Cooperative Ramp Merging for Mixed Traffic with Connected Automated Vehicles and Human-Operated Vehicles

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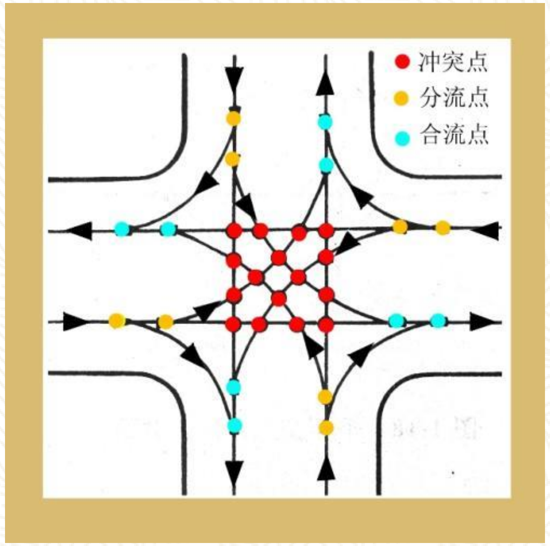
1. Cooperative Ramp Merging
2. Hybrid Model Predictive Control and Real Time Computations
3. Microscopic Right-of-Way Trading Mechanism
4. Modeling Car-Following Heterogeneities
5. Short-term Trajectory Prediction
6. Trajectory Planning and Tracking

Background



Traffic conflict is the most fundamental problem in transportation science and engineering

At least in theory, it is possible to mitigate or eliminate traffic conflicts, in the mixed traffic environment with connected automated vehicles (CAVs) and human-operated vehicles (HVs)

The proposed mechanism is called Cooperative Decision-Making for Mixed Traffic (i.e., CDMMT)

Background

China, EU and US will start to make highly automated cars around 2020-2025

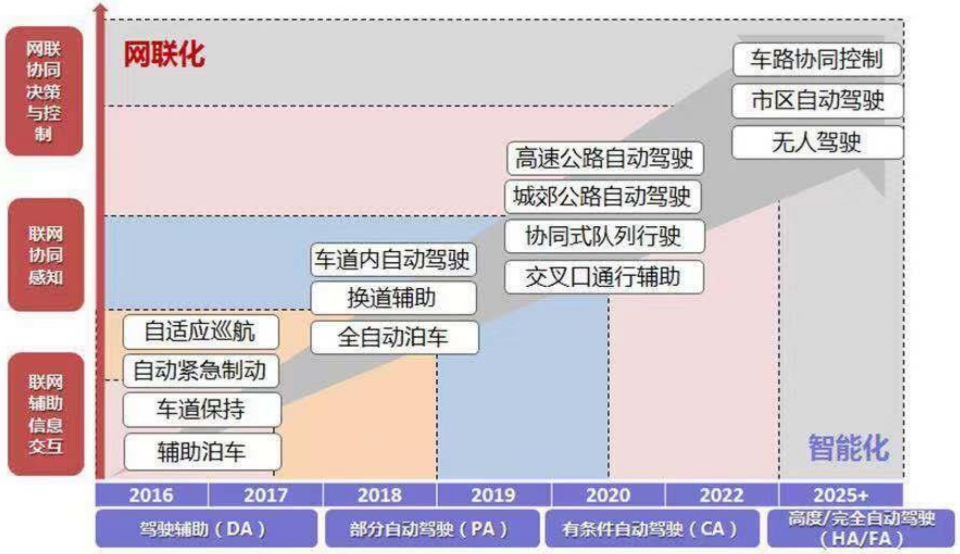
DA/PA → CA/HA → FA

Information exchange → sensing and fusion → **cooperative decision-making and control**

Baidu 百度 pony.ai 蔚来 NIO

WAYMO Ford

TESLA



Source：Chinese National Standard for CAV Industry

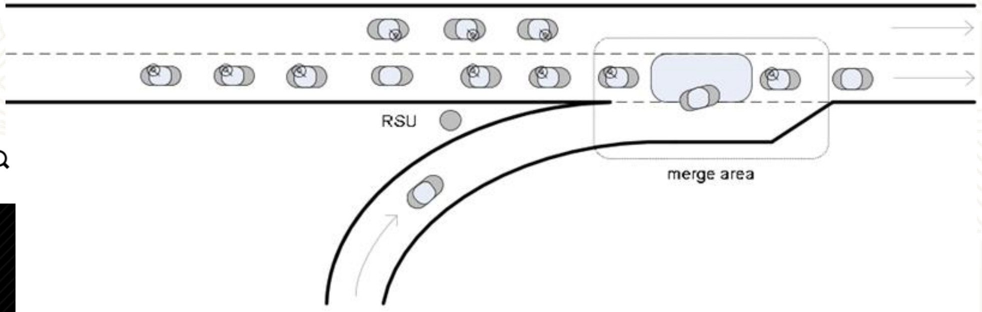
Key Challenges

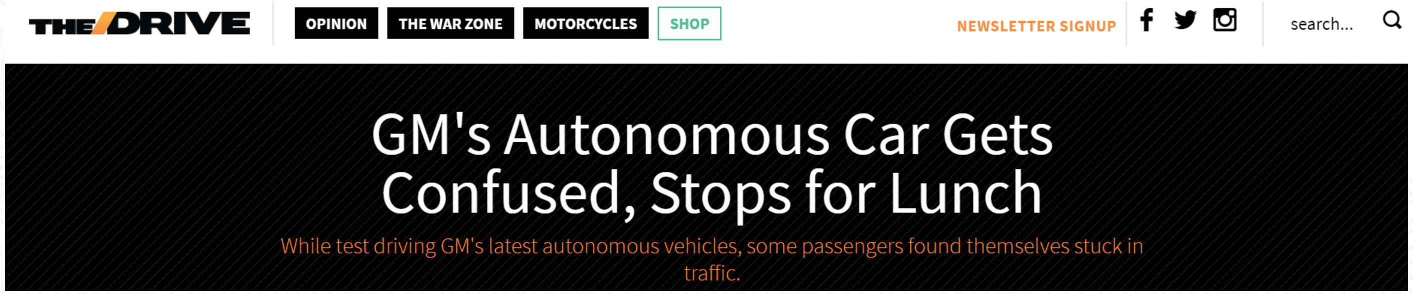
Technical difficulties (hardware, sensing, communication)

Mixed traffic (human are myopic, stochastic, and non-cooperative)

System-efficient (cooperation is not necessarily system-improving)

Ethical dilemma (puppy vs. a group of people)

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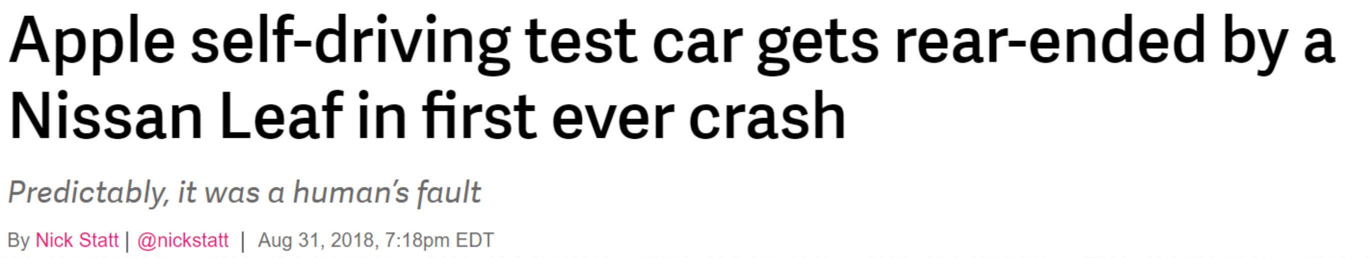
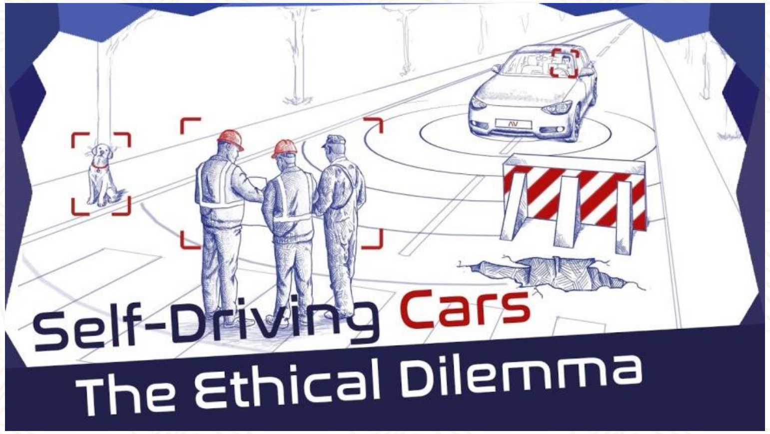
GM's Autonomous Car Gets Confused, Stops for Lunch

While test driving GM's latest autonomous vehicles, some passengers found themselves stuck in traffic.


Apple self-driving test car gets rear-ended by a Nissan Leaf in first ever crash

Predictably, it was a human's fault

By Nick Statt | @nickstatt | Aug 31, 2018, 7:18pm EDT



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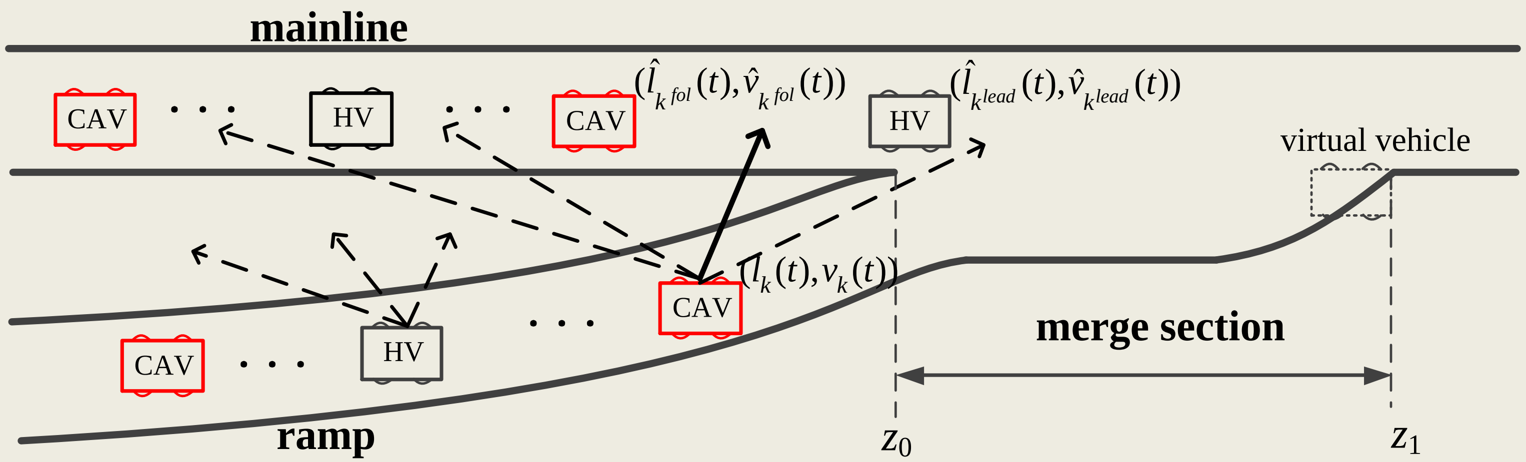
CDMMT: A Bi-level Programming Framework



bi-level optimization

upper-level: merge sequencing

lower-level: trajectory design

Sun, Z., Huang, T., & Zhang, P. (2020). Cooperative decision-making for mixed traffic: A ramp merging example. *Transportation research part C: emerging technologies*, *120*, 102764.

Upper-level: merge sequencing (filling *n* ramp vehicles into *m+1* gaps)

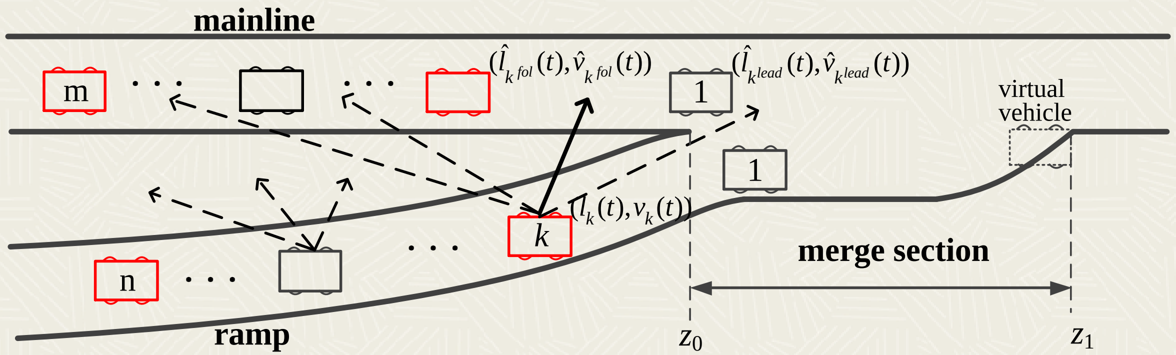
$$f_k(s_k) = \min_{x_k \in X_k, \hat{q}_T^k = \{q_1^k, q_2^k, \ldots, q_T^k\}} \{D_k(s_k, x_k) + f_{k-1}(s_{k-1})\}, k = 1,2,\ldots,n$$

$$s.t.\ f_0(s_0) = 0$$

$$s_1 = m + 1$$

$$s_{k+1} = s_k - x_k + 1, k = 1,2,\ldots,n-1$$

$$D_k(s_k, x_k) = g_{t_f}^k\left(p_{t_f}^k\right) + \tilde{g}^{k-1}$$



$f_k(s_k)$: The minimum system cost from the initial stage to stage *k*

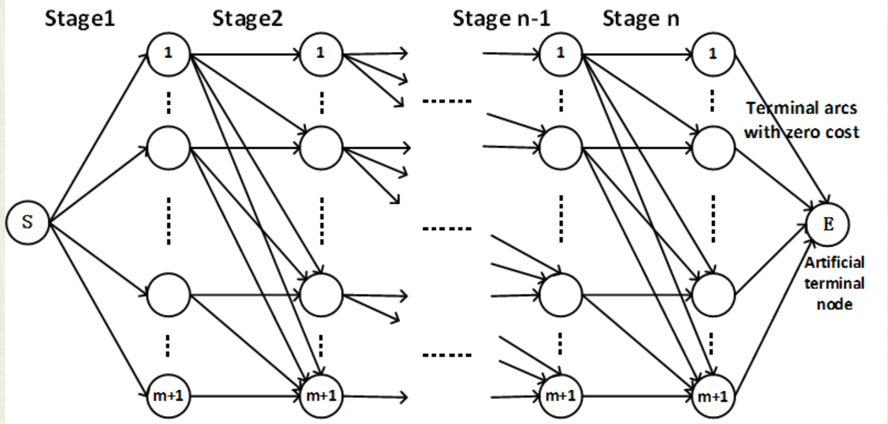
s_k: The number of available mainline gaps for ramp vehicle *k*

x_k: The gap taken by ramp vehicle *k*

D_k: The cost of the merge maneuver pertaining to ramp vehicle *k*

$\boldsymbol{g_{t_f}^k}$: The objective function of the lower-level trajectory design problem pertaining to ramp vehicle *k*

$\tilde{g}^{k-1}$: The cost for mainline vehicles that are not directory involved in any merging maneuver



