seconds)	Network mobility (unit: seconds)
No VSLC	9.5262e+05	9.1878e+07
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VSLC-DDPG	**9.9546e+05**	7.2324e+07
VSLC-TD3	9.8919e+05	**6.1384e+07** 33.19% lower

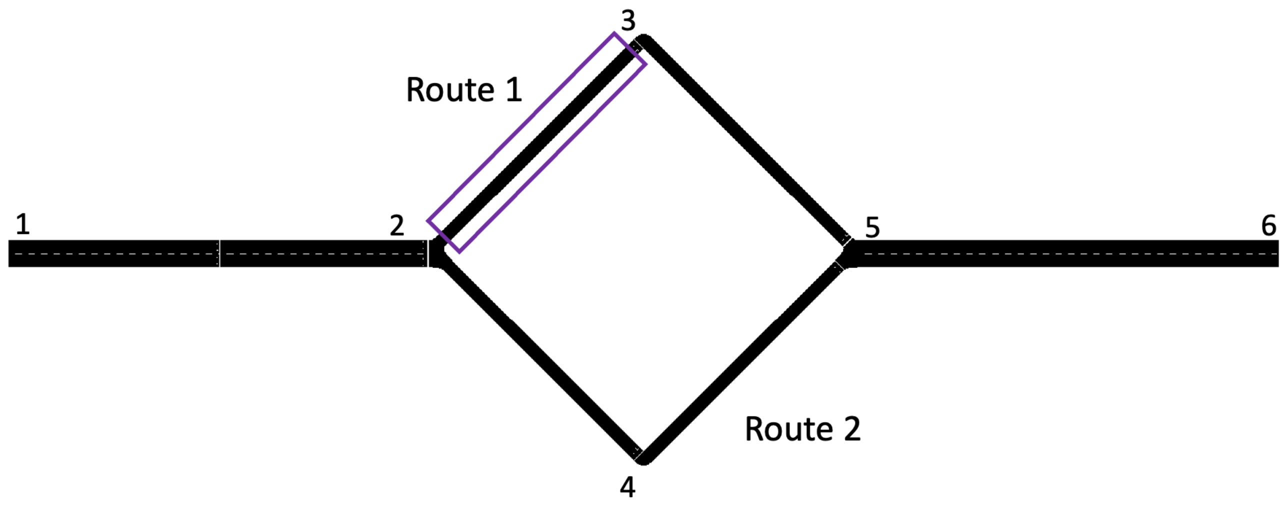
Comparison with other methods

Method	Network safety (units: seconds)		Network mobility (unit: seconds)	
No VSLC	9.5262e+05		9.1878e+07	
VSLC-DQL	8.8534e+05	7.05% lower	1.1302e+08	23% higher
VSLC-SAC	9.2121e+05		8.4903e+07	
VSLC-DDPG	**9.9546e+05**		7.2324e+07	
VSLC-TD3	9.8919e+05		**6.1384e+07**	

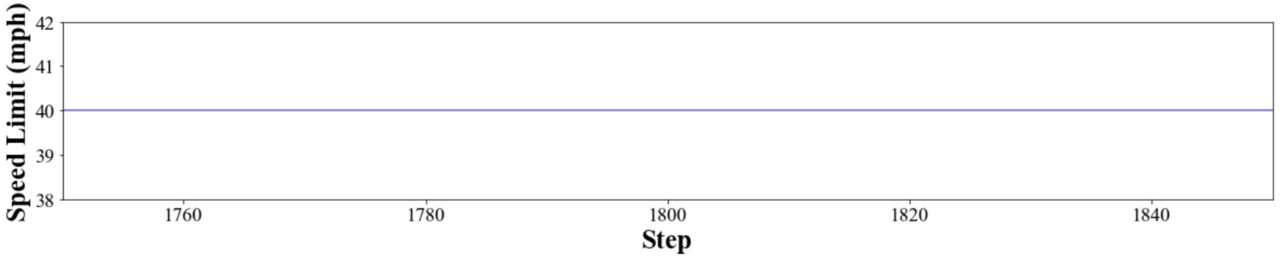
Assessment of Different Traffic Control Strategies

Different traffic control strategies

- No VSL
- Traffic engineering practice
- VSLC implementation to improve network mobility
- VSLC implementation to improve network safety



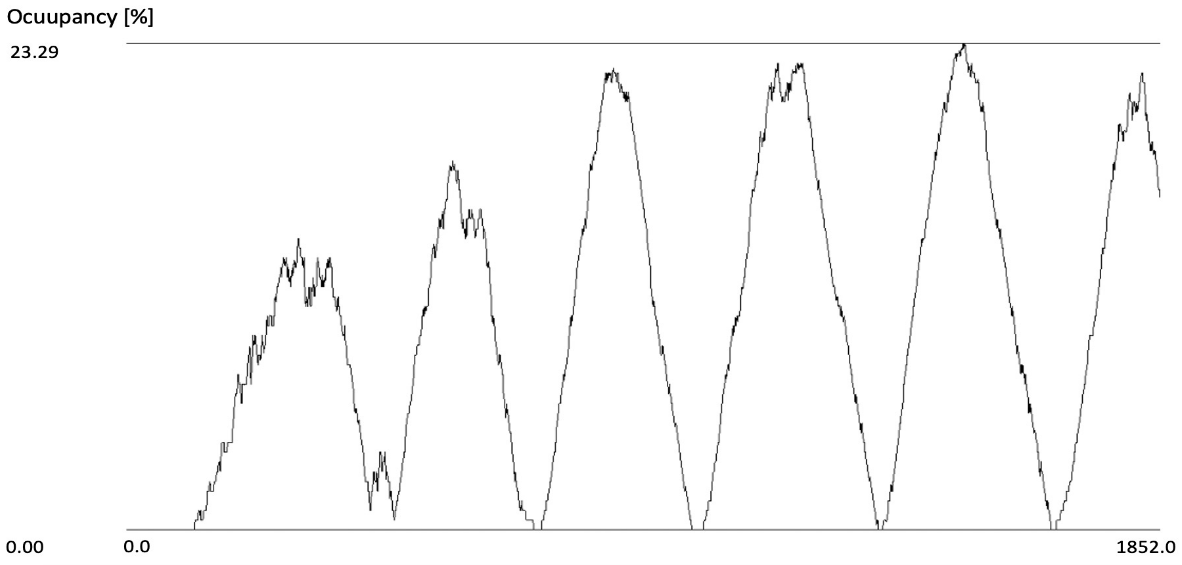
Routing: No VSL control



Routing

49.41 %

50.59%



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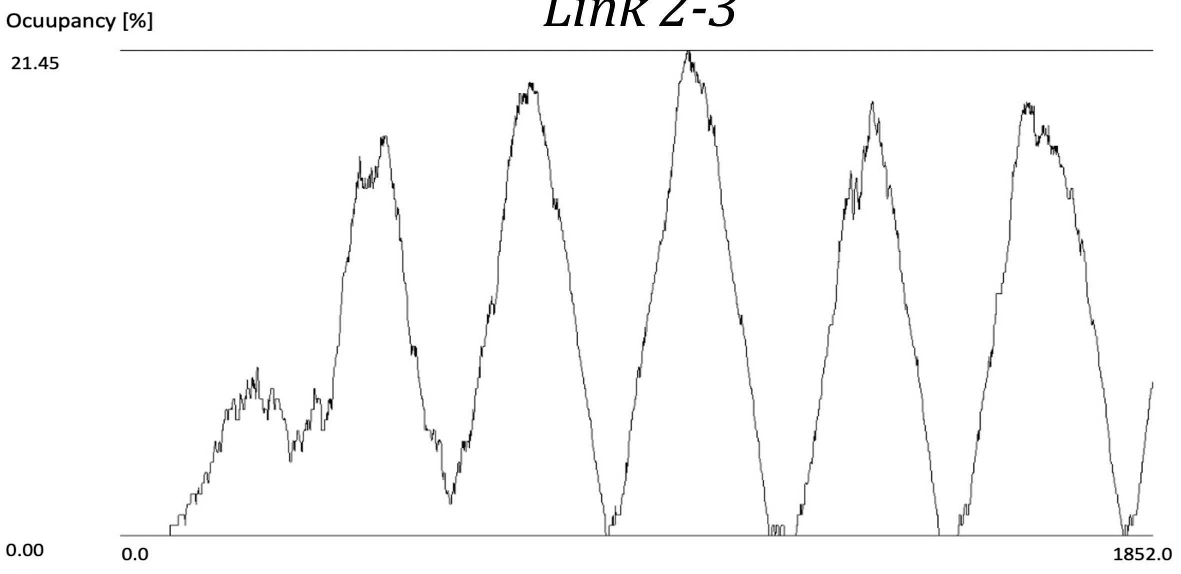

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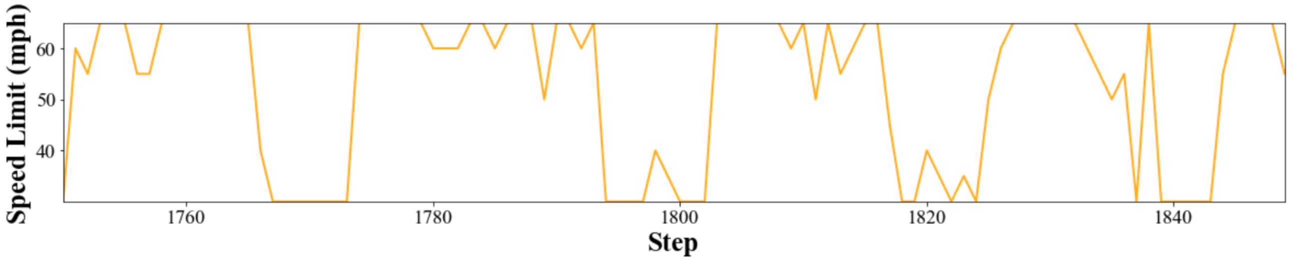
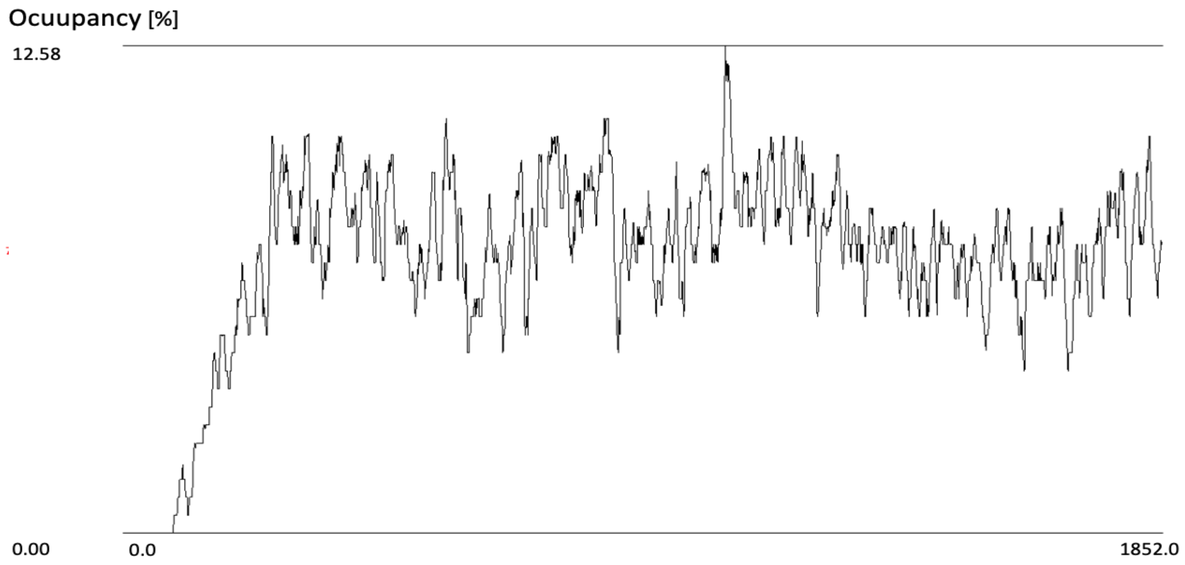
Routing: Traffic engineering practice



Routing

50.32%



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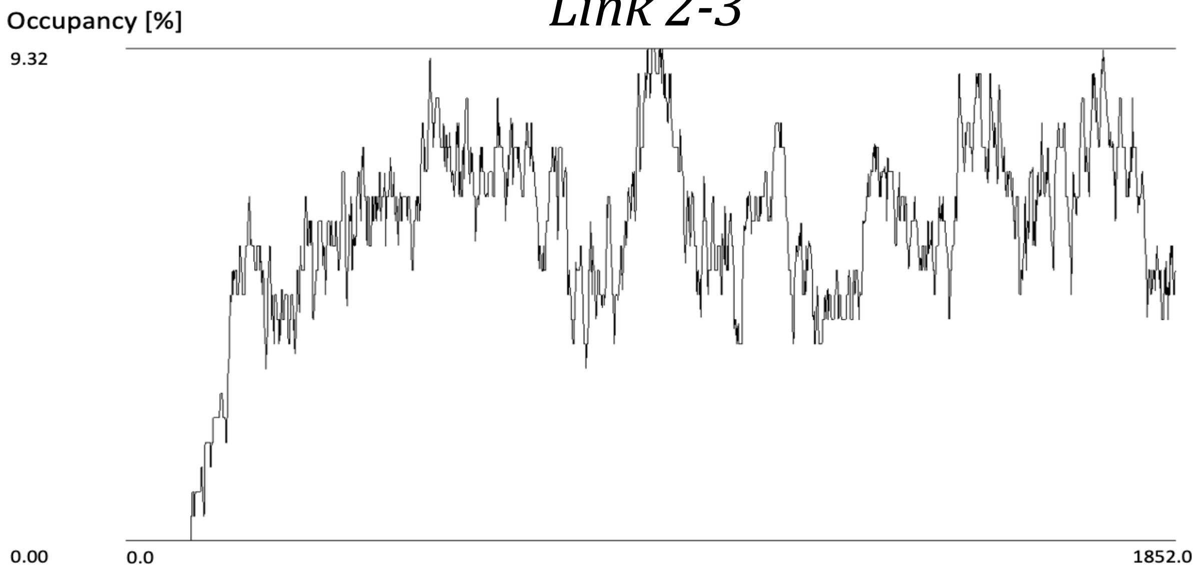
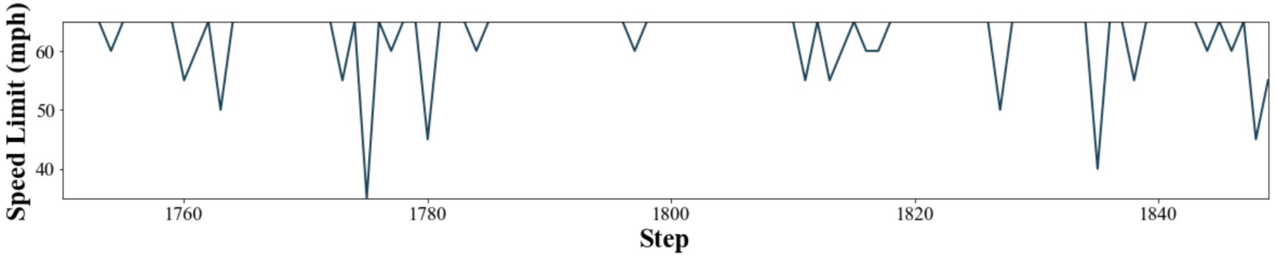
49.68%



