World Electric Vehicle Journal

Review

Energy Management Strategies for Hybrid Electric Vehicles: A Technology Roadmap

Vikram Mittal [1,*] and Rajesh Shah [2]

[1] Department of Systems Engineering, United States Military Academy, West Point, NY 10996, USA
[2] Koehler Instrument Company, Bohemia, NY 11716, USA; rshah@koehlerinstrument.com
* Correspondence: vikram.mittal@westpoint.edu; Tel.: +1-845-938-5507

Abstract: Hybrid electric vehicles (HEVs) are set to play a critical role in the future of the automotive industry. To operate efficiently, HEVs require a robust energy management strategy (EMS) that decides whether the vehicle is powered by the engine or electric motors while managing the battery's state of charge. The EMS must rapidly adapt to driver demands and optimize energy usage, ideally predicting battery charge rates and fuel consumption to adjust the powertrain in real time, even under unpredictable driving conditions. As HEVs become more prevalent, EMS technologies will advance to improve predictive capabilities. This analysis provides an overview of current EMS systems, including both rule-based and optimization-based approaches. It explores the evolution of EMS development through a technology roadmap, highlighting the integration of advanced algorithms such as reinforcement learning and deep learning. The analysis addresses the technologies that underly this evolution, including machine learning, cloud computing, computer vision, and swarm technology. Key advances and challenges in these technologies are discussed, along with their implications for the next generation of EMS systems for HEVs. The analysis of these technologies indicates that they will play a key role in the evolution of EMS technology, allowing it to better optimize driver needs and fuel economy.

Keywords: energy management systems; technology roadmap; deep learning; reinforcement learning; hybrid electric vehicles

check for updates

Citation: Mittal, V.; Shah, R. Energy Management Strategies for Hybrid Electric Vehicles: A Technology Roadmap. *World Electr. Veh. J.* **2024**, *15*, 424. https://doi.org/10.3390/wevj15090424

Academic Editors: Wenming Yang and Anna Pinnarelli

Received: 21 August 2024
Revised: 12 September 2024
Accepted: 16 September 2024
Published: 18 September 2024

1. Introduction

The automotive industry has been powered by the internal combustion engine for over a century. However, the industry is moving away from traditional internal combustion engines due to concerns about climate change and foreign oil dependence [1]. Recently, many countries have banned the sale of automobiles that use only internal combustion engines due to harmful emissions [2]. While the end goal is for the entire automotive sector to transition to electric vehicles (EVs) powered by renewable energy, this shift is currently limited by the cost of batteries and the associated vehicle range [3]. Meanwhile, hybrid electric vehicles (HEVs) can achieve many of the advantages of EVs while avoiding issues related to range. HEVs use both an internal combustion engine and a battery/motor assembly to power the vehicle [4].

Inherent in HEVs is their energy management strategy (EMS), which sets the conditions for when the vehicle is powered by the engine versus the battery/motor assembly. The EMS plays a key role in ensuring the vehicle operates under optimal conditions to minimize fuel consumption. The goal of this review paper is to provide a technology roadmap for the EMSs used in HEVs. It first discusses the significance and current state of the EMSs in modern HEVs. It then develops a technology roadmap for future EMSs based on market trends. This paper then presents a comprehensive review of the technologies driving the evolution of EMSs, including machine learning, computer vision, cloud computing, and swarm technology. These technologies are discussed in relation to EMSs, with a particular focus on how their advances affect overall fuel and energy consumption.

2. Overview of Energy Management Systems

2.1. Importance of Hybrid Technologies

In theory, EVs offer better performance, lower operating costs, and help achieve carbon neutrality when compared to traditional vehicles. However, they also come with significant challenges. One of the biggest issues is the size and cost of the requisite battery pack [5]. Currently, these packs use Li-ion batteries with an energy density of about 220 Whr/kg. For example, the Tesla Model S has a 120 kWh battery pack weighing roughly 540 kg [6]. At a cost of USD 118 per kWh, this results in a USD 14,160 battery pack for the Model S [7]. The high cost of the battery pack makes EVs prohibitively expensive for many consumers.

Another issue is the weight of the battery pack, which affects the vehicle's overall energy consumption since the power required for locomotion scales with vehicle weight [8]. For example, a Toyota Camry weighs 1545 kg [9], whereas a Tesla Model S weighs about 2045 kg [10]. This 32% weight increase leads to an estimated 25% rise in the amount of power required for locomotion. In traditional vehicles, energy is generated onboard by the engine. In EVs, energy is produced off-site and stored in the battery, but this introduces inefficiencies, such as transmission and charging losses, each about 90% efficient [11]. Therefore, a Tesla Model S requires 54% more energy from the grid than what the Toyota Camry would need from its onboard engine. Although grid energy is generally cleaner and more efficient, these extra demands can offset some of the environmental benefits of EVs [11].

HEVs mitigate the cost and weight issues by using smaller battery packs and downsized engines. For instance, the Toyota Camry Hybrid weighs only 45 kg more than the standard Camry since it only has a 1 kWh battery pack [12]. The minimal weight difference means that the power required by the HEV for locomotion is comparable to the traditional version. Additionally, the HEV benefits from regenerative braking and uses battery power when the engine is least efficient. As a result, the fuel economy improves from 28 mpg city/39 mpg highway to 51 mpg city/53 mpg highway [9,12]. This increase in fuel efficiency contributes significantly to carbon neutrality goals by 2050 [13].

Assuming a mix of city and highway driving and USD 4 per gallon of gasoline, the improved fuel economy of the hybrid Camry translates to savings of around USD 4600 over 100,000 miles compared to the non-hybrid variant of the Camry. Although these savings may not fully offset the hybrid's higher initial cost at present, rising fuel prices, government incentives, and decreasing battery costs are expected to make the total cost of ownership for HEVs lower than that of their non-electrified counterparts in the near future [14]. Moreover, the increased fuel economy of the HEV results in a significant reduction in fossil fuels used and carbon emitted when compared to a traditional vehicle.

2.2. Hybrid Topologies

As shown in Figure 1, HEVs typically use parallel, series, or power-split architectures based on the engine and battery/motor configuration. Even traditional vehicles feature a degree of hybridization, as the battery/motor starts the engine, though it doesn't assist with locomotion.

A series HEV is the simplest, functioning as a battery-powered EV where a generator-driven engine supplies power to the battery or motor, which propels the wheels. Its main advantage is weight reduction due to the absence of a mechanical transmission, and the engine operates at its most efficient points since it is independent of driving conditions. However, the need for a large battery, engine, and accessories increases cost, and energy conversion inefficiencies arise from converting mechanical to electrical power and back [15,16].

In parallel HEVs, both the engine and motor can drive the vehicle, with the EMS selecting the most efficient power source. The motor typically propels the vehicle at low speeds, increasing fuel economy. Meanwhile, the engine propels the vehicle at higher speeds and loads. This architecture requires a smaller battery pack than the series design and avoids inefficiencies related to energy conversion [17,18].

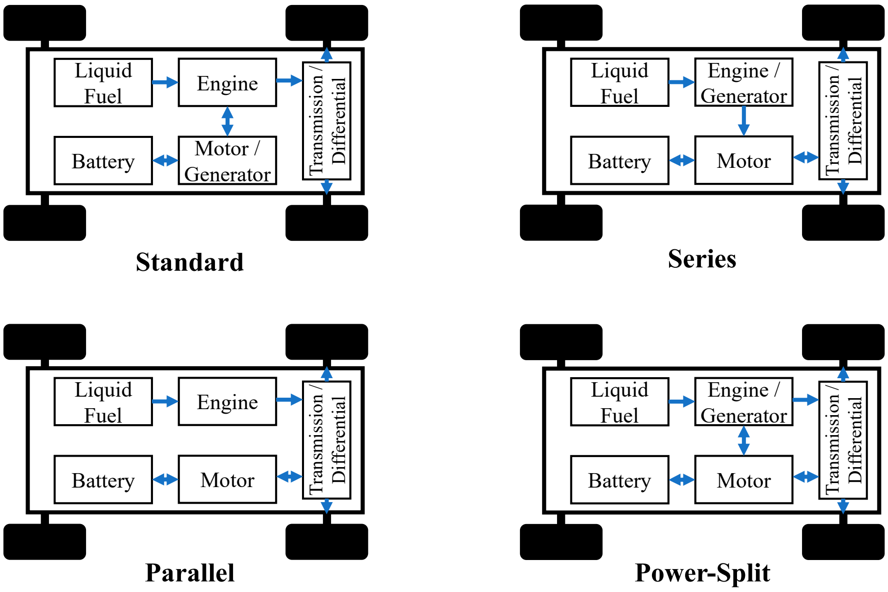

Figure 1. The four different hybrid electric vehicle architectures.

