World Electric Vehicle Journal

MDPI

Review

Are We Testing Vehicles the Right Way? Challenges of Electrified and Connected Vehicles for Standard Drive Cycles and On-Road Testing

Elia Grano [1], Manfredi Villani [2], Henrique de Carvalho Pinheiro [1,*] and Massimiliana Carello [1]

[1] Department of Mechanical and Aerospace Engineering (DIMEAS), Politecnico di Torino, 10129 Turin, Italy; elia.grano@polito.it (E.G.); massimiliana.carello@polito.it (M.C.)
[2] Center for Automotive Research (CAR), The Ohio State University, Columbus, OH 43212, USA; villani.5@osu.edu
* Correspondence: henrique.decarvalho@polito.it

Abstract: Standard driving cycles have been the method of choice for testing vehicle performance for decades, both in research and at the regulatory level. These methodologies offer the significant advantage of test reproducibility, allowing for consistent comparisons between vehicles. However, their inability to reflect real-world driving conditions has become increasingly evident. This issue was first exacerbated by the advent of hybrid and plug-in hybrid vehicles, which introduced new complexities in powertrain operation. Legislators attempted to adapt testing procedures to account for electric energy usage in emissions assessments, but these efforts have largely failed to address the technical challenges posed by modern vehicles. As a result, the gap between real-world fuel consumption and type-approval values has continued to grow. The introduction of ADAS technologies has further widened this discrepancy, as standard driving cycles are no longer capable of accurately representing modern vehicle performance. In light of these challenges, this paper critically evaluates the limitations of standard drive cycles and on-road testing procedures, explores how hybrid and connected vehicles further complicate performance assessment, and proposes directions for improving these methodologies.

Keywords: driving cycles; on-road testing; electric vehicles; hybrid vehicles; connected vehicles; traffic modelling; testing; automotive homologation

Academic Editor: Paulo J. G. Pereirinha

Received: 23 December 2024
Revised: 20 January 2025
Accepted: 5 February 2025
Published: 11 February 2025

Citation: Grano, E.; Villani, M.; de Carvalho Pinheiro, H.; Carello, M. Are We Testing Vehicles the Right Way? Challenges of Electrified and Connected Vehicles for Standard Drive Cycles and On-Road Testing. *World Electr. Veh. J.* **2025**, *16*, 94. https://doi.org/10.3390/wevj16020094

1. Introduction

Air pollution is widely acknowledged as a leading risk factor for chronic noncommunicable diseases and is estimated to surpass all other known environmental risk factors in its contribution to global morbidity and mortality [1]. Since vehicular traffic is a major contributor to air pollution [2,3], legislators around the world have been trying to curb tailpipe emissions for decades. Among early initiatives, the United States enforced their first federal standard in 1975 [4] and the European Union in 1993 [3]. More recent legislative actions have extended their focus to reduce Greenhouse Gas (GHG) emissions from road vehicles in major automotive markets [5], a critical target given that road transport contributes significantly to total anthropogenic GHG emissions [3,6].

To enforce emissions regulations, policymakers, researchers, and automakers have relied heavily on standardized Driving Cycles (DCs). The performance in terms of energy consumption and emissions of a vehicle, in particular Light-Duty Vehicles (LDVs), is typically evaluated on a chassis dyno under controlled and repeatable conditions, which include the time series of vehicle speed, that is, the DC. This methodology allows for consistent comparisons across different vehicles, and it has been instrumental in ensuring regulatory compliance. However, standardized DCs fail in reflecting real-world driving conditions, which has become increasingly evident over time [5,7]. The growing gap between standard driving cycle assessments and real-world vehicle performance has become a critical issue, particularly with the rise of advanced powertrains that leverage multiple energy sources (e.g., fuel and batteries), such as hybrids and plug-in hybrids, or the introduction of Advanced Driver Assistance Systems (ADAS) that leverage connectivity and onboard sensors to implement some level of driving automation. Interestingly, the gap is systematically larger for electrified vehicles than conventional ones [5].

While attempts have been made to adapt testing procedures to account for the complexities introduced by modern powertrain systems, particularly in hybrid and plug-in hybrid vehicles, these adaptations have not fully addressed all the challenges. For instance, major modifications have been introduced in drive cycle testing protocols to account for the use of electric energy in plug-in hybrid vehicles [8]. However, these modifications remain limited in their ability to handle the full range of complexities presented by modern vehicles [9]. The introduction of on-road testing protocols has been an important step toward improving the representativeness of vehicle performance assessments [3,10]. On-road testing allows us to check regulation compliance by measuring emissions under real-world driving conditions, helping to bridge the gap between laboratory tests and actual vehicle operation. Nonetheless, on-road testing still presents shortfalls, particularly due to the technical limitations of testing equipment and unsatisfactory exploration of the variability range of environmental factors that can influence test results [3,11,12].

Further challenges are posed by ADAS that implement some level of driving automation, such as Predictive Cruise Control (PCC) or Eco-driving, which neither traditional DCs nor modern on-road testing protocols can fully address. While DC testing provides a means to evaluate basic energy consumption and emissions, it cannot capture the real-time, dynamic interactions with traffic, clouds, and infrastructure that driving automation technologies depend on. Indeed, these interactions are not represented in standard DCs, which rely on predefined speed profiles and fixed road conditions. At the same time, on-road testing protocols cannot fully capture real-world variability [11]. Therefore, results are not statistically relevant to quantify the impact of ADAS technologies on vehicle performance. These challenges are not only critical for regulatory compliance but also pose significant barriers within the industrial and research fields that urge to be addressed [13]. As ADAS technologies for energy efficient driving continue to evolve, there is an increasing need for novel testing frameworks that can better represent their real-world impact and performance, fostering accurate research and development efforts. Current testing methodologies often fall short of providing reliable comparisons or quantifying the full energy benefits of ADAS under diverse driving conditions, leading to inconsistent results across studies [14,15].

This paper provides a comprehensive overview of global vehicle testing methodologies, focusing on their limitations in the context of evolving vehicle technologies. Emphasis is placed on identifying gaps in the standardization of testing procedures, particularly for Connected and Automated Vehicles (CAVs). The discussion addresses high-level challenges while referencing key studies that detail specific methodologies, tools, and data sources. Building on this foundation, the paper explores potential pathways to improve testing frameworks, better aligning them with the complexities of real-world vehicle operation.

The paper structure is organized to reflect the chronological evolution of vehicle testing methodologies. Section 2 outlines the construction of standardized driving cycles, providing the basis for understanding the subsequent testing frameworks. Section 3 discusses chassis dynamometer testing, a traditional method for type-approval and regulatory compliance. Section 4 examines on-road testing, highlighting its capacity to address the representativeness gap of laboratory tests. Sections 5 and 6 delve into challenges introduced by electrified powertrains and connectivity/automation, respectively. Section 7 proposes potential solutions to these challenges, offering a systematic comparison of test methodologies, their applicable scenarios, advantages, and limitations. Finally, Section 8 concludes the paper by outlining future research directions and advancements in testing protocols to better capture the complexities of CAV operation under real-world conditions.

2. Construction of Standardized Driving Cycles

When used for vehicle performance assessment, a driving cycle should reflect real-world vehicle usage and be practical for laboratory execution—neither too lengthy nor overly complex—while maintaining repeatability and reproducibility. Practical limitations related to chassis dyno technologies were severely limiting the representativeness of DCs in the past, but advances over the years have enabled the development of more dynamic and intricate cycles. Because of this, literature references generally distinguish two types of DCs [16]:

1. Modal, composed of a sequence of constant speed segments.
2. Transitory, which better reflects real usage.

Figure 1 illustrates this distinction by comparing a modal cycle, the New European Driving Cycle (NEDC) [17], against a dynamic cycle, the Worldwide harmonized Light-duty Test Cycle (WLTC) [18]. The WLTC replaced the NEDC for type-approval in Europe in 2017. As shown, the speed profile of the WLTC is significantly more dynamic than that of the NEDC, with the latter consisting of a sequence of steady-state phases, designed to align with the technical constraints of testing equipment available in the 1970s, when it was first developed [5].

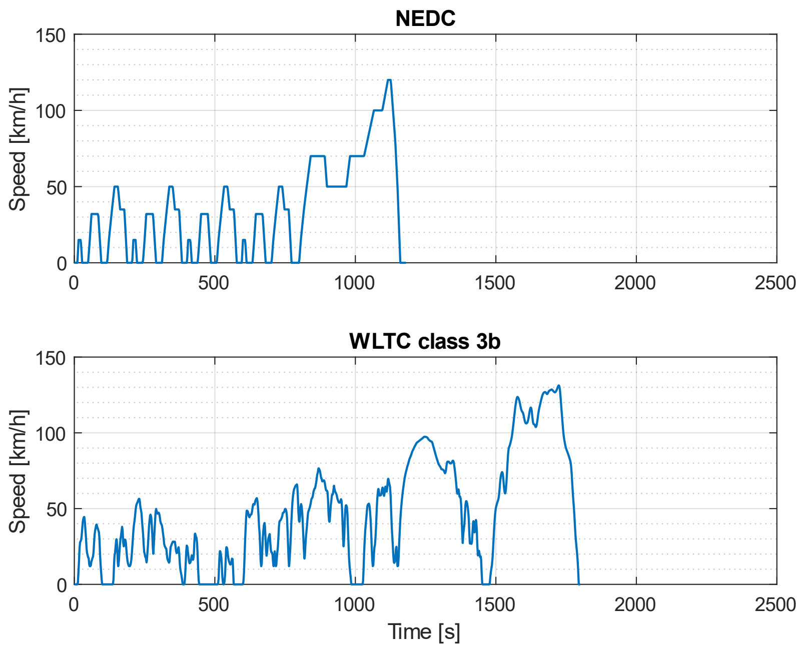

Figure 1. Comparison between the old (NEDC) and new (WLTC class 3b) statutory driving cycles for passenger cars type-approval. WLTC is differentiated into class 1, class 2, class 3a, and class 3b depending on the power-to-mass ratio and maximum speed of the vehicle, with WLTC class 3b being the most demanding.

The methodology for the development of modern "real-world" DCs, such as the WLTC, is a well consolidated practice consisting of the four main steps listed below [19,20]:

1. Route selection
   Route selection is crucial because the chosen path must represent the actual network and typical traffic flow conditions, which are influenced by factors like land use, road

type, topography, and population density [21]. A thorough understanding of these factors ensures accurate data and minimizes bias, making driving cycle development a purpose-driven and region-specific process [22].

2. Data collection
   Data collection is crucial as the reliability and representativeness of collected data directly influence the outcomes. Two primary methods are used: the chase car method, where an instrumented vehicle follows a target car to record second-by-second speed data, and the on-board measurement method, which involves installing instruments on selected vehicles to capture data along predetermined routes [22,23]. The chase car method is cost-effective but may struggle with aggressive driving behaviors and low sample sizes, while the on-board measurement method offers higher accuracy at the expense of increased cost and complexity. A hybrid approach can balance cost and representativeness [22,24].
3. Cycle construction
   Four major approaches to DC construction exist: micro-trip-based, segment-based, pattern classification, and modal cycle construction.
   The micro-trip-based construction method divides real-world driving data into micro-trips, which are segments of driving activity between two adjacent stops, including any idle periods. These micro-trips are assigned to bins and selected to create a driving cycle that matches the target parameters of the population. This method is particularly effective at capturing stop-go traffic patterns, which are known to significantly impact fuel use and emissions [25,26]. However, it is limited in distinguishing between roadway types and traffic conditions.
   The segment-based construction method extends the micro-trip approach by considering roadway type and traffic congestion during segment selection. Segments are trip portions categorized by traffic conditions or physical road characteristics, and they can start and end at any speed. This method is especially useful for expressways, where stop-go patterns are rare, and the micro-trip method may not be applicable. However, constructing such cycles requires careful matching of speed and acceleration at the junctions of connected segments.
   The pattern classification method divides entire trips into heterogeneous classes based on statistical analyses of kinematic sequences, such as speed and acceleration patterns. Succession probabilities are used to estimate the likelihood and chronology of sequences, and driving cycles are constructed by reconnecting sequences in line with these probabilities. This method effectively captures diverse traffic patterns but requires extensive data for initial classification, making it time intensive.
   The modal cycle construction method divides driving patterns into acceleration, deceleration, cruising, and idling modes. It applies the Markov Chain theory to chain these modes based on their transition probabilities. Data is clustered into modal bins and DCs are constructed by chaining speed profile portions from these modal bins while ensuring continuity in speed and acceleration [27]. This approach reflects real-world traffic conditions and is highly effective in capturing modal transitions. However, in regions with smooth traffic flow, where modal events are fewer or longer, it may face challenges.
4. Cycle assessment
   Cycle assessment is essential to ensure that the DC accurately reflects real-world driving patterns in a specific area. Parameters such as the number of stops per distance, average speed, and maximum speed were used in the past. Over time, more sophisticated metrics have been incorporated into cycle assessments, such as time proportions, averages, standard deviations, and specific emission-related parameters like root mean square acceleration and positive acceleration kinetic energy [28–30]. After having selected a

proper set of metrics, the candidate cycle with the smallest deviation from the collected data characteristics is selected as the most representative [31].

The interested reader can reference [19,24,32–34] for further details.

3. Chassis Dynamometer Testing

The traditional method for measuring LDVs emissions during type-approval involves operating a vehicle on a rolling road dynamometer according to a predefined DC, during which pollutant emissions are collected [32]. The capability of these cycles to represent real-world driving conditions is, thus, of prime interest for the assessment of vehicle emissions [24]. This methodology has been in place in major automotive markets since the first regulations on vehicle emissions were established in the mid-1970s in the US.

In the effort to establish representative test methodologies, Europe, the US, China, and many other countries have moved away from outdated modal cycles over time, adopting more representative "real-world" DCs tailored to their regional characteristics. In Europe, the transition from the NEDC to the WLTC was completed in 2020, marking a significant overhaul of the type-approval procedure to align with the Worldwide Harmonized Light-duty Test Procedure (WLTP) [35] (Figure 1). Similarly, China, which previously relied on the NEDC, adopted the WLTP [36] through its statutory driving cycle, the China Light-duty Test Cycle (CLTC) [37] (Figure 2). The US enforces their Corporate Average Fuel Economy (CAFE) standards [38] using two distinct transitory driving cycles: the Federal Test Procedure (FTP-75) [39] and the US EPA Highway Fuel Economy Test Cycle (HWFET) [40] (Figure 3), contributing 55% and 45%, respectively, to the overall fuel economy calculation.

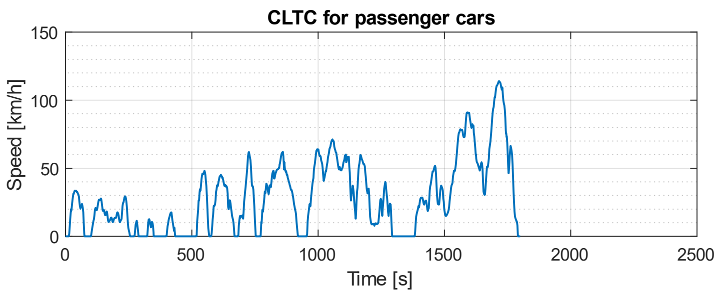

Figure 2. China's statutory driving cycles for passenger cars type-approval.

