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05.01.00 – Axborot texnologiyalari, boshqaruv va kompyuter grafikasi
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05.01.05 – Axborotlarni himoyalash usullari va tizimlari. Axborot xavfsizligi
05.01.06 – Hisoblash texnikasi va boshqaruv tizimlarining elementlari va qurilmalari
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05.01.11 – Raqamli texnologiyalar va sun’iy intellekt
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05.03.02 – Metrologiya va metrologiya ta’minoti
05.04.01 – Telekommunikasiya va kompyuter tizimlari, telekommunikasiya tarmoqlari va qurilmalari. Axborotlarni taqsimlash
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08.00.03 – Sanoat iqtisodiyoti
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08.00.15 – Tadbirkorlik va kichik biznes iqtisodiyoti
08.00.16 – Raqamli iqtisodiyot va xalqaro raqamli integratsiya
08.00.17 – Turizm va mehmonxona faoliyati

Ma’lumot uchun, OAK Rayosatining 2024-yil 28-avgustdagi 360/5-son qarori bilan “Dissertatsiyalar asosiy ilmiy natijalarini chop etishga tavsiya etilgan milliy ilmiy nashrlar ro‘yxati”ga texnika va iqtisodiyot fanlari bo‘yicha “Muhandislik va iqtisodiyot” jurnali ro‘yxatga kiritilgan.

Muassis: “Tadbirkor va ishbilarmon” MChJ

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ENERGY MANAGEMENT STRATEGIES FOR HYBRID ELECTRIC VEHICLES: A COMPREHENSIVE REVIEW

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Abstract. Hybrid electric vehicles (HEVs) rely on advanced energy management systems (EMS) to optimally coordinate power flow between multiple energy sources, thereby enhancing fuel efficiency and reducing emissions. This comprehensive review examines 304 peer-reviewed publications, with an in-depth analysis of 30 highly relevant studies published between 2009-2024. Four principal EMS categories are identified: optimization-based methods, predictive control strategies, learning-based techniques, and hybrid approaches. Recent findings report fuel economy improvements of 4.7-13.2% and battery life extensions of up to 54.9%. The analysis reveals a clear transition toward intelligent, adaptive, and real-time control frameworks. In particular, hybrid architectures integrating reinforcement learning with model predictive control demonstrate strong potential for practical implementation and next-generation vehicle integration.

Keywords: Hybrid electric vehicles; Energy management systems; Model predictive control; Reinforcement learning; Optimization methods; Intelligent control; Multi-objective optimization; Real-time implementation.

Annotatsiya. Gibrid elektr transport vositalari (HEV) bir nechta energiya manbalari oʻrtasida quvvat oqimini optimal boshqarish orqali yoqilgʻi samaradorligini oshirish va chiqindilarni kamaytirishda energiyani boshqarish tizimlariga (EMS) tayanadi. Ushbu ilmiy sharh 2009-2024-yillar oraligʻida chop etilgan 304 ta taqrizdan oʻtgan maqolani qamrab oladi hamda ularning ichidan 30 ta eng dolzarb tadqiqot chuqur tahlil qilindi. EMSning toʻrtta asosiy yoʻnalishi aniqlangan: optimallashtirishga asoslangan usullar, bashoratli boshqaruv strategiyalari, oʻrganishga asoslangan metodlar va gibrid yondashuvlar. Soʻnggi tadqiqotlar yoqilgʻi sarfini 4.7-13.2% gacha kamaytirish hamda batareya xizmat muddatini 54.9% gacha uzaytirish imkonini koʻrsatadi. Tahlillar intellektual va moslashuvchan real vaqtli boshqaruv tizimlariga oʻtish tendensiyasini tasdiqlaydi. Xususan, mustahkamlovchi oʻrganish va modelga asoslangan bashoratli boshqaruvni birlashtirgan gibrid arxitekturalar amaliy joriy etish uchun yuqori salohiyatga ega.

Kalit soʻzlar: Gibrid elektr transport vositalari; Energiya boshqaruv tizimi; Modelga asoslangan bashoratli boshqaruv; Mustahkamlovchi oʻrganish; Optimallashtirish usullari; Intellektual boshqaruv; Koʻp mezonli optimallashtirish; Real vaqtli boshqaruv.

Аннотация. Гибридные электрические транспортные средства (HEV) опираются на современные системы управления энергией (EMS) для оптимального распределения мощности между несколькими источниками энергии, что способствует повышению топливной экономичности и снижению выбросов. В данном обзоре проанализированы 304 рецензируемые публикации, из которых 30 наиболее значимых исследований, опубликованных в 2009-2024 гг., рассмотрены детально. Выделены четыре основные категории EMS: методы, основанные на оптимизации, стратегии предиктивного управления, методы обучения и гибридные подходы. Современные исследования демонстрируют снижение расхода топлива на 4.7-13.2% и увеличение срока службы аккумуляторов до 54.9%. Результаты свидетельствуют о переходе к интеллектуальным, адаптивным системам управления в реальном времени. Наибольший потенциал для практической реализации демонстрируют гибридные решения, объединяющие методы обучения с подкреплением и модельно-прогнозирующее управление.

Ключевые слова: Гибридные электрические транспортные средства; Система управления энергией; Модельно-прогнозирующее управление; Обучение с подкреплением; Методы оптимизации; Интеллектуальное управление; Многокритериальная оптимизация; Управление в реальном времени.

INTRODUCTION

The transportation sector accounts for approximately 24% of global energy-related CO_2 emissions, highlighting the strategic importance of developing fuel-efficient and low-emission vehicle technologies as a cornerstone of sustainable development. Hybrid electric vehicles (HEVs) provide an effective and technologically viable solution by integrating internal combustion engines (ICE) with electric propulsion systems, thereby significantly enhancing fuel efficiency and reducing environmental impact compared to conventional vehicles. The overall performance and efficiency of HEVs largely depend on the energy management system (EMS), which governs the real-time power distribution between the engine and electric motor(s) to satisfy driver demand while simultaneously optimizing multiple performance objectives.

The energy management problem in HEVs is inherently complex due to nonlinear system dynamics, multiple operating modes, stochastic driving conditions, and the need to balance competing objectives such as fuel consumption minimization, battery health preservation, emission reduction, and drivability enhancement. Over the past two decades, substantial research efforts have led to the development of increasingly advanced EMS methodologies, progressing from conventional rule-based strategies toward intelligent learning-based and predictive control approaches capable of adapting to varying driving conditions and achieving near-optimal real-time performance.

This review presents a comprehensive and systematic analysis of state-of-the-art energy management strategies for HEVs by synthesizing findings from 304 peer-reviewed publications, including an in-depth examination of the 30 most relevant studies. The analysis focuses on the evolution of fundamental EMS approaches, comparative evaluation of different methodologies in terms of fuel economy, computational efficiency, and real-time applicability, architecture-specific considerations across various HEV configurations, and the emerging technological trends that are shaping the future development of intelligent energy management systems.

LITERATURE REVIEW

Hybrid electric vehicles (HEVs) are categorized into several architectural configurations, each characterized by distinct structural features that create specific energy management requirements and performance opportunities. The principal HEV architectures include series, parallel, series-parallel (power-split), plug-in hybrid, and fuel cell hybrid configurations.

In a series hybrid configuration, the internal combustion engine (ICE) drives a generator that produces electrical energy to power the electric motor or charge the battery. Since the engine is mechanically decoupled from the wheels, it can operate within its optimal efficiency range, thereby enhancing overall system efficiency. This configuration is particularly well suited for urban driving conditions characterized by frequent stop-and-go operation [13].