Power-split HEVs combine series and parallel architectures for greater efficiency in mixed driving conditions. The engine, generator, and motor are decoupled, allowing flexible control, with power merging through mechanical and electrical paths via a planetary gear set [17,19]. This flexibility enhances engine efficiency and control.

HEVs are further categorized into mild, plug-in, and full hybrids. Mild hybrids use a parallel architecture, turning off the engine when braking or stopped, but do not provide electric propulsion. Plug-in and full hybrids, using power-split designs, provide electric propulsion. Both recharge via an onboard generator, though plug-in hybrids can also use grid electricity. This paper focuses on EMS in plug-in and full hybrid vehicles, which are more complex than those in mild hybrids [20,21].

2.3. Importance of Energy Management Strategies

Given that most commercial HEVs use power-split technology, the EMS is critical because it determines engine and motor conditions to minimize fuel consumption and emissions while still meeting the driver's power demands [17]. Furthermore, the EMS helps ensure that the battery bank maintains the necessary state of charge (SOC). At its most fundamental level, an EMS takes data from various inputs, such as vehicle speed, battery SOC, and driver demand. The EMS uses these inputs in an algorithm that determines the power split between the engine and motor, optimizing overall vehicle performance [22]. The evolution of the EMS involves the use of more powerful algorithms to further improve vehicle performance, efficiency, and emissions.

The EMS plays a central role in hybrid power architecture, particularly in relation to fuel efficiency. As illustrated in Figure 2, if the EMS relies too heavily on the internal combustion engine, the increased weight of the HEV could result in worse fuel consumption than a comparable standard vehicle. The fuel consumption is typically quantified as miles traveled per gallon of fuel (MPG). Conversely, if the EMS accurately predicts fuel needs and limits engine use, the HEV can potentially achieve a better miles per gallon equivalent (MPGe) than even EVs. Note that MPGe is a measure of how efficiently a vehicle uses energy, expressed in terms of the distance a vehicle can travel on the amount of energy equivalent to one gallon of gasoline. It is defined by the equation:

$$\text{MPGe} = \frac{\text{Distance Travelled [miles]}}{\text{Energy Consumed [kWhr]}} \times \text{Energy Content of Gasoline [kWhr/gallon]}.$$

The potential higher MPGe for HEV compared to a similar EV is due to the smaller battery pack of the HEV, which decreases the weight of the vehicle, resulting in a lower power draw associated with locomotion [23].

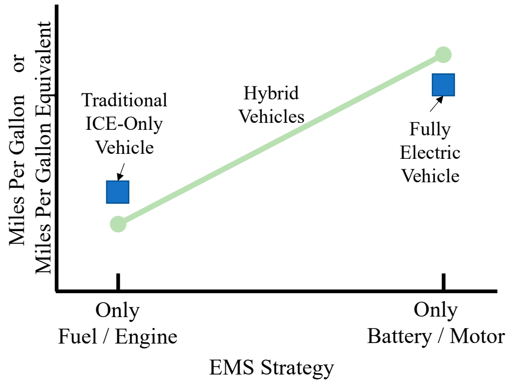

Figure 2. Qualitative depiction of the miles per gallon and miles per gallon equivalent for an internal combustion engine, electric vehicle, and an HEV.

Developing an optimal EMS is challenging, primarily due to the need to balance performance with fuel economy. The EMS must quickly respond to driver demands while optimizing energy use, which becomes difficult in unpredictable driving conditions. Ideally, it would accurately predict future battery charge rates and fuel consumption to adjust the powertrain in real time. However, these predictions are complex and often imprecise, making it hard for the EMS to effectively anticipate future driving conditions and optimize the power split.

3. Current Energy Management Strategies

3.1. Rule-Based EMS

The most basic EMS is a rule-based EMS, which predetermines the operating states of a hybrid system using predefined rules to manage how the system functions. These rules are built from heuristics, intuition, human experience, and mathematical models tailored to specific scenarios [24]. The EMS distributes power between the engine and battery, ensuring both operate within their most efficient ranges [25].

There are two primary types of rule-based EMSs. The first is deterministic, which controls vehicle components based on specific driving demands and system limits. This method relies on established parameters for each component, combined with engineering experience and research data. It adjusts power distribution and component status dynamically, responding to changes in driving conditions and system requirements [26].

The second type is a fuzzy logic-based EMS, which enhances the standard rule-based system by incorporating fuzzy logic. Instead of focusing solely on state variables like power demand and vehicle speed, this system also accounts for the rate of change in these variables, offering a more nuanced approach to decision-making [26].

While rule-based strategies are effective and relatively easy to implement, they are constrained by specific operating conditions and lack adaptability to varying driving cycles [26]. These controllers are popular due to their simplicity and real-time application suitability, but they often rely on basic engineering intuition, such as the charge-depleting/charge-sustaining strategy, which is less efficient than more advanced approaches [27]. Current rule-based EMSs struggle to account for variations in trip lengths or traffic conditions without employing complex driving pattern recognition systems [28].

3.2. Optimization-Based Strategies

The goal of an optimization strategy is to minimize a cost function, which typically includes emissions, fuel consumption, and torque requirements [1]. Unlike rule-based strategies, optimization strategies do not directly manage real-time energy usage. Instead, they derive real-time control decisions from the vehicle's cost function.

These algorithms typically calculate the optimal power split between the engine and motor for a specific drive cycle. However, the solutions they produce are optimal only for that particular cycle, which is usually represented as a set of vehicle speed points over time [28]. Consequently, they may not be optimal or even charge-sustaining for other driving cycles. Without predicting future driving conditions in real time, it is impossible to directly apply these control laws during vehicle operation [29].

Optimization-based EMS can be classified into two main types. The first is global optimization, which focuses on minimizing the cost of the entire driving condition and applies optimal control theory to achieve a global solution. The second is instantaneous optimization, which aims to minimize fuel consumption and other parameters at each moment of the drive cycle [26].

For global optimization to perform at its best, it requires extensive data about the vehicle, such as battery SOC, driving conditions, driver behavior, and route information [1]. However, due to limitations in computational methods like linear programming, dynamic programming, and genetic algorithms, global optimization is not feasible for real-time control. Instead, it is typically optimized for a predetermined drive cycle. While dynamic programming (DP) can compute multi-stage optimization decisions when the entire driving cycle is known, it is too computationally intensive for real-time application.

Instantaneous optimization strategies, such as model predictive control (MPC) and the equivalent consumption minimization strategy (ECMS), address some of these limitations. MPC predicts future power demand using real-time driving data and adjusts the power distribution between the engine and battery to minimize fuel consumption. ECMS, on the other hand, simplifies the dynamic optimization problem by minimizing equivalent fuel consumption at each time step, turning it into an instantaneous optimization problem [30].

An alternative to optimization is a dynamic rule-based strategy, where the rule set is continuously updated based on changing driving conditions. For example, Basma et al. studied a dynamic rule-based EMS that incorporated elements of dynamic programming. Their study proposed a comprehensive methodology for designing EMS in HEVs to achieve near-optimal consumption results. They found that, for distances up to 120 km, the dynamic rule-based EMS reduced fuel consumption by 15% compared to a basic rule-based system [31]. Although the reductions in fuel consumption were small, even slight improvements can significantly impact overall vehicle performance. The proposed controller balances the optimality of global optimization techniques with real-time implementation [28].

3.3. Issues

While rule-based and optimization-based strategies are useful for hybrid energy management, they are primarily based on the state-of-charge of the battery, the vehicle speed, and the energy demands as shown in Figure 3. The input values for EMSs using current strategies are responsive in nature, in that they reflect the current demands of the vehicle. There are a number of parameters that they do not capture. In particular, they do not account for the future needs of the vehicle. Additionally, they do not account for variables external to the vehicle—to include traffic and weather—which can also impact the overall efficiency of the vehicle. Consider the following four cases:

Case 1: A vehicle is cruising on a highway but is about to enter an urban area requiring frequent braking. Current EMS strategies would increase engine load on the highway to keep the batteries fully charged. However, upon entering the urban zone, if the batteries are already fully charged, they cannot absorb energy from regenerative braking, leading to wasted energy. A predictive EMS aware of the transition to urban driving could optimize the charge level to ensure capacity for regenerative braking energy, improving overall efficiency.