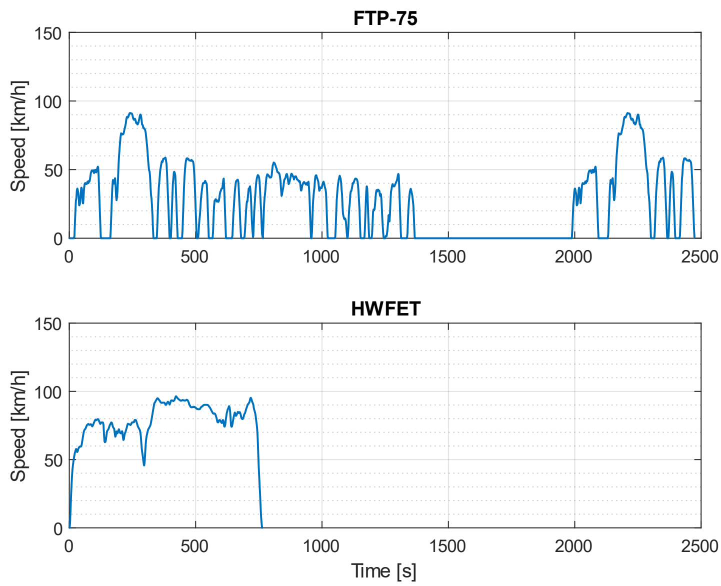

Figure 3. United States' CAFE procedure statutory driving cycles for passenger cars type-approval.

The use of DCs for vehicle type-approval is a mature methodology having the great advantage of reproducibility, thus, offering a level field for the comparison of different vehicles. Anyway, it has several shortfalls that have emerged over the years which may threaten real-world performance representatives, which is crucial to ensure proper legislation enforcement. Three major critical points are identified in [16]:

1. DCs represent an artificial sequence that cannot be found in real-life operation, or a specifically measured single sequence of defined length.
2. DCs statistically do not reflect the parameters of real-life operation of a vehicle.
3. DCs are fully deterministic and, thus, easily detectable during emission tests.

Proof of the limited representativeness of DCs is provided by several studies that examined the widening gap between type-approval and real-world performance of vehicles across major markets between the mid-1990s and mid-2010s. In Europe, the divergence between official and real-world fuel economy increased from 9–10% in the early-2000s to 45–50% in the mid-2010s, exacerbated by the introduction of mandatory CO_2 targets in 2009 [5,41,42]. Similar trends are observed in China, where the gap grew from 12% in 2008 to 27% in 2015, with studies highlighting weaknesses in the NEDC test procedure itself as a key contributor [43,44]. In the US, CAFE values show increasing divergence, rising from 14% in 2004 to 31% in 2015 [5,45]. Figure 4 summarizes those numbers by plotting the trend of the gap in major automotive markets worldwide. As it is possible to see, all type-approval procedures show an enlarging gap over the years. The only exception is represented by US EPA label values, which are calculated by applying corrective coefficients that are periodically adjusted. US EPA label values are not used to check regulatory compliance.

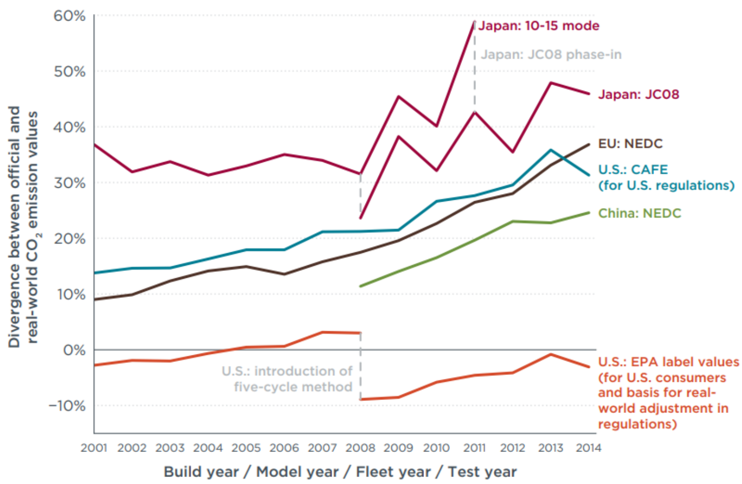

Figure 4. Evolution of the gap between real-world and type-approval CO_2 emissions in major automotive markets between 2001 and 2014 [5].

Overall, two key takeaways can be extracted from the presented overview:

1. Countries using modal cycles (EU and China before the transition to WLTP) exhibit a greater gap than those using transient cycles (US), suggesting a better representativeness of the latter ones.
2. The gap is significant even in countries having strict test procedures relying on transient cycles (US) [46], suggesting that the shortfall is not only caused by the weaknesses of the NEDC test methodology.

Besides the DC itself, major limitations of the NEDC testing procedure were the exploitation of flexibilities and tolerances during chassis dynamometer testing, significantly contributing to the gap growth in the EU and China [47–49]. Studies demonstrated that the procedure failed to represent real-world conditions, with on-road emissions measured with the Portable Emissions Measurement System (PEMS) exceeding official values by up to 30% in China even when normalized to the NEDC [44]. Weak enforcement and unrealistic road load coefficients, as shown in comparative studies between EU and US procedures [46], further exacerbated the issue, prompting the transition to the WLTP.

Experimental studies conducted in 2017 estimated that the adoption of the WLTP could have reduced the gap between real world and type-approval fuel consumption down to 10÷15% [50]. Reasons for this include, but are not limited to, improved representativeness of the test cycle, more realistic determination of road load, and revised gear shifting schedules. An in-depth discussion about the causes behind this achievement is available in [51]. As it is possible to see in Figure 5, the WLTP introduced an offset that brought type approval values in Europe closer to real world ones, but it did influence the trend of growth.

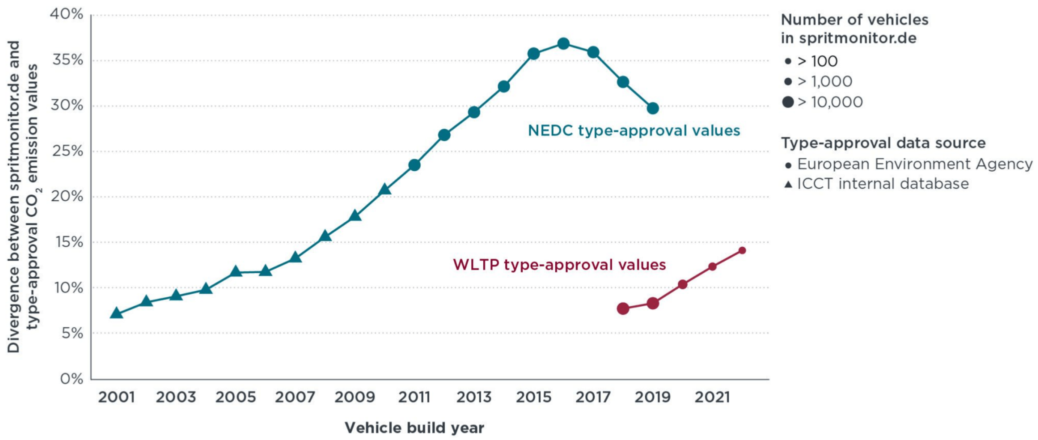

Figure 5. Evolution of the gap between real-world and type-approval CO_2 emissions [7].

Confirmation about the improved representativity of WLTP for fuel economy testing comes from [52], which on the other hand shows a significant shortfall for pollutant emissions. This thesis was strengthened by many authors who dedicated their research effort to the analysis of real-world NO_x emissions from European diesel-powered vehicles [3,11,52], that are widely diffused in the continent [53]. In general, there is strong evidence that WLTP testing largely underestimates NO_x emissions, with real world values that are 5–16 times larger than type-approval ones. Shortfalls exist even when the CLTC is used in place of WLTC [54], suggesting that the problem does not only reside in the test cycle but encompasses the whole test procedure. Strong evidence exists about the optimization of NO_x reduction systems for the type-approval cycle [11]. While performance optimization for the homologation test does not breach the law, it results in underestimation of vehicle emissions if the test procedure is not truly representative of real-world conditions. This evidence raises concerns about the use of deterministic DCs for homologation purposes because they are easily detectable, potentially triggering illegal cycle-beating systems [55]. Examples from the past are the US diesel truck scandal in 1995 [3,56] and the Dieselgate scandal in 2015 [3,57].

4. On-Road Testing

The advent of PEMS revolutionized vehicle emissions testing starting in the mid-1990s, allowing for on-road testing. PEMS gained prominence during the US diesel truck emissions scandal, eventually leading to their adoption for on-road testing of US trucks in 2003. In the EU, the Joint Research Center (JRC) began PEMS testing for Heavy-Duty Vehicles (HDVs) in 2004 and LDVs in 2007. These efforts resulted in off-cycle measurement requirements for HDVs by 2014 and the introduction of Real Driving Emissions (RDE) testing for LDVs in 2017 [3]. In 2020, China adopted RDE testing for monitoring purposes, enforcing it legislatively from 2023 onwards [10]. A comprehensive overview of RDE testing procedures is available in [3,58,59].

The introduction of RDE testing marked a pivotal advancement in vehicle type-approval. While deterministic laboratory tests remain essential for providing repeatable and explicit compliance evidence, non-reproducible RDE tests serve as a validation tool to enforce legislation under real-world conditions [58]. EU's RDE framework sets boundary conditions to RDE testing with the goal to cover 95% of real-world driving conditions, defining proper ranges for parameters like altitude, ambient temperature, payload, and dynamics as reported in Tables 1 and 2, and Figure 6. Trip specifications are provided to include urban, rural, and motorway driving in similar proportions [58]. Additionally, the basis of in-service conformity and surveillance test are laid [59].

Table 1. Valid Euro 6d RDE trip components [60,61].

Parameter	Trip Portion	Limit Range
Total duration		Between 90 and 120 min
Distance	Urban Rural Motorway	>16 km >16 km >16 km
Composition	Urban Rural Motorway	29 to 44% of total distance 23 to 43% of total distance 23 to 43% of total distance
Average speed	Urban Rural Motorway	15 to 40 km/f 60 to 90 km/h >90 km/h (>100 km/h for at least 5 min)

Table 2. Valid Euro 6d RDE trip boundary conditions [60,61].

Parameter	Boundary Type	Limit Range
Total mass		≤90% of maximum vehicle weight
Altitude	Moderate Extended	0 to 700 m 700 to 1300 m
Altitude difference		≤100 m between start and finish
Cumulative altitude gain		≤12 m/km
Ambient temperature	Moderate Extended	0 to 30 °C −7 to 0 °C and 30 to 35 °C
Stop percentage		6 to 30% of urban time
Maximum speed		145 km/h (160 km/h for a maximum of 3% of motorway driving time)
High dynamic boundary		95th percentile of $v{\cdot}a$ curve
Low dynamic boundary		Relative positive acceleration curve
Use of auxiliaries		Not recorded

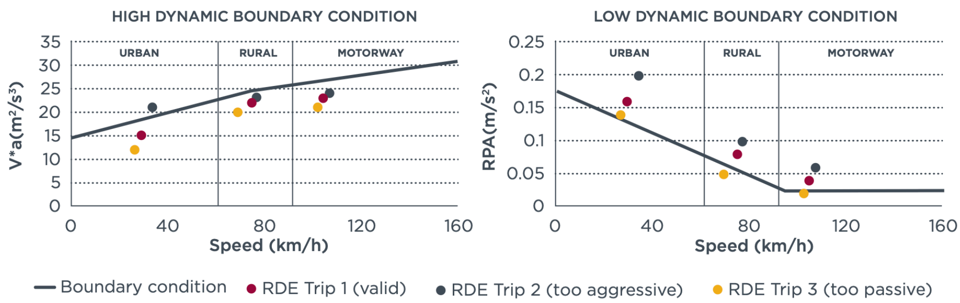

Figure 6. Euro 6d RDE test dynamic limits [62].

According to [11], where experimental analyses are presented to assess representativeness, RDE tests effectively capture real-world emissions under normal driving conditions. However, disproportionally high emissions are recorded under sporty driving conditions outside the RDE regulation boundaries, with 2–8 times higher NO_x emissions and 1.4–1.8 times higher CO_2 emissions. Besides coverage gaps of the current RDE boundaries, ref. [12] highlighted the risk of test detection (mainly due to the presence of PEMS) and the importance of stricter oversight of in-service conformity tests. Harsh critics are moved in [3] to the data post-processing procedure applied when analyzing RDE test results. Indeed, besides excluding driving conditions not categorized as "normal", the Euro 6 standard applies a conformity factor to account for technical uncertainties and measurement variability inherent in PEMS as described by Equation (1) [3,59].

$$RDE_{lim,x} = CF_x \; EU6_{lim,x} \tag{1}$$

where $EU6_{lim,x}$ is the Euro 6 standard emission limit for the substance x, $RDE_{lim,x}$ is the RDE test emission limit for the pollutant x, and CF_x is the conformity factor that applies for the pollutant x.

The recorded emissions are normalized by applying the RDE evaluation factor as shown in Equation (2) [59]. The evaluation factor is a multiplicative coefficient that is lower or equal to 1 depending on the ratio between specific CO_2 emissions during the RDE test over that of the WLTP.

$$\widetilde{m}_x = RF \; m_x \tag{2}$$

where m_x is the recorded specific emission for the pollutant x, RF is the evaluation factor, and $\widetilde{m}_x$ is the corrected specific emission for the pollutant x.

5. Hybrid Electric Powertrains

Hybrid Electric Vehicles (HEVs) consist of two different mechanical actuators, generally an Internal Combustion Engine (ICE) and an Electric Motor (EM). Energy is stored in the tank as chemical energy (fuel) and in the Energy Storage System (ESS) as chemical energy (batteries), electrostatic energy (capacitors), or a combination of both (supercapacitors). The most common case is having one ICE and one EM for propulsion and a battery pack as ESS. Appendix A offers an overview of HEVs powertrain architectures, which can be grouped into three main categories based on their topology [63,64]: series, parallel, and power split.

Besides topology, a vital feature for the characterization of HEVs is the possibility to charge the ESS from an external source. In case this possibility exists, the name Plug-in Hybrid Electric Vehicle (PHEV) is used. PHEVs introduce further complexity to hybrid powertrains by having two different external energy inputs: indeed, the user can provide energy to the vehicle by both refueling and recharging the ESS.

5.1. HEVs Control

HEVs introduce at least one additional degree of freedom in powertrain control with respect to CVs. This additional degree of freedom is handled by the vehicle's Energy Management Strategy (EMS), a control algorithm that manages the power flows within the powertrain, generally developed to increase energy efficiency without deteriorating vehicle performance. EMSs can be classified into three main categories [63,65–67]:

1. Rule-Based (RB)
   RB EMSs rely on predefined rules or logical conditions to manage the distribution of power between the ICE and the EMs. These rules are usually designed based on heuristic knowledge, vehicle operating modes, or specific performance targets. Two different types of RB-EMS can be identified [65]: deterministic and fuzzy.

