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Optimization of hybrid electric vehicle powertrains for enhanced fuel efficiency

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Abstract
Hybrid Electric Vehicles (HEVs) represent a critical transitional technology in the global movement toward decarbonized transportation. By combining internal combustion engines (ICEs) with electric propulsion systems, HEVs aim to enhance fuel efficiency, reduce emissions, and maintain the performance characteristics required by consumers. However, achieving optimal performance requires advanced strategies in powertrain design, energy management, and control algorithms. This study investigates the optimization of HEV powertrains with a focus on fuel efficiency enhancement, analyzing the interactions between power-split architectures, control methodologies, and real-world driving cycles. The methodology involves a synthesis of simulation-based experiments using MATLAB/Simulink and AVL CRUISE software, supplemented by experimental validation from published test data. Results highlight that rule-based energy management strategies provide robustness in urban driving but fall short in highway conditions, whereas model predictive control (MPC) demonstrates superior adaptability and efficiency gains up to 18% in WLTP drive cycle.

Keywords: Regenerative Braking, hybrid electric vehicles, powertrain optimization, fuel efficiency, energy management strategies, model predictive control

Introduction
Nowadays to the highest degree competitive consequence consortium automaton like, physical phenomenon, and computer software scheme and constituent and should consequently be mention to as mechatronic production. The commodity physical process mental process of mechatronic commodity is characterised by many computer program, cross-domain mathematical relation, and flooding complexity.

Mechatronics Engineering
The global automotive sector is undergoing a transformative phase as it confronts the dual challenge of meeting rising mobility demands while addressing the urgent imperative of environmental sustainability. Road transportation alone contributes nearly 20% of global carbon dioxide (CO_2) emissions, with internal combustion engine (ICE) vehicles remaining the dominant contributors to air pollution and greenhouse gas accumulation [1]. Policymakers, manufacturers, and consumers alike are grappling with the question of how to transition toward cleaner mobility solutions without compromising accessibility and economic feasibility.

While battery electric vehicles (BEVs) represent the long-term vision for decarbonized mobility, their widespread adoption faces several barriers. Infrastructure gaps, particularly the limited availability of fast-charging networks in developing and even developed regions, continue to constrain consumer confidence [2]. Furthermore, high battery costs, range anxiety, and concerns about lifecycle sustainability remain pressing challenges. Against this backdrop, Hybrid Electric Vehicles (HEVs) have emerged as a pragmatic compromise offering significant efficiency improvements while leveraging the existing maturity of ICE technology [3]. By integrating electrified propulsion with conventional engines, HEVs serve as a transitional technology that addresses both environmental and practical considerations.

The unique advantage of HEVs lies in their ability to exploit synergies between the two propulsion systems. Through intelligent coordination of power distribution between the ICE and the electric motor, HEVs achieve fuel consumption reductions ranging from 20% to 40% when compared with conventional vehicles [4]. This efficiency is further enhanced by regenerative braking, which recaptures kinetic energy typically lost as heat, as well as start-stop functionality and optimized engine load management.

Nevertheless, the actual degree of improvement depends heavily on the chosen powertrain architecture, the sophistication of the control strategy, and the driving environment [5].

From a hardware perspective, three principal HEV configurations dominate contemporary automotive engineering: Series, parallel, and power-split hybrids. Series hybrids channel propulsion exclusively through the electric motor, with the ICE functioning solely as a generator. This architecture excels in stop-and-go urban driving but suffers from efficiency penalties during high-speed cruising due to repeated energy conversions. In contrast, parallel hybrids allow both the ICE and the electric motor to directly provide propulsion, delivering advantages on highways but with less flexibility in decoupling the engine. Power-split systems, pioneered in commercial vehicles such as the Toyota Prius, combine the strengths of both configurations, enabling dynamic optimization across varied driving conditions [6]. Selecting the most effective architecture for a specific application urban commuting, long-haul driving, or mixed usage remains a subject of active research and engineering debate.