Case 2: A vehicle is driven at low speeds over a long distance, which typically favors electric propulsion. In a power-split or series hybrid, the engine eventually runs to recharge the battery. However, if the driver is near home and using a plug-in hybrid, running the engine to recharge the battery would be less efficient than simply plugging into the grid. A predictive EMS could account for the proximity to a charging station, minimizing inefficient engine use and saving energy for grid charging.

Case 3: A vehicle operates at medium speed, favoring electric propulsion, but encounters a significant traffic jam where it will be idling for an extended period. Without foresight, the batteries may drain during idle time, forcing the engine to compensate. A predictive EMS, aware of the upcoming congestion, could have prioritized engine use before the jam to keep the batteries charged, reducing idling emissions and energy consumption.

Case 4: A vehicle is approaching an extended uphill climb. Running the engine in hybrid mode during the ascent will strain the system, causing inefficient energy usage. With predictive awareness of the terrain, the EMS could run the engine at a higher load before reaching the climb to build up energy reserves, allowing the vehicle to tackle the hill more efficiently using stored battery power.

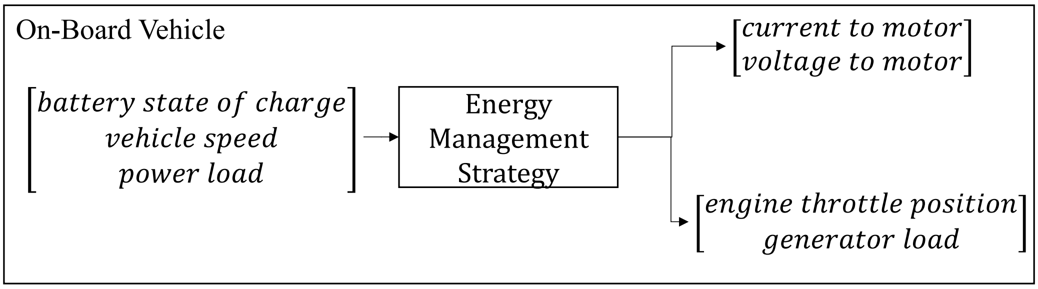

Figure 3. State diagram for current EMS for HEV.

In all four cases, increased efficiencies can be realized through an EMS that uses predictive analysis, understanding driver behavior, and external entities to predict upcoming power needs.

4. Technology Roadmap

Given the issues discussed in the previous section, the EMS will evolve to better optimize fuel consumption and vehicle performance. Figure 4 displays a projected roadmap for the EMS for HEVs based on the evolution of the underlying technologies. In particular, the current rule-based and optimization-based EMSs will be replaced with more advanced versions that can adapt to a driver's habits. Over the long term, EMS will evolve to include numerous external factors, including traffic and weather. Each of these stages of EMS technology will be discussed in the subsequent sections.

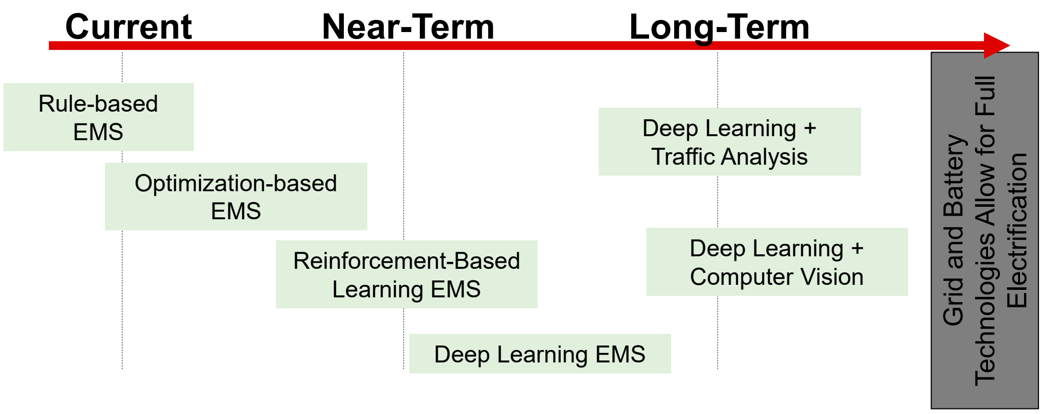

Figure 4. Technology roadmap for the evolution of EMSs for HEVs.

"Long-term" in this roadmap is loosely defined as being 20 years out. By the end of that period, HEVs may become obsolete to fully electric vehicles with new battery chemistries [32]. These batteries will eliminate the weight and cost issues associated with lithium-ion batteries. Further, roadmaps past 20 years for a rapidly changing field carry significant uncertainty.

A summary of each EMS is given in Table 1, including their positive and negative characteristics. The near- and mid/long-term EMSs are discussed in detail in the following sections.

Table 1. Summary of different energy management strategies.

EMS	Positives	Negatives
Rule-Based	Simple with minimal computational power. Uses existing technology.	Does not account for future driver needs or individual driving habits.
Optimization-Based	Improved fuel efficiency compared to rule-based EMS.	More computationally intensive than rule-based EMS. Does not account for future driver needs or individual driving habits.
Reinforcement-Based Learning	Improved fuel efficiency from predicting future states. Behavior tailored to individual driver.	Computationally intensive and difficult to achieve real-time control. Uncertainty in future driver need predictions.
Deep Learning-Based	Improved fuel efficiency from predicting future states with reducing uncertainty in future state predictions.	Computationally intensive and difficult to achieve real-time control.

4.1. Near-Term EMS

Current rule-based and optimization-based EMSs do not account for individual driving habits. However, in the near term, EMSs will be able to adapt to unique driving conditions, as shown in Figure 5. In particular, reinforcement learning (RL)-based EMSs are one of the newest ways to manage energy. This strategy learns from historical data and uses the previous driving data for learning and application. A RL-based EMS can be implemented to derive the optimal control policy by using inputs such as vehicle speed, driver power demand, and SOC to determine the engine power. This approach adapts to unpredictable driving cycles and achieves lower fuel consumption compared to dynamic programming [33].

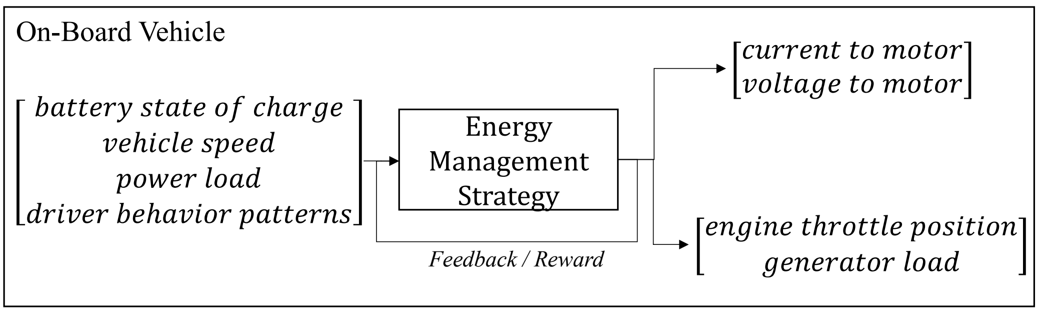

Figure 5. State diagram for near-term EMS for HEV.

At its core, an RL system consists of two main elements: a learning agent and an environment. The agent continuously interacts with the environment, receiving commands and selecting actions based on those inputs. When the agent takes an action, the environment shifts to a new state, and a reward corresponding to the transition is calculated and sent back to the agent [34]. The goal of RL is for the agent to maximize its total reward, or end goal, by learning how to effectively interact with the environment [35]. This cycle repeats continuously. While RL has many advantages, it also has notable challenges. Excessive use of RL can lead to an overload of possible states, diminishing its effectiveness. It is also known for being "data-hungry", requiring constant data and computation. Additionally, RL systems often have to learn from a scalar reward signal, which can be sparse, noisy, or delayed, making the learning process more difficult [27].