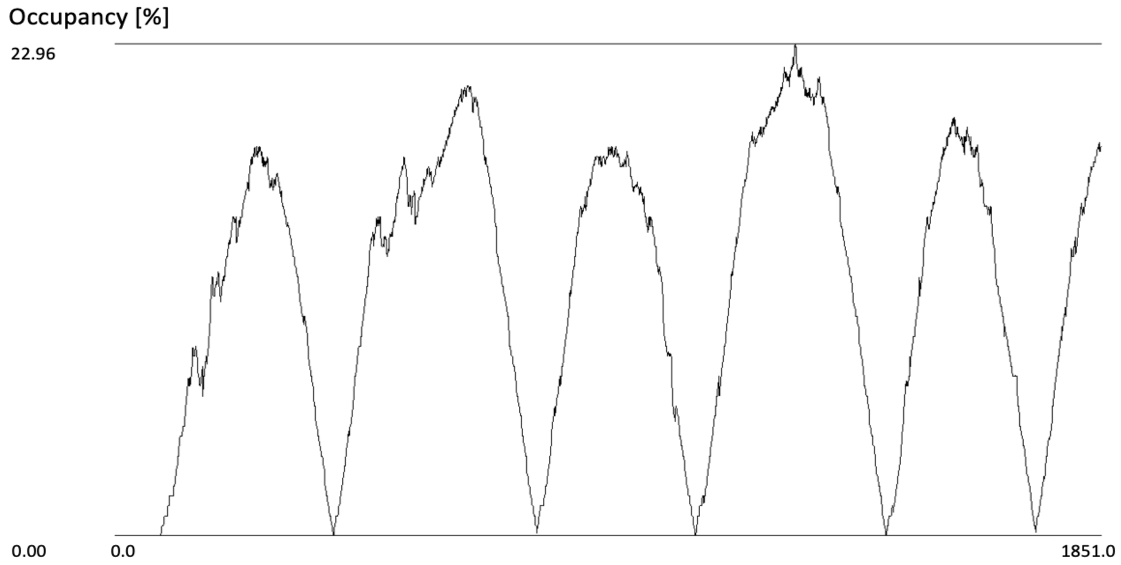
Link 2-4

Routing: VSLC implementation (mobility)



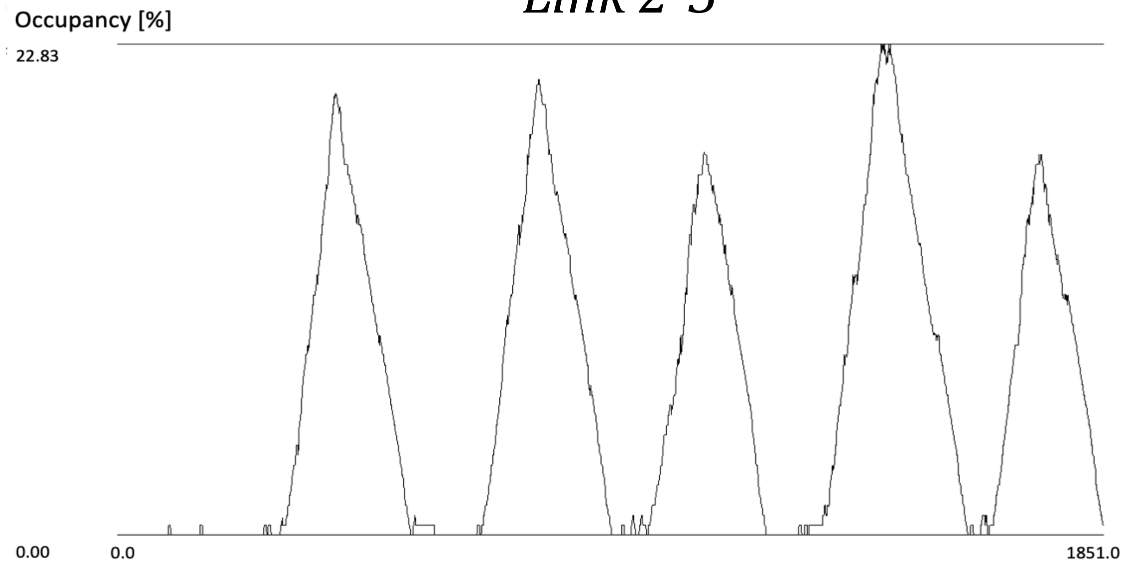
Routing

64.35%



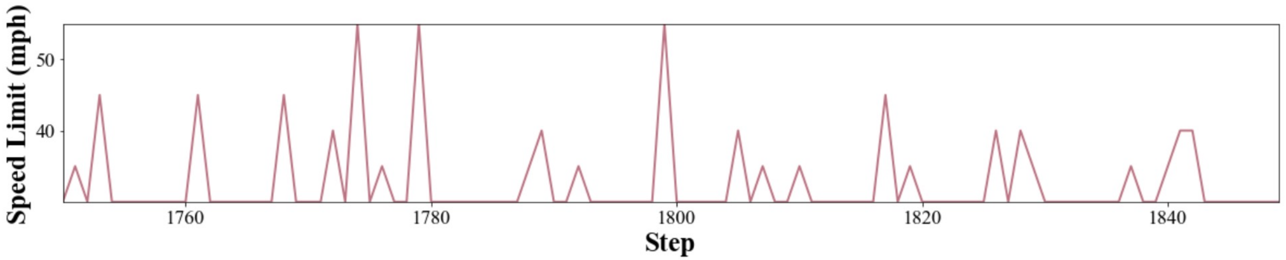
Link 2-3

35.65%



Link 2-4

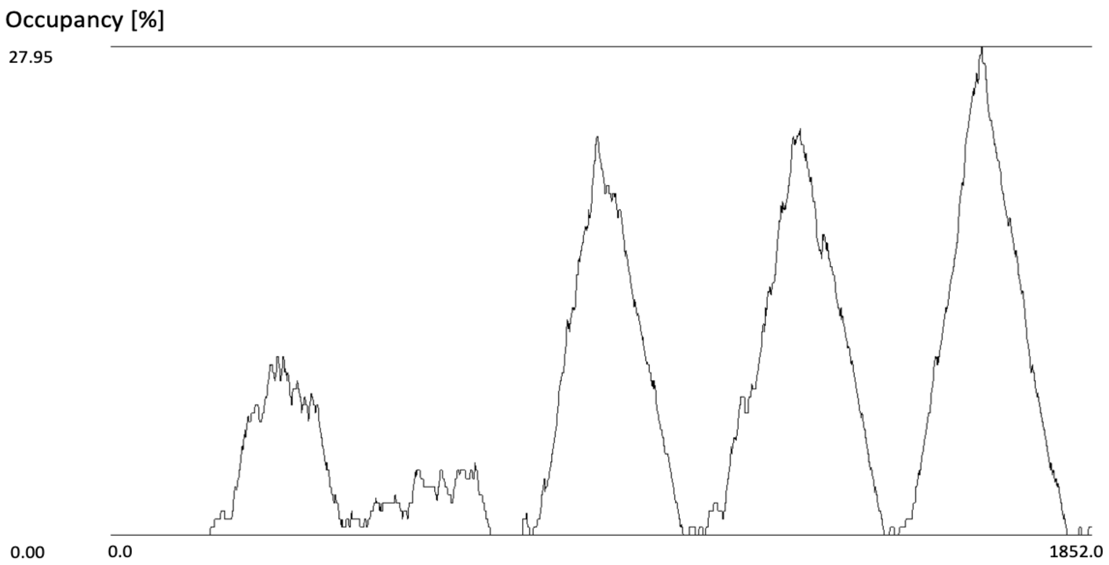
Routing: VSLC implementation (safety)



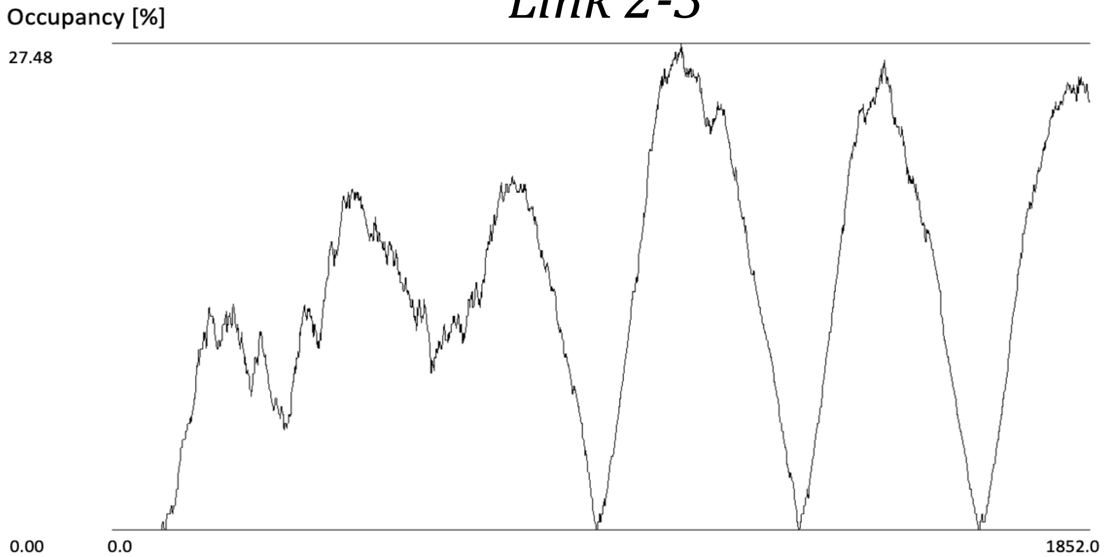
Routing

26.38%

73.62%



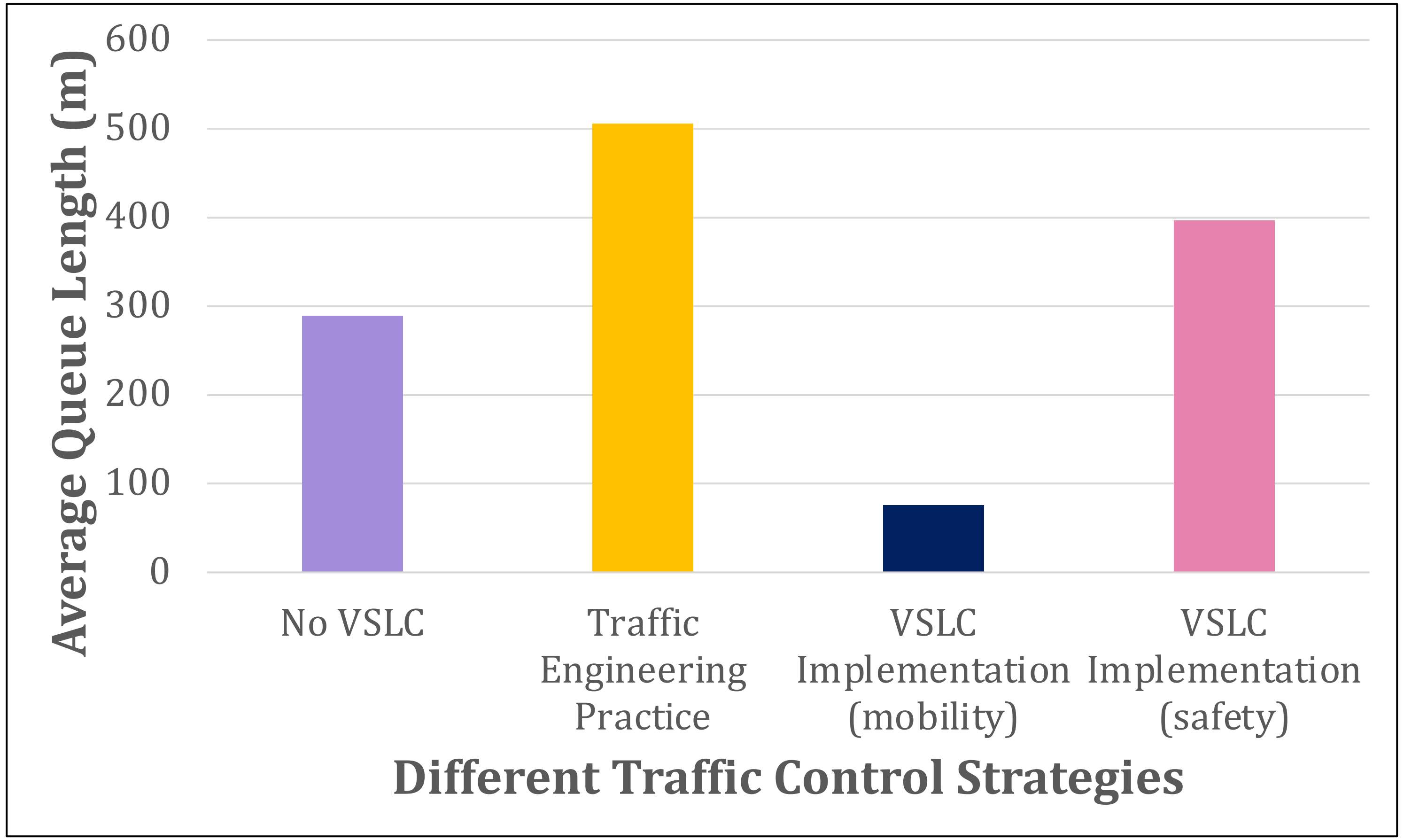
Link 2-3

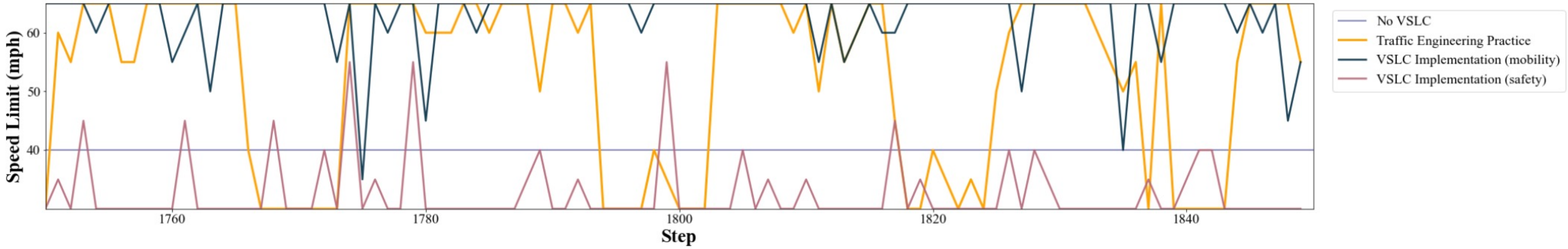


Link 2-4

Network Mobility

	Total travel time (sec)
No VSL	9.188e+07
Traffic engineering practice	1.534e+08
VSLC implementation (mobility)	6.576e+07
VSLC implementation (safety)	1.349e+08

