

Review on Key Techniques and Research Progress of Eco-driving Control for Connected and Automated Vehicles

Jie Li¹, Abbas Fotouhi², Yonggang Liu^{1*}, Yuanjian Zhang³, and Zheng Chen^{4*}

¹ = State Key Laboratory of Mechanical Transmissions & College of Mechanical and Vehicle Engineering, Chongqing University, 400044, Chongqing, China

² = Advanced Vehicle Engineering Centre, School of Aerospace, Transport and Manufacturing, Cranfield University, Cranfield, Bedfordshire, MK43 0AL, UK.

³ = Department of Aeronautical and Automotive Engineering, Loughborough University, Leicestershire, LE11 3TU, UK.

⁴ = Faculty of Transportation Engineering, Kunming University of Science and Technology, Kunming, 650500, China

* = Correspondence: andyliuyg@cqu.edu.cn (Liu, Y.) and chen@kust.edu.cn (Chen, Z.)

Abstract: With the development of connected and automated vehicles (CAVs) communication and automation technologies, the great energy-saving potential of CAVs has gradually been highlighted. With access to substantial surrounding information and automated control, CAVs can automatically plan ecological driving behaviours to significantly reduce energy consumption, which is normally defined as eco-driving. Currently, eco-driving is recognized as an effective method to improve energy economy of individual CAVs and promote the overall energy economy of transportation, without much hardware investment. To review the scattered eco-driving literature and promote the development of eco-driving, this study systematically reviews the state-of-the-art in this field. The basic principles of eco-driving and energy management systems are firstly discussed to figure out the relationship between eco-driving and powertrain control. Then, related eco-driving studies are classified into three categories according to their applications in terms of single-vehicle scenario, car-following operation, and multi-vehicle co-operation. The key characteristics of various eco-driving studies are in-depth addressed, and the energy-saving potential for cooperative eco-driving is further emphasized. Finally, the potential development trends are provided, thereby contributing to the development of eco-driving techniques.

Highlights:

- A comprehensive survey of eco-driving for connected and automated vehicles.
- The coupling relationship investigation of eco-driving and energy management.
- The energy-saving potential discussion of cooperative eco-driving.
- The potential development trends and research gaps of eco-driving.

Key words: Connected and automated vehicles, hybrid electric vehicles, eco-driving, energy economy, optimal control, velocity optimization, energy management strategy.

Word Count: 9918

Nomenclature:

Abbreviations

ACC	adaptive cruise control
CACC	cooperative adaptative cruise control
CAV	connected and automated vehicle
DDPG	deep deterministic policy gradient
DLFC	distributed linear feedback control
DP	dynamic programming
DRL	deep reinforcement learning
Eco-ACC	ecological adaptive cruise control
Eco-CACC	ecological cooperative adaptative cruise control
EMS	energy management strategy
EV	electric vehicle
HDV	human-driven vehicle
HEV	hybrid electric vehicle
HIL	hardware-in-the-loop
ICE	internal combustion engine
ICEV	internal combustion engine vehicle
IDM	intelligent driver model
IDP	iterative dynamic programming
LPS	Legendre pseudo-spectral
LSTM	long short-term memory
MCTS	Monte Carlo tree search
MPC	model predictive control
OCP	optimal control problem
PHEV	plug-in hybrid electric vehicle
PID	proportional-integral-derivative
PLF	predecessor-leader following
PMP	Pontryagin's minimum principle
RL	reinforcement learning
SOC	state of charge
SPaT	signal phase and timing of traffic light
V2V	vehicle-to-vehicle
V2X	vehicle-to-everything

Symbols

J_c	energy consumption cost of powertrain
u_c	control vector
x_c	state vector
a_v	longitudinal acceleration (m/s ²)
v	driving speed (m/s)
T_p	driving torque of powertrain (Nm)
i_p	gear ratio of powertrain
J_e	energy consumption of motion (kWh)
t	time (s)
s	distance (m)

s_f	total driving distance (m)
ρ	traffic density (veh/km)
q	traffic flow (veh/h)
v_w	effective traffic velocity (m/s)
$\rho_{\max}$	maximum traffic density (veh/km)
$q_{\max}$	maximum traffic flow (veh/h)
$\Delta\rho$	traffic density deviation(veh/km)
Δq	traffic flow deviation(veh/h)

1. INTRODUCTION

Due to the increasing concern about energy consumption and energy crisis, energy-saving technology in transportation has been persistently researched. Currently, the mainstream solutions to save energy saving promotion involve lightweight techniques, high-efficient internal combustion engine (ICE), transportation electrification, etc. [1-3]. Among these studies, energy-saving roadmaps can be primarily divided into two categories, i.e., hardware upgrade and optimization, as well as software improvement. Hardware upgrade includes, but are not limited to, more efficient ICE, lightweight technology, hybrid powertrain, fuel cell technologies, etc. Instead, software improvement typically indicates the controlling techniques with the incorporation of multiple channel information. For instance, hybrid electric vehicles (HEVs) and plug-in HEVs (PHEVs) are currently widely accepted solutions, due to preferable energy consumption economy. While, energy management strategies (EMS) in HEVs and PHEVs play a critical role in energy-saving performance promotion [4]. On the other hand, the rapid development of connected and automated vehicle (CAV) technologies is promoting advancements in different aspects of transportation, including driving safety, driving comfort, and high travel efficiency [5]. Energy saving performance is not mainly considered in the initial development stage of CAVs, however, with the gradual maturity of main targets (such as driving safety and travel efficiency), the energy saving control of CAVs is now recognised as a prospective opportunity. By absorbing abundant surrounding information via vehicle-to-everything (V2X) communications and locating the vehicle position, the energy-saving performance can be further promoted. Meanwhile, most newly sold CAVs have been equipped with Level 2 and higher autonomous driving capability, enabling speed planning and tracking to a great extent. In this context, the automation in speed planning and steering control provides an unprecedented opportunity to improve energy efficiency. As a result, energy-saving technologies of CAV have gradually become a prominent research focus which is typically referred to as eco-driving control [6]. It should be noted that, unlike the earlier eco-driving works for human-driven vehicles (HDVs), eco-driving for CAVs attempt to adaptively optimize driving behaviours [7] instead of drive's decisions [8].

Broadly speaking, energy-saving control technologies of CAVs encompass eco-driving control and EMSs, and some literature also integrate these two categories of approach into a single control problem [9]. Eco-driving control and EMS of CAVs have similar structure but exhibit notable differences. For the similar frameworks, they both leverage information from V2X technologies to improve energy economy. While the crucial difference is that eco-

1
2 driving control focuses on ecological velocity planning, and the latter concentrates on the optimization of powertrain
3 control. Moreover, on some occasions, the execution of eco-driving control normally combines with EMSs,
4 especially in connected PEHVs/HEVs. Thus, in this paper, we discuss the progress of eco-driving control and clearly
5 distinguish these two categories of energy-saving control method, in a most challenging target, i.e., PHEVs.
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11 Intuitively, the aim of eco-driving control is to optimize velocity profile to reduce energy consumption while
12 satisfying complex constraints imposed by vehicle dynamics, driving safety, driving comfort, etc. Meanwhile, eco-
13 driving control methods can be divided into three major categories according to the implementation scenarios,
14 including single-vehicle, car-following and multi-vehicle eco-driving control. In different scenarios, the constraints
15 of eco-driving control are caused by various elements of driving environment and the host vehicle. In single-vehicle
16 scenarios, velocity profile of the host vehicle are typically optimized with the consideration of complex conditions,
17 traffic lights and powertrain systems [10]. The driving speed is planned for the whole driving trip, so as to promote
18 the energy economy of the host vehicle. Moreover, optimization-based methods are widely exploited to optimize
19 the driving speed, and common solutions include dynamic programming (DP), Pontryagin's minimum principle
20 (PMP), model predictive control (MPC) and Legendre pseudo-spectral (LPS) method [11]. Meanwhile, the eco-
21 driving control in car-following scenarios is relatively standardized, in which the driving speed of the host vehicle
22 is optimized to follow that of the preceding vehicle and reduce energy consumption simultaneously [12]. That
23 scenario is typically carried out under congested urban road conditions. While the ultimate optimization target of
24 the first two kinds of eco-driving control still aims at improving the energy economy of single vehicle. By contrast,
25 eco-driving control in multi-vehicle scenarios extends the control target from controlling optimization of single
26 vehicle to that of multiple vehicles, and the optimization objective is generally defined as the overall energy
27 economy of all the engaged vehicles [13]. In this case, multiple CAVs can share information, including driving
28 intentions, driving status, etc., to cooperatively optimize the synchronous motion, and finally achieve an overall
29 energy economy improvement.
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53 Over the past decade, substantial studies have been conducted on research of eco-driving control, and some
54 related literature reviews in terms of energy saving techniques have emerged [14, 15]. However, to the best of the
55 authors' knowledge, there is still a lack of specialized and in-depth reviews on eco-driving, especially when
56 considering energy management in PHEVs/HEVs. The reason is that there have been a variety of energy-saving
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technologies of CAVs, which are developed recently, including eco-driving, eco-routing and EMS of CAVs, and from the control perspective of view, these approaches exhibit similar and overlapped structures. Hence, in most literature reviews, eco-driving control is typically fused with other energy-saving techniques of CAVs, such as EMSs of CAVs. Additionally, it has been observed that only a few studies have recognized the significant potential for energy-saving through cooperative eco-driving across multiple vehicles. Most of existing studies with respect to coordination driving concentrate on improvement of safety, traffic efficiency and string stability. To foster an in-depth understanding of eco-driving control, this study summarizes the state-of-the-art eco-driving techniques in terms of principle, single-vehicle, car-following and multi-vehicle scenarios. The relationship and collaboration between eco-driving control and EMSs are addressed. Then, the studies of eco-driving control are classified into three scenarios to introduce. Finally, the potential developing trends and research directions are discussed.