A growing trend is the combination of RL with deep learning (DL), a technique known as deep reinforcement learning (DRL). While both DL and RL are forms of machine learning, they operate differently; DL involves learning from a training set and applying that knowledge to new data, whereas RL focuses on learning through trial and error [36]. DL identifies patterns in the data by analyzing current information and teaching algorithms to recognize important features. When combined, DRL systems prevent the overload of states while retaining the adaptability needed for dynamic environments. DRL is widely used in areas such as robotics, HVAC control systems, ramp metering, and more. In the automotive sector, it has been applied to technologies like lane-keeping assistance and autonomous braking systems.

4.2. Mid/Long-Term EMS

Figure 6 displays the state diagram for the mid/long-term EMS for HEV. The major change from the near-term systems is that in the long-term, the EMS will be off-loaded from the vehicle through the use of cloud-computing. In doing so, the system can take multiple complex inputs from external sources, such as traffic and weather. With the processing partially off-loaded, the EMS can then fuse all of this data with onboard vehicle data to account for individual driving behaviors [37].

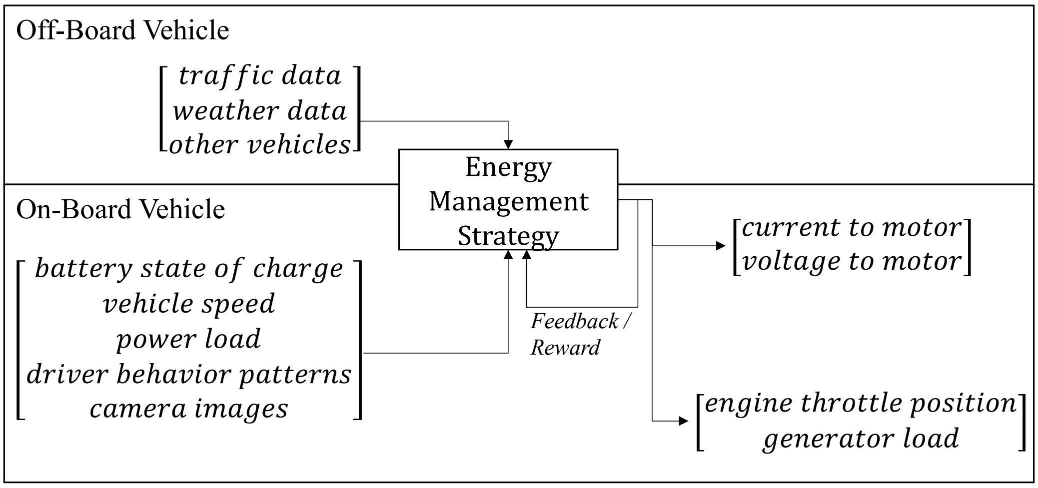

Figure 6. State diagram for mid/long-term EMS for HEV.

Additionally, the EMS can take in data from other vehicles in the area, especially those that are ahead of the current vehicle. In doing so, the EMS can receive data that may not necessarily be available through traffic data or from onboard sensors. For example, the system would be able to identify the instant that the vehicle in front of it starts to brake. Moreover, the EMS could detect when additional, unpredicted loads may be placed on the vehicle, such as a wind gust or a change in road grade. The connectivity between the vehicles becomes much more useful as other systems, such as autonomous driving, become more prevalent in vehicles.

Meanwhile, the onboard sensing systems will leverage improved machine learning algorithms to include several new sensors. In particular, advances in computer vision will allow the hybrid EMS to make well informed decisions based on processing images of the road. The image can provide real-time traffic data that can be fed into the EMS, allowing it to adjust the energy strategy accordingly.

4.3. Comparison to Other Studies

Given the critical role of HEVs and their EMS, several comprehensive reviews have examined both current and future developments in EMS technologies. For example, Saiteja et al. provided a thorough evaluation of existing rule-based and optimization-based EMSs, emphasizing the challenge of balancing model robustness with computational simplicity [38]. Their review highlighted the increasing complexity of future EMSs, which will need to integrate data from infrastructure, geographic information systems, and other vehicles to optimize energy management. This integration will demand more sophisticated predictive models while maintaining computational efficiency.

A similar study by Zhang et al. extended these insights by examining the incorporation of intelligent transportation systems into the EMS frameworks [39]. Their analysis predicted that data from infrastructure and other vehicles would significantly enhance vehicle performance and efficiency. However, they noted that this increased data flow would also introduce considerable computational complexity, presenting new challenges for EMS optimization.

Another study by Yang et al. explored conventional and future EMS approaches, focusing on the integration of vehicle-to-vehicle and vehicle-to-infrastructure connections [21]. Their study underscored the value of DRL algorithms, which offer greater flexibility than traditional rule-based or optimization-based systems. By considering multiple parameters simultaneously, DRL allows EMSs to dynamically adapt, improving both vehicle performance and efficiency.

All of these studies point to a common trend: future EMSs will require the ability to process vast amounts of external data from vehicles, infrastructure, and geospatial sources to better predict driving conditions and optimize energy management. This is in line with the technology roadmap presented in this paper, where the focus is on leveraging additional information to achieve more comprehensive and accurate EMS predictions.

While the other reviews in the literature provide valuable insights into the evolution of EMS, this study takes a different approach. Rather than merely focusing on current EMS challenges and the benefits of future EMS systems, this study explores the natural progression of EMS as it begins to harness cutting-edge advancements in machine learning, cloud computing, computer vision, and swarm technologies. These advancements will enable future EMSs to become more adaptive, capable of real-time optimizations, and ultimately more effective in balancing performance and energy efficiency. This study not only looks at the future potential of EMS but also highlights how it will fundamentally change as new technologies continue to shape its development.

5. Research Advances

The evolution of the EMS for HEVs will leverage advances in a number of technology fields. Table 2 lists out the relevant technology fields and their impact. These include machine learning, cloud computing, computer vision, and swarm theory.

Table 2. Different technology fields and the impact that they will have on energy management strategies.

Technology Field	Impact
Machine Learning	Custom EMS algorithms that evolve with driver behavior
Cloud Computing	Processing of large data and combining onboard and off-board sensors
Computer Vision	Predictive modeling of driving behavior
Swarm Technology	New optimization algorithms for EMS

5.1. Machine Learning

Artificial intelligence (AI) algorithms allow a computer to collect and process information similar to human intelligence. Machine learning (ML) is a type of AI that allows computers to effectively learn through algorithms that evolve as more data are collected [31]. ML is used in a variety of technology fields, including data analytics and cyber security; it has the potential to allow the EMS to improve its algorithms based on driver behavior, traffic patterns, and weather. In particular, ML algorithms underlie DRL-based EMSs.

A research team from UC Riverside attempted to implement a DRL-based EMS into plug-in hybrid vehicles with limited success [40]. The largest issue was that the algorithms included a substantial delay time to modify the vehicle behavior. As such, the results from the study indicated that this EMS worked well in routes that were without variation. While ideal for public transportation, where vehicles have an identical route every day, this would cause issues for general automotive usage.

Hu et al. developed a system model for a DRL-based EMS in an HEV [27] to autonomously learn the optimal policy based on data inputs. The study used ADVISOR, a software that models vehicle powertrains, to model the DRL-based EMS for the HEV [27]. The researchers combined both online and offline learning techniques by training the deep-reinforced neural network offline under the urban dynamometer driving schedule and then applying the online learning under the new European driving cycle. The study found an eight percent improvement in fuel economy for the urban drive cycle and a three percent improvement for the highway drive cycle. These improvements are due to the DRL-based EMS being able to optimize the powertrain operations over the large variations seen in the urban drive cycle; meanwhile, the variations in the highway drive cycle are less substantial.

A number of different research teams are evaluating ML algorithms that can further support the development of a DRL EMS. In particular, these studies seek to improve the fuel efficiency of the vehicle through an improved EMS while reducing the computation time, making the EMS more responsive. Sun et al. used a soft actor–critic scheme that sought to maximize fuel economy while still maintaining a degree of flexibility such that the algorithm was adaptable to set operating conditions [41]. Another study by Lin et al. used an adaptive hierarchical management strategy, which is an advanced data-driven algorithm [42]. This study found similar fuel consumption to a rule-based EMS, however, with better vehicle performance. Liu et al. and Zhou et al. used a twin delayed deep deterministic policy gradient, which optimized the EMS through penalizing irrational actions [43,44]. Both studies built a number of simulations that found a substantial computational reduction coupled with approximately a five percent improvement in fuel consumption. Meanwhile, Tang et al. used a double DRL EMS, which sought to control the engine and transmission separately, resulting in a significant improvement in computational efficiency and a modest reduction in fuel consumption [45].