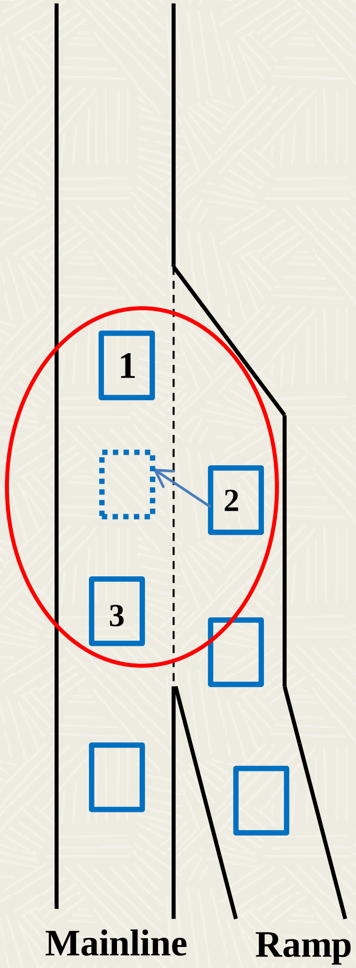
Cooperative Ramp Merging

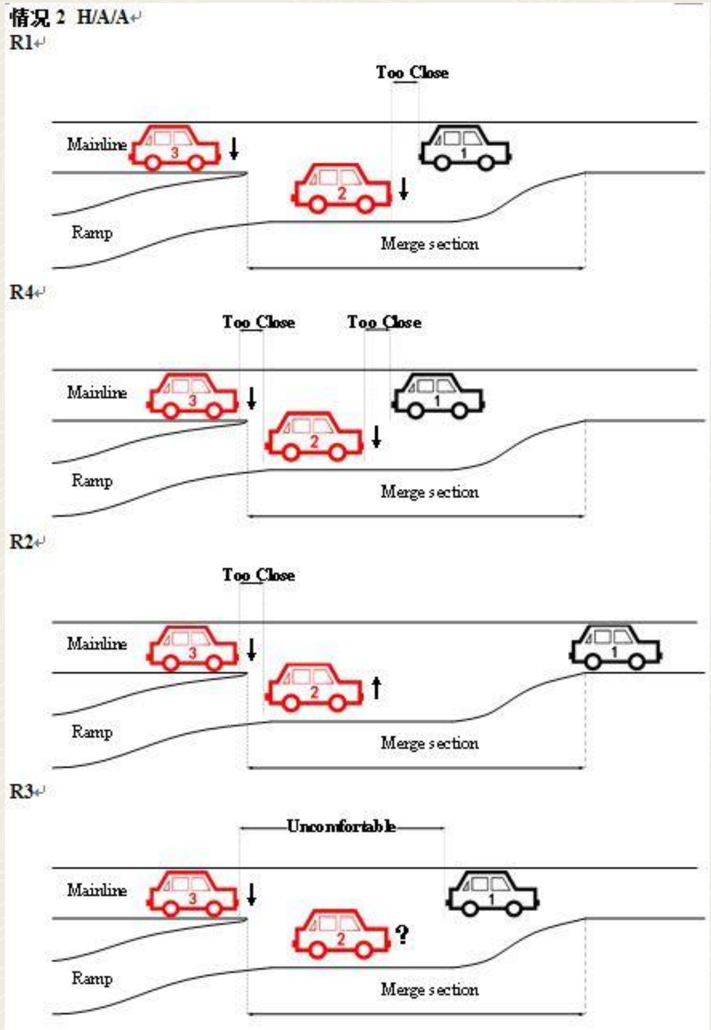
Case-based control strategies

Conditions	Cooperative Merging Control Strategy
C1: HHA	R2/R3: vehicle 3 slower
C2: HAA	R1/R4: vehicle 2 slower, vehicle 3 slower; R2: vehicle 2 faster, vehicle 3 slower; R3: vehicle 2 undetermined, vehicle 3 slower
C3: AHA	R1: Vehicle 1 faster; R2: Vehicle 3 slower; R3/R4: Vehicle 1 faster & Vehicle 3 slower
C4: AAA	R1: Vehicle 1 faster, Vehicle 2 slower, Vehicle 3 slower; R2: Vehicle 2 faster, Vehicle 3 slower, Vehicle 1 faster; R3/R4: Vehicle 1 faster, Vehicle 2 undetermined, Vehicle 3 slower
C5: HAH	R1: Vehicle 2 slower; R2: Vehicle 2 faster R3: Vehicle 2 undetermined;
C6: AHH	R1/R3: Vehicle 1 faster
C7: AAH	R1: Vehicle 1 faster, Vehicle 2 slower; R2: Vehicle 1 faster, Vehicle 2 faster; R3: Vehicle 1 faster, Vehicle 2 slower
C8: AHN	R1/R3: Vehicle 1 faster
C9: AAN	R1/R3: Vehicle 1 faster, Vehicle 2 slower
C10: HAN	R1/R3: Vehicle 2 slower
C11: NHA	R2/R3: Vehicle 3 slower
C12: NAA	R2/R3: Vehicle 2 faster, Vehicle 3 slower
C13: NAH	R2/R3: Vehicle 2 faster

"N" stands for "Null" it is used as a placeholder. "H" stands for a human-operated vehicle; "A" stands for a CAV

R 1: vehicle 2 is "too close" to vehicle 1
R 2: vehicle 2 is "too close" to vehicle 3
R 3: vehicle 2 is neither "too close" to vehicle 1 nor vehicle 3, but the it is uncomfortable to merge
R 4: vehicle 2 is "too close" to vehicle 1 and vehicle 3





Cooperative Ramp Merging

Lower-level: trajectory design (multi-object optimal control)

$$g_t^k(p_t^k) = \begin{cases} \min\limits_{q_t^k \in Q_t^k} \{d_t^k(p_t^k, q_t^k) + g_{t-\tau}^k(p_{t-\tau}^k)\}, & q_t^k \neq \emptyset \\ \infty, & q_t^k = \emptyset \end{cases}, \forall t = t_0^k + \tau, t_0^k + 2\tau, \dots, t_f^k, \; k = 1,2,\dots,n$$

$$g_{t_0}^k(p_{t_0}^k) = \sum_{i \in K}(v_i(t_0^k) - v^e)^2, \forall k = 1,2,\dots,n$$

$$p_{t_0}^k = \{v_i(t_0^k), l_i(t_0^k) | i \in K\}, \forall k = 1,2,\dots,n$$

State transition:

$$l_i(t+\tau) = l_i(t) - v_i(t)\tau - 0.5u_i(t)\tau^2,$$
$$\forall i \in K, t = t_0^k, t_0^k + \tau \dots, t_f^k - \tau, k = 1,2,\cdots,n$$

$$v_i(t+\tau) = v_i(t) + u_i(t)\tau,$$
$$\forall i \in K, t = t_0^k, \dots, t_f^k - \tau, k = 1,2,\cdots,n$$

Final-state constraint:

$$U_k(t_f^k) \geq 0, \forall k = 1,2,\dots,n$$

Lateral dynamics

$t_0^k, \dots, t_f^k$: The time stamps of a trajectory design period
p_t^k: The states of all vehicles in set K at time t
q_t^k: The set of decisions of vehicles in set K at time t
v^e: Desired speed
$U_k(t_f^k)$: Merging utility

Cooperative Ramp Merging

Lower-level: trajectory design (multi-object optimal control)

Vehicle k

Longitudinal dynamics

Non-cooperative:

$u_k(t+1) = u_{mic}(S_k(t), v_k(t), v_l(t))$

Faster:

$v_k(t) + u_k(t)\tau \geq v_{mic}(S_k(t), v_k(t), v_l(t))$
$v_k(t) + u_k(t)\tau \leq v^e$

Slower:

$v_k(t) + u_k(t)\tau \leq v_{mic}(S_k(t), v_k(t), v_l(t))$
$v_k(t) + u_k(t)\tau \geq 0$

Undetermined:

$v_k(t) + u_k(t)\tau \leq v^e$
$v_k(t) + u_k(t)\tau \geq 0$

Vehicle $\hat{k}^{lead}$

Non-cooperative:

$u_{\hat{k}^{lead}}(t+1) = u_{mic}\left(S_{\hat{k}^{lead}}(t), v_{\hat{k}^{lead}}(t), v_l(t)\right)$

Faster:

$v_{\hat{k}^{lead}}(t) + u_{\hat{k}^{lead}}(t)\tau \geq v_{mic}\left(S_{\hat{k}^{lead}}(t), v_{\hat{k}^{lead}}(t), v_l(t)\right)$
$v_{\hat{k}^{lead}}(t) + u_{\hat{k}^{lead}}(t)\tau \leq v^e$

Vehicle $\hat{k}^{fol}$

Non-cooperative:

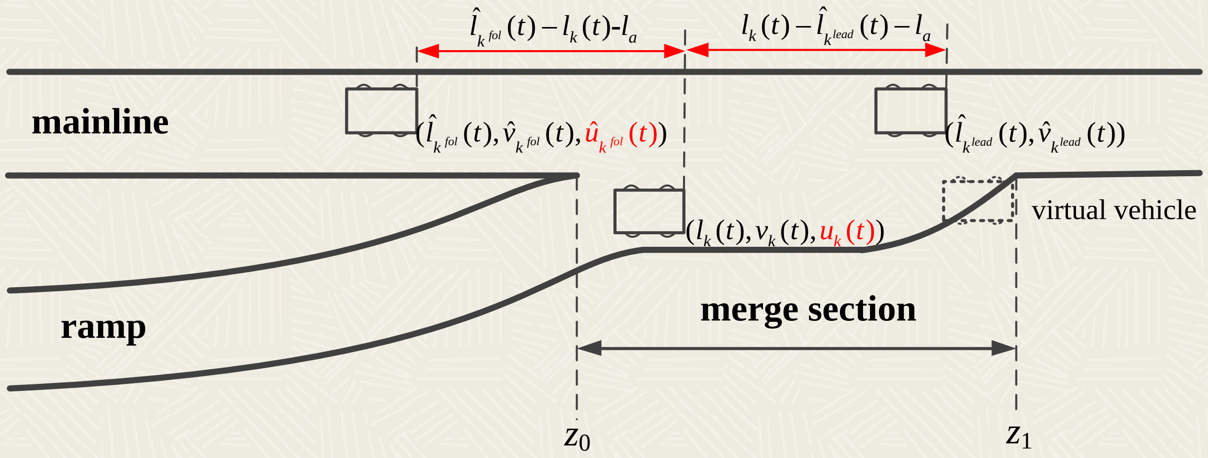
$u_{\hat{k}^{fol}}(t+1) = u_{mic}\left(S_{\hat{k}^{fol}}(t), v_{\hat{k}^{fol}}(t), v_l(t)\right)$

Slower:

$v_{\hat{k}^{fol}}(t) + u_{\hat{k}^{fol}}(t)\tau \geq 0$
$v_{\hat{k}^{fol}}(t) + u_{\hat{k}^{fol}}(t)\tau \leq v_{mic}\left(S_{\hat{k}^{fol}}(t), v_{\hat{k}^{fol}}(t), v_l(t)\right)$

Cooperative Ramp Merging

Lateral dynamics



$$U_k(t)=\begin{cases}-1, & |\hat{u}_k(t)|>b_{safe}\\ -1, & |\hat{u}_{k^{fol}}(t)|>b_{safe}\\ -1, & l_k(t)-\hat{l}_{k^{lead}}(t)-l_a<L_0^A,\forall\, k\epsilon\Phi_A\\ -1, & l_k(t)-\hat{l}_{k^{lead}}(t)-l_a<L_0^H,\forall\, k\epsilon\Phi_H\\ -1, & \hat{l}_{k^{fol}}(t)-l_k(t)-l_a<L_0^A,\forall\, \hat{k}^{fol}\epsilon\Phi_A\\ -1, & \hat{l}_{k^{fol}}(t)-l_k(t)-l_a<L_0^H,\forall\, \hat{k}^{fol}\epsilon\Phi_H\\ 1-\eta_1|\hat{u}_k(t)|-\eta_2\left|\hat{u}_{k^{fol}}(t)\right|, & o.w.\end{cases}$$

Longitudinal dynamics

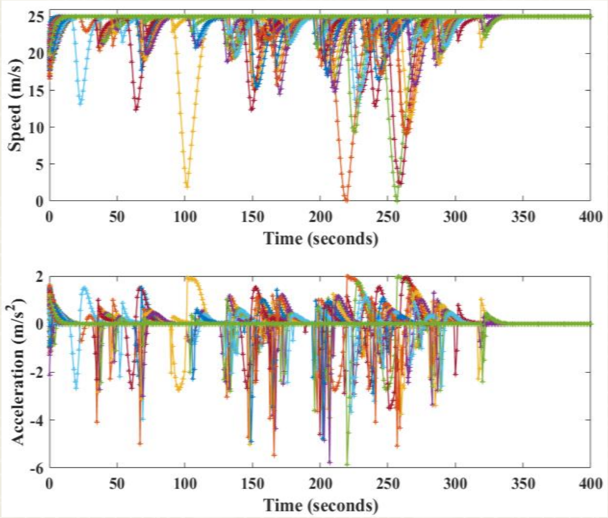
- Newell’ s simplified car following model
- Gipps
- IDM/EIDM
- ……

$$u_{mic}(S_k(t),v_k(t),v_l(t))$$

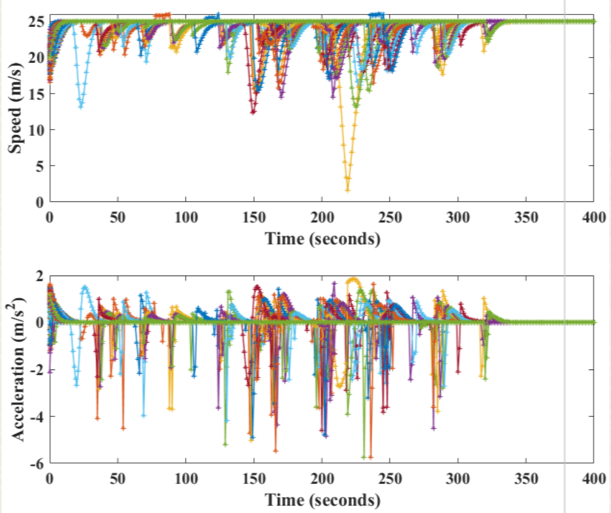
b_{safe}: The maximum allowable deceleration rate
l_a: Equivalent vehicle length
L_0^A: Minimum gap for CAVs
L_0^H: Minimum gap for HVs
η_1: Safety parameter
η_2: Politeness parameter

