CTR

Centre for Traffic Research

Traffic Management and Traffic Control

vti

KTH VETENSKAP OCH KONST

LINKÖPINGS UNIVERSITET

Feature importance analysis for automatic incident detection with lane-level data

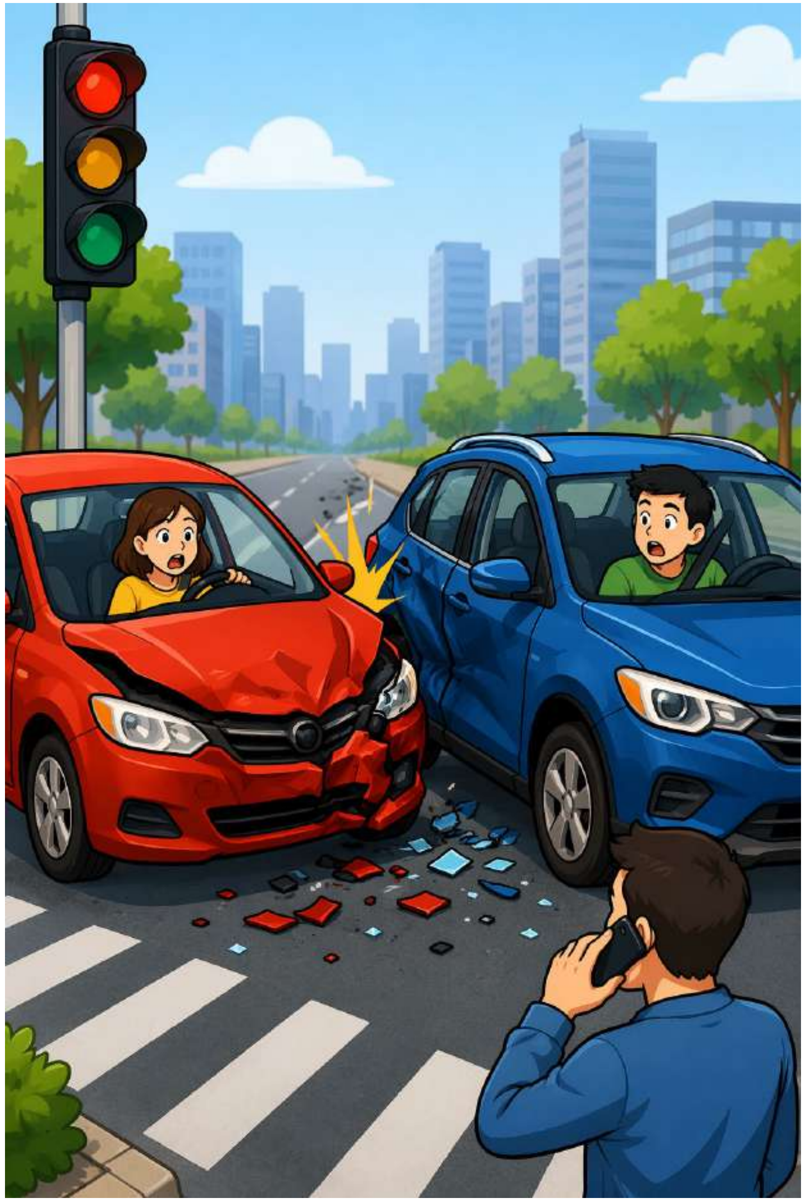
Henrik Fredriksson, David Gundlegård, Clas Rydergren, Rasmus Ringdahl (LiU)

Ellen Grumert, Kinjal Bhattacharyya, Viktor Bernhardsson, Johan Olstam (VTI)

Rodrigo Marquez-Lucero, Magnus Nordenvaad (TrV)

Agenda

- Introduction
- Scenario and data description
- Feature analysis
- Kernel density-based AID method
- Preliminary results

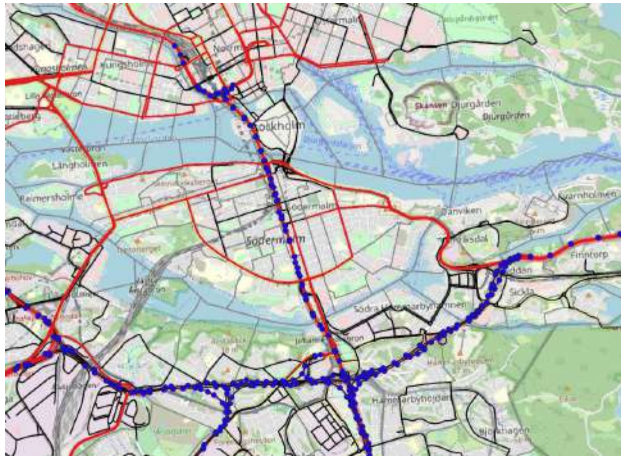


Introduction

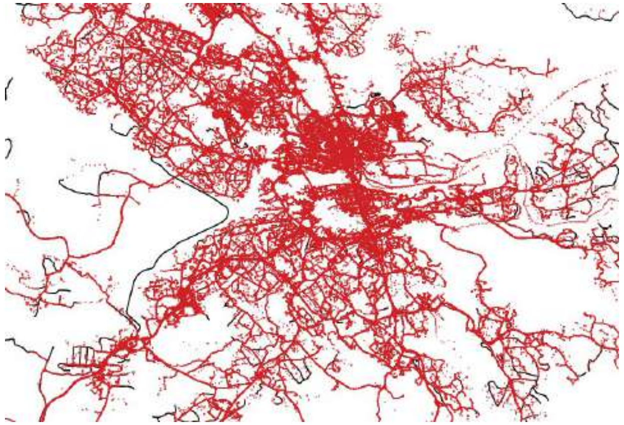
- Around 20 000 incidents yearly in Stockholm.
- Automatic incident detection (AID)
- Use available data sources
- False alarms of incidents in existing systems
- Project goals:
  - State-of-the-art literature review
  - Identify suitable algorithms for Swedish conditions
  - Develop and evaluate algorithms for test locations

Ytradar (Navtech)

Incidentdata

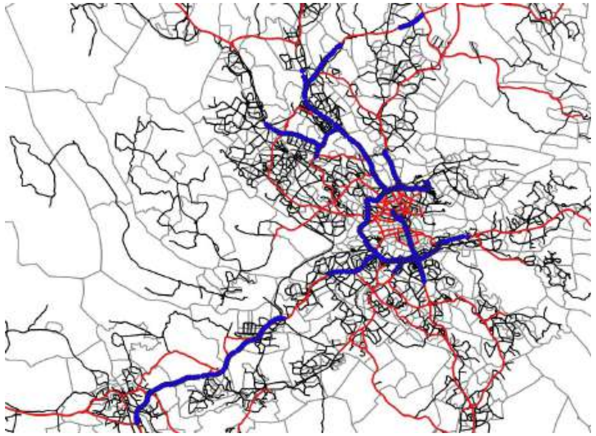


MCS (vehicle-by-vehicle)



Detailed GPS-data

Data from connected vehicles

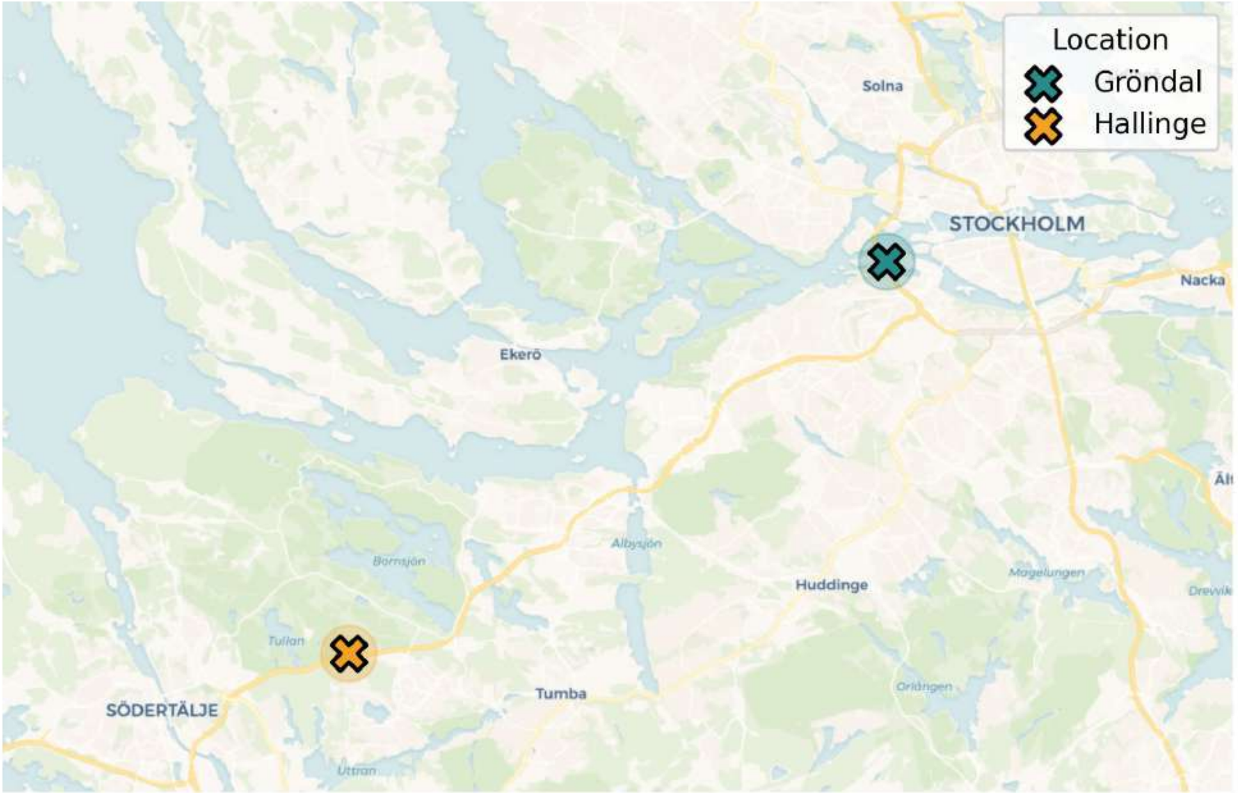


Travel times from GPS-data

LINKÖPING UNIVERSITY

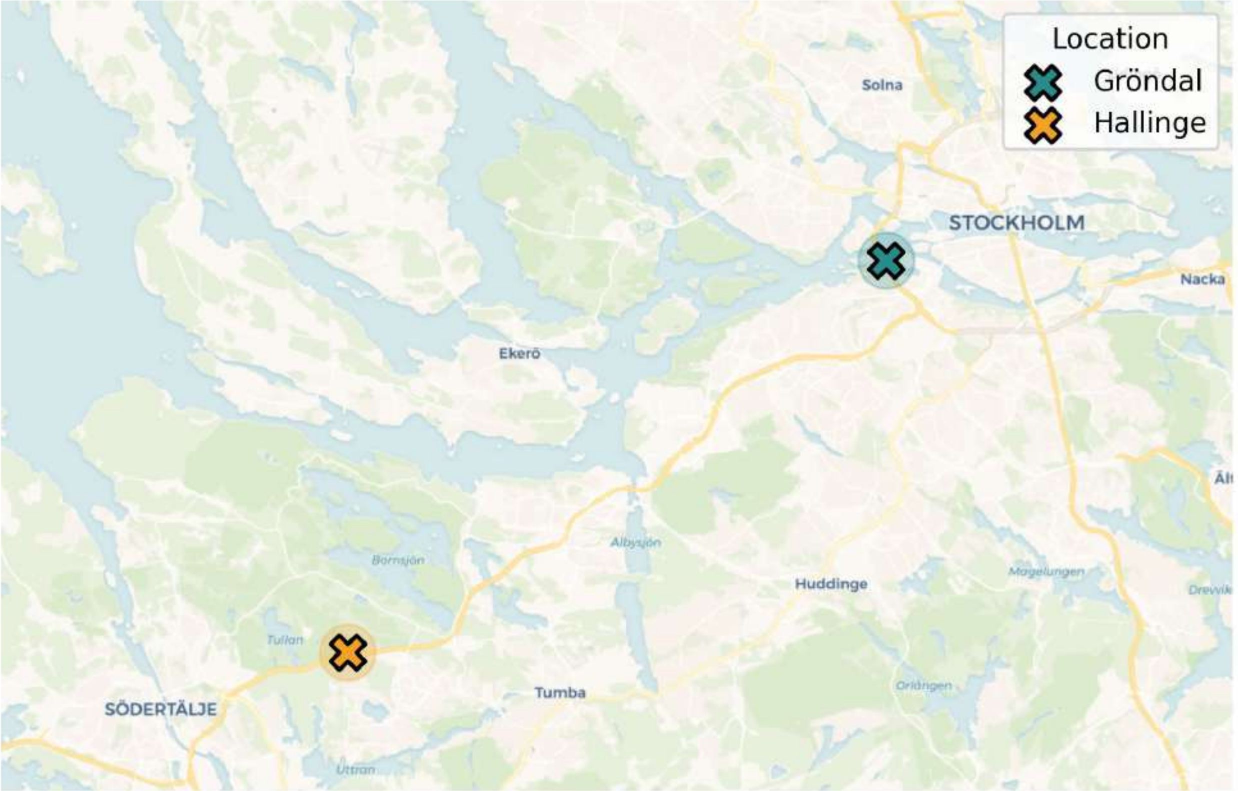
Study locations

- Gröndal
  - 3 months
  - 28 incidents
  - 4 lanes
- Hallinge
  - 2 years
  - 60 incidents
  - 3 lanes



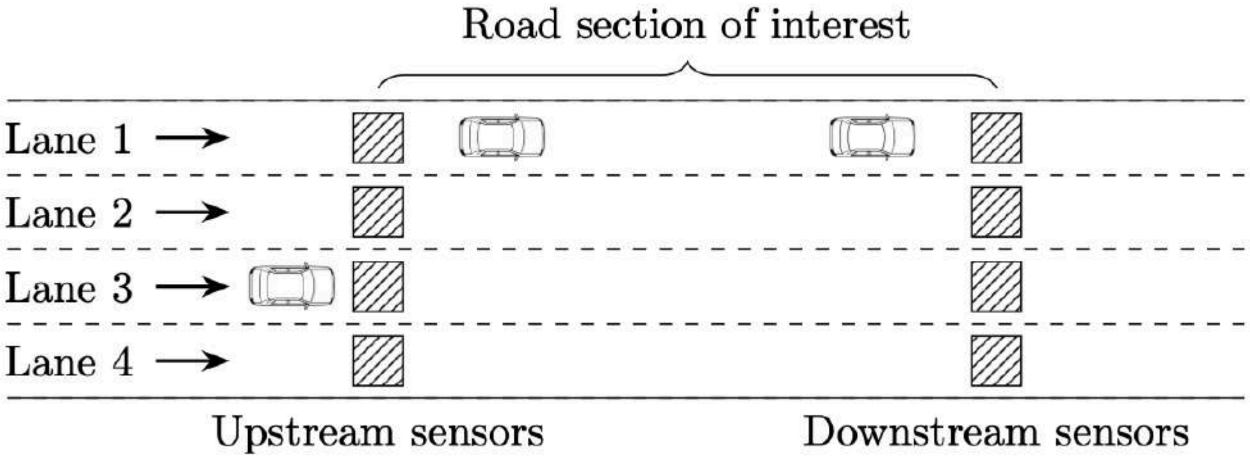
Study locations

- Data with one-minute resolution
- Lane-based features
  - Speed
  - Flow
  - Occupancy
  - Density
  - Headway



Scenario setup

- Segments defined by sensors
- Incident are mapped to closest upstream sensor
- Detect incident between sensors
- Features
  - for each lane
  - between lanes
  - between sensors
- Nearby incident may affect



Feature analysis

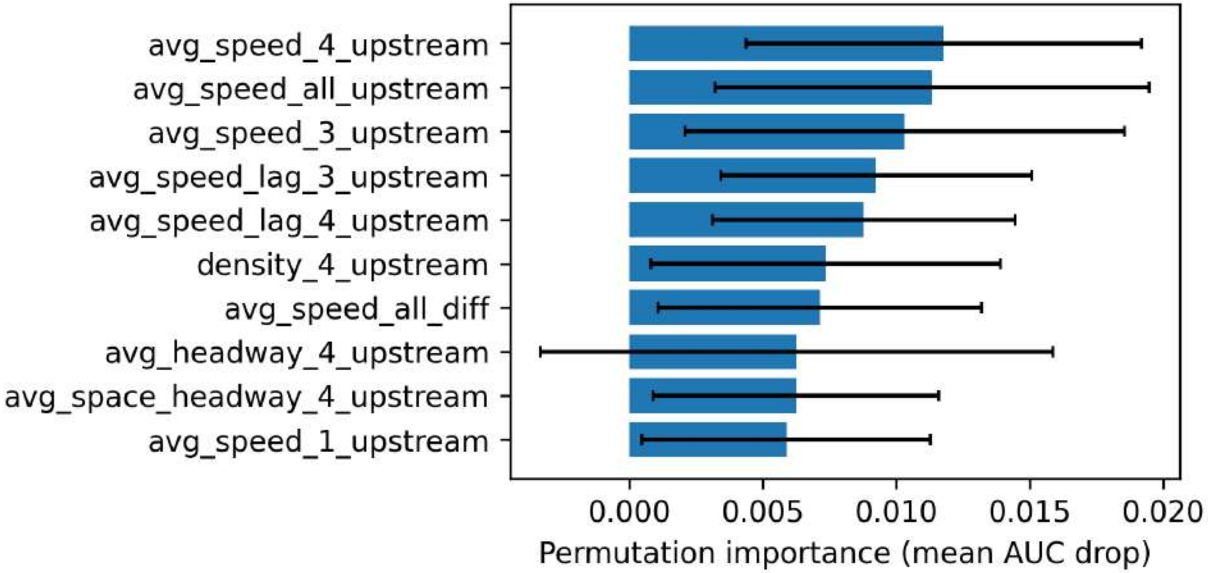
- Which features are important to detect incidents?
- Do we need use data for each lane?
- Permutation importance

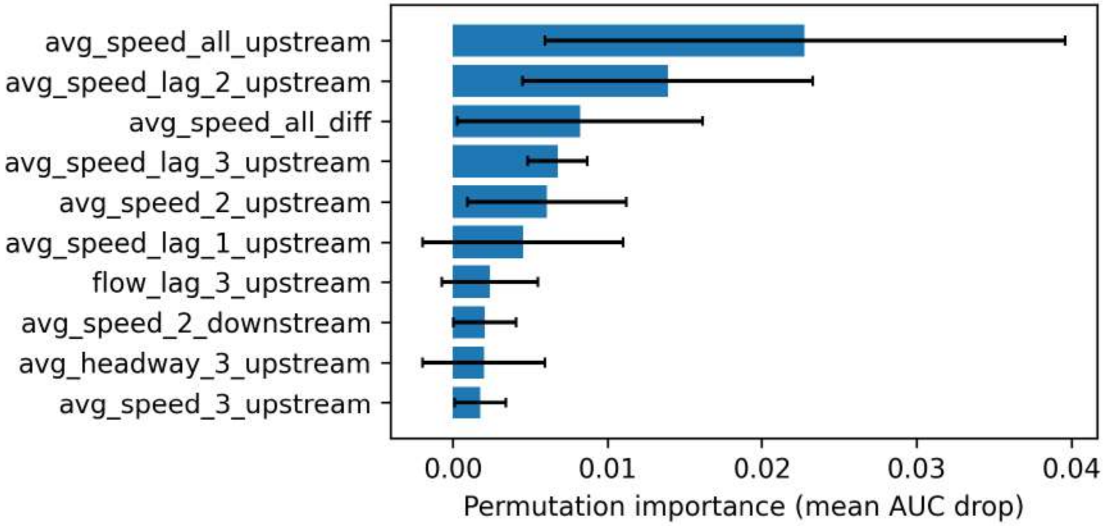
Feature analysis

- Models
  - Random forest
  - XGBoost
  - LightBGM
  - CART
  - LASSO
- Evaluation
  - Detection rate (DR)
  - False alarm rate (FAR)
  - Mean time to detection (MTTD)

Results

- Important features
  - Travel speed
  - Rightmost lane
  - Upstream sensor
- Aligns with previous results
- Large uncertainties



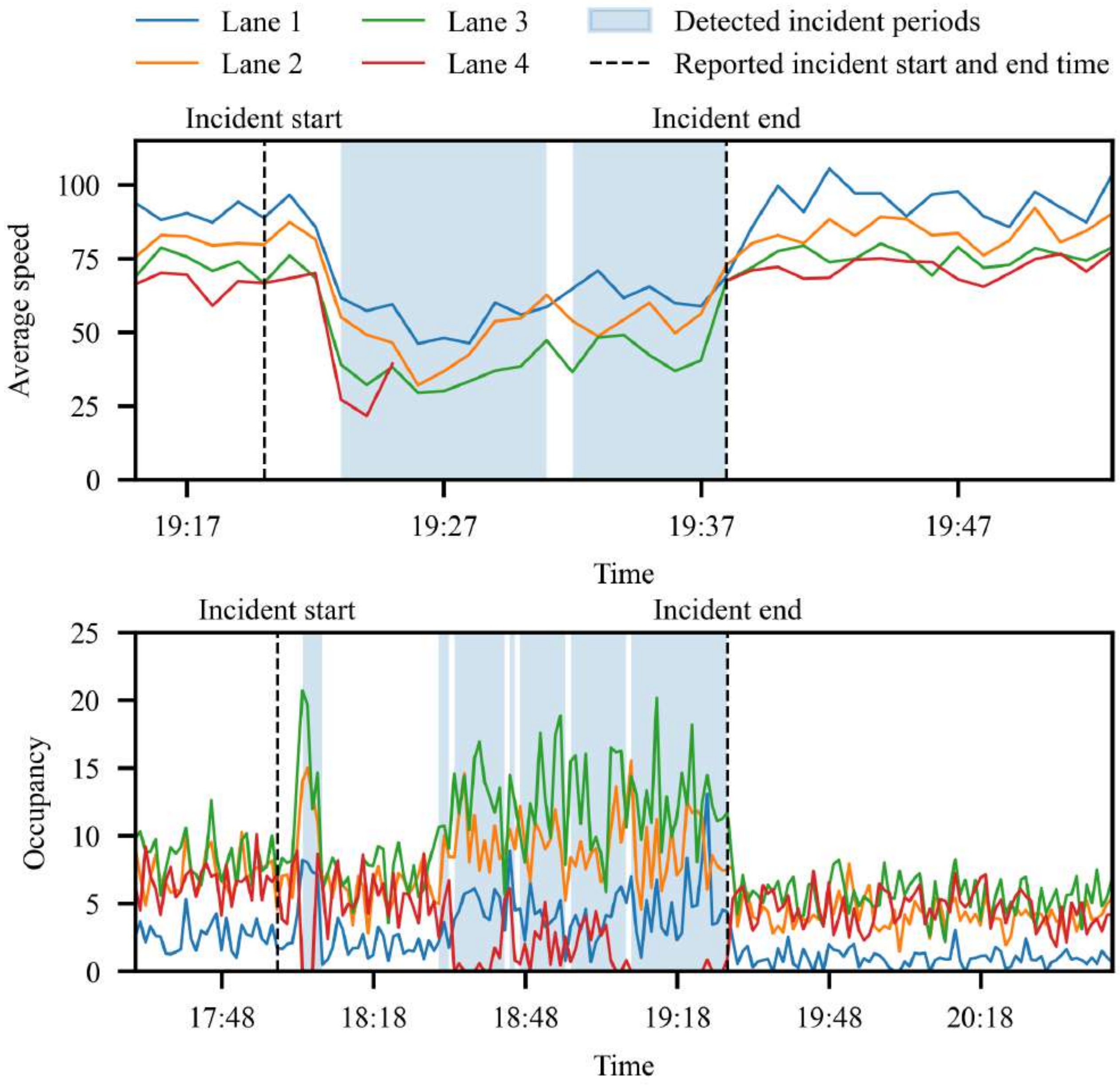


Results

- Lane-based data gives
  - Lower FAR
  - Higher precision
  - Higher ROC-AUC
  - Lower MTTD

TABLE III
PERFORMANCE METRICS ACROSS MODELS AND DATASETS. HIGHER IS BETTER EXCEPT FAR AND MTTD. KEY RESULTS ARE HIGHLIGHTED IN GREEN AND RED.