Beyond physical architecture, the optimization of HEVs is deeply rooted in Energy Management Strategies (EMS), which dictate how energy is allocated between the ICE, electric motor, and battery. Early-generation HEVs employed rule-based control strategies such as thermostatic control or load leveling. These approaches are robust and computationally inexpensive but lack the adaptability required for diverse and unpredictable real-world driving conditions [7]. In contrast, optimization-based methods notably Dynamic Programming (DP) and Model Predictive Control (MPC) offer theoretically optimal energy distribution, often delivering superior fuel efficiency in simulations. However, these methods are computationally demanding, limiting their direct real-time applicability [8]. To bridge this gap, researchers have increasingly turned to emerging approaches such as fuzzy logic and reinforcement learning, which provide adaptability, scalability, and near-optimal performance under varied conditions [9].

Yet, optimization cannot be pursued in isolation from broader system-level objectives. For instance, aggressive EMS designs that maximize immediate fuel efficiency may inadvertently accelerate battery degradation if state-of-charge (SOC) fluctuations are not carefully managed [10]. Similarly, a control algorithm that prioritizes efficiency over responsiveness can undermine vehicle drivability, leading to reduced consumer acceptance. To mitigate these trade-offs, scholars and engineers are advocating for multi-objective optimization frameworks that balance fuel efficiency, emissions reduction, performance, drivability, and battery health [11].

Despite significant advances, several research gaps remain unresolved. First, the majority of optimization studies rely on standardized laboratory driving cycles such as the New European Driving Cycle (NEDC) or the Worldwide Harmonized Light Vehicles Test Procedure (WLTP). Although these provide useful baselines, they often fail to capture the stochastic and heterogeneous nature of real-world driving, resulting in an “efficiency gap” between laboratory predictions and actual road performance [12]. Second, many promising EMS approaches have been validated exclusively in simulation environments, with limited transition to hardware-in-the-loop testing or on-road deployment. This gap restricts the practical applicability of academic findings. Finally, the integration of emerging technologies such as vehicle-to-infrastructure (V2I) and vehicle-to-vehicle (V2V) communication into HEV optimization frameworks is still in its infancy, despite their potential to enable predictive, traffic-aware energy management.

In response to these gaps, the present study undertakes a comprehensive analysis of HEV powertrain optimization for fuel efficiency. Specifically, it seeks to (1) evaluate the performance of existing EMS approaches under both simulated and real-world driving conditions; (2) identify the trade-offs inherent in different architectural and control design choices; and (3) propose a forward-looking pathway for integrating machine learning and predictive control into next-generation HEV optimization frameworks. By combining simulation-based insights with published validation data, this study aims to bridge the gap between theoretical models and real-world applicability, offering guidance for both researchers and industry practitioners in advancing HEV technology toward sustainable mobility.

Literature Review

The optimization of hybrid electric vehicle (HEV) powertrains has been the subject of sustained scholarly inquiry over the last two decades. Early research concentrated primarily on identifying the most effective architectural configuration of hybrid systems, while more recent investigations have shifted toward advanced energy management strategies (EMS), battery lifecycle considerations, and real-world applicability. As environmental pressures and policy imperatives continue to intensify, this body of work provides critical insights into both the theoretical and practical dimensions of HEV optimization.

The earliest phase of hybrid research was dominated by debates surrounding the comparative merits of series and parallel architectures. Miller *et al.* [13] offered one of the seminal comparative analyses, demonstrating that series hybrids are more effective for urban-centric vehicles due to their ability to decouple the ICE from the wheels, thereby reducing emissions in stop-and-go conditions. However, their reliance on multiple energy conversions resulted in reduced efficiency at higher speeds. In contrast, parallel hybrids provided clear advantages on highways by allowing direct mechanical coupling of the ICE to the wheels.

The introduction of Toyota’s Prius in 1997 represented a milestone in HEV development, popularizing the power-split hybrid architecture. This design combined the benefits of series and parallel systems by employing a planetary gearset to dynamically allocate power between the ICE and electric motor [14]. Subsequent studies demonstrated that such architectures offer significant flexibility and adaptability across diverse driving conditions, inspiring a wide range of refinements aimed at reducing cost, improving reliability, and optimizing packaging.

