IEEE Access
Multidisciplinary : Rapid Review : Open Access Journal

Received 5 June 2025, accepted 20 June 2025, date of publication 23 June 2025, date of current version 29 July 2025.

Digital Object Identifier 10.1109/ACCESS.2025.3582527

TOPICAL REVIEW

Cutting-Edge EMS Technologies for EVs and HEVs: Recent Developments and Future Directions

YASHAR FARAJPOUR[1], ARMIN LOTFY[1], (Student Member, IEEE), HICHAM CHAOUI[1], (Senior Member, IEEE), AND SOUSSO KELOUWANI[2], (Senior Member, IEEE)

[1]Department of Electronics, Carleton University, Ottawa, ON K1S 5B6, Canada
[2]Department of Mechanical Engineering, Université du Québec à Trois-Riviéres, Trois-Riviéres, QC G8Z 4M3, Canada

Corresponding author: Hicham Chaoui (hicham.chaoui@carleton.ca)

ABSTRACT Energy Management Strategies (EMS) are critical for optimizing energy utilization, improving performance, and reducing environmental impact in Electric Vehicles (EVs) and Hybrid Electric Vehicles (HEVs). This study aims to address the growing complexities in EMS development by introducing a novel classification framework that organizes existing methodologies into rule-based, optimization-based, and intelligent transportation system (ITS)-based approaches. The research systematically explores the influence of advanced powertrain architectures and charging technologies on EMS objectives. Recent advancements, such as the integration of machine learning, predictive controls, and multi-objective optimization, are analyzed to highlight their contributions to addressing challenges in modern electrified transportation systems. Key findings demonstrate the importance of emerging trends like vehicle-to-everything (V2X) communication and renewable energy integration in enhancing EMS capabilities. The study concludes by emphasizing the necessity of adaptive and innovative solutions to meet the increasing demands of energy-efficient and sustainable transportation. This work provides a comprehensive and objective representation of current advancements, offering insights to guide future research and practical applications in the field.

INDEX TERMS Energy management strategy (EMS), classification, category, electric vehicle (EV), hybrid electric vehicle (HEV), optimization, battery, driving cycle, renewable energy, intelligent transportation systems (ITS), vehicle-to-everything (V2X), EV charging.

NOMENCLATURE

4WD	4-wheel-drive.
A-ECMS	Adaptive Equivalent Consumption Minimization Strategy.
ACC	Adaptive Cruise Control.
ADP	Adaptive Dynamic Programming.
AFLC	Adaptive Fuzzy Logic Controller.
AFLC-IEMS	Adaptive Fuzzy Logic Controller-based Intelligent Energy Management Strategy.
AI	Artificial Intelligence.
ANN	Artificial Neural Network.
ANFIS	Adaptive Neuro-Fuzzy Inference System.
ATSAC	Auto-Tune Soft Actor-Critic.
BEV	Battery Electric Vehicle.
BMS	Battery Management System.
BPNN	Backpropagation Neural Network.
CACC	Cooperative Adaptive Cruise Control.
CCA	Cooperative Collision Avoidance.
CD/CS	Charge Depleting/Charge Sustaining.
CO2	Carbon Dioxide.
DDPG	Deep Deterministic Policy Gradient.
DFSS	Design for Six Sigma.
DHP	Dual Heuristic Programming.
DQN	Deep Q-network.
DP	Dynamic Programming.
DRL	Deep Reinforcement Learning.
ECMS	Equivalent Consumption Minimization Strategy.
EF	Equivalent Factor.

The associate editor coordinating the review of this manuscript and approving it for publication was Xiaosong Hu.

EM	Electric Motor.
EMS	Energy Management Strategy.
EPA	Environmental Protection Agency.
ES	Extremum Seeking.
ESS	Energy Storage Systems.
EV	Electric Vehicle.
FC	Fuel Cell.
FCEV	Fuel Cell Electric Vehicle.
FCHEV	Fuel Cell Hybrid Electric Vehicle.
FD	Frequency Decoupling.
FLC	Fuzzy Logic Controller.
FTP	Federal Test Procedure.
GA	Genetic Algorithm.
GaN	Gallium Nitride.
GHG	Greenhouse Gas.
GT	Game Theory.
G2V	Grid to Vehicle.
GWO	Grey Wolf Optimization.
HEV	Hybrid Electric Vehicle.
HESS	Hybrid Energy Storage Systems.
HHO	Harris Hawks Optimization.
HDP	Heuristic Dynamic Programming.
HIL	Hardware-in-loop.
IEMS	Intelligent Energy Management Strategy.
ICE	Internal Combustion Engine.
ITS	Intelligent Transportation System.
JSPSOBAT	Jellyfish, PSO, and BAT.
LP	Linear Programming.
LQR	Linear Quadratic Regulator.
LSTM	Long Short-Term Memory.
LTI	Linear Time Invariant.
MEA	More Electric Aircraft.
MLP	Multilayer Perceptron.
MPC	Model Predictive Control.
MPDTC	Model Predictive Direct Torque Control.
MRAS	Model Reference Adaptive System.
NO-F	Non-optimization-fuzzy.
NOx	Nitrogen Oxides.
NN	Neural Networks.
NSGA-II	Non-Dominated Sorting Genetic Algorithm II.
OCPP	Open Charge Point Protocol.
PAEB	Pedestrian Automatic Emergency Braking.
PEMFC	Proton Exchange Membrane Fuel Cells.
PIC	Proportional-Integral Controller.
PID	Proportional-Integral-Derivative.
PM	Particulate Matter.
PHEV	Plug-In Hybrid Electric Vehicle.
PMP	Pontryagin's Minimum Principle.
PSO	Particle Swarm Optimization.
PSO-F	Particle Swarm Optimization-Fuzzy.
RC	Robust Control.
RFOSMC	Robust Fractional-Order Sliding Mode Control.
RL	Reinforcement Learning.
RNN	Recurrent Neural Network.
RUL	Remaining Useful Life.
SAC	Soft Actor-Critic.
SA	Simulated Annealing.
SiC	Silicon Carbide.
SLNE	Scalable Learning in Novel Environment.
SMC	Sliding Mode Control.
SMSPO	Sliding Mode State and Perturbation Observer.
SOC	State-of-charge.
SOH	State-of-health.
SVM	Support Vector Machine.
TLBO	Teaching–learning-based Optimization.
V2G	Vehicle to Grid.
V2H	Vehicle to Home.
V2I	Vehicle to Infrastructure.
V2P	Vehicle to Pedestrian.
V2V	Vehicle to Vehicle.
V2X	Vehicle to Everything.
VOC	Volatile Organic Compound.
WTW	Well-to-wheel.

I. INTRODUCTION

Electric Vehicles (EVs) are playing a pivotal role in shaping the future of transportation, driven by the growing demand for sustainable and environmentally responsible solutions.

Advantages of electrifying the transportation fleet include but not limited to:

- Environmental and public health benefits.
- Economic stability and energy security.
- Renewable energy integration.
- Higher energy efficiency and lower maintenance costs.

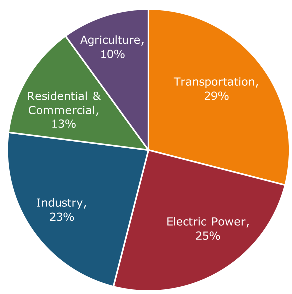

FIGURE 1. Total U.S. GHG emissions by economic sector in 2021 [3].

The combustion of fossil fuels in conventional vehicles poses substantial environmental challenges due to the emission of various pollutants. Internal combustion engine (ICE) vehicles are major contributors to global greenhouse gas (GHG) emissions and urban air quality degradation. The oxidation of fossil fuels results in the release of carbon dioxide (CO_2), nitrogen oxides (NO_x), particulate matter (PM), volatile organic compounds (VOCs), and other harmful GHGs into the atmosphere. These emissions contribute directly to anthropogenic global warming, climate change, and adverse public health outcomes. Among all economic sectors, the transportation sector is recognized as a predominant source of CO_2 emissions globally [1], [2]. In 2022, the United States Environmental Protection Agency (EPA) reported that the transportation sector was responsible for approximately 29% of the nation's total GHG emissions, making it the single largest emitting sector [3]. Figure 1 illustrates the proportional contributions of various economic sectors to national GHG emissions. Similar statistics have been reported by environmental agencies in other countries, reinforcing the global consensus that the transportation sector is a leading driver of GHG emissions [4], [5], [6].

While EVs depend on electricity primarily produced by fossil fuel power plants—thus contributing to greenhouse gas (GHG) emissions—the resultant environmental impact is geographically shifted away from heavily populated urban regions. This relocation of tailpipe pollutants effectively helps in improving public health and air quality in urban areas [7], [8], [9], [10]. This transition aligns with global efforts to achieve carbon neutrality and meet the objectives outlined in international agreements such as the Paris Agreement [11], [12]. According to Table 1 [13], which compares two electrification scenarios in New York, Chicago, and Houston, full electrification (100%) could prevent 774, 341, and 157 premature deaths per month, respectively. From an economic perspective, the full electrification scenario could generate monthly health benefits valued between $1500 and $7700 million US dollars for New York, Chicago, and Houston.

TABLE 1. Projected premature monthly deaths reduction and monthly economic benefits from lower PM2.5 and ozone levels [13].

Region	EV share	Avoided deaths PM2.5	Avoided deaths Ozone	Benefits ($ Millions)
New York	18% LDV*	99	36	$1317.3
	100%	420	354	$7732.7
Chicago	18% LDV	37	19	$563.1
	100%	185	159	$3298.2
Houston	18% LDV	8	6	$140.8
	100%	84	73	$1578.7

* LDV: Light Duty Vehicle

The heavy reliance of the transportation sector on petroleum-based fuels makes it particularly vulnerable to fluctuations in oil prices and the geopolitical instability of oil-exporting regions. Such fluctuations can have far-reaching economic consequences, affecting both businesses and consumers. In contrast, EVs can be powered by electricity generated from a broad mix of energy sources, including fossil fuels, nuclear power, hydroelectricity, wind, solar, biomass, tidal, and geothermal energy. This diversification of energy sources serves to enhance energy security by reducing dependence on oil imports. Utilizing domestically produced electricity minimizes a nation's susceptibility to disruptions in oil supply and geopolitical conflicts, thereby bolstering energy independence and strengthening national security [14], [15], [16]. Moreover, the cost of electricity generation is typically lower and more stable compared to oil and gasoline, resulting in significant long-term savings for EV owners in terms of fuel expenditures. Table 2 shows a comparative analysis of efficiency and driving cost between different types of ICE and electric motor (EM)-equipped vehicles such as plug-in hybrid EVs (PHEVs) and fuel cell EVs (FCEVs), that is calculated based on WTW (well-to-wheel) analysis. Additionally, EVs have inherently lower maintenance costs over their lifespan due to fewer mechanical parts and the absence of complex systems required for combustion engines [17], [18].

TABLE 2. Efficiency and energy consumption comparison across different vehicle technologies [19], [20].

Fuel type	Engine	Overall Efficiency (%)	Energy Used (kWh/km)
Gasoline	ICE	14%	1.36
Diesel	ICE	20%	0.95
PHEV	ICE+EM	45%	0.42
FCEV	EM	22%	0.87
BEV	EM	67%	0.28

Based on Fig. 2, there is a clear trend of exponential growth in global EV sales. The figure illustrates that China, Europe, and the United States are leading this transition, accounting for the majority of global EV adoption. This rapid growth aligns well with the discussion on the advantages of electrifying the transportation fleet.

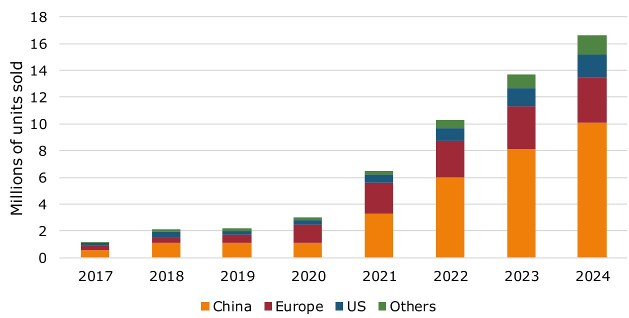

FIGURE 2. EV sales growth in China, Europe, US and other countries, 2016-2024 [21].

Energy Management Strategy (EMS) manages the power flow between different energy sources and propulsion systems in a way that improves vehicle performance, energy efficiency, and battery health while minimizing costs and environmental impact. The EV's components and structure influence the specific EMS objectives, as depicted in Fig. 3. If a vehicle incorporates different energy sources (gasoline, lithium-ion batteries, fuel cells, or super capacitors) or propellers (ICE and EM), the EMS can be employed to manage power usage and distribution between these components [22], [23], ultimately maximizing driving range [24], reducing emissions [25], minimizing battery degradation [26], [27], [28], and optimizing fuel consumption [23], [29], [30].

Beyond reducing battery wear, the EMS in a single-source-powered EVs like BEVs can extend driving range by optimizing the speed profile [31], [32]. EMS can also be used for smart charging scheduling to reduce energy cost [33], [34], [35]. EMS also facilitates V2X (vehicle to everything) integration, allowing vehicles to communicate with other vehicles and infrastructure to improve efficiency and safety [36], [37].

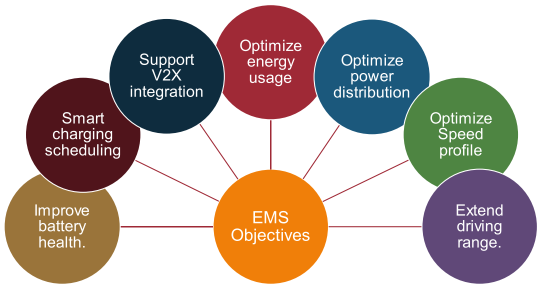

FIGURE 3. Key Objectives of EMSs.

In summary, EVs offer significant advantages in terms of reducing GHG emissions, improving public health, and enhancing energy security. As the adoption of EVs continues to grow worldwide, EMSs are becoming increasingly important to optimize the performance of an electrified transportation fleet.

This paper focuses on the classification and analysis of EMS specifically for ground vehicles, including EVs and HEVs, while excluding applications in aerial vehicles and marine vessels. It highlights the interplay between powertrain topologies, hybridization levels, and charging technologies in shaping EMS objectives. A structured classification of rule-based, optimization-based, and Intelligent Transportation Systems (ITS)-based EMS approaches is provided, exploring their implementation challenges and potentials for real-world applications. Additionally, the study discusses how emerging technologies, including advanced powertrain architectures and energy storage systems (ESS), influence EMS design. The scope extends to identifying critical research gaps and outlining future directions for developing adaptive and efficient EMS solutions tailored to meet the demands of modern ground-based electrified transportation systems.

This paper presents a comprehensive and updated review of the most recent advances and publications in EMS for EVs and HEVs. This study begins with an in-depth analysis of EV and HEV powertrain architectures, various energy storage systems (ESS), and charging technologies. These elements are essential considerations for selecting appropriate EMS strategies and defining relevant optimization objectives and constraints. Furthermore, this work uniquely includes intelligent transportation systems (ITS) as a distinct EMS category, recognizing that ITS technologies contribute significantly to reducing energy consumption, enhancing route planning, and improving driving safety, an aspect frequently neglected in previous reviews. The proposed EMS classification integrates learning-based methods as a subcategory of optimization-based EMS, diverging from earlier works that treat them separately. This integration is justified because learning-based EMS fundamentally relies on solving optimization problems during both training and deployment. For instance, neural networks optimize their parameters by minimizing loss functions related to energy consumption or tracking error; reinforcement learning algorithms iteratively approximate optimal policies by maximizing cumulative rewards through Bellman-optimality; and support vector machines identify decision boundaries via convex optimization formulations. This study explores powertrain topologies, hybridization, and charging technologies in Section II, novel classifications of EMSs in Section III, the challenges in Section IV, the future trends in Section V, and concludes the discussion in Section V-H.

II. EV AND HEV TECHNOLOGIES

A. POWERTRAIN TOPOLOGIES

Powertrain topology is fundamental in determining the objectives and the complexity of the required EMS. Fig. 4 exhibits simplified schematic representations of different powertrain topologies including (a) ICE, (b) BEV, and multiple HEV architectures, such as (c) series HEV, (d) parallel HEV, and (e) series-parallel HEV.

ICE Powertrain: The conventional ICE powertrain comprises a combustion engine, fuel tank, and transmission, providing direct power to the drivetrain. This system lacks any form of electrification and therefore has limited opportunities for energy management optimization. However, the existing literature present eco-driving modes for reducing consumption and emission [38], [39], [40]

BEV Powertrain: Propulsion is achieved through an electric motor. The absence of a combustion engine simplifies the powertrain, making EMS primarily focused on optimizing battery use, enhancing regenerative braking, and maintaining an efficient speed profile to maximize range [41], [42], [43].

Series HEV Powertrain: The electric motor exclusively powers the drivetrain, while a smaller ICE (range extender) functions as a generator to either supply energy to the motor or recharge the battery. These vehicles typically feature larger battery packs compared to parallel hybrids. The EMS manages ICE on/off operations to optimize fuel efficiency, ensure the ICE operates at peak efficiency, and maximize the use of stored battery energy. Additionally, the EMS effectively controls regenerative braking to extend the driving range and enhance overall efficiency, ensuring seamless transitions between power sources [44], [45], [46].

Parallel HEV Powertrain: In parallel HEVs, both the combustion engine and the electric motor are directly linked to the transmission, allowing them to provide propulsion simultaneously or independently. The EMS in this setup is complex, as it needs to balance the power contributions from the electric motor and the engine to optimize fuel economy and reduce emissions while delivering sufficient performance [47], [48], [49], [50].

Series-Parallel HEV Powertrain: This topology integrates both series and parallel architectures, allowing either the ICE or the electric motor to power the vehicle based on driving conditions. The power splitter used in this setup allows transitions between power sources, enhancing overall efficiency and flexibility. The EMS manages this hybrid structure to achieve optimal energy distribution and performance under varying operational demands [51], [52], [53], [54].

Table 3 summarizes and compares the key characteristics of these powertrain topologies, providing a quick reference for understanding their relative driving ranges, efficiencies, benefits, drawbacks, and optimal use cases.

Table 4 provides a comparison of different energy storage systems (ESS) used in EVs and HEVs, specifically focusing on lithium-ion batteries, fuel cells, and supercapacitors. The comparison is based on key metrics such as energy density and power density. Energy density is the amount of energy stored in a system per unit mass, indicating how much energy is available to sustain operation over time (measured in Wh/kg). Power density is the rate at which energy can be delivered per unit mass, indicating how quickly the system can provide power to meet immediate demands (measured in W/kg). Lithium-ion batteries exhibit moderate to high energy density and power density, making them highly suitable for long-range BEVs and PHEVs, despite concerns related to cost and charging time.

Fuel cells have significant benefits, such as elevated energy density and swift refilling capabilities; yet, their extensive implementation is obstructed by the constraints of hydrogen infrastructure and the intricacies of on-board storage. To tackle these problems and improve system performance, several methods have been proposed. In [55], an Integrated Water Management Energy Management Strategy (IWM-EMS) was developed to regulate the hydration dynamics of the PEMFC. Hydration imbalance, whether due to membrane dehydration or flooding, results in non-uniform current density distribution, leading to localized thermal and electrochemical stress. This degradation mechanism is functionally analogous to the SOC imbalance in battery cells, as addressed in [56], which was shown to negatively impact system durability. To address this challenge, Moghadari et al. incorporated water management control into the EMS framework. The proposed strategy achieved a 4.09% improvement in hydrogen consumption efficiency, highlighting its effectiveness in enhancing overall fuel cell performance and operational longevity. Multi-Stack Fuel Cell Systems (MFCS) have been suggested as a feasible alternative to conventional Single-Stack Fuel Cell Systems (SFCS). MFCS architectures provide superior efficiency, enhanced dependability, increased operational longevity, and zero-emission functionality, rendering them especially appropriate for high-demand and mission-critical applications. A primary benefit of MFCS is its intrinsic redundancy; if one stack malfunctions, others can sustain system functionality, thereby guaranteeing uninterrupted power supply. Moreover, MFCS exhibits diminished hydrogen consumption, decreased degradation rates, and an elongated system lifespan relative to SFCS, hence reinforcing its appropriateness for next-generation clean energy systems [57].

Supercapacitors stand out for their exceptionally high power density, ideal for applications needing rapid energy delivery such as regenerative braking, although their low energy density limits driving range. Other types of ESS for EVs can be found in [58], [59], [60], [61], [62], and [63].

B. LEVELS OF HYBRIDIZATION

As illustrated in Fig. 5, vehicles can be classified into various levels of hybridization based on their functionalities and propulsion capabilities. It should be noted that the scales depicted in this figure are intended solely for illustrative and comparative purposes, and may not represent exact quantitative values. The spectrum begins with conventional gasoline vehicles equipped with an ICE engine and extends to fully electric BEVs with only electric propulsion. Table 5 also shows the electric motor and battery sizes for different types of EVs.

Micro Hybrid: Micro hybrids feature minimal electric propulsion, incorporating start/stop functionality and regenerative braking to reduce fuel consumption. The electric motor only supports the ICE during idle or start-up phases, making EMS simpler but still effective in enhancing fuel efficiency [64], [69].

Mild Hybrid: Mild hybrids use an electric motor to provide supplementary power to the ICE, particularly during acceleration, thus reducing fuel usage. Although the ICE is downsized compared to micro hybrids, they still cannot operate on electric power alone. The EMS aims to strategically allocate power between the motor and engine, specifically during idling, to optimize efficiency and reduce emissions [64], [69].