The remainder of this article is structured as follow: Section 2 elaborates the principle of eco-driving control, and the relationship between eco-driving and EMSs for CAVs is discussed. In Section 3, the eco-driving control approaches in single-vehicle scenarios are introduced. Vehicle-following eco-driving methods are elaborated in Section 4. The progress of multi-vehicle eco-driving is illustrated in Section 5, and potential research trends are discussed in Section 6. Finally, the main conclusions are presented in Section 7.

2. PRINCIPLE AND DIFFERENCES OF ECO-DRIVING CONTROL AND ENERGY MANAGEMENT

The primary aim of eco-driving control for CAVs is to optimize velocity profile for energy-saving in different scenarios. On the other hand, the objective of EMSs in PHEVs/HEVs is to achieve lower energy consumption of powertrain while fulfilling power demands of the vehicle. Previous studies have investigated the fundamentals of eco-driving control based on the Newton's second law [15], in which the energy lost generated by aerodynamic drag is verified as the only term that can be optimized by speed planning. Consequently, most studies for eco-driving control attempt to plan velocity to reduce the motion energy consumption [16]. When it comes to driving vehicles, the energy consumption of vehicles mainly consists of two parts: "wheel-to-distance" and "tank-to-wheel" [17]. The first part represents the energy consumption to fulfil the kinetic energy requirement of motion, and the other one indicates the energy consumption of the powertrain system. Moreover, these two types of energy consumption are strongly coupled, leading to indispensable fusion of eco-driving control and EMSs in some situations. Therefore,

before elaborating the state-of-the-art of the eco-driving control in different scenarios, it is imperative to have a deep analysis of distinction and relationship between eco-driving control and EMSs.

To comprehensively analyse the differences between eco-driving control and EMS, the structure of an energy-saving control system of CAVs is illustrated in Fig. 1, wherein the whole structure can be divided into three layers. The first layer accounts for accessing to driving environment information which can be realized by V2X communication, sensors, etc. This layer dose not has remarkable difference between the eco-driving or EMS systems. Plenty of information are delivered to CAVs under different the driving scenarios, such as speed limits, surrounding vehicles' states and route information [18, 19]. The second layer is responsible for control of the driving speed. This layer mainly encompasses with two categories: full driver control and eco-driving control, due to different autonomous driving levels. When the driving speed is partially determined by driver, the energy-saving control system cannot accurately anticipate the whole velocity profiles of CAVs, and only an instantaneous desired speed value can be obtained. Under level 3 or higher autonomous driving, the driving speed can be automatedly planned by CAVs according to the surrounding driving environment information, which is the so-called eco-driving control technique. To conclude, the second layer generates desired the velocity profile, and the eco-driving control is mainly executed in this layer.

The final layer takes charge of the control of the powertrain system, which outputs a driving torque to fulfil the required power of the desired driving speed. In this layer, the EMS is employed to optimize powertrain control and meanwhile reduce energy consumption. Since the required power is mainly determined by driving speed and road grade, the whole velocity profiles impose significant effect on EMSs in the third layer. For the pure EMSs of CAVs, the whole velocity profiles cannot be obtained directly, which is also the challenging in this field. Hence, an efficient velocity prediction algorithm is normally employed to predict future velocity profiles considering the influence of driving environment information and drivers [20]. By contrast, the EMSs integrated with eco-driving control system can determine or acquire the whole velocity profiles and preferably optimize the powertrain control.

Despite the same aim, i.e., energy-saving of “tank-to-wheel”, it can be found that eco-driving control focus on velocity optimization, whereas EMSs concentrate on powertrain control optimization. In fact, these two categories of techniques mainly operate at different layers in an energy-saving control system. However, in some cases, eco-driving control and EMSs can be integrated to obtain the optimal energy-saving performance [21],

whereas two critical technical problems need to be tackled, including (i) the situations that need to fuse eco-driving control and EMS, and (ii) the methods of integration of eco-driving control and EMS.

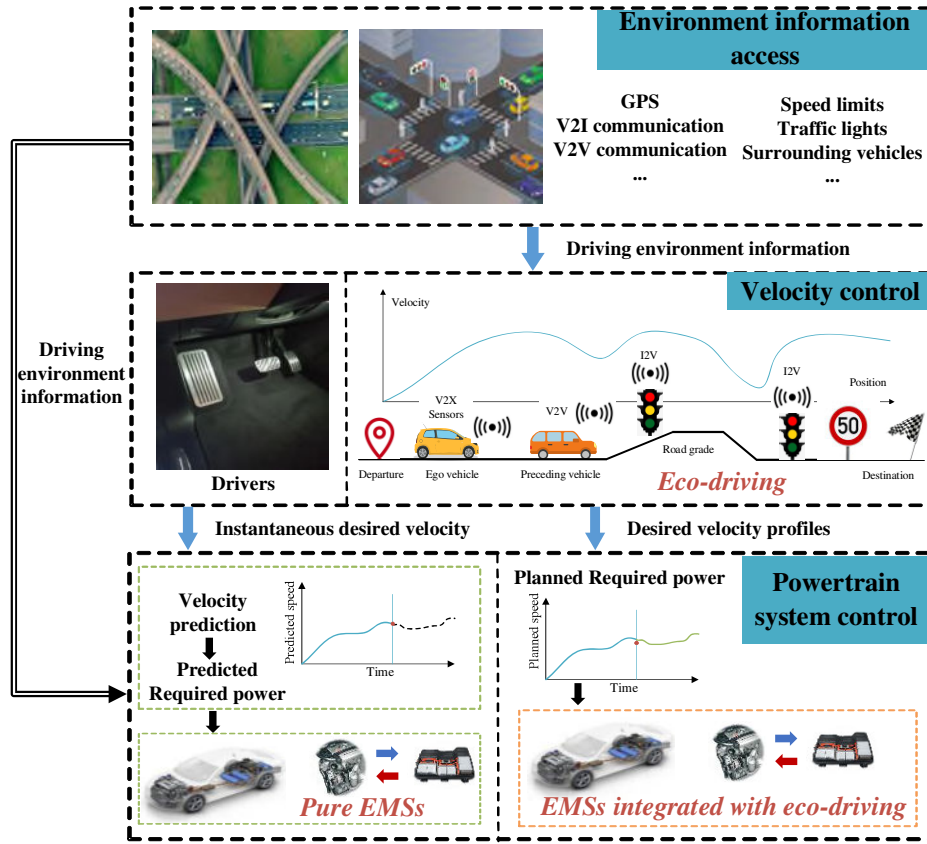


Fig. 1. The structure of energy-saving control system for CAVs.

For the situations that need cooperation between eco-driving control and EMS, the key consideration is whether the “tank-to-wheel” energy efficiency can be directly improved via velocity planning and vehicle motion model. As introduced above, the “tank-to-wheel” energy consumption is determined by powertrain control and driving speed. Therefore, in powertrain system with single power source and fix transmission ratio, a specific speed value corresponds with one unique powertrain energy consumption. The eco-driving control can directly optimize powertrain energy consumption via velocity planning, and only the vehicle motion model is developed in the optimal control problem (OCP) of eco-driving. By contrast, for a more complicated powertrain system, such as a hybrid system, a driving speed value yields various powertrain energy consumption values depending on the control decisions of different EMSs. Moreover, the ecological velocity and the optimal EMS are strongly coupled, bringing difficulty in separately solving the OCPs of eco-driving and EMS. Hence, both the vehicle motion model and the powertrain model should be developed in the OCP of eco-driving, thereby integrating the characteristics of the

powertrain system into eco-driving. The coupling relationship of eco-driving and EMS has been comprehensively analysed in [22], and the schematic of the OCPs for eco-driving and EMS is shown in Fig 2. It can be found that the car motion model and the powertrain model are employed in traditional eco-driving approaches and EMSs, respectively, whereas for the co-optimization of eco-driving and EMS, both the two models should be integrated into one OCP.

Taking the eco-driving control of a HEV, which is equipped with a parallel powertrain configuration and an automatic transmission, as an example, the OCPs of eco-driving are compared in terms of being incorporated with EMS and non-incorporated with EMS. For the OCP of eco-driving incorporating with EMS, the powertrain energy consumption cost is set as the objective function, and the optimal control problem can be formulated as:

$$J_c = \int_0^{s_f} \frac{dcost_{energy}(u_c, x_c)}{v(s)} ds \quad (1)$$

$$u_c = [a_v, T_p, i_p]^T \quad (2)$$

$$x_c = [v, t, SOC]^T \quad (3)$$

where J_c represents the objective function, u_c is the control vector, x_c is the state vector, a_v denotes the longitudinal acceleration of vehicle, T_p means the driving torque of powertrain, i_p is the gear ratio of powertrain. While, for the OCP of traditional eco-driving without incorporating EMS, the motion energy consumption is defined as the objective function for velocity optimization, as:

$$J_e = \int_0^{s_f} (F_v(u_s, x_s) \cdot v(s)) ds \quad (4)$$

$$u_e = a_v \quad (5)$$

$$x_e = [v, t]^T \quad (6)$$

where J_e indicates the objective function, u_e and x_e are the control vector and state vector. Apparently, compared with traditional eco-driving, the co-optimization of eco-driving and EMS integrates all control and state variables of vehicle and powertrain in one OCP, thereby achieving optimal performance in energy economy. By contrast, the traditional eco-driving technique can merely achieve a sub-optimal ecological velocity profile without considering the characteristics of powertrain. In this case, the EMS optimizes the powertrain control under a sub-optimal driving

speed, and consequently, the optimal energy economy cannot be reached without incorporating the EMS.

