1

First Bode Lecture: Gunter Stein 1989

Karl Johan Åström Anders Rantzer

Acknowledgements : Matthieu Barreau, Mladen Čičić, Frank Jiang, Ting Bai, Yuchao Li, Truls Nyberg, Vandana Narri, Miguel Aguiar, Jonas Mårtensson, Henrik Sandberg, Dimos Dimarogonas, Dan Work, Carlos Canudas-de-Wit

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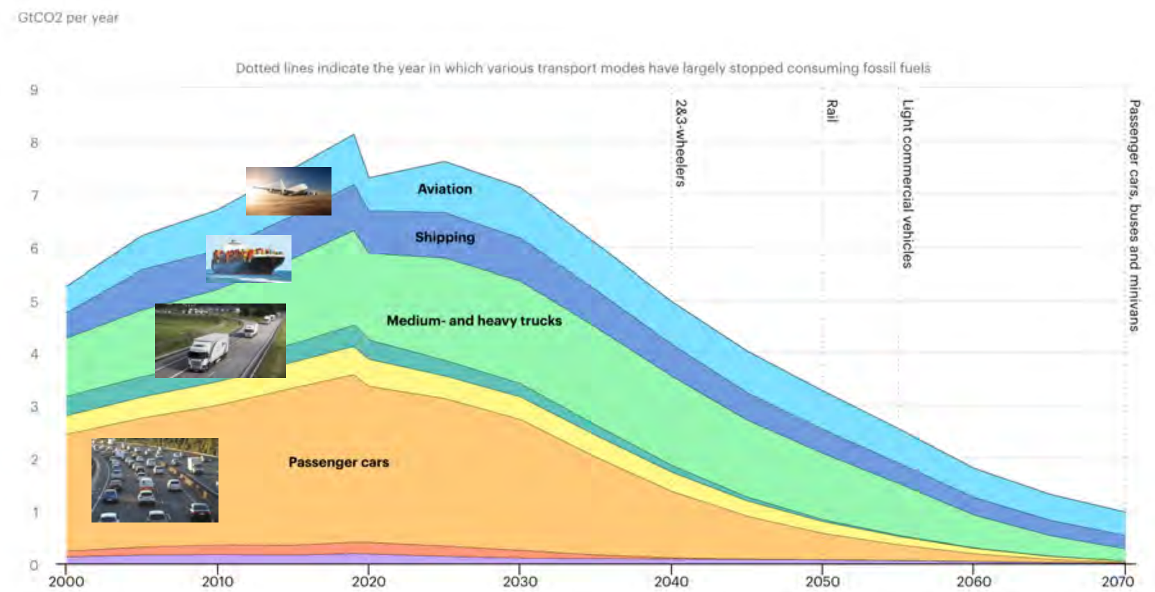
Transport CO2 Emissions in the Sustainable Development Scenario



International Energy Agency, http://www.iea.org

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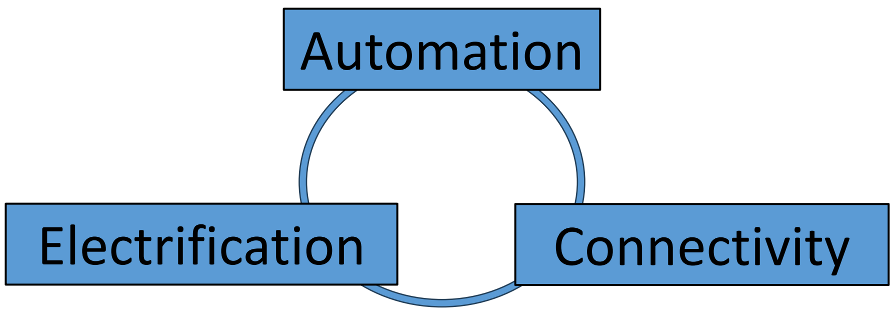
The Transformation of the Transport Sector



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The Transformation of the Transport Sector

Volvo


Einride

Automation

Electrification

Connectivity

Scania


Ma et al., 2024

Jiang et al., 2020

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Self-driving Vehicles?

Society of Automotive Engineers
Levels of Driving Automation (2014)


Waymo

Sergey Brin, Google, 2012

Google's Sergey Brin: You'll ride in robot cars within 5 years

Ordinary folks will have access to self-driving cars in the next few years, the Google cofounder said at a California bill signing today.

Elon Musk, Tesla, 2016

"I really consider autonomous driving a solved problem," he said. "I think we are probably less than two years away."


Stockholm Public Transport

Volvo Group

www.zf.com

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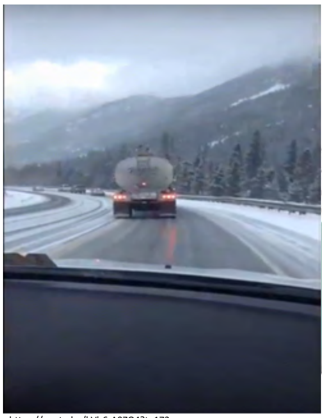
Self-driving Vehicles? Not Yet!

Steven Shladover, UC Berkeley, 2018

"I usually tell today's students that they can work with this for the whole of their career. In my opinion, the technology will be fully developed around 2075 – perhaps a little earlier, or perhaps a little later."

https://www.reddit.com



https://youtu.be/kVI-6-A9ZO4?t=173


npr
Feds Say Self-Driving Uber SUV Did Not Recognize Jaywalking Pedestrian In Fatal Crash


The New York Times
Driverless Car Gets Stuck in Wet Concrete in San Francisco
Though driverless cars have not been blamed for any serious injuries or crashes in the city, they have been involved in several jarring episodes.


Tesla FSD Keeps Trying To Drive Into A Train: Video


Waymo Recalls Robotaxis to Give Telephone Poles a Higher 'Damage Score'

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Why is transportation hard to automate?

UNCERTAINTY

Control is the science of uncertainty

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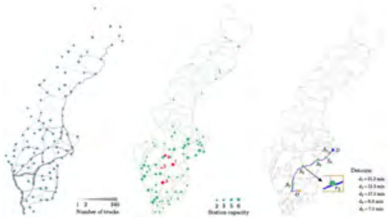
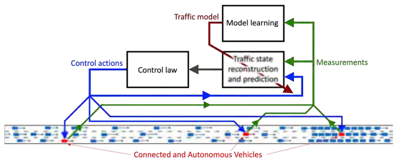
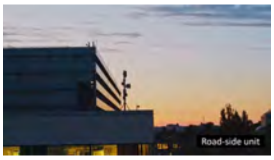
Network optimization



Traffic control



Vehicle autonomy



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Uber Automated Vehicle Accident in 2017

Grembek et al., UC-ITS-2018-13, 2018

Pravin Varaiya

a) Left-turning Honda and Uber's AV Volvo are on the collision course

b) Left-turning Honda does not see Uber's AV Volvo

c) Uber's AV Volvo does not see left-turning Honda

Automated vehicle and human drivers had insufficient information to resolve the situation

- How should automated vehicles handle **occlusions**?
- How should they **reason** about potential vehicles or other road users in occluded areas?

