



A Systematic Review on Artificial Intelligence-Centric Energy Management Strategies for Hybrid Electric Vehicles

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Abstract

In the midst of uncertainties and wavering commitments over a fully electric future, hybrid electric vehicles (HEVs) have gained increasing attention as a sustainable solution to reduce fuel consumption and emissions in the transportation sector. At the core of their performance is the Energy Management Strategy (EMS), which governs the efficient distribution of power among internal combustion engines (ICE), electric motors (EM), and battery systems. Conventional EMS approaches, such as rule-based and optimisation-based strategies, often struggle to adapt to the variability of real-world driving conditions. In response, Artificial Intelligence (AI)-based techniques have emerged as powerful alternatives, offering data-driven, adaptive, and enhanced energy distribution control. This systematic review analyses AI-based EMS for HEVs using studies from 2015 to 2025 sourced from Google Scholar, Springer, and IEEE Xplore. A PRISMA-compliant screening process yielded 32 studies for synthesis. The review focuses on fuzzy logic (FL), neural networks (NN), reinforcement learning (RL), and hybrid models combining heuristic and learning-based methods. Across the reviewed literature, FL achieves moderate fuel efficiency improvements with the highest interpretability. NN approaches report high fuel reduction with strong generalisation capability while RL methods demonstrate superior adaptability to previously unseen driving conditions, though at higher computational cost. Future research directions are discussed including Explainable AI (XAI) and Human-in-the-Loop (HITL) frameworks aligned with Industry 5.0 principles, aimed at developing more transparent, user-centric, and deployable EMS for next-generation HEVs.

1 Introduction

In today's evolving field of environmental technology, the shift toward sustainable and eco-conscious solutions has become increasingly critical. Ongoing challenges such as climate change, resource depletion, and environmental deterioration demand forward-thinking strategies to reshape the global energy landscape [1–5]. In the transportation sector,

the focus on electrification stems from a deep recognition of the environmental drawbacks inherent in traditional combustion-powered propulsion systems [6–9]. Conventional vehicles powered by internal combustion engines (ICE), which have been dominating the passenger's and commercial vehicle's market are one of the major contributors to greenhouse gas emissions and air pollution [10–12]. Transitioning to electrified vehicles marks a significant move toward reducing the adverse environmental after-effects of traditional transportation. Central to this transition is the drive to improve energy efficiency. Fossil fuel-powered vehicles often suffer from poor well-to-wheel efficiency, raising both environmental and economic concerns [13, 14]. Advancing energy-efficient technologies thus becomes essential in achieving a highly sustainable transportation system network.

The urgency of climate action is highlighted by the global commitment to the 2°C target set forth in the Paris Agreement [15, 16]. To avoid severe climate consequences, nations around the world have pledged to cap the increase in global temperatures to below 2°C above pre-industrial

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levels. Transportation electrification is a key contributor to meeting this goal, as it helps cut emissions and supports a cleaner mobility future [17, 18]. This initiative aligns with the broader objectives of the United Nations Sustainable Development Goals (SDGs), particularly SDG 7 (Affordable and Clean Energy) and SDG 13 (Climate Action) [19–22]. By supporting the transition to clean energy and reducing greenhouse gas emissions, electrification contributes meaningfully to global sustainability efforts. A major benefit of this transition is the potential to significantly lower net carbon emissions. As electric and hybrid vehicles gradually replace conventional models, the transportation sector is positioned to make a substantial reduction in its overall carbon footprint, paving an essential step towards a greener, more sustainable future.

Hybrid Electric Vehicles (HEVs) have gained attention as an effective solution to lower emissions and enhance fuel efficiency. These vehicles integrate ICEs with electric motors (EMs) and battery systems, merging the strengths of both traditional and electric vehicles (EV) while mitigating many of their individual shortcomings [23]. A crucial factor in the performance and energy efficiency of an HEV is its Energy Management Strategy (EMS). The EMS is responsible for intelligently regulating the distribution of power among the ICE, EM, and battery systems to reduce fuel usage, extend battery lifespan, and ensure smooth operation under varying driving conditions. While conventional EMS methods, such as rule-based and optimization-based strategies, are widely adopted for their simplicity and straightforward implementation, they often lack the flexibility to adapt to dynamic driving scenarios and unable to leverage real-time learning from data.

In recent years, the rapid advancement of Artificial Intelligence (AI) has paved the way for a new generation of intelligent EMS capable of learning, adapting, and optimizing in real-time [24]. Techniques such as neural networks (NN), reinforcement learning (RL), and hybrid AI algorithms have demonstrated significant improvements in fuel efficiency and responsiveness. These data-driven approaches enable the EMS to model complex non-linear systems, learn driver behaviour patterns, and optimize control decisions based on past experiences and current operating conditions [25, 26].

This review aims to provide a systematic overview of the development of AI-based EMS for HEVs, with particular focus on recent contributions involving machine learning (ML), deep reinforcement learning (DRL), and advanced optimization methods. The highlights of this paper include comparative studies, key advancements, and evaluation of methodologies reported in the literature. Additionally, it identifies emerging trends and research gaps, providing insight into future directions for the development of a state-of-the-art user-centric AI-based EMS frameworks.

The remainder of this paper is structured as follows: Sect. 2 introduces HEV architectures and discusses a number of conventional EMS design configurations based on each architectures. Section 3 explores various AI-based approaches applied to EMS, including fuzzy logic (FL), NN and RL. Sect. 4 discusses explainable AI (XAI) as an approach to pave the way towards developing a more user-centric EMS in the spirit of Industry 5.0. Finally, Sect. 5 concludes the paper.

1.1 Search Methodology

To ensure rigour and reproducibility, this review follows a structure search protocol aligned with the Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA) guidelines [27]. The literature search was conducted across three major academic databases: Google Scholar, Springer, and IEEE Xplore. These databases were selected for their comprehensive coverage of engineering, applied science, and transportation research, ensuring broad retrieval of peer-reviewed contributions to AI-based EMS for HEVs.

1.1.1 Search Strings

The following Boolean search strings were applied across title, abstract, and keywords fields:

- ("hybrid electric vehicle" OR "HEV" OR "PHEV" OR "FCHEV") AND ("energy management strategy" OR "EMS" OR "power management") AND ("artificial intelligence" OR "machine learning" OR "deep learning" OR "fuzzy logic" OR "neural network" OR "reinforcement learning" OR "deep reinforcement learning")
- Supplementary terms included: "fuel cell hybrid", "plug-in hybrid", "drive cycle", "state of charge", "explainable AI", "XAI", "human-in-the-loop"

1.1.2 Timeframe

The search was restricted to publications from January 2015 to December 2025 to capture both foundational contributions and the latest advances in AI-based EMS. The lower bound was set at 2015 to include the early application of FL and NN in this domain, while the upper bound ensures alignment with the most recent developments in DRL, XAI, and human-in-the-loop (HITL) frameworks.

1.1.3 Inclusion and Exclusion Criteria

Articles were evaluated using the following criteria:

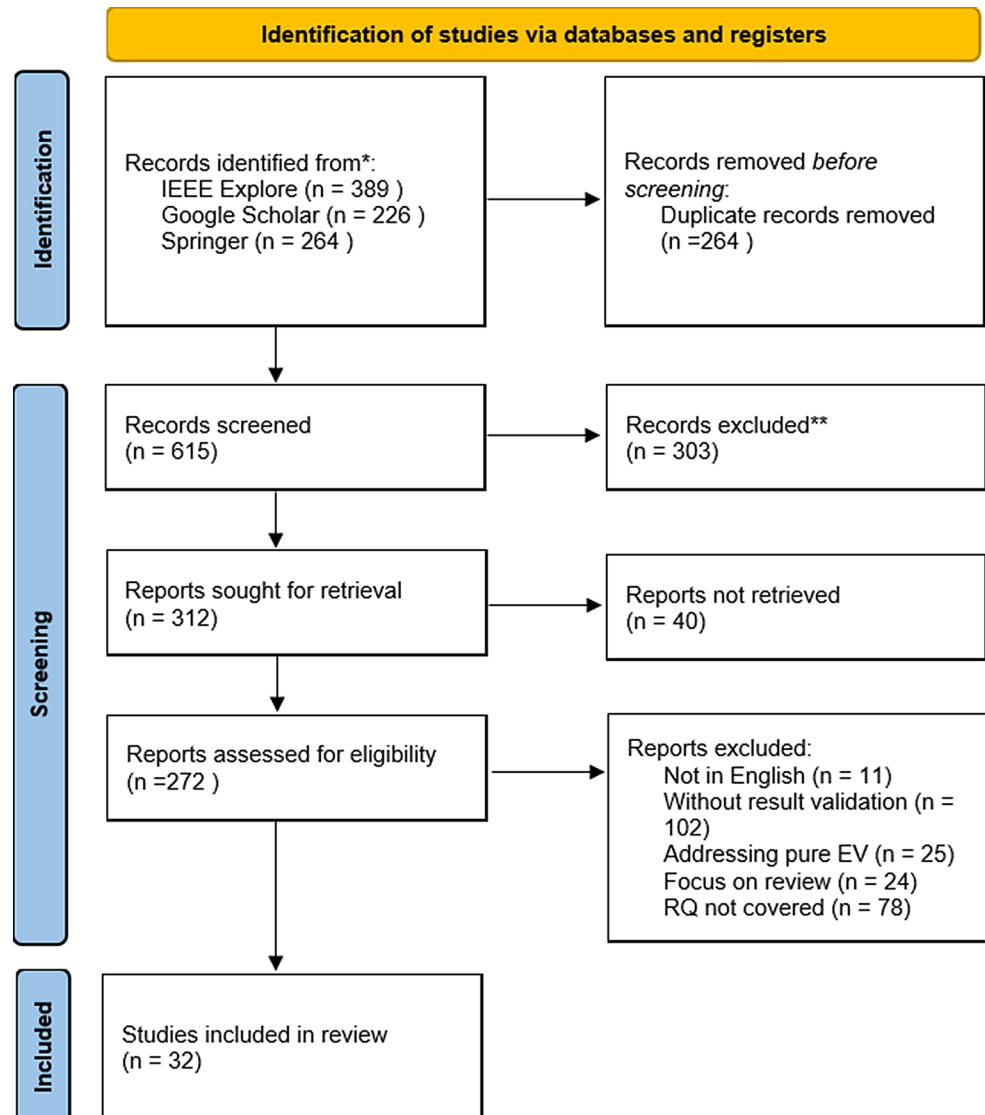
Inclusion criteria: (i) peer-reviewed journal articles and conference papers; (ii) studies proposing or evaluating AI-based EMS for HEVs, PHEVs, or FCHEVs; (iii) studies reporting quantifiable performance metrics (e.g., fuel reduction, state of charge (SoC) regulation, computational cost); (iv) English-language publications.

