



Developing and Evaluating the Driving and Powertrain Systems of Automated and Electrified Vehicles (AEVs) for Sustainable Transport

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Background

➤ Challenges for road transport

Oil dependency

95% of motor vehicles depend on oil for energy



Emissions

20% of GHG emissions come from combustion engines



Safety

1.2 million people die on the road each year

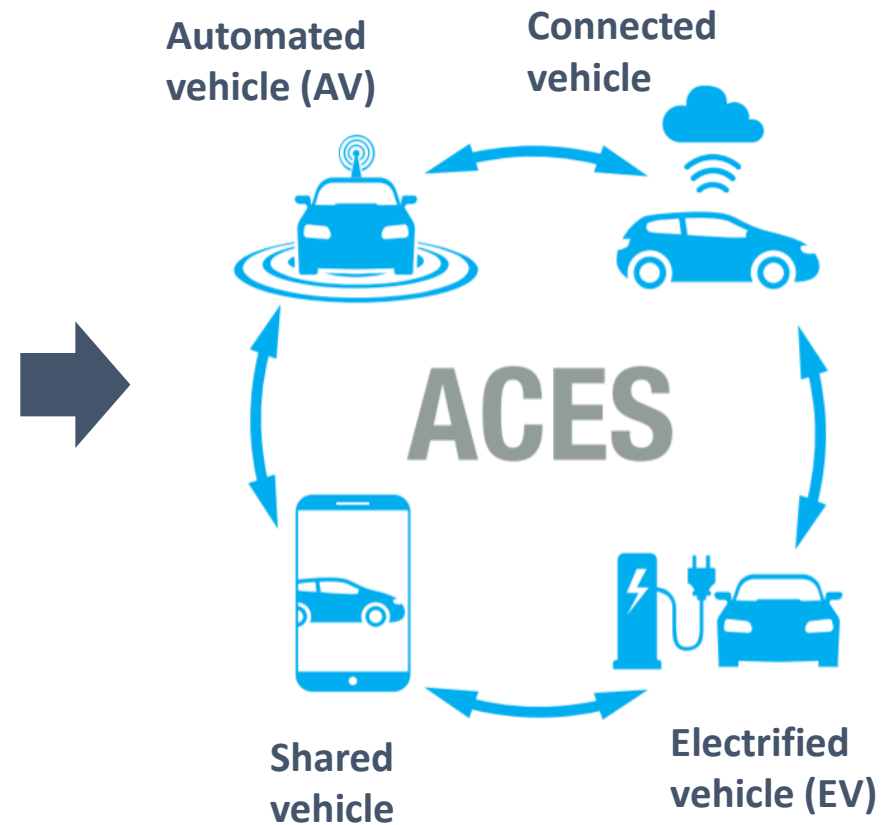


Congestion

\$305 billion are lost each year in the US due to jams



➤ Opportunities – ACES vehicles



Background

➤ Automated and electrified vehicles (AEVs)

With increasing market penetration, AEVs are gathering momentum worldwide.

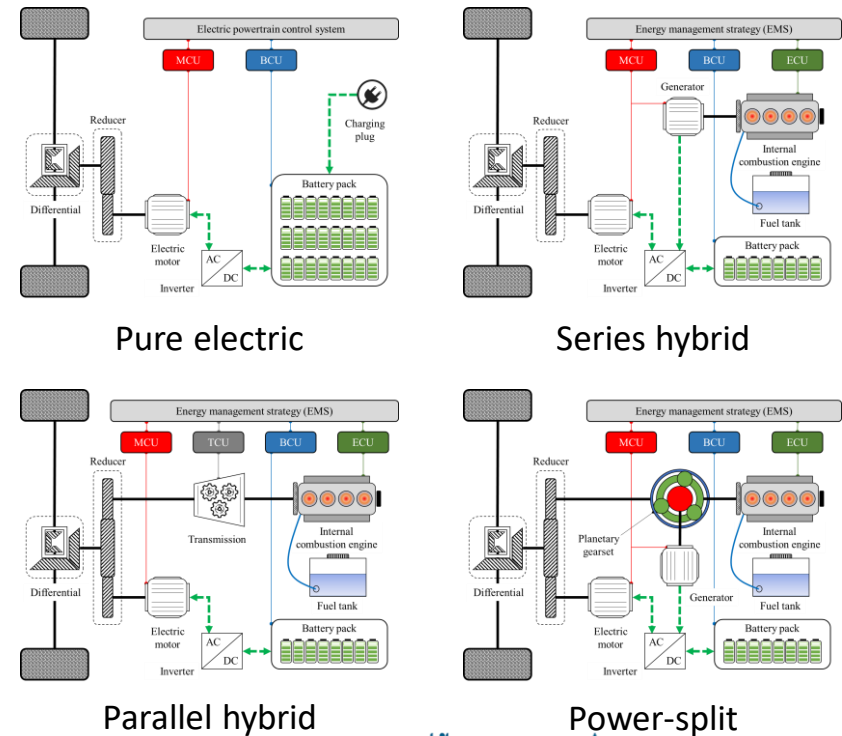
a) Automated driving systems of AVs

ADAS FEATURES			PARTIAL AUTOMATION
Aiding	Warning	Assisting	
Definition Aiding features can improve the driver's visibility by providing additional display or illumination.	Warning features alert the driver to potential danger through sensory cues (auditory, visual or haptic).	Assisting features can engage in steering, acceleration, and/or brake systems if necessary.	Automated features allow the vehicle to be driven/stopped without driver intervention in certain scenarios.
Feature (year) Night vision (NV, 2000) Rear view camera (2002) Adaptive front lighting system (AFS, 2006) Surround view system (SVS, 2007)	Park assist (2002) Forward collision warning (FCW, 2003) Lane departure warning (LDW, 2005) Blind spot detection / rear cross traffic alert (BSD/RCTA, 2006) Driver monitoring system (DMS, 2006)	Adaptive cruise control (ACC, 2007) Lane keeping assist (LKA, 2010) Automatic parking (2006) Autonomous emergency braking (AEB, 2008) Pedestrian avoidance (2014) Intelligent speed adaptation (ISA, 2018)	Single lane highway autopilot (2016) Autonomous valet parking (2017) Traffic jam autopilot (2017) Highway autopilot with lane changing (2018) Urban autopilot (2022)
Technology Mono cameras Infrared (night vision) Laser lights	Mono and stereo cameras Radar (short) Steering inertia Ultrasonic	Mono and stereo cameras Radar (short and long) Lidar Ultrasonic	Mono and stereo cameras Radar (short and long) Lidar GPS/mapping Ultrasonic
Others		Drivers begin to share control	
		System integration	

Categories of advanced driver assistance systems (ADAS)

Adapted from Boston Consulting Group (BCG)

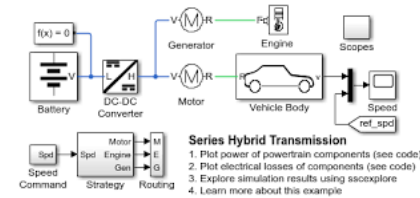
b) Electrified powertrain systems of EVs



Motivations - Driving & powertrain systems of AEVs

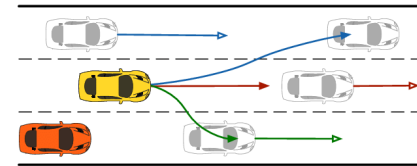
1) Design optimization (*automotive engineer*)

How can the driving and powertrain systems of AEVs be optimized for taking advantage of their (mechanical and electrical) components and (energy and driving) controllers? It is important for bringing collective improvements in energy efficiency, greenhouse gas (GHG) emissions, ride comfort, safety, and cost-effectiveness.



2) Behaviour modelling (*civil engineer*)

How can microscopic traffic models be developed for accurately reproducing AEVs' driving behaviours in traffic simulation? It is essential for predicting the impact of AEVs on traffic flow and for maximizing their benefits to the road network.



3) Real-world assessment (*policy maker*)

How can the driving performances (e.g., energy and safety) of AEVs be evaluated in real-world conditions? It is critical for understanding the properties of commercially available AEVs and for anticipating potential problems associated with their widespread application.