In a parallel hybrid configuration, both the engine and the electric motor are mechanically connected to the drivetrain, enabling either or both power sources to propel the vehicle. This architecture provides considerable flexibility in power distribution; however, it requires advanced coordination strategies to ensure efficient interaction between the two propulsion sources [7], [23].

The series-parallel (power-split) configuration integrates the advantages of both series and parallel architectures through the use of a planetary gear set, which enables continuously variable power distribution between mechanical and electrical paths. This configuration, exemplified by the Toyota Prius, achieves high fuel efficiency while offering operational versatility. At the same time, it introduces increased control complexity due to multiple operating modes and power flow paths [2], [30].

Plug-in hybrid electric vehicles (PHEVs) expand conventional HEV architectures by incorporating larger battery packs that can be charged from external power sources, allowing extended all-electric driving capability. Energy management in PHEVs must effectively coordinate charge-depleting and charge-sustaining operating modes to maximize efficiency and battery longevity [12], [21].

Fuel cell hybrid electric vehicles (FCHEVs) employ hydrogen fuel cells as the primary energy source, complemented by batteries or supercapacitors to handle peak power demands and regenerative braking. In this architecture, energy management strategies must carefully balance hydrogen consumption, fuel cell durability, and overall system efficiency to ensure sustainable performance [14], [22].

Figure 1 presents the distribution of HEV architectures examined in the reviewed literature. The analysis indicates that power-split configurations (20%) and parallel architectures (16.7%) represent the most extensively investigated platforms, reflecting their practical relevance and technological maturity within contemporary hybrid vehicle development (Figure 1).

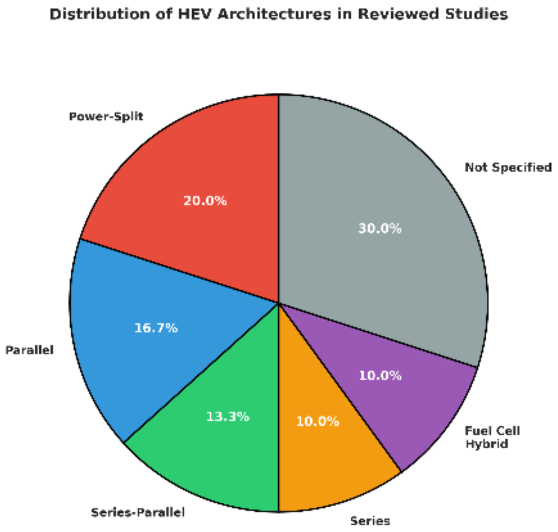

Figure 1. Distribution of HEV architectures in reviewed studies (n=30).

The energy management problem in HEVs is typically formulated as an optimal control problem. The objective is to minimize a cost function over a driving cycle while satisfying system constraints. The general formulation can be expressed as:

Minimize:

$$J = \int_{t0}^{tf} L(x(t), u(t), t)\, dt$$

Subject to:

$$\dot{x}\ (t) = f(x(t), u(t), t)$$
$$x\_\min \leq x(t) \leq x\_\max$$
$$u\_\min \leq u(t) \leq u\_\max$$

In the presented formulation, J denotes the cost function, which typically represents fuel consumption or equivalent fuel consumption over the driving cycle. The variable x(t) represents the system state variables, such as battery state of charge and vehicle speed, while u(t) denotes the control variables, including engine torque, motor torque, and gear ratio. The function L(·) defines the instantaneous cost at each time step, and f(·) characterizes the nonlinear system dynamics governing the powertrain behavior. The constraints specify the feasible operating regions for both state and control variables, ensuring that physical, mechanical, and operational limitations are satisfied. In the context of multi-objective optimization, the cost function is further extended to incorporate additional performance criteria, enabling the simultaneous consideration of fuel efficiency, battery health, emission reduction, and overall system performance.

$$J = \int_{t0}^{tf} \left[w_1 * L_{fuel(\cdot)} + w_2 * L_{battery}(\cdot) + w_3 * L_{emissions(\cdot)} + w_4 * L_{drivability(\cdot)} \right] \mathrm{dt}$$

Where w_i are weighting factors that balance competing objectives [2], [12].

The principal challenge in hybrid electric vehicle energy management lies in the fact that globally optimal solutions generally require complete knowledge of the future driving cycle, which is not available during real-time operation. This limitation has stimulated the development of causal and adaptive control strategies capable of achieving near-optimal performance without relying on future driving information. As a result, contemporary research increasingly focuses on intelligent algorithms that balance optimality with real-time feasibility.

The effectiveness of energy management strategies is assessed through a comprehensive set of performance metrics. Fuel economy represents the primary evaluation criterion and is typically expressed as fuel consumption per unit distance (L/100 km or mpg) or as a percentage improvement relative to baseline strategies [1], [19]. Battery state of charge (SOC) sustainability reflects the ability of the system to maintain

SOC within acceptable operational limits, commonly within the 30-70% range for HEVs [20], [29]. Long-term battery health is evaluated through degradation indicators such as capacity fade, cycle life, and depth-of-discharge characteristics [2], [12]. Computational efficiency is equally critical, as real-time implementation requires computation times significantly shorter than control intervals, often measured in milliseconds [1], [23]. Environmental performance is assessed through reductions in CO_2, NOx, and particulate matter emissions [17]. Additionally, drivability considerations include the smoothness of power delivery, frequency of engine start-stop events, and overall system responsiveness, all of which influence user experience and operational quality [20].

From a methodological perspective, energy management strategies for HEVs can be systematically classified into five principal categories: rule-based approaches, optimization-based methods, model predictive control techniques, reinforcement learning strategies, and hybrid frameworks that integrate multiple paradigms. Figure 2 presents the distribution of these methodological categories within the reviewed literature, highlighting the growing diversification and technological advancement of contemporary EMS research (Figure 2).

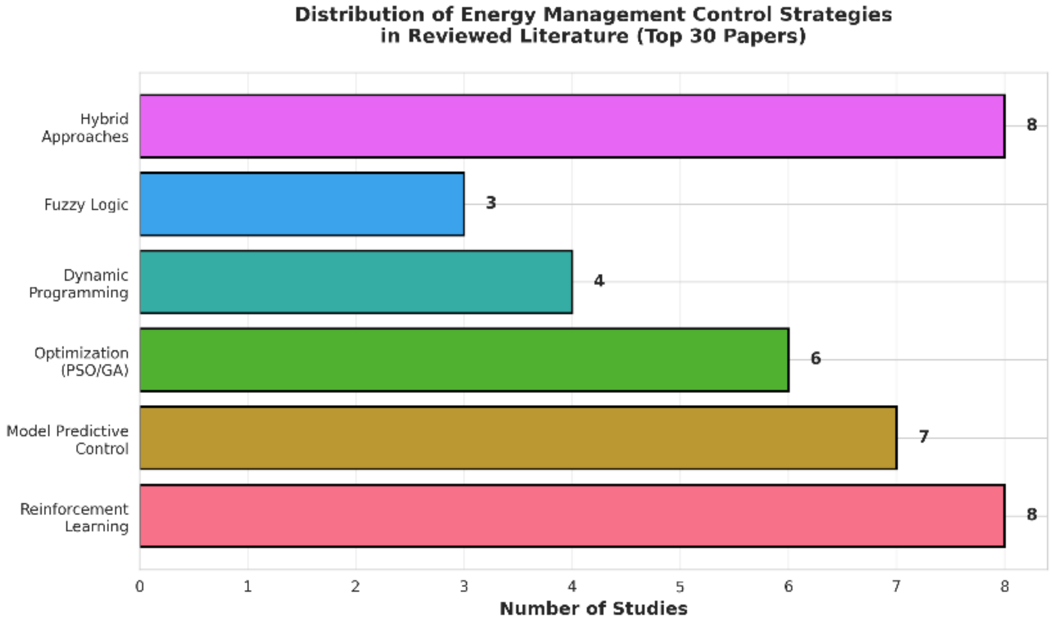

Figure 2. Distribution of energy management control strategies in reviewed literature (n=30).