Results – q1:1000veh/h q2:1000veh/h 50% CAV

Speed profiles and acceleration profiles

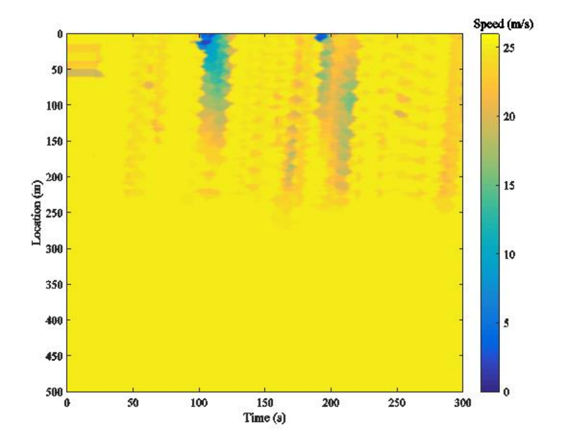


non-cooperative

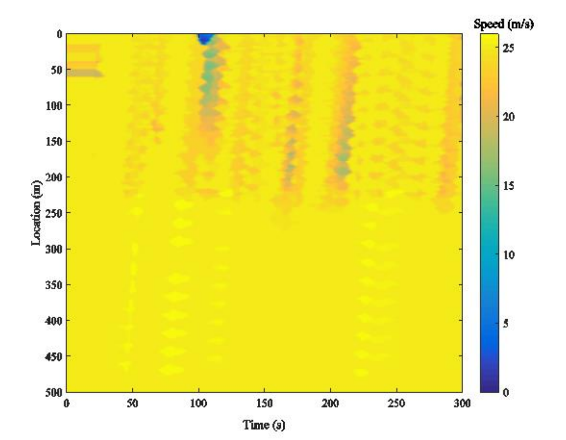


cooperative

Speed contours

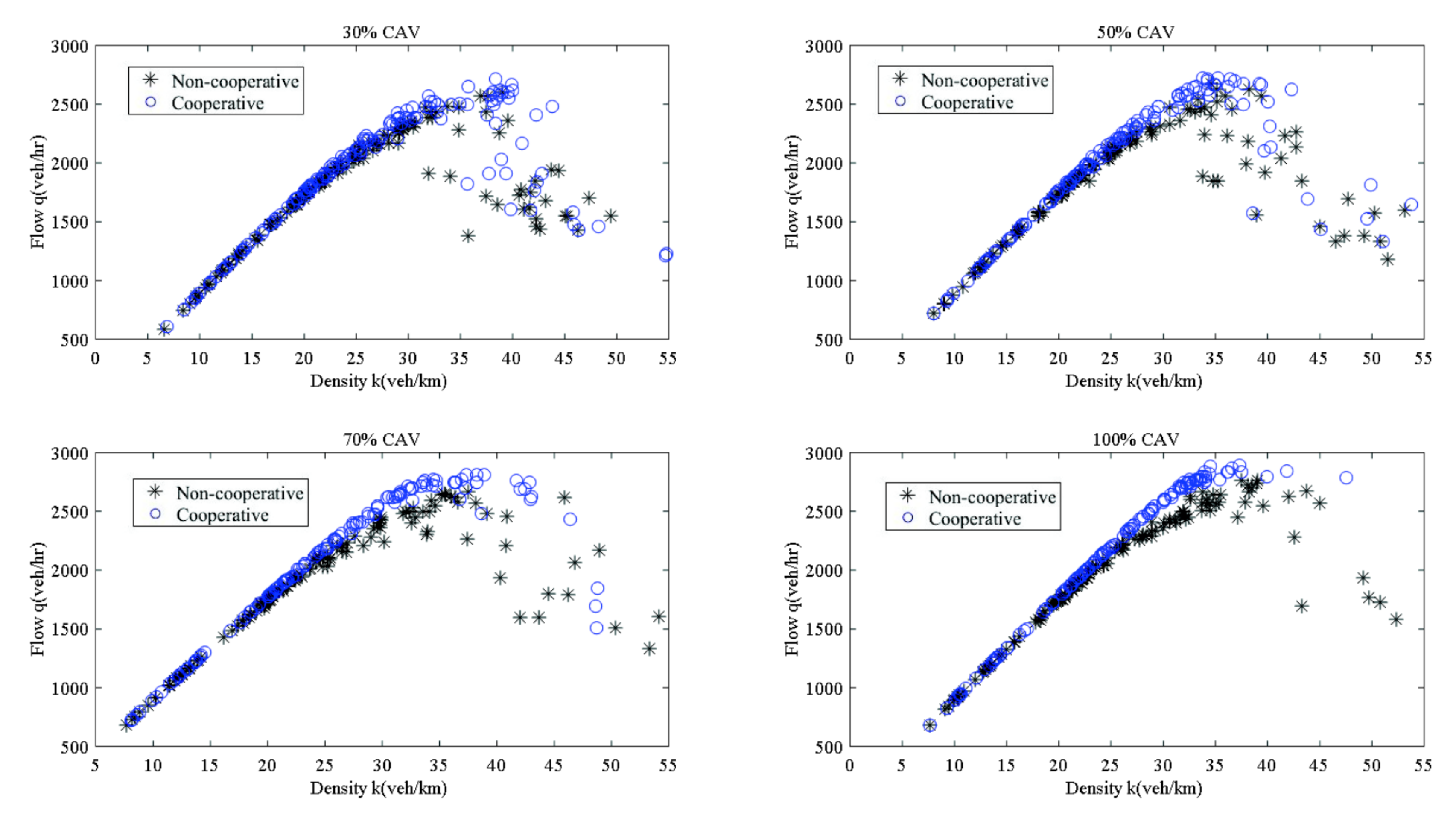


non-cooperative



cooperative

Results – Flow-Density Diagrams



- **Capacity increases with the increase of CAV penetration (up to about 20%)**
- **CDMMT can further improve the capacity by about 10% - 15% in the case of high penetration**

Sun, Z., Huang, T., & Zhang, P. (2020). Cooperative decision-making for mixed traffic: A ramp merging example. *Transportation research part C: emerging technologies*, *120*, 102764.

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Hybrid Model Predictive Control and Real Time Computations

System Stochasticity is not considered in the deterministic-CDMMT mechanism

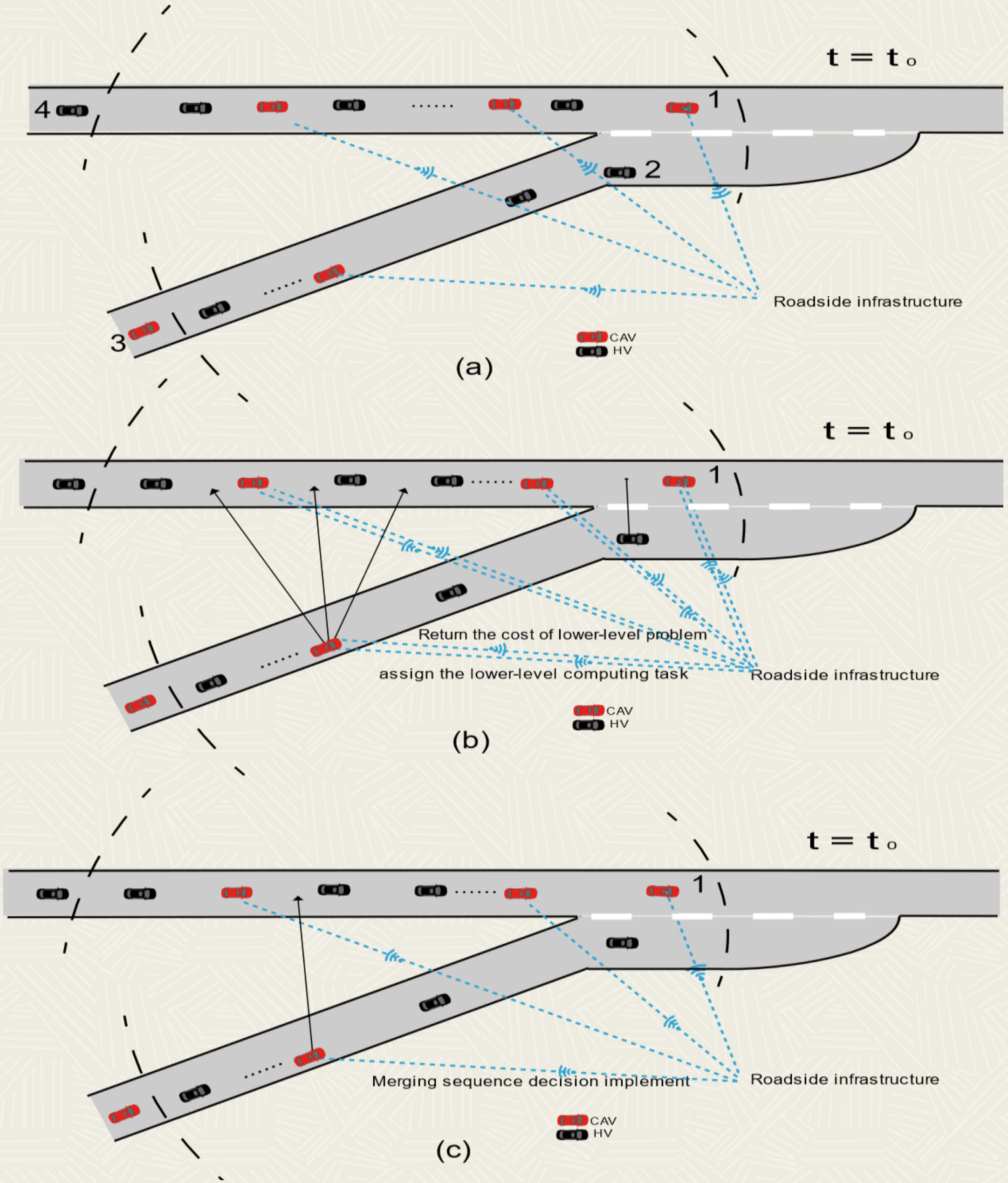
The centralized control improves system-efficiency, however, computational efficiency becomes a critical issue

Solution:

- **Closed-loop control (model predictive control)**
- **Hybrid Centralized-Decentralized system**
- **Use computational-efficient solution approach**

Gao, Z., Li, Z., Huang, T., & Sun, Z. (2020). Cooperative Ramp Merging In Mixed Traffic Closed-loop Optimal Control and Real Time Computing. *Presented at 100th Annual Meeting of the Transportation Research Board, Washington, D.C., 2021.*

Hybrid Model Predictive Control and Real Time Computations



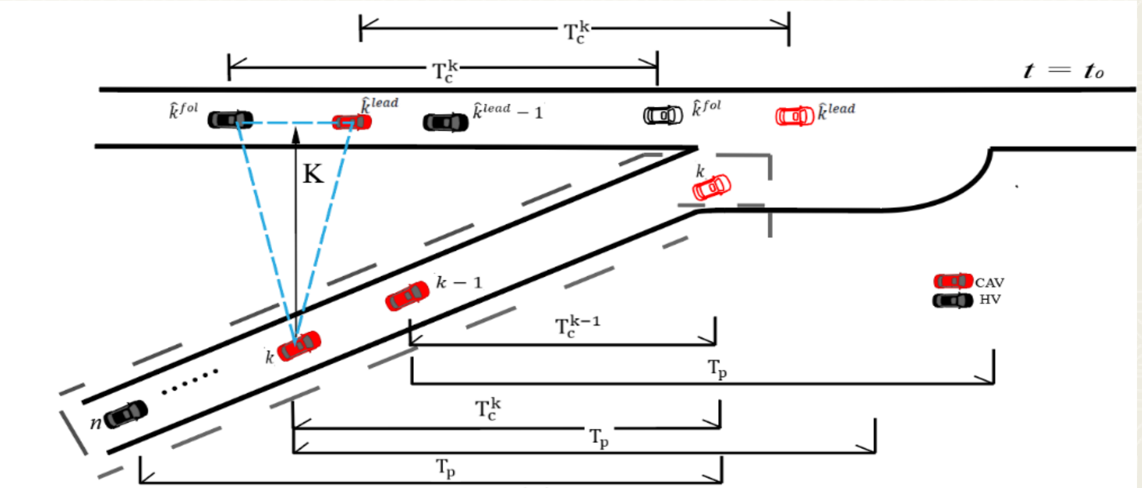
Step 1. At time *t*, the communication between the RSU and the CAVs in the communication zone is established. Then the states of vehicles will be adopted and shared by RSU (centralized controller).

Step 2. As shown in the Figure(b), after the establishment of communication, **the centralized controller will assign the specific lower-level problem computing tasks to OBUs** through the iteration of upper-level problem. All the OBU controllers will receive the assignment of the lower-level problem and the information of neighboured vehicles.

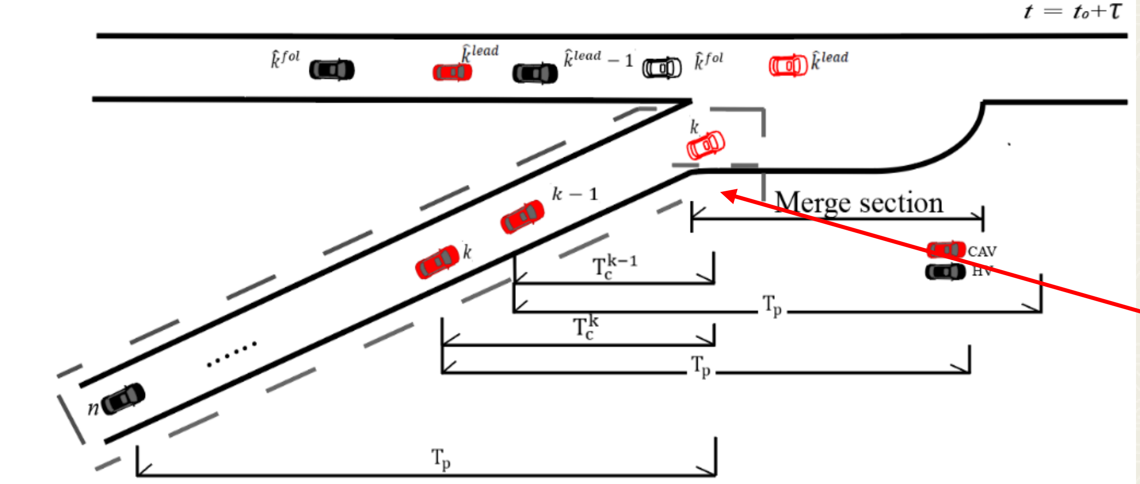
Step 3. OBUs solve the lower-level problem and return the optimal trajectory consisting of speed and location to the centralized controller.

Step 4. RSU solves the upper-level sequencing problem according to the feedback in Step3 and transfers the optimized merging sequences to CAVs. Just as shown in Fig.(c), ramp CAV determines the specific merging gap and implements the lower-level longitudinal control after receiving the order of RSU. Then go to Step 1 ($t = t+\tau$).

Hybrid Model Predictive Control and Real Time Computations



(a)



(b)

T_c^k: Control horizon

T_p: The predictive horizon

$\exists T_c^k, l_k(t_0 + T_c^k + \tau | t_0) \geq l_e \wedge l_k(t_0 + T_c^k | t_0) \leq l_e). l_k(t_0 + T_c^k | t_0)$

$l_k(t_0 + T_c^k | t_0)$ denotes the location of vehicle k;

