Intelligent Intersection

Distributed Vehicle Control for Situation-Aware, Safe, and Efficient Driving

Closing Event

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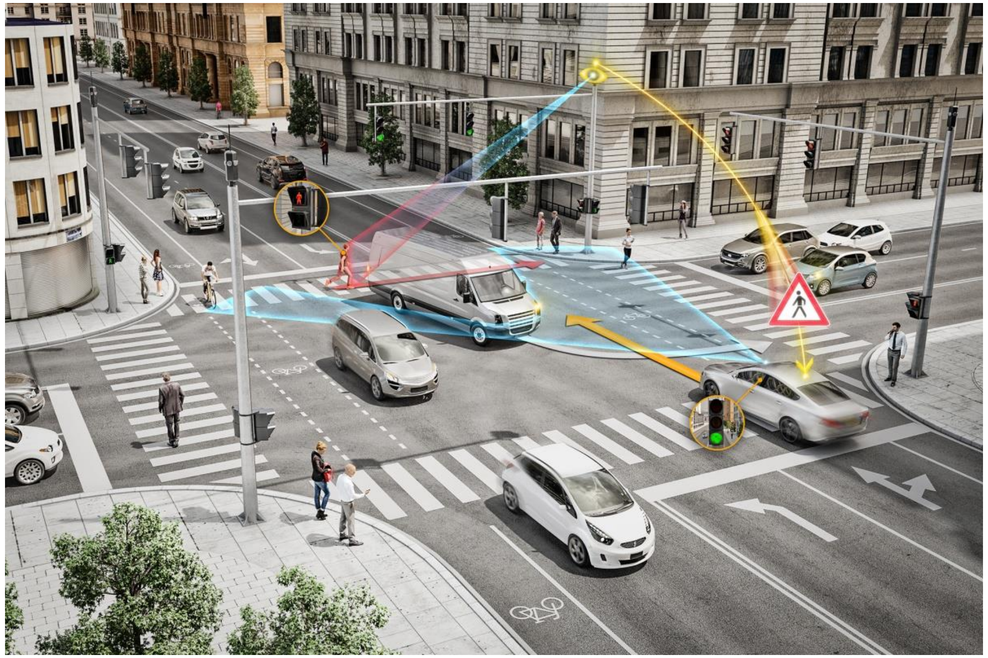
Vehicle Control for Situation-Aware, Safe & Efficient Driving

- **Motivation**
- **Overview**
- **Selected Results**
  - Multi-Agent Intersection Model
  - Obstacle Avoidance MPC
  - Co-Simulation-based Validation
  - Soft Inputs for HDVs
- **Summary**



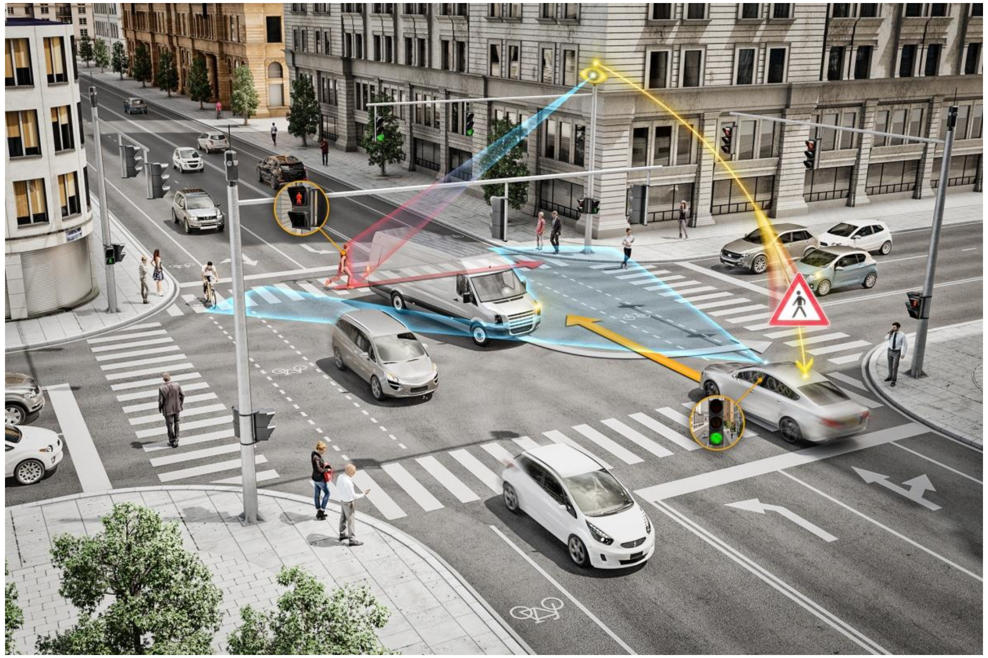
https://www.smartcitiesworld.net/news/news/smart-intersection-aims-to-increase-safety-2422

Motivation

- Collision-Free Automated Urban Driving
  - connected and automated vehicles (CAVs)
  - safety & efficiency
  - passenger comfort & environmental impact

- Model-Predictive Obstacle Avoidance (CAVs)
  - complex multi-agent scenarios
  - exploit 5G collective perception functionality
    - position predictions & shapes of other agents
  - flexible control problem formulation
  - globally optimal solution

- Soft Inputs for Human Drivers
  - connect & inform human drivers
  - human-machine interfaces (HMIs)