2. Optimization-Based (OB)
OB EMSs are those obtained from the solution of an optimal control problem, a general formulation of which is given in [68]. This family of EMSs applies optimization techniques to determine the best control actions at each instant of time to minimize a cost function along a driving mission. Optimization techniques can be divided into global and local based on the solution space they look over, and into online and offline based on whether the optimization is performed in real-time during the driving mission or precomputed using prior knowledge of the entire mission trajectory.
3. Learning-Based (LB)
LB EMSs for HEVs primarily leverage Machine Learning (ML) to implement an agent that reacts in the best possible way to the observed environmental conditions. To achieve this, the agent undergoes a training phase in which it learns from its prior experience. Depending on how the training data is organized, ML can be divided into three categories: supervised learning, reinforcement learning, and unsupervised learning [66].

The classification above provides a framework for understanding HEVs EMS strategies. Most of the presented approaches are general enough to be expanded to other control problems, finding broader application in advanced vehicle technologies (Section 6). The interested reader can reference Appendix B for a comprehensive overview of EMSs, with relevant examples of applications from the literature.

5.2. PHEVs Use

PHEVs owners can provide energy to the vehicle by both refueling and recharging the ESS. They generally operate in two major distinct modes [9]:

1. Charge Depleting (CD), in which power mostly comes from the ESS.
2. Charge Sustaining (CS), in which power mostly comes from the fuel.

The possibility of using different energy sources makes the vehicle performance dependent on user's charging behavior, which is generally non-homogeneous within the population [63]. If the driver does not charge the ESS regularly, the state of charge will be low and, thus, more fuel will likely be used.

Several studies attempted to analyze the charging behavior of PHEVs drivers to determine the causes of variability. One of the most intuitive factors is the trend of fuel and electricity prices, with drivers that change their habits as a response to fluctuations [69]. A key role is played by people's stopping tolerance for battery recharging, which may hinder the use of PHEVs at their best. According to [70], there exists a critical stopping tolerance at which drivers start driving on gasoline rather than electricity. ESS size can be leveraged to mitigate this effect, with larger ESSs offering increased range between consecutive charging events [69,70]. As a consequence, PHEVs are generally designed to have long All-Electric Range (AER) and are, therefore, characterized by high Hybridization Ratio (HR, see Appendix A) and high-capacity ESS. Charging infrastructure availability is another crucial element in promoting a correct charging behavior in PHEVs owners [71]. Evidence exists that drivers that take advantage of public and workplace infrastructure regularly cover significantly more electric mileage than those who don't [72].

The complexity of PHEVs is handled by legislative framework in EU, China, and US by means of complex procedures that aim at determining the vehicle's AER and its emissions under both CD and CS mode. A unique emission value is obtained combining those under CD and CS mode by means of a weighted average based on the Utility Factor (UF), as described by Equation (3) [8].

$$m_{x,weighted} = \sum_{j=1}^{k} \left(UF_j \, m_{x,CD,j}\right) + \sum_{j=1}^{k} \left(1 - UF_j\right) m_{x,CS} \tag{3}$$

where j is the index number of the considered phase, k is the number of phases driven until the end of the transition cycle from CD to CS, $m_{x,weighted}$ is the weighted emission for the pollutant x, $m_{x,CD,j}$ is the mass emission of the compound x of phase j under CD mode, and $m_{x,CS}$ is the charge-sustaining mass emission of compound x. Further details are available in [8].

The UF is used as a weight coefficient to account for the use of energy from the ESS rather than from fuel. It effectively scales down emissions recorded under CS mode, progressively making those under CD more prominent. Its value progressively changes during the test as the vehicle accumulates distance in CD mode. UF curves have been defined in the attempt to account for the variability factors discussed above [8,73], an example of which is provided in Figure 7.

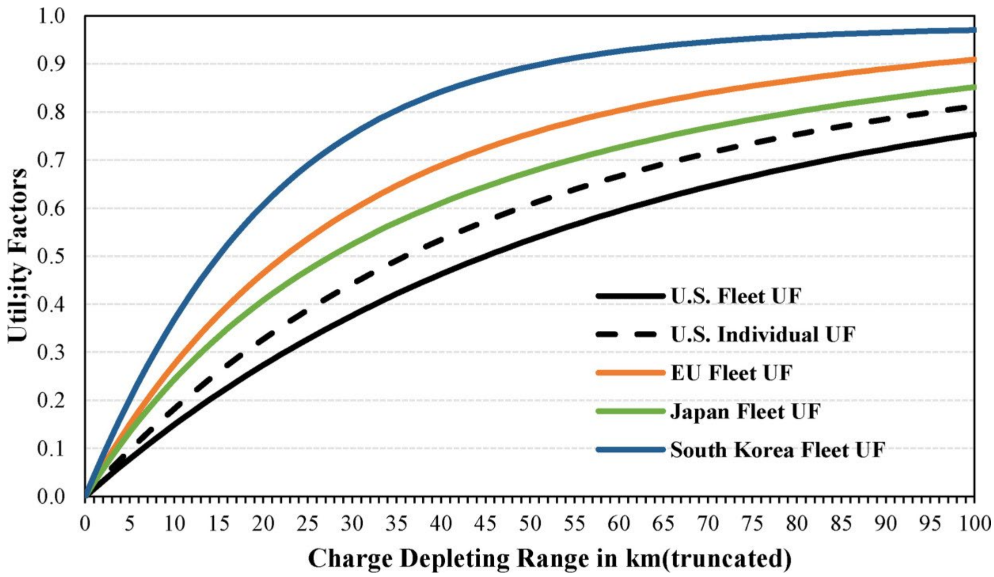

Figure 7. Utility factor curves for different countries [74].

5.3. Discussion for HEVs

HEVs are a viable option to meet the increasingly stringent GHG emission standards [54,75,76] as they enable engine downsizing, kinetic energy recovery, electrification of auxiliaries and more, although they do not provide a clear advantage in terms of pollutant emissions [54,76,77]. They started their rise in the automotive market almost three decades ago and today have a significant share [78].

HEVs add an extra layer of complexity in high-level powertrain control compared to ICEVs and BEVs, offering the possibility to satisfy the vehicle power demand in multiple different manners. Most of the EMSs available in the literature today require one or more reference cycles for design and/or tuning, making DC prediction and construction active fields of research [79]. Natural choices for cycle selection for this purpose are those used for regulatory compliance. While this approach may ensure favorable results during testing, it may bring significant discrepancies in real-world performance, potentially undermining the gains in fuel efficiency and emission reductions expected by lawmakers. Confirmation of this comes from the evidence brought by some authors who highlighted that the gap between real-world and type-approval fuel consumption is systematically larger for HEVs than ICEVs [5]. Research effort should be dedicated to understanding the causes of this phenomenon.

Complexity is further increased in the case of PHEVs. This category of vehicles offers flexibility by allowing energy inputs from both refueling and recharging but performance heavily depends on users' charging behavior, which varies significantly across the population. Despite several studies highlighting how much charging behavior can impact PHEVs use, current regulations fail to account for these variations [74,80]. As a result, PHEVs may meet emissions standards under controlled testing conditions but perform differently in real-world scenarios, undermining the potential environmental benefits of the technology. As proof of this, reference [81] pinpoints a growing gap between real-world and WLTP fuel consumption for PHEVs, with the latter being three to five times lower than real values.

6. Connected and Automated Vehicles

Advanced Driver Assistance Systems (ADASs) have progressively transformed the automotive landscape, pushing the boundaries of mobility and reshaping the way vehicles operate in real-world environments. ADAS initially emerged with systems designed to support drivers in safety-critical conditions, such as anti-lock braking systems and traction control. Over time, these technologies evolved to include more complex functionalities like adaptive cruise control, lane-keeping assistance, and automated emergency braking. As the availability of sensors and computational power on board of vehicles increased, connectivity emerged. CAVs are today envisioned as critical enablers for safer, more efficient, and environmentally friendly transportation systems [14,15].

Energy-efficient ADAS features implement the concept of eco-driving, defined in [68], to improve vehicle control based on preview information made available from the surrounding traffic, the infrastructure and the cloud. Therefore, from a high-level perspective, these offer the possibility to improve vehicle operation by interacting with the surrounding environment. This can occur through two classes of mechanisms [14]:

1. Anticipation
   Connected vehicles have the potential to interact with the infrastructure, gather information from the cloud and perceive the environment in their surroundings to anticipate probable slowdowns, prepare for road grade variations, and predict the most likely actions of neighboring vehicles.
2. Cooperation
   In case connectivity enables vehicle-to-vehicle interactions, much more information can be made available. Deliberate exchange of intentions by vehicles and infrastructure allows CAVs to cooperate rather than compete, coordinating movements for a “common” good.

Besides the high-level classification introduced above, a recent literature review article [15] individuated eight active research areas that are impacted by ADASs: powertrain control, vehicle platooning, car-following, intersection management, speed planning, traffic control, lane changing, and on-ramp merging. Table 3 provides an overview of each of them, quantifying their energy-saving potential as reported by the authors and providing relevant literature references.

Table 3. Fields of research impacted by ADASs.

Optimization Approach	Description	Relevant Literature	Expected Benefit	
Powertrain control	Optimization of powertrain operation based on evolving environment	[82–85]	2–12% ** 5–15% *	[14] [15]
Vehicle platooning	Forming and coordinating a line of CAVs to minimize energy consumption	[86–90]	4–13% *	[15]
Car-following	Minimization of energy consumption of a CAV following a leader	[91–95]	4–50% ** 6–10% *	[14] [15]
Intersection management	Optimization of the trajectory of CAVs approaching intersections	[96–100]	2–50% ** 2–58% *	[14] [15]
Lane changing	Cooperation of CAVs for lateral position change	[101–104]	8–48% ** 47–60% *	[14] [15]
On-ramp merging	Cooperation of CAVs for smooth on-ramp merging	[105–108]	3–57% * 48–52% *	[15] [105]*

Table 3. *Cont.*

Optimization Approach	Description	Relevant Literature	Expected Benefit	
Traffic control	Exploitation of CAVs to smooth traffic flow	[96,109–112]	20–34% *	[15]
Speed planning and control	Speed modulation in the presence of other vehicles	[113–116]	9–40% *	[15]

* Energy saving; ** Efficiency gain.

6.1. Virtual Simulation

Typically, the potential of ADASs and eco-driving technologies is first demonstrated through simulations. Authors arbitrarily select a route of interest or build artificial test scenarios to stress their technology [92]. Traffic conditions are often neglected [116] or modeled in a simplistic manner, either by simulating the lead vehicle velocity profile by means of a DC [89,93,95] or by using macroscopic traffic models [117,118], both simply resulting in a reduction of the maximum speed at which the ego vehicle can travel [119–121]. While macroscopic traffic models are very useful to gather preview information for optimization purposes [114,115], they cannot accurately reproduce the complex vehicle-to-vehicle interactions that characterize real-world driving [26] and, therefore, cannot be used to reliably demonstrate the benefits of ADASs.

Some literature examples exist that attempt to introduce real-world variability in the assessment of ADASs benefits through simulations. Some authors proposed the use of multiple DCs recorded along the same route [113] to simulate a lead vehicle constraining a speed planning algorithm. A further step forward is made with the use of micro-traffic simulations, which is widespread to prove lane changing [101,102,104], merging [105–108], and intersection management algorithms [96,98,99]. Micro-traffic models are effective at describing the complex interactions that characterize real world driving, representing a viable opportunity for solving the limitations related to ADASs performance assessment. Leveraging this increased level of detail, efforts have been made to establish a connection between detailed vehicle models and micro-traffic simulators. An example is [103], where the movement of a vehicle in a micro-traffic simulation is used to extract velocity profiles that are then used as DCs for a powertrain model in Simulink. The tested ADAS controls the vehicle in the micro-traffic simulator and the energy benefit is assessed with an a-posteriori run of the Simulink model. Even though this set up effectively establishes an open-loop connection between the traffic model and the vehicle model, it cannot ensure causality between powertrain actuation and vehicle motion. To solve this issue, closed-loop co-simulation setups have been presented in [26,122,123] that preserve causality between powertrain actuation and vehicle motion. While the combination of accuracy and causality marks a significant step in the direction of properly simulating ADASs, the complexity of micro-traffic-based simulations and their computational burden are open points yet to be addressed.

6.2. Experimental Testing

Experimental tests are not immune to limitations [120]. On-road testing is often conducted in protected conditions to ensure safety [91,94], thus, not capturing real-world vehicle-to-vehicle interactions variability. An interesting setup to address this limitation is shown in [100], where a passenger car on a test track virtually interacts with vehicles simulated in a micro traffic simulator. A further step forward is made in [97], where an eco-approach and departure algorithm is tested on an open road in real traffic conditions. Both [97] and [100] deploy their algorithms as speed advice for the driver, with no direct actuation of the powertrain, making it difficult to distinguish the influence of the driver from that of the algorithm itself.

Real-world on-road testing is affected by uncertainties due to environmental factors like traffic, weather, and surface conditions, which in turn impact vehicle parameters, such as rolling resistance and tire radius. A statistical approach to testing would allow handling such uncertainties but is impractical due to the large number of trials needed, which would escalate complexity and cost.

6.3. Discussion for CAVs

CAVs are perceived as key enablers for cleaner and safer transportation. Improvements offered by anticipative and cooperative features of CAVs allow virtuous speed modulation, with benefits that extend to the surrounding traffic too, indirectly contributing to energy efficiency of conventional vehicles [96,109–112].

The complexity of ADASs systems brings most authors at developing customized test conditions to assess the benefit of their technology. The construction of artificial test scenarios and/or simplified traffic conditions is beneficial to show how the presented technology works and impacts vehicle operation in specific conditions, as it eliminates uncertainties related to real-world driving. Anyway, the removal of such uncertainties is the reason why this methodology is unsuitable for reliably demonstrating the actual benefits of new ADASs. A conflict of interest often arises, as authors aim to showcase the superiority of their technology, which can lead to the design of overly favorable test conditions. This bias contributes to the significant variability in results, as illustrated in Table 3, when compared to technologies tested under more balanced conditions.

Compared to traditional vehicles, CAVs introduce additional degrees of freedom to vehicle control systems as they take away the longitudinal vehicle control from the driver (at least partly), and/or the lateral one. Because of this, traditional testing methodologies that impose a DC are unsuitable as they do not allow freedom in speed modulation. Being that the interaction with the environment is crucial for CAVs, dedicated testing methodologies must be developed.

Lack of standardization in testing procedures at both simulation and experimental level causes confusion when comparing different technological solutions, representing a literature gap that must be filled. Virtuous examples in this direction are the closed-loop co-simulation frameworks presented in [26,122,123], which preserve causality while offering the chance of simulating accurate vehicle models within realistic traffic scenarios.

