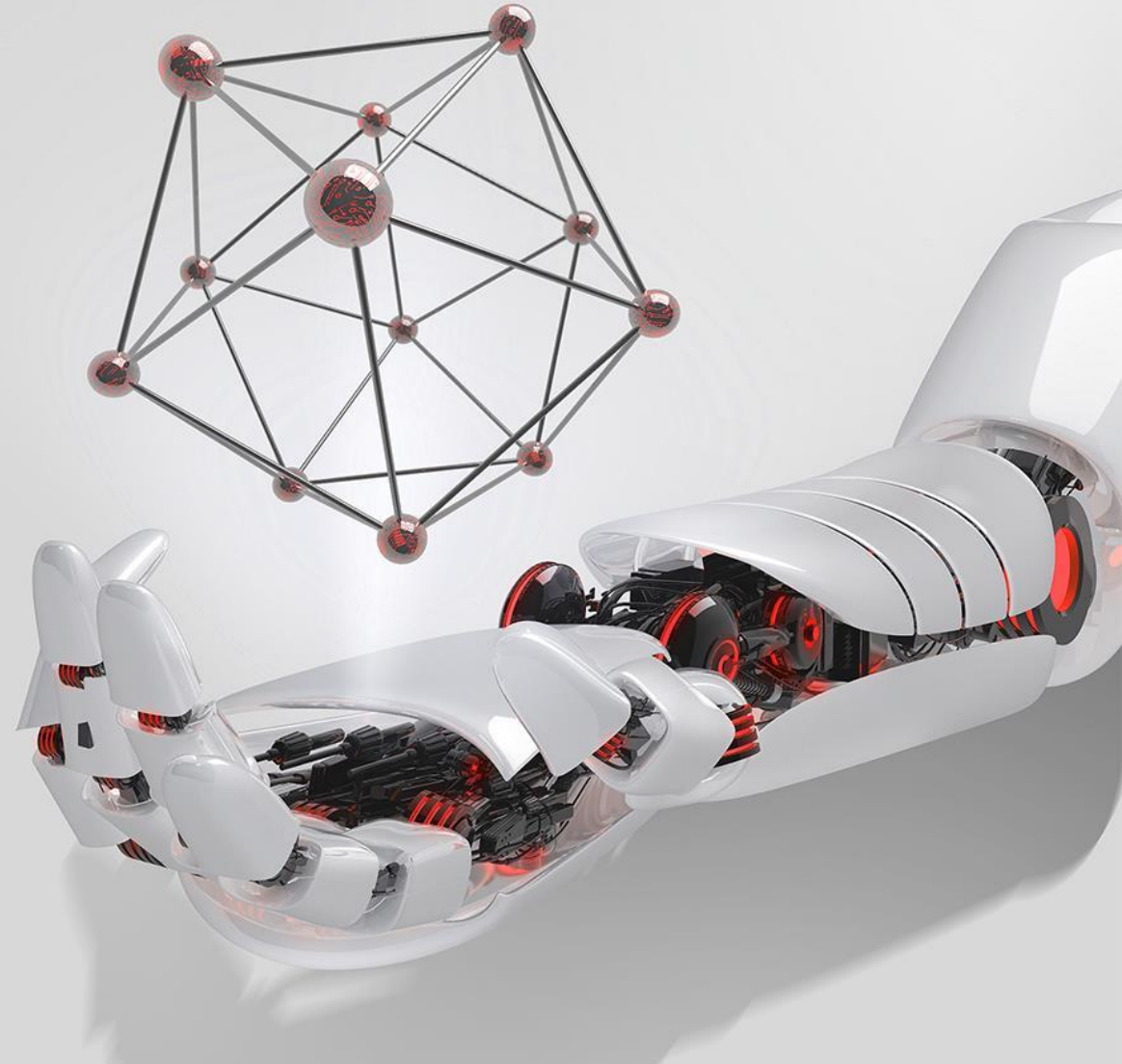


Large-scale Systems Optimization

From Oscillatory Physics to
High-dimensional Vector Memories



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VSAONLINE

Online Speakers' Corner on Vector Symbolic Architectures and
Hyperdimensional Computing

<https://sites.google.com/ltu.se/vsaonline/home>



Contents

Huawei's Traffic Solution - TrafficGO

1. Optimization based on the traffic physics (OBELISC)

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- Exploiting the physics of road traffic
- Oscillator-based modelling and nonlinear control
- Efficient neural representation and control
- Observations

2. Optimization based on traffic closed-loop causality (TRAMESINO)

- Exploiting causality in road traffic control
- High-dimensional vector algebra for associative memories
- Efficient neural associative memories
- Observations



Traffic Intelligent Twins (TrafficGo)

Inclusive AI, making urban transportation safer while yielding new levels of energy-efficiency

Traffic Prediction

Precise prediction of vehicle and pedestrians flows as well as traffic congestion with the benefit of multiple data sources

Road Network Analysis

Information from analysis of key roads and intersections summarized to present highly effective suggestions on optimizing traffic flows

Accident Monitoring and Control

Real-time monitoring and alarm notification of traffic emergencies, violations, heavy congestion, and other incidents; monitoring of trajectories and behaviors for tourist coaches, passenger buses, tanker trucks, taxis, commercial trucks, school buses, and other vehicle types;

Traffic Light Optimization

Integration of multiple data sources for 24/7 traffic light coordination; cross-intersection and regional traffic light coordination for real-time optimization; compatible with mainstream traffic signal control systems

Traffic Parameter Awareness

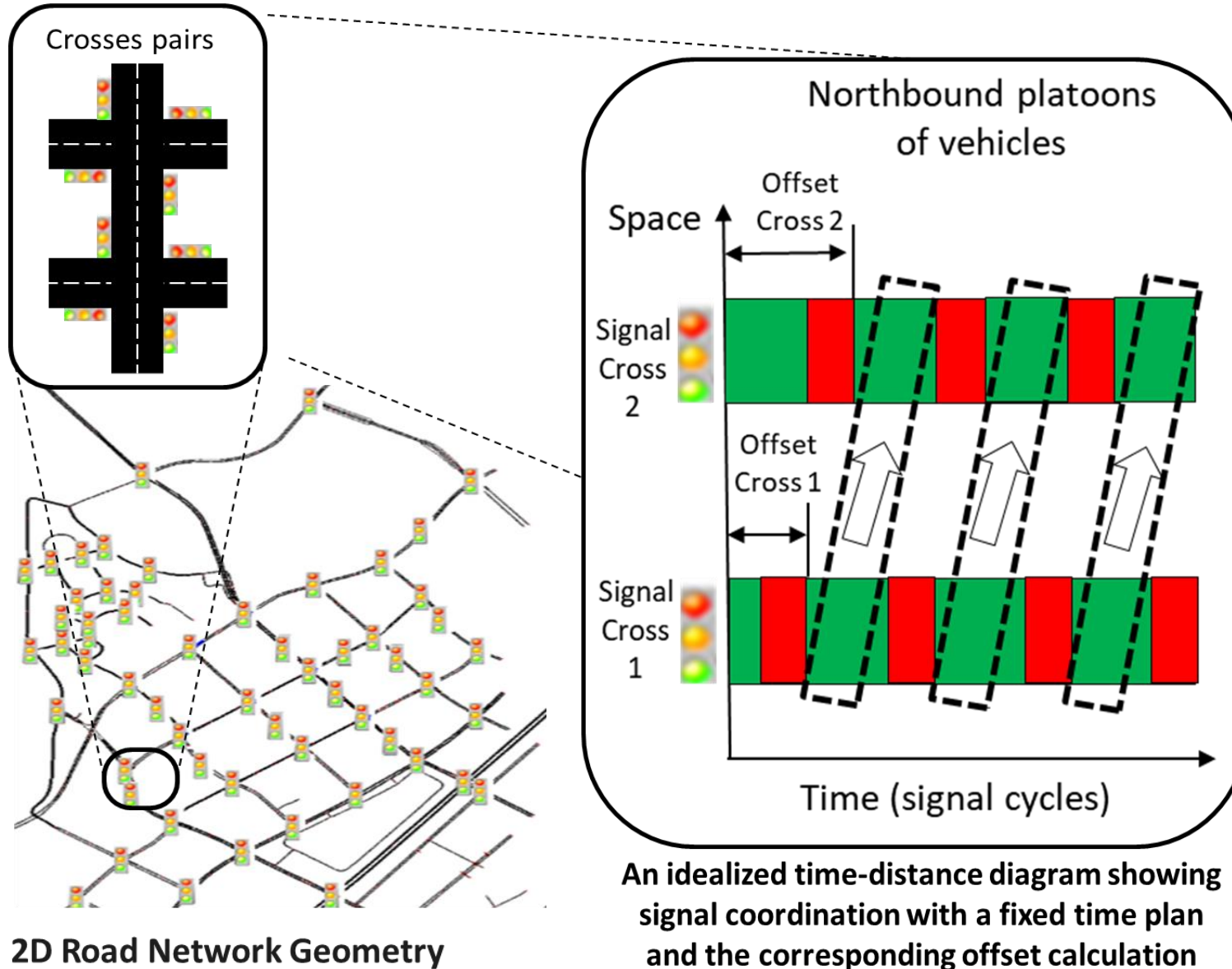
Awareness of more than 10 types of traffic parameters involving motor vehicles, non-motorized vehicles, and pedestrians; GIS map displayed on a large HD screen in real time; traffic optimization effect comparison and traffic index ranking

An aerial photograph of a busy city intersection. The scene is filled with various vehicles including cars, motorcycles, and a few buses. Pedestrians are crossing the street at several points. The traffic is moving in multiple directions, creating a complex pattern of movement. The image is used as a background for a presentation slide.