Using ML to support RL and DRL in EMS for HEVs offers clear advantages, but several significant challenges need to be addressed. One of the primary difficulties is the requirement for large volumes of high-quality, diverse data to train the ML models effectively. In the context of HEVs, gathering data that accurately represents the broad range of driving conditions, weather variations, and vehicle states is a complex task. Incomplete or biased data can lead to models that underperform or fail to generalize to real-world scenarios. Moreover, creating comprehensive datasets can be costly and time-consuming, particularly when simulating rare or extreme driving conditions necessary for training robust RL and DRL models.

Another challenge lies in the computational complexity of ML-augmented RL and DRL algorithms. These models often require significant processing power and memory, which can hinder their ability to operate in real-time within the hardware-constrained environments typical of vehicles. Ensuring that these systems remain responsive without compromising on performance or accuracy is difficult. Additionally, safety and robustness remain concerns, especially in unpredictable or edge case scenarios. RL and DRL models may behave unpredictably when confronted with conditions they have not encountered during training, which could lead to unsafe decisions or actions. Balancing exploration and exploitation, a key challenge in RL, becomes even more critical in real-world applications where mistakes can lead to costly or dangerous outcomes, requiring advanced methods to ensure system safety while maintaining optimal performance.

5.2. Cloud Computing

Cloud computing moves data into the cloud for on-demand processing, decreasing the onboard processing requirements. It is an efficient method of processing a large amount of data, especially when compiling data from numerous different sources [46]. Cloud computing would allow for rapid processing of data for a vehicle to determine how to optimize the EMS. Further, it also allows for the optimization of a group of vehicles as opposed to a single vehicle.

A study by Hu et al. proposed that traffic information and cloud computing in intelligent transportation systems can enhance HEV energy management since vehicles obtain real-time data through intelligent infrastructures and/or connected vehicles [27]. The study proceeded to develop and assess a series of RL algorithms that incorporate this external data into an HEV EMS [26]. A study by Du et al. found similar results when incorporating traffic data through cloud computing [47].

Several other research groups have studied the incorporation of off-board sensors for a hybrid EMS. A study by Liu et al. integrated cloud computing with RL and DRL for hybridized tracked vehicles [48]. In their analysis, they used a parallel processing scheme, where a cloud-based EMS receives real-time data from the vehicle, which in turn generates artificial data to better train the onboard EMS. Their study found a savings in fuel economy of approximately 10 percent for their scheme when compared to conventional RL methods. Zhang et al. identified cloud computing as having the processing power necessary to determine a global optimization in real-time [49]. Further, they found that cloud computing could allow the vehicle to optimize fuel economy and battery state of health, which is difficult to do with localized computing. Another study by Hou and Song used cloud computing to optimize battery usage and degradation. In their study, they identified that cloud computing allows for external inputs that can provide for predictive analysis [50].

Leveraging cloud computing to support EMS for HEVs offers significant benefits but also presents several challenges. Cloud computing can provide virtually unlimited computational power and storage, allowing EMS to process large datasets, run complex simulations, and optimize energy management strategies in real-time. This capability can enhance decision-making, leading to more efficient fuel consumption, improved battery management, and overall better vehicle performance. Furthermore, the cloud enables continuous updates and access to external data sources, such as weather forecasts and traffic patterns, allowing the EMS to dynamically adjust energy strategies based on real-world conditions. This adaptability can significantly improve energy efficiency and reduce emissions across varying driving environments.

However, there are notable difficulties in integrating cloud computing with EMS for HEVs. A primary concern is the reliance on stable, high-bandwidth communication between the vehicle and the cloud, which may not always be feasible, particularly in remote or rural areas. Latency issues can also arise, causing delays in real-time decision-making, which is critical for optimizing energy use on the go. Additionally, ensuring the security and privacy of data transmitted to and from the cloud is a major challenge, as vulnerabilities in communication channels could expose sensitive vehicle or driver information to cyberattacks. Managing data synchronization between cloud and onboard systems is another difficulty, as any misalignment between cloud-processed decisions and vehicle operations could lead to inefficiencies or unsafe driving conditions.

5.3. Computer Vision

Computer vision (CV) is a form of AI that allows computers to analyze images to understand the visual world. Many of the inputs used by drivers are related to visual cues (e.g., stop lights, heavy traffic, off-ramps). As such, computer vision would allow for the vehicle to take in similar inputs as a driver and make realistic real-time changes to the EMS to accommodate perturbations in driving needs [51]. Similarly, autonomous driving algorithms coupled with CV are also continuing to improve and provide more robust accommodations for changes in traffic patterns, weather, and driving needs.

Several studies have looked at incorporating computer vision with the EMS. A study from Wang et al. found an improvement in fuel economy of 4.3–8.8 percent for DRL algorithms with the inclusion of visual information based on simulated highway and urban drive cycles [52]. Their study included traffic as well as stop lights that were assessed through visual means. A schematic of their study is shown in Figure 7. Other studies on computer vision have found similar improvements in fuel economy. Research by Chen et al. identified that a 10 percent reduction in fuel economy is possible, with no processing lag, by using cameras to identify road types and conditions [51]. Another study by Zhang et al. uses computer vision to predict future vehicle propulsion needs, including potential traffic issues, and provides that data to the EMS [53]. A research study by Tang et al. developed models to analyze the use of computer vision with DRL to support both car following in addition to feeding traffic data into the EMS [54].

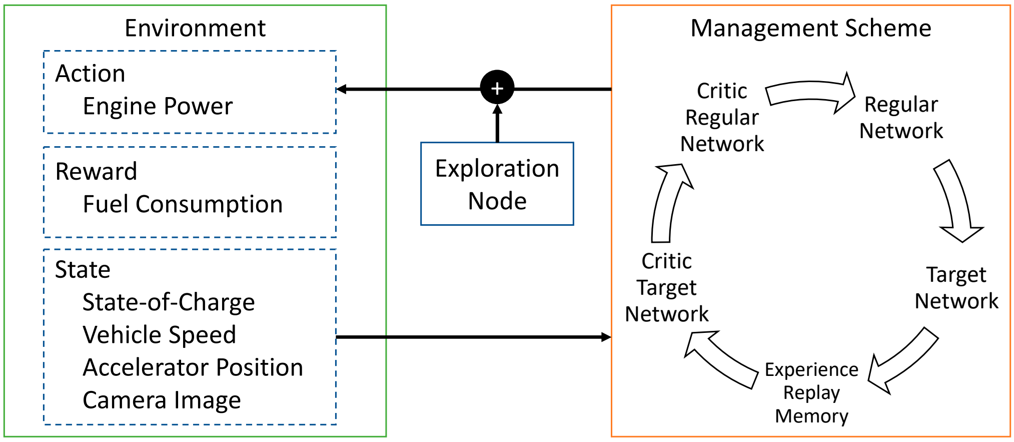

Figure 7. Schematic of the EMS modeled by Wang et al. [52].

Using computer vision to support EMS for HEVs offers significant advantages but also presents unique challenges. Computer vision enables the EMS to analyze visual data from onboard cameras and sensors, providing real-time insights into the vehicle's surroundings. This capability allows the EMS to make more informed decisions by detecting road conditions, traffic patterns, and obstacles, helping optimize energy usage based on the driving environment. For instance, by recognizing stop-and-go traffic or upcoming terrain changes, the system can adjust power distribution to the electric motor and internal combustion engine, improving fuel efficiency and battery life. Computer vision also supports advanced driver-assistance systems, contributing to more efficient energy management by enabling smoother driving patterns and better control over acceleration and braking.

Despite these benefits, integrating computer vision into EMS for HEVs poses several challenges. The first challenge is the computational demand required to process high-resolution images and video streams in real-time, especially in resource-constrained vehicle environments. Computer vision algorithms, particularly those based on deep learning, require significant processing power, which can strain the vehicle's hardware and limit real-time responsiveness. Additionally, ensuring the reliability of computer vision systems in diverse and unpredictable conditions, such as low light, heavy rain, or fog, is a critical concern. Vision-based EMS must be able to handle these variations while maintaining accurate environmental perception, which is difficult to achieve consistently. Another challenge is the potential for false positives or misinterpretation of visual data, leading to incorrect decisions that could negatively impact energy efficiency or vehicle safety.

