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Co-Optimization of Eco-Driving and Energy Management for Connected HEV/PHEVs near Signalized Intersections: A Review

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Abstract: Currently, road transport constitutes a considerable proportion of global fossil fuel consumption, as well as CO_2 and pollutant emissions. To mitigate transportation energy consumption, two primary approaches have emerged: the large-scale adoption of Hybrid Electric Vehicles (HEVs) and Plug-In Electric Vehicles (PHEVs), as well as the implementation of eco-driving strategies, which present an immediate and low-cost solution. In this context, this paper provides a comprehensive review of these two technologies and their integration for connected HEV/PHEVs. We summarize the framework of recent approaches to incorporate fusion road information in single-vehicle and multi-vehicle scenarios, respectively, wherein we compare their advantages, their disadvantages, and their effectiveness in reducing energy consumption. Additionally, we reflect on the future development directions of cooperative optimization in EMS and eco-driving strategies from various perspectives. This comprehensive review underscores the importance and potential impact of these approaches in addressing environmental challenges in transportation systems, thereby offering useful insights for new researchers and practitioners in this area.

Keywords: cooperative optimization; review; eco-driving; energy management; signalized intersection; energy consumption; HEV/PHEVs

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Citation: Wang, Z.; Dridi, M.; El Moudni, A. Co-Optimization of Eco-Driving and Energy Management for Connected HEV/PHEVs near Signalized Intersections: A Review. *Appl. Sci.* **2023**, *13*, 5035. https://doi.org/10.3390/app13085035

Academic Editor: Filipe Soares

Received: 24 February 2023
Revised: 1 April 2023
Accepted: 11 April 2023
Published: 17 April 2023

1. Introduction

Urban cities have been focusing on energy shortages and environmental issues in recent years. The transportation sector, which accounts for nearly three-quarters of total petroleum consumption, is the most energy-consuming system. According to reports [1], energy consumption in the U.S. transportation sector accounted for approximately 28% of total U.S. energy use in 2021. Moreover, the International Energy Agency (IEA) states that the transportation sector, which has the highest reliance on fossil fuels, contributed to 37% of CO_2 emissions from end-use sectors during the same year, which caused the share of transportation in global energy-related carbon dioxide emissions to increase by two percentage points to reach 26% [2]. It is evident that the majority of our daily energy consumption is attributed to our movements. In response to reducing energy consumption and emissions related to transportation, scholars and researchers have proposed many approaches, which can be summarized based on two technical aspects.

The first aspect is to use alternative energy sources as much as possible to replace traditional fossil fuels, such as the promotion of new energy taxis, buses, subways, passenger cars, and trains; the so-called new energy sources would be obtained from renewable resources such as hydrogen, solar, and wind. With these new energy sources, new powertrain types have been created for the purpose of using electricity that comes from these renewable energy sources. For instance, Hybrid Electric Vehicles (HEVs) and Pure Electric Vehicles (PEVs) have been developed, which offer better fuel efficiency compared to traditional Internal Combustion Engine (ICE) vehicles. However, even though we surmise that the widespread adoption of PEVs and HEVs could alleviate energy shortages, charging infrastructure limitations and range anxiety are major obstacles to their large-scale rollout, while, unlike PEVs, HEVs are formed by adding additional energy sources and storage systems, which offer a temporary solution to the above two issues under existing conditions. Therefore, they are a suitable choice during the transition period before moving to large-scale PEVs. Such a trend is also reflected in the market share performance, as Figure 1 shows. The market share of HEVs has increased significantly, capturing 3.2% of the light vehicle market in 2013 and 5.5% in 2021. PHEVs sales began in 2011, and their market share has grown every year. As of 2021, PEVs accounted for 3.2% of the light vehicle market. Consequently, the Energy Management System (EMS) of these vehicles has become an increasingly important issue.

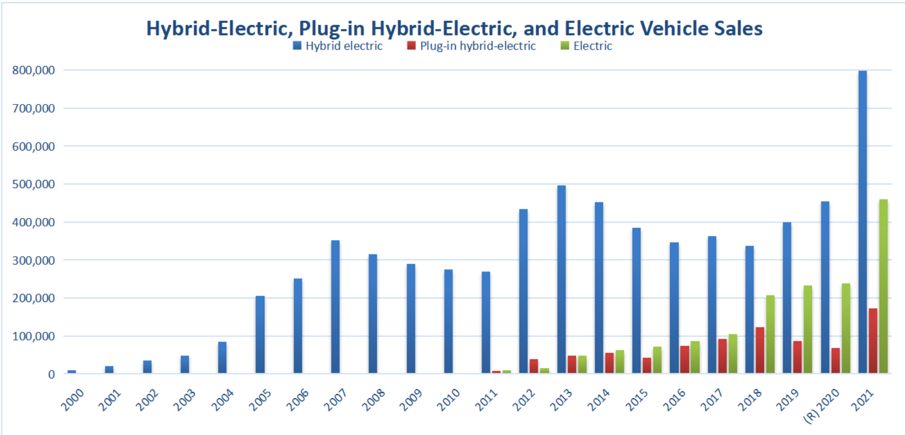

Figure 1. Sales illustration of HEV/PHEV/PEV on the US market [1].

In order to better understand the following reviewed EMS solutions, Figure 2 illustrates the structural differences between the three types of Electrical Vehicles (EVs). In the case of a Hybrid Electrical Vehicle (HEV), both an engine (ICE) and an electric drive power the drivetrain. The electric motor's battery is charged by regenerative braking and a generator connected to the ICE, allowing for the use of smaller engines and improved fuel efficiency. Furthermore, for a Plug-In HEV (PHEV), the battery is charged not only by regenerative braking and the generator, but also by an external electric power source. Finally, a Pure EV (PEV) is solely powered by its battery, which is charged using an outside electric power source.

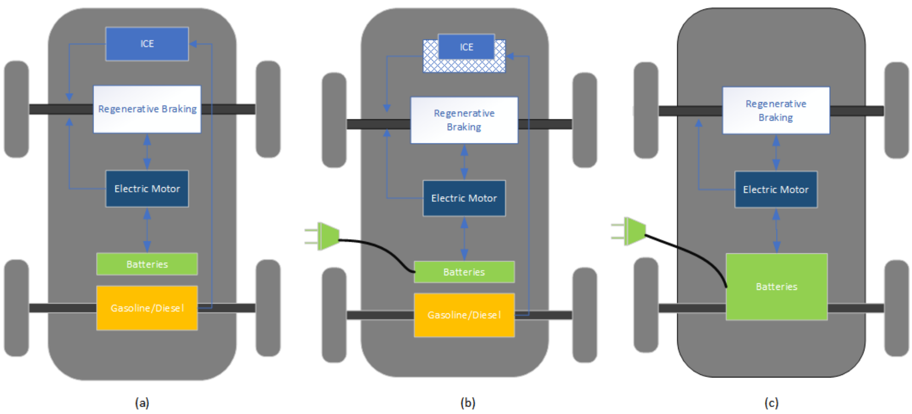

Figure 2. Basic structure of different EV types. (**a**) HEV. (**b**) PHEV. (**c**) PEV.

Meanwhile, the second aspect focuses on improving efficiency of transportation systems and encouraging fuel-efficient driving, such as Ecological Driving (eco-driving) strategies. The concept of eco-driving involves optimizing and regulating the speed of vehicles based on various factors such as the route information and surrounding environment, which include speed limits, locations of stop signs, and Signal Phase and Timing (SPaT) information provided by Intelligent Transportation System (ITS) technology. More details, such as the use of Connected Vehicles (CVs), can lead to enhanced road safety, smoother traffic flow, and energy conservation through Vehicle-to-Vehicle (V2V) and Vehicle-to-Infrastructure (V2I) communication. V2V communication enables vehicles equipped with communication technology to exchange information, thereby preventing collisions and enabling coordinated movement. On the other hand, V2I communication enables vehicles to communicate with roadside units and infrastructure, such as traffic signals, which allows for better coordination between them. The transportation system has evolved with the integration of smart and connected technologies, as shown in Figure 3, not only for vehicles, but also for the road network, which has become smarter with the deployment of intelligent traffic infrastructures and sensors.

