Analyzing the Improvements of Energy Management Systems for Hybrid Electric Vehicles Using a Systematic Literature Review: How Far Are These Controls from Rule-Based Controls Used in Commercial Vehicles?

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Featured Application: This work is useful for researchers interested in the study of energy management systems for hybrid electric vehicles. In addition, it is interesting for institutions related to the market of this type of vehicle.

Abstract: The hybridization of vehicles is a viable step toward overcoming the challenge of the reduction of emissions related to road transport all over the world. To take advantage of the emission reduction potential of hybrid electric vehicles (HEVs), the appropriate design of their energy management systems (EMSs) to control the power flow between the engine and the battery is essential. This work presents a systematic literature review (SLR) of the more recent works that developed EMSs for HEVs. The review is carried out subject to the following idea: although the development of novel EMSs that seek the optimum performance of HEVs is booming, in the real world, HEVs continue to rely on well-known rule-based (RB) strategies. The contribution of this work is to present a quantitative comparison of the works selected. Since several studies do not provide results of their models against commercial RB strategies, it is proposed, as another contribution, to complete their results using simulations. From these results, it is concluded that the improvement of the analyzed EMSs ranges roughly between 5% and 10% with regard to commercial RB EMSs; in comparison to the optimum, the analyzed EMSs are nearer to the optimum than commercial RB EMSs.

1. Introduction

The reduction of emissions related to road transport is a challenge that is being faced all over the world. In the EU, passenger cars and vans ("light commercial vehicles") are responsible for around 12% and 2.5%, respectively, of the total EU emissions of carbon dioxide (CO_2), the main greenhouse gas [1]. On 21 January 2020, the European Parliament and the Council modified the Regulation (EU) 2019/631 (adopted on 17 April 2019) setting CO_2 emission performance standards for new passenger cars and for new vans in the EU [2]. It sets new EU fleet-wide CO_2 emission targets for the years 2025 and 2030, both for newly registered passenger cars and for newly registered vans. These targets are

defined as a percentage reduction from the 2021 starting points. For cars, it aims for a 15% reduction from 2025 onwards and a 37.5% reduction from 2030 onwards.

To adhere to these regulations, downsized engines, powertrain electrification, lower rolling resistance tire and the use of lightweight materials have been investigated intensively over the past few decades. Hybridization is a viable step toward powertrain electrification [3]. Apart from hybridization, since most of the future powertrain systems will continue to have a combustion engine (conventional powertrain and HEV as well), it should be noted that it is still fundamental to develop new technologies for combustion engines to improve the efficiency and the engine emissions level [4,5].

To take advantage of the emission reduction potential of hybrid electric vehicles (HEVs), appropriate design of their energy management systems (EMSs) to control the power flow between the engine and the battery is essential.

In a conventional (non-hybrid) vehicle, there is no need for an energy management strategy: the driver decides the instant power delivery using the brake and accelerator pedals and, in manual transmission vehicles, decides which gear is engaged at any time. In a hybrid vehicle, on the other hand, there is an additional decision that must be taken due to its ability to recover energy during braking or driving downhill: how much power is delivered by each of the energy sources on-board of the vehicle. The recovered energy can be stored in the battery and deployed at a later time to assist the prime mover to provide tractive power. This is why all hybrid vehicles include an energy management controller, interposed between the driver and the component controllers. As mentioned, the aim of the energy management system is to determine the optimal power split between the on-board energy sources. The decision regarding what to consider optimal depends on the specific application: in most cases, the strategies tend to minimize the fuel consumption, but optimization objectives could also include the minimization of pollutant emissions, maximization of battery life or—in general—a compromise among all the above goals [6].

Apparently, the optimal control policy depends on the characteristics of the drive cycle. Computing the optimal control sequence, it is thus essential to know the power and velocity requests in advance [7]. Therefore, the optimal control depends explicitly on the power requests and engine velocity. Although the optimal control cannot be implemented in real time, its determination is necessary for several reasons: (1) to evaluate the fuel consumption reduction potential of a hybrid vehicle; (2) to benchmark real-time control strategies; and (3) to improve the optimality of a real-time strategy using predicted trajectories.

Then, at first glance, the easiest way to get a hybrid vehicle up and running with a real-time implemented strategy is to define a set of rules that decide when to use the electric machine and when not to use it [7]. This is known as rule-based (RB) EMS. The RB EMSs can be sub-classified into deterministic and fuzzy-logic strategies.

Apart from this, optimal control-based approaches have been explored as well to determine the optimal control policy. Thus, the concept of the equivalent consumption minimization strategy (ECMS) was developed. In ECMS, the cost of using the stored energy in the battery is weighed against the cost of using fuel with an introduced "equivalence factor". Hereafter, real-time strategies that are based upon the observations obtained with Pontryagin's minimum principle are further developed.

The real-time control of plug-in hybrids is more involved in the sense that a depleting strategy is required, such that a constant state-of-energy reference does not work. Real-time strategies that use predictive information, coming from an on-board navigation system, to enhance optimality represent a research topic that has attracted attention as well.

Taking everything into account, a logical classification of HEV control strategies is rule-based and optimization-based strategies [8–10]. On the one hand, it can be concluded that rule-based strategies can be easily implemented in real controllers and their rules can be determined based on human intelligence, heuristics or mathematical models. On the other hand, global optimum solutions can be obtained by performing optimization over a predefined driving cycle. However, this means that it is not possible to perform real-time energy management. In any case, the results of these optimum solutions can be used to benchmark other control strategies and as a basis to define rules for online

implementation. The cited online implementation results in the definition of new sub-categories inside the optimization-based control strategies: offline and online strategies.

Offline techniques require knowledge of the entire driving cycle. As mentioned before, they can be seen as a good analysis, design and assessment tool for other types of strategies. However, due to their computational complexity, they are not directly implementable for real-time operation. In this category, the following strategies can be highlighted: linear programming (LP), dynamic programming (DP) and metaheuristic search methods. LP solves the problem of fuel consumption optimization by approximating a convex nonlinear optimization problem with a linear programming method. Its problem is that the approximate formulation restricts its application to simple series HEV architectures. DP uses a numerical or analytical model to compute the optimal control strategy to achieve the best fuel consumption. It is able to deal with nonlinearity to find the global optimal solution. Finally, metaheuristic search methods solve optimization problems using stochastic search techniques that reproduce natural processes (e.g., genetic algorithms, particle swarm optimization and simulated annealing). They are effective to solve complex optimization problems with nonlinear, multimodal and non-convex objective functions. All of these offline optimization strategies cannot be used in real-time applications but can provide a benchmark for design and comparison.

Online strategies are used when real-time analysis is required. In these strategies, the global criterion of global optimization techniques has to be reduced to an instantaneous optimization. It is achieved by introducing a cost function that only depends on the present state of the system parameters. The following strategies are included in this category: equivalent consumption minimization strategy (ECMS) and model predictive control (MPC). In ECMS, an equivalent fuel factor is calculated that is the actual fuel consumption that is required to recharge the batteries and to recover the energy of the regenerative braking. Then, the total equivalent fuel consumption is the sum of the real fuel consumption of the internal combustion engine (ICE) and the equivalent fuel consumption of the electric motor. Based on this total equivalent fuel consumption, an instantaneous cost function can be calculated and minimized without the necessity for future predictions. The disadvantage of this strategy is that it does not guarantee charge sustainability. MPC was introduced as EMS to tackle the issue of the DP algorithm based on a receding-horizon control strategy instead of considering all future information about the driving cycle. MPC works as follows: (1) it calculates the optimal inputs over a prediction horizon to minimize the objective function subject to the constraints; then, (2) it implements the first element of the derived optimal inputs to the physical plant; finally, (3) it moves the entire prediction horizon forward and repeats the first step.

Another category that that should be mentioned, apart from rule-based and optimization-based strategies, is learning-based strategies. They use recent advanced data mining schemes for massive historical and real-time information to derive the optimal solution of the control problem. Learning-based algorithms can be incorporated into model-based approaches to tune the control parameters, derive the thresholds for RB EMSs or recognize driver patterns. Some interesting sub-categories of learning-based strategies are reinforcement learning (RL) and neural network learning (NNL). This category is evolving quickly with the development of machine learning (ML).

Literature Review

There are recent works that have analyzed the scientific literature related to EMSs for hybrid vehicles [8–11]. The common approach of these reviews is to classify the EMSs depending on the nature of the algorithm that the EMS is based on. Then, the advantages and disadvantages of each kind of EMS are discussed and also the evolution of the EMSs and the future trends.

Martinez et al. published in 2017 a work about EMS for plug-in HEVs (PHEVs) [11]. In this work, it was stated that EMSs are usually divided into two principle groups: rule-based and optimization-based strategies. The study presented a section focusing on optimization-based strategies and their strengths and limitations. It concluded that "the EMS cannot be really optimized unless detailed information about the future route is available. Since strong uncertainties surrounding driving

experience hinder accurate predictions, augmented vehicular connectivity and evolution toward increasing levels of autonomy will mark a watershed for fuel consumption reduction and strategy optimization". Apart from this, in the overview of EMSs, the authors stated that the popularity of RB strategies in the HEV industry is due to their ease of implementation and understanding and their performance for low levels of hybridization. Although their drawbacks have been evidenced through simulations when they are compared to optimization-based EMSs, the authors remarked that fair comparisons are only applicable if a certain level of drive cycle information is available, which is generally not the case in real life.