5.4. Swarm Technology

Another technological field that will play a role in the long term is swarm technology. Swarm technology allows for multiple systems to work together. Although swarm technology is primarily aimed towards drones, some of the optimization techniques can be applied to EMS. In particular, swarm technology is tied to vehicle-to-vehicle communication, where the EMS can optimize globally across a group of vehicles.

Zhang et al. highlighted how swarm-based vehicle-to-vehicle (V2V) communication can optimize future EMSs for HEVs by allowing vehicles to share real-time data, such as speed and road conditions, to improve energy management [55]. Using a model predictive control framework, the study optimized torque split and gearshift in parallel HEVs, enhancing fuel economy while minimizing gearshift frequency. By simplifying the gearshift assumption over prediction horizons, the system achieves computational efficiency close to traditional methods. The study found that this integration of V2V communication into swarm-based EMS frameworks shows potential for significant improvements in real-time energy optimization and vehicle performance.

A similar study by Baker et al. explored the use of V2V communication to develop a more predictive EMS to improve fuel economy in HEVs [56]. By leveraging swarm technology, multiple vehicles can share real-time data, such as speed and traffic conditions, to enhance the accuracy of the speed prediction method, which was based on real-world driving data and a drive cycle database. This information informed a predictive powertrain controller to optimize engine operation. Simulations with a high-fidelity Toyota Prius model found that this approach can improve fuel economy by up to 6% over a baseline EMS, capturing up to 85% of the benefits of perfect speed prediction, even with real-world prediction errors. The findings highlight the potential of integrating V2V communication and swarm technology into predictive EMS, yielding significant gains in fuel economy compared to strategies that rely solely on local vehicle information.

Furthermore, the optimization of swarms is complex and must account for numerous factors internal and external to a swarm; these challenges are akin to those for optimizing an EMS. In particular, particle swarm optimization has been found effective for optimizing an EMS for fuel consumption [57]. For example, Wu et al. performed work to optimize an EMS using particle swarm optimization for a plug-in hybrid vehicle [58]. Particle swarm optimization takes a complex decision space and identifies a number of different solutions; these solutions then move around the decision space following mathematical algorithms to identify the optimal solution. The study by Wu et al. used this algorithm to identify the optimal periods to run the plug-in hybrid off batteries given a broad range of external factors, finding that this optimization strategy can result in significant fuel savings. More recent work by Chen et al. used particle swarm optimization to optimize the operating scheme of the EMS in real-time [57]. Their study simplified the EMS to a series of rule-based operating conditions and optimized across these rules. Their results indicated that their scheme could operate in near real-time and showed significant improvement over traditional rule-based schemes. Similar studies have found particle-swarm optimization to improve the EMS for fully electric vehicles [59] and hybrid fuel cell vehicles [60].

Swarm technology can greatly enhance EMS for HEVs by enabling vehicles to communicate and collaborate with each other, optimizing energy use across a network of vehicles. This collective decision-making allows for more efficient route planning, traffic management, and energy distribution, as vehicles can share information about road conditions, traffic patterns, and available charging infrastructure. By functioning as part of a coordinated system, HEVs can reduce energy consumption and improve battery performance, particularly in congested urban environments where real-time coordination is essential.

However, implementing swarm technology in EMS also presents challenges. One of the primary difficulties is maintaining reliable, low-latency communication between vehicles, especially in high-density traffic or remote areas. Ensuring data synchronization across multiple vehicles in dynamic environments is also complex, as delays or inconsistencies could lead to inefficient or conflicting decisions. Additionally, securing the network of interconnected vehicles against cyber threats is critical, as a breach in communication protocols could disrupt the entire swarm, leading to potential safety hazards or energy inefficiencies.

5.5. Summary of Technology Studies

Significant research has been performed on advancing the aforementioned technologies for incorporation into the EMS of HEVs. Table 3 provides a summary of the studies discussed in the previous sections.

Table 3. Summary of relevant studies related to each technological field.

Research	Ref	Summary
Machine Learning		
Qi et al.	[40]	Modeling/testing a DRL-based EMS
Hu et al.	[27]	Modeling/testing a DRL-based EMS
Sun et al.	[41]	Improved algorithms for EMS
Lin et al.	[42]	Improved algorithms for EMS
Liu et al.	[43]	Improved algorithms for EMS
Zhou et al.	[44]	Improved algorithms for EMS
Tang et al.	[45]	Improved algorithms for EMS
Cloud Computing		
Hu et al.	[27]	Cloud computing to incorporate traffic data
Du et al.	[47]	Cloud computing to incorporate traffic data
Liu et al.	[48]	On Board / Off Board EMS data fusion
Zhang et al.	[49]	Cloud computing processing optimization for EMS
Hou and Song	[50]	Using cloud computing to optimize DRL-based EMS
Computer Vision		
Wang et al.	[52]	Computer vision to predict driver needs
Chen et al.	[51]	Computer vision to identify road type / conditions
Zhang et al.	[54]	Computer vision to predict driver needs
Tang et al.	[54]	Computer vision to support DRL-based EMS
Swarm Technology		
Zhang et al.	[55]	Swarm technology to support V2V integration into EMS
Baker et al.	[56]	Swarm technology to support V2V integration into EMS
Chen et al.	[57]	Using particle swarm optimization for DRL-based EMS
Wu et al.	[58]	Using particle swarm optimization for DRL-based EMS
Kachroudi et al.	[59]	Using particle swarm optimization for electric vehicles
Sarma et al.	[60]	Using particle swarm optimization for fuel cell vehicles

The integration of ML, cloud computing, computer vision, and swarm technology will significantly advance the evolution of EMS for HEVs. ML and cloud computing will play a crucial role in establishing and enhancing RL and DRL schemes within EMS. ML allows for adaptive learning based on real-time and historical data, optimizing energy usage and powertrain control to improve fuel efficiency and performance. Cloud computing, with its vast computational resources, enables the continuous refinement of these algorithms, allowing the EMS to adapt dynamically to changing driving conditions by leveraging real-time data from multiple sources. Together, ML and cloud computing will facilitate more responsive and intelligent EMS systems capable of optimizing energy management across diverse driving scenarios.

The addition of computer vision and swarm technology into EMS will further expand the system's capabilities. Computer vision will enable vehicles to better understand their surroundings by processing visual data from onboard sensors, allowing the EMS to adjust energy strategies based on road conditions, traffic, and obstacles. Swarm technology will support inter-vehicle communication, enabling coordinated energy management across a fleet of HEVs. By sharing data on road conditions, traffic patterns, and charging infrastructure, the EMS in each vehicle can optimize its performance within a collective network, reducing overall energy consumption. While implementing these technologies presents challenges, substantial progress in other sectors, such as autonomous driving and networked systems, is paving the way for their integration into HEV EMS, providing new opportunities for efficiency and performance improvements.

6. Conclusions and Recommendations

HEVs are expected to play a critical role in the future of the automotive industry, serving as a bridge between current internal combustion engines and fully electric vehicles. Given the limited readiness of global charging infrastructure and the higher build costs of EVs, HEVs represent the best option in the near term for certain geographical locations and user groups. HEVs offer a cleaner alternative to traditional vehicles while mitigating common issues with electric vehicles, such as range limitations and charging times. The benefits of HEVs rely heavily on having an effective EMS to optimize the vehicle's drive parameters.

This study provided a summary of current and future EMSs for HEVs, highlighting the reliance on rule-based and optimization-based strategies in existing systems. Future EMSs are expected to incorporate technologies from emerging fields, including machine learning, computer vision, cloud computing, and swarm technology. The paper presents a roadmap for EMS development, predicting advancements that will enhance optimization and decrease vehicle fuel consumption, potentially approaching the MPGe of electric vehicles.

This study indicates that industry stakeholders should invest in integrating advanced ML algorithms, computer vision, swarm technology, and cloud computing to enhance EMS capabilities. Collaboration with technology providers specializing in these areas and predictive analytics can accelerate the development of next-generation EMSs. Additionally, companies should advocate for and contribute to the development of charging infrastructure to support the transition to fully electric vehicles in the longer term. Further research should include longitudinal studies to assess the real-world performance of advanced EMSs and their impact on fuel consumption and vehicle efficiency, cross-disciplinary research to explore synergies between EMS technologies and other automotive innovations, and investigations into how different driving patterns and user behaviors influence the effectiveness of various EMS strategies. As EMS technology evolves, HEVs will increasingly bridge the gap until the automotive industry transitions fully to electric vehicles, achieving greater fuel efficiency and environmental benefits.