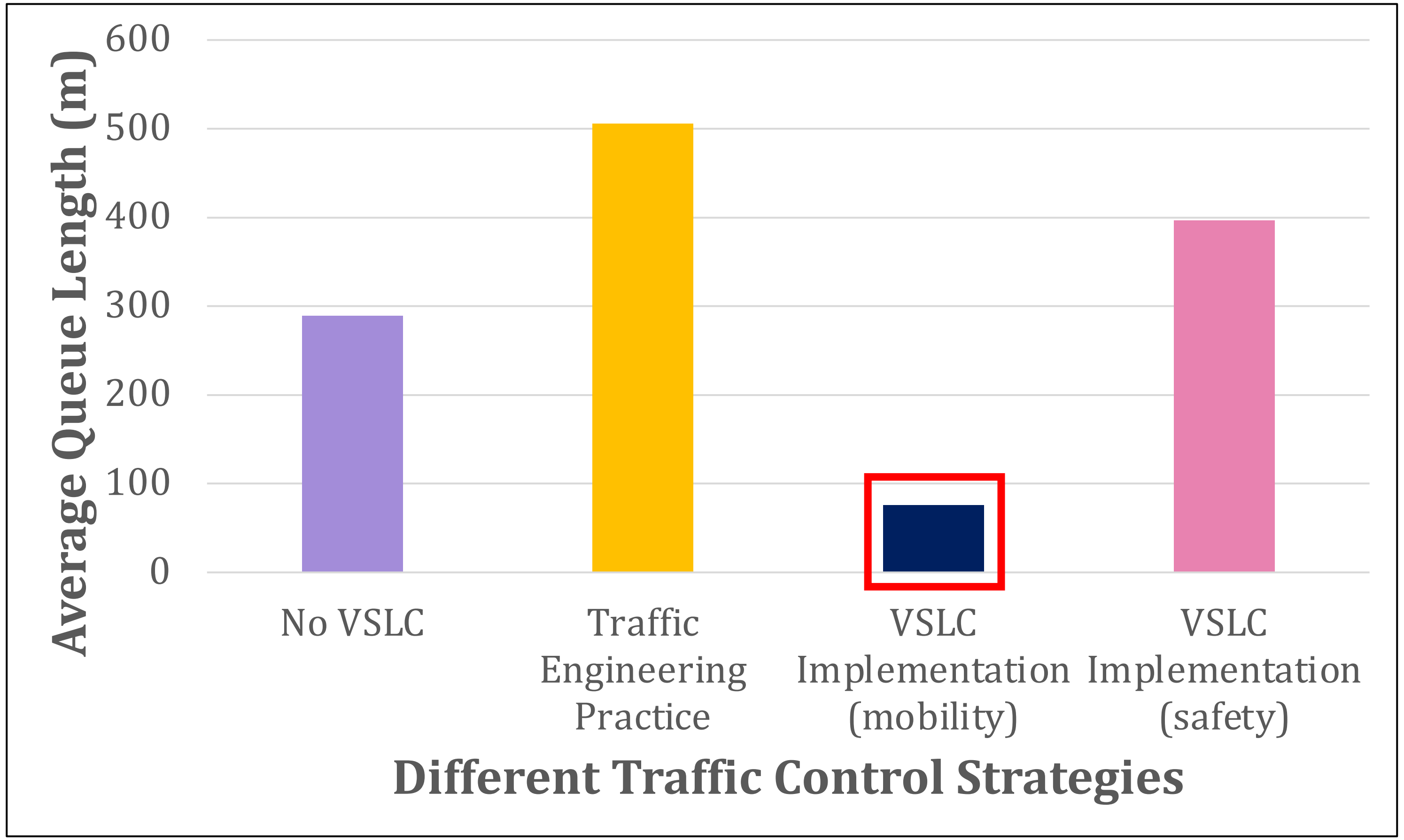


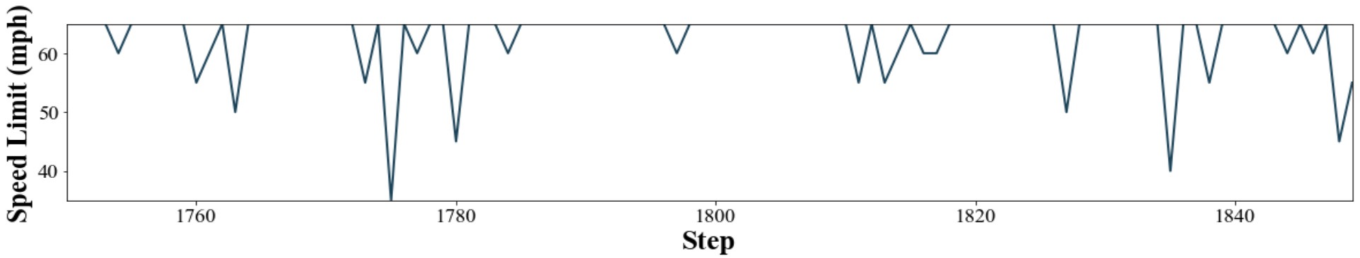


Network Mobility

	Total travel time (sec)
No VSL	9.188e+07
Traffic engineering practice	1.534e+08
VSLC implementation (mobility)	6.576e+07
VSLC implementation (safety)	1.349e+08

28.43% lower

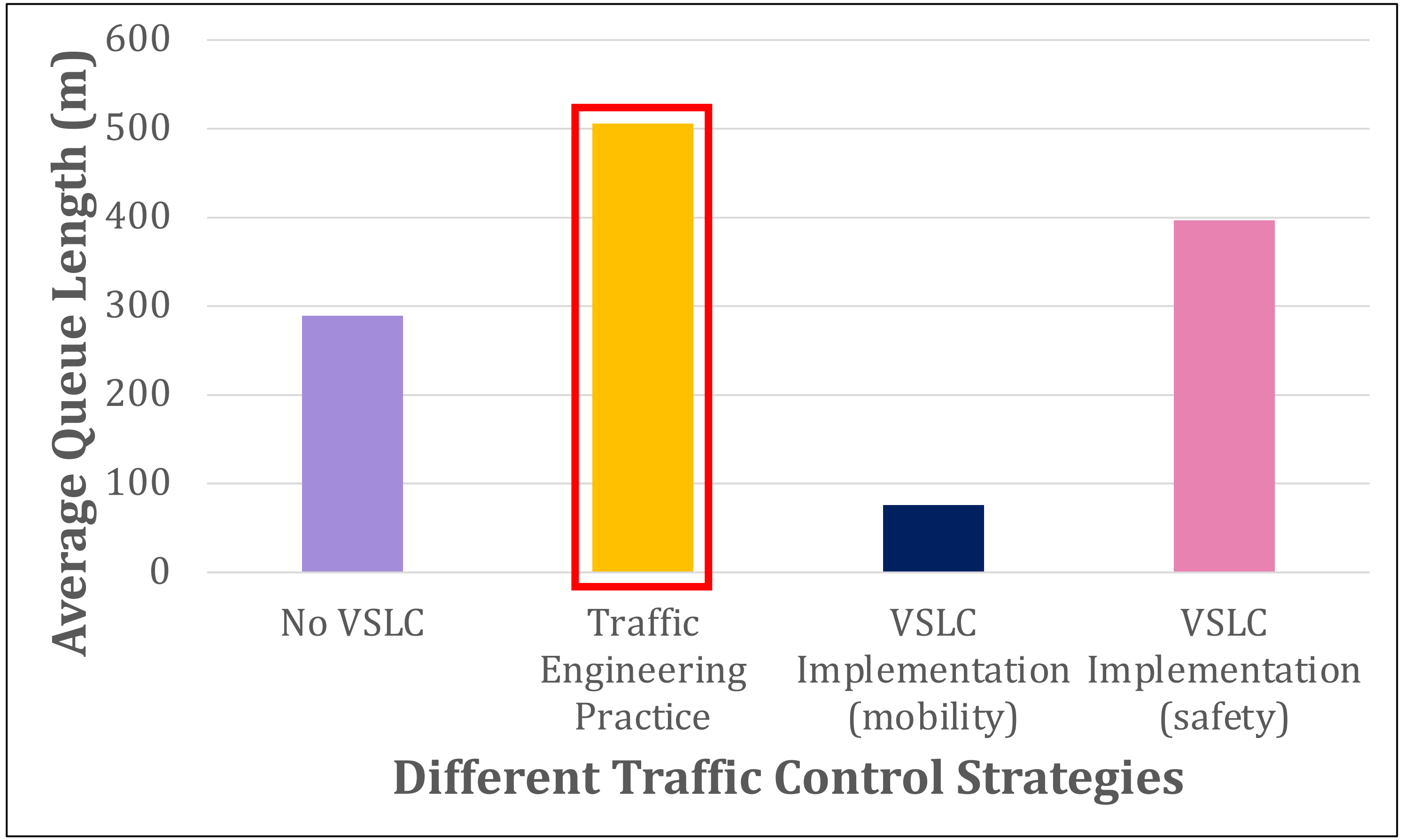


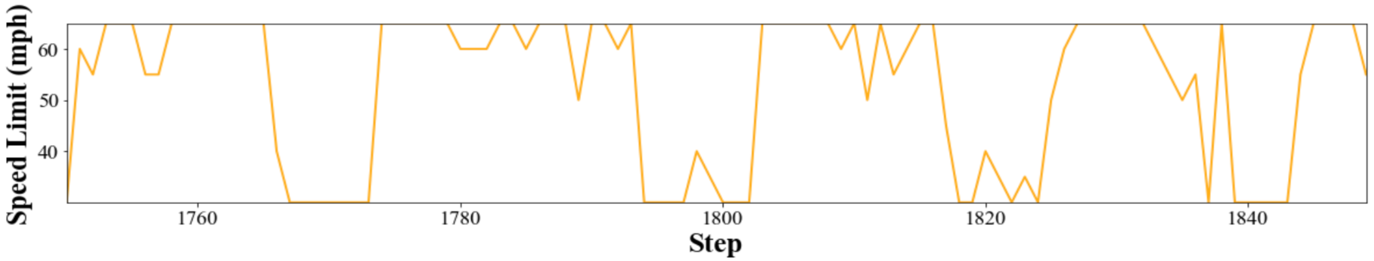


Network Mobility

	Total travel time (sec)
No VSL	9.188e+07
Traffic engineering practice	1.534e+08
VSLC implementation (mobility)	6.576e+07
VSLC implementation (safety)	1.349e+08

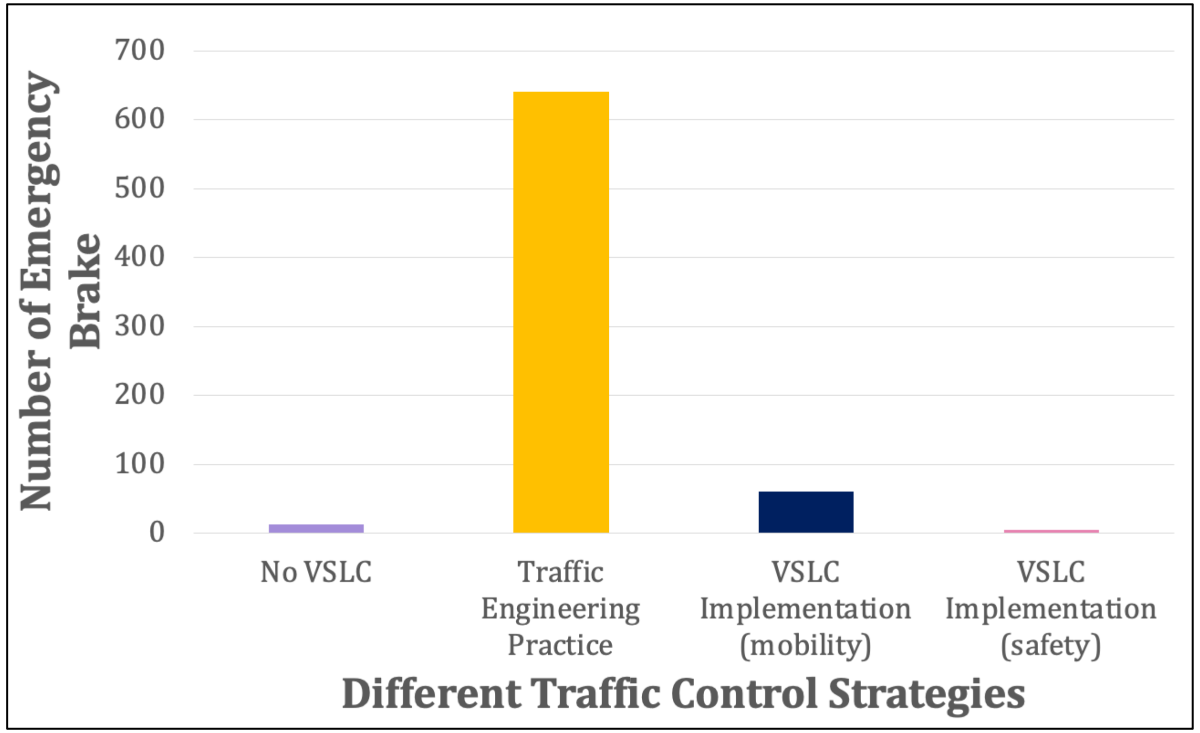
67% higher

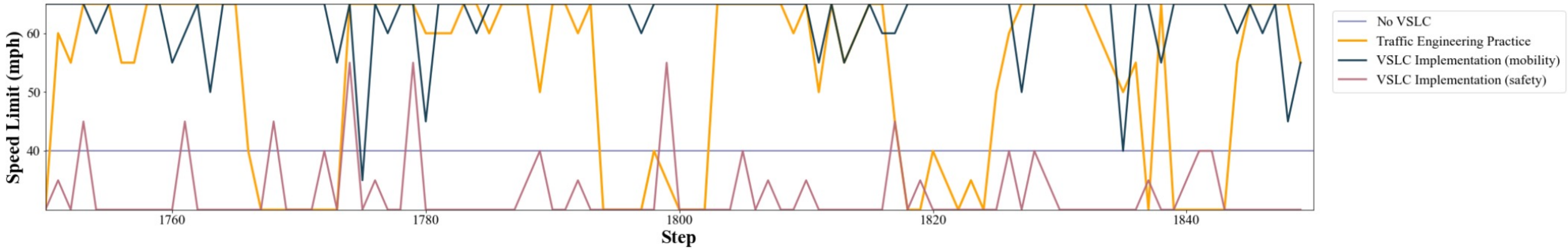




Network Safety

	Lane change frequency (%)	$\sum log(TTC)$	$log(TTC)$ due to lane change
No VSL	13.97	9.526e+05	6.27e+04
Traffic engineering practice	26.66	1.005e+06	9.81e+04
VSLC implementation (mobility)	10.13	9.149e+05	5.36e+04
VSLC implementation (safety)	14.25	1.002e+06	6.32e+04