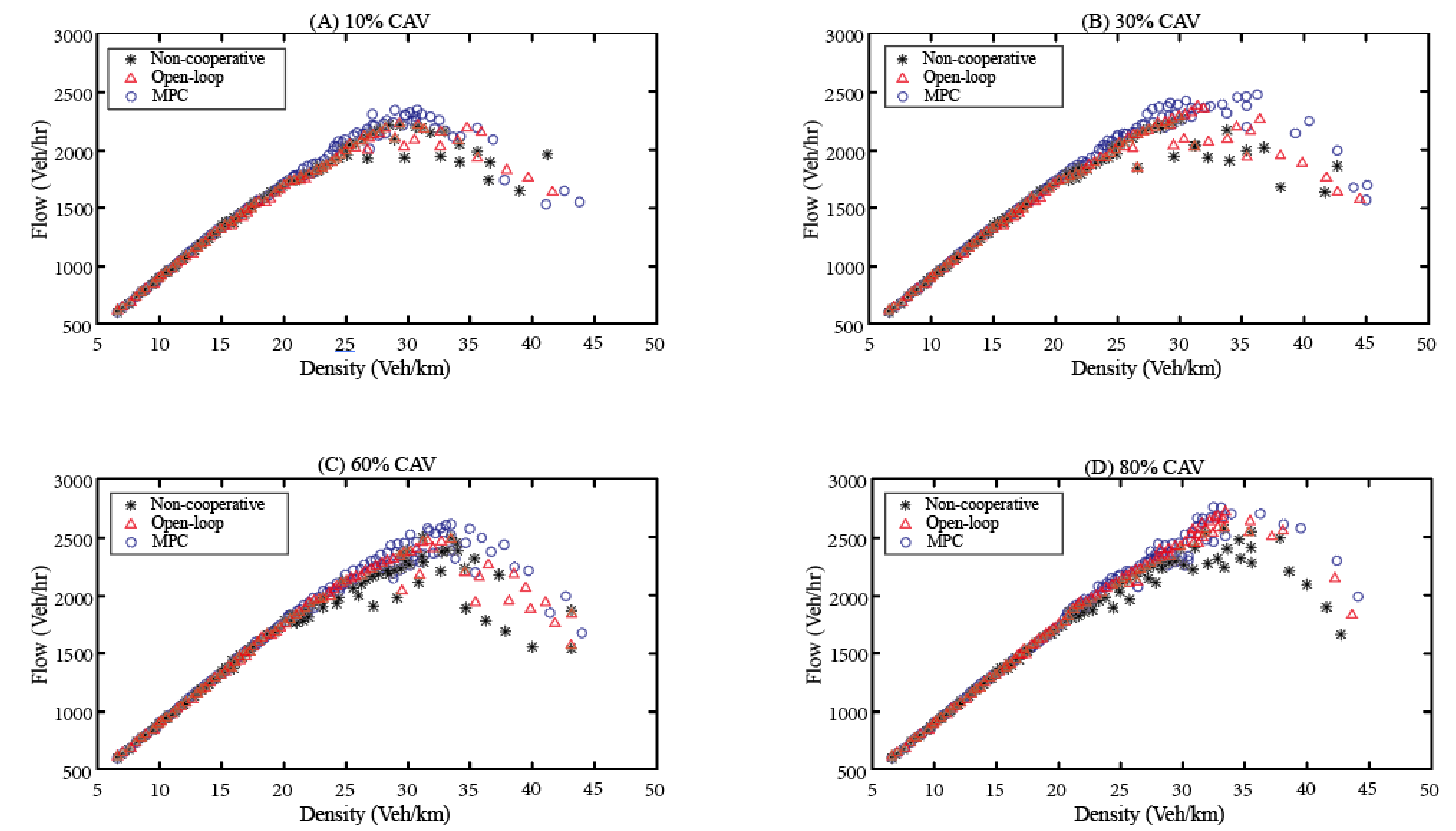
$(t_0 + T_c^k | t_0)$ represents the predictive time $t_0 + T_c^k$ at real time t_0;

$$T_c^{\widehat{k}^{fol}} = T_c^{\widehat{k}^{lead}} = T_c^k$$

$$T_p = T_c^n$$

l_e: the end of ramp control zone

Results – Flow-Density Diagrams



Results – Average Computational Time (Seconds)

Vehicle per group: 16; Traffic flow: 1500:1500							
Pene	Average Lower-level optimization cases per timestamp	Calculation time of Centralized system (Seconds)			Calculation time of hybrid system (Seconds)		
		DMC	DP	Bang-Bang	DMC	DP	Bang-Bang
20%	1.03	0.056	0.31	0.0378	0.042	0.256	0.0374
40%	1.57	0.094	0.71	0.0588			
60%	1.61	0.095	0.82	0.0846			
80%	1.56	0.10	0.87	0.1078			
100%	1.76	0.11	1.43	0.1135			
Vehicle per group: 50; Traffic flow: 1500:1500							
Pene	Average Lower-level optimization cases per timestamp	Calculation time of Centralized system (Seconds)			Calculation time of hybrid system (Seconds)		
		DMC	DP	Bang-Bang	DMC	DP	Bang-Bang
20%	1.89	0.11	1.27	0.06	0.041	0.254	0.0379
40%	2.73	0.16	2.12	0.11			
60%	3.41	0.20	3.01	0.16			
80%	3.67	0.24	3.48	0.23			
100%	3.69	0.24	3.62	0.24			

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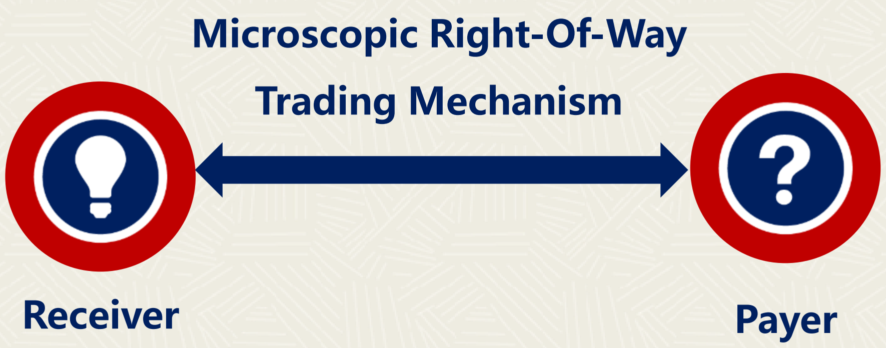
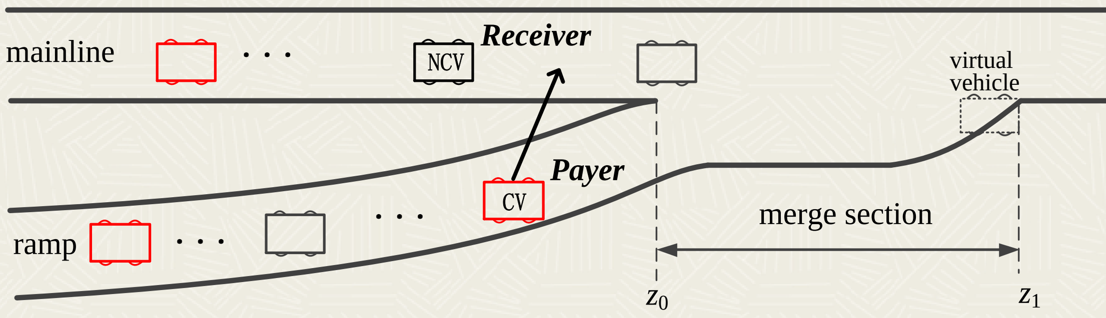
Microscopic Right-of-Way Trading Mechanism

In academia, CAVs are always designed to be more cooperative, which conflicts the self-interest nature of human

Under the assumption of rationality, both CAVs and HVs can behave cooperatively (i.e., yielding or slowing down) if enough incentive can be provided

The proposed mechanism is called Microscopic Right-of-Way Trading Mechanism for Cooperative Decision-Making (i.e., Micro-ROWTM)



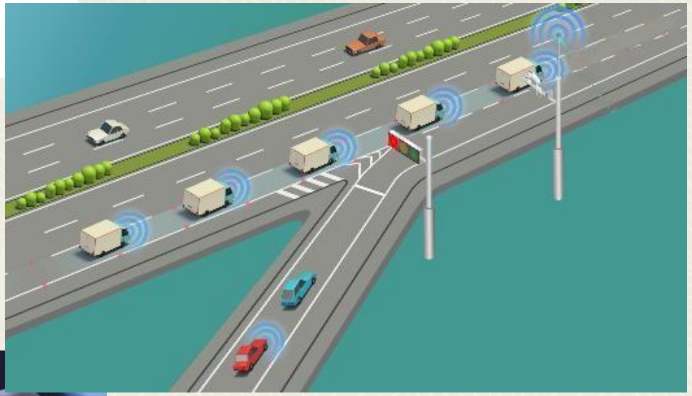


CV: Cooperative Vehicles
NCV: Non-Cooperative Vehicles

Sun, Z., Qin, Z., Ma, R., & Gao, Z. (2020). Microscopic Right-Of-Way Trading Mechanism for Cooperative Decision-Making: Theories and Preliminary Results. *Presented at 100th Annual Meeting of the Transportation Research Board, Washington, D.C., 2021.*

Microscopic Right-of-Way Trading Mechanism

- Right-of-way trading
- Mixed traffic (NCVs & CVs)
- Game-theoretic
- Individual rationality & system-efficiency
- Dominant-strategy incentive-compatibility (DSIC) under incomplete information
- Envy-minimization



Microscopic Right-of-Way Trading Mechanism

Definitions

Total cost of payer (A)/receiver (B):

$$\Delta U_j = \underbrace{\boxed{\eta_j \Delta e_j}}_{\text{Psychological cost}} + \underbrace{\boxed{\sigma_j \left(\tilde{t}_j^f - \tilde{t}_j^0 - t_j^f + t_j^0\right)}}_{\text{Travel time cost}} + \underbrace{\boxed{\kappa_j \left(\sum_{t=\tilde{t}_j^0}^{t=\tilde{t}_j^f} g_j(t) - \sum_{t=t_j^0}^{t=t_j^f} g_j(t)\right)}}_{\text{Fuel consumption cost}} = r_j \times \Delta c_j^T$$

Payoff of payer: $N_A \triangleq \Delta U_A - p = r_A \times \Delta c_A{}^T - p$

Payoff of receiver: $N_B \triangleq \Delta U_B + p = r_B \times \Delta c_B{}^T + p$

Total avenue: $\Delta\,\omega \triangleq N_A + N_B = r_A \times \Delta c_A{}^T + r_B \times \Delta c_B{}^T$

- η_j: Unit price of psychological change;
- Δe_j: Psychological change component;
- σ_j: Value of time;
- κ_j: Gas price;
- r_j: Reported attributes set;
- Δc_j: Basic cost changes set;
- p: Trading price;

Trading rules

1. Equal Allocation:

The payoff of payer and receiver is equal (i.e., half of the total revenue).

2. Double auction:

The trading price is a linear combination of the payoffs reported by payer and receiver.

3. Dynamic Negotiation:

Imitating the process of bargaining in reality to determine a trading price that both payer and receiver are satisfied with.

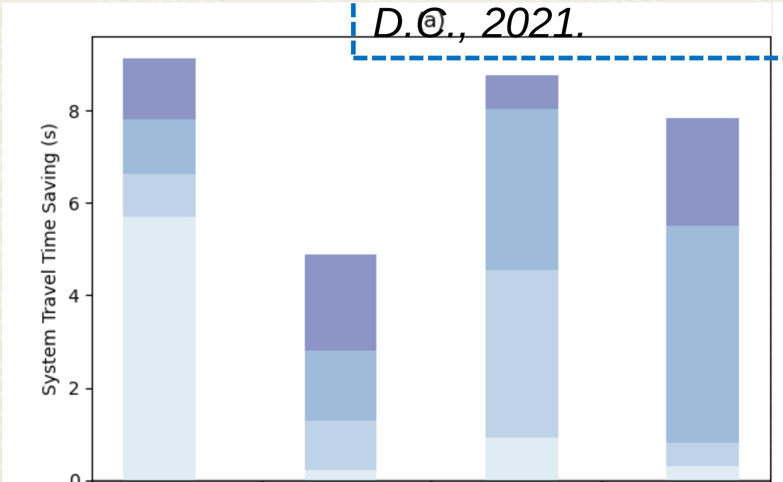
4. A constrained optimization method:

Using the optimization method to find a trading price meets the conditions of individual rationality, system-improvement, and DSIC to minimize the envy.

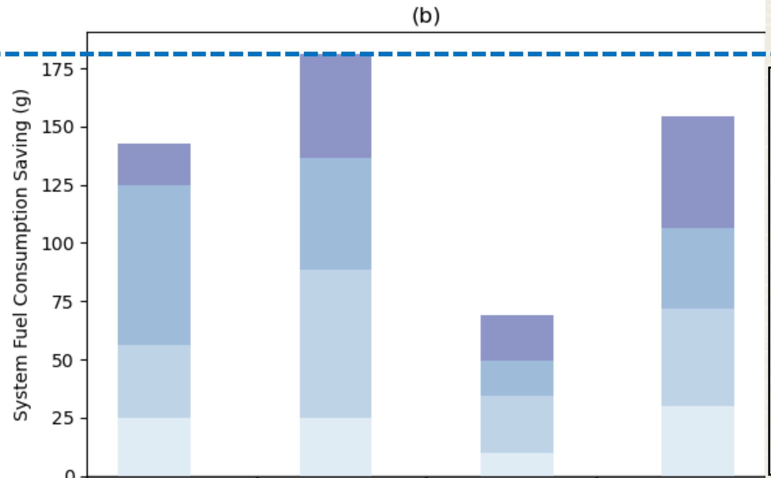
Microscopic Right-of-Way Trading Mechanism

Results

Sun, Z., Qin, Z., Ma, R., & Gao, Z. (2020). Microscopic Right-Of-Way Trading Mechanism for Cooperative Decision-Theories and Preliminary Results. *Presented at 100th Annual Meeting of the Transportation Research Board, Wash D.C., 2021.*



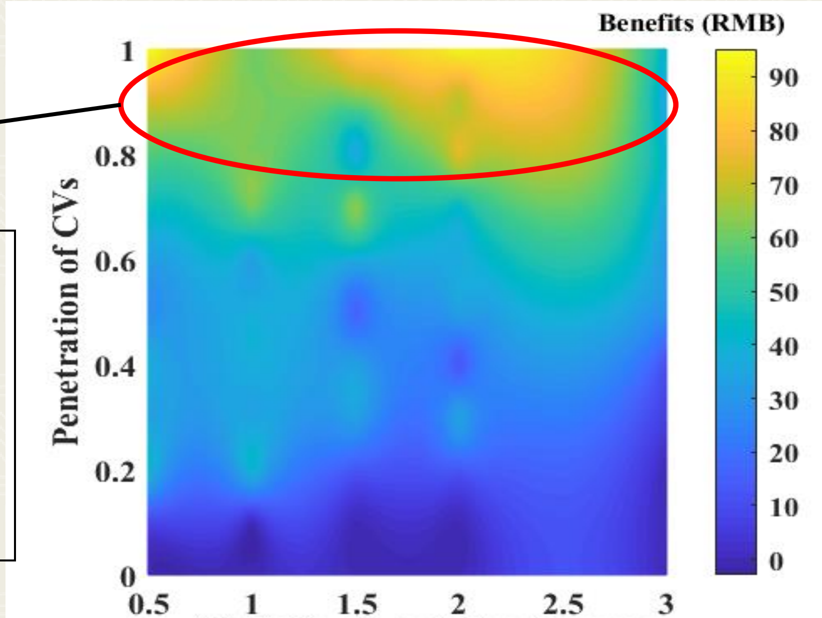
	q1:q2=900:900	q1:q2=1000:500	q1:q2=1100:700	q1:q2=1300:1000
4 Group(s)	9.140	4.884	8.773	7.835
3 Group(s)	7.820	2.794	8.040	5.491
2 Group(s)	6.620	1.284	4.540	0.810
1 Group(s)	5.710	0.210	0.930	0.294
0 Group(s)	0.000	0.000	0.000	0.000



	q1:q2=900:900	q1:q2=1000:500	q1:q2=1100:700	q1:q2=1300:1000
4 Group(s)	142.592	181.418	69.134	154.197
3 Group(s)	124.640	136.711	49.449	106.538
2 Group(s)	56.061	88.756	34.677	71.726
1 Group(s)	25.176	25.155	10.076	30.121
0 Group(s)	0.000	0.000	0.000	0.000

The **travel time** and **fuel consumption** saved by each group optimization under different flow ratios. (q_1: mainline flow, q_2: ramp flow)

$q_1 : q_2 = 900 : 900$ (light traffic): Each group saved **2.29 seconds** and **35.65g fuel** on average;
$q_1 : q_2 = 1300 : 1000$ (heavy traffic): Each group saved **1.96 seconds** and **38.55g fuel** on average;



(c) Ratio of mainline to ramp

Value of time: ***80 RMB/hour***
Fuel cost: ***7 RMB/Liter***
Applying CDMMT Ramp Merging on congested ramps, the direct cost saving is around ***80-100 RMB/hour/section***
Applying CDMMT Ramp Merging on the 47 merge section of the 2nd ring road of Chengdu, the direct cost saving is around ***7M RMB per year***