Rule-based strategies represent some of the earliest and most widely implemented approaches for energy management in hybrid electric vehicles (HEVs). These methods rely on deterministic or fuzzy logic rules derived from engineering knowledge and practical experience to regulate power distribution between the internal combustion engine (ICE) and the electric propulsion system. Their conceptual simplicity, reliability, and low computational demand have contributed to their widespread industrial adoption.

Deterministic rule-based control employs threshold-based logic to switch operating modes according to vehicle speed, power demand, and battery state of charge (SOC). Owing to their computational efficiency and ease of implementation, these strategies are particularly suitable for embedded automotive systems. However, their performance depends strongly on predefined calibration rules, which may limit adaptability under highly variable driving conditions [14].

Fuzzy logic control enhances conventional rule-based methods by addressing the nonlinear and uncertain characteristics of HEV systems through linguistic rules and membership functions. Jin et al. [6] proposed an improved fuzzy control strategy optimized offline using dynamic programming to refine membership functions and rule sets. The resulting approach achieved performance close to globally optimal strategies while maintaining real-time applicability. Similarly, Zhao et al. [9] integrated fuzzy control with particle swarm optimization (PSO) to enhance self-learning and self-adaptive capabilities. By optimizing controller parameters via PSO, the method improved robustness while preserving computational efficiency. Dan-hong et al. [11] further advanced fuzzy logic energy management by employing genetic algorithms (GA) to optimize power allocation factors. Their strategy effectively reduced fuel consumption and enhanced regenerative braking energy recovery through optimized coordination between high-power-density supercapacitors and high-specific-energy batteries.

Although rule-based strategies offer operational stability and implementation simplicity, their performance is inherently influenced by calibration quality and predefined logic structures. Consequently, contemporary research increasingly incorporates learning-based and optimization-based methodologies to achieve higher adaptability and performance gains.

Optimization-based strategies formulate energy management as a mathematical optimization problem and apply numerical algorithms to obtain optimal or near-optimal solutions. Dynamic programming (DP) provides a globally optimal benchmark by discretizing state and control spaces and solving the Bellman equation backward in time. Despite its theoretical optimality, DP requires full knowledge of the driving cycle and entails significant computational effort, which restricts its direct real-time implementation [2], [28].

Yu et al. [28] proposed a DP-based control strategy for hybrid energy storage systems (HESS), explicitly accounting for the efficiencies of all system components. Under the Shanghai driving cycle, the method increased the regenerative energy recovery ratio by 3% while maintaining fuel consumption levels comparable to nonlinear coordination strategies and reducing battery cycling frequency. Particle swarm optimization (PSO), a population-based metaheuristic inspired by swarm intelligence, has also been extensively applied to HEV energy management due to its ability to handle nonlinear and multi-modal optimization problems. Chen et al. [18] developed an online suboptimal EMS using improved PSO (IPSO), demonstrating effective convergence suitable for real-time applications. Hwang et al. [19] implemented PSO for real-time optimization in power-split HEVs, achieving a composite fuel economy of 46.8 mpg, corresponding to a 9.4% improvement over the baseline control model. Panday et al. [3] compared PSO with genetic algorithms and dividing rectangle algorithms for power-split optimization, confirming PSO's competitive efficiency and solution quality. Furthermore, Chen et al. [27] extended PSO to dynamic particle swarm optimization (DPSO) for integrated energy management and transmission control, highlighting the advantages of coordinated powertrain optimization.

Genetic algorithms (GA), inspired by evolutionary mechanisms such as selection, crossover, and mutation, have been applied to both offline parameter tuning and multi-objective optimization problems in HEV energy management [11], [14]. Although optimization-based methods may involve considerable computational demand, ongoing advancements in algorithm design and computational hardware continue to enhance their feasibility for practical implementation. Through model simplification, efficient heuristics, and hybrid frameworks, these strategies increasingly balance optimality with real-time applicability, thereby contributing to the advancement of intelligent energy management systems.

Model predictive control (MPC) has emerged as a highly effective framework for energy management in hybrid electric vehicles (HEVs), providing a systematic methodology for constraint handling, multi-objective optimization, and operation within finite prediction horizons. Its structured optimization-based architecture enables coordinated power distribution while ensuring real-time feasibility under practical operating constraints.

In 2009, Borhan et al. [30] were among the first to implement MPC for the energy management of power-split HEVs. In their approach, nonlinear powertrain dynamics and associated constraints were linearized at each sampling instant, and a receding-horizon linear MPC scheme was employed to determine the optimal power-split ratio based on the updated system model. Simulation results across multiple driving cycles demonstrated improved fuel economy compared to conventional control strategies while confirming the method's suitability for real-time implementation.

Subsequent developments have extended MPC to nonlinear formulations. Yu et al. [2] proposed a hybrid two-layer control architecture combining multi-objective nonlinear MPC with rule-based control (RB-NMPC) for series-parallel HEVs. The strategy optimized torque distribution between the engine and electric motors while simultaneously accounting for fuel efficiency and battery degradation. For the P0P2 configuration under the UDDS cycle, RB-NMPC achieved a 4.7% improvement in fuel efficiency compared to rule-based control and reduced battery capacity loss by 19.1% relative to dynamic programming (DP). Under the HWFET cycle, the approach reduced capacity fade by 16.3% for P0P2 and by 67.0% for P1P2 compared to DP, demonstrating the effectiveness of multi-objective optimization within an MPC framework.

Jiahui et al. [7] applied MPC to parallel HEVs equipped with continuously variable transmission (CVT), integrating both torque split and gear ratio optimization. By employing the Gauss pseudo-spectral method for discretization, the authors significantly reduced computational complexity while achieving measurable improvements in overall energy efficiency.

Li et al. [24] introduced a bi-level hybrid MPC algorithm for HEVs with a P2 hybrid powertrain architecture. In this structure, the upper control layer determined optimal engine-motor torque distribution using linear time-varying MPC (LTV-MPC), whereas the lower layer optimized gear ratio through hybrid MPC techniques. Real-vehicle dynamometer experiments confirmed real-time feasibility and demonstrated a reduction in fuel consumption from 7.05 L/100 km to 6.2 L/100 km, corresponding to a 12.1% improvement, alongside noticeable reductions in pollutant emissions.

Adaptive MPC has further enhanced robustness under varying operating conditions. Jia et al. [22] developed an adaptive MPC (AMPC)-based energy management system for fuel cell hybrid electric vehicles (FCHEVs). Their approach incorporated a linear parameter-varying (LPV) prediction model to capture system parameter variations while preserving real-time applicability. Model parameters were updated online at each control interval to reflect changes in battery state of charge (SOC). Hardware-in-the-loop (HIL) experiments demonstrated that the proposed AMPC-based EMS outperformed four alternative real-time strategies in reducing hydrogen consumption and mitigating fuel cell current fluctuations. Moreover, it achieved the smallest optimality gap relative to offline DP benchmarks.