Exclusion criteria: (i) review papers without novel EMS contribution; (ii) studies exclusively addressing pure EVs without hybrid powertrain context; (iii) papers without simulation or experimental validation; (iv) grey literature, theses, and non-peer-reviewed reports.

1.1.4 Screening Process and PRISMA Summary

The screening process followed a three-stage approach. In the first stage (identification), database searches returned a combined total of approximately 879 records. After removing duplicates across databases, 615 unique records remained. In the second stage (screening), titles and abstracts were reviewed against inclusion/exclusion criteria, reducing the pool to 303 potentially relevant articles. In the third stage (eligibility), full-text review was conducted, and 240 papers were excluded due to insufficient validation detail, or absence of AI components. This yielded a final set of 32 studies for qualitative synthesis, from which the most representative and impactful contributions, particularly those published after 2018 were selected for detailed discussion in this review. The PRISMA flow diagram summarising this process is presented in Fig. 1.

Fig. 1 PRISMA flow diagram illustrating the article identification, screening, eligibility assessment, and inclusion process. Records retrieved from Google Scholar ($n \approx 226$), Springer ($n \approx 264$), and IEEE Xplore ($n \approx 389$). After duplicate removal, abstract screening, and full-text eligibility assessment, 32 studies were retained for synthesis



1.1.5 Quality Assessment of Included Studies

To ensure methodological rigour, each of the 32 included studies was assessed against four quality criteria adapted from established systematic review practice:

1. *Validation type*: whether results were verified through software simulation only, hardware-in-the-loop (HIL) testing, or vehicle-level experiments;
2. *Reporting completeness*: whether the study provided quantifiable performance metrics (fuel reduction percentage, SoC regulation error, or computational cost);
3. *Baseline comparability*: whether the proposed EMS was benchmarked against a clearly defined conventional strategy (e.g., rule-based, ECMS, or dynamic programming); and
4. *Drive cycle diversity*: whether validation was conducted on a single standardised cycle or multiple cycles.

Studies meeting all four criteria were prioritised for detailed discussion. Studies meeting criteria (2) and (3) but using simulation only were retained for synthesis but flagged as simulation-validated throughout Table 2, 3 and 4. This quality filtering, rather than an arbitrary sample size cap, explains the relatively small final set of 32 studies and reflects the community-wide gap between the volume of published AI-based EMS research and the subset that meets sufficient reporting standards for rigorous comparative synthesis.

Table 1 Comparison of this review against existing HEV EMS reviews

Feature	Wang et al. [28]	Pan et al. [29]	Urooj and Nasir [30]	Cao et al. [31]	This Review
FL-based EMS	✓	✓	✓	✓	✓
NN-based EMS	✓	✓	✓	✓	✓
RL / DRL EMS	Partial	Partial	✓	✓	✓
Industry / Society 5.0 alignment	×	×	×	×	✓
XAI integration	×	×	×	×	✓
HITL framework	×	×	×	×	✓
Cross-cutting challenges	×	×	×	×	✓
Structured comparative tables	×	×	×	Partial	✓
Safety / ISO 26262 discussion	×	×	×	×	✓

✓=covered; Partial=briefly mentioned without systematic treatment; ×=not addressed

1.2 Positioning within Existing Reviews and Novelty Statement

Several review papers have addressed EMS for HEVs, yet each presents notable limitations. Wang et al. [28] and Pan et al. [29] provide broad overviews of hybrid EMS categories but do not specifically examine deep learning or RL approaches in depth. Urooj and Nasir [30] and Cao et al. [31] survey intelligent EMS techniques but do not address emerging concerns such as explainability, safety certification, or human-centric design as shown in Table 1. No existing review simultaneously covers FL, NN, RL, XAI, and HITL frameworks within a unified comparative analysis. Furthermore, prior reviews largely omit the practical barriers to real-world deployment, including ECU memory constraints, ISO 26262 compliance, and dataset representativeness which all of which are critical for industrial adoption.

This review addresses these gaps and makes the following specific contributions:

1. First systematic review to simultaneously cover FL, NN, RL, XAI, and HITL frameworks in AI-based HEV EMS within a unified comparative structure.
2. Introduction of a dedicated cross-cutting technical challenges analysis covering generalisation, dataset bias, real-world validation gaps, ECU constraints, and safety certification.
3. Three structured comparative tables (study-level, AI-class, and EMS objective-based) enabling rigorous, consistent comparison across AI methods.
4. Integration of Industry 5.0 and human-centric design principles as a future research framework, linking EMS development to broader societal and regulatory trends.

Scope: This review focuses on HEVs including series, parallel, and series-parallel configurations, as well as PHEVs and FCHEVs where AI-based EMS contributions are directly relevant. Pure BEV energy management is excluded. Both simulation-validated and hardware-in-the-loop (HIL) validated studies are included, with explicit distinction drawn between the two.

2 HEV Architecture

HEVs utilize a combination of ICEs and EMs to improve energy efficiency and reduce emissions. The architectural layout of an HEV significantly affects its EMS, as each configuration presents different opportunities and challenges in power distribution. The three most common HEV architectures are series, parallel, and series-parallel [32].

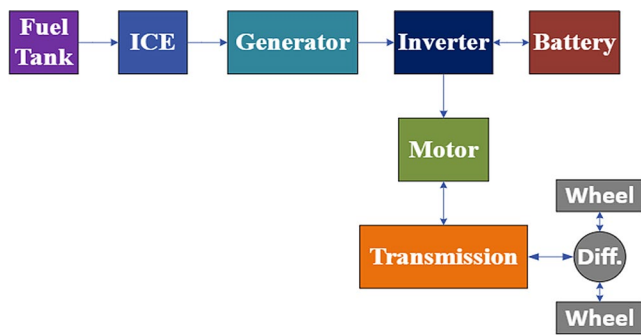


Fig. 2 Series HEV topology

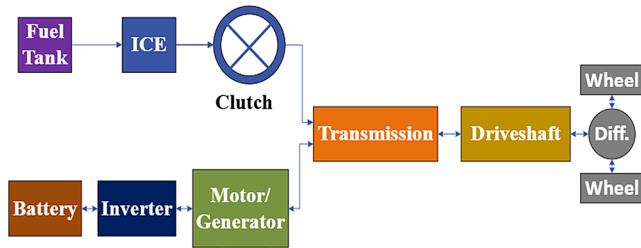


Fig. 3 Parallel HEV topology

2.1 Series HEV

In a series HEV, the ICE is not mechanically connected to the wheels. Instead, it serves solely to generate electricity, which either powers the EM or charges the battery [33, 34]. The EM is the only propulsion source, offering simplified mechanical design and better efficiency in urban driving conditions as shown in Fig. 2. However, overall efficiency may decrease at constant high-speed driving with infrequent stops such as on the highways due to high energy demand and strain on battery usage. The EMS for series HEVs primarily focuses on optimizing the operation of the ICE turning the generator and thus affecting the battery's charging/discharging behaviour [35]. Series HEVs are particularly suited to low-speed, stop-and-go urban driving conditions. Studies have shown that employing the Equivalent Consumption Minimization Strategy (ECMS) in series HEVs can reduce fuel consumption by up to 44% in urban missions compared to rule-based EMS [36]. This decoupling allows the ICE to run at its optimal efficiency point, reducing fuel consumption and emissions in congested city traffic. Due to their simpler mechanical design and greater control over ICE operation, series configurations are favoured in urban transit systems and short-distance logistics vehicles [37].

2.2 Parallel HEV

In a parallel HEV, both the ICE and EM are directly connected to the drivetrain and can independently or jointly provide propulsion as shown in Fig. 3. This configuration

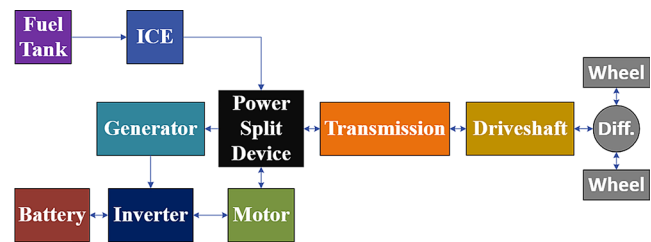


Fig. 4 Series-parallel HEV topology

allows more flexibility in selecting power sources and improving fuel economy across diverse driving conditions [23, 38]. However, it demands a more complex EMS to effectively coordinate the ICE and EM. Parallel HEVs are best suited for applications that involve high-speed or constant-speed driving, such as highway commuting [30, 31]. In these scenarios, the ICE can directly drive the wheels, operating efficiently at medium to high load points. The EM supplements the ICE during acceleration or uphill driving. This will improve overall system efficiency without significantly increasing cost or system complexity. Adaptive rule-based strategies have demonstrated improved performance, achieving better fuel economy over deterministic approaches across standard urban and highway drive cycles [39–41].

2.3 Series-Parallel HEV

Series-parallel HEVs combine features of both series and parallel configurations. They can switch between operating modes based on driving conditions, providing a balance between efficiency and performance [28, 29, 42]. This flexibility enables dynamic power splitting between ICE and EM, which requires advanced EMS algorithms as shown in Fig. 4. This makes them suitable for a wide range of driving conditions, combining city and highway performance perks in a single system. These hybrids dominate the mainstream hybrid and plug-in hybrid market. Strategies like ECMS are commonly used to optimize power allocation in real-time. The complexity of this architecture presents a challenging but promising platform for the implementation of intelligent EMS [23, 43, 44].

2.4 Application Suitability

The architecture of a HEV plays a critical role in determining its drivetrain structure, energy flow, control complexity, and application suitability. A comparison of the three primary HEV architectures—series, parallel, and series-parallel—highlighting their respective features and use cases, is shown in Table 2.

Table 2 Comparison of HEV architectures by application, cost, and performance

Type	Series HEV	Parallel HEV	Series-Parallel HEV
Application Suitability	Urban driving with frequent stop-and-go traffic	Highway driving with constant speed	Mixed conditions: urban and highway
Cost and Complexity	Simpler and less expensive	More complex and expensive	Moderately complex and costly
Performance Characteristics	Limited performance, especially at high speed	Better performance and flexibility; can run short distances on only EM	Balanced performance combining both series and parallel modes

2.5 Influence of HEV Architecture on AI-Based EMS Design

The choice of HEV architecture does not merely define the mechanical powertrain. It fundamentally constrains the design space for AI-based EMS. Each topology presents distinct control challenges that influence the choice of AI method, input dimensionality, reward formulation, and real-time feasibility.

In series HEVs, the decoupling of the ICE from the drivetrain simplifies control by reducing the system to a single-output problem: optimising ICE operating point and battery charging behaviour. This relative simplicity makes FL-based EMS particularly well-suited, as rule bases can be defined over a tractable input space (e.g., SoC, power demand). However, the battery bears the full propulsion burden, which places heightened importance on SoC management and battery health preservation. Recent work by Cavus and Bell [45] demonstrates that deep learning-based battery health prediction, specifically LSTM-Transformer hybrid models can achieve state-of-the-art accuracy in estimating State of Health (SOH) and Remaining Useful Life (RUL) in EV fleets. Integrating such health-aware diagnostics into series HEV EMS represents a promising direction for extending battery lifespan without sacrificing fuel efficiency. For RL-based EMS in series configurations, reward design is relatively straightforward: penalise fuel consumption and SoC deviation. However, the absence of direct mechanical coupling means that the RL agent must learn the indirect relationship between ICE output and vehicle speed, which might delay convergence.