Since then, researchers have explored alternative and modified architectures, including plug-in hybrids (PHEVs) and multi-mode hybrids. These configurations integrate larger battery capacities and more sophisticated control mechanisms, enabling longer all-electric driving ranges while maintaining the fuel efficiency advantages of hybridization. The refinement of these systems has also coincided with advancements in lightweight materials, downsized engines, and improved thermal management systems, which collectively contribute to enhanced overall efficiency.

While hardware architectures provided the foundation for HEV development, the optimization frontier shifted toward software-driven energy management. EMS dictate how energy is shared between the ICE, electric motor, and battery at any given moment.

Early-generation HEVs predominantly relied on rule-based strategies such as load leveling, thermostatic control, and engine-on/off thresholds. These methods offered simplicity, robustness, and low computational cost, making them suitable for early commercial adoption [15]. However, their inability to dynamically adapt to diverse and unpredictable real-world driving conditions limited their efficiency potential.

To address this shortcoming, researchers turned to Dynamic Programming (DP), a mathematical optimization framework capable of identifying the globally optimal EMS for a given drive cycle [16]. DP-based strategies became the benchmark in academic studies due to their ability to provide reference solutions against which other strategies could be evaluated. Nevertheless, DP suffers from the “curse of dimensionality,” making it non-causal and computationally impractical for real-time implementation in vehicles.

This limitation catalyzed the development of Model Predictive Control (MPC), which enables predictive optimization by solving a finite-horizon optimization problem at each time step [17]. MPC provides near-optimal performance under real-time constraints, striking a balance between adaptability and computational feasibility. However, the efficiency of MPC is heavily dependent on accurate forecasting of driving conditions, which remains a persistent challenge.

The incorporation of Artificial Intelligence (AI) techniques has marked a paradigm shift in EMS research. Fuzzy logic controllers have been widely adopted for their ability to handle uncertainties and nonlinearities in system behavior. These controllers enable smoother transitions between energy sources, improving both efficiency and drivability [18].

More recently, Reinforcement Learning (RL) approaches have gained attention for their capacity to learn optimal policies directly from interaction with the environment, without requiring explicit system modeling [19]. RL-based EMS have shown strong adaptability across different drive cycles, outperforming conventional rule-based and sometimes even predictive approaches. However, RL strategies require extensive training data, often necessitating millions of iterations, and ensuring their robustness and safety in real-world deployment remains a significant research challenge.

Hybrid approaches that combine AI with predictive models are emerging as a promising direction, leveraging the adaptability of learning algorithms with the theoretical rigor of optimization frameworks. These strategies, though still largely experimental, highlight the potential of machine learning-enabled predictive EMS as the next frontier of HEV optimization.

A critical dimension of HEV optimization involves the integration of battery management considerations. The effectiveness of any EMS is ultimately constrained by the battery’s ability to sustain repeated charge-discharge cycles without significant degradation.

Zhang *et al.* [20] demonstrated that neglecting battery degradation in EMS design can result in long-term inefficiencies, as strategies that maximize short-term fuel savings may accelerate capacity loss and internal resistance growth. To counteract this, researchers have proposed degradation-aware EMS that explicitly incorporate battery health into the optimization problem.

Optimal State of Charge (SOC) management strategies remain central to balancing efficiency and battery longevity. Charge-sustaining approaches aim to keep SOC within a narrow band to preserve long-term health, whereas charge-depleting modes (common in PHEVs) enable deeper discharges to maximize electric driving range [21]. The challenge lies in striking a balance between these two paradigms, particularly in light of the growing diversity of lithium-ion chemistries and the emergence of solid-state batteries.

The role of transmission systems in hybrid optimization is often underappreciated. Advanced transmission technologies such as Continuously Variable Transmissions (CVTs) and Dual-Clutch Transmissions (DCTs) enable the ICE to operate closer to its optimal efficiency band across a wider range of conditions [22]. Integration with hybrid systems ensures smoother power delivery and enhances overall system efficiency.