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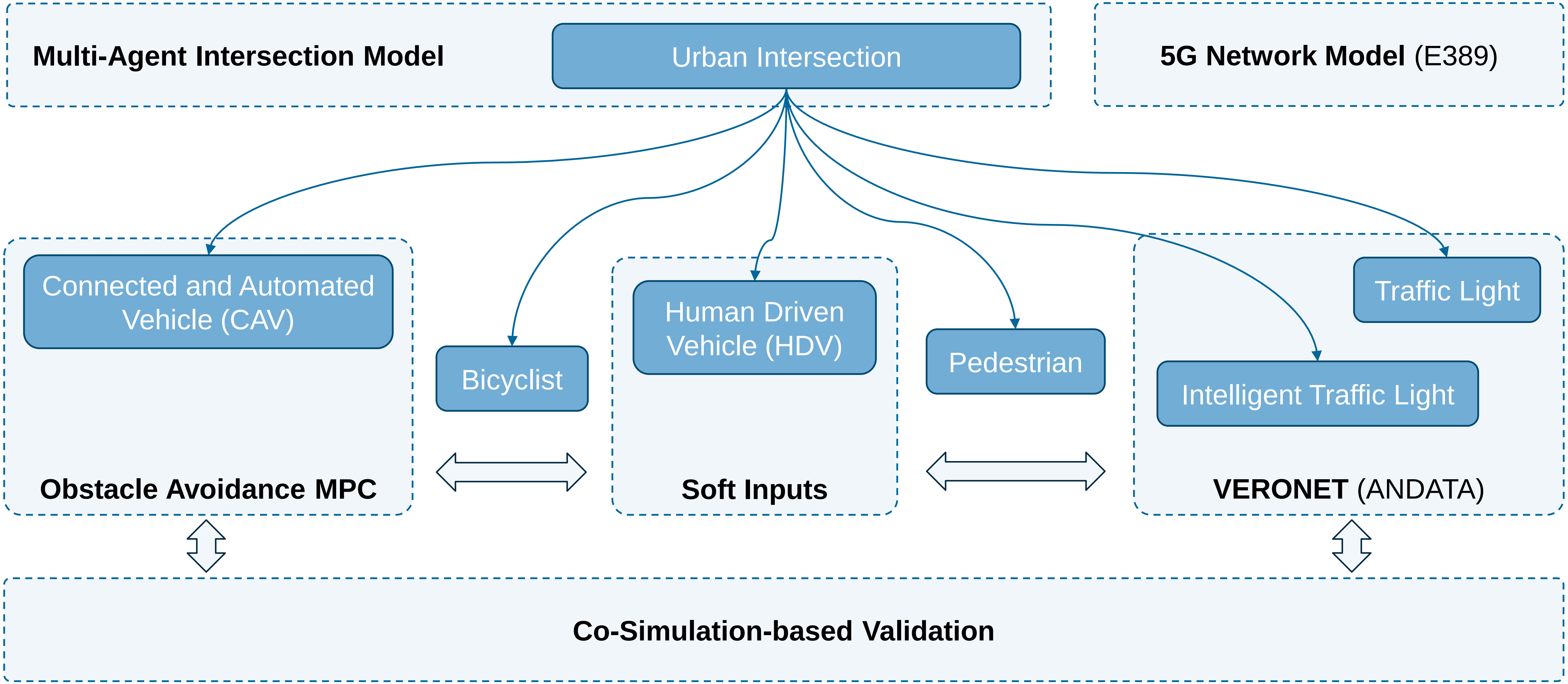
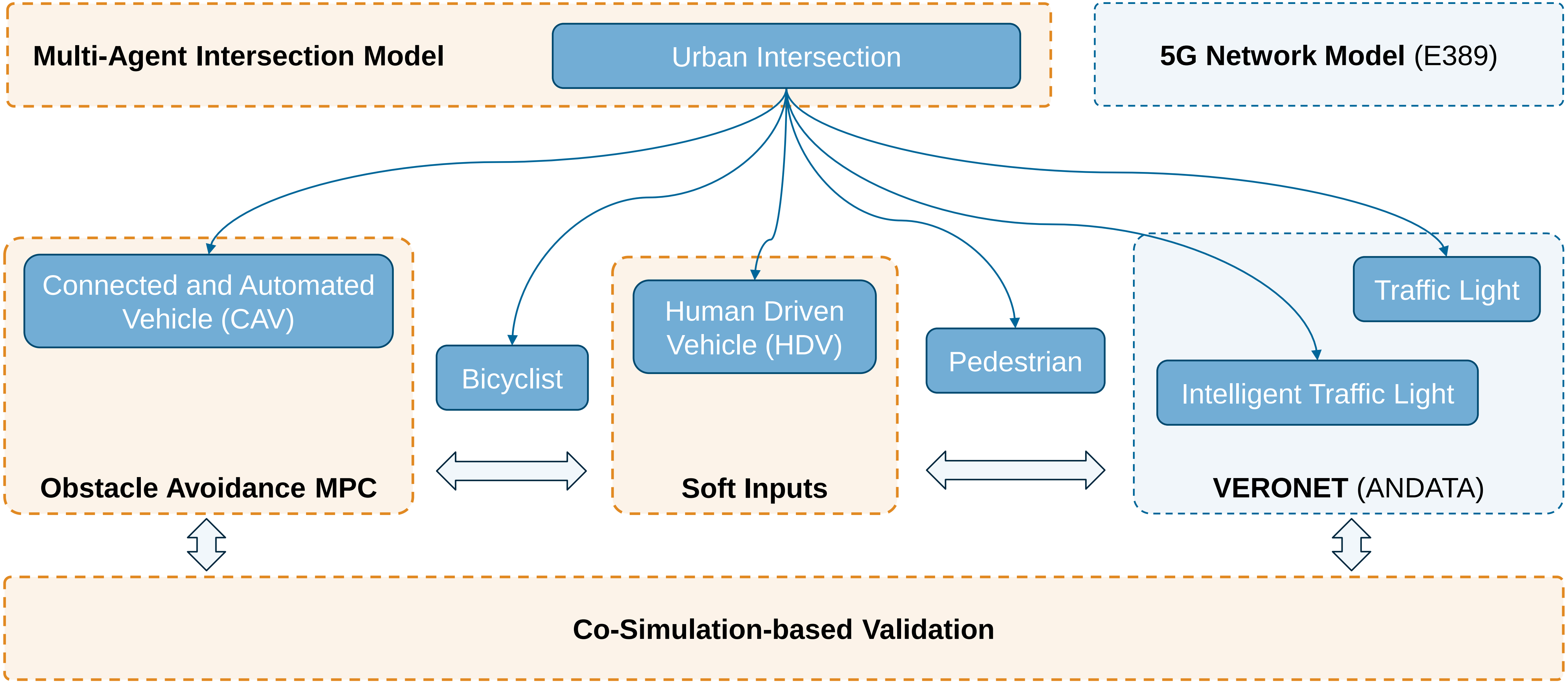
Overview



Multi-Agent Intersection Model
Urban Intersection
5G Network Model (E389)
Connected and Automated Vehicle (CAV)
Bicyclist
Human Driven Vehicle (HDV)
Pedestrian
Traffic Light
Intelligent Traffic Light
Obstacle Avoidance MPC
Soft Inputs
VERONET (ANDATA)
Co-Simulation-based Validation

Overview



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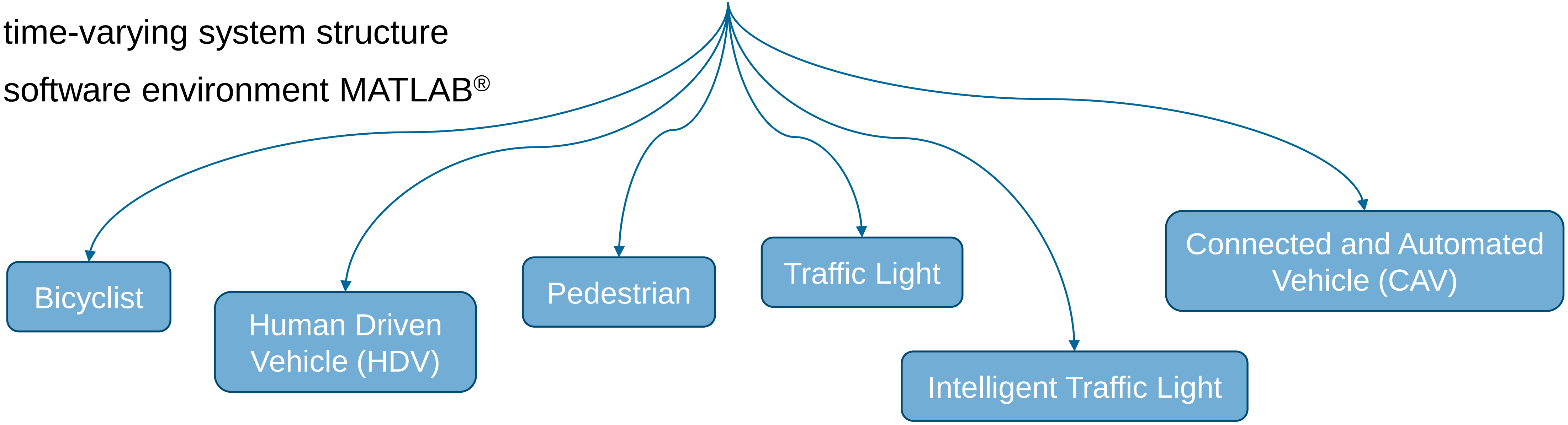
Multi-Agent Intersection Model

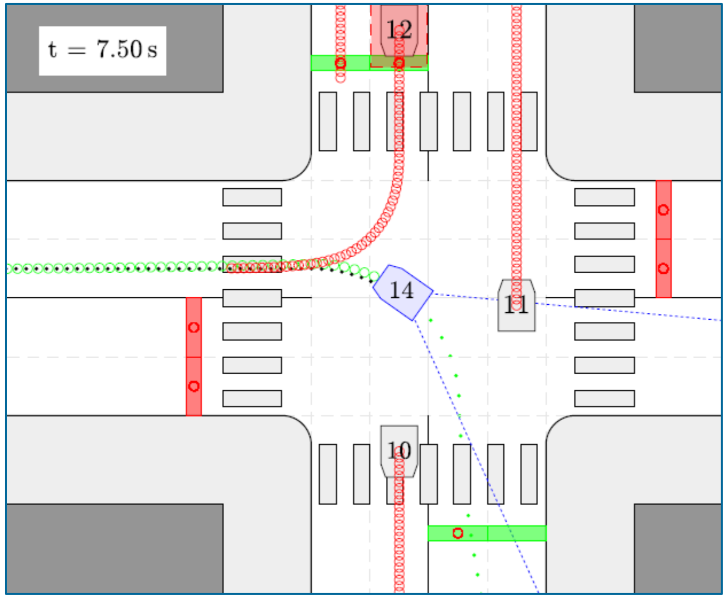
- Main Goals
  - flexible & modular simulation framework for testing 5G-enabled control- and communication concepts
  - special focus on simulation of heterogeneous intersection traffic participants (agents)
  - time-varying system structure
  - software environment MATLAB®



"Provide the right information at the right time to the right agent."

