electronics

Review

Energy Efficiency of Connected Autonomous Vehicles: A Review

Hamed Faghihian *,† and Arman Sargolzaei †

Department of Mechanical Engineering, University of South Florida, Tampa, FL 33620, USA; a.sargolzaei@gmail.com
* Correspondence: hfaghihian@usf.edu
† These authors contributed equally to this work.

Abstract: Connected autonomous vehicles (CAVs) have emerged as a promising solution for enhancing transportation efficiency. However, the increased adoption of CAVs is expected to lead to a rise in transportation demand and, subsequently, higher energy consumption. In this context, electric CAVs (E-CAVs) present a significant opportunity to shape the future of efficient transportation systems. While conventional CAVs possess the potential to reduce fuel consumption, E-CAVs offer similar prospects but through distinct approaches. Notably, the control of acceleration and regenerative brakes in E-CAVs stands out as an area of immense potential for increasing efficiency, leveraging various control methods in conjunction with the cooperative and perception capabilities inherent in CAVs. To bridge this knowledge gap, this paper conducts a comprehensive survey of energy efficiency methods employed in conventional CAVs while also exploring energy efficiency strategies specifically tailored for E-CAVs.

Keywords: energy efficiency; electric vehicles; range increase; connected autonomous vehicles

Citation: Faghihian, H.; Sargolzaei, A. Energy Efficiency of Connected Autonomous Vehicles: A Review. *Electronics* **2023**, *12*, 4086. https://doi.org/10.3390/electronics12194086

Academic Editor: Felipe Jimenez

Received: 7 August 2023
Revised: 14 September 2023
Accepted: 25 September 2023
Published: 29 September 2023

1. Introduction

1.1. Motivation

Economic and environmental considerations encourage the automotive industry to move toward using electric vehicles (EVs). However, the emergence and penetration of EVs are uncertain [1]. The development and penetration of EVs have some barriers. Among all of these barriers, the range and efficiency of these vehicles have attracted much attention. The increasing efficiency of EVs has been studied in different research [2]. It could be addressed either by means of increasing the efficiency of electric motors [3], by increasing the efficiency of batteries by thermal control [4], by charging procedure control [5], by making them more efficient with better power electric components and semiconductors [2], or by achieving better efficiency by means of optimizing the vehicle route [6]. Another approach for increasing the efficiency of EVs presented in [7] is to optimize energy consumption by using an energy management strategy under different driving cycles. The authors of [8] challenged increasing battery size since increasing battery size would lead to environmental impacts and carbon footprint. Addressing all of the barriers mentioned above is challenging and costly. However, E-CAVs can address some of these energy-related challenges. E-CAVs benefit from the advantages of electrification, connectivity, and autonomous mode driving simultaneously.

E-CAVs are EVs equipped with sensors and technologies to enhance different levels of autonomous driving. They are opening up a new era of vehicle development. CAVs and E-CAVs are equipped and configured with different communication and sensing technologies with software and hardware for handling complex computations. They can utilize vehicle-to-vehicle (V2V) communications and vehicle-to-infrastructure (V2I) communications. An E-CAV equipped with these powerful technologies can have access to a vast amount of data and can interact with other vehicles. All of these potentials bring new opportunities for more efficient driving. The increase in efficiency could be achieved by either V2V communication or V2I communication [9]. However, while the energy efficiency of CAVs has been the main topic of several studies [10–13], the energy efficiency of E-CAVs has not been investigated widely. This paper highlights the efficiency-enhancing potentials of E-CAVs, drawing upon previous research and considering the unique capabilities of E-CAVs. Notably, it should be acknowledged that, while all the energy loss reduction potentials identified in CAVs for internal combustion engine vehicles (ICEVs) are applicable to E-CAVs, the effectiveness of each potential may vary between ICEVs and electric vehicles (EVs).

1.2. Methodology

The methodology used for preparing this paper includes the following steps. (1) Formulating basic concepts of energy efficiency which help to provide details and concepts used for energy efficiency. This will help the reader investigate key factors in the amount of energy a vehicle demands for operating. (2) Investigating studies involving methods, novelties, or optimization algorithms for decreasing the amount of fuel/energy consumption in vehicles using any autonomous mode or utilizing any connectivity feature. To find related literature, specified keywords were used. These keywords were extracted by checking similar review papers. The investigated papers were categorized into two main categories: the conventional CAVs category and the E-CAVs category. Based on the approach used in the investigated papers, they were classified into different subcategories. Each subcategory determines the technology/method used for increasing efficiency. (3) Screening of the papers to be eligible to be considered significant and reliable work. This step is necessary to filter papers. The authors used papers that have significant quality in the assessment of the amount of possible energy saving. In addition to this, it was important for authors to check the paper for a method that is exactly implementable using CAV features. (4) Extraction of data in this work was based on reported methods and the corresponding amount of energy saving or fuel consumption reduction in comparison to the baseline conditions. The authors investigated papers that provide realistic, applicable methods with proper comparison to the baseline condition. Papers that used non-standard baseline situations were not considered. (5) Analysis of the data was performed by comparing reported values in different categories. This analysis is based on significant works with a reliably reported amount of efficiency gain in comparison to the baseline situation. The analysis shed light on different available investigated methods and also the amount of each different potential implementation both in conventional CAVs and E-CAVs.

1.3. Objective and Contribution

Despite the high number of review papers on methods and state-of-the-art in EVs' efficiency, and also the great number of CAVs efficiency-related review papers, there is a lack of survey papers specifically determining the state-of-the-art in energy-related issues of E-CAVs. Therefore, the objective of this paper is to show the knowledge gap in determining and identifying of potentials of E-CAVs in increasing energy efficiency. While there are surveys discussing CAVs' potential in increasing ICEVs' energy/fuel efficiency, there is a lack of studies to bridge these methodologies into E-CAVs. The contributions of this paper are as follows: (1) We compare all of the existing energy-efficiency-related techniques and identified that EVs can benefit from these techniques although they have not been implemented since researchers mistakenly believe that EVs are already energy efficient. (2) We provide a comprehensive resource for researchers to adopt and implement other available algorithms into E-CAVs while considering the limitations and advantages. (3) In addition, we determine that the existing techniques can benefit from regenerative brake systems, which can bring new development and improve the energy efficiency of EVs. To summarize, this paper addresses the existing lack of implementation of energy-efficiency-related algorithms for EVs, which has been shown in a graphical illustration at the end of this paper. As depicted by illustration, one of the main issues for this knowledge gap is the general assumption that researchers consider EVs more efficient than ICEVs.

The structure of this paper is outlined as follows: In Section 2, we delve into the energy principles of vehicles, addressing the potential and methods for enhancing energy efficiency in CAVs. Section 3 presents a survey of the energy efficiency potentials in CAVs across six main classifications. Section 4 focuses on reviewing energy-efficient approaches specifically tailored for E-CAVs.

2. Energy Consumption Principles

The first step toward determining how energy is consumed in a vehicle is to investigate the governing equation. The basic energy equation for a vehicle is $E_t = E_c$, where E_t is traction energy which could be produced by the motor or engine and is delivered to the wheels, and E_c is the energy consumed by the vehicle. The total consuming energy is defined as

$$E_c = E_{air} + E_{roll} + E_{acc} + E_g, \tag{1}$$

where E_{air} is the aerodynamic energy consumption term, E_{RR} is the amount of energy consumed to overcome rolling resistance force, E_{acc} is the amount of energy that consumed for the acceleration of the vehicle, E_g is the amount of energy consumed in changing the height of a vehicle, namely, concerning vehicle elevation. The aerodynamic force could result in energy perturbation known as:

$$E_{air} = \frac{1}{2}\rho_a A \int_0^{S_f} C_D v^2(s)\, ds, \tag{2}$$

where ρ_a is the air density, A is the frontal area of the vehicle, and C_D is the drag coefficient. $V(s)$ denotes the speed of the vehicle as a function of path parameter s. S_f is the final position over the path. The rolling resistance force is induced due to the contact between the tire and the road. The amount of this force is mostly related to the tire structure and material, the tire pressure which controls deflection and road handling of the tire, and the vehicle weight. For a specific vehicle, this force is defined as

$$F_{RR} = mg\mu, \tag{3}$$

where F_{RR} is rolling resistant force, m is the vehicle mass, and g and μ are the gravitational forces acceleration and rolling resistance coefficients respectively. Therefore, the rolling resistance energy term (E_{RR}) can be written as:

$$E_{RR} = mg\mu \int_0^{S_f} v(s)\, ds. \tag{4}$$

E_g can be described as follows:

$$E_g = mg\Delta h, \tag{5}$$

where Δh is the change in the altitude of the vehicle. E_{acc} is the amount of energy consumed for the acceleration of the vehicle.

$$E_{acc} = Mg \int_0^{S_f} a(s)\, ds, \tag{6}$$

where M represents total inertial effects, including mass and rotary components of the vehicle drivetrain and wheels. $a(s)$ refers to vehicle acceleration as the path parameter function. In conventional ICEVs, this energy term will be lost, but in electric or hybrid EVs, a portion of this energy would be recovered in terms of regenerative braking. Therefore, the energy consumption for HEV and EV can be written as

$$E_c = E_{air} + E_{roll} + E_g + E_{acc} - E_{rb}, \tag{7}$$

where E_{rb} is the recovered energy with regenerative braking. The amount of recovered energy could be key to addressing and minimizing the energy consumption of the vehicle. This is further discussed in Section 4.1. The equation for energy could be written as force terms. As depicted in Figure 1, by converting energy terms to force terms, the equation of force equilibrium could be written as

$$F_{trac} = M\frac{dv}{dt} + mgsin(\theta) + F_{air} + F_{RR}, \tag{8}$$

where F_{trac} is the traction force acting on the wheel from the surface, which can be positive during acceleration or can be negative during braking (either normal or regenerative braking), θ is the road slope as shown in Figure 1, and F_{air} is aerodynamic force. With constant C_D, (2) is

$$E_{air} = \frac{1}{2}\rho_a A C_D S_f(\bar{v}^2 + \sigma^2), \tag{9}$$

where $\bar{v}$ is the average speed over any distance interval, σ is the standard deviation, and

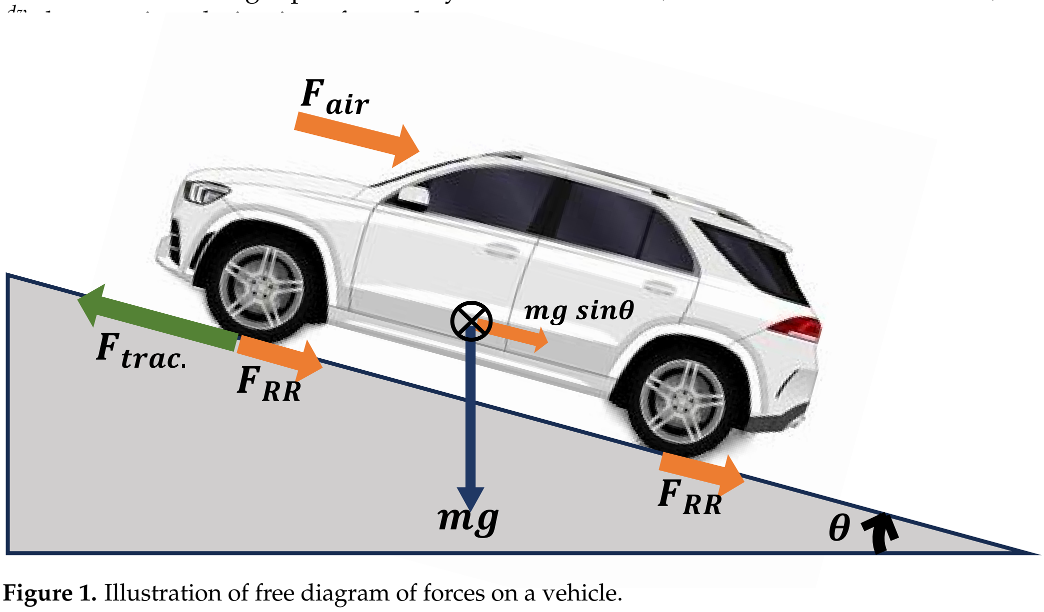

Figure 1. Illustration of free diagram of forces on a vehicle.