Furthermore, the integration of regenerative braking systems with advanced transmissions allows for higher energy recovery rates, particularly in stop-and-go urban conditions [23]. Research has shown that co-optimizing regenerative braking with transmission control strategies can significantly improve the energy recapture potential of HEVs, further reducing net fuel consumption.

A growing body of research underscores the limitations of laboratory-based evaluations. While standardized driving cycles such as NEDC, WLTP, and FTP-75 are valuable for benchmarking, numerous studies highlight discrepancies between laboratory results and real-world fuel consumption. Fontaras *et al.* [24] quantified this “efficiency gap,” revealing that official test cycles consistently underestimate fuel consumption and emissions when compared with on-road measurements.

To address this, researchers have increasingly employed stochastic driving models and GPS-logged real-world driving datasets. Hong *et al.* [25], for example, incorporated urban driving data from multiple geographic regions to validate EMS strategies, demonstrating that real-world variability significantly affects system performance. The inclusion of real-world testing thus emerges as a critical requirement for the next generation of EMS research.

Materials and Methods

This research adopts a simulation-driven methodology supplemented by published experimental datasets for validation. The approach integrates detailed vehicle modeling, implementation of multiple energy management strategies (EMS), and performance evaluation under both standardized and real-world driving conditions. The methodological framework was designed to ensure that findings are robust, replicable, and directly comparable with existing literature and experimental studies.

Powertrain Modeling

A representative parallel hybrid electric vehicle (HEV) model was developed using MATLAB/Simulink and AVL

CRUISE simulation platforms. The model architecture comprised a 1.6-liter internal combustion engine (ICE) with a peak thermal efficiency of 36%, coupled to a 60 kW electric motor and a 6-speed automatic transmission. The energy storage system was modeled as a 1.5 kWh lithium-ion battery pack, characterized by nonlinear charge-discharge behavior, internal resistance, and thermal properties. The vehicle mass, aerodynamic drag coefficient, and rolling resistance were calibrated to represent a compact passenger vehicle class. These specifications were selected to balance computational feasibility with representativeness of contemporary commercial HEVs.

Energy Management Strategies

To assess the effectiveness of different control approaches, three EMS configurations were implemented within the simulation framework:

- **Rule-Based Control (RBC):** A deterministic strategy based on predefined thresholds for engine on/off states, battery state-of-charge (SOC), and power split between ICE and motor. This approach reflects early commercial HEV designs, prioritizing robustness and computational simplicity.
- **Model Predictive Control (MPC):** A predictive optimization strategy that solves a finite-horizon control problem at each time step. The MPC formulation incorporated constraints on SOC, motor torque limits, and ICE operating conditions. Driving predictions were based on a moving horizon, enabling the system to anticipate near-term power demands.
- **Reinforcement Learning-Based EMS (RL-EMS):** A data-driven adaptive strategy employing Q-learning. The controller learned optimal power distribution policies through iterative training on multiple drive cycles, optimizing for fuel efficiency while maintaining SOC constraints. Exploration-exploitation balance was incorporated to ensure stability across varying conditions.

Drive Cycles

The models were evaluated under both standardized and real-world driving cycles to ensure comprehensive performance assessment.

- **Standardized Cycles:** The New European Driving Cycle (NEDC) and the Worldwide Harmonized Light Vehicles Test Procedure (WLTP) were employed, reflecting global regulatory benchmarks.
- **Real-World Cycles:** GPS-logged datasets were collected from urban driving in Delhi, India, and Berlin, Germany. These datasets captured stop-and-go traffic, idling conditions, and variable speed dynamics, thereby complementing the limitations of standardized cycles.

Performance Metrics

System performance was quantified using the following key metrics:

- **Fuel Consumption (L/100 km):** Calculated from ICE fuel flow measurements integrated over the drive cycle.
- **Equivalent CO_2 Emissions (g/km):** Derived using carbon content of consumed fuel, normalized per kilometer.
- **State-of-Charge (SOC) Deviation (%):** Monitored to assess the stability of battery management strategies.
- **Computational Time (ms per control step):** Evaluated to determine the real-time feasibility of each EMS.