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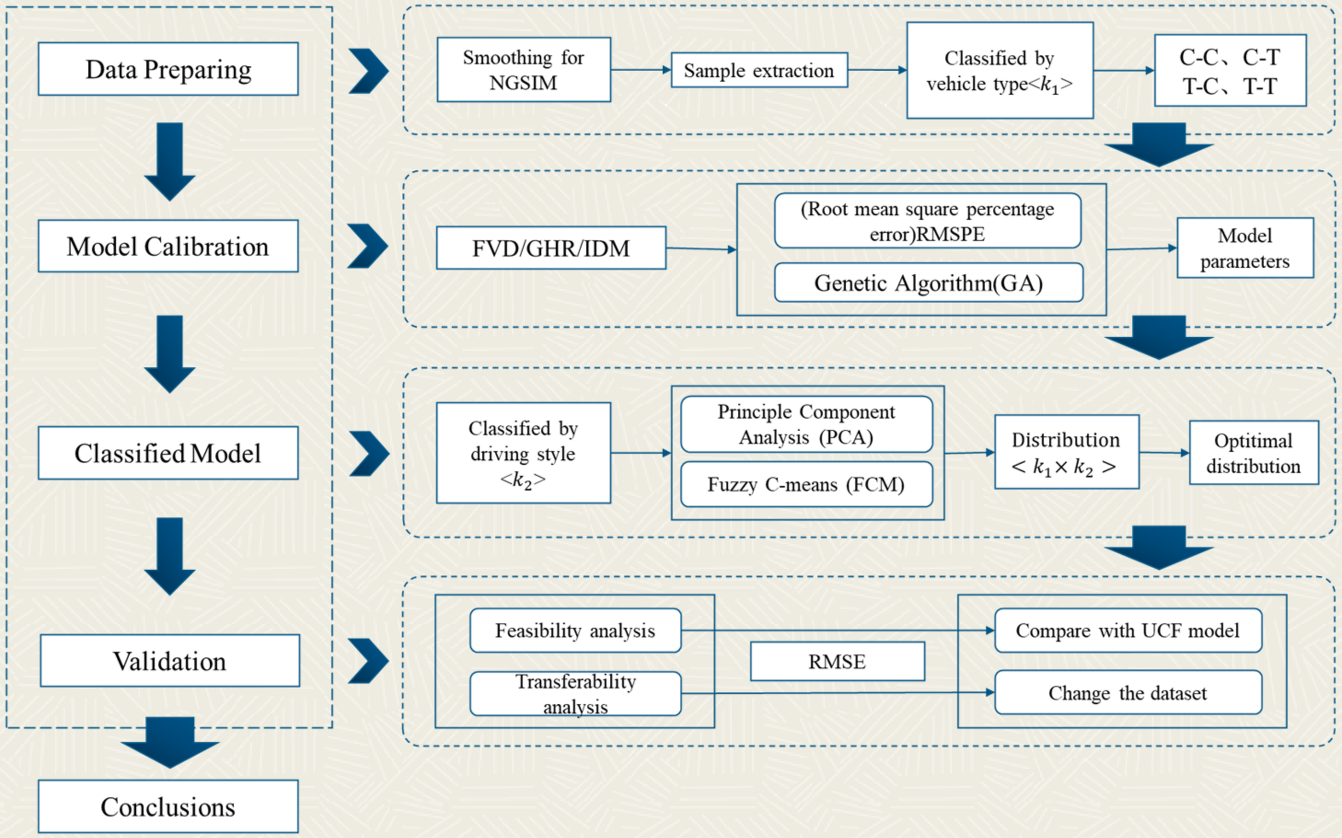
Modeling Car-Following Heterogeneities

- According to Litman's prediction, by 2040, 50% of traffic will be CAVs (Litman, T. ,2014).
- The emergence of connected automated vehicles (CAVs) has led to the problem of mixed traffic, i.e., traffic comprised of conventional human-operated vehicles (HVs) and CAVs(Huang, T., and Z. Sun.,2019).
- In mixed traffic, the decision-making and/or control of CAVs largely depends on accurate description and prediction of HVs' behaviors (Chen, D. et al,2020; Jin, S. et al,2020).

This underscored the necessity of better understanding the heterogeneities of human driving behaviors



Sun., Z., X. Yao, Z. Qin, P. Zhang, Z. Yang. (2021). Modeling Car-Following Heterogeneities by Considering Leader–Follower Compositions and Driving Style Differences. *Transportation Research Record: Journal of the Transportation Research Board, 2021. 2021: 1-14.*

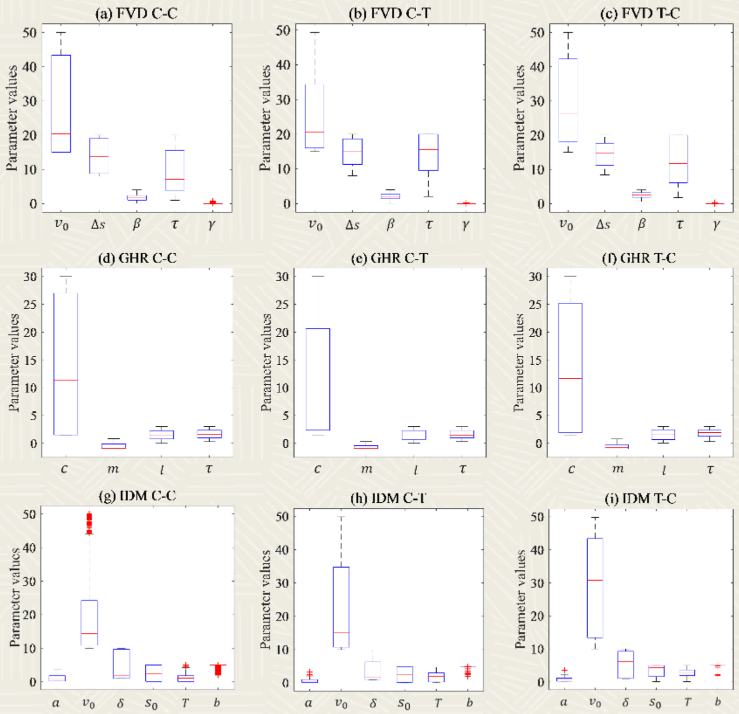
Modeling Car-Following Heterogeneities

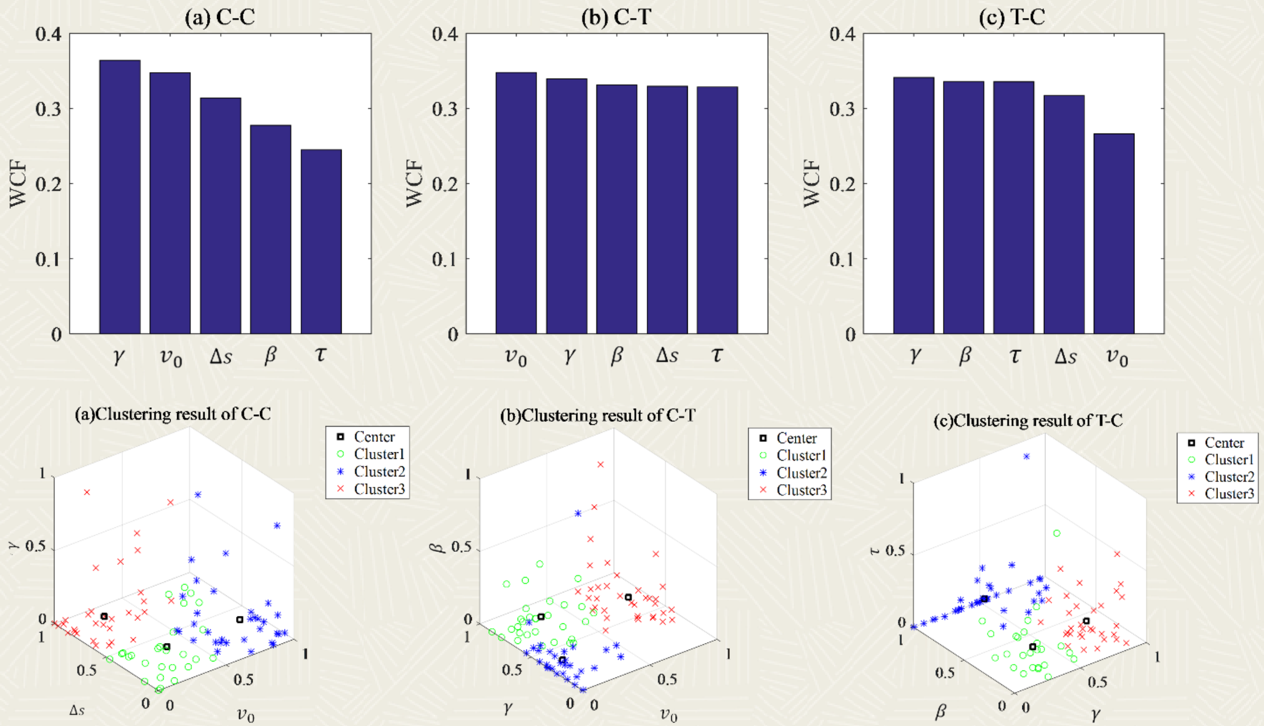
➢ Model Calibration results

- Some parameters are highly consistent across the board, while others are quite different in different leader-follower compositions

➢ PCA and FCM results

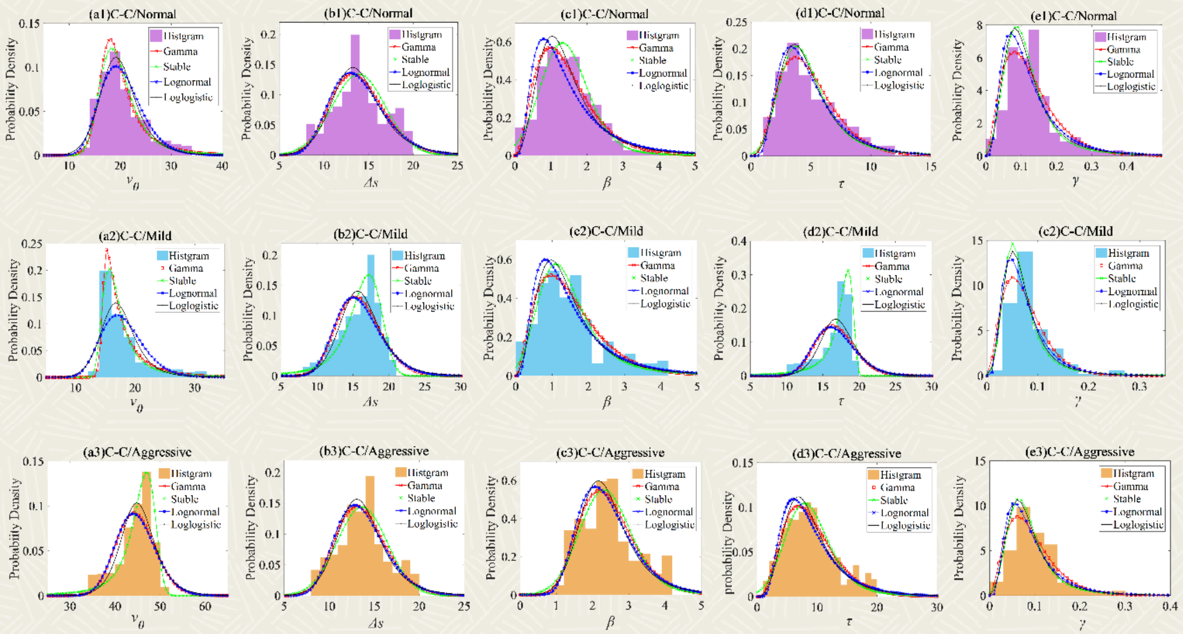
- The orders of Weighted contribution of feature (WCF) are quite different across different compositions.
- Such clustering results were attributed by the underlying driving style differences.
- The results are also consistent with the commonly recognized "aggressive-normal-mild" driving style classification.



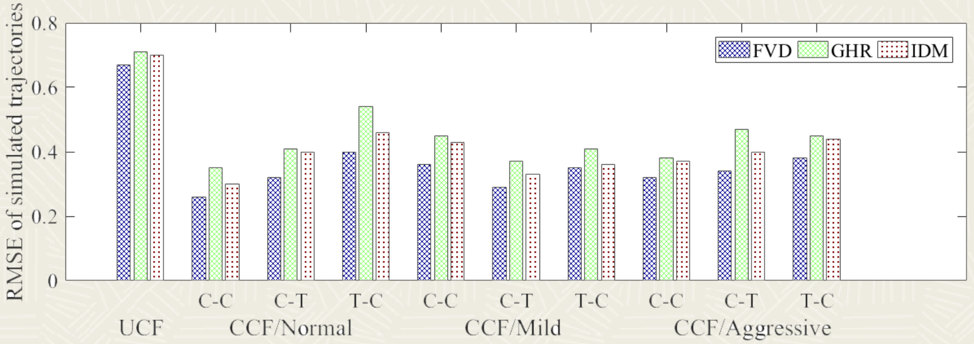


Modeling Car-Following Heterogeneities

- **Distribution fitting for car-following parameters**
  - Stable distribution has the best performance compared to the other distributions
- **Comparisons between CCF and UCF models**
  - In all cases, the estimation errors of CCF models are much smaller compared to UCF model, clearly show that the proposed CCF models can more accurately describe the heterogeneities in car-following behaviors.
- **Transferability analysis using US-101 dataset**
  - The CCF models calibrated using FVD and IDM in general outperforms the GHR model.
  - The estimation errors of CCF models are much smaller compared to UCF model



Model	Leader-follower compositions	$RMSE_{CCF}$ / $RMSE_{UCF}$			Improvement of RMSE
		Normal	Mild	Aggressive	
FVD	C-C	0.29/0.40	0.45/0.57	0.36/0.53	20.79%-49.05%
	C-T	0.42/0.62	0.31/0.60	0.44/0.61	
	T-C	0.39/0.50	0.35/0.61	0.41/0.66	
GHR	C-C	0.40/0.53	0.56/0.68	0.55/0.68	14.94%-50.27%
	C-T	0.32/0.64	0.52/0.62	0.40/0.64	
	T-C	0.59/0.69	0.49/0.66	0.57/0.62	
IDM	C-C	0.33/0.55	0.47/0.61	0.41/0.67	19.21%-48.26%
	C-T	0.43/0.67	0.27/0.53	0.45/0.65	
	T-C	0.52/0.64	0.43/0.65	0.40/0.67	