In summary, the OCPs of eco-driving are formulated, which are executed in terms of cooperating and non-cooperating with EMS, to illustrate the coupling relationship of eco-driving and EMS. It is critical for eco-driving control to cooperate with EMSs in a complicated powertrain system, thereby contributing to the optimality solving of energy-saving performance. Some classical schemes to integrate eco-driving and EMS, including sequential optimization, co-optimization and data-driven based methods EMSs, are normally implemented to integrate eco-driving control, and these approaches are elaborated in Section 3.

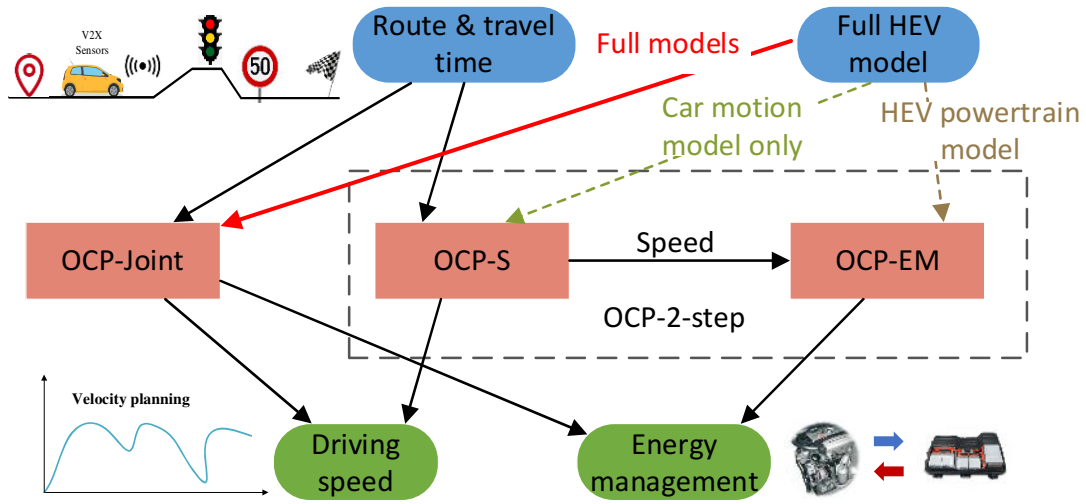


Fig. 2. A schematic of the relationships in an OCP for eco-driving and EMS. Reproduced from [22].

3. ECO-DRIVING CONTROL IN SINGLE-VEHICLE SCENARIOS

Prior knowledge of different driving conditions can be leveraged to plan velocity profiles to promote energy efficiency. Eco-driving control in single-vehicle scenarios enables to promote energy efficiency for CAVs benefiting from accessing to substantial information and realizing more precise automation control. As shown in Fig 3, in the single-vehicle scenario, the host vehicle will optimize the driving speed subject to different constraints in complicated driving conditions while reducing energy consumption. To clarify the latest eco-driving control in this field, the eco-driving control is classified based on some key considerations, including the powertrain characteristics, signal phase and timing (SPaT) information and road states, and each group of eco-driving is then comprehensively elaborated.

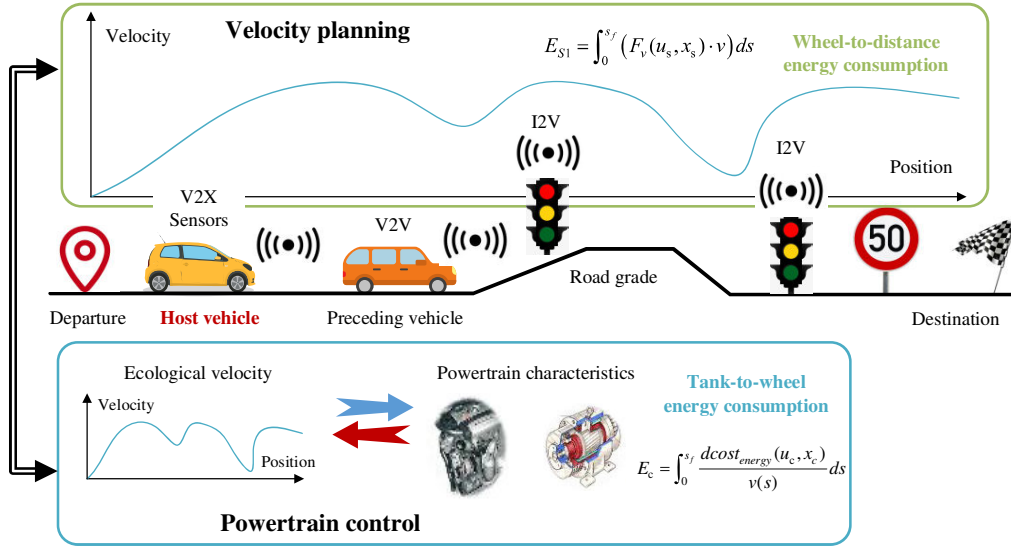


Fig. 3. The schematic of the eco-driving in single-vehicle scenarios

3.1. Eco-Driving Control Considering Powertrain Systems

As previously discussed, it is necessary to integrate the eco-driving control with the EMS when the energy efficiency of the powertrain system cannot be directly improved based on velocity optimization and vehicle motion model. In particular, hybrid powertrain systems are the most common scenarios in which the eco-driving should be developed by considering the different characteristics of powertrain. The reason lies in that hybrid systems generate more degrees of freedom, e.g., power-split ratio and battery state-of-charge (SOC), in the OCP of eco-driving [23]. Generally, the eco-driving approaches by considering powertrain systems have been studied in three manners, including sequential optimization, co-optimization and data-driven based schemes.

Sequential optimization approaches have been widely leveraged to solve the OCP of eco-driving for PEHVs/HEVs. These approaches are typically executed in a step-by-step manner, and the OCPs of eco-driving are decomposed into two subsequent procedures, i.e., velocity optimization and EMS [24]. In the velocity optimization part, the velocity profile is optimized to reduce energy consumption. For PHEVs/HEVs, the fuel consumption cannot be directly calculated according to the driving states (including driving speed, acceleration and SOC), due to the existence of multiple degrees of freedoms in powertrain. Hence, the kinetic energy consumption of wheels is usually defined as the objective function [25]. In the second step, the powertrain control is optimized, which is mainly achieved via EMSs and gear shifting optimization, based on the velocity profiles generated in the first step. Accordingly, the energy consumption of powertrain can be defined as the objective function. In [26], a bi-level eco-

driving approach is designed for fuel cell HEVs, the required kinetic energy of wheels is defined as the cost function for speed optimization. Additionally, the energy consumption can also be set as the cost function for speed optimization. In this occasion, the EMS in the second step should be predesigned to eliminate the freedom of powertrain. For instance, Wang *et al.* [27] investigated a bi-level eco-driving scheme based on MPC, in which a predesigned EMS is employed to estimate the energy consumption of powertrain for speed optimization. Obviously, the ideal decoupling of eco-driving and EMS can remarkably reduce computational burden. However, the ecological velocity and the optimal EMS strongly interact with each other. Consequently, it has been verified that the global optimal energy economy in the whole trip cannot be achieved by simple sequential methods [22, 28].

To further promote the energy-saving performance, some studies attempt to develop co-optimization eco-driving, which optimizes the driving speed by integrating energy efficiency of the powertrain. Among these studies, the most intuitional method is to optimize driving speed and EMS simultaneously. Kim *et al.* [28] designed a co-optimization eco-driving method to optimize speed trajectories and EMS for a fuel-cell PHEV using the DP algorithm, wherein all state variables and control variables of eco-driving and EMS are integrated into an OCP. Similarly, a co-optimization strategy is designed for connected PHEVs by using an iterative DP (IDP) algorithm [29]. Despite the preferable optimality in energy-saving performance, traditional co-optimization methods are not pragmatic for implementation, as the huge computational burden is intractable to address in online controllers. To balance the optimality and computational efficiency, recently, more studies attempt to realize co-optimization in a hierarchical way [30]. In [31], the working principles of sequential optimization and co-optimization are analysed, as shown in Fig. 4. To promote the energy-saving performance, a data-driven energy consumption model of PEHV is developed to integrate energy consumption of powertrain into the OCP of velocity planning. Chen *et al.* [32] investigated a two-step eco-driving method, which incorporates the characteristics of HEV powertrain into the speed optimization step without an explicit use of a powertrain model. Wei *et al.* [33] designed a constant-speed hydrogen consumption model of fuel-cell HEV, so that the eco-driving approach can estimate hydrogen consumption of powertrain while planning ecological velocity. To conclude, the key consideration to balance the optimality and the computational efficiency is to develop a hierarchical framework and incorporate the characteristics of powertrain into the speed optimization step [34]. In addition, to the applications in PEHVs/HEVs, it has been verified that

integrating the characteristics of powertrain into speed optimization step of electric vehicles (EVs) also shows superiority in energy economy improvement [35].