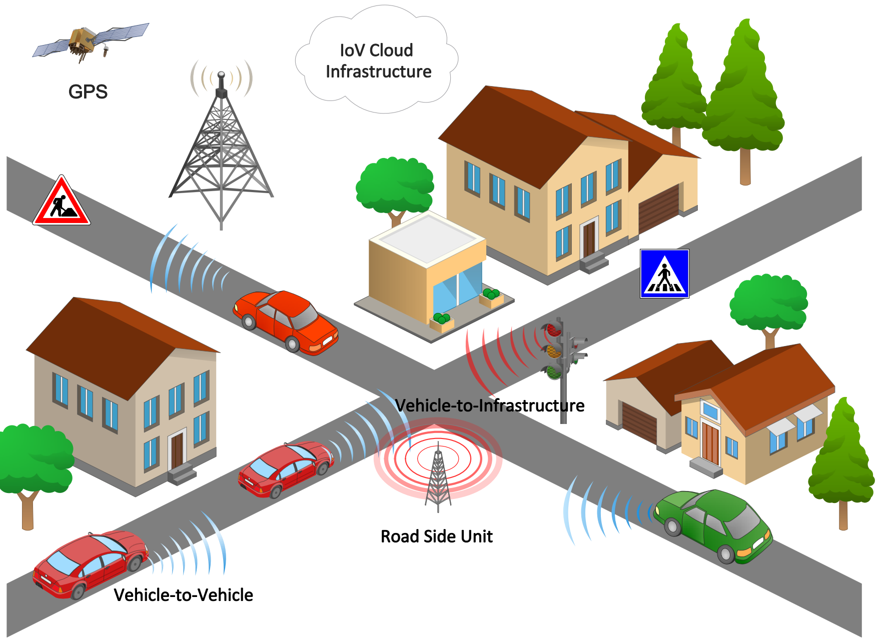

Figure 3. Schematic of ITS technology.

Therefore, with the rapid development of Intelligent Transportation Systems (ITS) and the increasing emphasis on sustainable mobility, connected Hybrid Electric Vehicles (HEVs) and Plug-In Hybrid Electric Vehicles (PHEVs) have emerged as crucial components in the global effort to reduce emissions, improve energy efficiency, and achieve sustainable transportation. The integration of advanced Energy Management Systems (EMS) and eco-driving strategies in connected HEV/PHEVs has the potential to address these challenges by optimizing single-vehicle and transportation system performance. The choice of this topic is motivated by the growing demand for effective solutions that can harness the benefits of connected vehicle technologies and cooperative systems to enhance the performance of HEV/PHEVs in diverse traffic conditions. The importance of this topic lies in its potential to provide valuable insights for researchers, policymakers, and practitioners, thereby guiding the development of innovative EMS and eco-driving strategies that can maximize fuel economy, reduce emissions, and improve traffic flow.

This review paper aims to provide a comprehensive overview of recent advances and challenges in the development and implementation of EMS and eco-driving strategies for connected HEV/PHEVs. We will analyze the current state of research, identify critical research gaps, and propose potential directions for future studies in this field. By doing so, we hope to contribute to the ongoing efforts toward achieving more sustainable and efficient transportation systems. In order to review these two aspects comprehensively, this report is organized as follows: Section 2 introduces the basic architectures of HEV/PHEV. Section 3 outlines the types of EMS as the basics of cooperative optimization approaches. Section 4 defines eco-driving in the context of cooperative optimization with EMS and systematically reviews its research methods. Section 5 summarizes the framework of newer approaches to cooperative optimization in single-vehicle and multi-vehicle scenarios for HEV/PHEVs, respectively, discussing their optimization objectives, constraints, control logic, and effectiveness in reducing energy consumption. Finally, future studies and conclusions are presented in Sections 6 and 7.

2. Architecture of HEVs/PHEVs

To fully understand the potential of HEV/PHEVs as an approach for sustainable transportation, it is important to examine the architecture of HEV/PHEVs and the EMS that govern their performance. EMS are the core determinant of HEV/PHEV performance and are closely linked to the vehicles' architecture. Thus, we will provide a comprehensive overview highlighting the key components that make up these vehicles and their respective roles in the energy management process.

Generally, the structure of HEVs/PHEVs offers additional flexibility to optimize their engine operation regions compared with ICE vehicles, as the latter can only adjust their engine speed to regulate their torque in response to a driver's power demand. The key characteristics of HEV/PHEVs which are different from the ICE vehicles, are listed as follows [3]:

- Recover the regenerative braking energy as much as possible;
- Reduce the idling energy cost by turning off the engine;
- Achieve an optimal distribution of power among various power sources;
- Reduce the size of the ICE while ensuring that the vehicle's maximum requirements are still met;
- Tend to be more complex and costly, as they necessitate additional controllers;
- Have a weight that is 10–30% greater than that of ICE vehicles.

As depicted in Figure 2, a motor assists the engine to operate in a higher efficiency area in an HEV/PHEV, which is able to achieve better fuel efficiency. To accomplish this, HEVs/PHEVs need to distribute power among various power sources (e.g., the engine and battery) in response to varying driving conditions. Typically, there are three types of HEV powertrains, which are also utilized in PHEVs, except that PHEVs have a charging port that allows the battery to be charged directly from the grid. The three types are series hybrid, parallel hybrid, and combined(series–parallel) hybrid, respectively, [4]. In a series hybrid powertrain system, a motor/generator set is powered by the engine to drive the vehicle; in a parallel hybrid system, either the battery with a motor/generator set is used or the engine is used to drive the vehicle according to the torque demand; In a combined hybrid system, vehicles have the ability to operate as a series or parallel hybridization.

2.1. Series Hybrid System

In a series hybrid drive system, as depicted in Figure 4, the IC Engine serves as an Auxiliary Power Unit (APU), thereby effectively increasing the distance range of a purely electric vehicle. One of the advantages of this configuration is that the IC Engine can be employed at a point where the efficiency and emissions are at their highest levels, because it is not dependent on the mechanical requirements of the vehicle in this form. Furthermore, the loss brought on by the gears or clutch is reduced by the lack of a mechanical connection between the vehicle and the IC Engine, and using the Electric Motor enables the continued use of regenerative braking. Nevertheless, this configuration requires an IC Engine, Electric Generator, and Electric Motor, and the added weight could offset the benefits described earlier. Based on these characteristics, series HEV/PHEVs are more suitable for low-speed operating conditions in urban areas and not for highway driving conditions.

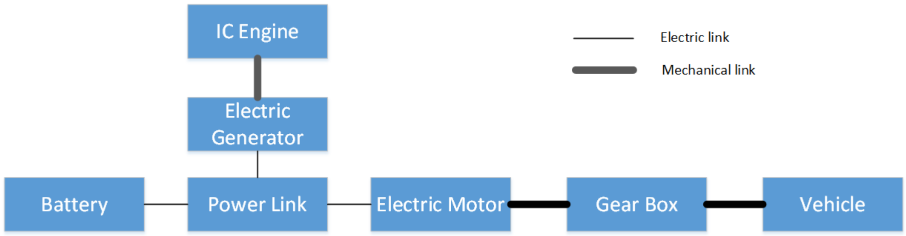

Figure 4. Series hybrid configuration.

2.2. Parallel Hybrid System

In a parallel hybrid drive system, both the IC Engine and Electric Motor operate simultaneously. As illustrated in Figure 5, compared to the series hybrid system, the parallel configuration only requires the IC Engine and Electric Motor, thereby eliminating the Electric Generator and reducing the total weight and complexity. Furthermore, the auxiliary power effect of the Electric Motor enables a reduction in the power of the IC Engine and battery capacity. Additionally, because the IC Engine remains mechanically connected to the drive system, the energy utilization of the engine in the parallel hybrid system is relatively high, which results in higher fuel efficiency than in the series hybrid drive system. However, the IC Engine's operating conditions are influenced by the driving conditions, and frequent changes in driving conditions can cause the engine to operate inefficiently, which results in increased emissions compared with the series type. Therefore, the parallel hybrid system is better matched with the operating conditions where the car is driven steadily at medium and high speeds and is most suitable for driving on intercity roads and highways.