7. Overall Discussion

The advent of new technologies in the automotive industry is posing challenges to testing procedures, both at the experimental and simulation level, as they introduce new degrees of freedom for manufacturers to optimize performance and for drivers to personalize their travel experience. Every time a new degree of freedom is introduced, a whole range of previously unexpected scenarios opens. In this context, vehicle testing protocols must evolve to capture real-world conditions, but the evidence shows that they are falling short in this regard. This section proposes a discussion about modern testing procedures and explores possible scenarios to overcome their limitations. A summary of the findings is provided in Table 4.

Currently applied testing protocols have been developed with the aim of being at the same time reproducible and representative of real-world conditions. Lawmakers have long been trying to ensure reproducibility and representativity by only relying on DCs, but evidence about a persistent gap in both fuel consumption and noxious emissions between type-approval and real-world conditions, as well as scandals related to the use of cycle-beating technologies, have led to the introduction of on-road testing with PEMS. In this framework, DCs in repeatable conditions are used to enforce legislative limits and non-repeatable RDE measurements are used to check compliance with real-world conditions.

Even though the combined use of DCs and RDE testing constitutes a significant step in the direction of more representative testing procedures, many challenges have yet to be addressed. Harsh critics are moved to European's RDE framework about how measurements uncertainty of PEMS is handled, resulting in a data post-processing procedure that many fear to be watering down legislative constraints on noxious emissions. While conformity factors (Equation (1)) are needed to account for the much larger measurement uncertainty of PEMS compared to laboratory equipment, they may represent a loophole that manufacturers can exploit to successfully homologate vehicles that do not fully comply with emission standards in real-world conditions.

A simple solution to this problem would be to move the RDE test out of the road to eliminate uncertainties related to PEMS technology. This may be done by recording the speed profile and elevation change of the vehicle on an RDE-compliant route, to then measure emissions on the same profile in a lab test. Real-world representativeness may be enhanced by recording boundary conditions such as environmental temperature and reproducing them in a controlled environment. Besides completely eliminating the need for PEMS, this methodology would significantly ease the measurement of non-combustion emissions with respect to on-road conditions.

The approach of moving the RDE test to the lab would combine reproducibility and representativeness, offering the chance to completely eliminate the need for standardized DCs to check compliance with legislative requirements. Even though at first sight this approach might appear similar to random cycle generation, it actually is not. As discussed in the Construction of Standardized Driving Cycles section, random cycle generation approaches rely on previously recorded data to generate new cycles. This would not be the case for the proposed methodology, which would effectively capture the response of the whole vehicle system to evolving conditions without constraining its speed, marking a significant step forward in the direction of addressing the problems related to CAV testing discussed in Section 6 (Connected and Automated Vehicles).

Three critical aspects would emerge if this approach was adopted:

1. The powertrain should be actuated by a test driver or a dedicated controller to constrain the vehicle to follow the recorded speed profile during laboratory measurement, thus, disabling ADAS functionalities. This would lead to simple detection of test conditions.
2. Disabling ADAS functionalities results in having less information made available to the powertrain controller, which may cause differences in vehicle performance with respect to real-world conditions.
3. CAVs react to evolving conditions, thus, statistical relevance of the test must be ensured. Repeating the measurement of the speed profile multiple times until a sufficiently wide range of traffic and environmental conditions is captured would be impractical.

The most immediate solution to problems number 1 and 2 would be to solely test vehicles on-road, but this would bring back the need for PEMS. Additionally, this solution would not solve problem number 3. A different approach would be to record sensors' outputs and control signals during the on-road speed profile measurement. Once in the protected environment, injecting the same sensor signals would allow us to virtually recreate the same road conditions encountered during speed profile measurement, and comparing laboratory test control signals with on-road ones would provide indication about possible use of test detection system. Still, the problem of statistical significance remains to be addressed.

A viable way to achieve statistical relevance of the tested scenarios is represented by the closed-loop co-simulation framework discussed in Section 6.3 (Connected and Automated Vehicles—Discussion). The available literature [26,122,123] shows that, if properly developed, such methodology has the potential of being capable of building test routes and simulating vehicle performance under different traffic conditions in a repeatable manner, offering the possibility to shift the legislation focus from the concept of standard DC to that of standard driving scenario. The main technological challenge in this context lays in introducing the vehicle in the simulation loop. Two main approaches are available to achieve this:

1. Hardware-in-the-loop co-simulation, requiring the development of an experimental setup capable of triggering vehicle sensors to allow the perception of the simulated scenario.
2. Model-in-the-loop co-simulation, requiring the development of a simulation-based homologation procedure relying on a validated vehicle model.

The hardware-in-the-loop approach is preferable as it allows us to test the actual vehicle without relying on a virtual model, but the number of tested scenarios may be limited due to practicality constraints. Challenges are also related to the speed of the simulation framework, which must be real time capable. The model-in-the-loop approach would relax both these constraints at the price of introducing a model in place of the actual vehicle, thus, introducing accuracy issues that must be carefully evaluated. The development of a robust standardized validation methodology to ensure the model truly represents the actual vehicle becomes vital in this context.

Table 4. Summary of existing and proposed test methods.

Test Method	Pros	Cons
Chassis dyno testing with statutory DC	• Highly repeatable • Precise measurement equipment	• Poor representativeness of real-world conditions • Simple detection • Unsuitable for CAVs
RDE testing with PEMS	• Highly representative for confirmation after DC testing • Suitable for CAVs	• Non repeatable • Large measurement uncertainty • Possible detection • Poorly representative for emissions assessment (only one random walk in the real world)
Chassis dyno testing with speed profile recorded in the real world	• Highly repeatable • Highly representative • Precise measurement equipment • Suitable for CAVs	• Speed profile recording emissions measurement in distinct phases • Difficult to ensure the vehicle behaves in the same way in the two phases • Statistical significance limited by practicality constraints on the number of test cases
Chassis dyno testing in a simulated traffic scenario based on a micro-traffic model	• Highly repeatable • Potentially highly representative • Precise measurement equipment • Suitable for CAVs	• Complex experimental setup • Need for real-time traffic simulation • Statistical significance limited by practicality constraints on the number of test cases
Simulation-based testing in a simulated traffic scenario based on a micro-traffic model	• Highly repeatable • Potentially highly representative • Precise measurement equipment • Suitable for CAVs • Statistically significant	• Need for a standardized traffic model • Need for a robust vehicle model validation method

Incorporating traffic conditions into vehicle performance testing frameworks is a critical step toward accurately evaluating the impact of modern vehicle technologies. As demonstrated in [26], traffic congestion significantly influences energy consumption, with large variations observed even along identical routes. These findings highlight the necessity of shifting from traditional deterministic approaches to stochastic, scenario-based testing frameworks that capture the variability of real-world conditions. The reasons why research effort should be dedicated to the development of closed-loop traffic-in-the-loop simulations are not limited to those just discussed. Indeed, these tools offer the possibility of testing the performance of vehicle control strategies in diverse scenarios in a repeatable manner, assessing their robustness against evolving road, traffic, and vehicle conditions. Further, they are essential for the construction of a virtual test ground to assess the impact of ADAS and connectivity features in a fair and repeatable manner, easing the comparison between different technologies.

8. Conclusions

Legislative efforts to adapt homologation procedures to increasingly complex vehicle systems are not delivering the expected results. Evidence is clear that both fuel consumption and noxious emissions from vehicles in real driving scenarios are well above legislative limits.

Deterministic DCs are easily detectable and direct manufacturers' focus on performance optimization under test conditions, which are proven not to represent real-world driving accurately. Furthermore, they constrain vehicle speed to a predefined profile, making them unsuitable for testing automated vehicles. The introduction of RDE testing marked a significant step forward in increasing representativeness. However, RDE results are hindered by large measurement uncertainties and the limited number of practical test runs, reducing the range of conditions tested and the statistical significance of results.

The introduction of closed-loop traffic-in-the-loop simulation frameworks capable of preserving causality between powertrain actuation and vehicle motion offers the chance of introducing the concept of statistical robustness within vehicles testing protocols, shifting their focus from the concept of standard driving cycle to that of standard driving scenarios. Further, they lay the foundation for establishing a level ground for CAVs testing and for the assessment of driver habits on vehicle performance, facilitating the comparison of different technological solutions in a fair, robust, and reproducible manner.

Looking ahead, testing methodologies must evolve to better represent the complexities of electrified powertrains, driving automation and connectivity features. Several avenues for future research emerge:

1. Driving scenarios standardization
   Future testing frameworks should shift from static, deterministic DCs to dynamic, standardized driving scenarios. This process has initiated with the introduction of on-road testing protocols, but the creation of standardized virtual simulation tools that can reproduce the complexity of the real-world is still far to come. While on-road testing protocol laid the foundations for standardizing environmental conditions and driving dynamic range further work is required to account for factors such as traffic congestion, CAV penetration rates, and the availability of information from infrastructure and the cloud.
2. Traffic incorporation
   Advanced traffic-in-the-loop simulation frameworks are emerging, enabling realistic and reproducible traffic conditions while maintaining causality between powertrain actuation and vehicle movement. Future research should focus on developing traffic control policies that produce macroscopic realism and selecting controllers that accurately represent diverse vehicle behaviors, including varying levels of aggressiveness and automation, to enable heterogeneous traffic flows.
3. Performance optimization
   Current traffic-in-the-loop models are often tailored to demonstrate specific features and lack optimization for broader performance. Establishing standardized virtual testing scenarios would eliminate the need for custom setups, allowing researchers to focus on improving computational efficiency and achieving real-time capabilities essential for hardware-in-the-loop testing in simulated traffic environments.
4. Vehicle incorporation
   Vehicle integration will be particularly critical if the proposed virtual framework is used for legislative enforcement. Research should explore the suitability of model-

in-the-loop and hardware-in-the-loop approaches, each with its advantages and limitations, to determine the most appropriate method for testing.

5. Performance metrics
   To ensure statistical significance, multiple tests under diverse conditions will be necessary. This requires the development of novel performance metrics capable of capturing variability under evolving conditions, providing a more comprehensive assessment of vehicle performance.

By addressing these challenges, future testing methodologies can better capture the complexities of modern vehicles and their operating environments, overcoming the limitations of current approaches. This would ensure effective legislative enforcement and establish a robust framework for testing and comparing diverse vehicular technologies.

Author Contributions: Conceptualization, E.G. and H.d.C.P.; Methodology, E.G., M.V. and H.d.C.P.; Software, E.G.; Validation, E.G. and M.V.; Formal Analysis, E.G.; Investigation, E.G.; Resources, M.V. and M.C.; Data Curation, E.G.; Writing—Original Draft Preparation, E.G.; Writing—Review and Editing, E.G., M.V. and H.d.C.P.; Visualization, M.V. and H.d.C.P.; Supervision, M.V. and M.C.; Project Administration, M.C.; Funding Acquisition, M.C. All authors have read and agreed to the published version of the manuscript.

Funding: This research received no external funding.

Data Availability Statement: No new data were created or analyzed in this study. Data sharing is not applicable to this article.

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

Appendix A. HEV Powertrain Topologies

This appendix provides an overview of the primary powertrain topologies used in hybrid electric vehicles (HEVs), which define how energy flows within the system and how various components interact to deliver power.

HEV powertrains can be classified into three main topologies [63,64]:

1. Series
   Series hybrids consist of one ICE, one EM that serves as a generator, and at least one EM for propulsion. The ICE powers the generator to produce electric energy which can be either directly used by the traction EM or stored in the ESS. Series hybrids allow the ICE to operate at peak efficiency regardless of wheel speed but encounter generally high drivetrain losses due to the numerous energy conversion processes [63].
2. Parallel
   Parallel architectures are composed of ICE and at least one EM, and both these components are connected to the driveline to provide traction. Powertrain control is responsible for splitting the torque request from the driver between the ICE and EM. Parallels have smaller drivetrain losses and lower capital costs compared to series because they need one less EM to operate. Depending on where the EM is located, parallel architectures can be categorized as P0 (or P1r), P1 (or P1f), P2, P3, P4, and P5 [124].
3. Power split
   Power-split architectures combine the benefits of both series and parallel hybrids. They consist of one ICE and two EM. A planetary gear set is used to connect these three elements and the transmission together, serving as power-splitting device. Compared to the other two, power split topologies comprise higher capital costs and greater control complexity but offer the beneficial aspects of both series and parallels [125].

Hybrid vehicles can be characterized according to their Hybridization Ratio (HR), defined by means of Equation (A1) [126]:

$$HR = \frac{P_{EM,max}(\omega^*)}{P_{PWT,max}} \tag{A1}$$

where ω^* is the rotational speed of the motor crankshaft at which the maximum powertrain power is expressed, $P_{EM,max}(\omega^*)$ is the maximum power of the electric motor when the crankshaft is rotating at ω^*, and $P_{PWT,max}$ is the maximum power that the powertrain can deliver. Slightly different definitions can be found in [127,128]. According to Equation (A1), the HR ranges from 0, in the case of CVs, to 1, in the case EVs, with HEVs that range between these two extremes. Generally speaking, the higher the HR, the more expensive the vehicle. Indeed, low-HR HEVs require both cheaper EMs and smaller ESS.

Appendix B. Energy Management Strategies for HEVs

This appendix provides an in-depth overview of EMSs as applied to HEVs. EMSs play a critical role in managing power flows within the powertrain to optimize energy efficiency, minimize emissions, and maintain performance. While initially developed for HEVs, many of these strategies are adaptable to a wide range of control problems, including those found in EVs and CAVs. Their adaptability stems from their foundational principles, which are often general enough to address challenges such as dynamic power allocation, predictive decision-making, and real-time adaptability in complex systems.

This appendix elaborates on each category, detailing their methodologies, applications, and inherent trade-offs. References to key studies and examples are provided to guide readers interested in exploring specific EMS implementations.

By bridging concepts across vehicle architectures, the discussion in this appendix underscores the broader relevance of EMSs in advanced vehicle technologies, complementing the insights provided in Section 6.

RB EMSs are based on a set of predefined rules based on heuristics. They can be categorized as deterministic or fuzzy:

1. Deterministic RB EMSs
   Deterministic RB EMSs use strict, predefined rules for decision-making. They are conceptually simple and easily real-time implementable [65], often by means of state machines [129,130]. Examples of EMSs belonging to the category of deterministic RB methods are available in [131–133].
2. Fuzzy RB EMSs
   Fuzzy-logic RB EMSs are still based on a set of rules but apply fuzzy logic to handle imprecision and variability. Unlike deterministic strategies, fuzzy RB EMS can deal with a range of values for inputs and produce gradual control outputs rather than binary decisions. This approach enables smoother transitions between operating modes and allows the EMS to adapt more flexibly to varying driving conditions. Fuzzy RB EMSs deliver better fuel economy than deterministic ones, but they can only be optimized for specific drive cycles [65]. The interested reader can reference [134–139] for practical examples of fuzzy logic RB EMSs.

RB EMSs are intuitive and easily implementable but cannot fully capture the potential fuel economy benefits that HEV architectures offer. To achieve globally optimal solutions, a rigorous mathematical model and formal optimization methods are required [140].