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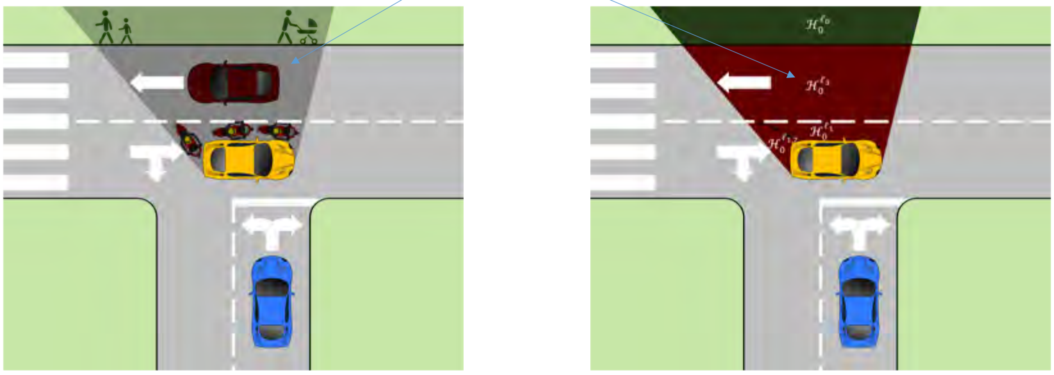
Occlusion

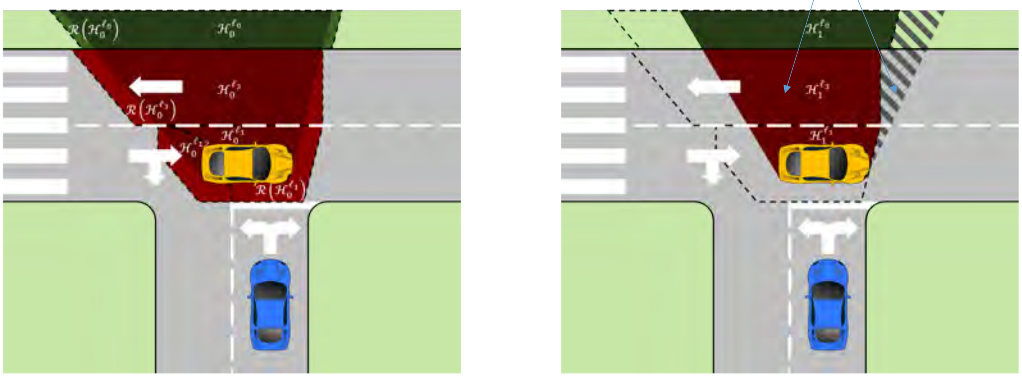
Areas not seen from the **blue ego vehicle**



Nyberg, Gaspar Sanchez, Narri et al., 2024

Foresee the unseen

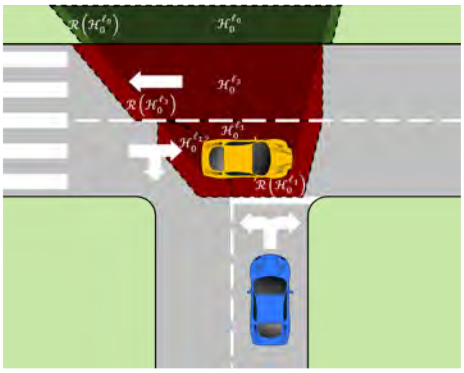
Propagate sets in occluded regions based on lane properties

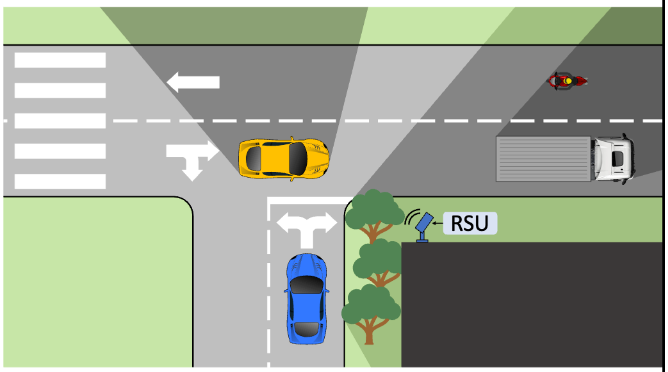


Nyberg, Gaspar Sanchez, Narri et al., 2024

Share the unseen

Ego vehicle situational awareness can be enhanced by roadside unit (RSU) sharing information about occluded areas





Supported by ETSI standard ITS-G5 for V2X communication with Collaborative Perception Messages sent at 10 Hz

Nyberg, Gaspar Sanchez, Narri et al., 2024

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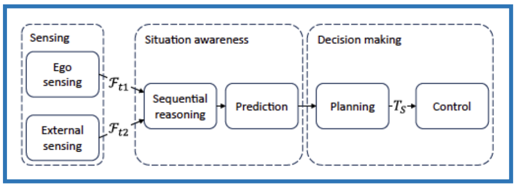
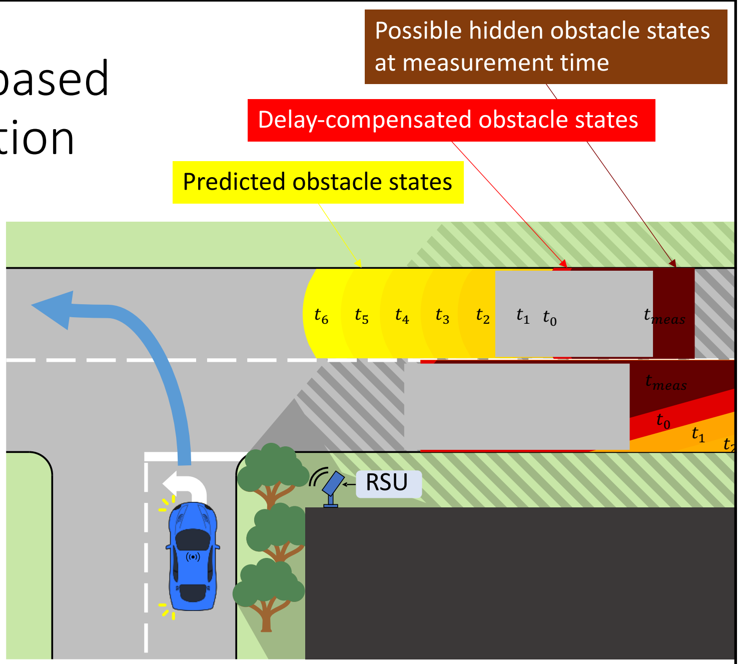
Sequential reasoning based on shared set information