The same classification was carried out in the case of the work of Xu et al. [8], where the EMSs were firstly categorized as rule-based strategies and optimization-based strategies. On the one hand, two strategies are categorized as rule-based strategies: deterministic rule-based (RB) and fuzzy logic-based (FLB). On the other hand, the optimization-based strategies presented are the equivalent consumption minimization strategy (ECMS), model predictive control (MPC), deterministic dynamic programming (DDP), Pontryagin's minimum principle (PMP), stochastic dynamic programming (SDP), neural network-dynamic programming (NN-DP), reinforcement learning (RL) and adaptive dynamic programming (ADP). From them, ECMS and MPC are classified as instantaneous optimization; PMP, DDP and SDP as global information-driven optimization; and RL, NN-DP and ADP as data-driven strategies. The performance of the strategies considered is qualitatively analyzed based on the following parameters: fuel economy, realization degree, computational burden, computational time and real-time performance. The results of this analysis are summarized in a radar chart where the EMSs are rated for each parameter using five levels. For example, in the case of real-time performance:

> "The rule-based strategy can be regarded as the first level, due to its convenience in adjusting parameters, its simplicity, and its practicality, while the DP-based strategy can be regarded as the last level, due to its being time consuming and requiring a tremendous amount of memory. ECMS and the MPC-based strategy, as instantaneous strategies, can be considered as the second level. Meanwhile, the ADP-based strategy (containing the RL-based strategy and the NDP-based strategy) can be implemented based on updating data, and can therefore be regarded as the second level. The SDP-based strategy can be regarded as the third level, while the PMP-based strategy can be considered as the fourth level due to the difficulty it has in solving the Hamiltonian function."

In 2019, another article was also published [9]. The EMSs considered in this work are classified into 15 categories: deterministic RB, FLB, deterministic DP, quadratic programming (QP), game theory (GT), genetic algorithm (GA), convex optimization, particle swarm optimization (PSO), NN-based, analytical optimization, PMP, different versions of ECMS, SDP, different versions of MPC and RL-based. In this work, Section 3 presented a valuable analysis of the fundamentals of each kind of EMS together with the evolution of control strategies, i.e., how a particular strategy evolved from its predecessor. At the end of this section, a new way of classification is presented that goes further than previous traditional classifications that proposed two categories: offline and online strategies. The reason is that "although online EMS can execute in CPU-time within simulation, they may not be apposite for real-time application. Hence, the full-fledged simulation-based online EMSs must go through a simplification process before being encoded on the hardware of ECU". Thus, they proposed a new classification for these simplified versions of EMSs as: premeditated, casual and blended. Premeditated EMSs comprise a precalculated control policy which is not altered until the EMS is reprogrammed via human intervention. Since the control policy is premeditated, the EMS makes the control decisions almost instantly based on the values of inputs. This class of EMSs performs only a few computations to make each control decision. The casual EMSs are neither dependent on precalculated control policies nor on future knowledge of the real-world drive cycle. Unlike premeditated EMSs, casual EMSs have to execute major calculations at each time-step to yield a control decision. Finally, blended EMSs combine the benefits of both premeditated and casual EMSs. Blended EMSs alleviate the

drawbacks of both premeditated and casual EMSs in terms of their real-time implementation. The novel classification strategy will eventually motivate future researchers to articulate EMS not just for the sake of simulation-based performance but also for their real-time and real-world implementation. Furthermore, the work, focused on this new classification that only considered online strategies (called "utilitarian EMSs"), provided an in-depth section developing the implementation of these EMSs from theoretical foundation to hardware implementation.

More recently, in 2020, Tran et al. [10] presented a state-of-the-art with two parts: (1) an overview of HEV topologies and (2) a review of the EMSs based on historical perspectives and the main concepts of each control strategy. According to the authors, "although several alternative classifications can be found in the literature, the generally accepted arrangements agree with the existing EMSs, which include three major types: rule-based (RB), optimization-based (OB) and learning-based (LB). The RB-EMSs can be sub-classified into deterministic and fuzzy-logic EMSs working based on a set of predefined rules without prior knowledge of the trip. By contrast, OB-EMSs can be classified into offline and online optimisation based on the information level of driving conditions employed". After this classification, a comprehensive comparison was provided, highlighting their controllability contributions, fundamental principles and advantages and disadvantages. As a result, the research gaps were identified and corresponding future research directions were provided. Apart from this, the idea of a versatile EMS that could include a mixture of different techniques (RB, OB and LB) forming an integrated EMS (iEMS) is proposed in this work.

Having reviewed these works, it is clear that the existing EMSs are classified into categories whose fundamentals are widely studied. The evolution of these EMSs and the future trends towards a global optimal in real time are also provided. However, although the quantity of works dealing with EMSs is numerous and, consequently, the results provided by them in terms of vehicle performance are large, the comparisons provided by the works do not go beyond advantages/disadvantages, challenges and implementation issues, i.e., there are only qualitative comparisons. It would be interesting to collect the results to quantify the improvement of trending EMSs with respect to RB strategies that are the common EMSs for HEVs in industry.

Apart from this, if the works referenced in these reviews are analyzed, it can be deduced that the common practice in them is to propose an EMS that is compared with the optimum EMS (normally, the DP or any of its variants). The results show how close to the optimum they are. It would be interesting to compare the proposed EMS with RB strategies that are implemented in real HEVs as a way of determining the room for improvement of commercial HEVs. However, comparison with RB strategies is less common in this kind of work.

Another problem of the works that propose novel EMSs is that each study considers a different vehicle model and the units taken for comparing different performance parameters (e.g., fuel consumption) are different. It would be necessary to express the results in dimensionless form to make possible the quantitative comparison of all the works.

In summary, it is clear that although the development of novel EMSs that seek the optimum performance of HEVs is booming, in the real world, the HEVs continue to rely on well-known RB strategies. Therefore, there are some questions that arise from this fact:

1. How far are the proposed EMSs with respect to the RB EMSs that are implemented in the HEV industry?
2. Is it possible to quantify how these strategies are moving closer to the optimum?
3. Would it be possible to identify the technologies that obtain the best results?

Taking everything into account, the contribution of this work is to elaborate a quantitative comparison of works that developed EMSs. Furthermore, the focus of this work is to compare the proposed EMSs not only with the optimum but with RB strategies that are used in the HEV industry. Since several studies do not provide results of their models against RB strategies, it is proposed as another contribution of this work to complete their results using the tool FASTSim developed by the

National Renewable Energy Laboratory (NREL) [12] to reproduce the vehicle models proposed and obtain their results when they operate using a RB strategy. FASTSim was chosen since it matches well with the fuel economy test of the United States Environmental Protection Agency (EPA) for light-duty vehicles. The key components and vehicle outputs have been validated by comparing the model outputs to test data for many different vehicles to provide confidence in the results. FASTSim's efficiency estimates match most EPA test data within 5%, and almost all within 10%, for many different vehicles and powertrains (its database includes hundreds of existing vehicles which were validated with these ranges).

The RB strategy that the NREL tool uses for its simulations is explained in Appendix A.

2. Methods

The methodology followed to develop this review is a summarized version of the PRISMA Statement [13] in which some steps have been merged. In the previous section, the rationale for the review in the context of what is already known was described and an explicit statement of the questions being addressed with reference to participants, interventions, comparisons, outcomes and study design was provided. This method has been mainly used in medicine but, given its success in evidence-based approaches, its use has been extended to other fields such as economy, education and engineering.

PRISMA adopted the definitions used by the Cochrane Collaboration [14]. The PRISMA Statement consists of a 27-item checklist and a four-phase flow diagram (see [13]). The aim of the PRISMA Statement is to help authors to improve the reporting of systematic reviews and meta-analyses. The general concepts and topics covered by PRISMA are all relevant to any systematic review. However, as PRISMA reports, some modifications of the checklist items or flow diagram will be necessary in particular circumstances. In Table 1, the five stages proposed in this work to follow the PRISMA Statement are shown.

Table 1. Stages proposed in the systematic literature review following the PRISMA Statement.

	INTRODUCTION
1.	Question formulation and objectives
	METHODS
2.	Locating studies
3.	Study selection and evaluation
	RESULTS
4.	Analysis and synthesis
	DISCUSSION
5.	Reporting and using the results

The first stage, the question formulation and objectives, is included at the end of the Introduction section. The two stages included in "Methods" are developed below.

As in alternative methodologies, after presenting the justification and the objectives that motivate the research, the next stage is to locate the studies. The protocol followed to conduct the search is described as follows. The search began by querying citation databases using search strings and keywords. All the databases of the Web of Science and Scopus were considered. The keywords selected were those most often used in the literature to describe energy management systems (EMSs) that control the power flow of the components of hybrid electric vehicles (HEVs). Table 2 lists the 32 keywords identified in this stage. These keywords were combined to create the following string:

- TI = (hybrid electric vehicle OR plug-in hybrid electric vehicle OR hybrid electric vehicle OR HEV OR PHEV) AND TI = (energy management OR control) NOT TI = (fuel cell OR FCV)

Table 2. Keywords identified for the search.

plug-in hybrid electric vehicle, hybrid electric vehicle, plug-in hybrid electric vehicle (PHEV), hybrid electric vehicle (HEV), power-split HEV, 48 V hybrid electric vehicle, parallel hybrid electric vehicle, power split hybrid electric vehicle, multi-modal hybrid electric vehicle, hybrid, 48 V mild hybrid electric vehicle, connected plug-in hybrid electric vehicle	energy management, energy management strategy, real-time energy management strategy, HEV energy management, control strategy, multi-objective energy management, hybrid electric vehicle energy management	rule-based control, model predictive control, Pontryagin's minimum principle, Q-learning, reinforcement learning, dynamic programming, equivalent consumption minimization strategy, ECMS, optimal control, on-line optimal control, real time optimization, charge sustaining control

Specifically, following the PRISMA flow diagram, the use of this string resulted in 171 records in the identification phase. Then, a second phase of screening was carried out without excluding any record. Thirdly, the eligibility phase described below was conducted, reducing the records to 36.