Objectives

1) Design optimization

- To explore the optimal sizing of key components of a flex-fuel hybrid powertrain for improving its energy efficiency, GHG emissions, and cost-effectiveness.
- To perform integrated multiobjective optimization of adaptive cruise control (ACC) and energy management strategy (EMS) for enhancing energy efficiency, ride comfort, and tracking capability

2) Behaviour modelling

- To develop a free-flow driving behaviour model considering dynamics of the electrified powertrain.
- To extend free-flow and car-following behavioural models for capturing effects of road geometry on AVs.
- To develop a physics-augmented behaviour modelling framework that introduces mechanical features and controller designs of AVs into traffic flow theory

3) Real-world assessment

- To compare energy and safety performances between ACC vehicles and human-driven vehicles (HDVs) in platooning experiments on public roads
- To investigate the impacts of time-gap settings of commercial ACC systems on the energy consumption of vehicle platoons examined on test tracks.



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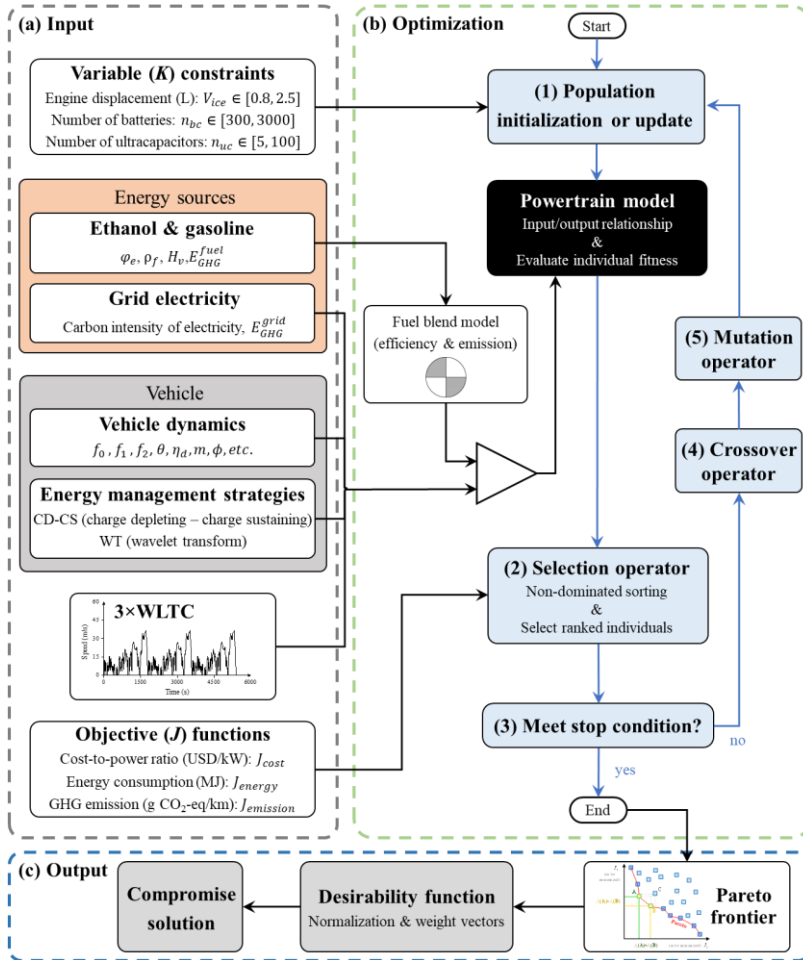
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Contributions – Design optimization

CH. 3. Optimal sizing of key components for a flex-fuel hybrid powertrain

❖ Methodology



❖ Objective

To develop a Pareto method that can address the multi-objective optimal sizing of key components for the development of a flex-fuel hybrid powertrain.

❖ Problem in math

$$J_{cost} = \frac{c_{ice}(V_{ice}) + c_{bc} \cdot n_{bc} + c_{uc} \cdot n_{uc}}{P_{ice}^{max}(V_{ice}) + \epsilon_{bp} \cdot P_{bc}^{max} \cdot n_{bc} + \epsilon_{up} \cdot P_{uc}^{max} \cdot n_{uc}},$$

$$J_{energy} = \frac{1}{1000} \int_{t_0}^{t_f} (H_v(\varphi_e) \cdot \dot{m}(t) + P_{bp}(t) + P_{up}(t)) dt,$$

$$J_{emission} = \frac{1}{d} \int_{t_0}^{t_f} \left(E_{GHG}^{fuel}(\varphi_e) \cdot H_v(\varphi_e) \cdot \dot{m}(t) + E_{GHG}^{grid} \cdot (P_{bp}(t) + P_{up}(t)) \right) dt$$

$$\begin{cases} V_{ice}^{min} \leq V_{ice} \leq V_{ice}^{max}, \\ n_{uc}^{min} \leq n_{uc} \leq n_{uc}^{max}, \\ n_{bc}^{min} \leq n_{bc} \leq n_{bc}^{max}, \end{cases}$$



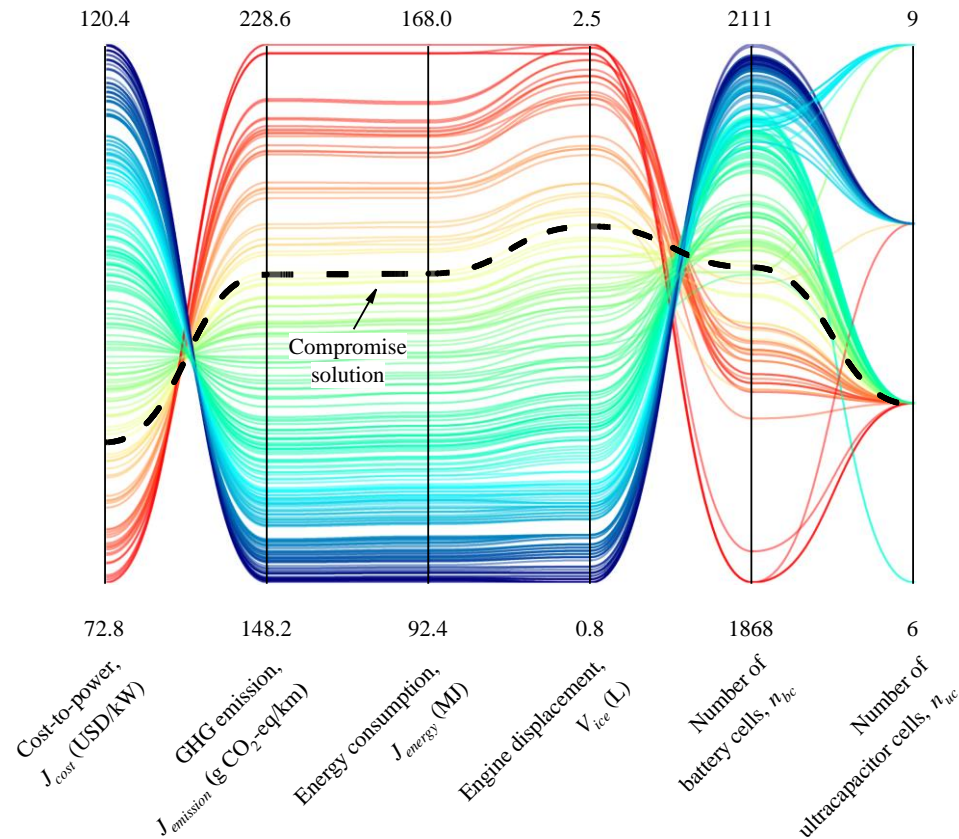
Contributions – Design optimization

❖ Main contributions

- Trade-offs between different design objectives are revealed.
- An ethanol-gasoline blend model is considered.
- Design solutions are provided as per the power utility generation portfolio and automobile fuel properties of the target region.

❖ Main conclusions in this chapter

- Better performances of the PHEV, regarding GHG emissions and energy consumption, are associated with larger battery size and smaller engine displacement but result in a higher cost-to-power ratio.
- For E25-fuelled PHEVs in markets with world average electricity carbon intensity, every 1.0 USD/kW increase in cost-to-power ratio leads to savings of 1.6 MJ energy consumption and 1.7 g CO₂-eq/km WTW GHG emissions.
- A clear benefit of using E25 in the hybrid propulsion system is identified, where the energy consumption and GHG emissions can be reduced by 5.9% and 12.3%, respectively.