Parallel HEVs introduce torque-coupling between the ICE and EM, requiring the EMS to coordinate two mechanically linked power sources simultaneously [38, 39]. This increases input dimensionality significantly: EMS inputs typically include vehicle speed, acceleration, SoC, ICE torque demand, EM torque capacity, and gear position [46, 47]. For NN-based EMS, this higher-dimensional input space plays to the strengths of multilayer perceptrons and recurrent architectures, which excel at modelling nonlinear multi-variable mappings [46, 48]. However, the need for precise torque coordination under transient conditions poses a challenge for offline-trained models, which may not generalise to rapidly changing real-world driving patterns [44, 49]. For RL agents operating in parallel HEV environments,

the action space must accommodate both continuous torque split ratios and discrete gear selections, creating a hybrid discrete-continuous control problem that requires algorithms such as DDPG or TD3 rather than standard DQN [50, 51].

Series-parallel HEVs present the most complex control challenge, as the EMS must manage dynamic mode switching between series, parallel, and electric-only operation in addition to continuous power splitting [42, 43]. This discrete-continuous hybrid control space is particularly challenging for conventional FL systems, which may require prohibitively large rule bases to cover all operating modes [52, 53]. RL-based approaches, particularly those using hierarchical or multi-agent frameworks, are better positioned to handle mode switching, as the agent can learn mode transition policies as high-level actions over a continuous lower-level control space [51]. For NN-based EMS, the inclusion of mode indicator variables as inputs can partially address this complexity, though ensuring smooth transitions without oscillation remains an open challenge [44, 48]. The complexity of series-parallel architectures also has direct implications for safety certification: the larger state space increases the difficulty of formally verifying AI controller behaviour under all possible operating conditions, as discussed further in Sect. 3.4.

3 AI in EMS

AI has emerged as a transformative tool in addressing the limitations of traditional EMS in HEVs. Unlike static rule-based systems, AI-based EMS can learn from data, adapt to dynamic driving environments, and optimize power distribution in real-time. Recent research has shown promising results using various AI techniques, including FL, NN, RL that combine ML with optimization algorithms.

3.1 FL-Based EMS

FL is a mathematical framework designed to handle uncertainty and imprecision, enabling more flexible and human-like decision-making processes. FL systems are composed of linguistic variables, fuzzy sets, rule bases, and inference mechanisms. Striking a balance between complexity and simplicity, FL offers an adaptable control strategy that

can be deployed in real time (online) and further enhanced through offline optimization. An important extension to traditional FL systems is the concept of fuzzy interpolation, which addresses the limitations posed by sparse or incomplete rule bases. Constructing a comprehensive rule base is often impractical in real-world applications especially for high-dimensional inputs or evolving environments such as HEV EMS. Fuzzy interpolation techniques allow the system to infer plausible outputs by estimating intermediate or missing rules based on surrounding ones. This is achieved through methods that assess similarity or distance between fuzzy sets and apply weighted reasoning to approximate outputs where explicit rules are lacking. For example, Kóczy–Hirota linear interpolation has been shown to yield robust performance even with reduced rule coverage. This enhances system adaptability, reduces memory requirements, and improves inference speed, all of which are crucial for real-time embedded control in HEVs.

Gaoua et al. [54] introduced a two-level FL-based method for managing multiple electrical power sources in response to varying user profiles and diverse vehicle configurations. At the first level, the system considers proprioceptive variables related to the instantaneous energy states of the sources. The second level incorporates exteroceptive variables linked to mission objectives and road conditions to minimize energy consumption. The methodology includes an offline optimization phase using Genetic Algorithms (GA) to fine-tune the FL parameters based on the mission profile. During online, real-time operation, the system executes standard FL procedures, namely fuzzification, rule evaluation, and defuzzification. In this framework, the fuzzification block defines linguistic variables such as EM current demand and super-capacitor voltage (inputs), while

the battery current acts as the output. These variables are mapped using triangular, trapezoidal, or Gaussian membership functions to describe their operational domains [54]. To reduce computational overhead in real-time applications, the embedded converter employs trapezoidal membership functions.

Singh et al. [47] demonstrated that advanced intelligent control algorithms, such as Fuzzy Logic Controllers (FLC) and Elman Neural Networks (ENN). This significantly enhance fuel economy by optimizing power distribution based on real-time parameters as shown in Fig. 5 [47]. These strategies utilize inputs including regenerative braking status, battery SoC, and torque demand to coordinate the operation of key powertrain components such as the ICE, EM, and generator. The FLC approach uses a rule-based system to model the nonlinear behavior of HEV components, aiming to maintain them within efficient operating zones, thereby reducing fuel consumption. Due to its simplicity, FLC offers fast computation and ease of implementation. On the other hand, ENN provides a predictive control mechanism capable of capturing temporal dependencies, allowing it to forecast future states and make proactive control decisions. Singh et al. [47] validated their ENN-based EMS using a real-time hardware-in-the-loop (HIL) setup on an Field-Programmable Gate Array (FPGA) - based Micro-LabBox platform. Results showed that ENN outperformed conventional strategies by reducing speed mismatches and improving fuel economy by up to 89.47%, while FLC achieved around a 50% improvement. These gains were observed across standard drive cycles such as NEDC, UDDS, and FTP, where the intelligent systems helped maintain the operation of energy sources within their optimal efficiency regions and improved regenerative braking

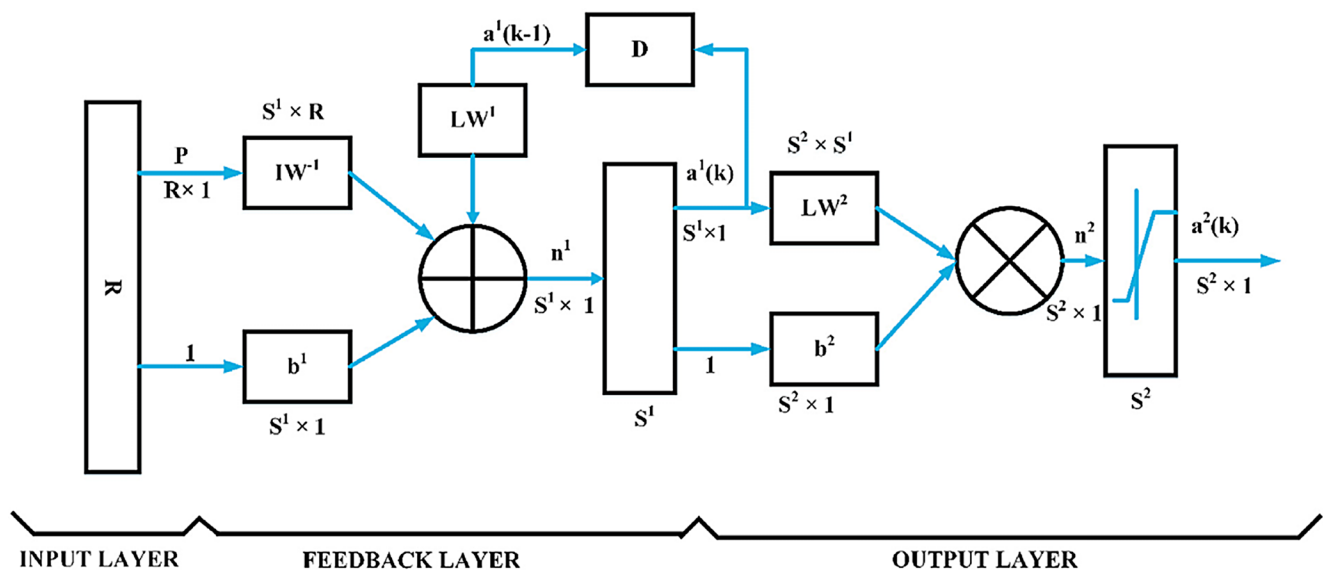


Fig. 5 Mathematical model of ENN [47]

energy recovery [47]. This study highlights the advantages of integrating adaptive EMS strategies using FL and NN for more efficient and environmentally friendly HEVs.

Guler et al. [52] extended this approach by implementing an Adaptive Fuzzy Logic Controller (AFLC) within a comprehensive simulation framework that evaluated system performance across various realistic driving conditions, including urban, highway, and mixed drive cycles. These scenarios were designed to reflect typical vehicle usage: frequent stop-and-go traffic for urban cycles, sustained high speeds for highways, and variability for mixed conditions. The AFLC features a hierarchical control architecture in which a high-level decision system selects between Type-1 FLC (T1-FLC) and Interval Type-2 FLC (IT2-FLC), based on real-time uncertainty estimations as shown in Fig. 6 [52]. Decision thresholds are continuously adjusted using environmental data—such as road gradient, traffic density, and weather conditions—acquired from onboard sensors and vehicle data. In low-to-moderate uncertainty environments (e.g., urban traffic), T1-FLC is applied to maintain efficiency with lower computational demand. In contrast, under high-uncertainty conditions (e.g., steep terrain or heavy rain), the system switches to IT2-FLC, which offers greater robustness despite higher computational complexity. Input variables such as vehicle speed, acceleration, SoC, ICE torque demand, and road slope are processed through fuzzy inference mechanisms with multiple membership functions to determine the optimal power split strategy. The proposed control strategy yielded a significant reduction in fuel consumption—from 7.26 L/100 km to 6.69 L/100 km—equating to a 7.8% efficiency gain. Additionally, the battery SoC increased from 72.7% to 75.8%, indicating better energy

utilization [52]. The AFLC's ability to adapt to different driving conditions enhances its robustness and ensures consistent energy efficiency and battery management in diverse real-world scenarios.

Mazouzi et al. [53] proposed a methodology that integrates a FL-based EMS optimized through a GA, offering a systematic approach to enhance fuel efficiency in fuel cell hybrid electric vehicles (FCHEVs). Their optimization process encompasses four critical phases: selecting the appropriate membership function types, tuning fuzzy variable ranges, fine-tuning membership function parameters, and adjusting rule weights. This multi-stage procedure effectively automates the tuning of FL parameters, overcoming the limitations of manual adjustment and ensuring optimal power distribution between the fuel cell and battery. Validation was conducted through simulations using the ADVISOR platform combined with MATLAB/SIMULINK, applying the EUDC driving cycle to assess real-world driving conditions. The results demonstrated a significant improvement in fuel efficiency—specifically, a 28.5% reduction in fuel consumption and has highlighted the robustness of the optimized fuzzy EMS in managing energy flows more effectively over the drive cycle [53]. This method not only enhances operational efficiency but also contributes to reducing low-efficiency fuel cell operation, ultimately leading to a more sustainable vehicle performance.