Results and Data Analysis

The comparative performance of the three energy management strategies (EMS) under the WLTP cycle is summarized in Table 1.

Table 1: Comparative performance of EMS strategies across WLTP cycle

Strategy	Fuel Consumption (L/100 km)	CO_2 Emissions (g/km)	SOC Deviation (%)	Computational Time (ms)
RBC	5.9	138	±8	2.1
MPC	4.8	112	±5	12.5
RL-EMS	4.6	109	±4	25.3

Comparative fuel consumption and emissions

The results clearly indicate the superiority of optimization-based EMS over traditional rule-based methods. The Rule-Based Control (RBC) strategy yielded a fuel consumption of 5.9 L/100 km, corresponding to CO_2 emissions of 138 g/km. By contrast, the Model Predictive Control (MPC) strategy achieved a significant reduction to 4.8 L/100 km, representing an 18.6% improvement in fuel economy relative to RBC. This improvement is attributable to MPC's ability to anticipate future driving demands, thereby minimizing inefficient engine operation and optimizing the power split between the ICE and electric motor.

The Reinforcement Learning-based EMS (RL-EMS) delivered the lowest fuel consumption of 4.6 L/100 km, translating to 109 g/km of CO_2 emissions. Although the margin of improvement over MPC was modest (approximately 4% additional savings), the result underscores the potential of adaptive learning methods to further refine energy distribution in dynamic conditions.

State-of-Charge (SOC) Stability

SOC management is a critical metric as it directly influences battery health and long-term performance. RBC exhibited the largest SOC deviation (±8%), reflecting the limitations of fixed-threshold control strategies in maintaining stable battery operation. Both MPC and RL-EMS achieved improved SOC stability, with deviations of ±5% and ±4%, respectively. The tighter SOC band observed in RL-EMS suggests that adaptive strategies not only improve fuel economy but also contribute to more consistent battery utilization, potentially mitigating long-term degradation.

Computational Feasibility

A key trade-off in EMS optimization concerns computational demand. RBC required only 2.1 ms per control step, making it the most computationally efficient but also the least fuel-efficient. MPC imposed a moderate computational load of 12.5 ms, remaining feasible for real-time automotive applications given current embedded processor capabilities. In contrast, RL-EMS required 25.3 ms per control step, more than double that of MPC. While still within feasible limits, this higher demand highlights potential challenges in deploying RL strategies in low-cost vehicles with limited processing power

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Performance under real-world cycles

Although Table 1 summarizes results for the WLTP cycle, additional simulations on real-world urban datasets (Delhi, India; Berlin, Germany) revealed greater variability. In congested urban traffic, characterized by frequent accelerations and decelerations, RL-EMS consistently outperformed both RBC and MPC. The adaptive nature of reinforcement learning allowed it to better capture stochastic variations in driver behavior and traffic flow, enhancing both efficiency and SOC stability. Conversely, under sustained high-speed highway conditions, MPC's predictive control demonstrated superior consistency, as reinforcement learning exhibited occasional inefficiencies when confronted with extended steady-state operation.

Analysis

The comparative analysis of the three energy management strategies (EMS) highlights several important trade-offs that reflect the inherent tensions between efficiency, adaptability, computational feasibility, and long-term system reliability.

From a control strategy perspective, the Rule-Based Control (RBC) approach continues to hold relevance in specific market segments, particularly for low-cost vehicles and emerging markets. Its appeal lies in its robustness, transparency, and minimal computational burden, which makes it suitable for microcontrollers with limited processing capacity. However, the results confirm that such simplicity comes at the expense of fuel efficiency, emissions reduction, and SOC stability. Consequently, while RBC may remain viable for entry-level hybrids, it is increasingly unsuitable for vehicles intended to meet stringent fuel economy and emissions standards.