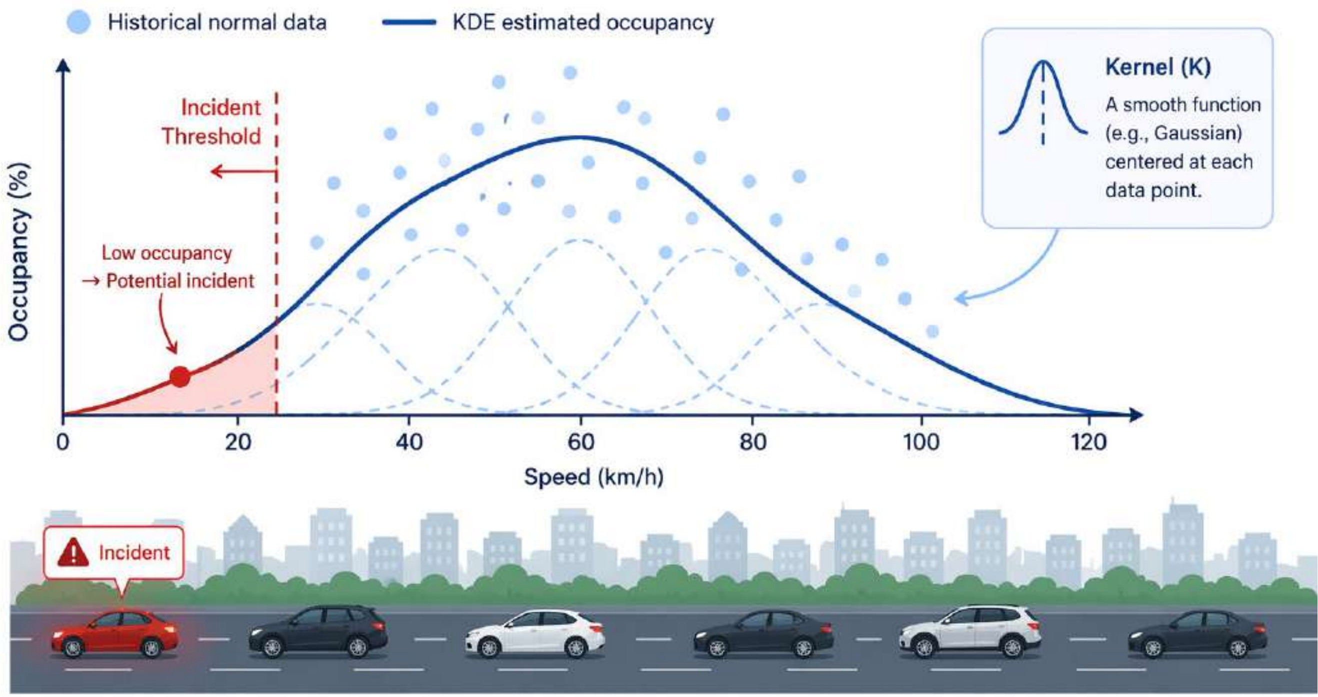
Metric	Feature set	RF	CART	XGB	LBGM	LASSO
DR (%)	Lane-level	67.86	**82.14**	78.57	78.57	100.00
	Aggregated	85.71	85.71	89.29	85.71	100.00
	Both	71.43	75.00	82.14	75.00	100.00
FAR (%)	Lane-level	**0.074**	0.410	0.174	0.131	3.270
	Aggregated	0.155	0.556	0.251	0.115	**6.482**
	Both	0.094	0.414	0.179	0.140	3.223
Precision [0,1]	Lane-level	**0.84**	0.48	0.71	0.76	**0.14**
	Aggregated	0.72	0.40	0.63	0.77	0.07
	Both	0.81	0.49	0.71	0.75	0.14
F1-score [0,1]	Lane-level	**0.75**	0.54	0.71	0.72	0.24
	Aggregated	0.69	0.49	0.67	0.70	**0.13**
	Both	0.74	0.56	0.72	0.71	0.13
AUC [0,1]	Lane-level	**0.96**	**0.81**	**0.96**	**0.96**	**0.96**
	Aggregated	0.93	**0.81**	0.92	0.91	0.92
	Both	0.96	0.83	0.96	0.96	0.96
MTTD (MM:SS)	Lane-level	03:18	02:20	03:27	03:08	01:02
	Aggregated	**04:17**	04:05	03:38	03:20	01:32
	Both	03:39	02:28	**02:20**	03:40	01:00



Lane 1
Lane 2
Lane 3
Lane 4
Detected incident periods
Reported incident start and end time
Incident start
Incident end
Average speed
100
75
50
25
0
19:17
19:27
19:37
19:47
Time
Incident start
Incident end
Occupancy
25
20
15
10
5
0
17:48
18:18
18:48
19:18
19:48
20:18
Time

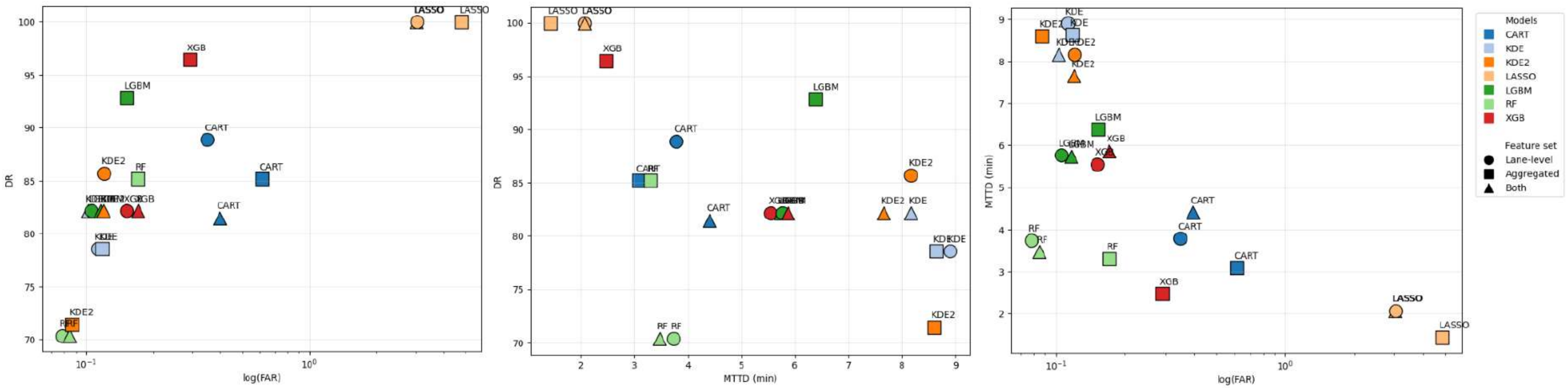
Kernel density estimation

- Non-parametric method to estimate probability density of normal traffic behavior
- Learns distribution of historical (incident-free) patterns
- Speed and occupancy



Metric	Model / Feature set	CART	KDE	KDE2	LASSO	LGBM	RF	XGB
DR (%)	Lane-level	91.6667	90.0	93.3333	100.0	93.3333	86.6667	95.0
	Aggregated	91.6667	46.6667	85.0	100.0	93.3333	75.0	96.6667
	Both	93.3333	93.3333	91.6667	100.0	93.3333	88.3333	95.0
FAR (%)	Lane-level	0.1553	0.5050	0.5149	4.2093	0.0616	0.0275	0.1697
	Aggregated	0.2493	0.1299	0.4764	5.8944	0.2388	0.0285	0.7558
	Both	0.1537	0.4803	0.4978	3.8788	0.0584	0.0273	0.1577
Precision	Lane-level	0.2715	0.1214	0.1091	0.0270	0.5282	0.6599	0.3298
	Aggregated	0.1249	0.0357	0.0734	0.0189	0.1975	0.4936	0.0992
	Both	0.2769	0.1246	0.1155	0.0295	0.5414	0.6716	0.3465
F1-score	Lane-level	0.3297	0.1959	0.1762	0.0523	0.5141	0.4881	0.4272
	Aggregated	0.1683	0.0353	0.1157	0.0369	0.2700	0.2865	0.1703
	Both	0.3361	0.1992	0.1856	0.0570	0.5199	0.5053	0.4411
AUC	Lane-level	0.7093	0.8971	0.8755	0.9531	0.9348	0.9452	0.9447
	Aggregated	0.6280	0.9311	0.8863	0.9336	0.9122	0.9245	0.9295
	Both	0.7130	0.9026	0.8791	0.9561	0.9347	0.9470	0.9447
MTTD	Lane-level	03:19	03:07	03:02	00:58	03:35	04:23	02:40
	Aggregated	03:56	11:15	04:16	00:52	02:53	08:58	01:42
	Both	03:32	03:19	03:08	01:02	03:13	04:09	02:35

Relation between FAR, DR, MTTD



Not covered in this presentation

- Clustering of non-incident days
- Threshold calibration and optimization
- SHAP analysis
- New metrics for AID evaluation
- Hyperparameter optimization
- FAR analysis

Thank you listening!

LINKÖPING
UNIVERSITY

Multimodal Incident Analysis

LiU: Anna Danielsson, David Gundlegård, Rasmus Ringdahl, Clas Rydergren

KTH: Daniel Chaves, Wilco Burghout, Matej Cebecauer, Erik Jenelius

Multimodal traffic management II

Project group

Anna Danielsson

David Gundlegård

Clas Rydergren

Rasmus Ringdahl

Matej Cebecauer

Wilco Burghout

Erik Jenelius

Daniel Chaves

Multimodal traffic management

1. Tänk om
2. Optimera
3. Bygg om
4. Bygg nytt

- The four-step principle combined with urbanization means that traffic systems are often **managed at the capacity limit**.
- Small changes in supply can have a **large impact** on system performance and significant socioeconomic effects.
  - It is important to have good **decision-making support and analysis tools** for management and control.
- The long-term goal is to be able to evaluate and monitor action plans in real time

Overall goal

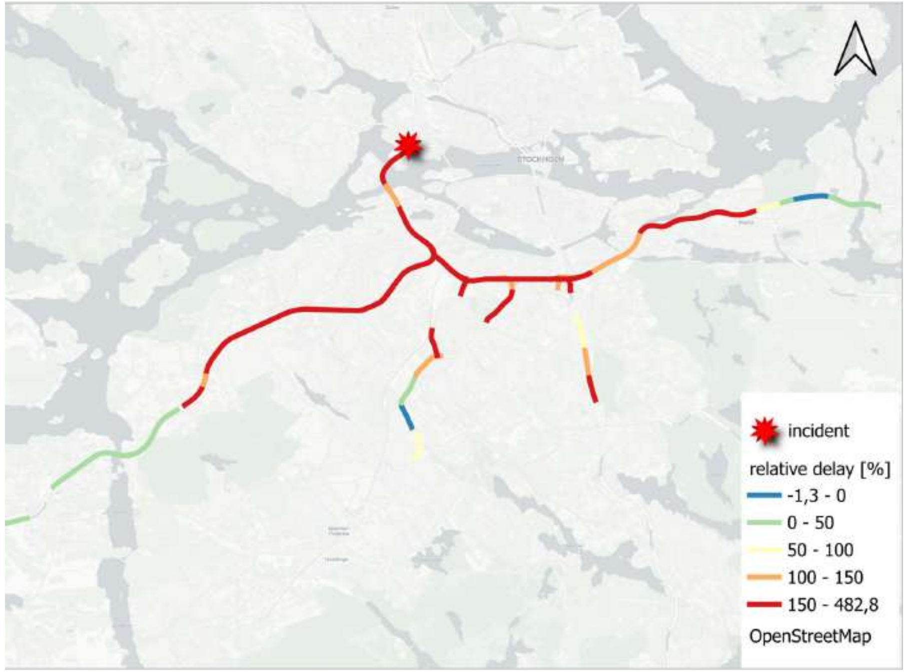
- Better understanding of **multimodal travel patterns**
- New methods for estimating and predicting **multimodal demand**
- New methods for predicting **mode and route choice**
- Identify **synergies and challenges** with multimodal traffic management

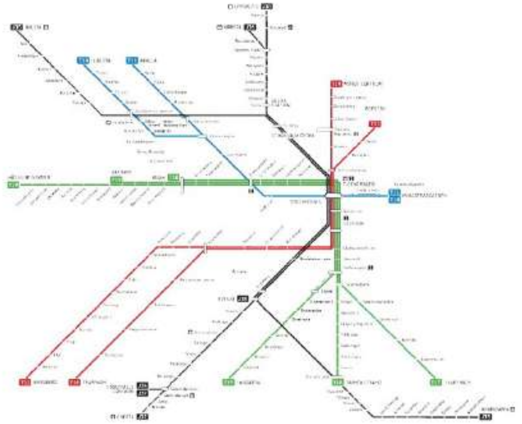
Questions related to incident managment

- How can we predict **traffic state during incidents** (including the effects of route and mode choice)?
- Which traffic flows are **most affected** by the incident (and have the greatest impact on the incident)?
- What multimodal **redirection options** are available for these traffic flows?
- How does the redirection affect **future traffic states**?

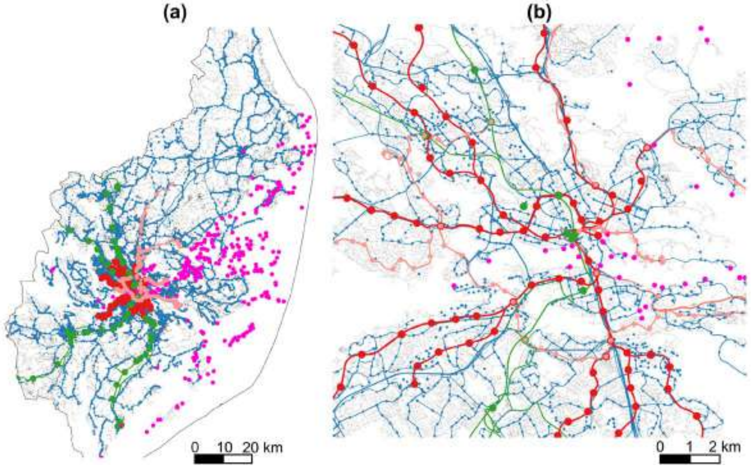
Introduction

- We analyse and compare the impact of road and public transport incidents on two levels
  - Network level
  - Local level
    - Total delay within each mode
    - Mode shifts
- The results can provide insights in understanding the transport system and prioritise between management actions

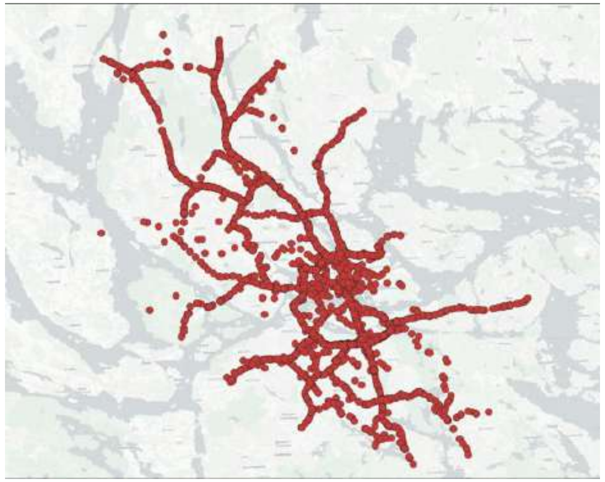




Public transport tap-in data

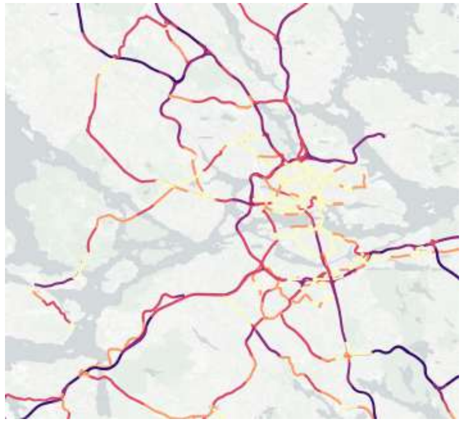


GTFS data

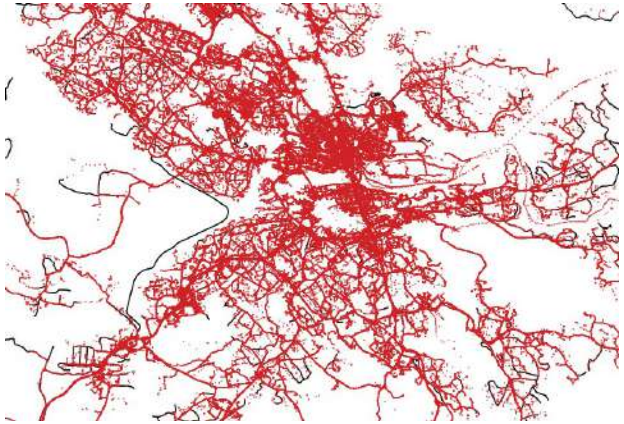


Incident data

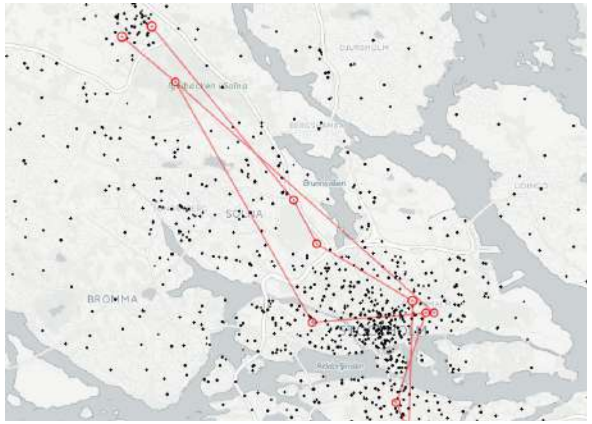
Data sources for multimodal incident analysis



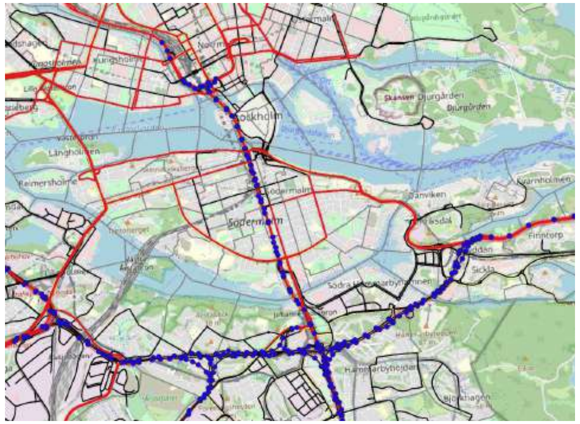
Traveltime data



INRIX data



Mobile network data



MCS data

LINKÖPINGS UNIVERSITET

KTH VETENSKAP OCH KONST

CTR

Method

Multimodal data fusion

Incident reconstruction	• Clustering of reports belonging to the same event
Expected travel pattern estimation	• Clustering of travel times to find typical travel time patterns • Estimation of the expected travel time if there would not have been an incident
Spatial analysis area identification	• Isolate spatial effect of incident • Identify origin-destination pairs impacted by the incidents
Temporal range identification	• Identify the time window where the incident had an impact