OB EMSs apply optimization techniques to determine the best control actions at each instant of time to minimize a cost function along a driving mission. Below is a brief description of the most relevant optimization techniques used in HEVs EMSs:

1. Dynamic Programming (DP)
DP is a global optimization technique that solves a discretized version of the optimal control problem [141,142], with discretization that can be made both in the time domain [143,144] and in the space domain [82]. DP is capable of finding the global optimum but is computationally expensive. Therefore, it is widely used offline as the benchmark for results obtained from online controllers.
2. Pontryagin's Minimum Principle (PMP)
The PMP, first formulated in 1956, is a generalization of the Euler–Lagrange equations to problems with constrained control inputs. It is used to convert global optimization problems into local ones [145]. This approach can provide near-optimal results when the drive cycle is known in advance [146]. The interested reader can reference [147] for an in-depth mathematical description of PMP.
Many examples of the application of PMP are available in the literature, seeking to minimize CO_2 emissions [147] and fuel consumption [148,149]. References that use multivariate expressions for instantaneous cost are available too [150].
3. Equivalent Consumption Minimization Strategy (ECMS)
The ECMS was first introduced in 2000 by [151] and then deepened by [152] and expanded to power-split topologies by [153]. The rationale behind ECMS is to solve a local optimization problem at each time instant to determine the power split that minimizes the instantaneous equivalent fuel consumption. References [147,154,155] show proof of the equivalence between PMP and ECMS, evidencing how the ECMS can be obtained from the PMP under proper assumptions. Being that the ECMS is a local optimization problem which does not require any information in advance, it is a suitable technique for real-time HEVs control.
The ECMS relies on an equivalence factor that weights fuel displacement due to the use of energy from the ESS. The larger the equivalence factor, the less energy will be drained from the ESS. In simplest formulations the equivalence factor is just a constant for charge and one for discharge tuned to optimize vehicle performance on one or more driving cycles [156], or is derived from the powertrain's components efficiency maps [152,157]. More advanced approaches propose functions to enforce constraints on parameters like battery state of charge [154,158,159], state of health [160], and road load [161–163]. Overall, ECMS can provide results close to DP while being real-time implementable [164], but is very sensitive to the tuning.
4. Model Predictive Control (MPC)
MPC is a real-time implementable OB control that relies on a plant model to calculate the optimal control actions over a prediction horizon. It is a well consolidated approach that has a wide array of industrial applications [165]. The first step in MPC control is the solution of an optimization problem aimed at minimizing a cost function over the prediction horizon, obtaining the sequence of control actions that minimizes the global cost within the prediction horizon. Then, only the first portion of the control trajectory is applied to the plant. Finally, the prediction horizon is moved forward with the vehicle, and the cycle is started over [166]. An in-depth mathematical description of MPC is available in [167]. Many literature references exist that apply MPC to the control of HEVs [168,169]. While some assume that the reference speed profile is known within the prediction horizon [170–172], others propose stochastic models to forecast vehicle power demand [173–176].

OB techniques are not limited to those discussed above, with approaches like Linear Programming (LP) [177,178], Genetic Algorithm (GA) [179–181], Particle Swarm Optimization (PSO) [182–184], Simulated Annealing (SA) [185,186] and Divider RECTangle (DIRECT) [187,188] that have been proposed in several studies [63].

LB EMSs for HEVs primarily leverage ML to implement an agent that reacts in the best possible way to the observed environmental conditions. Depending on how the training data is organized, ML can be divided into three categories:

1. Supervised learning
   Supervised learning is today the most common ML framework for the development of LB EMSs. The adjective "supervised" is because training data is labelled: the model learns by associating input features (like speed, battery state, and road conditions) with optimal control actions (e.g., power split between engine and motor). Optimal control theory is generally used to generate labeled data for training [66].
   Methods such as Artificial Neural Networks (ANN) [189–191] and Support Vector Machines (SVM) [192,193] are widely used, often producing EMSs that can predict the best energy allocation for anticipated driving conditions. These systems are typically accurate in predictable scenarios but lack adaptability to unplanned events.
2. Reinforcement learning
   Reinforcement learning is a class of ML techniques in which the training is performed without label data. The aim of the training is to maximize an accumulated reward by means of a trial-and-error interaction with the environment, eventually learning an ideal control approach. The reward is received as feedback from actions taken within the driving environment [66,194].
   Reinforcement learning techniques used in HEVs' EMSs include Q-learning [195–198] and advanced methods like Deep Q-Networks (DQN) [199–203] and Deep Deterministic Policy Gradients (DDPG) [204,205]. EMSs based on reinforcement learning are advantageous in complex, changing environments because they refine strategies through experience, improving fuel efficiency and system performance over time. This adaptability makes RL-based approaches well-suited for real-world, unpredictable driving scenarios.
3. Unsupervised learning
   Unsupervised learning can be employed for three primary objectives: dimensionality reduction, association, and clustering. They operate by identifying patterns in unlabeled data, thus, the training process does not rely on a reward function.
   Examples are available in the literature that combine clustering techniques with OB EMSs [206] and RB EMSs [207–209] in order to tune critical parameters based on driving conditions. Techniques like K-means clustering or principal component analysis (PCA) can reveal underlying driving profiles, allowing the EMS to adjust strategies according to real-time driving conditions. These approaches are particularly valuable for online applications, offering flexible adaptability with lower computational demands than RL.

Overall, LB EMSs enhance the adaptability and performance of HEVs by leveraging diverse data-driven approaches. Each method provides unique benefits, with supervised learning offering high accuracy for predictable tasks, reinforcement learning enabling continuous improvement in dynamic environments, and unsupervised learning allowing for pattern recognition and adaptive control without extensive labeled data requirements. This classification helps in selecting the most appropriate learning-based EMS approach based on specific operational needs and computational constraints of HEV systems.

References

1. Al-Kindi, S.G.; Brook, R.D.; Biswal, S.; Rajagopalan, S. Environmental determinants of cardiovascular disease: Lessons learned from air pollution. *Nat. Rev. Cardiol.* **2020**, *17*, 656–672. [CrossRef] [PubMed]
2. Zhang, K.; Batterman, S. Air pollution and health risks due to vehicle traffic. *Sci. Total Environ.* **2013**, *450–451*, 307–316. [CrossRef] [PubMed]

3. Hooftman, N.; Messagie, M.; Van Mierlo, J.; Coosemans, T. A review of the European passenger car regulations—Real driving emissions vs local air quality. *Renew. Sustain. Energy Rev.* **2018**, *86*, 1–21. [CrossRef]
4. U.S. Environmental Protection Agency. Timeline of Major Accomplishments in Transportation, Air Pollution, and Climate Change. Available online: https://www.epa.gov/transportation-air-pollution-and-climate-change/timeline-major-accomplishments-transportation-air (accessed on 4 February 2025).
5. Tietge, U.; Díaz, S.; Yang, Z.; Mock, P. From Laboratory to Road: A Comparison of Official and Real World Fuel Consumption and CO_2 Values for Passenger Cars in Europe, the United States, China, and Japan. 2017. Available online: https://theicct.org/wp-content/uploads/2021/06/Lab-to-road-intl_ICCT-white-paper_06112017_vF.pdf (accessed on 4 February 2025).
6. Filonchyk, M.; Peterson, M.P.; Zhang, L.; Hurynovich, V.; He, Y. Greenhouse gases emissions and global climate change: Examining the influence of CO_2, CH_4, and N_2O. *Sci. Total Environ.* **2024**, *935*, 173359. [CrossRef]
7. Dornoff, J.; Valverde Morales, V.; Tietge, U. On the Way to "Real World" CO_2 Values? The European Passenger Car Market After 5 Years of WLTP. 2024. Available online: https://theicct.org/publication/real-world-co2-emission-values-vehicles-europe-jan24 (accessed on 4 February 2025).
8. United Nations Economic Commission for Europe. United Nations Global Technical Regulation on Worldwide Harmonized Light Vehicles Test Procedures (WLTP)—Amendment 4. 2018. Available online: https://unece.org/fileadmin/DAM/trans/main/wp29/wp29wgs/wp29gen/wp29registry/ECE-TRANS-180a15am4e.pdf (accessed on 4 February 2025).
9. Paffumi, E.; De Gennaro, M.; Martini, G. Alternative utility factor versus the SAE J2841 standard method for PHEV and BEV applications. *Transp. Policy* **2018**, *68*, 80–97. [CrossRef]
10. He, H.; Yang, Z. China Phase 3 New Passenger Car Fuel Consumption: Proposed Implementation Rule. 2014. Available online: https://theicct.org/publication/china-phase-3-new-passenger-car-fuel-consumption-proposed-implementation-rule (accessed on 4 February 2025).
11. Triantafyllopoulos, G.; Dimaratos, A.M.; Ntziachristos, L.D.; Bernard, Y.; Dornoff, J.; Samaras, Z.C. A study on the CO_2 and NO_x emissions performance of Euro 6 diesel vehicles under various chassis dynamometer and on-road conditions including latest regulatory provisions. *Sci. Total Environ.* **2019**, *666*, 337–346. [CrossRef]
12. van Mensch, P.; Cuelenaere, R.F.A.; Ligterink, N.E. Assessment of Risks for Elevated NOx Emissions of Diesel Vehicles Outside the Boundaries of RDE. 2017. Available online: https://publications.tno.nl/publication/34623933/5YfkNy/TNO-2017-R10862.pdf (accessed on 4 February 2025).
13. Schlenoff, C.I.; Kootbally, Z.; Rachakonda, P.K.; Lightman, S.; Vassilev, A.T.; Wollman, D.A.; Griffor, E.R. *Standards and Performance Metrics for On-Road Automated Vehicles*; National Institute of Standards and Technology: Gaithersburg, MD, USA, 2024. [CrossRef]
14. Vahidi, A.; Sciarretta, A. Energy saving potentials of connected and automated vehicles. *Transp. Res. Part C Emerg. Technol.* **2018**, *95*, 822–843. [CrossRef]
15. Noroozi, M.; Moghaddam, H.R.; Shah, A.; Charkhgard, H.; Sarkar, S.; Das, T.K. An AI-Assisted Systematic Literature Review of the Impact of Vehicle Automation on Energy Consumption. *IEEE Trans. Intell. Veh.* **2023**, *8*, 3572–3592. [CrossRef]
16. Günther, R.; Wenzel, T.; Wegner, M.; Rettig, R. Big data driven dynamic driving cycle development for busses in urban public transportation. *Transp. Res. Part D Transp. Environ.* **2017**, *51*, 276–289. [CrossRef]
17. DieselNet. ECE 15 + EUDC/NEDC. Available online: https://dieselnet.com/standards/cycles/ece_eudc.php (accessed on 4 February 2025).
18. DieselNet. Worldwide Harmonized Light Vehicles Test Cycle (WLTC). Available online: https://dieselnet.com/standards/cycles/wltp.php (accessed on 4 February 2025).
19. Galgamuwa, U.; Perera, L.; Bandara, S. Developing a General Methodology for Driving Cycle Construction: Comparison of Various Established Driving Cycles in the World to Propose a General Approach. *J. Transp. Technol.* **2015**, *5*, 191–203. [CrossRef]
20. André, M.; Joumard, R.; Vidon, R.; Tassel, P.; Perret, P. Real-world European driving cycles, for measuring pollutant emissions from high- and low-powered cars. *Atmos. Environ.* **2006**, *40*, 5944–5953. [CrossRef]
21. Brundell-Freij, K.; Ericsson, E. Influence of street characteristics, driver category and car performance on urban driving patterns. *Transp. Res. Part D Transp. Environ.* **2005**, *10*, 213–229. [CrossRef]
22. Tong, H.Y.; Hung, W.T. A Framework for Developing Driving Cycles with On-Road Driving Data. *Transp. Rev.* **2010**, *30*, 589–615. [CrossRef]
23. Tong, H.Y.; Hung, W.T.; Cheung, C.S. On-Road Motor Vehicle Emissions and Fuel Consumption in Urban Driving Conditions. *J. Air Waste Manag. Assoc.* **2000**, *50*, 543–554. [CrossRef]
24. André, M. The ARTEMIS European driving cycles for measuring car pollutant emissions. *Sci. Total Environ.* **2004**, *334–335*, 73–84. [CrossRef] [PubMed]
25. Chen, C.; Huang, C.; Jing, Q.; Wang, H.; Pan, H.; Li, L.; Zhao, J.; Dai, Y.; Huang, H.; Schipper, L.; et al. On-road emission characteristics of heavy-duty diesel vehicles in Shanghai. *Atmos. Environ.* **2007**, *41*, 5334–5344. [CrossRef]
26. Grano, E.; Villani, M.; Ahmed, Q.; Carello, M. *Leveraging Traffic-in-the-Loop Simulations to Assess the Impact of Traffic on Vehicle Energy Consumption*; SAE Technical Paper 2025-01-8054; SAE International: Detroit, MI, USA, 2025.