Stochastic MPC formulations have also been introduced to explicitly address driving uncertainty. Chen et al. [21] proposed a stochastic MPC framework for power-split plug-in HEVs that integrates reinforcement learning techniques and probabilistic forecasting of future driving conditions. By accounting for uncertainty in driving patterns, the approach improved robustness and adaptability compared to deterministic MPC implementations.

Overall, MPC offers several distinct advantages, including systematic constraint management, predictive optimization capability, and the flexibility to incorporate multi-objective cost functions. Although computational demand can increase in nonlinear formulations and extended prediction horizons, ongoing advancements in model simplification, efficient optimization algorithms, and hybrid MPC-learning architectures continue to enhance practical applicability. These developments position MPC as one of the most promising and versatile frameworks for next-generation intelligent energy management systems in hybrid electric vehicles.

Reinforcement learning (RL) has attracted increasing attention in hybrid electric vehicle (HEV) energy management due to its capability to learn optimal control policies through interaction with the operating environment, without requiring explicit system models. This model-free characteristic enables RL-based strategies to adapt dynamically to varying driving conditions and achieve near-optimal real-time performance under uncertain operational scenarios.

Among classical RL algorithms, Q-learning represents a widely adopted model-free method that learns optimal action-value functions through temporal-difference learning. Musa et al. [20] developed a Q-learning-based energy management system (EMS) that optimizes internal combustion engine (ICE) activation and torque distribution. The proposed strategy achieved an average 5% improvement in fuel economy compared to dynamic programming (DP), while maintaining effective charge-sustaining operation and limiting ICE activations to fewer than two per minute. This balance contributed simultaneously to enhanced drivability and improved energy efficiency.

The SARSA (State-Action-Reward-State-Action) framework has also demonstrated strong applicability in real-time control. Bo et al. [1] proposed a real-time EMS for off-road HEVs based on the expected SARSA algorithm. In this approach, the driving environment was represented as a transition probability matrix of electric power demand, and optimal control laws were derived offline. The Kullback-Leibler divergence rate was employed as an evaluation metric for adaptive switching between control strategies. The proposed method achieved a maximum fuel economy improvement of 13.2% and reduced computational time by more than 99.8% compared to benchmark approaches, including conventional RL, stochastic DP, and DP. These results demonstrate the method’s strong adaptability to complex off-road conditions without requiring prior knowledge of the complete driving cycle.

Kong et al. [13] implemented a real-time RL-based EMS for series hybrid electric tracked vehicles. A recursive algorithm was used to derive and periodically update the transition probability matrix of power demand. The RL controller continuously updated its policy to accommodate changing driving conditions. Experimental results showed a 6% reduction in fuel consumption under the primary driving schedule and an 8% reduction under validation conditions compared to stationary control strategies.

Deep reinforcement learning (DRL) has further expanded the potential of learning-based EMS. Hu et al. [4] provided a comprehensive review of RL applications in HEV and PHEV energy management, covering classical algorithms such as Q-learning, Dyna, and SARSA, as well as hybrid frameworks integrating RL with predictive control, deep learning, and MPC. Advanced methodologies, including TD(λ)-learning, inverse RL, actor-critic structures, and Q(λ)-learning, were frequently combined with deep neural networks to enable adaptive real-time decision-making. Reported results indicated that Q-learning improved ride quality and energy-related objectives by 24% and 50%, respectively, in hybrid bicycle applications, while hybrid DRL frameworks achieved substantial gains in both computational efficiency and fuel economy for tracked hybrid vehicles.

To address estimation bias, Shuai et al. [26] proposed a model-free double Q-learning approach for charge-sustaining control in connected hybrid vehicles. By mitigating overestimation bias inherent in standard Q-learning and leveraging connectivity information, the strategy enhanced control stability and energy efficiency.

Adaptive reinforcement learning methods have also demonstrated strong performance under dynamic driving environments. Song et al. [15] developed an adaptive RL-based EMS employing Dirichlet clustering to classify driving conditions and expectation-maximization algorithms for real-time model updates. The proposed strategy improved fuel economy by 5-10% while maintaining final SOC stability. Compared to Deep Q-Network (DQN) and Deterministic Policy Gradient (DDPG) approaches, the method produced more stable engine operating points and more compact operational states.

To reduce the gap between simulation and real-world implementation, Hu et al. [8] introduced a hybrid data-driven and simulation-based RL framework. By combining real operational data with simplified simulation models, the method achieved a near-optimal policy that reduced fuel consumption by approximately 6.10% compared to DP solutions obtained using high-fidelity simulation models. This hybrid learning strategy effectively strengthened the transferability of RL-based EMS from simulation environments to practical applications.

Overall, reinforcement learning offers several strategic advantages, including model-free adaptability, robustness under uncertainty, and the capability to discover highly efficient control policies beyond manually designed heuristics. Although RL methods require sufficient training data and careful convergence design, ongoing advancements in adaptive algorithms, hybrid learning architectures, and computational hardware continue to enhance their reliability, efficiency, and real-time applicability. As a result, reinforcement learning represents a highly promising direction for next-generation intelligent energy management systems in hybrid electric vehicles.

Recognizing that no single methodology can simultaneously maximize optimality, computational efficiency, robustness, and adaptability, recent research has increasingly concentrated on hybrid approaches that integrate complementary strengths from multiple control paradigms. These integrative frameworks aim to balance predictive capability, learning adaptability, and real-time feasibility within a unified energy management architecture.

One notable direction is reinforcement learning (RL)-enhanced model predictive control (MPC). Yang et al. [29] proposed an RL-based real-time intelligent energy management strategy embedded within an MPC framework. In this hybrid structure, RL was employed to enhance the predictive optimization process of MPC by improving adaptability to changing driving conditions. The resulting approach achieved measurable improvements in fuel economy while preserving real-time implementability.

Another line of research combines fuzzy logic control with optimization techniques. Zhao et al. [9] optimized fuzzy controller parameters using particle swarm optimization (PSO), whereas Dan-hong et al. [11] applied genetic algorithms for systematic parameter tuning. These hybrid strategies retain the interpretability and robustness of fuzzy logic while significantly improving performance through structured optimization, thereby narrowing the gap between heuristic and globally optimal control methods.

The integration of rule-based control with nonlinear model predictive control (NMPC) has also demonstrated promising results. Yu et al. [2] developed a two-layer architecture in which the rule-based layer managed mode selection and high-level decision-making, while NMPC optimized continuous control variables such as torque distribution. This hierarchical structure achieved a favorable balance between computational efficiency and near-optimal system performance.

Hierarchical optimization has further expanded the potential of hybrid EMS architectures. Bai et al. [12] introduced a hierarchical optimization-based EMS for plug-in hybrid electric vehicles equipped with hybrid energy storage systems. The first optimization layer employed variable-threshold dynamic programming to allocate power between the engine and the energy storage system. The second layer utilized adaptive low-pass filtering and power-limit management to distribute energy between the battery and supercapacitor. This adaptive power allocation strategy extended battery service life by 54.9% compared to global dynamic programming, while improving life-cycle economic performance by 12.4%.

Connectivity-enhanced hybrid control has also emerged as a significant advancement. A two-layer real-time optimal control scheme for connected intelligent HEVs was proposed in [5], where the upper layer optimized vehicle speed trajectories using traffic network information, and the lower layer applied the alternating direction method of multipliers (ADMM) to allocate torque between the engine and electric motor. Under the China typical urban driving cycle, this strategy achieved a 6.96% improvement in fuel economy compared to conventional rule-based EMS.