Full Hybrid: Full hybrids introduce electric drive capability and can operate using the ICE, the electric motor, or both simultaneously. The ICE is downsized further in these vehicles compared to mild hybrids. These systems employ EMS to manage transitions between power sources, thus improving both fuel efficiency and driving dynamics. Full hybrids offer a greater level of electric assistance, which increases the complexity of the EMS [64], [69], [70].

Plug-in Hybrid (PHEV): PHEVs are equipped with larger battery packs that can be recharged externally. This enables longer electric-only driving ranges compared to above-mentioned hybrids before the ICE engages. Thus, the ICE in these vehicles is considerably smaller. The EMS in PHEVs is designed to prioritize electric

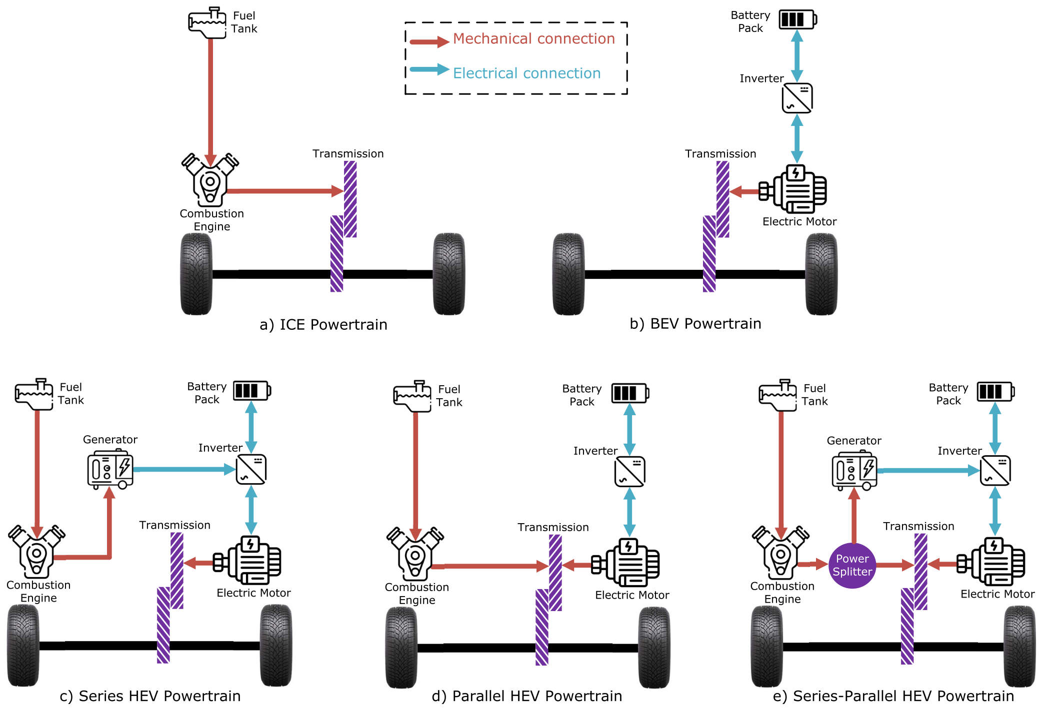

FIGURE 4. Simplified schematics of different powertrain topologies; (a) conventional ICE vehicle, (b) single-source powered BEV, (c) series HEV, (d) parallel HEV, (e) series-parallel HEV.

driving where possible while managing energy reserves and ensuring a smooth transition to hybrid operation as needed [69], [70], [71], [72].

Full Electric (BEV): BEVs rely entirely on battery power for propulsion, with no ICE present. Hence, the required battery capacity ranges from 40 to above 100 kWh. The EMS in these vehicles focuses on efficient battery management, including optimal charging schedules, maximizing regenerative braking, and optimizing speed profile. BEVs require sophisticated EMS to improve driving range and battery health while minimizing energy costs [72], [73].

C. CHARGING TECHNOLOGIES

EV charging technologies encompass various methods that facilitate the transfer of electrical energy to recharge the batteries of electric and hybrid vehicles. These technologies can be broadly categorized into conductive charging, inductive charging, and battery swapping. Conductive charging, the most common method, involves using a physical connection to transfer power from the charging station to the vehicle. Inductive charging, a wireless approach, employs electromagnetic fields to transfer energy without direct physical contact. Lastly, battery swapping allows for a fast turnaround by replacing a depleted battery with a fully charged one, making it ideal for fleet operations [74], [75], [76]. Table 6 compares different features of these charging methods.

Table 7 provides a concise comparison of different conductive EV charging levels, including Level 1, Level 2, Level 3, and the next generation of Ultra-Fast chargers. Each level is characterized by attributes such as voltage, power output, charging speed, typical charging time, type of charger, and preferred locations for use. The table aims to highlight the distinctions in capabilities, infrastructure, and practical applications between various charging levels, offering a clear overview for users and stakeholders interested in understanding the technological differences in EV charging solutions.

In summary, the variation in powertrain architecture significantly impacts the design and requirements of EMSs to be able to achieve defined criteria. The selection of topology defines the architecture and criteria of energy sources engaged, as well as the operational limitations and control goals that need to be considered. An in-depth knowledge of powertrain characteristics is crucial for developing EMS strategies that efficiently manage energy flow and improve overall vehicle performance. The subsequent section provides an in-depth categorization of EMSs, examining the methodologies utilized to tackle the control challenges associated with various EV and HEV configurations.

III. ENERGY MANAGEMENT STRATEGIES (EMSs)

EMS optimizes power flow between energy sources and propulsion systems in EVs and HEVs. The goal of EMS is to enhance vehicle performance and maintain battery health while minimizing costs and environmental impact.

TABLE 3. Comparison of powertrain topologies.

ICE	**Driving Range:** High (depends on fuel tank size). **Efficiency:** Moderate to Low. **Advantages:** Well-established. infrastructure, high power density. **Disadvantages:** High emissions, lower efficiency, fuel dependency. **Application:** Long-distance travel, heavy-duty vehicles.
BEV	**Driving Range:** Moderate to High (depends on battery capacity). **Efficiency:** High. **Advantages:** Zero tailpipe emissions, high energy efficiency, lower maintenance. **Disadvantages:** Limited charging infrastructure, range anxiety, long charging times. **Application:** Urban commuting, passenger cars.
Series HEV	**Driving Range:** Moderate (electric range plus ICE support). **Efficiency:** Moderate to High. **Advantages:** ICE runs at optimal efficiency, extended electric range. **Disadvantages:** More complex system, higher cost due to larger battery. **Application:** Urban and suburban driving, range extension vehicles.
Parallel HEV	**Driving Range:** High. **Efficiency:** Moderate. **Advantages:** Ability to use both ICE and electric motor for propulsion, high power availability. **Disadvantages:** Complex EMS, ICE cannot always run at peak efficiency. **Application:** Highway driving, versatile power demands.
Series-Parallel HEV	**Driving Range:** High. **Efficiency:** High. **Advantages:** Flexibility in power source usage, efficient energy management. **Disadvantages:** Most complex powertrain, high cost. **Application:** Mixed urban and highway driving, versatile applications.

TABLE 4. Comparison of different types of ESS for EVs and HEVs [58], [59], [60], [61], [62], [63].

ESS type	Energy density (Wh/kg)	Power density (W/kg)	Advantages	Disadvantages	Applications
Lithium-ion battery	118-250	200-430	High energy density, efficient for long driving ranges, mature technology	High cost, potential safety issues, long charging time	BEVs, PHEVs
Fuel cell	800-1000 (including hydrogen storage)	900-2000	High energy output, rapid refueling, zero tailpipe emissions	Limited hydrogen infrastructure, high cost, hydrogen storage complexity	FCEVs, range-extended HEVs
Supercapacitor	10-15	+10,000	Extremely high power density, rapid charging/discharging, long cycle life	Low energy density, limited driving range capabilities	HEVs, public transportation buses, regenerative braking

TABLE 5. Electric motor power and battery capacity of different EVs [64], [65], [66], [67], [68].

Vehicle type	Electric motor power (kW)	Battery capacity (kWh)
Micro Hybrid	2–5	0.5–1
Mild Hybrid	5–20	1–2
Full Hybrid	20–50	1–2
Plug-in Hybrid	50–100	8–30
Full Electric	100–300+	40–100+

Various battery health indicators (HIs), including the SOH, are essential for assessing and sustaining the performance and dependability of EVs. The precision of these HIs directly affects the efficacy of energy management measures and the overall operational safety of EV systems [79]. She et al. [80] developed an LSTM-based methodology designed for the multistage constant current (MsCC) charging technique to assess critical battery health parameters. The suggested method utilizes the temporal learning capabilities of LSTM networks to capture the nonlinear aging dynamics while charging, facilitating precise and reliable HI estimate across different battery aging phases.

EMS manages various energy components to extend driving range, reduce emissions, and minimize battery wear. For BEVs, EMS focuses on efficient battery use, smart charging schedules, and optimizing speed profiles. In HEVs, it also balances the power contributions from the ICE and EM. Advanced EMS also integrates V2X capabilities to improve efficiency and safety.

Fig. 6 shows a concise graphical classification of EMSs, which are divided into rule-based, optimization-based, and

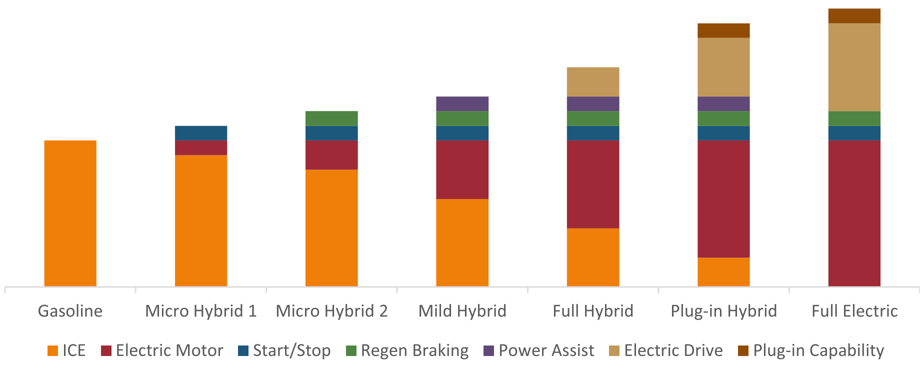

FIGURE 5. Hybridization levels of vehicles based on their features and electric drive capability.

TABLE 6. Comparison of different EV charging methods [74], [75], [76].

Attribute	Conductive Charging	Inductive Charging	Battery Swapping
Physical Contact	Yes	No	N/A*
Power Supply	AC/DC	AC (magnetic induction)	DC (pre-charged)
Charging Circuit	Onboard/Offboard	Offboard	N/A*
Power Flow	Uni/Bidirectional	Unidirectional	Direct battery swap
Charging Speed	Moderate	Slow to moderate	Instantaneous
Infrastructure	Charging cable and plug	Charging pad on ground	Battery swap stations
Efficiency	High (80-95%)	Moderate (70-80%)	Very High
Use Case	Public/Residential	Public/Residential	Fleet and taxi operations

**N/A: Not Applicable.*

TABLE 7. Comparison of different conductive EV charging levels [76], [77], [78].

Attribute	Level 1	Level 2	Level 3	Ultra-Fast
Voltage	AC (120 V)	AC (208-240 V)	DC (300-800 V)	DC (800+ V)
Power	1.4-1.9 kW	7-22 kW	50-350 kW	400-500 kW
Speed	Slow	Moderate	Fast	Very fast
Charging Time	11-36 hours	2-6 hours	20-40 minutes	10-15 minutes
Type	Onboard	Onboard	Offboard	Offboard
Location	Residential	Residential, public stations	Highways, commercial stations	Highways, commercial stations

intelligent transportation system (ITS)-based approaches. Further details and some example methods for each subcategory are included in Table 8 [58], [69], [81], [82], [83], [84], [85], [86], [87].

A. RULE-BASED EMSs

These strategies are used to manage energy distribution in hybrid and electric vehicles based on a set of predefined rules or conditions. These rules are often designed based on expert knowledge, engineering intuition, or experimental results, and they are typically easy to implement and computationally efficient. Rule-based EMSs are primarily used for real-time control, making them suitable for managing energy flow dynamically during vehicle operation without requiring significant computational resources. These strategies are generally divided into deterministic and fuzzy subcategories.

1) DETERMINISTIC RULE-BASED EMSs

In these methods, the system operates based on fixed, non-adaptive rules that are not influenced by statistical variation or probabilistic outcomes. In other words, given the same set of inputs, the deterministic EMS will always provide the same output, resulting in predictable and consistent energy management decisions.

· **Thermostat On/Off** techniques are simple, rule-based strategies used in HEVs to manage the operation of the ICE. The ICE is switched on or off based on predefined battery state-of-charge (SOC) thresholds to keep the SOC within a desired range. When the SOC falls below a lower limit, the ICE turns on to recharge the battery, and it turns off when the SOC reaches an upper limit. This approach aims to operate the ICE at its most efficient point while minimizing idle time. While thermostat-based EMS are simple to execute and proficient in sustaining steady battery SOC levels, they demonstrate restricted adaptability to changing driving conditions. This unresponsiveness may cause poor power distribution, resulting in heightened stress and frequent battery cycling. As a result, these tactics may diminish battery efficiency and reduce its longevity over time. Furthermore, in swiftly evolving operational contexts, thermostat

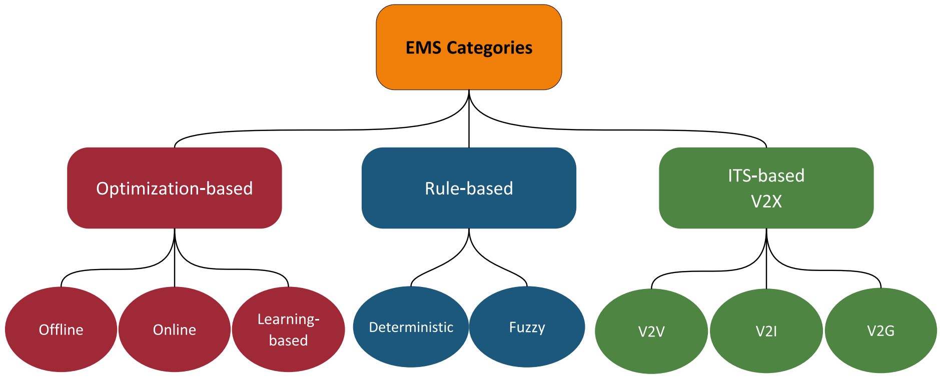

FIGURE 6. EMS classification for EVs and HEVs along with subcategories and example methods.

TABLE 8. Proposed EMS classification for EVs and HEVs.

Categories	Subcategories	Example methods
Rule-based	Deterministic	• Thermostat On/Off • Power Follower • State-Machine
	Fuzzy	• Conventional • Adaptive • Predictive
Optimization-based	Offline	• Dynamic Programming (DP) • Genetic Algorithm (GA) • Particle Swarm Optimization (PSO) • Pontryagin's Minimum Principle (PMP) • Game Theory (GT) • Simulated Annealing (SA) • Linear Programming (LP)
	Online	• Equivalent Consumption Minimization Strategy (ECMS) • Robust Control (RC) • Model Predictive Control (MPC) • Pseudospectral • Frequency Decoupling (FD) • Sliding Mode Control (SMC) • Extremum Seeking (ES)
	Learning-based	• Reinforcement Learning (RL) • Neural Networks (NN) • Support Vector Machine (SVM)
ITS	Vehicle to Everything (V2X)	• Vehicle to Infrastructure (V2I) • Vehicle to Vehicle (V2V) • Vehicle to Grid (V2G)

EMS frequently demonstrates inferior performance relative to more adaptive, intelligent control methodologies [88], [89], [90].

· **Power Follower** strategies aim to dynamically adjust the ICE or generator output to directly meet the real-time power demands of the EM. Unlike Thermostat On/Off approaches that focus on maintaining the battery SOC within a specific range, power follower EMS minimizes unnecessary battery cycling by closely aligning the power generation with immediate power needs. This method aims to operate the ICE at its optimal efficiency point, thus reducing fuel consumption and enhancing overall system efficiency [88], [91].

Fig. 7 shows the operating principle diagram of a power follower strategy, that control engine on/off sessions according to the battery SOC and the real-time power demand of the EM. If the battery SOC is high and the vehicle is cruising at a constant speed (low power requirements), the ICE is off. When the SOC drops below the lower limits or when the vehicle is accelerating and requires higher power, the ICE turns on to match the demanded power and recharge the battery pack [90], [92].

Power follower EMS is well-suited for applications in series HEVs, where the ICE functions as a generator to power the electric motor or recharge the battery. It is particularly effective for urban and heavy-duty vehicles, such as buses or trucks, that experience frequent changes in power demand. The strategy helps maintain fuel economy during conditions like acceleration, cruising, and regenerative braking by dynamically responding to varying power demands. However, frequent start-stop cycles of the ICE, driven by the need

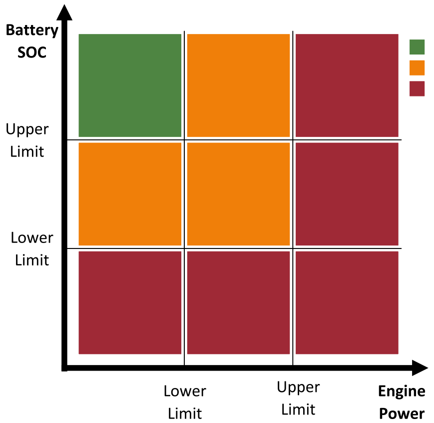

FIGURE 7. The rule table of a power follower strategy for a series HEV.

to constantly follow power demands, can lead to increased engine wear and suboptimal performance under low load conditions. Additionally, the strategy may not be ideal for situations where power demands are minimal, as operating the ICE at very low power levels may lead to inefficient fuel consumption. Despite these limitations, power follower EMS provides a simple yet effective control method that can significantly enhance fuel economy while reducing the reliance on battery charging.

· **State-Machine** control is a method used to optimize power flow in HEVs by defining various operational states, each representing a specific mode of power requirements. The state machine EMS transitions between these states based on real-time conditions and predefined thresholds, such as vehicle speed, driver power demand, or battery SOC. It operates with a set of rules for determining which power sources to activate and when to switch between different modes, making it effective for real-time control. The primary goal is to maintain system efficiency, improve fuel economy, and reduce component wear by ensuring that each power source is used optimally according to the driving scenario.

Previously published research provide diverse applications of state machine control for managing complex hybrid power systems. Reference [93] introduces a hybrid EMS for a photovoltaic-proton exchange membrane fuel cell-battery system, utilizing a 15-step SMC framework combined with fuzzy logic-based Maximum Power Point Tracking (MPPT) to dynamically optimize power distribution among the sources, with the objective of maximizing energy efficiency and extending battery longevity. In this arrangement, the photovoltaic (PV) array acts as the principal energy source, and the proton exchange membrane fuel cell (PEMFC) operates as a supplementary source to assist the battery during low SOC or high-load scenarios. Simulation findings corroborate the methodology, demonstrating an average efficiency improvement of 2.3% relative to traditional tactics, with a maximum efficiency of 97.2% in high-load conditions and sustaining 96.5% stable power output for a 7.5-second duration. Another paper introduces a multi-mode state machine EMS for fuel cell EVs, where driving patterns are identified using neural networks to adaptively switch between EMS modes, enhancing fuel efficiency and system stability [94]. Other publications [95], [96] similarly employ state machine control for hybrid tramways and low-floor light rail vehicles, using droop control to mitigate power fluctuations and enhance system efficiency. Although state-machine-based EMS are easy to deploy and offer several operational modes to maintain the EM system's efficiency, they depend significantly on expert knowledge and manual calibration. This reliance might lead to subjective biases and restrict the method's generalization across diverse driving situations and vehicle configurations. Consequently, the resultant control rules may fail to exhibit real optimality, potentially resulting in inefficient energy allocation and diminished overall system efficiency [90], [97].

2) FUZZY RULE-BASED EMSs

These techniques employ fuzzy logic to deal with uncertainties and provide a more flexible decision-making process. Fuzzy rule-based EMSs rely on "If-Then" rules, which use approximate reasoning rather than precise numerical values. These rules provide adaptability to the system, allowing it to handle complex scenarios without the need for an exact mathematical model of the system [98]. The three main types of fuzzy rule-based EMSs are conventional, adaptive, and predictive [85].

· **Conventional Fuzzy Logic Controllers (FLCs)** operate in three main steps: fuzzification, inference, and defuzzification. In the fuzzification stage, real-world inputs (e.g., power demand, battery state-of-charge) are converted into fuzzy values using membership functions, which map crisp inputs into linguistic terms. During the inference stage, a set of predefined fuzzy rules (e.g., If-Then rules) is applied to the fuzzified inputs to derive fuzzy outputs, simulating expert decision-making. Finally, in the defuzzification stage, fuzzy outputs are converted back into crisp values to control the system, such as adjusting power distribution between the ICE and EM. This process allows FLCs to handle uncertainties and produce smooth, efficient control actions.

