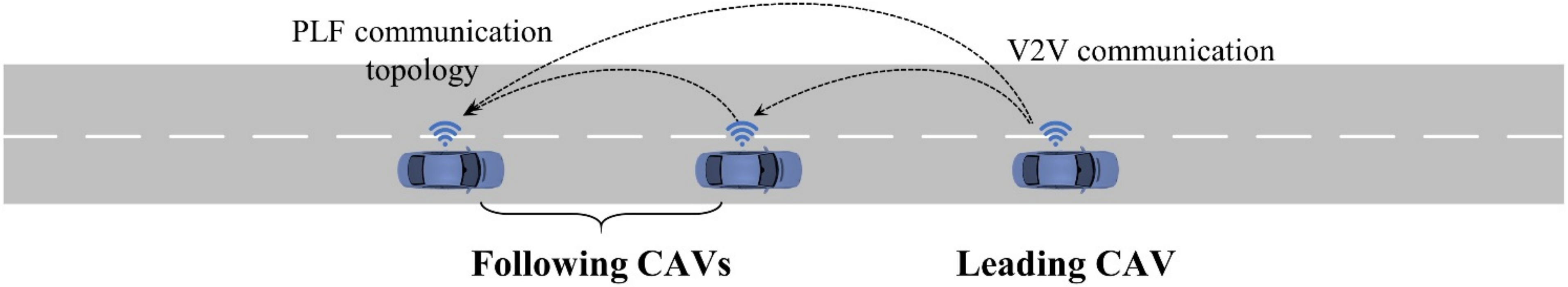
# Stochastic Driver Model Based Controller for Human-Lead Vehicle Platooning

Shuhan Wang, Jia Hu, Yiming Zhang

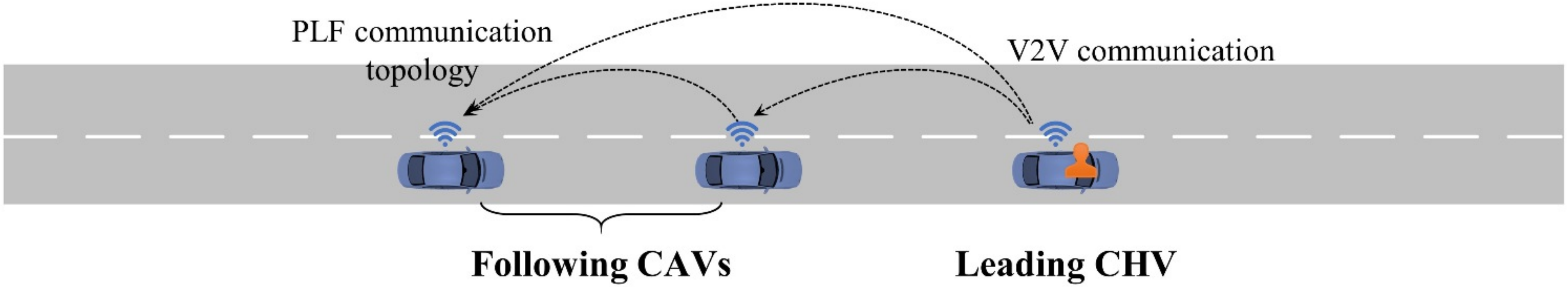
# Motivation

Cooperative Adaptive Cruise Control (CACC) forms Connected Automated Vehicles (CAVs) into a platoon. The following headway between vehicles can be much smaller.




❗There are no proven autonomous driving technologies capable of safely leading a CACC platoon on open roads.