Author Contributions: Conceptualization, V.M. and R.S.; methodology, V.M.; validation, V.M.; formal analysis, V.M. and R.S.; investigation, V.M. and R.S.; writing—original draft preparation, V.M. and R.S.; writing—review and editing, V.M. and R.S.; project administration, R.S. 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 as part of this research effort.

Conflicts of Interest: Dr. Vikram Mittal is an employee of the United States government. Dr. Rajesh Shah is an employee of Koehler Instruments Company. The paper reflects the views of the scientists and not their respective companies.

References

1. Panday, A.; Bansal, H. A Review of Optimal Energy Management Strategies for Hybrid Electric Vehicles. *Int. J. Veh. Technol.* **2014**, *2014*, 160510. [CrossRef]
2. Morfeldt, J.; Kurland, S.D.; Johansson, D.J. Carbon Footprint Impacts of Banning Cars with Internal Combustion Engines. *Transp. Res. Part D Transp. Environ.* **2021**, *95*, 102807. [CrossRef]
3. Hasan, M.K.; Mahmud, M.; Habib, A.A.; Motakabber, S.M.; Islam, S. Review of Electric Vehicle Energy Storage and Management System: Standards, Issues, and Challenges. *J. Energy Storage* **2021**, *41*, 102940. [CrossRef]
4. Denton, T. *Electric and Hybrid Vehicles*; Routledge: New York, NY, USA, 2020.
5. Iclodean, C.; Varga, B.; Burnete, N.; Cimerdean, D.; Jurchiş, B. Comparison of Different Battery Types for Electric Vehicles. In *IOP Conference Series: Materials Science and Engineering*; IOP Publishing: Bristol, UK, 2017; Volume 252, p. 012058.
6. Miao, Y.; Hynan, P.; Von Jouanne, A.; Yokochi, A. Current Li-Ion Battery Technologies in Electric Vehicles and Opportunities for Advancements. *Energies* **2019**, *12*, 1074. [CrossRef]

7. Ziegler, M.S.; Song, J.; Trancik, J.E. Determinants of Lithium-Ion Battery Technology Cost Decline. *Energy Environ. Sci.* **2021**, *14*, 6074–6098. [CrossRef]
8. Gillespie, T.D. *Fundamentals of Vehicle Dynamics*; SAE International: Warrendale, PA, USA, 1992.
9. Toyota. 2022 Camry Specifications. Available online: https://www.toyota.com/camry/ (accessed on 25 May 2024).
10. Tesla. Tesla Model S. Available online: https://www.tesla.com/models (accessed on 25 May 2024).
11. Kosai, S.; Nakanishi, M.; Yamasue, E. Vehicle Energy Efficiency Evaluation from Well-to-Wheel Lifecycle Perspective. *Transp. Res. Part D Transp. Environ.* **2018**, *65*, 355–367. [CrossRef]
12. Toyota. 2022 Camry Hybrid. Available online: https://www.toyota.com/camryhybrid/2022/ (accessed on 25 May 2024).
13. X-Engineer.org. What is the Difference between micro, Mild, Full, And Plug-in Hybrid Electric Vehicles. Available online: https://x-engineer.org/automotive-engineering/vehicle/hybrid/micro-mild-full-hybrid-electric-vehicle/ (accessed on 31 May 2024).
14. Weiss, M.; Zerfass, A.; Helmers, E. Fully Electric and Plug-In Hybrid Cars—An Analysis of Learning Rates, User Costs, and Costs for Mitigating CO_2 and Air Pollutant Emissions. *J. Clean. Prod.* **2019**, *212*, 1478–1489. [CrossRef]
15. 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 2010; pp. 5844–5849.
16. Silva, C.; Ross, M.; Farias, T. Evaluation of Energy Consumption, Emissions, and Cost of Plug-In Hybrid Vehicles. *Energy Convers. Manag.* **2009**, *50*, 1635–1643. [CrossRef]
17. Zhang, F.; Wang, L.; Coskun, S.; Pang, H.; Cui, Y.; Xi, J. Energy Management Strategies for Hybrid Electric Vehicles: Review, Classification, Comparison, and Outlook. *Energies* **2020**, *13*, 3352. [CrossRef]
18. Li, X.; Williamson, S.S. Comparative Investigation of Series and Parallel Hybrid Electric Vehicle (HEV) Efficiencies Based on Comprehensive Parametric Analysis. In Proceedings of the 2007 IEEE Vehicle Power and Propulsion Conference, Arlington, TX, USA, 9 September 2007; pp. 499–505.
19. Lanzarotto, D.; Marchesoni, M.; Passalacqua, M.; Prato, A.P.; Repetto, M. Overview of Different Hybrid Vehicle Architectures. *IFAC-PapersOnLine* **2018**, *51*, 218–222. [CrossRef]
20. Hao, L.; Wang, Y.; Bai, Y.; Zhou, Q. Energy Management Strategy on a Parallel Mild Hybrid Electric Vehicle Based on Breadth First Search Algorithm. *Energy Convers. Manag.* **2021**, *243*, 114408. [CrossRef]
21. Yang, C.; Zha, M.; Wang, W.; Liu, K.; Xiang, C. Efficient Energy Management Strategy for Hybrid Electric Vehicles/Plug-In Hybrid Electric Vehicles: Review and Recent Advances under Intelligent Transportation System. *IET Intell. Transp. Syst.* **2020**, *14*, 702–711. [CrossRef]
22. Zhou, J.; Li, M.; Xu, M. Optimization-Based Control Strategy for Large Hybrid Electric Vehicles. *SAE Tech. Pap.* **2018**, *2018*, 10.
23. Jung, H. Fuel Economy of Plug-In Hybrid Electric and Hybrid Electric Vehicles: Effects of Vehicle Weight, Hybridization Ratio and Ambient Temperature. *World Electr. Veh. J.* **2020**, *11*, 31. [CrossRef]
24. Hofman, T.; Steinbuch, M.; Van Druten, R.; Serrarens, A. Rule-Based Energy Management Strategies for Hybrid Vehicles. *Int. J. Electr. Hybrid Veh.* **2007**, *1*, 71–94. [CrossRef]
25. Jalil, N.; Kheir, N.A.; Salman, M. A Rule-Based Energy Management Strategy for a Series Hybrid Vehicle. In Proceedings of the 1997 American Control Conference, Albuquerque, NM, USA, 6 June 1997; pp. 689–693.
26. Zhu, Y.; Li, X.; Liu, Q.; Li, S.; Xu, Y. A Comprehensive Review of Energy Management Strategies for Hybrid Electric Vehicles. *Mech. Sci.* **2022**, *13*, 147–188. [CrossRef]
27. Hu, Y.; Li, W.; Xu, K.; Zahid, T.; Qin, F.; Li, C. Energy Management Strategy for a Hybrid Electric Vehicle Based on Deep Reinforcement Learning. *Appl. Sci.* **2018**, *8*, 187. [CrossRef]
28. Basma, H.; Mansour, C.; Halaby, H.; Radwan, A.B. Methodology to Design an Optimal Rule-Based Energy Management Strategy Using Energetic Macroscopic Representation: Case of Plug-In Series Hybrid Electric Vehicle. *Adv. Automob. Eng.* **2018**, *7*, 3.
29. Horrein, L.; Bouscayrol, A.; Cheng, Y.; Dumand, C. Hybrid Energy Management Strategy for Hybrid Electric Vehicle. In Proceedings of the 2015 IEEE Vehicle Power and Propulsion Conference, Montreal, QC, Canada, 19 October 2015; pp. 1–6.
30. Yu, Y.; Jiang, J.; Min, Z.; Wang, P.; Shen, W. Research on Energy Management Strategies of Extended-Range Electric Vehicles Based on Driving Characteristics. *World Electr. Veh. J.* **2020**, *11*, 54. [CrossRef]
31. Jane, R.S.; James, C.; Kim, T. Using AI-ML to Develop Energy and Exergy Flow Characterizations for Multi-Domain Operations. In Proceedings of the Artificial Intelligence and Machine Learning for Multi-Domain Operations Applications, Baltimore, MD, USA, 12 April 2021; Volume 11746, p. 1174628.
32. Nenadic, N.G.; Trabold, T.A.; Thurston, M.G. Cell Replacement Strategies for Lithium-Ion Battery Packs. *Batteries* **2020**, *6*, 39. [CrossRef]
33. Torreglosa, J.P.; Garcia-Triviño, P.; Vera, D.; López-García, D.A. 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? *Appl. Sci.* **2020**, *10*, 8744. [CrossRef]
34. Qi, X.; Wu, G.; Boriboonsomsin, K.; Barth, M.J.; Gonder, J. Data-Driven Reinforcement Learning-Based Real-Time Energy Management System for Plug-In Hybrid Electric Vehicles. *Transp. Res. Rec.* **2016**, *2572*, 1–8. [CrossRef]
35. Xia, W.; Li, H.; Li, B. A Control Strategy of Autonomous Vehicles Based on Deep Reinforcement Learning. In Proceedings of the 9th International Symposium on Computational Intelligence and Design, Hangzhou, China, 10 December 2016; IEEE: Piscataway, NJ, USA, 2016; pp. 198–201.