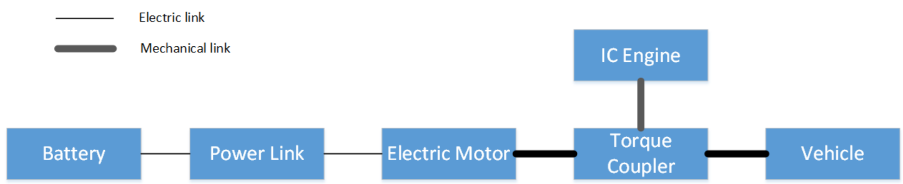

Figure 5. Parallel hybrid configuration.

2.3. Combined Hybrid System

The combined hybrid system (Figure 6) combines the characteristics of the series and parallel hybrid systems; compared to the series hybrid system, it incorporates additional transmission routes for mechanical power, while, compared to the parallel hybrid system, it introduces more transmission routes for electric power. The combined hybrid system gains flexibility by dividing the power between the motor and the generator, and this complex configuration generally makes it more costly and difficult to control. However, the advantages of this combined hybrid system are also obvious: on the one hand, it can be applied to a variety of vehicle operating conditions, and the vehicle's economy and emissions can be guaranteed, whether on the inter-city arterial road or on the highway; on the other hand, this system is suitable for all sizes of vehicles.

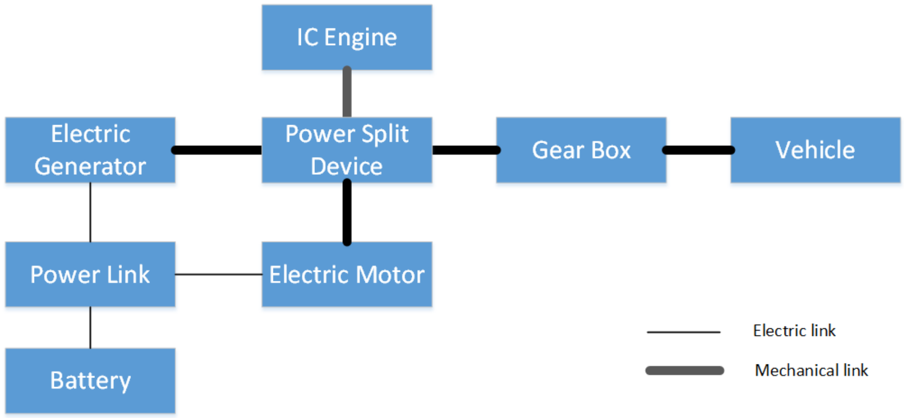

Figure 6. Combined hybrid configuration.

After having examined the architecture of HEV/PHEVs, we can now turn our attention to the Energy Management Strategies (EMSs) that are commonly used in HEV/PHEVs, as well as the key factors that influence their design and optimization. By examining the EMSs in detail, we can gain a deeper understanding of how these strategies are developed and optimized to ensure maximum efficiency and performance in various driving conditions.

3. Energy Management Strategy for HEV/PHEVs

EMSs are critical, as they determine the allocation and flow of energy between the powertrain components and energy storage system. By optimizing the EMSs, HEV/PHEVs can achieve higher efficiency and better performance in a wide range of driving conditions. In this section, we will examine the different types of EMSs that are commonly used for HEV/PHEVs. Through a detailed analysis of EMSs, we aim to provide a comprehensive understanding of the key principles and strategies that underlie the design and optimization of HEV/PHEVs.

Normally, the energy management problem for a HEV/PEHV is formulated as the following [5]:

$$\begin{aligned} &\min_{x,u} J(x,u) \\ &\text{s.t. } G(x) \leq 0 \end{aligned} \tag{1}$$

where $x \in X$ denotes the state variables of the hybrid system, such as vehicle distance, speed, State of Charge (SOC), fuel consumption, etc. The control variable $u \in U$ is usually defined as the ratio of power or torque demand. The constraint conditions $G(x)$ represent limitations on power or velocity, torque, and the final SOC. The objective function J can be defined to minimize energy consumption, exhaust emissions, delay battery aging, or maintain vehicle mobility, or it may define combinations of these objectives.

Given the aforementioned formulation, significant efforts have been directed towards the development of more efficient powertrain systems and EMSs for HEV/PHEVs. The classification of these strategies is illustrated in Figure 7.

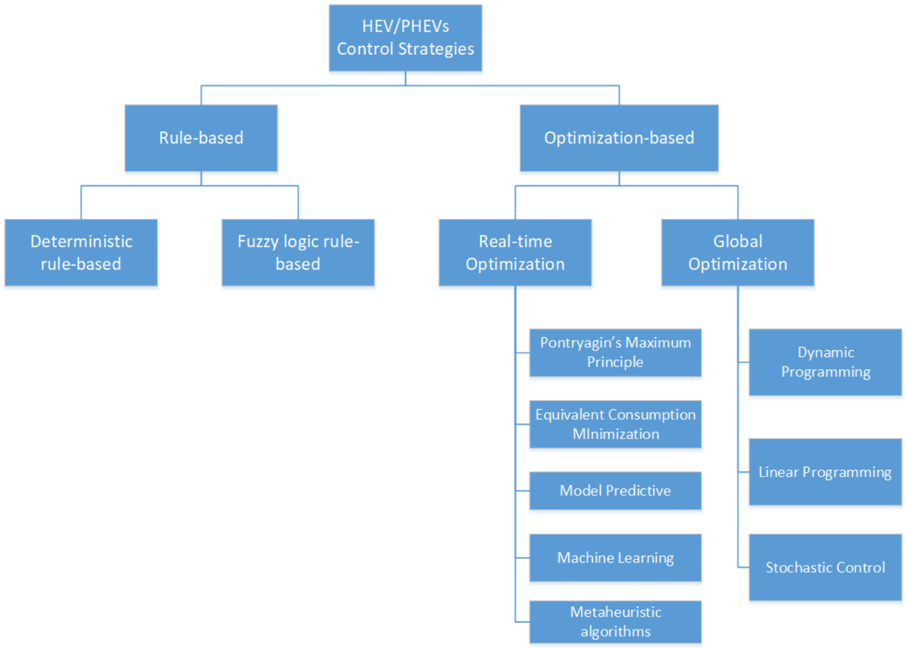

Figure 7. Classification of HEV/PHEV control strategies [6].

3.1. *Rule-Based EMS*

Rule-based control strategies are usually extracted from the existing control experience to meet the characteristics of each component, which belong to the class of real-time strategy. The main research directions can be divided into two categories. The first category is based on a deterministic logic threshold, such as [7]. The researchers divided the operation of PHEVs into Charging Depleting (CD) and Charging Sustaining (CS) mode by setting the SOC threshold value. The other category is using fuzzy logic, such as the works of [8,9]. Rule-based EMSs have shown promising results since the early 2000s, but they are not guaranteed to be optimal, since they are based only on instantaneous outputs. In fact, these rules are determined by the car manufacturer using standard speed profiles that do not always accurately represent real-world conditions.

3.2. *Optimization-Based EMS*

The optimization-based strategies are often derived from optimization theory, specifically optimal control theory. Furthermore, the solution to this Optimal Control Problem (OCP) can be divided into two main classes: those that attempt to compute a local solution in real-time, usually online, and those that compute a global solution, typically offline [10,11].

3.2.1. Real-Time Optimization Methods

Real-time strategies aim to determine the allocation of power sources at each time step while simultaneously minimizing the cost function (e.g., fuel economy, power, and emissions). This class of strategy has been widely developed in recent years due to its relative ease of implementation. It can be subdivided as follows:

- Pontryagin's Maximum Principle (PMP), which is the main method in optimal control theory, obtains the optimal control variable by solving the extreme values of the Hamilton function at each moment. It is easily implemented in order to find the optimal control; see [12,13].
- Equivalent Consumption Minimization (ECM) is an approach that calculates the total fuel consumption by combining the fuel used by an ICE and the equivalent fuel consumption of the electric motor. This unifies the calculation of power from both sources [14]. It is also a form of PMP that has been proven to yield a maximum fuel

economy under certain conditions [15]. An adaptive method [16] has been developed based on ECM. This method continually updates the equivalent factor by taking into account changing driving conditions, and it calculates the equivalent consumption in real-time as a function of the current system output. This allows the system to operate without future driving condition information [17].