Adaptive dynamic programming (ADP) further contributes to hybrid strategy development. Liu et al. [23] proposed a computationally efficient ADP approach for parallel HEVs. The algorithm rapidly computed optimal control actions while iteratively updating the approximated value function based on real-time fuel and electricity consumption data, even under limited computational resources. Engine on/off switching and torque distribution were solved using one-step lookahead approximation and Pontryagin's minimum principle. Processor-in-the-loop Monte Carlo simulations demonstrated that the proposed method achieved fuel efficiency superior to adaptive PMP and close to theoretical optimal solutions, while reducing onboard memory requirements by at least 70%.

Overall, hybrid energy management strategies represent the contemporary frontier of HEV research. By integrating predictive optimization, adaptive learning, hierarchical decision-making, and connectivity-based intelligence, these approaches provide a practical pathway toward achieving near-optimal performance alongside real-time implementability and robust adaptability across diverse operating conditions.

RESEARCH METHODOLOGY

This study adopts a systematic review methodology to examine recent advancements in energy management strategies (EMS) for hybrid electric vehicles. A total of 304 peer-reviewed publications published between 2009-2024 were systematically identified and screened using leading academic databases. Following the application of predefined inclusion criteria, including topical relevance, methodological rigor, and scholarly impact, 30 high-quality studies were selected for comprehensive in-depth analysis. The selected literature was systematically classified into rule-based methods, optimization-based approaches, model predictive control techniques, reinforcement learning strategies, and hybrid frameworks. A comparative evaluation was subsequently performed based on key performance indicators, including fuel economy, computational efficiency, and real-time implementability, ensuring a structured and analytically robust assessment of contemporary EMS developments.

ANALYSIS AND RESULTS

Figure 3 provides a comparative evaluation of fuel economy improvements and battery life extensions achieved by selected energy management system (EMS) approaches identified in the reviewed literature (Figure 3).

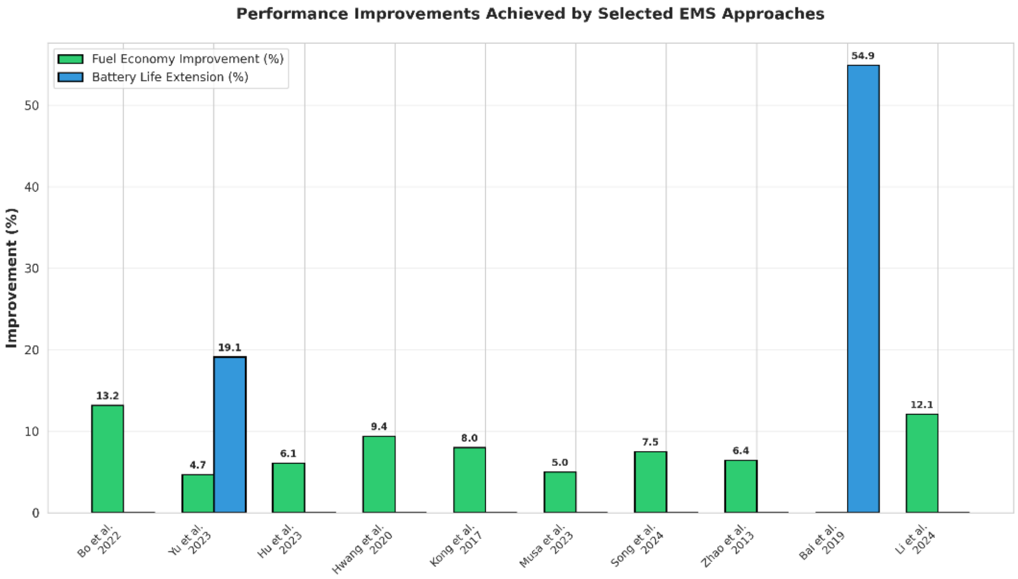

Figure 3. Performance improvements achieved by selected EMS approaches compared to baseline strategies.

The analysis presented in Figure 3 provides several important insights into the performance of contemporary energy management strategies. Reported fuel economy improvements range from 4.7-13.2% relative to baseline control strategies. The highest improvement, 13.2%, was reported by Bo et al. [1] using the expected SARSA algorithm for off-road HEVs. This was followed by Li et al. [24], who achieved a 12.1% improvement through linear time-varying model predictive control (LTV-MPC). Hwang et al. [19] reported a 9.4% enhancement using particle swarm optimization (PSO), while Kong et al. [13] demonstrated an 8% improvement through reinforcement learning applied to tracked hybrid vehicles.

The variation in reported performance gains reflects differences in baseline strategies, vehicle architectures, driving cycles, and evaluation methodologies. Studies benchmarking against conventional rule-based controls generally report larger relative improvements than those compared with more advanced reference strategies such as dynamic programming. This variation highlights the contextual dependency of performance outcomes and underscores the importance of standardized evaluation frameworks.

Battery life extension has emerged as a critical research focus in recent years. Bai et al. [12] reported a 54.9% improvement in battery service life through a hierarchical optimization strategy with adaptive power allocation in a plug-in hybrid electric bus. Similarly, Yu et al. [2] demonstrated a 19.1% reduction in battery capacity loss compared to dynamic programming by employing multi-objective nonlinear MPC that explicitly incorporated battery aging into the optimization process. These findings emphasize the strategic value of multi-objective optimization frameworks that simultaneously enhance fuel efficiency and battery longevity, particularly in plug-in hybrids equipped with high-capacity battery systems.

In terms of computational efficiency, Bo et al. [1] reported a reduction in elapsed computation time exceeding 99.8% compared to benchmark algorithms, while also achieving superior fuel economy. This result illustrates that well-designed learning-based approaches can effectively reconcile optimality with real-time feasibility.

Figure 4 further illustrates the inherent trade-off between computational efficiency and optimality across different EMS methodologies, providing a structured perspective on the balance between theoretical performance and practical implementability (Figure 4).

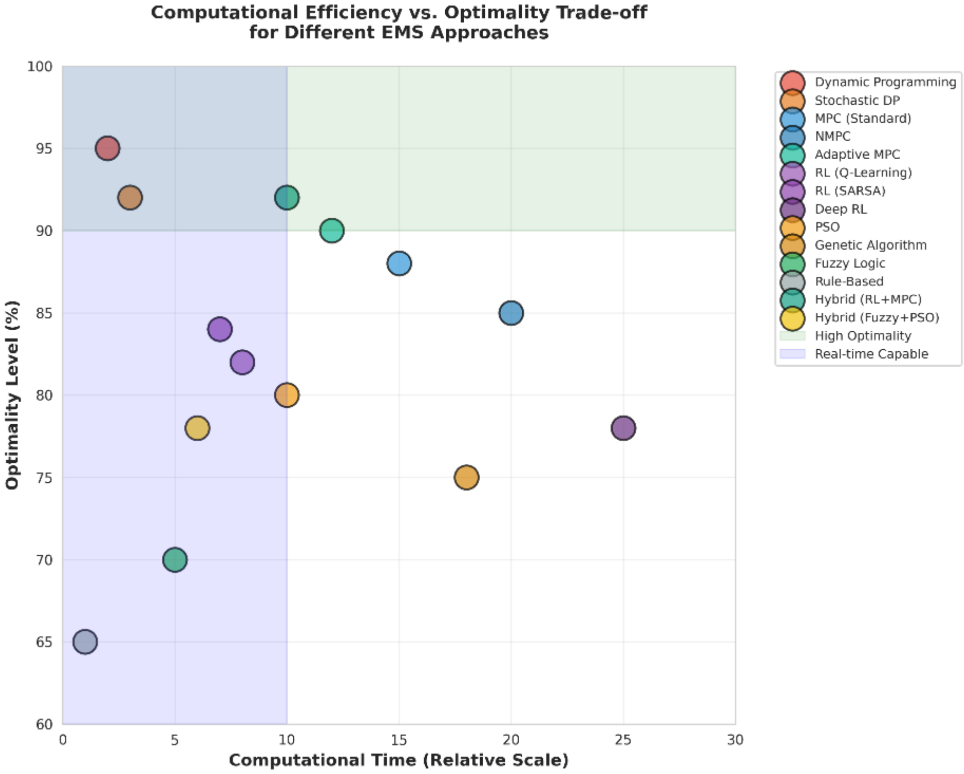

Figure 4. Computational efficiency vs. optimality trade-off for different EMS approaches.