To decrease aerodynamic losses, based on Equation (9), average speed and its deviation are the only parameters that can minimize this energy term by means of vehicle dynamics. It is worth noting that minimizing the average speed would increase drive time and decrease traffic flow, which is undesirable in most cases, but decreasing speed deviation is more feasible. The term $m\frac{dv}{dt}$ in Equation (8) shows the necessary force for acceleration or deceleration. In conventional vehicles, the deceleration force comes from brakes, while the acceleration force comes from the power transmission system. In acceleration, when this force is positive, the energy transferred from the power transmission system would be

$$E_{acc} = \frac{1}{2}m(v_f^2 - V_0^2), \tag{10}$$

where v_f and v_0 are the final and initial speeds. In deceleration time intervals, the term $m\frac{dv}{dt}$ is not positive. In these time intervals, it is incorrect to use Equation (10) since all braking energy cannot be recaptured. Therefore, it was necessary to define E_{rb} as an energy term in Equation (7). To summarize, in acceleration time intervals, Equation (10) determines the energy flow from power transmission to the wheels. In deceleration time intervals, E_{rb} shows the energy flow from the wheel to the power module of an EV. Based on this analysis, speed variation is undesirable and it is important to minimize σ in any segment of the drive cycle.

3. Energy-Saving Methods in CAV

In Ref. [11], challenges against CAVs' development were studied. Based on this study, energy efficiency could be a future obstacle toward CAV development. This is because the fact that autonomous mode will increase the number of trips, and without the optimization of energy consumption, the development of CAVs will bring new challenges against the total energy consumption for transportation. The authors of [12] reviewed control algorithms and presented a planning architecture for CAVs to reduce energy consumption by means of control algorithms like eco-driving, powertrain control, eco-routing, and real-time planning. In Ref. [13], methods to increase energy efficiency with traffic-based approaches, smart cities, and new mobility technologies were surveyed. Based on the literature survey [14], different methods of increasing efficiency in CAVs have been studied, and the progress and state-of-the-art of these approaches and methods have been addressed. In this section, we discuss seven common approaches for reducing the energy consumption of conventional CAVs.

3.1. Road Statement

Road statement anticipation can help a CAV optimize its fuel consumption based on road curvature and elevations using a road 3D map. Information like road curvature, elevation, and traffic information can be transferred to the vehicle via V2I communication. These data can be further analyzed for energy consumption reduction. Traffic information is also transferable to the vehicle from a local traffic management center. It is also possible for a connected vehicle to receive this information from a crowed-sourced tool like Waze, Google Maps, Inrix, and Here WeGo. Road status anticipation can be a good source for both human drivers and automated algorithms for the reduction of fuel consumption [15]. It has been shown that, even in the absence of connectivity, this information could be retrieved based on historical data [16]. In this regard, the amount of fuel consumption reduction varies between 2% [17] and 11.6% for heavy-duty vehicles [18].

3.2. Fleet Timing

Each vehicle in a fleet or traffic can optimize its driving cycle to reduce its braking and acceleration. There are several approaches for planning vehicles either in traffic or prior to intersections. For instance, the main idea discussed in [14] is to minimize stops and idling caused by intersections. This can be achieved by receiving the intersection signal phase and timing (SPaT). In Ref. [19], as a primitive usage of this system, time signals were transferred to the drivers to alert them about the traffic situation and about intersections. Fuel consumption reduction was reported between 7% and 14% at intersections. In another work, by using traffic light signals and an optimal control algorithm, a total reduction of 59% fuel consumption was reported [20]. This reduction of fuel consumption was achieved by using intersection signals with vehicle radars data together in predictive cruise control. In another work, an optimization algorithm was used to ensure safety while decreasing the total traffic fuel consumption. In this approach, instead of optimizing the fuel consumption just for one vehicle with microscopic fuel consumption models, the total traffic fuel consumption is optimized [21]. This study demonstrated that the prior fuel consumption reduction reported by other techniques was inaccurate since safety and travel time factors were not considered realistically.

In Ref. [22], a two-level model for traffic signal timing and trajectory planning is considered. The first level optimizes arrival time for traffic control by using dynamic programming (DP). The second layer considers fuel consumption by general pseudospectral optimal control. The work reported an average 10.38% reduction in fuel consumption.

In Ref. [23], a cooperative control method was proposed for vehicles with V2I capabilities. Vehicles' speed and traffic light timing were optimized simultaneously, showing a significant reduction in total fuel consumption for vehicles by 23.7%.

The Eco-Approach and Departure (EAD) is another promising technique to benefit from signalized intersection data to minimize fuel consumption. This method is based on calculating optimal speed trajectory by receiving data from the SPaT system and the Geometric Intersection Description (GID). The primary goal of speed trajectories is to decelerate the vehicle in a manner where it reaches the intersection at the green light. If it cannot make the vehicle reach the green light, it plans the vehicle to decelerate with the least fuel consumption. The designed speed trajectory can be delivered to the driver or the control system of a CAV [21,24–26]. In the literature, numerous eco-driving strategies for the EAD are presented [27–29]. These works reported various amounts of fuel consumption reduction ranging from 2.02% to 58%. In Ref. [29], by considering powertrain characteristics and implementing numerical and experimental models on a three-intersection environment, a 12–28% reduction in fuel consumption was achieved. This work showed the implementation of the EAD system along signalized corridors. However, the fuel consumption reduction in the above-mentioned methods is measured during a small portion of the path, which is unrealistic. The optimization methods can cause traffic interruptions for other vehicles, resulting in fuel consumption increase in surrounding vehicles. To address this, two possible strategies are suggested in the literature: (1) selfish optimization or micro-optimization, and (2) optimization by considering mixed traffic flow, which is a macro-optimization method among a group of vehicles. The simulation in [30] showed that using fleet timing data can increase efficiency by 29% with the selfish optimization method. It could increase by 26% in 100% CAVs in a network of vehicles using group optimization [31].

3.3. Merging and Lane Changing

Lane selection and merging are known as challenging maneuvers for both human drivers and automated driving systems [32]. The fuel consumption or energy consumption side of lane changing and merging has been investigated in the literature [33–35]. There is a huge number of simulations for lane changing using the MOBIL lane change model [33].

Based on the literature, there are two methods to minimize fuel consumption during merging and lane changing. The first method is based on energy/fuel consumption optimization of the merging vehicle by changing velocity and acceleration [34,35]. This method can be achieved by only anticipation and without cooperation. The second method is based on the optimization of energy/fuel consumption in the passing traffic that the vehicle is merging into, because merging a vehicle into another lane would affect coming traffic. If the merging vehicle can anticipate other vehicles' speed and intentions by V2V communications, it can do so in a more efficient manner. By receiving traffic timing, vehicle speed, and spacing information, energy consumption could be optimized between 7% and 14% [36]. The traffic-related fuel consumption during merging or lane changing should be addressed with cooperation between merging vehicles and vehicles in the lane. In literature, fuel consumption is not the most important goal of related works, although based on the study in [37], cooperation can reduce fuel consumption in a macro-simulation.

3.4. Car Following

Car following algorithms are known as the primitive AV features. There is a great number of works toward the optimization of vehicles using these features. However, more recent works have put more focus on cooperative adaptive cruise control (CACC) and platooning. The main difference between CACC and other car-following features is shown in Figure 2. CACC and platooning are considered in some literature interchangeably. However, the difference between CACC and platooning is the hierarchy. In CACC, each vehicle can join or leave the cooperation driving at any time.

Platooning is well known in literature to bring both ADAS capabilities and decrease drag-induced energy losses. This is more significant among trucks since these vehicles suffer from a high amount of drag coefficients due to their cubic end structure [38–40]. Several experiments in the US, Europe, and Japan demonstrated a 5–15% increase in efficiency. During the past several years, different aspects of platooning have been addressed and the technology seems to have matured [41]. In addition, several review papers addressed the progress of this technology [42–44]. Vehicles in a platoon can benefit from increased efficiency due to drag force reduction, fuel consumption optimization methods based on data from V2V and V2I connection, and cooperation toward shaping a fleet of vehicles. Some works like [45] show a much better fuel efficiency increase in the simulation of a 100% platooning effect for 10 vehicles using Model Predictive Control (MPC). This work reported around 50% fuel efficiency increase in an ICEV in some drive cycles. The total energy-saving effect of platooning is considerable. This is due to the fact that this energy/fuel-saving method is effective on a large portion of travel distances. However, the primary motivation to develop CACC is to increase ADAS features, but it is expected that the resulting harmonizing effect with this strategy would increase the total vehicle efficiency [46]. The harmonization effect would decrease braking events and finally lead to less deviation from the average speed. In the model presented in [47], the CACC effect claimed to decrease fuel consumption by 50% in comparison to ACC algorithms with 100% penetration by traffic harmonization.