- Set of possible hidden obstacles computed based on reachability analysis using RSU and other sensors information together with traffic rules
- Ego vehicle plans its motion under guarantee to stay in the safe set:

$$
\begin{aligned}
&\textbf{foreach } \mathcal{H}^{\ell}_{t_{\text{latest}}} \in \mathcal{H}^{\mathcal{L}}_{t_{\text{latest}}} \\
&\quad \textbf{foreach } i \in 1 \textbf{ to } N \\
&\qquad t_a \leftarrow t_{\text{latest}} + (i-1)\Delta t \\
&\qquad t_b \leftarrow t_{\text{latest}} + i\Delta t \\
&\qquad \boxed{\mathcal{O}^{\ell}_{[t_a,t_b]} \leftarrow occ(\mathcal{R}(\mathcal{H}^{\ell}_{t_{\text{latest}}}, M^{\ell}, [t_a,t_b]), \mathbf{0})} \\
&\qquad \mathcal{O}_{[t_a,t_b]} \leftarrow \mathcal{O}_{[t_a,t_b]} \cup \mathcal{O}^{\ell}_{[t_a,t_b]} \\
&\mathcal{T} \leftarrow \text{generateTrajectories}(x^{\text{ego}}_{t_{\text{latest}}}) \\
&\boxed{\mathcal{T}_s \leftarrow \text{getSafeTrajectories}(\mathcal{T}, \langle \mathcal{O}_{[t_{\text{latest}}, t_{\text{latest}}+\Delta t]}, \ldots, \mathcal{O}_{[t_a,t_b]} \rangle)} \\
&T \leftarrow \text{getBestTrajectory}(\mathcal{T}_s) \\
&\textbf{return } T
\end{aligned}
$$



Nyberg, Gaspar Sanchez, Narri et al., 2024

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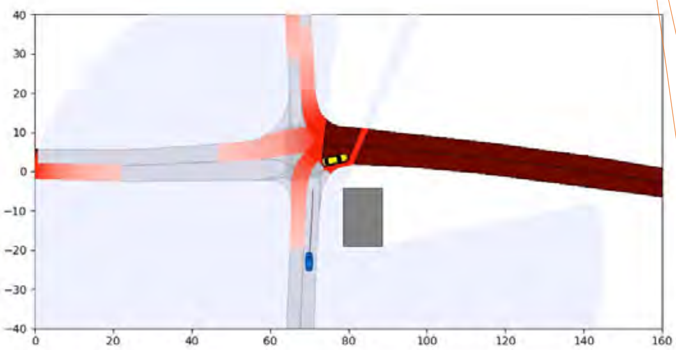
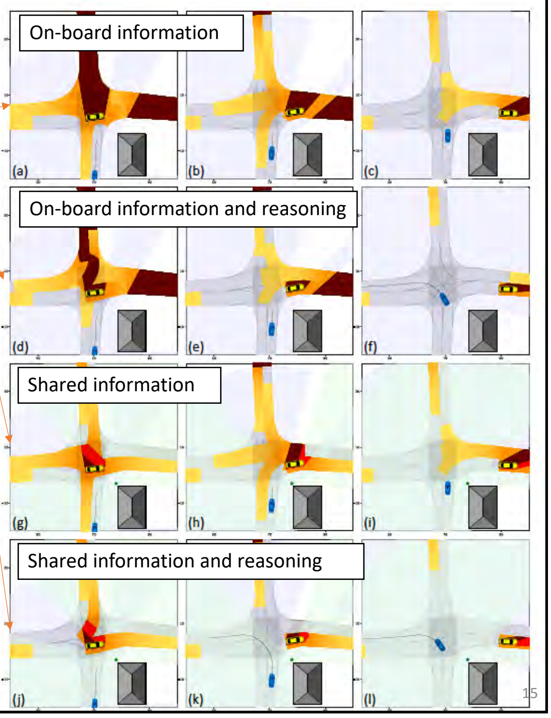
Simulation evaluation with increasing level of shared information and reasoning





Althoff et al., 2017; Orzechowski et al., 2018; Nyberg, Gaspar Sanchez, Narri et al., 2024

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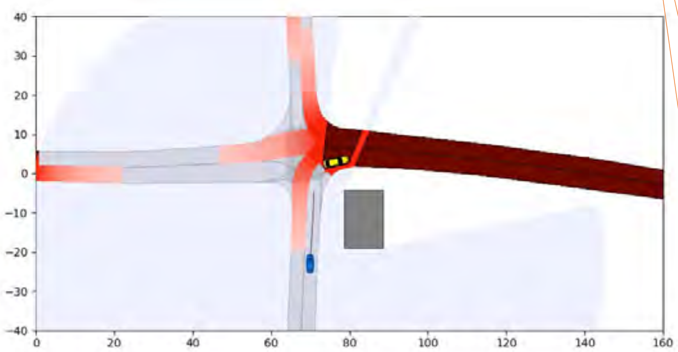
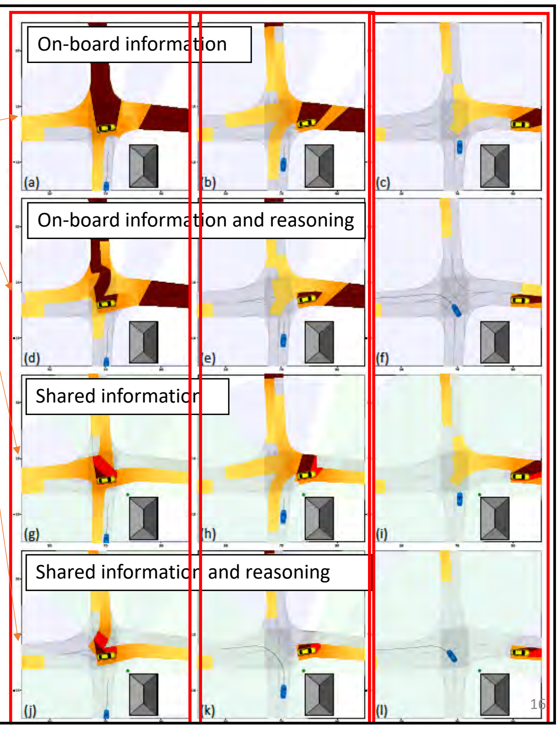
Simulation evaluation with increasing level of shared information and reasoning





Althoff et al., 2017; Orzechowski et al., 2018; Nyberg, Gaspar Sanchez, Narri et al., 2024

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Experimental evaluation on Scania test track