Yang et al. [55] have proposed an innovative approach that combines FLC with particle swarm optimization (PSO) to address the challenges of real-time energy management and uncertainty in control parameters. The methodology involves designing a FL rule-based EMS that optimizes the storage and release of flywheel kinetic energy, thereby

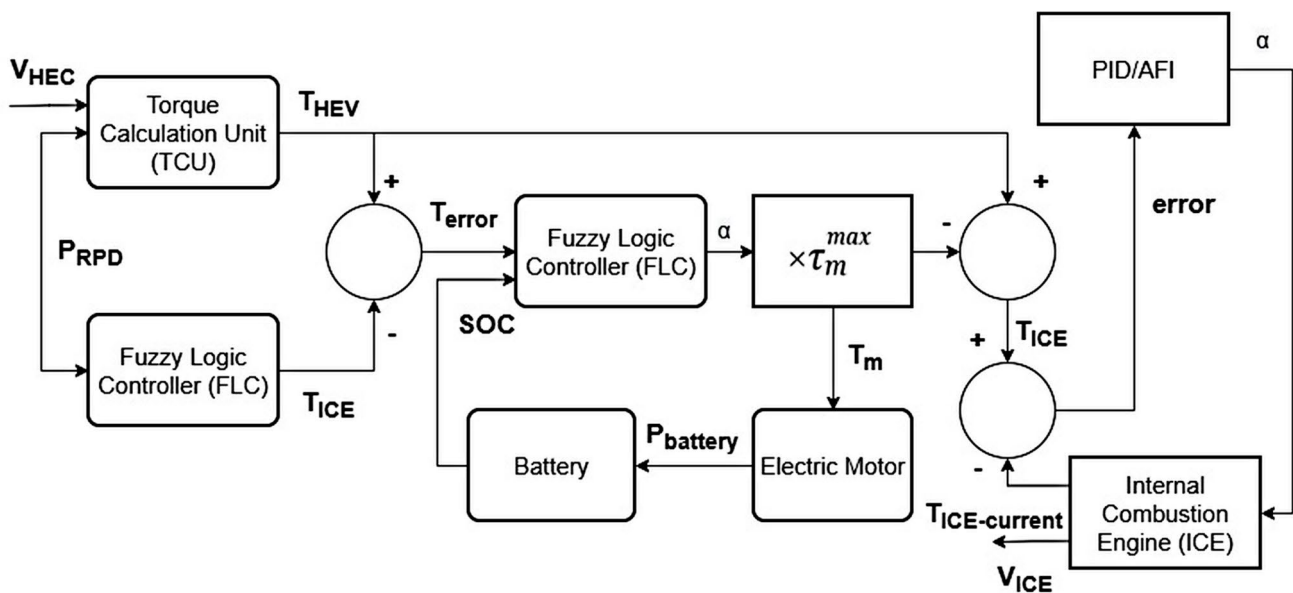


Fig. 6 AFLC-IEMS architecture [52]

enhancing system efficiency. To eliminate the subjectivity and limitations of manually set fuzzy rules, PSO is employed to optimize the membership functions of the fuzzy controller and has ensured more accurate and adaptive control under varying driving conditions. The multi-objective optimization framework developed integrates fuel consumption and emission reduction to achieve a significant data improvements in fuel efficiency. Specifically, simulation results under different drive cycles such as UDDS, CHTC-LT, and ZBTC demonstrate reductions in equivalent fuel consumption by approximately 7.287%, alongside reductions in carbon monoxide (CO), hydrocarbons (HC), and nitrogen oxides (NO_x) emissions by 22.35%, 26.89%, and 31.13%, respectively [55]. Further optimization with PSO enhances fuel economy by an additional 0.243%, and emission reductions are further improved by over 10%, confirming the effectiveness of this combined approach in diverse driving scenarios.

The FL-based EMS highlights a well-balanced profile with strong emphasis on real-time implementability and interpretability. Owing to its rule-based structure, FLC enables transparent decision-making and low computational burden, making it suitable for real-time deployment on embedded automotive controllers. However, the chart also reveals limitations in adaptability and scalability, as the reliance on predefined rules constrains its ability to generalize across diverse driving conditions and vehicle configurations. These characteristics suggest that while FL remains a reliable and mature solution for HEV EMS, its standalone application may be insufficient for highly dynamic or large-scale scenarios without adaptive enhancement mechanisms.

3.2 NN-Based EMS

NNs, particularly Multilayer Perceptrons (MLPs), have gained widespread adoption in HEV EMS due to their strong capability to model complex non-linear relationships between input features and target outputs.

Millo et al. [46] developed an MLP-based model to predict fuel consumption in parallel HEVs using a diverse set of driving inputs, including vehicle speed, acceleration, gear position, road slope, and SoC as shown in Fig. 7 [46]. Trained on a combination of simulated and real-world driving data—such as WLTC, CADC, and UDDS, the model achieved high predictive accuracy, with an R^2 value exceeding 0.95 and a root mean square error (RMSE) below 0.15 L/100km. Beyond accurate fuel consumption estimation, this data-driven approach enabled the formulation of advanced EMS strategies that significantly outperformed conventional rule-based systems. Across various driving cycles, the MLP-based method yielded an average fuel saving of 9.2%, with a peak reduction of 12.1% observed on the WLTC cycle. These findings highlight the potential of supervised learning in enhancing both the prediction accuracy and energy optimization capabilities of EMS frameworks.

In a more advanced application, Liu et al. [56] proposed a controllable NN-based approach for EMS in fuel cell hybrid electric vehicles (FCHEVs). This method integrates multiple technical innovations to deliver superior fuel economy and computational efficiency. A key feature is the inclusion of the target SoC as an explicit input to the NN which is analogous to the equivalent factor used in traditional ECMS, thereby making the NN controllable as shown in Fig. 8 [56]. This allows the system to adjust its outputs

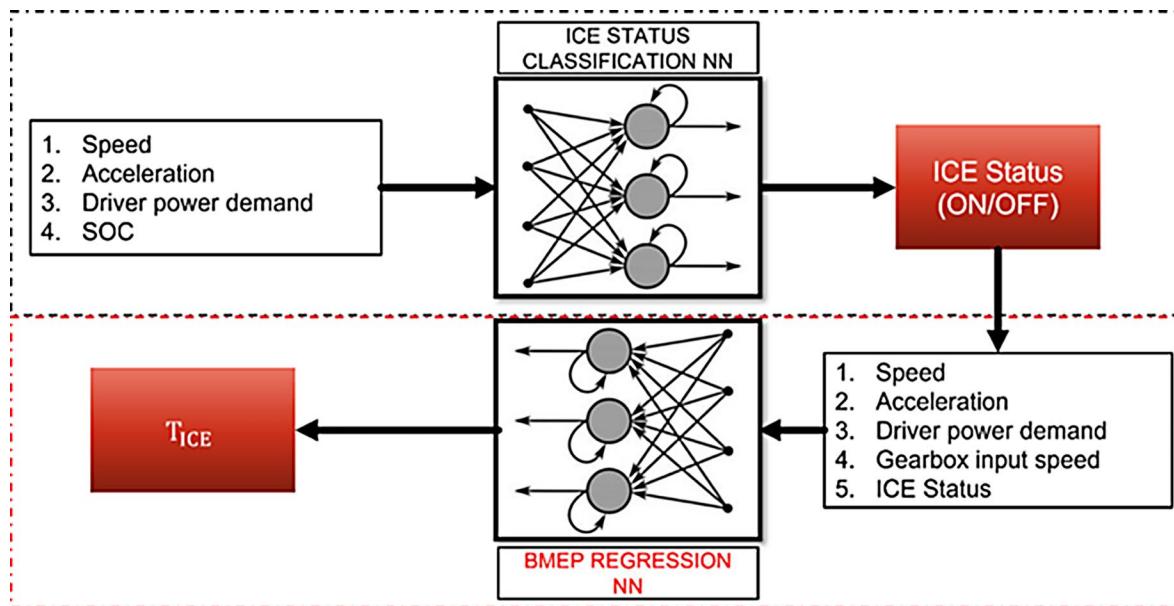


Fig. 7 EMS based on two LSTM NN architecture representation [46]

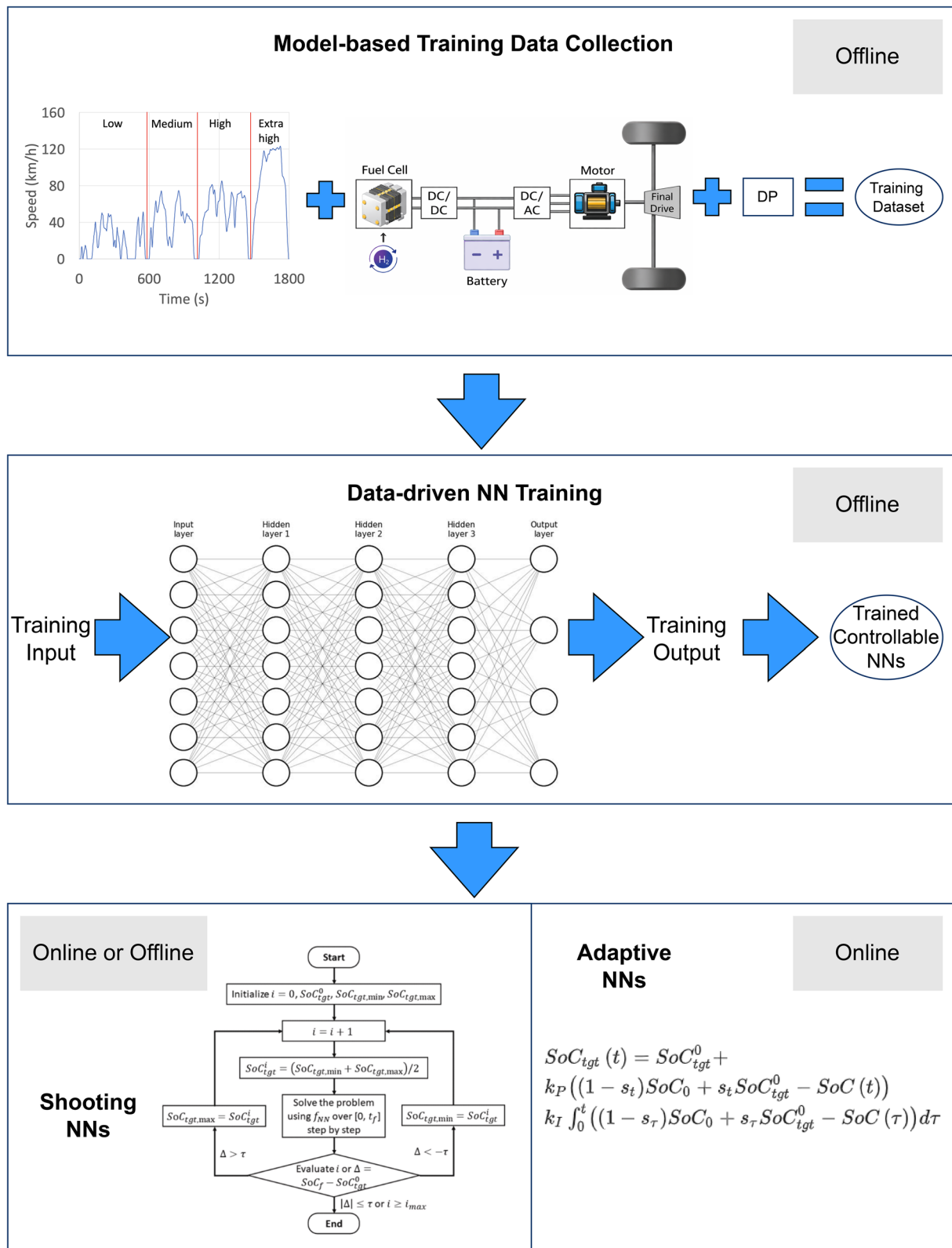


Fig. 8 Framework of the proposed controllable NN-based EMS [56]