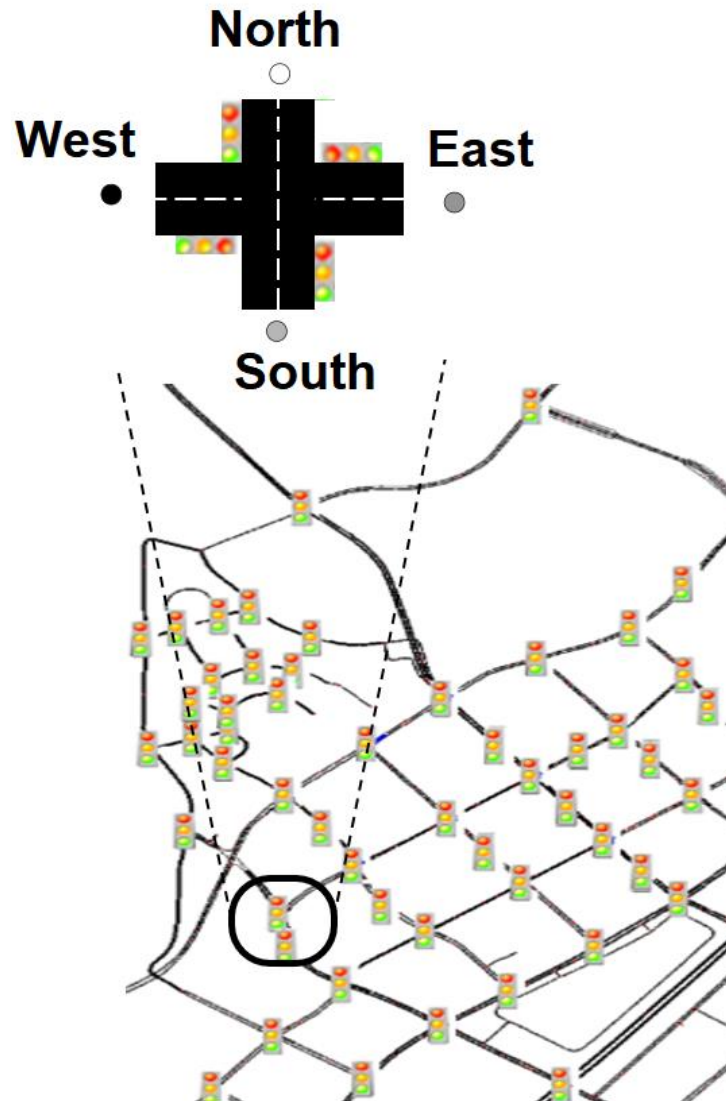
Optimization based on the traffic physics

Source: <https://www.youtube.com/watch?v=6uf2QNtYpII>

Space-time physics of traffic



Exploiting the physics of road traffic



Single cross dynamics

Oscillator-based modelling and nonlinear control

$$\frac{d\theta_i(t)}{dt} = \underbrace{\omega_i(t)}_{\text{Internal properties}} + \underbrace{k_i(t) \sum_{j=1}^N A_{ij} \sin(\theta_j(t) - \theta_i(t))}_{\text{Network coupling}} + \underbrace{F_i \sin(\theta^*(t) - \theta_i(t))}_{\text{External coupling}}$$

where:

θ_i - the amount of green time of traffic light i

ω_i - the frequency of traffic light i oscillator

k_i - the flow of cars passing through the direction controlled by oscillator i

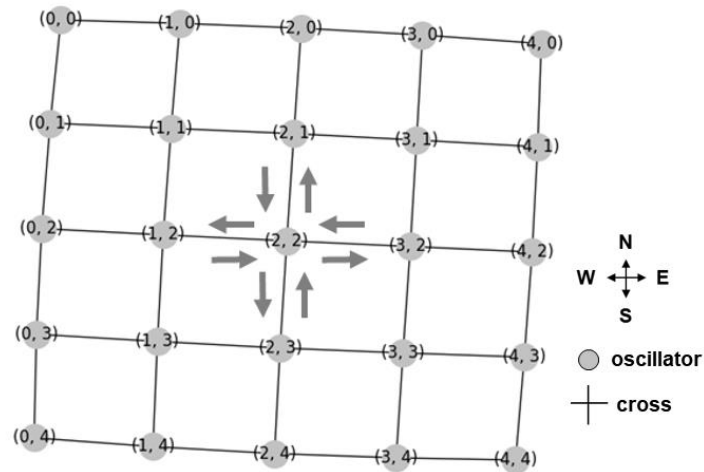
A_{ij} - the static spatial adjacency coupling between oscillator i and oscillator j

F_i - the coupling of external perturbations (e.g. maximum cycle time per phase)

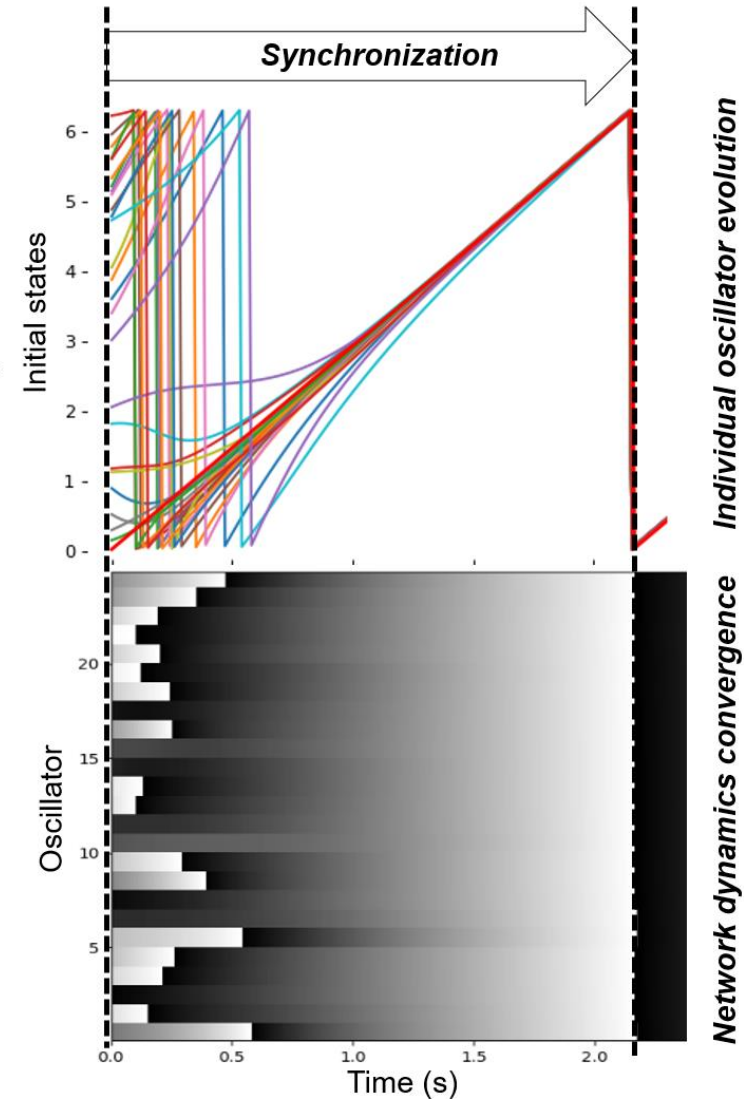
θ^* - the external perturbation (e.g. traffic signal limits imposed by law)