Quantifying incident impact

Network level incident impact

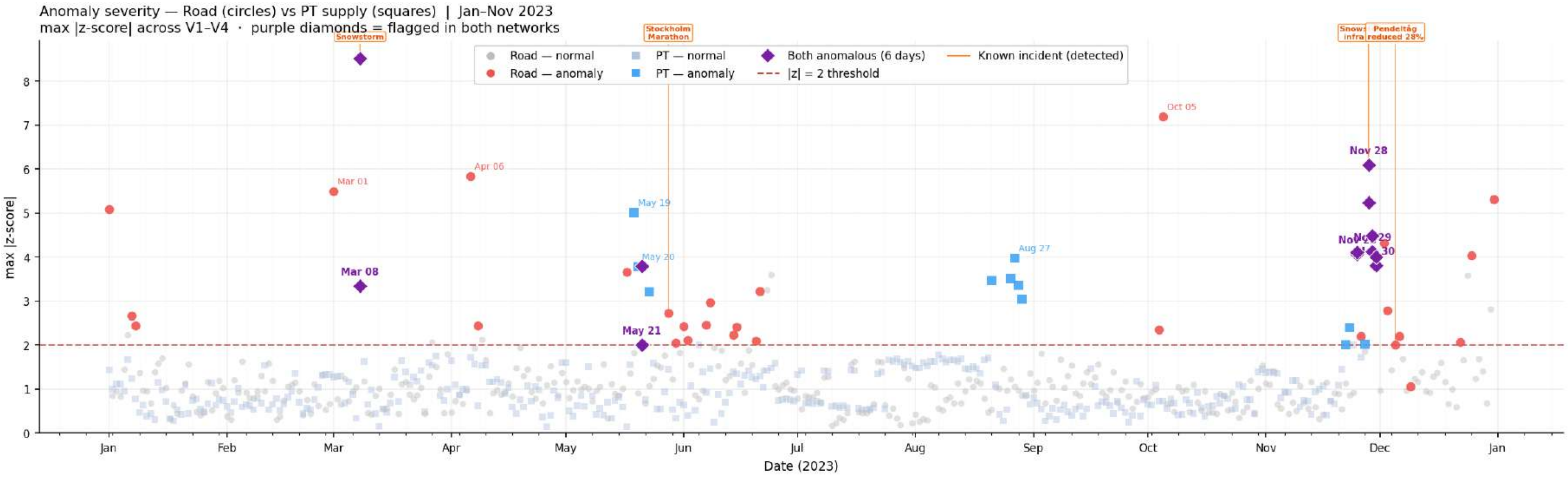
- Link travel times
- Total travel time weighted with traveller count
- Total traveller count (high and low)
- Total delay

Local level incident impact

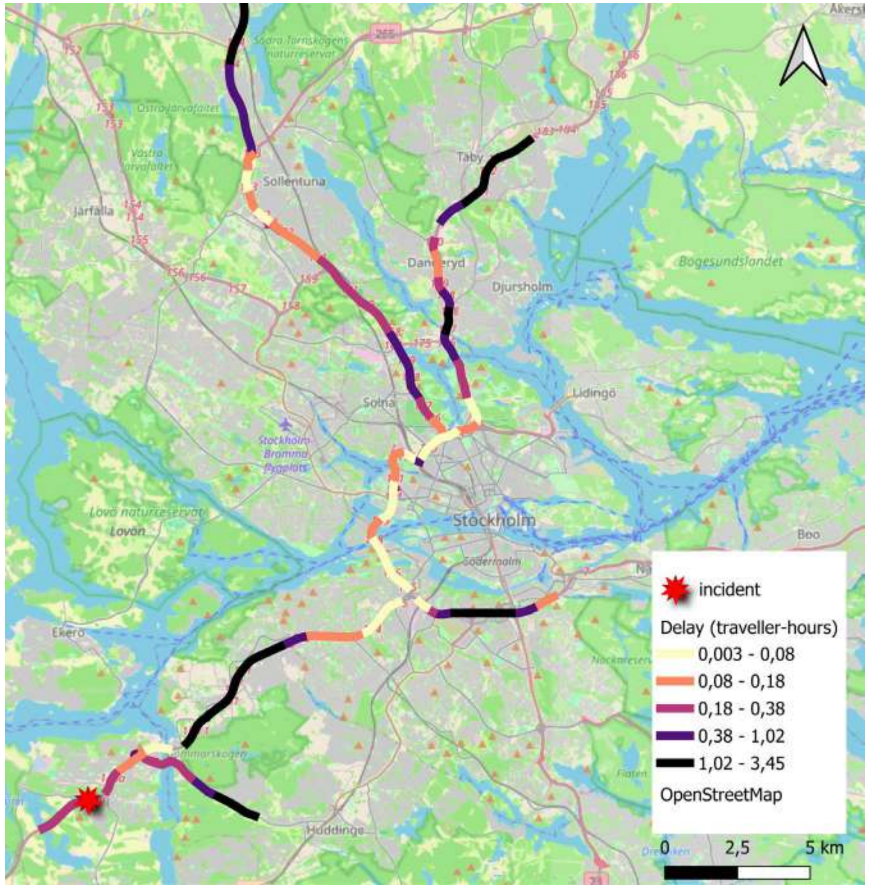
- Total delay upstream of the incident
- Mode shifts in identified originating zones

Results

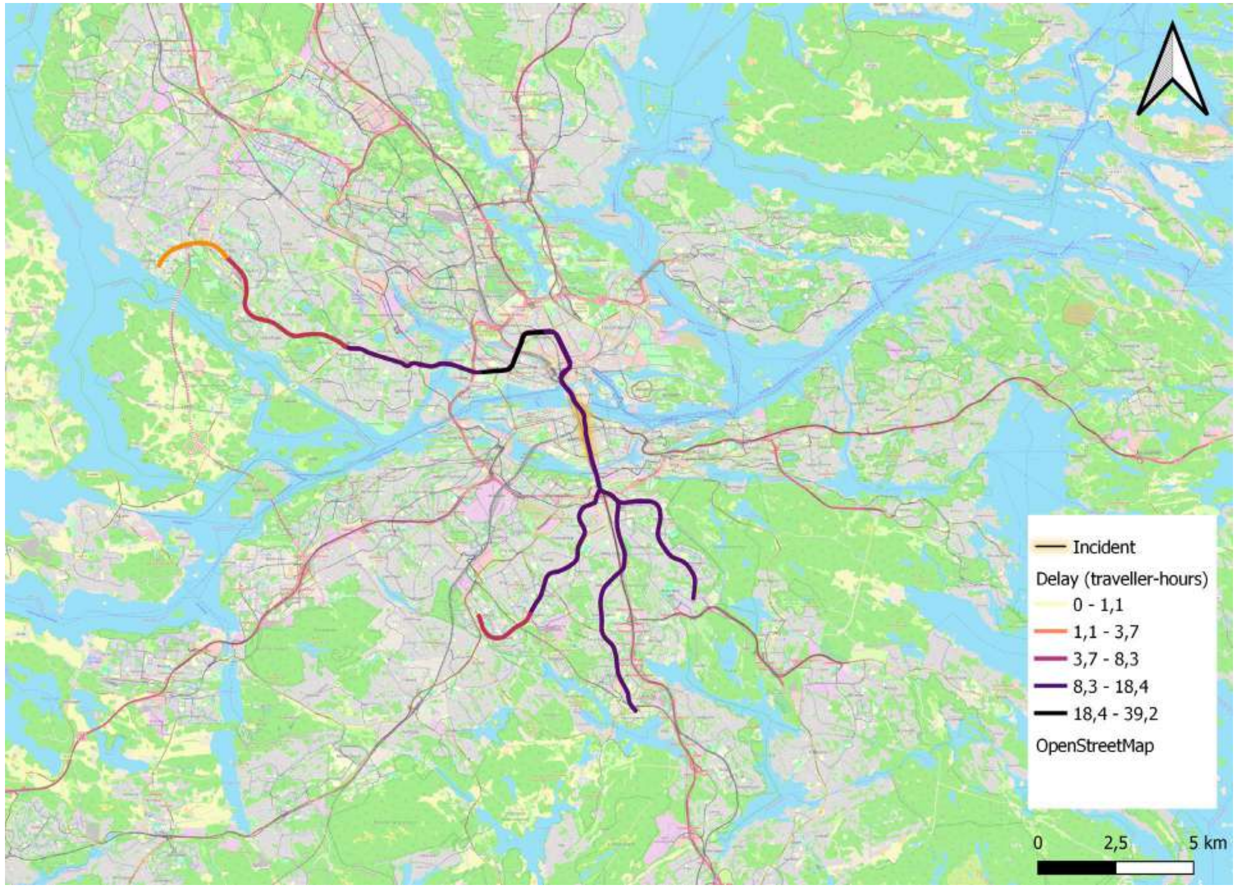
Network-wide impact days



Total delay upstream of the incident

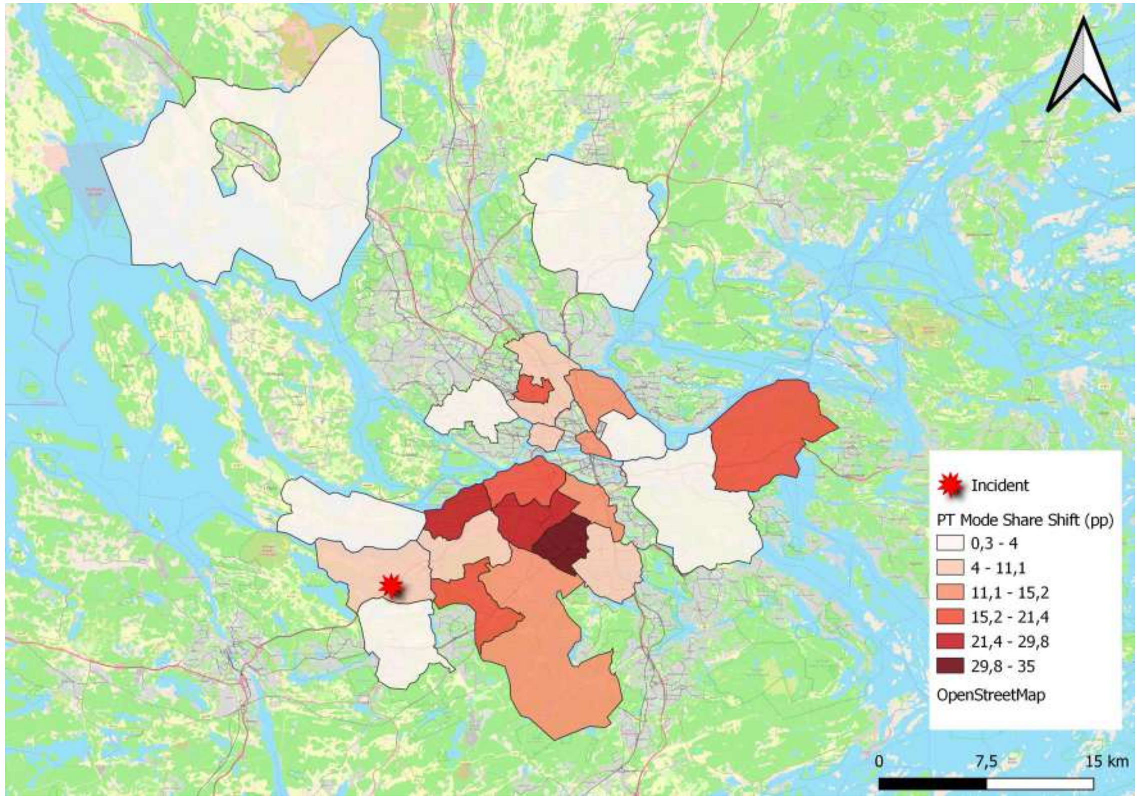


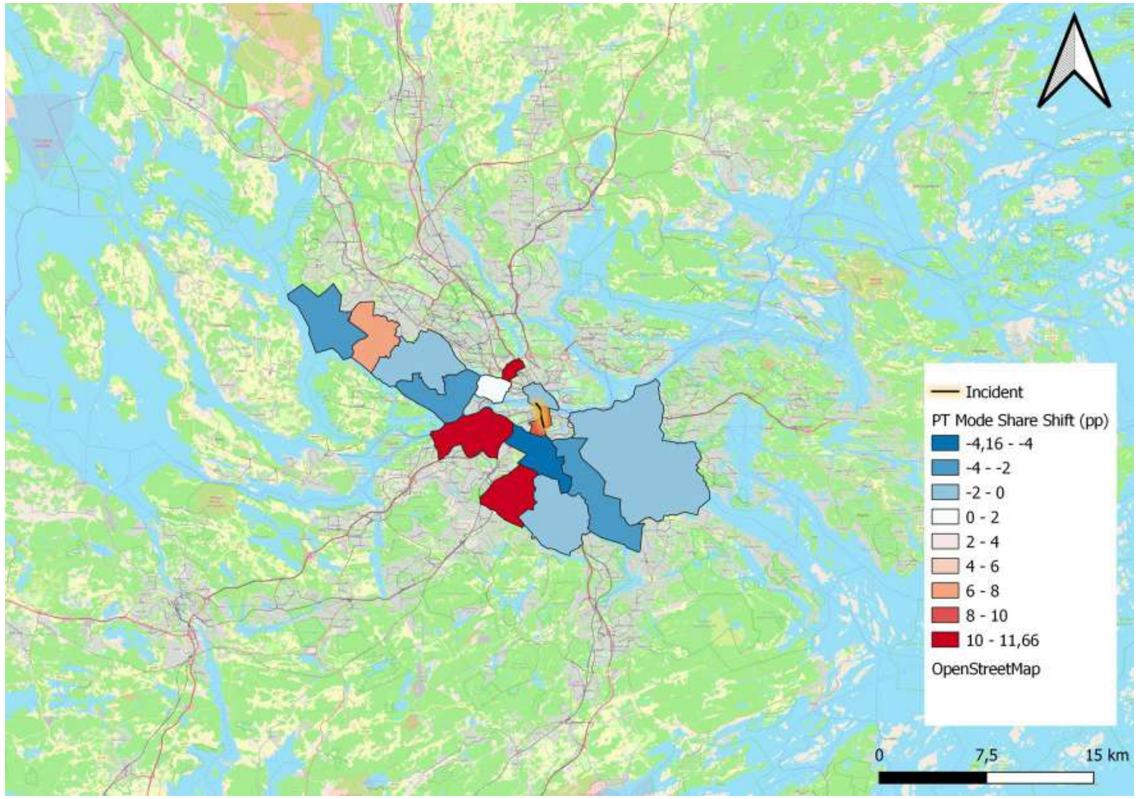
Road Incident – E4 Södertäljevägen south
Accident / stationary vehicle – 6:35 am



PT incident – Gamla Stan - Skanstull Metro Green Line
Power Outage - 6:30 am

Public Transport Mode Share Shift





Road Incident – E4 Södertäljevägen south
Accident / stationary vehicle – 6:35 am

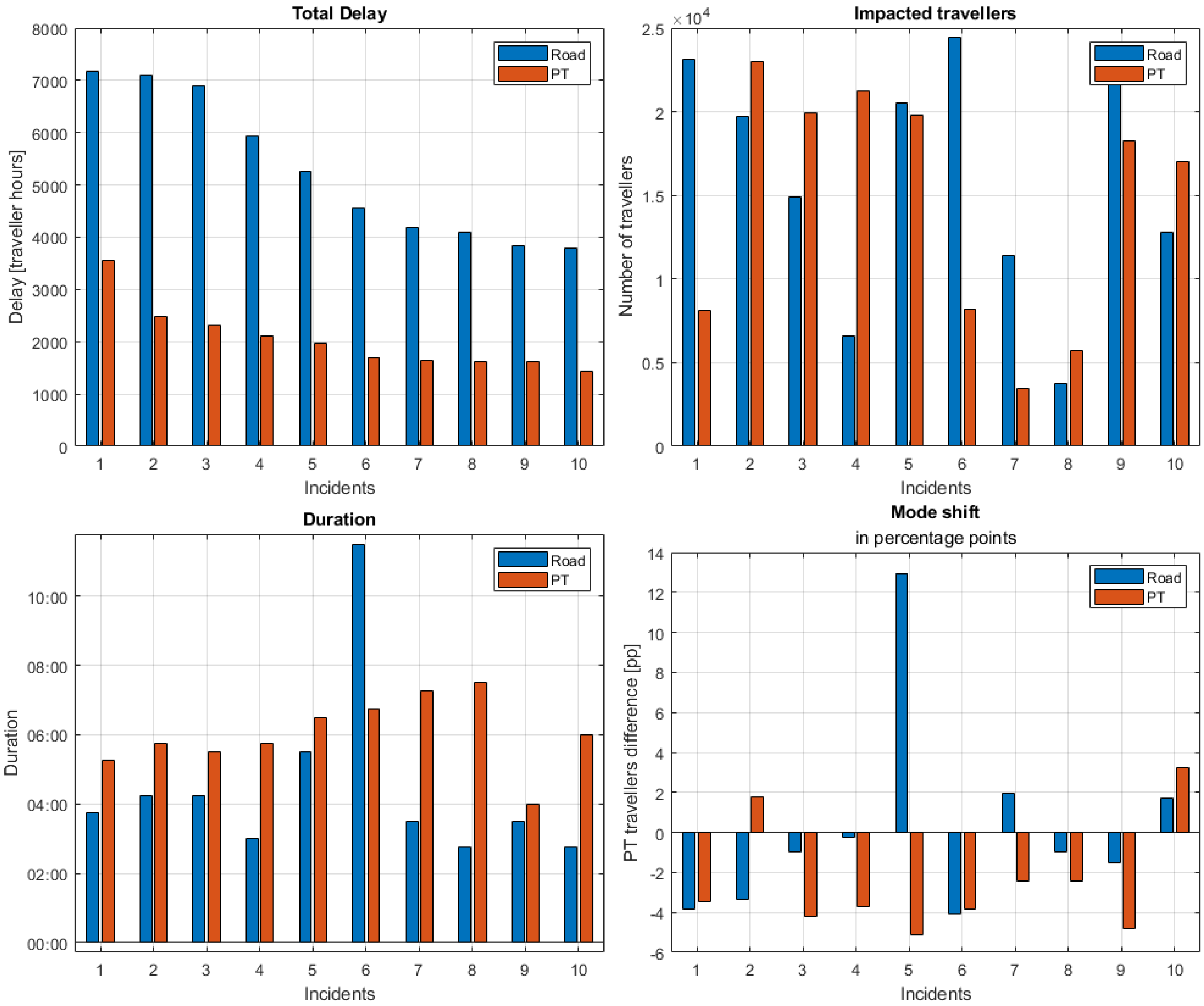
PT incident – Gamla Stan - Skanstull Metro Green Line
Power Outage - 6:30 am

Top 10 Road Incidents

Road incident	Cause	Location	Start time
R 1	Slow queue / stationary vehicle	E4 Essingeleden north	07:30
R 2	Accident with heavy vehicle / object on the road	E4 Uppsalavägen north	13:44
R 3	Accident / emergancy corridor	E4 Södertäljevägen north	14:45
R 4	Emergancy corridor / Accident	E4 Södertäljevägen south	07:55
R 5	Accident / stationary vehicle	E4 Södertäljevägen south	06:35
R 6	Burning vehicle / Road damage	E4 Essingeleden north	07:24
R 7	Stationary vehicle	E4 Norra länken south	16:16
R 8	Stationary vehicle	E18 Kymlingelänken west	15:41
R 9	Accident with heavy vehicle / object on the road	E4 Essingeleden north	06:49
R 10	Stationary vehicle	E4 Södertäljevägen north	15:52

Top 10 PT Incidents

PT incident	Cause	PT modes	Lines	Start time
PT 1	signal / vehicle failure	TRAIN	43	12:45
PT 2	signal	METRO	17, 18, 19	06:30
PT 3	signal / vehicle failure	METRO	17, 18, 19	05:45
PT 4	security incident / vehicle failure	METRO	17, 18, 19	14:15
PT 5	vehicle failure	METRO	17, 18, 19	15:15
PT 6	signal / vehicle failure	TRAIN	40, 41	05:45
PT 7	infrastructure / vehicle failure	TRAIN	43, 44	05:00
PT 8	infrastructure	TRAIN	43, 44	14:30
PT 9	signal	METRO	17, 18, 19	06:00
PT 10	incident / security incident / special event	METRO	17, 18, 19	14:45


Total Delay
Delay [traveller hours]
Incidents
Road
PT
Impacted travellers
Number of travellers
Incidents
Duration
Duration
Incidents
Mode shift
in percentage points
PT travellers difference [pp]
Incidents

Conclusion

- The results show that
  - **Weather incidents and major events** have impact on network level in both road and PT network
  - Road incidents have larger impact on **delay** compared to public transport incidents
  - The **duration** of the public transport incidents is longer than of the road incidents
  - During major public transport incidents, travellers tend to **shift mode**
  - **Accidents and rail network incidents** are overrepresented among the incidents with high impact on delay
- These insights can be used to
  - prioritize between actions in multimodal traffic management centres
  - learn from recurrent events, such as tunnel closings, and make an estimate on the impact
  - build prediction models to use a decision support tools in multimodal traffic management

Future work

Multimodal Incident Analysis and Cross-Mode Impacts for Coordinated Traffic Management (MIA)

- Quantify and explain cross-mode impact propagation (why and how incidents spread across modes)
- Derive multimodal severity and resilience indicators that can directly support coordinated decisions in traffic management centres
- Develop agent-based simulation to model how travellers and operators respond to incidents across modes

Project web page:

Thank you!

anna.a.danielsson@liu.se

daca2@kth.se

LINKÖPINGS UNIVERSITET

KTH VETENSKAP OCH KONST

How do sporting events impact public transportation crowding and urban mobility networks?