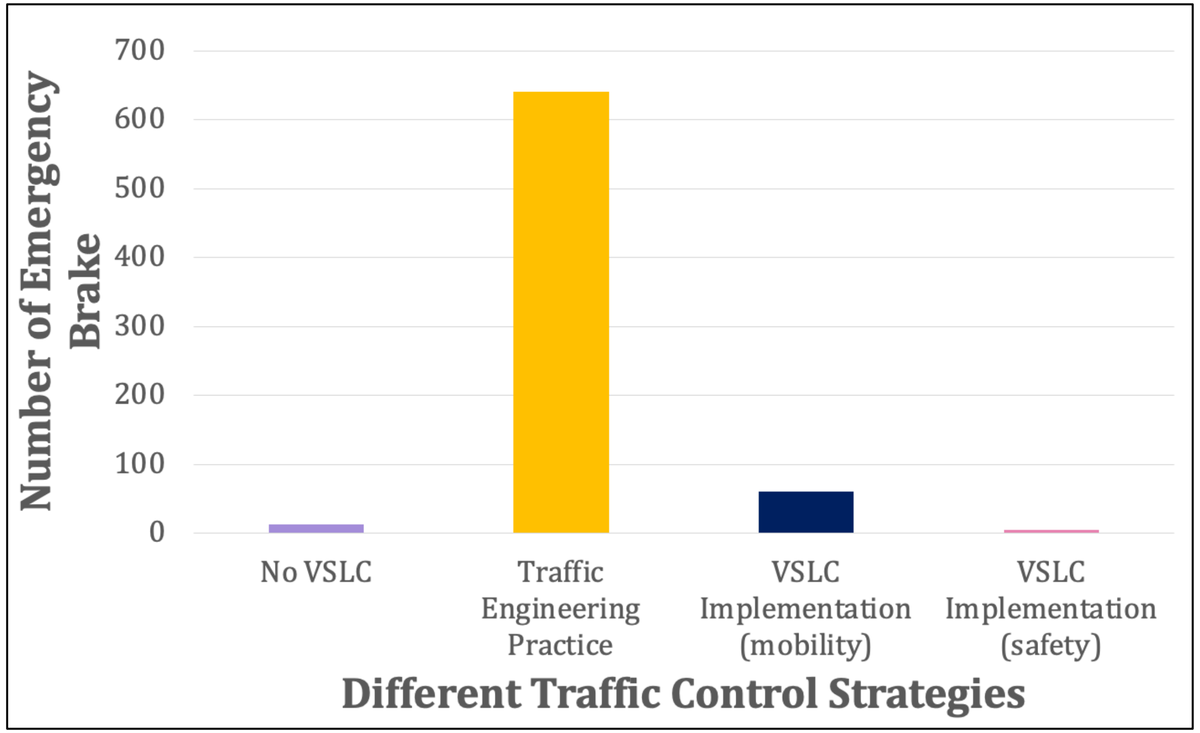


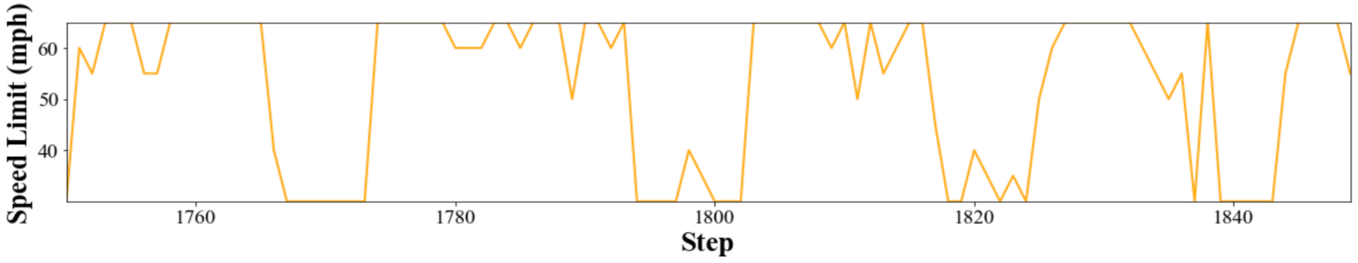


Network Safety

	Lane change frequency (%)	$\sum log(TTC)$	$log(TTC)$ due to lane change
No VSL	13.97	9.526e+05	6.27e+04
Traffic engineering practice	26.66	$\boxed{1.005e+06}$	9.81e+04
VSLC implementation (mobility)	10.13	9.149e+05	5.36e+04
VSLC implementation (safety)	14.25	1.002e+06	6.32e+04

5.5% higher





Network Safety

	Lane change frequency (%)	$\sum log(TTC)$	$log(TTC)$ due to lane change
No VSL	13.97	9.526e+05	6.27e+04
Traffic engineering practice	26.66	1.005e+06	9.81e+04
VSLC implementation (mobility)	10.13	9.149e+05	5.36e+04
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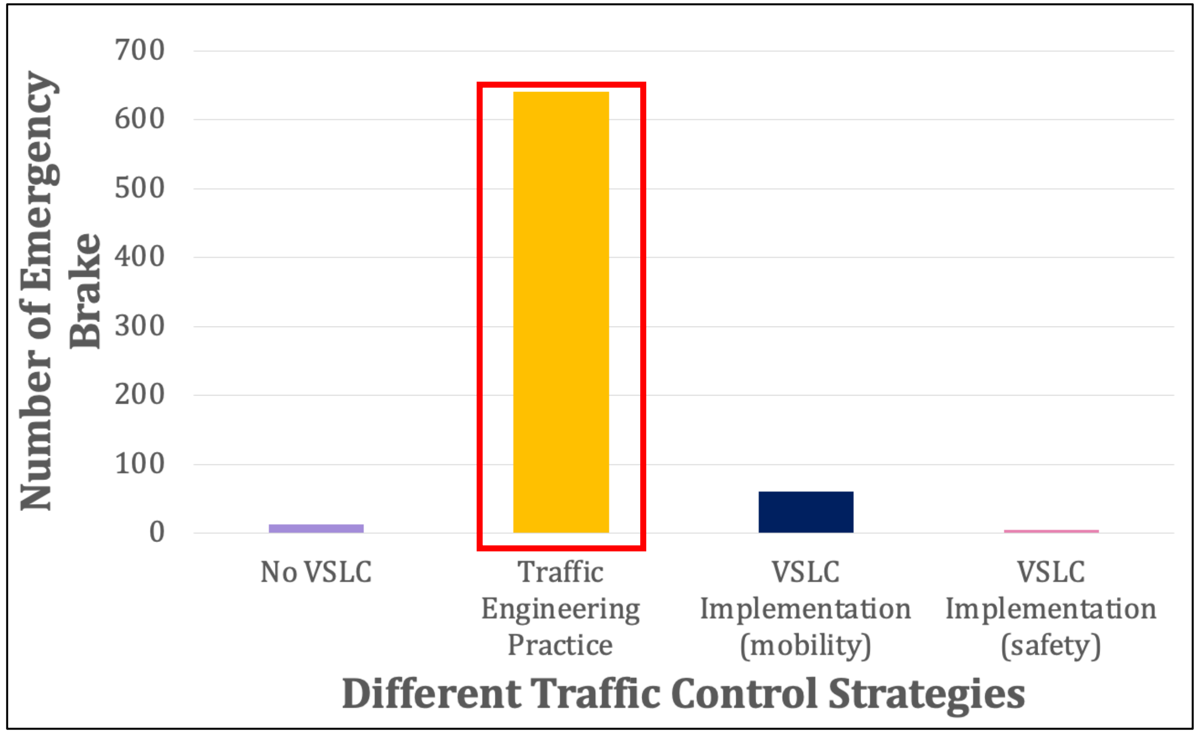
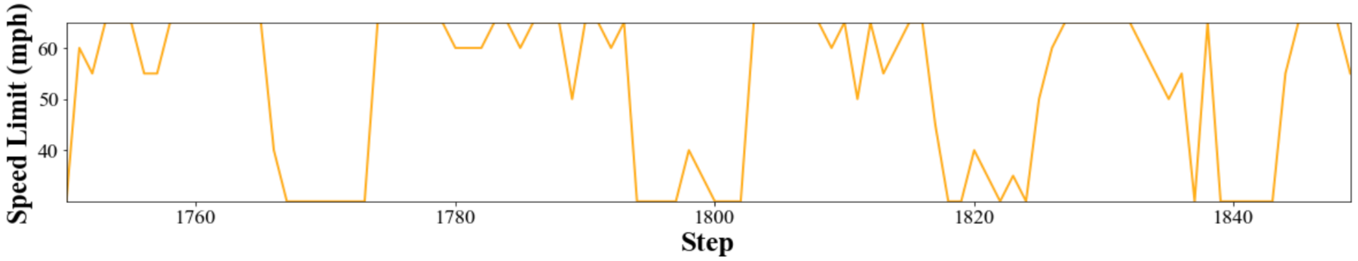
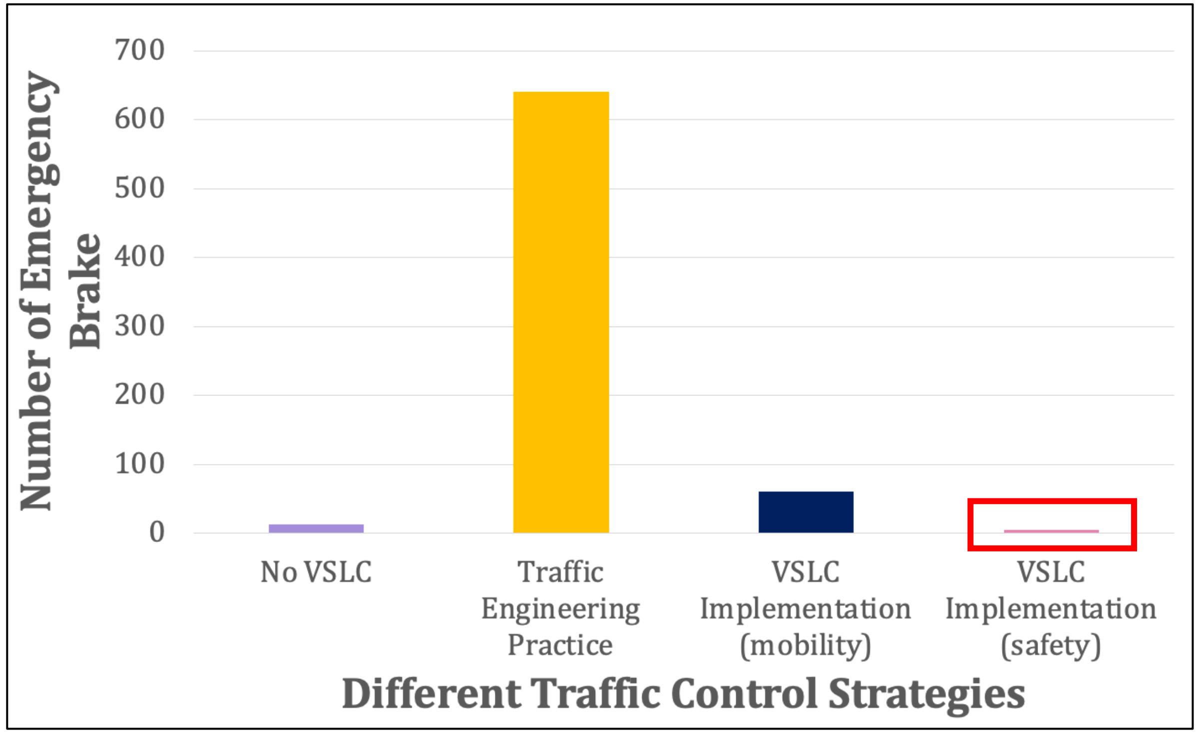


5.5% higher

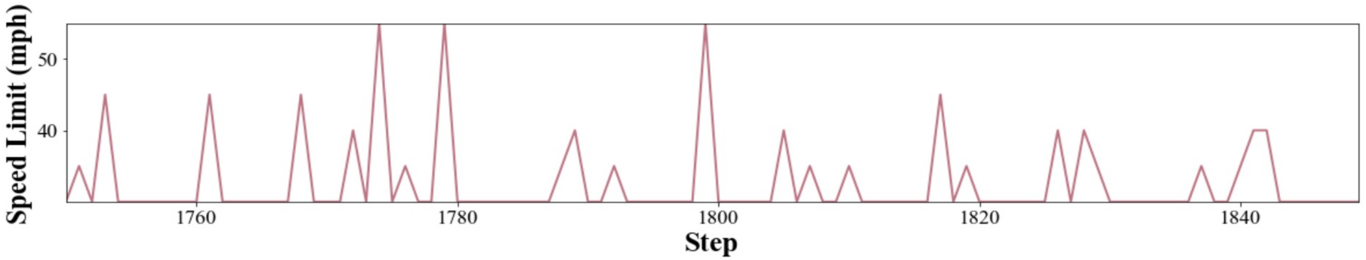


Network Safety

	Lane change frequency (%)	$\sum log(TTC)$	$log(TTC)$ due to lane change
No VSL	13.97	9.526e+05	6.27e+04
Traffic engineering practice	26.66	1.005e+06	9.81e+04
VSLC implementation (mobility)	10.13	9.149e+05	5.36e+04
VSLC implementation (safety)	14.25	1.002e+06	6.32e+04