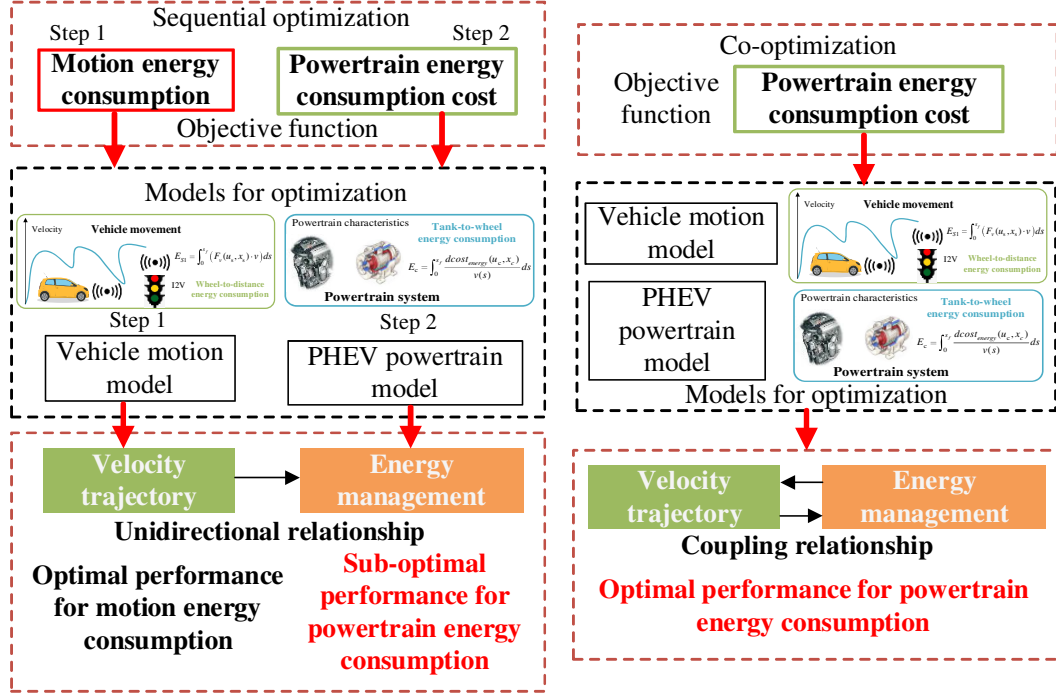


Fig. 4. The principal comparison of two eco-driving approaches for PHEVs, including sequential optimization and co-optimization. Reproduced from [31].

To summarize, integration of characteristics of the powertrain into eco-driving has been certificated to bring notable improvement in energy-saving performance. To balance the optimality and computational efficiency, most studies tend to achieve co-optimization eco-driving in a hierarchical framework, in which the characteristics of powertrain are involved in the speed optimization.

3.2. Eco-Driving Control Considering Traffic Lights

In urban driving scenarios, traffic lights are one of the major factors affecting the velocity profiles of vehicles. The unnecessary accelerations/decelerations and stops before traffic lights may seriously deteriorate energy economy and driving comfort of vehicles. With the help of V2X technology, the anticipation of SPaT information can help CAVs reasonably plan driving speed before approaching traffic lights, thereby significantly reducing energy consumption. A great number of eco-driving approaches have been investigated considering the effect of traffic light [36, 37]. The main aim of eco-driving control at signalized intersections is to avoid unnecessary speed fluctuations before traffic lights, thereby reducing energy consumption.

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3 Earlier eco-driving studies have designed some logical rules which calculate a constant speed to pass traffic
4 lights according to the SPaT information [38]. However, a constant speed is not practical and might lead to some
5 errors in real driving scenarios. Some studies decompose the optimal speed trajectory at intersections into several
6 motion stages, thereby approximating the optimal velocity profiles in a computationally efficient way. Lin *et al.* [39]
7 analysed the optimal ecological velocity to pass signalized intersections, and two- or three-stage operation rules are
8 proposed to approximate the optimal speed trajectory. Furthermore, the eco-driving control at signalized
9 intersections can be defined as a OCP and solved by optimization algorithms. Sun *et al.* [40, 41]. proposed an
10 optimal eco-driving control strategy for CAVs at multiple signalized intersections, wherein the optimal speed is
11 solved by DP incorporating the effect of uncertain signal timing. In [33], a bi-level DP method is introduced to solve
12 the speed planning problem online among multiple signalized intersections in a computationally efficient manner.
13 However, optimization-based methods normally lead to high computational burden in complex OCPs. With the
14 development of machine learning technique, reinforcement learning (RL) method has been gradually employed in
15 the eco-driving control at signalized intersections [42]. Liu *et al.* [43] designed a variable light spacing and
16 trigonometric signal model to train a deep reinforcement learning (DRL) controller, which is designed to enhance
17 the adaptability and energy economy in multi-light scenarios. Wegener *et al.* [44] designed a DRL-based eco-driving
18 controller which takes into account both preceding vehicles and SPaT information in urban scenarios. Furthermore,
19 in [45], potential-based shaping functions are employed to mitigate the difficulty of training the DRL-based
20 controller, finally promoting the performance of eco-driving.

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22 However, most previous approaches do not consider the influence of traffic uncertainty, such as waiting queues
23 and slow traffic flows, which might deteriorate speed planning performance. This problem can be mitigated by
24 simple mode-switching rules, in which the host vehicle typically switches to car-following mode or emergency
25 braking modes when approaching the waiting queues or preceding vehicles [34]. For instance, Bai *et al.* [46]
26 developed a hybrid RL-based eco-driving strategy which consists of three modes, including SPaT-oriented mode,
27 car-following-oriented mode and emergency braking mode. Despite the preferable performance of adaptability in
28 urban scenarios, this type of method cannot avoid unnecessary idling and speed fluctuations at signalized
29 intersections. To further promote the energy efficiency of eco-driving, some studies predict the potential influence
30 of waiting queue so as to avoid unnecessary idling. Dong *et al.* [47] investigated an improved queue discharge

prediction method considering both vehicle and driver dynamics. Based on the prediction of waiting queue, a hierarchical eco-driving strategy is then proposed combining DP and MPC. In [48], a vehicle queue predictor is designed based on intelligent driver model (IDM), and the influence of waiting queue is transferred to the constraints in the OCP of eco-driving which is following solved by IDP. The improvement of the proposed method is verified, compared with the conventional eco-driving strategies for both EVs and internal combustion engine vehicles (ICEVs). Recently, traffic flow models based on shock-wave theory are gradually implemented in the prediction of waiting queue. Yang *et al.* [49] constructed a waiting queue predictor based on shockwave theory, and the velocity profiles subject to the constraints of queue are optimized. Dong *et al.* [50] proposed the concept of virtual traffic light by combining shockwave theory and queue estimation, and a velocity OCP is formulated to treat the constraints from virtual traffic lights. To further promote the accuracy of the queue predictions, Sun *et al.* [51] employed a long short-term memory (LSTM) neural network to predict traffic flow. The waiting queue prediction is then obtained by combining shockwave theory and traffic flow prediction. The mathematical formulations of classical traffic flow model are presented, as:

$$\begin{cases} \frac{\partial \rho(d,t)}{\partial t} + \frac{\partial q(d,t)}{\partial d} = 0 \\ v_w = \frac{\Delta q}{\Delta \rho} \end{cases} \quad (7)$$

where $\rho(d,t)$ and $q(d,t)$ represent the traffic density and flow at position d and time t , respectively. The parameter v_w is the effective velocity of a shockwave, whereas $\Delta \rho$ and Δq indicate the changes of traffic density and flow between different regions. This model assumes that there exists a relationship between traffic flow and traffic density, as shown in Fig. 5. It can be found that with the increase in traffic density, there is a corresponding growth in traffic flow until it reaches its maximum capacity. However, after reaching this peak point, traffic flow decreases as traffic density continues to increase. At the point of maximum traffic density, it is assumed that a waiting queue will be formed. This model can be leveraged to predict the forming and dissipating of waiting queue at intersections.

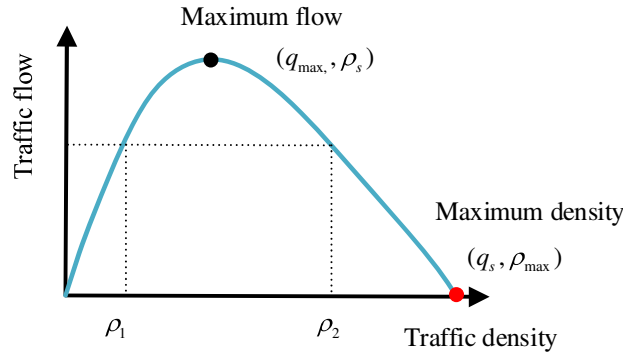


Fig. 5. The flow-density diagram for the LWR model.

To conclude, the energy-saving performance of eco-driving at signalized intersections is adequately justified.

The ecological velocity is optimized considering the influence of SPaT or waiting queues so as to minimize energy consumption and avoid unnecessary energy consumption. The influence of waiting queue has gained more attention, contributing to the adaptability promotion of eco-driving in real-world.