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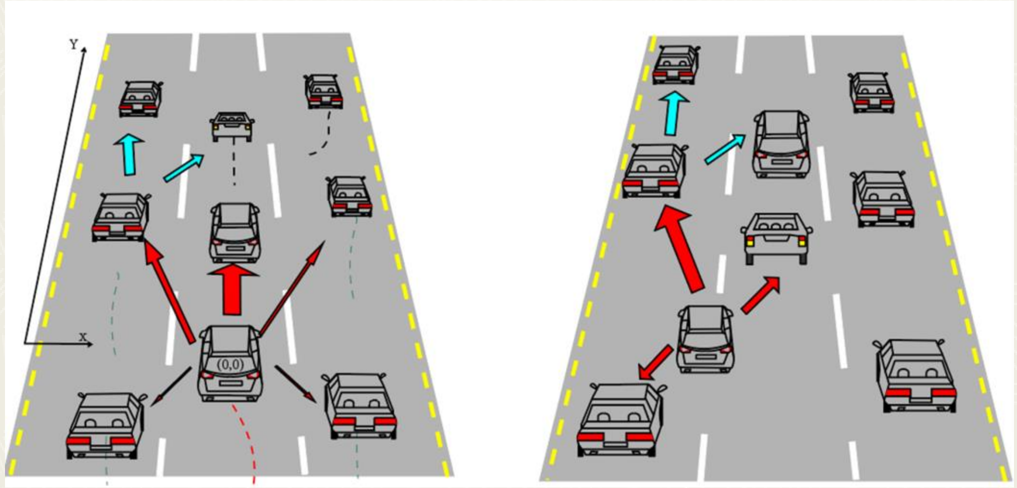
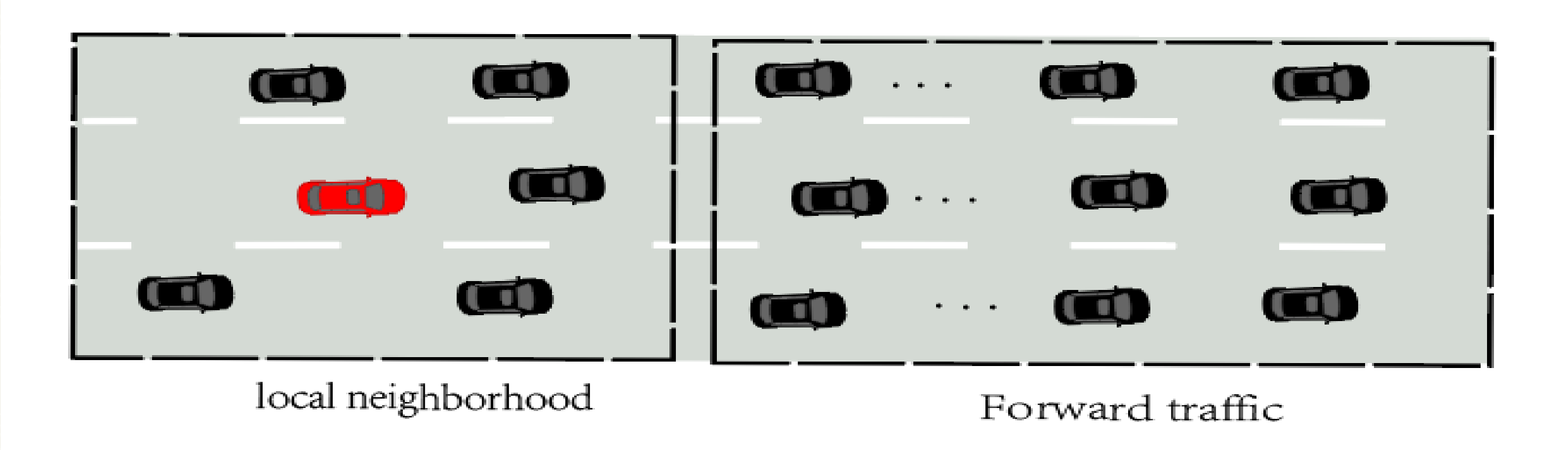
Short-term Trajectory Prediction

Accurately predicting trajectory of surrounding manual vehicles is the key premise to ensure that the CAVs can plan its own trajectory safely and reliably



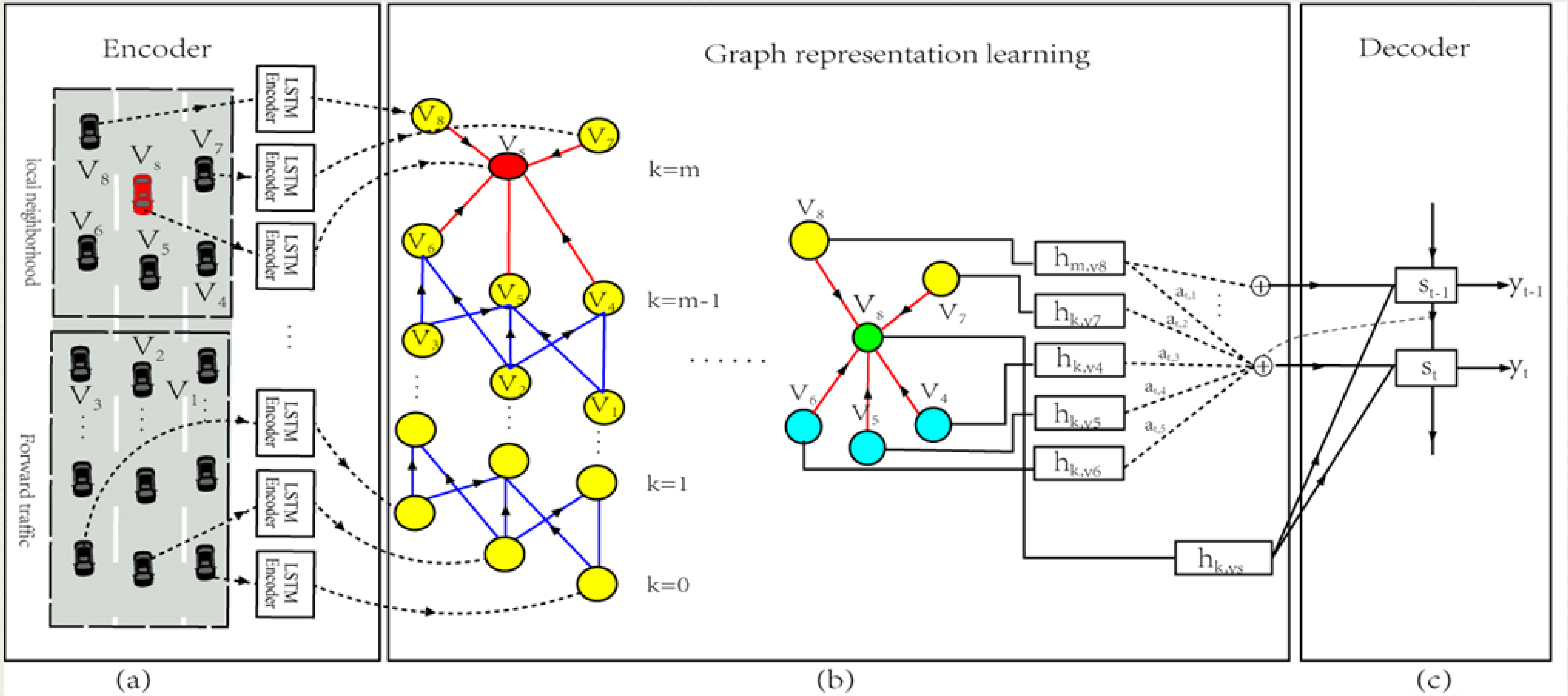
- **Learning-based LSTM network (GR-LSTM)**



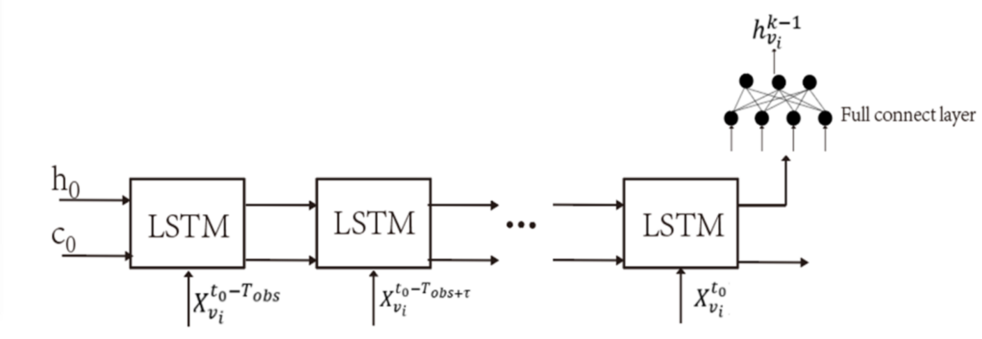
local neighborhood vehicles & vehicles as far ahead as sensors can detect

Zhao, R., Gao, Z., Sun, Z. (2021). Modeling spatio-temporal interactions for vehicle trajectory prediction based on graph representation learning. *IEEE ITSC 2021*.

Architecture of GR-LSTM model



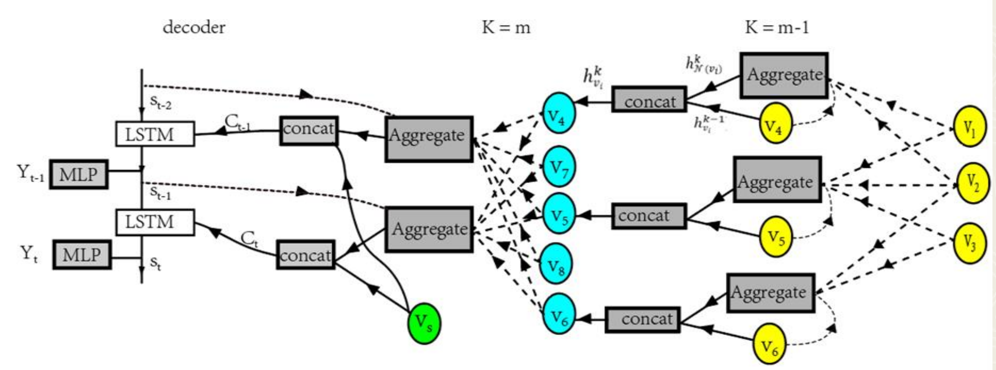
Short-term Trajectory Prediction



$$Where:\ X_{v_i} = [X_{v_i}^{t_0-T_{obs}}, X_{v_i}^{t_0-T_{obs+\tau}}, \cdots, X_{v_i}^{t_0}], \forall v_i \in V, \text{where } X_{v_{i,}}^{t_0} = \left(x_{v_{i,}}^{t_0}, y_{v_{i,}}^{t_0}\right)$$

$$h_{v_j}^{m-1} = LSTM(X_{v_i}, h_0)\ t \in \{t_0 + 1 \dots t_0 + T_{pred}\}$$

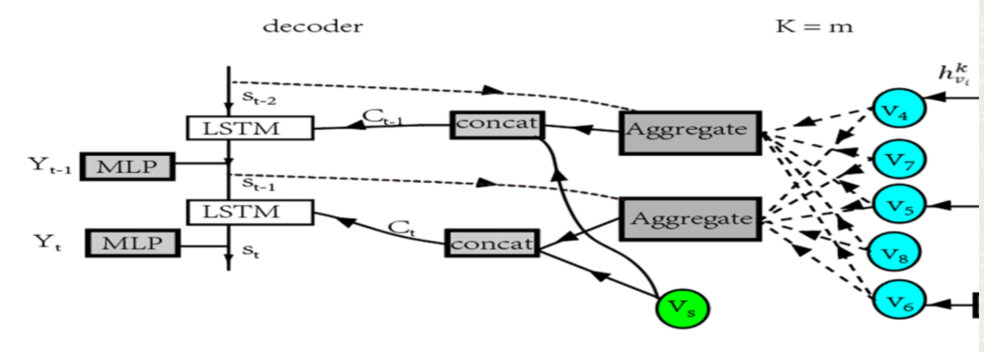
Graph representation learning



$$h_{\mathcal{N}\,(v_i)}^{k} = \text{Aggregator}(h_{v_j}^{k-1}, h_{v_i}^{k-1})\ \forall v_j \in \mathcal{N}\,(v_i), k = 1,2 \dots m-1$$

$$h_{v_i}^{k} = \sigma\left(W^k \cdot concatenate\left(h_{v_i}^{k-1}, h_{\mathcal{N}\,(v_i)}^{k}\right)\right), k = 1,2 \dots m-1$$

The LSTM Decoder



$$h_{\mathcal{N}\,(v_s)}^{m,t-1} = \text{Aggregator}(h_{v_j}^{m-1}, s_{t-1})\ \ \forall v_j \in \mathcal{N}\,(v_s), t \in \{t_0 + 1 \dots t_0 + T_{pred}\}$$

$$C_t = \sigma\left(W \cdot concatenate\left(h_{v_s}^{m-1}, h_{\mathcal{N}\,(v_s)}^{m,t-1}\right)\right)$$

$$s_t = LSTM(s_{t-1}, C_t), t \in \{t_0 + 1 \dots t_0 + T_{pred}\}$$

$$\hat{Y}^t = MLP(s_t; W_z)$$

Short-term Trajectory Prediction

Results

Baselines:

***Vanilla-LSTM (V-LSTM)*[1]**: uses a sequence of past trajectories to predict a sequence of future trajectories
***Social LSTM (S-LSTM)*[2]**: model of an LSTM-based neural network with social pooling for pedestrian trajectory prediction
***Interaction-aware Kalman neural network (IaKNN)*[3]**: added a Kalman filter layer to the interaction-aware layer
Convolutional social pooling LSTM (CS-LSTM): LSTM with convolutional social pooling and maneuvers, including the maneuver-based decoder used for generating a multimodal predictive distribution

Quantitative Results:

Quantitative results of our **GR-LSTM** compared with those of baseline approaches. Evaluation metrics are reported in terms of RMSE in meters.

Prediction horizon(s)	V-LSTM	S-LSTM	IaKNN	CS-LSTM	GR-LSTM(2)
1	0.74	0.68	0.62	0.63	0.68
2	1.44	1.28	1.03	1.27	1.17
3	2.57	2.27	1.97	2.09	1.74
4	4.23	3.32	2.93	3.12	2.64
5	5.92	4.46	4.12	4.27	3.32

S. H. Park, B. Kim, C. M. Kang, C. C. Chung, and J. W. Choi, "Sequence-to-sequence prediction of vehicle trajectory via LSTM encoder-decoder architecture," in *2018 IEEE Intelligent Vehicles Symposium (IV)*, 2018: IEEE, pp. 1672-1678.

N. Deo and M. M. Trivedi, "Convolutional social pooling for vehicle trajectory prediction," in *Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition Workshops*, 2018, pp. 1468-1476.

C. Ju, Z. Wang, C. Long, X. Zhang, G. Cong, and D. E. Chang, "Interaction-aware kalman neural networks for trajectory prediction," *arXiv preprint arXiv:1902.10928*, 2019.