5.18% higher

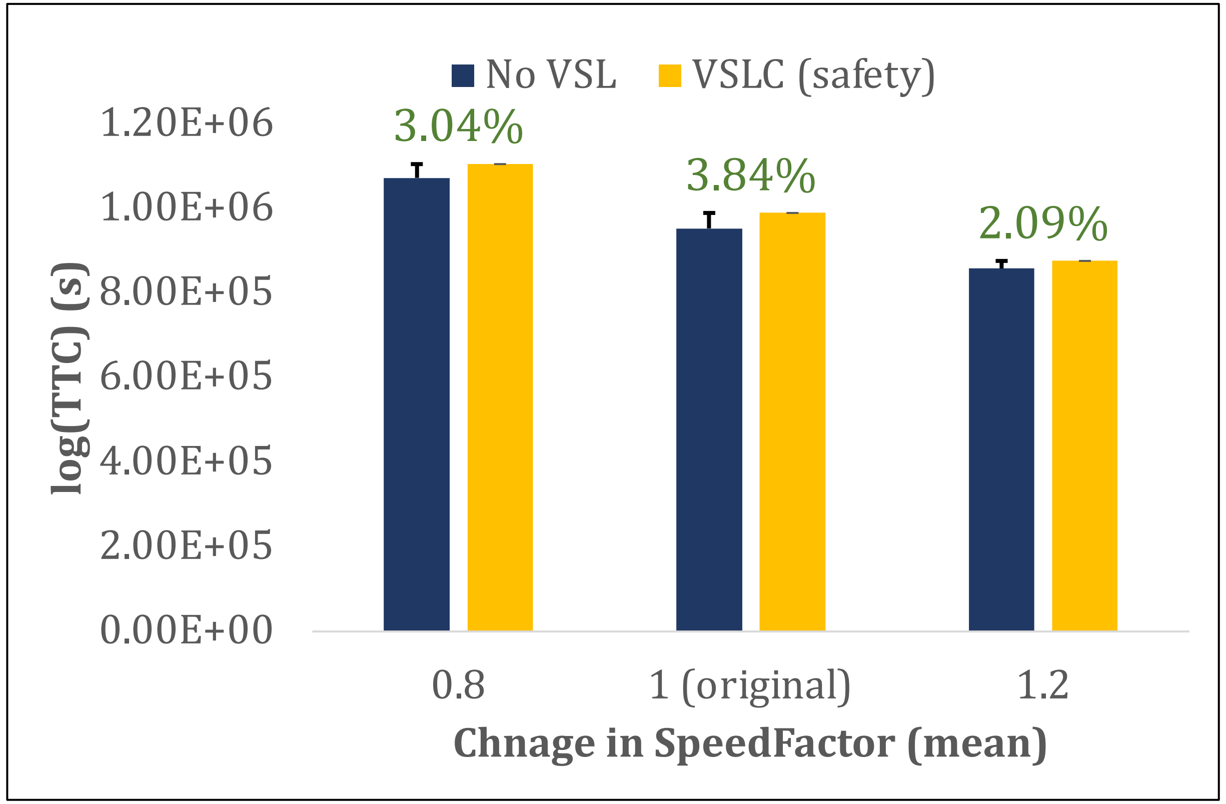


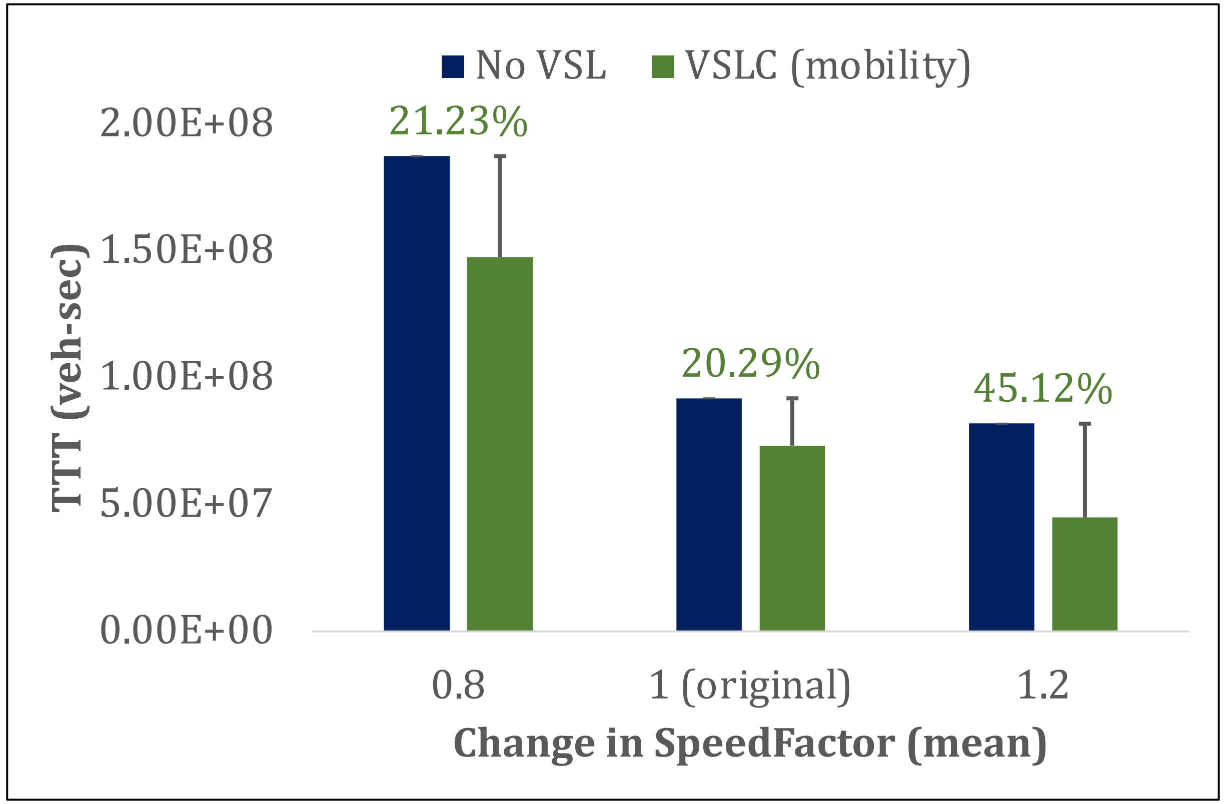
Assessment of Generalization of the Agent

Traffic & driving behavior attributes:

- O-D Demand
- “lcspeedGain”
- Mean values of “speedFactor”
- Deviation values of “speedFactor”

- **Mean**


No VSL
VSLC (safety)
1.20E+06
1.00E+06
8.00E+05
6.00E+05
4.00E+05
2.00E+05
0.00E+00
log(TTC) (s)
3.04%
3.84%
2.09%
0.8
1 (original)
1.2
Chnage in SpeedFactor (mean)


No VSL
VSLC (mobility)
2.00E+08
1.50E+08
1.00E+08
5.00E+07
0.00E+00
TTT (veh-sec)
21.23%
20.29%
45.12%
0.8
1 (original)
1.2
Change in SpeedFactor (mean)

Sensitivity of VSLC placement in the Network

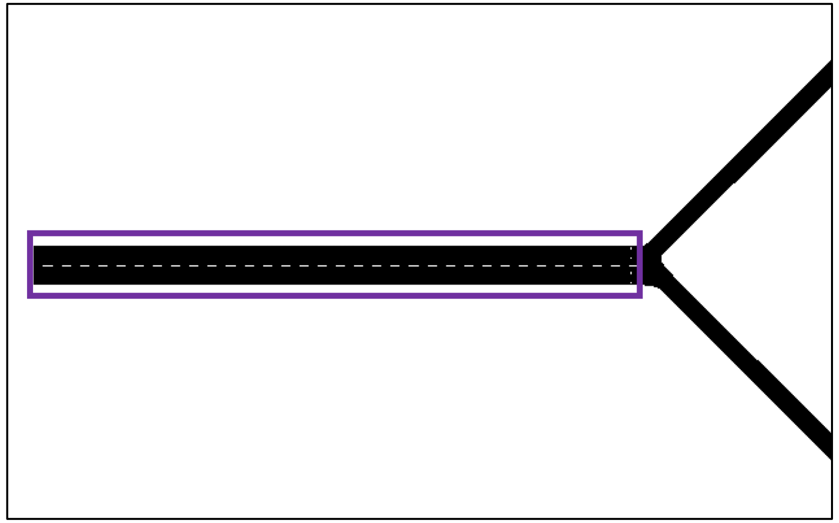


Figure: (a) One VSL in the Link 1-2

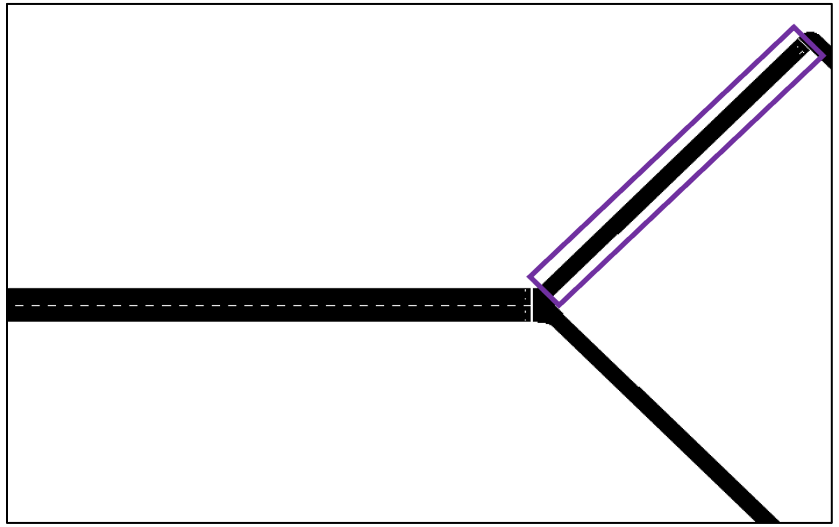


Figure: (b) One VSL in the Link 2-3

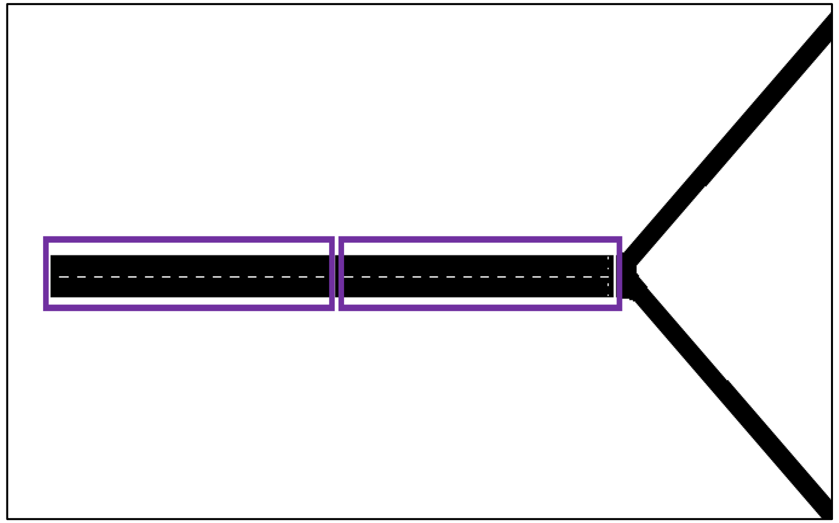


Figure: (c) Two VSLs in the Link 1-2

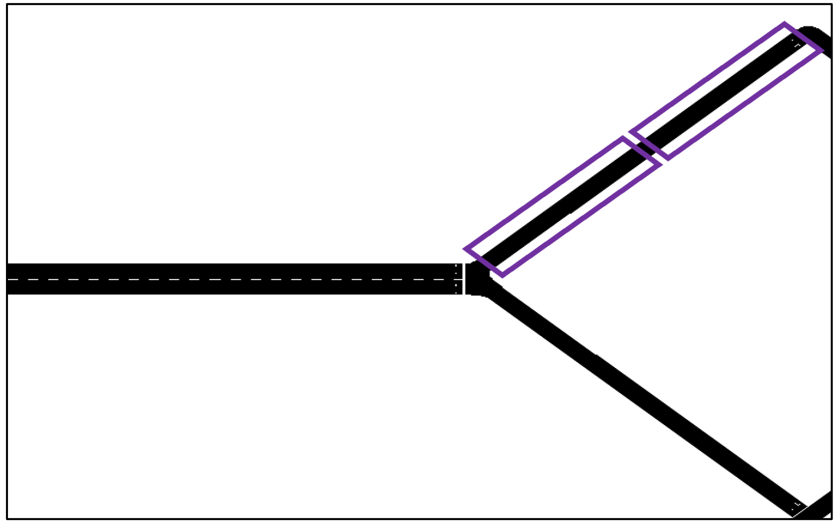
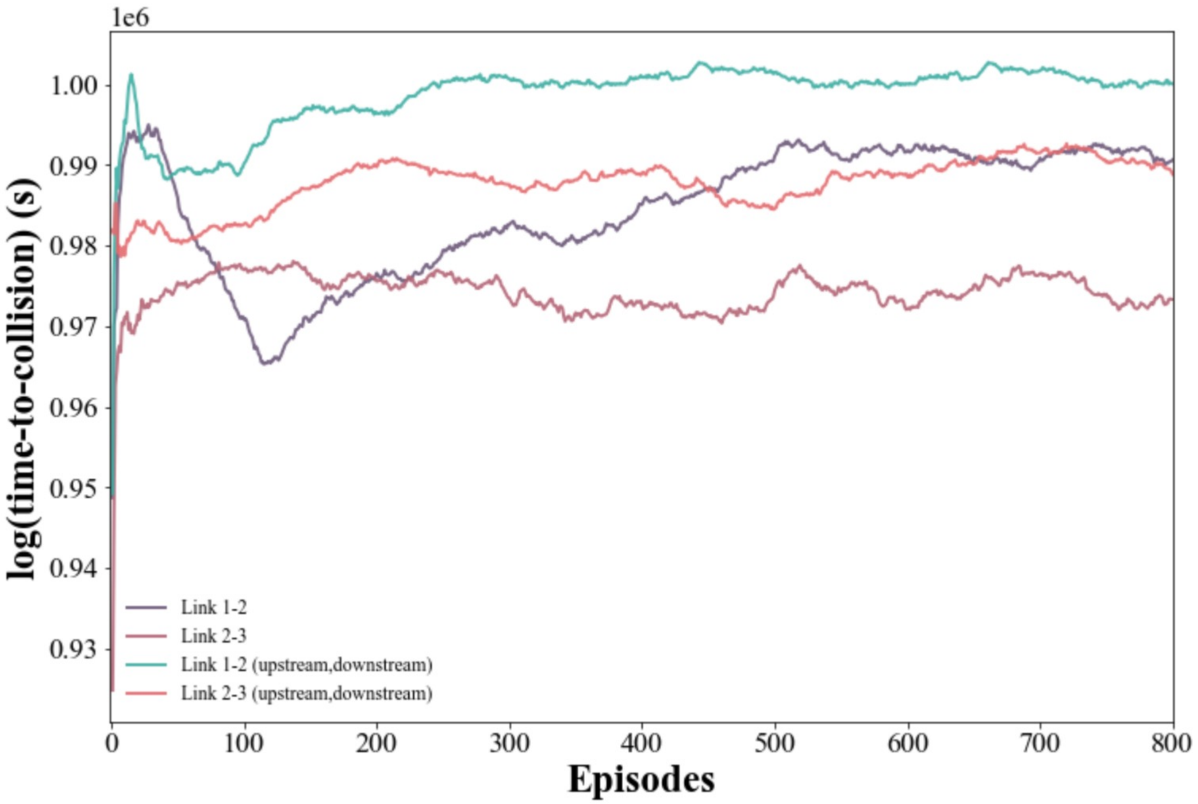