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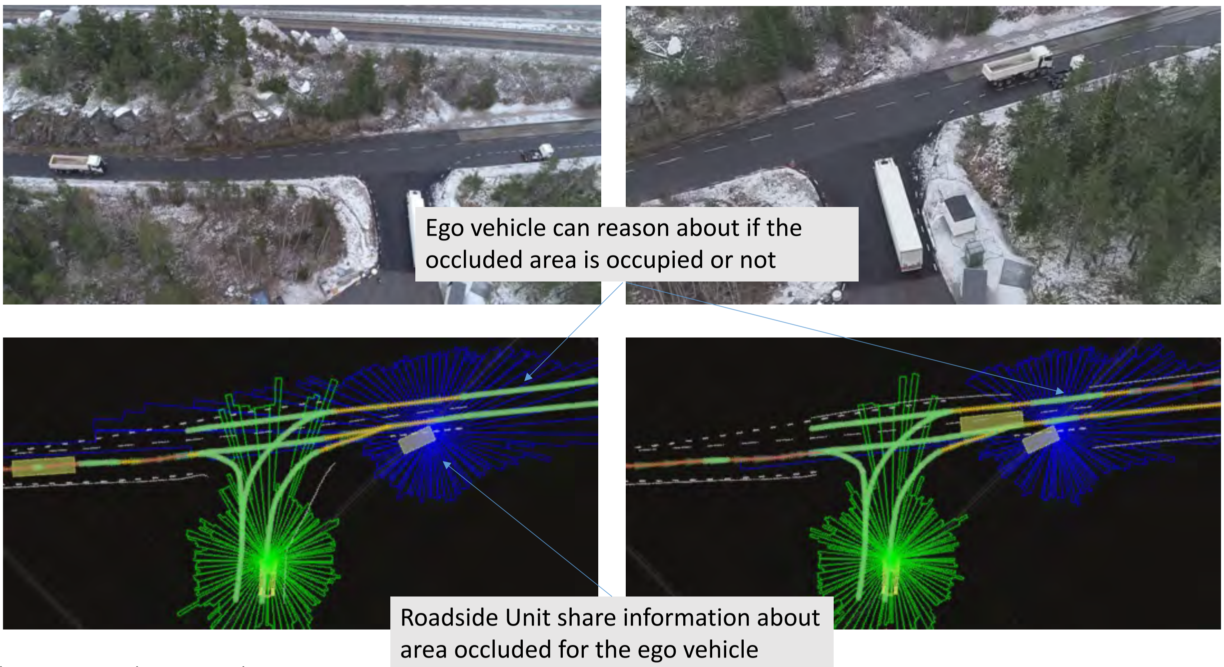

Nyberg, Gaspar Sanchez, Narri et al., 2024

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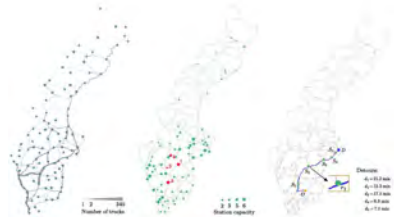
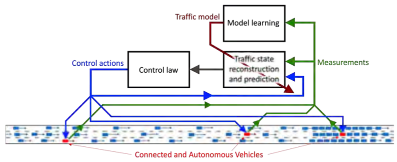
Network optimization



Traffic control



Vehicle autonomy

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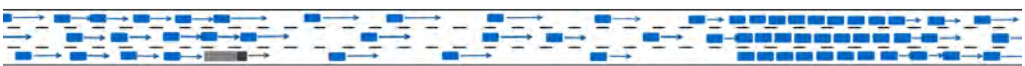
Use automated truck platoons to regulate car traffic

- Trucks are slower than cars and act as moving bottlenecks in traffic
- **Idea:** Regulate cars moving into congested area by controlling platoon velocity



Jin et al., 2018; Čičić, & J, 2018

Stern et al., 2018

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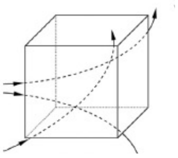
Flows according to Euler and Lagrange

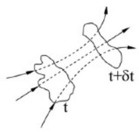
Leonhard Euler (1707-1783)

Joseph-Louis Lagrange (1736-1813)

Euler was looking at fluid motion focused on specific locations in the space through which the fluid flows as time passes.



Lagrange was looking at fluid motion where the observer follows an individual fluid parcel as it moves through space and time



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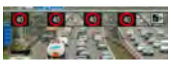
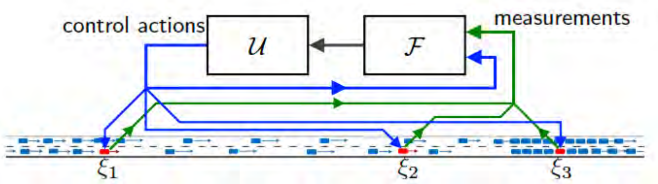
From Eulerian to Lagrangian traffic control



Leonhard Euler (1707-1783)
Stationary observer of the flow
Traffic control based on fixed infrastructure
High deployment costs and limited flexibility

Joseph-Louis Lagrange (1736-1813)
Observers moves with the flow
Traffic control based on mobile sensors and actuators
Need for a new system theoretic foundation



Edie, 1963; Papageorgiou et al., 1991; Hegyi et al., 2005; Ferrara et al., 2018; Yu & Krstić, 2019; Gloudemans et al., 2023

Work et al., 2008; Delle Monache et al., 2019; Barreau et al., 2021
Čičić & J, 2018; Piacentini et al., 2018

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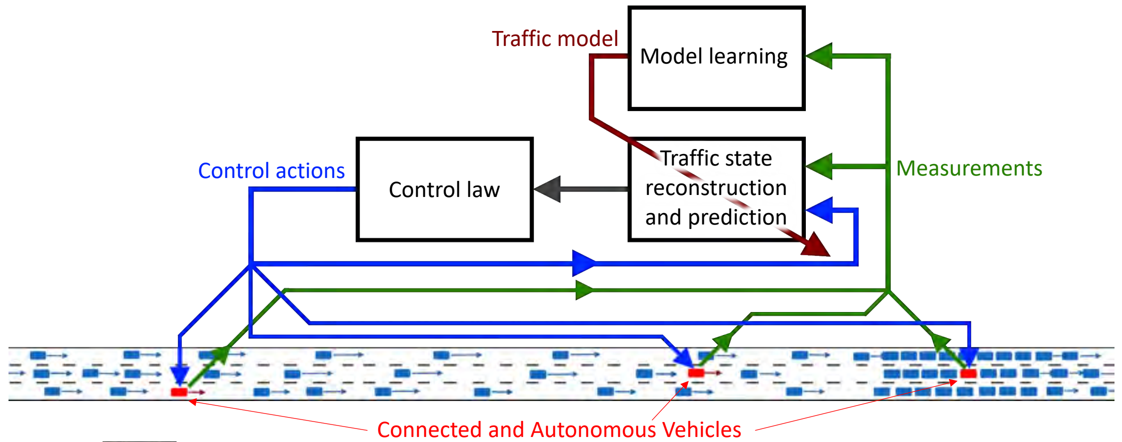
Lagrangian traffic control system