Multi-Agent Intersection Model

- Organization of Real-Time Access to Nearby Agents
  - basic control concepts
    - car-following models,
    - social-force pedestrian models,
    - Stanley controller, …
  - advanced control designs
    - obstacle-avoidance MPC,
    - model-predictive intersection control, …
- Lean & Flexible Model Structure
  - easy integration in model-based control tasks
  - straight forward extension or inclusion of additional functionality
- Few Generic Agent Tasks Generate Rich Emanating Behavior



Multi-Agent Intersection Model

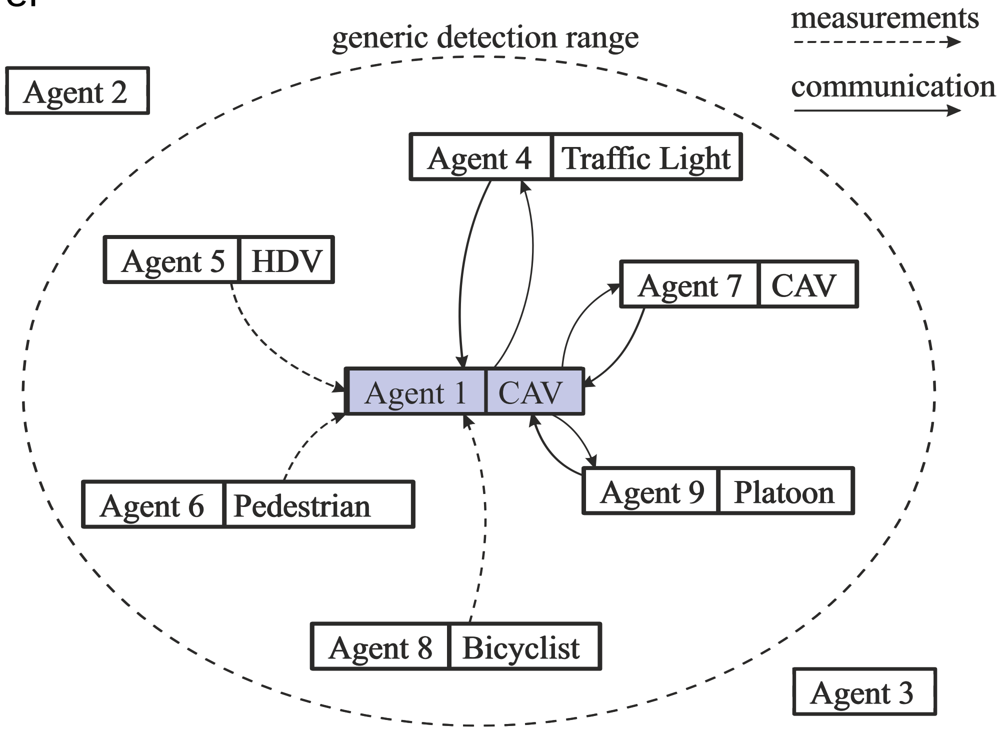
“Provide the right information at the right time to the right agent.”

Multi-Agent Intersection Model: Generic Agent Tasks

1) getEgoStateEstimate
   - retrieve/estimate ego state via communication, sensor fusion or observer
2) getNearbyAgents
   - retrieve set of relevant neighbor agents
3) collectObstaclePredictions
   - retrieve/measure/estimate neighbor state and motion predictions or
   - create proxy predictions
   - identify nearest relevant agent for car-following control
4) getEgoReferences
   - retrieve control goals/references
5) u = AgentController.step
   - compute control law
6) setInput(u)
   - apply control law

synchronization step

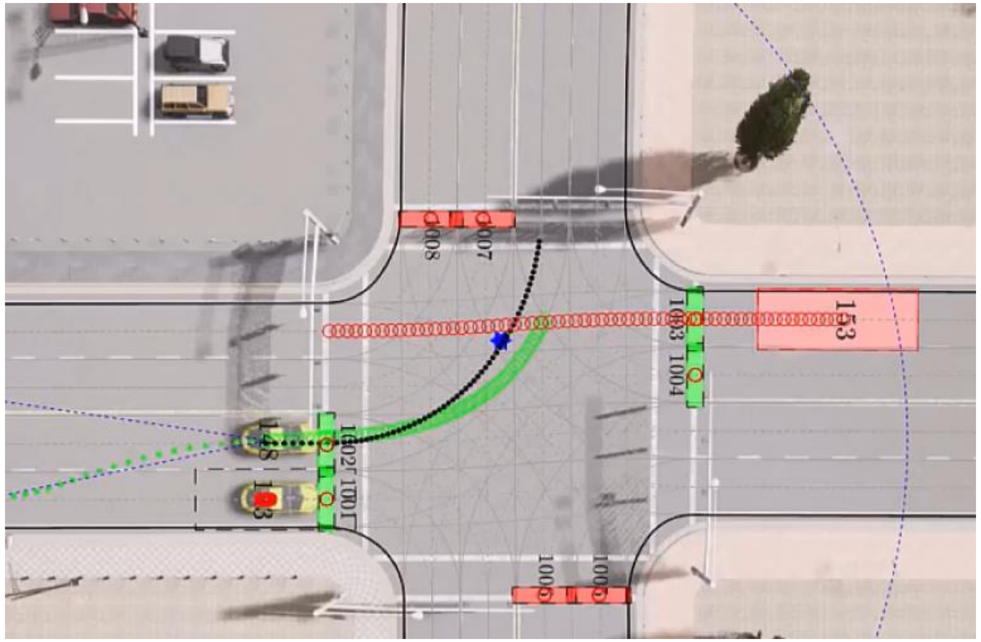
7) EOMstep(x, Input)
   - compute ego EOMs / evolve time step



co-simulation software

Obstacle Avoidance MPC

- Main Goals
  - collision-free & efficient automated driving for CAVs
  - analysis of CAV control concept
    - safety & efficiency
    - passenger comfort & environmental impact
    - traffic situation complexity
    - information level
      - 5G collective perception
      - V2X communication
  - Model-Predictive Obstacle Avoidance Control
    - advanced & versatile optimal control concept
    - V2X communication
    - flexible problem formulation
    - global optimal solution via precise mixed-integer-based obstacle avoidance constraints

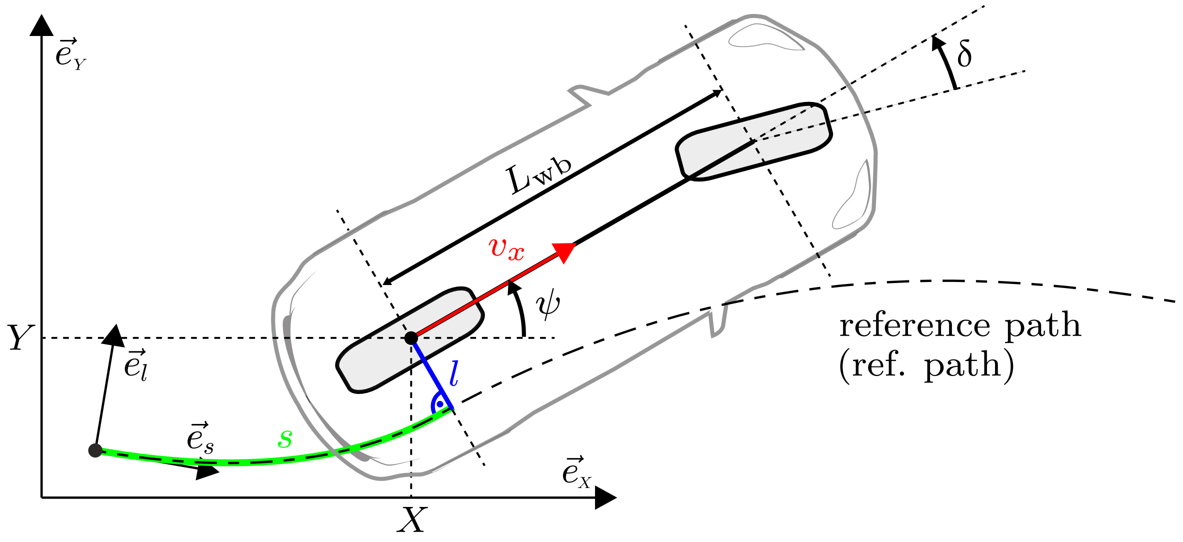


Multi-Agent Intersection Model as prediction model for OA-MPC

"Unified, efficient, and accurate solution to the obstacle avoidance (OA) problem."