- Model Predictive Control (MPC) is an advanced process control method that adheres to a set of constraints. In the context of EMSs for HEV/PHEVs, it is a strategy that combines online system parameter updates with optimal control to predict future velocities and optimize fuel consumption based on them. A typical example can be found in [18], where the authors formulated the energy management problem of a combined HEV as a nonlinear Optimal Control Problem with constraints. Two different cost functions were defined, and the MPC strategy was used to determine the power split between the IC Engine and electrical machines at each sample time. The results demonstrated a significant improvement in fuel economy compared to a commercially available controller in the Powertrain System Analysis Toolkit (PSAT) software. For more reviews of MPC-based EMS, please refer to [19].
- Machine learning, in recent years, has become a popular and useful technique for addressing various problems in many research fields, including as an EMSs method for HEV/PHEVs. It has great potential to improve the computation process and adaptability. The applications of machine learning to energy management can be generally classified into two categories [20]. The first involves using a single algorithm, such as reinforcement learning algorithms [21,22], to derive the energy management policy. The second category involves combining other information or algorithms with machine learning methods, such as predictive algorithms, trip information, and MPC [23–26].
- Metaheuristic algorithms are a type of computational intelligence paradigm that are especially useful for solving complex optimization problems with a vast search space of potential solutions [27]. They use general methods that can be applied to different types of optimization problems, without relying on specific knowledge, and aim to find near-optimal solutions within a reasonable amount of computation time. They are widely used in engineering, science, and business to tackle a range of optimization problems, including those encountered in HEV/PHEV EMSs. The most commonly used metaheuristic algorithms in HEV/PHEVs EMSs are Simulated Annealing(SA), the Genetic Algorithm(GA), and Particle Swarm Optimization (PSO) [28–30]. These algorithms do not require the calculation of derivatives, but instead use alternative methods to identify candidates for the optimal solution. This search for the optimal solution is guided by certain parameters that help to overcome local minima, although convergence to global optima cannot be generally guaranteed [11].

3.2.2. Global Optimization Methods

The concept of Dynamic Programming (DP) is essential for developing strategies to find an optimal global solution. DP utilizes Bellman's optimality principle and decomposes complex problems into simpler subproblems. Normally, Deterministic Dynamic Programming (DDP) has been used to calculate a theoretical lower bound for consumption on specific speed profiles [31]. However, DDP has a curse of dimensionality, meaning that the computational cost increases exponentially with the number of state and control variables, thereby making it impractical for use in real-time applications, particularly for large systems. Some works have proposed techniques for reducing the dimension of the state or control space to overcome this limitation [32,33]. Additionally, future trips information can be considered in the EMS formulation in order to minimize the total trip fuel consumption, either through a mixed-integer linear programming problem [34], or through a Stochastic Dynamic Programming (SDP) framework [35,36].

In conclusion, EMSs are a crucial aspect for HEV/PHEVs, and they play a vital role in achieving their energy efficiency and reducing their environmental impact. The various optimization techniques offer a range of options for designing EMSs that meet the specific requirements of different HEV/PHEV applications. Furthermore, the integration of eco-driving strategies with EMSs can result in improvement in more aspects, such as significant fuel savings, increased safety, and driving comfort. In order to fully understand the complex integration technique, we will explore the various eco-driving strategies that are not limited by HEV/PHEV first in the next section.

4. Eco-Driving Strategy for Connected Vehicles

As mentioned before, eco-driving is a cost-effective and immediate approach to reduce fuel consumption and emissions [37], as the driver plays a major role in determining vehicle performance. Meanwhile, the concept of eco-driving has various definitions and scopes in the literature; for example, the authors in [38] defined it as vehicle purchase and post-purchase decisions, and in [39], the authors pointed out that, for eco-driving behavior, including driving, cabin comfort, trip planning, load management, fuelling, and six maintenance classes, wherein the driving behavior is further divided into acceleration/deceleration, cruise, idling and driving mode selection, and parking. However, In the following context, eco-driving will be limited to the driving behaviors or driver control of the vehicle during a journey that can influence fuel consumption and emissions. The typical research methods used to study eco-driving technology include laboratory testing, on-road experiments, and numerical modeling. We will explain these methods in detail to aid the reader's understanding.

4.1. Laboratory Testing

There are various methods to measure different driving styles, including the use of a chassis dynamometer, engine dynamometer, or driving simulator. Engine dynamometer testing requires following specific procedures set out in regulations for the testing of the engine and exhaust after-treatment system [40]. Similarly, a chassis dynamometer requires standard operation by the operator. These kinds of dynamometers generally need to be located in the laboratory and designed to meet regulatory standards. The results from the laboratory dynamometer are highly precise and reliable, and influencing factors (e.g., test cycles, road resistance, and climate conditions) can always be fully controlled. In addition, a driving simulator is also commonly used to study driving behaviors; it comprises a fixed-base car mock-up equipped with a steering wheel, acceleration pedal, and brake pedal indicators that display the road scenario. The driver operates the driving simulator according to the virtual traffic environment. The primary advantage of driving simulators is that they offer a safe and effective way to examine various factors that impact driver performance [41].

4.2. On-Road Experiments

On-road experiments offer valuable data for evaluating actual driver performance. They are generally less accurate and repeatable than laboratory testing. The commonly used on-road research methods for eco-driving include Portable Emissions Measurement Systems (PEMS), data loggers, odometer reading, fuel use, and surveys [37].

4.3. Numerical Modelling

Numerical modeling is a commonly used tool for evaluating the performance of new eco-driving and eco-routing algorithms. The reason why it has become popular is that it allows researchers to assess the efficacy of these strategies or algorithms without the need for actual field experiments, which result in great savings of both study time and cost. However, its results are typically less precise and dependable than those obtained through laboratory testing or on-road experiments.

However, when novel eco-driving strategies are proposed in any case, two significant scenarios are typically considered: freeways [42,43], and signalized intersections on urban roads [44–47]. Since the first scenario is beyond the scope of this thesis, we will focus on investigating the literature that covers the second scenario. There are numerous dynamic eco-driving models currently available, which vary in their design, formulation of the problem solution (including mathematical formulation, interacting modules, input space, and others), and the energy and traffic models used to connect the eco-driving service to energy and dynamics [48]. In the early models of dynamic eco-driving, the fuel-optimal speed trajectory was estimated and advised using the equipped vehicle's dynamic status, location information, and SPaT data. For instance, Mandava et al. [49] proposed arterial velocity planning, which aimed to maximize the probability of encountering a green light when approaching a signalized intersection. Building on this concept, Barth et al. [44] expanded on the model to determine energy-efficient (de)acceleration profiles based on remaining green/red time and distance from the vehicle to the intersection. Despite the aforementioned models considering similar inputs for fuel-optimal velocity estimation, they employ varying methodologies to process the inputs, and all of their assumptions are based on the assumption of no interference from other surrounding vehicles.

Therefore, to account for the impact of other surrounding traffic factors, the concept design of the eco-driving strategy was adjusted to consider queue discharge information and the status of the preceding vehicle. Therefore, in order to implement the advice speed in actual complex traffic conditions, the authors [50] proposed the Predictive Cruise Control (PCC) model, which minimized travel time under both free-flow and stop-and-go traffic conditions while providing energy-efficient (de)acceleration strategies. In addition to traffic signal and preceding vehicle factors, Queue Length Estimation (QLE) techniques, which are based on commonly installed induction loop sensor systems, helped the predictive speed assistance system, which showed fuel savings of 8–11% [51]. Similar research can be found in [52–54].

Although V2I technology has simplified the process of acquiring real-time SPaT information on signalized intersections with pre-timed signal control, obtaining precise future SPaT data remains challenging due to variations in pre-timed traffic signals and traffic environment fluctuations. To tackle this issue, the probabilistic signal timing approach has been developed, which utilizes real-time SPaT data and historical average timing data for each signal status [55]. For example, the Green Light Optimized Speed Advisory (GLOSA) has been implemented for fully and semi-adaptive traffic lights, thereby leveraging empirical signal and detector data as a solution [56], while, from the vehicle control perspective within the transportation system, the eco-driving problem for Connected and Autonomous Vehicles (CAVs) has been formulated as a data-driven, chance-constrained robust optimization problem. DP has been applied to solve this optimization problem to enhance the controller's robustness when dealing with uncertain signal timing, regardless of random variable distribution [57,58]. Despite these developments, obtaining precise and accurate future SPaT information remains challenging due to technological barriers and the dynamic operation of actuated, coordinated, and adaptive traffic signals. As ITS technology advances, new possibilities may open up to address this challenge.