Čičić et al., 2021; Barreau, Aguiar, J, 2021

Wu et al., 2021; Lee et al. 2024

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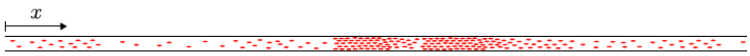
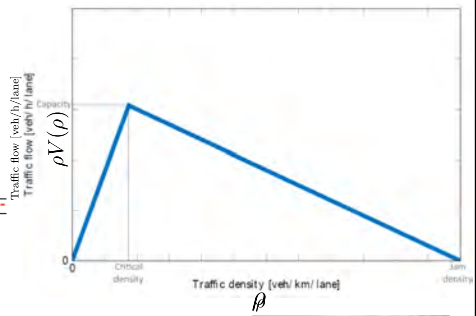
Fundamental diagram of traffic flow

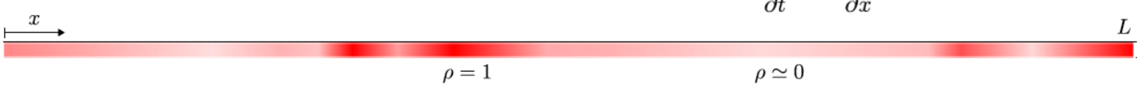
Microscopic traffic model with 329 vehicles $\dot{x}_i(t) = V\left(\rho(t, x_i(t))\right)$





Macroscopic traffic model with density function $\rho : \mathbb{R}^+ \times [0, L] \mapsto [0, 1]$

$$\frac{\partial \rho}{\partial t} + \frac{\partial V(\rho)\rho}{\partial x} = 0$$



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Traffic model with N probing vehicles

$$\frac{\partial \rho}{\partial t} + \frac{\partial V(\rho)\rho}{\partial x} = \gamma^2 \frac{\partial^2 \rho}{\partial x^2}, \quad (t,x) \in [0,T] \times [0,L]$$
$$\dot{x}_i(t) = V(\rho(t, x_i(t))), \quad t \in [0,T], i = 1, \dots, N$$

Control of a coupled PDE-ODE system

Lebacque et al., 1998; Delle Monache & Goatin, 2014; Barreau, Selivanov, J, 2020; Barreau, Aguiar et al., 2021

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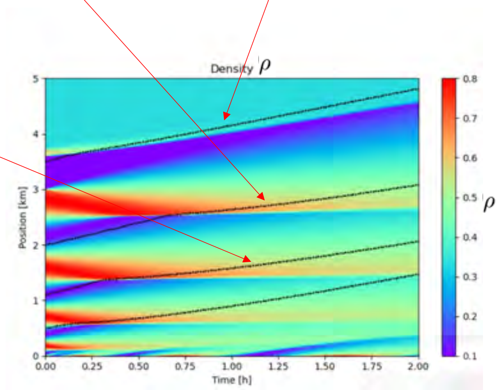
Traffic model with N probing vehicles

$$\frac{\partial \rho}{\partial t} + \frac{\partial V(\rho)\rho}{\partial x} = \gamma^2 \frac{\partial^2 \rho}{\partial x^2}, \quad (t,x) \in [0,T] \times [0,L]$$
$$\dot{x}_i(t) = V(\rho(t, x_i(t))), \quad t \in [0,T], i = 1, \dots, N$$

Control of a coupled PDE-ODE system



Lebacque et al., 1998; Delle Monache & Goatin, 2014; Barreau, Selivanov, J, 2020; Barreau, Aguiar et al., 2021

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Learning-based traffic state reconstruction

How can we out of noisy measurements from probe vehicles $\boxed{\{x_i(t), \underbrace{\rho(t, x_i(t))}_{\rho_i(t)}, \underbrace{V(\rho_i(t))}_{V_i(t)}\}_{i \in [\![1,N]\!]}}$

reconstruct the density $\hat{\rho}^\star = \arg\min_{\hat{\rho}} \int_0^T \|\rho(t,\cdot) - \hat{\rho}(t,\cdot)\|^2 dt$?

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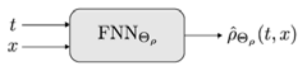
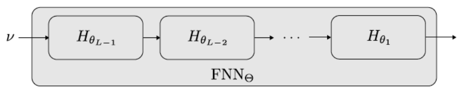
Neural network model

Model density and velocity as feedforward neural networks



with each layer having a set of parameters to be trained:



$$\min_{\Theta_\rho} \frac{1}{N} \sum_{i=1}^{N} \int_0^T \left|\hat{\rho}_{\Theta_\rho}(t, x_i(t)) - \rho_i(t)\right|^2 dt \qquad \min_{\Theta_V} \frac{1}{N} \sum_{i=1}^{N} \int_0^T \left|\hat{V}_{\Theta_V}(\rho_i(t)) - V_i(t)\right|^2 dt$$

Barreau, Selivanov, J, 2020; Barreau, Aguiar, J, 2021

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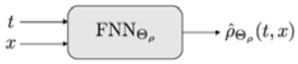
Physics-informed neural network model

Model density and velocity as feedforward neural networks



with each layer having a set of parameters to be trained:

$$\min_{\Theta_\rho} \frac{1}{N}\sum_{i=1}^{N}\int_0^T \left|\hat{\rho}_{\Theta_\rho}(t,x_i(t)) - \rho_i(t)\right|^2 dt \qquad \min_{\Theta_V} \frac{1}{N}\sum_{i=1}^{N}\int_0^T \left|\hat{V}_{\Theta_V}(\rho_i(t)) - V_i(t)\right|^2 dt$$

under **physical constraints**

$$\frac{\partial \hat{\rho}_{\Theta_\rho}}{\partial t} + \frac{\partial \hat{V}_{\Theta_V}(\hat{\rho}_{\Theta_\rho})\hat{\rho}_{\Theta_\rho}}{\partial x} = \gamma^2 \frac{\partial \hat{\rho}_{\Theta_\rho}}{\partial x^2} \qquad \left|\frac{\partial \hat{V}_{\Theta_V}}{\partial \rho}\right|_+ = 0$$

- Physics-informed neural networks [Raissi, Perdikaris, Karniadakis, 2019]
- Application to traffic modeling [Barreau, Selivanov, J, 2020; Barreau, Aguiar, J, 2021]