Dynamic programming (DP) and stochastic DP achieve the highest levels of optimality, typically within the 90-95% range, although they require substantial computational resources (relative computation time 2-3). Consequently, these methods are particularly well suited for offline optimization and benchmarking purposes [2], [28]. In contrast, adaptive MPC, hybrid RL-MPC frameworks, and expected SARSA represent balanced approaches that achieve 84-92% optimality while maintaining moderate computational demands (relative time 7-12), thereby supporting real-time implementation [1], [22], [29]. Rule-based strategies and fuzzy logic controllers provide the fastest computation (relative time 1-5) and remain attractive for embedded applications with constrained resources, typically achieving 65-70% optimality [6], [9]. Recent advances in adaptive dynamic programming [23] and improved particle swarm optimization [18], [19] demonstrate that intelligent algorithm design can significantly enhance efficiency, enabling high-performance outcomes with reduced computational burden.

Beyond theoretical optimality, real-time EMS implementation requires careful consideration of practical constraints. Modern automotive electronic control units (ECUs) generally operate within 100-200 MHz clock frequencies and limited onboard memory, necessitating execution within control intervals of 10-100 milliseconds [23], [24]. Real-time strategies often employ reduced-order models that preserve essential dynamics while enabling rapid computation; therefore, maintaining consistency between high-fidelity simulation models and real-time control models is essential [8], [22]. Advanced EMS architectures may incorporate additional sensing and connectivity capabilities, such as GPS data, traffic information, and vehicle-to-vehicle communication, which enhance predictive performance while increasing system complexity [5], [26]. Robustness and reliability remain critical, as production vehicles must operate consistently under diverse driving conditions, component aging, and sensor variability [14]. Furthermore, calibration effort significantly influences development cost and deployment timelines; consequently, strategies with structured and manageable parameter sets are particularly advantageous [6], [11].

Several studies have demonstrated successful real-time validation. Li et al. [24] confirmed the feasibility of their LTV-MPC strategy through real-vehicle dynamometer testing. Jia et al. [22] validated adaptive MPC performance via hardware-in-the-loop experiments on a scaled fuel cell hybrid system. Liu et al. [23] conducted processor-in-the-loop Monte Carlo simulations to verify computational efficiency under realistic hardware constraints.

Power-split (series-parallel) architectures present particularly demanding energy management challenges due to multiple operating modes and continuously variable power distribution through planetary gear mechanisms. Borhan et al. [30] were among the first to implement MPC for power-split HEVs, formulating the power management problem as a nonlinear optimization task that was linearized at each sampling instant. By employing a receding-horizon control framework, the approach achieved improved fuel economy compared to conventional strategies while preserving causality and real-time applicability.

Hwang et al. [19] applied particle swarm optimization to the AHS II power-split system, minimizing equivalent fuel consumption while satisfying dynamic performance constraints. The proposed method achieved a composite fuel economy of 46.8 mpg, corresponding to a 9.4% improvement, and demonstrated rapid convergence suitable for real-time deployment. Chen et al. [21] developed a stochastic MPC framework for power-split plug-in HEVs, integrating reinforcement learning to address uncertainty in future driving conditions and enhancing robustness relative to deterministic MPC formulations.

Al-Aawar et al. [10] proposed a two-stage optimal control framework for split-power hybrid configurations. The first stage applied calculus-of-variations-based optimization to minimize fuel consumption, while the second stage incorporated fuzzy logic control to enhance drivability and operational smoothness. Additionally, a robust system identification model was introduced to predict powertrain dynamics by representing both the internal combustion engine and electric motor-generator units within a unified state-space framework. Collectively, these studies demonstrate the growing maturity and practical viability of advanced control strategies for complex power-split HEV architectures.

Parallel HEVs feature comparatively simpler mechanical architectures; however, they still require advanced control strategies to ensure effective coordination between the internal combustion engine and the electric motor. Jiahui et al. [7] addressed energy management for parallel HEVs equipped with continuously variable transmission (CVT), integrating torque-split and gear-ratio optimization within a model predictive control (MPC) framework. By applying the Gauss pseudo-spectral method to discretize the optimization problem, the authors significantly reduced computational burden while improving overall energy efficiency. Liu et al. [23] proposed an adaptive dynamic programming (ADP) approach for parallel HEVs, resolving engine on/off switching and torque distribution using one-step lookahead approximation and Pontryagin's minimum principle. The method achieved fuel efficiency close to the theoretical optimum while reducing onboard memory requirements by at least 70%, thereby enhancing practical implementability. Yu et al. [2] investigated series-parallel HEVs with P0P2 and P1P2 configurations using a rule-based nonlinear MPC (RB-NMPC) strategy that simultaneously optimized torque distribution, fuel efficiency, and battery degradation, demonstrating clear architecture-specific performance advantages.

Fuel cell hybrid electric vehicles (FCHEVs) present distinct energy management challenges associated with fuel cell durability, hydrogen consumption, and inherently slower fuel cell dynamics. Jia et al. [22] developed an adaptive MPC strategy based on a linear parameter-varying prediction model that accounts for system parameter variations. The proposed AMPC method optimally allocated load current between the fuel cell and battery in real time, achieving balanced trade-offs among hydrogen consumption, fuel cell current fluctuation, battery SOC maintenance, and power demand satisfaction. Hardware-in-the-loop validation confirmed that this approach achieved the smallest optimality gap compared to offline dynamic programming among four real-time EMS alternatives. A real-time rule-based EMS incorporating multi-objective optimization for FCHEVs was presented in [14], where genetic algorithms were employed to determine optimal battery charge-discharge criteria. The strategy minimized hydrogen consumption, improved fuel cell durability, and achieved a more stable fuel cell power change rate (14.8314 W/s versus 17.0771 W/s under the NEDC cycle) compared to DP-based control, while maintaining SOC within admissible limits to support battery longevity. Additionally, Caux et al. [16] introduced a combinatorial optimization framework for offline energy management in hybrid fuel cell vehicles, efficiently coordinating energy distribution between a fuel cell and supercapacitor storage system to maximize overall system efficiency.