Obstacle Avoidance MPC: Control Design

- Assumptions
  - planar poses, shapes & position predictions of surrounding traffic participants available
    - 5G collective perception
    - V2X communication
    - prediction module
  - ego vehicle shape represented as circle centered at rear axle
  - pre-defined reference path available (Frenet frame)
  - backward vehicle motions disregarded



"Unified, efficient, and accurate solution to the obstacle avoidance (OA) problem."

Obstacle Avoidance MPC: Control Design

- Kinematic Single-Track Model
  - no consideration of tire slip, non-linear

$$\dot{\boldsymbol{x}} = \begin{bmatrix} \dot{X} \\ \dot{Y} \\ \dot{\psi} \\ \dot{v}_x \end{bmatrix} = \begin{bmatrix} v_x \cos\psi \\ v_x \sin\psi \\ v_x \tan(\delta)/L_{\mathrm{wb}} \\ a_x \end{bmatrix}$$

$$\boldsymbol{x} = \begin{bmatrix} X, & Y, & \psi, & v_x \end{bmatrix}^{\mathrm{T}}$$

$$\boldsymbol{u} = \begin{bmatrix} \delta, & a_x \end{bmatrix}^{\mathrm{T}}$$

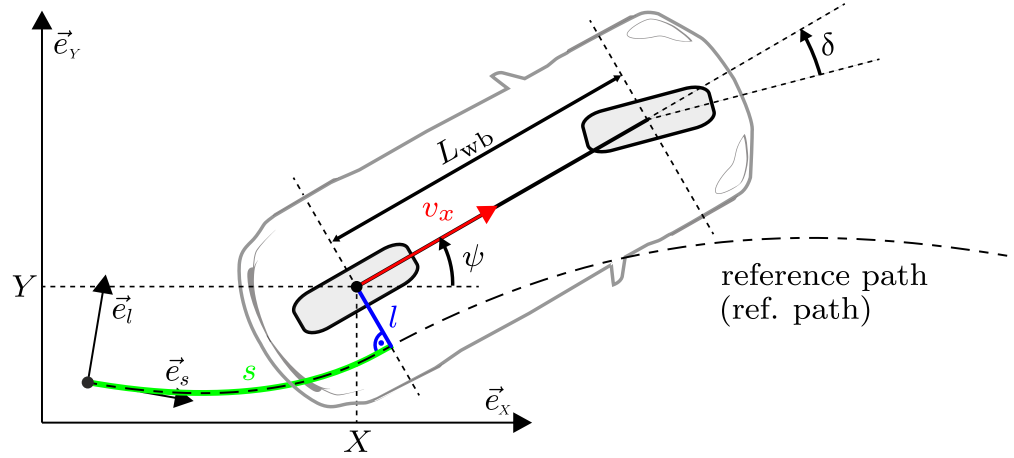
$$\xrightarrow{\mathcal{F}} \qquad \xleftarrow[\mathcal{F}^{-1}]{}$$

- Flatness-Based Transformation
  - linear prediction model (two double integrators)

$$\dot{\boldsymbol{z}} = \begin{bmatrix} 0 & 1 & 0 & 0 \\ 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 1 \\ 0 & 0 & 0 & 0 \end{bmatrix} \boldsymbol{z} + \begin{bmatrix} 0 & 0 \\ 1 & 0 \\ 0 & 0 \\ 0 & 1 \end{bmatrix} \boldsymbol{\nu}$$

$$\boldsymbol{z} = \begin{bmatrix} y_1, & \dot{y}_1, & y_2, & \dot{y}_2 \end{bmatrix}^{\mathrm{T}}$$

$$\boldsymbol{\nu} = \begin{bmatrix} \ddot{y}_1, & \ddot{y}_2 \end{bmatrix}^{\mathrm{T}}$$



- *Frenet coordinates*
  - $\boldsymbol{y} = \begin{bmatrix} y_1, & y_2 \end{bmatrix}^{\mathrm{T}} = \begin{bmatrix} s, & l \end{bmatrix}^{\mathrm{T}}$
  - separation of longitudinal & lateral control

- Cartesian coordinates
  - $\boldsymbol{y} = \begin{bmatrix} X, & Y \end{bmatrix}^{\mathrm{T}}$
  - precise maneuvers (e.g., parking)

Obstacle Avoidance MPC: Control Design

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zero-order hold

  - *Frenet coordinates*
    - $\boldsymbol{y} = \begin{bmatrix} y_1, & y_2 \end{bmatrix}^{\mathrm{T}} = \begin{bmatrix} s, & l \end{bmatrix}^{\mathrm{T}}$
    - separation of longitudinal & lateral control
  - Cartesian coordinates
    - $\boldsymbol{y} = \begin{bmatrix} X, & Y \end{bmatrix}^{\mathrm{T}}$
    - precise maneuvers (e.g., parking)

- Model-Predictive Control
  - discrete-time (zero-order hold)

$$\boldsymbol{z}_{k+1} = \underbrace{\begin{bmatrix} 1 & T_\mathrm{s} & 0 & 0 \\ 0 & 1 & 0 & 0 \\ 0 & 0 & 1 & T_\mathrm{s} \\ 0 & 0 & 0 & 1 \end{bmatrix}}_{\boldsymbol{A}_\mathrm{d}} \boldsymbol{z}_k + \underbrace{\begin{bmatrix} T_\mathrm{s}^2/2 & 0 \\ T_\mathrm{s} & 0 \\ 0 & T_\mathrm{s}^2/2 \\ 0 & T_\mathrm{s} \end{bmatrix}}_{\boldsymbol{B}_\mathrm{d}} \boldsymbol{\nu}_k$$

  - optimization problem

$$\begin{aligned} \min_{\boldsymbol{\mathcal{V}},\boldsymbol{\mathcal{Z}}} \; & (J + r_s \boldsymbol{s}) \\ \text{s.t.} \; & \boldsymbol{z}_{k+j+1} = \boldsymbol{A}_\mathrm{d} \boldsymbol{z}_{k+j} + \boldsymbol{B}_\mathrm{d} \boldsymbol{\nu}_{k+j}, \\ & \boldsymbol{\nu}_{k+j} \in \mathcal{W}, \\ & \boldsymbol{z}_{k+j+1} \in \mathcal{Z}, \\ & \boldsymbol{s} \geqslant \boldsymbol{0}, \end{aligned}$$

  - cost function

$$J = \sum_{j=0}^{N_\mathrm{p}-1} \left(\boldsymbol{e}_{k+j+1}^{\mathrm{T}} \boldsymbol{Q} \, \boldsymbol{e}_{k+j+1} + \boldsymbol{\nu}_{k+j}^{\mathrm{T}} \boldsymbol{R} \boldsymbol{\nu}_{k+j} \right)$$

Obstacle Avoidance MPC: Control Design

- Model-Predictive Control
  - discrete-time (zero-order hold)

er hold

$$\boldsymbol{z}_{k+1} = \underbrace{\begin{bmatrix} 1 & T_\mathrm{s} & 0 & 0 \\ 0 & 1 & 0 & 0 \\ 0 & 0 & 1 & T_\mathrm{s} \\ 0 & 0 & 0 & 1 \end{bmatrix}}_{\boldsymbol{A}_\mathrm{d}} \boldsymbol{z}_k + \underbrace{\begin{bmatrix} T_\mathrm{s}^2/2 & 0 \\ T_\mathrm{s} & 0 \\ 0 & T_\mathrm{s}^2/2 \\ 0 & T_\mathrm{s} \end{bmatrix}}_{\boldsymbol{B}_\mathrm{d}} \boldsymbol{\nu}_k$$

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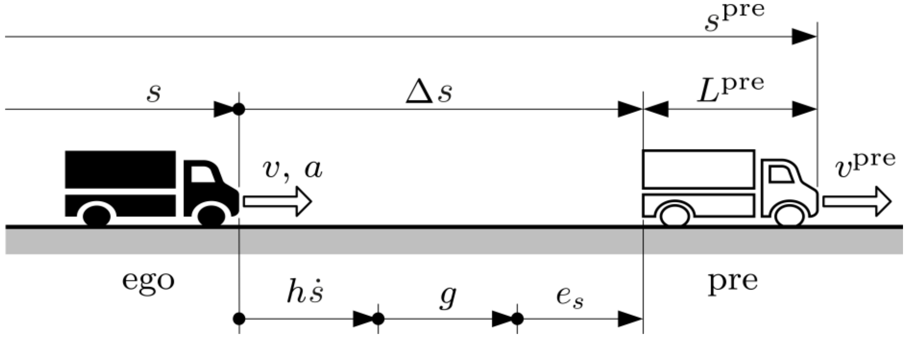
- position error (Cartesian)

$$\boldsymbol{e} = \begin{bmatrix} e_X \\ e_Y \end{bmatrix} = \begin{bmatrix} X \\ Y \end{bmatrix} - \begin{bmatrix} X_\mathrm{ref} \\ Y_\mathrm{ref} \end{bmatrix}$$