3.3. Eco-Driving Control Considering the Road State

With the help of V2X communication, CAVs have access to substantial road state information, such as speed limits, road grades and road curvatures. The prior knowledge of road state can be transferred to different constraints or inputs in the OCP of eco-driving and ultimately contribute to energy efficiency optimisation. Among these road states, road speed limit is a basic constraint and is taken into account in most studies of eco-driving [52]. For instance, Ye *et al.* [53] introduced a discrete DP algorithm to optimize ecological velocity under different speed limits, while realizing a preferable trade-off between precision and computational. Han *et al.* [54] proposed an eco-driving control approach using analytical state-constrained optimal solution, and take into account the maximum road speed limit. In addition, road curvature also imposes effect on safe speed when driving on a curve road. Recently, the effect of curved roads has gradually gained more attention in the studies of eco-driving [55, 56]. Ding *et al.* [57] designed an instantaneous fuel consumption model considering the horizontal curvature, and the ecological velocity is then optimized combining the DP algorithm and the proposed fuel consumption model. In this work, the characteristics of optimal velocity profiles at curved roads are comprehensively analysed in terms of entering to and leaving from a curved road. Padilla *et al.* [58] proposed a model that approximates cornering forces into the longitudinal axis of the vehicle. Based on the proposed model, a general eco-driving OCP is designed, which can

be used for front wheel drive and rear wheel drive configurations of the vehicle. Obviously, both speed limit and road curvature are normally transferred to spatiotemporal constraints in the OCPs of eco-driving.

Additionally, road grade is another crucial factor which directly affects the required power of vehicles. The anticipation of road grade can be beneficial for the ecological speed planning and powertrain control in the whole trip. For instance, PHEVs typically tend to consume more electric energy before entering a downhill road. Hu *et al.* [59] introduced an integrated optimal controller to promote fuel efficiency for connected HEVs on rolling terrain. In this work, the future road grade is taken as one of optimization inputs to optimize both driving speed and EMS, the OCP is then solved by PMP. In [60], two fuel-prioritized feedback controllers are presented to execute eco-driving for ICEVs, the controllers are implemented combining analytical control laws and instantaneous road grade information only, thereby yielding a light computing load. Moreover, the CAVs with different powertrain systems are recognised to show various characteristics in ecological velocity on slopes. Zhuang *et al.* [61] investigated an eco-driving controller for EVs, in which the ecological velocity on varying slopes are optimized by DP, the result demonstrate that the optimal velocity of EVs on varying slopes may cause a high charge and discharge rate of the battery, and consequently resulting in a quick battery fade. Due to the high kinetic and potential energy, eco-driving on hills is more significant for heavy trucks [62]. Hauenstein *et al.* [25] investigated the eco-driving of heavy trucks on hills, in which the fuel-saving was mainly realized by coasting before slopes. Zhang *et al.* [63] established an eco-driving model with a detailed dynamics analysis for slope driving. To enhance the computational efficiency, a tailored planning algorithm is designed to solve the OCP of eco-driving on slopes based on IDP.

To summarize, most road states have impact on the speed limits and required power of vehicle, such as road curvature and road grade. To handle the influence of the road states, studies in this field typically transfer the road states to constraints and inputs in the OCPs of eco-driving in which different optimization-based methods are employed to realize eco-driving in various scenarios. With more road states integrated, energy efficiency of eco-driving is remarkably promoted [64], however, the straightforward integration of road state and eco-driving poses a challenge in achieving a balance between the energy-saving performance and the computational load in the OCP of eco-driving.

4. ECO-DRIVING CONTROL IN CAR-FOLLOWING SCENARIOS

The implementation of eco-driving in car-following scenario significantly contributes to energy-saving on urban roads, especially in congestion traffic conditions. Compared with eco-driving for single vehicle mentioned, the aim of eco-driving in car-following scenarios not only contains energy-saving, but also driving safety and comfort, considering the influence of preceding vehicles. For CAVs, adaptive cruise control (ACC) system has been widely implemented to automatically plan the velocity of host vehicle to follow preceding vehicles with the inter-vehicle distance maintained in a safe range [65, 66]. However, earlier studies in ACC normally overlook the potential of reducing energy consumption in car-following scenarios. To further improve energy economy, the technology of ecological ACC (Eco-ACC) is advanced, which attempts to promote energy efficiency and other performance simultaneously [67, 68]. In addition, benefiting from the increasing penetration rate of CAVs, vehicles are capable of sharing information and cooperating driving behaviours, so as to reduce more energy consumption [69]. The elaboration of eco-driving in car-following scenarios is divided into two types: individual Eco-ACC and cooperative Eco-ACC.

4.1. Eco-Driving in Car-Following Scenarios

As introduced above, eco-driving in car-following scenarios (simplified as Eco-ACC) derives from the ACC technology which is usually regulated by proportional-integral-differential (PID) control algorithm. For instance, Zhang *et al.* [70] designed a PID-based ACC system for trucks under different inter-vehicle distances, and the algorithm is verified efficient in improving fuel economy and decreasing pollution. Despite the preferable reliability performance of traditional ACC systems, it is tricky for PID controller to comprehensively promote the performance in terms of energy-saving, safety and comfort.

To further promote the performance of energy-saving, most studies tend to achieve Eco-ACC via optimization-based algorithm design. Among these methods, MPC is widely employed in the velocity optimization by considering the motion of preceding vehicles. Xie *et al.* [71] proposed a hierarchical Eco-ACC method for EVs and classify car-following scenarios into four modes, in which the motor torque in each mode is modified by MPC to reduce energy consumption. Bae *et al.* [72] presented an Eco-ACC controller to avoid front collisions while reducing energy consumption for connected PHEVs. In this study, a velocity-tracking controller is employed to follow the optimal reference velocity via MPC, and significant energy-saving potential is resulted by simulation

and experiment tests. This experimental test is conducted by encompassing the real vehicle and controller in the loop. Nie *et al.* [34] designed a real-time dynamic predictive cruise control approach, and a car-following oriented controller is established by MPC. In this work, the items related with energy consumption, car-following and jerk are utilized to develop the objective function of MPC. Vajedi *et al.* [67] investigated an Eco-ACC method for connected PHEVs based on nonlinear MPC, the Eco-ACC is demonstrated to promote fuel economy and driving safety simultaneously. Additionally, RL has gained more attention recently due to its potential in solving complex and nonlinear eco-driving OCP, compared with optimization-based methods. Li *et al.* [73, 74] designed Eco-ACC systems based on approximate dynamic programming (ADP), which show superior performance in energy-saving and robustness. The Eco-ACC systems are designed in a learning-based way, in which an actor-critic structure is employed, whereas the deviation of car-following and the energy consumption are integrated into the input of the controller. Qu *et al.* [75] proposed a car-following model for electric CAVs based on a deep deterministic policy gradient (DDPG) algorithm, which enables to reduce the modelling constraints and dampen traffic oscillations. In [76], a DDPG algorithm is developed to learn the continuous longitudinal accelerations/decelerations of eco-driving to reduce the fuel consumption for CAVs. The information of the host vehicle, preceding vehicles and SPaT are integrated into the inputs of DDPG model.

Besides, it has been verified that the motion of preceding vehicles influences the eco-driving performance in car-following scenarios [77]. In this case, some studies are investigated to improve the energy economy combining velocity prediction and Eco-ACC. Some earlier studies have acknowledged that the preceding vehicle normally maintains a low acceleration and a constant speed within a prediction horizon. For instance, Tajeddin *et al.* [78] predicted the acceleration of the preceding vehicle through an exponential equation, and nonlinear MPC is employed to achieve predictive Eco-ACC considering future motion of preceding vehicles. Li *et al.* [79] assumed that the acceleration of preceding vehicle maintains at a constant within prediction horizon to mitigate the computing burden of MPC. Similarly, some studies assume that the acceleration of preceding vehicles maintains at a constant within receding horizon due to the small prediction horizon [80]. However, the assumption that the acceleration of preceding vehicles keeps constant within prediction horizon is not practical in all situations, and it might affect the performance of Eco-ACC. Therefore, velocity prediction is employed to further improve the energy economy in Eco-ACC systems [81]. In [82], an explicit MPC method is leveraged to reduce energy consumption for EVs with

the help of predicted movement of preceding vehicles. A Bayes Network model is established to predict the movement of preceding vehicles. Zhou *et al.* [83] developed a nested bi-level speed prediction method to predict the speed of preceding vehicles, in which the traffic speed and the speed of preceding vehicle are forecasted via a hierarchical framework. In this study, an efficient algorithm for simultaneous optimization of the speed planning and EMS is developed based on stochastic MPC, and notable improvement of available optimality is raised compared with the DP-based benchmark.

To summarize, the Eco-ACC technique mainly focus on comprehensively improving the performance of energy-saving, safety, and comfort in car-following scenarios. In particular, the movement of preceding vehicles can directly influence the application of Eco-ACC on host vehicle, whereas the movement prediction of preceding vehicles has been widely applied to further promote the energy economy by combining with MPC methods. Albeit the preferable performance of movement prediction technologies, the prediction errors are intractable to completely eliminate [84, 85], thus possibly deteriorating the energy economy of Eco-ACC.

4.2. Cooperative Eco-Driving in Car-Following Scenarios

Benefiting from the rapid development of CAV technology, vehicles can share information through V2X communication and coordinate movement to realize superior performance in car-following scenarios, which is typically defined as cooperative adaptative cruise control (CACC) [86]. Earlier studies of CACC attempt to reduce inter-vehicle distance by coordinating movement, thereby improving safety and traffic capacity. Over the past few years, the technical challenges of string stability, V2X communication, control algorithm have been preferably addressed, and the CACC undergoes towards maturity [87, 88]. In [89], the impacts of CACC on safety, energy and emission are investigated based on the experimental data collected from real-world conditions. The results demonstrate that the CACC system can improve safety, energy economy and emission, compared with the ACC system and HDVs. Bian *et al.* [90] proposed a multiple-predecessor following strategy for CAVs, which reduces headway with the support of vehicle-to-vehicle (V2V) communication. In particular, the CACC system is considered efficient in improving fuel economy of heavy trucks, since smaller headway contributes to the reduction of aerodynamic drag force [91].