Oscillator-based modelling and nonlinear control

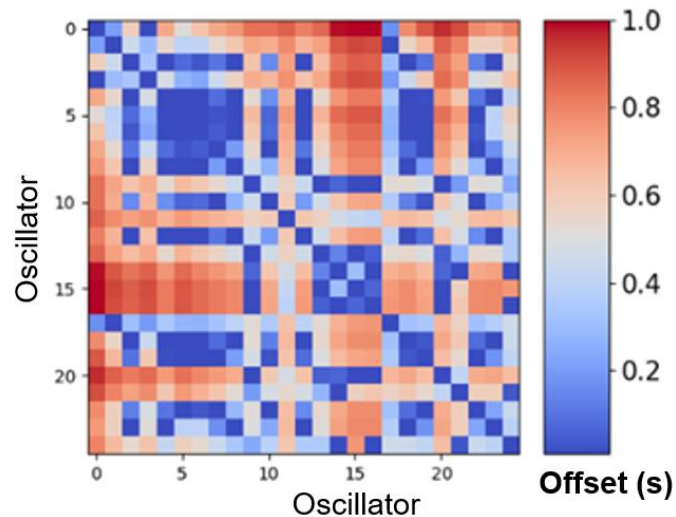
a. Example road network topology



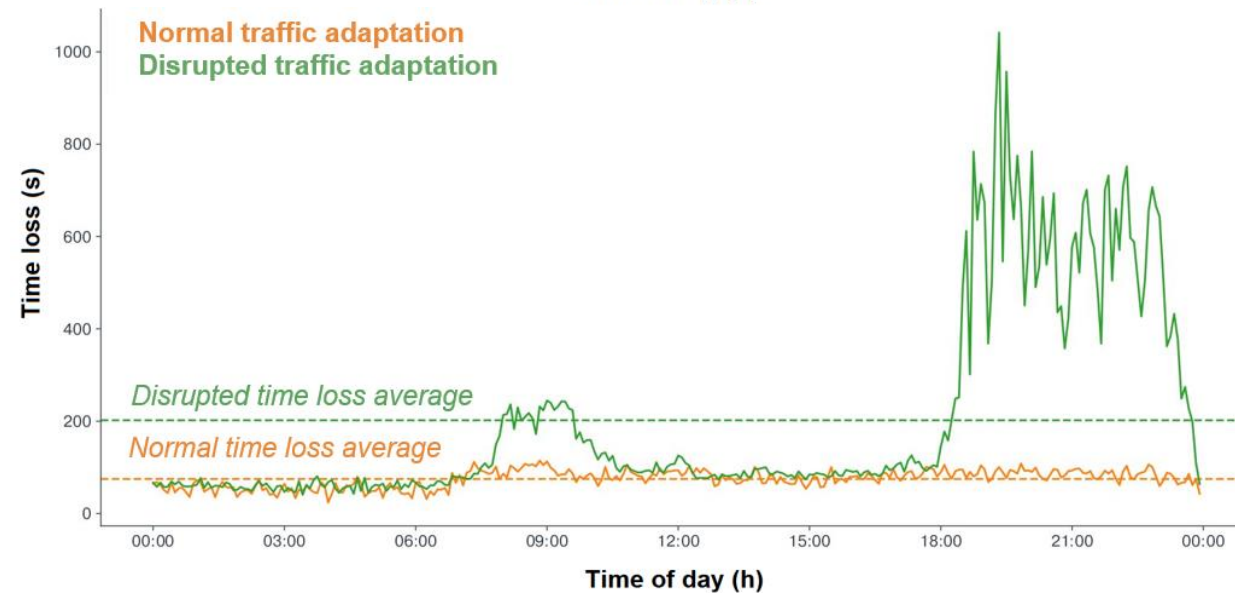
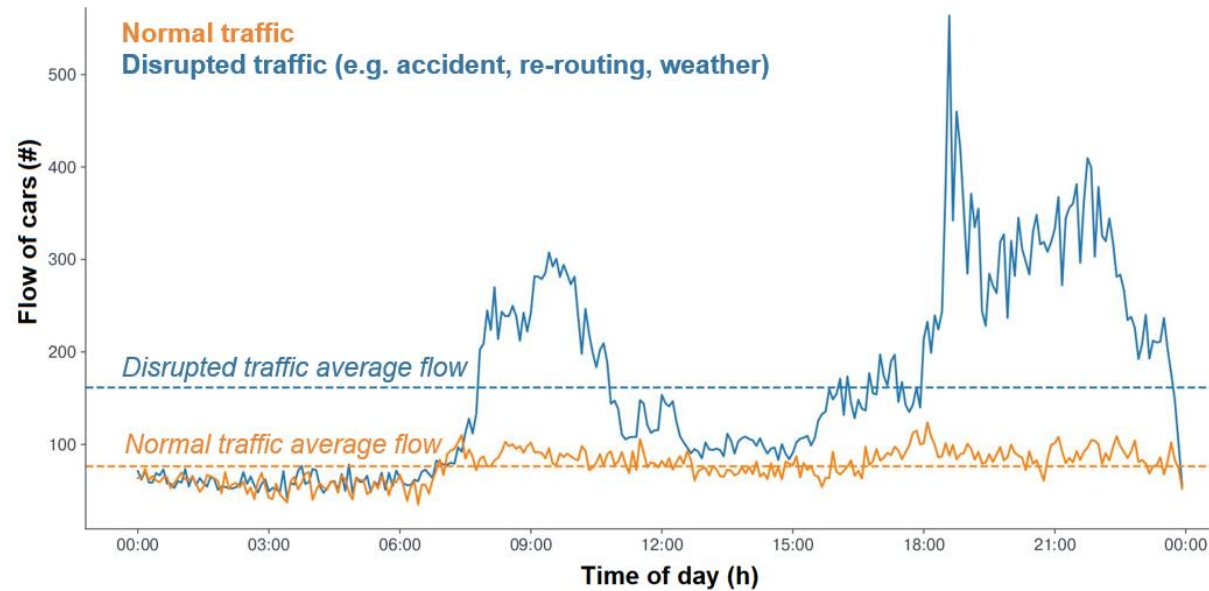
b. Dynamics of the oscillator network



c. Time to synchronization (offset)



Oscillator-based modelling and nonlinear control



Oscillator-based modelling and nonlinear control

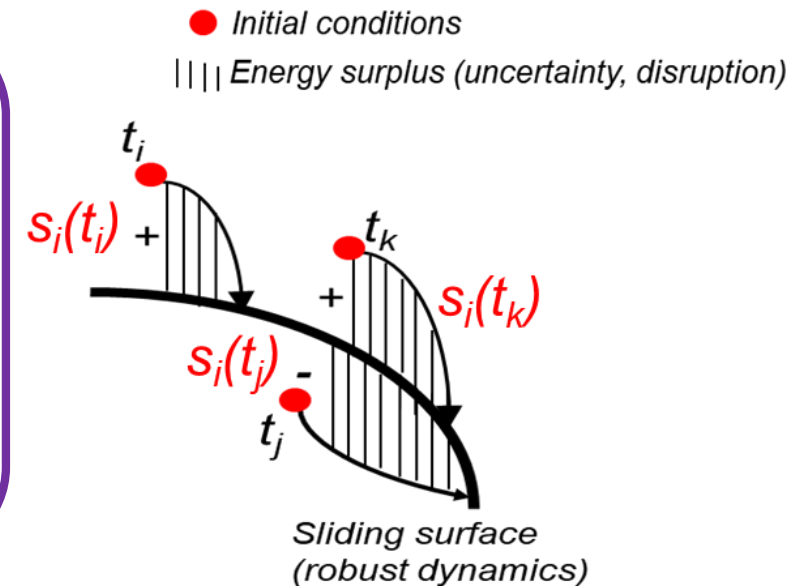
$$\frac{d\theta_i(t)}{dt} = \underbrace{\omega_i(t)}_{\text{Internal properties}} + \underbrace{k_i(t) \sum_{j=1}^N A_{ij} \sin(\theta_j(t) - \theta_i(t))}_{\text{Network coupling}} + \underbrace{F_i \sin(\theta^*(t) - \theta_i(t))}_{\text{External coupling}} + \underbrace{u_i(t)}_{\text{Regularizing control law}}$$

with

$$\begin{aligned} u_i(t) &= \epsilon_1 \int_0^t \hat{s}_i(\tau) d\tau \\ \frac{\hat{s}_i(t)}{dt} &= \epsilon_2 \left(\sum_{i,j} (\hat{s}_j(t) - \hat{s}_i(t)) + s_i(t) \right) \\ \frac{s_i(t)}{dt} &= \epsilon_3 \sum_j \left(s_j(t) - \frac{\hat{s}_i(t)}{dt} \right) - \text{sign}(\hat{s}_i(t)) \frac{d^2\theta_i(t)}{dt^2} \end{aligned}$$