Fig. 8 illustrates an example of membership functions for an FLC that governs the contribution of the EM based on input variables such as battery SOC and power demand of the HEV. This example employs a Sugeno fuzzy model, where the output is represented as numerical values. The output of the FLC is a scaling factor, denoted as α, which is then used to adjust the EM power. Equation (1) demonstrates this relationship. Here, α is a multiplier ranging between 0 and 1, where 0 indicates no contribution from the EM, and 1 signifies that the entire power demand is met by the EM. The corresponding rule table for this FLC is provided in Table 9.

$$
\begin{aligned}
P_{EM} &= \alpha \times P_{demand}, \\
P_{ICE} &= P_{demand} - P_{EM}, \\
\alpha &= \begin{cases} 0, & ICE \\ 0.5, & ICE + EM \\ 1, & EM \end{cases}
\end{aligned} \tag{1}
$$

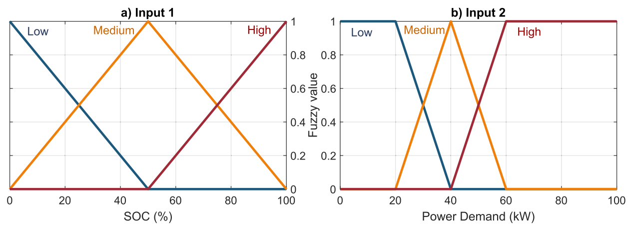

FIGURE 8. Input membership functions for (a) battery SOC and (b) power demand of a simple FLC for an HEV.

TABLE 9. FLC rule table.

Power demand	Battery SOC (%) Low	Medium	High
Low	ICE	EM	EM
Medium	ICE	ICE+EM	EM
High	ICE	ICE	EM

Boumediene et al. [99] propose a fuzzy logic-based EMS for a hybrid energy storage system combining a Li-ion battery and a supercapacitor to power an electric scooter. The system aims to enhance efficiency and extend battery life by utilizing the battery for sustained power and the super capacitor for peak power demands, with fuzzy logic managing energy distribution. Simulation results demonstrate that this approach improves efficiency, increases the autonomy, and optimizes the use of both energy sources effectively. A similar study [100] presents an FLC-based EMS for an HEV, which optimizes power distribution between the internal combustion engine and electric motor based on torque demand, battery SOC, and regenerative braking. Real-time validation demonstrates improved fuel economy, faster response, and minimal mismatch between desired and achieved vehicle speeds. Keskin and Urazel [101] propose a conventional FLC EMS for a dual storage system consisting of a battery and supercapacitors to extend battery lifespan and improve the range of electric drive vehicles. Simulation results demonstrate that the proposed strategy outperforms a logic threshold-managed dual storage system in reducing battery consumption and degradation. Another paper [102] explores the same problem and presents an FLC optimized using a teaching-learning-based optimization (TLBO) approach. Compared to particle swarm optimization-fuzzy (PSO-F) and non-optimization-fuzzy (NO-F) strategies, the TLBO-fuzzy method showed improved power-sharing performance, extending battery lifespan, reducing output power by 6.4% compared to PSO-F and 35% compared to NO-F, and increasing battery SOC by up to 30%. Moreover, in the literature, there are other studies that investigate combining FLC with other approaches such as ANN, PSO, and sliding mode control (SMC) for improved performance [103], [104], [105], [106].

FLC-based EMSs are fundamentally reliant on specialized knowledge and heuristic frameworks, which may fail to encompass the system's complete complexity, thereby resulting in reduced efficiency. Furthermore, FLC-based EMSs generally necessitate prior knowledge of the controlled system and exhibit limited flexibility to dynamically changing surroundings or unfamiliar operating patterns [107].

· **Adaptive Fuzzy Logic Controllers (AFLC)** have been designed to overcome the limitations of conventional FLCs by incorporating adaptability to dynamic and uncertain conditions. This approach employs mechanisms such as intelligent algorithms, real-time adjustments, or multiple types of fuzzy controllers to handle changing situations effectively. The flexibility element in AFLC-based energy management strategies entails a trade-off between enhanced performance and elevated computational costs. AFLCs reduce the necessity for manual tuning of fuzzy rules by facilitating real-time parameter adjustments; yet, they include supplementary hyperparameters—such as learning rates and adaptation thresholds—that necessitate meticulous calibration. Inadequate adjustment of these parameters can jeopardize system stability and result in inferior performance [108].

A study cited in [109] proposes an AFLC-based Intelligent EMS (AFLC-IEMS) for energy distribution improvement in HEVs. It uses Type 1 and Type 2 FLCs, leading to a decrease in fuel consumption from 7.26 Liters/100 km down to 6.69 Liters/100 km, as well as an increase in the battery SoC from 72.7% to 75.8%. Another study [110] combines FLC with switching control to improve the fuel cell's durability and the economy of fuel cell hybrid EV (FCHEV). Compared with a Proportional-Integral Controller (PIC) and power follower method, the combined strategy improved fuel economy by 13% and 9%, respectively. Siddula [111] employ an Adaptive Neuro-Fuzzy Inference System (ANFIS) that dynamically regulates power among components like batteries and motors. Beheshtikhoo et al. [112] introduce two type-2 FLCs on the demand-side of a smart home EMS, that integrates renewable energy sources and an EV. Based on the simulation results, the proposed strategy reduces 71% of the cost of the electricity received from the power grid. Other studies in this field that are worthy of mention are cited in [113], [114], [115], [116], [117], [118], and [119]

· **Predictive Fuzzy** controllers incorporate predictive elements to anticipate future conditions based on system dynamics and input data trends. These systems often use neural networks (NN), deep learning (DL), or other intelligent control methods to forecast driving conditions and optimize the FLC's decision-making process, thereby improving efficiency and component longevity in real-time scenarios. A paper [120] proposes a combination of FLC and model predictive direct torque control (MPDTC) method. The simulation results show improvements in reducing harmonics, torque and flux ripples, and better SOC management. A recent publication [121] explores employing FLC and Long short-term memory (LSTM) NN trained on historical data. The reported results show better energy efficiency, slight range extension, and better prediction accuracy compared to conventional methods. Pan et al. [122] develop an EMS for EVs, considering random load fluctuations and air conditioning loads that impact motor torque control. The strategy includes predicting driving conditions using Markov theory and evaluating logic threshold and fuzzy control strategies under different conditions. Simulation and hardware-in-loop (HIL) tests demonstrate improved driving range and mitigated battery SOC decline. The strategy offers optimized energy use by up to 8.14% compared to the logic threshold strategy.

Fuzzy EMS also has some challenges, including reliance on expert knowledge for defining fuzzy rules, limited adaptability to rapidly changing conditions, and suboptimal performance in dynamic environments. Although adaptive fuzzy EMS addresses the adaptability challenge by tuning membership functions and control rules in response to varying conditions, it still often requires significant computational resources and may struggle with high complexity. Predictive fuzzy EMS enhances performance by using future predictions and learning from historical data, offering greater efficiency and adaptability in real-time. However, it requires higher computational requirements and needs a significant amount of accurate historical data to achieve effective prediction and adaptation.

Fig. 9 presents a comparative chart of the performance of the various rule-based EMS methods discussed. In conclusion, rule-based EMSs exhibit a range of trade-offs concerning implementation simplicity and control performance. Basic heuristics, including thermostat control and power-following strategies, are easy to implement, computationally efficient, and necessitate minimal system modeling. These approaches frequently lead to inefficient energy use and diminished system performance. Advanced rule-based techniques, including state-machine-based logic and fuzzy inference systems, enhance energy efficiency by integrating a higher level of system knowledge and adaptability. Fuzzy logic controllers have shown efficacy in reducing fuel consumption and enhancing drivetrain performance through improved management of engine load and power flow across diverse operational conditions. Adaptive fuzzy control improves system responsiveness and robustness in dynamic driving conditions, though it increases design complexity and necessitates greater amounts of parameter tuning. Predictive fuzzy control strategies, utilizing future state estimations or traffic forecasts. These methods can yield notable efficiency enhancements through proactive control decisions; however, they place considerable demands on computational resources and necessitate advanced modeling frameworks, which in turn elevate system design complexity and integration challenges [87], [123], [124]. It should be noted that this figure provides a general comparison, and the performance of each individual method may vary depending on specific use cases and the inclusion of adaptive or predictive techniques such as NN, ANFIS, PSO, SMC, RL. This comparative assessment has been developed based on considerations of the methods' underlying architecture, required mathematical equations, computational and memory demands, and general implementation complexity. For further performance analysis on each technique, the authors recommend referring to [88], [91], [93], [99], [109], and [120].

B. OPTIMIZATION-BASED EMSs

Optimization-based EMS for EVs and HEVs are developed to optimize energy resource allocation, enhancing efficiency and minimizing operational costs. These systems are divided into offline, online, and learning-based approaches. Offline methods compute optimal strategies using historical data or known conditions, delivering globally optimal solutions but lacking real-time adaptability. Online methods, on the other hand, dynamically adjust energy management decisions during operation, offering real-time adaptability but demanding higher computational resources compared to rule-based EMSs. Learning-based optimization employs machine learning techniques to dynamically adapt and improve strategies based on experience. While primarily employed in an online context, these techniques are sometimes combined with offline methods, warranting their classification as a separate subcategory.

1) OFFLINE OPTIMIZATION-BASED EMSs

Offline optimization-based EMSs calculate optimal strategies using predefined driving cycles or historical data. These methods solve the energy distribution and efficiency problem globally by considering all constraints and parameters of the system, providing theoretically optimal solutions. However, they rely on full knowledge of the driving cycle and involve significant computational resources, which make them unsuitable for real-time applications. Instead, offline EMS serves as benchmarks or tools for developing rule-based or adaptive strategies for real-world implementations. Some of the well-known offline EMS methods are described in the following.

· **Dynamic Programming (DP)** is a global optimization algorithm widely used in EMS for EVs and HEVs. It computes the optimal control strategy by breaking the problem into smaller subproblems, solving each recursively to achieve the theoretical global optimum. Although DP can provide globally optimal solutions for energy management issues, its significant processing demands, prolonged time requirements, and necessity for prior information make it impracticable for real-time use. Consequently, DP-based methodologies are generally utilized as offline techniques and are esteemed as standard instruments for assessing the efficacy and optimality of alternative, more computationally effective tactics [97], [125]. The cost function of a DP algorithm for a general HEV power distribution problem can be formulated as:

$$J = \sum_{k=0}^{N-1} g(x_k, u_k, k) + h(x_N) \tag{2}$$

where, the function $g(x_k, u_k, k)$ denotes the instantaneous cost at each discrete time step k, commonly measuring factors such as fuel consumption, greenhouse gas emissions, or total

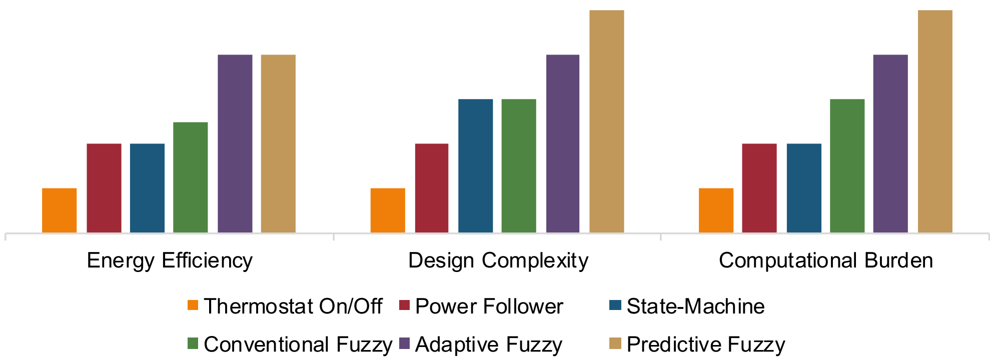

FIGURE 9. Rule-based EMSs performance comparison chart.

TABLE 10. Advantages and disadvantages of rule-based EMS methods.

Ref.	EMS method	Advantages	Disadvantages
[88], [89]	Thermostat On/Off	Simple design, easy implementation	Inefficient energy use, large fluctuations
[88], [90]–[92]	Power Follower	Directly follows load, simple and reactive	Poor optimization, limited adaptability
[94]–[96]	State-Machine	Structured control, clear operational logic	Limited flexibility, fixed transitions
[85], [99]–[106]	Conventional Fuzzy	Good for nonlinear systems, handles uncertainty	Requires expert-defined rules, suboptimal adaptation
[109]–[119]	Adaptive Fuzzy	Adaptive to changes, improves energy efficiency	Complex design, higher computational requirements
[120]–[122]	Predictive Fuzzy	Predicts future conditions, highly efficient	High complexity, requires extensive data and computation

energy usage. The terminal cost $h(x_N)$ addresses end-of-horizon objectives, typically established in EMS to penalize unfavorable final states, such as deviations from a target battery SOC or deterioration in battery SOH at the final time step. The variable x_k represents the vector of state variables at time step k, encompassing battery SOC, SOH, hydrogen content in fuel cell systems, or total distance traveled. The states are essential for identifying the optimal control actions u_k, including power distribution between an internal combustion engine and an electric motor, as well as the allocation of electrical current among hybrid energy storage devices such as batteries, supercapacitors, and fuel cells. In this context, N signifies the total number of time steps within the optimization horizon.

The state variables evolve according to the system dynamics:

$$x_{k+1} = f(x_k, u_k, k) \tag{3}$$

where $f(x_k, u_k, k)$ represents the system dynamics (e.g., battery SOC update).

The DP algorithm solves the problem using Bellman's recursive equation:

$$V_k(x_k) = \min_{u_k} \left[g(x_k, u_k, k) + V_{k+1}(x_{k+1}) \right] \tag{4}$$

where, $V_k(x_k)$ is the value function representing the minimum cost from time step k to N, and the boundary condition at the final step is defined as $V_N(x_N) = h(x_N)$.

The optimization process must respect physical and operational constraints such as state constraints and control constraints. The optimal control sequence u_k^* is determined by solving:

$$u_k^* = \arg\min_{u_k} \left[g(x_k, u_k, k) + V_{k+1}(x_{k+1}) \right] \tag{5}$$

These equations are solved iteratively, starting from the final state and working backward to the initial state. While DP guarantees a globally optimal solution, it requires discretization of state and control variables, leading to high computational demands, commonly known as the curse of dimensionality.

A recently published research proposes a DP-based fuzzy logic strategy for a FCHEV bus, optimizing power allocation based on actual driving cycles. Results show improved energy efficiency compared to rule-based methods, particularly under high-energy-demand conditions [126]. An Adaptive DP (ADP) integrated with velocity planning is also proposed in the literature [127] that achieves 98.01% of DP energy optimality under urban driving conditions while enhancing driving comfort and safety. Lee et al. [128] optimize EMS for FCHEV using DP, enhancing fuel economy and

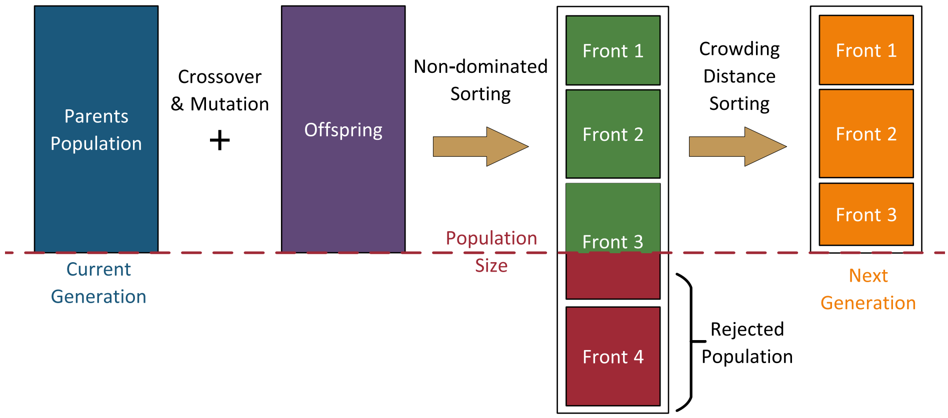

FIGURE 10. NSGA-II workflow showing population evolution through non-dominated sorting and crowding distance for next-generation selection.

system durability. Simulation results show a 6.46% reduction in hydrogen consumption compared to conventional strategies. A different study [129] investigates Dual Heuristic DP (DHP) for HEV, combining DP principles with NN for power allocation. Results confirm robust adaptability and improved fuel economy across various driving conditions. A hierarchical EMS for HEVs based on ADP is proposed in [130], which optimizes speed planning and energy distribution in car-following scenarios. In contrast to other DP methods, the proposed system ensures real-time control and also reduces fuel consumption. Another heuristic DP (HDP)-based online EMS for PHEVs is explored in [131] to minimize fuel consumption by utilizing a backpropagation NN (BPNN) to model the vehicle's nonlinear dynamics. Simulations on a real-world route show the strategy achieves 98% speed-tracking accuracy and reduces fuel consumption and emissions compared to existing online strategies, though it is approximately 4% less efficient than offline global optimization methods. Liu et al. [132] address the challenge of applying a DP-based EMS for PHEVs on trip paths without GPS data. By introducing a hybrid trip model to estimate vehicle-speed trajectories and optimizing the SOC search range, the proposed method reduces DP computational load and achieves over 78% accuracy in trajectory prediction while maintaining effective fuel consumption rates in practical scenarios.

· **Genetic Algorithm (GA)** optimization is a nature-inspired method used to find optimal solutions by mimicking the processes of selection, crossover, and mutation. GA is commonly applied for single-objective optimization, such as minimizing fuel consumption or emissions in EVs and HEVs. However, in real-world EMS applications, multiple conflicting objectives often exist, such as balancing energy efficiency and component longevity. To address this, multi-objective extensions like Non-Dominated Sorting Genetic Algorithm II (NSGA-II) are employed [133], [134]. NSGA-II efficiently handles multiple objectives by sorting solutions into Pareto fronts and maintaining diversity through crowding distance, making it a powerful tool for achieving balanced trade-offs in multi-objective EMS optimization.

Fig. 10 illustrates the evolution from the current generation to the next generation in the NSGA-II. The process is described as follows [133], [134]:

1) Generating a random population of parents.
2) Performing crossover and mutation to generate offspring.
3) Combining parents and offspring and evaluating fitness of each individual.
4) Performing non-dominated sorting to divide solutions on different fronts.
5) Performing crowding distance sorting to pass the individuals with highest rank and crowding distance to the next generation by considering maximum population size.
6) Repeating steps 2 to 5, until stopping criteria (maximum number of generations or error gradient) meets.

Lu et al. discuss the application of GA in EMS of FCHEV focusing on improving energy utilization and extending fuel cell life [135]. Another paper uses GA to optimize power tracking EMS parameters for FCHEVs, achieving fuel consumption reductions of 17.6% and 9.7% under urban and highway driving cycles [136]. GA also has been used to optimize FLC parameters in [137], [138], [139], and [140]. The combination of NSGA-II optimization and NN modeling is employed in [141] to extend driving range by up to 22% and mitigate battery aging by 20%, in a similar fashion to [32]. Liu et al. [142] employed GA with deep learning in an EMS for a PHEV. GA is utilized to search the global optimal controls based on the powertrain model, and deep learning trains the NN model that is connecting the inputs and control actions. Simulations demonstrate improvements in fuel economy and adaptability to real-time applications compared to the conventional charge depleting/charge sustaining (CD/CS) method. Maherchandani et al. in [143] introduce an innovative energy management strategy that combines GA with

Pontryagin's Minimum Principle (PMP) to determine the appropriate equivalency factor. The hybrid GA-PMP method integrates the global search efficacy of GA with the real-time optimization prowess of PMP, and simulation results indicate enhanced performance in minimizing hydrogen use relative to the independent PMP method. Ankar et al. [144] employ NSGA-III to optimize battery and supercapacitor configurations in hybrid energy storage systems (HESS), achieving up to a 76.38% increase in battery cycle life. The study also demonstrates a 42.14% reduction in lifecycle costs. A similar study [145] uses NSGA-II to optimize HESS for PHEVs, minimizing cost, weight, and battery degradation. Results show substantial reductions in HESS size and lifecycle costs compared to conventional systems. A GA-based EMS for HESS considering temperature effects is proposed in [146] that achieved 3.3% better energy economy across different ambient temperatures. Another GA-based real-time adaptive EMS for PHEVs is published in [147] to optimize energy utilization by dynamically regulating parameters such as driving cycle, distance, and battery SOC. By integrating equivalent consumption minimization strategy (ECMS), driving cycle recognition, and FLC, the approach achieves 14.82% reduced fuel consumption under high power demand while maintaining adaptability to varying driving conditions.

The main challenges of GA-based EMS lie in their computational complexity, adaptability, and dependency on accurate parameter settings. The iterative nature of GAs often leads to high computational costs, making real-time application difficult, especially for dynamic driving conditions. While GAs are robust in handling non-linear and multi-objective optimization problems, their performance heavily relies on proper tuning of parameters such as population size, mutation rate, and crossover rate, which can be time-consuming and require extensive knowledge. Additionally, GAs may converge prematurely to local optima if diversity within the population is not maintained. Finally, their integration into EVs and HEVs requires efficient data collection and model accuracy to ensure that the EMS aligns with real-world conditions and constraints.

· **Particle Swarm Optimization (PSO)** is another evolutionary optimization algorithm used in EMS to minimize objectives like fuel consumption and emissions in EVs. PSO works by simulating the social behavior of particles (solutions) that move through a solution space, updating their positions based on personal and collective experiences to find optimal or near-optimal control strategies for energy distribution [148], [149].