Last but not least, regarding the dynamic eco-driving control for platoons of vehicles at signalized intersections, the concept has attracted the interest of some researchers. A primary approach to address the impacts of platooning involves precise identification of the leading vehicles for each phase and providing slightly varied guidance to each vehicle within the platoon. For example, in [59], an algorithm was designed to account for real-time signal information and traffic conditions, as well as group vehicles into platoons based on their permutations, and the simulation results showed significantly reduced fuel consumption and emissions while also minimizing travel time and improving traffic flow. Similarly, Ref. [60] developed algorithms by characterizing the optimal speed profiles for platoon-based optimization and highlighted the importance of accurately estimating the vehicle's position and speed again, especially for platooning scenarios. In addition to the homogeneous CAV fleet, the heterogeneous traffic flow, including both CAVs and Human-Driven Vehicles (HDVs), is also a hot issue that needs to be addressed urgently. In [61], a suggestion-based control framework based on MPC was proposed to optimize fuel efficiency in heterogeneous urban traffic. The authors considered that the recommended velocity from CAVs are non-binding with HDVs, which means that the driver of an HDV can choose to follow or not to follow the suggested velocity. In the simulation, this assumption was expressed as a certain probability β. At last, the simulation results showed the proposed control strategy's efficacy. Even though research on dynamic eco-driving for platoons has received limited attention so far, it provides a basis for significantly improving the energy-saving and emission-reduction potential of existing models.

Here, we conclude the main elements for developing eco-driving models near signalized intersections:

- Optimization problem formulation and methods:
  Most proposed eco-driving systems employ mathematical programming to estimate optimal speed profiles for energy and/or traffic efficiency objectives. These objectives include improving energy efficiency (minimizing vehicle tractive force/fuel consumption [52,54,62]), traffic efficiency (minimize idling time [44,50,63]), or a combination of safety, energy consumption, emissions, and traffic flow efficiency objectives [47,58,61]. Generally speaking, for models that incorporate a fuel consumption model, energy efficiency calculations are integrated with optimal problem solutions, while for others, speed trajectories are derived from simulation tools and input into fuel consumption and emissions models. Simultaneously, various optimization frameworks have been proposed for different objectives. These include Model Predictive Control (MPC) approaches focused on trip time and kinetic energy loss [50], fuel–optimal speed profile estimations based on a linear blend of traffic efficiency and emissions [53], and optimal controllers based on the formation of tight and fast-moving platoons for fuel efficiency optimization [62].
- Analysis boundary:
  The analysis boundary for a dynamic eco-driving system typically includes the area of the road network where the system can affect CAVs. This area comprises both the upstream road section leading to the signalized intersection and the downstream section where the benefits of eco-driving strategies are realized [48].
- Vehicle dynamic model and energy model:
  In many research works, constant acceleration [49,52,53] and non-linear acceleration models [47,64] were taken into account to connect with eco-driving services and were adopted to estimate optimal velocity. In addition to these traditional vehicle dynamics models, trigonometric functions were developed to replicate the increase/decrease of an equipped vehicle speed profile while considering the comfortable objective in [44]. These vehicle models were employed to depict the progression of a vehicle's speed from the current speed to the target speed and eventually to the desired speed. Regarding the energy models, according to [65], they can be classified based on their transparency into white-box, grey-box, and black-box models. White-box models are constructed based on the physical or chemical processes of the engine, black-box models treat the entire vehicle or the engine alone as a black box, and grey-box models are the most suitable energy models for evaluating eco-driving systems because of their balance between accuracy and simplicity.

Furthermore, the efficiency of CAV operation depends heavily on the drivers'compliance: if drivers do not follow the recommended speed advice provided by CAV technology, the benefits of the system will reduce a lot. However, the human-related factor is so unpredictable in reality, as the human can be influenced by so many factors, such as personal traits, cognitive and psychomotor functions, situational factors, acceptance, and trust [66], which is now gradually becoming an important topic that will get more attention. In the following section, we will more deeply analyze the integration of eco-driving strategies with energy management systems for Hybrid and Plug-In Hybrid Vehicles. By doing so, we aim to explore the potential synergies and opportunities for improvement in both environmental sustainability and energy efficiency.

5. Co-Optimization of Eco-Driving Strategy and EMSs for HEV/PHEVs

As previously mentioned, the integration of eco-driving and EMSs of HEV/PHEVs are essential for enhancing the energy-saving and environmentally friendly potential of vehicular traffic. The effectiveness of EMSs depend on predicting future states of vehicular traffic, such as velocity and surrounding traffic information. These data can be partially obtained through ITS technology. As a result, the co-optimization of eco-driving strategies and EMSs for HEV/PHEVs become further developed. The current literature can be classified into two categories based on different scenarios, namely, single-vehicle and double/multi-vehicle scenarios.

5.1. Single-Vehicle Scenarios

In the past decade, most research literature in the cooperative optimization of eco-driving and Energy Management Systems (EMS) for HEV/PHEVs has focused on the single-vehicle scenario, where the most valued target is to optimize the power split considering traffic or road information and progressively taking safety constraints into account, but rarely considering other vehicle interactions, such as overtaking and lane-changing.

- Cooperative Optimization for HEVs:
  In most situations, the cooperative optimization framework for HEVs has been designed to minimize energy consumption by first optimizing the speed profile. Next, the power distribution is optimized by following the ideal speed suggested by the eco-velocity planning system. As Figure 8 shows, this concept relies on a two-level optimization framework, which includes both the vehicle and powertrain levels. However, the complex nature of driving in real-world scenarios makes it impractical to optimize the entire velocity trajectory. Therefore, the analysis boundary is typically restricted near to the intersection, thus allowing better integration of EMS with the traffic and road conditions, such as SPAT information and speed limits. Numerous methods have been proposed to tackle the two-layer problem. For instance, for only considering one signalized intersection, Ref. [67] decomposed the hybrid optimal problem into two subproblems. First, the optimal speed profile was computed by solving a nonlinear time-varying optimal problem. Then, the Krylov subspace method was employed to improve computational efficiency. After that, the optimal torque split ratio and gear shift schedule were determined by combining PMP and numerical methods in the bi-level MPC framework. For considering continuous intersections, Ref. [68] introduced a novel cooperative optimization framework for HEVs, which was similarly designed to minimize energy consumption by optimizing velocity trajectories first, then optimizing the power split based on a genetic algorithm to solve the complex fuel consumption model of HEVs. The simulation results of the proposed optimal speed algorithm were compared to the results of a real driving test and a single-intersection optimization algorithm. These comparisons showed that the proposed strategy was more effective in reducing fuel consumption and intersection passing time. Finally, as an example for considering as many real traffic scenarios as possible, Ref. [69] developed an MPC-based strategy that fully considered the three main objectives: safe driving, energy management, and exhaust emission reduction. To address these objectives, the study designed a driving scenario classifier to determine the corresponding vehicle mode. Furthermore, the simulation was conducted in a realistic urban traffic environment using Simulation of Urban MObility (SUMO), and the results demonstrated that the proposed strategy guaranteed safe driving throughout the entire trip, reduced fuel consumption and exhaust emissions, and kept the battery in a healthy SOC range. The study showed the effectiveness and robustness of the proposed strategy for potential online applications. Moreover, more specific HEV-related references can be seen in Table 1.

Table 1. Summary of exemplary works on co-optimization of eco-driving and energy management for HEV/PHEVs near signalized intersections.