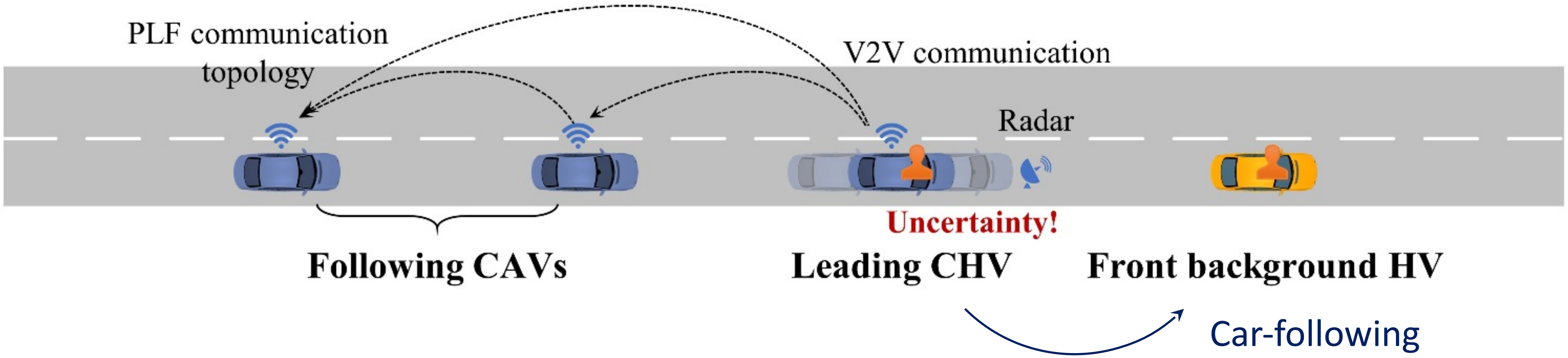
Human-lead CACC, with a connected human-driven vehicle (CHV) leading the way, combines human expertise with vehicle connectivity and autonomy.



# Motivation

The *uncertainty of human drivers* may destroy cruising comfort, safety, and string stability.

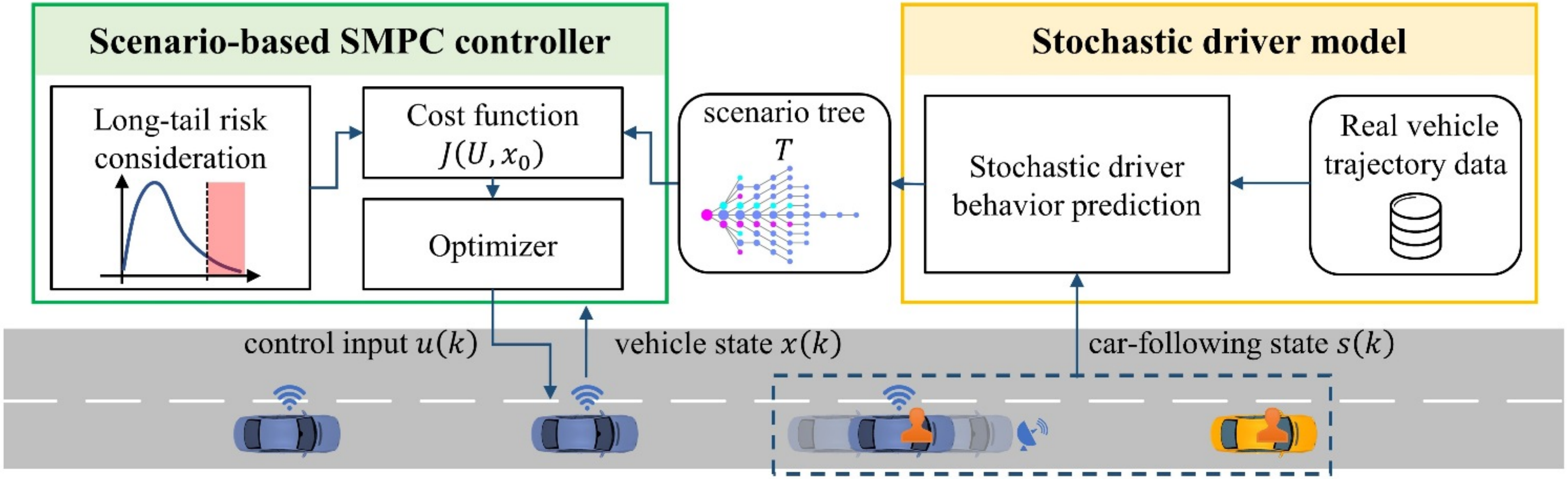
- Speed oscillation
- Hard brakes




This work aims to propose a *stochastic driver model based human-lead platoon controller* to cope with the uncertainty of the leading CHV.

# Problem formulation

*Control Structure*




- **Stochastic driver model**: This model predicts uncertain behaviors of the leading CHV using real-time traffic data. Predictions are presented as a scenario tree.
- **Scenario-based SMPC controller**: This controller calculates the optimal action of each CAV follower based on the scenario tree.