dynamically to meet specific final SoC goals, improving adaptability across different driving cycles and operational constraints. The MLP network is trained offline using data generated by dynamic programming (DP), which ensures that the network closely approximates globally optimal control policies. During real-time operation, a shooting method is employed to iteratively determine the optimal target SoC that minimizes hydrogen consumption while satisfying terminal SoC requirements. As a result, the controllable NN achieves approximately 99.7% of the fuel efficiency of DP at just 5% of its computational cost. This is comparable to shooting-based ECMS methods. To further enhance real-time responsiveness, the EMS incorporates an adaptive NN mechanism that fine-tunes its parameters on-the-fly based on SoC feedback and recognized driving patterns. This adaptive capability boosts robustness and efficiency under dynamic and uncertain driving conditions. Empirical validation shows that this approach delivers over 3% average fuel savings compared to standard ECMS, a 95% reduction in computational demand enabling real-time feasibility, and an additional 1% improvement in fuel economy over adaptive ECMS during real-world driving scenarios [56]. Together, these innovations enable precise control of final SoC, practical real-time implementation through efficient DP approximation, and strong adaptability to real-world variability and closing the performance gap between offline optimality and online adaptability in FCHEV energy management.

The study conducted by Naguib et al. [48] employs a NN-based EMS designed to optimize the control of multi-mode power-split HEVs. The methodology involves initially utilizing a DP algorithm to generate globally optimal control data across various driving conditions and drive cycles, including city and highway patterns. This offline data serves as a training dataset for the NN model, enabling it to learn the complex relationships between driving conditions, mode selection, and power distribution strategies. Once trained, the NN is implemented in real-time, providing near-optimal control with significantly reduced computational demands, thus facilitating deployment in vehicle electronic control units (ECUs). This approach effectively enhances fuel efficiency, as demonstrated by the results showing the NN-based EMS achieving fuel consumption within 2% of the DP benchmark across diverse drive cycles [48]. The strength of this methodology lies in its ability to adapt to different driving behaviours and conditions while maintaining low computational complexity, leading to improved fuel economy and operational robustness in real-world scenarios.

Jondhle et al. [57] utilized a recurrent neural network (RNN) based approach for advanced energy management in HEVs, emphasizing precise prediction of power demand and optimal energy distribution. The RNN architecture

comprises three layers: input, hidden (recurrent), and output layers, where the hidden layer employs fully connected nodes to capture temporal dependencies in the input data. The network's parameters include weights P, Q, and R, representing connections between input-hidden, hidden-output, and recurrent hidden layers, respectively. Data normalization, via min-max scaling, is applied to input parameters such as speed, SoC, fuel cell power, and ultracapacitor metrics, within the range [0, 1], ensuring numerical stability and improved convergence during training [57]. The RNN model processes these parameters to forecast phase delays and adjust power allocation dynamically and has produced result in a more efficient energy use. The approach not only reduces unnecessary fuel consumption but also enhances overall system responsiveness by adapting to driving conditions in real time. This detailed data-driven method demonstrates a significant improvement in fuel efficiency across various drive cycles by intelligently managing the hybrid energy sources without compromising vehicle performance.

Chen et al. [58] highlights various methods aimed at optimizing fuel efficiency across different driving conditions for plug-in hybrid electric vehicles (PHEVs). Traditional rule-based control approaches often lack adaptability and fail to leverage real-time data, resulting in suboptimal performance. To address this, recent studies have employed advanced techniques such as adaptive energy management systems integrated with artificial neural networks (ANNs), which provide superior generalization capabilities and can predict near-optimal power distribution strategies dynamically. Specifically, Chen et al. [58] utilized a NN-enhanced energy management approach that models the relationship between driving patterns, battery state, and fuel consumption. This method leverages a comprehensive training dataset derived from diverse driving cycles such as NEDC, WLTC, and real-world cycles to improve the ANN's predictive accuracy. The incorporation of multiple driving patterns enables the system to adapt effectively to variations in driving behavior, leading to significant improvements in fuel efficiency, with reported fuel savings exceeding 96% compared to baseline rule-based strategies across numerous cycles [58]. It should be noted that this figure represents the maximum improvement reported relative to a rule-based ECMS baseline under specific drive cycle conditions (NEDC, WLTC, and real-world cycles); direct cross-study comparisons are limited by differences in baseline methods, drive cycles, and vehicle configurations, as reflected in Table 3. This approach demonstrates that data-driven NN models can enhance the accuracy of energy management and optimize fuel consumption in real-world driving scenarios.

NN-based EMS demonstrates a more balanced trade-off between adaptability, performance, and real-time feasibility. NN exhibit strong capability in capturing nonlinear

Table 3 Study-level comparison of AI-Based EMS

Ref (Year)	AI Class	Drive Cycle	Baseline Method	Fuel Reduction (%)	Validation Type	HEV Architecture
Singh et al. [47]	FL+NN (ENN)	NEDC, UDDS, FTP	Rule-based	~50–89%	HIL (FPGA)	Series-Parallel
Guler et al. [52]	AFLC (T1/IT2-FLC)	Urban, Highway, Mixed	Standard FLC	7.8%	Simulation	Parallel
Gaoua et al. [54]	Two-Level FL+GA	Mission-based	Rule-based	N/A	Simulation	Series
Mazouzi et al. [53]	GA-Optimised FL	EUDC	Standard FL	28.5%	Simulation (ADVISOR)	FCHEV
Yang et al. [55]	PSO-Tuned FLC	UDDS, CHTC-LT, ZBTC	Standard FLC	7.3%	Simulation	Flywheel HEV
Millo et al. [46]	MLP (supervised)	WLTC, CADC, UDDS	Rule-based	9.2% avg	Simulation	Parallel PHEV
Liu et al. [56]	Controllable NN+DP	Multiple cycles	ECMS	>3%	Simulation	FCHEV
Naguib et al. [48]	NN trained on DP data	City+Highway	DP benchmark	Within 2% of DP	Simulation	Power-split HEV
Jondhle et al. Jondhle2024	RNN-based EMS	Multiple	Baseline	Significant	Simulation	HEV
Chen et al. [58]	ANN-enhanced ECMS	NEDC, WLTC, Real-world	Rule-based ECMS	>96%	Simulation	PHEV
Hu et al. [50]	A-DDPG / A-TD3 (RL)	NEDC, UDDS, Tianjin	Conventional	9–18.5%	Simulation+ Real data	HEV
Estrada et al. [49]	CNN+DDQL	Markov Chain cycles	Rule-based	Improved	Simulation	HEV
Hu et al. [59]	DRL-based EMS	Multiple	Rule-based	10.09%	Simulation	HEV
Liu et al. [60]	RDPO (DRL+RBRS)	3 standard cycles	Rule-based	Competitive	Simulation	Power-split HEV
Hu et al. [61]	Distributed DRL (ApeX)	Fleet driving cycles	Conventional	4.5%	Simulation+ V2X	Fleet HEV

relationships between driving conditions and powertrain behavior, enabling near-optimal fuel efficiency improvements across varying drive cycles. While computational requirements are higher than those of rule-based methods, real-time implementation remains feasible, particularly when training is performed offline. Nevertheless, reduced interpretability remains a notable limitation, which may hinder acceptance in safety-critical automotive applications. Overall, NN-based EMS represents a promising middle ground between traditional heuristic approaches and fully autonomous learning-based strategies.

3.3 RL-Based EMS

RL is a subfield of ML in which an agent learns to make optimal decisions by interacting with an environment and receiving feedback in the form of rewards or penalties. Unlike supervised learning, which relies on labeled datasets, RL learns through trial and error, progressively refining its policy to maximize cumulative rewards over time. The RL process involves states, actions, rewards, and policies that guide the agent's behaviour.

Recent advancements in applying RL to HEV EMS have demonstrated significant improvements in fuel efficiency across various driving conditions. Hu et al. [50] implemented advanced RL algorithms such as Adaptive Deep Deterministic Policy Gradient (A-DDPG) and Adaptive Twin Delayed Deep Deterministic Policy Gradient (A-TD3),

leveraging expert demonstration (ED) data derived from standard drive cycles (e.g., NEDC, UDDS) and real-world traffic data collected from Tianjin city roads as shown in Fig. 9 [50]. The incorporation of apprenticeship-based RL methods led to faster convergence and up to 18.5% reduction in fuel consumption in the NEDC cycle compared to conventional strategies. Similar benefits were observed in the UDDS cycle, though the extent of improvement varied with the specific algorithm and configuration. When tested on real-world Tianjin data obtained via GPS and inertial sensors—fuel economy gains ranged from approximately 9% to 18.5%, especially under guidance from ED. Other standard drive cycles, including FTP75, US06, and WVM, also exhibited consistent fuel savings between 3% and 18.5%, highlighting the robustness and adaptability of RL-based approaches. Overall, integrating expert demonstrations and domain-adaptive meta-learning not only accelerated RL training but also enhanced EMS optimization across diverse scenarios, underscoring the strong potential of RL strategies to improve HEV energy efficiency [50].