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Training physics-informed neural network

$$\begin{aligned}
\underset{\Theta_\rho,\Theta_V}{\text{argmin}} \quad & \frac{1}{N}\sum_{i=1}^{N}\left\{\int_0^T \left|\hat{\rho}_{\Theta_\rho}(t,x_i(t)) - \rho_i(t)\right|^2 dt + \int_0^T \left|\hat{V}_{\Theta_V}(\rho_i(t)) - V_i(t)\right|^2 dt\right\} \\
\text{s. t.} \quad & \frac{\partial \hat{\rho}_{\Theta_\rho}}{\partial t} + \frac{\partial \hat{V}_{\Theta_V}(\hat{\rho}_{\Theta_\rho})\hat{\rho}_{\Theta_\rho}}{\partial x} = \gamma^2 \frac{\partial \hat{\rho}_{\Theta_\rho}}{\partial x^2} \\
& \left|\frac{\partial \hat{V}_{\Theta_V}}{\partial \rho}\right|_+ = 0
\end{aligned}$$

with Lagrangian relaxation

$$\begin{aligned}
&\arg\min_{\Theta_\rho,\Theta_V}\max_{\lambda_\rho,\lambda_V} \frac{1}{N}\sum_{i=1}^{N}\int_0^T \left\{|\hat{\rho}_{\Theta_\rho}(t,x_i(t)) - \rho_i(t)|^2 + |\hat{V}_{\Theta_V}(\rho_i(t)) - V_i(t)|^2\right\}dt \\
&\quad + \lambda_\rho \iint_{[0,T]\times[0,L]} \left|\frac{\partial \hat{\rho}_{\Theta_\rho}}{\partial t}(\nu) + \frac{\partial \hat{V}_{\Theta_V}(\hat{\rho}_{\Theta_\rho})\hat{\rho}_{\Theta_\rho}}{\partial x}(\nu) - \gamma^2 \frac{\partial^2 \hat{\rho}_{\Theta_\rho}}{\partial x^2}(\nu)\right|^2 d\nu + \lambda_V \int_0^1 \left|\frac{\partial \hat{V}_{\Theta_V}}{\partial \rho}(\rho)\right|^2 d\rho \\
&=: \arg\min_{\Theta_\rho,\Theta_V}\max_{\lambda_\rho,\lambda_V} \mathcal{L}_{\lambda_\rho,\lambda_V}(\Theta_\rho,\Theta_V)
\end{aligned}$$

Barreau, Selivanov, J, 2020; Barreau, Aguiar, J, 2021; Barreau, 2024 30

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Training physics-informed neural network

$$
\begin{aligned}
&\arg\min_{\Theta_\rho,\Theta_V}\max_{\lambda_\rho,\lambda_V} \frac{1}{N}\sum_{i=1}^{N}\int_0^T \left\{ |\hat{\rho}_{\Theta_\rho}(t, x_i(t)) - \rho_i(t)|^2 + |\hat{V}_{\Theta_V}(\rho_i(t)) - V_i(t)|^2 \right\} dt \\
&+ \lambda_\rho \iint_{[0,T]\times[0,L]} \left| \frac{\partial \hat{\rho}_{\Theta_\rho}}{\partial t}(\nu) + \frac{\partial \hat{V}_{\Theta_V}(\hat{\rho}_{\Theta_\rho})\hat{\rho}_{\Theta_\rho}}{\partial x}(\nu) - \gamma^2 \frac{\partial^2 \hat{\rho}_{\Theta_\rho}}{\partial x^2}(\nu) \right|^2 d\nu + \lambda_V \int_0^1 \left| \frac{\partial \hat{V}_{\Theta_V}}{\partial \rho}(\rho) \right|^2 d\rho \\
&=: \arg\min_{\Theta_\rho,\Theta_V}\max_{\lambda_\rho,\lambda_V} \mathcal{L}_{\lambda_\rho,\lambda_V}(\Theta_\rho,\Theta_V)
\end{aligned}
$$

Primal problem

$$\Theta_\rho^*(\lambda_\rho), \Theta_V^*(\lambda_V) = \arg\min_{\Theta_\rho,\Theta_V} \mathcal{L}_{\lambda_\rho,\lambda_V}(\Theta_\rho,\Theta_V)$$

Dual problem

$$\lambda_\rho^*(\Theta_\rho), \lambda_V^*(\Theta_V) = \arg\max_{\lambda_\rho,\lambda_V} \mathcal{L}_{\lambda_\rho,\lambda_V}(\Theta_\rho,\Theta_V)$$

Primal-dual gradient descent iterations

Primal step

$$
\begin{aligned}
\Theta_\rho^{k+1} &= \Theta_\rho^k - \alpha_\Theta^k \nabla_{\Theta_\rho}\mathcal{L}_{\lambda_\rho,\lambda_V}(\Theta_\rho,\Theta_V)\\
\Theta_V^{k+1} &= \Theta_V^k - \alpha_\Theta^k \nabla_{\Theta_V}\mathcal{L}_{\lambda_\rho,\lambda_V}(\Theta_\rho,\Theta_V)
\end{aligned}
$$

Dual step

$$
\begin{aligned}
\lambda_\rho^{k+1} &= \lambda_\rho^k - \alpha_\lambda^k \nabla_{\lambda_\rho}\mathcal{L}_{\lambda_\rho,\lambda_V}(\Theta_\rho,\Theta_V)\\
\lambda_V^{k+1} &= \lambda_V^k - \alpha_\lambda^k \nabla_{\lambda_V}\mathcal{L}_{\lambda_\rho,\lambda_V}(\Theta_\rho,\Theta_V)
\end{aligned}
$$

- Multiple dual steps for each primal
- Uniform and importance sampling of the integrals

Barreau, Aguiar, J, 2021; Barreau, 2024

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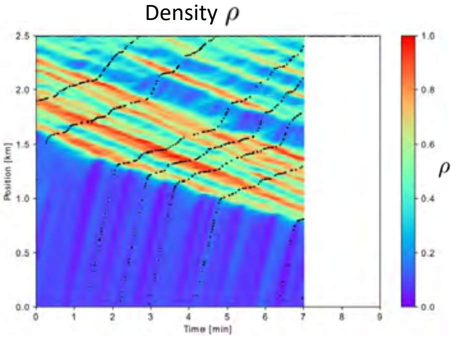
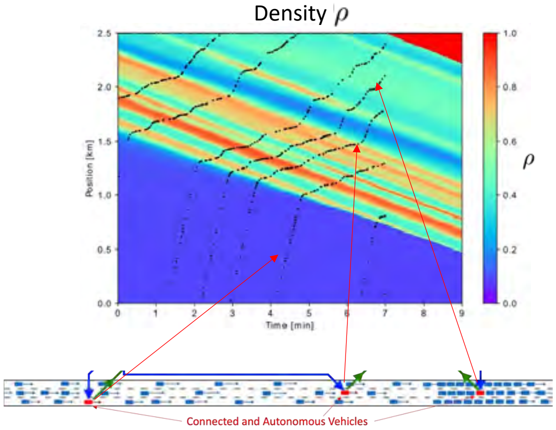
Micro (vehicle) simulated density over time interval [0,7] min