A real-time EMS for FCHEV aimed at reducing trip costs by optimizing hydrogen usage and energy storage is proposed in [150]. It uses DP for strategy derivation and PSO for real-time application. The strategy achieved comparable performance to DP in reducing trip costs. PSO has also been used in the literature for optimizing the membership functions of FLC [151], [152], [153], [154]. The published results show that the optimized EMS can improve driving range by 5.9% in well-known driving cycles and reduced fuel cell degradation by 21.4% compared to baseline strategies [151]. Perez-Davila and Fernandez [155] propose another PSO-optimized EMS for HEV and fuel cell EREV that determines the current ratio between the battery and fuel cell system. They reported 9% to 12% improvement in driving range. An EMS based on the combination of Jellyfish, PSO, and BAT (JSPSOBAT) optimizers is proposed to tune a PI controller for reducing hydrogen consumption and operational stress in fuel cell, battery, and supercapacitor systems [156]. The results demonstrate superior performance compared to state-machine, classical PI, and other optimization strategies, reducing hydrogen consumption and stress on the energy source. Omakor et al. [157] present an EMS for a battery-ultracapacitor HESS, optimized using PSO on an FLC. By minimizing battery current and power fluctuations and optimizing FLC rules based on battery temperature, the EMS enhances battery lifespan and performance. Spano et al. [158] highlight the trade-off between upsizing power sources to enhance fuel economy and downsizing to reduce production costs during manufacturing. To address this, they propose an innovative PSO approach that efficiently balances these competing objectives, enabling the optimal design of parallel HEVs to simultaneously maximize fuel economy and minimize production costs. A similar study also employs multi-objective PSO for finding the optimal sizes for batteries and supercapacitors in FCHEVs and provides recommendations based on the driving conditions [159].

PSO typically requires the full search process to complete before providing a solution, making it unsuitable for real-time applications. Its limitations include premature convergence, parameter sensitivity, and difficulty managing constraints or dynamic environments, often necessitating hybridization or customization. In real-time scenarios, the population size is reduced, some variables are ignored, or the search space is simplified to decrease computational demands, which may compromise the ability to find globally optimal solutions.

· **Pontryagin's Minimum Principle (PMP)** also known as optimal control is an offline EMS that optimizes control policies by minimizing the Hamiltonian to determine the optimal power split between energy sources in HEVs, or optimal vehicle speed in EVs. Adapting PMP for online use prevents it from guaranteeing globally optimal solutions, as it cannot fully account for future conditions or constraints during the optimization process. The Hamiltonian (H) and the cost function over time (J) in general form is defined in Equations (7) and (8) [160], [161]:

$$H(x(t), u(t), \lambda(t), t) = L(x(t), u(t), t) + \lambda^{\top}(t) f(x(t), u(t), t) \tag{6}$$

$$J(x(t), u(t), t) = \psi(x(t_f^-)) + \int_{t_0}^{t_f^-} L(x(t), u(t), t)\, dt \tag{7}$$

where, $x(t)$ is the state variable, $u(t)$ is the control variable, $\lambda(t)$ is the costate variable (often referred to as the Lagrange multiplier in this context), representing the sensitivity of the system to changes in the state, ψ is the terminal cost, which accounts for the state at the final time step t_f. This is often used to penalize or optimize the final state of the system. t_0 is the initial time, $L(x(t), u(t), t)$ is the cost (performance objective), $f(x(t), u(t), t)$ is the system dynamics, describing how the state evolves over time based on the state and control variables.

The optimal control law (u^*) is obtained by minimizing the Hamiltonian with respect to the control variable $u(t)$. (u^*) is calculated based on the necessary conditions for optimality given in Equation (8).

$$\begin{aligned}
\dot{x}(t) &= \frac{\partial H(x^*, u^*, \lambda^*, t)}{\partial \lambda} = f(x(t), u(t), t) \\
\dot{\lambda}(t) &= -\frac{\partial H(x^*, u^*, \lambda^*, t))}{\partial x} \\
\frac{\partial H}{\partial u} &= 0 \\
u^* &= \arg\min_u H(x, u, \lambda, t) \Rightarrow H(x^*, u^*, \lambda^*, t) \\
&\leq H(x^*, u, \lambda^*, t)
\end{aligned} \tag{8}$$

The boundary conditions for such a problem is defined as $x(t_0)$ and $x(t_f)$.

Zhang et al. [41] address the limited driving range of EVs by proposing an in-vehicle energy optimal control based on PMP to improve motor-drive efficiency. Using a PMP approach based on Lagrange-Euler formula that considers energy consumption and speed demand, the proposed EMS ensures the motor operates in its high-efficiency region. In another research [162], a robust design approach based on Design for Six Sigma (DFSS) is proposed to enhance the EMS for PHEVs in real-time. By integrating a multi-island GA, Monte Carlo simulation, and SOC constraints within PMP, the proposed method achieves up to 19.66% fuel consumption reduction compared to conventional strategies and delivers energy-saving performance close to DP. To enhance battery life in battery-supercapacitor HESS, A study [163] proposes an online hybrid EMS combining PMP and RL. By using RL to predict the optimal costate and an analytical approach for initial costate estimation, the EMS effectively minimizes battery degradation and maintains supercapacitor charge sustainability under uncertain and untrained driving cycles, achieving 900 more discharge cycles compared to an offline EMS. Song et al. [164] introduce a real-time EMS based on PMP to balance fuel economy and power source durability in hybrid systems. By incorporating performance degradation models for fuel cells and batteries, an online co-state updating method, and a fuel cell power variation limiting factor, the EMS optimizes hydrogen consumption and durability. Simulation results demonstrate around 38% improvement in fuel cell lifespan and average daily operating costs compared to rule-based EMS and comparable numbers to DP. An adaptive PMP based on velocity prediction that adjusts the costate variable in real-time is proposed in [165] for a battery supercapacitor EV to address PMP's limitation of a fixed costate under uncertain driving conditions. Simulations on varying road slopes and driving cycles reveal that the proposed EMS improves battery health and efficiency compared to rule-based strategies and PMP without velocity prediction. A similar study employs an improved Markov-based velocity prediction and online driving pattern recognition optimized by PSO [166]. Simulations demonstrate a 4% reduction in hydrogen consumption and smoother fuel cell operation compared to rule-based EMS, achieving performance close to offline optimal algorithms. Nguyen et al. [167] published a research that recognizes driving pattern using ANFIS and updates the costate variables of PMP to improve EMS performance in a HESS battery-supercapacitor EV. The real-time simulations on Federal Test Procedure (FTP) cycle show reduction in the root mean square of the battery current by 11.4%. Since PMP relies on future driving condition knowledge for optimality, Kim et al. [168] address the limitation by proposing a methodology to update control parameters based on past driving patterns for vehicles with repeated cycles, such as buses or delivery trucks. By estimating the costate from driving conditions and energy consumption patterns, the approach ensures the final SOC converges to the desired value over repeated drives.

PMP has notable drawbacks, primarily its reliance on prior knowledge of the driving cycle, making it essentially an offline approach. PMP also requires an explicitly defined precise mathematical model of the system, which may not always be feasible in practical scenarios. While PMP can be adapted for real-time applications, it must be combined with other algorithms, such as machine learning or predictive methods, to estimate the costate or adapt to dynamic conditions. However, even with these adaptations, PMP cannot guarantee global optimality in real-time applications.

· **Game Theory (GT)** models the interaction between multiple power sources in HEVs as a non-cooperative or cooperative game, aiming to optimize energy distribution. In this approach, players (such as battery, fuel cell, supercapacitor) plan their actions to minimize their individual costs (e.g., energy consumption, degradation) while considering the behavior of others. In a general form, the number of players in GT is defined as $\mathcal{N} = \{1, 2, \ldots, n\}$, where each player i has a strategy set specified by $S_i = \{s_i^1, s_i^2, \ldots, s_i^m\}$. Thus, the combined strategy set for all players is $S = S_1 \times S_2 \times \cdots \times S_n$ [169], [170].

The payoff function u for player i is defined as:

$$u_i(s_1, s_2, \ldots, s_n, t_k) = u_i(S, t_k) \tag{9}$$

where, S is the strategy profile of all players at time t_k.

A Nash Equilibrium is achieved when no player can improve their payoff by unilaterally changing their strategy:

$$u_i(s_i^*, s_{-i}^*, t_k) \geq u_i(s_i, s_{-i}^*, t_k), \quad \forall s_i \in S_i, \quad \forall i \in \mathcal{N} \tag{10}$$

In mixed strategies, the probability of player i choosing strategy s_i is $p_i(s_i)$. The expected payoff E is:

$$E[u_i] = \sum_{s_1 \in S_1} \cdots \sum_{s_n \in S_n} u_i(s_1, \ldots, s_n) \prod_{j=1}^{n} p_j(s_j) \tag{11}$$

For cooperative games, the total utility or social welfare W is:

$$W = \sum_{i \in \mathcal{N}} u_i(S) \tag{12}$$

The strategy profile is optimized across the entire driving cycle, $T = \{t_1, t_2, \ldots, t_N\}$:

$$\max_{S} \sum_{k=1}^{N} \sum_{i \in \mathcal{N}} u_i(s_i(t_k), s_{-i}(t_k), t_k) \tag{13}$$

For each time step t_k, the payoff function u of each strategy s is solved:

$$s_i^*(t_k) = \arg\max_{s_i} u_i(s_i, s_{-i}, t_k), \quad \forall i \in \mathcal{N} \tag{14}$$

The, the state of each energy source is updated based on the chosen strategies:

$$x_i(t_{k+1}) = f_i(x_i(t_k), s_i^*(t_k)), \quad \forall i \in \mathcal{N} \tag{15}$$

Eventually, the total cost J over the entire driving cycle can be calculated as:

$$J = \sum_{k=1}^{N} \sum_{i \in \mathcal{N}} u_i(s_i^*(t_k), s_{-i}^*(t_k), t_k) \tag{16}$$

References [169] and [170] are provided for further in-depth research about GT algorithm.

Ruan et al. [171] propose a data-driven cooperative differential GT-based EMS for hybrid electric propulsion systems in flying cars, addressing the coupling dynamics of multiple generator units. Using a NN-based adaptive DP algorithm to approximate Nash equilibrium and Pareto solutions, the proposed model achieves a 2.67% and 6.22% reduction in fuel consumption compared to non-cooperative and rule-based EMS, while improving exhaust gas temperature control and battery SOC stability. In another study, Nash equilibrium is used to optimize energy flow between the ICE and the EM while considering constraints like SOC and thermal reliability, in a PHEV [172]. Ghaderi et al. [173] propose a GT-based strategy for a multi-stack FCHEV with three fuel cells and a battery, addressing the complexity of power distribution. The EMS improves hydrogen consumption and degradation costs by 6% compared to a rule-based strategy, while remaining close to DP performance. An efficient EMS for PHEVs incorporating a motor current alert mechanism to prevent prolonged high currents is proposed in [174]. Using a multi-step Markov chain for velocity prediction and cooperative GT, the strategy optimizes group and individual energy profits. Simulations and tests show a 71% reduction in large motor current occurrences and a 10.28% fuel consumption reduction. A similar study also employs the same principles of GT with the same driving condition prediction algorithm for FCHEV, resulting in 6.82% reduced hydrogen consumption [175]. Another publication develops a min-max GT-based discrete optimization approach for real-time management of fuel cell and battery degradation in FCHEVs [176]. By quantifying aging and decoupling lifetime competition between the two power sources, validations through hardware-in-the-loop (HIL) show the method improves system economy and reduces degradation.

GT-based EMS offer effective frameworks for managing the interaction of different power sources or agents with possibly divergent agendas. The intrinsic intricacy of interactions among these entities substantially increases computational requirements, presenting significant challenges for real-time implementation. Obtaining precise and prompt resolutions to game-theoretic models—such as Nash equilibrium—amid dynamic and variable driving situations necessitates substantial processing power and effective solvers, which are frequently unfeasible in embedded automotive systems. Furthermore, GT-based EMS depends on accurate system modeling and predictive abilities (such as anticipated power demand or driving behaviors) to produce significant and reliable results, which are challenging to achieve in practical applications due to model uncertainties and fluctuations in operating conditions. Furthermore, a tangible implementation of the game framework—where each participant functions as an independent decision-making entity—requires an advanced control architecture to coordinate decentralized strategies, thus complicating system integration, elevating design complexity, and potentially impacting overall system stability. Reconciling the trade-offs among computing efficiency, solution optimality, and practical practicality is a significant obstacle to the extensive use of GT-based EMS in real-time vehicle applications [177].

· **Simulated Annealing (SA)** is an optimization technique inspired by the annealing process in metallurgy, used to find near-optimal solutions for energy distribution in HESS. SA explores the solution space by iteratively adjusting the power allocation between energy sources, guided by an objective function such as fuel efficiency, battery degradation, or emission reduction. It accepts both improving and, occasionally, worsening solutions to escape local optima, with the likelihood of accepting worse solutions decreasing over time (controlled by a cooling schedule).

A study proposes a strategy for power-split PHEVs, combining PMP to optimize battery current and SA to determine engine-on power and current coefficients, with battery SOH considerations [178]. Simulations show the method reduces fuel consumption compared to CD/CS modes. Yang et al. [179] recommend an EMS for PHEVs that integrates the genetic SA with an interval type-2 FLC to optimize energy efficiency while considering air conditioning energy consumption. The EMS reduces fuel consumption by up to 17.77% compared to rule-based methods and ensures faster and more consistent cabin temperature regulation, compared to both rule-based and adaptive equivalent consumption minimization strategy (ECMS) strategies in cooling and heating modes. An interesting research is conducted by Machado et al. [180] that present a multilayer EMS for a small urban EV, combining long-term rule-based management, short-term optimization using a hybrid metaheuristic approach (combining PSO and SA), and a high-speed DC to DC controller using a linear-quadratic regulator. The strategy optimizes power sharing and source usage, and demonstrates improved performance with lower installed capacities on a reduced-scale prototype. The same research team also published a paper focused on developing an EMS that dynamically restricts search space and uses SA for optimization in order to reduce the size and capacity of onboard power sources, while achieving performance improvements. In [181], the authors optimize the EMS of a multi-mode HESS by proposing an adaptive mode switch strategy using SA. The strategy enhances system efficiency by optimizing the supercapacitor's SOC and battery power while reducing mode-switching frequency and excessive battery power output. Simulations and experiments show the developed model outperforms rule-based strategies by improving energy efficiency, ensuring battery safety, and allowing the supercapacitor to handle peak power demands and braking energy.

However, SA-based EMS encounters significant obstacles in real-time applications owing to its comparatively sluggish convergence rate and the computational duration necessary to attain near-optimal solutions. Moreover, the efficacy of simulated annealing is acutely dependent on the calibration of critical parameters—namely, cooling schedule, initial temperature, and termination criteria—which profoundly affect both solution quality and computing efficiency [182], [183], [184].

· **Linear Programming (LP)** is a mathematical optimization technique used to minimize or maximize an objective function, such as fuel consumption, energy cost, or emissions, while satisfying linear constraints. In this context, LP models the energy flow between power sources and power demands under constraints like SOC limits, power limits, and drivetrain requirements. LP is computationally efficient and well-suited for offline or real-time EMS when system dynamics and objectives can be approximated with linear relationships. However, it struggles to handle nonlinearities and uncertainties inherent in real-world EV and HEV operations, often requiring extensions like mixed-integer or nonlinear programming for more complex systems.

Considering a simple HEV EMS problem, that minimizes the total energy consumption, the cost function can be formulated as:

$$J = \int_{t_0}^{t_f} \left(F_{\text{fuel}}(P_{\text{eng}}(t)) + w_{\text{bat}} \cdot P_{\text{bat}}(t) \right) dt \qquad (17)$$

where F_{fuel} is fuel consumption rate as a function of engine power $P_{\text{eng}}(t)$, $P_{\text{bat}}(t)$ is battery power, and w_{bat} is weighting factor for battery power.

The total power demand P_{req} must equal the sum of engine and battery power:

$$P_{\text{req}}(t) = P_{\text{eng}}(t) + P_{\text{bat}}(t) \qquad (18)$$

The control variable $u(t)$ is the power split ratio, which can be defined as:

$$\begin{aligned} P_{\text{eng}}(t) &= u(t) \cdot P_{\text{req}}(t) \\ P_{\text{bat}}(t) &= (1 - u(t)) \cdot P_{\text{req}}(t) \\ 0 \le\ & u(t) \le 1 \end{aligned} \qquad (19)$$

Considering the constraints for SOC, P_{eng}, and P_{bat} the EMS optimization problem is:

$$\begin{aligned} \min_{u(t)} J = \int_{t_o}^{t_f} & \left(F_{\text{fuel}}(u(t) \cdot P_{\text{req}}(t)) + w_{\text{bat}} \right. \\ & \left. \cdot (1 - u(t)) \cdot P_{\text{req}}(t) \right) dt \end{aligned} \qquad (20)$$

Reference [185] is recommended for a comprehensive exploration of the concept of LP.

Using model reference adaptive control and mixed-integer LP, Siddique and Gabbar [186] proposed an EMS for a nuclear-renewable HESS to support fast charging stations. The strategy fulfills the power demand of the fast charging station while reducing the generation cost and waste of energy. A different study develops an LP-based heuristic algorithm for smart charge and discharge scheduling of EVs within a time-space network model to reduce peak loads [187]. An improved two-stage heuristic algorithm addresses uncertainties in EV demands and departure times, demonstrating the potential of EVs to stabilize power grids and optimize energy usage through vehicle-to-grid (V2G) systems. A similar paper [188] also proposes a mixed integer LP model for active and reactive power management in smart distribution networks, leveraging EV chargers' capabilities. The model optimizes energy cost and voltage profile while adhering to network and EV charging constraints. The results demonstrate reduced energy cost and loss, improved voltage profiles, and support for higher EV penetration into the grid within acceptable computation times. Considering socio-economic factors, an optimized EV charging network distribution using statistical approaches based on LP and Bayesian theory is proposed in [189]. The results demonstrate that this method minimizes grid impact while ensuring a safe, cost-effective, and accessible fast charging infrastructure across large geographical areas. In [190], an offline LP-based benchmark is integrated with an instantaneous optimization model for FCHEVs to minimize the equivalent power of the fuel cell and battery, manage battery SOC, and penalize fuel cell load changes to reduce degradation. Simulations demonstrate that the recommended model enhances fuel economy, improves load change control, and achieves optimal performance under varying driving cycles without the need for parameter adjustments. Ghandriz et al. [191] developed a real-time predictive EMS for hybrid electric heavy vehicles, employing MPC and sequential LP to optimize power split, vehicle velocity, and battery SOC over horizons of 5-20 km. The proposed method proves to be faster and simpler than sequential quadratic programming, delivering near-optimal trajectories while effectively regulating acceleration, braking, and battery usage, as validated using a high-fidelity vehicle model.

Yet, LP has limitations that can impact its applicability in complex systems. One major drawback is its inability to handle nonlinear relationships, which are common in real-world problems such as EMS for vehicles or grids. Additionally, LP requires constraints and the objective function to be linear, which may oversimplify the problem and result in suboptimal solutions. It also struggles with handling uncertainty or dynamic changes, as it is typically designed for static or deterministic scenarios. These limitations often necessitate extensions, such as mixed-integer or nonlinear programming, to address more complex and realistic problems (as mentioned above).

Fig. 11 illustrates the trade-offs among offline optimization-based EMSs. The scales are for comparative purposes only, as the efficiency, design complexity, and computational burden of each algorithm heavily depend on the specific problem. As shown, DP achieves the highest energy efficiency due to its ability to guarantee global optimization. However, it is hindered by significant computational burden and design complexity, making it impractical for real-time applications. GT exhibits the highest design complexity, demanding processing power comparable to DP, but its energy efficiency in EMS problems is relatively low. GA and PSO generally deliver similar efficiency, with GA being slightly more complex and computationally demanding due to operations such as selection, crossover, and mutation, whereas PSO relies on simpler particle updates. Among these methods, PMP strikes a balance, with lower computational burden compared to most methods (except LP) and efficiency results close to but slightly below those of DP. However, PMP's design complexity is higher than most other methods, except for DP and GT. SA achieves better fuel economy than LP but significantly lags behind other algorithms in efficiency. Lastly, LP stands out as the least computationally demanding and simplest method to implement. However, its reliance on linear approximations limits its ability to deliver satisfactory energy efficiency under dynamic conditions.

Table 11 compares the introduced offline optimization-based EMSs with regards to their advantages and disadvantages.

2) ONLINE OPTIMIZATION-BASED EMSs

Online optimization-based EMSs in EVs and HEVs dynamically determine optimal control actions during real-time operation. These methods aim to balance energy efficiency, performance, and computational feasibility under changing driving conditions. Unlike offline methods, online approaches adapt to real-time inputs, such as driver behavior and road conditions, making them more suitable for practical applications. However, their design requires balancing computational complexity and accuracy to ensure responsiveness without compromising performance.

· **Equivalent Consumption Minimization Strategy (ECMS)** is a real-time approach widely used in HEVs. It aims to minimize fuel consumption by translating energy usage across different power sources, such as fuel and electricity, into a common metric known as equivalent fuel consumption. ECMS operates by optimizing the power split between the ICE and the EM in real-time, ensuring that the total energy cost is minimized while maintaining charge-sustaining (CS) operation of the battery. This strategy leverages instantaneous energy equivalence without requiring complete knowledge of future driving conditions, making it computationally efficient and suitable for real-time applications.