Despite substantial potential benefits of CACC system, few studies have been conducted with the aim of promoting the energy-saving performance of CACC. Recently, the energy-saving potential of CACC system has

gained more attention [92]. This category of study is typically defined as the cooperative eco-driving in car-following scenarios (simplified as Eco-CACC). Instead of the predictive Eco-ACC, Eco-CACC leverages the cooperative information obtained from V2V communications, and enables to accurately plan ecological velocity by considering the future motion of preceding vehicles. The schematics of Eco-CACC and Eco-ACC are shown in Fig. 6 for comparison.

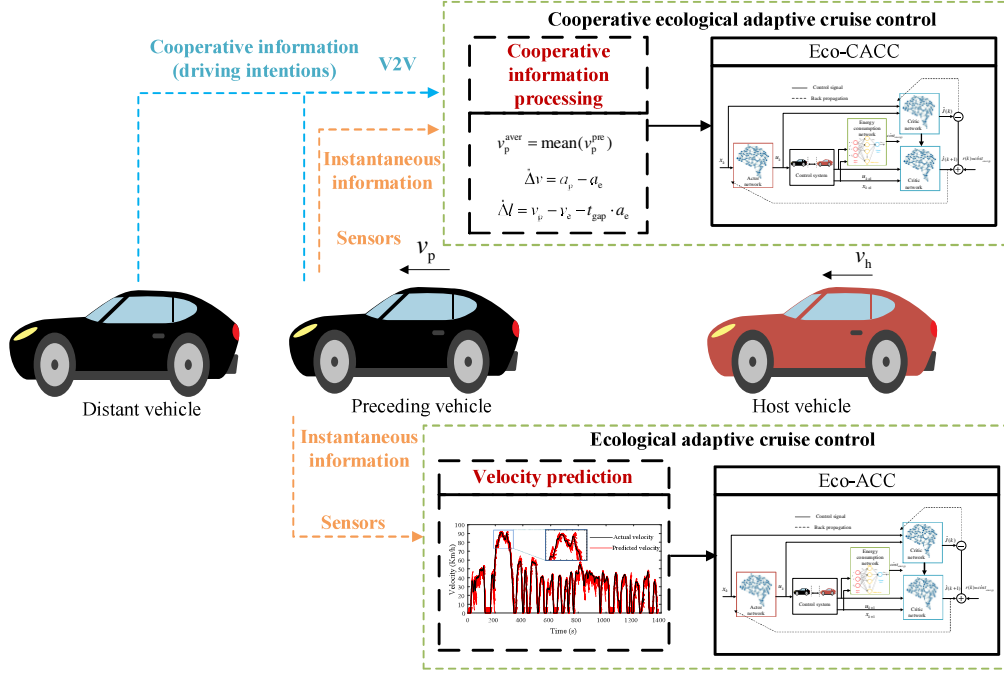


Fig. 6. The schematic of cooperative eco-driving and eco-driving in car-following scenarios.

In the Eco-CACC field, most studies normally are focused on coordinated eco-driving via sharing information of driving intention, and each vehicle plans its velocity considering the shared information [93]. For instance, Bertoni *et al.* [94] presented an Eco-CACC system to minimize the energy consumption for CAVs based on nonlinear MPC. The velocity trajectory preview of preceding vehicle is leveraged to ensure speed smoothing and energy-saving. To further damp unnecessary speed fluctuations, the driving intentions of preceding vehicle, including average velocity and average acceleration, are transferred to the host vehicle to further reduce energy consumption and avoid unnecessary fluctuations in [95]. In this work, an ecological CACC system is introduced to improve fuel economy for PHEVs based on ADP algorithm. Kim *et al.* [96] designed an Eco-CACC approach, which leverages the cooperative information of preceding vehicle, obtained from V2V communication, to reduce energy consumption. In this study, the future acceleration intention within a prediction horizon is applied for energy-

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3 saving based on a learning-based MPC scheme. Not only cooperative information is transmitted from preceding
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5 vehicles, but also the information from far ahead CAVs provides potential opportunities for energy saving. To
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7 mitigate the affection of prediction accuracy, Shen *et al.* [97] investigated an energy-efficient connected cruise
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9 control approach in mixed traffic conditions, in which the host vehicle has access to information of distant connected
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11 vehicles with the help of V2X communication. The behaviours of distant CAVs may affect the behaviour of vehicles
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13 surrounding the host vehicle as traffic waves propagate, and this characteristic can be estimated traffic modelling.
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17 Despite the preferable performance in energy-saving via information interaction, the sharing of accurate
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19 information also raises privacy concerns. To improve the energy economy while guaranteeing privacy, Zhang *et al.*
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21 [98] developed an information perturbation mechanism which is applied to transmit the perturbed velocity of
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23 preceding vehicle based on V2V communication. The cooperative information is leveraged in a predictive speed
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25 planner, and the fuel consumption and emissions are reduced while providing privacy protection. In [99], a robust
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27 ecological CACC system is investigated considering the privacy assurance of preview information. The impact of
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29 privacy assurance in the communication data is studied, and a robust MPC is applied to reduce fuel consumption
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31 with large preview error. However, most existing studies of Eco-CACC considering privacy guarantee are
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33 conducted on fuel-powered vehicles, the impact of such privacy guarantee on Eco-CACC systems for other types
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35 of vehicles, such as connected PHEVs/HEVs and EVs, still requires further investigation.
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39 In general, cooperative eco-driving in car-following scenarios normally optimize velocity by considering the
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41 cooperative information derived from V2V communication. With the help of V2V technique, the host vehicle can
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43 accurately obtain the future movement and the driving intention of preceding vehicles, thereby mitigating the
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45 adverse effect of prediction error resulting by velocity prediction algorithms. To clearly distinguish the differences
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47 of various eco-driving in car-following scenarios. The features comparison of different types of eco-driving in car-
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49 following scenarios is summarised in Table 1, where some classical studies in this field are selected to present.
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53 To sum up, the energy-saving potential of eco-driving in car-following scenarios has been widely
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55 acknowledged, especially for urban conditions. The movement of preceding vehicle has significant effect on the
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57 performance of eco-driving control. Generally, mainly two methods have been utilized to mitigate the influence of
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59 preceding vehicle movement. About the first category, the speed prediction is employed in Eco-ACC systems to
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61 take into account the influence of preceding vehicle. By contrast, the other category of eco-driving attempt to
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coordinate movement for energy-saving in car-following scenarios with the help of V2V communication. Moreover, instead of prediction-based schemes, the potential for realizing energy-saving via information sharing based on V2V communication has gradually attracted more attention.

Table 1 Summary of selected eco-driving in car-following scenarios

Category	Sources of future information	Information content	Main features	Selected references
Eco-driving without future information	-	-	• Speed planning is remarkably affected by the movement of preceding vehicles	Xie <i>et al.</i> [71]
Prediction-based eco-driving	Prediction algorithms	• Predicted velocity of preceding vehicles	• The prediction errors may affect the performance of eco-driving	Zhang <i>et al.</i> [82]
Cooperative eco-driving	Cooperative information from preceding CAVs	• Velocity/acceleration preview of preceding vehicles	• The performance relies on the accuracy of cooperative information	Bertoni <i>et al.</i> [94] and Kim <i>et al.</i> [96]
		• Driving intention of preceding vehicles	• The affection of cooperative information accuracy is mitigated	Li <i>et al.</i> [95]
	Cooperative information from distant CAVs	• Perturbated velocity of preceding vehicles	• Improve energy economy while guaranteeing privacy	Huang <i>et al.</i> [99]
		• Velocity and position preview of distant CAVs	• Adapt to the car-following scenarios in mixed traffic	Shen <i>et al.</i> [97]

5. COOPERATIVE ECO-DRIVING CONTROL IN MULTI-VEHICLE SCENARIOS

With the continuous development of CAV technologies, the penetration rate of CAVs is expected to notably increase in the future. In this context, not only information sharing but also movement coordination in a connected environment can be gradually attained, and accordingly, the increasing opportunities for cooperative driving stimulate the studies of cooperative eco-driving for multi-vehicle [100].

The cooperative eco-driving of multi-vehicle focus on coordinating the movement of multiple CAVs and following the optimization of overall energy consumption for multi-vehicles. Intuitively, multi-vehicle can be regarded in the form of vehicle platoon, for which the overall energy consumption is optimized considering the influence of all CAVs in the platoon. Therefore, the investigation of platoon-level cooperative eco-driving has been developed rapidly and has become a popular research focus [101]. Additionally, other potential application scenarios of cooperative eco-driving have also been summarized and analysed in this section. As shown in Fig. 7, the selected cooperative eco-driving schemes in multi-vehicle scenarios are presented. Specifically, a common acceptable target is typically designed in terms of platoon-level or area-level. Furthermore, the influence of heterogeneity, including

powertrain systems and automated level, on cooperative eco-driving may require to be tackled in these scenarios. The studies of cooperative eco-driving for multi-vehicle are described in vehicle platoons and other scenarios, respectively.