Sliding Mode Control

$$0 < \epsilon_1 < \epsilon_2 < \epsilon_3 < 1$$



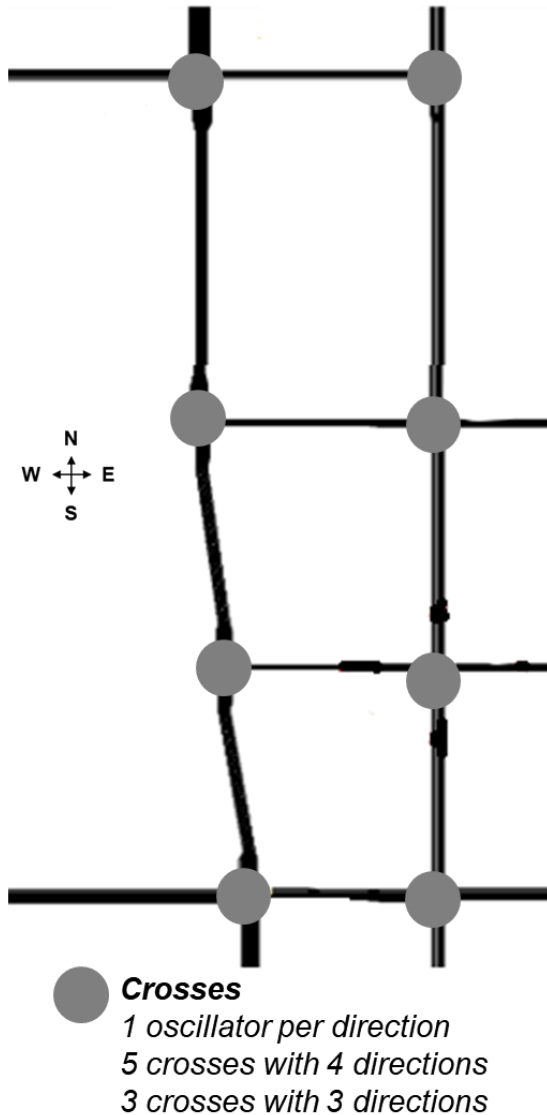
where:

$s_i(t)$ - the surplus energy of traffic light i oscillator

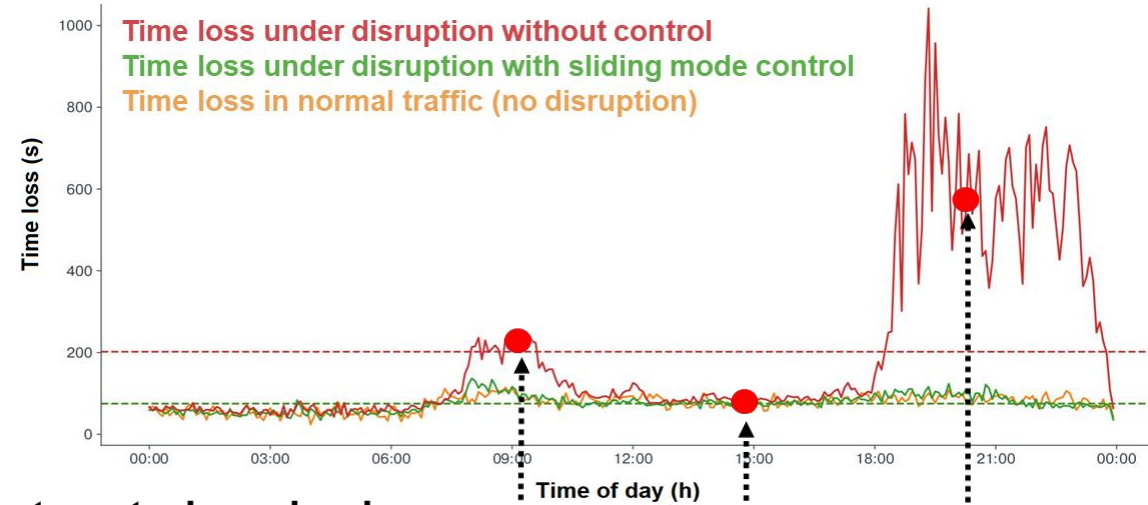
$\hat{s}_i(t)$ - the estimated surplus energy of traffic light i oscillator