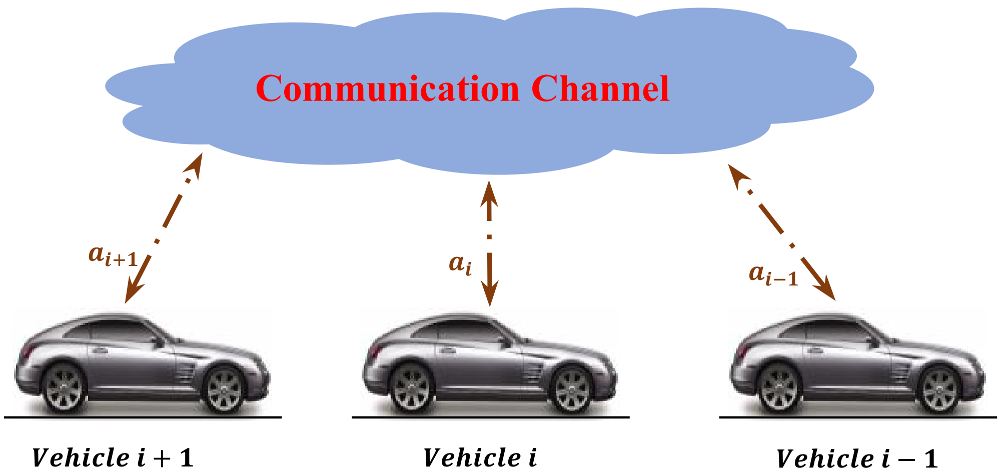

Figure 2. CACC diagram.

The conventional ACC optimization method is selfish optimization, which means that the algorithm tries to find the local optimum in fuel efficiency for the vehicle utilizing this feature [48], whereas recent work on CACC's look for a "social optimum" [49]. Some work has been performed by considering the total fuel consumption as the cost function of the optimization algorithm in CACC. The results in this section are interesting. Social optimization on energy consumption for ICEVs reported up to 50%, based on the simulation in [47]. This total reduction in energy consumption of a fleet of vehicles over a long travel distance is among the greatest values that can be achieved.

There are also some other issues in developing CACC technology that should be addressed. For instance, a CACC control algorithm should be able to ensure safety, string stability, cyber security, and driver and passenger comfort. It is worth noting that increasing fuel efficiency without considering other aspects would not be applicable. In Ref. [50], a multi-objective optimization algorithm was used to consider mobility, safety, driver comfort, and fuel consumption. By simulation, 33% fuel consumption reduction was reported. This was achieved by considering the simultaneous optimization of fuel efficiency and other objective functions, including safety and driver comfort. Another technique is presented in [51], in which energy consumption reduction, safety, and ride comfort are used as objective functions. In a CACC, the dynamic model for the ith vehicles in a CACC or platoon at the time t is defined as follows:

$$\begin{cases} \dot{x}_i(t) = v_i(t), \\ \dot{v}_i(t) = a_i(t), \end{cases} \tag{11}$$

where $i = \{1, 2, 3, \ldots n\}$ denotes the vehicle identification number, and $x_i(t)$, $v_i(t)$ and $a_i(t)$ denote the position, velocity, and acceleration of the ith vehicle at time t, respectively.

Based on (8), if the road slope θ is considered equal to zero, then the acceleration for the vehicle with an internal combustion engine could be written as follows:

$$a_i(t) = \frac{1}{M_i}F_{trac,i} - \frac{1}{m_i}(F_{air,i} - F_{RR,i}), \tag{12}$$

where m_i, M_i, $F_{trac,i}$, $F_{air,i}$, $F_{RR,i}$ denote the mass of the ith vehicle, total inertia (including mass and rotary components equivalent inertia) of the ith vehicle, traction force for the ith vehicle, drag force for the ith vehicle, and rolling resistance, respectively. Note that the traction force could be positive during acceleration or negative in braking mode; therefore, it could be written as:

$$F_{trac,i} = \frac{\eta_i(t)P_i(t)}{v_i(t)} - F_{b,i}(t), \tag{13}$$

where $\eta_i(t)$ is the engine efficiency, $P_i(t)$ is the engine power, and $F_{b,i}(t)$ is the brake force. The drag force and rolling resistance force in (12) can be defined as

$$F_{air,i} = \frac{1}{2}\rho_a C_{D,i} A_i v_i^2(t), \tag{14}$$

$$F_{RR,i} = m_i g \mu. \tag{15}$$

The total power of the vehicle acting on this model is dependent on the engine efficiency. To ensure safety, a minimum distance should be considered. On the other hand, too much spacing would decrease road capacity and also prevent the drag force reduction beneficial of CACC. Therefore, it is important to set vehicle distance around an optimum value. The distance between two vehicles consists of two parts: one of them is known as fixed headway distance and the other one should be related to the vehicle velocity. Based on [52], designed safe distance can be calculated by

$$d_{des}(v_i(t)) = \tau v_i(t) + d_0, \tag{16}$$

where τ is a fixed value, and d_0 is the headway distance that can be set by driver habits or can be left fixed.

In conventional CACC, the controller tries to set the distance between two vehicles to remain within a desired value derived in (16). This goal could be achieved by receiving shared data with other vehicles. Other vehicles can share either their velocity or acceleration or both. In an ideal case, the follower vehicle can receive the acceleration and velocity of the following vehicle via V2V communications and can detect the actual distance to the following with radar or Lidar sensor as feedback. The controller can then set its distance near the desired value calculated in (16).

As mentioned previously, to optimize fuel efficiency, the total consumed energy should be minimized. To optimize the consumption of whole vehicles in a string, the total power indicated in (13) should be minimized. Note that the power term in this equation denotes the consumed power at time t for the i^{th} vehicle. Therefore, to optimize the whole string of vehicles operating in CACC mode or platooning, the total consumed energy is

$$E_{T,whole} = \Sigma_1^n \int_0^T P_i(t)\, dt, \tag{17}$$

where n is the number of vehicles in the string of CACC, and T is the total time. The engine power and its efficiency could be derived from engine torque and velocity using an engine map. Moreover, the engine power could be approximated from approximate models [53]. Therefore, by including energy optimization within the controller, total consumed energy could be minimized. The platooning or CACC operation mode could play a significant role in a total vehicle drive cycle since this mode can operate in a remarkable driving time of a vehicle for its whole life.

3.5. Cooperation on Intersection

In Section 3.2, the effect of having knowledge about the timing of an intersection was discussed, but performing cooperation is more than sending and receiving signals, known as signaling. In signaling, each vehicle receives the timing signal from the intersection and can manage to decrease fuel consumption. This could be achieved with less unnecessary acceleration and braking. In cooperation mode, the intersection control can also do much more to handle passing traffic, decrease wait time, and eliminate wait time for CAVs receiving data from an intersection.

In the best scenario, with 100% CAVs at an intersection, the red light could be omitted using V2I and V2V communications. These ideas are the topics of several works. For instance, in [54], a cooperation system is presented to help all vehicles cross an intersection without any collision by providing a safe maneuver for every vehicle to pass the intersection. The authors of [55] used two-level optimization in controllers. The traffic controller optimizes traffic flow and minimizes waiting time, and the vehicle controller controls vehicle speed to minimize fuel consumption. In Ref. [56], a similar idea was used to control an intersection consisting of a mixture of CAVs and human-driven vehicles. The effect of partially connected vehicles investigated in [57] shows that the 10% connected vehicle environment leads to a maximum 6.4% increase in fuel efficiency, which was achieved by the Eco-Driving System (EDS), while it was shown that using the same system with 50% vehicles with connectivity capabilities would lead to maximum 14.3% increase in fuel efficiency [36]. It is also worth noting that different parameters, rather than just CAV penetration, can affect the total energy efficiency achievement with this method. In Ref. [27], the authors claimed to obtain a maximum of 58.1% fuel efficiency. The effect of omitting the traffic light could be significant since vehicles consume energy for braking and acceleration. The feasibility of this goal and its prerequisites were surveyed in [58–60]. An average of 50% increase in fuel efficiency was reported in [61] through cooperation between vehicles in the real world. This has been achieved by developing an intelligent intersection coordinator. In another work reported in [62,63], the authors performed vehicle-in-the-loop with Mixed Integer Linear Programming (MILP) optimization. With this method, a 20% reduction in energy consumption was reported. In the MILP, the controller creates a live picture of the intersection based on the V2V connection and the speed and location of each vehicle, and the controller actively gives access to each vehicle to handle minimum energy consumption. In Ref. [63], the desired arrival time is added to the optimization objective to avoid delay and increase the performance of the intersection as well as safety. Adding and testing these strategies are vital to examine practicability. In a more recent work , a learning-based algorithm was used to increase the fuel efficiency of vehicles interacting with intersections [64]. It reported an increase in fuel efficiency by around 18%.

In Ref. [65], a reinforcement-learning-based method, named "energy efficiency intersection control and CAVs' speed control" (E^2-ICCAV), was introduced. The controller tries to minimize waiting time (to near zero) for every CAV. Results from both simulation and vehicle-in-the-loop (VIL) showed better performance in average waiting time in comparison to MPC-based optimizations. The results for this paper were only reported in terms of average waiting time. It is reasonable that, by decreasing average waiting time, one may obtain more CAVs passing the intersections without stopping or a significant decrease in their velocity, which could lead to better efficiency. It is worth noting that, as intersections pose only a small portion of a whole normalized driving cycle, therefore, it is not a correct idea to expect a significant increase in a whole drive cycle energy efficiency by just increasing energy efficiency around intersections.

3.6. Cooperation in Harmonizing Traffic

Traffic harmonization can be an unexpected outcome of using CAVs. It can increase fuel/energy efficiency by minimizing speed deviations, unnecessary braking and acceleration, and decreasing multiple stop-and-go situations in moving traffic. Traffic harmonization features can increase drivers' motivation to use CAVs to decrease average travel time in congested areas. The effect of traffic harmonization on increasing or decreasing energy consumption by vehicles has not yet been evaluated very well. The aim of most of the studies on traffic harmonization was to improve traffic characteristics. The authors of [66] investigated the effect of cooperative speed harmonization on fuel consumption, levering emissions, and reduction in travel and travel time in a highly utilized intersection. The study showed that this speed harmonization would also affect non-CAVs positively. Based on this work, the total emission reduction could be between 5% and 11% for CAV penetration from 40% to 100% respectively.

CAVs can coordinate and harmonize traffic even at low penetration levels. V2I connections can decrease the over-saturation effect, which is the result of excessive vehicles using one path. Decreasing the over-saturation effect leads to an increase in traffic harmonization. The study in [67] showed that traffic harmonization will increase significantly by CAV technologies. Moreover, the effect of CACC and platooning on traffic harmonization was investigated in the paper [68].

Several works like [69,70] proposed some strategies that could be implemented within vehicle control like traditional ACC or CACC to maximize energy efficiency. These controllers are designed to increase efficiency by preventing moving jams or improving traffic harmonization. In Ref. [69], a vehicle driving system controller based on the MPC is introduced. In Ref. [71], a design of a cooperative control system was proposed for improving moving jams and traffic flow. The authors of [70] developed a machine-learning-based controller to work with vehicle networks to reduce traffic congestion. These papers did not directly aim for fuel efficiency improvement, but based on energy relationships provided earlier in this chapter, fuel efficiency improved as well. Cancellation of traffic jams is an effective method of energy consumption reduction, especially in ICEVs. ICEVs are suffering from low-efficiency values at low-speed acceleration and idling in moving jams in cities. Utilization of CACC has been shown to have a harmonization effect by improving string stability and preventing shock waves in the traffic. Based on the study in [72], a 5–25% fuel consumption reduction was reported in both simulation and experimental results. Another idea that could be used in CAVs is to utilize the "theory of jam absorption" [73]. It has been shown that a single vehicle is capable of absorbing traffic jams without making a new jam. This theory has been implemented [74]. The study was conducted among more than 20 vehicles resembling traffic waves. By imposing the shock-wave-absorbing autonomous vehicle, the shock wave decreased significantly. The study outcome showed up to a 40% reduction in fuel consumption. This idea has been investigated in several other works [75–77]. The amount of this decrease has been studied in depth in [78].