Reconstructed and predicted density over [0,9] min using PINN model



Trained model captures traffic dynamics despite sparse sampling

Liu et al., 2021; Delle Monache et al., 2022

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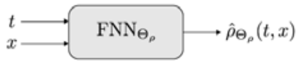
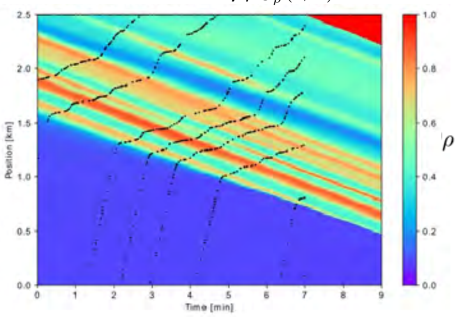
Trained PDE model captures density evolution observed in real data

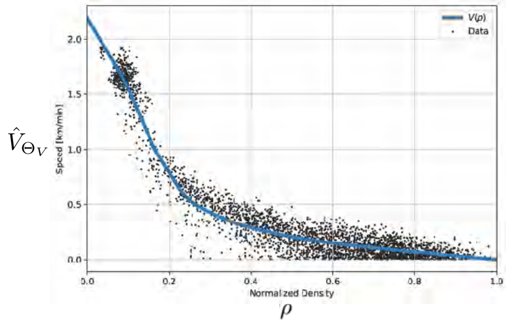


Estimated density $\hat{\rho}_{\Theta_\rho}(t,x)$



Trained NN velocity model captures relationship observed in real data

Estimated velocity $\hat{V}_{\Theta_V}(\rho)$



Liu et al., 2021; Delle Monache et al., 2022

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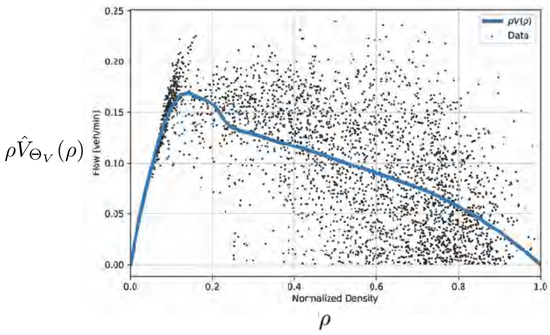
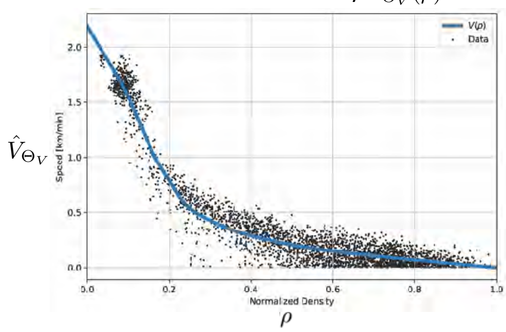
Estimated fundamental diagram $\rho\hat{V}_{\Theta_V}(\rho)$



Trained NN velocity model captures relationship observed in real data

Estimated velocity $\hat{V}_{\Theta_V}(\rho)$



Liu et al., 2021; Delle Monache et al., 2022

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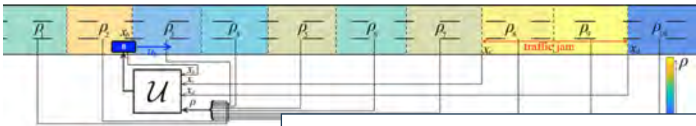
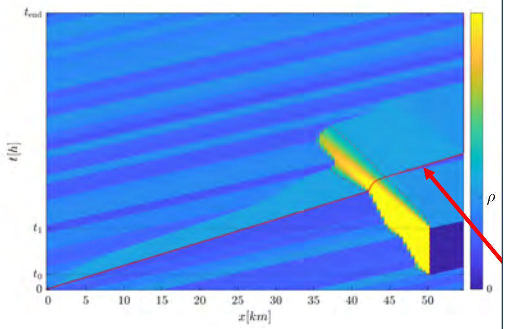
Control truck platoon velocity to dissipate traffic congestion



Without truck platoon control



Tru

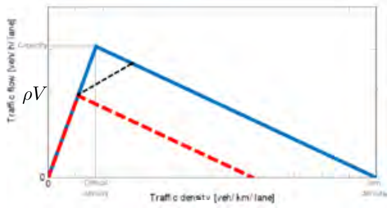
Truck platoon velocity control

Controlled platoon velocity

$$\dot{x}_i(t) = \min(V(\rho(t, x_i(t))), u(t))$$

reduces road capacity

$$V(\rho(t, x_i(t))) \leq V_{\text{con}}(\rho(t, x_i(t)), u(t))$$



Giorgio, 2002; Delle Monache & Goatin, 2014; Cicic and J, 2018; Liu et al., 2021

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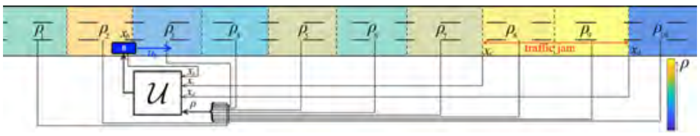
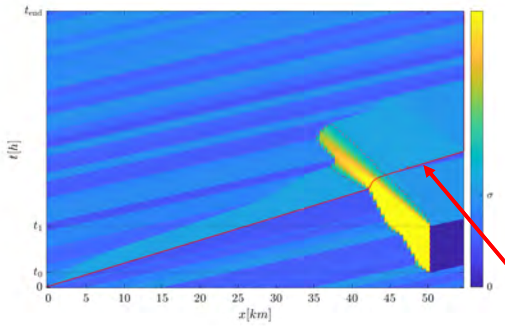
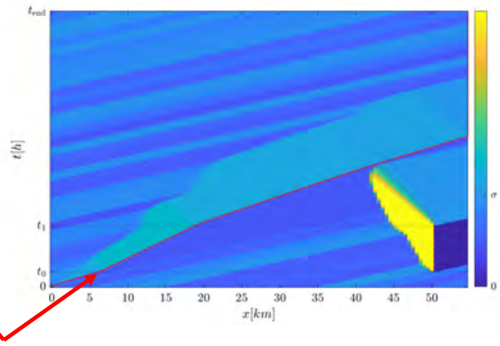
Control truck platoon velocity to dissipate traffic congestion