Oscillator-based modelling and nonlinear control

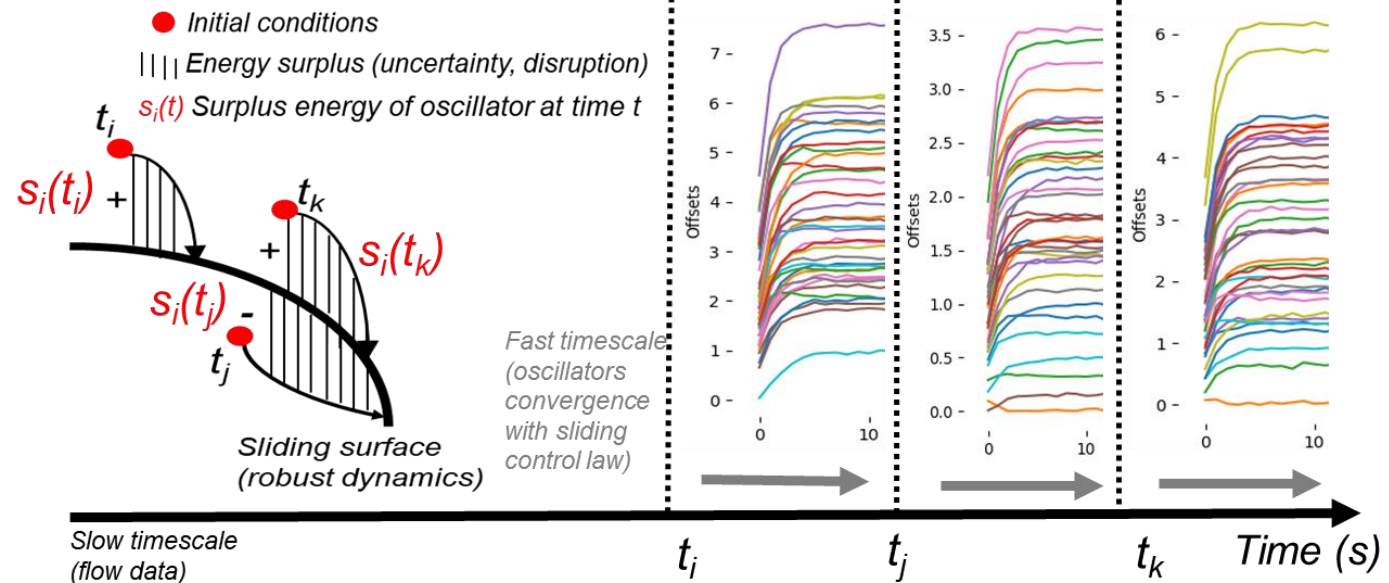
Real road network layout



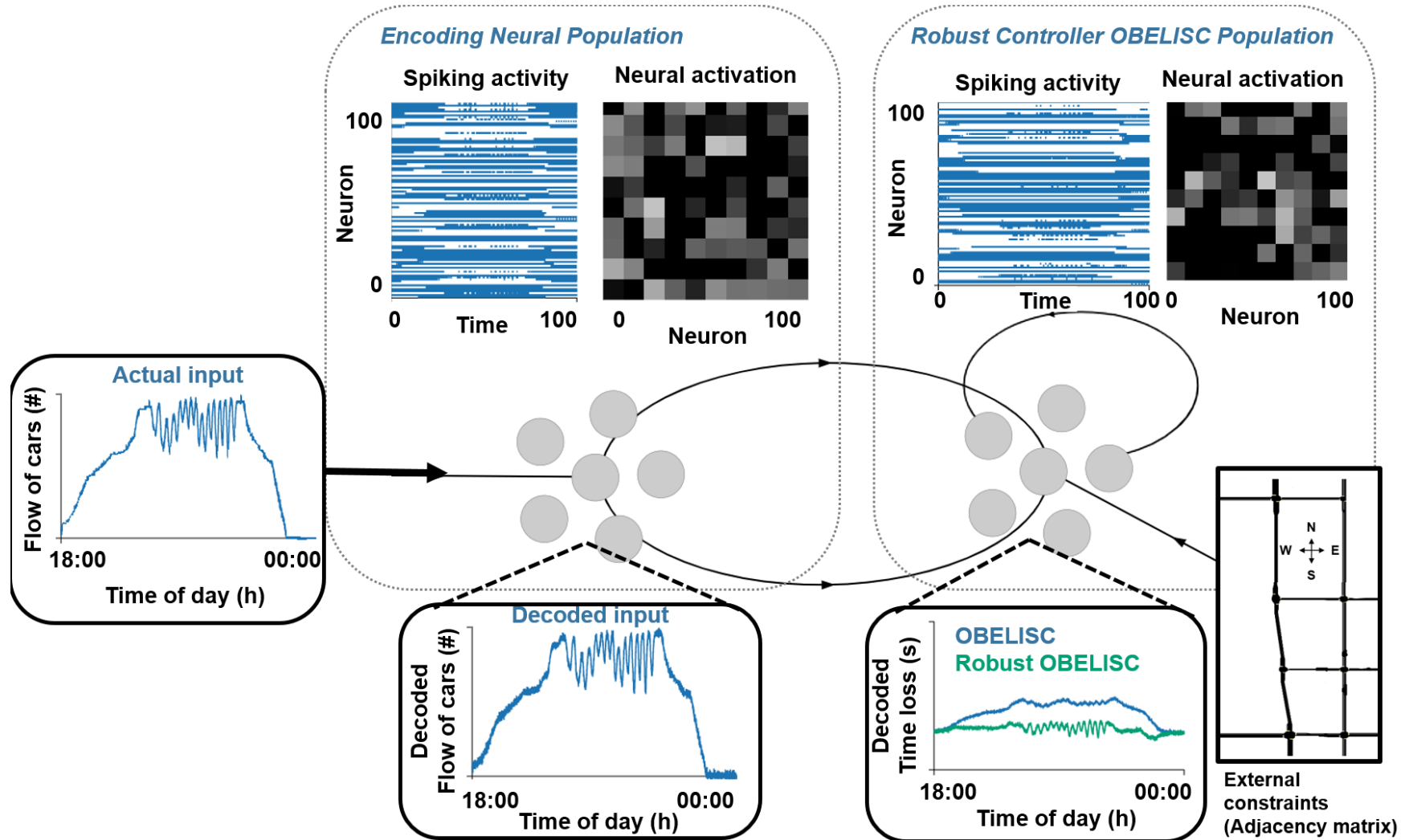
Traffic profile in the road network



Robust control mechanism



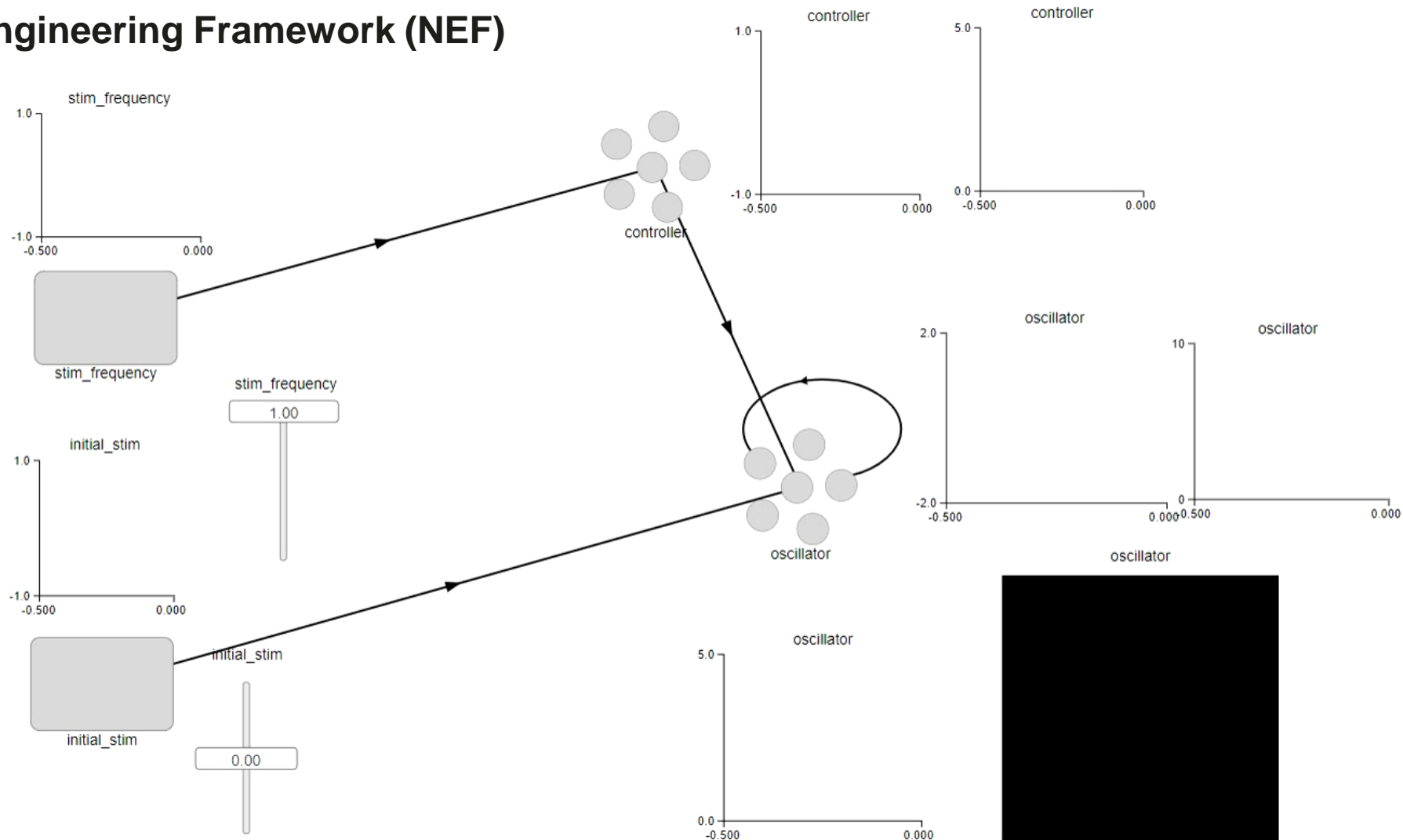
Efficient neural learning



Efficient neural learning

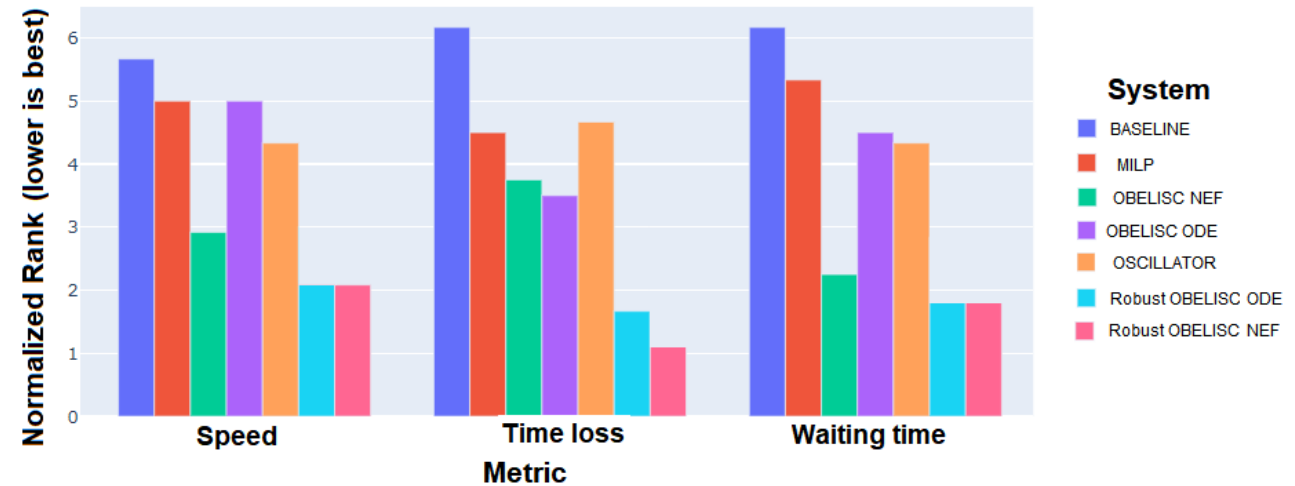
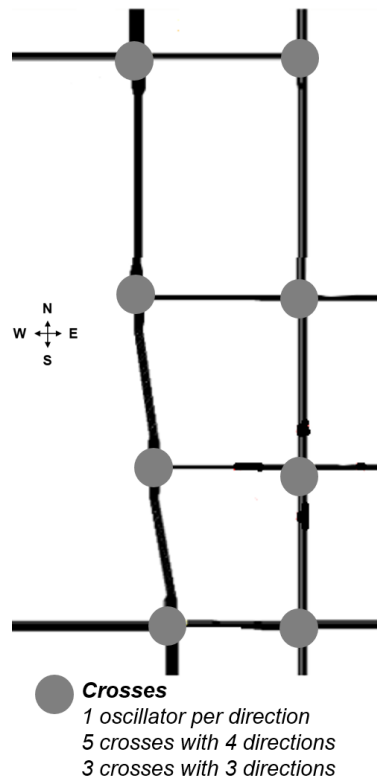
Learning in spiking neural networks

Neural Engineering Framework (NEF)



Experiments & Results

The **experiments and evaluation** use the **SUMMER-MUSTARD** (Summer season Multi-cross Urban Signalized Traffic Aggregated Region Dataset) real-world dataset, which contains 59 days of real urban road traffic data from 8 crosses in a city in China*



Model	Single cross Region (8 crosses)	
MILP	0.0510	0.3930
OSCILLATOR	0.0568	0.4544
Robust OBELISC ODE	0.0489	0.4534
Robust OBELISC NEF	0.0071	0.0426

* <http://doi.org/10.5281/zenodo.5025264>

Observations

OBELISC

Oscillator-Based Modelling and Control using Efficient Neural Learning for Intelligent Road Traffic Signal Calculation

- Traffic control is a **multi-dimensional problem** to be optimized under **deep uncertainty**.
- A system using a **network of oscillators** capturing **the (periodic) spatial and temporal interactions** among different crosses in a **road traffic network**.
- A **control mechanism** that strengthens the **adaptation capabilities** towards global consensus under **high-magnitude traffic disruptions**.
- A **lightweight learning system** that exploits the **coupling interactions** among different controlled oscillators.
- An **end-to-end system (modelling, control, inference)** with proven potential for real-world deployment.