The criteria used for including or excluding studies were formulated to refine the search and to only retrieve the most relevant literature. The main reasons of exclusion were the following: (1) the vehicle considered for the study was a fuel cell vehicle or a pure electric vehicle; (2) the vehicle considered for the study had a topology that is not common in the HEV industry; (3) the vehicle considered for the study had components that are not commonly used in commercial HEVs; (4) the EMS proposed was tested using a driving cycle that was not standard and whose data were not available; (5) the topic of the paper did not correspond to the development of a new EMS for HEVs; (6) the study was focused on the charging infrastructure of EVs and/or HEVs and its EMSs; and (7) the study did not provide enough information to reproduce the test in the cases that it is necessary. Also excluded from our study were dissertations, textbooks, conference proceedings, working papers and other unpublished work. Apart from this, since this research field is in continuous evolution, to avoid the analysis of obsolete EMSs, avoid reanalyzing works that were included in previous reviews and place the focus on the recent advances, the search period considered in our study was from 2019 to July 2020. The selection of this period is in line with extending the review carried out in [9] that analyzed the evolution of EMS from 1993 to 2019, as shown in Figure 1.

The classification shown in Figure 2 was considered to categorize the EMS for this analysis. It can be considered as the traditional classification of EMS. According to this classification, the works included are categorized as follows:

1. 5 works categorized as RB EMSs: ref. [15–19].
2. 9 works categorized as ECMS EMSs: ref. [20–28].
3. 8 works categorized as MPC EMSs: ref. [29–36].
4. 9 works categorized as other online optimization-based (OB) EMSs: ref. [37–45].
5. 5 works categorized as learning-based (LB) EMSs: ref. [46–50].
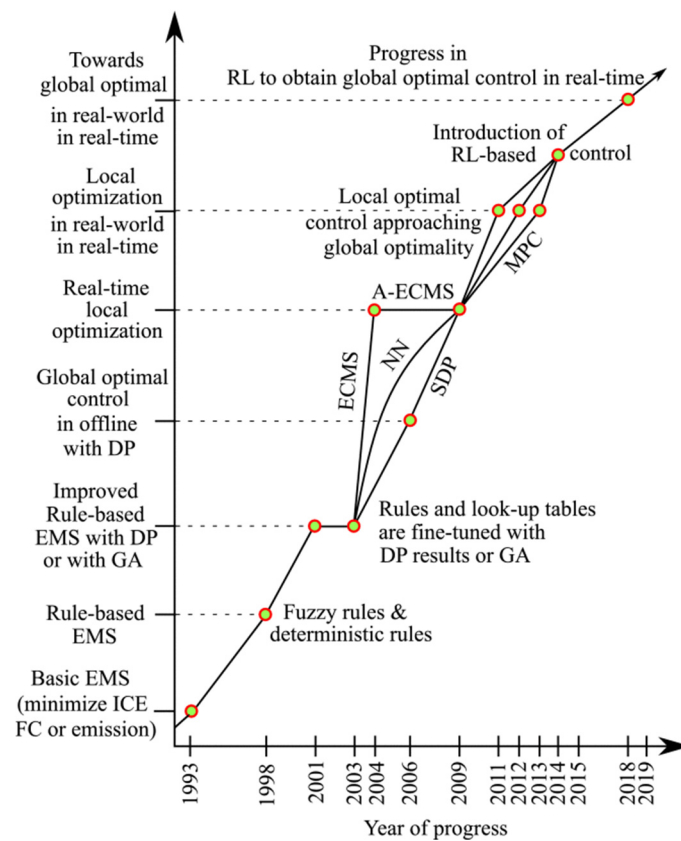
Figure 1. Tentative evolution of EMSs from 1993 to 2018 [9]. (ICE—internal combustion engine, FC—fuel consumption, DP—dynamic programming, GA—genetic algorithm, NN—neural networks, SDP, stochastic dynamic programming, A-ECMS—adaptive equivalent consumption minimization strategy, MPC—model predictive control, RL—reinforcement learning).
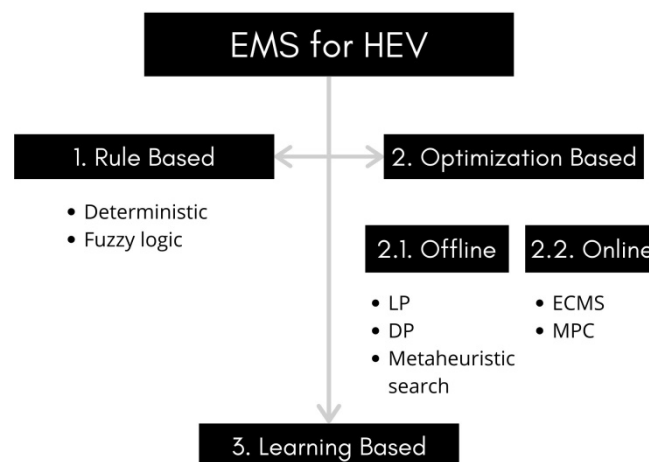
Figure 2. EMS classification. (DP—dynamic programming, LP—linear programming, ECMS—equivalent consumption minimization strategy, MPC—model predictive control).

3. Results

After the eligibility phase, each study was analyzed for its descriptive, methodological and thematic content using a standard template. This first analysis enabled the authors to identify and categorize the studies' key thematic aspects. The analysis was organized following the categories proposed previously.

3.1. Analysis and Synthesis

3.1.1. RB EMSs

Although the first RB EMSs were never designed focusing on optimal power split, there are recent works focused on using optimization techniques to optimize the rules of commonly used RB control strategies (prevalent among commercial HEVs) such as the electric assist control strategy (EACS), power follower control strategy (PFCS) or charge depletion–charge sustaining (CDCS) strategy. In [15], a novel concept for RB EMS was developed: the threshold-changing mechanism. Predefined power thresholds instead of predefined states were used in the operating rules to achieve charge-sustaining operation of the HEV. Furthermore, in previous RB EMSs, the thresholds depended only on the battery state of charge (SOC) while, in this work, they depended on both the SOC and the engine speed. The proposed strategy was compared against the DP results, representing the global optimal solution, and the EACS results, representing the commercial solution. Furthermore, a simplified version of the proposed EMS was also developed to facilitate real-time applications and is included in the comparison. In [16], the rule-based EMS to be optimized was based on a fuzzy control. The fuzzy controller was designed to optimize the transmission efficiency instead of the classical EMS that focused on minimizing the consumption rate. As was proposed in [15], instead of proposing an EMS that depended only on SOC, the fuzzy controller considered both the engine torque and the SOC. A PSO algorithm was used to optimize the fuzzy controller membership functions. The results showed the comparison of the fuzzy EMS with and without optimizing its membership functions. It would have been interesting to add a comparison with the optimum strategy and with a common RB EMS. Buccoliero et al. [19] proposed an improved version of slope-weighted energy-based rapid control analysis (SERCA). SERCA had been applied to powertrains characterized by two operative modes solely. The proposed strategy allowed the application of this strategy to powertrains with more operative modes (multimode). The proposed strategy was compared to the optimum represented by DP and with a fast algorithm for multimode power-split HEVs, showing good quality results compared to the globally optimal solution. In [18], a blended EMS was proposed to overcome the limitations of the common CDCS scheme. Classical blended strategies relied on detailed or rough trip information to achieve near optimum energy allocation. The EMS proposed was a blended strategy that was able to overcome the poor adaptability and unsatisfactory real-time performance of typical EMSs with near-optimal fuel economy. Simulations were used to compare the proposed strategy with the offline optimal solution searched by DP and a typical commercial EMS represented by the CDCS scheme. The results revealed a good fuel economy compared to the DP and fast calculation speed compared to CDCS. Finally, in [17], the threshold values of a RB control strategy for multimode HEVs were optimized, combining an optimization algorithm with the minimum equivalent fuel consumption rate concept. The proposed control was compared with the fuel consumption obtained by the DP algorithm to verify the performance of the proposed control strategy and with the RB strategy before being optimized. The results showed that the fuel economy obtained was quite close to the optimal solution.

3.1.2. ECMS EMSs

The equivalent consumption minimization concept is based on equating the consumption of electrical energy to the corresponding fuel consumption with an equivalence factor. The control parameters of ECMS are sensitive to the driving cycles. With the prior knowledge of a certain driving cycle, the control parameters of ECMS can be tuned to obtain the near-global optimal solutions. However, for other driving cycles, the control effects are deteriorated. Therefore, the current research into this kind of EMS is focused on correcting the control parameters online according to the vehicle states, and the resulting EMSs are usually known as adaptive ECMS (A-ECMS). In [20], the ECMS was modified based on the following ideas: it is common that the SOC set for the power-maintaining hybrid vehicle ranges between 0.5 and 0.6, but there is still room for the continued use of electric energy; from statistical data, it is observed that the time that the vehicle spends at high acceleration