Anastasios Skoufas

Researcher/PhD Candidate – Public Transportation Systems

KTH Royal Institute of Technology

skoufas@kth.se

CTR Day
Stockholm, June 16, 2026

Public Transit Crowding under Planned Special Events, Across Contexts

Funded by the MIT Global Seed Funds

Start date: May 1, 2025
End date: January 31, 2027

Riccardo Fiorista

Researcher

PhD Candidate (MIT)

Anson Stewart

Deputy Director - Research Scientist (MIT)

<u>Principal Investigator</u>

Jinhua Zhao

Professor (MIT)

Erik Jenelius

Professor (KTH)

Oded Cats

Professor (TU Delft)

Guest Professor (KTH)

Anastasios Skoufas

Researcher

PhD Candidate (KTH)

Sporting events and their two-fold effect on society

Sport facilities **contribute to** pedestrian and economic **activity** beyond areas close to the sports event venue

Major sports events generated **$5 billion** and attracted **7.4 million visitors** in 2023 (with 88% being non-District residents)

Yes, **but**…

NEWS WEATHER I TEAM SPORTS GAME CENTER WATCH LIVE

Fast rising ridership brings more revenue, but also headaches for Metro

by Tom Roussey | Thu, February 27, 2025 at 6:13 PM
Updated Thu, February 27, 2025 at 10:19 PM

U.S. & WORLD THE SCENE POLITICS INVESTIGATIONS NEWSLETTERS 55° Watch 24/7

NBC4 Newsletters Watch 24/7 Our News Standards 35 WEATHER ALERTS

TRANSPORTATION

Potomac Yard Metro station could have 1+ hour of crowding after arena events: report

"It will be a crowded station, but it will be able to accomplish its goal of helping everyone get on the Metro and leave by that area," a consultant said

By Adam Tuss, News4 anchor & transportation reporter • Published February 6, 2024 • Updated on February 6, 2024 at 4:40 pm

Log in or create a free profile to save articles

Source: Office of the Deputy Mayor for Planning and Economic Development (DMPED), 2024

Source: https://dc.curbed.com/2019/10/3/20897154/dc-metro-wma

Selected time period and sporting events

Time period: Spring 2024 (workdays)

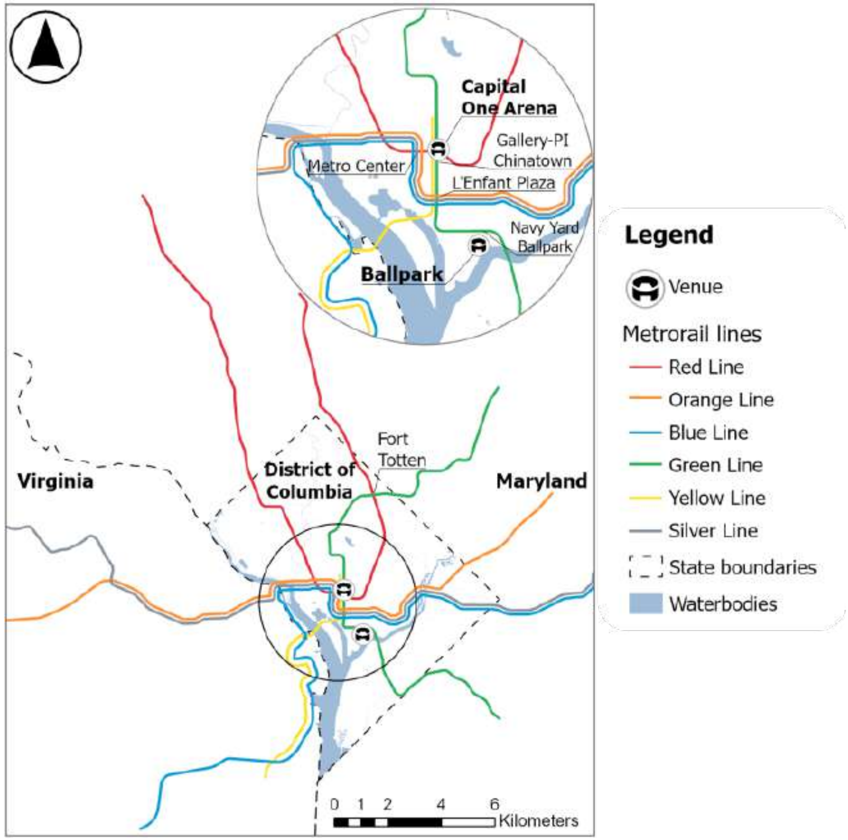
	14 Nationals baseball games	**8 Capitals** hockey games	**10 Wizards** basketball games
START	16:00 – 18:45	19:00	19:00
	23,785	18,432	16,885

13 control days (days **without any event** in Washington, DC)

Source: https://dc.curbed.com/2019/10/3/20897154/dc-metro-wma

The urban transportation system of Washington, DC, US

Metro

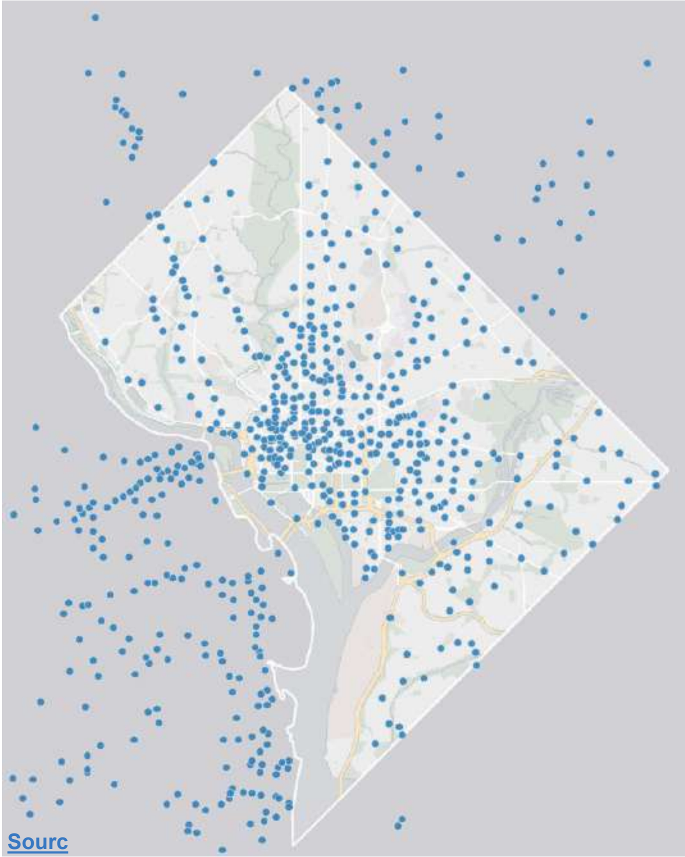


It is a tap-in and tap-out system

97 stations

6 lines

Bike sharing



[Source](#)

720 stations

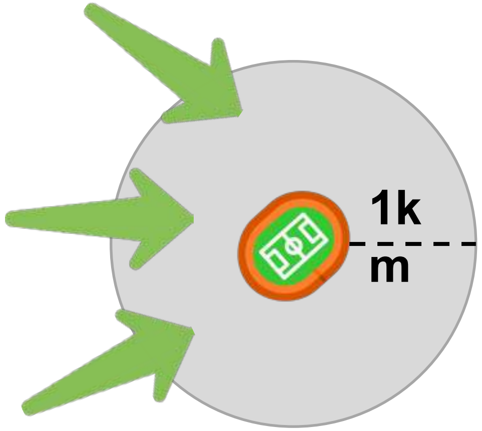
Classic bikes & E-bikes

Ride-hailing

Uber, Lyft, Curb, and DChail

Use of the Uber H3 hexagons (ca. 1700 hexagons in DC)

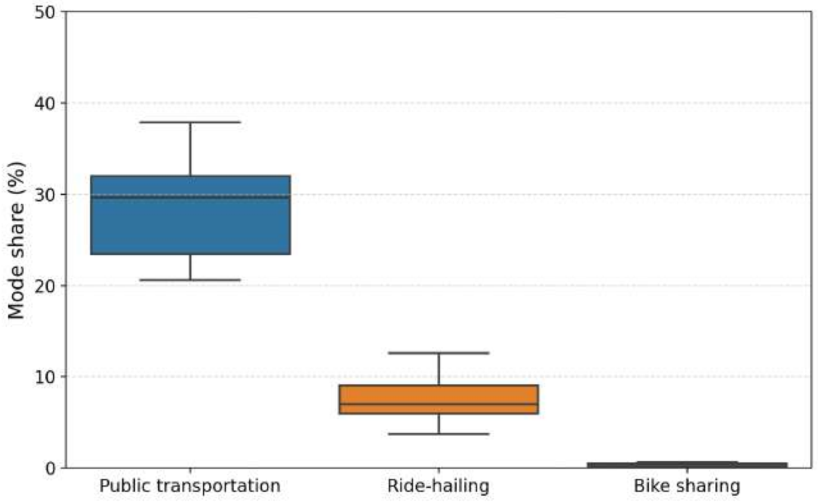
Event-related mode share (%) before the sports game starts



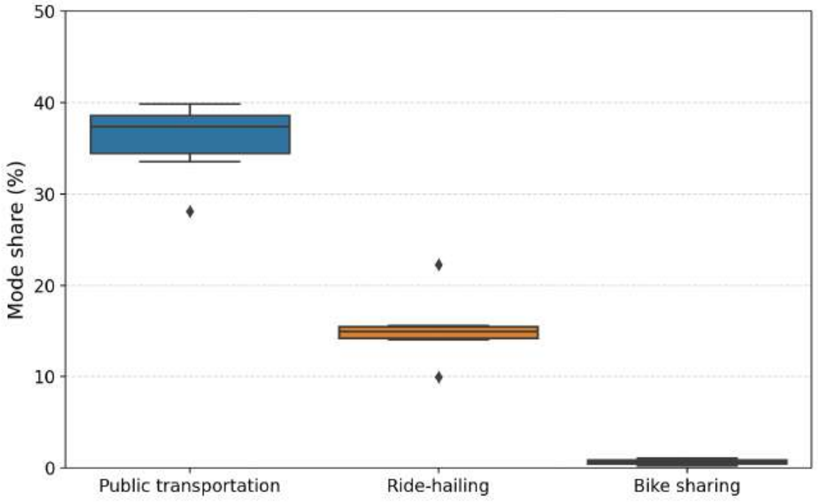
Before the game starts (0-4h)

$$\frac{\sum_{i=1}^{n}\Delta_{\text{tap-outs}}}{recorded\ attendance}$$

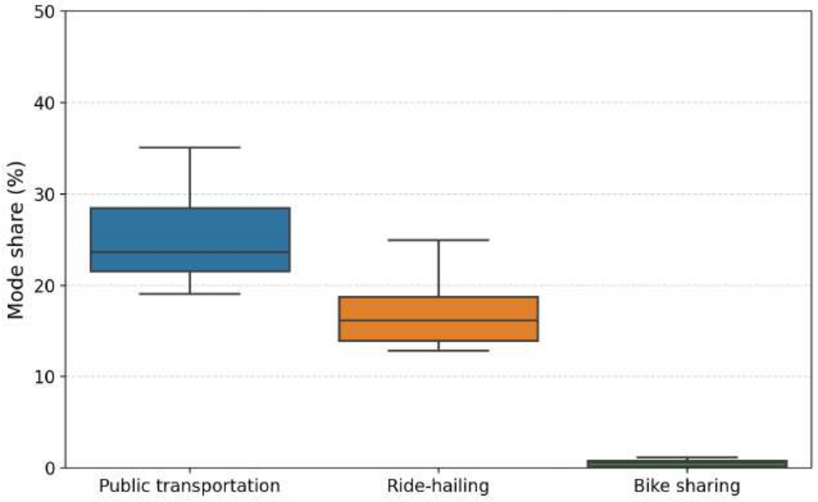
Nationals baseball games



Capitals hockey games



Wizards basketball games

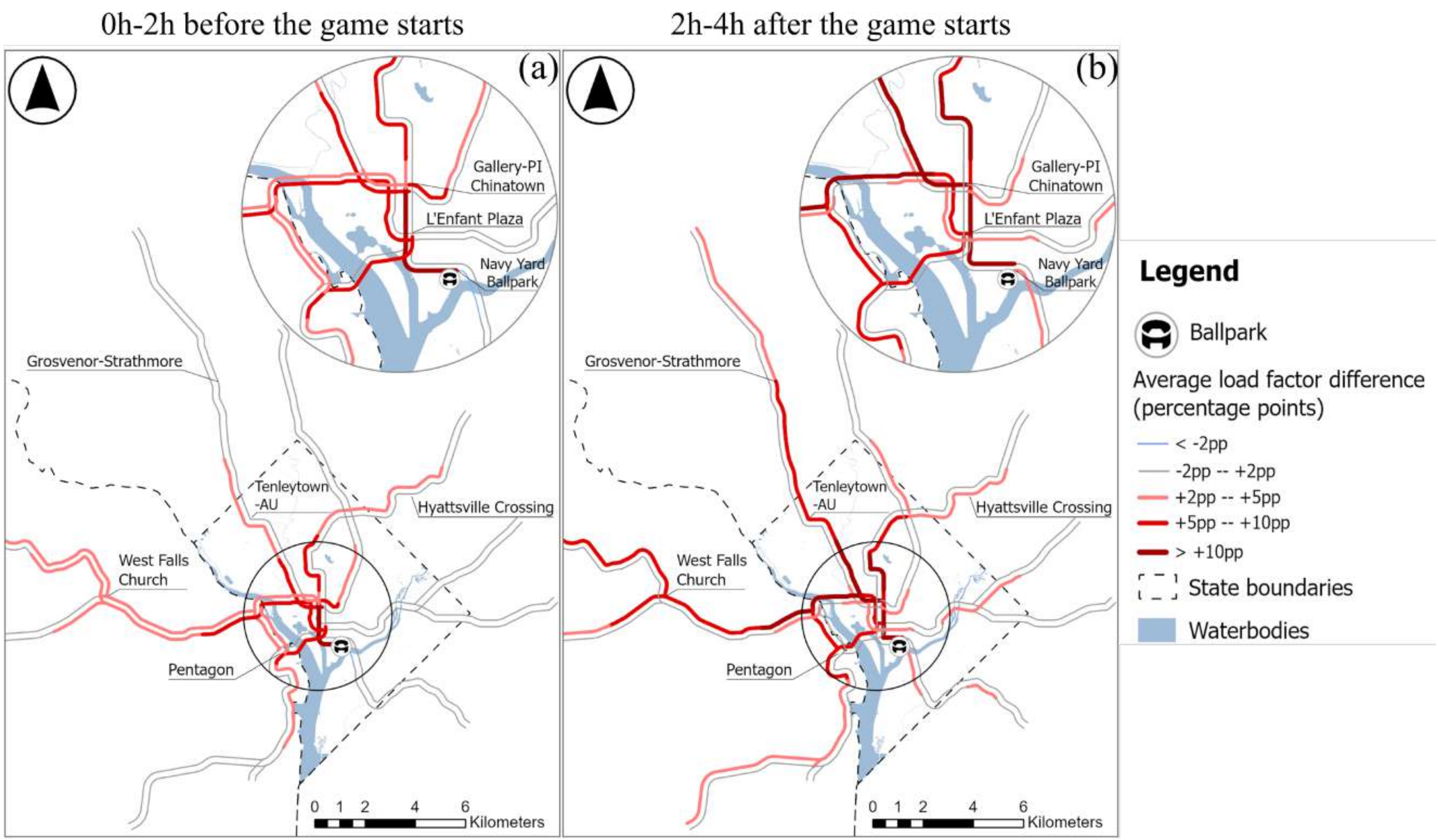


Public transport on-board crowding contributions (Nationals Baseball games)

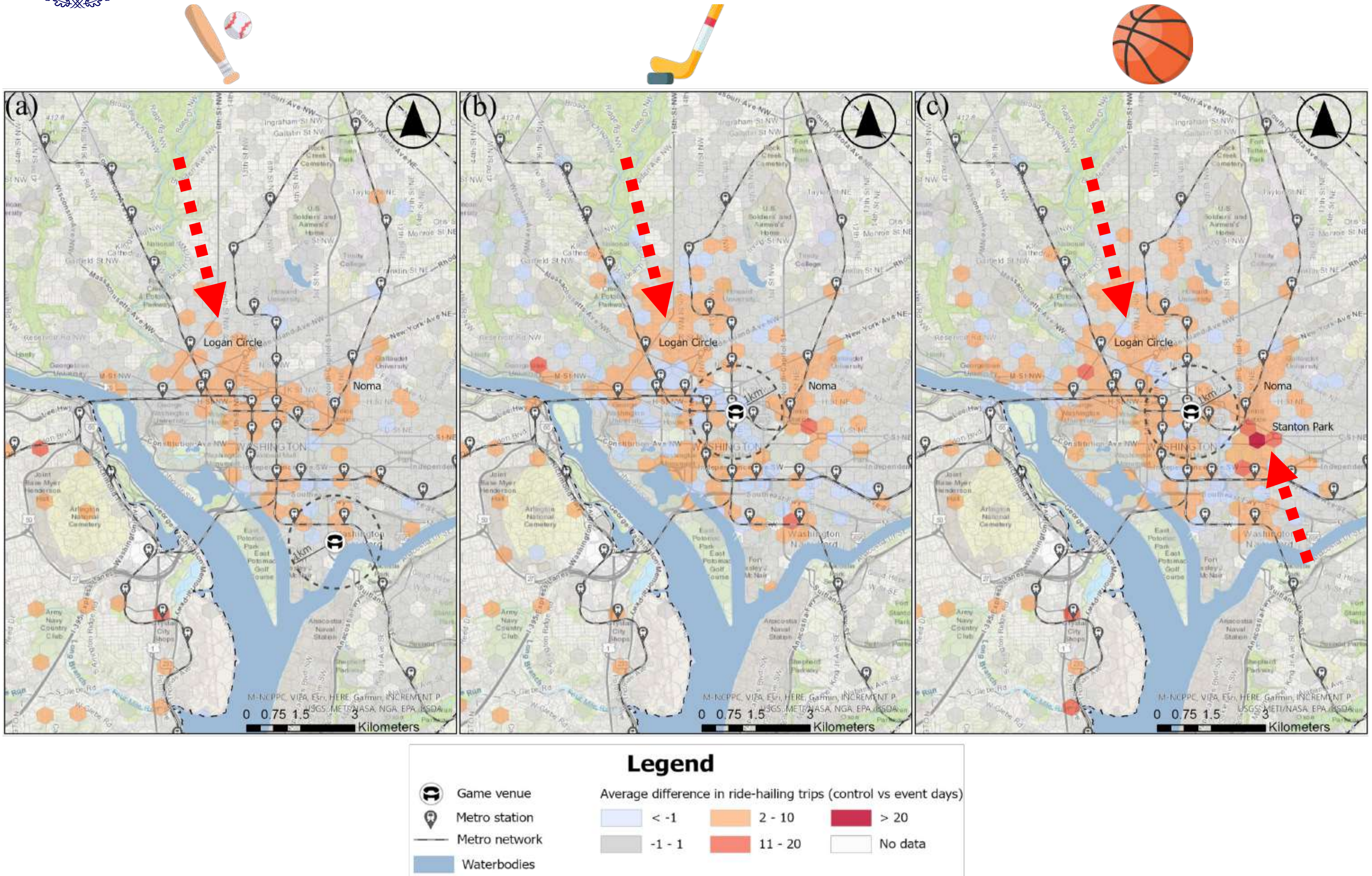
Metric:
Load factor
(passengers/seating capacity) (%)
per network segment and time window

Load factor (event days)
–
Load factor (control days)

(in percentage points – pp)



Origins of ride-hailing trips before sports games (0-4h)



Metric:
Average difference in generated ride-hailing trips per H3 Hexagon and time window

Average number of trips (event days)
–
Average number of trips (control days)

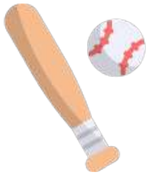
Higher ride-hailing demand

in areas with

lower metro accessibility

e.g., Logan Circle, Stanton Park

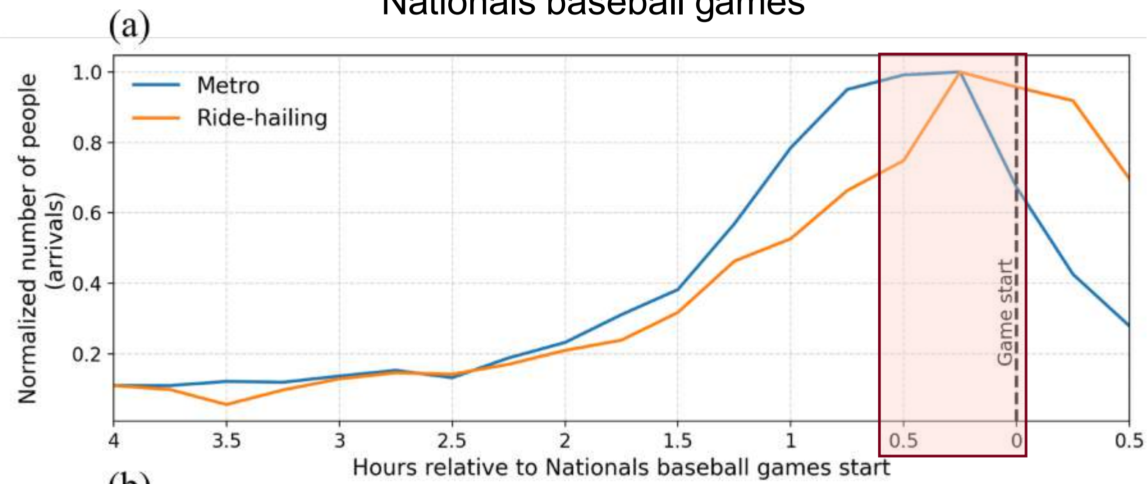
Comparative arrival and departure patterns