# Problem formulation

## *System Dynamics of The Following CAVs*

*System state*

$$=\left(h^* - h \;,\; - \;, h^* - h \;,\; - \;,\; \right)$$

*Control input*

$$=$$

*Dynamics*

$$( \; +1) = \quad ( \;) + \quad ( \;) + \quad ( \;)$$

$$= \; {}_{5*5} + \begin{bmatrix} 0 & -1 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & -1 \\ 0 & 0 & 0 & -1 & 0 \\ 0 & 0 & 0 & 0 & -1 \\ 0 & 0 & 0 & 0 & -\frac{1}{} \end{bmatrix} * \Delta \qquad = \begin{bmatrix} 0 \\ 0 \\ 0 \\ 0 \\ \frac{1}{} \end{bmatrix} * \Delta \qquad = \begin{bmatrix} 0 & 0 \\ 1 & 0 \\ 0 & 0 \\ 0 & 1 \\ 0 & 0 \end{bmatrix} * \Delta \qquad = \begin{bmatrix} \; \end{bmatrix}$$

The gap between the desired distance and the actual distance between the leading vehicle and the ego vehicle

The speed error between the leading vehicle and the ego vehicle

The gap between the desired distance and the actual distance between the preceding vehicle and the ego vehicle

The speed error between the preceding vehicle and the ego vehicle

The acceleration of the ego vehicle

: The first-order inertial delay parameter of the ego vehicle's system
: The acceleration of the leading CHV
: The acceleration of the preceding CAV

# Problem formulation

## *Stochastic Driver Model*

The future behavior of the leading CHV is modeled as a stochastic car-following model

$$( \quad +1)= \left[ \quad ( \quad ( \quad )) - \quad ( \quad ) \right] + {}_{0}\sqrt{\quad ( \quad )} \Delta \quad ( \quad )$$

Deterministic function

In the deterministic part, the optimal velocity model (OVM) is adopted:

$$( \quad ( \quad )) = \frac{\ _{0}}{2} \left[ \tanh\left( \frac{( \quad )}{\quad} - \quad \right) + \tanh \quad \right]$$

Stochastic source

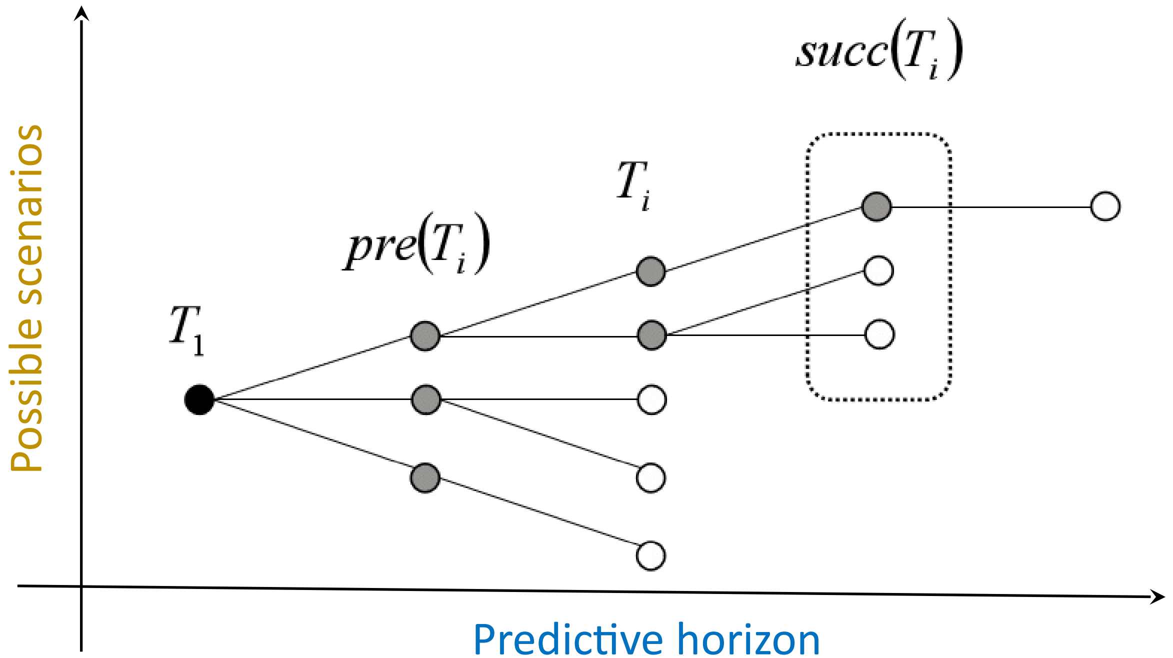
In the stochastic part, follows a Wiener process, which is adopted to describe the random acceleration deviations.