27. Lin, J.; Niemeier, D.A. Regional driving characteristics, regional driving cycles. *Transp. Res. Part D Transp. Environ.* **2003**, *8*, 361–381. [CrossRef]
28. Nesamani, K.S.; Subramanian, K.P. Development of a driving cycle for intra-city buses in Chennai, India. *Atmos. Environ.* **2011**, *45*, 5469–5476. [CrossRef]
29. Tong, H.Y.; Tung, H.; Hung, W.T.; Nguyen, V.H. Development of driving cycles for motorcycles and light-duty vehicles in Vietnam. *Atmos. Environ.* **2011**, *45*, 5191–5199. [CrossRef]
30. Shi, Q.; Zheng, Y.; Wang, R.; Li, Y. The study of a new method of driving cycles construction. *Procedia Eng.* **2011**, *16*, 79–87. [CrossRef]
31. Lin, J.; Niemeier, D.A. An exploratory analysis comparing a stochastic driving cycle to California's regulatory cycle. *Atmos. Environ.* **2002**, *36*, 5759–5770. [CrossRef]
32. Achour, H.; Olabi, A.G. Driving cycle developments and their impacts on energy consumption of transportation. *J. Clean. Prod.* **2016**, *112*, 1778–1788. [CrossRef]
33. Hung, W.T.; Tong, H.Y.; Lee, C.; Pao, L. Development of a practical driving cycle construction methodology: A case study in Hong Kong. *Transp. Res. Part D Transp. Environ.* **2015**, *12*, 115–128. [CrossRef]
34. Tutuianu, M.; Bonnel, P.; Ciuffo, B.; Haniu, T.; Ichikawa, N.; Marotta, A.; Pavlovic, J.; Steven, H. Development of the World-wide harmonized Light duty Test Cycle (WLTC) and a possible pathway for its introduction in the European legislation. *Transp. Res. Part D Transp. Environ.* **2015**, *40*, 61–75. [CrossRef]
35. United Nations Economic Commission for Europe. Worldwide Harmonized Light Vehicles Test Procedure. 2014. Available online: https://unece.org/fileadmin/DAM/trans/main/wp29/wp29r-1998agr-rules/ECE-TRANS-180a15e.pdf (accessed on 4 February 2025).
36. International Council on Clean Transportation. Chian's Stage 6 Emission Standard for New Light-Duty Vehicles (Final Rule). 2017. Available online: https://theicct.org/wp-content/uploads/2021/06/China-LDV-Stage-6_Policy-Update_ICCT_20032017_vF_corrected.pdf (accessed on 4 February 2025).
37. DieselNet. China Light-Duty Vehicle Test Cycle (CLTC). Available online: https://dieselnet.com/standards/cycles/cltc.php (accessed on 4 February 2025).
38. National Highway Traffic Safety Administration. Corporate Average Fuel Economy. Available online: https://www.nhtsa.gov/laws-regulations/corporate-average-fuel-economy (accessed on 4 February 2025).
39. DieselNet. FTP-75. Available online: https://dieselnet.com/standards/cycles/ftp75.php (accessed on 4 February 2025).
40. DieselNet. EPA Highway Fuel Economy Test Cycle (HWFET). Available online: https://dieselnet.com/standards/cycles/hwfet.php (accessed on 4 February 2025).
41. Tietge, U.; Díaz, S.; Mock, P.; German, J.; Bandivadekar, A.; Ligterink, N. From Laboratory to Road: A 2016 Update of Official and Real-World Fuel Consumption. 2016. Available online: https://theicct.org/publication/from-laboratory-to-road-a-2016-update (accessed on 4 February 2025).
42. Ligterink, N.E.; Eijk, A.R. Update Analysis of Update Analysis of Real-World Fuel Consumption of Business Passenger Cars Based on Travelcard Nederland Fuelpass Data. 2014. Available online: https://publications.tno.nl/publication/34610190/Lp81A4/TNO-2014-R11063.pdf (accessed on 4 February 2025).
43. Qin, L.; Ben Dror, M.; Kang, L.; Sun, H.; An, F. Real-World and Certified Fuel Consumption Gap Analysis. 2016. Available online: http://www.icet.org.cn/admin/upload/2016092336232621.pdf (accessed on 4 February 2025).
44. Zhang, S.; Wu, Y.; Liu, H.; Huang, R.; Un, P.; Zhou, Y.; Fu, L.; Hao, J. Real-world fuel consumption and CO_2 (carbon dioxide) emissions by driving conditions for light-duty passenger vehicles in China. *Energy* **2014**, *69*, 247–257. [CrossRef]
45. Greene, D.L.; Khattak, A.J.; Liu, J.; Wang, X.; Hopson, J.L.; Goeltz, R. What is the evidence concerning the gap between on-road and Environmental Protection Agency fuel economy ratings? *Transp. Policy* **2017**, *53*, 146–160. [CrossRef]
46. Kühlwein, J. Official vs. Real-World Road-Load Parameters in EU Vehicle Efficiency Testing. 2016. Available online: https://theicct.org/sites/default/files/ICCT_Coastdowns-EU_201605_fs.pdf (accessed on 4 February 2025).
47. Kadijk, G.; Verbeek, M.; Smokers, R.; Spreen, J.; Patuleia, A.; van Ras, M.; Norris, J.; Johnson, A.; O'Brien, S.; Wrigley, S.; et al. Supporting Analysis Regarding Test Procedure Flexibilities and Technology Deployment for Review of the Light Duty Vehicle CO_2 Regulations. 2012. Available online: https://publications.tno.nl/publication/34622247/QesCIL/kadijk-2012-supporting.pdf (accessed on 4 February 2025).
48. Stewart, A.; Hope-Morley, A.; Mock, P.; Tietge, U. Quantifying the Impact of Real-World Driving on Total CO_2 Emissions from UK Cars and Vans. 2015. Available online: https://www.theccc.org.uk/publication/impact-of-real-world-driving-emissions (accessed on 4 February 2025).
49. Ntziachristos, L.; Mellios, G.; Tsokolis, D.; Keller, M.; Hausberger, S.; Ligterink, N.; Dilara, P. In-use vs. type-approval fuel consumption of current passenger cars in Europe. *Energy Policy* **2014**, *67*, 403–411. [CrossRef]

50. Fontaras, G.; Ciuffo, B.; Zacharof, N.; Tsiakmakis, S.; Marotta, A.; Pavlovic, J.; Anagnostopoulos, K. The difference between reported and real-world CO_2 emissions: How much improvement can be expected by WLTP introduction? In Proceedings of the World Conference on Transport Research—WCTR 2016, Shanghai, China, 10–15 July 2016. [CrossRef]
51. Tsokolis, D.; Tsiakmakis, S.; Dimaratos, A.M.; Fontaras, G.; Pistikopoulos, P.K.; Ciuffo, B.; Samaras, Z.C. Fuel consumption and CO_2 emissions of passenger cars over the New Worldwide Harmonized Test Protocol. *Appl. Energy* **2016**, *179*, 1152–1165. [CrossRef]
52. Chindamo, D.; Gadola, M. What is the Most Representative Standard Driving Cycle to Estimate Diesel Emissions of a Light Commercial Vehicle? *IFAC-Pap.* **2018**, *51*, 73–78. [CrossRef]
53. del Rosal, I. European dieselization: Policy insights from EU car trade. *Transp. Policy* **2022**, *115*, 181–194. [CrossRef]
54. Wang, Y.; Hao, C.; Ge, Y.; Hao, L.; Tan, J.; Wang, X.; Zhang, P.; Wang, Y.; Tian, W.; Lin, Z.; et al. Fuel consumption and emission performance from light-duty conventional/hybrid-electric vehicles over different cycles and real driving tests. *Fuel* **2020**, *278*, 118340. [CrossRef]
55. Kageson, P. Cycle-Beating and the EU Test Cycle for Cars. 1998. Available online: https://www.transportenvironment.org/uploads/files/T_2024-04-29-143215_wscv.pdf (accessed on 4 February 2025).
56. U.S. Environmental Protection Agency. Navistar International Transportation Corporation Diesel Engines Settlement. Available online: https://www.epa.gov/enforcement/navistar-international-transportation-corporation-diesel-engines-settlement (accessed on 4 February 2025).
57. U.S. Department of Justice—Office of Public Affairs. Volkswagen AG Agrees to Plead Guilty and Pay $4.3 Billion in Criminal and Civil Penalties; Six Volkswagen Executives and Employees are Indicted in Connection with Conspiracy to Cheat U.S. Emissions Tests. Available online: https://www.justice.gov/opa/pr/volkswagen-ag-agrees-plead-guilty-and-pay-43-billion-criminal-and-civil-penalties-six (accessed on 4 February 2025).
58. Claßen, J.; Krysmon, S.; Dorscheidt, F.; Sterlepper, S.; Pischinger, S. Real Driving Emission Calibration—Review of Current Validation Methods against the Background of Future Emission Legislation. *Appl. Sci.* **2021**, *11*, 5429. [CrossRef]
59. DieselNet. EU: Cars and Light Trucks: RDE Testing. Available online: https://dieselnet.com/standards/eu/ld_rde.php (accessed on 4 February 2025).
60. Transportpolicy.net. EU: Light Duty: Real Driving Emissions (RDE). Available online: https://www.transportpolicy.net/standard/eu-light-duty-real-driving-emissions (accessed on 4 February 2025).
61. European Commission and Council of the European Union. Commission Regulation (EU) 2016/427 amending Regulation (EC) No 692/2008 as regards emissions from light passenger and commercial vehicles (Euro 6), (2016). *Off. J. Eur. Union* **2016**, *59*, L82.
62. Mock, P. Real-Driving Emissions Test Procedure for Exhaust Gas Pollutant Emissions of Cars and Light Commercial Vehicles in Europe. 2017. Available online: https://theicct.org/publication/real-driving-emissions-test-procedure-for-exhaust-gas-pollutant-emissions-of-cars-and-light-commercial-vehicles-in-europe (accessed on 4 February 2025).
63. Taherzadeh, E.; Radmanesh, H.; Mehrizi-Sani, A. A Comprehensive Study of the Parameters Impacting the Fuel Economy of Plug-In Hybrid Electric Vehicles. *IEEE Trans. Intell. Veh.* **2020**, *5*, 596–615. [CrossRef]
64. Wu, G.; Zhang, X.; Dong, Z. Powertrain architectures of electrified vehicles: Review, classification and comparison. *J. Frankl. Inst.* **2015**, *235*, 425–448. [CrossRef]
65. Wirasingha, S.G.; Emadi, A. Classification and Review of Control Strategies for Plug-In Hybrid Electric Vehicles. *IEEE Trans. Veh. Technol.* **2011**, *60*, 111–122. [CrossRef]
66. Jui, J.J.; Ahmad, M.A.; Molla, M.M.; Mohd Rashid, M.I. Optimal energy management strategies for hybrid electric vehicles: A recent survey of machine learning approaches. *J. Eng. Res.* **2024**, *12*, 454–467. [CrossRef]
67. Panaparambil, V.S.; Kashyap, Y.; Castelino, R.V. A review on hybrid source energy management strategies for electric vehicle. *Int. J. Energy Res.* **2021**, *45*, 19819–19850. [CrossRef]
68. Sciarretta, A.; De Nunzio, G.; Ojeda, L.L. Optimal Ecodriving Control: Energy-Efficient Driving of Road Vehicles as an Optimal Control Problem. *IEEE Control Syst. Mag.* **2015**, *35*, 71–90. [CrossRef]
69. Tal, G.; Nicholas, M.A.; Davies, J.; Woodjack, J. Charging Behavior Impacts on Electric Vehicle Miles Traveled: Who is Not Plugging In? *Transp. Res. Rec.* **2014**, *2454*, 53–60. [CrossRef]
70. Arslan, O.; Yıldız, B.; Karaşan, O.E. Impacts of battery characteristics, driver preferences and road network features on travel costs of a plug-in hybrid electric vehicle (PHEV) for long-distance trips. *Energy Policy* **2014**, *74*, 168–178. [CrossRef]
71. Morrissey, P.; Weldon, P.; O'Mahony, M. Future standard and fast charging infrastructure planning: An analysis of electric vehicle charging behaviour. *Energy Policy* **2016**, *89*, 257–270. [CrossRef]
72. Boston, D.; Werthman, A. Plug-in Vehicle Behaviors: An analysis of charging and driving behavior of Ford plug-in electric vehicles in the real world. *World Electr. Veh. J.* **2016**, *8*, 916–925. [CrossRef]
73. *SAE Standard J2841_201009*; Utility Factor Definitions for Plug-In Hybrid Electric Vehicles Using Travel Survey Data. SAE International: Warrendale, PA, USA, 2010. [CrossRef]

74. Raghavan, S.S.; Tal, G. Plug-in hybrid electric vehicle observed utility factor: Why the observed electrification performance differ from expectations. *Int. J. Sustain. Transp.* **2022**, *16*, 105–136. [CrossRef]
75. Wang, A.; Xu, J.; Zhang, M.; Zhai, Z.; Song, G.; Hatzopoulou, M. Emissions and fuel consumption of a hybrid electric vehicle in real-world metropolitan traffic conditions. *Appl. Energy* **2022**, *306*, 118077. [CrossRef]
76. Huang, Y.; Surawski, N.C.; Organ, B.; Zhou, J.L.; Tang, O.H.; Chan, E.F. Fuel consumption and emissions performance under real driving: Comparison between hybrid and conventional vehicles. *Sci. Total Environ.* **2019**, *659*, 275–282. [CrossRef] [PubMed]
77. Bagheri, S.; Huang, Y.; Walker, P.D.; Zhou, J.L.; Surawski, N.C. Strategies for improving the emission performance of hybrid electric vehicles. *Sci. Total Environ.* **2021**, *771*, 144901. [CrossRef]
78. Eurostat. Trade and Production of Hybrid and Electric Cars. Available online: https://ec.europa.eu/eurostat/statistics-explained/index.php?title=Trade_and_production_of_hybrid_and_electric_cars#Production_of_hybrid_and_electric_cars (accessed on 4 February 2025).
79. Liu, T.; Tan, W.; Tang, X.; Zhang, J.; Xing, Y.; Cao, D. Driving conditions-driven energy management strategies for hybrid electric vehicles: A review. *Renew. Sustain. Energy Rev.* **2021**, *151*, 111521. [CrossRef]
80. Hamza, K.; Laberteaux, K.P. Utility Factor Curves for Plug-in Hybrid Electric Vehicles: Beyond the Standard Assumptions. *World Electr. Veh. J.* **2023**, *14*, 301. [CrossRef]
81. Plötz, P.; Link, S.; Ringelschwendner, H.; Keller, M.; Moll, C.; Bieker, G.; Dornoff, J.; Mock, P. Real-World Usage of Plug-in Hybrid Vehicles in Europe: A 2022 Update on Fuel Consuumption, Electric Driving and CO_2 Emissions. 2022. Available online: https://theicct.org/publication/real-world-phev-use-jun22/ (accessed on 4 February 2025).
82. Hellström, E.; Ivarsson, M.; Åslund, J.; Nielsen, L. Look-ahead control for heavy trucks to minimize trip time and fuel consumption. *Control Eng. Pract.* **2009**, *17*, 245–254. [CrossRef]
83. Hellström, E.; Åslund, J.; Nielsen, L. Design of an efficient algorithm for fuel-optimal look-ahead control. *Control Eng. Pract.* **2010**, *18*, 1318–1327. [CrossRef]
84. 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]
85. Zhang, C.; Vahidi, A.; Pisu, P.; Li, X.; Tennant, K. Role of terrain preview in energy management of hybrid electric vehicles. *IEEE Trans. Veh. Technol.* **2010**, *59*, 1139–1147. [CrossRef]
86. Liang, K.-Y.; Mårtensson, J.; Johansson, K.H. Heavy-Duty Vehicle Platoon Formation for Fuel Efficiency. *IEEE Trans. Intell. Transp. Syst.* **2016**, *17*, 1051–1061. [CrossRef]
87. Song, M.; Chen, F.; Ma, X. Organization of autonomous truck platoon considering energy saving and pavement fatigue. *Transp. Res. Part D Transp. Environ.* **2021**, *90*, 102667. [CrossRef]
88. Hussein, A.A.; Rakha, H.A. Vehicle Platooning Impact on Drag Coefficients and Energy/Fuel Saving Implications. *IEEE Trans. Veh. Technol.* **2022**, *71*, 1199–1208. [CrossRef]
89. Ma, F.; Yang, Y.; Wang, J.; Liu, Z.; Li, J.; Nie, J.; Shen, Y.; Wu, L. Predictive energy-saving optimization based on nonlinear model predictive control for cooperative connected vehicles platoon with V2V communication. *Energy* **2019**, *189*, 116120. [CrossRef]
90. Zhao, W.; Ngoduy, D.; Shepherd, S.; Liu, R.; Papageorgiou, M. A platoon based cooperative eco-driving model for mixed automated and human-driven vehicles at a signalised intersection. *Transp. Res. Part C Emerg. Technol.* **2018**, *95*, 802–821. [CrossRef]
91. Turri, V.; Kim, Y.; Guanetti, J.; Johansson, K.H.; Borrelli, F. A model predictive controller for non-cooperative eco-platooning. In Proceedings of the 2017 American Control Conference (ACC), Seattle, WA, USA, 24–26 May 2017. [CrossRef]
92. Li, S.E.; Peng, H. Strategies to minimize the fuel consumption of passenger cars during car-following scenarios. *Proc. Inst. Mech. Eng. Part D J. Automob. Eng.* **2011**, *226*, 419–429. [CrossRef]
93. Manzie, C.; Watson, H.; Halgamuge, S. Fuel economy improvements for urban driving: Hybrid vs. intelligent vehicles. *Transp. Res. Part C Emerg. Technol.* **2007**, *15*, 1–16. [CrossRef]
94. 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. [CrossRef]
95. 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]
96. 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]
97. Hao, P.; Wu, G.; Boriboonsomsin, K.; Barth, M.J. Eco-Approach and Departure (EAD) Application for Actuated Signals in Real-World Traffic. *IEEE Trans. Intell. Transp. Syst.* **2019**, *20*, 30–40. [CrossRef]
98. Ferreira, M.; D'Orey, P.M. On the impact of virtual traffic lights on carbon emissions mitigation. *IEEE Trans. Intell. Transp. Syst.* **2012**, *13*, 284–295. [CrossRef]
99. 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]