Table 1 summarizes significant works. It shows in different scenarios how much fuel consumption could be saved by using CAV features.

Table 1. Comparison of CAV potentials for fuel consumption reduction in conventional CAVs based on significant studies.

Road Statement	
Offline data [17,18]	2–11.6%
Fleet Timing	
Using traffic light data [19]	7–14%
Traffic data + optimal control algorithm [20]	up to 59%
EAD [27,28]	2.02–58%
EAD + powertrain consideration [29]	12–28%
Micro optimization [30,31]	26–29%
Merging and Lane Change	
Selfish Optimization [36]	7–14%
Car Following	
Trucks platooning [39,40]	5–15%
MPC + platoon (100% platooning) [45]	50%
Social optimization of CACC [47]	up to 50%
Multi-objective optimization with considering safety and driver comfort [50]	33%
Cooperation on Intersection	
Cooperation at intersections [36,57]	6.4–14.3%
Omitting physical traffic light [27]	50–58%
MILP optimization with optimization [63]	20%
Using a learning-based approach [64]	18%
Cooperation on Traffic Harmonization	
Traffic harmonization at an intersection [66]	5–11%
Traffic harmonization by CACC [78]	5–25%
Jam absorption [75,77]	40%

4. Energy-Saving Methods in E-CAV

Based on the recent development of EVs in market penetration, it is expected that, in the future, EVs will be market-leading technology. It is expected that new developments in vehicle technology will be implemented in EVs. Implementation of CAV technologies on EVs could be the same as ICEVs, but with some differences in energy consumption. The energy consumption impact of CAVs should be addressed on EVs because one of the most important challenges of EVs is the range of vehicles. The range of an EV is dependent on the amount of energy consumption. In addition to the effect of lower energy consumption on increasing vehicle range, higher demand for electric energy for EVs in the future can be another problem and should be minimized. The efficiency of E-CAVs should be increased to counteract the increase of demands in transportation.

During the past several years, the number of available EVs was limited and most of the work on CAVs was conducted based on ICEV. It is expected that CAV technologies will be implemented on EVs in the near future. Therefore, it is important to investigate the possible effects due to this change.

Energy efficiency in ICEVs is mostly reported by the amount of increase or decrease in fuel consumption, while in EVs, a change in batteries' State Of Charge (SOC) is considered as the amount of energy consumption. When it comes to energy consumption, two major issues differentiate EVs from ICEVs. The first one is the fact that efficiency maps in electric machines are different from the ones in ICEVs. The efficiency of an ICEV is reported by means of specific fuel consumption while the efficiency of an electric powertrain is reported as a ratio of electric energy delivered as mechanical power [79]. The second differentiation issue is the fact that electric motors can work as regenerative brakes. The regeneration capability of an electric motor can be a great potential for an E-CAV.

4.1. Regenerative Braking Improvement Effect on E-CAVs

As shown theoretically, EVs and ICEVs share common fundamental principles when it comes to energy consumption. Therefore, any of the discussed CAVs' capabilities can be developed in E-CAVs effectively. By considering the energy Equation (7), the term regeneration brake would make a great difference between EVs and ICEV energy consumption during driving. Therefore, it is important to study the RBS mechanism and effect to investigate how conventional CAVs are differentiated from E-CAVs.

The regenerative brake system can improve the range of vehicles and decrease the amount of energy that would be dissipated to the environment as heat. The brake system has been known as responsible for the energy dissipation source of vehicles. It is known as the major energy dissipation source. The brake system is investigated as the source of up to 50% of the total losses of the traction system power [80]. The efficiency and effectiveness of RBS have been pumped up by introducing and developing the efficient RBS [81]. The developed form of RBS has attracted attempts from the automobile industry [82]. RBS can store recovered energy in different forms like rotating flywheel [83] or in the form of a hydraulic or springs system [84]. However, the most common and developed form of energy recovery is an energy storage system that can easily produce electric energy for further use. Super-capacitors and batteries are known as energy storage systems that can store and deliver electric energy with high efficiency. A hybrid design for using both batteries and super/ultra-capacitors is also another approach to increase the efficiency of storing regenerated energy [85].

CAV technologies bring new opportunities in using regeneration brakes more effectively. At an early step, the vehicle (driver or automated driving system) should be informed about upcoming events or situations. In the study in [86], an energy-optimal deceleration system was introduced to enhance regenerative brakes. It showed a 33% improvement in regenerative brake effectiveness for CAVs compared to human drivers. The potential for energy efficiency gains with regenerative braking in CAVs is worth exploring. The amount of possible increase in energy efficiency with RBS in CAVs could be investigated by checking relationships for a vehicle. As shown in the previous chapter, the relationship for E-CAVs is mostly the same as ICEVs. However, the traction force (13) should be written as follows:

$$F_{trac,i} = \frac{\eta_i(t)P_i(t)}{v_i(t)} - F_{b,i}(t) - F_{rb,i}(t). \tag{18}$$

Data from an official U.S. government source on fuel economy [87] reveals that braking dissipates a substantial amount of traction power as heat, especially in gasoline vehicles with 25% of traction power being lost as heat during braking. As shown in Figure 3, it is even a bit more in city driving cycles. Based on the same study, the amount of braking loss energy in EVs is almost the same (Figure 4), but when the EV is equipped with an RBS, a portion of this loss will recuperate. This study sheds light on how effective a regenerate brake could be in increasing energy efficiency in CAVs. The RBS system cannot recover all of the braking energy, since the regeneration system has its own losses and limitations.

To evaluate the efficiency of the regeneration mode, a practical case study on EV operation in the Rotterdam area was performed [88]. The efficiency of the regeneration brake is defined as

$$VRE = \frac{W_{reg}}{W_{brake}}, \tag{19}$$

where VRE is "Vehicle Regeneration Efficiency", W_{reg} is the amount of regenerated brake energy stored in a useful form (charging battery), and W_{brake} is the total amount of brake energy. In accordance with this study, the VRE measured between 59% and 69% in EVs [88].

In a conventional hydraulic braking system, the distribution of braking force between the front and rear wheels is determined by vehicle mass distribution and braking acceleration. This ensures optimal braking force, preventing wheel lockup and maintaining vehicle stability. The RBS adds some complexity to vehicle braking. There are three methods of combining the regenerating brake with the ordinary braking system in literature [79]. The utilization of RBS can vary in any of the following situations or conditions:

- **Parallel configuration**: In this configuration, the amount of braking force from the RBS and from the hydraulic braking system always depends on the braking master cylinder. The mechanical distributor system could be set up so that, in low levels of deceleration demand (which is equivalent to low brake master cylinder pressure), the RBS is operating solely [89]. This configuration is the basic configuration of combining RBS with a hydraulic system, and it does not need any control strategy to switch between different braking systems.
- **Series brake with optimal feel**: In the series braking system, the braking procedure is divided into two separate modes. In the first mode, where the braking demand deceleration is within a certain value, the braking force will be exerted by the RBS at the driven wheels. In the second mode, when the braking demand deceleration is greater than a certain value, the mechanical braking system would operate on both front and rear wheels. In the second mode, the RBS is also performing regeneration but the mechanical braking system is responsible for the rest of the necessary torque for matching the whole vehicle's deceleration with the deceleration demand [90]. This system brings optimal braking feel and the braking system acts like that in traditional vehicles. It is also noticeable that this braking strategy keeps vehicle dynamics just like a conventional vehicle. However, this minimizes the utilization of RBS.
- **Series brake with maximum energy recovery**: In this braking combination method, the goal is to maximize energy recovery. Therefore while the brake deceleration demand is less than the maximum feasible deceleration, the vehicle utilizes RBS braking force at the driven wheels (in most cases front wheels). If the RBS braking force is not enough to match the braking deceleration demand, the mechanical brake system at the rear wheels is then used to supply the additional force needed to achieve the desired deceleration [79].

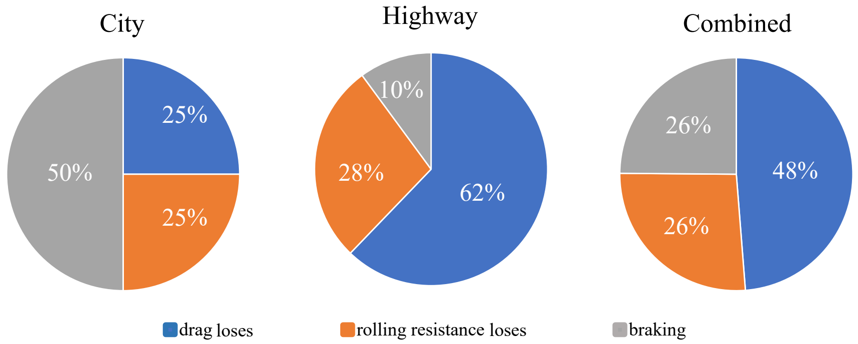

Figure 3. The average share of different energy-consuming components of energy delivered to wheels in cities, highways, and combined cycles in gasoline vehicles (Data obtained from [87]).

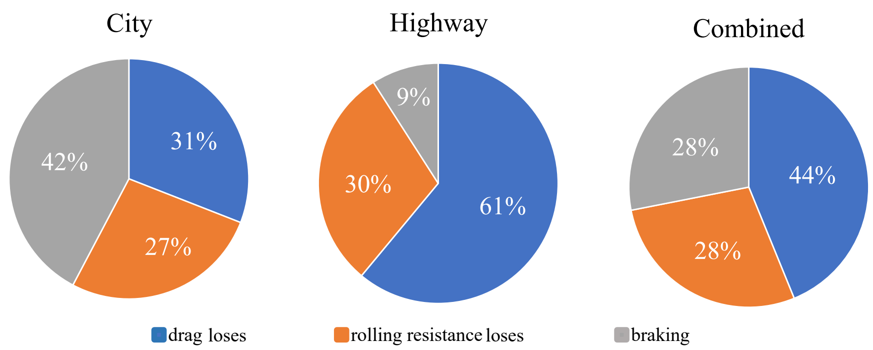

Figure 4. The average share of different energy-consuming components of energy delivered to wheels in cities, highways, and combined cycles in EVs (Data obtained from [87]).