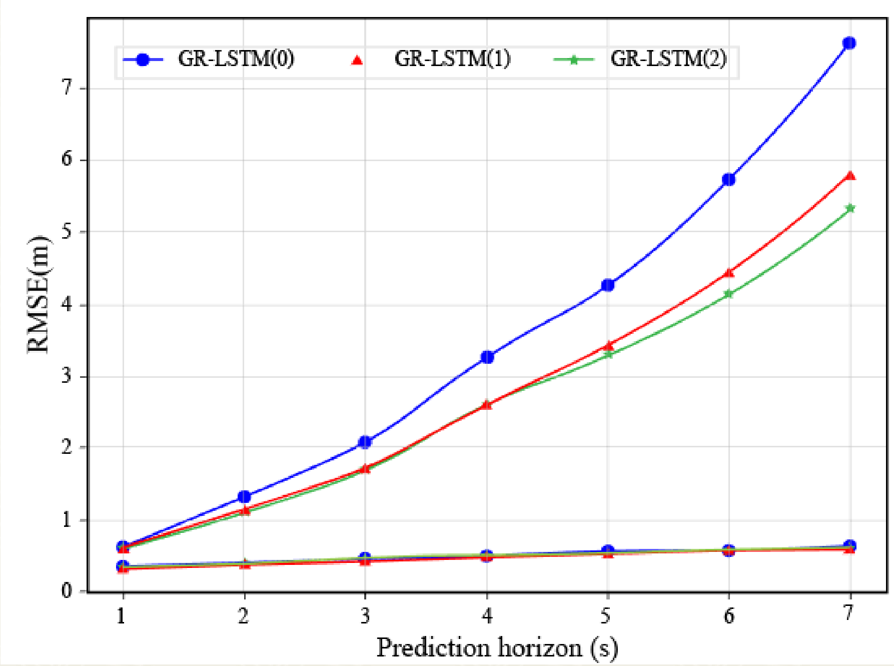
Short-term Trajectory Prediction

Results

Relationship Between The Number Of Rows Of Forward Vehicles and The Prediction Accuracy

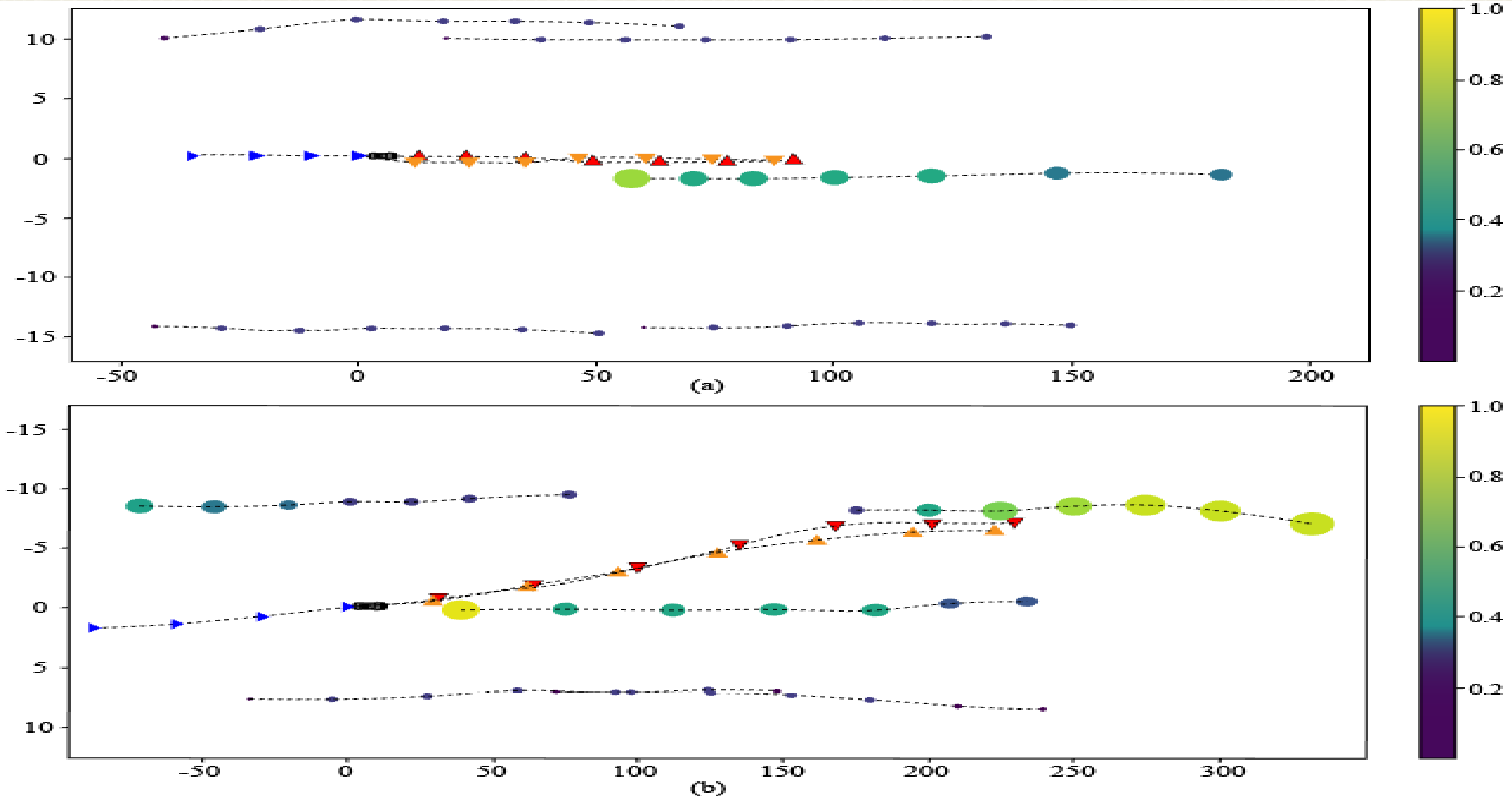
QUANTITATIVE RESULTS OF THE SELECTION OF DIFFERENT ROWS OF FORWARD VEHICLES IN THE GR-LSTM MODEL. EACH CELL IN THE TABLE IS THE RMSE/ADE

Prediction horizon(s)	GR-LSTM(0)	GR-LSTM(1)	GR-LSTM(2)	GR-LSTM(3)
1	0.69/0.47	0.68/0.46	**0.68/0.47**	0.70/0.48
2	1.35/0.79	1.22/0.73	**1.17/0.70**	1.28/0.75
3	2.10/1.02	1.82/0.94	**1.74/0.91**	1.93/0.99
4	3.27/1.34	2.66/1.18	**2.64/1.14**	2.77/1.23
5	4.27/1.63	3.46/1.45	**3.32/1.38**	3.51/1.52
6	5.74/2.10	4.44/1.79	**4.16/1.65**	4.29/1.80
7	7.68/2.62	5.82/1.96	**5.37/1.84**	5.42/1.93



Short-term Trajectory Prediction

Results



Attention weights predicted by the graph attention mechanism. (a): Lane keeping case; (b): Lane changing case

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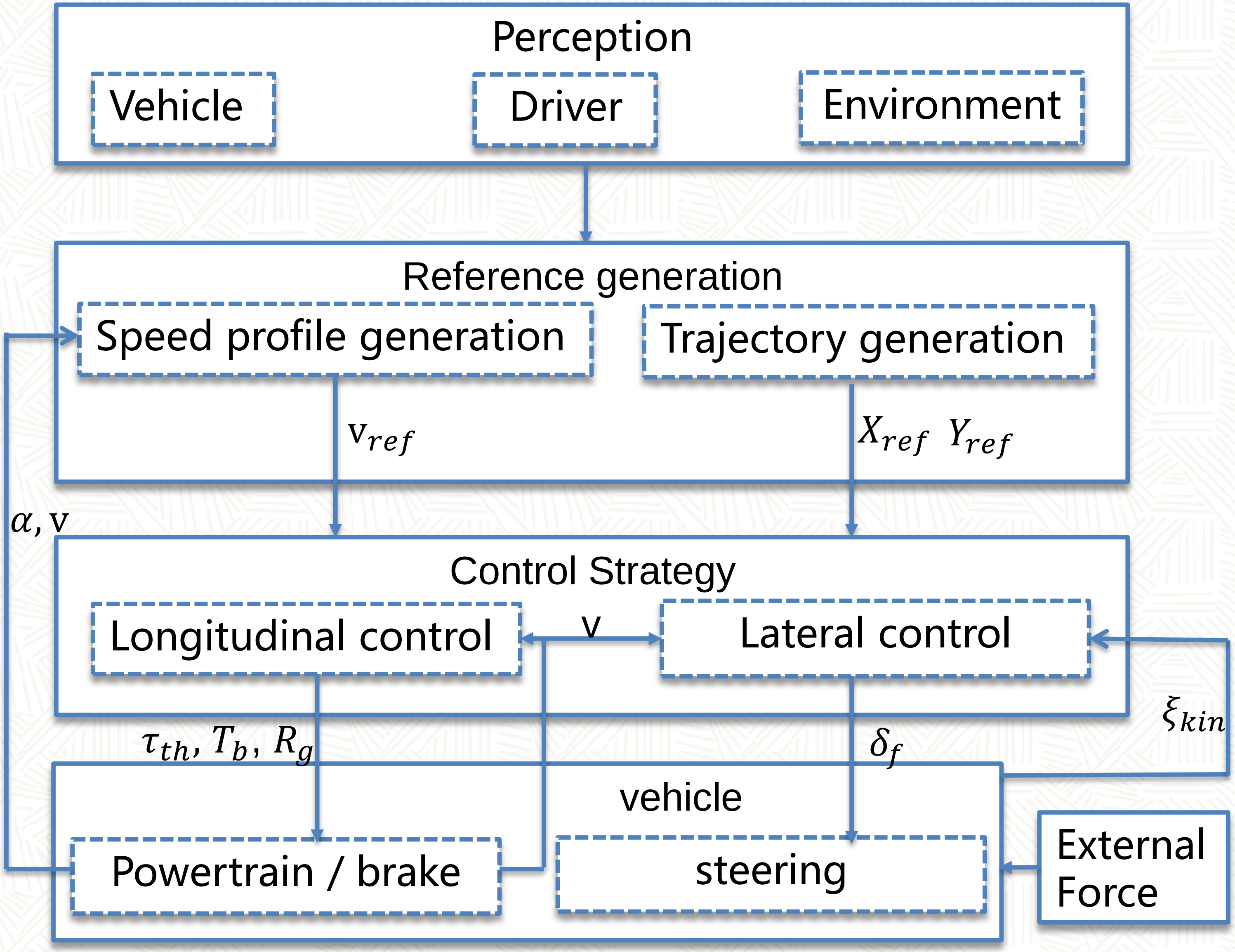
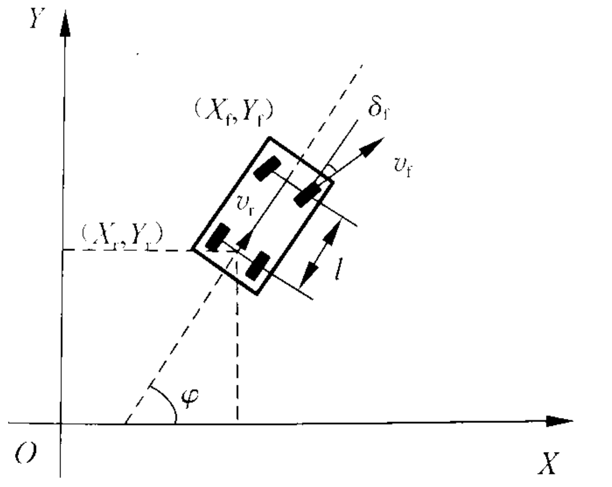
Trajectory Planning and Tracking

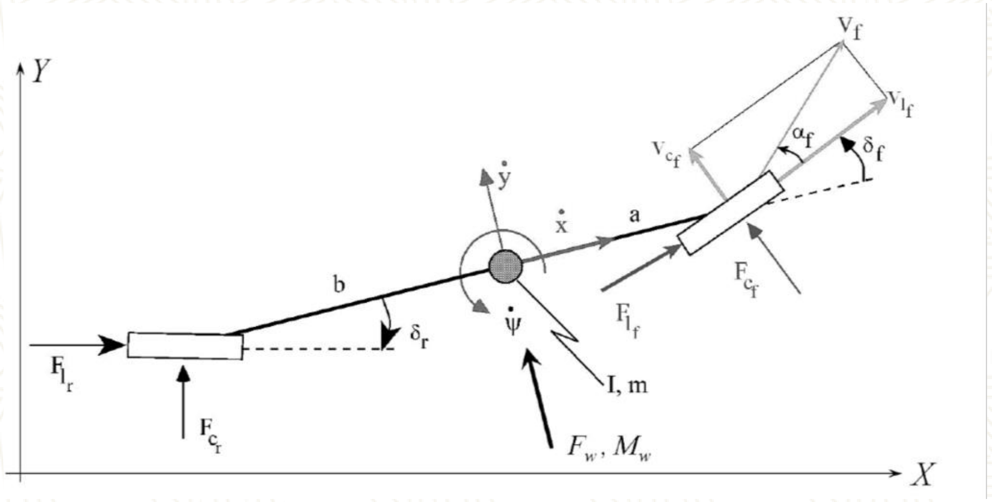
Integration of traffic decisions (strategic-level) and vehicle control (tactical-level)

- **Cooperative trajectory planning**
- **Control Strategy and Speed Planning**
- **Vehicle kinematics model and dynamical model**



Vehicle Models: vehicle kinematics model & vehicle dynamical model





$$\begin{bmatrix}\dot{X}_r\\ \dot{Y}_r\\ \dot{\varphi}\end{bmatrix}=\begin{bmatrix}\cos\varphi\\ \sin\varphi\\ \tan\delta_f/l\end{bmatrix}v_r$$

$$m\ddot{x} = m\dot{y}\dot{\varphi} + F_{xf,l} + F_{xf,r} + F_{xr,l} + F_{xr,r}$$

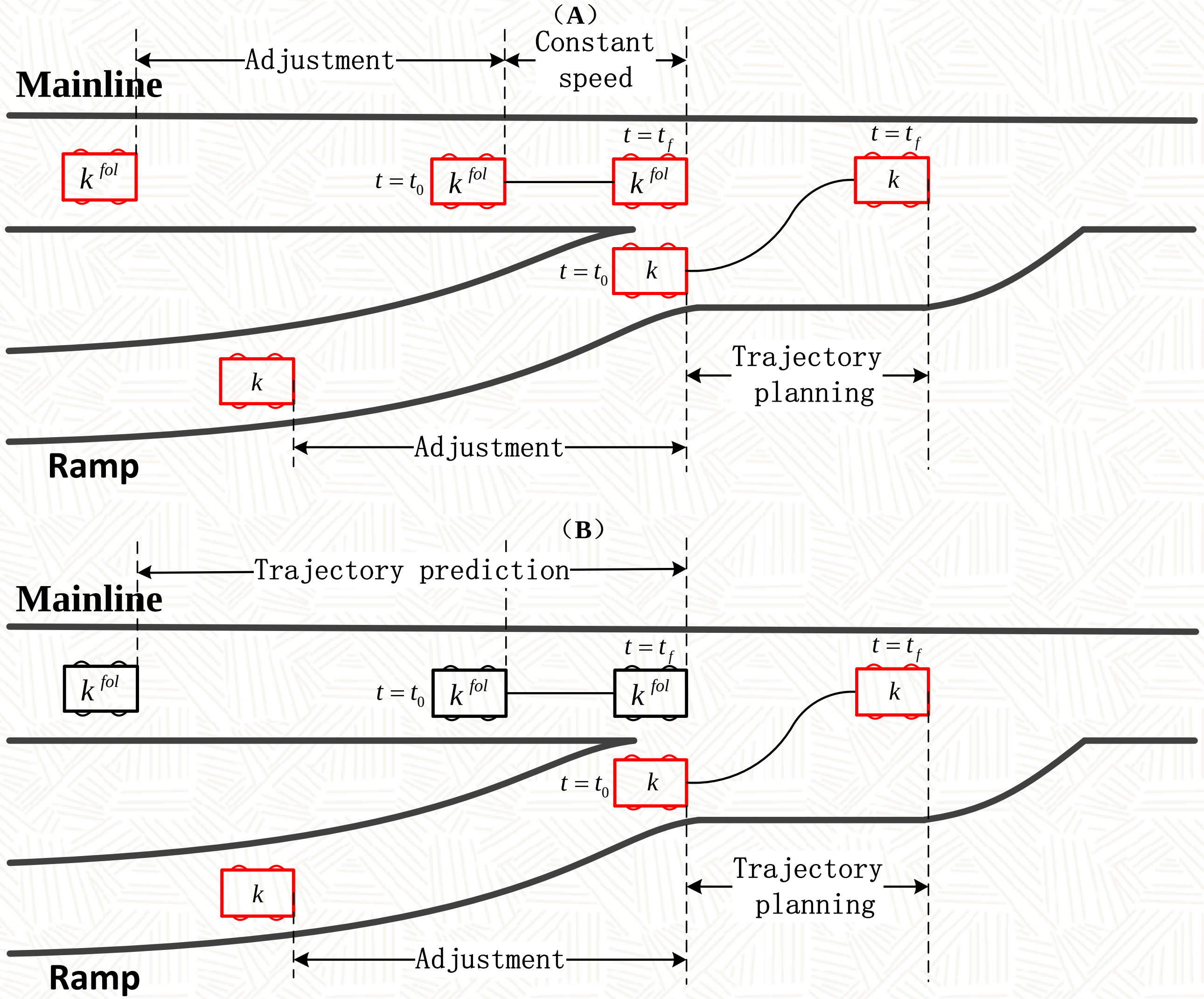
$$m\ddot{y} = -m\dot{x}\dot{\varphi} + F_{yf,l} + F_{yf,r} + F_{yr,l} + F_{yr,r}$$

$$I\ddot{\varphi} = a\left(F_{yf,l} + F_{yf,r}\right) - b\left(F_{yr,l} + F_{yr,r}\right) + c\left(-F_{xf,l} + F_{xf,r} - F_{xr,l} + F_{xr,r}\right)$$