In contrast to conventional rule-based control strategies, DRL-based EMS architectures offer several compelling advantages. Unlike rule-based systems which rely on pre-programmed logic and lack adaptability, DRL methods dynamically learn optimal strategies by interacting with the environment. This adaptability is enabled by DRL's use of deep neural networks (DNN), which capture complex, non-linear mappings between state-action pairs and their

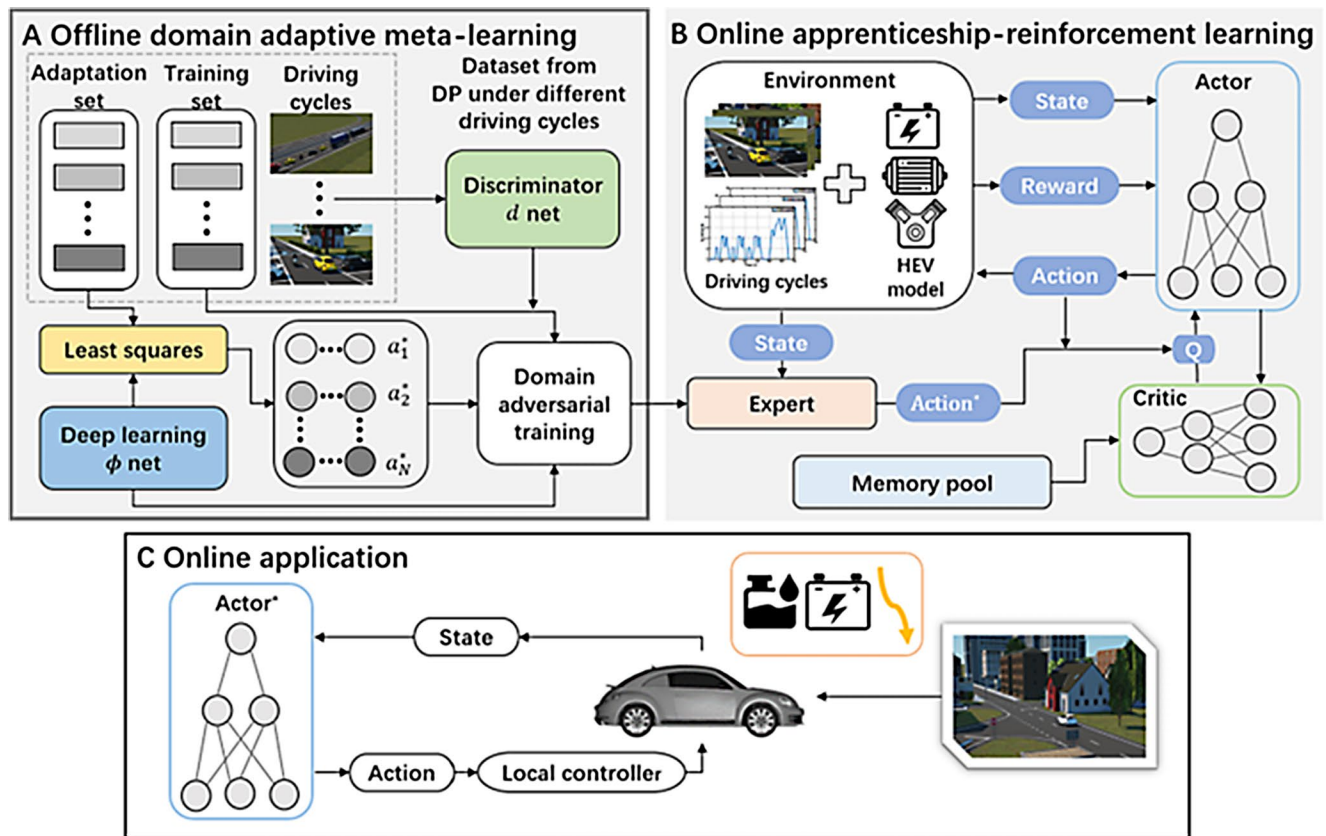


Fig. 9 HEV EMS design by A-DDPG and A-TD3 [50]

associated value estimates [49]. This capability equips DRL to handle high-dimensional control problems and extensive state spaces, making it well-suited for HEV applications. Estrada et al. [49] proposed a hybrid modeling approach that leverages convolutional neural networks (CNNs) for accurate prediction of pollutant emissions, capturing transient effects more effectively than traditional static models. Their methodology involved developing lightweight CNNs trained on experimental data collected from chassis dyno tests, which enhanced the precision of emission forecasts during varying ICE states. Additionally, they employed a Double Deep-Q learning (DDQL) algorithm within a co-simulation framework to optimize the EMS, resulting in improved fuel efficiency and reduced emissions. To ensure the EMS adapts effectively to real-world driving conditions, they trained the DDQL model with driving cycles generated through a Markov Chain-based approach from actual recordings, which introduced greater variability and realism into the cycle data [49]. This approach led to notable improvements in drive cycle simulation accuracy and fuel consumption prediction, effectively optimizing energy usage across diverse driving patterns. The combined methodology not only accelerates simulation speeds up to ten times faster than real-time but also enhances the applicability of the

models for real-time control and vehicle testing scenarios, contributing to more efficient energy utilization on different drive cycles.

Hu et al. [59] demonstrated that a DRL-based EMS can substantially outperform rule-based strategies, achieving a 10.09% reduction in fuel consumption and an 8.05% decrease in equivalent fuel usage. These improvements are primarily attributed to the DRL agent's ability to learn from historical data and continuously optimize control actions in real-time. Notably, DRL does not require expert-designed models or control rules as it relies solely on state observations and reward feedback. This contrasts with other learning-based EMS approaches, such as Neural Dynamic Programming (NDP) and Fuzzy Q-learning (FQL), which depend heavily on domain expertise and complex control formulations [59]. Additionally, the stability of the DRL algorithm can be enhanced through architectural designs such as stabilized Q-target networks, further reinforcing its applicability in real-time control scenarios.

In a subsequent study, Hu et al. [61] proposed a distributed DRL-based EMS built on a cloud-enabled architecture inspired by the ape-X framework as shown in Fig. 10 [61]. In this system, each vehicle functions as a local actor that interacts with its unique driving cycle and selects actions

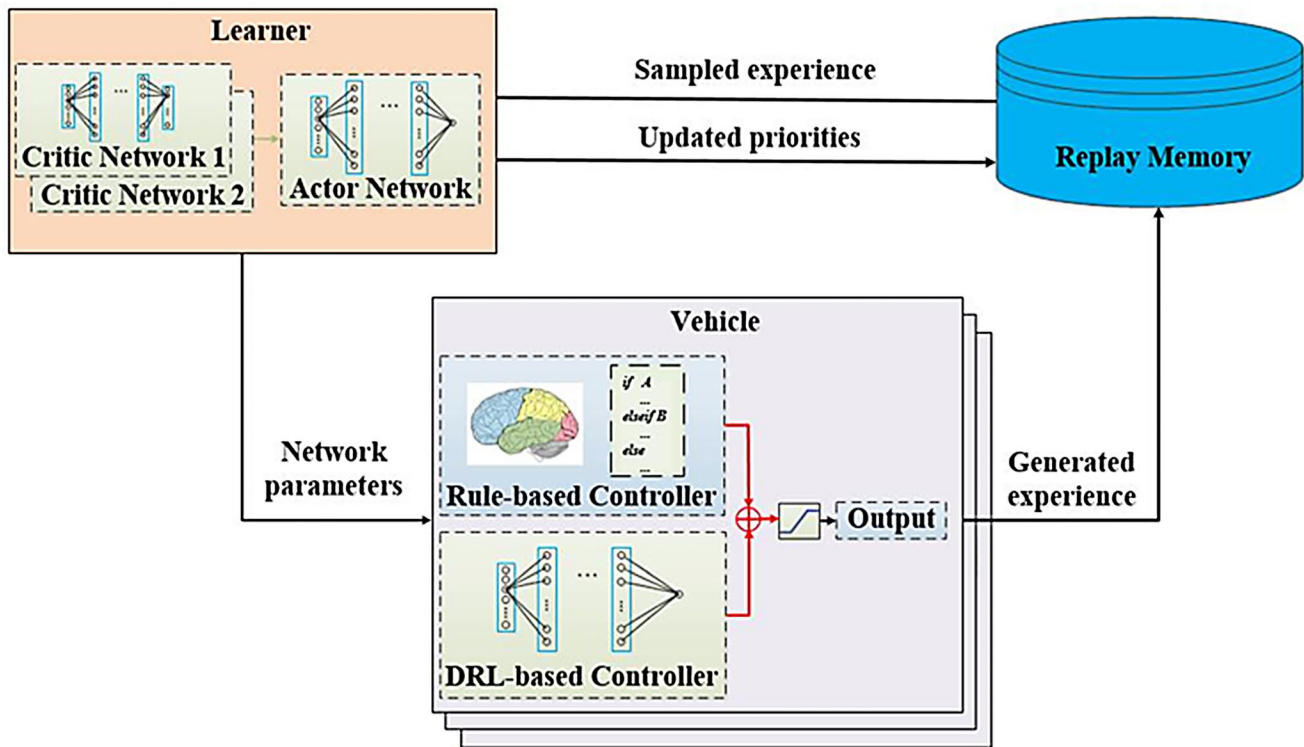


Fig. 10 Distributional SLC HEV EMS framework [61]

using a shared global NN. Experience data from each vehicle is asynchronously transmitted to a cloud server for centralized experience replay and model updating. This design not only accelerates training across a fleet of vehicles but also enables scalable deployment. To ensure operational safety, a baseline rule-based EMS is retained as a supervisory layer, with the DRL controller serving as an adaptive module that compensates for uncertainties and dynamic conditions. Real-time data exchange is facilitated via 4G/5G-enabled vehicle-to-everything (V2X) communication, enabling low-latency coordination. The approach achieved an additional 4.5% reduction in fuel consumption compared to conventional control, demonstrating its scalability and effectiveness in real-world fleet operation [61].

Liu et al. [60] introduced a DRL-based framework named the Rule-Driven Policy Optimization (RDPO) EMS, which integrates a NN controller with a rule-based restraint system (RBRS). In this architecture, the NN component interacts with the simulated HEV environment and driving scenarios by generating control actions and learning from the resulting trajectories of states, actions, and rewards. The RBRS functions as a safety mechanism that filters control signals to prevent irrational outputs, ensuring that the NN operates within predefined safe limits. This hybrid approach not only enhances control reliability but also eliminates the need for post-training calibration or rule-tuning. The

RDPO framework was validated over three standard drive cycles and demonstrated a competitive fuel economy of 4.495 L/100 km while maintaining safety-compliant control signals. Furthermore, the approach supports direct deployment to new drive cycles without requiring additional training, emphasizing its real-time applicability and generalization capability [60].

Collectively, these studies illustrate the significant progress and promise of RL- and DRL-based EMS frameworks in HEVs. By learning optimal control strategies from experience, these systems overcome the limitations of traditional rule-based approaches and offer scalable, adaptive, and energy-efficient solutions for real-world vehicle operation. RL-based EMS illustrates a highly adaptive and performance-oriented profile, with pronounced strengths in adaptability and scalability. By learning optimal control policies through interaction with the environment, RL enables significant fuel efficiency improvements under diverse and previously unseen driving conditions. However, this also reflects increased computational complexity and limited explainability, which pose challenges for real-time deployment and regulatory acceptance. These findings indicate that while RL-based EMS offers substantial potential for next-generation HEV control, its practical adoption necessitates the integration of safety constraints, XAI techniques, and HITL validation frameworks.