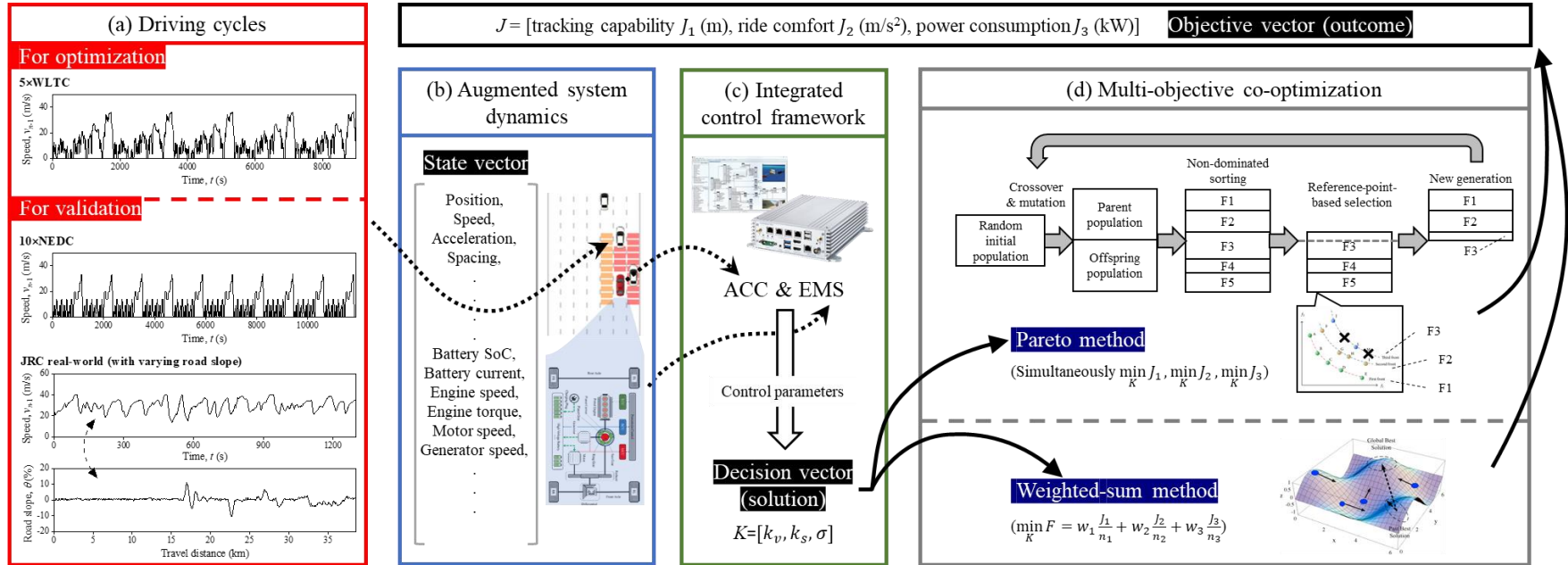
Yinglong He et al. Multiobjective component sizing of a hybrid ethanol-electric vehicle propulsion system. *Applied Energy*. 2020 May 15; 266:114843. (SCI, IF = 8.4, JCR Q1)



Contributions – Design optimization

CH. 4. Multi-objective co-optimization of ACC and EMS for AEVs

❖ Methodology



❖ Problem in math

$$\begin{cases} \min_K J_1 = \frac{1}{t_f - t_0} \int_{t_0}^{t_f} \|s_n(t) - s_{n,des}(t)\|_2 dt, \\ \min_K J_2 = \frac{1}{t_f - t_0} \int_{t_0}^{t_f} \|a_n(t)\|_2 dt, \\ \min_K J_3 = \frac{1}{1000 (t_f - t_0)} \left(\int_{t_0}^{t_f} \dot{m}_f(t) H_v dt + (SoC(t_f) - SoC(t_0)) Q_b U_b \right), \end{cases}$$

❖ Objective

To investigate the multi-objective co-optimization of the ACC and EMS control systems using the Pareto method.



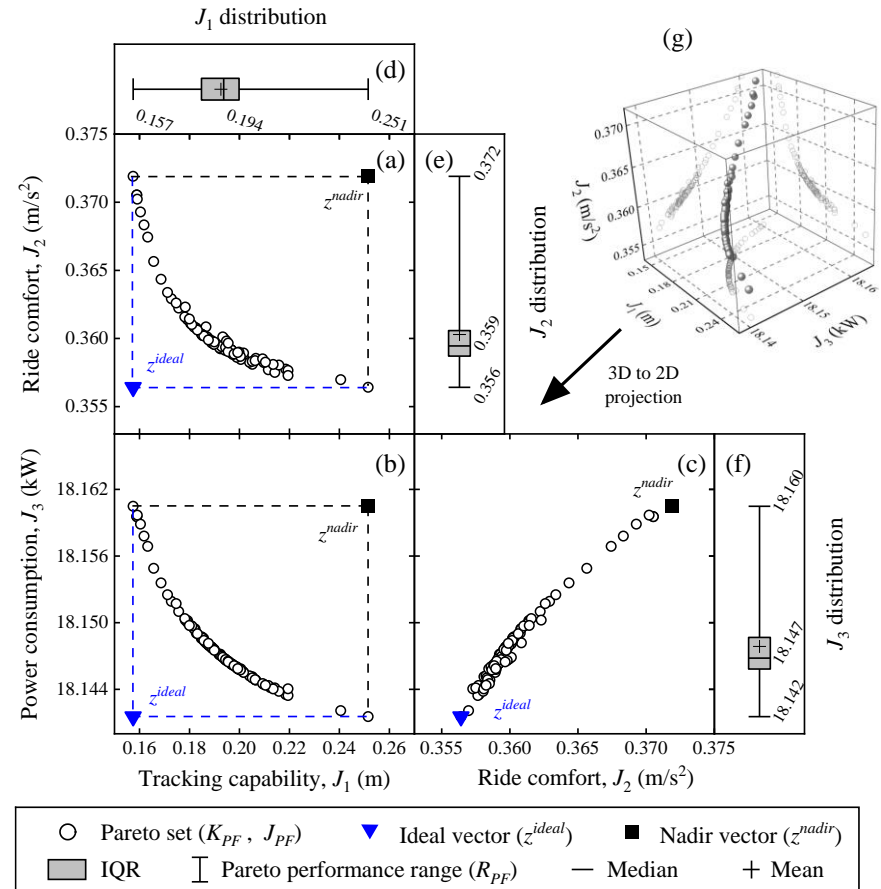
Contributions – Design optimization

❖ Main contributions

- The comparison between the Pareto and the scalarization methods reveal that the latter cannot determine the normalization factors that can optimally scale the objective functions if the high-level Pareto knowledge is unknown before the optimization begins.

❖ Main conclusions in this chapter

- The Pareto frontier suggests that the comfort and the energy targets are harmonious, but they both conflict with the safety target. Their objective values are measured on different scales.
- The Pareto optimum for ACC and EMS systems, relative to the baseline, can reduce energy consumption (by 7.57%) and tracking error (by 68.94%), while simultaneously satisfying ride comfort needs.
- Sensitivity analysis proves that the vehicle reaction time impacts significantly on tracking safety, but its effect on energy saving is trivial.