Feng et al. [192] developed a novel ECMS for HEVs that dynamically adjusts the EF based on current speed and minimum engine operation time. Using a self-organizing map NN, speed patterns are identified and optimal EFs are determined for specific driving cycles. An FLC further adjusts engine operation time to maintain battery SOC within limits and account for engine start hysteresis. Simulations show the proposed ECMS improves fuel economy by up to 7.87% over conventional methods, and significantly reduces peak battery currents. An Adaptive ECMS (A-ECMS) is proposed in [193] for 4-wheel-drive (4WD) plug-in FCHEV to optimize power distribution between the front and rear motors, fuel cell system, and battery. Variable equivalent factors (EF) are determined based on the dragonfly algorithm. The proposed EMS outperforms conventional ECMS and a rule-based strategy by 2% in terms of energy efficiency. Unlike conventional A-ECMSs that rely on CS conditions, a proposed method in [194] defines and iteratively calculates a near-optimal EF based on actual driving conditions. Simulations demonstrate improved adaptability with minimal loss of optimality compared to traditional A-ECMS. Experimental validation under real-world driving conditions is also provided that confirms its effectiveness. A hierarchical EMS is also proposed in [195] for multi-stack fuel cell systems, combining a rule-based layer to activate fuel cells based on power demand, SOC, and degradation, and an ECMS for power distribution. Another study combines ECMS with MPC for plug-in hybrid electric buses to prevent motor overheating under urban conditions [196]. The motor temperature is integrated into the MPC cost function as an optimization term, and the Grey Wolf Optimization (GWO) algorithm is used to minimize the objective function offline. Simulation and HIL tests verify the strategy, showing a fuel consumption reduction of 15% under urban and combined driving cycles. The GWO is also similarly used to divide the driving cycle of an electric bus into segments based on vehicle stop times and optimizes the EF for each segment [197]. Simulation results demonstrate an 18.72% reduction in fuel consumption compared to conventional ECMS. K-means and K-nearest neighbors algorithms is employed to classify paths in [198],

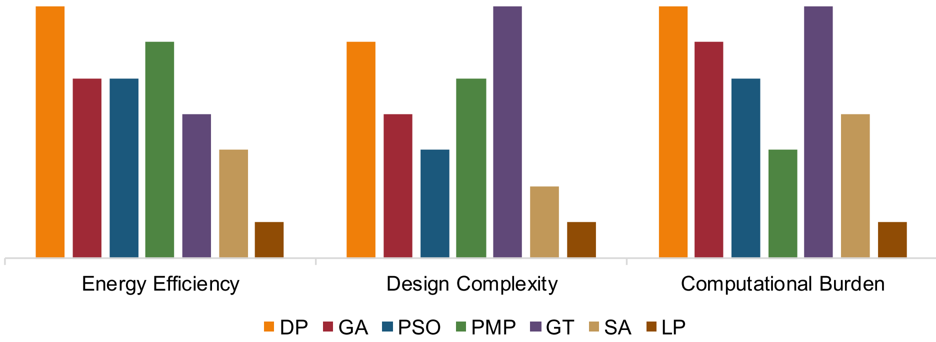

FIGURE 11. Offline optimization-based EMSs performance comparison chart.

TABLE 11. Advantages and disadvantages of offline optimization-based EMS methods.

Ref.	EMS method	Advantages	Disadvantages
[126]–[132]	DP	Achieves global optimality, handles complex dynamics	High computational burden, unsuitable for real-time use
[135]–[147]	GA	Handles multi-objective optimization, avoids local optima	May converge slowly, requires careful parameter tuning
[148]–[159]	PSO	Fast convergence, relatively simple to implement	Risk of local optima, sensitive to parameter settings
[160]–[168]	PMP	Computationally efficient, near-optimal results	Requires prior knowledge of driving cycle, relies on exact mathematical model
[171]–[176]	GT	Models multi-agent interactions, adaptive to system changes	Complex modeling, high computational requirements, sub-optimal results
[178]–[181]	SA	Flexible for nonlinear problems, easy implementation	Slow convergence, computationally intensive for large problems, stochastic nature and inconsistent results
[186]–[191]	LP	Simple and efficient for linear problems	Limited to linear systems, struggles with nonlinear constraints

while an MPC predicts the battery SOC. This study optimizes the EF based on the reference SOC trajectory for an A-ECMS. In the context of an A-ECMS, the GWO is employed to iteratively determine the optimal EF based on the gear-switching data generated by DP for for PHEV buses [199]. Compared to DP, the strategy increases fuel consumption by only 3.23%, while avoiding the curse of dimensionality. Guercioni et al. [200] also conducted a research on the same concept. A recently published paper proposes An A-ECMS for flywheel HEVs [201]. The strategy integrates driving condition recognition using a PSO-based support vector machine (SVM) and target SOC path tracking derived from DP. Simulation results demonstrate the developed model improves the thermal efficiency of the ICE and the EM, reducing comprehensive energy consumption by 9.31% and 3.31% compared to a rule-based EMS and traditional ECMS, respectively. Additionally, it achieves a more stable SOC, and enables the flywheel to recover 37.35% of braking energy. Abdelhalim et al. [202] develop a comprehensive EMS for standalone renewable HESS integrating photovoltaic panels, fuel cells, batteries, and supercapacitors. Four strategies including PIC, ECMS, ECMS optimized with Harris Hawks Optimization (ECMS-HHO), and SM are evaluated. Simulation results show that ECMS-HHO outperforms others, achieving the lowest hydrogen consumption and highest efficiency. By contrast, SM shows the highest hydrogen consumption, indicating lower efficiency. ECMS-HHO is highlighted as the most efficient and sustainable EMS for standalone renewable HESS.

The efficacy of the Equivalent use ECMS is significantly dependent on the precise calibration of the EF, which reconciles fuel and electric energy use. An inadequately calibrated EF might result in suboptimal energy distribution and diminished system efficiency. Due to the variability of real-world driving conditions, static EF values frequently prove inadequate, necessitating adaptive tuning strategies to ensure maximum performance. Notwithstanding its real-time functionality, ECMS exhibits significant limitations: it presumes a charge-sustaining state, demonstrates a lack of stability under transient or fluctuating SOC levels, and provides solely heuristic solutions devoid of global optimality. These problems underscore the necessity for enhanced or adaptable ECMS variations to more effectively manage complex and dynamic settings [90], [203].

· **Robust Control (RC)** is designed to ensure optimal energy distribution under uncertainties and varying operating conditions. Unlike traditional EMS strategies, RC explicitly accounts for uncertainties such as unpredictable driving conditions, component degradation, or external disturbances. This approach typically involves formulating the EMS as a control problem with predefined performance criteria and uncertainty bounds. Using techniques like H∞ control or linear quadratic regulators (LQR) with robustness constraints, the RC EMS ensures that the vehicle meets energy efficiency and performance goals despite these uncertainties. The system optimizes power flow between components such as the ICE, EM, and battery while maintaining SOC and minimizing fuel consumption. RC strategies are particularly effective in real-world scenarios where precise system modeling and predictive methods alone may not suffice, providing reliable performance under dynamic and challenging conditions.

To meet the high-performance requirements of electric buses for the Beijing Winter Olympics (2022), a dual-motor coaxial propulsion system with a single planetary gear set was developed, accompanied by a shift control method using a hierarchical LQR algorithm [204]. The upper controller employs a robust tracking LQR to regulate the speed change rate of the output shaft during gear shifting, reducing actuator load. Meanwhile, the lower controller uses a disturbance suppression LQR to control shift force and enhance system adaptability to disturbances. Bench tests confirm that hierarchical LQR reduces vehicle impact by 19.17% and shift force by 32.48%, at the cost of a slight 5.03% increase in shift time, outperforming the PIC overall. Yang et al. [205] present a robust fractional-order sliding-mode control (RFOSMC) for a HESS in EVs. A rule-based strategy generates the battery current reference. RFOSMC is developed to handle nonlinearities and uncertainties in the HESS, employing a sliding-mode state and perturbation observer (SMSPO) for real-time perturbation estimation.

In [206], Babazadeh and Karimi present a robust two degree of freedom feedback-feedforward control strategy to regulate the load voltage of an islanded microgrid in the presence of unmodeled dynamics and uncertainties. The design transforms the control problem into a nonconvex optimization problem, which is then simplified using linear matrix inequality-based optimization, a common RC approach. Simulations demonstrate the proposed scheme's strong robustness against load parameter uncertainties and unknown dynamics.

A robust EMS for FCHEVs is published in [207] to handle uncertainties in system parameters and operational conditions. By analyzing the impact of parametric uncertainty on fuel consumption minimization, the authors develop a supervisory control framework. Muthyala et al. [208] conduct a comparative analysis of real-time Adaptive Equivalent Consumption Minimization Strategy (A-ECMS) and rule-based EMS in long-haul heavy-duty PHEVs. It underscores the benefits of predictive EMS with A-ECMS, which adjusts in real-time according to route data, resulting in enhanced fuel efficiency and battery optimization. The rule-based EMS, albeit more straightforward, is deficient in its adaptation to diverse driving conditions. Simulation outcomes indicate that A-ECMS realizes substantial energy savings compared to the rule-based methodology.

Another RC-based EMS for fuel cell hybrid emergency power systems in More Electric Aircraft (MEA) focuses on maximizing battery and supercapacitor energy utilization without relying on load profile-dependent parameters [209]. The strategy enhances robustness and minimizes hydrogen consumption. Simulations and experiments demonstrate improved performance compared to conventional ECMS.

While RC offers significant advantages in managing uncertainties and ensuring system stability, it has several drawbacks. The design process is often complex, requiring precise mathematical models and advanced tools like linear matrix inequalities or H∞ synthesis, which can be computationally intensive and challenging to implement. Robust control strategies may also lead to conservative solutions, prioritizing stability over optimal performance, especially when faced with significant uncertainties. Additionally, these methods often involve higher computational requirements for real-time applications, limiting their feasibility in systems with tight resource constraints. Tuning and calibration can also be demanding, requiring expert knowledge to achieve a balance between robustness and performance. These factors make robust control less accessible and more resource-intensive compared to other EMSs [210].

· **Model Predictive Control (MPC)** is an advanced online optimization-based control strategy widely used in EVs and HEVs. As depicted in Fig. 12, MPC predicts future system states over a finite time horizon using a dynamic model and optimizes control inputs to minimize a cost function, such as fuel consumption or battery degradation, while satisfying constraints like power demand and SOC limits. By updating decisions at each step with real-time data, MPC adapts to changing conditions, making it highly effective for dynamic and complex scenarios.

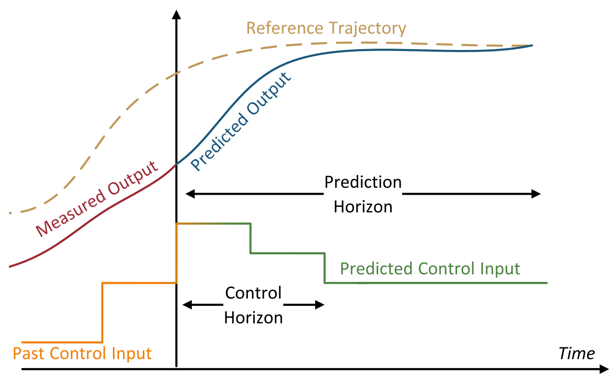

FIGURE 12. A conceptual diagram illustrating MPC operation.

MPC rely on dynamic models of the system, most often linear empirical models obtained by system identification. The linear time invariant (LTI) model of the plant is expressed in Equation (21) [211], [212]:

$$\begin{aligned} x(k+1) &= Ax(k) + Bu(k) \\ y(k) &= Cx(k) + Du(k) \end{aligned} \tag{21}$$

where, $x(k)$ is the state vector at step k, $u(k)$ is the control input, $y(k)$ represents the output, and the matrices A, B, C, and D represent the system dynamics in state-space form, where A is the state matrix that relates the current state to the next state without considering the input, B is the input matrix that defines how control inputs affect the state, C is the output matrix that maps the internal state to the output, and D is the feedthrough matrix that represents the direct effect of the input on the output.

The control objective of MPC is to minimize a cost function that penalizes deviations from the reference trajectory and minimizes control effort. The cost function for MPC can be expressed as [211] and [212]:

$$J = \sum_{k=0}^{PH-1} \left((y(k) - y_{ref})^T Q (y(k) - y_{ref}) + u(k)^T R u(k) \right) \tag{22}$$

In this equation, PH is the prediction horizon. Longer horizons increase computational burden, whereas it may not lead to generating better results necessarily [213]. y_{ref} is the reference output vector. Q is the state weighting matrix, which penalizes deviations from the desired reference state. R is the control weighting matrix, which penalizes the magnitude of the control input to avoid aggressive actuation.

The state constraints also needs to be defined based on the nature of the problem and the available hardware.

The MPC problem is solved at each time step using the predicted system response. It generates an optimal control sequence, from which only the initial control input is implemented. The prediction model, along with state and control variable constraints, ensures the system operates within safe boundaries while achieving the desired performance.

An MPC-based EMS is proposed in [214] for a hybrid EV charging station to optimize power flow among various energy sources, including a photovoltaic system, battery, fuel cell, grid connection, and fast charging units. Long-term simulations over 25 years demonstrate that the EMS significantly outperforms a benchmark state-based strategy, achieving a 25.3% reduction in utilization costs, a 60% decrease in grid dependency, and enhanced overall efficiency. A long short-term memory (LSTM) method is proposed for driving cycle prediction within an MPC framework by Chen et al. [215]. the proposed MPC-based EMS reduces energy dissipation by up to 15.3% compared to an FLC-based EMS while alleviating battery stress. Additionally, incorporating battery aging awareness in EMS design slightly extends battery life. A similar study also combines LSTM with MPC in PHEVs and achieves comparable results to DP [72]. Moghadari et al. [216] propose a predictive health-conscious EMS for multi-stack FCHEVs to reduce operating costs, including hydrogen usage, fuel cell degradation, and energy storage expenses. The strategy combines a rule-based approach for optimal fuel cell activation and an MPC algorithm for power distribution, enhanced by a stacked bidirectional LSTM velocity predictor. Testing shows the proposed model achieves near-optimal performance compared to DP (within 3.728%) and outperforms the ECMS by up to 5.154%. In an interesting method proposed in [217] the EMS problem is formulated as a nonlinear optimal control problem, and a convolutional NN-based speed predictor is used to forecast vehicle speed for MPC. A double-delay Q-Learning algorithm solves the receding horizon optimization in the MPC module, enhancing adaptability to dynamic environments. Simulations show that the proposed strategy achieves fuel consumption comparable to offline stochastic DP and has a single-step computation time of 23 milliseconds. A supervisory control strategy for HESS in EVs is proposed by Larijani et al. [218] to split power between the battery and supercapacitor, aiming to mitigate battery degradation. The proposed intelligent energy management strategy (IEMS) uses linear parameter-varying MPC with a control-oriented battery model and a cost function minimizing battery power loss and supercapacitor voltage errors. Simulations demonstrate significant reductions in battery degradation metrics, such as up to 30.26% and 25.85% reductions in discharge and charge peak currents, 9.71% in ampere-hour throughput, and 4.78% in capacity loss, compared to a baseline strategy. In [219], DP is used offline to determine the HEV's reference battery SOC, then an MPC optimizes power distribution between the battery and generator (ICE). A hierarchical MPC framework is proposed for optimizing both power demand and EMS in EVs with a HESS under vehicle-following scenarios [220]. At the vehicle-following level, vehicle-to-vehicle(V2V) and vehicle-to-infrastructure(V2I) communications are utilized to enable real-time velocity planning, optimizing EM consumption and ensuring safety. At the EMS level, power is allocated to minimize battery degradation and power losses. Simulations demonstrate that total operation costs are reduced by 4.69-14.55% compared to traditional EMS approaches, with results closely approximating the globally optimal solutions obtained through offline DP. A data-driven MPC strategy with a dual-model framework is proposed for FCEVs to enhance economic performance and control robustness under diverse driving environments [221]. The dual-model framework consists of a nominal system, built using a mathematical equivalent circuit model with precise parameters, and a practical system, established with a real-time Gaussian process to predict state transitions within predictive horizons and improve disturbance tolerance. A novel control input fusion function is integrated to merge control inputs from both systems, optimizing powertrain efficiency.

MPC-based EMSs provide flexibility and adaptability, making them well-suited for real-time optimization problems. However, they can face challenges when processing power is limited, particularly in complex systems with long prediction horizons or numerous constraints. Their performance heavily relies on the accuracy of the underlying LTI model. Inaccuracies or oversimplifications in the model can result in suboptimal control decisions. Additionally, tuning the weighting factors in the cost function requires significant expertise and careful, problem-specific adjustments. Furthermore, MPC can struggle to handle abrupt changes in operating conditions or highly nonlinear system dynamics, which may limit its robustness in certain scenarios.

· **Pseudospectral** EMS methods are advanced optimization techniques for managing energy flow in hybrid systems. These methods approximate solutions to optimal control problems by transforming them into finite-dimensional nonlinear programming problems using orthogonal polynomials, such as Legendre or Chebyshev polynomials, to discretize state and control variables over a time horizon [222]. Pseudospectral EMSs excel at solving complex, high-dimensional problems with nonlinear dynamics and constraints, providing high accuracy and global optimization capabilities. Traditionally, their computational intensity limited their use to offline optimization. However, recent research has introduced adaptive and improved variants, enabling their application in real-time EMS.

He et al. [223] utilized the Radau Pseudospectral Method to develop an energy-efficient eco-driving control method focused on improving vehicle speed and acceleration profiles to address the optimal control problem with high accuracy. Technology successfully reduced energy consumption by 26% compared to traditional non-optimized driving strategies, while preserving drivability. Simulations on a series hybrid school bus demonstrate that the pseudospectral method achieves results close to DP with greater computational efficiency, while the two-level strategy effectively adapts power management based on road-grade predictions, outperforming traditional online approaches like ECMS. Another EMS for hybrid electric tracked vehicles using a pseudospectral method is proposed in [224] to optimize two-track velocity planning and power distribution. Simulation and field experiments demonstrate that the proposed EMS improves fuel economy by 3.92% compared to DP with reduced computational burden, and by 14.85% compared to rule-based EMS without velocity optimization. Gao et al. [225] improves the efficacy of NMPC for automated vehicle motion planning through the implementation of adaptive Lagrange discretization and hybrid obstacle avoidance constraints. These techniques diminish processing demands while maintaining precision, employing adaptive polynomial orders and a blend of elliptic and linear constraints. Simulation and experimental findings indicate a 74% enhancement in accuracy and a 60% increase in computing efficiency compared to conventional methods. Zhao et al. [226] introduces a multi-objective global optimization approach for energy management in series-parallel PHEVs, combining the Radau Pseudospectral Knotting Method (RPKM) with the Non-dominated Sorting Genetic Algorithm II (NSGA-II). The method improves energy efficiency and battery longevity by 26.74%-53.87% under suburban driving conditions, utilizing RPKM for initial optimization and NSGA-II for subsequent refinement, demonstrating performance comparable to dynamic programming, with enhanced speed and consistency in convergence. The technique enhances the performance of ultracapacitors, reduces battery energy loss, and outperforms the conventional logic threshold control strategies in simulations. Other very similar research in the field of logic threshold control strategy optimization for HEVs with HESS also are published in [227] and [228]. Multani [229] focuses on the application of the pseudospectral collocation method as a scalable and computationally efficient alternative to DP for solving large and complex optimal control problems in HEVs. In order to improve the acceleration (rotational speed and torque) response of HEVs, Radau pseudospectral method is applied to solve the trajectory optimization problem [230]. The same concept is also employed in [231] to increase computational efficiency.

The primary drawback of pseudospectral EMS is the significant computational intensity, which can limit their applicability for real-time systems, especially in resource-constrained environments. These methods require solving nonlinear programming problems, which may become infeasible for large-scale or highly dynamic systems due to the computational burden. Additionally, their performance heavily relies on precise system modeling, and inaccuracies in the model can lead to suboptimal results. Furthermore, implementing pseudospectral methods demands advanced expertise in numerical optimization, making them less accessible compared to simpler, heuristic-based strategies such as rule-based or ECMS approaches.

· **Frequency Decoupling (FD)** technique is used to separate power demand into low-frequency and high-frequency components for efficient power allocation between energy sources, such as batteries and supercapacitors (or also known as ultracapacitors) in the EMS of HEVs and FCHEVs. Low-frequency components, representing sustained power demands, are handled by the battery due to its high energy density, while high-frequency components, caused by rapid acceleration or braking, are managed by supercapacitors or other high-power auxiliary sources, which excel at fast charge and discharge cycles. Tools like wavelet transform provide multi-resolution analysis for precise decomposition, whereas low-pass filters offer a simpler method for separation based on a predefined cutoff frequency. By reducing large current fluctuations and smoothing power flow, FD minimizes battery stress, improves energy efficiency, and extends the lifespan of the HESS. Fig. 13 presents a schematic diagram of an FD-based EMS, which allocates the demanded power between the fuel cell, battery, and ultracapacitor in an FCHEV using low-pass and high-pass filters.

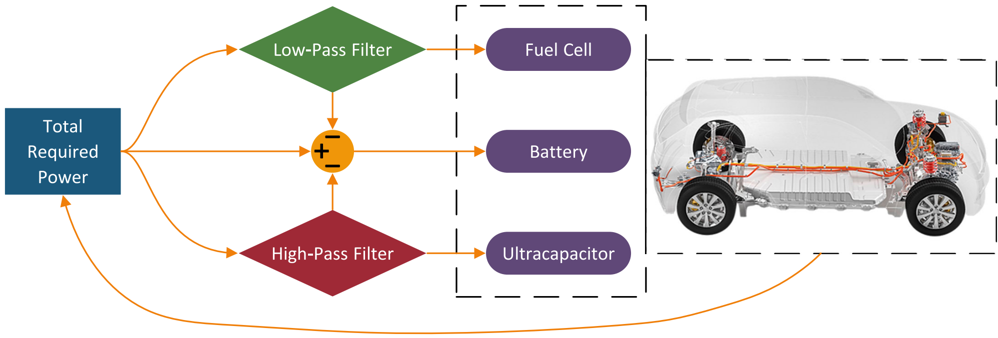

FIGURE 13. A simplified diagram of FD EMS for an FCHEV equipped with fuel cell, battery, and ultracapacitor.