State variables $\xi_{kin} = [X_r\ ,\ \ Y_r\ ,\ \ \varphi]^T$
Control variables $u_{kin} = [v_r\ ,\ \delta_f]^T$

State-space expression $\dot{\xi}(t) = f_{\mu(t)}^{2\omega}(\xi(t), u(t))$
State variables $\xi_{kin} = [X_r\ ,\ \ Y_r\ ,\ \ \varphi]^T$
Control variables $u_{kin} = [v_r\ ,\ \delta_f]^T$

Cooperative trajectory planning



Cost Function

$$
\left\{
\begin{array}{l}
w_1(t_f - t_0) \\
w_2(x_k(t_f)) \\
w_3 \int_{t_0}^{t_f} \omega_k^2(t) \\
w_4 \int_{t_0}^{t_f} j_{kx}^2(t)\,dt + \int_{t_0}^{t_f} j_{ky}^2(t)\,dt \\
w_5 J
\end{array}
\right.
$$

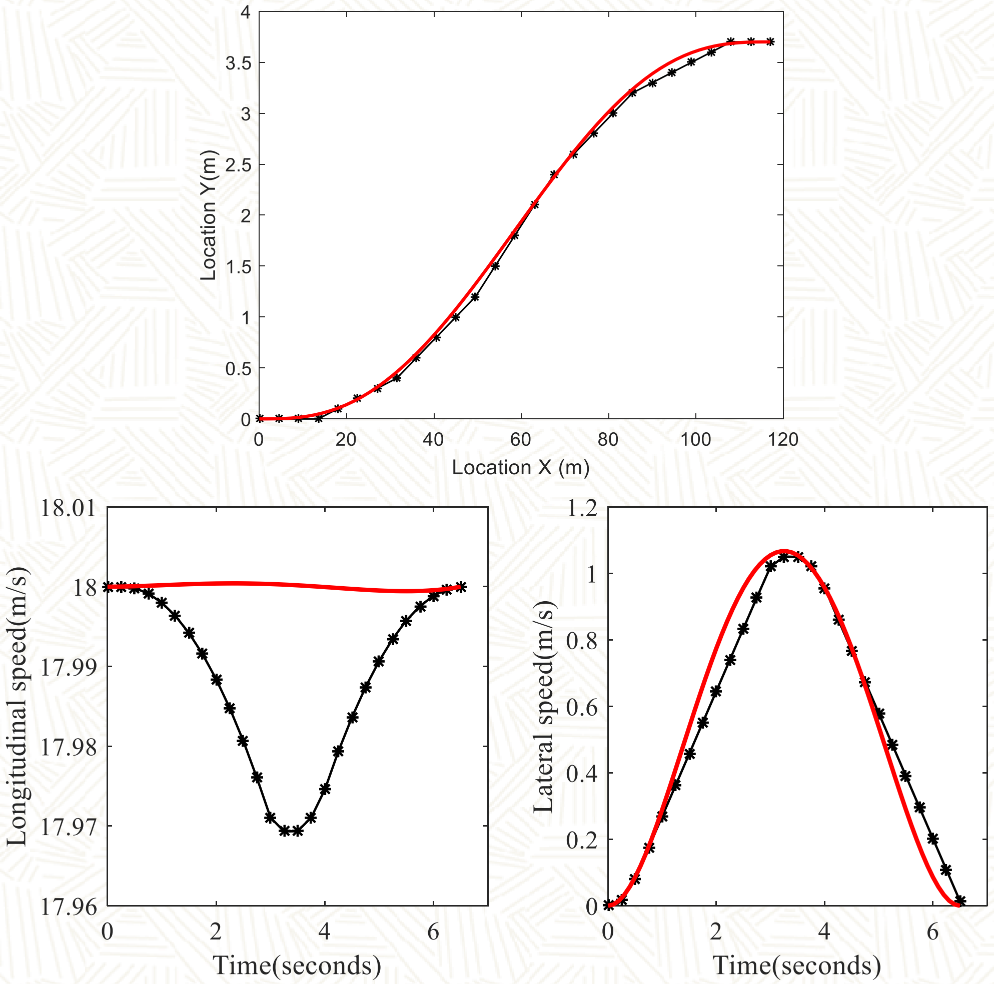
→ Efficiency

→ Comfort & Smoothness

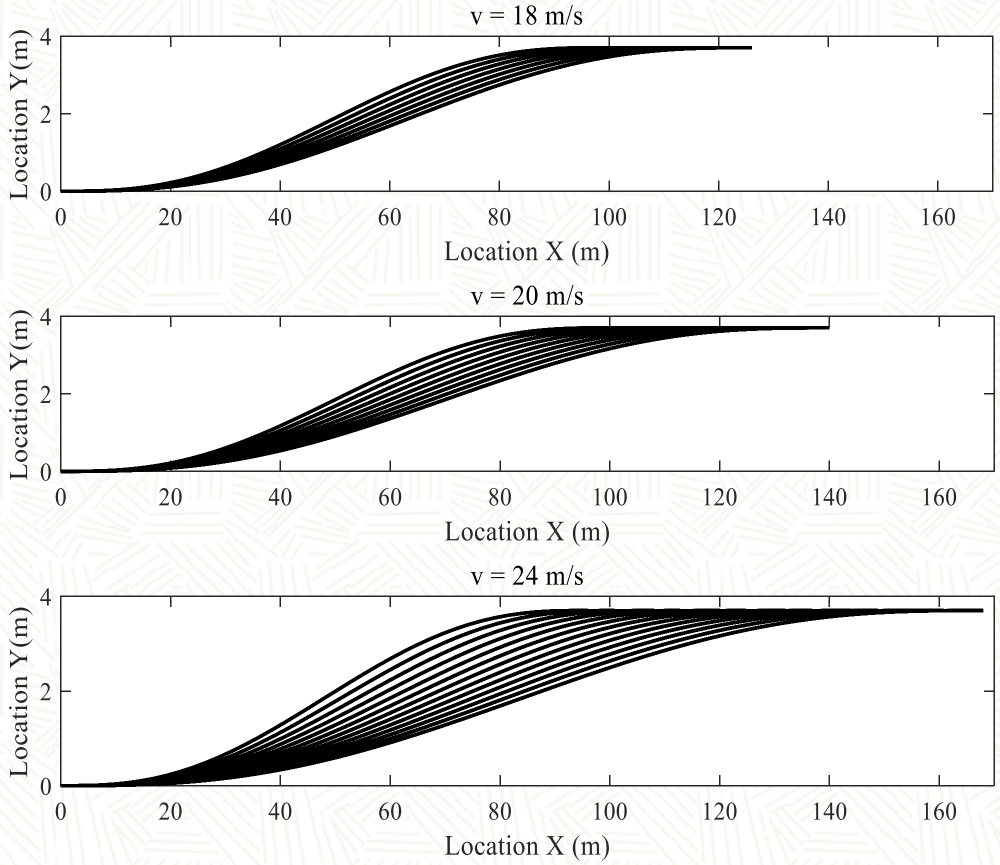
→ Cooperativity

Based on CDMMT

Results——trajectory planning



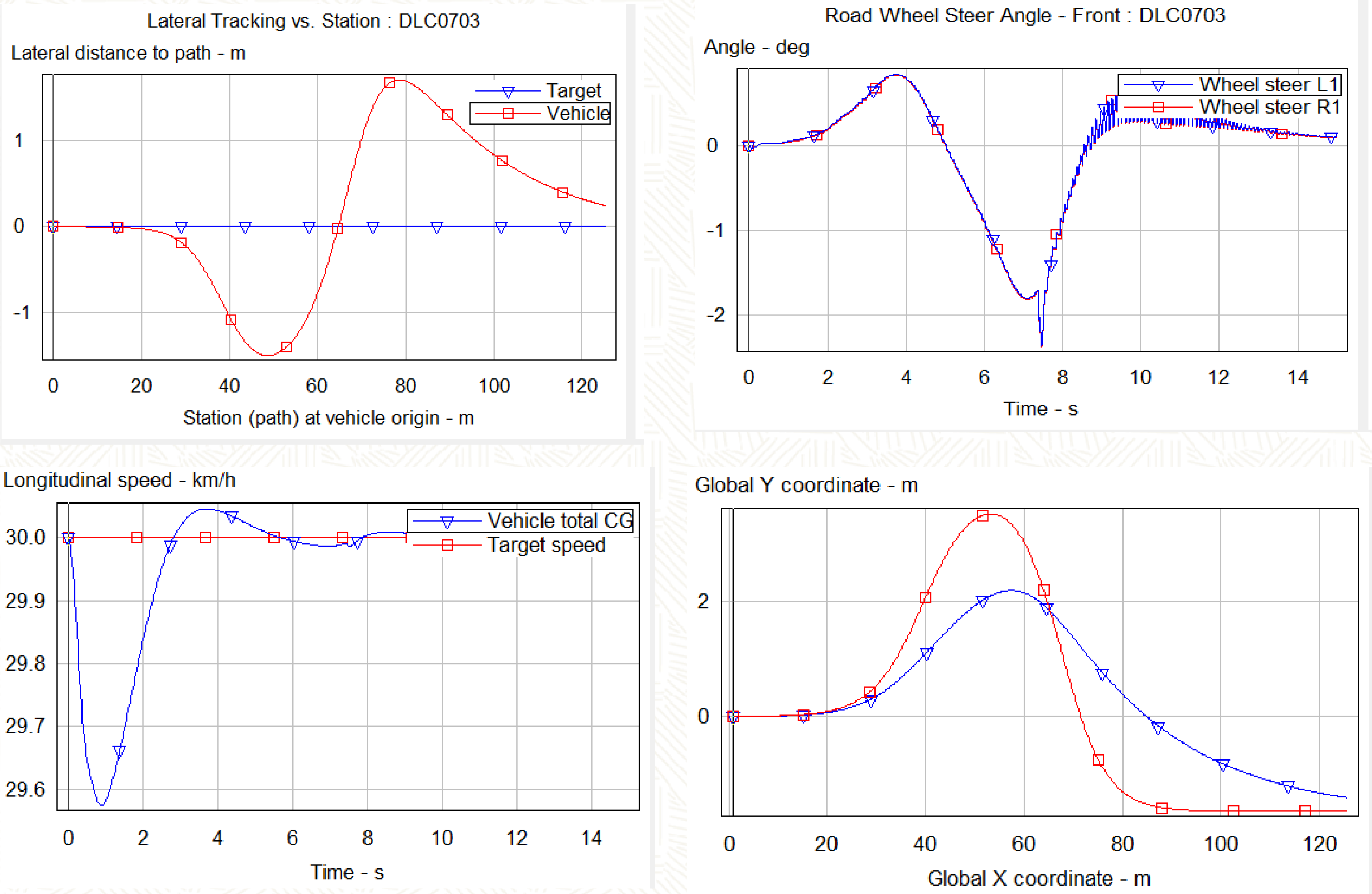
merging trajectory with a constant speed of 24 m/s



merging trajectory under different speed

Trajectory Tracking

simulation results of trajectory tracking under constant speed



Trajectory Tracking

Speed profile generation （Optimality Theory)

Based on a given trajectory(S) ⇒ Cost Function

$$\omega_1 \int_{t_0}^{t_n} (S'')^2 dt \rightarrow$$

$$\omega_2 \int_{t_0}^{t_n} (S''')^2 dt \rightarrow$$

Measures of the speed profile smoothness(comfort)

$$\omega_3 \int_{t_0}^{t_n} (S - S_{ref})^2 dt \rightarrow$$

Measures of the trajectory tracking error(MPC)

$$\omega_4 \int_{t_0}^{t_n} (V_{max} - V_t)^2 dt \rightarrow$$

Measures of the trajectory tracking efficiency

V_{max}

→ limiting-velocity of road V_r （Known）

→ limiting-velocity according to the curvature of the road V_c

$$V_c = \sqrt{\frac{DgR}{2H}}$$

⇒ $V_{max} \le \min(V_r , V_c)$

D:distance between rear wheels

R:Turning radius

H:Height of car body center of gravity to ground

Trajectory Tracking——Current work

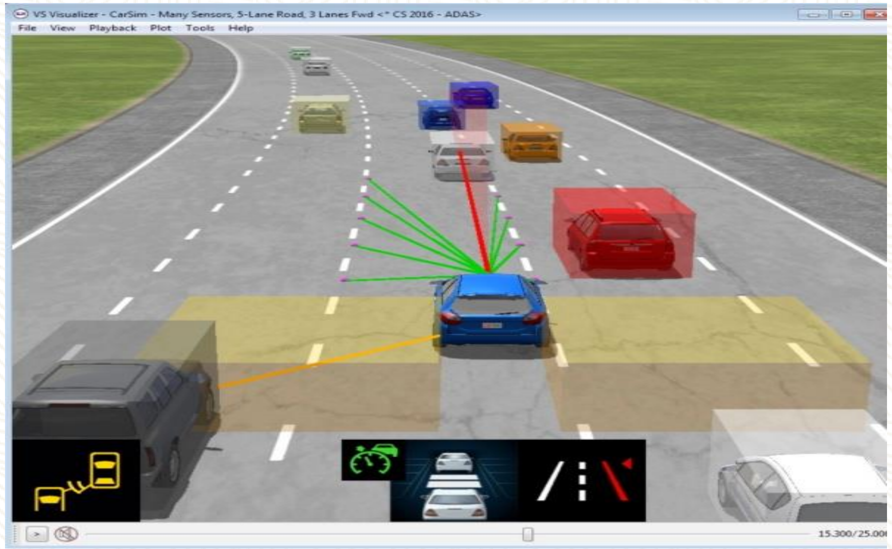
1. Solving the optimal model of speed profile generation

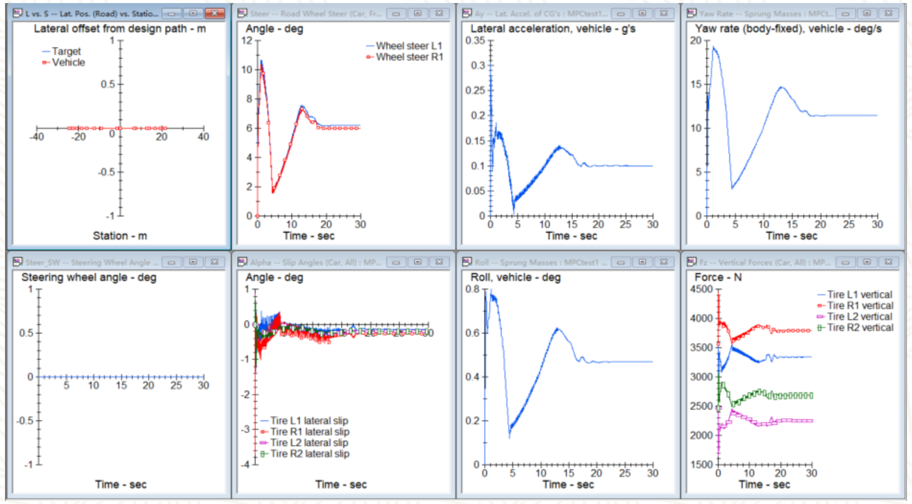
Method: Dynamic programming/Quadratic programming /QP+DP

2. Designing the speed tracking controller based on PID

3. Designing the longitudinal and lateral coupling controller (Tracking a given trajectory with a desired speed profile)

4. Evaluating the tracking performance of the designed controller according to the joint simulation results





Future directions

Integration of trajectory planning and trajectory tracking (considering trajectory re-planning)

Time-delay systems

Game theoretical approach for microscopic right-of-way trading considering heterogeneous users and bounded rationality

Stochasticity in the problem (HV, CAV)

Generalization: e.g., intersections

Road test experiments

Reference list

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Acknowledgements

Group Members @SWJTU

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