Figure: (c) Two VSLs in the Link 2-3

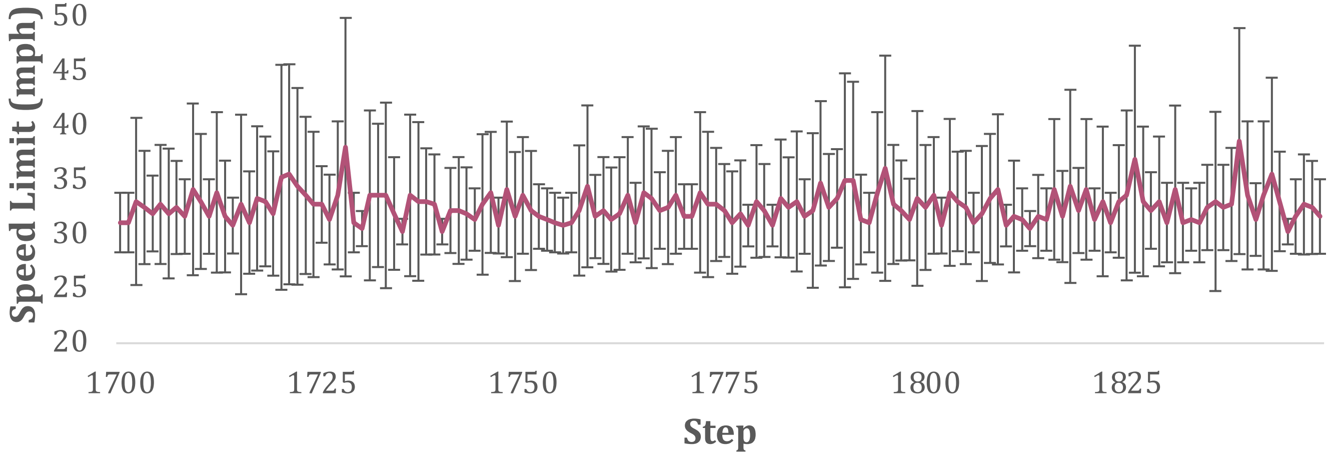
VSLC Placement for Safety Improvement

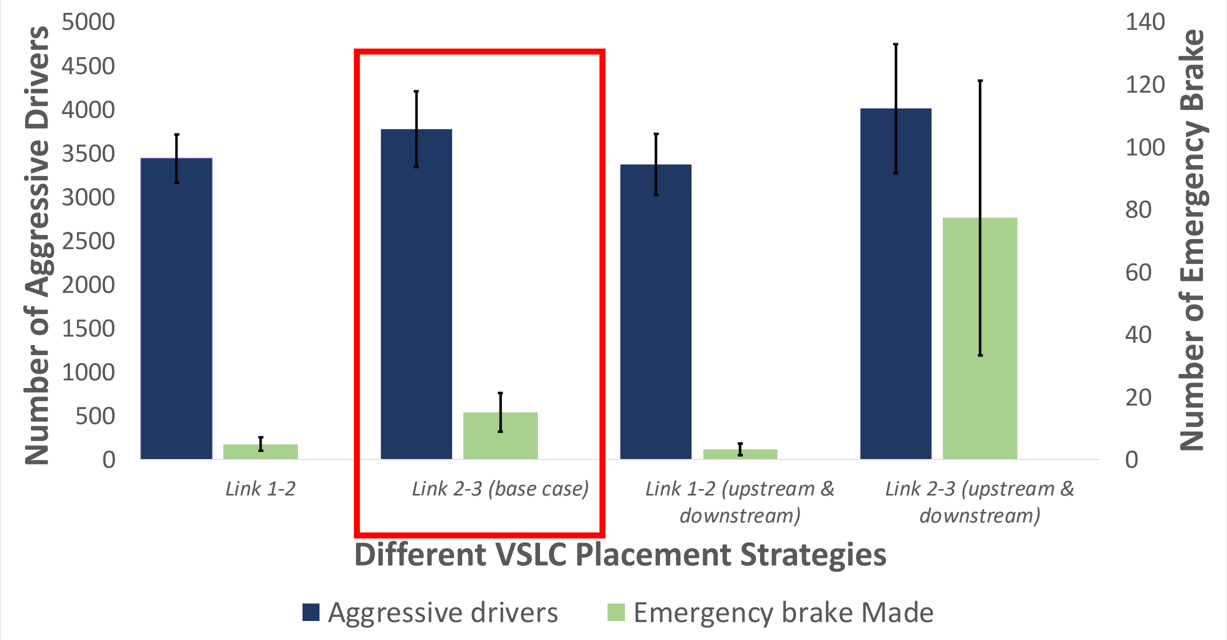


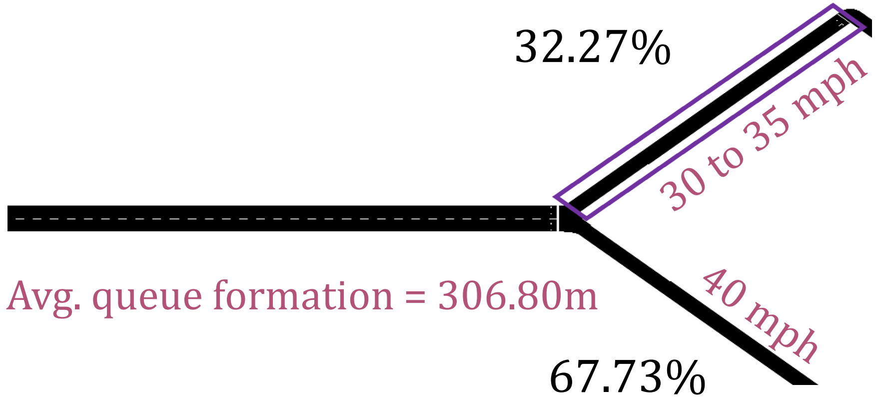
	Routing		Lane change frequency (%)	Network mobility		Network safety	
	Route 1 (%)	Route 2 (%)		Total Travel Time of all vehicles (sec)	Delay due to Lane change (sec)	$\sum \log(TTC)$	$\log(TTC)$ due to Lane change
Link 1-2	50.34 (2.97)	49.66 (2.97)	16.22 (2.43)	1.220e+08 (1.651e+07)	3.193e+05 (7.9723e+04)	9.936e+05 (2.1186e+04)	7.065e+04 (5.875e+03)
Link 2-3	32.27 (7.17)	67.73 (7.17)	13.20 (2.51)	8.778e+07 (1.7735e+07)	2.626e+05 (8.4913e+04)	9.799e+05 (1.5826e+04)	6.696e+04 (5.225e+03)
Link 1-2 (upstream, downstream)	49.77 (2.77)	50.23 (2.77)	16.92 (3.31)	9.774e+07 (1.6262e+07)	3.182e+05 (1.0164e+05)	9.952e+05 (2.5877e+04)	6.709e+04 (7.341e+03)
Link 2-3 (upstream, downstream)	43.99 (5.84)	56.01 (5.84)	19.26 (6.71)	1.228e+08 (3.2419e+07)	3.585e+05 (1.6093e+05)	9.891e+05 (3.3130e+04)	8.455e+04 (1.8834e+04)

VSLC Placement for Safety Improvement

- **Base case**







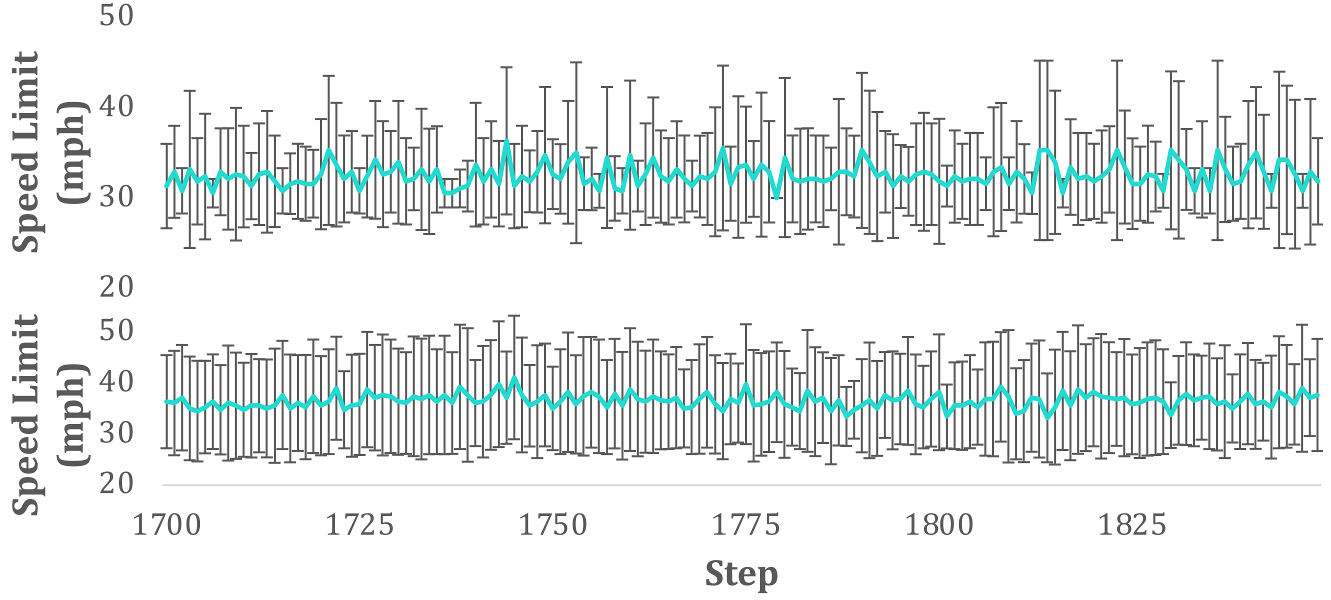
Avg. queue formation = 306.80m

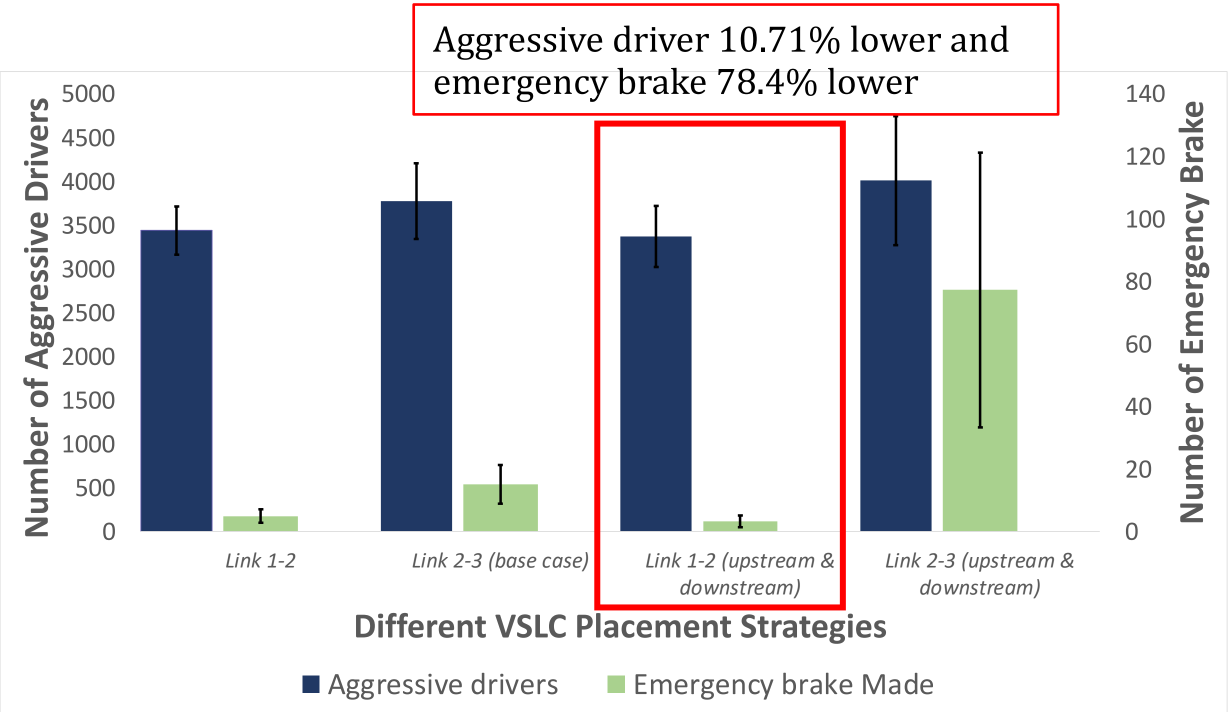
	Lane change frequency (%)	$\boldsymbol{log}(\boldsymbol{TTC})$ due to lane change	$\sum \boldsymbol{log}(\boldsymbol{TTC})$
Link 2-3 (base case)	13.20	6.696e+04	9.799e+05

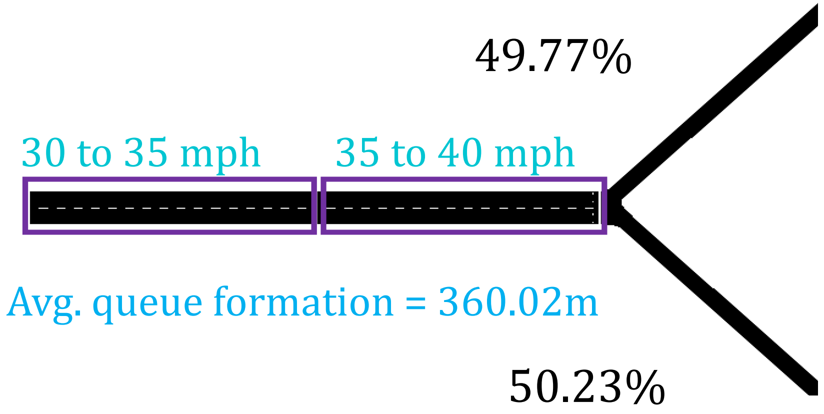
Avg. value shown for queue, routing & the Table

VSLC Placement for Safety Improvement

- **VSLC in the upstream & downstream of Link 1-2**







	Lane change frequency (%)	$log(TTC)$ due to lane change	$\sum log(TTC)$	
Link 2-3 (base case)	13.20	6.696e+04	9.799e+05	
Link 1-2 (upstream & downstream)	16.92	6.709e+04	9.952e+05	**1.56%**