- position error (Frenet)

$$\boldsymbol{e} = \begin{bmatrix} e_s \\ e_l \end{bmatrix} = \begin{bmatrix} \Delta s(t) - h\,\dot{s}(t) - g \\ l(t) - l_\mathrm{ref} \end{bmatrix}$$

$$\boldsymbol{Q} = \mathrm{diag}(q_s, q_l) \qquad \boldsymbol{R} = \mathrm{diag}(r_1, r_2)$$



Obstacle Avoidance MPC: Control Design

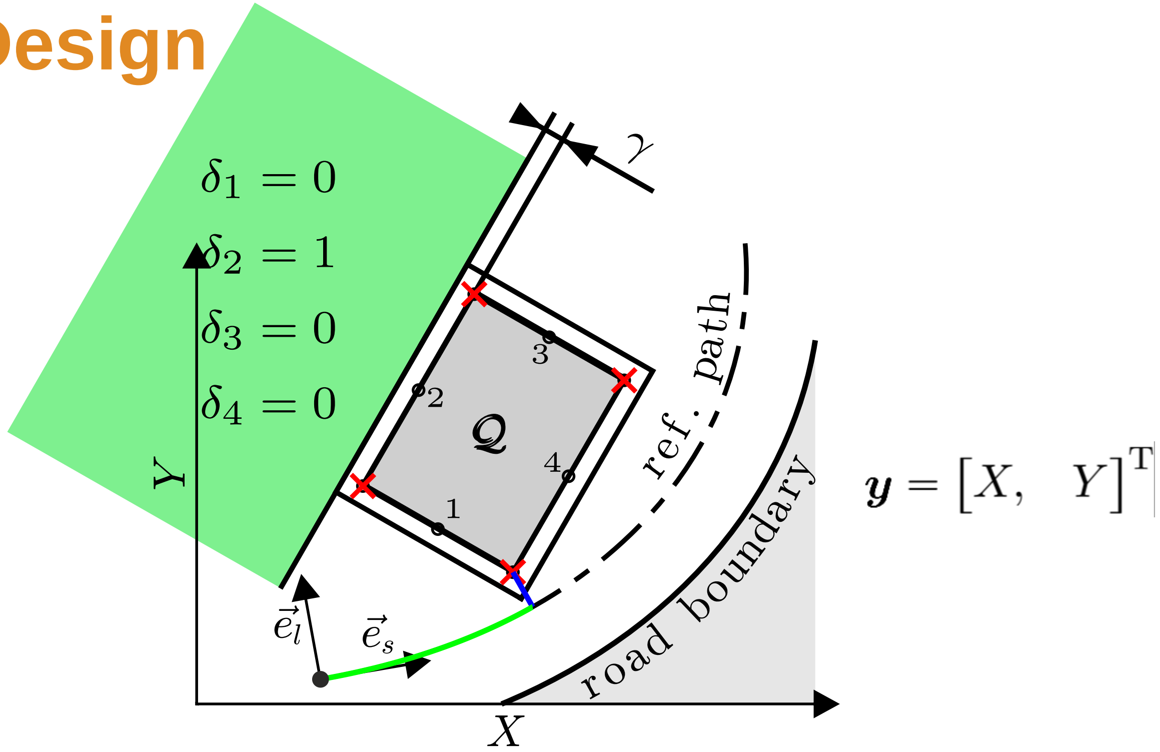
- Obstacle Avoidance Constraints
  - convex obstacle shape in flat coordinates

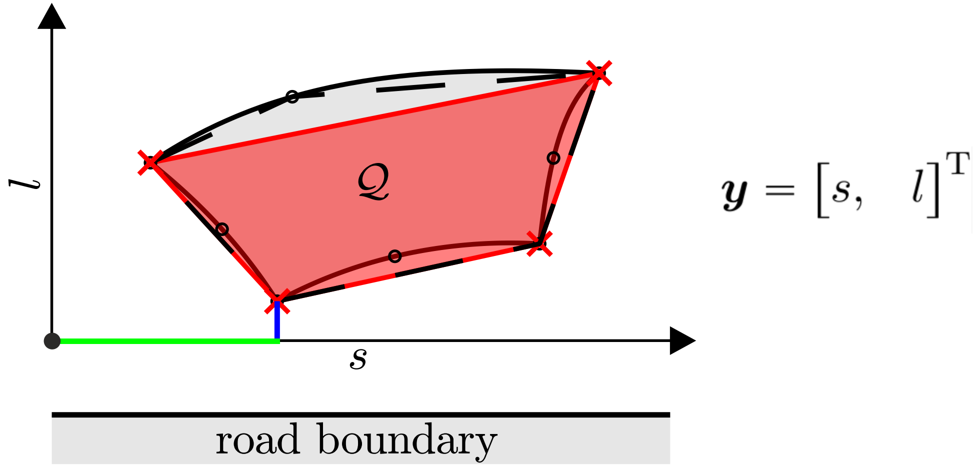
$$\mathcal{Q} = \left\{ (y_1, y_2) : \boldsymbol{G} \begin{bmatrix} y_1, & y_2 \end{bmatrix}^{\mathrm{T}} \leqslant \boldsymbol{f} \right\}$$

  - Big-M method, exclusion constraints $(y_1, y_2) \notin \mathcal{Q}$

$$\begin{aligned} \boldsymbol{f} - \boldsymbol{G} [y_1, y_2]^{\mathrm{T}} + (\gamma - s)\, \mathbb{1} \leqslant M \left(\mathbb{1} - \boldsymbol{\delta} \right)\ , \\ s \geqslant 0\,, \\ \mathbb{1}^{\mathrm{T}} \boldsymbol{\delta} \geqslant 1\,, \end{aligned}$$

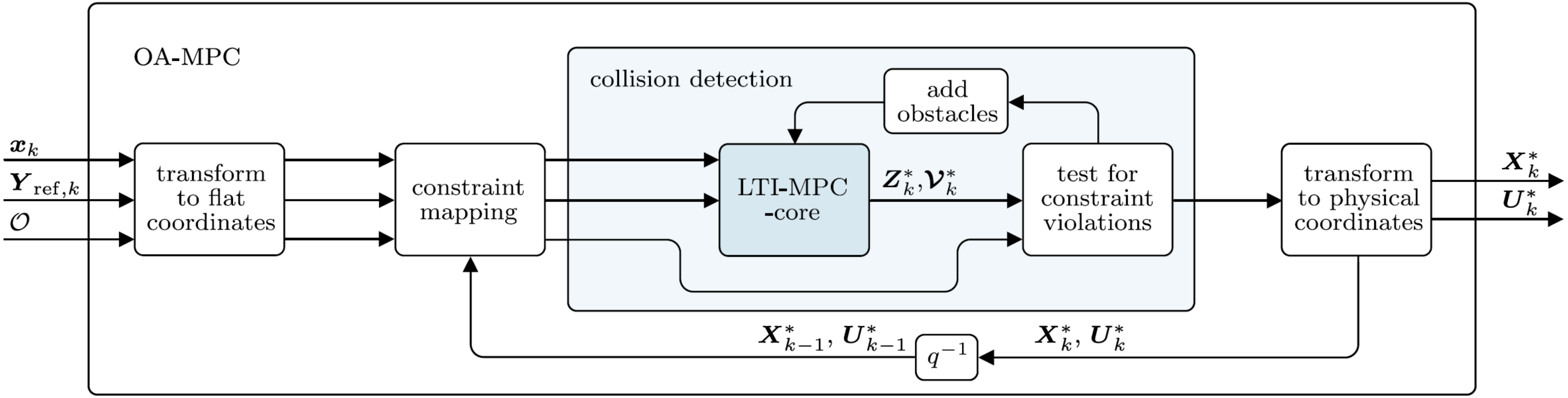
  - soft constrained
  - MIQP problem
  - distortions in Frenet frame due to reference path curvature
  - compensated by mapping more vertices