is relatively short; hence, it will not cause the battery SOC to significantly decrease. Based on these premises, the ECMS was modified using an optimization algorithm to allow cautious use of the battery when its SOC is lower than the target. To verify its performance, the improved ECMS, the conventional ECMS and a commonly used RB EMS (specifically the CDCS strategy) were compared. The results confirmed the effectiveness of the proposed control strategy but it was commented that, under other working conditions, the fuel-saving results would change. Wang et al. [24] proposed an adaptive law that updated the equivalence factor of the ECMS according to the vehicle state. The authors focused on the ease of implementing the adaptive law in real time and conducted hardware in the loop simulations in dSPACE to validate their EMS. Their A-ECMS was compared with a common strategy used in mass production vehicles. The results showed that, although the proposed EMS showed good performance, its results compared to the RB strategy were very similar for fuel consumption, although improvements were observed in the battery's ability to sustain the SOC. The feasibility of adopting a trip planning assisted EMS was studied in [26]. Their authors stated that despite recent advances, the automotive industry had not been able to adopt it since there were still many open questions about its feasibility that needed to be answered prior to production. They proposed an ECMS-based EMS to verify the real-time implementability and to analyze its sensitivity to real-world driving conditions. Hardware in the loop (HIL) experiments were carried out to perform the sensitivity analysis. The results were compared to the fuel consumption of a baseline EMS (a common RB strategy). Although traffic mispredictions deteriorated the fuel economy of the proposed EMS, its results were remarkably better than the baseline EMS even in the worst-case scenarios. Another approach for ECMS is proposed in [25] that considers not only energy consumption and power performance but emission reduction. A weighting coefficient of emission performance was proposed. The higher was this coefficient, the more attention was paid to the optimization of emission indicators. The comparison of the proposed EMS with different weighting coefficients against DP validated the accuracy of the proposed control algorithm. In [22], it was proposed a time-windowed ECMS (which compared cost functions integrated during a fixed time interval) that relied on Pontryagin's minimum principle (PMP), with some modifications. The proposed EMS was divided into three parts: the driving status determination, the powertrain status management and the time-windowed ECMS. The first determined the vehicle state flags and the driver demand torque; the second determined appropriate driving modes based on the vehicle state flags and driver demand torque; and finally, the ECMS determined the optimal power-split ratio and the optimal mode flags solving the real-time optimal problem of minimizing fuel consumption. The proposed control algorithm was evaluated by comparing its results with the results of previous research (two previous algorithms based on the same approach of ECMS and from which the proposed was derived), showing better fuel economy. However, it lacked a comparison against a DP or a common RB EMS to support the presented results. Wu et al. [23] commented on the problems of the ECMS-based EMS related to determining the equivalence factor (e.g., using averaged efficiencies, using prior trip information, etc.) in the introduction of their work. The proposed EMS fitted for real-time control without using any prior trip information. The equivalence factor of the optimization model was defined as the efficiency of gasoline energy transferring to battery energy. Another two coefficients depending on the battery SOC were introduced to control the battery SOC to change in the predefined interval. The simulation for standard driving cycles demonstrated that the proposed EMS could maintain the battery SOC in the expected interval. At the same time, it showed a better fuel economy performance than a commonly used RB EMS and previous EMS based on A-ECMS. The work presented in [21] also proposed an A-ECMS based on the idea that the propulsion and recuperation efficiencies cannot be considered constant. In their EMS, the controller was composed by a higher-level controller and a lower-level controller. The higher-level controller utilized model predictive control (MPC) for the prediction of the optimal velocity profile over a finite time horizon, with periodically updated efficiencies from the lower-level controller. The adaptive ECMS (A-ECMS)-based lower-level controller then made use of the optimal velocity profile for the energy management control of the HEV. To evaluate the validity of the proposed EMS, its fuel economy was compared with a baseline method based on a common RB

EMS. In [28], it was proposed a strategy that included offline and online parts: the offline part used historical traffic data and an optimization algorithm to optimize the thresholds of mode switching and the equivalence factor of the ECMS; in the online part, a supervisory control generated mode switching signals and an adaptive equivalence factor for instantaneous optimization for the ECMS. The effectiveness of the proposed strategy was demonstrated by simulation results compared with a practical strategy (a common RB control) and with the DP, regarded as the benchmark. The results indicated that the proposed strategy was much nearer to that of the DP than that of the RB. Other work that considered an A-ECMS for multi-objective purposes (minimizing gasoline consumption, minimizing electricity consumption and prolonging battery life) was presented in [27]. In this case, the two objectives of energy consumption and battery loss were balanced in the cost function by a weighting factor that changed in real time. The real-time performance of the proposed EMS was guaranteed by the tuning of this weighting factor by a recurrent neural network (RNN). This RNN was trained offline by DP utilizing historical traffic data. To verify the performance of the proposed EMS, it was compared against the DP results and the conventional CDCS strategy. This showed that the proposed EMS possessed the desired effectiveness and adaptability to various driving cycles and met the multiple control objectives.

3.1.3. MPC EMSs

The MPC was introduced to overcome the issue of the DP algorithm that obtains the global optimum control when all future information is known in advance (driving cycle, state of the vehicle, etc.). Such conditions are impractical for real-time applications. The MPC operates based on a receding-horizon control strategy with a predictive scheme. However, the performance of MPC is sensitive to the model quality and sensor accuracy. To minimize the mismatch and disturbances, the horizon length of the MPC has to be tuned. In [29], an MPC was proposed to solve the conflict between the energy consumption cost and the equivalent battery life cost. The proposed EMS was examined by real-world driving cycles under different preview horizons (5, 10 and 15 s). Meanwhile, global optimization algorithms like the DP as well as an RB method were compared with the predictive controller. The results indicated that the proposed MPC could significantly reduce the equivalent battery life loss cost and thus the total cost (more than 12.2% for the three preview horizons, compared to the CDCS method). A similar idea was proposed in [34], which added driving safety to the energy consumption and battery degradation objectives. An MPC was proposed to minimize the combined cost of the energy consumption cost, the equivalent cost of battery life lost and driving safety over a moving horizon. To evaluate the proposed method, it was compared to other methods, such as CDCS and DP, showing a significant advantage compared to conventional methods. The focus in [31] was on improving the vehicle speed prediction accuracy and computational efficiency of MPC. The use of a search acceleration method was proposed, specifically the A* algorithm, to reduce the calculation time while optimizing the EMS. Furthermore, the accelerated MPC was combined with an RB strategy extracted from the DP results. The proposed EMS was compared with DP and a common RB method, resulting in a fuel economy near to the DP and better than the RB. In addition, HIL tests were performed to validate its real-time performance. Zhang et al. [33] highlighted that the research about MPC EMSs in PHEVs was focused on three aspects: solution algorithms in the receding horizon, methods of future velocity profile acquisition and SOC reference trajectory planning methods. They developed a new velocity prediction method called synthesized velocity profile prediction (SVPP), which integrated macroscopically and microcosmically predicted velocities obtained by the participatory sensing data (PSD)-based method and the Markov chain (MC), respectively, which were synthesized by the linear regression method. The capability of the proposed scheme in terms of fuel economy was demonstrated by comparing this metric with those of DP and CDCS EMS through simulation. A different approach to velocity prediction, based on the idea of distributing the computation load using mobile edge computation and on-board vehicle control units, was presented in [30]. The resulting method was called compound velocity profile prediction (CVPP) and was applied

to the EMS of a PHEV. The proposed EMS was compared to DP, other MPC methods and the CDCS strategy. Compared with other MPC-based methods, the CVPP-MPC achieved better fuel economy as a result of a more accurate velocity prediction. In [32], to reduce online computation time and microprocessor hardware resources, the solution adopted was to obtain the explicit MPC (EMPC) control laws by solving the multi-parameter quadratic programming optimization problem offline. Then, the laws were used online to realize the real-time control. A DP-based control strategy and an RB control strategy were considered benchmark strategies for the verification of the proposed EMPC-based EMS through simulation. As the prediction horizon increased, although the fuel economy of a common MPC EMS and the proposed EMPC EMS remained nearly the same, the computation time of the first increased significantly while the computation time of the proposed one was nearly unchanged. A similar idea was proposed in [35], an EMS including two parts: offline modeling and online optimization. The offline modeling contained a Markov chain model. In the online optimization part, a Markov chain model was used to predict demand torque over a finite receding horizon and the sequential quadratic programming (SQP) algorithm was adopted to optimize the comprehensive cost function that included a novel adaptive factor. The proposed SQP-SMPC EMS was also compared with the traditional MPC, DP optimization and an RB strategy. Results indicated that the proposed strategy was effective for the given driving condition, with excellent fuel economy and vehicle-following performance. Finally, in [36], it was highlighted that several works ignored the effects of engine torque on the transmission efficiency. The transmission efficiency was derived based on the efficiencies of different components. An MPC was proposed with the capacity to deal with constrained optimal problems in a finite horizon, as in the EMS. The proposed EMS was benchmarked against an RB strategy, inspired by the Toyota Prius control, representing a strategy with easy implementation and real-time capability. Compared with this, the proposed strategy ensured high powertrain transmission efficiency and, as a result, an improvement in equivalent fuel economy.

3.1.4. OB EMSs

The objective of optimization-based (OB) EMSs is to find the optimal control sequence (i.e., reference power demand) that minimizes a cost function while meeting the dynamic state constraints, such as the global state constraints (e.g., battery SOC) and local state constraints (e.g., power limit, speed limit and torque limit) [10]. The cost functions can be different representations, such as the fuel consumption, the hybridization costs, the payload weight of the vehicle, the exhaust gas emissions, etc. This work is focused on online strategies, i.e., those that can be implemented in real-time applications. Some of the strategies in this category, apart from ECMS and MPC, are robust control, extremum seeking, decoupling control, pseudospectral optimal control and sliding mode control, among others. For example, an adaptive EMS with velocity forecast formulated into a mixed-integer optimization problem was presented in [43]. An approximate dynamic programming was proposed for optimizing the power split and gear shift and a multi-stage neural network (MSNN) for velocity forecast. The power split control and the discrete gear shift control were jointly optimized without prior knowledge of the driving cycle and system model. The proposed EMS was compared with a common RB EMS and with a DP that was regarded as the benchmark. Simulation results indicated close fuel economy with respect to DP and effective online application. The same authors, Li and Görges [44], presented a different approach based on an adaptive cruise control method based on action-dependent heuristic dynamic programming (ADHDP) that generated the gear shift command and the power split between the engine and the electric motor. This control was realized without prior knowledge of the driving cycle, facilitating online implementation. The near-optimality and robustness of the proposed EMS was validated by a comparison with DP results. Machine learning logic employed as online controller for multimode HEVs was proposed in [38]. The machine learning logic was employed to select the current operating mode for the HEV powertrain and thus the specific set of clutches that needs to be engaged. The advantage of the presented methodology was the flexibility to be applied to different HEV powertrain configurations. Compared to the optimal DP benchmark,