Yinglong He et al. Multiobjective co-optimization of cooperative adaptive cruise control and energy management strategy for PHEVs. IEEE Transactions on Transportation Electrification. 2020 Feb 17; 6(1):346-355. (SCI, IF = 5.4, JCR Q1)



Contributions – Behaviour modelling

CH. 5. Introducing EV dynamics into microscopic traffic models

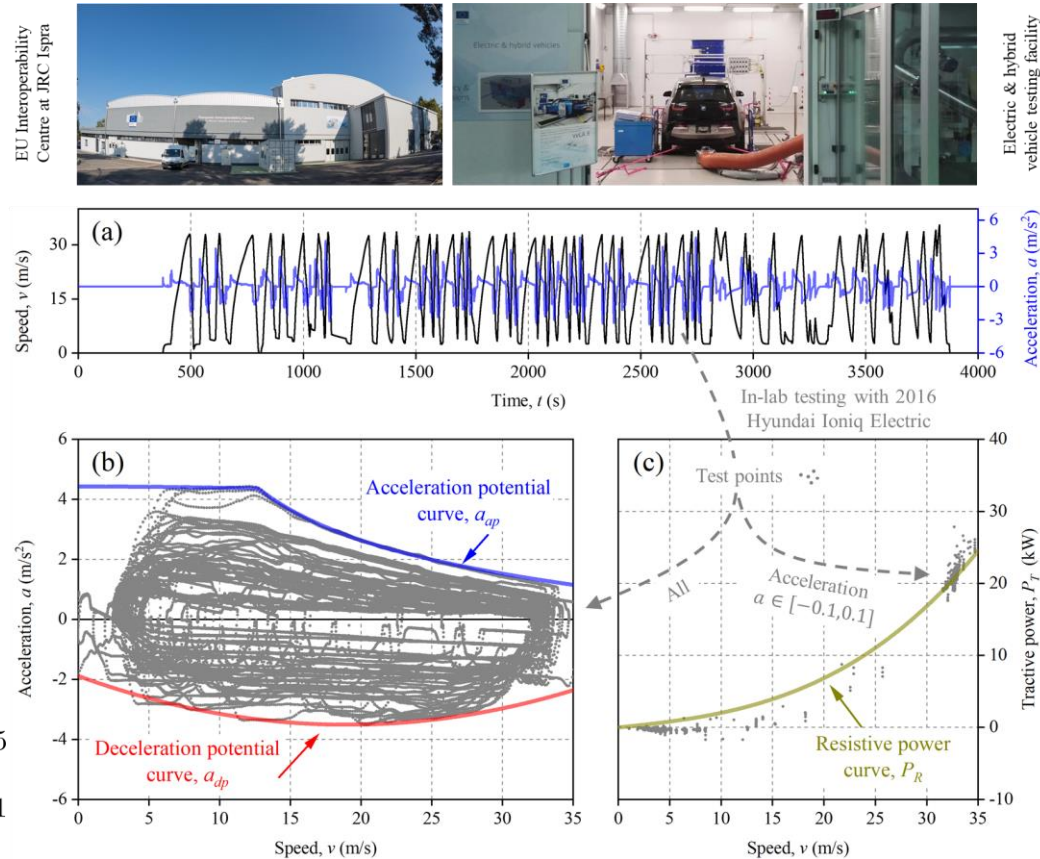
❖ Objective

To develop a free-flow driving behaviour model considering the dynamics of EVs.

❖ Methodology

- Acceleration potential curve (a_{ap})
- Deceleration potential curve (a_{dp})
- Driving behaviour function (a_n): Based on the driver's willingness to use the vehicle's full acceleration & deceleration potentials.

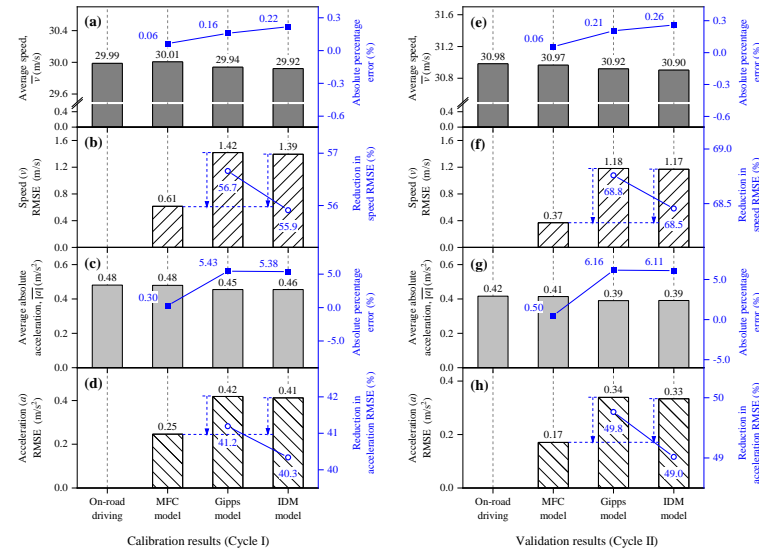
$$a_n(t) = \begin{cases} a_{ap}(v_n(t)) \cdot DS \cdot \left(1 - c_1 \cdot \left(1 - \frac{v_n(t)}{V_D(t)}\right)^{c_0}\right), & 0 \leq \frac{v_n(t)}{V_D(t)} < 0.5 \\ a_{ap}(v_n(t)) \cdot DS \cdot \left(1 - \left(1 + \frac{v_n(t) - V_D(t)}{c_3}\right)^{c_2}\right), & 0.5 \leq \frac{v_n(t)}{V_D(t)} < 1 \\ a_{dp}(v_n(t)) \cdot DS \cdot \left(1 - \left(1 - \frac{v_n(t) - V_D(t)}{c_3}\right)^{c_2}\right), & \frac{v_n(t)}{V_D(t)} \geq 1 \end{cases}$$



Yinglong He et al. Introducing electrified vehicle dynamics in traffic simulation. Transportation Research Record. 2020 Jul 7; 2674(9):776-791 (SCI, IF = 0.748, JCR Q4)



Contributions – Behaviour modelling

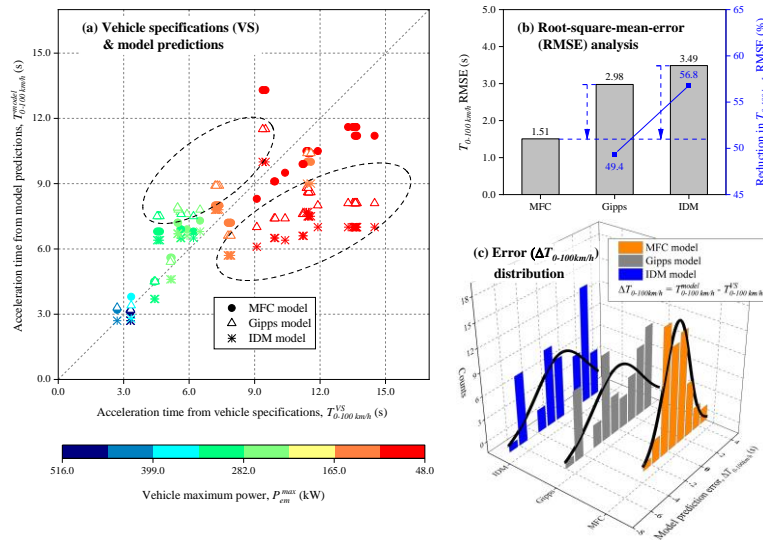


❖ Main contributions

- The model presented here is hitherto the only investigation to incorporate the dynamics of EVs into microscopic traffic simulation.

❖ Main conclusions in this chapter

- The acceleration and deceleration potential curves underlying the model can accurately capture the dynamics of the EV tested on the chassis dynamometer.
- In traffic simulation, the model can ensure a smooth transition between different acceleration and deceleration levels while avoiding obvious oscillations or overshoots when approaching the reference speed.
- When reproducing the on-road driving trajectories, the model can deliver significant reductions in RMSE of speed (by 69%) and acceleration (by 50%) compared with benchmarks.
- The model can accurately predict the vehicle 0-100 km/h acceleration specifications, where its RMSE is 49.4% and 56.8% lower than those of Gipps and IDM models, respectively.