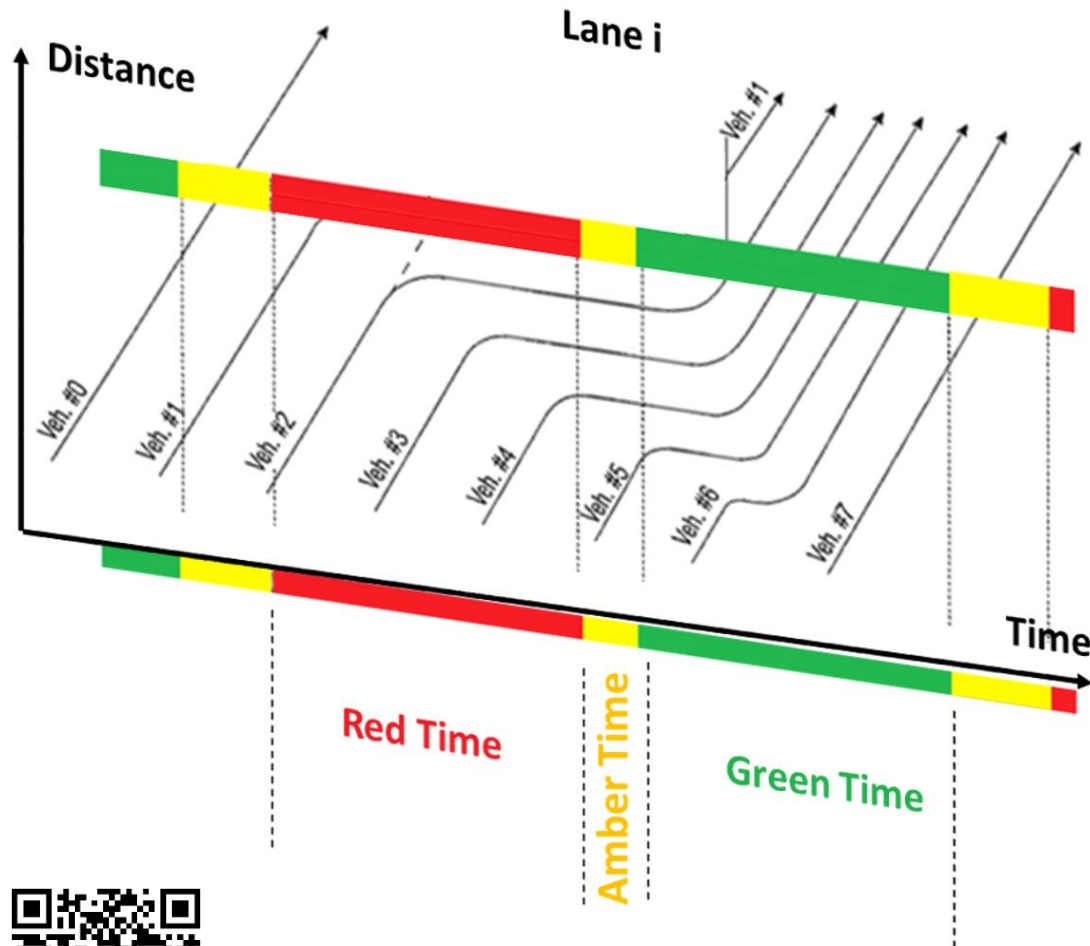
An aerial photograph of a busy city intersection. The scene is filled with various vehicles including cars, motorcycles, and a few buses. Pedestrians are crossing the street at several points. The traffic is moving in multiple directions, creating a complex pattern of movement. The image is used as a background for a presentation slide.

Optimization based on traffic causality

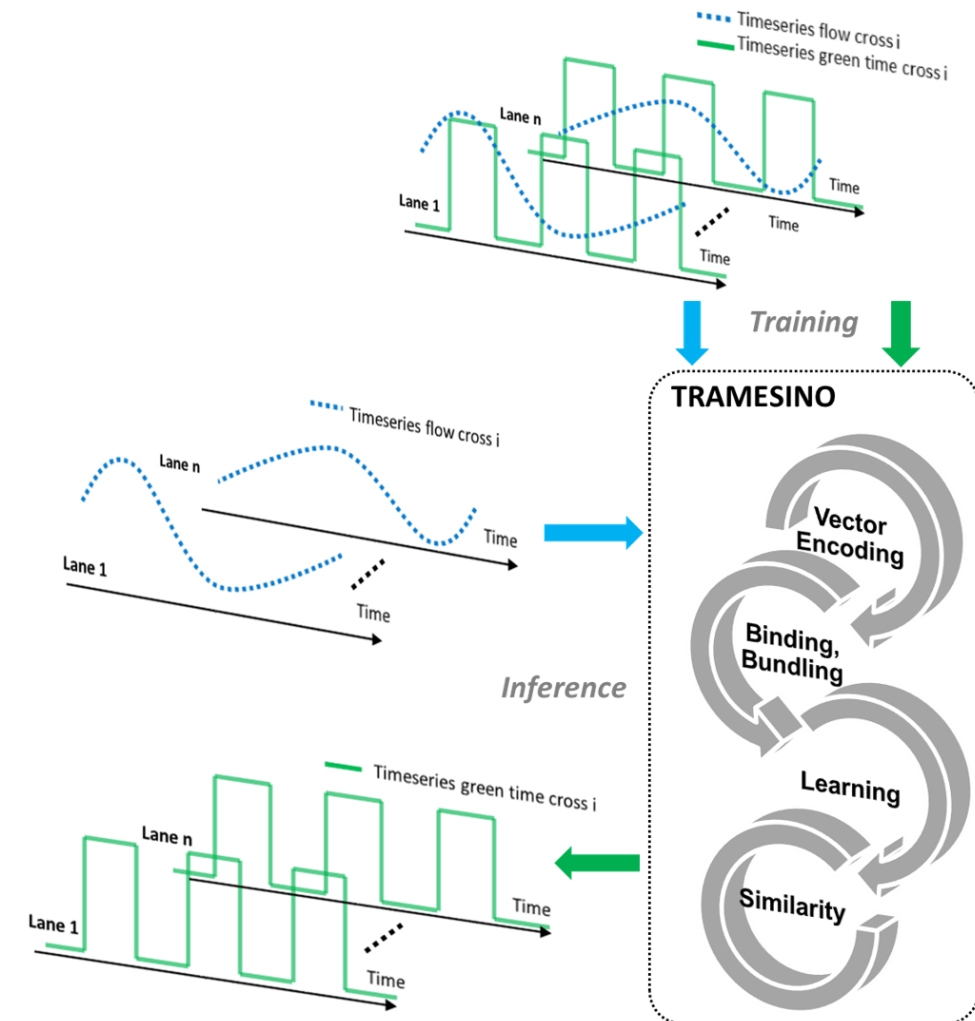
Source: <https://www.youtube.com/watch?v=6uf2QNtYpII>