In most of the studies, just the effect of slow deceleration is investigated. It means that the effect of using both regenerative braking and mechanical braking is less investigated, while some sharp decelerations are inevitable. An opportunity for E-CAVs to increase efficiency is to minimize power losses by minimizing speed variations. However, speed variations lead to brake losses. In E-CAVs, inevitable speed reduction could be programmed to be performed by RBS to ensure minimum energy loss. This means that E-CAVs could benefit from this opportunity that has not been investigated in any of the E-CAVs' energy consumption studies.

The following sections will review previous research aimed at harnessing the potential of E-CAVs to enhance overall efficiency.

4.2. Fleet Timing

As mentioned in Section 3.2, this method is based on reducing unnecessary acceleration, deceleration, and idling. Since EVs and most HEVs can eliminate the idling effect, it is expected that this connectivity-based technology does not influence E-CAVs as much as internal combustion engine CAVs. In addition to eliminating the idling effect on energy consumption, E-CAVs can benefit from RBS to recuperate the amount of energy that they lose due to unnecessary acceleration and brakes.

It is worth noting that EVs' motor energy efficiency varies with different amounts of torque and speed demand, as shown in Figure 5. For instance, an experimental study in [91] used particle swarm optimization to increase the efficiency of EVs using efficiency map data. This means that the E-CAVs can benefit from SPaT or any other similar signaling system to maximize its efficiency during a trip to increase energy efficiency.

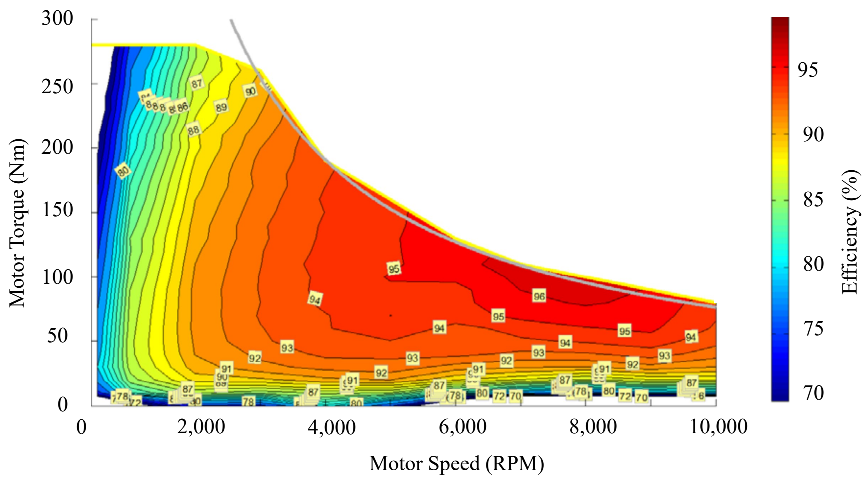

Figure 5. The energy efficiency map for the combined powertrain system of Nissan Leaf EV. The rated power for this powertrain is around 80 KW with a maximum torque of 280 NM. The image is from [92].

EVs cannot regenerate all of the energy during regenerative braking. Therefore, it is not advisable to provide excess energy to the vehicle during unnecessary acceleration and rely on regenerative braking to recover it. Some of this energy will dissipate, especially during sudden braking, often resulting from the driver's unawareness of upcoming events. This means that, even with an efficient RBS, E-CAVs can benefit from their connectivity and anticipation of traffic timing to increase efficiency.

In this regard, some studies have been conducted to investigate the effect of SPaT and similar systems on E-CAVs efficiency. The authors of [93] proposed an MPC to analyze the influence of traffic lights on eco-driving mode. They used an eco-driving optimization method based on dynamic programming to increase energy efficiency. This method generates optimal velocity profiles designed to minimize energy consumption. The proposed eco-driving uses signalized intersections based on V2I communication. These data can be transferred to the control system of a vehicle. The effect of eco-driving on decreasing energy consumption of an EV was also investigated in [94]. It reported between 8% and 31% increase in the energy efficiency of a single vehicle exposed to a traffic light. Another technique under this category is the EAD system. The EAD discussed previously in Section 3.2 using this method in E-CAVs is also reported in [95]. The authors of [96] showed an increase in energy efficiency by 21.9% by using a similar method. This method not only increases efficiency but also decreases travel time. If the travel time is not an important parameter in microscopic modeling, there is the potential for even greater gains in energy efficiency. With an increased travel time of 65.5%, an increase of 47% in energy efficiency was reported. These results were investigated in [97] by using a reinforcement learning control algorithm.

4.3. Car Following, Anticipation, and CACC

In the car following mode, the energy consumption of the follower vehicle is affected by the following car. Therefore, in [98], an energy-optimal adaptive cruise controller was developed, and the effect of this controller was investigated in E-CAVs. The study reported a 2–4% increase in energy efficiency.

In another work in [99], an eco-CACC approach for EV models is presented. The approach can minimize energy consumption in autonomous mode by using a nonlinear MPC method. Simulations in real-world driving conditions with a powertrain-included model for two scenarios were performed. The results determined a meaningful decrease in energy consumption by this approach. Energy consumption in the highway scenario reported a 15.4% decrease, while for the urban scenario, it was 75%. Drag reduction is known as one of the methods for increasing energy efficiency in a string of following vehicles. However, this approach is not practical and should not be considered as a method for energy consumption reduction. The authors of [99] avoided using the drag force reduction strategy. Their method benefits from the reduction in energy consumption by using vehicle powertrain transmission in an optimum mode. Their work cleared the fact that energy optimum trajectories can dramatically affect energy efficiency in E-CAVs.

In addition to using optimization algorithms for increasing the efficiency of E-CAVs, the optimization algorithm must consider safety limitations, realistic driving cycles, and sudden inevitable brakes. In this regard, in [100] a safe and eco-driving control algorithm for an E-CAV with an MPC controller was developed. The control scenario is the same as the ACC controller with the implemented optimization algorithm. The proposed controller is designed with constrained optimization for safety and feasibility. Simulation results on several scenarios were examined. The results show that between 8% and 44% energy efficiency increase is achievable.

In Ref. [101], a model-based reinforcement learning algorithm was examined to investigate efficiency in eco-driving. A more detailed longitudinal model of vehicle, powertrain, and battery model was used. The results of this work suggest that this method can result in the reasonably same reduction in energy consumption of E-CAVs.

4.4. Merging

Despite the large number of works on merging in conventional CAVs, the merging effect on reducing energy consumption is not well established. The authors of [36] suggest optimization algorithms with fuel consumption as the goal function. In Ref. [34], the effect of informing and coordinating vehicles in merging zones on decreasing fuel consumption was studied. These studies show that, by using CAV capabilities, efficiency could be increased. Although these works did not investigate EV models, it is clear that organizing merging vehicles' acceleration regimes can increase energy efficiency both in ICEVs and EVs. Informing and cooperating with vehicles in a merging zone can lead to an increase in energy efficiency by optimizing their speed profile for the least energy consumption. The authors of [102] used merging data in eco-ACC for ICEVs. Their approach can be established with the EV model. It is hard to find any reported energy reduction amount for

E-CAVs during merging. There is not any suggestion on how much E-CAVs' features can increase energy efficiency.

4.5. Cooperation on Traffic Harmonization

With more market penetration, traffic harmonization would increase. Automation and connectivity lead to shock wave reduction, which can significantly reduce unnecessary deceleration. By checking energy equations, it is expected that decreasing traffic congestion and eliminating stops can be less beneficial for EVs in comparison to ICEVs. This originates from two capabilities of EVs: (1) the fact that electric motors do not use any energy during stops, and (2) the fact that string stability and traffic harmonization decrease braking. Since EVs are capable of regenerating a portion of braking, harmonization makes less change to their energy efficiency. There is not any significant study on E-CAVs for determining the energy consumption reduction effect of traffic harmonization with connection and autonomous systems capabilities. There are some works that determine the effect of traffic stabilization on E-CAV energy consumption by considering the platooning effect. In Ref. [103], the effect of E-CAV on a homogeneous traffic stream was studied by using a proposed algorithm for platooning energy reduction. The results of this study suggested that, for a group of 16 E-CAVs, the homogeneous traffic stream can lead to a 5.2% increase in total energy efficiency. It should be noted that a small energy consumption reduction for a group of several vehicles over a long distance is more effective than an energy consumption reduction over a short distance for only a limited number of vehicles.

Table 2 summarizes how much energy efficiency could be gained using CAV features.

Table 2. Comparison of CAV potentials for fuel consumption reduction in E-CAVs based on significant studies.

Fleet Timing	
Eco-driving at signalized intersections [94]	8–31%
EAD [95]	21.9%
Selfish optimization + EAD [97]	47%
Car Following, Anticipation, and CACC	
Optimal deceleration planning with RBS [86]	33%
Eco-CACC with MPC [99]	15.4–75%
Multi-objective optimization considering safety and feasibility [100]	8–44%
Cooperation on Traffic Harmonization	
Traffic harmonization effect of E-CAVs [103]	5.2%

5. Summary

5.1. Challenges

Risk assessment and safety issues are among the most important issues in the development of E-CAVs. It is worth noting that every energy optimization algorithm should consider safety as an important issue. In most of the works considering energy efficiency algorithms or optimization procedures, the safe distance between vehicles has been considered as a preliminary condition for analyzing or evaluating fuel or energy consumption. Other risks like communication errors, faults, and cyber-attacks have not been studied in works related to energy efficiency. It is important for every work considering energy efficiency to analyze how the developed algorithms can deal with different risks.

5.2. Conclusion and Future Directions

In this paper, different algorithms of energy improvement in CAVs are discussed to address the state of research in E-CAVs. E-CAVs tend to be the future of transportation. Energy optimization in EVs using the capabilities of CAVs seems an important issue to address. The extracted results show that, through the development of EVs and CAVs, transportation can benefit from both safety and energy saving. This survey study shows that E-CAVs could be as beneficial as internal combustion engine CAVs. However, studies suggest a lower reduction gain in E-CAVs. These lower results are due to the fact that energy wasting in EVs is different from ICEVs and the fact that EVs are losing less energy with braking and idling.

In accordance with this study, there is not any framework for determining the share of the utilization of vehicles in each mode through their lifetime. It is important to study the share of each part to determine technology demands for the significant energy reduction of CAVs. This prioritization could be different among applications of any vehicle and its local servicing area. For example, for vehicles operating mostly on highways, it is important to prioritize the eco-CACC system for a significant reduction in energy consumption. In city-operating vehicles, cooperative intersection control can be more beneficial. Moreover, it is important to prioritize each technology share in energy consumption reduction for E-CAVs to determine which technology has greater effect to develop in a chronological manner. It should be noticed that frameworks should be capable of considering total energy consumption reduction over whole driving modes of vehicles and also over a significant number of vehicles. This should be given attention to avoid selfish energy optimization methods, which could result in non-optimized energy consumption for groups of neighboring vehicles in mixed traffic.