Heavy-duty and off-road hybrid vehicles present further challenges due to high power demands, frequent start-stop operation, and variable terrain conditions. Zhao et al. [17] proposed a fuzzy equivalent consumption minimization strategy (F-ECMS) for heavy-duty power-split HEVs. By minimizing an instantaneous cost function and adaptively tuning fuzzy weighting factors according to SOC and elapsed time, the strategy achieved fuel economy improvements of 4.43% and 6.44% under the NRTC and HETC transient test cycles, respectively, while maintaining improved SOC stability compared to telemetry-based ECMS. Bo et al. [1] developed an expected SARSA-based EMS tailored for off-road HEVs, representing the driving environment as a transition probability matrix of electric power demand. The Kullback-Leibler divergence rate was employed to enable adaptive switching between control strategies. This approach achieved a 13.2% fuel economy improvement and demonstrated robust adaptability to complex off-road conditions without requiring prior knowledge of the complete driving cycle. Kong et al. [13] implemented a real-time RL-based EMS for series hybrid electric tracked vehicles, employing a recursive algorithm to update power-demand transition probabilities. The strategy achieved a 6-8% reduction in fuel consumption compared to stationary control methods. Bai et al. [12] examined a plug-in hybrid electric bus operating under frequent stop conditions in urban environments. Their hierarchical optimization framework with adaptive power allocation extended battery service life by 54.9% and improved life-cycle economic performance by 12.4%, underscoring the strategic importance of battery health management in high-utilization commercial applications.

The analysis of the temporal evolution of EMS research, as illustrated in Figure 5, reveals several significant emerging trends in the development of intelligent and adaptive energy management systems (Figure 5).

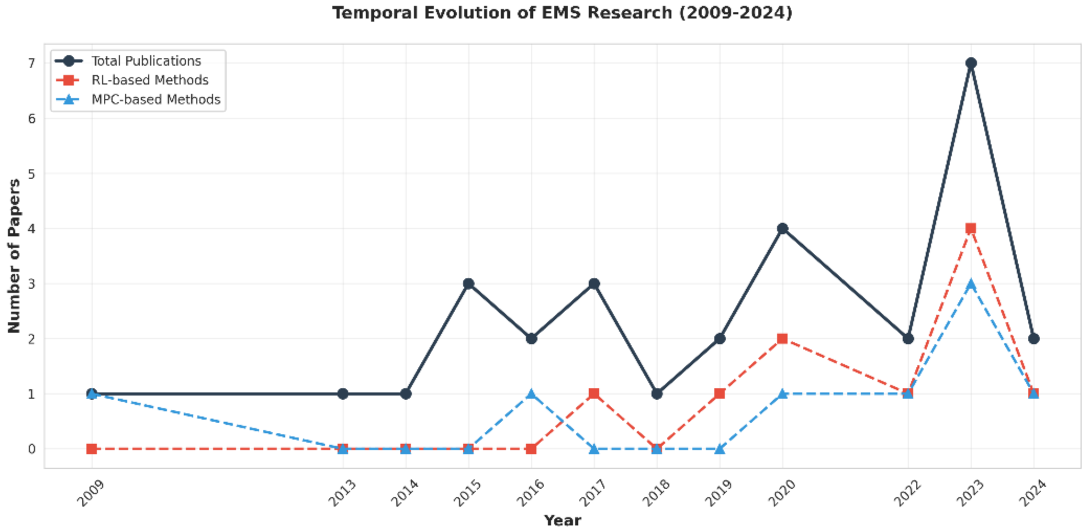

Figure 5. Temporal evolution of EMS research from 2009 to 2024, showing the rise of RL and MPC methods.

A clear shift toward learning-based methodologies has become evident in recent years. The number of reinforcement learning (RL)-based studies has increased substantially since 2017-2023, with four publications in 2023 alone included among the top 30 reviewed papers. This growth reflects increasing confidence in RL's capability to deliver near-optimal performance while ensuring real-time feasibility and adaptability under dynamic operating conditions [1], [4], [8], [15], [20], [29].

Another prominent trend is the integration of connectivity and intelligent control. Contemporary studies increasingly incorporate vehicle connectivity, GPS data, and vehicle-to-vehicle communication to enhance predictive and adaptive energy management. The two-layer control architecture for intelligent connected HEVs [5] and the double Q-learning framework for connected vehicles [26] illustrate this direction. Through connectivity-enabled foresight, vehicles can anticipate traffic conditions, optimize routes, and coordinate with infrastructure, thereby improving overall system efficiency.

Modern EMS research also demonstrates a strong emphasis on multi-objective optimization. Beyond fuel economy, recent studies explicitly incorporate battery health [2], [12], fuel cell durability [14], [22], emission reduction [17], [24], and drivability [10], [20] into unified optimization frameworks. This integrated perspective acknowledges that real-world vehicle performance must satisfy diverse technical, environmental, and user-oriented requirements.

Hybrid methodological frameworks have become increasingly prevalent, with many recent publications combining multiple control paradigms [2], [8], [12], [22], [29]. This evolution indicates that the field is transitioning from comparisons of isolated techniques toward the structured integration of complementary strengths to achieve balanced and robust performance.

Furthermore, the growing emphasis on hardware validation reflects the maturation of the research domain. Hardware-in-the-loop experiments [22], processor-in-the-loop simulations [23], and real-vehicle validation studies [24] demonstrate that contemporary EMS research increasingly prioritizes practical deployment and industrial applicability, moving beyond purely simulation-based evaluations.

Despite these significant advancements, several research challenges remain and continue to stimulate further innovation. The simulation-to-reality gap remains a key consideration, as strategies that perform exceptionally in simulation environments may encounter practical constraints related to model uncertainty, sensor noise, and unmodeled dynamics. Hu et al. [8] addressed this issue through hybrid data-driven and simulation-based learning; nevertheless, broader methodological refinements are required to ensure consistent real-world performance.

Driving-cycle dependency also influences performance outcomes, as strategies optimized for urban cycles may not generalize optimally to highway conditions. Adaptive learning-based methods [1], [15], which dynamically recognize and adjust to driving patterns, represent promising pathways toward improved generalization.

Computational constraints remain relevant for production electronic control units (ECUs) with limited processing power and memory capacity. Although algorithmic efficiency has improved considerably, complex nonlinear MPC and deep reinforcement learning implementations continue to require careful optimization to ensure real-time feasibility [23].

Accurate modeling of battery aging presents another ongoing research priority. While simplified degradation models [2], [12] enable real-time implementation, further refinement of electrochemical aging representations could enhance long-term battery health optimization.

In addition, validation and benchmarking methodologies vary across studies, complicating direct comparison of reported performance metrics. The development of standardized benchmarking frameworks and open-source simulation platforms would further strengthen methodological transparency and comparability.

Finally, transferability across vehicle platforms remains an important research objective. Strategies tailored to specific architectures often require recalibration for different configurations. The development of transferable and generalizable learning-based algorithms capable of adapting across diverse vehicle types constitutes a promising direction for future research [4].

The energy management problem inherently involves multiple competing objectives that must be carefully balanced within a unified optimization framework. One of the most significant trade-offs concerns fuel economy and battery health. While intensive battery utilization can enhance short-term fuel efficiency, it may accelerate degradation and increase long-term operational costs. Yu et al. [2] demonstrated that multi-objective nonlinear MPC explicitly incorporating battery aging achieved a 19.1% reduction in capacity loss while maintaining competitive fuel efficiency. Similarly, Bai et al. [12] reported that hierarchical optimization with adaptive power allocation extended battery service life by 54.9% and improved life-cycle economic performance by 12.4%, highlighting the benefits of coordinated long-term resource management.

Another fundamental consideration is the balance between optimality and computational efficiency. The inherent trade-off between achieving theoretically optimal performance and ensuring real-time implementability has driven substantial methodological innovation. Hybrid control architectures [2], [8], [22], [29] and computationally efficient algorithms [1], [23] exemplify structured approaches to reconciling high-performance optimization with practical real-time constraints.