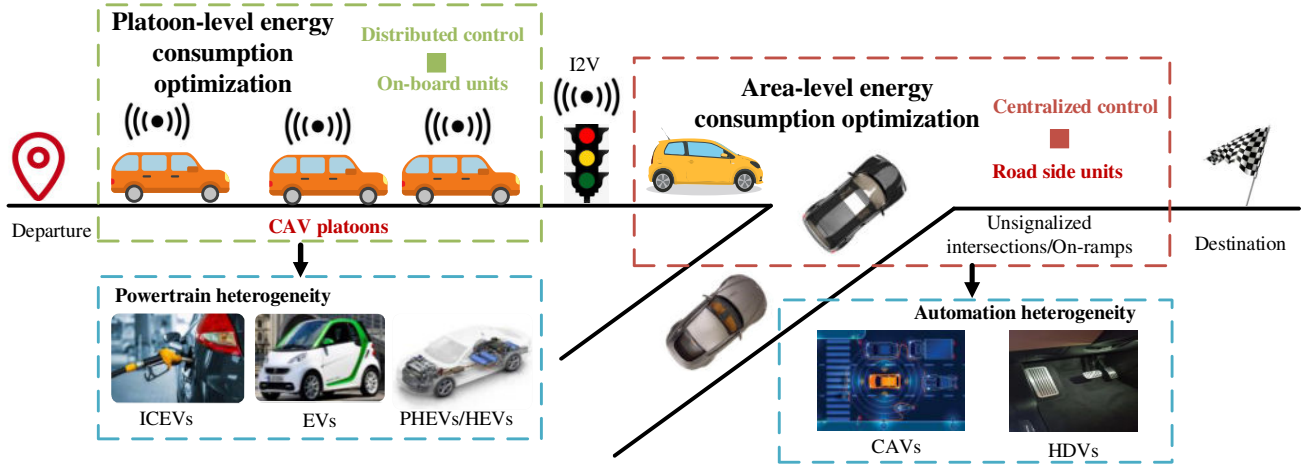


Fig. 7. The schematic of cooperative eco-driving in multi-vehicle scenarios.

5.1. Cooperative Eco-Driving for Vehicle Platoons

Due to the rapid development of CACC techniques for vehicle platoons, the energy efficiency of the overall platoon has attracted much attention under the contexts of pertinent energy crisis. In this case, CAV platoons can share cooperative information and coordinate their movements, thereby seeking for a minimization of overall energy consumption [102]. Distinguishing from cooperative eco-driving in car-following scenarios, the cooperative eco-driving for vehicle platoons attempt to minimize the energy consumption of vehicle platoon instead of single vehicle [103], thus notably contributing to the sustainability of transportation.

Earlier works realize the energy-saving for vehicle platoons via velocity optimization of leading vehicle, and the remaining CAVs in platoon are controlled through a CACC system to guarantee the string stability. Sakhdari *et al.* [104] introduced a distributed cooperative eco-driving system, in which the movement of leading vehicle is optimized to improve platoon's energy economy based on a nonlinear MPC approach. Zhai *et al.* [105] optimized an Eco-CACC method for heterogenous vehicle platoons combining MPC and distributed linear feedback control (DLFC). The whole vehicle platoon is assumed to be a desired rigid body, and in this manner, the MPC is employed to plan ecological velocity for the leading vehicle to reduce the overall energy consumption of vehicle platoon, whereas the following vehicles are controlled via DLFC to guarantee the string stability.

To reduce computational burden, a cooperative eco-driving control problem for CAV platoon is transformed into parts of a multi-objective function using the band-stop function, and the particle swarm optimization algorithm is leveraged to quickly obtain the approximate optimal solution [106]. In [107], an Eco-CACC method is designed at signalized intersections for CAVs, wherein the advantages of the eco-driving and CACC strategies are combined. The leading vehicle plans ecological velocity based on a modified DP algorithm considering the SPaT information, whereas the following vehicles attempt to follow the leading vehicle to realize the same energy-saving goal.

However, the simple ecological velocity planning of the leading vehicle may not result in the platoon-level optimality of overall energy consumption, which may be deteriorated due to various factors, such as communication structures and the heterogeneity of CAV platoons. To clarify the influence of different communication topologies, the Eco-CACC system under different communication topologies are compared in [108], including predecessor following, leader following and predecessor-leader following (PLF). This research finds that PLF topology shows superior performance in all the fields, compared with other topologies due to its complete communication links. Similarly, Ma *et al.* [109] introduced an Eco-CACC method based on nonlinear MPC for electric CAVs, and the performance in terms of following stability, energy economy and driving comfort is proven to be significantly improved. A communication structure of PLF is employed which means that the vehicle in the platoon would receive the information of preceding vehicle and leading vehicle. The reference input sequences, including the velocity, acceleration and position within the prediction horizon, are defined as the signal series delivered by V2V communication.

The heterogeneity of vehicles in a platoon presents another challenge in implementing cooperative eco-driving for platoons, since the differences in energy consumption characteristics and automation level make it difficult to optimize platoon-wide energy economy. He et al. [110] explored a cooperative eco-driving approach for a mixed platoon, which involves EVs and ICEVs, based on a simplified optimal control model. In this study, the effect of mixed traffic composition on the cooperative eco-driving system is analysed. In [111], an Eco-CACC system is advanced to improve the total fuel economy for mixed platoons, which consist of CAVs and HDVs, based on a hierarchical framework. In this research, a reference speed is optimized offline via DP considering various vehicle characteristics and traffic data, and a hybrid distributed MPC is employed to control CAVs in the mixed platoon. In addition, CAV platoons are not constant all the time, and the changes of platoon may affect the platoon-wide energy

economy. On this account, Wang *et al.* [112] proposed a cooperative eco-driving system, aiming to minimize the platoon-wide energy consumption for CAVs. In this study, several protocols for different stages of the CACC operation along freeway are designed, including sequence determination, gap closing and gap opening, etc., and the overall energy consumption and emissions are respectively reduced by 2% and 17%, compared with an existing CACC system.

To summarize, the cooperative eco-driving for CAV platoons has been widely validated to show superior performance in overall energy economy promotion [113]. The technical foundations of classical CACC system, such as communication topology and stability control, effectively contribute to the development of cooperative eco-driving for vehicle platoons. Furthermore, this group of cooperative eco-driving approaches seeks for a “social optimum” goal of energy consumption instead of a “selfish” energy-saving target. However, most existing studies merely plan ecological speed for leading vehicles, whereas the impact of mixed platoons, including the heterogeneity in powertrain and automation level, on energy economy still requires further investigation.

5.2. Cooperative Eco-Driving in Other Scenarios

The cooperative eco-driving of vehicle platoon provides an unprecedented opportunity to reduce energy consumption for multiple vehicles. However, the application scenarios of this kind of cooperative eco-driving are limited, as only commercial vehicles tend to form vehicle platoons in most situations. There are still more application scenarios of cooperative eco-driving are expected to emerge. Specifically, the typical potential application scenarios include on-ramps, intersections, lane changing etc.

The on-ramp merging is a classical scenario for cooperative driving on urban highways, in which vehicles need to reasonably plan their movements, and finally improve the safety, traffic efficiency and energy economy [114]. However, the energy-saving potential of cooperative merging operations gains limited attention to now, and most studies do not focus on reducing the energy consumption in this scenario. In [115], an unconstrained optimal control problem of cooperative merging is formulated, and the Hamiltonian function is applied to derive an analytical solution for a centralized controller. This work proves that coordination at on-ramps can significantly reduce fuel consumption and travel time. Jing *et al.* [116] designed a cooperative merging approach, in which a cooperative multi-player game is formulated as the global optimal merging problem. In this article, the global optimal problem is decomposed into multiple two-player games. Then, the PMP is applied to derive an analytical solution and

comprehensively promote fuel economy, travel time and passenger comfort. Similarly, Zhao *et al.* [117] designed a centralized ramp merging system for CAVs based on a hierarchical framework. The proposed coordination system consists of a ramp-level and a vehicle-level, wherein the upper level can regulate the ramp inflow rate and optimize merging sequence, and the lower level realizes the motion control of individual vehicles.

Through review the state-of-art researches, we can summarise that most on-ramp merging studies neglect the influence of multi-lane traffic. To further improve the energy economy in multi-lane traffic, Liu *et al.* [118] applied a RL controller to select the optimal lane before entering the merging zone, and a time-energy optimal control algorithm is adopted to promote fuel economy and traffic efficiency in the on-ramp. In addition to the merging scenarios, Aoki *et al.* [119] introduced a cooperative and ecological lane-selection strategy to reduce fuel consumption while ensuring road safety. This strategy can select the optimal line and optimal target vehicle to follow, and selfish back-to-back lane-changing behaviours are avoided by the developed cooperative mechanism.

Moreover, the coordination driving at unsignalized intersections greatly contribute to energy economy, safety and traffic efficiency. Deng *et al.* [120] presented a bi-level optimization algorithm to coordinate the merging of CAVs at unsignalized intersections. Xu *et al.* [121] comprehensively evaluate the performance of four state-of-the-art cooperative driving strategies under various conditions in terms of travel time, energy consumption, computation time and fairness. The Monte Carlo tree search (MCTS)-based strategy is validated to achieve the best performance in fuel consumption at unsignalized intersections. However, most existing cooperative driving strategies at signal-free intersections are mainly focused on safety and traffic efficiency, instead of energy efficiency. In [122], a cooperative eco-driving approach for electric CAVs at unsignalized intersections is presented to generate the optimal ecological velocity, and the OCP is formulated as a single-level optimization and solved by PMP algorithm. The proposed method is demonstrated to show superior performance of energy-saving compared with non-cooperative eco-driving and an IDM model.