36. Li, D.; Zhao, D.; Zhang, Q.; Chen, Y. Reinforcement Learning and Deep Learning Based Lateral Control for Autonomous Driving [Application Notes]. *IEEE Comput. Intell. Mag.* **2019**, *14*, 83–98.
37. Bejgam, R.; Sunkari, S.; Keshipeddi, S.B.; Rangaraju, M.R.; Dunde, V. A Brief Study on Hybrid Electric Vehicles. In Proceedings of the 2021 Third International Conference on Inventive Research in Computing Applications (ICIRCA), Coimbatore, India, 15 September 2021; pp. 54–59.
38. Saiteja, P.; Ashok, B. Critical review on structural architecture, energy control strategies and development process towards optimal energy management in hybrid vehicles. *Renew. Sustain. Nergy Rev.* **2022**, *157*, 112038. [CrossRef]
39. Zhang, F.; Hu, X.; Langari, R.; Cao, D. Energy management strategies of connected HEVs and PHEVs: Recent progress and outlook. *Prog. Energy Combust. Sci.* **2019**, *73*, 235–256. [CrossRef]
40. Qi, X.; Luo, Y.; Wu, G.; Boriboonsomsin, K.; Barth, M.J. Deep Reinforcement Learning-Based Vehicle Energy Efficiency Autonomous Learning System. In Proceedings of the 2017 IEEE Intelligent Vehicles Symposium (IV), Los Angeles, CA, USA, 11 June 2017; pp. 1228–1233.
41. Sun, W.; Zou, Y.; Zhang, X.; Guo, N.; Zhang, B.; Du, G. High Robustness Energy Management Strategy of Hybrid Electric Vehicle Based on Improved Soft Actor-Critic Deep Reinforcement Learning. *Energy* **2022**, *258*, 124806. [CrossRef]
42. Lin, Y.; Chu, L.; Hu, J.; Zhang, Y.; Hou, Z. DRL-ECMS: An Adaptive Hierarchical Equivalent Consumption Minimization Strategy Based on Deep Reinforcement Learning. In Proceedings of the 2022 IEEE Intelligent Vehicles Symposium (IV), Aachen, Germany, 4 June 2022; pp. 235–240.
43. Liu, Z.E.; Zhou, Q.; Li, Y.; Shuai, S. An Intelligent Energy Management Strategy for Hybrid Vehicle with Irrational Actions Using Twin Delayed Deep Deterministic Policy Gradient. *IFAC-PapersOnLine* **2021**, *54*, 546–551. [CrossRef]
44. Zhou, J.; Xue, S.; Xue, Y.; Liao, Y.; Liu, J.; Zhao, W. A Novel Energy Management Strategy of Hybrid Electric Vehicle via an Improved TD3 Deep Reinforcement Learning. *Energy* **2021**, *224*, 120118. [CrossRef]
45. Tang, X.; Chen, J.; Pu, H.; Liu, T.; Khajepour, A. Double Deep Reinforcement Learning-Based Energy Management for a Parallel Hybrid Electric Vehicle with Engine Start–Stop Strategy. *IEEE Trans. Transp. Electrif.* **2021**, *8*, 1376–1388. [CrossRef]
46. Gill, S.S.; Xu, M.; Ottaviani, C.; Patros, P.; Bahsoon, R.; Shaghaghi, A.; Golec, M.; Stankovski, V.; Wu, H.; Abraham, A.; et al. AI for Next Generation Computing: Emerging Trends and Future Directions. *Internet Things* **2022**, *19*, 100514. [CrossRef]
47. Du, A.; Han, Y.; Zhu, Z. Review on Multi-Objective Optimization of Energy Management Strategy for Hybrid Electric Vehicle Integrated with Traffic Information. Energy Sources, Part A Recovery Util. *Environ. Eff.* **2022**, *44*, 7914–7933.
48. Liu, T.; Tian, B.; Ai, Y.; Wang, F.Y. Parallel Reinforcement Learning-Based Energy Efficiency Improvement for a Cyber-Physical System. *IEEE/CAA J. Autom. Sin.* **2020**, *7*, 617–626. [CrossRef]
49. Zhang, Y.; Liu, H.; Zhang, Z.; Luo, Y.; Guo, Q.; Liao, S. Cloud Computing-Based Real-Time Global Optimization of Battery Aging and Energy Consumption for Plug-In Hybrid Electric Vehicles. *J. Power Sources* **2020**, *479*, 229069. [CrossRef]
50. Hou, J.; Song, Z. A Hierarchical Energy Management Strategy for Hybrid Energy Storage via Vehicle-to-Cloud Connectivity. *Appl. Energy* **2020**, *257*, 113900. [CrossRef]
51. Chen, J.; Shu, H.; Tang, X.; Liu, T.; Wang, W. Deep Reinforcement Learning-Based Multi-Objective Control of Hybrid Power System Combined with Road Recognition under Time-Varying Environment. *Energy* **2022**, *239*, 122123. [CrossRef]
52. Wang, Y.; Tan, H.; Wu, Y.; Peng, J. Hybrid Electric Vehicle Energy Management with Computer Vision and Deep Reinforcement Learning. *IEEE Trans. Ind. Inform.* **2020**, *17*, 2857–2868. [CrossRef]
53. Zhang, Y.; Huang, Z.; Zhang, C.; Lv, C.; Deng, C.; Hao, D.; Chen, J.; Ran, H. Improved Short-Term Speed Prediction Using Spatiotemporal-Vision-Based Deep Neural Network for Intelligent Fuel Cell Vehicles. *IEEE Trans. Ind. Inform.* **2020**, *17*, 6004–6013. [CrossRef]
54. Tang, X.; Chen, J.; Yang, K.; Toyoda, M.; Liu, T.; Hu, X. Visual Detection and Deep Reinforcement Learning-Based Car Following and Energy Management for Hybrid Electric Vehicles. *IEEE Trans. Transp. Electrif.* **2022**, *8*, 2501–2515. [CrossRef]
55. Zhang, F.; Hu, X.; Liu, T.; Xu, K.; Duan, Z.; Pang, H. Computationally Efficient Energy Management for Hybrid Electric Vehicles Using Model Predictive Control and Vehicle-to-Vehicle Communication. *IEEE Trans. Veh. Technol.* **2021**, *70*, 237–250. [CrossRef]
56. Baker, D.; Asher, Z.; Bradley, T. V2V Communication Based Real-World Velocity Predictions for Improved HEV Fuel Economy. *SAE Tech. Pap.* **2018**, *2018*, 11.
57. Chen, Z.; Xiong, R.; Wang, K.; Jiao, B. Optimal Energy Management Strategy of a Plug-In Hybrid Electric Vehicle Based on a Particle Swarm Optimization Algorithm. *Energies* **2015**, *8*, 3661–3678. [CrossRef]
58. Wu, X.; Cao, B.; Wen, J.; Bian, Y. Particle Swarm Optimization for Plug-In Hybrid Electric Vehicle Control Strategy Parameter. In Proceedings of the 2008 IEEE Vehicle Power and Propulsion Conference, Harbin, China, 3 September 2008; pp. 1–5.
59. Kachroudi, S.; Grossard, M.; Abroug, N. Predictive Driving Guidance of Full Electric Vehicles Using Particle Swarm Optimization. *IEEE Trans. Veh. Technol.* **2012**, *61*, 3909–3919. [CrossRef]
60. Sarma, U.; Ganguly, S. Determination of the Component Sizing for the PEM Fuel Cell-Battery Hybrid Energy System for Locomotive Application Using Particle Swarm Optimization. *J. Energy Storage* **2018**, *19*, 247–259. [CrossRef]