Avg. value shown for queue, routing & the Table

Discussion

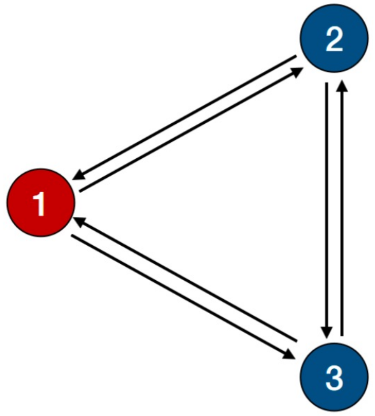
- We proposed a DRL model for optimal control of VSLCs to improve network mobility and safety considering rerouting behavior of vehicles.
- We demonstrated the generalizability of the control algorithm across different traffic and driving behavior attributes as well as the performance of the proposed model compared with state-of-the-art DRL models.
- We assessed the efficacy of various traffic control algorithms and analyze the spatial distribution of VSLC implementations, with a focus on improving overall network mobility and safety.
- Future studies: Implementation on a large-scale network for traffic mobility and safety improvement

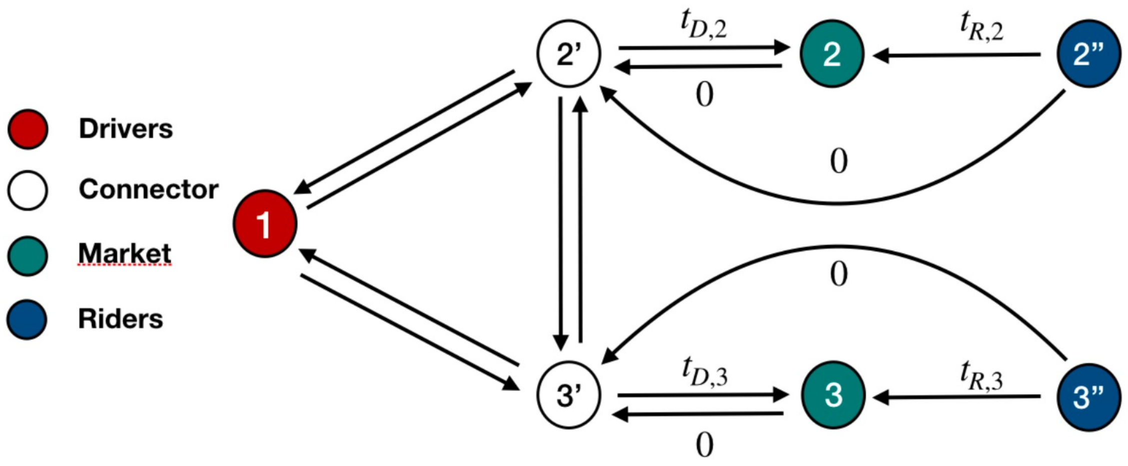
Chapter 4: Spatial pricing of ride-sourcing services in a congested transportation network

Afifah, F., & Guo, Z. (2022). Spatial pricing of ride-sourcing services in a congested transportation network. *Transportation Research Part C: Emerging Technologies*, *142*, 103777.

Problem Statement

- In ride-sourcing services, transportation network companies (TNCs) provides pricing information to riders and drivers.
- **Motivation**
  - The impact of pricing information by TNC on relocation of drivers, riders’ mode choice and traffic congestion has not been fully explored.





Problem Statement

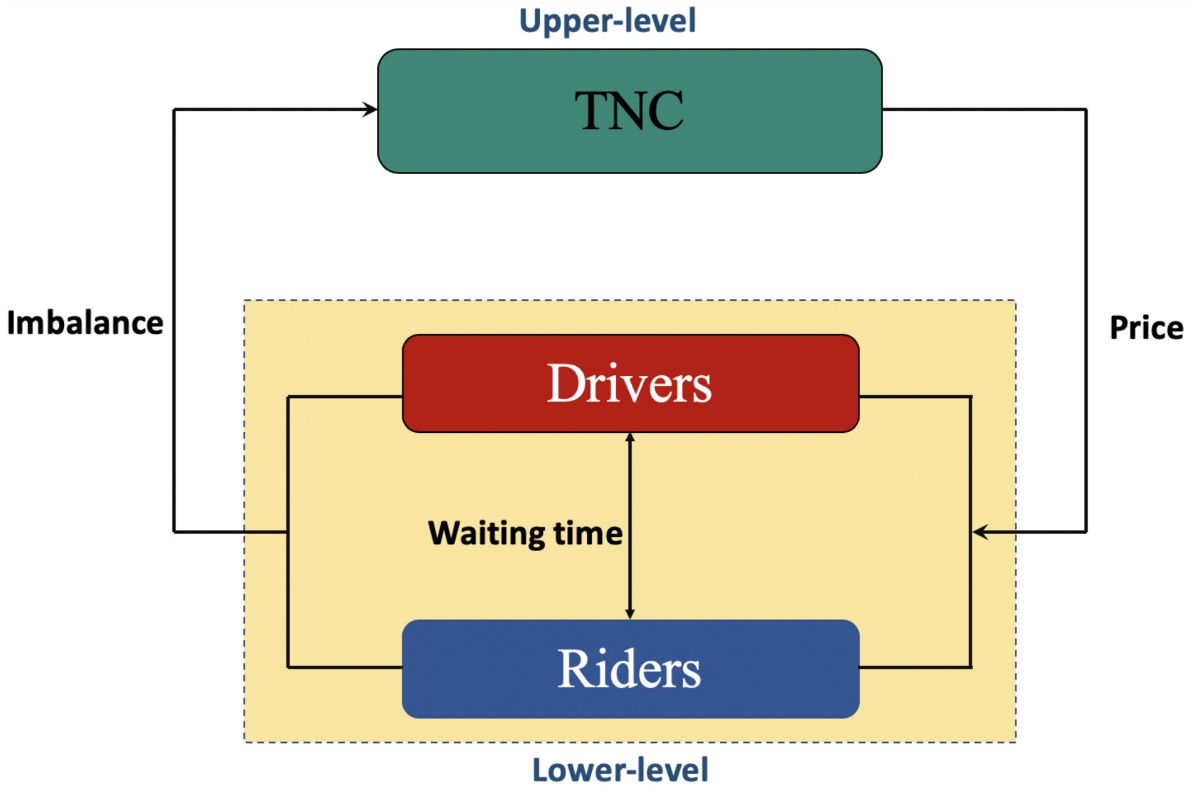
- **Research Gap**
  - **Research on the potential value of dynamic pricing** [31,32,33]. Most of these studies focus on temporal aspects and do not consider traffic equilibrium and transportation congestion.
  - **Research on congestion effect**.
    - Vignon et al. [34]: The impact of both solo and pooling ride-sourcing services on traffic congestion. Nevertheless, it does not address the impact of spatial/dynamic pricing on congested network conditions.
    - Li et al. [35]: The optimal spatial pricing to maximize profits under different congestion pricing policies. However, the model is non-convex and the global optimal is not guaranteed.
- **Objective of the study**
  - Develop a modeling framework that captures the ride-sourcing behaviors more accurately to systematic analyze the impacts of spatial pricing on transportation efficiency.
  - Develop a scalable solution approach to address the computational challenges posed by the bi-level nature of the problem.

Key Assumptions

- Only one TNC serves in the study area
- The travel demand not requesting TNC services shifts to car driving
- Waiting time = Matching time + Pick-up time

Modeling Strategies

- Bi-level Optimization
  - Lower-level problem: capture the interactions between drivers' relocation, riders' mode choice, and all travelers' routing decisions.
  - Upper-level problem: a TNC determines spatial pricing strategies to fulfill its own objective in a two-sided markets.



Modeling Strategies

Rider's demand $d_s = D_s - b_s \rho_s$ (2)

Driver's utility function $U_{rs} = \beta_{0,s} - \beta_1 t_{rs} + \beta_2 \rho_s$ (3)

- D_s, b_s : Coefficient of demand function
- ρ_s : Locational price at s
- β : Utility function parameter

Lower-level

Modeling Strategies

Rider's demand $d_s = D_s - b_s\rho_s$ 2

Driver's utility function $U_{rs} = \beta_{0,s} - \beta_1 t_{rs} + \beta_2 \rho_s$ 3

- D_s, b_s : Coefficient of demand function
- ρ_s : Locational price at s
- β : Utility function parameter

Driver-rider interaction: Combined Distribution and Assignment (CDA) 4a

$$\underset{\check{v},\, \hat{v},\, q \in \mathbb{R}_+}{\text{Minimize}} \sum_{a \in A} \int_0^{v_a} \underbrace{\boxed{t_a(v_a)\, dv}}_{\text{Wardrop User Equilibrium}} + \frac{1}{\beta_1} \sum_{r \in \mathcal{R}} \sum_{s \in \mathcal{S}} \underbrace{\boxed{q_{rs}\,(\ln q_{rs}}}_{\text{Entropy of trip distribution}} - \underbrace{\boxed{1 - \beta_2\rho_s - \beta_{0,s})}}_{\text{Logit choice model}}$$

Traffic flow conservation constraints 4b

Lower-level

Modeling Strategies

TNC decision making behavior

$$\underset{\rho\,\epsilon\,\mathbb{R}^S}{\text{minimize}} \sum_{s\,\in\,\mathcal{S}} \boxed{m_s} \rightarrow \text{Total imbalance} \quad (1a)$$

$$m_s = \left| \underbrace{\boxed{\textstyle\sum_{r\,\in\,\mathcal{R}} q_{rs}}}_{\text{Driver Supply}} - \underbrace{\boxed{(D_s - b_s\rho_s)}}_{\text{Rider Demand}} \right| \;\forall\, S \quad (1b)$$

4 → CDA model: driver relocation and route choices constraints (1c)

→ Constraints

Upper-level

Rider's demand $d_s = D_s - b_s\rho_s$ (2)

Driver's utility function $U_{rs} = \beta_{0,s} - \beta_1 t_{rs} + \beta_2\rho_s$ (3)

- D_s, b_s : Coefficient of demand function
- ρ_s : Locational price at s
- β : Utility function parameter

Driver-rider interaction: Combined Distribution and Assignment (CDA) (4a)

$$\underset{\check{v},\,\hat{v},\,q\in\,\mathbb{R}_+}{\text{Minimize}} \sum_{a\,\in A} \int_0^{v_a} \underbrace{\boxed{t_a(v_a)\,dv}}_{\text{Wardrop User Equilibrium}} + \frac{1}{\beta_1} \sum_{r\,\in\,\mathcal{R}} \sum_{s\,\in\,\mathcal{S}} \underbrace{\boxed{q_{rs}\,(\ln q_{rs}}}_{\text{Entropy of trip distribution}} - \underbrace{\boxed{1 - \beta_2\rho_s - \beta_{0,s})}}_{\text{Logit choice model}}$$

Traffic flow conservation constraints (4b)

Lower-level

Solution Approach

Lemma (Balancing ride supply and demand)

ρ^* optimizes problem (1) if and only if ride supply and demand are balanced at each location given ρ^*. In addition, ρ^* is unique.

Decision making of TNC can be reformulated as

$$\sum_{r \in \mathcal{R}} q_{rs}^*(\rho) = d_s^*(\rho), \forall s \in \mathcal{S} \qquad (5)$$

where $q_{rs}^*(\rho) \in_{\boldsymbol{q}} (4)$, and $d_s^*(\rho) = D_s - b_s \rho_s$

Single-level Convex Reformulation

Theorem (Single-level convex reformulation)

ρ solves bi-level problem (1) if and only if ρ solve single-level problem (6) .

$$\min_{\hat{\boldsymbol{v}},\check{\boldsymbol{v}},\boldsymbol{q},d\in_{+}} \quad \frac{\beta_1}{\beta_2}\sum_{a\in\mathcal{A}}\int_0^{v_a} t_a(\mathrm{v_a})\mathrm{d}u + \frac{1}{\beta_2}\sum_{r\in\mathcal{R}}\sum_{s\in\mathcal{S}} q_{rs}(\ln q_{rs} - 1 - \beta_{0,s}) \ldots \tag{6a}$$

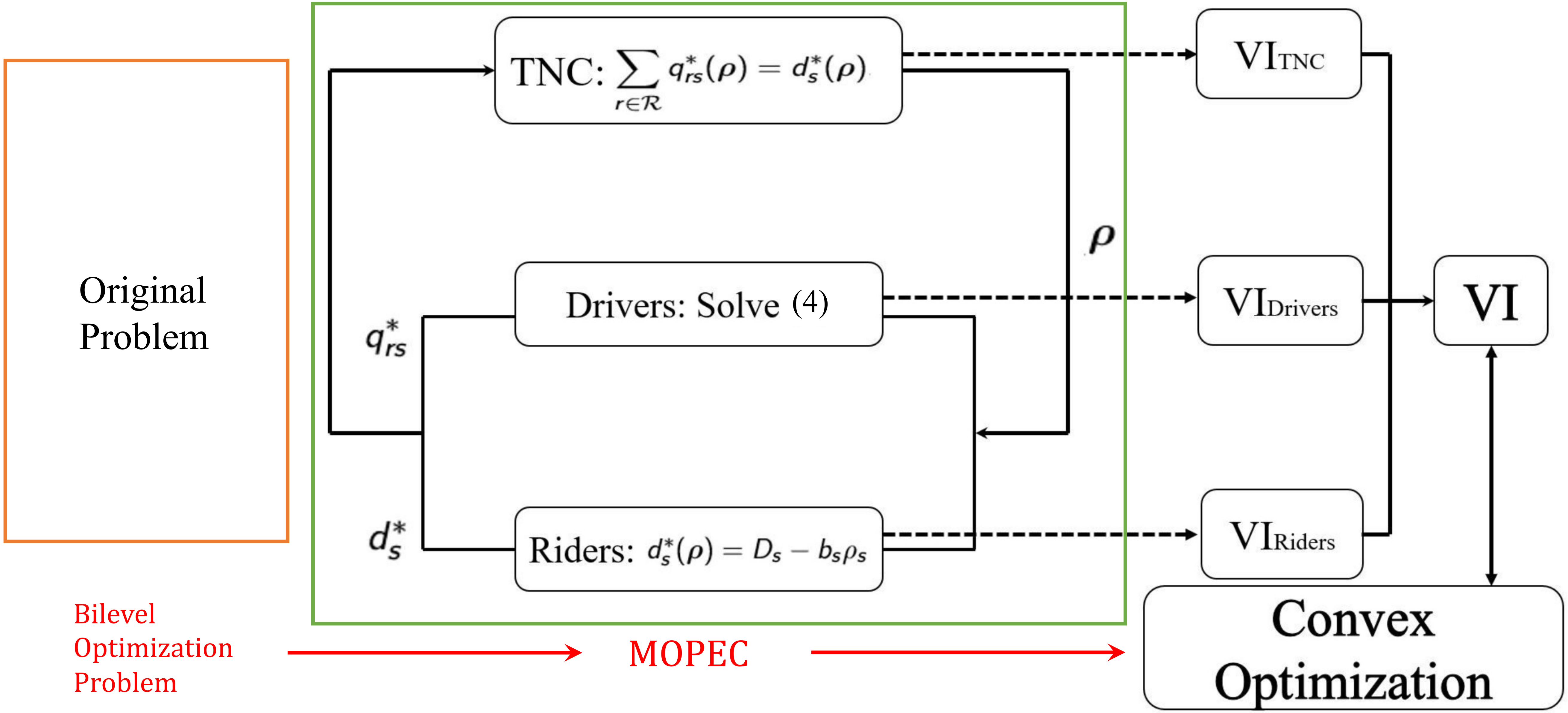
$$\ldots + \sum_{s\in\mathcal{S}} \frac{1}{b_s}\left(\frac{d_s^2}{2} - D_s d_s\right) \tag{6b}$$