Performance must also be harmonized with drivability. Although frequent engine start-stop events and rapid power transitions may enhance fuel economy, excessive switching can adversely affect driver comfort and perceived vehicle smoothness. Musa et al. [20] addressed this issue by limiting internal combustion engine (ICE) activations to fewer than two per minute while still achieving a 5% improvement in fuel economy. Al-Aawar et al. [10] employed a two-stage control framework incorporating fuzzy logic to ensure smooth power delivery alongside fuel optimization, thereby maintaining high drivability standards.

In fuel cell hybrid electric vehicles (FCHEVs), a critical balance must be achieved between hydrogen efficiency and fuel cell durability. Jia et al. [22] formulated a multi-objective optimization problem that simultaneously minimized hydrogen consumption, reduced fuel cell current fluctuations, maintained battery SOC stability, and satisfied power demand constraints. The resulting strategy demonstrated the most favorable overall performance among the evaluated real-time approaches.

Recent research has also emphasized the integration of thermal management with energy management. Hu et al. [25] proposed a multi-horizon MPC framework for connected HEVs that jointly optimizes power and thermal management, recognizing that component temperature significantly influences system efficiency, reliability, and durability.

Effective multi-objective optimization in advanced energy management systems requires rigorous cost-function formulation with appropriately defined weighting factors, robust constraint handling, and, in many cases, hierarchical or sequential optimization architectures. By decomposing complex control problems into smaller, tractable subproblems, such structured frameworks enhance computational efficiency while preserving solution feasibility and overall system performance [2], [12], [22].

CONCLUSIONS AND RECOMMENDATIONS

Based on a comprehensive assessment of contemporary research, several strategically important directions emerge for future investigation in hybrid electric vehicle (HEV) energy management systems (EMS). First, deep reinforcement learning combined with transfer learning presents significant potential. Although deep RL has demonstrated strong performance [4], current implementations often require extensive retraining for each vehicle platform. The development of transferable learning frameworks, incorporating meta-learning and domain adaptation techniques, would enable pre-trained models to adapt efficiently to new vehicle configurations with minimal additional data, thereby accelerating industrial deployment.

Second, integrated vehicle-level optimization represents a critical advancement. Rather than treating EMS in isolation, future research should pursue coordinated control architectures that integrate energy management with thermal control [25], predictive cruise control, route planning, and charging infrastructure interaction in plug-in hybrid electric vehicles (PHEVs). Such holistic system-level optimization can unlock additional efficiency gains and enhance overall vehicle intelligence.

Third, uncertainty quantification and robust control methodologies remain essential for real-world deployment. Practical vehicle operation involves uncertainties in component characteristics, sensor measurements, and driving conditions. The development of EMS architectures capable of explicitly modeling and managing uncertainty through stochastic MPC [21], robust optimization, or probabilistic reinforcement learning would significantly enhance reliability and operational resilience.

Fourth, explainable artificial intelligence (AI) is becoming increasingly important as learning-based EMS architectures grow in complexity. Interpretability is essential for validation, calibration, safety certification, and regulatory acceptance. Research in explainable AI methods that provide transparent insight into learned control policies will facilitate broader adoption in production vehicles.

Fifth, cloud-based learning and fleet-level optimization offer transformative potential. Connected vehicles enable distributed data aggregation, allowing fleet-wide experience to continuously refine EMS strategies. Federated learning approaches, which preserve data privacy while enabling collaborative model improvement, represent a particularly promising research frontier.

Sixth, multi-agent coordination will become increasingly relevant for connected and autonomous vehicle ecosystems. Coordinated energy management across multiple vehicles, enabled by game-theoretic models and multi-agent reinforcement learning, can optimize traffic flow and collective efficiency at a system-wide level.

Seventh, aging-aware predictive maintenance integrated with EMS can enhance lifecycle performance. By anticipating component degradation and adjusting control strategies accordingly, such integration can extend vehicle lifespan and reduce total cost of ownership.

Eighth, standardized benchmarking frameworks and open-source simulation platforms would significantly strengthen research comparability and methodological transparency. Unified evaluation protocols and shared datasets would enable fair cross-study assessment and accelerate scientific progress.

Ninth, hardware-software co-design represents a forward-looking approach in which control algorithms are developed in conjunction with dedicated computational accelerators, such as neural network processors, to enable advanced real-time strategies beyond conventional ECU limitations.

Tenth, lifecycle and sustainability analysis should be incorporated into EMS research. Future investigations should consider manufacturing impacts, operational efficiency, end-of-life recycling, and overall environmental footprint, rather than focusing exclusively on operational fuel consumption.

This comprehensive review synthesizes state-of-the-art developments in energy management systems for hybrid electric vehicles based on an analysis of 304 peer-reviewed publications, including an in-depth examination of 30 key studies published between 2009-2024. The findings reveal a clear evolution from conventional rule-based strategies toward advanced learning-based and predictive control methodologies capable of delivering near-optimal performance under real-time operational constraints.

The field demonstrates substantial methodological diversity, encompassing optimization-based techniques such as dynamic programming and particle swarm optimization, model predictive control frameworks, reinforcement learning approaches including Q-learning, SARSA, and deep RL, and increasingly sophisticated hybrid architectures that integrate complementary paradigms.

Modern EMS strategies achieve notable performance gains, with fuel economy improvements ranging from 4.7-13.2% and battery service life extensions reaching up to 54.9%. These advancements translate into meaningful reductions in operational costs and environmental impact.

Significant progress has also been made in computational efficiency. Strategies such as expected SARSA [1] have demonstrated a 99.8% reduction in computation time while improving fuel economy by 13.2%, and adaptive dynamic programming [23] has reduced onboard memory requirements by approximately 70% while maintaining near-optimal performance.

Architecture-specific optimization has emerged as a critical design consideration, as different HEV configurations—including power-split, parallel, series-parallel, and fuel cell hybrids—require tailored EMS structures aligned with their mechanical and electrical characteristics.

Multi-objective optimization frameworks increasingly balance fuel efficiency, battery health, emissions reduction, drivability, and component durability. Hierarchical and structured optimization approaches [2], [12], [22] provide systematic mechanisms for achieving these trade-offs.

The research landscape also reflects a pronounced shift toward intelligent and adaptive control systems leveraging reinforcement learning and vehicle connectivity. Hybrid RL-MPC architectures [29] represent a leading direction, combining predictive optimization with adaptive learning to achieve both optimality and real-time feasibility.

Moreover, the growing emphasis on hardware validation, real-vehicle experimentation, and deployment-oriented evaluation indicates that the field is transitioning from purely theoretical exploration toward production-ready implementation.

Although important challenges remain—including simulation-to-reality transfer, cross-platform adaptability, computational scalability for advanced algorithms, and the need for standardized benchmarking—the overall trajectory of research demonstrates strong momentum toward intelligent, robust, and scalable EMS architectures.

As the automotive industry continues its electrification transition, advanced energy management systems will play a decisive role in shaping the competitiveness, efficiency, and environmental sustainability of hybrid electric vehicles. The convergence of progress in machine learning, vehicle connectivity, and high-performance embedded computing suggests that the coming decade will witness the widespread deployment of adaptive EMS platforms capable of continuous learning and optimization across diverse operating conditions. Such systems will enhance not only individual vehicle efficiency but also enable fleet-level coordination and smart-grid integration, contributing meaningfully to the development of a more sustainable and intelligent transportation ecosystem.

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