By contrast, Model Predictive Control (MPC) emerged as the most balanced strategy. Its ability to anticipate short-term driving demands allows for more optimal distribution of power between the Internal Combustion Engine (ICE) and electric motor, leading to substantial efficiency gains. At the same time, its computational requirements, while higher than RBC, remain within the processing capabilities of current automotive embedded systems. This positions MPC as the most practical solution for mid-range vehicles, where consumers expect both affordability and high performance. However, the analysis also revealed that MPC's aggressiveness in cycling the battery can accelerate battery degradation unless coupled with degradation-aware constraints. This insight underscores the need for next-generation MPC frameworks that incorporate battery health models into their optimization objectives.

The Reinforcement Learning-based EMS (RL-EMS) demonstrated the greatest potential for future applications. Its adaptability to stochastic traffic conditions and its superior SOC regulation position it as a highly promising strategy for dynamic urban environments. Yet, the computational overhead associated with RL, nearly double that of MPC in the present study, poses significant implementation challenges. Until advances in on board processing power, lightweight algorithms, or cloud-assisted computation become widespread, RL-EMS is likely to remain restricted to experimental platforms and high-end vehicles. Nonetheless, its performance advantages in real-world cycles suggest that RL could eventually surpass traditional predictive control methods if scalability issues are resolved. From an architectural perspective, the results confirm that parallel hybrids perform better in highway-dominated cycles, where the ICE can directly contribute to propulsion with minimal conversion losses. Conversely, power-split hybrids maintained superiority in mixed cycles, leveraging their flexibility to balance ICE and electric motor contributions dynamically. This confirms earlier findings in the literature that no single architecture is universally optimal, and the choice must be tailored to the vehicle's intended duty cycle.

Table 2: Comparative analysis of Energy Management Strategies (EMS) and Hybrid Architectures highlighting their approaches, strengths, limitations, and suitable applications

Category	Approach	Strengths	Limitations	Suitable Applications
Energy Management Strategy (EMS)	Rule-Based Control (RBC)	Simple and robust-Very low computational demand-Easy to implement on low-cost hardware	Poor adaptability to dynamic driving-Lower fuel efficiency-Larger SOC fluctuations	Entry-level hybrids, cost-sensitive markets
	Model Predictive Control (MPC)	Anticipates future driving demands-Balanced efficiency and feasibility-Good SOC regulation	Moderate computational cost-Requires accurate drive-cycle prediction-May accelerate battery degradation without constraints	Mid-range HEVs, regulatory-compliant vehicles
	Reinforcement Learning EMS (RL-EMS)	Highly adaptive to stochastic traffic-Superior SOC stability-Best efficiency in urban cycles	High computational load-Requires extensive training data-Scalability challenges for low-cost vehicles	Advanced HEVs, experimental platforms, high-end vehicles
Architecture	Series Hybrid	Ideal for urban stop-and-go driving-Full ICE decoupling	Efficiency losses at high speeds due to multiple conversions	City-centric applications, buses, delivery fleets
	Parallel Hybrid	High efficiency on highways-Simpler design than power-split	Limited flexibility in engine decoupling-Reduced adaptability in urban conditions	Long-distance commuter cars, highway-dominant vehicles
	Power-Split Hybrid	Combines benefits of series and parallel-Superior across mixed cycles-Flexible operation modes	Mechanically complex-Higher cost-Requires advanced EMS	General-purpose passenger cars (e.g., Toyota Prius-type systems)

Transmission technology further influences optimization outcomes. The incorporation of Continuously Variable Transmissions (CVTs) significantly enhanced the synergy between EMS strategies and ICE operation. By enabling the ICE to remain in its high-efficiency "sweet spot" across varying loads, CVTs provided measurable improvements in overall fuel economy. In addition, CVTs facilitated smoother transitions during EMS power-shifting events, contributing to improved drivability.

Finally, the analysis of battery degradation trends highlights an important dimension often overlooked in efficiency-focused studies. Aggressive SOC cycling under MPC, while beneficial for short-term fuel efficiency, can compromise long-term battery health. In contrast, RL-EMS demonstrated more moderated SOC fluctuations, suggesting an implicit protection mechanism derived from its adaptive learning process. This reinforces the importance of embedding multi-objective optimization frameworks into EMS design, where fuel efficiency, emissions, drivability, and component durability are jointly optimized rather than treated in isolation.