A comprehensive review highlights the role of low pass filters in HESS for EVs [232]. It discusses four types of low pass filters (fixed, optimal, adaptive, and combination), their role in ensuring smooth power distribution, and the challenges and limitations associated with future EMS improvements. A wavelet transform-based EMS is developed in [233] for PHEVs to reduce battery stress by separating transient and peak power demands. A 3-level decomposition is identified as optimal through simulations and HIL testing. To extend fuel cell lifespan and improve fuel economy in FCHEVs, Fu et al. [234] propose an FD EMS with FLC optimized using GA. The method splits power into low, middle, and high-frequency components for the fuel cell, battery, and ultracapacitor, respectively, resulting in reduced power fluctuations and hydrogen consumption. Another study employs the Haar wavelet transform and adaptive fuzzy filters for FCHEVs, achieving a 7.94% improvement in fuel economy compared to ECMS while extending fuel cell lifespan [235]. Samia et al. [236] compare Haar wavelet decomposition and Fourier transform, concluding that wavelet analysis excels due to its robustness and dynamic performance, making it ideal for real-time applications. Badji et al. [237] propose a method using power frequency splitting and Energetic Macroscopic Representation to address fuel cell starvation, reduce battery stress, and improve fuel economy. In battery-ultracapacitor HESS applications, a multilevel control system for residential microgrids is presented in [238]. The system employs real-time FD and average current control for DC/DC converters, achieving voltage regulation close to 1% and demonstrating adaptability for EV applications. A recently published adaptive predictive EMS for FCHEV trucks [239] utilizes wavelet NN-based speed prediction and dynamic weight distribution. This strategy achieves a 20.91% reduction in operating costs and real-time feasibility, with computation times below 0.02 seconds. Li et al. [240] focus on hydrogen fuel cell hybrid trains, developing a Two-Layer Deep Deterministic Policy Gradient EMS. By integrating an FD algorithm, the method stabilizes fuel cell output, reduces hydrogen consumption by 16.3 kg/100 km, and enhances system efficiency and stability.

In FD, inaccuracies in frequency separation can result in suboptimal power allocation, and reducing overall system efficiency. The method often relies on predefined frequency ranges for energy sources, which may struggle to adapt to dynamic driving conditions. Additionally, implementing advanced techniques like wavelet transforms requires expertise in the field. In terms of energy efficiency, FD typically underperforms compared to other online approaches, such as ECMS and MPC.

· **Sliding Mode Control (SMC)** strategies are widely used in HEVs and FCHEVs due to their ability to handle system uncertainties and external disturbances. SMC operates by driving the system states toward a predefined sliding surface and maintaining them there, ensuring fast response and high control accuracy. In EMS applications, SMC effectively manages power allocation between energy sources such as fuel cells, batteries, and ultracapacitors, mitigating rapid power fluctuations and improving system stability. Its inherent robustness to parameter variations and disturbances makes it suitable for dynamic driving conditions. However, challenges such as chattering, which causes high-frequency oscillations in control inputs, and the need for precise system modeling can limit its efficiency and practical implementation.

A double integral SMC using Lyapunov theory is developed for an FCHEV equipped with a fuel cell-battery-supercapacitor alongside a wireless charging system in order to ensure stability [241]. The proposed method outperforms PID and Lyapunov controllers in both simulations and HIL tests. For independent power flow control in an urban EV, a similar integral SMC is also applied to a synchronous reluctance motor for stabilization, while an FD EMS supervises a battery-supercapacitor HESS [242]. FD (Haar wavelet transform, adaptive filters) is combined with an adaptive integral terminal SMC for a model-free DC-bus voltage control for FCHEVs in [243]. The strategy achieves reduced fuel consumption and power fluctuations compared to operational mode and FLC strategies. A higher-order SMC with a super-twisting technique is proposed by Prasad et al. [244] for SOC estimation and management in a battery-supercapacitor HESS, which efficiently rejects disturbances, minimizes chattering, and enables accurate source parameter tracking using rule-based strategies. In a similar fashion, another study employs a backstepping super-twisting SMC combined with FLC for FCHEV HESS [245]. The proposed EMS reduces hydrogen consumption and maintains supercapacitor SOC, and outperforms conventional PI and deterministic rule-based EMSs. Furthermore, a super-twisting SMC is compared against conventional SMC and integral SMC for a HESS in [246]. The HIL tests and simulations of the models demonstrate better stability, resilience, and dynamic performance from the super-twisting SMC model. Ding et al. [247] develops a robust adaptive SMC method to address transient coupling disturbances in HEVs. Their method provides accurate torque tracking for the ICE and EM under parameter perturbations and unknown driving conditions. Also, Wang et al. [248] propose an ultra-local model-based EMS with a bus voltage supervisor for battery-supercapacitor HESS. Using an integral SMC observer to improve current demand distribution, the model achieves 65%-69% faster dynamic response and 36%-41% lower voltage spikes compared to conventional PI method.

SMC offers robustness to system uncertainties and disturbances. But one of its main issues is chattering, a high-frequency oscillation in the control signal caused by the discontinuous nature of SMC, which can lead to actuator wear and energy losses. Additionally, SMC requires precise system modeling to design the sliding surface, making it sensitive to modeling errors in practical implementations. The controller's performance can degrade in systems with unmodeled dynamics or noise, as these can affect the accuracy of the control response. Moreover, while higher-order SMC methods mitigate chattering, they increase implementation complexity and computational demands.

· **Extremum Seeking (ES)** methods are online adaptive EMS optimization algorithms used to find the optimal operating points in FCHEV systems, typically. They try to maximize efficiency and minimize hydrogen consumption. These methods track the maximum power or maximum efficiency points of fuel cell systems, even under varying operating conditions and degradation levels. Techniques such as adaptive recursive least squares, fractional-order calculus, and high-pass or band-pass filtering are commonly incorporated to enhance convergence speed, robustness, and the ability to handle multimodal optimization surfaces.

The ES optimization process involves iteratively adjusting a system's input to find the optimal output. It starts by generating a small periodic perturbation signal, which is added to the control input and applied to the system. The system's response to this perturbed input is measured and demodulated by multiplying it with the perturbation signal to extract gradient information. The demodulated signal is filtered to remove noise, providing a clean gradient estimate. Using this gradient, the control input is updated to move closer to the optimal point. The process repeats until convergence criteria (such as minimal change in input or output values) are met [249].

In [250] proposed method employs an online extremum-seeking control algorithm to dynamically identify the optimal Oxygen Excess Ratio (OER) that maximizes net power output for a given load current. This approach exploits the unipolar peak characteristic of the net power curve with respect to the OER, enabling real-time adaptation without the need for extensive offline modeling or datasets. The core principle involves applying a small perturbation to the OER and observing the resulting trend in net power output, thereby inferring the system's relative position with respect to the optimal operating point. In [251], an online ES-based EMS is proposed for hybrid electric trams to optimize power distribution between fuel cells and supercapacitors using adaptive recursive least squares. The method outperforms state-machine control and ECMS in hydrogen consumption, efficiency, and fuel cell dynamics under scaled-down test conditions. An OES-based Optimized Energy Management Strategy (OES-OEMS) is presented in [251] to tackle the dynamic performance characteristics and aging impacts of fuel cell systems. This technique facilitates the real-time identification and monitoring of both the Maximum Efficiency (ME) and Maximum Power (MP) operating points of the fuel cell. As the system's behavior changes owing to degradation, thermal dynamics, or load fluctuations, the suggested method constantly adjusts by identifying optimal operating settings in real-time without depending on offline modeling or lengthy calibration data.

The ES-based EMS exhibit several limitations despite their effectiveness in real-time optimization and adaptability. A primary concern is the reliance on perturbation-based input signals, which may introduce oscillations that can adversely impact system stability and performance if not carefully calibrated. Furthermore, ES algorithms often demonstrate slow convergence rates in high-dimensional or complex systems, rendering them less suitable for scenarios with rapidly changing operating conditions. Their sensitivity to noise and disturbances in the system output can result in inaccurate gradient estimation, potentially leading to convergence at suboptimal solutions. In systems characterized by multiple local optima, ES methods require robust mechanisms to ensure global optimality, which may increase implementation complexity. Moreover, the necessity of precise parameter tuning, including perturbation frequency and amplitude, demands significant expertise, which can hinder practical deployment in dynamic or uncertain environments.

Fig. 14 provides a comparative analysis of the introduced online optimization-based EMSs in terms of energy efficiency, design complexity, and computational demand. It is important to emphasize that the scales are for general comparative purposes, as the performance of each EMS method can vary depending on the specific problem and any complementary techniques employed. As shown, ECMS, one of the most widely used EMSs, offers relatively good energy efficiency while being simple to implement and requiring the least computational resources. In contrast, RC, while relatively complex to design and computationally demanding, often achieves moderate energy efficiency due to its primary focus on system stability over fuel economy. MPC and Pseudospectral (stated as Pseudo.) methods deliver excellent energy efficiency but are among the most complex to design and require significant processing power. FD and SMC, known for their ease of implementation and suitability for real-time applications, provide relatively modest energy efficiency gains compared to other methods. Although ES has global optimization capabilities, it struggles to guarantee optimal results in real-time applications.

The advantages and disadvantages of each online optimization-based EMS are mentioned in Table 12, along with the respective references.

3) LEARNING OPTIMIZATION-BASED EMSs

Learning-based EMSs represent a class of advanced algorithms that leverage machine learning techniques such as NN, RL, and SVM to optimize power distribution in EVs and HEVs. A key advantage of learning-based methods is their ability to integrate seamlessly with offline optimization algorithms to refine policies or with online optimization strategies to enhance adaptability. This integration capability makes them versatile and powerful tools for improving energy efficiency, reducing fuel consumption, and mitigating degradation of components like batteries and fuel cells. Thus, learning-based EMSs are categorized separately, bridging the gap between conventional optimization methods and intelligent control techniques. The advantages of learning-based EMSs include their adaptability to diverse driving conditions, scalability to complex systems, and capacity to learn from data, improving decision-making in real-time. However, their high computational demands during training, reliance on extensive datasets, and potential challenges in ensuring safe exploration during deployment are among the possible limitations [252].

RL is categorized distinctly from NN because it focuses on decision-making through sequential interactions with the environment to maximize cumulative rewards, while NN are primarily used for function approximation and data representation. Deep learning, a subcategory of NN, employs multi-layered architectures for learning hierarchical representations, and when combined with RL, forms deep reinforcement learning (DRL), a powerful approach that exploits both methods for dynamic and high-dimensional optimization problems. SVM, on the other hand, belongs to an entirely different category, relying on optimization and kernel methods rather than layered architectures [253], [254].

· **Reinforcement Learning (RL)** methods leverage data-driven techniques to develop adaptive and optimal EMS for HEVs, FCEVs, and other modern transportation systems. These methods, including algorithms like Q-learning, deep reinforcement learning (DRL), deep Q-networks (DQN), and policy optimization methods, aim to address challenges such as fuel economy, battery health, power distribution, and system robustness. RL-based EMS methods stand out due to their ability to adapt to varying and unknown driving conditions without relying on predefined models or future driving information. They can also integrate with hybrid optimization frameworks or hierarchical structures, enhancing their performance and applicability across diverse use cases.

In RL an agent learns to make decisions by interacting with an environment to achieve a specific goal. The general process of RL involves the following steps [255]:

1) ⟹Environment Interaction: The agent interacts with the environment by taking actions based on its current state.
2) ⟹State Observation: The agent observes the new state of the environment after performing the action.
3) ⟹Reward Feedback: The agent receives a reward signal from the environment, which quantifies the immediate benefit or penalty of the action.
4) ⟹Policy Update: The agent updates its policy, a mapping of states to actions, based on the observed state, action, reward, and new state, aiming to maximize cumulative future rewards.
5) ⟹Exploration and Exploitation: The agent balances exploration (trying new actions to discover their effects) with exploitation (choosing the best-known actions to maximize rewards).
6) ⟹Learning Algorithm: An algorithm such as Q-learning, Deep Q-learning, or Policy Gradient is used to adjust the agent's decision-making strategy by optimizing a value or policy function.
7) ⟹Convergence: Over time, the agent improves its policy and converges to an optimal or near-optimal strategy for achieving its goal.

This iterative learning process continues until the agent's performance meets predefined criteria or the maximum number of iterations is reached. Zheng et al. [256] apply Q-learning, DQN, and deep deterministic policy gradient (DDPG) to the energy management of FCHEVs, focusing on fuel economy and fuel cell durability based on a fuel cell degradation model. The paper highlights RL's adaptability in addressing degradation models and compares the algorithms in terms of convergence, efficiency, and robustness in dynamic environments. According to the findings, the Q-learning-based EMS presents the best convergence performance, while the DDPG-based EMS achieves the best fuel economy(only 2.79% lower than to the DP as the benchmark). DRL is employed in [257] to develop an EMS for series HEVs, showing superior adaptability without requiring future driving predictions. The study formulates EMS problem as a Markov decision process, and integrates cumulative trip information for effective SOC guidance. The method achieves fuel economy close to DP (3.5% gap) and outperforms MPC while maintaining high computation speeds. Another study highlights the complexity of integrating adaptive cruise control into EMS, resulting in multi-scale objectives and a large exploration space, which limits online

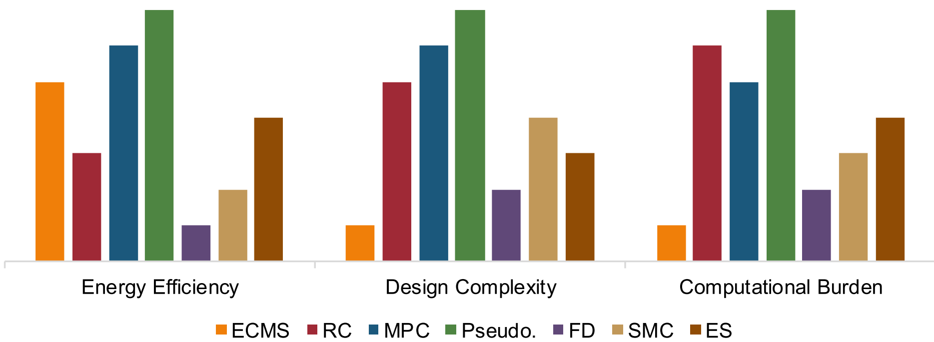

FIGURE 14. Online optimization-based EMSs performance comparison chart.

TABLE 12. Advantages and disadvantages of online optimization-based EMS methods.

Ref.	EMS method	Advantages	Disadvantages
[192]–[202]	ECMS	Good energy efficiency, simple implementation, very low computational burden	Performance depends on accurate EF tuning, struggles with dynamic scenarios
[204]–[209]	RC	Ensures robustness under uncertainties, effective in handling disturbances	Complex design process, high computational demand, does not prioritize energy efficiency
[72], [211]–[221]	MPC	Solid energy economy, predictive capabilities, handles constraints and nonlinearities	Relatively high computational demand, requires accurate LTI model and extensive tuning
[222]–[235]	Pseudo.	Achieves near-global optimality, highly accurate for complex dynamics	Very complex design process, computationally intensive, challenging for real-time applications
[232]–[240]	FD	Effective in separating power demands, reduces transient stresses on components	Limited energy efficiency, requires predefined frequency ranges and expertise for tuning
[241]–[248]	SMC	Robust to disturbances, ensures system stability under dynamic conditions	Chattering effect, requires careful tuning, moderate computational complexity
[250], [251]	ES	Adaptive real-time optimization, tracks system variations effectively	Prone to oscillations, slower convergence, sensitive to noise and perturbation settings

applications due to computational demands [258]. To address this, a hierarchical RL-based model is proposed with an upper layer planning SOC and time-headway trajectories and a lower layer executing control variables. The self-learning strategy, validated in car-following scenarios with GPS data, achieves less than 3% gap in energy consumption compared to DP, while reducing computational load significantly. Wang et al. [259] propose four DRL-based EMSs with multi-objective optimization, including fuel cost and battery health, for HEVs. Their comparative analysis highlights that soft actor-critic (SAC)-based EMS achieves the best balance of fuel efficiency and battery health. The study offers insights into parameter tuning and driving cycle performance. Generalization to unseen environments is addressed in [260] by enhancing DRL algorithms using auto-tune SAC (ATSAC), which automatically adjusts learning rates and synthesizes realistic training cycles. Results show improved computational efficiency (52%) and fuel economy (1.8%) compared to SAC and Twin-delayed DDPG in real-world urban and suburban driving conditions. Another similar study published by the same research team is also published to improve engine torque and gear-shifting control [261]. Xu et al. [262] introduced a systematic four-phase framework consisting of modeling, pre-training, transferring, and fine-tuning to improve the efficacy of Dueling Deep Deterministic Policy Gradient (DDPG)-based EMS. This methodology aims to enhance initial policy performance and expedite convergence during training. The pre-training phase allows the agent to obtain basic information, which is subsequently transferred and refined in the target environment. In order to optimize the durability and thermal stability of lithium-ion batteries and PEMFC stacks under real-world driving scenarios, Zhang et al. [263] introduce a DRL-based EMS for FCVs. Using SAC for stable performance, the EMS minimizes costs related to SOH degradation, over-temperature penalties, and hydrogen consumption. A proximal policy optimization-based EMS for parallel electric-hydraulic HEVs is introduced to optimize working mode switching and balance performance parameters using entropy evaluation and learning-based control [264]. Reward-directed policy optimization, combining NN multi-constraint strategy and a rule-based-restraints system, is proposed by Liu et al. [265]

to enhance fuel economy and minimize irrational control signals in power-split HEVs. This method demonstrates online adaptability and competitive fuel efficiency across diverse driving cycles, outperforming conventional DRL agents. To address adaptability in unknown environments, a different study proposes Scalable Learning in Novel Environment (SLNE)-based EMS for FCHEVs that integrates a memory library composed of the Dirichlet process clustering algorithm combined with the Chinese restaurant process using the expectation-maximization algorithm for updates and DQN [266]. The results show 5% better fuel economy and 4.5% mitigation in fuel cell degradation compared to a conventional DQN strategy. Zare and Boroushaki [267] introduce two offline and online hybrid knowledge-assisted RL algorithms combining DDPG and DQN that achieve optimal EMS actions for HEVs. This method reduces fuel consumption by 7.26% in offline mode and 5.67% in online mode. On the flip side, although the proposed algorithm is significantly faster than other RL-based rivals in their comparison, it still struggles for real-time applications. Lotfy et al. [268]presents a real-time multi-objective adaptive EMS using a Multi-Agent RL framework and Twin Delayed DDPG methods. The EMS optimizes power distribution, balances battery cells, mitigates aging, and achieves a final SOC within 0.3% of the DP benchmark. DRL also used to address SOC imbalance in cyber-physical EVs caused by battery mismatches by Chen et al. [269]. Using gradient sharing for enhanced exploration and ISO/IEC 15118 standards for secure communication, it optimizes SOC balancing and DC bus voltage regulation.

RL-based EMSs offer significant advantages, but they also present notable challenges. One key drawback is the reliance on extensive training data and computational resources, which can limit real-time adaptability and scalability for diverse driving scenarios. RL algorithms often exhibit slow convergence and instability, especially under novel or highly dynamic environments, leading to suboptimal performance. Additionally, the exploration process inherent to RL can result in the generation of irrational or unsafe control actions during training, posing risks to physical systems if not adequately constrained. Furthermore, RL-based EMS may suffer from limited generalization to unseen driving conditions due to the reliance on training-specific data, reducing their robustness. Lastly, hyperparameter tuning and reward function design require expert knowledge, making the implementation process complex and time-consuming. These limitations highlight the need for further advancements in RL methodologies to enhance their practicality and reliability in real-world EMS applications.

· **Neural Network (NN)** NN-based EMS utilize machine learning models, such as Artificial NN (ANN) and Recurrent NN (RNN), to intelligently govern the power flow among energy sources in EVs and HEVs. By learning from data, these models can capture complex non-linear relationships, optimize efficiency, and adapt to varying driving conditions more effectively than conventional rule-based or heuristic methods. As a result, NN approaches have become increasingly prominent for improving fuel economy, reducing component stress, and enhancing overall system longevity and stability.

Fig. 15 illustrates a shallow five-layer NN with [2, 20, 10, 5, 2] neurons in each layer, trained to predict input power demand and power loss based on the rotor speed and electromagnetic torque [74].

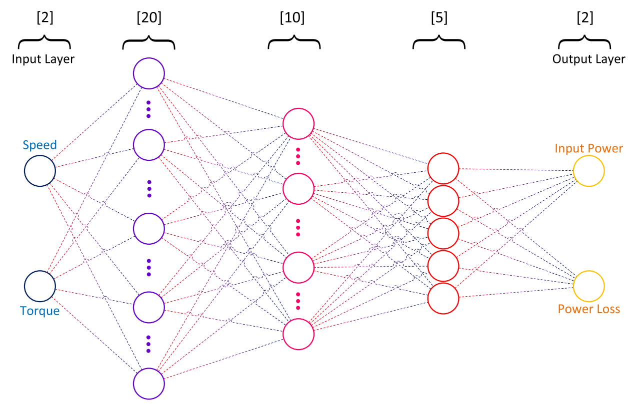

FIGURE 15. Five-layer NN architecture mapping rotor speed and torque inputs to input power and power loss outputs [74].