3.4 Cross-Cutting Technical Challenges in AI-Based EMS

Beyond the method-specific limitations identified in individual FL, NN, and RL subsections, a set of systemic challenges cut across all AI-based EMS approaches. These challenges represent the primary barriers between current research results and industrial deployment, and must be addressed before AI-based EMS can achieve widespread adoption in commercial HEVs.

3.4.1 Generalisation Across Unseen Drive Cycles

The majority of reviewed EMS studies validate their approaches on a fixed set of standardised drive cycles such as NEDC, WLTC, UDDS, or FTP-75. While performance on these cycles is necessary for benchmarking, it is insufficient to demonstrate real-world robustness. Real driving conditions exhibit stochastic variability including variable traffic density, road gradients, weather conditions, and driver behaviour that standardised cycles do not capture [49].

Studies that exclusively report performance on a single cycle risk overfitting their controller to that cycle's specific speed-time profile. Cross-cycle generalisation tests, where the model is trained on one cycle and evaluated on another, are reported in fewer than 30% of the reviewed papers. Liu et al. [44] directly addressed this gap by combining naturalistic driving big data with DRL, demonstrating significantly improved generalisation across diverse real-world scenarios. Similarly, federated and distributed learning approaches, such as the ApeX-based DRL framework proposed by Hu et al. [61], partially address this limitation by training across diverse real-world driving scenarios. However, the community lacks a standardised protocol for reporting generalisation performance, limiting cross-study comparability.

3.4.2 Data Bias and Dataset Representativeness

AI-based EMS models are only as reliable as the data on which they are trained [24]. In NN and DRL approaches, training datasets are typically derived from simulation environments (e.g., MATLAB/Simulink, ADVISOR) or a narrow set of standardised drive cycles [46, 58]. These datasets may not represent the full distribution of real-world driving conditions, particularly for diverse geographic regions, climates, and driver demographics. Dataset bias manifests in reduced performance when the deployed model encounters operating conditions outside its training distribution [44]. This is particularly concerning for RL agents trained in simulation, which may fail to transfer their learned policies to real vehicles which is a problem known as the sim-to-real gap [50].

Future work should prioritise the development of diverse, large-scale real-world driving datasets for EMS training, akin to what Cavus et al. [62] demonstrated in EV charging demand forecasting, where regionally diverse behavioural data significantly improved model generalisation. Similarly, Cavus et al. [63] demonstrated that robust forecasting under incomplete real-world data, achieving acceptable accuracy with up to 25% missing observations, underscores the importance of data-resilient modelling approaches for practical EMS deployment.

3.4.3 Real-World Validation Rates

An analysis of the reviewed literature reveals a substantial gap between simulation-based and real-world validation [33]. Over 85% of the reviewed AI-based EMS studies rely exclusively on software simulation, with fewer than 10% reporting vehicle-level experimental validation. HIL testing, which bridges the gap between simulation and physical deployment, is reported in approximately 5 to 8% of studies, notably, Singh et al. [47] validated their ENN-based EMS on an FPGA-based MicroLabBox platform, representing one of the few examples of real-time HIL validation in the reviewed literature.

Similarly, Naguib et al. [48] highlighted the importance of ECU-compatible deployment, emphasising that simulation-only results are insufficient for confirming readiness in production vehicles. This prevalence of simulation-only validation raises questions about the practical applicability of reported performance improvements, as simulation models inevitably introduce idealising assumptions regarding vehicle dynamics, sensor noise, and actuator delays [49]. Future studies should consider adopting a tiered validation strategy: software-in-the-loop (SIL) followed by HIL testing in order to transition more simulation-based studies towards real-world readiness.

3.4.4 Embedded ECU Implementation Constraints

Commercial HEV energy management controllers must operate within strict resource constraints imposed by automotive-grade electronic control units (ECUs), which typically offer limited flash memory, constrained RAM, and tight real-time execution budgets per control cycle [26, 48]. DNNs and DRL agents, which may require millions of floating-point operations per inference, are generally undeployable with these constraints in their standard form [50, 60].

Beyond memory and compute constraints, the demands placed on ECUs by RL-based EMS raise broader implementation concerns. The high inference cost of actor-critic architectures, such as those used in DDPG and TD3, can introduce decision-making latency on resource-constrained

ECUs. In safety-critical driving scenarios, such delays can transform avoidable hazards into unavoidable ones, posing a direct risk to vehicle and occupant safety. This problem is further compounded as richer and more diverse training datasets are incorporated to improve model generalization.

Greater data complexity translates directly into higher computational demand at inference time. This places additional strain on ECU memory and processing budgets [50, 60]. At the algorithm level, real-world driving conditions are highly dynamic, requiring the EMS to react within milliseconds to sudden changes in speed, load, and road gradient. The readiness of current RL algorithms to meet these reaction time requirements under such variability remains uncertain. Most validation studies rely on standardised simulation environments that do not capture the full stochasticity of on-road operation [48]. Until these constraints are systematically addressed through model compression, policy distillation, or hardware-aware training, RL-based EMS should be considered research-stage despite its strong simulation performance.

3.4.5 Safety Certification Challenges (ISO 26262)

The deployment of AI-based controllers in safety-critical automotive systems requires compliance with functional safety standards, most notably ISO 26262 for road vehicles [64]. This standard mandates systematic hazard analysis, safety goal definition, and formal verification of system behaviour under fault conditions. AI models particularly DNNs and RL agents present fundamental challenges for ISO 26262 compliance due to their opacity as it is difficult to formally prove that a NN will not produce unsafe control outputs for any possible input [65, 66].

Hybrid approaches that combine AI controllers with rule-based safety layers, such as the RDPO framework proposed by Liu et al. [60], represent a pragmatic mitigation strategy, constraining AI outputs within pre-verified safe bounds. Ante-hoc XAI methods, including decision trees and attention mechanisms, offer partially verifiable decision

logic and may facilitate compliance with Automotive Safety Integrity Level (ASIL) requirements [67]. Regulatory bodies and automotive OEMs are increasingly calling for AI governance frameworks that address these certification challenges [66], and future EMS research should explicitly engage with ISO 26262 requirements during the controller design phase.

3.5 Summaries of Related Researches

Table 3 presents a study-level comparison of all AI-based EMS contributions reviewed, enabling direct benchmarking across AI class, drive cycle, baseline method, reported fuel reduction, and validation type. Table 4 synthesises performance characteristics at the AI-class level, providing a consolidated view of adaptability, real-time feasibility, interpretability, and deployment maturity. Table 5 compares AI approaches from an EMS objective perspective, examining optimisation type, multi-objective capability, constraint handling, training requirements, and safety compliance.

4 User-Centered and Transparent AI Strategies for EMS

4.1 Human-Integrated Solutions for Industry 5.0

The next frontier of HEV energy management lies in harmonizing AI with human-centric design. This approach coincides with the aspiration of Industry 5.0 which emphasizes collaboration between human competency and machine intelligence, enabling personalized, resilient, and ethical system behaviour without sacrificing efficiency [68]. In fact, the aim is to obtain higher efficiency through the synergy between human and machine in order for humanity to progress towards the vision of a super-smart society, also known as Society 5.0 [69].

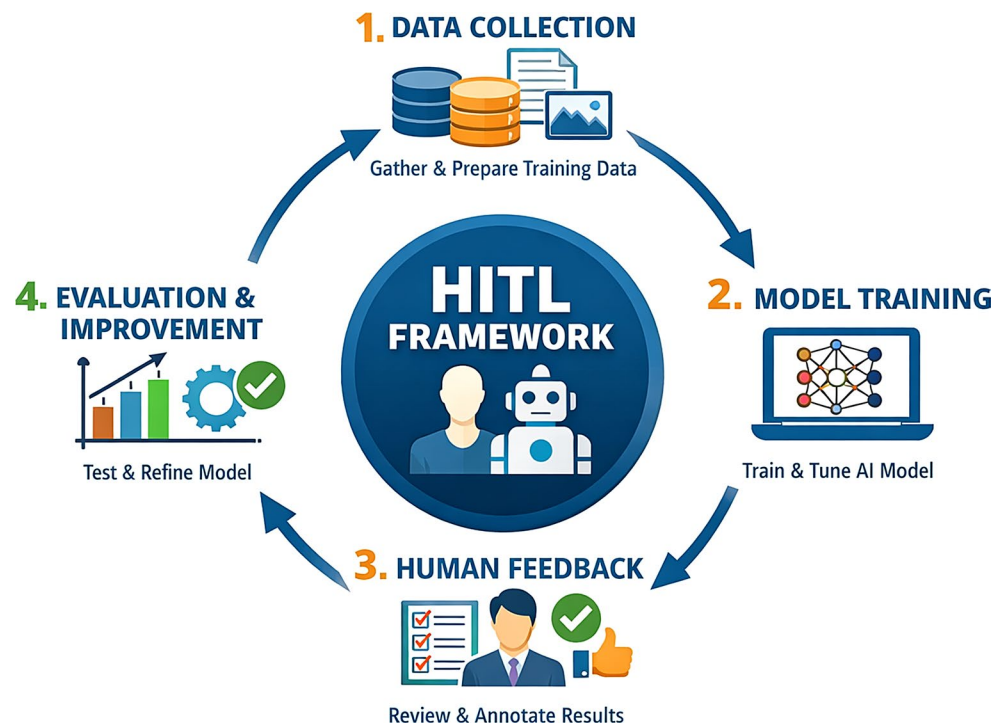
In this context, future EMS are expected to evolve from fully autonomous AI-based decision-makers into interactive

Table 4 AI-Class comparative summary of EMS approaches

AI Class	Typical Algorithms	Fuel Reduction Range (%)	Adaptability	Real-Time Feasibility	Interpretability	Deployment Maturity
FL	FLC, IT2-FLC, AFLC, GA/PSO-Tuned FL	7–89%	Low–Moderate	High (real-time deployable)	High (rule-transparent)	Medium
NN	MLP, ANN, RNN, ENN, Controllable NN	3–96%	Moderate–High	Moderate (offline train)	Low (black-box)	Medium–High
RL / DRL	DQN, DDQL, A-DDPG, A-TD3, RDPO, ApeX-DRL	4.5–18.5%	High	Low–Moderate (complex inference)	Very Low	Low–Medium
Hybrid (FL+NN)	FLC+ENN, AFLC+sensor fusion	50–89%	High	Moderate	Moderate	Medium
Hybrid (NN+RL)	CNN+DDQL, Distributed DRL+rule-safety layer	4.5–10%	Very High	Low (resource-intensive)	Very Low	Low

Table 5 EMS objective-based comparison of AI approaches

AI Class	Optimisation Type	Multi-Obj. Capability	Constraint Handling	Training Requirement	Deployment Maturity	Safety Compliance
FL	Heuristic / Rule-based	Limited (single-obj focus)	High (SoC bounds built-in)	Low (manual expert tuning)	Industrial-ready	High
NN	Supervised / Imitation Learning	Moderate (multi-input)	Moderate (learned constraints)	High (diverse datasets needed)	Simulation-validated	Moderate
RL / DRL	Reward maximisation	High (multi-objective reward)	Low–Moderate (safety risks during exploration)	Very High (environment interaction)	Research / early-stage	Low
Hybrid (FL+NN)	Rule+Data-driven	Moderate–High	High	Moderate	Lab / HIL validated	Moderate–High
Hybrid (NN+RL)	DL+Policy gradient	Very High	Moderate (with safety layer)	Very High	Simulation+V2X	Low–Moderate

Fig. 11 HITL Framework

co-pilots, where human drivers remain in the loop for critical decisions, preference adaptations, and situational awareness. This concept known as HITL approach allows EMS to not only optimize energy flow based on dynamic driving and environmental conditions but also adapt to driver behaviour, comfort, and intent. By leveraging ML models integrated with feedback from the driver, such systems can improve trust, transparency, and safety in AI-driven control strategies.