Classification	Reference	Modelling Approach	Application	Verification	Achievements
Single-Vehicle Scenario	[67]	– Bi-level MPC – C/GMRES – PMP	HEV	Simulation	– Improve energy efficacy and computational speed
	[68]	– GLOSA – Genetic Algorithm	HEV	Simulation	– Reduce fuel consumption and passing time
	[70]	– Co-optimization – Trigonometric speed profile – MILP	PHEV	Simulation	– Average 24% fuel savings in urban driving conditions
	[71]	– Trigonometric speed profile – Queuing Profile Prediction – Rule-based power-split controller	HEV(Toyota Hybrid System)	Simulation	– Average energy saving was about 8.7% while maintaining mobility performance
	[72,73]	– Two-level receding-horizon control framework – Ecological Adaptive Cruise Controller (ECO-ACC)	PHEV	Hardware-in-the-loop(HIL) simulation	– Reduced energy consumption while avoiding collisions and complying with traffic signals
	[69]	– Bi-level MPC – Driving scenario classifier – Electric-Assist Control	HEV	Simulation	– Reduced the fuel consumption by 34.10% while keeping the battery healthy – Reduced the exhaust emissions (HC, CO, NOx) by 25.36%, 72.30%, and 30.39%
	[74]	– Deep-learning-based queue-aware – Trigonometric speed profile	PHEB	Simulation	– 18.7–24.0% energy efficiency improvements on various traffic congestion levels
	[75]	– Multi-objective hierarchical optimal strategy – MPC-based speed planning strategy – A-ECMS-based EMS	HEV	Simulation	– Improved riding comfort and fuel economy by avoiding stopping at the signalized intersection

Table 1. *Cont.*

Classification	Reference	Modelling Approach	Application	Verification	Achievements
Double/Multi-Vehicle Scenario	[76]	– Hierarchical control architecture – MPC – ECMS	Connected HEVs	Simulation	– Improved fuel efficiency and mobility of the transportation system, reduced CO_2 emissions
	[77]	– Hierarchical control architecture – MPC – DP	Connected HEVs	Simulation	– Better fuel economy and better control performance compared to [76]
	[78]	– Closed-loop hierarchical control architecture – MPC	Connected HEVs	Simulation	– Improved average fuel economy with periodically updated efficiencies from the lower level controller
	[79]	– Two-level cooperative control scheme – Adaptive cruise control strategy – SQP	Connected HEVs	Simulation	– Confirmed the string stability of cooperative control system – Real-time optimization performance of energy consumption
	[80]	– Multi-objective optimization – MPC – Simulated annealing algorithm	Connected HEVs	Simulation	– Superior performance in reducing the fuel consumption and exhaust emissions of the hybrid electric vehicle queue, as well as in improving traffic smoothness
	[81]	– Hierarchical framework – Resistance network generation – ADMM algorithm	PHEVs	HIL simulation	– Improved the energy saving and real-time performances of the torque distribution issue, and significant reduction in computational burden
	[82]	– Gaussian process (GP) model – Double Delayed Q-learning (DDQL) algorithm	PHEVs	Simulation	– Reached 97.31% energy economy compared to DP strategy – Highlighted its huge potential for online implementation

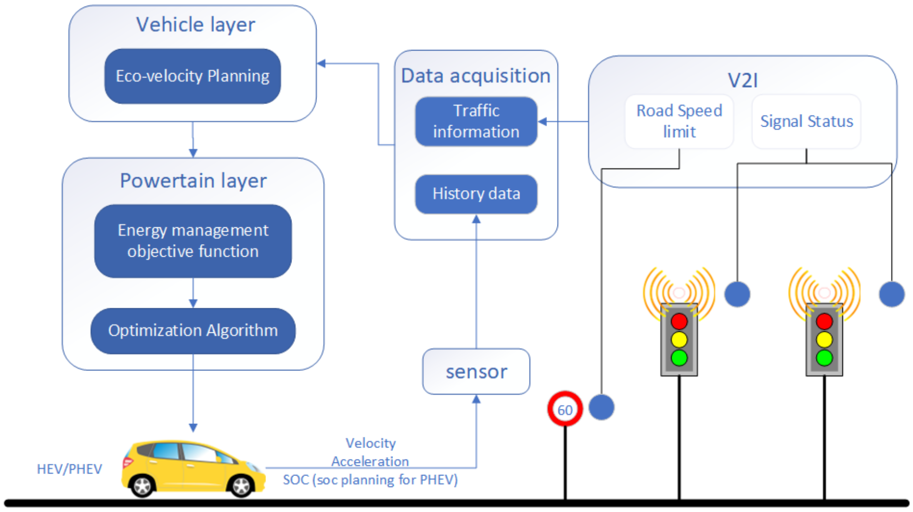

Figure 8. The Scenario of single-vehicle cooperative optimization logic based on V2I information.

The studies mentioned above focus on the intersection as a specific scenario and determine the constraints based on the real-time state of the signalized intersection. However, there is another way of considering the signalized intersection scenario that includes their possible encounters in the uncertainty of future traffic information. One such approach was proposed by [83], who used a novel statistical traffic model to generate stochastic driving behavior and formulate the EMS of HEVs as a bi-level hierarchical optimization problem. This formulation led to an effective upper-level problem that could be solved online as a global optimization using a low-dimension deterministic DP and could be optimized offline using Stochastic Dynamic Programming (SDP), which is embedded with stochastic traffic behavior in the lower level. Simulation results showed reasonable over-consumption compared to deterministic optimization and manageable computational times for both offline and online parts. Another recent work by [84] proposed an adaptive co-optimization method of speed planning and EMS with dynamic probabilistic constraints. The proposed composite sequence generation model enabled dynamic probabilistic constraints by forecasting the upcoming speed distribution of the preceding vehicle. This was based on the probability relationship among future speed sequence, historical speed sequence, and macroscopic traffic state of downstream road segments. By accounting for both large-scale and small-scale traffic disruptions, this method enhanced prediction accuracy by around 10% when compared to purely sequence-based models. Additionally, the distribution divergence was reduced by over 57%. Simulation results indicated a 14.81% increase in driving safety and relatively high energy efficiency compared to existing co-optimization methods under the same car-following conditions.

- Cooperative Optimization for PHEVs:
  Compared to the cooperative optimization of hybrid electric vehicles (HEVs), PHEVs have an additional feature, which allows for the depletion of the battery for electric propulsion and recharging of the battery pack. This makes the Energy Management Systems (EMS) for PHEVs more complex, since the State of Charge (SOC) planning aims for battery depletion during a trip [85]. To tackle this challenge, typical work such as [70] integrated an eco-driving assistance system with the co-optimization of vehicle dynamics and powertrain operations. In this approach, the vehicle dynamic optimization was approximated using the trigonometric speed profile, and the powertrain operation optimization was formulated as a nonlinear constrained optimization problem, which was solved using Mixed-Integer Nonlinear Programming (MINP). The performance of the proposed system was evaluated at different automation levels and achieved an average of 24% fuel savings under typical urban driving conditions. Refs. [72,73] developed an ecological adaptive cruise controller (ECO-ACC) for

PHEVs by considering deterministic traffic SPaT information over the entire route. The energy-saving potential of this receding-horizon control framework was finally validated by hardware-in-the-loop (HIL) simulation results across a range of traffic situations. Regarding machine learning methods, Ref. [74] proposed an innovative Deep-Learning-Based Queue-Aware Ecological Approach and Departure (DLQ-EAD) system for a Plug-In Hybrid Electric Bus (PHEB) that provided an online optimal trajectory for the vehicle that considered both the downstream traffic conditions (i.e., traffic lights, queues) and the vehicle powertrain efficiency. The simulation showed that the proposed DLQ-EAD can achieve 18.7–24.0% energy efficiency improvements for a single PHEB on various traffic congestion levels. In addition, with regard to the traditional optimization methods, such as those mentioned in the previous HEV part, many studies [86–89] did not deal with the signalized intersection as a special scenario. Instead, they proposed an eco-driving base EMS for PHEVs based on a velocity optimization algorithm by utilizing the velocity bounds via V2V and V2I communication, wherein the power split of connected PHEVs and fuel economy could be optimized over a given prediction horizon. Generally, the first step is to plan a global optimal SOC trajectory with the available traffic information. Then, fuel economy is further improved by optimizing the velocity and power split at different levels. However, the driver's behavior with respect to this type of method is often ignored in the simulation results; the performance is dependent on the driver's behavior in real conditions.