fuel economy and ease of online optimal controllability were simultaneously achieved. In [40], it was highlighted the importance of dynamic transmission efficiency (DTE) due to its influence on the overall powertrain efficiency. Therefore, when considering the EMSs of PHEVs, the best way to optimize the comprehensive efficiency was to take the DTE of the transmission system into consideration. The proposed EMS method considered the effect of the ICE, electric motor and planetary coupling transmission system (PCTS) for a comprehensive dynamic efficiency. An improved dynamic efficiency optimization strategy (Improved-DEMS) was proposed as EMS that considered the trade-off between energy consumption and the fatigue life of the planetary coupling transmission system. The EMS was verified compared to an RB strategy. The results demonstrated that the work efficiency of the ICE, electric motor and PCTS were the highest for the Improved-DEMS and experimental results using the HIL simulation test supported real-time validation. In [37], a methodology that involved two online iteration loops to simultaneously update the predictive model of velocity trajectories and optimize the control sequence was proposed. It was defined as dual-loop online intelligent programming (DOIP). Its performance was compared with DP. Moreover, a driver-in-the-loop (DiL) experiment was carried out to demonstrate its real-time implementation. The effect of considering stochastic vehicle mass for optimization of EMSs of PHEVs was studied in [41]. This factor has a strong relationship with the required power and the required power will in turn affect the optimal SOC prediction. This work responded to this problem by investigating a receding horizon control (RHC)-based EMS together with a predictive model of terminal SOC constraint constructed by the partial least squares method. Simulation results, which compared the proposed EMS to DP results and to a common RB EMS, showed that the proposed predictive model was reasonable and was able to optimally predict the terminal SOC constraint at every receding horizon. In [42], the optimization problem of controlling the transmission ratio and the power-split ratio was solved by using a standard convex quadratic programming (QP) modeling method. A minimum equivalent fuel consumption problem was formulated and converted to a QP problem. The results obtained indicated that the computational efficiency and effectiveness of the QP-based modeling method were high enough to be applied to real-world vehicle controllers and resulted in a good fuel economy compared to DP results. A different approach from the commented above was presented by Shabbir and Evangelou [39] that proposed the optimal primary source strategy (OPSS) that was built on two fundamental design principles: threshold changing and load leveling. As compared to conventional RB control strategies, the OPSS was found to deliver significantly improved fuel economy which was remarkably close to that achieved by the optimization-based ECMS, while the design of the OPSS was simple and robust as compared to other optimization-based strategies. This made it more suitable for real-time implementation. Finally, in [45], the real-time implementation of particle swarm optimization (PSO) algorithm was proposed to reduce the fuel consumption of power-split HEVs. A basic RB control was implemented as the base model with an initial EMS, and the simulation result was compared to the manufacturer data. Compared with the RB control, PSO could find the minimum instantaneous fuel consumption at each moment, achieve real-time control and improve the fuel economy of power-split HEVs.

3.1.5. LB EMSs

Reinforcement learning (RL) mimics the learning process in the human brain. It maximizes the reward by interacting with and exploring the environment. RL algorithms are model-free and learn the optimal EMS solution in a trial-and-error manner. In many cases, human expertise can provide optimal training samples or preferences for the learning agent to guide exploration in the training process. There also exist large amounts of prior knowledge in the energy management of HEVs, some of which can be applied to learning-based EMSs to improve their sampling efficiency. These methods are concluded as the main future trend in the EMSs [10]. In [47], RL was used as EMS for super-mild HEVs. The proposed RL-based EMS was adopted to obtain the optimum control policy that takes the vehicle speed, driver's power demand and state of charge (SOC) as the input and the engine power as the output. The results showed that, compared with DP, this method could not only be

adapted to random driving cycles and reduce fuel consumption, but it could also be implemented online because of its small calculation volume. Learning control algorithms can also be combined with other control strategies, as was proposed in [48]. The proposed EMS combined batch-wise iterative learning control (ILC) and time-wise model predictive control (MPC). ILC theory is a powerful tool for dynamical systems with repetitive operation due to its ability to adjust the control input from batch to batch. The ILC technique can be combined with a predictive control technique: an MPC utilizes the repetitive nature of the batch operation and performs batch-wise feedback together with real-time predictive control. A combination of MPC and ILC was proposed to not only speed up the response time but also effectively reduce the speed ripples. The proposed EMS was validated by comparing it with DP and an RB EMS, showing a performance that approached that of DP. Moreover, it was verified for robustness and real-time processing capacity. In [46], a novel model-free algorithm, named Dyna-H, was constructed to overcome the difficulties related to the easy online application of a previously studied RL-based control based on Q-learning. To validate the effectiveness of the proposed Dyna-H-based EMS, the DP-based results were used as a benchmark. Compared with DP, although the proposed EMS results were suboptimal, the computational time indicated that they can be applied in real-time. Following a similar premise, that the optimization and training processes of RL can be very slow and resource-intensive, a new approach to accelerating the learning process is proposed in [49]. The EMS embedded expert knowledge into a deep deterministic policy gradient. By incorporating this prior knowledge, the proposed framework not only accelerated the learning process but also achieved a better fuel economy, thus making the energy management system relatively stable. DP served as the benchmark to validate its performance through simulations. Finally, Xu et al. [50] presented a parametric study on several factors during the RL-based EMS development. The main results showed that learning experience selection could effectively reduce the vehicle fuel consumption; the vehicle fuel consumption reduced as action discretization increased; and increasing the states discretization was detrimental to the fuel consumption.
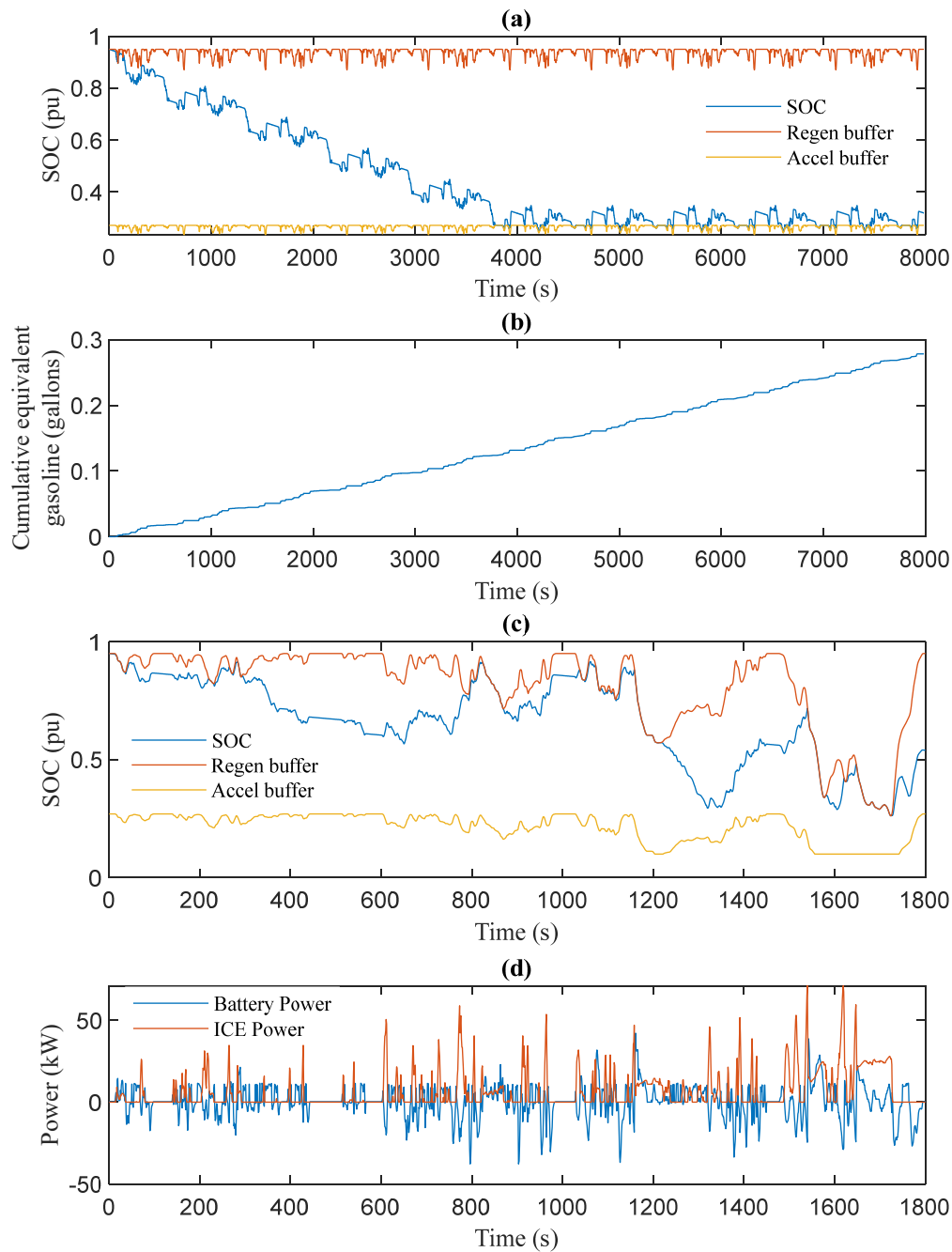
3.1.6. Simulation Results

Reviewing the analysis of the selected works, it is clear that the validation of the proposed EMSs was carried out against the global optimum represented by the DP results. Apart from this, these EMSs are often compared to common RB EMSs that represent the strategies currently implemented in commercial PHEVs. However, from the proposed selection, there are a few works that neglect this last comparison that would be interesting for the purpose of this review [16,22,42,44,46,49–51]. To fulfil this gap, the data provided in these works related to the characteristics of the vehicle model were used to develop vehicle models and carry out simulations of the corresponding driving cycles in FASTsim. This software uses an RB EMS commonly used by commercial HEVs described in Appendix A.

In Figures 3–6, some of the simulations results obtained are shown.