However, the practical implementation of Industry 5.0 principles in EMS remains largely conceptual. Current studies rarely quantify how human-AI collaboration affects driving efficiency, safety, or driver acceptance. Future research should focus on developing experimental test beds or simulation frameworks that evaluate how EMS can balance

automation and human adaptability under real-world driving conditions.

4.2 Human-in-the-loop EMS

The HITL concept integrates human judgment into the AI decision-making loop to produce EMS behaviour that is adaptive, personalised, and ethically accountable [70]. In contrast to fully automated systems, HITL frameworks incorporate the driver as an active participant, as illustrated in Fig. 11. The broader application of HITL in intelligent systems has been surveyed by Kuru [71] and Retzlaff et al. [72]; in the HEV context, the goal is to ensure that the EMS respects driver comfort and situational priorities alongside technical optimisation objectives.

In practice, a HITL EMS accepts inputs from the driver both explicitly (e.g., Eco or Sport mode selection, zone-based EM-only preferences) and implicitly (e.g., inferred acceleration and braking patterns). These signals are fused with vehicle telemetry (SoC, fuel level, power demand) and contextual factors such as road gradient, traffic density, and weather to inform the power-split decision. The AI component then dynamically adjusts ICE, EM, and energy storage system outputs in a manner consistent with both energy efficiency targets and driver intent. One concrete realisation of this loop is Reinforcement Learning from Human Feedback (RLHF) [72], in which driver discomfort signals (e.g., objection to abrupt mode switching) are encoded as negative reward shaping, causing the policy to converge toward smoother control transitions without sacrificing fuel economy.

HITL also directly addresses the trust barrier to AI-based EMS adoption. By keeping the driver in the decision loop and allowing explicit override of AI actions, HITL systems reduce the perception of opaque algorithmic control and support compliance with emerging data governance and functional safety standards. Trustworthy EMS must further uphold privacy-preserving data practices and bias-free energy allocation; incorporating ethical auditing modules and transparency-by-design mechanisms into the development lifecycle is therefore recommended alongside the technical HITL architecture.

Despite its potential, real-time HITL integration in HEV EMS remains largely at the conceptual or offline simulation stage [71]. Future work should prioritise closed-loop prototype validation and hardware-in-the-loop experiments that quantify the trade-offs between driver trust, system

responsiveness, and fuel efficiency under dynamically changing conditions.

4.3 Explainable AI for EMS

XAI encompasses methods that make AI decisions interpretable to human users [65]. In the EMS context, this means translating numerical control outputs (SoC thresholds, ICE torque commands, regenerative braking levels) into explanations meaningful to the driver, such as “switching to electric mode to preserve battery health at low speed.” Without such translation, the opacity of DNN- and RL-based controllers hinders driver acceptance and complicates regulatory compliance [73].

XAI techniques divide into two families. Ante-hoc methods embed interpretability by design: decision trees and rule-based systems produce directly traceable control logic [67], while attention mechanisms highlight which driving-state features (speed, SoC, road gradient) most strongly influence each control action. Post-hoc methods explain pre-trained black-box models after the fact: SHapley Additive exPlanations (SHAP) values provides global feature-importance scores across the power-split policy, and Local Interpretable Model-Agnostic Explanations (LIME) algorithm constructs local linear approximations of individual decisions [65]. The XAI-based conceptual EMS framework, illustrating how explanation generation is coupled to the human interface and how performance datasets are returned for model retraining, is shown in Fig. 12.

XAI is also central to adaptive and personalised EMS operation. As the system continuously updates its policy from real-time driving data, XAI ensures that each

Fig. 12 XAI - based EMS conceptual framework

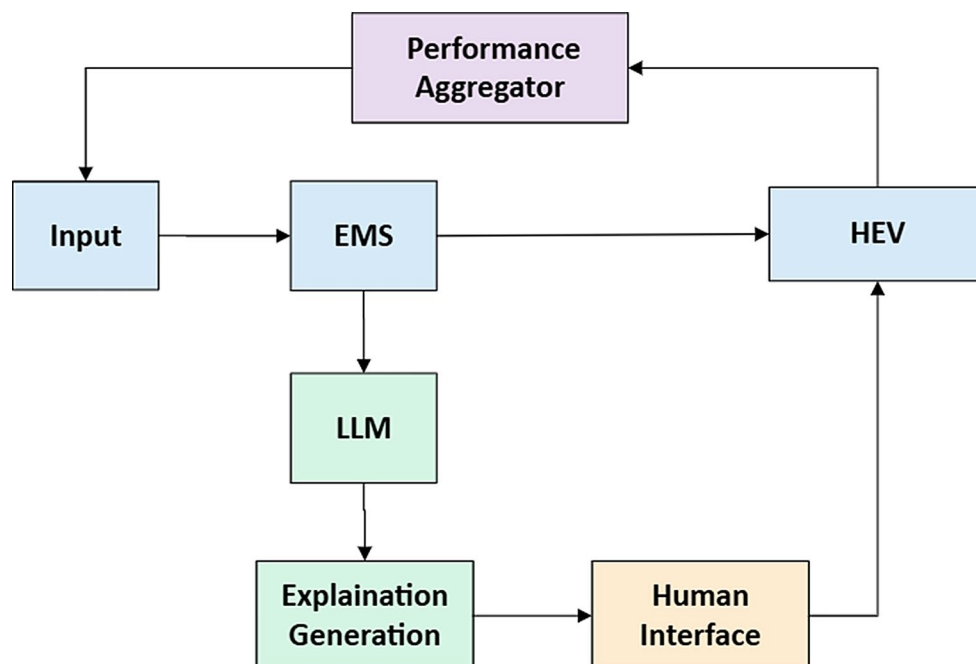


Table 6 Comparative summary of XAI and HITL approaches for HEV EMS

Approach	Integra- tion Level	Process- ing Load	Impact on EMS Performance	Real-Time Feasible	Maturity Level
SHAP [65]	Post-hoc	Low	Feature importance scores explaining power-split decisions after-the-fact	Yes (offline analysis)	Research
LIME [65]	Post-hoc	Low– Moderate	Local approximation of control logic for specific driving instances	Yes (with latency trade-off)	Research
Decision Trees [67]	Ante-hoc	Negligible	Directly interpretable rule extraction; limited accuracy for complex EMS	Yes	Mature
Attention Mechanisms [67]	Ante-hoc	Moderate	Highlights which driving states (speed, SoC, road gradient) drive control actions	Conditional	Emerging
RLHF [72]	HITL	High	Reward function shaped by driver feedback; aligns EMS with comfort preferences	Conditional	Research
Eco/Sport Mode Inputs	HITL	Negligible	Explicit driver preference injection; adjusts power-split weighting in real time	Yes	Deployed
Driver Feedback Loop (RL) Kuru [71]	HITL	Moderate	Implicit driver signals (braking, acceleration) continuously adapt EMS policy	Conditional	Research

adaptation is accompanied by a human-understandable rationale which prevents the erosion of driver trust that uncommunicated autonomous adjustments would otherwise cause. Driver feedback on explanations can in turn be used to refine the decision model, creating a mutually improving human-system loop. This socio-technical coupling supports the personalisation goals of Industry 5.0.

The principal barrier to XAI deployment in production EMS is computational overhead: more interpretable models typically incur inference-time costs that conflict with the millisecond-scale control budgets of automotive ECUs. Future work should therefore prioritise lightweight explainability techniques that compressed attention heads, rule-distilled approximations of DNN policies that remain feasible on embedded hardware. Table 6 summarises the integration level, processing load, EMS performance impact, real-time feasibility, and maturity of the main XAI and HITL methods considered in this review.

5 Conclusion

This systematic review has examined AI-based EMS for HEVs, synthesising 32 peer-reviewed studies identified through a PRISMA-compliant search of Google Scholar, Springer, and IEEE Xplore (2015–2025). The following key findings emerge from the comparative analysis.

Among the three primary AI paradigms reviewed, FL-based EMS represents the most mature approach, showing the strongest potential for near-term deployment based on simulation evidence. Its rule-transparent structure, low computational overhead, and compatibility with embedded ECU constraints make it suitable for near-term industrial adoption, particularly in series and parallel HEV configurations. Reported fuel efficiency improvements range from

7% to 89%, with the highest gains achieved when FL is combined with optimisation algorithms such as GA or PSO. However, FL's reliance on predefined rule bases limits its adaptability to previously unseen driving scenarios without manual re-tuning.

NN-based EMS demonstrates the strongest overall balance between fuel efficiency, adaptability, and real-time feasibility. MLP, RNN, and ANN approaches trained on DP-optimal data consistently achieve near-DP fuel economy at a fraction of the computational cost, with reported improvements of 3% to 96% over rule-based baselines. The primary limitation of NN-based EMS is its reduced interpretability. It is a concern directly addressed by the XAI and HITL frameworks discussed in Sect. 4.

RL-based EMS, particularly DRL approaches, shows the highest adaptability and scalability, with distributed architectures enabling fleet-wide learning and continuous policy improvement. Reported fuel savings of 4.5% to 18.5% understate the long-term potential of RL, which improves as training data accumulates. However, RL currently exhibits the lowest real-time feasibility due to high inference complexity, the lowest interpretability due to policy opacity, and the greatest safety certification challenges under ISO 26262. These barriers must be systematically addressed before RL-based EMS can achieve industrial readiness.

Looking forward, the integration of XAI techniques and HITL mechanisms offers a promising pathway toward EMS that is simultaneously high-performing, transparent, and user-centric which is consistent with the collaborative human-machine philosophy of Industry 5.0. In summary, AI-driven EMS represents a significant and accelerating advancement in HEV control. FL shows strongest readiness for near-term deployment, subject to real-world validation while NN approaches offer the best performance-feasibility balance for medium-term adoption and RL, with appropriate

safety constraints and XAI integration, represents the long-term frontier for adaptive, fleet-scale energy management.

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