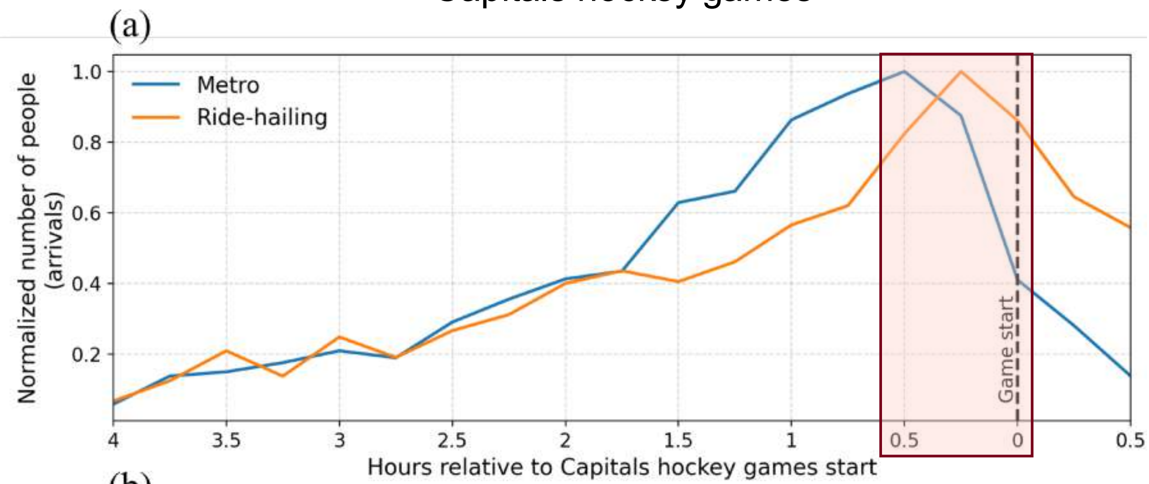


Nationals baseball games

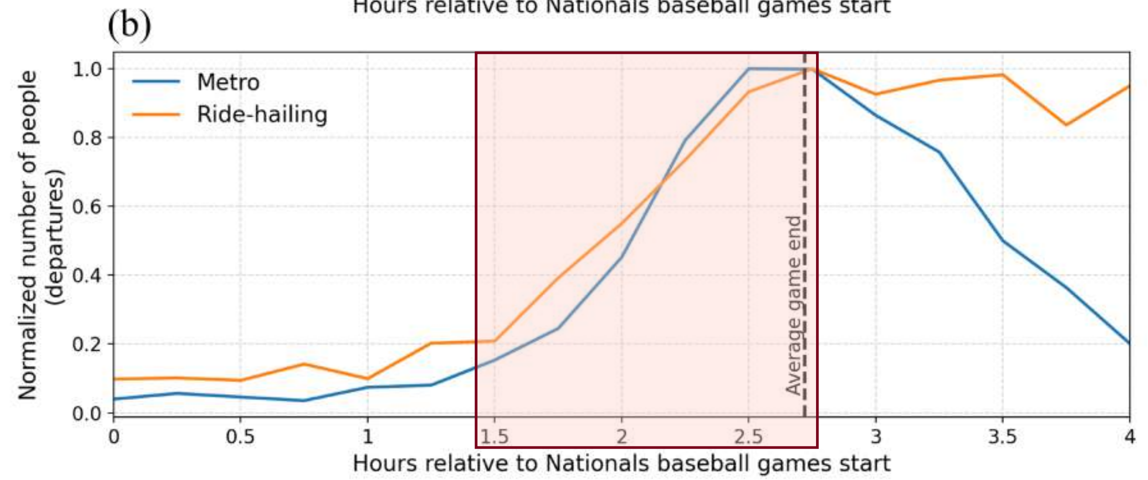
Capitals hockey games

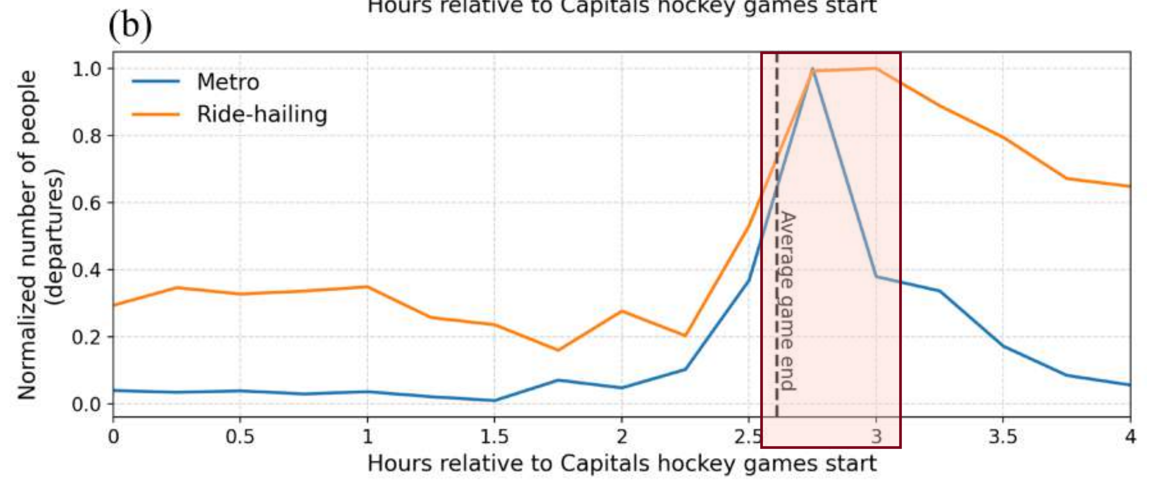
Arrivals





Departures





Discussion & Conclusions (1/2)

Largest modal share (25%-35%)

The **remaining** travel **demand** is served by other modes

Public transport crowding impact is **not** just local

Higher ride-hailing demand in areas with **lower metro accessibility**

The sporting **event characteristics** (e.g., length) can shape **different departure profiles**

Results can assist in transportation **planning** for **future** sporting **events**

Discussion & Conclusions (2/2)

Travel Demand Management Strategies – *“Aim to reduce the base load from congested corridors.”*

Alternative route recommendation

Enhanced remote work during large-scale sporting events

Design of an event PT line

Next steps: Continue working with one-time, large-scale planned special events in Stockholm

Beyoncé Renaissance World Tour Stockholm, 2023

Sweden’s football UEFA games

Thank you for your attention!
Any questions?

Anastasios Skoufas

Researcher/PhD Candidate – Public Transportation Systems

KTH Royal Institute of Technology

skoufas@kth.se

T-Twin: Digital Twin Sandbox for Network-Level Traffic Control

2026-06-16 CTR-Day

T-Twin Project: Participants

Project Team

KTH

- Zhenliang Ma (PI)
- Jonas Jostmann
- Marina Wiemers
- Leizhen Wang

VTI/LiU

- Clas Rydergren
- Johan Olstam
- Kinjal Bhattacharyya

Trafikverket

- Tomas Julner

Reference Group

Trafikverket/Consultants

- Carl Sundbom
- Johan Liljeros
- Otto Astrand
- Johan Petersson

Stockholm Stad

- Triin Reimal

Trafik Stockholm

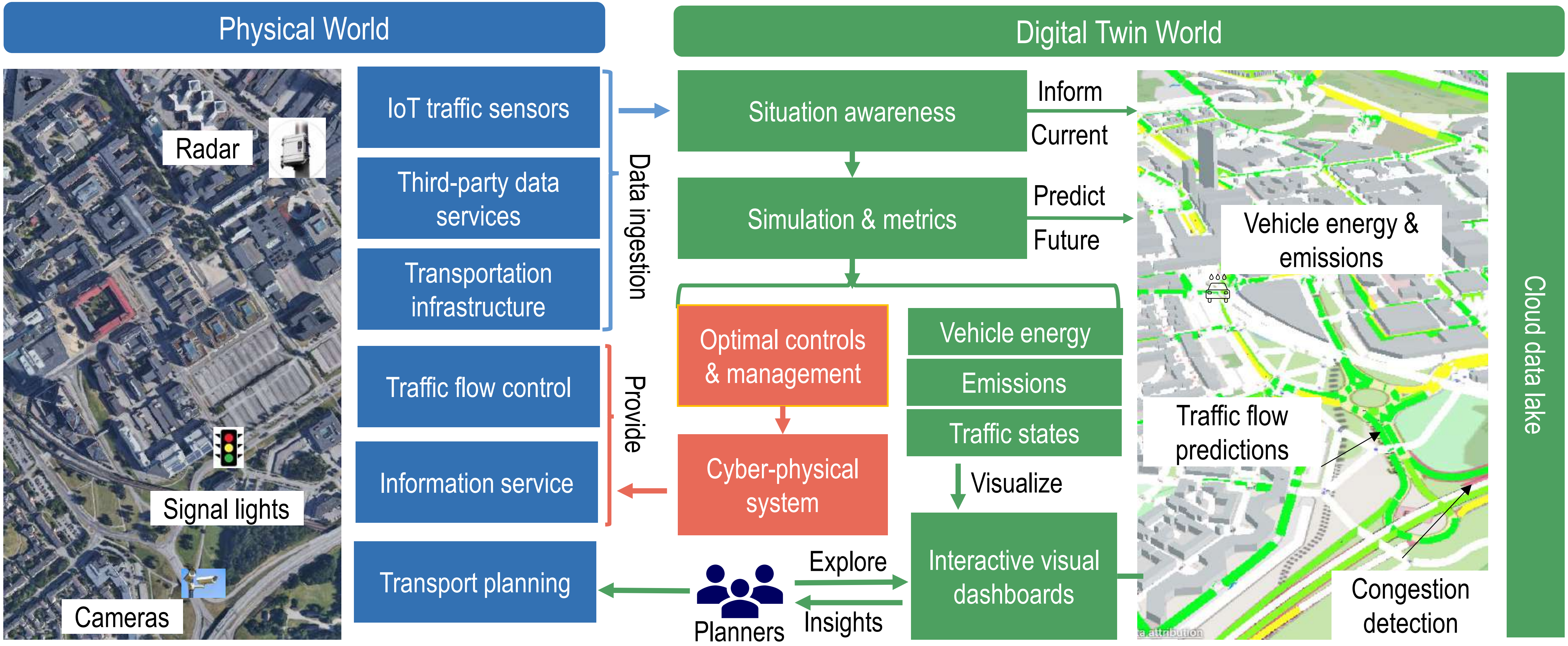
- Juan Lopez Vasquez
- Michael Warnhjelm

Aimsun

- Athina Tympakianaki

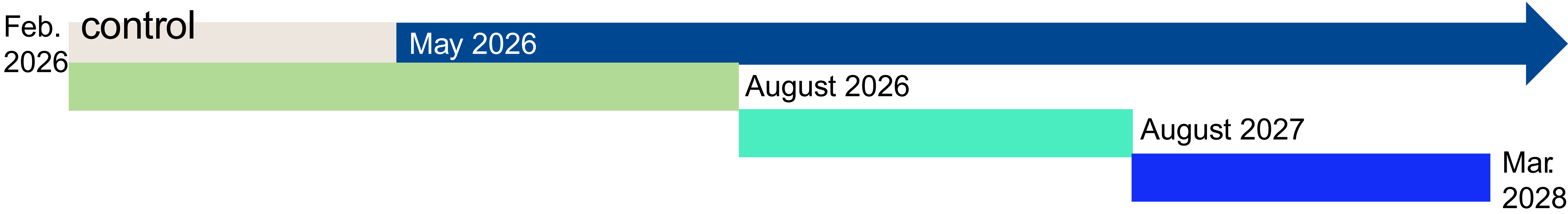
Project duration:
2.5 years (2026 – 2028)

5D DT: 3D visual + real-time data + sim. + control (T-Twin)



Project Plan

Develop and test **T-Twin sandbox** for integrated motorway and urban traffic control



WP1 Mapping current practices and needs

Requirements for the DT sandbox

WP2 Developing the T-Twin sandbox

Modula lab-version DT sandbox aligns with TDIS architecture

WP3 Building the traffic control optimizer

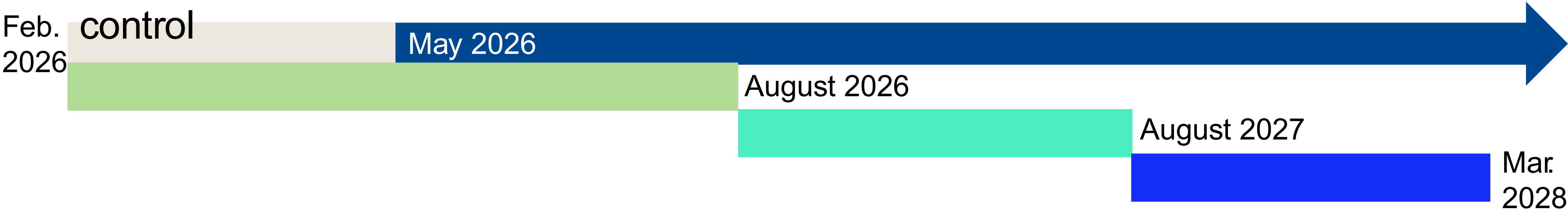
DT-based, adaptive network-level traffic control method

WP4 Demonstration, and scalability roadmap

Control strategies for Södra länken and T-Twin scale up plans

Project Plan

Develop and test **T-Twin sandbox** for integrated motorway and urban traffic control



WP1 Mapping current practices and needs

Requirements for the DT sandbox

WP2 Developing the T-Twin sandbox

Modula lab-version DT sandbox aligns with TDIS architecture

WP3 Building the traffic control optimizer

DT-based, adaptive network-level traffic control method

WP4 Demonstration, and scalability roadmap

Control strategies for Södra länken and T-Twin scale up plans

WP1: Mapping current practices and needs

Results of preparation meetings with Trafikverket, Stockholm Stad and Trafik Stockholm :

	Control	Data/Sensing

Urban	• Mixture of fixed coordinated traffic controls and fully actuated
	• Time-of-day-based signal plans (based on known demand patterns)
	• Thresholds often based on expert knowledge/ experience rather than current conditions
	• Currently no method to evaluate usefulness of alternative control methods apart from real-world testing
		• Loop detectors in front of traffic lights
		  • But: requires additional programming work for Stockholm Stad to send/store the data
		  • **How much time would that require/ realistic during project?**

Motorway	• Speed recommendations, Congestion warning via MCS • Tunnel closures • Limited ramp metering at controlled intersections feeding the motorway • Fixed threshold-based reactive control: when congestion forms MCS shows speed recommendations, proactive system missing	• Real-time traffic data from TDIS via API available • Includes Flows, speeds in 1 minute resolution

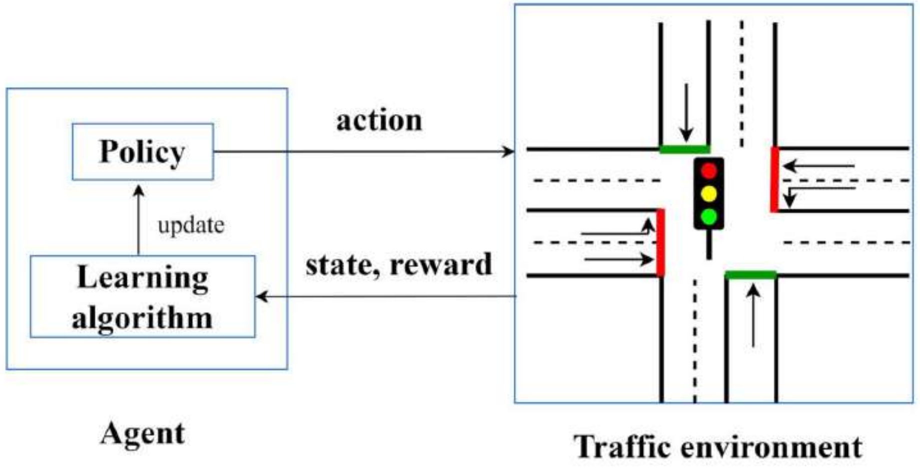
Needs:

→ Optimized (proactive) real-time control

→ Tool that enables safe & efficient evaluation of alternative control strategies

WP1: Literature study – Reinforcement Learning for TSC

- DT and Reinforcement Learning (RL)-based traffic control
  - Optimal control is learned by interacting with the environment (or simulated environment)
- Shows promising results in the literature, but haven't been successfully applied in the real-world yet
- Reasons for that include:
  - Robustness:
    - Sensitive to distribution shifts
  - Transferability
    - Sim-to-Real Gap
  - Interpretability
    - Policy contained in a Deep Neural Network – Not human readable

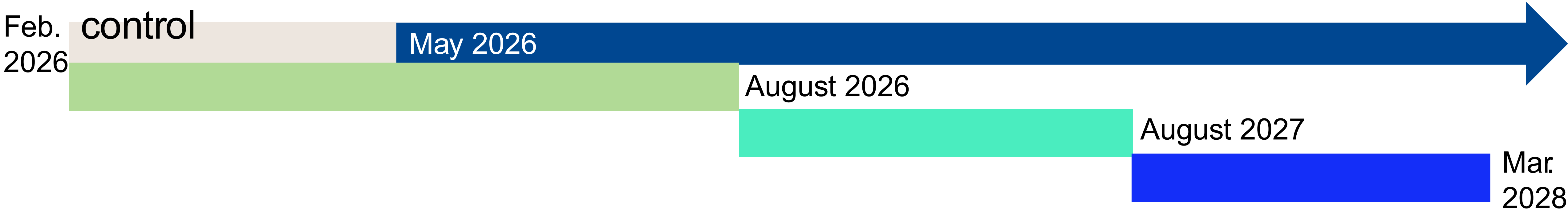


RL-based TSC Set-Up

→ Digital Twin enables continuous learning and fine tuning on real-world observation improving **robustness** and **transferability**

Project Plan

Develop and test **T-Twin sandbox** for integrated motorway and urban traffic control



WP1 Mapping current practices and needs

Requirements for the DT sandbox

WP2 Developing the T-Twin sandbox

Modula lab-version DT sandbox aligns with TDIS architecture

WP3 Building the traffic control optimizer

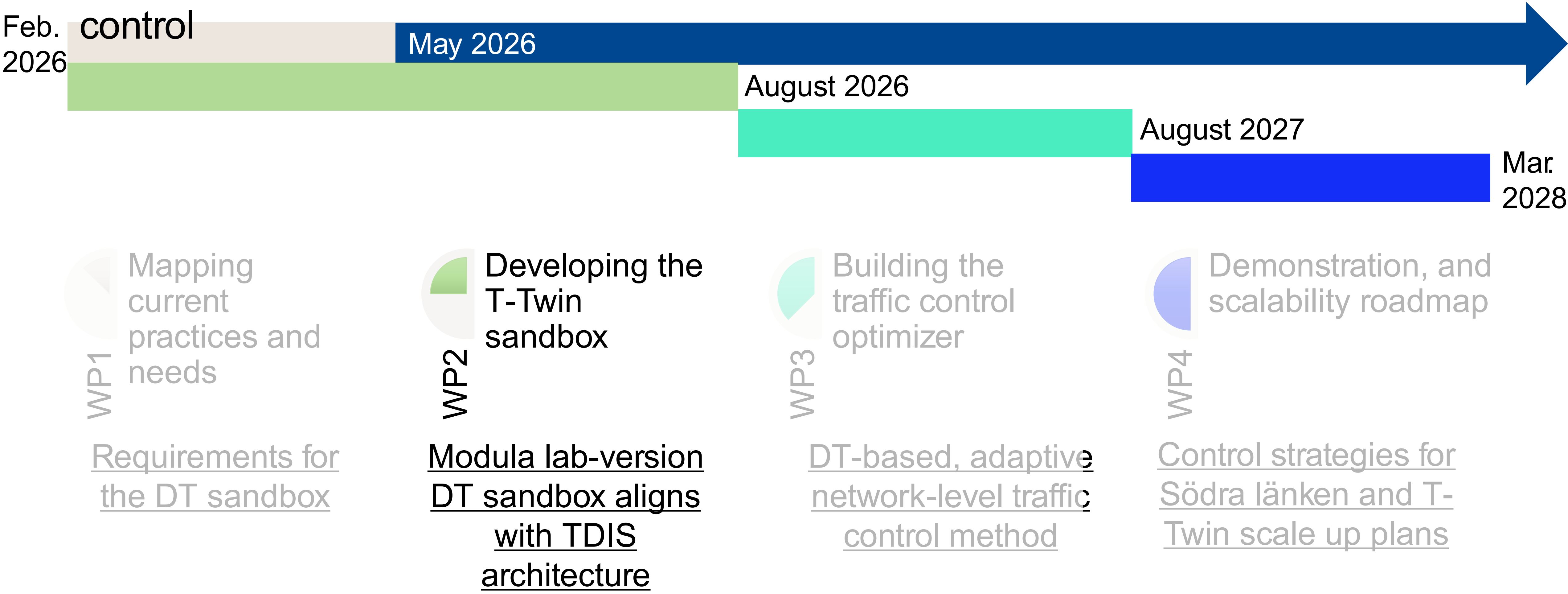
DT-based, adaptive network-level traffic control method