Figure 3 shows the results corresponding to [46]. Figure 3a shows the evolution of the battery SOC for 10 NYC-HEV driving cycles. It can be seen that the SOC decreases cycle by cycle until reaching a minimum level (around 30%) at the middle of the simulation. Then, it remains at around 30% until the end of the simulation. In the original results [46], this level of SOC was reached at the end of the 10 driving cycles. This is consistent with the results of other works (e.g., a previous work of this team [52]) that showed that the SOC trajectory descended more abruptly to the final level for classical RB EMSs such as CDCS than for optimized EMSs, which showed a smoother descent. Figure 3c,d, which show the SOC evolution and the powers of electric motor and ICE, respectively, are also included to show the performance of the RB EMS in detail. They show these variables during 1 NYC-HEV. With regard to Figure 3c, apart from the SOC, two limits related to the EMS operation are presented (see Appendix A): the "Regen. buffer" (regenerative buffer) is the upper SOC limit that maintains room for regenerative braking based on the vehicle speed and mass; and "Accel. buffer" (acceleration buffer) is the lower SOC limit that ensures battery energy for accelerating at slower speeds. When the SOC reaches the "Regen buffer" limit (second 800 in Figure 3c), the EMS prioritizes the use of the battery

for accelerating to discharge it and increase its capacity for absorbing the power from regenerative braking. Correspondingly, when the SOC reaches the "Accel buffer" limit (around second 4000 in Figure 3a), the EMS avoids excessive use of the battery for accelerating and prioritizes the use of ICE and, therefore, battery SOC depletion is avoided.

Apart from this, the subplots of Figures 4–6 are organized as follows: (a) represents the battery SOC for the corresponding driving cycle (see the titles of the figures); (b) represents the powers of the battery and the ICE for the corresponding driving cycle; and (c) represents the cumulative equivalent gasoline consumption in gallons for the corresponding driving cycles.
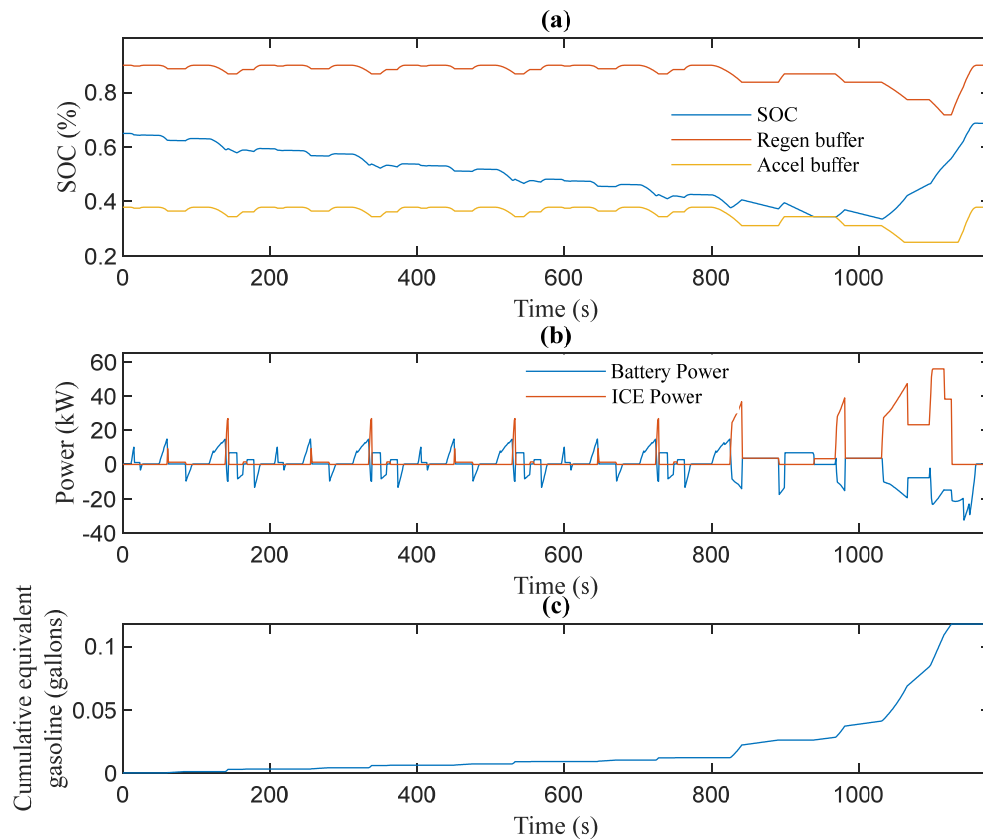

Figure 3. FASTsim simulation results for the HEV of [46]. (**a**) Battery SOC after 10 NYC-HEV cycles; (**b**) cumulative equivalent gasoline consumption in gallons for 10 NYC-HEV cycles; (**c**) battery SOC for one NYC-HEV cycle; (**d**) powers of the battery and the ICE.
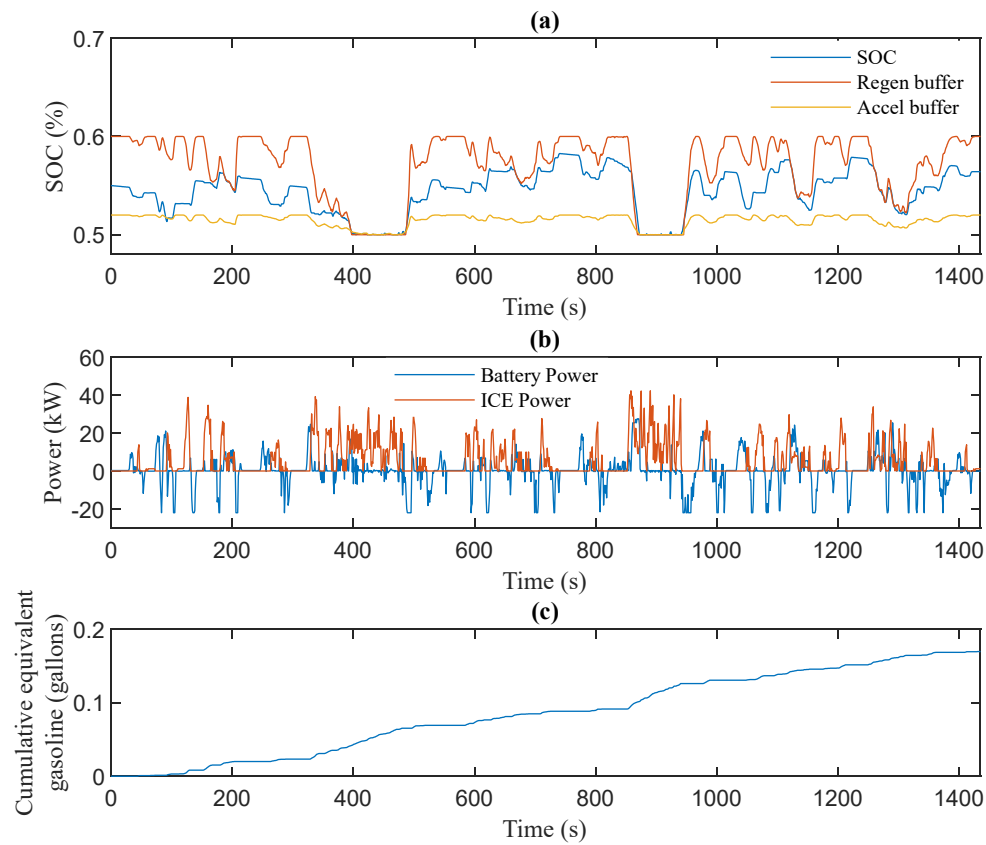
Figure 4. FASTsim simulation results for the HEV of [44] for LA92 cycle. (**a**) Battery SOC; (**b**) powers of the battery and the ICE; (**c**) cumulative equivalent gasoline consumption in gallons.
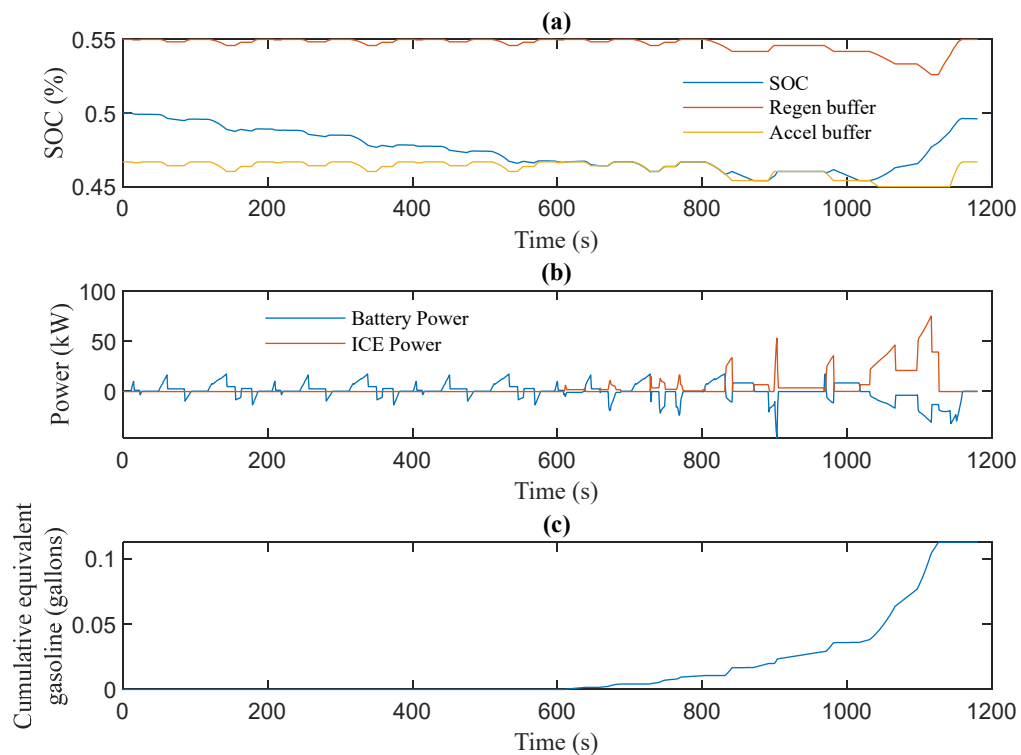
Figure 5. FASTsim simulation results for the HEV of [42] for NEDC cycle. (**a**) Battery SOC; (**b**) powers of the battery and the ICE; (**c**) cumulative equivalent gasoline consumption in gallons.