subject to

(4b)

$$(\rho_s) \qquad \sum_{r\in\mathcal{R}} q_{rs} = d_s, \forall s \tag{6c}$$

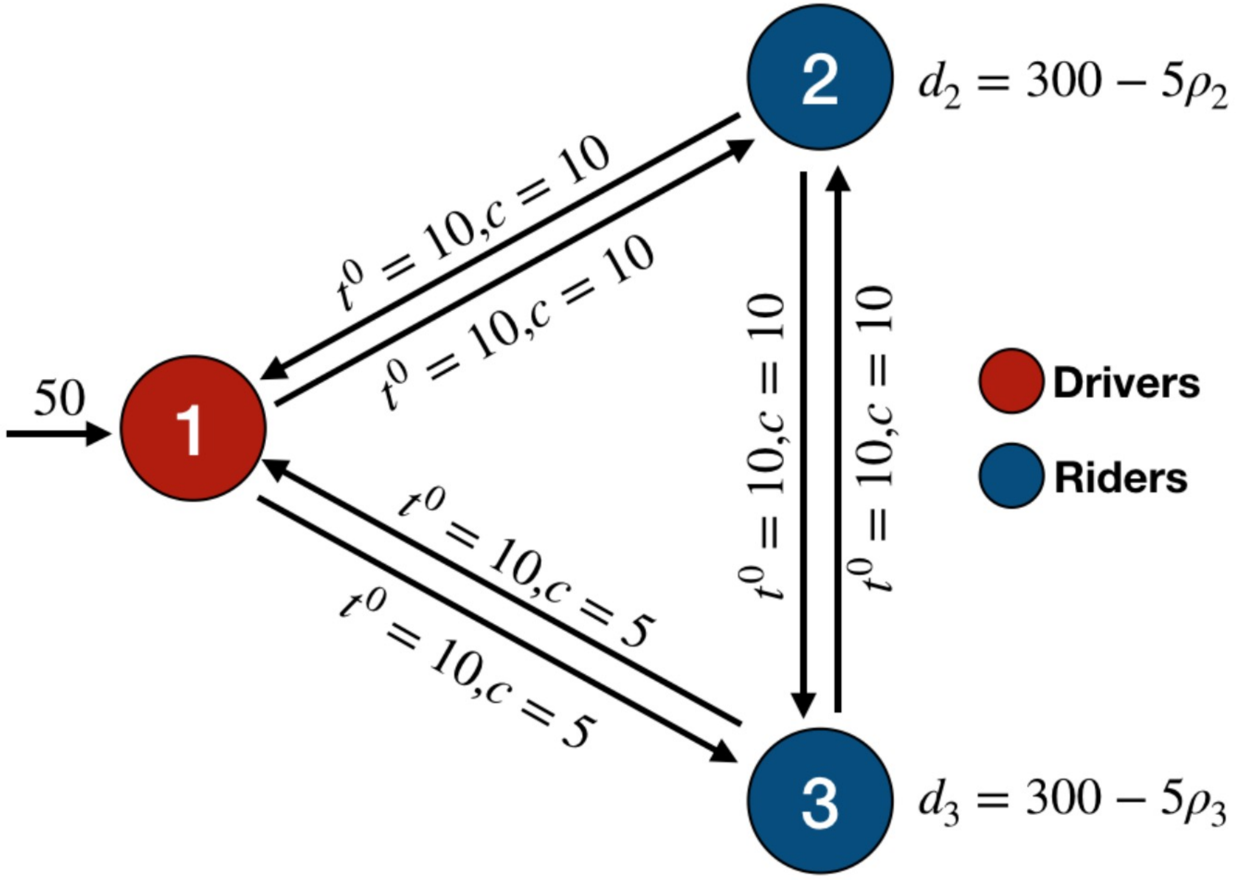
Reformulation Strategies



Test Network - Three-nodes Example

- 3 nodes, 6 links
- Lower capacity between node 1 and 3
- Demand function $d_s = 300 - 5\rho_s$
- Link travel time

$$t_a = t_a^0[1 + 0.15 * {}^{v_a}/{c_a}^{2})$$



Results - Equilibrium Prices and Total Travel Time

Figure: (a) Spatial Pricing

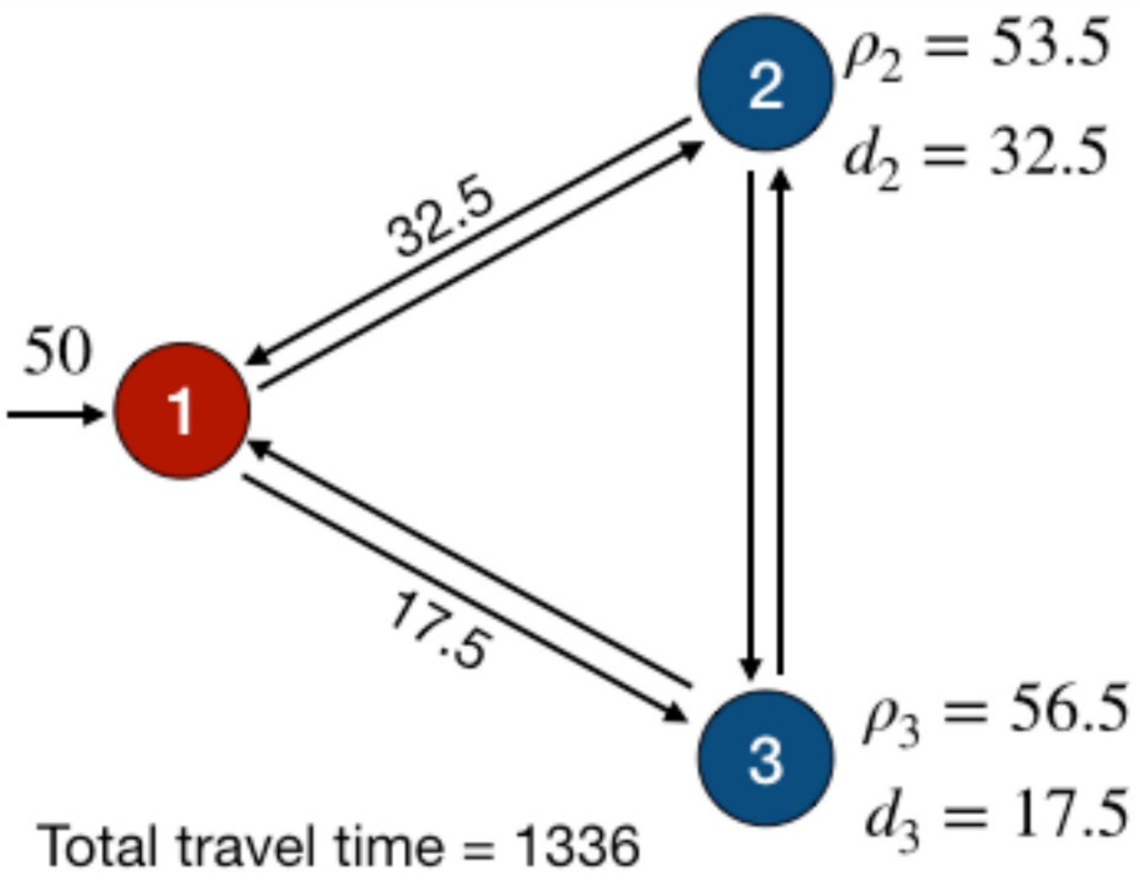
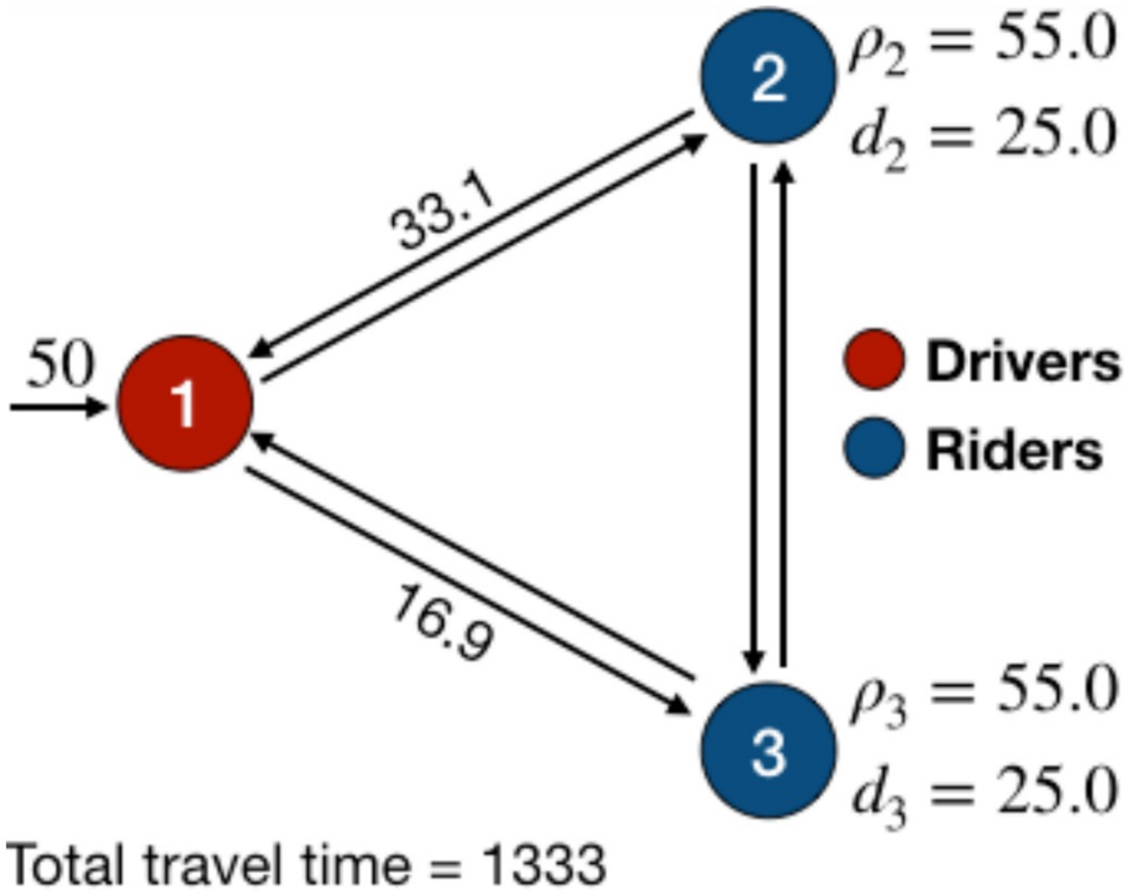


Figure: (b) Uniform Pricing



Discussion

- Modeling: formulated a new modeling framework for ride-sourcing spatial pricing problems, considering leader-follower structure of TNCs, riders, and drivers, and transportation network.
- Computation: under mild assumptions, the problem can be reformulated as a convex optimization problem, which can be efficiently solved by commercial nonlinear solver, such as IPOPT.
- Existence and uniqueness of optimal solutions are proved.
- Potential extension: temporal aspects? multiple TNCs?

Chapter 5: Conclusions

Contributions

In Chapter 2 we proposed a two-stage stochastic traffic equilibrium model that captures adaptive routing behavior with locational en-route traffic information from I2V technologies. The model is formulated as a convex stochastic optimization problem, allowing for efficient scalability through the use of stochastic programming algorithms.

In Chapter 3, we proposed a twin-delay deep deterministic policy gradient model that allows for the effective control of VSLCs in a network, taking into account the rerouting behavior of vehicles.

In Chapter 4, we proposed a Stackelberg framework for spatial pricing of ride-sourcing services considering traffic congestion with convex reformulation.

Future Research Directions

- Obtaining reliable information
  - Multi-source information
  - Cybersecurity
  - Privacy-preserving
- Understanding equity impact
- Multi-modal information sharing

Journals and Conference

- Journal Publications
  - **Afifah, F.**, Guo, Z. (2022). Spatial pricing of ride-sourcing services in a congested transportation network. Transportation Research Part C: Emerging Technologies, 142, 103777.
  - **Afifah, F.**, Guo, Z., Abdel-Aty, M., 2023. System-level impacts of en-route information sharing considering adaptive routing. Transportation Research Part C: Emerging Technologies 149,104075.
  - Guo, Z., **Afifah, F.**, Qi, J., Baghali, S. (2021). A Stochastic Multiagent Optimization Framework for Interdependent Transportation and Power System Analyses. IEEE Transactions on Transportation Electrification, 7(3), 1088-1098.
  - Siddique, C., **Afifah, F.**, Guo, Z., Zhou, Y. (2022). Data mining of plug-in electric vehicles charging behavior using supply-side data. Energy Policy, 161, 112710.
- Conference
  - **Afifah, F.**, Guo, Z. Spatial Pricing of Ride-sourcing Services in Congested Transportation Network, TRB Annual Meeting 2020
  - **Afifah, F.**, Guo, Z., Abdel-Aty, M., Impacts of I2V Information Sharing on Connected Vehicles Safety in an Interconnected Network, TRB Annual Meeting 2021
  - Siddique, C., **Afifah, F.**, Guo, Z., Zhou, Y. Data mining of plug-in electric vehicles charging behavior using supply-side data,TRB Annual Meeting 2021
  - Horrey, W. J., Benson, A., Guo, Z., **Afifah, F.**, Hamann, C. J., Santiago, K. R., Expectations and Understanding of Advanced Driver Assistance Systems Among Drivers, Pedestrians, Bicyclists, and Public Transit Riders.TRB Annual Meeting 2021
  - **Afifah, F.**, Guo, Z., Abdel-Aty, M., Impacts of I2V Information Sharing on Connected Vehicles Safety in an Interconnected Network, IISE Annual Conference 2022

Awards

- ORC Doctoral Fellowship University of Central Florida 2019
- Second Place Winner for poster presentation on ”Spatial Pricing Of Ride-sourcing Services In A Congested Transportation Network”, 2021 INFORMS Annual Conference, October 24-27, 2021, Anaheim, California

Thank You

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