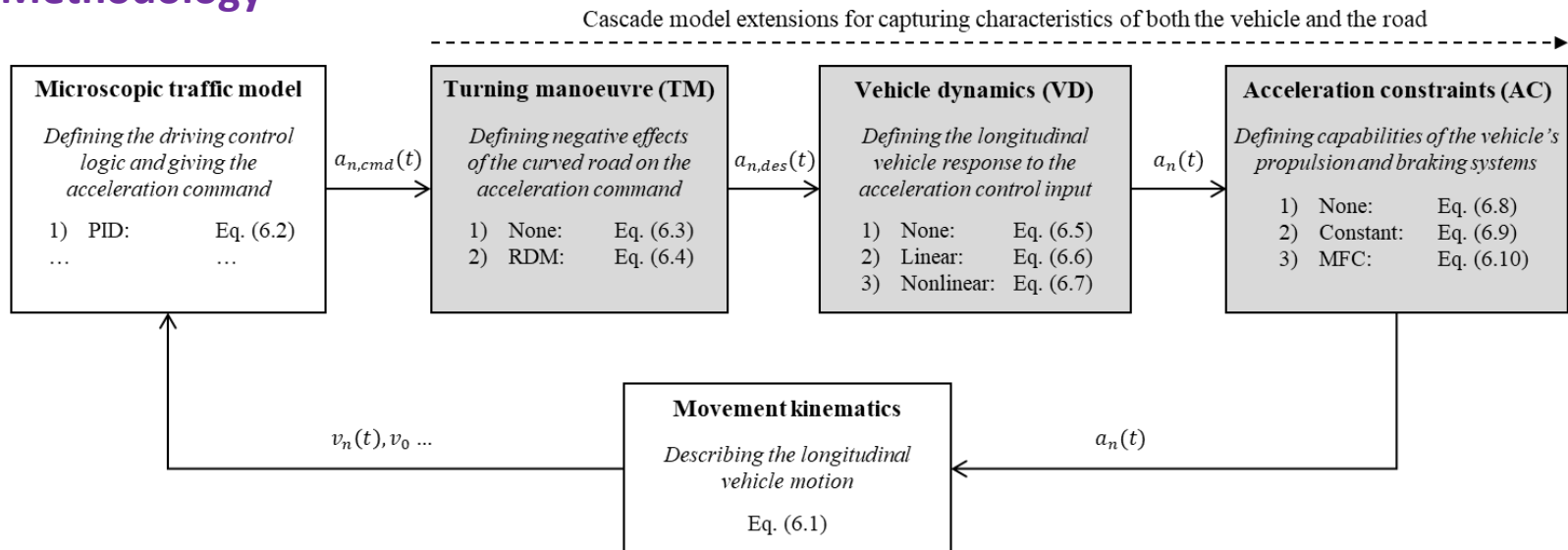
Contributions – Behaviour modelling

CH. 6. Introducing road geometry into microscopic traffic models for AVs

❖ Objective

To propose a generic approach to extend any of the (free-flow or car-following) microscopic traffic models characterized by acceleration functions.

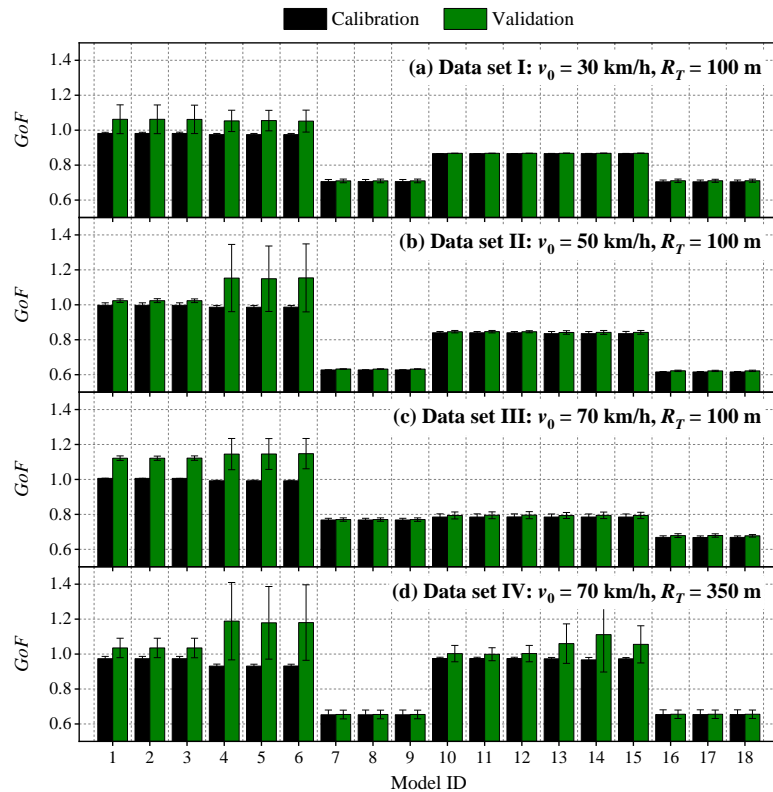
❖ Methodology



Yinglong He et al. Introducing the effects of road geometry into microscopic traffic models for automated vehicles. IEEE Transactions on Intelligent Transportation Systems. 2021. (Under Review)



Contributions – Behaviour modelling



Acceleration constraints (AC)	A	B	C	A	B	C	A	B	C	A	B	C	A	B	C	A	B	C
Vehicle dynamics (VD)	None, Eq. (6.5)			Linear, Eq. (6.6)			Nonlinear, Eq. (6.7)			None, Eq. (6.5)			Linear, Eq. (6.6)			Nonlinear, Eq. (6.7)		
Turning manoeuvre (TM)	None, Eq. (6.3)									RDM, Eq. (6.4)								

❖ Main contributions

- To propose a generic cascade approach to extend any of the (free-flow or car-following) microscopic models.
- To investigate all possible combinations of the basic microscopic model and the extensions, namely, the base model (ID = 1) and its extended variants (IDs = 2-18).
- To capture the effects of road geometry (i.e., slope and curvature) on the driving behaviour of automated vehicles (AVs).

❖ Main conclusions in this chapter

- Two submodels, i.e., the nonlinear vehicle dynamics (NVD) and the radius difference method (RDM), can extend the microscopic model to effectively capture the effects of road slope and road curvature, respectively, on automated driving.
- Specifically, the NVD is the dominant factor contributing to increasing (by 34.9% on average) model accuracy.
- When simulating reckless turning behaviours (i.e., the vehicle turns at high speeds), the inclusion of the developed RDM is significant for model performance, and the models extended with both the NVD and the RDM can achieve the largest accuracy gains (39.6%).



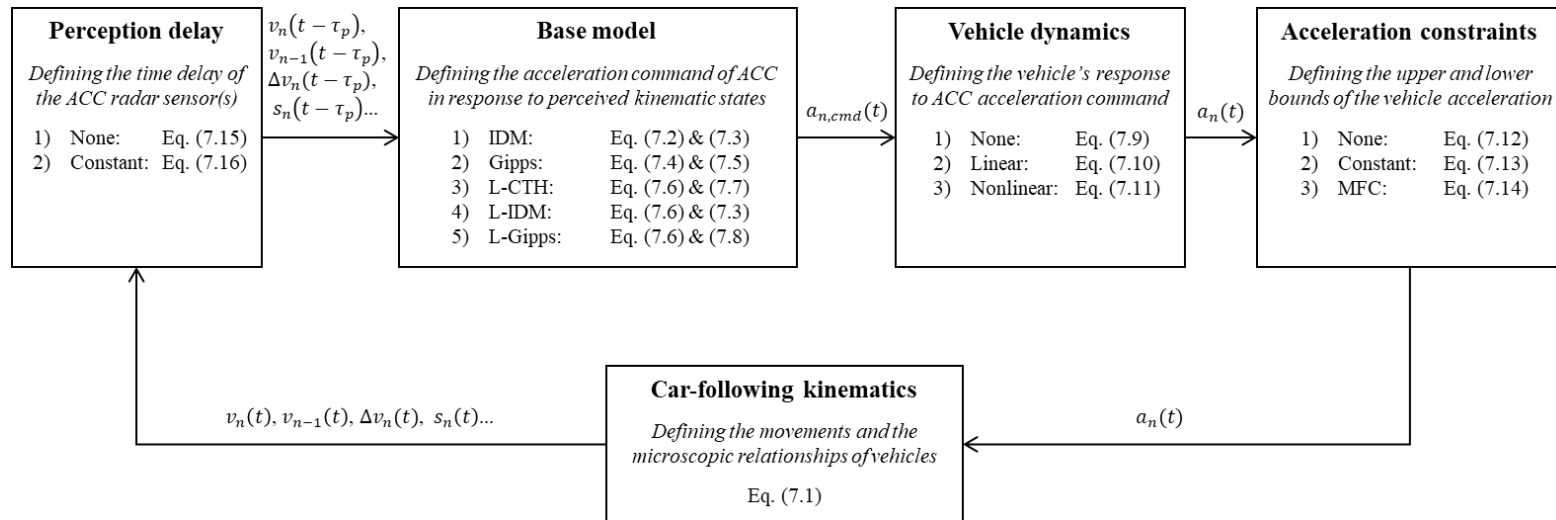
Contributions – Behaviour modelling

CH. 7. Physics-augmented models to simulate the behaviour of commercial ACC

❖ Objective

To develop a physics-augmented behaviour modelling framework that introduces mechanical features and controller designs of AVs into traffic flow theory.