WP4 Demonstration, and scalability roadmap

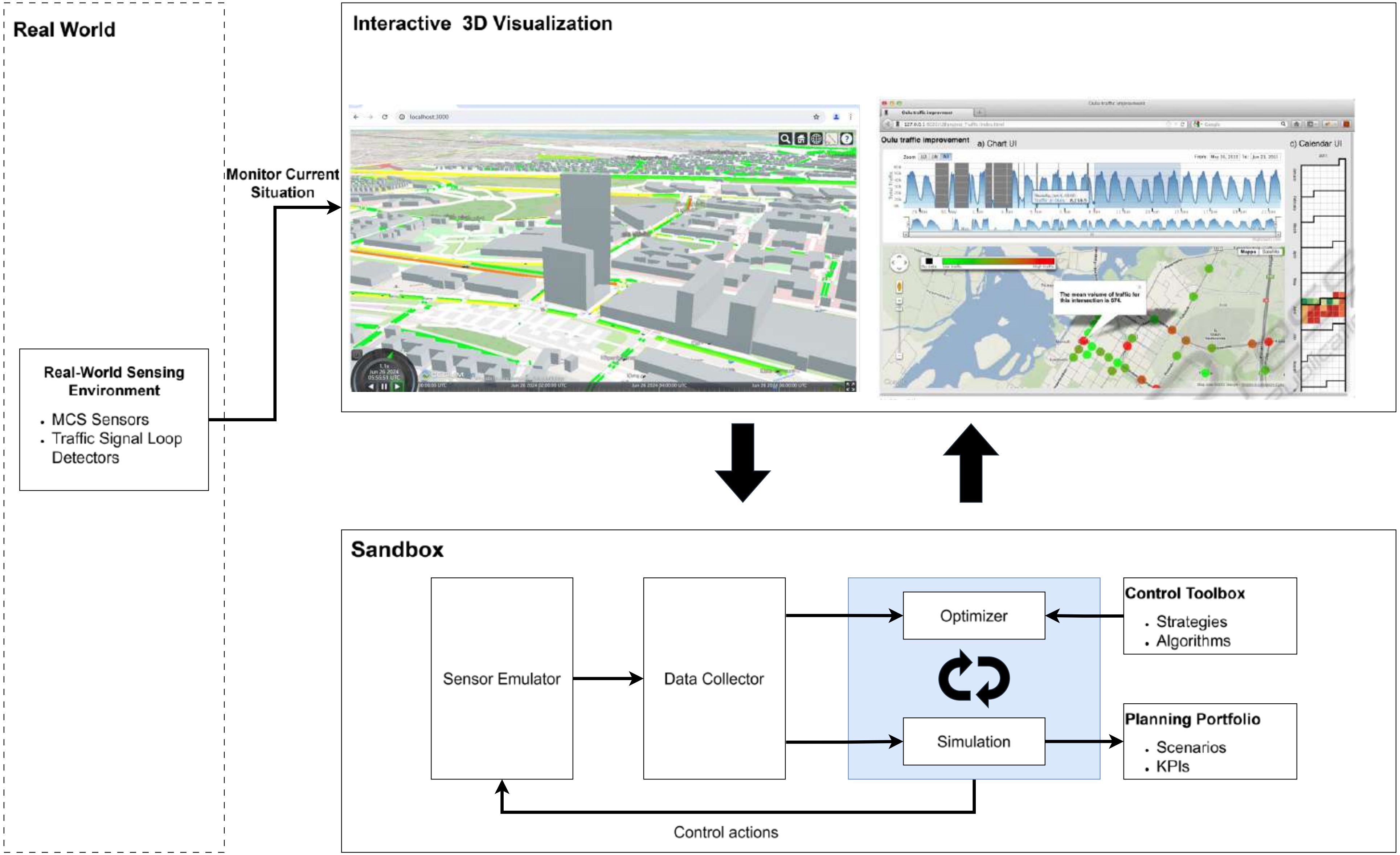
Control strategies for Södra länken and T-Twin scale up plans

Project Plan

Develop and test **T-Twin sandbox** for integrated motorway and urban traffic control



WP2: Developing the T-Twin sandbox

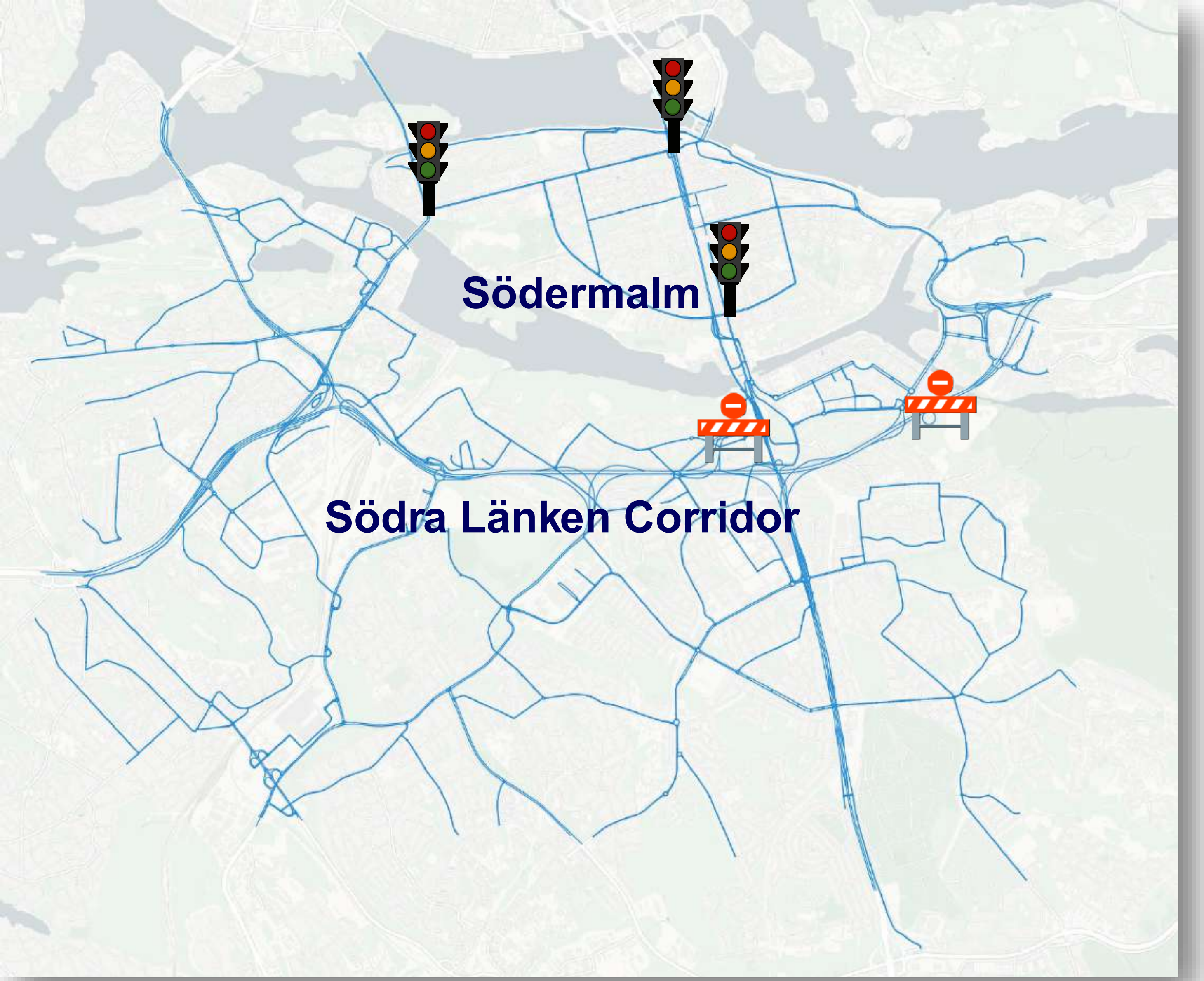


Case Study Area

Requirements

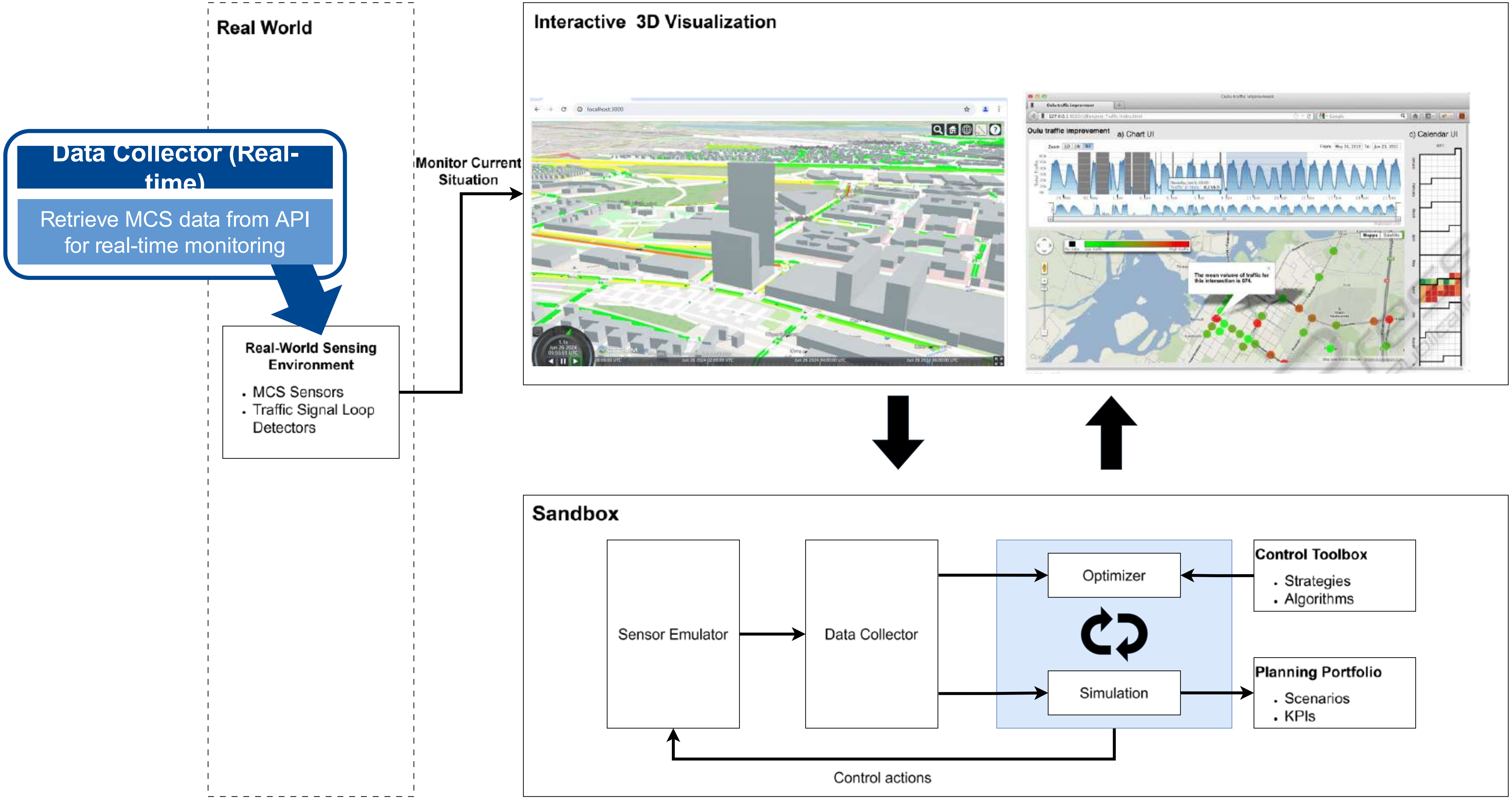
- Network Level Traffic Control (→ Urban + Motorways)
- Existing control infrastructure (traffic lights, variable speed limits, …)
- Data availability

→ Södra Länken (motorway) + Södermalm (urban area)



Road Closure icon by Icons8

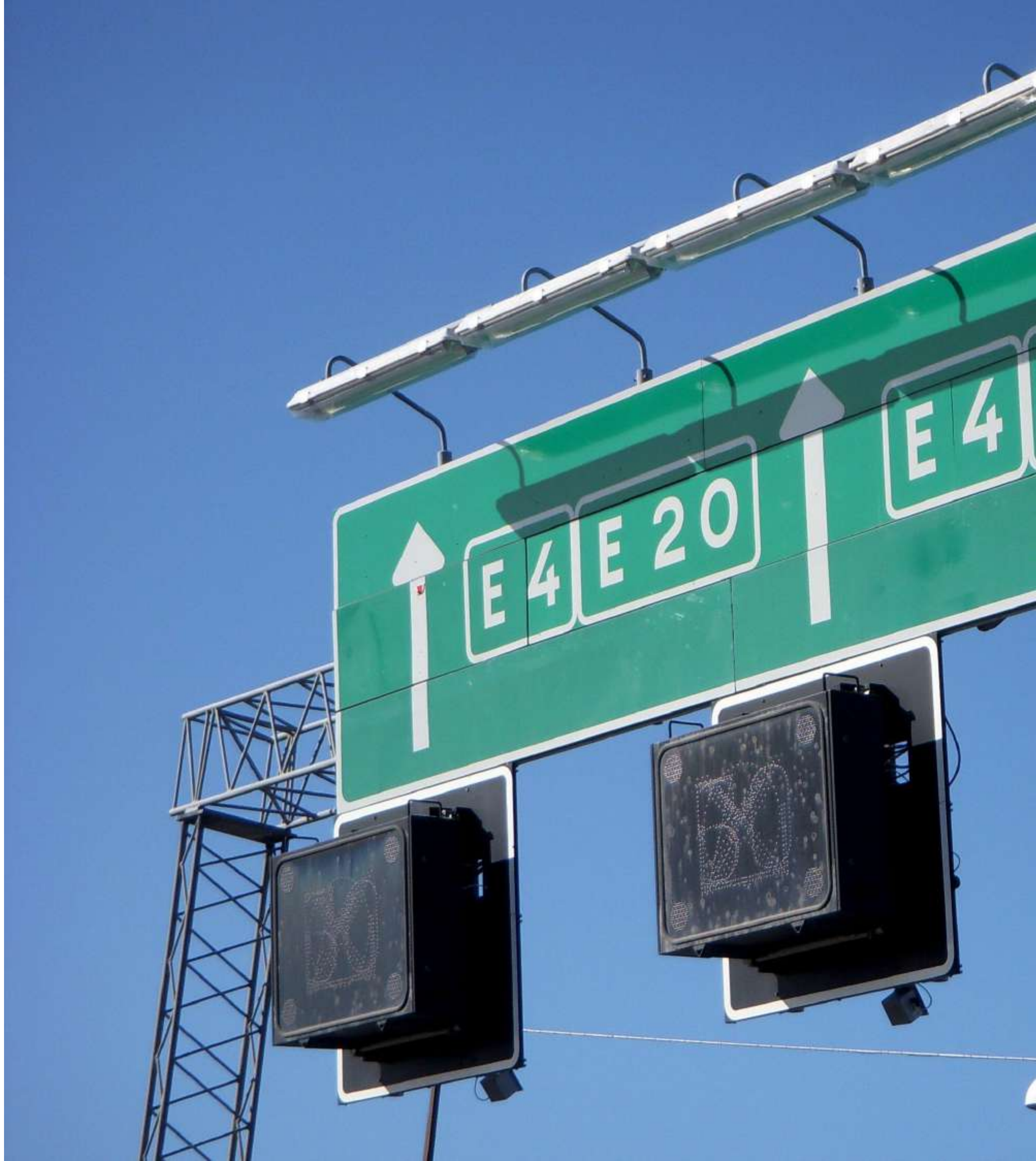
WP2: T-Twin Sandbox Development Plan



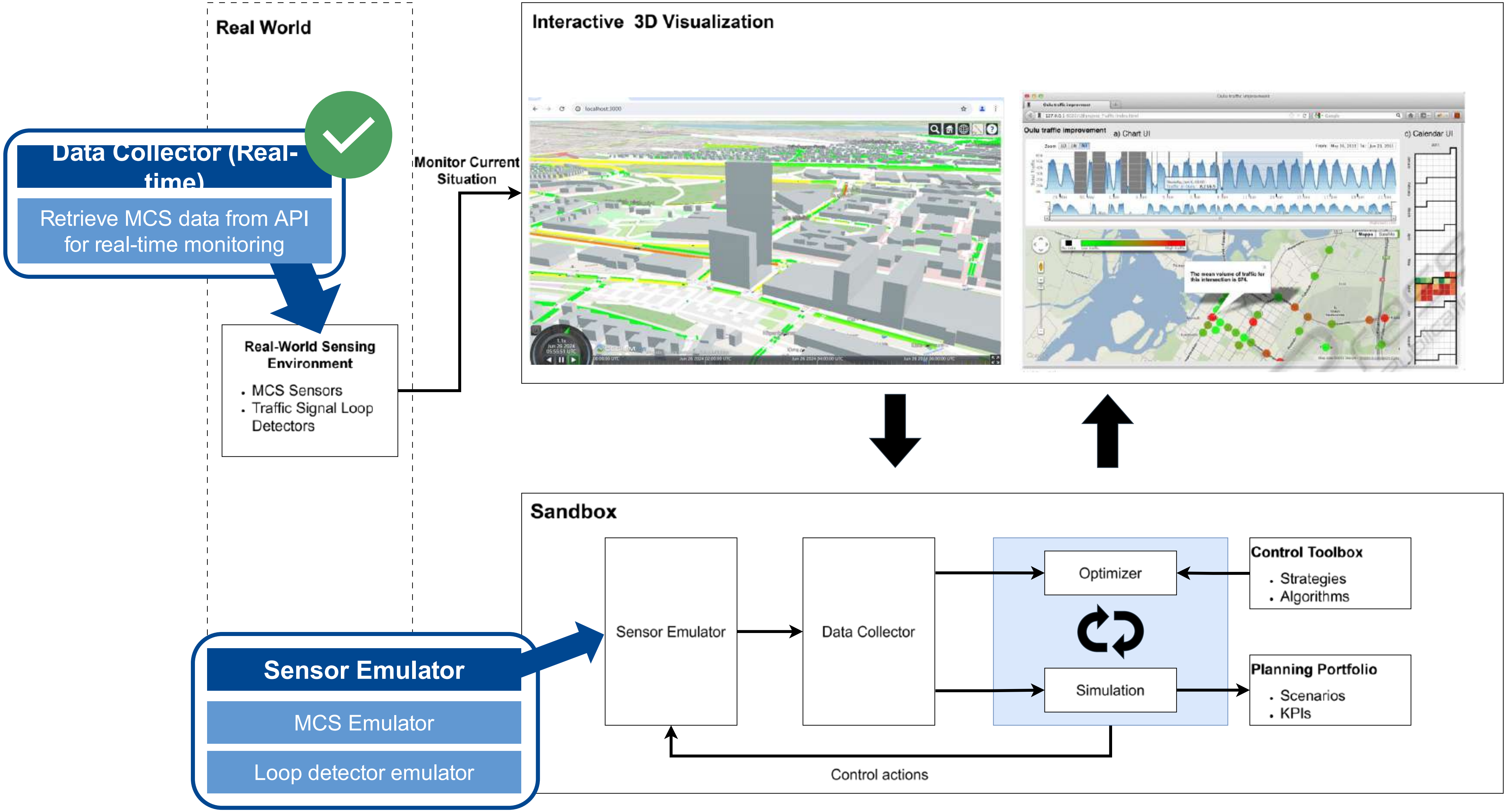
Data Collector

- Trafikverket collects data from MCS radar detectors and publishes in 1 minute aggregation
  - Avg. Speed
  - Avg. Flow

API → Processing → Mapping to correct roads → visualization platform



WP2: T-Twin Sandbox Development Plan



Sensor Emulator

Sensor data from loop detectors/radar is often not accurate

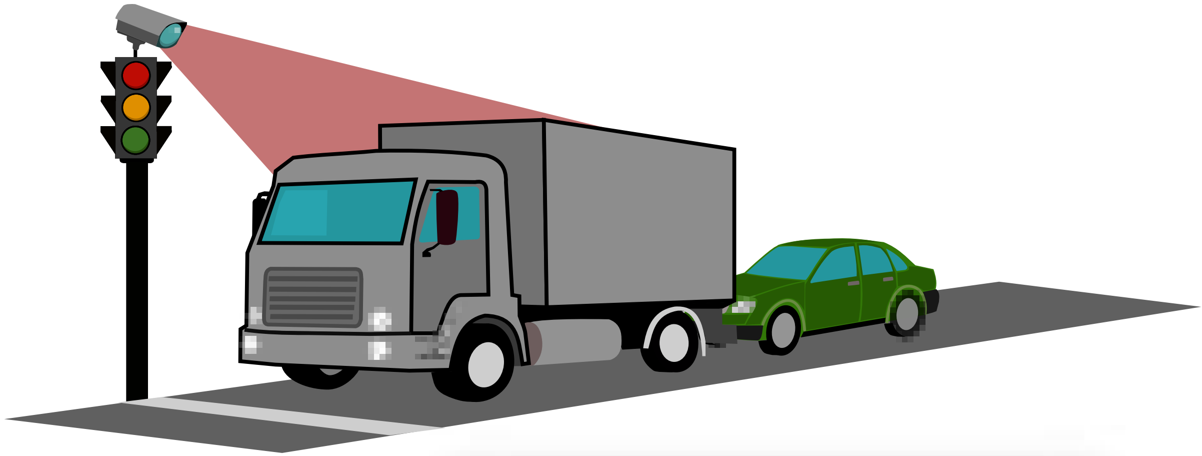
Examples:

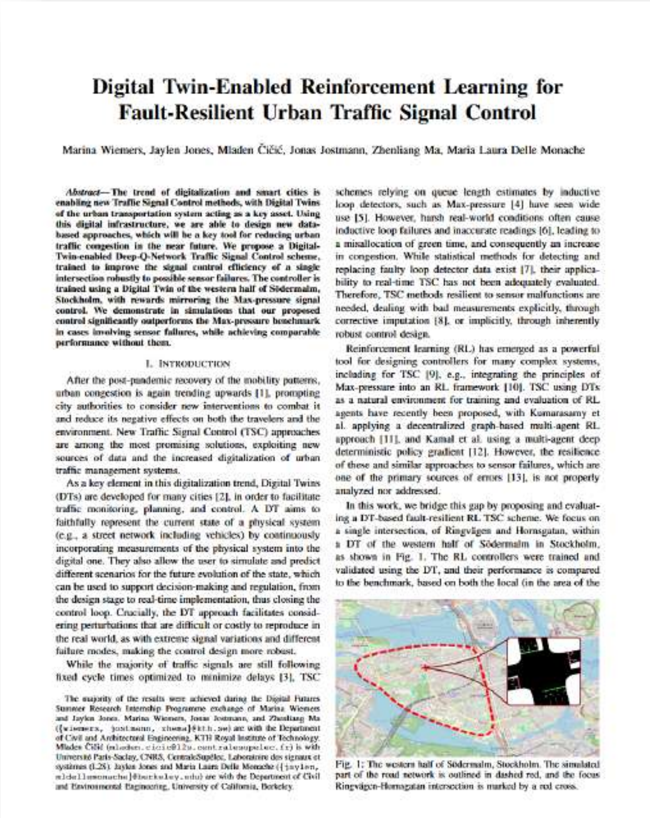
- Occlusion
- Double detection through loop detectors
- Blackout
- Weather dependent sensor failures

→**Problem when training RL-based tsc algorithms in perfect simulation (sim-to-real gap)**

→ Publication shows training with failures improves RL performance

M. Wiemers, J. Jones, M. Cicic, J. Jostmann, Z. Ma, M. L. Delle Monache, "*Digital Twin-Enabled Reinforcement Learning for Fault-Resilient Urban Traffic Signal Control*", Accepted for presentation at European Control Conference (ECC 2026)





Digital Twin-Enabled Reinforcement Learning for Fault-Resilient Urban Traffic Signal Control

Marina Wiemers, Jaylen Jones, Mladen Čičić, Jonas Jostmann, Zhenliang Ma, Maria Laura Delle Monache

***Abstract*— The trend of digitalization and smart cities is enabling new Traffic Signal Control methods, with Digital Twins of the urban transportation system acting as a key asset. Using this digital infrastructure, we are able to design new data-based approaches, which will be a key tool for reducing urban traffic congestion in the near future. We propose a Digital-Twin-enabled Deep-Q-Network Traffic Signal Control scheme, trained to improve the signal control efficiency of a single intersection robustly to possible sensor failures. The controller is trained using a Digital Twin of the western half of Södermalm, Stockholm, with rewards mirroring the Max-pressure signal control. We demonstrate in simulations that our proposed control significantly outperforms the Max-pressure benchmark in cases involving sensor failures, while achieving comparable performance without them.**

I. INTRODUCTION

After the post-pandemic recovery of the mobility patterns, urban congestion is again trending upwards [1], prompting city authorities to consider new interventions to combat it and reduce its negative effects on both the travelers and the environment. New Traffic Signal Control (TSC) approaches are among the most promising solutions, exploiting new sources of data and the increased digitalization of urban traffic management systems.

As a key element in this digitalization trend, Digital Twins (DTs) are developed for many cities [2], in order to facilitate traffic monitoring, planning, and control. A DT aims to faithfully represent the current state of a physical system (e.g., a street network including vehicles) by continuously incorporating measurements of the physical system into the digital one. They also allow the user to simulate and predict different scenarios for the future evolution of the state, which can be used to support decision-making and regulation, from the design stage to real-time implementation, thus closing the control loop. Crucially, the DT approach facilitates considering perturbations that are difficult or costly to reproduce in the real world, as with extreme signal variations and different failure modes, making the control design more robust.

While the majority of traffic signals are still following fixed cycle times optimized to minimize delays [3], TSC schemes relying on queue length estimates by inductive loop detectors, such as Max-pressure [4] have seen wide use [5]. However, harsh real-world conditions often cause inductive loop failures and inaccurate readings [6], leading to a misallocation of green time, and consequently an increase in congestion. While statistical methods for detecting and replacing faulty loop detector data exist [7], their applicability to real-time TSC has not been adequately evaluated. Therefore, TSC methods resilient to sensor malfunctions are needed, dealing with bad measurements explicitly, through corrective imputation [8], or implicitly, through inherently robust control design.

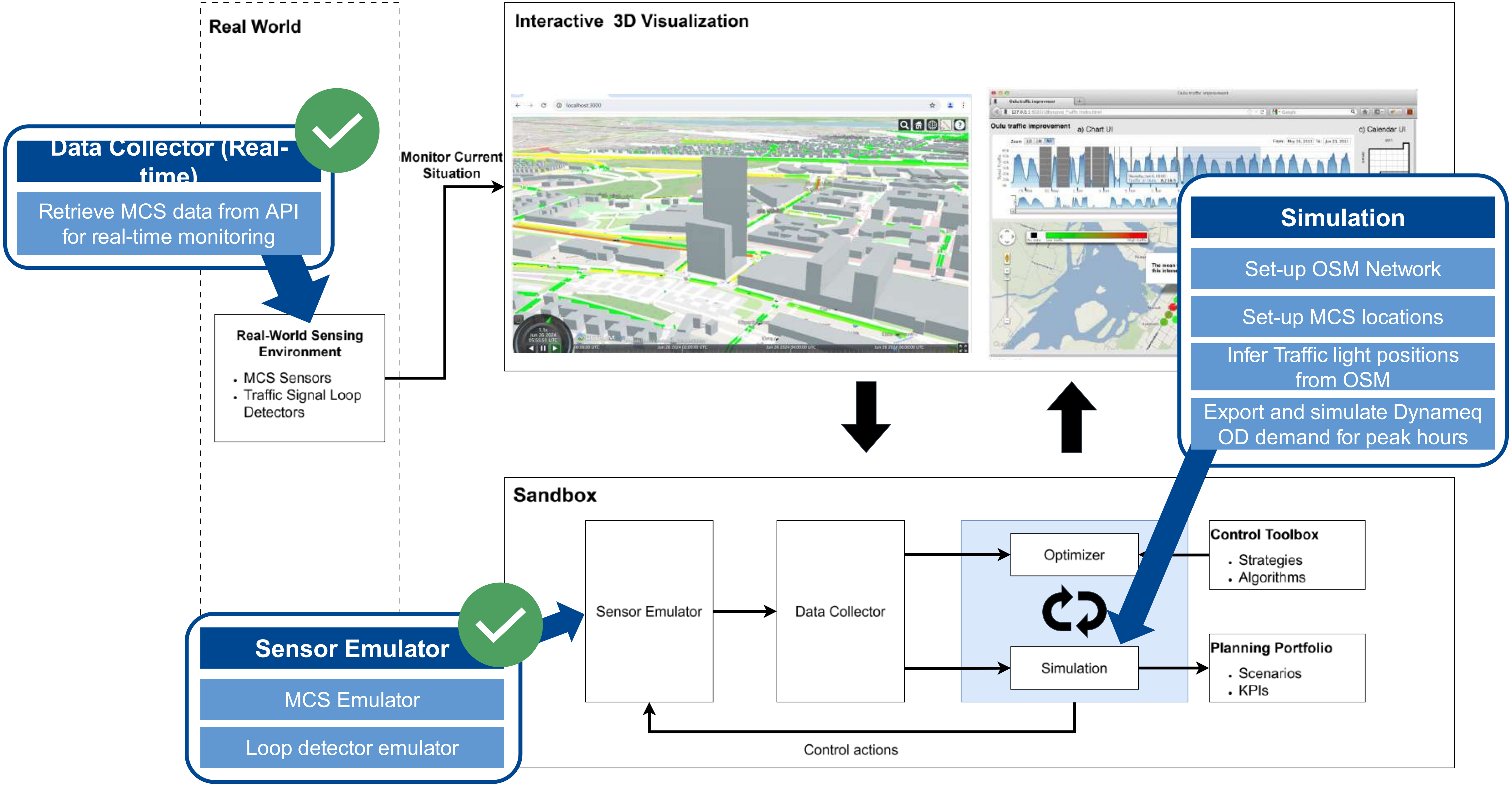
Reinforcement learning (RL) has emerged as a powerful tool for designing controllers for many complex systems, including for TSC [9], e.g., integrating the principles of Max-pressure into an RL framework [10]. TSC using DTs as a natural environment for training and evaluation of RL agents have recently been proposed, with Kumarasamy et al. applying a decentralized graph-based multi-agent RL approach [11], and Kamal et al. using a multi-agent deep deterministic policy gradient [12]. However, the resilience of these and similar approaches to sensor failures, which are one of the primary sources of errors [13], is not properly analyzed nor addressed.

In this work, we bridge this gap by proposing and evaluating a DT-based fault-resilient RL TSC scheme. We focus on a single intersection, of Ringvägen and Hornsgatan, within a DT of the western half of Södermalm in Stockholm, as shown in Fig. 1. The RL controllers were trained and validated using the DT, and their performance is compared to the benchmark, based on both the local (in the area of the

Fig. 1: The western half of Södermalm, Stockholm. The simulated part of the road network is outlined in dashed red, and the focus Ringvägen-Hornsgatan intersection is marked by a red cross.

The majority of the results were achieved during the Digital Futures Summer Research Internship Programme exchange of Marina Wiemers and Jaylen Jones. Marina Wiemers, Jonas Jostmann, and Zhenliang Ma ({wiemers, jostmann, zhema}@kth.se) are with the Department of Civil and Architectural Engineering, KTH Royal Institute of Technology. Mladen Čičić (mladen.cicic@l2s.centralesupelec.fr) is with Université Paris-Saclay, CNRS, CentraleSupélec, Laboratoire des signaux et systèmes (L2S). Jaylen Jones and Maria Laura Delle Monache ({jaylen, mldellemonache}@berkeley.edu) are with the Department of Civil and Environmental Engineering, University of California, Berkeley.

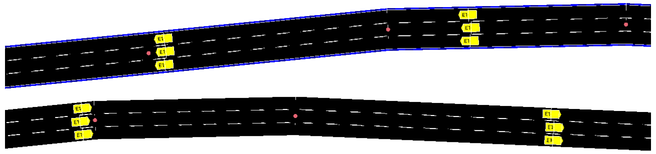
WP2: T-Twin Sandbox Development Plan

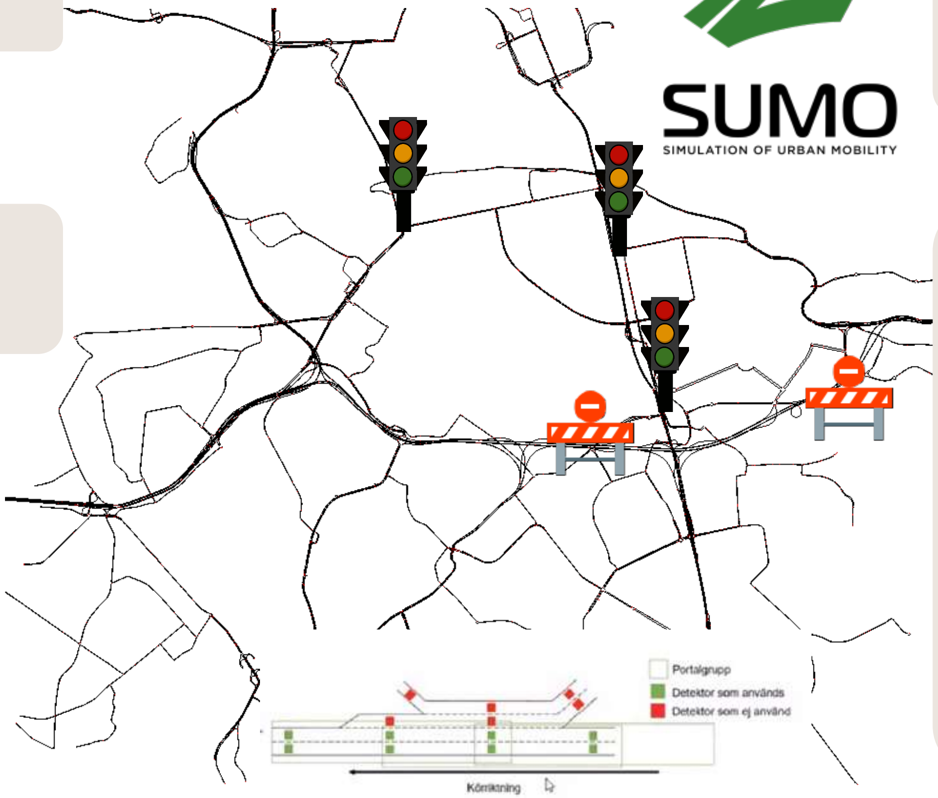


Sandbox – Simulation Set-Up

Replicated Network in SUMO

Mapped and implemented > 500 actual MCS detector locations





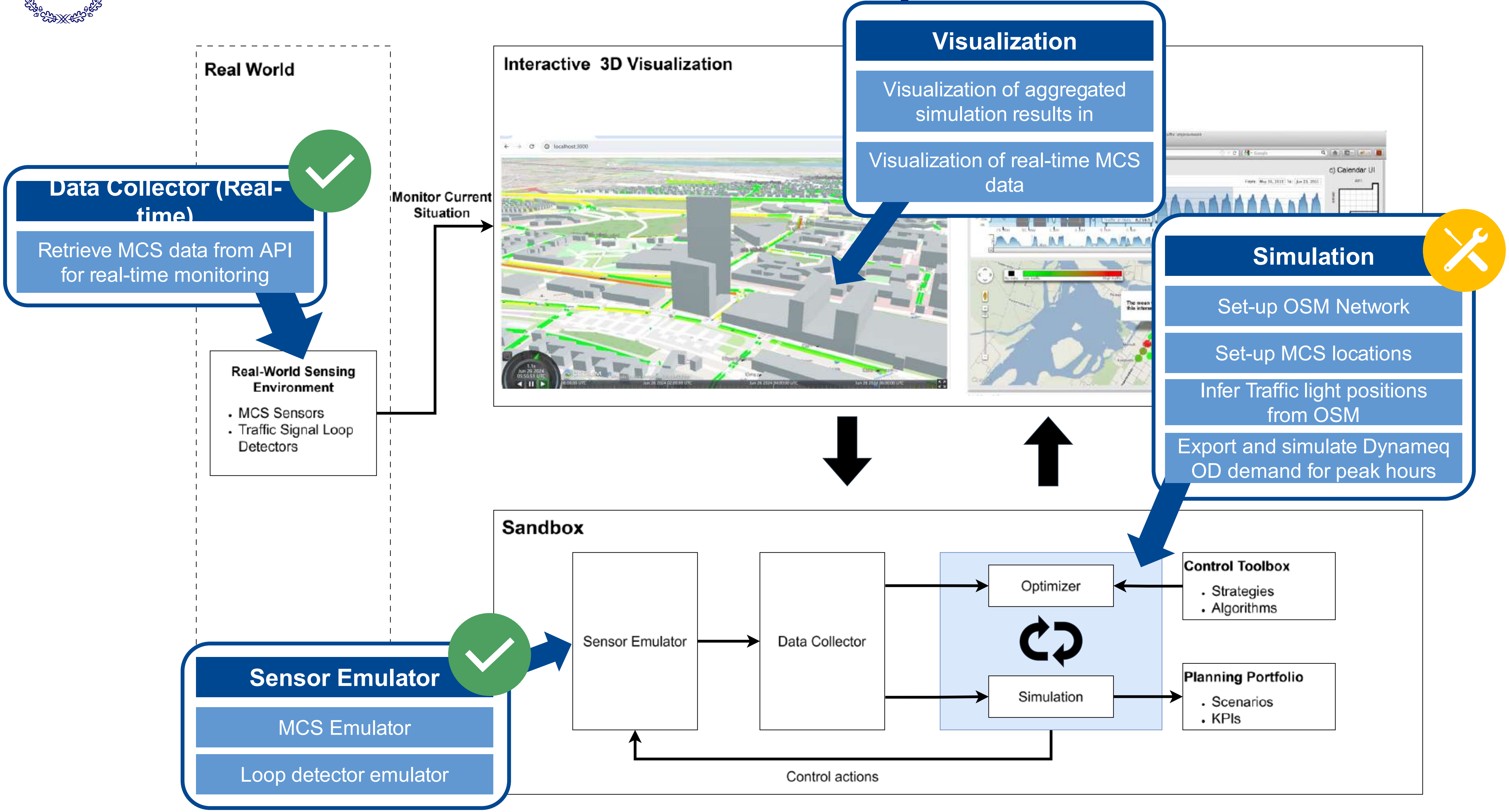
Implemented Traffic Signals in urban area

Implemented Tunnel Closure logic

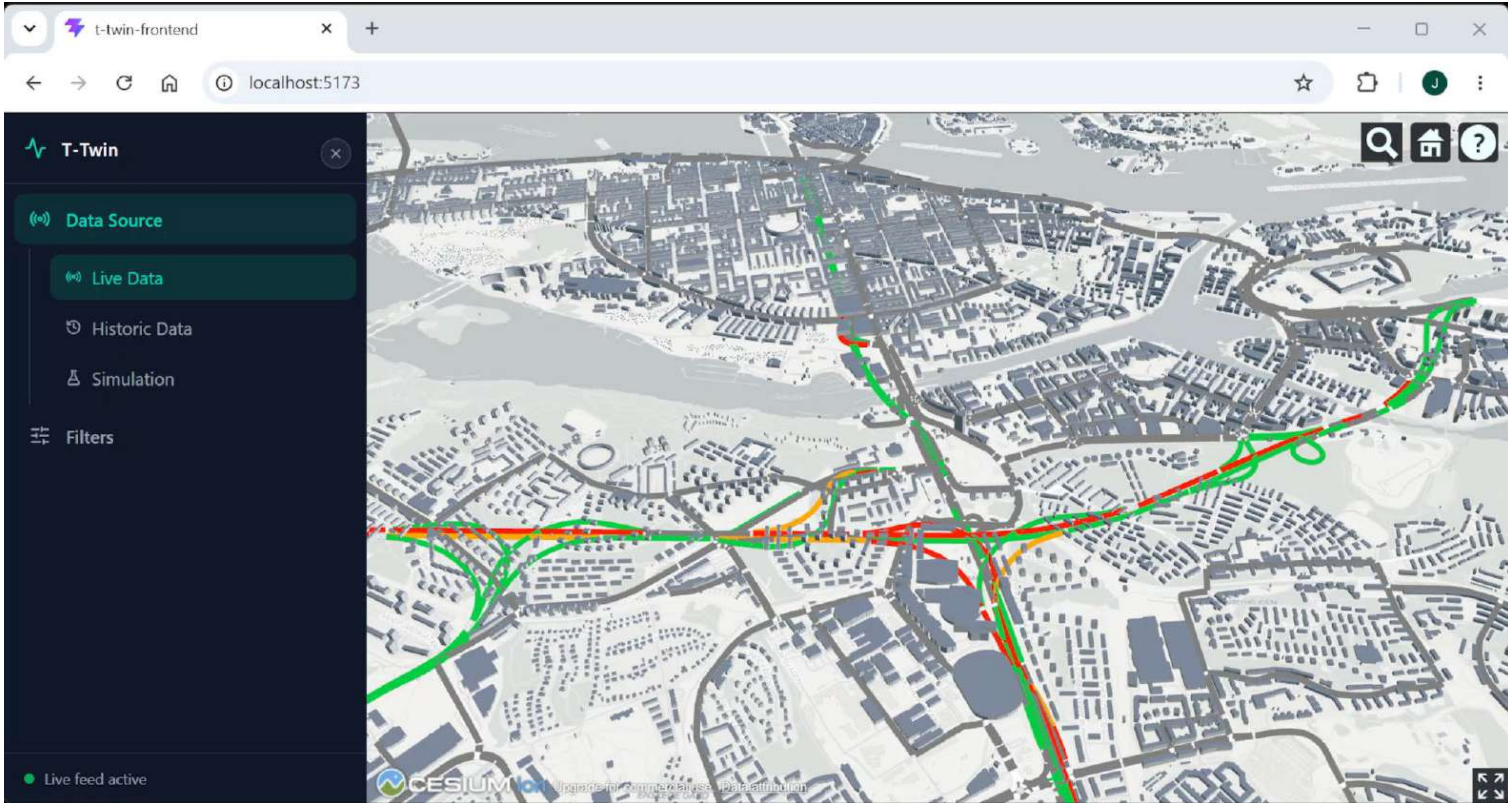
- Sliding window speed calculations of tunnel MCS detectors
- 90% of vehicles < threshold close 2 tunnel entries
- Implemented waiting vs. rerouting logic

Road Closure icon by [Icons8]()

WP2: T-Twin Sandbox Development Plan



Visualization



Summary

WP 1:

- Workshops and literature synthesis to understand current state and needs for network level traffic control

WP 2:

- Implemented connectors to retrieve real-time traffic flow data from motorways
- Implemented sensor emulator for training RL for TSC
- Implemented simulation network and tunnel control logic
- Implemented visualization platform for historic and real-time data motorway data

Outlook

WP 3:

- Implement network level traffic control optimizer

WP 4:

- Implement cyber physical control step for case study region


KTH
VETENSKAP
OCH KONST
Thank you!