Obstacle Avoidance MPC: Control Design

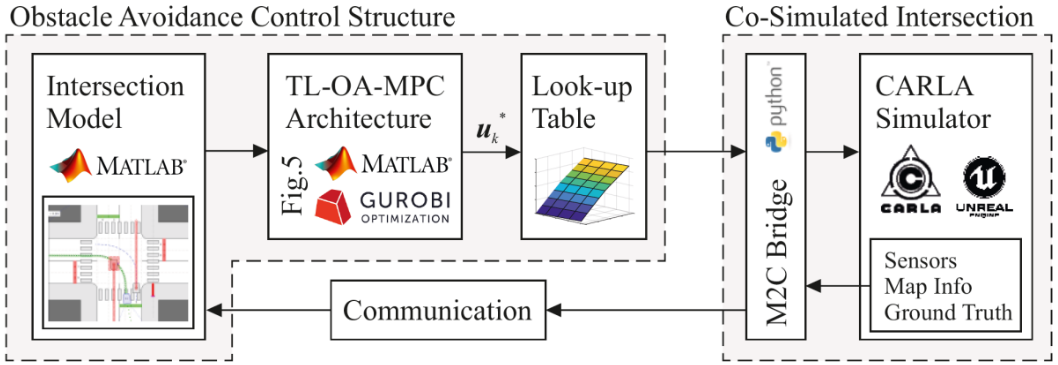
- Control Architecture

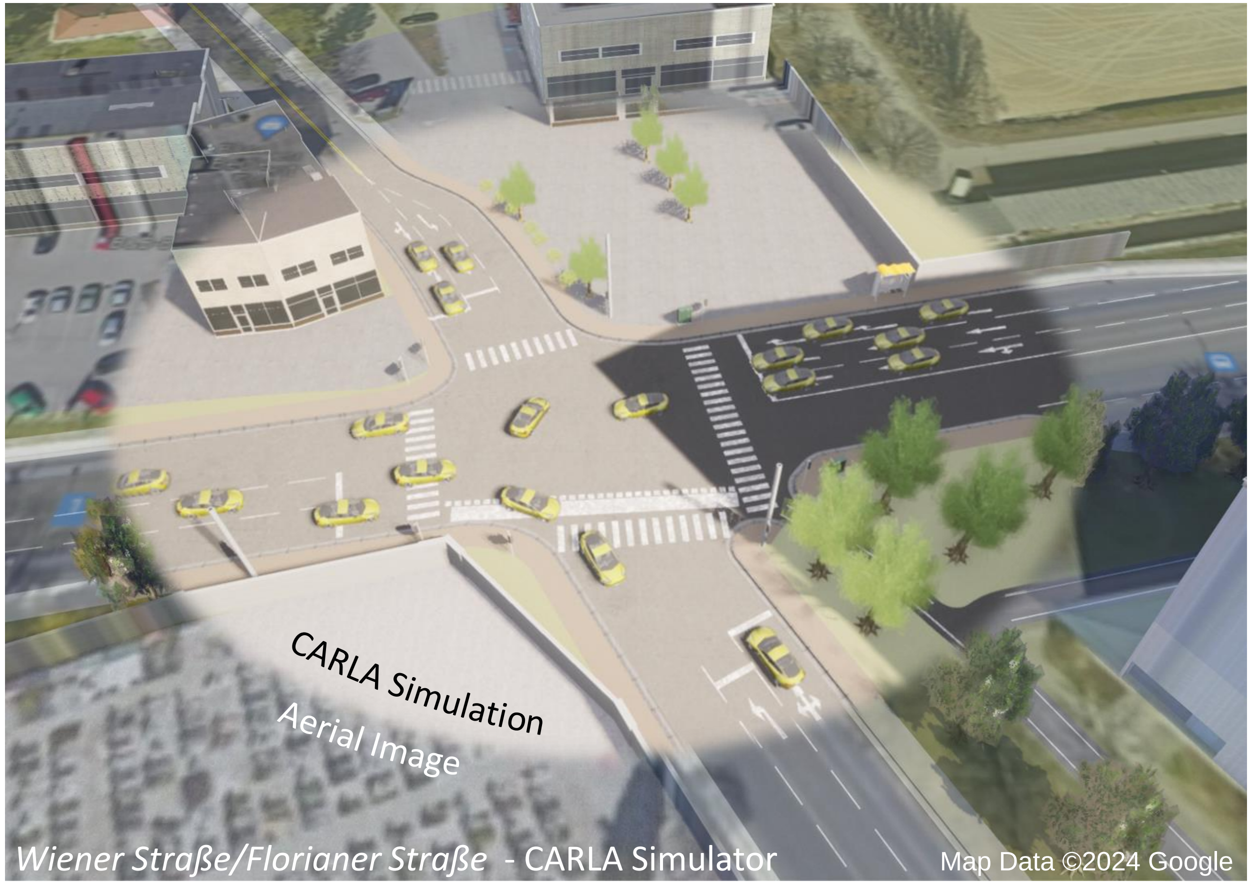


"Unified, efficient, and accurate solution to the obstacle avoidance (OA) problem."

Co-Simulation-based Validation

- CARLA Simulator
  - hyper-realistic traffic simulator for development & validation of autonomous driving applications
    - multi-body dynamics of masses & chassis
    - gear box, clutch, engine, and tire models
    - simulation of multiple interacting vehicles
- Co-Simulation Architecture
  - combines the following modules:
    - Multi-Agent Simulation Model
    - CARLA Simulator
    - Communication Module





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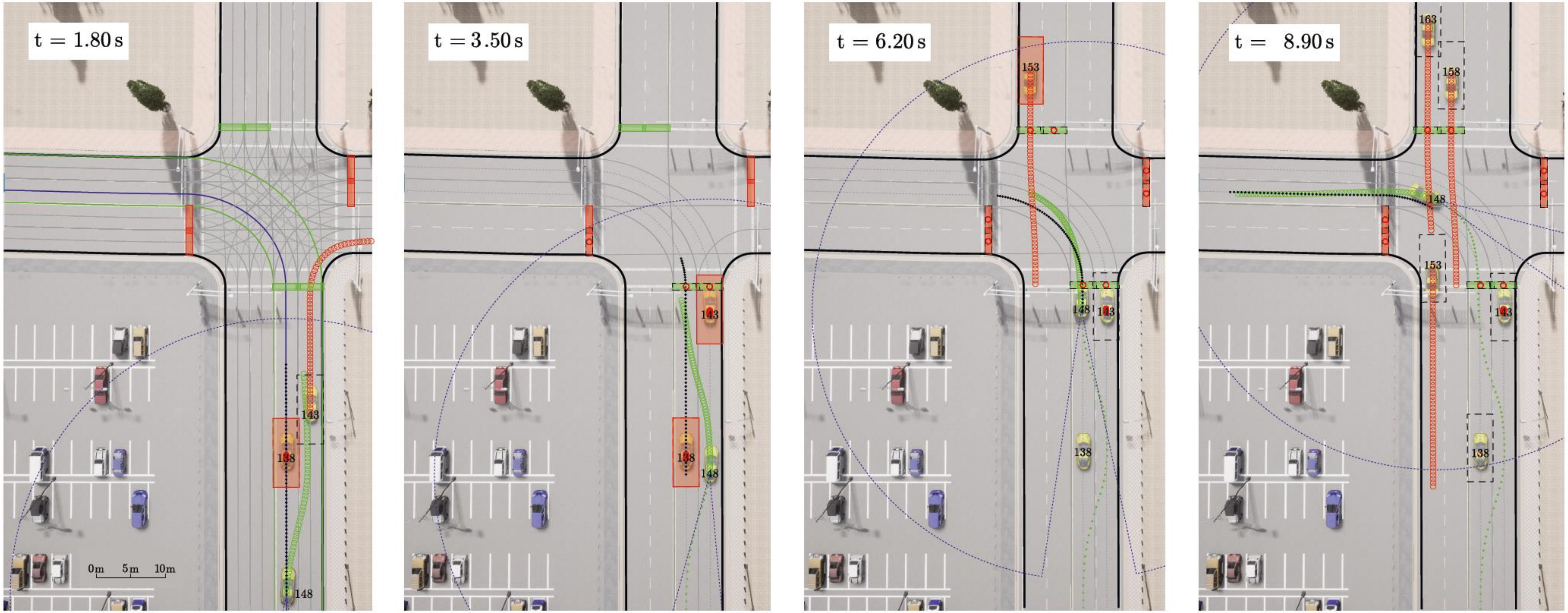