An ANN-based power management strategy for an HEV is proposed in [270] that integrates renewable energy sources and energy storage systems. By comparing ANN-based control with multiple traditional strategies (PI, state-machine, FD-FLC, and ECMS), the proposed approach reduces hydrogen consumption by 2.4% to 6.7%. Building upon the potential of AI-based design, Millo et al. [271] develop an EMS using deep learning-based RNN to emulate near-optimal DP solutions and minimize CO2 emissions. The approach demonstrates improved fuel economy in both CS and CD scenarios, surpassing a baseline rule-based strategy by approximately 5%. Focusing on mitigating battery aging and balancing power between batteries and supercapacitors, Ribeiro and Munoz [272] employ a Multilayer Perceptron (MLP) NN combined with a Proportional-Integral-Derivative (PID) controller for managing real driving cycles. the study explores multiple optimization algorithms for controller tuning and validates that a NN-based EMS can effectively reduce battery current stress and prolong battery life. Another paper combines an ECMS with dual NN to avoid reliance on pre-defined battery SOC [43]. The Bayesian regularization and backpropagation networks predict near-optimal EFs and engine on/off decisions, delivering fuel economy close to DP. Integration of deep learning with an improved MPC framework is also published in [72]. This work tests multiple prediction models and culminates in an LSTM-MPC-based EMS with robust fuel-saving performance. Validated against global optimal solutions and simpler rule-based methods, the approach yields significant improvements across diverse driving cycles. Omer et al. [273] introduce a FD EMS enhanced by NN optimization algorithms for managing power flow in a HESS consisting of fuel cell, battery, and supercapacitor. By coupling an adaptive SMC with an NN-tuned FLC, the approach improves fuel economy, reduces load fluctuations, and prolongs fuel cell life. Elman NN and FLC are also combined in [274] to adaptively manage power split between an ICE and an EM, aiming to maximize fuel economy and maintain battery health. The approach outperforms conventional strategies and provides a rapid, accurate response validated through controller HIL testing. Leveraging an ANN trained on motor-inverter data and GA optimization, another study develops a multidimensional EMS to minimize EV losses and extend driving range [32]. By modeling accurate efficiency and power loss maps, the EMS optimizes speed profiles and reduces consumption significantly (12%-17%) compared to baseline driving cycles. Adopting a combined ANN and PSO approach, [275] targets intelligent FLC-based charge and discharge management for EV batteries under varying irradiation conditions. The strategy ensures maximum power extraction, stable grid connection, and effective V2G integration, achieving high efficiency and load continuity. Focusing on an HEV equipped with a fuel cell, battery, DC generators, and supercapacitor, Benhammou et al. [95] compares multiple EMS strategies, including PI, state-machine, ANN and ANFIS approaches. The ANN-based EMS achieves outstanding energy efficiency and fuel savings by effectively exploiting kinetic energy and maintaining system stability. Concluding the series, this last contribution reaffirms the role of advanced NN-based strategies in capturing free energy and optimizing hybrid powertrain performance, showcasing the broad potential of intelligent EMS methods evolving through successive research efforts.

Regarding the limitations of NN, the training process is computationally intensive and requires substantial offline resources, including large datasets and careful hyperparameter tuning. Moreover, selecting an appropriate network architecture is non-trivial and often involves trial and error, which can be time-consuming. Once deployed, NNs do not adapt to changing conditions in real-time unless additional mechanisms, such as online learning, are incorporated, which adds complexity. Furthermore, NNs can be prone to overfitting, particularly with limited or imbalanced datasets, potentially reducing generalizability. Lastly, their “black-box” nature makes them less interpretable, hindering transparency and trust in critical applications.

· **Support Vector Machine (SVM)** SVM techniques have been increasingly adopted in EMS to classify driving patterns, predict optimal power distribution, and enhance system adaptability. By serving as a powerful, data-driven classification and regression tool, SVM can assist in translating complex system behavior and operational data into more effective and computationally efficient control strategies. As a result, SVM-based EMS methods enable real-time decision-making that improves fuel economy, prolongs battery life, and ensures robust performance across varying conditions and vehicle architectures.

For instance, [276] applies a Gaussian SVM for pattern recognition to identify optimal energy allocation in a hybrid powertrain, using ECMS-based strategies to minimize both fuel consumption and battery aging. By training the SVM on globally optimized solutions from DP, it effectively balances multiple objectives in real-time. Expanding on the role of SVM, Benhammou et al. [277] introduce a direct torque control-SVM approach to enhance torque and speed performance in a fuel cell-battery-supercapacitor HEV. By integrating SVM-based control with ANFIS and model reference adaptive system (MRAS) estimators, the system achieves higher supply efficiency and reduces reliance on fuel cells and batteries. Further advancing SVM's utility, another research employs SVM for driving pattern recognition as a part of an intelligent EMS that also utilizes random forests for power distribution decisions [278]. With SVM identifying the appropriate driving pattern, the EMS adapts its strategy to minimize energy loss and prolong component life. In [279] and [280], semi-supervised SVMs are introduced to recognize driving styles, thereby informing a deep reinforcement learning-based EMS. The SVM's classification enhances the EMS's ability to reduce battery capacity loss by dynamically tailoring power distribution. A GWO-SVM combination refines an adaptive MPC-based EMS, targeting cost reduction and enhanced battery lifespan through multi-objective optimization [281]. The SVM, integrated with a GWO, helps generalize the EMS to different scenarios and drive cycles. Swain et al. [282] focus on SVM for forecasting lithium-ion battery remaining useful life, leveraging extensive preprocessing and hyperparameter tuning. By combining SVM with other methods like random forest, the approach yields accurate battery health predictions under variable operating conditions. Similarly, [283] applies SVM for battery health status prediction and SOC estimation, enabling real-time EMS adjustments. By extracting simple rules from PMP solutions, the SVM helps translate global optimization into online control. Compared to the aforementioned works, the SVM here directly interfaces with advanced mathematical optimization methods, ensuring both global optimality and practical adaptability in EMS design. Chatterjee et al. [284] show that SVM classification aids in selecting and predicting optimal power distribution between fuel cells and batteries in a dual-source FCHEV, leading to improved efficiency. By comparing SVM-driven predictions to alternative strategies like MPC, FLC, and ECMS, this study affirms that SVM can highlight the most efficient energy management methods. The same research team also employed SVM alongside KNN and Naive Bayes to develop a more accurate ensemble EMS classifier for FCHEVs, achieving up to 98% accuracy [285]. In a different study, SVM facilitates the extraction of a mode shift map from DP results in a multi-mode HEV, integrating seamlessly with ECMS for real-time online EMS. The

SVM-derived shift map ensures smooth mode transitions, improving efficiency and performance.

Despite its effectiveness in handling nonlinearities and achieving satisfactory classification or regression performance, SVM-based EMS present some limitations. First, the selection and tuning of kernel functions and parameters can be challenging, requiring expert knowledge or time-consuming heuristic approaches. Additionally, the training complexity, which can grow significantly with large datasets, may hinder real-time implementation for systems with high-dimensional input features. Moreover, SVMs are inherently batch learners, and adapting to changing conditions or integrating new data streams demands frequent retraining, leading to computational overhead. Finally, the interpretability of SVM-based EMS remains limited, making it difficult to communicate underlying decision rules and justify operational strategies.

Fig. 16 compares the performances of RL, NN, and SVM-based EMSs. It should be noted that the scales shown are intended solely to provide a general sense of their relative differences. The actual performance of each approach is highly dependent on the specific problem characteristics, the available hardware, and a variety of other parameters. The RL-based approaches typically exhibit strong capabilities in optimization and adaptation to previously unseen conditions. Theoretically, they can achieve energy efficiency scores comparable to those obtained through global optimization methods. Nevertheless, they rank among the most exhaustive and complex EMSs to design. In terms of processing power requirements, RL methods generally involve ongoing learning processes, thus necessitating substantial computational resources for real-time implementation. In contrast, although NN-based EMSs can deliver high energy efficiency performance, they are comparatively simpler to implement. Since the training process occurs offline, the trained NN EMS demands minimal computational overhead, resulting in rapid and lightweight real-time operation. Meanwhile, as SVM is fundamentally a classification and regression tool, its energy efficiency performance is somewhat lower than that of the aforementioned learning-based EMSs. However, due to its inherent simplicity, SVM can be implemented with minimal complexity and, in online applications, can be considered the least demanding option in terms of processing power. Table 13 contrasts the discussed learning-based optimization-based EMSs along with their features and respective references, for further studies.

C. INTELLIGENT TRANSPORTATION SYSTEM (ITS)-BASED EMSs

An ITS-based EMS focuses on using real-time traffic and infrastructure data to optimize energy usage across different modes of transport. By integrating information from traffic signals, road sensors, cameras, and other intelligent systems, the EMS can dynamically adjust vehicle power demands to reduce congestion, minimize emissions, and increase overall efficiency. Furthermore, the system's capability to respond to incidents, enforce traffic laws, and adapt speed limits based on current conditions ensures that the EMS decisions are not only optimized for fuel or battery consumption, but also for the broader goals of safety, coordination, and smarter network utilization.

1) VEHICLE TO EVERYTHING (V2X)

V2X-based EMS represent an advanced framework that integrates vehicular energy optimization with real-time communication technologies to enhance efficiency, sustainability, and operational performance in EVs and HEVs. V2X encompasses multiple communication paradigms, including V2I, V2V, V2G, vehicle to home (V2H), and vehicle to pedestrian (V2P) enabling vehicles to interact dynamically with their surroundings. By leveraging these technologies, EMSs can make predictive and adaptive decisions, minimize energy losses, reduce GHG emissions, and improve component longevity to align with smart transportation and sustainable energy goals. Fig. 17 depicts the most widely used V2X technologies.

In [37] the proposed EMS integrates V2X communication to utilize out-vehicle information, enhancing conventional EMSs that rely solely on in-vehicle data. By combining cooperative eco-driving guidance and A-ECMS, the system optimizes driving behavior and energy consumption. Gao et al. [286] develops a scenario-oriented adaptive ECMS that utilizes short-term speed predictions derived from a high-precision Variational Mode Decomposition- Radial Basis Function (VMD-RBF) neural network. The proposed method enhances SOC stability, decreases hydrogen consumption by as much as 7.06 g/km, and demonstrates resilience to prediction errors. A novel DL model which combines deep restricted Boltzmann machines and bidirectional LSTM is proposed by Pei et al. [287] to predict vehicle velocity time series for HEVs. Leveraging V2V and V2I, the model improves prediction accuracy and, when applied to an MPC EMS, demonstrates superior fuel economy compared to existing methods. Another study explores the integration of FCEVs with V2V to enhance energy efficiency and reduce emissions in autonomous transportation systems [288]. The findings highlight that driving conditions, such as speed, stopping frequency, and acceleration, influence fuel cell and battery performance. Liu et al. [289] evaluate the impact of Cooperative Adaptive Cruise Control (CACC) on traffic mobility and fuel consumption in mixed traffic using a state-of-the-art traffic flow modeling framework. Results show that CACC-equipped vehicles, utilizing V2V, achieve up to 50% fuel savings compared to adaptive cruise control (ACC) vehicles without V2V, while also improving freeway capacity by 15-19%. Another study employs CACC based on non-linear MPC using V2V integration [290]. The findings on various driving cycles show 6-16% better energy saving performance compared to conventional ACC models. Other similar studies focused on ACC using V2V and V2I integration can be found in [291], [292], and [293].

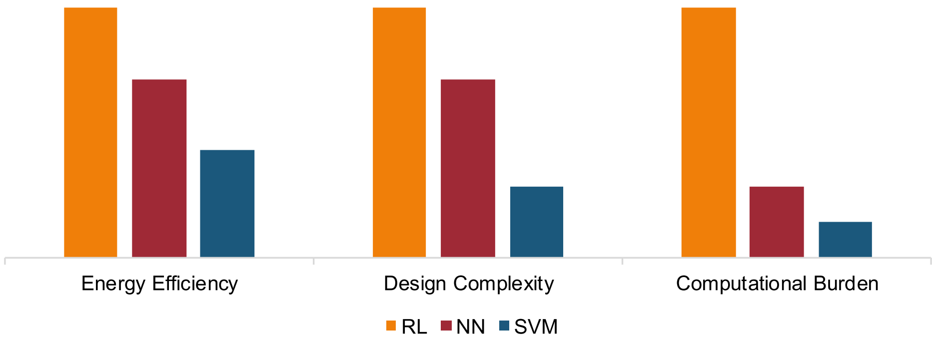

FIGURE 16. Learning-based optimization-based EMSs performance comparison chart.

TABLE 13. Advantages and disadvantages of learning-based optimization-based EMS methods.

Ref.	EMS method	Advantages	Disadvantages
[256]–[269]	RL	Adapts to dynamic scenarios, can achieve energy efficiency comparable to global optimization solutions	Complex and time-consuming design process, ongoing learning at runtime requires substantial computational power and careful tuning, irrational and unpredictable decision, if not constrained
[43], [72], [95], [270]–[275]	NN	Offers high energy efficiency, once trained offline, provides rapid, lightweight inference at runtime, very effective in modeling nonlinearities	Limited adaptability after deployment, requires extensive offline training and careful architecture/hyperparameter selection, prone to overfitting
[276]–[285]	SVM	Straightforward implementation, minimal computational load during operation, very effective in regression and classification	No inherent mechanism for online adaptation, selection and tuning of kernel function, the complexity increases quadratically with the size of the dataset

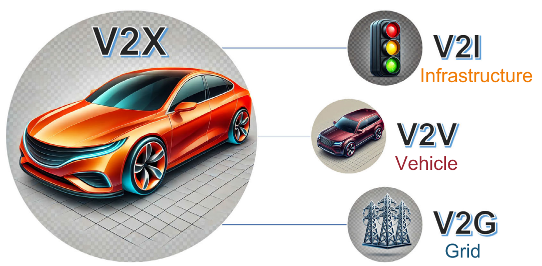

FIGURE 17. Examples of V2X communication technologies.

Regarding V2I, Mittal et al. [294] review various techniques for traffic light management in a book chapter and propose an artificial intelligence (AI)-based adaptive traffic control system to optimize signal synchronization based on real-time vehicle density. The system prioritizes emergency vehicles and dynamically adjusts green light duration, aiming to reduce congestion, pollution, and commute times while enhancing the efficiency of urban transportation systems. Also, Cao et al. [295] propose a DRL-based traffic signal control system to prioritize emergency vehicle passage while minimizing disruptions to conflicting traffic flows at intersections. Another recently published research employs RL to optimize traffic signal management [296]. Simulations using Simulation of Urban Mobility demonstrate that the approach significantly improves traffic efficiency at intersections compared to traditional traffic control methods.

Alsharif et al. [84] review the advancements in EMS for EVs integrated with smart grids through V2G operations, and emphasize their role in reducing fuel consumption and carbon emissions. The study provides a comprehensive analysis of EV technologies, energy resources, charging infrastructure, EMS classifications, and load management. Mauricette et al. [297] explore the resilience enhancement of urban multi-energy microgrids through coordinated V2G control strategies, particularly during islanding scenarios. Using a rolling horizon optimization approach, the study demonstrates that smart V2G control significantly reduces essential load curtailments and complements high photovoltaic penetration. The integration of EVs and renewable energy sources into smart grids is investigated in [298] through V2G and Grid to Vehicle (G2V) interactions. It analyzes challenges such as V2G interfacing, fast charging or discharging, and reliability. The paper presents simulation models and a case study to evaluate controller parameters affecting grid stability and control in interconnected systems. A recently published paper presents a hybrid methodology for efficient energy management in grid-connected photovoltaic-powered EV charging stations [299]. By combining the Spider Wasp optimizer for power flow optimization and the Multi-scale Hypergraph-based Feature Alignment Network for demand and supply prediction, the approach achieves improved power quality, reduced total harmonic distortion of 1.04%, and a high power factor of 0.986, outperforming existing methods in cost-efficiency and performance.

Vehicle to home (V2H) is also introduced as a dynamic power storage solution to support renewable energy integration and stabilize energy grids in [300]. The study highlights that V2H can significantly reduce the carbon footprint of domestic buildings in the UK by up to 87% while recovering up to 21.9 kWh/day of surplus renewable energy. Candan et al. [301] design a dynamic home EMS that leverages EVs as mobile emergency power sources and integrates local renewable energy sources to enhance grid resiliency during post-disaster conditions. Other notable research in the field of V2H are cited in [302], [303], [304], [305], [306], and [307]

Gelbal et al. [308] highlight the role of vehicle to pedestrian (V2P) communication in enhancing situational awareness and pedestrian safety, particularly in scenarios with no line of sight or adverse weather conditions. The research implements a Cooperative Collision Avoidance (CCA) algorithm tested in real-time simulations, and demonstrates its effectiveness in preventing collisions and improving safety for pedestrians and connected vehicles. Olivia et al. [309] presents the design and assessment of Vehicle-to-Infrastructure (V2I) in two applications for the management of intelligent intersections. The initial use case facilitates prioritized passage for emergency vehicles, whereas the subsequent case enhances pedestrian safety through real-time alerts. The validation of both applications demonstrated a reduction in emergency response times and an enhancement in driver awareness.

Despite its transformative potential, V2X communication faces several limitations that hinder its widespread adoption. V2I relies heavily on the deployment of smart infrastructure, which requires significant financial investments and coordinated urban planning, particularly in developing regions. V2V communication is constrained by network reliability and latency issues, which may compromise safety in critical scenarios. V2G and V2H technologies depend on bidirectional charging capabilities and standardized protocols, posing interoperability challenges between different vehicle and grid systems. Moreover, the impact of battery degradation and limited energy storage capacity reduces their long-term viability. V2P communication faces challenges in ensuring seamless interaction with pedestrian devices and sensors, particularly in environments with poor connectivity or non-tech-enabled pedestrians. Additionally, V2X systems must address privacy and cybersecurity vulnerabilities, as the exchange of sensitive data can be susceptible to unauthorized access, potentially compromising user safety and trust [310], [311].

This study does not compare V2X technologies in the same manner as previous cases because V2X encompasses a broad spectrum of communication protocols and applications, each designed to serve distinct purposes and operational scenarios. These technologies require different hardware configurations, software architectures, and network infrastructures. Given these variations, it is impractical to directly compare their efficiency, design complexity, and computational demands within a unified framework. Furthermore, their performance metrics often depend on contextual factors, such as deployment environments, data traffic patterns, and integration requirements, making standardized evaluation challenging. Instead, this study focused on highlighting the capabilities, applications, and challenges associated with V2X technologies rather than attempting a direct comparison.

IV. CHALLENGES

This section outlines key challenges in the development and implementation of EMS for EVs and HEVs. Addressing these issues is crucial for improving energy efficiency, extending battery life, and ensuring robust and secure operations. Some of the most important challenges are mentioned in the following.

A. OPTIMAL POWER DISTRIBUTION

As discussed in [119], [139], [144], [145], [163], [167], and [278] and numerous other studies, EMS in EVs face challenges in achieving optimal power distribution among multiple energy sources, such as batteries, fuel cells, and supercapacitors. The integration of these sources requires advanced controller designs to handle dynamic power flows effectively. One of the critical issues is ensuring stable power distribution while minimizing energy losses, especially when managing hybrid configurations. Variability in fuel cell output and frequent charging demands impose additional stress on battery performance, leading to accelerated degradation. Future designs must address the complexity of power split optimization to extend the lifespan of energy sources and improve overall system reliability.

B. BATTERY THERMAL MANAGEMENT AND AGING

Thermal management remains a pivotal challenge in EMS, as high temperatures induced by electrochemical reactions affect battery performance, efficiency, and safety [111], [146], [172], [179], [212], [215], [282]. Overheating can trigger thermal runaway, resulting in catastrophic failures, including explosions. Conversely, low temperatures reduce battery efficiency and increase internal resistance, leading to reduced power delivery and higher energy losses. Effective thermal management systems must ensure optimal temperature ranges through advanced cooling and heating mechanisms. Additionally, battery aging due to repetitive charge-discharge cycles and extreme operating conditions reduces lifespan and capacity. Developing predictive maintenance strategies and adaptive thermal regulation systems is necessary to mitigate aging effects and ensure long-term reliability. Xu introduces a novel Battery Thermal Management System (BTMS) utilizing microchannel liquid cooling, integrated with a Digital Twin (DT) framework in [312].

A Digital Twin is an exhaustive virtual depiction of a physical system that facilitates intricate simulation, forecasting, optimization, and regulation. The DT environment for the BTMS includes the physical system, its virtual counterparts—such as geometric, thermal, and operational model real-time data, service interfaces, and their interactions. The battery module is immediately submerged in a water-glycol cooling liquid, with microchannels created through small interstices between plates. This arrangement improves thermal performance by transitioning from traditional convective heat transfer to microchannel-scale transmission, markedly enhancing heat dissipation efficiency due to the increased cell surface-to-volume ratio [313]. A promising active cooling approach comprises the direct immersion of battery cells in dielectric fluids, providing improved thermal management without the danger of electrical short circuits. Williams et al. [314] conducted a research study of this method by submerging a four-cell Li-ion module, consisting of $LiFePO_4$ cylindrical cells, in 3M Novec 7000, a dielectric fluid that facilitates two-phase cooling. Boiling caused phase transition, which allowed the fluid to effectively transfer heat away from the cells. Under a 4C fast-charging situation, the system exhibited exceptional thermal uniformity, with the maximum cell temperature maintained at roughly 35 Â°C and a low inter-cell temperature differential of about 1 Â°C. Anamtawach et al. [315] devised a passive BTMS consisting of flat heat pipes paired with aluminum fins, placed between adjacent cells within a battery module. The heat pipes effectively conduct heat away from the cells by transferring it laterally to the connected fins, which then release the heat into the ambient air through natural convection. This design enhances thermal uniformity and decreases peak cell temperatures without the need for active components, providing a low-power, maintenance-free thermal management solution.