# Problem formulation

## *Scenario Tree*

The scenario tree is formulated by a maximum likelihood approach.

Starting from the root node, the scenario tree is expanded in the most likely direction.



# Problem formulation

*__Controller Design__*

Cost function of the scenario-based stochastic MPC problem

When a safety standard is broken, the CVaR cost is triggered with a very large weight .

$$( \ ,\ _0) = \sum_{\in \{} ¿ ( - ) ( - ) + \sum_{\in ¿} + \sum_{\in \{} ¿ \ max( (3) - ,0)$$

State error cost

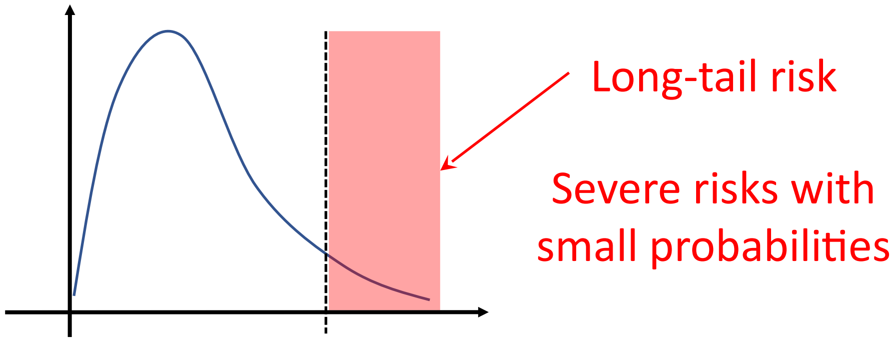
Control cost

Quadratic

Conditional Value-at-Risk (CVaR) cost

*s.t.* $= \quad () + \quad () + \quad (), \in \{ ¿$

$\le \quad \le \quad , \quad = 0, 1, \cdots, \quad -1$



# Problem formulation

*Solution*

**Not quadratic**

$$( \;,\; _0) = \sum_{\in \{} ¿ \;( \;-\; )\;( \;-\; ) + \sum_{\in ¿} \quad + \sum_{\in \{} ¿ \; max\left( \; (3) - \;, 0\right)$$

By introducing the decision variable , the cost function is transformed into a *convex* optimization problem

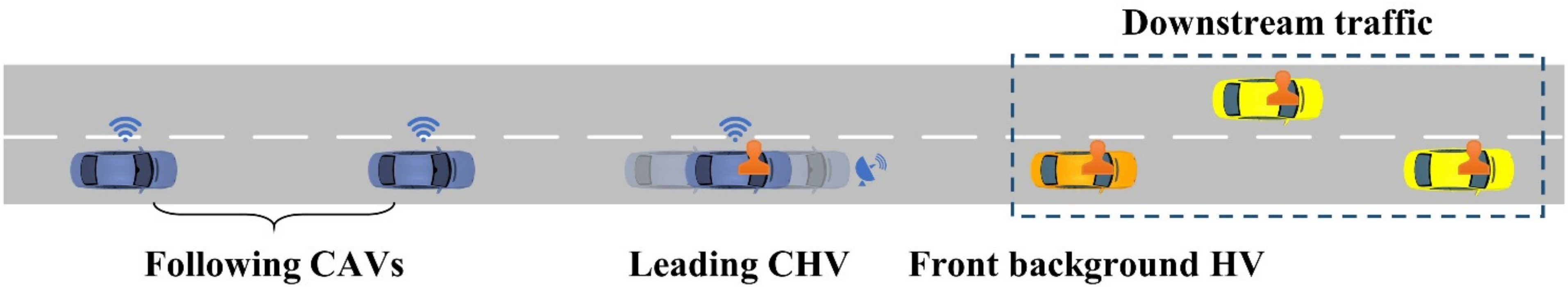
$$( \;,\; _0) = \sum_{\in \{} ¿ \;( \;-\; )\;( \;-\; ) + \sum_{\in ¿} \quad + \sum_{\in \{} ¿ \; ( \; )$$