Soft Inputs for HDVs

- Connect Human Drivers
  - with intelligent traffic control system
  - to increase road safety & efficiency
  - maneuver recommendations
    - speed adaption
    - lane change
    - situational awareness message (5G BSM)
  - transmitted via
    - ITS-G5 technology
  - received by on-board unit
    - human-machine interfaces
    - navigation system
    - 5G-enabled handheld

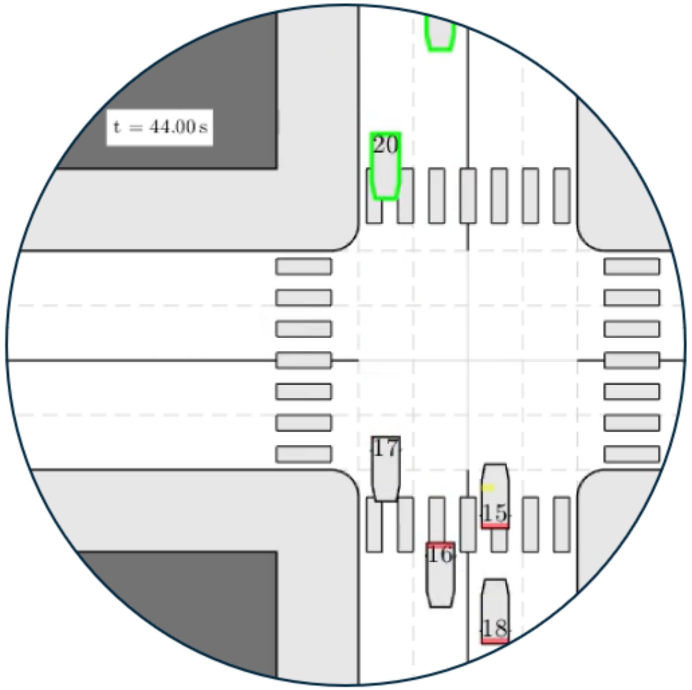
Bike2CAV

Connect bicyclists via V2X communication with 5G-ITS traffic monitoring system to inform about potential collision risks.

“Provide the right information at the right time to the right agent.”

Soft Inputs for HDVs

- Speed Adaption



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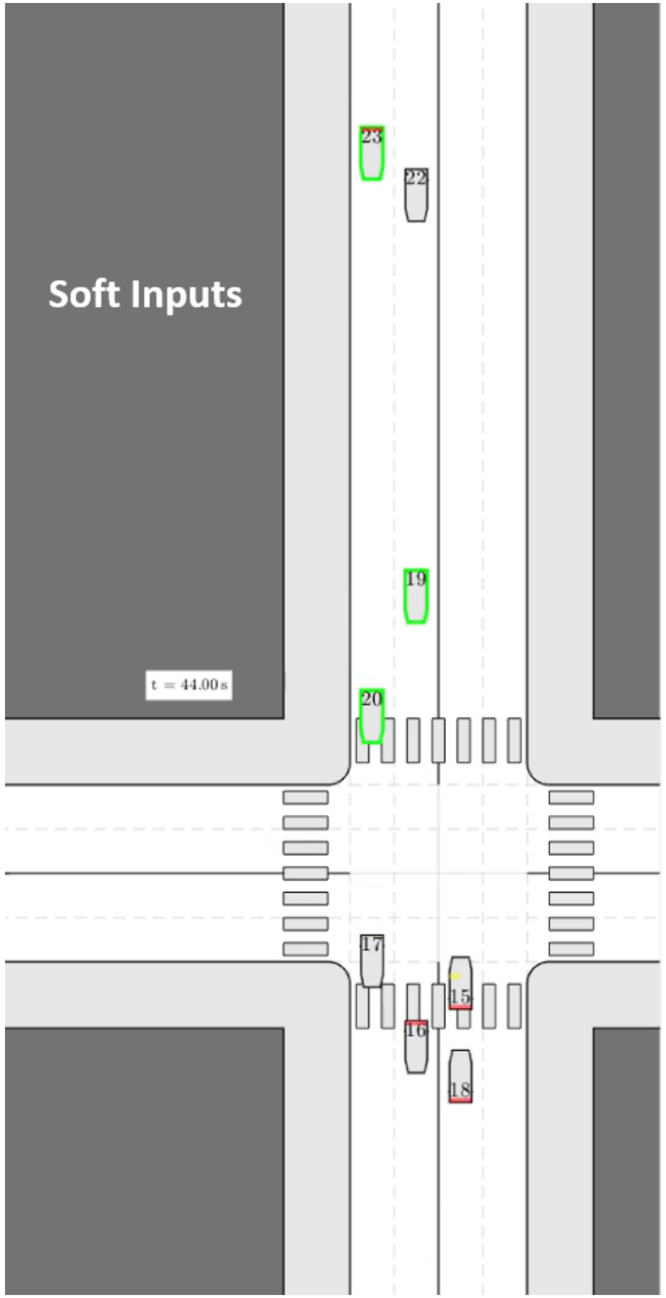
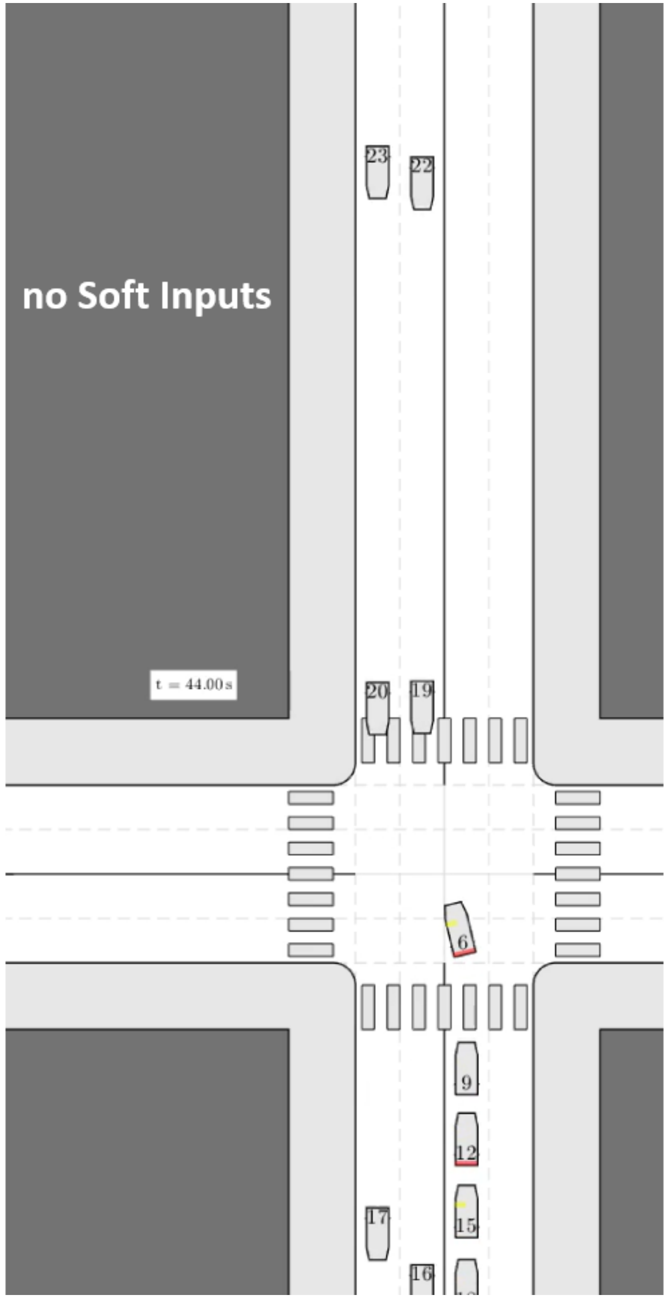
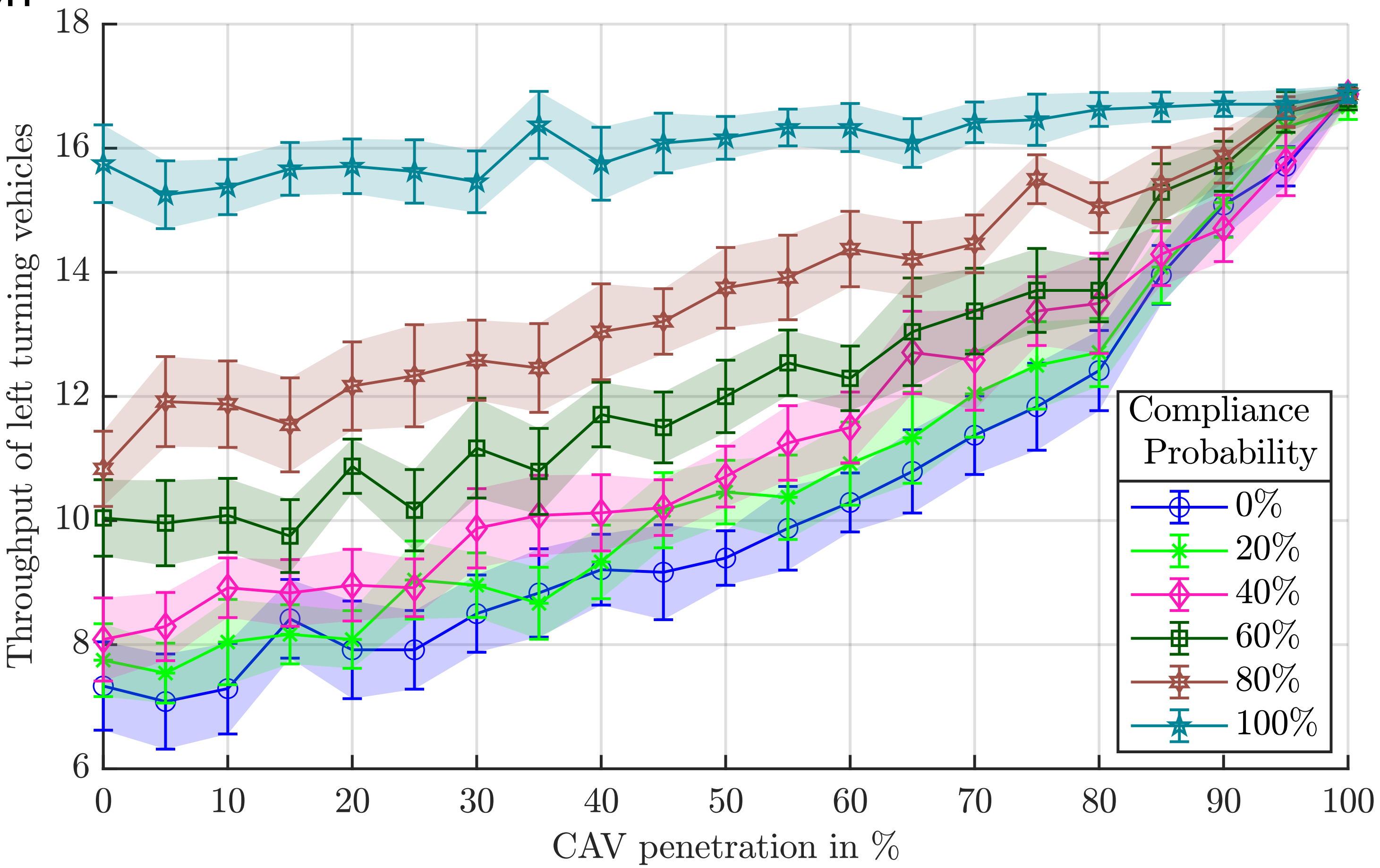