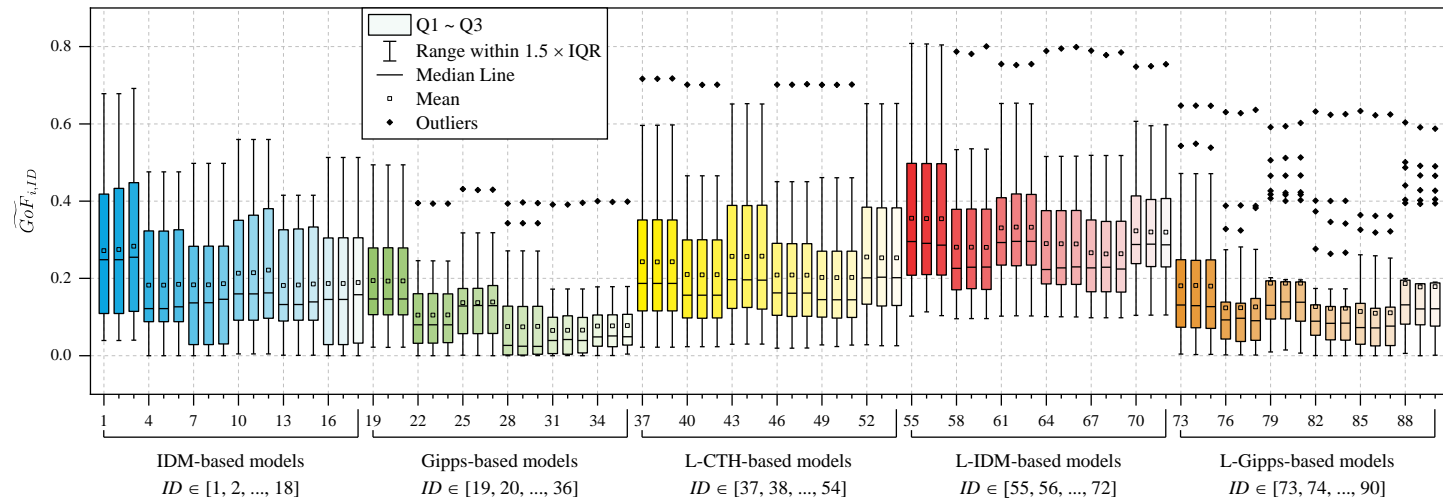
❖ Methodology



Yinglong He et al. Physics-augmented models to simulate commercial adaptive cruise control (ACC) systems. *Transportation Research Part C: Emerging Technologies*. 2021. (Under Review)



Contributions – Behaviour modelling



$$\widetilde{GoF}_{i,ID} = \frac{GoF_{i,ID} - GoF_{i,min}}{GoF_{i,min}} \quad \text{and} \quad GoF_{i,min} = \min_{ID=1,\dots,90} GoF_{i,ID}, \quad \text{for } i \in [1, \dots, 28] \text{ and } ID \in [1, \dots, 90]$$

❖ Main contributions

- To investigate the accuracy and robustness of car-following (CF) and adaptive cruise control (ACC) models used to simulate measured driving behaviour of commercial ACCs.
- To assess the contribution of each physical extension to the base model accuracy.

❖ Main conclusions in this chapter

- When a single extension has been applied, perception delay and linear vehicle dynamics have been the extensions to mostly increase modelling accuracy.
- Concerning models, Gipps-based ones have outperformed all other CF and ACC models in calibration.
- On the other hand, IDM-based models have been by far the most robust in validation, showing almost no crash when calibrated parameters have been used to simulate different trajectories.

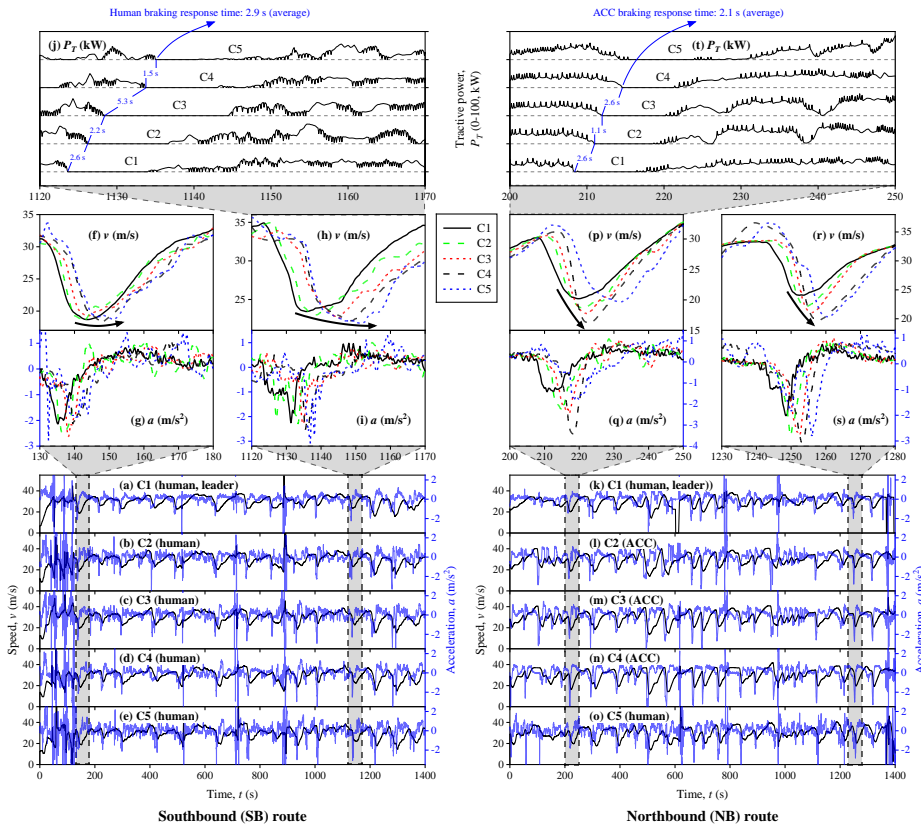


Contributions – Real-world assessment

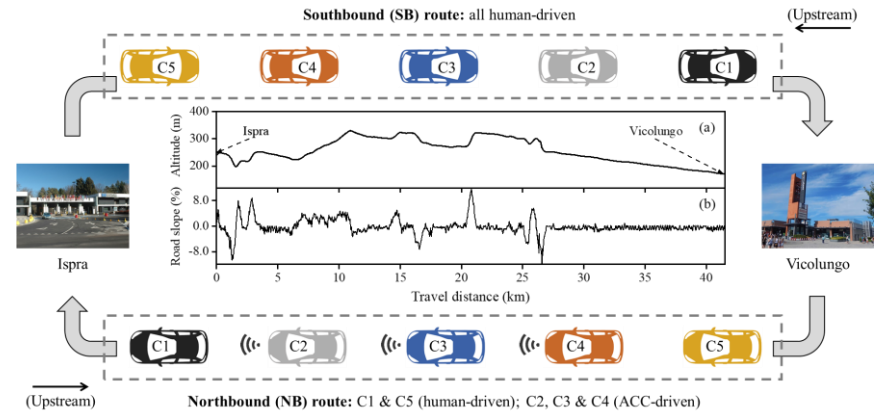
CH. 8. Energy and safety performances of ACC vehicles on public roads

❖ Objective

To compare energy and safety performances between ACC and human driving behaviours in platooning experiments on public roads.