$$s.t. \quad ( \; ) \geq \; (3) -$$

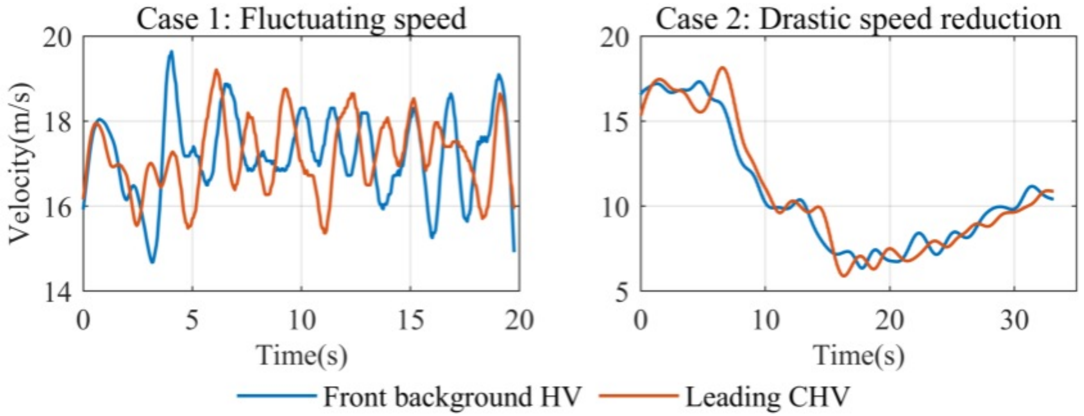
$$( \; ) \geq 0$$

# Evaluation

*Test Scenarios*




Real highway data




Case 1: Downstream traffic with fluctuating speed
Case 2: Downstream traffic with drastic speed reduction

*http://seutraffic.com/#/*

# Evaluation

*Experimental Design*

**Baseline HL-CACC controller**: The baseline controller is a conventional MPC-based controller. This controller assumes that disturbances, the acceleration of the leading CHV, remain constant in the predictive horizon.

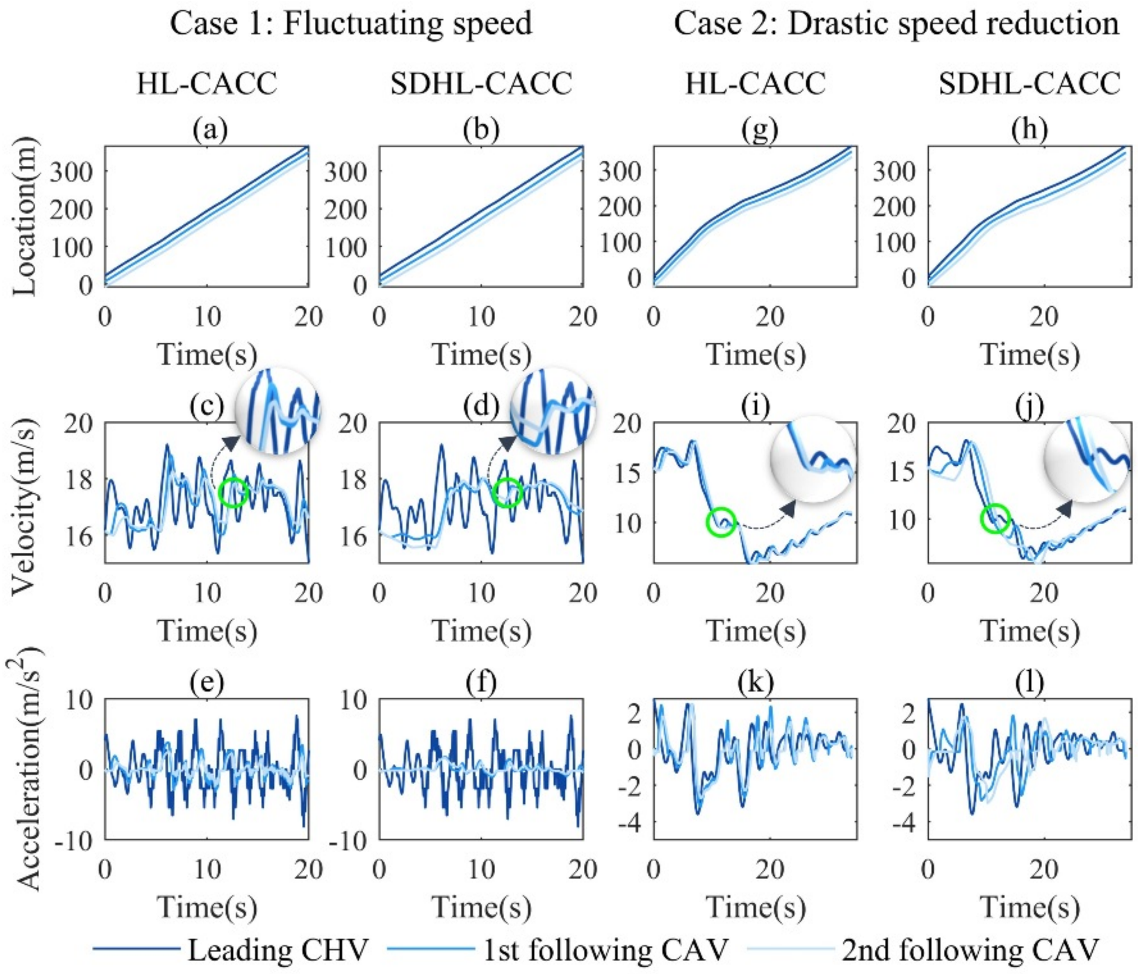
**Measurement of Effectiveness (MOE)**:

- Function validation: The function of the controller is validated by *vehicle trajectories*, including location, velocity, and acceleration.
- Comfort: Comfort is mostly evaluated by traffic oscillations, quantified by *the acceleration range of the following CAVs*
- Safety: Actual risk is measured by *following distance* between adjacent vehicles.
- String stability: String stability is evaluated by *the reduction of acceleration range* along the platoon.

*Zhang et al. (2022)*

# Evaluation

***Function validation***

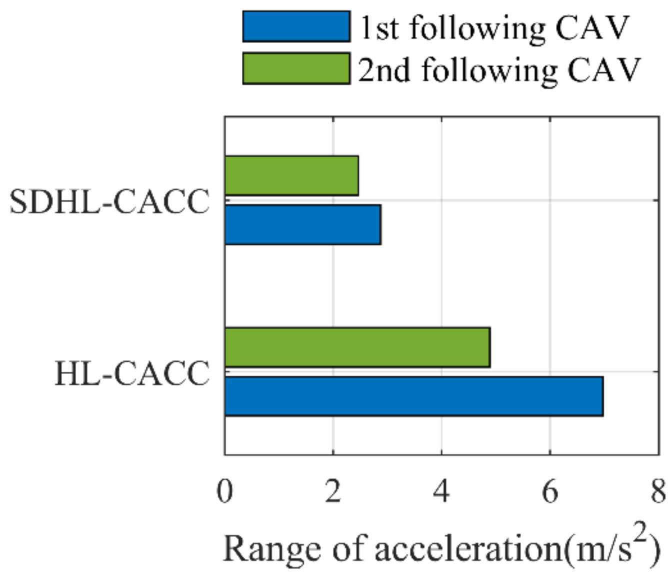


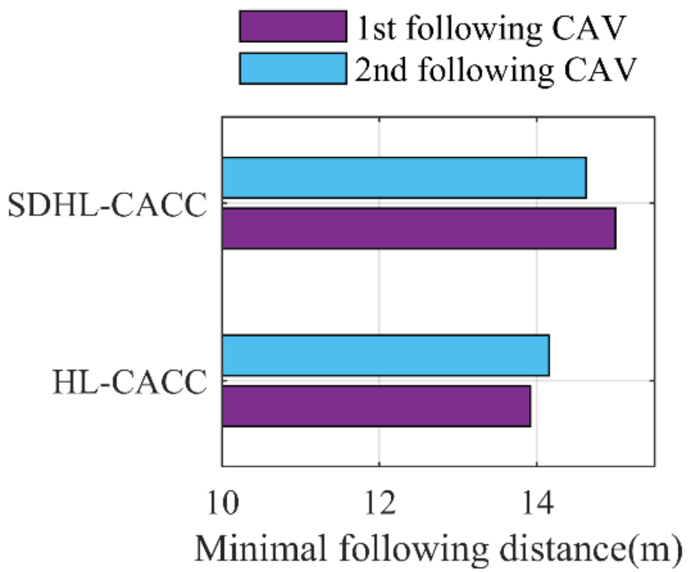

The proposed SDHL-CACC controller:

- Enable CAVs to maintain a consistent distance when following a leading CHV;
- Can relieve traffic fluctuations;
- Can anticipate the leading CHV's decelerating motions and maneuver the followers to proactively slow down.