Soft Inputs for HDVs

- Speed Adaption



“Provide the right information at the right time to the right agent.”

Summary

Soft Inputs for HDVs

Flatness-Based Mixed-Integer OA-MPC

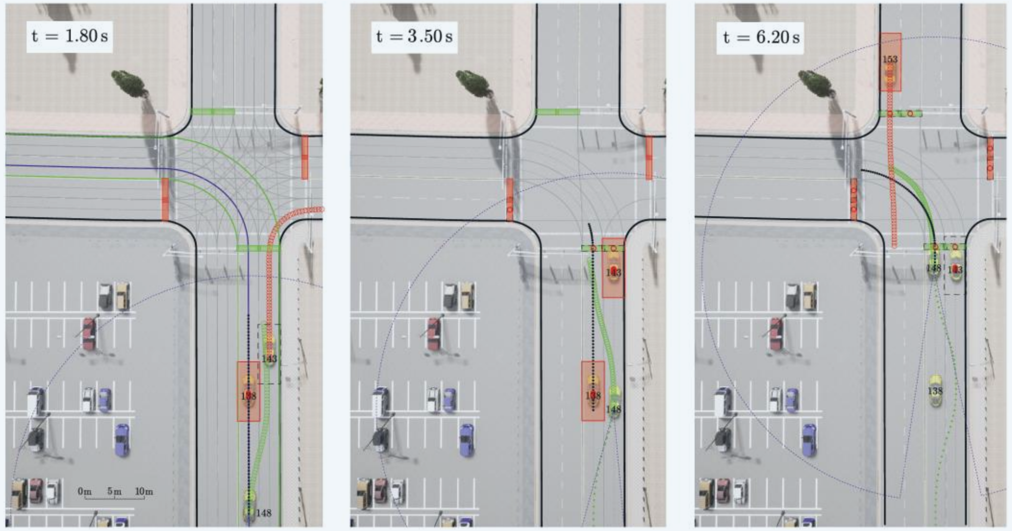
Two-Layer OA-MPC Architecture

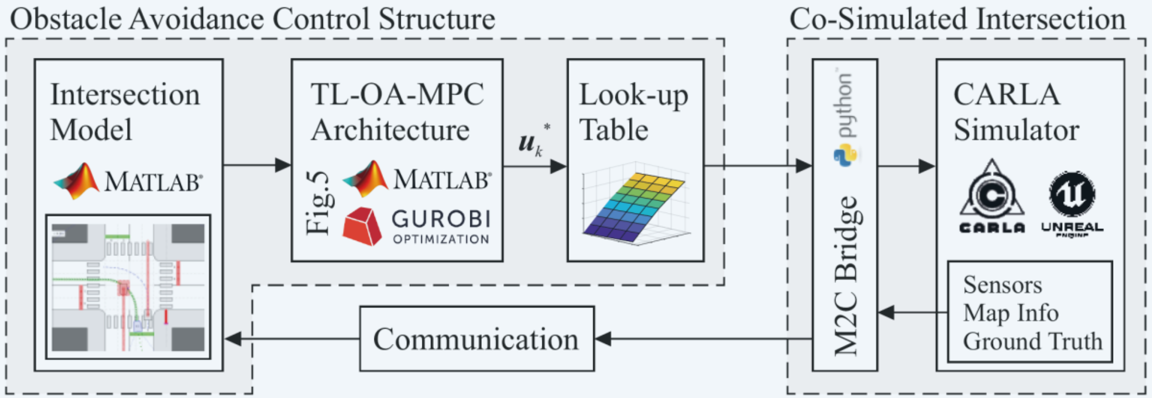
Lane Change OA-MPC

Intersection Models

Co-Simulation-based Validation

- CARLA Traffic Simulator





FFG
Promoting Innovation.

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Selected Publications

A.L. Gratzer, M. Broger, A. Schirrer, and S. Jakubek. "Flatness-Based Mixed-Integer Obstacle Avoidance MPC for Collision-Safe Automated Urban Driving." In *9th International Conference on Control, Decision and Information Technologies (CoDIT)*, pp. 1844-1849. IEEE, 2023.

A.L. Gratzer, A. Schirrer, and S. Jakubek. "Agile Multi-Agent Model Architecture for Intelligent Intersection Traffic Simulation." *IFAC-PapersOnLine* 55, no. 27 (2022): 89-95.

A.L. Gratzer, A. Schirrer, E. Thonhofer, F. Pasic, S. Jakubek, and C.F. Mecklenbräuker. "Short-Term Collision Estimation by Stochastic Predictions in Multi-Agent Intersection Traffic." In *2nd International Conference on Electrical, Computer and Energy Technologies (ICECET)*, pp. 1-6. IEEE, 2022.

A.L. Gratzer, S. Thormann, A. Schirrer, and S. Jakubek. "String stable and collision-safe model predictive platoon control." *IEEE Transactions on Intelligent Transportation Systems* 23, no. 10 (2022): 19358-19373.

A.L. Gratzer, M. Broger, A. Schirrer, and S. Jakubek, “Two-Layer MPC Architecture for Efficient Mixed-Integer-Informed Obstacle Avoidance in Real-Time”, *IEEE Transactions on Intelligent Transportation Systems*, submitted & under review

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