Without truck platoon control



With truck platoon control



Truck platoon trajectory

Cicic and J, 2018

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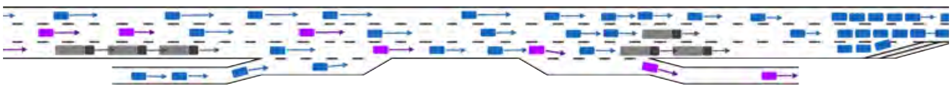
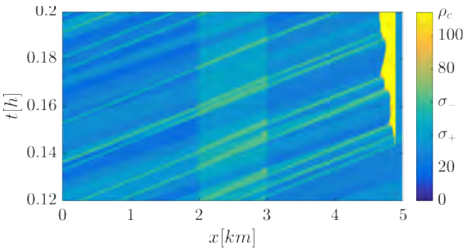
Truck platoon control reduces total travel time for all vehicles



Without truck platoon control



38% total travel time increase
due to traffic congestion

Cicic, Jin and J, 2019

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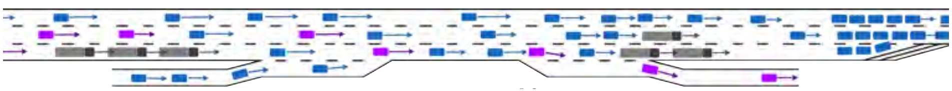
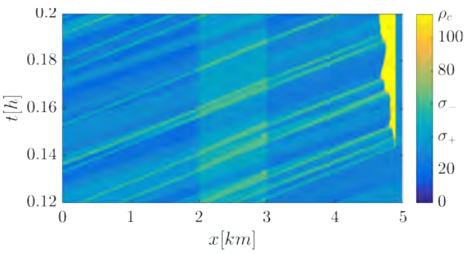
Truck platoon control reduces total travel time for all vehicles

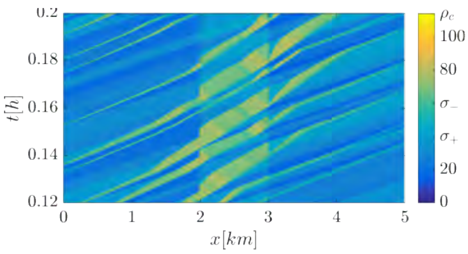


Without truck platoon control



38% total travel time increase
due to traffic congestion

With truck platoon control



8% total travel time increase
due to traffic congestion

Cicic, Jin and J, 2019

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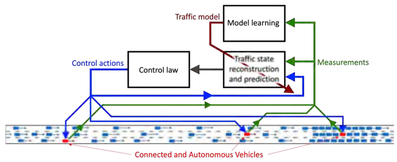
Network optimization

Traffic control



Vehicle autonomy

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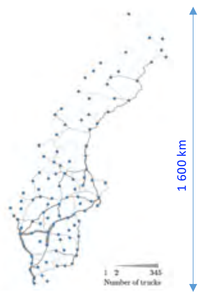
Distributed Charging Coordination of Electric Trucks

Consider 1 000 electric trucks travel over Swedish road network daily

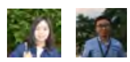
Problem: How can the trucks decide **where** and **when** to charge with

- Pre-planned routes
- Limited charging capacity
- Uncertain travel times and energy consumptions



Solution: Trucks update their charging plans supported by forecasts provided by the charging stations

- **Scalability:** Each truck computes its **own charging plan**, with no central coordination
- **Privacy:** Stations provide **aggregated** forecast information, and trucks never reveal their plans to others



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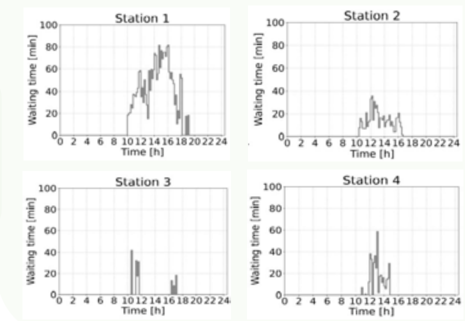
Rollout-based Truck Planning with Uncertain Charging Capacity

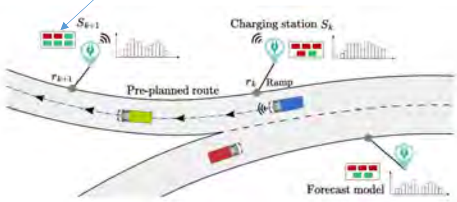
Waiting time forecast models for charging stations



Charging stations

a) Charge **waiting time forecast model** based on historical data

b) Assign charging spots as trucks arrive to charging station



Distributed rollout-based solution for truck planning

a) Truck talks to stations S_k, S_{k+1}, … to obtain **estimated waiting times**

b) Truck simulates the worst case if or if not charging at station S_k: Each simulated scenario leads to a linear program, fast to solve

c) Repeat the procedure when approaching next station S_{k+1}

Guaranteed feasible plans for all trucks

Consistently improving plans

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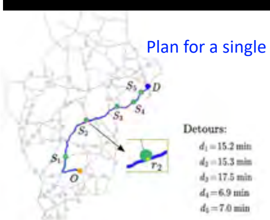
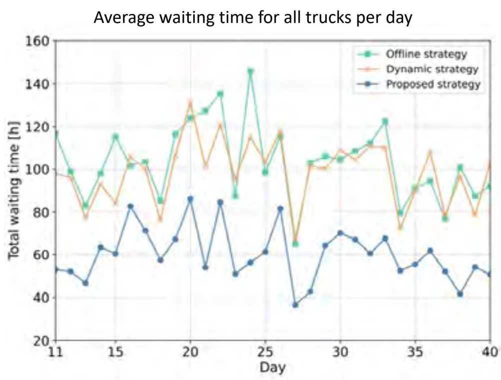
Evaluation over the Swedish road network

- **Reduced time for charging** is important for electric heavy vehicle adoption
- Evaluated on realistic freight transport missions and models for 1 000 electric trucks
- Our distributed charge plans give **50% lower waiting times**





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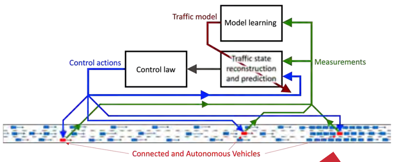
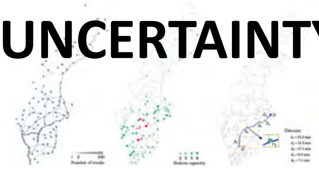
Control community develops the tools to mitigate uncertainty

Physics-data-driven modeling

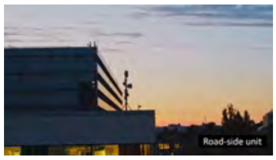


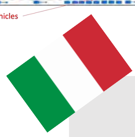
Stochastic forecasting

UNCERTAINTY



Safety-first set computing





Festina lente
Proceed quickly, but cautiously

Slides and papers available at people.kth.se/~kallej

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