Figure 6. FASTsim simulation results for the HEV of [49] for NEDC cycle. (**a**) Battery SOC; (**b**) powers of the battery and the ICE; (**c**) cumulative equivalent gasoline consumption in gallons.

In the simulations shown in Figure 4 corresponding to the HEV of [44] for the LA92 driving cycle, it can be clearly seen the effect of the battery SOC reaching the lower limit defined as "Accel buffer". When this occurs, the HEV is propelled by the ICE and the battery power is zero or negative (regenerative braking)—see Figure 4b. This leads to increases in the fuel consumption (Figure 4c).

Figure 5 shows the simulations corresponding to [42] for the NEDC driving cycle. In the original work, the proposed EMS maintained the SOC around the reference value (50%) following the tendency of the DP. However, another EMS presented in this work obtained by a separated optimization and not integrating the power-split ratio showed a SOC decrease for two thirds of the simulation and then an increase up to the reference value. This performance corresponds to the results of a common RB EMS shown in Figure 5a. Apart from this, the fuel consumption of this RB EMS shows a similar trajectory to the results of the original work, with a transition from a slight increase at the beginning of the cycle followed by a sharp increase at the end.

FASTsim simulation results for the HEV of [49] for NEDC cycle are shown in Figure 6. As in previous simulations, the SOC trajectory follows the tendency of the original work, although the RB EMS simulated here reaches a higher final SOC. This may worsen the fuel consumption for this strategy with regard to the LB proposed in the reference work.

4. Discussion

Once the gap in the results related to a comparison with an RB EMS commonly used in commercial PHEVs was filled, the resulting dataset was studied. To facilitate comparison, the results related to the fuel consumption (depending on the work, different variables were considered for this: fuel consumption, equivalent energy consumption, fuel economy, etc.) were normalized, rescaling data to have values between 0 and 1. In this scale, 1 corresponds to the optimum result, which in the vast majority of the works corresponds to DP, and 0 corresponds to the result of a common RB EMS. Thus,

the proposed EMS would achieve a rating between these values that gives information about how far it is with regard to the benchmarks. Figure 7 show boxplots for fuel consumption results for all the proposed EMSs (Figure 7a) and for the EMSs classified according to the categories presented previously. Figure 7a shows a median value of 0.7503 with broad interquartile and maximum–minimum ranges that indicate great differences among the performance of the EMSs studied. The upper skewness of this boxplot indicates that most of the EMSs are nearer to the optimum than to common RB EMSs. Figure 7b shows a comparison among the different categories of EMSs. RB, ECMS and OB show better medians (between 0.7 and 0.9) than MPC and LB (around 0.6). Apart from this, the difference between the spreads of ECMS with respect to the rest of the groups indicates that ECMS offer, in general, less variation between the performances of the different approaches. In addition, the lower spreads of RB and ECMS may be produced because these EMSs are more closed and allow less tuning: in the case of the ECMS, the equivalence factors used in the problem formulation and, in the case of RB EMSs, the rules edition, usually modify the thresholds. The rest of the groups (MPC, OB and LB) show more variation since these methodologies allow more approaches (e.g., for optimization-based methods, evolutionary algorithms, genetic algorithms and particle swarm optimization, among many other heuristics, can be found) that result in more variation in their performances. In general, it can be seen that the EMSs analyzed are closer to the optimum performance than to a common RB EMS. However, it would be interesting to quantify this improvement with regard to RB EMSs.
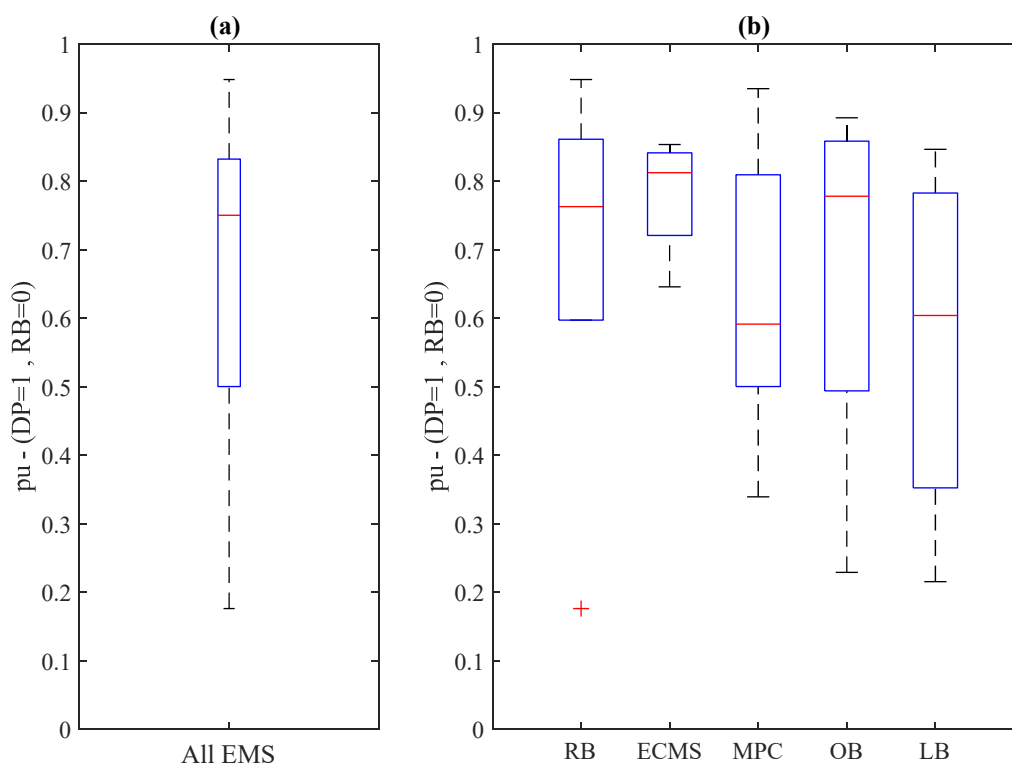

Figure 7. Normalized fuel consumption results for the EMSs of the works reviewed. (**a**) Boxplot for all the EMSs; (**b**) boxplot for the different categories of EMSs.

Figure 8 shows the percentage of improvement of the proposed EMSs with regard to the commercial RB EMSs of the normalized rescaled results. It can be seen that the medians for the different groups are around the range of 5% and 10%. It could be considered that the best results correspond to MPC EMSs with a higher median value and whose upper interquartile show results over 18%. ECMS and OB EMSs show similar results with regard to medians and similar spreads and could be considered as the following in the performance ranking. These results, according to the authors, make sense since these EMSs have a long trajectory of development. The worse results of LB EMSs may be due to their focus

on the real-time implantation that forces them to be more adaptable to disturbances and, consequently, more suitable for being applied to commercial vehicles. This differs from ECMS EMSs, which are less adaptable and whose good results, as stated in the analyzed works, can be worsened when there are unexpected disturbances.
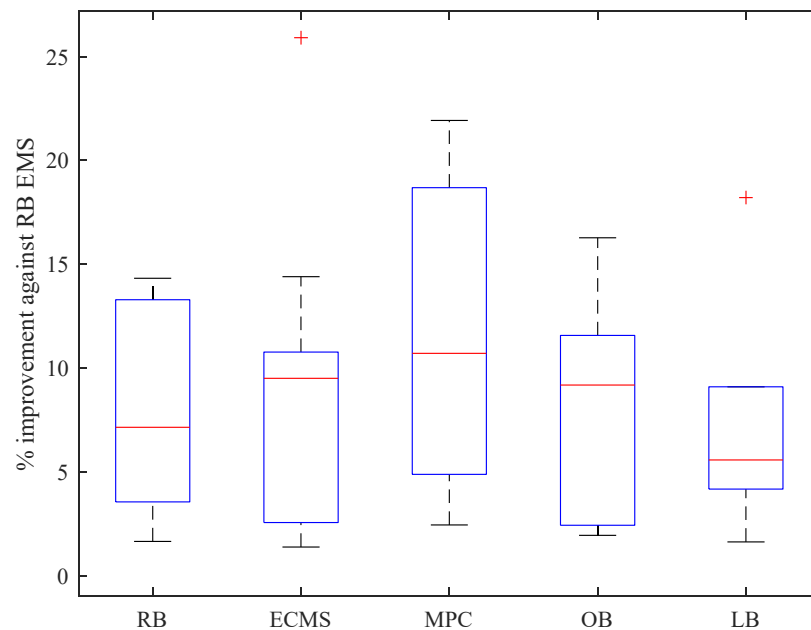
Figure 8. Fuel consumption improvement with respect to commercial RB EMSs.

Apart from this, the different rankings resulting from Figures 7 and 8 may be derived from the fact that each work estimated the optimum result from their own DP approach. It is possible that the approach used in some of them was better than those used in others and it affected to how close they were to the optimum. However, if the comparison only considers the common RB EMSs, this bias is avoided.

Another finding of the review was that although the validation of the implementation of the EMS in real time should be a significant part of these works, there is a clear absence of this. There are several works that fail to provide any kind of online validation of their EMS' performance. After the review, the following approaches were identified for this purpose: HIL simulation platform based on dSPACE real-time simulator [24,26], non-commercial HIL test benches [31,40], measuring the elapsed time of simulations and checking if they fit for real-time operation [30,32,38,42,46] and driver-in-the-loop (DIL) using the IPG Carmaker platform [37].