The analysis of single-vehicle scenarios in HEVs and PHEVs has demonstrated that cooperative optimization strategies can play a crucial role in shaping future green transportation. As we continue to advance our understanding of double/multi-vehicle scenarios, the lessons we will learn from these optimization strategies will pave the way for a more sustainable, efficient, and environmentally friendly transportation ecosystem.

5.2. Double/Multi-Vehicle Scenarios

The previous subsections covered the integration of ITS information and EMS for single-vehicle scenarios. These ideas can also be applied to double/multi HEV/PHEVs to further enhance overall performance or for a fleet with regards to fuel economy and traffic efficiency.

- Double-Vehicle Scenarios:
  The advent of ITS technology has made it more convenient to acquire V2I/V2V information about the surrounding traffic. In the double-vehicle scenario, cooperative optimization is typically carried out using a car-following model that takes into account the interaction between the two vehicles in order to balance fuel economy and safety. According to [3], two categories of strategies can be distinguished for double-vehicle scenario optimization. The first category is mainly based on Adaptive Cruise Control (ACC) systems, which aim to reduce traffic accidents, increase driving comfort, and improve traffic flow throughput [90]. Instead of the safety and traffic efficiency objectives, the integration of ACC and EMS means the optimization of them simultaneously, thereby adding another target that aims to improve fuel economy. In the car-following scenarios, the velocity of the preceding vehicle has a great impact on the following vehicle as an input for devising the following vehicle's EMS. A typical example is [91]; the authors developed an ACC system based on a nonlinear MPC for intelligent HEVs. This system took into account traffic safety, fuel economy, and ride comfort, therby ultimately improving energy efficiency and the integration of the control system. However, this integration of the ACC and EMS is usually carried out by predefining the preceding vehicle's velocity, which can be done by following certain rules. A similar work is [92]; an adaptive tube-based nonlinear model predictive control (AT-NMPC) approach was introduced for designing autonomous cruise control systems, which guaranteed robust satisfaction of the specified constraints, even in uncertain conditions, and enhanced the system's performance by adapting to changes

in the vehicle control-oriented model. Using a different approach in [93], an ecological ACC based on motion-dependent heuristic dynamic programming was developed to achieve multi-objective optimization. As Figure 9 illustrates, the aforementioned point about the pre-defining velocity of the preceding vehicle based on traffic light time when a signalized intersection is taken into account and the second category are based on Predictive Cruise Control (PCC). EMSs utilizing PCC are designed to make the most of future information by predicting the velocity of the preceding vehicle and using a predictive control algorithm to determine the optimal velocity and power split for the subject vehicle while considering the traffic disturbances [94]. Specifically, PCC-based EMSs are designed with the goal of maximizing the use of future information, which is achieved through the prediction of the preceding vehicle's velocity. An example is [95]; the work suggested an estimation method based on actual and past inter-vehicle distance data, as well as information on traffic and upcoming traffic lights, by employing a set of nonlinear, autoregressive (NARX) models to predict traffic behavior using a cooperative adaptive cruise controller (CACC) to achieve better fuel economy because of the advantages of information prediction. Moreover, some machine learning methods were introduced to the part of the preceding vehicle's prediction due to the complexity and stochastic nature of dynamic traffic, such as the Bayes network model used in [96], which showed a better prediction performance than the "constant acceleration" and "constant velocity" methods. The Gaussian process model was used in [97], which predicts leading vehicle velocity based on time series data and mean traffic flow speed drawn from cloud data. By the way, these machine-learning methods can also be leveraged to optimize complex systems with inconsistent objectives and stringent constraints. For example, Ref. [98] integrated a complete ACC and EMS through a proposed Deep Deterministic Policy Gradient-Based ECOlogical driving strategy (DDPG-ECO) that was based on deep reinforcement learning. The weights of multiple objectives were analyzed to optimize the training results. The simulation results showed that the DDPG-ECO approach achieved over 90% of the performance of DP-based methods while also ensuring good car-following performance. In conclusion, the integration of ACC and EMS aims to reduce fuel consumption by using specific driving cycles to approximate the velocity of the preceding vehicle without taking into account dynamic driving conditions. On the other hand, the integration of PCC and EMS focus more on predicting a preceding vehicles' state through dynamic traffic information, thereby further improving fuel economy. Both approaches prioritize safety and fuel economy when optimizing controls.

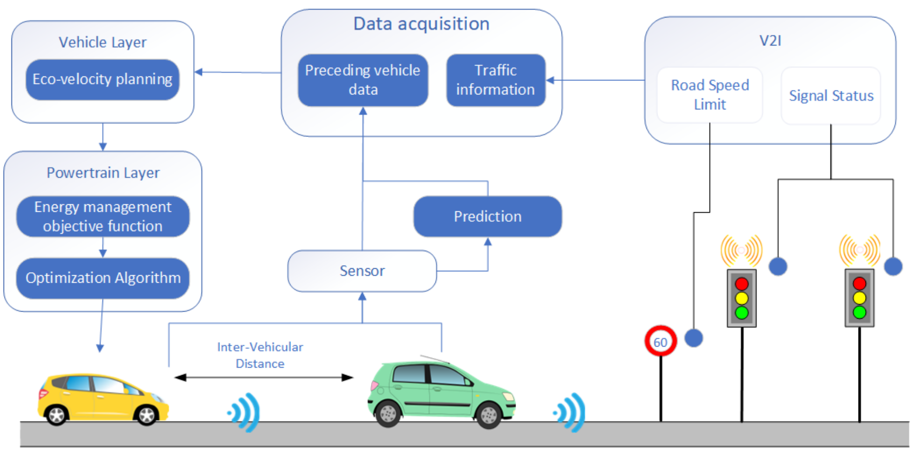

Figure 9. The scenario of double-vehicle considering the safety constraints with preceding vehicle.

- Multi-Vehicle Scenarios:

The multi-vehicle scenario has the potential to reduce air resistance for each vehicle, which can, in turn, increase road capacity, reduce fuel consumption, and improve road safety [99]. Therefore, there has been increased attention on the cooperative optimization of EMSs and eco-driving for HEV/PHEV platoons, and great efforts are being made towards proposing holistic approaches in this area. The most classic framework, as shown in Figure 10 and presented in [76,77], is a hierarchical energy management control strategy for a group of connected HEVs. At the higher level, MPC is used to incorporate SPaT information to predict the optimal velocity profile over a finite time horizon. At the lower level, the adaptive ECMS and DP are used separately as controllers to achieve power distribution by tracking the optimal speed of each HEV's higher-level controller. The effectiveness of the proposed control strategy has been validated through simulation results. However, it should be noted that the propulsion and recuperation efficiencies of HEVs were considered to be constant in this work. To reflect operating characteristics precisely, Ref. [78] considered the efficiency feedback of the two characters based on the above hierarchical energy management control strategy. The fuel economy of the system could be improved, and additional benefits could be achieved by synergizing the reduction of red light stopping, collision avoidance, and cooperative platoon information. Around the same time, Ref. [100] proposed a real-time MPC scheme for connected HEVs that relied on look-ahead traffic information, as well as a chain GP-based predictor to obtain the preceding vehicle's speed, assuming that the vehicle aimed to maintain an average speed that was reflected through the traffic density. The simulation results showed that the proposed method could avoid violations of the spacing corridor to ensure traffic safety and reduce energy consumption without requiring significant emergency acceleration or braking behavior. Moreover, several related works, such as [79,101,102], have confirmed the fuel-saving potential in platoons of HEV/PHEVs. However, optimizing the control strategy for a platoon and the EMS of each HEV simultaneously can be challenging due to the highly coupled nature of the nonlinear augmented system. Most of the current literature assumes a perfectly homogeneous traffic flow, which overlooks human-related factors. As heterogeneous traffic flow becomes more prevalent in multi-vehicle scenarios in the near future, it will further increase the complexity of traffic conditions, thus posing a more significant challenge to improving both the mobility of the traffic system and fuel economy.