Exploiting causality in road traffic control

Space-time Diagram of the Signalized Traffic Light Operation

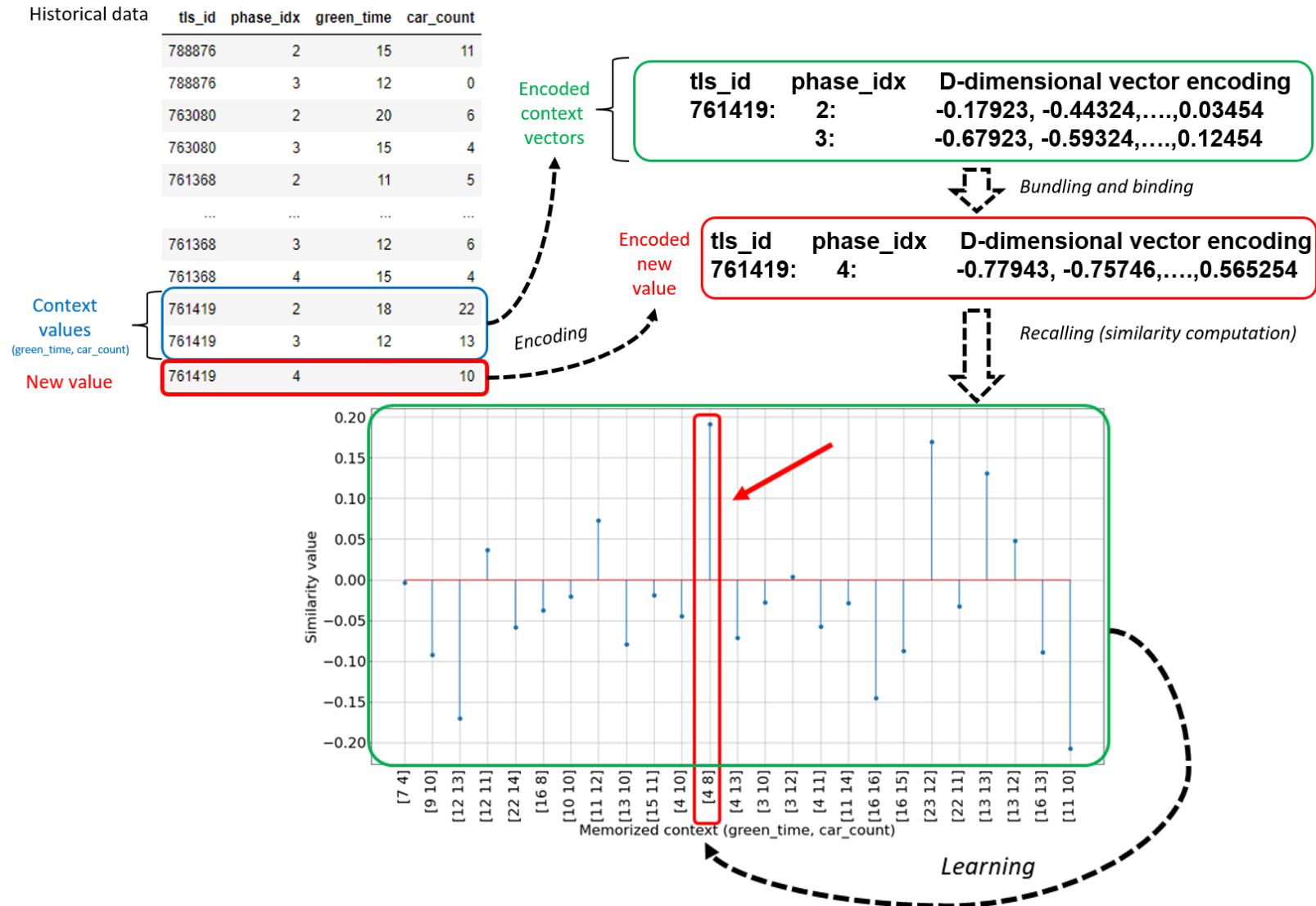


TRAMESINO Processing Steps for Training and Inference



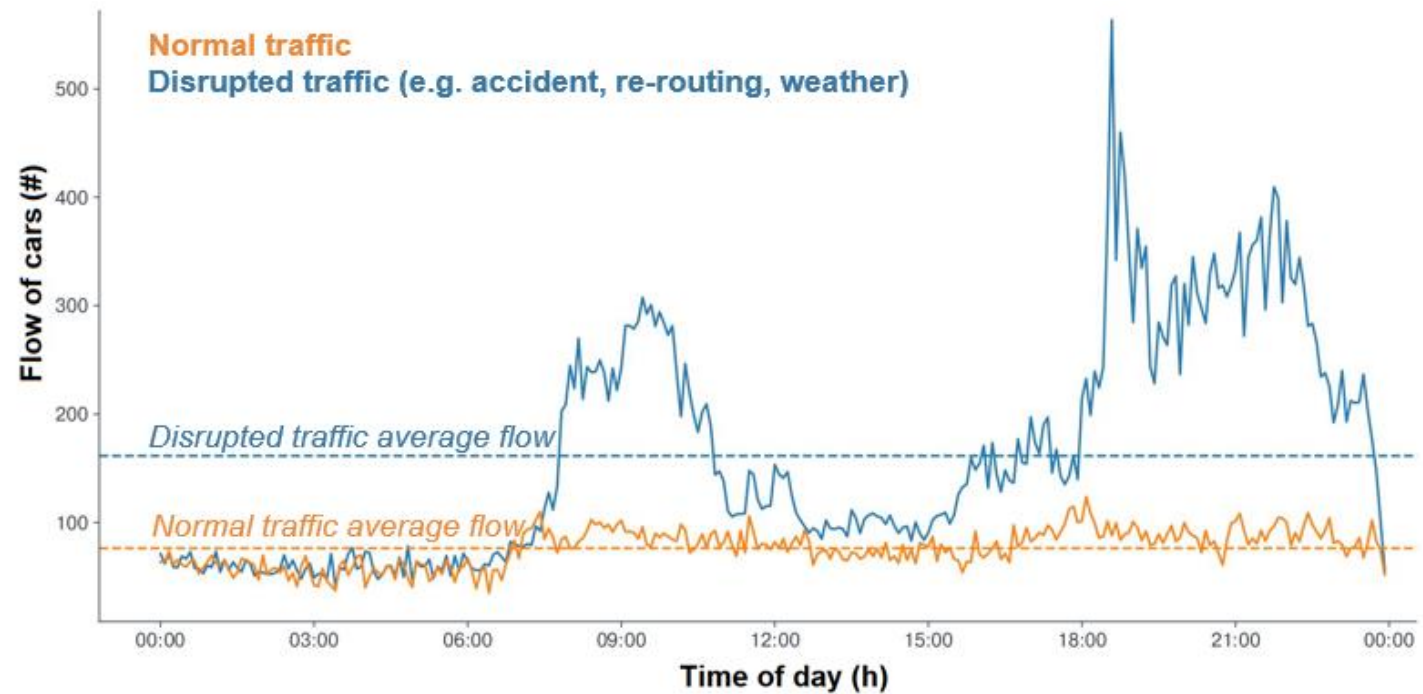
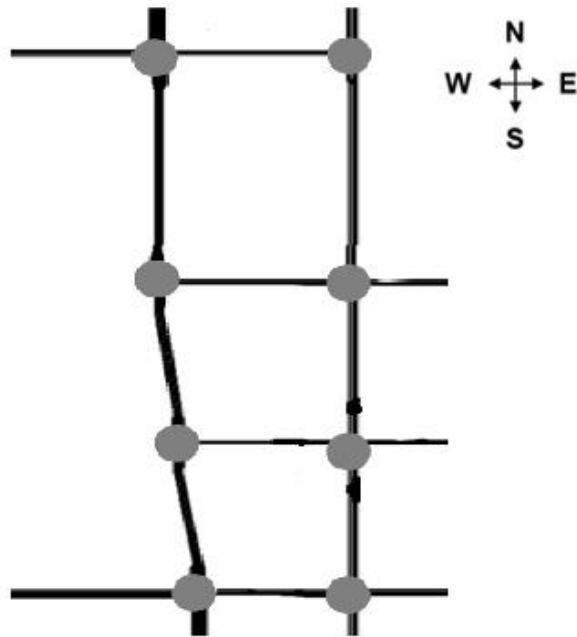
High-dimensional vector algebra for associative memories

High-dimensional vector representation and computation



Experiments & Results

The **experiments and evaluation** use the **SUMMER-MUSTARD** (Summer season Multi-cross Urban Signalized Traffic Aggregated Region Dataset) real-world dataset, which contains 59 days of real urban road traffic data from 8 crosses in a city in China* **reproduced** in **SUMO simulator**.