Results related to the maintenance of SOC were not considered for comparison since each work considered different ranges. These ranges sometimes depend on the battery technology used in the HEV studied or simply on the experience of the EMS designers. Furthermore, it is difficult to score this variable since an EMS that obtains a higher value of SOC at the end of the driving cycle does not necessarily perform better. According to the authors, maintaining the SOC within a specific range is an obligatory requirement that all the EMSs must meet. It would be interesting for future works to propose indexes that evaluate the SOC trajectories compared to the optimum. Aspects related to the time spent around the reference value (as a positive index) or the time spent at the SOC limits (as negative indexes since they would mean battery overcharge or depletion) could be considered.

Other research gaps found were related to some variables that were considered in the works reviewed and there is no consensus about their measurement. Avoiding battery degradation, for example, is one of the common objectives proposed for the EMSs. However, there is no reference to battery lifespan modeling. Efficiency improvement (overall or specific to a defined component) is also proposed as an objective. It would be necessary to specify clearly how this efficiency is calculated.

5. Conclusions

The overall objective of this work was to elaborate a quantitative comparison of recent works that developed EMSs for HEVs. The focus of this work was to compare the proposed EMSs with RB strategies that are used in the HEV industry instead of only doing so with the optimum. After the analysis presented, it is clear that it is difficult to draw definitive conclusions about which EMS methodology is the best since the aggregation of the results from different sources leads to errors that affect the results. Thus, this work comes to clarify the ranges of performance in which the most novel EMSs operate with regard to the technology that is commercially available. From the results, it is concluded that the improvement of these EMSs ranges roughly between 5% and 10%. Although from the review, it could be concluded that ECMS could be the EMS that offers more improvement, the works that propose it suggest that the good results obtained could be caused by the fact that some variables of the EMS were tuned with some previous information regarding the driving cycle or because the experiments proposed for the validation did not consider enough disturbances (in magnitude and frequency) to reflect a real operation scenario. Strategies that were presented a priori as the most suitable for real-time implementation, such as LB, showed slightly lower improvements and, after reviewing their methodology, it can be concluded that they could face the variability expected in real-life operation. It must be also highlighted that EMSs based on RB (considered as the most simple strategies), which have been developed from the SERCA approach, for example, offer reasonably good results with regard to the EMSs currently used in commercial HEVs.

Finally, regarding the research questions formulated in the Introduction, the following statements can be made:

- The most novel EMSs presented improvements roughly between 5 and 10% from those currently implemented in the HEV industry;
- Using the common RB EMSs and DP as benchmarks, it can be concluded that the EMSs that are being developed currently are nearer to the optimum than the common RB EMSs;
- Since the results of the different technologies are close, it would be interesting to focus on their capacity to be implemented in real-time controllers and encounter scenarios with frequent disturbances.

Author Contributions: Conceptualization, J.P.T.; methodology, J.P.T.; literature review, J.P.T., P.G.-T., D.V., D.A.L.-G.; simulations, J.P.T., P.G.-T., D.V., D.A.L.-G.; data analysis, J.P.T., P.G.-T., D.V., D.A.L.-G.; writing—original draft preparation, J.P.T.; writing—review and editing, J.P.T., P.G.-T., D.V., D.A.L.-G. All authors have read and agreed to the published version of the manuscript.

Appendix A

Future Automotive Systems Technology Simulator (FASTSim) was developed by NREL [53]. The modeling approach is very similar to the earlier MATLAB-based ADVISOR model but is released as a macro-enabled EXCEL file. The simulator can be used for conventional ICE vehicles, HEVs and EVs. The primary objective of FASTSim is to estimate the fuel economy, cost and performance of a vehicle with specified powertrain components over standard drive cycles. All saved vehicles are approximations of existing vehicles. Some examples of these vehicles are 2016 KIA Optima Hybrid, 2017 Toyota Prius Prime, 2016 Nissan Leaf, 2016 BMW i3 Rex PHEV, 2016 Ford C-MAX PHEV. This simulator is also free to download.

The inputs of the RB EMS used by FASTSim include:

- Battery minimum SOC;
- Battery maximum SOC;
- Level of discharge aimed at improving the fuel converter efficiency;

- Level of charge aimed at improving the fuel converter efficiency;
- Speed at which the battery energy reserved to assist acceleration reaches zero;
- Percentage of usable battery energy reserved to assist acceleration;
- Speed at which the fuel converter is turned on;
- Power at which the fuel converter is turned on.

The RB strategy is primarily based on the battery SOC. The operating range of the battery is limited by a specified maximum and minimum SOC. The strategy consists of three SOC zones within this range, as seen in Figure A1. The first zone is between the maximum SOC and the regenerative braking buffer (Regen Buffer). This area is calculated based on the mass and speed of the vehicle. It is the amount of battery energy reserved to capture a regenerative braking event. Similarly, the zone between the acceleration buffer SOC (Accel Buffer) and the minimum SOC is the amount of battery energy reserved to assist with accelerating the vehicle. Between the Regen Buffer and Accel Buffer, the strategy focuses on maximizing the fuel converter efficiency.
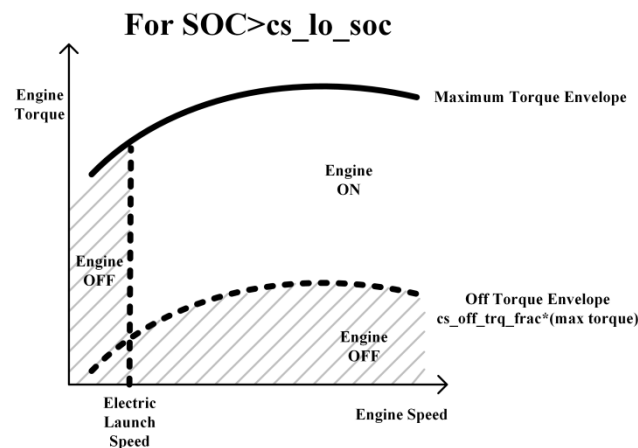

Figure A1. Engine operation/control variables relationships.

There are six variables that determine the limits of the control strategy. Their influence on the engine operation is shown in the schematics below, and they are described as follows:

- "cs_lo_soc": The lowest SOC corresponding to the minimum charge/discharge resistance of the energy storage system module.
- "cs_hi_soc": This parameter should be set slightly higher than the cs_lo_soc. More specifically, it should be set to a value less than the SOC at which the either the charge or discharge resistance increases dramatically.
- "cs_charge_trq": Defines the additional torque requested of the fuel converter to maintain an energy storage system SOC between cs_lo_soc and cs_hi_soc.
- "cs_electric_launch": Below this vehicle speed, the vehicle will operate as a pure electric vehicle; above this speed, the fuel converter will be used as the primary power source.
- "cs_off_trq_frac": Represents the fraction of max torque at each speed at which the engine should turn off. This parameter should be set to a value equal to the fraction of max torque at each speed at which the fuel converter efficiencies begin to drop dramatically.
- "cs_min_trq_frac": Represents the minimum fraction of max torque at each speed at which the engine will operate when lower torque fractions are requested. This parameter is typically set to a mid to high value (0.5–0.8) in order to force the fuel converter to operate in a high torque region of its efficiency map.

Once these parameters are defined, the common rule-based EMS is based on the following rules:

I. The state of the engine (on or off) is determined by the following rules (see Figure A1):

I.1. If the speed required is less than the electric launch speed, cs_electric_launch_spd, the engine could turn off.

I.2. If the SOC is higher than its low limit, the engine could turn off. If both the requested speed is less than the launch speed and the SOC is higher than the low limit, the engine will turn off.

I.3. If the torque required is less than a cutoff torque, cs_off_trq_frac fraction of the maximum torque, the engine could turn off. If both the requested torque is lower than this cutoff and the SOC is higher than the low limit, the engine will turn off.

II. The torque and speed load due to driving conditions are presented to the engine through the clutch. The energy management strategy determines how the torques from the engine and motor will combine to produce the required torque while maintaining charge in the battery. The process is described below (see also Figure A2):

II.1. When the battery SOC is below cs_soc_lo, additional torque is required from the engine to charge the battery. This additional charging torque is proportional to the difference between SOC and the average of cs_lo_soc and a high limit, cs_hi_soc.

II.2. This engine torque is prevented from being below a certain fraction, cs_min_trq_frac, of the maximum engine torque at the current operating speed. This is intended to prevent the engine from operating at an inefficiently low torque.

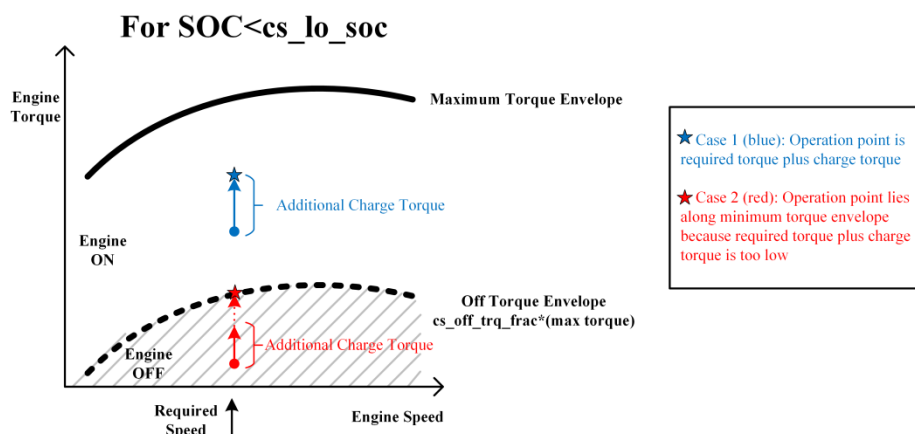II.3. Engine torque is only requested when the engine is on.

Figure A2. EMS operation when SOC is lower than "cs_lo_soc".

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