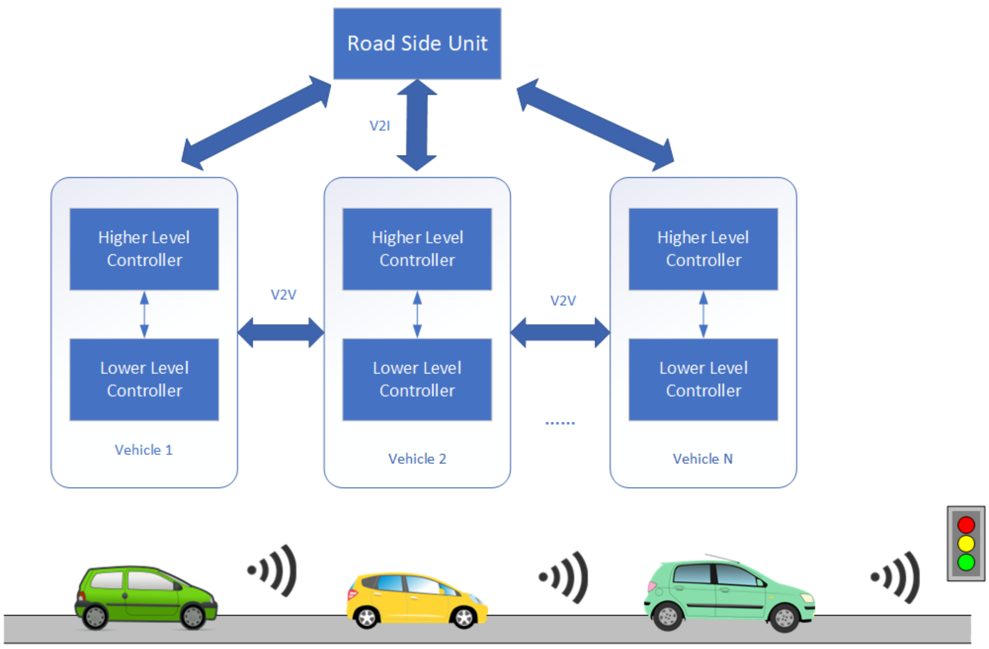

Figure 10. The hierarchical control framework of multi-vehicle scenario.

Finally, by integrating EMS and eco-driving strategies techniques, we can better address the challenges posed by human behavior and technological advancements in the context of ITS technology. In the next section, we will examine emerging developments in the field and discuss how these advances might shape the future. Through identifying potential research directions and opportunities, the development of the integration of these two techniques will enhance the performance of energy efficiency, environmental impact, and contribute to the global push towards a more sustainable transportation landscape.

6. Prospects and Future Trends

6.1. Exploring Lateral Vehicular Interactions and Heterogeneous Traffic for Enhanced EMS and Eco-Driving Strategies

The above literature analysis highlights that the integration of various data sources, such as traffic data, routes, and vehicle information, presents opportunities for the cooperative optimization of vehicle dynamics and powertrain systems with a considerable potential to reduce emissions and energy consumption. However, despite the wealth of research on this topic, there is a notable gap in the literature regarding the rigorous mathematical treatment of lateral vehicular interactions and their implications for trajectory planning along multi-lane road segments near signalized intersections. In realistic traffic conditions, lane-changing and merging maneuvers occur frequently. To address these challenges, several methods [103–105] have been proposed for legacy vehicles, which adopt stochastic controls to minimize the risk of collisions. The focus on safety can also be extended to connected HEV/PHEVs. As a result, the management of the single/double-vehicle or platoon while considering the lateral vehicular interaction behaviors in the future ITS environment, as well as simultaneously ensuring safety and achieving better fuel economy, will be one of the future research trends.

In addition, the heterogeneous traffic environment will become another interesting subject to explore in the future. According to [106], the full market penetration of CAV technologies is not expected until the 2060s. Consequently, mixed traffic streams consisting of Human-Driven Vehicles (HDVs) and connected PEV/HEV/PHEVs will face heterogeneous dynamics and stability. Recent studies have made progress for the platoon with the consideration of lateral vehicular interactions. For example, Ref. [107] proposed a distributed MPC method for a heterogeneous platoon, and [108] addressed control problems for heterogeneous vehicle platoons that were subject to disturbances and modeling errors. Nevertheless, it is crucial to develop a controller that can respond effectively to real-world traffic conditions while maintaining string stability to ensure safe transitional platoon maneuvers. This has been the main goal of the control algorithms proposed in most research to date and into the future.

6.2. Harnessing Machine Learning and Edge Computing for Advanced EMS and Eco-Driving Solutions

The previous literature analysis indicated that the level of sophistication for the cooperative optimization of EMS and eco-driving is gradually advancing. To address many human-factor-related issues, machine learning methods have become popular. These data-driven models integrate predictive models that utilize the driver's compliance with speed advice systems or other interactions with V2I and V2V services. By doing so, these models provide a more realistic representation of how these services may affect systems. In addition, leveraging empirical observations that encompass different driver types, vehicle types, and traffic conditions can enable accurate predictions regarding the performance of co-optimization applications. An example is [74], where deep learning was used to model state transitions based on an offline-trained graphical model, which significantly reduced the time complexity. Furthermore, two or more hybrid learning algorithms will be the direction of approaches for solving the cooperative optimization problem with more and more data sources. One of the application direction of the learning algorithm is to extract useful traffic information and perceive the behavioral characteristics of human-related factors from huge amounts of data, which makes the "brain" of connected HEV/PHEVs smarter, and another is application is the onboard implementation of the EMS, which makes its "behavior" more reliable.

In addition, online control requirements need more powerful calculation and processing capacity. To improve working efficiency, cooperative optimization frameworks must be able to allocate computing resources reasonably according to different calculation tasks. With the advent of the Internet of Things and 5G communications, centralized mobile cloud computing has given way to Mobile Edge Computing (MEC) in recent years. The primary feature of MEC is to push mobile computing, network control, and storage to network edges, thereby enabling computation-intensive and latency-critical applications on resource-limited mobile devices [109]. Therefore, the analysis and study of cooperative optimization under the Mobile Edge Computing architecture represent another important research direction.

6.3. Assessing the Real-World Impact of EMS and Eco-Driving Strategies

Ultimately, experimental validation of any proposed controllers is essential for evaluating its efficacy in real-life scenarios. While simulation tests are the primary validation tool in most reviewed works, they may not provide a precise approach that can be implemented and improved upon in a real-life environment. Although simulation tests satisfy the essential requirement of initial evaluation, several testing-related elements, including communication devices (sensors, V2V/V2I equipment), trajectory planning algorithms, and the EMS for determining the optimal power split for HEVs/PHEVs, pose a challenge to evaluating the real performance of proposed methods. To address this challenge, some researchers have developed HIL testing for relatively simple traffic conditions [110–112]. Therefore, there is a need to systematically investigate efficient approaches (such as those that are low-cost and easy to implement) to validate co-optimization performance.

7. Conclusions

This paper attempted to present an in-depth analysis of the cooperative optimization framework of EMS and eco-driving strategies for HEV/PHEVs, thus emphasizing the need for an integrated approach to promote energy efficiency and environmental sustainability. By clarifying the architectural differences between different hybrid types of HEV/PHEVs, we lay the groundwork for understanding the energy management strategies unique to each vehicle type. Our review of eco-driving strategies for connected vehicles further places these approaches in a broader traffic context. We have identified intersection scenarios as crucial moments for implementing co-optimization strategies and for categorizing them into single-vehicle and double/multi-vehicle cases. By examining the diverse methodologies in the literature, we highlight the strengths and limitations of each approach, thus fostering a deeper understanding of their practical implications. This comprehensive review underscores the potential for advancements in cooperative optimization techniques to facilitate more sustainable and efficient transportation systems. As the field continues to evolve, the need for novel strategies and interdisciplinary research will be critical in addressing future challenges and realizing the full potential of HEV/PHEVs in the global push toward a greener future.

Author Contributions: Conceptualization, investigation, writing—original draft preparation, Z.W.; writing—review and editing, investigation, M.D.; supervision, writing—review and editing, A.E.M. All authors have read and agreed to the published version of the manuscript.

Funding: This research received no external funding.

Institutional Review Board Statement: Not applicable.

Informed Consent Statement: Not applicable.

Data Availability Statement: The data presented in this study are available within the article or its references.

Conflicts of Interest: The authors declare no conflict of interest.

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