# Evaluation

*Comfort/Safety Quantification*



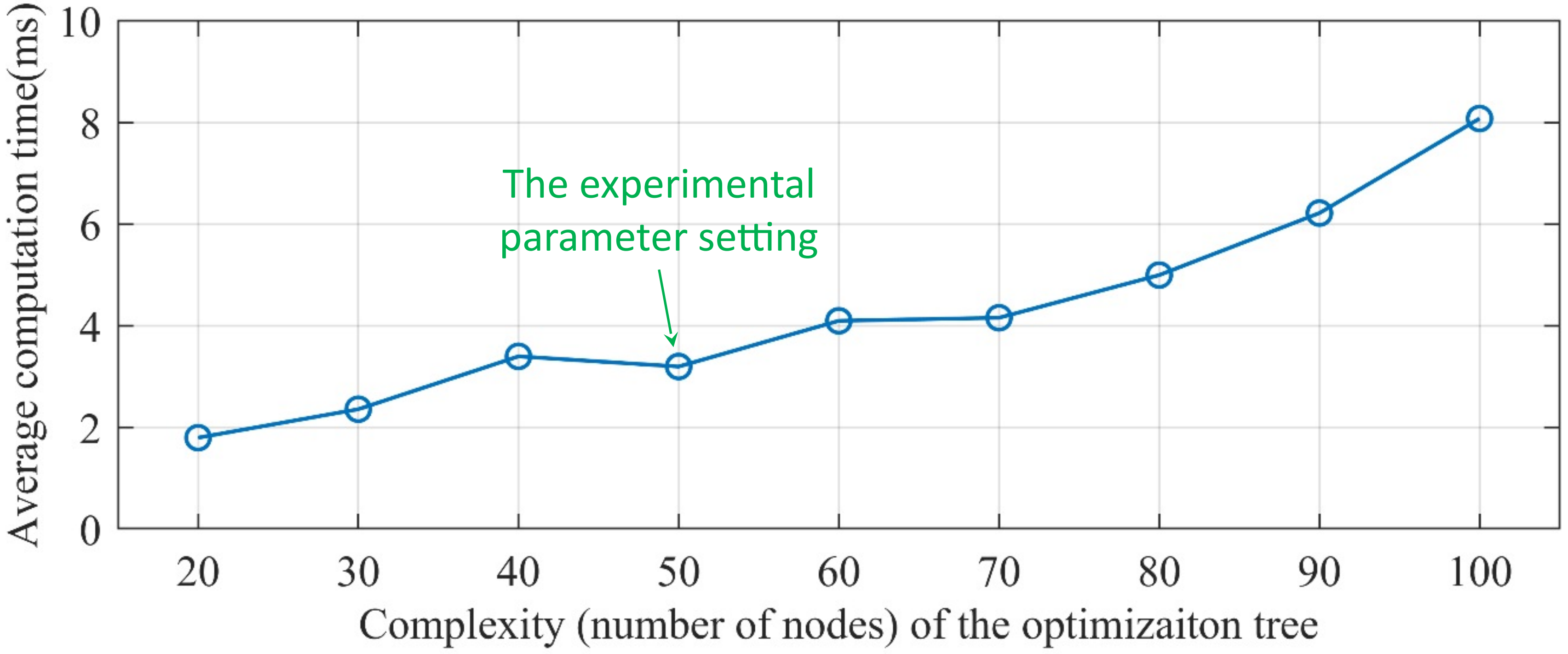




The proposed SD-HLCACC controller can:

- improve comfort by reducing the oscillation range.
- enhance safety by reducing the minimal distance between vehicles.
- guarantee string stability.

# Evaluation

## *Computation Efficiency Validation*




The computation time of the proposed SDHL-CACC controller is approximately 3.2 milliseconds when running on a laptop equipped with an Intel i5-13500H CPU.

The real-time computational efficiency of the proposed controller could be guaranteed.

# Conclusion

The proposed SDHL-CACC controller has the following features:

- Enhanced perceived safety in oscillating traffic;
- Guaranteed safety against hard brakes;
- Computational efficiency for real-time implementation.

The proposed SDHL-CACC controller makes the following methodological contributions:

- **Look before the leap**: All possible actions of the leading CHV are considered;
- **Contingency plan for long-tail risks**: Severe risks with small probability are prioritized;
- **Convex formulation**: A standard quadratic programming problem with linear constraints.

Challenges/Next Steps

- Consider the leading CHV’s lateral driving behaviors.
- How to address driving behavior diversity? An online optimized prediction model could be explored.

# Thanks for Listening