Figure 6 depicts the summary of studied potentials of CAVs and E-CAVs. Considering the fact that EVs are more efficient in energy consumption, they still have great potential to become more efficient using CAV technologies. In order to collect data for Figure 6, the results of Tables 1 and 2 were compared together. To conduct this comparison, similar approaches from each table were considered, and the reported bonds of each approach in CAVs and E-CAVs are summarized in Figure 6. For instance, the first row of Figure 6 shows the fleet timing approach efficiency gain reported. The minimum and maximum of this value are based on the fleet timing section of Table 1, and for E-CAVs, the fleet timing section of Table 2 is used. The huge difference between E-CAVs and CAVs with internal combustion engine are in the capability of EVs to collect vehicle kinetic energy with RBS. A developed RBS can reduce around 25% of energy consumption. Regeneration of this amount of energy is dependent on proposing methods for E-CAVs to avoid high deceleration brakes. High deceleration brakes lead the brake force split system to use the hydraulic brake. RBS needs specific regeneration torque and speed for higher efficiency during braking. This could be accessible if the vehicle trajectory establishment considers the RBS efficiency for decreasing total energy consumption.

Based on this review, the main findings are as follows:

- A number of articles have determined that the effect of CAVs' features in decreasing energy consumption is greater in conventional vehicles than in EVs.
- EVs are as capable as conventional vehicles to use connectivity and autonomous mode to decrease energy consumption, despite fewer studies.
- Research gaps in studying the effect of CAV technology on increasing E-CAV efficiency are found in:
    1. Merging and lane changing CAVs' feature;
    2. Cooperation at intersections;
    3. Using road statements.
- The most effective CAVs' features on energy efficiency which need more study are:
    1. How to maximize the utilization and efficiency of RBS using E-CAVs' capabilities;
    2. Implementation of eco-CACC algorithms in E-CAVs since it has more long-term effects.

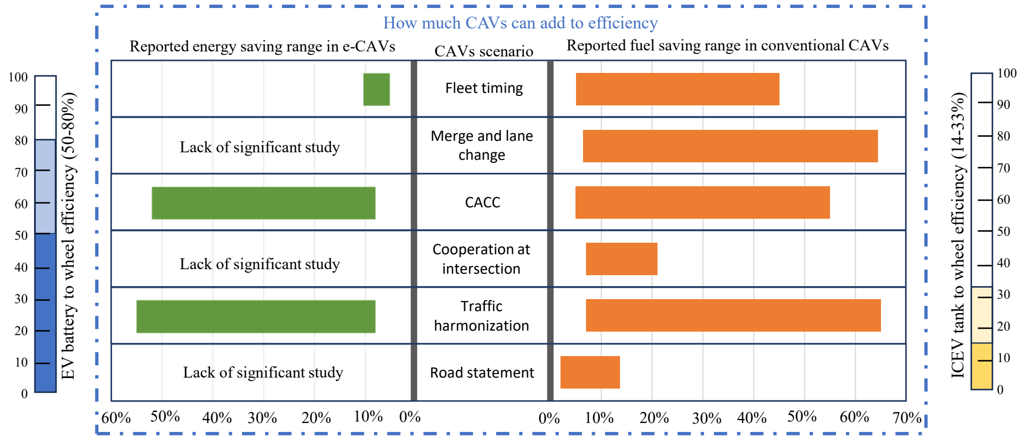

Figure 6. Comparison of conventional CAVs' and E-CAVs' fuel saving potentials in each scenario (results from significant studies), considering the fact that the tank-to-wheel efficiency of ICEVs is between 14% and 33%, while the tank-to-wheel efficiency of EVs is between 50% and 80% [104].

Author Contributions: Conceptualization, H.F.; methodology, H.F.; validation, A.S. and H.F.; formal analysis, H.F.; resources, A.S. and H.F.; writing original draft preparation, H.F.; writing—review and editing, A.S.; supervision, A.S.; project administration, A.S.; funding acquisition, A.S. All authors have read and agreed to the published version of the manuscript.

Funding: Partial support for this research was provided by the National Science Foundation under Grant No. ECCS-EPCN-2241718. Any opinions, findings, and conclusions, or recommendations expressed in this material are those of the authors and do not necessarily reflect the views of the sponsoring agency.

Data Availability Statement: Data sharing not applicable.

Conflicts of Interest: The authors declare no conflict of interest. The funders had no role in the design of the study; in the collection, analyses, or interpretation of data; in the writing of the manuscript; or in the decision to publish the results.

Abbreviations

The following abbreviations are used in this manuscript:

ACC	Adaptive Cruise Control
EV	Electric Vehicle
CACC	Cooperative Adaptive Cruise Control
CAV	Connected Autonomous Vehicle
EV	Electric Vehicle
E-CAV	Electric Connected Autonomous Vehicle
ICEV	Internal Combustion Engine Vehicle
RBS	Regenerative Brake System
SOC	State Of Charge
V2V	Vehicle to Vehicle
V2I	Vehicle to Infrastructure
VIL	Vehicle In the Loop

References

1. Statharas, S.; Moysoglou, Y.; Siskos, P.; Zazias, G.; Capros, P. Factors influencing electric vehicle penetration in the EU by 2030: A model-based policy assessment. *Energies* **2019**, *12*, 2739. [CrossRef]
2. Yadlapalli, R.T.; Kotapati, A.; Kandipati, R.; Koritala, C.S. A review on energy efficient technologies for electric vehicle applications. *J. Energy Storage* **2022**, *50*, 104212. [CrossRef]
3. Shao, L.; Karci, A.E.H.; Tavernini, D.; Sorniotti, A.; Cheng, M. Design approaches and control strategies for energy-efficient electric machines for electric vehicles—A review. *IEEE Access* **2020**, *8*, 116900–116913. [CrossRef]

4. Mali, V.; Saxena, R.; Kumar, K.; Kalam, A.; Tripathi, B. Review on battery thermal management systems for energy-efficient electric vehicles. *Renew. Sustain. Energy Rev.* **2021**, *151*, 111611. [CrossRef]
5. Genovese, A.; Ortenzi, F.; Villante, C. On the energy efficiency of quick DC vehicle battery charging. *World Electr. Veh. J.* **2015**, *7*, 570–576. [CrossRef]
6. De Cauwer, C.; Verbeke, W.; Coosemans, T.; Faid, S.; Van Mierlo, J. A data-driven method for energy consumption prediction and energy-efficient routing of electric vehicles in real-world conditions. *Energies* **2017**, *10*, 608. [CrossRef]
7. Sayed, K.; Kassem, A.; Saleeb, H.; Alghamdi, A.S.; Abo-Khalil, A.G. Energy-saving of battery electric vehicle powertrain and efficiency improvement during different standard driving cycles. *Sustainability* **2020**, *12*, 10466. [CrossRef]
8. Hung, C.R.; Völler, S.; Agez, M.; Majeau-Bettez, G.; Strømman, A.H. Regionalized climate footprints of battery electric vehicles in Europe. *J. Clean. Prod.* **2021**, *322*, 129052. [CrossRef]
9. Noei, S.; Parvizimosaed, M.; Noei, M. Longitudinal Control for Connected and Automated Vehicles in Contested Environments. *Electronics* **2021**, *10*, 1994. [CrossRef]
10. Vahidi, A.; Sciarretta, A. Energy saving potentials of connected and automated vehicles. *Transp. Res. Part C Emerg. Technol.* **2018**, *95*, 822–843. [CrossRef]
11. Ersal, T.; Kolmanovsky, I.; Masoud, N.; Ozay, N.; Scruggs, J.; Vasudevan, R.; Orosz, G. Connected and automated road vehicles: State of the art and future challenges. *Veh. Syst. Dyn.* **2020**, *58*, 672–704. [CrossRef]
12. Guanetti, J.; Kim, Y.; Borrelli, F. Control of connected and automated vehicles: State of the art and future challenges. *Annu. Rev. Control* **2018**, *45*, 18–40. [CrossRef]
13. Campisi, T.; Severino, A.; Al-Rashid, M.A.; Pau, G. The development of the smart cities in the connected and autonomous vehicles (CAVs) era: From mobility patterns to scaling in cities. *Infrastructures* **2021**, *6*, 100. [CrossRef]
14. Sciarretta, A.; Vahidi, A. *Energy-Efficient Driving of Road Vehicles*; Springer: Berlin/Heidelberg, Germany, 2020.
15. Asadi, B.; Zhang, C.; Vahidi, A. The role of traffic flow preview for planning fuel optimal vehicle velocity. In Proceedings of the Dynamic Systems and Control Conference, Cambridge, MA, USA, 12–15 September 2010; Volume 44182, pp. 813–819.
16. Wan, N.; Zhang, C.; Vahidi, A. Probabilistic anticipation and control in autonomous car following. *IEEE Trans. Control Syst. Technol.* **2017**, *27*, 30–38. [CrossRef]
17. Huang, W.; Bevly, D.M.; Schnick, S.; Li, X. Using 3D road geometry to optimize heavy truck fuel efficiency. In Proceedings of the 2008 11th International IEEE Conference on Intelligent Transportation Systems, Beijing, China, 12–15 October 2008; pp. 334–339.
18. He, C.R.; Maurer, H.; Orosz, G. Fuel consumption optimization of heavy-duty vehicles with grade, wind, and traffic information. *J. Comput. Nonlinear Dyn.* **2016**, *11*, 061011. [CrossRef]
19. Li, M.; Boriboonsomsin, K.; Wu, G.; Zhang, W.B.; Barth, M. Traffic energy and emission reductions at signalized intersections: A study of the benefits of advanced driver information. *Int. J. Intell. Transp. Syst. Res.* **2009**, *7*, 49–58.
20. Asadi, B.; Vahidi, A. Predictive use of traffic signal state for fuel saving. *IFAC Proc. Vol.* **2009**, *42*, 484–489. [CrossRef]
21. Rakha, H.; Kamalanathsharma, R.K. Eco-driving at signalized intersections using V2I communication. In Proceedings of the 2011 14th International IEEE Conference on Intelligent Transportation Systems (ITSC), Washington, DC, USA, 5–7 October 2011; pp. 341–346.
22. Jiang, Y.; Zhao, B.; Liu, M.; Yao, Z. A two-level model for traffic signal timing and trajectories planning of multiple CAVs in a random environment. *J. Adv. Transp.* **2021**, *2021*, 9945398. [CrossRef]
23. Xu, B.; Ban, X.J.; Bian, Y.; Wang, J.; Li, K. V2I based cooperation between traffic signal and approaching automated vehicles. In Proceedings of the 2017 IEEE Intelligent Vehicles Symposium (IV), Los Angeles, CA, USA, 11–14 June 2017; pp. 1658–1664.
24. Garcia-Castro, A.; Monzon, A.; Valdes, C.; Romana, M. Modeling different penetration rates of eco-driving in urban areas: Impacts on traffic flow and emissions. *Int. J. Sustain. Transp.* **2017**, *11*, 282–294. [CrossRef]
25. Mandava, S.; Boriboonsomsin, K.; Barth, M. Arterial velocity planning based on traffic signal information under light traffic conditions. In Proceedings of the 2009 12th International IEEE Conference on Intelligent Transportation Systems, St. Louis, MO, USA, 4–7 October 2009; pp. 1–6.
26. Asadi, B.; Vahidi, A. Predictive cruise control: Utilizing upcoming traffic signal information for improving fuel economy and reducing trip time. *IEEE Trans. Control Syst. Technol.* **2010**, *19*, 707–714. [CrossRef]
27. Jiang, H.; Hu, J.; An, S.; Wang, M.; Park, B.B. Eco approaching at an isolated signalized intersection under partially connected and automated vehicles environment. *Transp. Res. Part C Emerg. Technol.* **2017**, *79*, 290–307. [CrossRef]
28. Gao, Z.; LaClair, T.; Ou, S.; Huff, S.; Wu, G.; Hao, P.; Boriboonsomsin, K.; Barth, M. Evaluation of electric vehicle component performance over eco-driving cycles. *Energy* **2019**, *172*, 823–839. [CrossRef]
29. Wu, G.; Hao, P.; Wang, Z.; Jiang, Y.; Boriboonsomsin, K.; Barth, M.; McConnell, M.; Qiang, S.; Stark, J. Eco-approach and departure along signalized corridors considering powertrain characteristics. *SAE Int. J. Sust. Trans. Energy Environ. Policy* **2021**, *2*, 25–40. [CrossRef]
30. Wan, N.; Vahidi, A.; Luckow, A. Optimal speed advisory for connected vehicles in arterial roads and the impact on mixed traffic. *Transp. Res. Part C Emerg. Technol.* **2016**, *69*, 548–563. [CrossRef]
31. Kamalanathsharma, R.K.; Rakha, H.A.; Yang, H. Networkwide impacts of vehicle ecospeed control in the vicinity of traffic signalized intersections. *Transp. Res. Rec.* **2015**, *2503*, 91–99. [CrossRef]
32. Liu, K.; Gong, J.; Kurt, A.; Chen, H.; Ozguner, U. Dynamic modeling and control of high-speed automated vehicles for lane change maneuver. *IEEE Trans. Intell. Veh.* **2018**, *3*, 329–339. [CrossRef]