100. 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. [CrossRef]
101. 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]
102. Yao, H.; Li, X. Lane-change-aware connected automated vehicle trajectory optimization at a signalized intersection with multi-lane roads. *Transp. Res. Part C Emerg. Technol.* **2021**, *129*, 103182. [CrossRef]
103. Khattak, Z.H.; Smith, B.L.; Fontaine, M.D.; Ma, J.; Khattak, A.J. Active lane management and control using connected and automated vehicles in a mixed traffic environment. *Transp. Res. Part C Emerg. Technol.* **2022**, *139*, 103648. [CrossRef]
104. Ma, C.; Yu, C.; Yang, X. Trajectory planning for connected and automated vehicles at isolated signalized intersections under mixed traffic environment. *Transp. Res. Part C Emerg. Technol.* **2021**, *130*, 103309. [CrossRef]
105. Rios-Torres, J.; Malikopoulos, A.A. Automated and Cooperative Vehicle Merging at Highway On-Ramps. *IEEE Trans. Intell. Transp. Syst.* **2017**, *18*, 780–789. [CrossRef]
106. Xiao, W.; Cassandras, C.G. Decentralized optimal merging control for Connected and Automated Vehicles with safety constraint guarantees. *Automatica* **2021**, *123*, 109333. [CrossRef]
107. Min, H.; Fanf, Y.; Wu, X.; Wu, G.; Zhao, X. On-ramp merging strategy for connected and automated vehicles based on complete information static game. *J. Traffic Transp. Eng. (Engl. Ed.)* **2021**, *8*, 582–595. [CrossRef]
108. Liu, J.; Zhao, W.; Xu, C. An Efficient On-Ramp Merging Strategy for Connected and Automated Vehicles in Multi-Lane Traffic. *IEEE Trans. Intell. Transp. Syst.* **2021**, *23*, 5056–5067. [CrossRef]
109. 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]
110. Milanés, V.; Shladover, S.E.; Spring, J.; Nowakowski, C.; Kawazoe, H.; Nakamura, M. Cooperative Adaptive Cruise Control in Real Traffic Situations. *IEEE Trans. Intell. Transp. Syst.* **2014**, *15*, 296–305. [CrossRef]
111. Ma, J.; Li, X.; Shladover, S.; Rakha, H.A.; Lu, X.-Y.; Jagannathan, R.; Dailey, D.J. Freeway Speed Harmonization. *IEEE Trans. Intell. Veh.* **2016**, *1*, 78–89. [CrossRef]
112. Stern, R.E.; Cui, S.; Delle Monache, M.L.; Bhadani, R.; Bunting, M.; Churchill, M.; Hamilton, N.; Haulcy, R.; Pohlmann, H.; Wu, F.; 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]
113. Weißmann, A.; Görges, D.; Lin, X. Energy-optimal adaptive cruise control combining model predictive control and dynamic programming. *Control Eng. Pract.* **2018**, *72*, 125–137. [CrossRef]
114. Nasri, M.I.; Bektaş, T.; Laporte, G. Route and speed optimization for autonomous trucks. *Comput. Oper. Res.* **2018**, *100*, 89–101. [CrossRef]
115. Zheng, C.; Xu, G.; Xu, K.; Pan, Z.; Liang, Q. An energy management approach of hybrid vehicles using traffic preview information for energy saving. *Energy Convers. Manag.* **2015**, *105*, 462–470. [CrossRef]
116. Plin, P.; Aggoune, K.; Tang, L.; Confer, K.; Kirwan, J.; Deshpande, S.R.; Gupta, S.; Tulpule, P.J.; Canova, M.; Rizzoni, G. *Reducing Fuel Consumption by Using Information from Connected and Automated Vehicle Modules to Optimize Propulsion System Control*; SAE Technical Paper 2019-01-1213; SAE International: Detroit, MI, USA, 2019. [CrossRef]
117. Treiber, M.; Kesting, A. *Traffic Flow Dynamics: Data, Models and Simulation*; Springer: Cham, Switzerland, 2012.
118. Lighthill, M.J.; Whitham, G.B. On kinematic waves II. A theory of traffic flow on long crowded roads. *Proc. R. Soc. A Math. Phys. Eng. Sci.* **1955**, *229*, 317–345.
119. Paul, S.; Goyal, V.; Joshi, S.; Franke, M.; Tomazic, D.; Zeman, J. *Evaluation of Longitudinal ADAS Functions for Fuel Economy Improvement of Class 8 Long Haul Trucks*; SAE Technical Paper 2023-01-0217; SAE International: Detroit, MI, USA, 2023. [CrossRef]
120. Rengarajan, S.B.; Hotz, S.; Hirsch, C.; Lobato, P.; Gross, M.; Sturgeon, P.; Sarlashkar, J. Test Methodology to Quantify and Analyze Energy Consumption of Connected and Automated Vehicles. SAE Technical Paper 2019-01-0116; SAE International: Detroit, MI, USA, 2019. [CrossRef]
121. Jia, D.; Chen, H.; Zheng, Z.; Watling, D.; Connors, R.; Gao, J.; Li, Y. An Enhanced Predictive Cruise Control System Design with Data-Driven Traffic Prediction. *IEEE Trans. Intell. Transp. Syst.* **2022**, *23*, 8170–8183. [CrossRef]
122. Rajendran, A.V.; Hegde, B.; Ahmed, Q.; Rizzoni, G. Design and Development of Traffic-In-Loop Powertrain Simulation. In Proceedings of the 2017 IEEE Conference on Control Technology and Applications (CCTA), Maui, HI, USA, 27–30 August 2017. [CrossRef]
123. Zhao, J.; Wu, H.; Chang, C. *Virtual Traffic Simulator for Connected and Automated Vehicles*; SAE Technical Paper 2019-01-0676; SAE International: Detroit, MI, USA, 2019. [CrossRef]
124. Ireneusz, P.; Cieslik, W.; Szwajca, F. Energy Flow and Electric Drive Mode Efficiency Evaluation of Different Generations of Hybrid Vehicles under Diversified Urban Traffic Conditions. *Energies* **2023**, *16*, 794. [CrossRef]

125. Yang, Y.; Arshad-Ali, K.; Roeleveld, J.; Emadi, A. State-of-the-art electrified powertrains—Hybrid, plug-in, and electric vehicles. *Int. J. Powertrains* **2016**, *5*, 1–29. [CrossRef]
126. Sundstrom, O.; Guzzella, L.; Soltic, P. Torque-Assist Hybrid Electric Powertrain Sizing: From Optimal Control Towards a Sizing Law. *IEEE Trans. Control Syst. Technol.* **2010**, *18*, 837–849. [CrossRef]
127. Baumann, B.M.; Washington, G.; Glenn, B.C.; Rizzoni, G. Mechatronic design and control of hybrid electric vehicles in IEEE/ASME Transactions on Mechatronics. *IEEE/ASME Trans. Mechatron.* **2000**, *5*, 58–72. [CrossRef]
128. Bolvashenkov, I.; Herzog, H.G.; Engstle, A. Factor of hybridization as a design parameter for hybrid vehicles. In Proceedings of the International Symposium on Power Electronics, Electrical Drives, Automation and Motion, 2006 (SPEEDAM 2006), Taormina, Italy, 23–26 May 2006. [CrossRef]
129. Phillips, A.; Jankovic, M.; Bailey, K. Vehicle system controller design for a hybrid electric vehicle. In Proceedings of the 2000 IEEE International Conference on Control Applications. Conference Proceedings, Anchorage, AK, USA, 25–27 September 2000. [CrossRef]
130. Banvait, H.; Anwar, S.; Chen, Y. A rule-based energy management strategy for Plug-in Hybrid Electric Vehicle (PHEV). In Proceedings of the 2009 American Control Conference, St. Louis, MO, USA, 10–12 June 2009. [CrossRef]
131. Adhikari, S.; Halgamuge, S.K.; Watson, H.C. An Online Power-Balancing Strategy for a Parallel Hybrid Electric Vehicle Assisted by an Integrated Starter Generator. *IEEE Trans. Veh. Technol.* **2010**, *59*, 2689–2699. [CrossRef]
132. Overington, S.; Rajakaruna, S. High-Efficiency Control of Internal Combustion Engines in Blended Charge Depletion/Charge Sustenance Strategies for Plug-In Hybrid Electric Vehicles. *IEEE Trans. Veh. Technol.* **2015**, *64*, 48–61. [CrossRef]
133. Salisa, A.R.; Zhang, N.; Zhu, J.G. A Comparative Analysis of Fuel Economy and Emissions Between a Conventional HEV and the UTS PHEV. *IEEE Trans. Veh. Technol.* **2011**, *60*, 44–54. [CrossRef]
134. Lee, H.-D.; Koo, E.-S.; Sul, S.-K.; Kim, J.-S.; Kamiya, M.; Ikeda, H. Torque control strategy for a parallel-hybrid vehicle using fuzzy logic. *IEEE Ind. Appl. Mag.* **2000**, *6*, 33–38. [CrossRef]
135. Johnson, V.H.; Wipke, K.B.; Rausen, D.J. HEV Control Strategy for Real-Time Optimization of Fuel Economy and Emissions. In Proceedings of the Future Car Congress, Arlington VA, USA, 2–6 April 2000. [CrossRef]
136. Ming, L.; Ying, Y.; Liang, L.; Yao, L.; Zhou, W. Energy Management Strategy of a Plug-in Parallel Hybrid Electric Vehicle Using Fuzzy Control. *Energy Procedia* **2017**, *105*, 2660–2665. [CrossRef]
137. Li, S.G.; Sharkh, S.M.; Walsh, F.C.; Zhang, C.N. Energy and Battery Management of a Plug-In Series Hybrid Electric Vehicle Using Fuzzy Logic. *IEEE Trans. Veh. Technol.* **2011**, *60*, 3571–3585. [CrossRef]
138. Hajimiri, M.H.; Salmasi, F.R. A Fuzzy Energy Management Strategy for Series Hybrid Electric Vehicle with Predictive Control and Durability Extension of the Battery. In Proceedings of the 2006 IEEE Conference on Electric and Hybrid Vehicles, Pune, India, 18–20 December 2006. [CrossRef]
139. Poursamad, A.; Montazeri, M. Design of genetic-fuzzy control strategy for parallel hybrid electric vehicles. *Control Eng. Pract.* **2008**, *16*, 861–873. [CrossRef]
140. Malikopoulos, A.A. Supervisory Power Management Control Algorithms for Hybrid Electric Vehicles: A Survey. *IEEE Trans. Intell. Transp. Syst.* **2014**, *15*, 1869–1885. [CrossRef]
141. Bellman, R.E.; Dreyfus, S.E. *Applied Dynamic Programming*; Princeton University Press: Princeton, NJ, USA, 1962; p. 388.
142. Bertsekas, D.P. *Dynamic Programming and Optimal Control: Volume I*; Athena Scientific: Nashua, NH, USA, 2012; p. 613.
143. Heppeler, G.; Sonntag, M.; Sawodny, O. Fuel Efficiency Analysis for Simultaneous Optimization of the Velocity Trajectory and the Energy Management in Hybrid Electric Vehicles. *IFAC Proc. Vol.* **2014**, *47*, 6612–6617. [CrossRef]
144. Mensing, F.; Bideaux, E.; Trigui, R.; Tattegrain, H. Trajectory optimization for eco-driving taking into account traffic constraints. *Transp. Res. Part D Transp. Environ.* **2013**, *18*, 55–61. [CrossRef]
145. Geering, H.P. *Optimal Control With Engineering Applications*; Springer: Berlin/Heidelberg, Germany, 2007.
146. Kim, N.; Cha, S.W.; Peng, H. Optimal Equivalent Fuel Consumption for Hybrid Electric Vehicles. *IEEE Trans. Control Syst. Technol.* **2012**, *20*, 817–825. [CrossRef]
147. Stockar, S.; Marano, V.; Canova, M.; Rizzoni, G.; Guzzella, L. Energy-Optimal Control of Plug-in Hybrid Electric Vehicles for Real-World Driving Cycles. *IEEE Trans. Veh. Technol.* **2011**, *60*, 2949–2962. [CrossRef]
148. Onori, S.; Tribioli, L. Adaptive Pontryagin's Minimum Principle supervisory controller design for the plug-in hybrid GM Chevrolet Volt. *Appl. Energy* **2015**, *147*, 224–234. [CrossRef]
149. Hou, C.; Ouyang, M.; Xu, L.; Wang, H. Approximate Pontryagin's minimum principle applied to the energy management of plug-in hybrid electric vehicles. *Appl. Energy* **2014**, *115*, 174–189. [CrossRef]
150. Tang, L.; Rizzoni, G.; Onori, S. Optimal energy management of HEVs with consideration of battery aging. In Proceedings of the 2014 IEEE Conference and Expo Transportation Electrification Asia-Pacific (ITEC Asia-Pacific), Beijing, China, 31 August–3 September 2014. [CrossRef]
151. Paganelli, G.; Guerra, T.M.; Delprat, S.; Santin, J.-J.; Delhom, M.; Combes, E. Simulation and assessment of power control strategies for a parallel hybrid car. *Proc. Inst. Mech. Eng. Part D J. Automob. Eng.* **2000**, *214*, 705–717. [CrossRef]