* <http://doi.org/10.5281/zenodo.5025264>

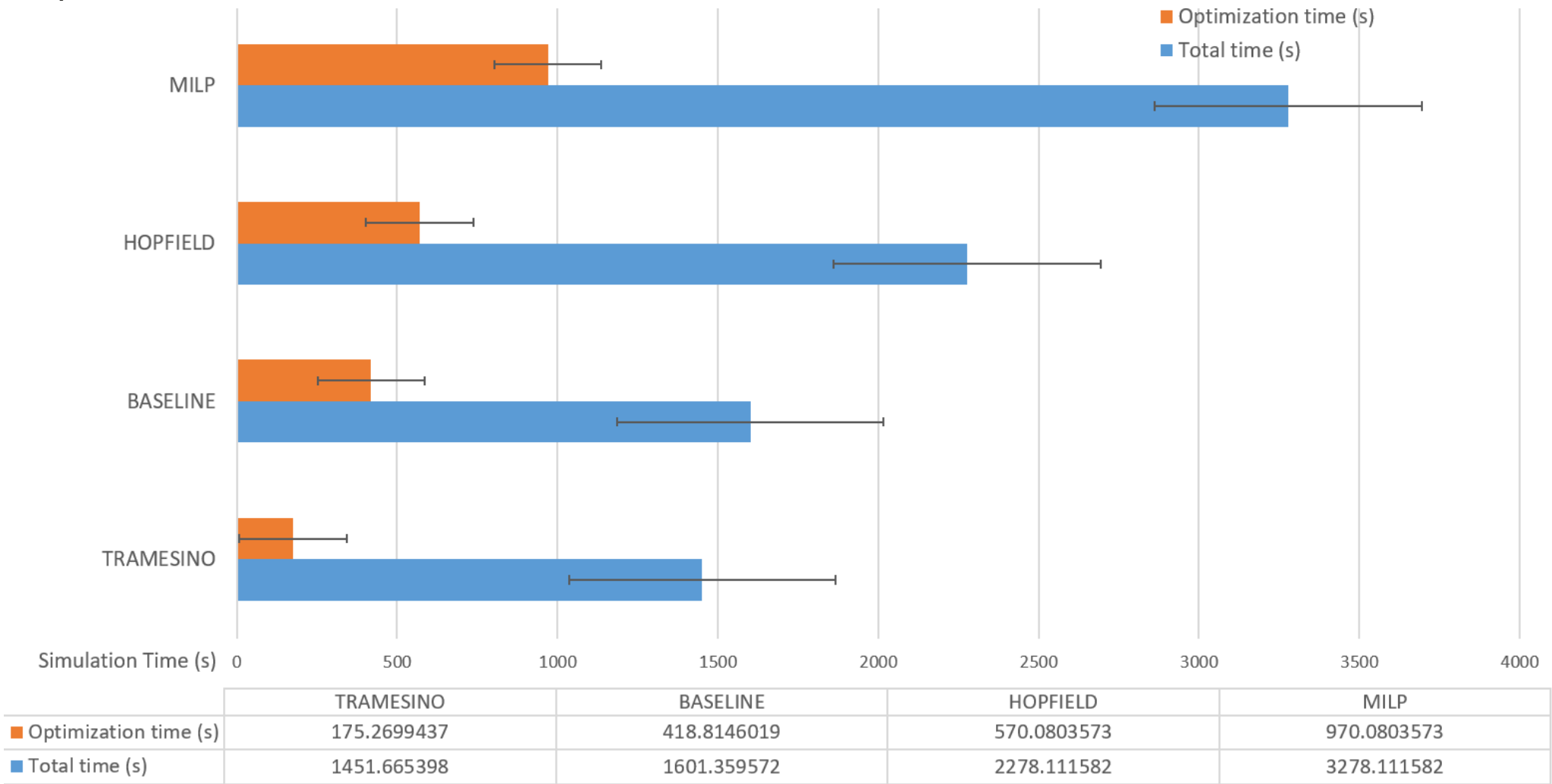
Experiments & Results

Traffic Key Performance Indices (KPI) evaluation

System/ Disruption level	N	L	M	H	Ranking	Deviation
<i>Average trip duration(s)</i>						
BASELINE	168.805	181.217	265.546	270.167	4	49.86%
MILP	118.336	132.406	167.173	167.673	1	0.0%
HOPFIELD	151.281	151.381	223.017	257.464	3	32.28%
TRAMESINO	156.379	157.371	203.775	236.224	2	28.44%
<i>Average speed(km/h)</i>						
BASELINE	58.15	56.78	49.38	47.50	4	10.95%
MILP	59.30	60.00	59.40	59.10	1	0.0%
HOPFIELD	59.48	59.97	49.28	46.18	3	9.84%
TRAMESINO	59.78	59.02	52.08	48.28	2	8.14%
<i>Waiting time(s)</i>						
BASELINE	16.45	18.53	32.59	35.13	4	7.02%
MILP	13.98	16.14	15.14	15.07	1	0.0%
HOPFIELD	13.98	14.96	29.32	37.29	3	5.84%
TRAMESINO	14.95	14.57	22.16	29.01	2	2.96%

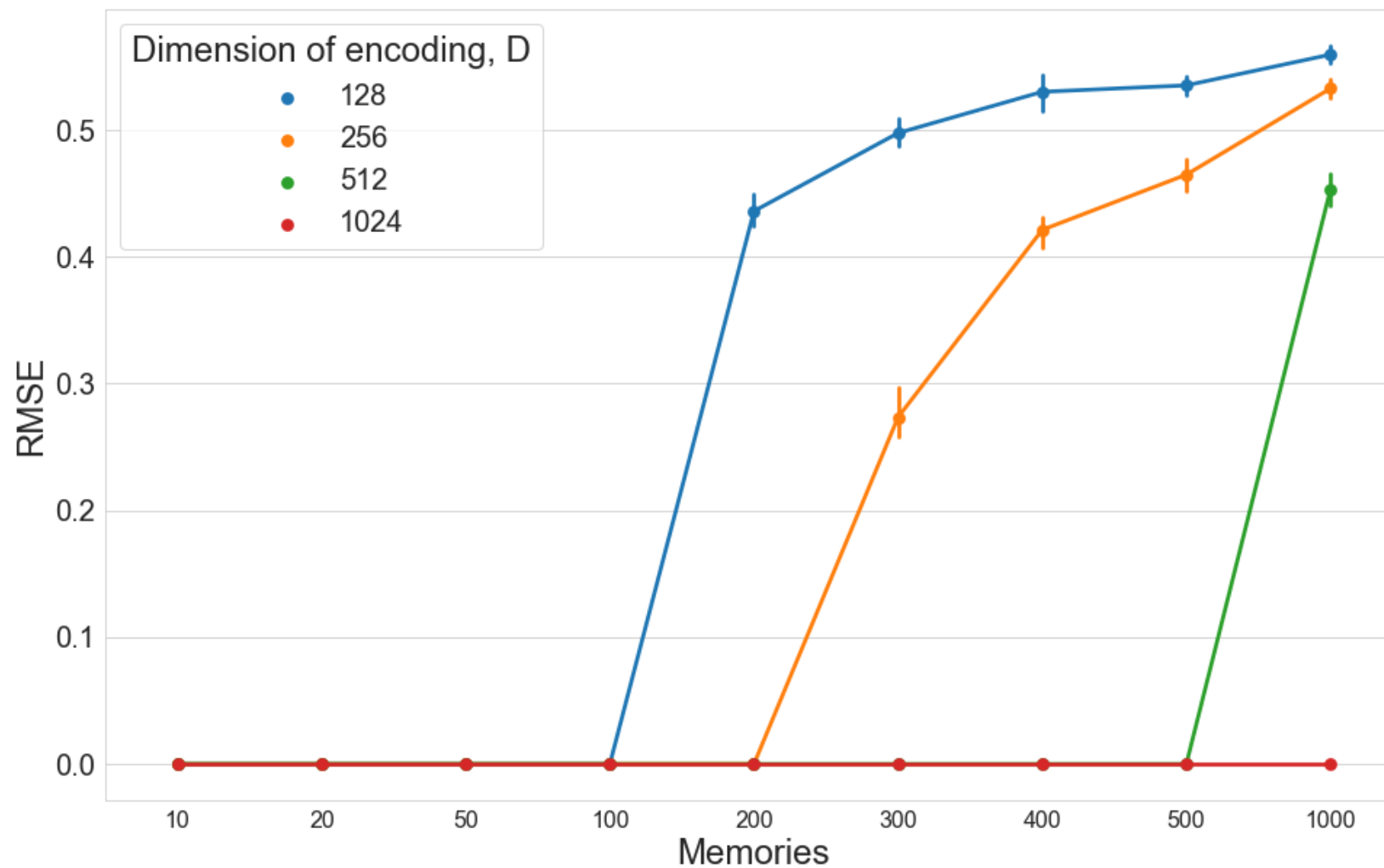
Experiments & Results

Run-time performance evaluation



Experiments & Results

Encoding/decoding accuracy of TRAMESINO memories



Observations

TRAMESINO

Trainable Memory System for Intelligent Optimization of Road Traffic Control

- The highly **non-linear and unpredictable** real-world **road traffic** situations need **timely actions**.
- A system that **models** only **relevant causal action-consequence pairs** within traffic data (i.e. green time – traffic count).
- A **memory mechanism** to store **traffic patterns** and **retrieve plausible decisions**.
- A **lightweight learning system encoding** and **manipulating traffic data** encoded in **high-dimensional vectors** using **spiking neural networks**.
- An **end-to-end system** that **learns temporal regularities** in traffic data and **adapts to abrupt changes**, while keeping **computation efficient** and **fast**.



Thank you.

Bring digital to every person, home, and organization for a fully connected, intelligent world.

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