❖ Methodology

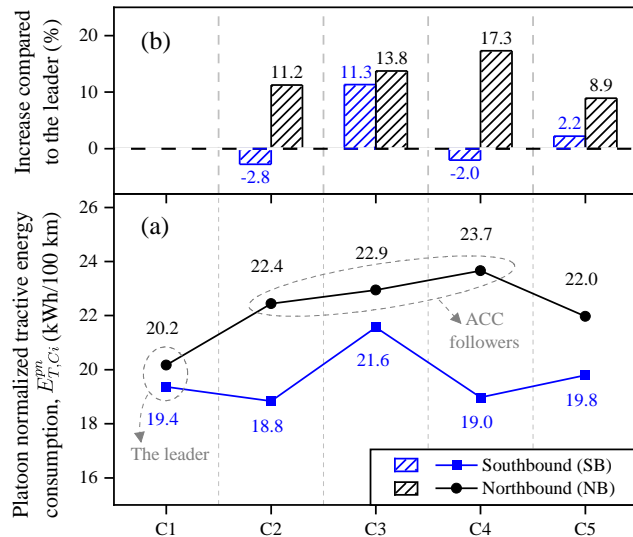
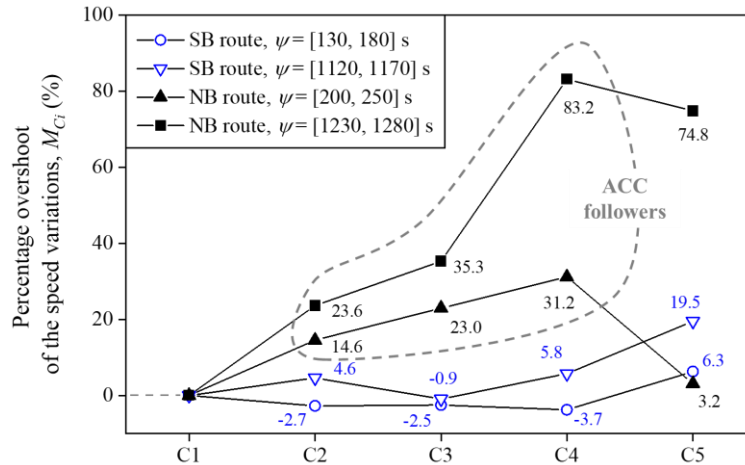


$$P_T(t) = \max \left[0, \left(f_0 \cdot \cos \theta + f_1 \cdot v_n(t) + f_2 \cdot v_n(t)^2 + mg \cdot \sin \theta + \phi m \cdot a_n(t) \right) \frac{v_n(t)}{1000} \right],$$

$$E_T = \frac{\int_0^{t_f} P_T(t) dt}{0.036 \cdot \int_0^{t_f} v_n(t) dt},$$



Contributions – Real-world assessment



❖ Main contributions

- To compare the driving behaviours between ACC systems and human drivers in real-world conditions.
- To reveal the energy impacts of commercial ACC systems.

❖ Main conclusions in this chapter

- Unlike human drivers, ACC followers lead to string instability. Their inability to absorb the speed overshoots may partly be explained by their high responsiveness.
- The tractive energy values of ACC followers tend to consecutively increase (by 11.2–17.3%).
- In general, therefore, existing commercial ACC systems have negative impacts on tractive energy efficiency.

Yinglong He et al. The energy impact of adaptive cruise control in real-world highway multiple-car-following scenarios. European Transport Research Review. 2020 Mar 24; 12(1):1-11. (SCI, IF = 1.727, JCR Q3)



Contributions – Real-world assessment

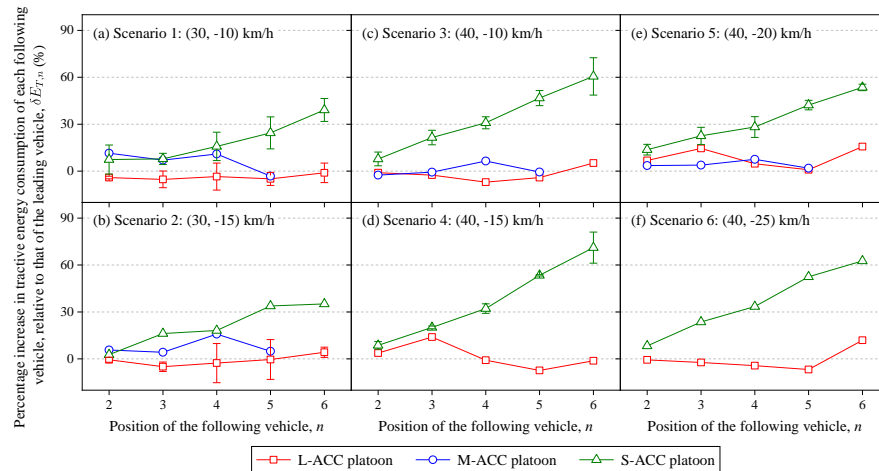
CH. 9. Energy impacts of time-gap settings on ACC vehicle platoons on test tracks

- ❖ **Objective** To investigate the impacts of different time-gap settings of commercial ACC systems on the energy consumption of vehicle platoons examined on test tracks.

Biagio Ciuffo et al. Requiem on the positive effects of commercial adaptive cruise control on motorway traffic and recommendations for future automated driving systems. Transportation Research Part C: Emerging Technologies. 2021 Sep 1; 130:103305. (SCI, IF = 8.1, JCR Q1)

- ❖ **Methodology**

- **S-ACC platoons:** The following vehicles are all controlled by ACC systems with a short time-gap setting.
- **M-ACC platoons:** The following vehicles are all driven by ACC systems with a medium time-gap setting.
- **L-ACC platoons:** The following vehicles are all regulated by ACC systems with a long time-gap setting.
- **SL-ACC platoons:** Two of the following vehicles are operated by ACC systems with a long time-gap setting, while the others utilize ACC systems with a short time-gap setting.

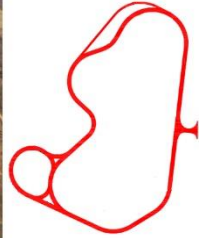
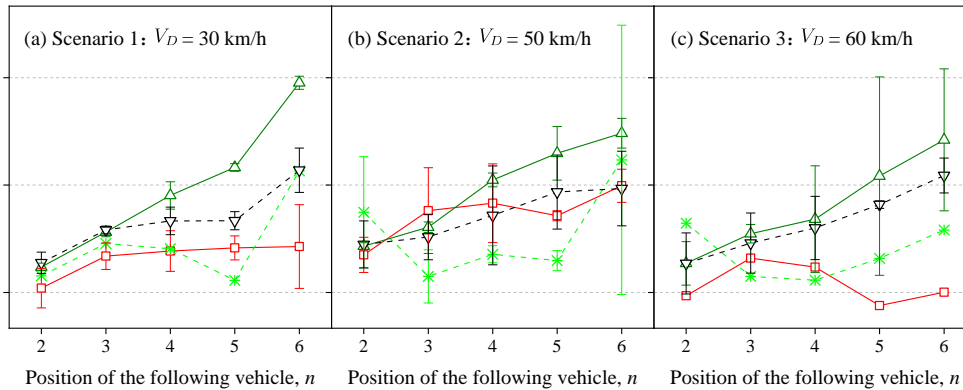


ZalaZone Dynamic Platform (DP)

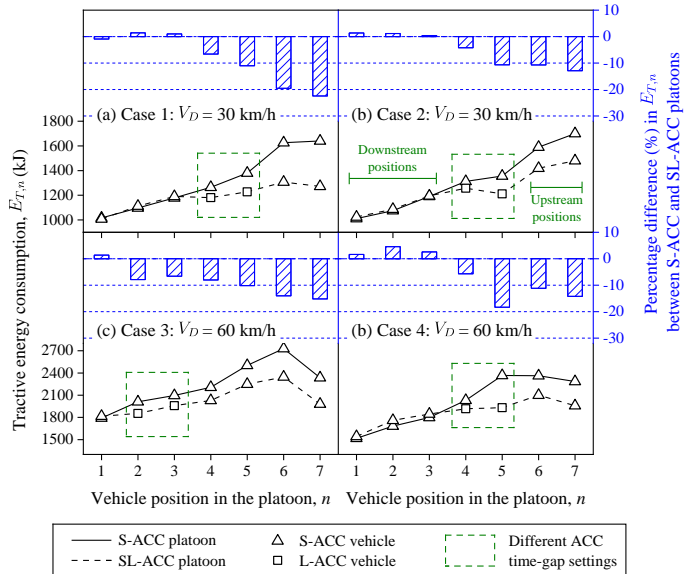


Contributions – Real-world assessment

Percentage increase in tractive energy consumption of each following vehicle, relative to that of the leading vehicle, $\delta E_{T,n}$ (%)



ZalaZone Handling Course (HC)



❖ Main contributions

- To systematically investigate the energy impacts of time-gap settings of commercial ACC systems in platooning experiments performed on test tracks.