33. Kesting, A.; Treiber, M.; Helbing, D. General lane-changing model MOBIL for car-following models. *Transp. Res. Rec.* **2007**, *1999*, 86–94. [CrossRef]
34. Rios-Torres, J.; Malikopoulos, A.A. Automated and cooperative vehicle merging at highway on-ramps. *IEEE Trans. Intell. Transp. Syst.* **2016**, *18*, 780–789. [CrossRef]
35. Kamal, M.A.S.; Mukai, M.; Murata, J.; Kawabe, T. Model predictive control of vehicles on urban roads for improved fuel economy. *IEEE Trans. Control Syst. Technol.* **2012**, *21*, 831–841. [CrossRef]
36. Kamal, M.A.S.; Taguchi, S.; Yoshimura, T. Efficient driving on multilane roads under a connected vehicle environment. *IEEE Trans. Intell. Transp. Syst.* **2016**, *17*, 2541–2551. [CrossRef]
37. Awal, T.; Murshed, M.; Ali, M. An efficient cooperative lane-changing algorithm for sensor-and communication-enabled automated vehicles. In Proceedings of the 2015 IEEE Intelligent Vehicles Symposium (IV), Seoul, Republic of Korea, 28 June–1 July 2015; pp. 1328–1333.
38. Al Alam, A.; Gattami, A.; Johansson, K.H. An experimental study on the fuel reduction potential of heavy duty vehicle platooning. In Proceedings of the 13th International IEEE Conference on Intelligent Transportation Systems, Funchal, Portugal, 19–22 September 2010; pp. 306–311.
39. Alam, A. Fuel-Efficient Heavy-Duty Vehicle Platooning. Ph.D. Thesis, KTH Royal Institute of Technology, Stockholm, Sweden, 2014.
40. Tsugawa, S. Results and issues of an automated truck platoon within the energy ITS project. In Proceedings of the 2014 IEEE Intelligent Vehicles Symposium Proceedings, Dearborn, MI, USA, 8–11 June 2014; pp. 642–647.
41. Kunze, R.; Ramakers, R.; Henning, K.; Jeschke, S. Organization and operation of electronically coupled truck platoons on German motorways. In *Automation, Communication and Cybernetics in Science and Engineering 2009/2010*; Springer: Berlin/Heidelberg, Germany, 2011; pp. 427–439.
42. Tsugawa, S.; Jeschke, S.; Shladover, S.E. A review of truck platooning projects for energy savings. *IEEE Trans. Intell. Veh.* **2016**, *1*, 68–77. [CrossRef]
43. Bishop, R.; Bevly, D.; Humphreys, L.; Boyd, S.; Murray, D. Evaluation and testing of driver-assistive truck platooning: Phase 2 final results. *Transp. Res. Rec.* **2017**, *2615*, 11–18. [CrossRef]
44. Zhang, L.; Chen, F.; Ma, X.; Pan, X. Fuel economy in truck platooning: A literature overview and directions for future research. *J. Adv. Transp.* **2020**, *2020*, 2604012. [CrossRef]
45. Dollar, R.A.; Vahidi, A. Quantifying the impact of limited information and control robustness on connected automated platoons. In Proceedings of the 2017 IEEE 20th International Conference on Intelligent Transportation Systems (ITSC), Yokohama, Japan, 16–19 October 2017; pp. 1–7.
46. Guo, Y.; Ma, J.; Leslie, E.; Huang, Z. Evaluating the effectiveness of integrated connected automated vehicle applications applied to freeway managed lanes. *IEEE Trans. Intell. Transp. Syst.* **2020**, *23*, 522–536. [CrossRef]
47. Liu, H.; Shladover, S.E.; Lu, X.Y.; Kan, X. Freeway vehicle fuel efficiency improvement via cooperative adaptive cruise control. *J. Intell. Transp. Syst.* **2021**, *25*, 574–586. [CrossRef]
48. HomChaudhuri, B.; Vahidi, A.; Pisu, P. Fast model predictive control-based fuel efficient control strategy for a group of connected vehicles in urban road conditions. *IEEE Trans. Control Syst. Technol.* **2016**, *25*, 760–767. [CrossRef]
49. Zheng, Y.; Li, S.E.; Li, K.; Borrelli, F.; Hedrick, J.K. Distributed model predictive control for heterogeneous vehicle platoons under unidirectional topologies. *IEEE Trans. Control Syst. Technol.* **2016**, *25*, 899–910. [CrossRef]
50. Zhong, Z.; Lee, J.; Zhao, L. Multiobjective optimization framework for cooperative adaptive cruise control vehicles in the automated vehicle platooning environment. *Transp. Res. Rec.* **2017**, *2625*, 32–42. [CrossRef]
51. He, Y.; Zhou, Q.; Makridis, M.; Mattas, K.; Li, J.; Williams, H.; Xu, H. Multiobjective co-optimization of cooperative adaptive cruise control and energy management strategy for PHEVs. *IEEE Trans. Transp. Electrif.* **2020**, *6*, 346–355. [CrossRef]
52. He, Y.; Ciuffo, B.; Zhou, Q.; Makridis, M.; Mattas, K.; Li, J.; Li, Z.; Yan, F.; Xu, H. Adaptive Cruise Control Strategies Implemented on Experimental Vehicles: A Review. *IFAC-PapersOnLine* **2019**, *52*, 21–27.
53. Guzzella, L.; Sciarretta, A. *Vehicle Propulsion Systems-Introduction to Modeling and Optimization*; Springer: Berlin, Germany, 2013.
54. Lee, J.; Park, B. Development and evaluation of a cooperative vehicle intersection control algorithm under the connected vehicles environment. *IEEE Trans. Intell. Transp. Syst.* **2012**, *13*, 81–90. [CrossRef]
55. Xu, B.; Ban, X.J.; Bian, Y.; Li, W.; Wang, J.; Li, S.E.; Li, K. Cooperative method of traffic signal optimization and speed control of connected vehicles at isolated intersections. *IEEE Trans. Intell. Transp. Syst.* **2018**, *20*, 1390–1403. [CrossRef]
56. Tajalli, M.; Hajbabaie, A. Traffic signal timing and trajectory optimization in a mixed autonomy traffic stream. *IEEE Trans. Intell. Transp. Syst.* **2021**, *23*, 6525–6538. [CrossRef]
57. Kamal, M.A.S.; Taguchi, S.; Yoshimura, T. Intersection vehicle cooperative eco-driving in the context of partially connected vehicle environment. In Proceedings of the 2015 IEEE 18th International Conference on Intelligent Transportation Systems, Gran Canaria, Spain, 15–18 September 2015; pp. 1261–1266.
58. Ferreira, M.; Fernandes, R.; Conceição, H.; Viriyasitavat, W.; Tonguz, O.K. Self-organized traffic control. In Proceedings of the Seventh ACM International Workshop on VehiculAr InterNETworking, Chicago, IL, USA, 24 September 2010; pp. 85–90.
59. Viriyasitavat, W.; Tonguz, O.K. Priority management of emergency vehicles at intersections using self-organized traffic control. In Proceedings of the 2012 IEEE Vehicular Technology Conference (VTC Fall), Quebec City, QC, Canada, 3–6 September 2012; pp. 1–4.