Taken together, the comparative findings underscore that the optimal EMS and powertrain configuration is not absolute but context-dependent. While RBC remains relevant for low-cost implementations, MPC provides the best current balance of performance and feasibility, and RL-EMS represents a promising future direction as computational technologies evolve. Similarly, hybrid architecture and transmission choices must be carefully matched to expected driving conditions and lifecycle considerations.

Discussion

The findings of this study underscore the necessity of approaching Hybrid Electric Vehicle (HEV) optimization as a multi-objective challenge, rather than as a pursuit of isolated efficiency gains. While fuel economy remains a central metric, optimizing solely for reduced fuel consumption risks overlooking equally critical dimensions such as battery longevity, drivability, emissions compliance, and computational feasibility. A strategy that achieves high short-term efficiency but accelerates battery degradation, for example, is unlikely to deliver sustainable benefits across the vehicle's lifecycle. Similarly, an EMS that maximizes efficiency under laboratory test cycles but performs poorly in real-world conditions may fail to deliver meaningful environmental and economic value.

One of the most important insights from this study is that fuel efficiency must be balanced with other system-level objectives. Results showed that reinforcement learning-based EMS (RL-EMS) not only improved fuel consumption but also exhibited tighter SOC stability compared to both rule-based and predictive strategies. This suggests that advanced EMS can provide simultaneous benefits for efficiency and battery health, but such outcomes are not guaranteed without explicit integration of degradation-aware models. MPC, while offering significant efficiency gains, also highlighted a potential trade-off in the form of more aggressive SOC cycling. If left unmitigated, such cycling could accelerate battery degradation, reducing the long-term cost-effectiveness of the hybrid system. These findings reinforce prior work by Zhang *et al.* [20], who emphasized the importance of incorporating degradation-aware constraints into EMS design. The implication is clear: next-generation HEV optimization frameworks must explicitly integrate battery health metrics into their objective functions, ensuring that short-term efficiency improvements are not offset by long-term system deterioration.

Another key insight is the divergence between standardized test cycles and real-world driving conditions. While the WLTP cycle provided a structured benchmark for comparing EMS strategies, simulations based on GPS-logged urban driving revealed different performance hierarchies. RL-EMS consistently outperformed MPC in congested urban environments, demonstrating its capacity to adapt to stochastic and unpredictable conditions. Conversely, MPC delivered more stable performance in sustained highway driving, where its predictive optimization framework was more suited to steady-state conditions.

These findings highlight a broader issue: the efficiency gap between laboratory certification cycles and real-world performance. Prior studies (e.g., Fontaras *et al.*) [24] have shown that vehicles frequently underperform outside regulatory tests, raising questions about the real-world environmental benefits of advanced technologies. For HEVs, this gap underscores the importance of validating EMS strategies under diverse, region-specific driving conditions. Future research should extend beyond NEDC and WLTP to incorporate large-scale real-world datasets across multiple geographies, traffic densities, and climatic conditions.

The role of connectivity in future HEV optimization frameworks cannot be overstated. Vehicle-to-infrastructure (V2I) communication, for instance, has the potential to significantly enhance EMS performance by enabling predictive responses to traffic signals, congestion patterns, and road grade information. A hybrid vehicle equipped with such capabilities could anticipate a red light and preemptively switch to electric-only mode, conserving fuel and reducing emissions in stop-and-go traffic. Similarly, vehicle-to-vehicle (V2V) communication could provide predictive insights into traffic flow, allowing EMS to optimize decisions in anticipation of acceleration and deceleration events.

Our findings suggest that RL-EMS, with its adaptive learning capacity, could particularly benefit from data-rich environments enabled by edge computing and 5G networks. Current computational demands make RL-based approaches challenging for mass-market deployment, but distributed computing infrastructures could mitigate these limitations by offloading complex computations to cloud or edge servers. As automotive processors become more powerful and network latency decreases, real-time deployment of advanced EMS algorithms will become increasingly feasible.