❖ Main conclusions in this chapter

- On the ZalaZone DP, the following vehicles in S-ACC platoons lead to string instability, and therefore, increased tractive energy consumption, which are on average 18.9-37.1% greater than those of their platoon leaders.
- On the ZalaZone HC, the ACC long time-gap setting can contribute to reducing the energy consumption. Specifically, SL-ACC platoons can achieve overall fuel savings of 6.1-9.8% compared with S-ACC platoons.



Deliverables

➤ Journal articles

(10 papers published + 2 papers under review)

1. Yinglong He, Chongming Wang, Quan Zhou, Ji Li, Michail Makridis, Huw Williams, Guoxiang Lu, and Hongming Xu*. Multiobjective component sizing of a hybrid ethanol-electric vehicle propulsion system. *Applied Energy*. 2020 May 15; 266:114843. (SCI, IF = 8.4, JCR Q1)
2. Yinglong He, Quan Zhou, Michail Makridis, Konstantinos Mattas, Ji Li, Huw Williams, and Hongming Xu*. Multiobjective co-optimization of cooperative adaptive cruise control and energy management strategy for PHEVs. *IEEE Transactions on Transportation Electrification*. 2020 Feb 17; 6(1):346-355. (SCI, IF = 5.4, JCR Q1)
3. Yinglong He, Michail Makridis, Konstantinos Mattas, Georgios Fontaras, Biagio Ciuffo*, and Hongming Xu. Introducing electrified vehicle dynamics in traffic simulation. *Transportation Research Record*. 2020 Jul 7; 2674(9):776-791 (SCI, IF = 0.748, JCR Q4)
4. Yinglong He, Michail Makridis*, Georgios Fontaras, Konstantinos Mattas, Hongming Xu, and Biagio Ciuffo. The energy impact of adaptive cruise control in real-world highway multiple-car-following scenarios. *European Transport Research Review*. 2020 Mar 24; 12(1):1-11. (SCI, IF = 1.727, JCR Q3)
5. Yinglong He, Konstantinos Mattas, Riccardo Dona, Giovanni Albano, and Biagio Ciuffo*. Introducing the effects of road geometry into microscopic traffic models for automated vehicles. *IEEE Transactions on Intelligent Transportation Systems*. 2021. (Under Review)
6. Yinglong He, Marcello Montanino*, Konstantinos Mattas, Vincenzo Punzo, and Biagio Ciuffo. Physics-augmented models to simulate commercial adaptive cruise control (ACC) systems. *Transportation Research Part C: Emerging Technologies*. 2021. (Under Review)



Deliverables

7. Biagio Ciuffo, Konstantinos Mattas, Michail Makridis, Giovanni Albano, Aikaterini Anesiadou, Yinglong He, Szilard Josvai, Dimitris Komnos, Marton Pataki, Sandor Vass, and Zsolt Szalay*. Requiem on the positive effects of commercial adaptive cruise control on motorway traffic and recommendations for future automated driving systems. *Transportation Research Part C: Emerging Technologies*. 2021 Sep 1; 130:103305. (SCI, IF = 8.1, JCR Q1)
8. Bin Shuai, Quan Zhou*, Ji Li, Yinglong He, Ziyang Li, Huw Williams, Hongming Xu, and Shijin Shuai. Heuristic action execution for energy efficient charge-sustaining control of connected hybrid vehicles with model-free double Q-learning. *Applied Energy*. 2020 Jun 1; 267:114900. (SCI, IF = 8.4, JCR Q1)
9. Quan Zhou*, Yinglong He, Dezong Zhao, Ji Li, Yanfei Li, Huw Williams, and Hongming Xu*. Modified particle swarm optimization with chaotic attraction strategy for modular design of hybrid powertrains. *IEEE Transactions on Transportation Electrification*. 2020 Aug 7. (SCI, IF = 5.4, JCR Q1)
10. Ji Li, Quan Zhou, Yinglong He, Huw Williams, and Hongming Xu*. Driver-identified supervisory control system of hybrid electric vehicles based on spectrum-guided fuzzy feature extraction. *IEEE Transactions on Fuzzy Systems*. 2020 Feb 11; 28(11):2691-2701. (SCI, IF = 8.8, JCR Q1)
11. Quan Zhou, Ji Li, Bin Shuai, Huw Williams, Yinglong He, Ziyang Li, Hongming Xu*, and Fuwu Yan. Multi-step reinforcement learning for model-free predictive energy management of an electrified off-highway vehicle. *Applied Energy*. 2019 Dec 1; 255:113755. (SCI, IF = 8.426, JCR Q1)
12. Ji Li, Quan Zhou, Yinglong He, Bin Shuai, Ziyang Li, Huw Williams, and Hongming Xu*. Dual-loop online intelligent programming for driver-oriented predict energy management of plug-in hybrid electric vehicles. *Applied Energy*. 2019 Nov 1; 253:113617. (SCI, IF = 8.426, JCR Q1)



➤ Conference papers

1. Yinglong He, Biagio Ciuffo*, Quan Zhou, Michail Makridis, Konstantinos Mattas, Ji Li, Ziyang Li, Fuwu Yan, and Hongming Xu*. Adaptive cruise control strategies implemented on experimental vehicles: A review. *9th IFAC Symposium on Advances in Automotive Control (AAC)*. 23-27 Jun 2019. Orleans, France.
2. Yinglong He, Michail Makridis, Konstantinos Mattas, Georgios Fontaras, Biagio Ciuffo*, and Hongming Xu. Enhanced MFC: Introducing dynamics of electrified vehicles for free flow microsimulation modelling. *Transportation Research Board (TRB) 99th Annual Meeting*. 12-16 Jan 2020. Washington DC, USA.
3. Yinglong He, Michail Makridis*, Georgios Fontaras, Konstantinos Mattas, Hongming Xu, and Biagio Ciuffo. The impact of adaptive cruise control on tractive energy consumption in real-world highway multiple-car-following scenarios. *Proceedings of TRA2020, the 8th Transport Research Arena: Rethinking transport - towards clean and inclusive mobility*. 27–30 Apr 2020. Helsinki, Finland.
4. Quan Zhou, Ji Li, Yinglong He, Bin Shuai, Huw Williams, Hongming Xu*, Yanfei Li, and Fuwu Yan. K-fold fuzzy learning for implementation of dynamic programming results in real-time energy management of the plug-in hybrid vehicle. *Applied Energy Symposium 2020: Low Carbon Cities and Urban Energy Systems*. 10-17 Oct 2020, Tokyo, Japan (Online).



Deliverables

➤ Academic awards

1. 04/2020: **Best Research Paper** (the 1st author) of the 8th Transport Research Arena (TRA, the foremost European transport event). “Rethinking transport - towards clean and inclusive mobility”. Helsinki, Finland.
2. 03/2020: **Front Cover Paper** (the 1st author) of IEEE Transactions on Transportation Electrification (SCI, IF = 5.4, JCR Q1), Volume 6, Issue 1, 2020.
3. 01/2020: **Best Simulation Application Paper Award** (the 1st author), 99th Annual Meeting of Transportation Research Board (TRB, the world's largest transportation research conference). Washington DC, USA.
4. 06/2018: **Finalist**, “Chunhui Cup” Chinese Overseas Students Innovation and Entrepreneurship, China



Thank you!