152. Paganelli, G.; Delprat, S.; Guerra, T.M.; Rimaux, J.; Santin, J.J. Equivalent consumption minimization strategy for parallel hybrid powertrains. In Proceedings of the IEEE 55th Vehicular Technology Conference, VTC Spring 2002, Birmingham, UK, 6–9 May 2002. [CrossRef]
153. Liu, J.; Peng, H. Modeling and Control of a Power-Split Hybrid Vehicle. *IEEE Trans. Control Syst. Technol.* **2008**, *16*, 1242–1251. [CrossRef]
154. Sciarretta, A.; Back, M.; Guzzella, L. Optimal control of parallel hybrid electric vehicles. *IEEE Trans. Control Syst. Technol.* **2004**, *12*, 352–363. [CrossRef]
155. Serrao, L.; Onori, S.; Rizzoni, G. A comparative analysis of energy management strategies for hybrid electric vehicles. *J. Dyamic Syst. Meas. Control* **2011**, *133*, 031012. [CrossRef]
156. Won, J.-S.; Langari, R.; Ehsani, M. An energy management and charge sustaining strategy for a parallel hybrid vehicle with CVT. *IEEE Trans. Control Syst. Technol.* **2005**, *13*, 313–320. [CrossRef]
157. Pisu, P.; Rizzoni, G. A supervisory control strategy for series hybrid electric vehicles with two energy storage systems. In Proceedings of the 2005 IEEE Vehicle Power and Propulsion Conference, Chicago, IL, USA, 7–9 September 2005. [CrossRef]
158. Paganelli, G.; Tateno, M.; Brahma, A.; Rizzoni, G.; Guezennec, Y. Control development for a hybrid-electric sport-utility vehicle: Strategy, implementation and field test results. In Proceedings of the 2001 American Control Conference, Arlington, VA, USA, 25–27 June 2001.
159. Gao, J.-P.; Zhu, G.-M.G.; Strangas, E.G.; Sun, F.-C. Equivalent fuel consumption optimal control of a series hybrid electric vehicle. *Proc. Inst. Mech. Eng. Part D J. Automob. Eng.* **2009**, *223*, 967–1100. [CrossRef]
160. Ebbesen, S.; Elbert, P.; Guzzella, L. Battery State-of-Health Perceptive Energy Management for Hybrid Electric Vehicles. *IEEE Trans. Veh. Technol.* **2012**, *61*, 2893–2900. [CrossRef]
161. Musardo, C.; Rizzoni, G.; Guezennec, Y.; Staccia, B. A-ECMS: An Adaptive Algorithm for Hybrid Electric Vehicle Energy Management. *Eur. J. Control* **2005**, *11*, 509–524. [CrossRef]
162. Tianheng, F.; Lin, Y.; Qing, G.; Yanqing, H.; Ting, Y.; Bin, Y. A Supervisory Control Strategy for Plug-In Hybrid Electric Vehicles Based on Energy Demand Prediction and Route Preview. *IEEE Trans. Veh. Technol.* **2015**, *64*, 1691–1700. [CrossRef]
163. Kazemi, H.; Fallah, Y.P.; Nix, A.; Wayne, S. Predictive AECMS by Utilization of Intelligent Transportation Systems for Hybrid Electric Vehicle Powertrain Control. *IEEE Trans. Intell. Veh.* **2017**, *2*, 75–84. [CrossRef]
164. Pisu, P.; Rizzoni, G. A Comparative Study of Supervisory Control Strategies for Hybrid Electric Vehicles. *IEEE Trans. Control Syst. Technol.* **2007**, *15*, 506–518. [CrossRef]
165. Qin, S.J.; Badgwell, T.A. A survey of industrial model predictive control technology. *Control Eng. Pract.* **2003**, *11*, 733–764. [CrossRef]
166. Huang, Y.; Wang, H.; Khajepour, A.; He, H.; Ji, J. Model predictive control power management strategies for HEVs: A review. *J. Power Sources* **2017**, *341*, 91–106. [CrossRef]
167. Camacho, E.F.; Bordons, C. *Model Predictive Control*, 2nd ed.; Springer: Berlin/Heidelberg, Germany, 2007; p. 405.
168. Spano, M.; Shiledar, A.; Gupta, S.; Villani, M.; Misul, D.; Canova, M.; Rizzoni, G. *Performance Evaluation of an Eco-Driving Controller for Fuel Cell Electric Trucks in Real-World Driving Conditions*; Sae Technical Paper 2024-01-2183; SAE International: Detroit, MI, USA, 2024. [CrossRef]
169. Villani, M.; Shiledar, A.; Block, B.; Spano, M.; Rizzoni, G. Optimal Eco-Driving with Infrastructure-to-Vehicle Communication for Speed Adaptation Based on Real-Time Dynamic Macroscopic Traffic Conditions. In Proceedings of the Conference on Sustainable Mobility, Catania, Italy, 18–20 September 2024. [CrossRef]
170. Yan, F.; Wang, J.; Huang, K. Hybrid Electric Vehicle Model Predictive Control Torque-Split Strategy Incorporating Engine Transient Characteristics. *IEEE Trans. Veh. Technol.* **2012**, *61*, 2458–2467. [CrossRef]
171. Borhan, H.A.; Zhang, C.; Vahidi, A.; Phillips, A.M.; Kuang, M.L.; Di Cairano, S. Nonlinear Model Predictive Control for power-split Hybrid Electric Vehicles. In Proceedings of the 49th IEEE Conference on Decision and Control (CDC), Atlanta, GA, USA, 15–17 December 2010. [CrossRef]
172. Borhan, H.; Vahidi, A.; Phillips, A.M.; Kuang, M.L.; Kolmanovsky, I.V.; Di Cairano, S. MPC-Based Energy Management of a Power-Split Hybrid Electric Vehicle. *IEEE Trans. Control Syst. Technol.* **2012**, *20*, 593–603. [CrossRef]
173. Ripaccioli, G.; Bernardini, D.; Di Cairano, S.; Bemporad, A.; Kolmanovsky, I.V. A stochastic model predictive control approach for series hybrid electric vehicle power management. In Proceedings of the 2010 American Control Conference, Baltimore, MD, USA, 30 June–2 July 2010. [CrossRef]
174. Di Cairano, S.; Bernardini, D.; Bemporad, A.; Kolmanovsky, I.V. Stochastic MPC With Learning for Driver-Predictive Vehicle Control and its Application to HEV Energy Management. *IEEE Trans. Control Syst. Technol.* **2014**, *22*, 1018–1031. [CrossRef]
175. Zeng, X.; Wang, J. A Parallel Hybrid Electric Vehicle Energy Management Strategy Using Stochastic Model Predictive Control With Road Grade Preview. *IEEE Trans. Control Syst. Technol.* **2015**, *23*, 2416–2423. [CrossRef]
176. Li, L.; You, S.; Yang, C. Multi-Objective Stochastic MPC-Based System Control Architecture for Plug-In Hybrid Electric Buses. *IEEE Trans. Ind. Electron.* **2016**, *63*, 4752–4763. [CrossRef]

177. Tate, E.D.; Boyd, S.P. Finding Ultimate Limits of Performance for Hybrid Electric Vehicles. In *Future Transportation Technology Conference & Exposition*; SAE International: Warrendale, PA, USA, 2000. [CrossRef]
178. Wu, G.; Boriboonsomsin, K.; Barth, M.J. Development and Evaluation of an Intelligent Energy-Management Strategy for Plug-in Hybrid Electric Vehicles. *IEEE Trans. Intell. Transp. Syst.* **2014**, *15*, 1091–1100. [CrossRef]
179. Desai, C.; Williamson, S.S. Optimal design of a parallel Hybrid Electric Vehicle using multi-objective genetic algorithms. In Proceedings of the 2009 IEEE Vehicle Power and Propulsion Conference, Dearborn, MI, USA, 7–11 September 2009. [CrossRef]
180. Chen, Z.; Mi, C.C.; Xiong, R.; Xu, J.; You, C. Energy management of a power-split plug-in hybrid electric vehicle based on genetic algorithm and quadratic programming. *J. Power Sources* **2014**, *248*, 416–426. [CrossRef]
181. Li, L.; Zhang, Y.; Yang, C.; Jiao, X.; Zhang, L.; Song, J. Hybrid genetic algorithm-based optimization of powertrain and control parameters of plug-in hybrid electric bus. *J. Frankl. Inst.* **2015**, *352*, 776–801. [CrossRef]
182. Eberhart, R.C.; Kennedy, J. A new optimizer using particle swarm theory. In Proceedings of the Sixth International Symposium on Micro Machine and Human Science, MHS'95, Nagoya, Japan, 4–6 October 1995. [CrossRef]
183. Chen, Z.; Xiong, R.; Cao, J. Particle swarm optimization-based optimal power management of plug-in hybrid electric vehicles considering uncertain driving conditions. *Energy* **2016**, *96*, 197–208. [CrossRef]
184. Chen, Z.; Xiong, R.; Wang, C.; Cao, J. An on-line predictive energy management strategy for plug-in hybrid electric vehicles to counter the uncertain prediction of the driving cycle. *Appl. Energy* **2017**, *185*, 1663–1672. [CrossRef]
185. Trovão, J.P.F.; Santos, V.D.N.; Pereirinha, P.G.; Jorge, H.M.; Antunes, C.H. A Simulated Annealing Approach for Optimal Power Source Management in a Small EV. *IEEE Trans. Sustain. Energy* **2013**, *4*, 867–876. [CrossRef]
186. Chen, Z.; Mi, C.C.; Xia, B.; You, C. Energy management of power-split plug-in hybrid electric vehicles based on simulated annealing and Pontryagin's minimum principle. *J. Power Sources* **2014**, *272*, 160–168. [CrossRef]
187. Finkel, D.E. DIRECT Optimization Algorithm User Guide. 2003. Available online: http://www2.peq.coppe.ufrj.br/Pessoal/Professores/Arge/COQ897/Naturais/DirectUserGuide.pdf (accessed on 4 February 2025).
188. Hao, J.; Yu, Z.; Zhao, Z.; Shen, P.; Zhan, X. Optimization of Key Parameters of Energy Management Strategy for Hybrid Electric Vehicle Using DIRECT Algorithm. *Energies* **2016**, *9*, 997. [CrossRef]
189. Yavasoglu, H.A.; Tetik, Y.E.; Ozcan, H.G. Neural network-based energy management of multi-source (battery/UC/FC) powered electric vehicle. *Int. J. Energy Res.* **2020**, *44*, 12416–12429. [CrossRef]
190. Millo, F.; Rolando, L.; Tresca, L.; Pulvirenti, L. Development of a neural network-based energy management system for a plug-in hybrid electric vehicle. *Transp. Eng.* **2023**, *11*, 100156. [CrossRef]
191. Xie, S.; Hu, X.; Xin, Z.; Brighton, J. Pontryagin's Minimum Principle based model predictive control of energy management for a plug-in hybrid electric bus. *Appl. Energy* **2019**, *236*, 893–905. [CrossRef]
192. Zheng, Y.; He, F.; Shen, X.; Jiang, X. Energy Control Strategy of Fuel Cell Hybrid Electric Vehicle Based on Working Conditions Identification by Least Square Support Vector Machine. *Energies* **2020**, *13*, 426. [CrossRef]
193. Liu, Y.; Zhang, Y.; Yu, H.; Nie, Z.; Liu, Y.; Chen, Z. A novel data-driven controller for plug-in hybrid electric vehicles with improved adaptabilities to driving environment. *J. Clean. Prod.* **2022**, *334*, 130250. [CrossRef]
194. Li, S.E. Deep Reinforcement Learning. In *Reinforcement Learning for Sequential Decision and Optimal Control*; Springer: Berlin/Heidelberg, Germany, 2023.
195. Chen, Z.; Hu, H.; Wu, Y.; Zhang, Y.; Li, G.; Liu, Y. Stochastic model predictive control for energy management of power-split plug-in hybrid electric vehicles based on reinforcement learning. *Energy* **2020**, *211*, 118931. [CrossRef]
196. Chen, Z.; Gu, H.; Shen, S.; Jiangwei, S. Energy management strategy for power-split plug-in hybrid electric vehicle based on MPC and double Q-learning. *Energy* **2022**, *245*, 123182. [CrossRef]
197. Liu, Y.; Wu, Y.; Wang, X.; Li, L.; Zhang, Y.; Chen, Z. Energy management for hybrid electric vehicles based on imitation reinforcement learning. *Energy* **2023**, *263*, 125890. [CrossRef]
198. Zhou, Q.; Li, J.; Shuai, B.; Williams, H.; He, Y.; Li, Z.; Xu, H.; Yan, F. Multi-step reinforcement learning for model-free predictive energy management of an electrified off-highway vehicle. *Appl. Energy* **2019**, *255*, 113755. [CrossRef]
199. Tang, X.; Chen, J.; Liu, T.; Qin, Y.; Cao, D. Distributed Deep Reinforcement Learning-Based Energy and Emission Management Strategy for Hybrid Electric Vehicles. *IEEE Trans. Veh. Technol.* **2021**, *70*, 9922–9934. [CrossRef]
200. Wang, H.; He, H.; Bai, Y.; Yue, H. Parameterized deep Q-network based energy management with balanced energy economy and battery life for hybrid electric vehicles. *Appl. Energy* **2022**, *350*, 119270. [CrossRef]
201. Tang, X.; Zhou, H.; Wang, F.; Wang, W.; Lin, X. Longevity-conscious energy management strategy of fuel cell hybrid electric Vehicle Based on deep reinforcement learning. *Energy* **2022**, *238*, 121593. [CrossRef]
202. Zheng, C.; Zhang, D.; Xiao, Y.; Li, W. Reinforcement learning-based energy management strategies of fuel cell hybrid vehicles with multi-objective control. *J. Power Sources* **2022**, *543*, 231841. [CrossRef]
203. Qi, C.; Zhu, Y.; Song, C.; Yan, G.; Xiao, F.; Wang, D.; Zhang, X.; Cao, J.; Song, S. Hierarchical reinforcement learning based energy management strategy for hybrid electric vehicle. *Energy* **2022**, *238*, 120599. [CrossRef]

204. Wu, Y.; Tan, H.; Peng, J.; Zhang, H.; He, H. Deep reinforcement learning of energy management with continuous control strategy and traffic information for a series-parallel plug-in hybrid electric bus. *Appl. Energy* **2019**, *247*, 454–466. [CrossRef]
205. Lian, R.; Peng, J.; Wu, Y.; Tan, H.; Zhang, H. Rule-interposing deep reinforcement learning based energy management strategy for power-split hybrid electric vehicle. *Energy* **2020**, *197*, 117297. [CrossRef]
206. Feng, J.; Han, Z.; Wu, Z.; Li, M. A Dynamic ECMS Method Considering Vehicle Speed Pattern and Minimum Engine Operation Time for a Range-Extender Electric Vehicle. *IEEE Trans. Veh. Technol.* **2022**, *71*, 4788–4800. [CrossRef]
207. Lei, Z.; Qin, D.; Zhao, P.; Li, J.; Liu, Y.; Chen, Z. A real-time blended energy management strategy of plug-in hybrid electric vehicles considering driving conditions. *J. Clean. Prod.* **2020**, *252*, 119735. [CrossRef]
208. Liu, Y.; Liu, J.; Qin, D.; Li, G.; Chen, Z.; Zhang, Y. Online energy management strategy of fuel cell hybrid electric vehicles based on rule learning. *J. Clean. Prod.* **2020**, *260*, 121017. [CrossRef]
209. Wang, Y.; Zhang, Y.; Zhang, C.; Zhou, J.; Hu, D.; Yi, F.; Fan, Z.; Zeng, T. Genetic algorithm-based fuzzy optimization of energy management strategy for fuel cell vehicles considering driving cycles recognition. *Energy* **2023**, *263*, 126112. [CrossRef]