60. Wu, J.; Qu, X. Intersection control with connected and automated vehicles: A review. *J. Intell. Connect. Veh.* **2022**, *5*, 260–269. [CrossRef]
61. Huang, S.; Sadek, A.W.; Zhao, Y. Assessing the mobility and environmental benefits of reservation-based intelligent intersections using an integrated simulator. *IEEE Trans. Intell. Transp. Syst.* **2012**, *13*, 1201–1214. [CrossRef]
62. Fayazi, S.A.; Vahidi, A. Vehicle-in-the-loop (VIL) verification of a smart city intersection control scheme for autonomous vehicles. In Proceedings of the 2017 IEEE Conference on Control Technology and Applications (CCTA), Maui, HI, USA, 27–30 August 2017; pp. 1575–1580.
63. Fayazi, S.A.; Vahidi, A. Mixed-integer linear programming for optimal scheduling of autonomous vehicle intersection crossing. *IEEE Trans. Intell. Veh.* **2018**, *3*, 287–299. [CrossRef]
64. Jayawardana, V.; Wu, C. Learning Eco-Driving Strategies at Signalized Intersections. *arXiv* **2022**, arXiv:2204.12561.
65. Wang, E.; Memar, F.H.; Korzelius, S.; Sadek, A.W.; Qiao, C. A Reinforcement Learning Approach to CAV and Intersection Control for Energy Efficiency. In Proceedings of the 2022 Fifth International Conference on Connected and Autonomous Driving (MetroCAD), Detroit, MI, USA, 28–29 April 2022; pp. 81–88.
66. Englund, C.; Chen, L.; Voronov, A. Cooperative speed harmonization for efficient road utilization. In Proceedings of the 2014 7th International Workshop on Communication Technologies for Vehicles (Nets4Cars-Fall), St. Petersburg, Russia, 6–8 October 2014; pp. 19–23.
67. Guo, Y.; Ma, J. Leveraging existing high-occupancy vehicle lanes for mixed-autonomy traffic management with emerging connected automated vehicle applications. *Transp. A Transp. Sci.* **2020**, *16*, 1375–1399. [CrossRef]
68. Dey, K.C.; Yan, L.; Wang, X.; Wang, Y.; Shen, H.; Chowdhury, M.; Yu, L.; Qiu, C.; Soundararaj, V. A review of communication, driver characteristics, and controls aspects of cooperative adaptive cruise control (CACC). *IEEE Trans. Intell. Transp. Syst.* **2015**, *17*, 491–509. [CrossRef]
69. Kamal, M.A.S.; Imura, J.i.; Hayakawa, T.; Ohata, A.; Aihara, K. Smart driving of a vehicle using model predictive control for improving traffic flow. *IEEE Trans. Intell. Transp. Syst.* **2014**, *15*, 878–888. [CrossRef]
70. Saleem, M.; Abbas, S.; Ghazal, T.M.; Khan, M.A.; Sahawneh, N.; Ahmad, M. Smart cities: Fusion-based intelligent traffic congestion control system for vehicular networks using machine learning techniques. *Egypt. Inform. J.* **2022**, *23*, 417–426. [CrossRef]
71. Wang, M.; Daamen, W.; Hoogendoorn, S.P.; van Arem, B. Cooperative car-following control: Distributed algorithm and impact on moving jam features. *IEEE Trans. Intell. Transp. Syst.* **2015**, *17*, 1459–1471. [CrossRef]
72. Talebpour, A.; Mahmassani, H.S. Influence of connected and autonomous vehicles on traffic flow stability and throughput. *Transp. Res. Part C Emerg. Technol.* **2016**, *71*, 143–163. [CrossRef]
73. Nishi, R.; Tomoeda, A.; Shimura, K.; Nishinari, K. Theory of jam-absorption driving. *Transp. Res. Part B Methodol.* **2013**, *50*, 116–129. [CrossRef]
74. Stern, R.E.; Cui, S.; Delle Monache, M.L.; Bhadani, R.; Bunting, M.; Churchill, M.; Hamilton, N.; Pohlmann, H.; Wu, F.; Piccoli, B.; et al. Dissipation of stop-and-go waves via control of autonomous vehicles: Field experiments. *Transp. Res. Part C Emerg. Technol.* **2018**, *89*, 205–221. [CrossRef]
75. He, Z.; Zheng, L.; Song, L.; Zhu, N. A jam-absorption driving strategy for mitigating traffic oscillations. *IEEE Trans. Intell. Transp. Syst.* **2016**, *18*, 802–813. [CrossRef]
76. Zheng, Y.; Zhang, G.; Li, Y.; Li, Z. Optimal jam-absorption driving strategy for mitigating rear-end collision risks with oscillations on freeway straight segments. *Accid. Anal. Prev.* **2020**, *135*, 105367. [CrossRef]
77. Wang, Y. Traffic Congestion and Shockwave Damping through Advanced Driver Assistance System (ADAS) Longitudinal Vehicle Control. Ph.D. Thesis, Rutgers The State University of New Jersey, School of Graduate Studies, New Brunswick, NJ, USA, 2022.
78. Lang, D.; Schmied, R.; Del Re, L. Prediction of preceding driver behavior for fuel efficient cooperative adaptive cruise control. *SAE Int. J. Engines* **2014**, *7*, 14–20. [CrossRef]
79. Ehsani, M.; Gao, Y.; Longo, S.; Ebrahimi, K.M. *Modern Electric, Hybrid Electric, and Fuel Cell Vehicles*; CRC Press: Boca Raton, FL, USA, 2018.
80. Hamada, A.T.; Orhan, M.F. An overview of regenerative braking systems. *J. Energy Storage* **2022**, *52*, 105033. [CrossRef]
81. Ko, J.; Ko, S.; Son, H.; Yoo, B.; Cheon, J.; Kim, H. Development of brake system and regenerative braking cooperative control algorithm for automatic-transmission-based hybrid electric vehicles. *IEEE Trans. Veh. Technol.* **2014**, *64*, 431–440. [CrossRef]
82. Panagiotidis, M.; Delagrammatikas, G.; Assanis, D. Development and use of a regenerative braking model for a parallel hybrid electric vehicle. *SAE Trans.* **2000**, *109*, 1180–1191.
83. Hsu, T.R. On a flywheel-based regenerative braking system for regenerative energy recovery. *arXiv* **2013**, arXiv:1311.6012.
84. Liu, S.; Martin, C.; Lashmore, D.; Schauer, M.; Livermore, C. Regenerative braking systems with torsional springs made of carbon nanotube yarn. *J. Phys. Conf. Ser.* **2014**, *557*, 012060. [CrossRef]
85. Zhao, W.; Wu, G.; Wang, C.; Yu, L.; Li, Y. Energy transfer and utilization efficiency of regenerative braking with hybrid energy storage system. *J. Power Sources* **2019**, *427*, 174–183. [CrossRef]
86. Kim, D.; Eo, J.S.; Kim, Y.; Guanetti, J.; Miller, R.; Borrelli, F. *Energy-Optimal Deceleration Planning System for Regenerative Braking of Electrified Vehicles with Connectivity and Automation*; Technical Report; SAE: Warrendale, PA, USA, 2020.
87. Where the Energy Goes: Gasoline Vehicles. Available online: https://www.fueleconomy.gov/feg/atv.shtml (accessed on 24 September 2023).

88. Van Sterkenburg, S.; Rietveld, E.; Rieck, F.; Veenhuizen, B.; Bosma, H. Analysis of regenerative braking efficiency—A case study of two electric vehicles operating in the Rotterdam area. In Proceedings of the 2011 IEEE Vehicle Power and Propulsion Conference, Chicago, IL, USA, 6–9 September 2011; pp. 1–6.
89. Jingming, Z.; Baoyu, S.; Xiaojing, N. Optimization of parallel regenerative braking control strategy. In Proceedings of the 2008 IEEE Vehicle Power and Propulsion Conference, Harbin, China, 3–5 September 2008; pp. 1–4.
90. Sangtarash, F.; Esfahanian, V.; Nehzati, H.; Haddadi, S.; Bavanpour, M.A.; Haghpanah, B. Effect of different regenerative braking strategies on braking performance and fuel economy in a hybrid electric bus employing CRUISE vehicle simulation. *SAE Int. J. Fuels Lubr.* **2009**, *1*, 828–837. [CrossRef]
91. Valladolid, J.D.; Patino, D.; Gruosso, G.; Correa-Flórez, C.A.; Vuelvas, J.; Espinoza, F. A novel energy-efficiency optimization approach based on driving patterns styles and experimental tests for electric vehicles. *Electronics* **2021**, *10*, 1199. [CrossRef]
92. Burress, T. Benchmarking state-of-the-art technologies. In Proceedings of the Oak Ridge National Laboratory (ORNL), 2013 US DOE Hydrogen and Fuel Cells Program and Vehicle Technologies Program Annual Merit Review and Peer Evaluation Meeting, Washington, DC, USA, 14–16 May 2013.
93. Miyatake, M.; Kuriyama, M.; Takeda, Y. Theoretical study on eco-driving technique for an Electric Vehicle considering traffic signals. In Proceedings of the 2011 IEEE Ninth International Conference on Power Electronics and Drive Systems, Singapore, 5–8 December 2011; pp. 733–738. [CrossRef]
94. Zhang, R.; Yao, E. Eco-driving at signalised intersections for electric vehicles. *IET Intell. Transp. Syst.* **2015**, *9*, 488–497. [CrossRef]
95. Qi, X.; Barth, M.J.; Wu, G.; Boriboonsomsin, K.; Wang, P. Energy impact of connected eco-driving on electric vehicles. In *Road Vehicle Automation 4*; Springer: Berlin/Heidelberg, Germany, 2018; pp. 97–111.
96. Qi, X.; Wang, P.; Wu, G.; Boriboonsomsin, K.; Barth, M.J. Energy and mobility benefits from connected ecodriving for electric vehicles. In Proceedings of the 2017 IEEE 20th International Conference on Intelligent Transportation Systems (ITSC), Yokohama, Japan, 16–19 October 2017; pp. 1–6. [CrossRef]
97. Bin Al Islam, S.; Aziz, H.M.A.; Wang, H.; Young, S.E. Minimizing energy consumption from connected signalized intersections by reinforcement learning. In Proceedings of the 2018 21st International Conference on Intelligent Transportation Systems (ITSC), Maui, HI, USA, 4–7 November 2018; pp. 1870–1875. [CrossRef]
98. Flehmig, F.; Sardari, A.; Fischer, U.; Wagner, A. Energy optimal adaptive cruise control during following of other vehicles. In Proceedings of the 2015 IEEE Intelligent Vehicles Symposium (IV), Seoul, Republic of Korea, 28 June–1 July 2015; pp. 724–729.
99. Bertoni, L.; Guanetti, J.; Basso, M.; Masoero, M.; Cetinkunt, S.; Borrelli, F. An adaptive cruise control for connected energy-saving electric vehicles. *IFAC-PapersOnLine* **2017**, *50*, 2359–2364.
100. Han, J.; Sciarretta, A.; Ojeda, L.L.; De Nunzio, G.; Thibault, L. Safe-and eco-driving control for connected and automated electric vehicles using analytical state-constrained optimal solution. *IEEE Trans. Intell. Veh.* **2018**, *3*, 163–172. [CrossRef]
101. Lee, H.; Kim, K.; Kim, N.; Cha, S.W. Energy efficient speed planning of electric vehicles for car-following scenario using model-based reinforcement learning. *Appl. Energy* **2022**, *313*, 118460. [CrossRef]
102. Kamal, M.A.S.; Hashikura, K.; Hayakawa, T.; Yamada, K.; Imura, J.I. Adaptive Cruise Control with Look-Ahead Anticipation for Driving on Freeways. *Appl. Sci.* **2022**, *12*, 929. [CrossRef]
103. Lu, C.; Dong, J.; Hu, L. Energy-efficient adaptive cruise control for electric connected and autonomous. *IEEE Intell. Transp. Syst. Mag.* **2019**, *11*, 42–55. [CrossRef]
104. Albatayneh, A.; Assaf, M.N.; Alterman, D.; Jaradat, M. Comparison of the overall energy efficiency for internal combustion engine vehicles and electric vehicles. *Rigas Teh. Univ. Zinat. Raksti* **2020**, *24*, 669–680. [CrossRef]