CTR DAY 2026

IMPROVING TRAFFIC SIGNAL CONTROL UTILIZING CONNECTED VEHICLE AND ABOVE GROUND DETECTION DATA (IMTRACS)

Rihanna Gebrehiwot, Johan Olstam, Kinjal Bhattacharyya

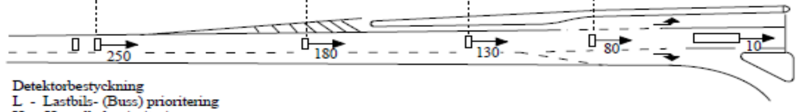
2026-06-16

LINKÖPINGS UNIVERSITET

BACKGROUND: CURRENT TRAFFIC SIGNAL CONTROL

- Swedish traffic signals use the time-gap method + LHOVRA via loop detectors
- These methods have served well, with goals such as:
  - Reducing rear-end collisions, reducing unnecessary amber time, prioritizing main road etc.

Funktion	Funktioners fördelning på detektorer				
L	L				
H		H	H		
O			O	O	
V				V	V
R				R	
A			A	A	A



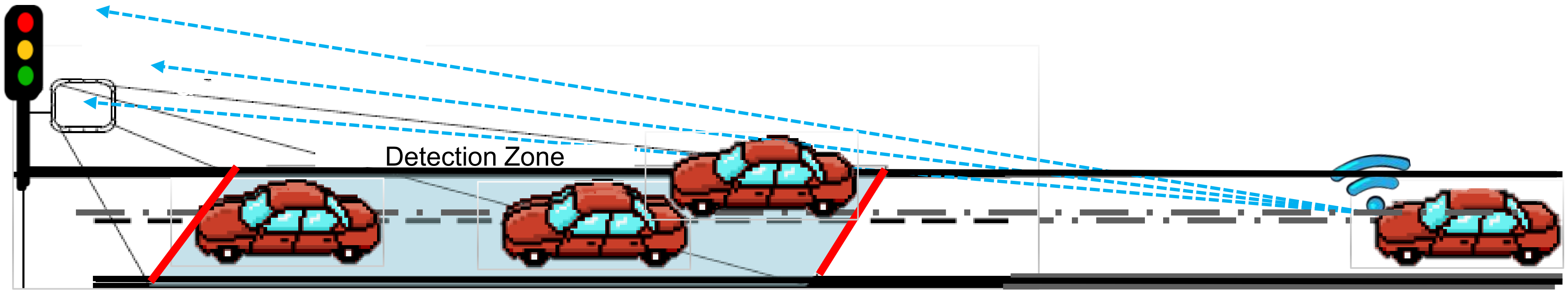
Detektorbestyckning
L - Lastbils- (Buss) prioritering
H - Huvudledsprioritering
O - Olycksreduktion (rödkörnings- och upphinnandeolyckor)
V - Variabelt gult
R - Rödkörningskontroll
A - Allrödvändning

Figur 8. Översikt över LHOVRA-tekniken för en tillfart med 70 km/h

BACKGROUND (CONT'D)

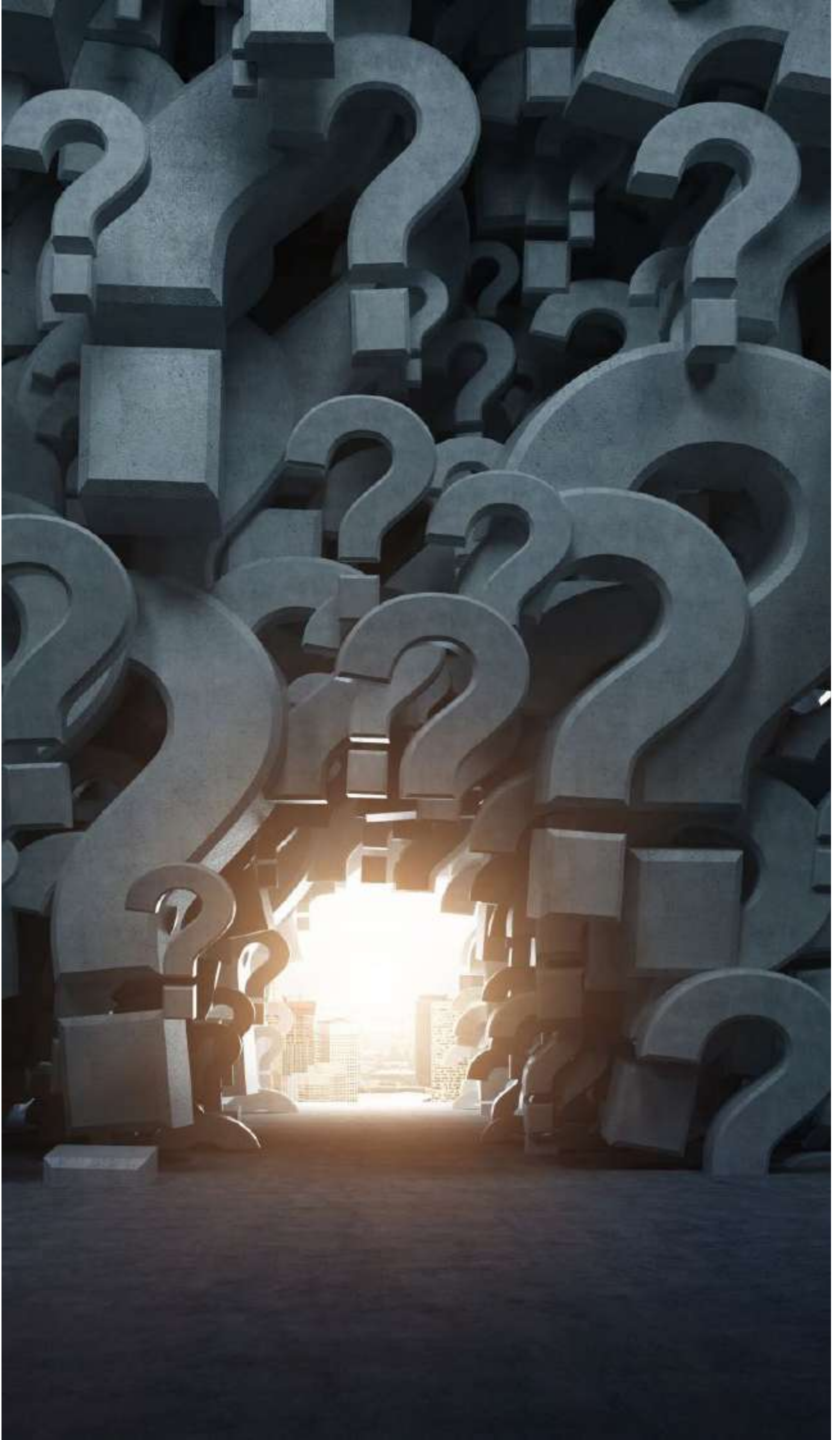
- Limitations:
  - No knowledge of green-time demand before the first detector
  - Limited information between detectors
  - Limited flexibility in adapting to new traffic needs

- Rapid advancements in AGD (lidar, radar, video) and Connected Vehicles (CVs) :
  - Continuous position and speed before & in between detectors
  - Potentially acceleration
  - Help to enhance accuracy and prediction

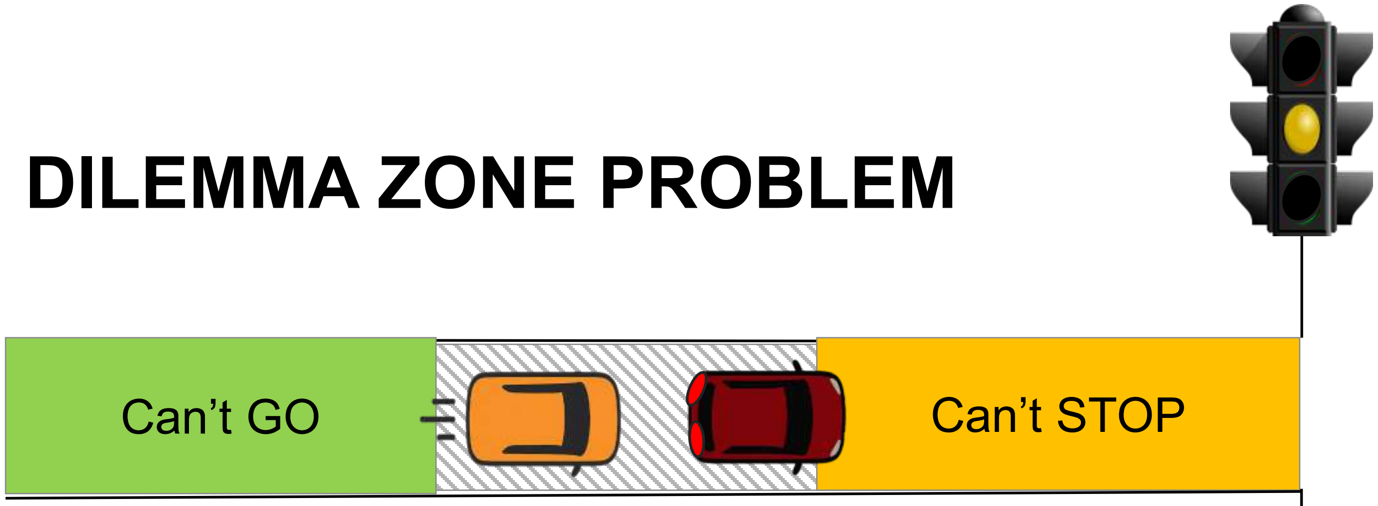


AIM

- How to utilize above ground detection (AGD) and connected vehicle (CV) data to improve decisions on:
  - When to end green phases in order to minimize delay and underutilization of green time
  - **How to manage safe and efficient transitions once a change has been decided (e.g. the OVR intentions).**



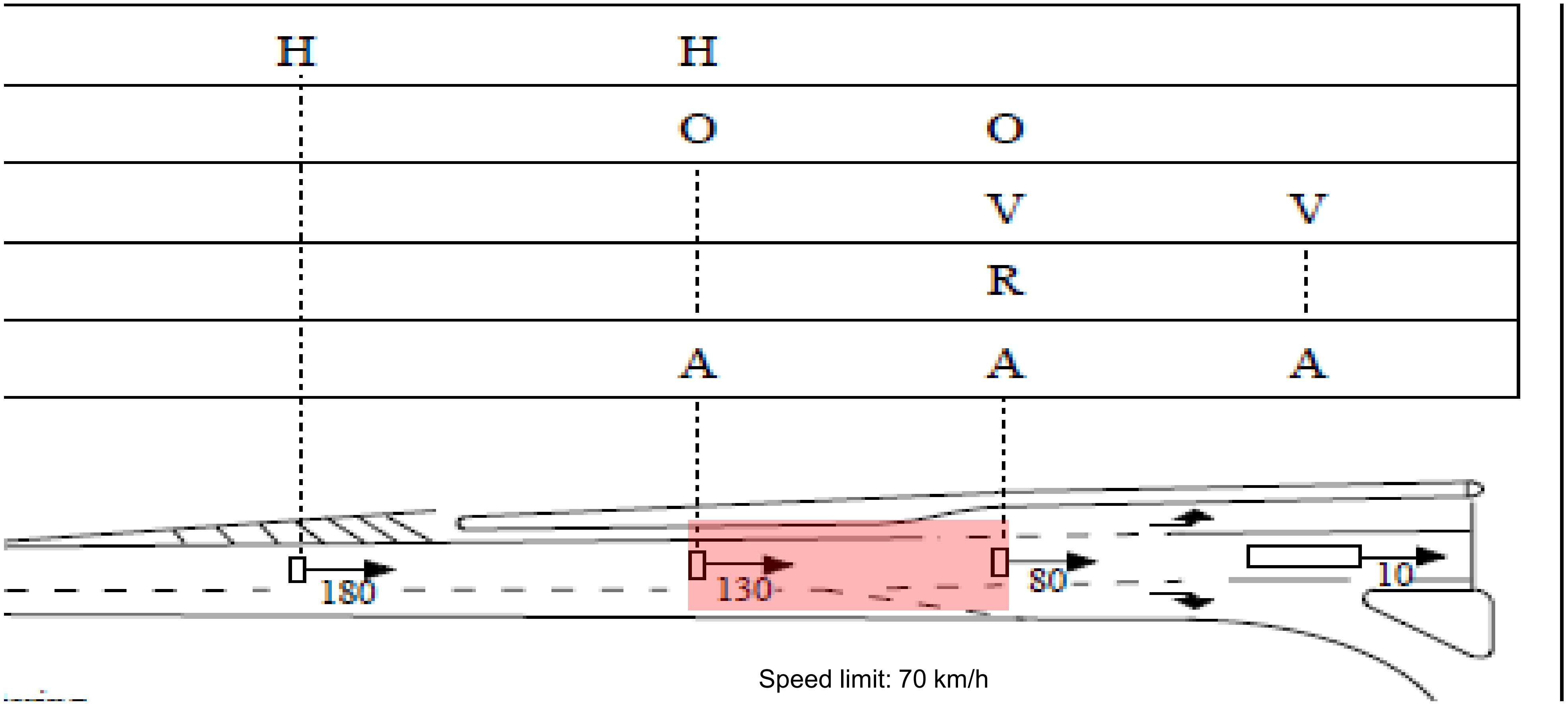
DILEMMA ZONE PROBLEM



- The **dilemma zone:** a critical safety challenge at signalized intersections
    - drivers face uncertainty during the transition from green to amber
    - red-light running (RLR) (when drivers accelerate to clear).
    - rear-end collisions (when drivers brake abruptly)

LINKÖPINGS UNIVERSITET

CURRENT SOLUTIONS FOR DILEMMA ZONE (IN SWEDEN)



OUR RESEARCH: TRAJECTORY-BASED APPROACH

- Objective:
  - Describe the state-of the art on trajectory-based rear-end collision mitigation
  - Evaluate the state-of-the-art algorithms in relation to the OV(R)-functions
  - To suggest an improved mitigation strategy for the transition from green to amber or green to red,
    - With variable amber and all-red intervals
    - Improving both safety and traffic flow
  - Develop models for drivers’ response when facing changes to amber.

LINKÖPINGS UNIVERSITET

FINDINGS FROM LITERATURE REVIEW

- Several interesting algorithms in literature that use AGD and CV data:
  - a lot of focus on rear-end collision mitigation
  - some focus on red light driving collision mitigation and optimizing amber and/or clearance interval
- Potential to combine with Swedish LHOVRA control
- Evaluation and comparison to the current Swedish OV(R)-function is needed before field test

LINKÖPINGS UNIVERSITET

Evaluation of rear-end collision mitigation algorithms

- Several interesting algorithms, BUT tested:
  - Primarily for a single intersection
  - Non-Swedish driver behavior assumptions
- Objective:
  - Compare trajectory-based algorithms with current cross-sectional OV(R) functions to identify their strengths and limitations.
  - Identify if there is a need for:
    - Enhancements to existing algorithms or
    - Development of an alternative trajectory-based algorithm

Method: select 1–3 algorithms → implement in SUMO/VISSIM → case study → compare vs. LHOVRA on: rear-end surrogates, RLR probability, delay, energy

vti

Integrated Intelligent Intersection control system (III-CS)

- Algorithms: Dynamic green extension and dynamic all red extension algorithms
- Dynamic green extension
  - Comparison-based heuristic for DGE’s real-time risk prediction
  - Dynamically terminates green at interval of lowest rear-end collision risk
  - Prevents undesirable max-out during high volume traffic

How the III-CS Works

Dynamic Green Extension (DGE)

Objective: Find the optimal green termination instant to minimize rear-end crash risk.

$$R(t) = \sum_i P_{i,t}^{Stop} * (1 - P_{i+1,t}^{Stop})$$

$$R(t + \Delta t) = \sum_i P_{i,t+\Delta t}^{Stop} * (1 - P_{i+1,t+\Delta t}^{Stop})$$

$$P_{i,t}^{Stop} = \frac{1}{1 + e^{\beta_0 + \beta_v v_i^t + \beta_d d_i^t}}$$

Basic principle:

Extend green if R(t) > R(t+ Δt)
Terminate green if R(t) ≤ R(t+ Δt)

*R(t) = risk at time t

Dynamic All-Red Extension (DARE)

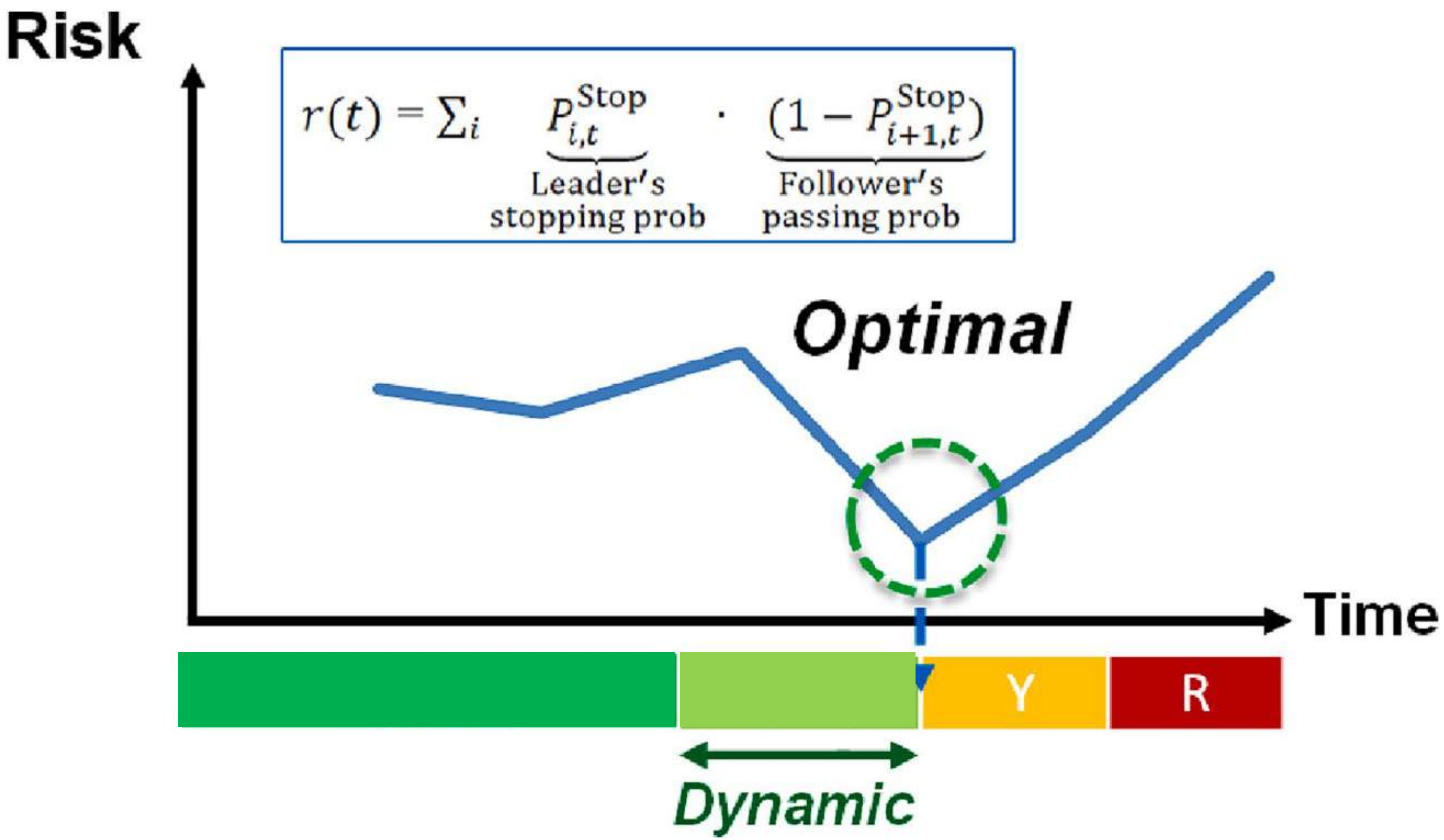
Objective: Prevent angled crashes from red-light runners entering during all-red.

Basic principle:

At each 0.1 s, predict whether any vehicle will still be in the intersection when all-red expires. If yes → extend all-red.

Yen-Hsiang Chen et al. (2023)

DGE design which terminates the green phase at the lowest risk



Past end green

vti

LHOVRA Limitations Addressed by III-CS

LHOVRA	III-CS
Binary gap-acceptance Extends green if ANY vehicle is in decision zone → no risk quantification	✓ Compares $R(t)$ vs $R(t')$;
No future-state prediction Reacts only to current detector states	✓ Projects vehicle positions Δt s ahead using shifted zone boundaries
Saturation under heavy traffic under heavy traffic, green always extends to the maximum → the system can no longer choose a safe moment to terminate	✓ Comparison logic operates even at saturation; always seeks minimum $R(t)$
R-function reliability cannot distinguish decelerating from speeding vehicles → leads to frequent unnecessary activations;	✓ DARE: trajectory projection → 100% detection, 7–12% false alarm rate

vti

Conclusion

- LHOVRA is robust but relies on binary gap logic with no explicit rear-end risk quantification.
- III-CS DGE is based on real-time comparison of risk.
- Field deployment yielded 18.5% fewer vehicles in dilemma zone and significantly smoother deceleration profiles.
- 100% RLR detection
- Next step: simulation validation in Swedish 70 km/h environment.

Foto Mark Cruz, Unsplash

Thank You for Your Attention

Any questions?

CTR vti LiU

LINKÖPINGS UNIVERSITET

Break

14.40-15.00