To sum up, benefiting from the development of technologies in communication and automated driving, cooperation driving has been widely investigated in the past decade. However, previous studies are primarily concentrated on improving driving safety and traffic efficiency, and the energy-saving potential is only highlighted recently. In this context, the CAV platoon is one of the mostly classical scenarios in cooperative eco-driving, which attempt to reduce the overall energy consumption for platoons. Additionally, the energy-saving potential of

cooperative eco-driving has been gradually explored in other scenarios, such as on-ramp merging and unsignalized intersections, in which the energy economy for a specific area is expected to be improved.

6. FUTURE WORKS AND DISCUSSIONS

As discussed above, substantial studies have been developed in the field of eco-driving, those technologies of eco-driving are expected to provide a significant contribution to the energy economy for a single vehicle, multiple vehicles and even a specific area. However, there are still some technical challenges that require further investigation. For this reason, the potential development directions of eco-driving are discussed, which may enlighten more novel studies in these fields.

6.1. Co-Optimization of Velocity and Powertrain Control

In PHEVs/HEVs, the velocity optimization and powertrain control are strongly coupled, and this relationship is overlooked or oversimplified in a variety of studies. In most approaches, eco-driving is normally isolated from powertrain control, and only longitudinal dynamics is considered in eco-driving. In this case, the co-optimization of eco-driving and powertrain control is crucial to obtain the optimal energy economy. One of the mostly classical cases is the co-optimization of eco-driving and EMS, some literature has been reported to address this problem [128, 129]. However, the powertrain control should not only be restricted to EMS, all control degrees of freedom in powertrain can affect the velocity optimization in eco-driving, such as gear shift schemes, regenerative braking, etc. Hence, the comprehensive optimization of eco-driving and powertrain control can remarkably improve the energy economy of eco-driving.

In addition, the direct integration of eco-driving and powertrain control notably increases the computational burden, which leads to another challenge of trading off the energy-saving performance and computing efficiency. To preferably address the problem of computational burden, the relationship between velocity optimization and powertrain control requires to be figured out. In this manner, an efficient mechanism and framework can be developed to construct an integrated control strategy to co-optimize the eco-driving and powertrain control.

6.2. Adaptive Eco-Driving in Mixed Traffic

Benefiting from the development of CAV technologies, the penetration rate of CAVs is constantly increasing in the past decades. However, an ideal connected and automated environment cannot be realized in the near future. Most previous studies assume that CAVs can accurately obtain environment information via V2X communications,

and the coordination driving can be achieved in different scenarios. While in the real-world conditions, the motion planning is unavoidably affected by HDVs, which may result in the deterioration of energy economy. Some studies have noticed the influence of uncertainty from HDVs at signalized intersections [40, 123], and some data-driven methods are employed to estimate the behaviours of HDVs. These studies can also be expanded to the cooperative eco-driving for multiple vehicles, since HDVs may intervene the coordination of CAVs. In this case, it is necessary to develop eco-driving approaches which are adaptive to the mixed traffic environment, including CAVs and HDVs. It's meaningful to explore the influence of HDVs on eco-driving control in different scenarios, such as intersections, and car-following. In this manner, the adaptive mechanism of eco-driving can be developed by considering the affection of HDVs. Correspondingly, the adaptive eco-driving in mixed traffic can be achieved and remarkably contribute to the energy economy in practical applications.

6.3. Cooperative Information Communication

The cooperative driving has been widely recognised as an effective method to improve energy economy, whereas current studies normally assume that CAVs can accurately receive cooperative information from V2X communication without communication delays. In practical applications, eco-driving is unavoidably affected by the communication delays and errors in cooperative information. The over ideal assumption constricts the implementation of eco-driving in real world. How to tackle the delays and errors in communication is significant to be investigated, and the robust of eco-driving to the limited connected environment should be strengthened.

Furthermore, the accurate cooperative information sharing generates the concerns about safety and privacy, especially for car-following and unsignalized intersection scenarios. Since the cooperative information may be shared within CAVs which do not belong to a platoon, and these problems have been investigated in the studies of conventional CAV techniques [126, 127]. However, few eco-driving studies improve energy economy while guaranteeing the safety and privacy in communications. Regarding practical implementations, how to enforce the safety and privacy of communications in cooperative eco-driving should also be addressed in the future.

6.4. Cooperative Eco-Driving in Multi-Vehicle Scenarios

As discussed above, eco-driving in multi-vehicle scenarios provides an unprecedented opportunity to reduce the overall energy consumption and realize a “social optimum” target. However, the energy-saving potential of coordination driving begins to be investigated recently. Currently, conventional cooperative driving technologies

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3 have been widely investigated in platoons, lane changing and other scenarios; whereas, the energy-saving
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5 performance is normally overlooked in those studies. Hence, more potential application scenarios for cooperative
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7 eco-driving require further exploration, such as under lane changing, unsignalized intersections and merging
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9 scenarios. The implementation of cooperative eco-driving not only improves energy economy for single vehicle,
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11 but brings potential to promote sustainability of the transportation.
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14 In addition, the coordination driving mechanism for vehicles with various powertrain systems is another
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16 challenge for cooperative eco-driving, as the differences in energy consumption characteristics are difficult to be
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18 accurately estimated in a computationally efficient way. Existing studies typically concentrate on the scenarios that
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20 CAVs have the same powertrain systems. As previously mentioned, the complex powertrain systems undoubtedly
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22 increase the computational burden of energy consumption estimation, and this challenge would be notably
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24 magnified in multi-vehicle scenarios. Therefore, the coordination mechanism for heterogeneous CAVs should also
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26 be developed to improve the energy economy of multiple vehicles.
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29 *6.5. Validation of Eco-Driving via Experiments*

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32 Among existing studies of eco-driving, most of them validate the performance of eco-driving via simulations,
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34 and only the basic performance can be demonstrated by simulation tests. Limited by the application of CAV
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36 technologies, it requires high cost to establish experiment platform based on real vehicles. In this context, some
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38 studies have conducted hardware-in-the-loop (HIL) methods to validate the proposed eco-driving strategies [124,
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40 125], in which virtual traffic environment is established based on traffic simulation software, such as VISSIM, and
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42 the real-time implementation can be verified via these tests. However, most HIL experiments concentrate on single
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44 traffic scenario, and the accuracy of vehicle and environment models still requires improvement. Moreover, the data
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46 to construct traffic models are typically collected from traffic simulation software, which may not reliably simulate
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48 the real-world environment. On the other hand, the experiments executed based on real vehicle are rarely reported,
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50 indicating that the validation and implementation of eco-driving require more investigation.
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54 Despite the great energy-saving potential of eco-driving, most validations of eco-driving are still conducted
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56 via simulation. Therefore, it is significant to develop reliable validation methods based on HIL or real vehicle
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58 platforms to evaluate the performance of eco-driving, including energy-saving, communication delays and
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feasibility. How to establish effective and accurate experiment platforms to validate eco-driving in a low-cost way is the technical challenge waiting to be tackled.

7. CONCLUSIONS

In this study, the state-of-the-art of eco-driving is comprehensively analysed and summarized, and the basic principle of eco-driving is illustrated. Moreover, the coupling relationship between eco-driving and EMS, which is normally overlooked or conflated in some studies, is thoroughly analysed. Correspondingly, the necessity and optimality in the coupling of eco-driving and EMS are analysed. By this manner, the situations and methods to co-optimize eco-driving approaches and EMSs are further summarized. Furthermore, eco-driving studies are generally classified into three categories, including single-vehicle, car-following and multi-vehicle, according to the application scenarios. The eco-driving approaches in different categories are systematically analysed, and the main features of various studies are presented and compared. The eco-driving approaches in single-vehicle scenarios are categorized according to the main considerations, including powertrain systems, traffic lights and road states. In addition, the eco-driving approaches in car-following scenarios are classified into Eco-ACC and Eco-CACC systems. The impact of preceding vehicles on eco-driving in this group is extensively analysed, and the existing approaches to tackle this issue are summarized.

Notably, the significant energy-saving potential of cooperative eco-driving in multi-vehicle scenarios is emphasized, as the “social optimum” target of eco-driving can improve the energy economy of a specific area with the help of cooperative eco-driving. In this context, the potential application scenarios of cooperative eco-driving are explored, including CAV platoons, on-ramp merging, lane changing and intersections. We can conclude that coordination driving in these scenarios has been widely studied in the field CAV technologies, whereas few previous studies focused on the improvement of energy economy. Moreover, energy-saving performance of coordination driving has only recently been reported, and cooperative eco-driving in multi-vehicle scenarios still requires further investigation.

In summary, the key techniques in eco-driving are adequately elaborated and compared, thereby supplying a better understanding in the up-to-date development of eco-driving. Based on the comprehensive discussion, the potential development trends are provided in terms of optimality control schemes, application scenarios and experiment validation, which are capable of inspiring more innovative studies in eco-driving technologies.

ACKNOWLEDGMENT

The work presented in this paper is funded by the National Natural Science Foundation (No. 52172400 and 52272395) in part, and the project of Chongqing Automobile Collaborative Innovation Centre (No. 2022CDJDX-004) in part. Any opinions expressed in this paper are solely those of the authors and do not represent those of the sponsors.

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Review on eco-driving control for connected and automated vehicles

Li, Jie; Fotouhi, Abbas; Liu, Yonggang; Zhang, Yuanjian; Chen, Zheng

2024-01-01

Elsevier

<https://doi.org/10.1016/j.rser.2023.114025>

Li J, Fotouhi A, Liu Y, et al., (2024) Review on eco-driving control for connected and automated vehicles. Renewable and Sustainable Energy Reviews, Volume 189, Part B, January 2024, Article number 114025