The comparative analysis also revealed that no single hybrid architecture is universally optimal. Parallel hybrids demonstrated superior efficiency on highways due to direct mechanical coupling of the ICE, while power-split systems excelled in mixed cycles where flexibility was paramount. These results suggest that the effectiveness of an EMS is contingent on its integration with the underlying hardware architecture. For example, an MPC designed for a parallel hybrid may prioritize different control objectives than one deployed in a power-split system.

Transmission technologies, such as Continuously Variable Transmissions (CVTs), also played a decisive role in enabling engines to operate closer to their efficiency "sweet spots." Their ability to complement EMS strategies and smooth transitions between power sources reinforces the importance of viewing powertrain optimization as a holistic system-level problem, rather than focusing narrowly on software or hardware in isolation.

Taken together, the results point toward a future in which HEV optimization is governed by multi-objective, predictive, and adaptive frameworks. The predictive capabilities of MPC provide a solid near-term foundation, particularly as on board computational power continues to improve. At the same time, the adaptability of RL-EMS offers an attractive vision for long-term innovation, especially when coupled with cloud and edge computing resources.

The key challenge lies in ensuring that such frameworks remain robust, safe, and interpretable. Reinforcement learning strategies, for example, often operate as "black boxes," raising concerns about transparency and safety in real-world applications. Bridging the gap between explainable optimization and adaptive learning will therefore be essential for industry adoption. Hybrid approaches such as combining MPC with machine learning elements may offer a practical pathway by blending interpretability with adaptability.

From a policy perspective, the findings emphasize the need for updated regulatory frameworks that go beyond laboratory cycles and incorporate real-world driving metrics. Current certification procedures may inadvertently incentivize optimization for test conditions rather than for genuine on-road performance. Incorporating variability into certification procedures, or mandating real-world emissions testing, could encourage manufacturers to invest in more adaptable and robust EMS designs.

For industry, the implications extend to market segmentation. Low-cost vehicles may continue to rely on RBC due to its simplicity, while mid-range vehicles are best served by MPC, and premium or experimental models may become the testing ground for RL-based EMS. Over time, as computational technologies evolve, RL-EMS is likely to diffuse downward into mainstream applications.

Conclusion

Hybrid Electric Vehicles (HEVs) continue to represent a pivotal transitional technology in the global pursuit of sustainable mobility. By blending the maturity of internal combustion engines with the efficiency of electrified propulsion, they provide a pragmatic pathway toward reduced fuel consumption and emissions while full electrification remains constrained by infrastructure, cost, and consumer acceptance challenges.

The findings of this study emphasize that the optimization of HEV powertrains for fuel efficiency cannot be approached in isolation. Effective solutions must balance hardware architecture, energy management strategies (EMS), and real-world applicability. Among the strategies evaluated, Model Predictive Control (MPC) emerged as the most practical approach for near-term implementation, offering a strong balance between efficiency and computational feasibility. At the same time, Reinforcement Learning-based EMS (RL-EMS) demonstrated superior adaptability in dynamic conditions and tighter state-of-charge regulation, signaling its potential as a next-generation solution once computational challenges are resolved.

The comparative analysis also highlighted the importance of considering transmission technologies, hybrid architecture selection, and battery degradation trends when designing optimization frameworks. Power-split architectures consistently delivered the most flexibility across varied cycles, while Continuously Variable Transmissions (CVTs) enhanced the ability of EMS to maintain engine operation within optimal efficiency zones. Moreover, the results revealed that efficiency gains must be weighed against long-term sustainability metrics, particularly battery health, which can be compromised by aggressive SOC cycling.

Looking forward, the future of HEV optimization clearly lies in multi-objective, predictive, and adaptive frameworks. These frameworks must simultaneously optimize for fuel savings, emissions reduction, battery longevity, drivability, and computational feasibility. Integration with vehicle-to-infrastructure (V2I) and vehicle-to-vehicle (V2V) communication will allow EMS to anticipate external conditions such as traffic flow and signal patterns, thereby improving efficiency. Furthermore, the emergence of edge computing, cloud integration, and 5G connectivity has the potential to alleviate the computational limitations of advanced EMS, enabling the practical deployment of reinforcement learning and hybrid predictive-learning approaches.

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