C. CHARGING INFRASTRUCTURE AND SCALABILITY

The widespread adoption of EVs is constrained by limited charging infrastructure and long recharge times [75], [76], [77], [78], [84], [186], [188], [189], [214], [241], [316]. The scalability of charging networks, particularly for fast-charging stations, requires substantial investment and technological advancements. Wireless inductive charging systems and ultra-fast chargers are emerging as potential solutions, but their implementation is hindered by high costs and compatibility issues. Future efforts should focus on developing cost-effective, scalable, and interoperable charging systems to support the growth of EVs.

D. ALGORITHM AND OPTIMIZATION LIMITATIONS

Some EMS optimization algorithms face computational complexity and slow convergence issues [317], [318], [319], [320], [321]. While these methods effectively minimize power losses and emissions, they often fail to achieve global optimality in real-time applications. Machine learning techniques, including RL and DNN, are promising alternatives, but they require extensive training datasets and computational resources. Addressing these limitations will be crucial for developing adaptive and intelligent EMS solutions.

E. INTEGRATION OF RENEWABLE ENERGY SOURCES

The integration of renewable energy sources presents multiple challenges due to their intermittent nature. Renewable sources such as solar and wind depend on weather conditions, leading to variability in energy production. This variability creates instability in power supply, requiring advanced forecasting and storage solutions to balance supply and demand [186], [202], [275], [300], [306], [322], [323], [324]. Furthermore, grid infrastructure must be upgraded to handle bidirectional energy flows for V2G systems, where EVs can act as energy storage units. Synchronizing renewable energy generation with EV charging patterns demands intelligent scheduling and predictive control algorithms. Additionally, managing harmonics, voltage fluctuations, and frequency deviations caused by renewable energy sources integration necessitates sophisticated control systems and energy storage technologies. Overcoming these challenges requires advancements in smart grid technologies, energy storage systems, and grid resilience planning.

F. POWER ELECTRONICS AND CONTROLLERS

The design of power converters and controllers poses a significant challenge in EMS implementation [76], [77], [78], [96], [104], [188], [325], [326]. Current designs suffer from switching losses, high ripple currents, and voltage stresses, which affect efficiency and reliability. The need for bidirectional converters that support energy flow between sources and loads introduces further complexity. Enhancing power electronics involves optimizing control strategies, reducing switching losses, and improving fault-tolerance mechanisms. Integrating new semiconductor materials, such as silicon carbide (SiC) and gallium nitride (GaN) [327], can provide higher efficiency and reliability, but their deployment requires substantial research and development.

G. ENVIRONMENTAL IMPACT

Despite the environmental benefits of EVs, the production and disposal of lithium-ion batteries pose sustainability challenges [328], [329], [330], [331], [332], [333]. Battery manufacturing involves energy-intensive processes that generate GHG, and improper disposal can lead to soil and groundwater contamination. Effective recycling methods and closed-loop supply chains must be developed to minimize environmental impact. Furthermore, sustainable materials and green manufacturing practices need to be prioritized to reduce the ecological footprint of EVs.

H. CYBERSECURITY CONCERNS

The integration of advanced technologies in EMS for EVs introduces significant cybersecurity vulnerabilities [311], [320], [334], [335], [336], [337], [338], especially for V2X systems. These vulnerabilities can compromise system operations, leading to unauthorized access, data manipulation, and disruption of critical functions. Ensuring cybersecurity requires multi-layered defenses, including encryption, intrusion detection systems, and secure communication protocols. Furthermore, real-time monitoring and anomaly detection techniques must be implemented to identify and mitigate potential threats. Aggarwal et al. [339] proposes a streamlined authentication mechanism for EVs and charging stations in a Vehicle-to-Grid (V2G) network, leveraging blockchain technology to guarantee data security, integrity, and user privacy. The proposed protocol allows secure and decentralized energy transactions, including charging and discharging, between EVs and the grid, thereby removing the necessity for a centralized authority that could represent a single point of failure. The solution guarantees trust, transparency, and resilience against malicious assaults in V2G communications by employing blockchain's distributed ledger and cryptographic techniques. Lai et al. [340] proposes Transformer-based architecture for an Intrusion Detection System (IDS) tailored for Vehicle-to-Everything (V2X) communications. The model utilizes the Transformer's capacity to identify long-range dependencies and intricate sequential patterns in V2X data, facilitating precise identification of abnormal or malicious activities. To mitigate privacy problems, the architecture features a privacy-preserving design that facilitates intrusion detection inside a distributed or federated learning framework. This guarantees that unprocessed vehicle data stays localized to edge devices, hence reducing the danger of data exposure while preserving detection efficacy. The methodology provides a scalable and secure Intrusion Detection System solution specifically designed for the distinct problems of Vehicle-to-Everything scenarios.

I. REAL-WORLD IMPLEMENTATION AND TESTING

Current EMS research is largely limited to simulations, necessitating experimental validation to address practical challenges. Future studies should focus on real-world testing to evaluate system performance under dynamic conditions. Pilot projects and field trials will provide valuable insights for refining EMS technologies.

V. FUTURE TRENDS

This section highlights future trends expected to shape EMS technologies. Advancements in machine learning, V2X communication, wireless charging, hybrid optimization techniques, and HESS are projected to drive progress. Additionally, the adoption of standardization, interoperability frameworks, and sustainable practices will support broader deployment of efficient EMS solutions.

A. ARTIFICIAL INTELLIGENCE (AI) AND MACHINE LEARNING INTEGRATION

The integration of AI and machine learning algorithms is revolutionizing EMS design [341], [342], [343], [344], [345]. RL and NN provide adaptive and data-driven solutions for dynamic energy optimization. These techniques can predict driving patterns, optimize energy allocation, and enhance system efficiency. Data-driven approaches offer considerable advantages. However, they necessitate access to large-scale, high-quality, and diverse datasets to ensure adequate generalization and accurately represent the system's underlying dynamics for effective decision-making. RL-based methods present the potential for adaptive and near-optimal control without requiring explicit system modeling; however, these approaches are constrained by substantial drawbacks. Their iterative exploration-exploitation techniques and reliance on high-dimensional state-action spaces result in longer training times, higher processing needs, and more sophisticated architectures.

Future research should focus on hybrid models that combine multiple algorithms for improved accuracy and robustness.

B. CLOUD-BASED EMS

Cloud computing offers new opportunities for real-time data analysis and EMS optimization [346], [347], [348], [349], [350]. Cloud-based EMS systems can collect and process data from vehicles, enabling predictive maintenance and adaptive control strategies. By integrating cloud infrastructure, EMS can deliver continuous updates, optimize routes, and improve energy efficiency. Several critical challenges must be addressed to ensure the reliability and robustness of cloud-integrated systems. These encompass challenges associated with the scalability and management of cloud infrastructure, the assurance of data privacy and cybersecurity, the reduction of communication latency, and the provision of reliable and high-speed internet connectivity. Addressing these limitations is essential for the reliable implementation of cloud-based solutions, particularly in real-time and safety-critical contexts.

C. ADVANCED BATTERY MANAGEMENT SYSTEMS (BMS)

Future EMS developments will emphasize accurate estimation of battery states, including SOC, SOH, and Remaining Useful Life (RUL). Deep learning and co-estimation methods will improve estimation accuracy, reducing costs and enhancing reliability. Advanced BMS technologies will also enable predictive diagnostics, extending battery lifespans and reducing maintenance needs [351], [352], [353], [354]. The effectiveness of data-driven techniques in BMS design is fundamentally contingent upon the availability of large-scale, high-fidelity, and diverse datasets, which presents a significant bottleneck in practical applications. LIBs are the predominant energy storage technology utilized in EVs, attributed to their high energy density and extended cycle life. LIBs demonstrate nonlinear and complex electrochemical behavior that is influenced by factors including temperature, aging, and operating conditions, which presents challenges for precise modeling and control. The selection and acquisition of informative and reliable features for training BMS algorithms are often limited by sensor constraints, noise, and data resolution, which directly impact the accuracy and generalization of the resulting models.

D. V2X INTEGRATION

V2X represents a major advancement in EMS. V2X enables communication between EVs and their environment [310], [311], [319], [355]. This integration improves traffic efficiency, enhances safety, and optimizes energy consumption by enabling cooperative driving and adaptive route planning. V2X also supports advanced applications such as autonomous driving and smart city infrastructure, facilitating seamless interaction between EVs and traffic management systems. Future developments in V2X will focus on enhancing communication reliability, reducing latency, and strengthening security protocols to prevent cyber threats. Additionally, V2X systems can leverage AI-driven analytics to process large volumes of data, enabling more intelligent decision-making and adaptive EMS strategies. The availability of larger and more diverse datasets generally enhances the performance of data-driven EMSs. Enhanced data availability facilitates more precise system modeling, superior generalization, and more adaptability to shifting operating conditions. This advantage entails a fundamental trade-off. With the increase in data volume, there is a corresponding rise in computational complexity, memory demands, and latency related to data processing, storage, and real-time inference. Excessive reliance on large-scale data may result in challenges such as data redundancy, quality assurance issues, and overfitting. Efficient data management strategies, including dimensionality reduction, feature selection, and online learning, are crucial for balancing the trade-off between data richness and system performance.

E. WIRELESS CHARGING TECHNOLOGIES

Wireless charging systems are emerging as a promising solution to address EV charging challenges [356], [357], [358], [359]. These systems, based on inductive or resonant coupling technologies, enable contactless energy transfer between the charger and the EV. Wireless charging eliminates the need for physical connectors, enhancing convenience and reducing wear and tear on charging ports. Dynamic wireless charging, where EVs can charge while in motion, is under active research and could significantly extend driving ranges without requiring long stops. Future advancements in wireless charging focus on improving energy transfer efficiency, reducing costs, and ensuring interoperability across different EV models. Moreover, integrating smart control systems and AI for load management can optimize energy distribution, minimize grid stress, and support renewable energy integration into the charging process.

F. STANDARDIZATION AND INTEROPERABILITY

Standardization and interoperability are crucial for the widespread adoption of EVs and the development of advanced EMS technologies. Ensuring compatibility across different charging systems, communication protocols, and EMS platforms requires global standards to be established. Lack of uniform standards can lead to fragmented systems, causing integration difficulties and limiting scalability. International standards, such as ISO 15118 for V2G communication interface for bi-directional charging/discharging and Open Charge Point Protocol (OCPP), aim to address these issues by promoting seamless communication between EVs, chargers, and grids [360], [361], [362], [363], [364], [365]. Enhanced interoperability will allow cross-platform compatibility, improving user convenience, reducing infrastructure costs, and accelerating EV adoption.

G. INTEGRATION OF AUTONOMOUS DRIVING

The convergence of autonomous driving and EVs is poised to significantly enhance the efficiency of EMSs. Autonomous vehicles rely on advanced real-time sensing, machine learning, and data-driven decision-making technologies. These systems can optimize energy consumption through precise control of vehicle dynamics, route planning, and traffic management. For example, autonomous EVs can adapt driving behaviors to maximize battery life by reducing unnecessary acceleration and braking [74], [366], [367], [368], selecting energy-efficient routes [369], [370], [371], [372], and even coordinating with other vehicles to minimize congestion [373], [374], [375], [376], [377]. Furthermore, predictive analytics in autonomous systems can forecast energy demands and integrate with renewable energy sources, leading to a smarter, more efficient EMS. This synergy represents a critical area of innovation for future transportation systems. The benefits outlined above considerably improve the functionality and intelligence of EVs, though they usually result in higher production costs. The increase in costs is mainly due to the incorporation of additional sensor systems and the implementation of high-performance computational platforms required for advanced perception, control, and decision-making algorithms. The necessity for real-time data acquisition, processing, and inference places significant demands on onboard electronic control units (ECUs), thereby increasing the overall cost and complexity of vehicle architecture. These challenges are anticipated to diminish over time as EV adoption continues to grow, leading to economies of scale and a reduction in unit costs. Furthermore, continuous progress in sensor fusion methods, edge computing, and model compression is expected to facilitate the development of more cost-effective vehicles that deliver similar functionality with a reduced number of sensors and lower computational demands.

H. ADVANCED BMS WITH RECONFIGURABLE CELL FEATURES

Advanced BMS with reconfigurable cell technology represent a promising future trend to enhance the efficiency of EMS. These systems allow dynamic reconfiguration

TABLE 14. Comparison of Rule-based, Optimization-based, and ITS-based EMS.

Aspect	Rule-based EMS	Optimization-based EMS	ITS-based EMS
Definition	Uses predefined rules based on expert knowledge or empirical results to control energy flow.	Employs mathematical optimization techniques to determine optimal energy distribution.	Leverages real-time traffic and infrastructure data for dynamic energy optimization.
Energy Efficiency	Moderate; focuses on operational simplicity rather than optimality.	High; capable of achieving near-optimal energy management under ideal conditions.	High; improves efficiency through real-time decision-making and cooperative systems.
Complexity	Low; easy to design and implement.	High; requires extensive modeling, tuning, and computational resources.	Very High; requires advanced communication infrastructure and integration with external systems.
Computational Demand	Low; suitable for real-time implementation with minimal hardware.	High; often computationally intensive, especially for real-time applications.	Very High; relies on real-time data processing and communication technologies.
Real-Time Feasibility	Excellent; well-suited for real-time control.	Variable; online methods like ECMS and MPC are feasible, but offline methods are not.	Good; real-time implementation relies heavily on robust communication systems.
Adaptability	Limited; lacks flexibility to adapt to dynamic or unexpected conditions.	Moderate to High; can adapt to varying conditions but depends on computational resources.	High; dynamically adjusts based on real-time traffic and environmental data.
Scalability	High; simple to deploy across diverse applications.	Moderate; depends on the availability of computational power and accurate models.	Moderate to Low; constrained by the availability of smart infrastructure and data reliability.
Cost	Low; minimal hardware and computational requirements.	High; requires advanced computational tools and resources.	Very High; involves significant investment in infrastructure and communication systems.
Main Advantage	Simplicity and ease of use.	Provides optimal or near-optimal energy management solutions.	Enables system-wide efficiency through integrated, cooperative decision-making.
Main Limitation	Limited performance in dynamic and complex scenarios.	Computationally expensive; may struggle with real-time applications.	Dependence on smart infrastructure and potential cybersecurity vulnerabilities.

of battery cell connections to adapt to changing energy demands, optimize power delivery, and maintain balanced SOC across cells. By redistributing load and isolating under performing or degraded cells, reconfigurable BMS can significantly improve battery performance, extend lifespan, and reduce overall degradation. Furthermore, the integration of reconfigurable BMS with EMS can provide better real-time control over energy resources, enabling higher energy utilization and improved reliability in electric vehicles [378], [379], [380], [381], [382]. This innovation aligns with the ongoing advancements in smart energy systems and underscores the importance of adaptive solutions in modern electrified transportation.

VI. CONCLUSION

This paper presents a comprehensive review of state-of-the-art EMS applied to various architectures of EVs and HEVs, as summarized in Table 14 highlighting their roles in improving energy efficiency, reducing greenhouse gas emissions, and enhancing battery lifespan. A broad spectrum of EMS technologies, including rule-based, optimization-based, and ITS-based approaches, as well as advancements in multi-objective optimization and machine learning were explored. The findings underscore the critical role of EMS in addressing challenges associated with power distribution, battery thermal management, and integration of renewable energy sources. While conventional EMS methods, such as rule-based strategies, offer simplicity and computational efficiency, their limited adaptability to dynamic conditions underscores the need for more advanced approaches. Optimization-based strategies, such as GA, DP, and MPC, demonstrate superior energy efficiency and adaptability but generally require significant computational resources. Learning-based methods, like RL and NN, emerge as promising solutions for real-time adaptability and dynamic scenario management, albeit with higher design complexity. Looking ahead, the integration of AI, V2X communication, and wireless charging technologies is set to revolutionize EMS design. These advancements will facilitate predictive analytics, enhance system adaptability, and enable seamless interaction between vehicles, infrastructure, and renewable energy grids. However, achieving widespread adoption requires overcoming challenges such as cybersecurity risks, the need for standardized protocols, and the scalability of charging infrastructure. Table 14 offers a concise comparison of the rule-based, optimization-based, and ITS-based EMS approaches by highlighting their strengths, weaknesses, and suitability for various applications. The continued evolution of EMS will be pivotal in supporting the global transition to sustainable and efficient transportation systems. This will require collaborative efforts among researchers, policymakers, and industry stakeholders to address technological, economic, and environmental challenges, ensuring the development of robust, adaptable, and scalable EMS solutions.

REFERENCES

[1] G. Simpkins, "Benefits of electric vehicle adoption," *Nature Rev. Earth Environ.*, vol. 4, no. 7, p. 432, Jun. 2023, doi: 10.1038/s43017-023-00465-2.
[2] X. Zhao, H. Hu, H. Yuan, and X. Chu, "How does adoption of electric vehicles reduce carbon emissions? Evidence from China," *Heliyon*, vol. 9, no. 9, Sep. 2023, Art. no. e20296. [Online]. Available: https://www.sciencedirect.com/science/article/pii/S2405844023075047
[3] *Sources of Greenhouse Gas Emissions | Us Epa*. Accessed: Nov. 15, 2024. [Online]. Available: https://www.epa.gov/ghgemissions/sources-greenhouse-gas-emissions
[4] *Greenhouse Gas Emissions—Canada.ca*. Accessed: Oct. 3, 2023. [Online]. Available: https://www.canada.ca/en/environment-climate-change/services/environmental-indicators/greenhouse-gas-emissions.html
[5] *Transport and Environment Statistics 2022—GOV.U.K.* Accessed: Oct. 3, 2023. [Online]. Available: https://www.gov.uk/government/statistics/transport-and-environment-statistics-2022/transport-and-environment-statistics-2022
[6] *Global Greenhouse Gas Emissions Data | U.S. EPA*. Accessed: Oct. 3, 2023. [Online]. Available: https://www.epa.gov/ghgemissions/global-greenhouse-gas-emissions-data
[7] I.-Y. L. Hsieh, G. P. Chossière, E. Gençer, H. Chen, S. Barrett, and W. H. Green, "An integrated assessment of emissions, air quality, and public health impacts of China's transition to electric vehicles," *Environ. Sci. Technol.*, vol. 56, no. 11, pp. 6836–6846, 2022.
[8] S. Pan, W. Yu, L. M. Fulton, J. Jung, Y. Choi, and H. O. Gao, "Impacts of the large-scale use of passenger electric vehicles on public health in 30 U.S. Metropolitan areas," *Renew. Sustain. Energy Rev.*, vol. 173, Mar. 2023, Art. no. 113100.
[9] R. H. Dolan, T. J. Wallington, and J. E. Anderson, "Large decreases in tailpipe criteria pollutant emissions from the U.S. light-duty vehicle fleet expected in 2020–2040," *Environ. Sci. Technol.*, vol. 58, no. 7, pp. 3205–3212, Feb. 2024.
[10] T. J. Wallington, J. E. Anderson, R. H. Dolan, and S. L. Winkler, "Vehicle emissions and urban air quality: 60 years of progress," *Atmosphere*, vol. 13, no. 5, p. 650, Apr. 2022.
[11] M. Salman, X. Long, G. Wang, and D. Zha, "Paris climate agreement and global environmental efficiency: New evidence from fuzzy regression discontinuity design," *Energy Policy*, vol. 168, Sep. 2022, Art. no. 113128.
[12] N. Reyseliani, A. Hidayatno, and W. W. Purwanto, "Implication of the Paris agreement target on Indonesia electricity sector transition to 2050 using TIMES model," *Energy Policy*, vol. 169, Oct. 2022, Art. no. 113184.
[13] S. Mousavinezhad, Y. Choi, N. Khorshidian, M. Ghahremanloo, and M. Momeni, "Air quality and health co-benefits of vehicle electrification and emission controls in the most populated United States urban hubs: Insights from New York, Los Angeles, Chicago, and Houston," *Sci. Total Environ.*, vol. 912, Feb. 2024, Art. no. 169577.
[14] P. Sridharan, "Energy security analysis of large scale EV penetration in California—2030," M.S. thesis, TU Delft, Delft, The Netherlands, 2018. [Online]. Available: https://resolver.tudelft.nl/uuid:8553445c-6d3a-4bd3-b1b5-4af466ede327
[15] Y. Li and Y. Chang, "Road transport electrification and energy security in the association of Southeast Asian nations: Quantitative analysis and policy implications," *Energy Policy*, vol. 129, pp. 805–815, Jun. 2019.
[16] N. Kumar, "Transition to electric economy from hydrocarbons: Let us not trade one energy dependence with another insecurity," in *Proc. 3rd Int. Meeting Appl. Geosci. Energy Expanded Abstr.*, Dec. 2023, pp. 1705–1709.
[17] R. Raustad, "Electric vehicle life cycle cost analysis," Electric Vehicle Transp. Center, Cocoa, FL, USA, Tech. Rep. FSEC-CR-2053-17, 2017.
[18] P. Suttakul, W. Wongsapai, T. Fongsamootr, Y. Mona, and K. Poolsawat, "Total cost of ownership of internal combustion engine and electric vehicles: A real-world comparison for the case of Thailand," *Energy Rep.*, vol. 8, pp. 545–553, Nov. 2022.
[19] D. Rimpas, D. Kaminaris, I. Al-Darraji, D. Piromalis, G. A. Vokas, P. Papageorgas, and G. Tsaramirsis, "Energy management and storage systems on electric vehicles: A comprehensive review," *Mater. Today, Proc.*, vol. 61, pp. 813–819, Mar. 2021. [Online]. Available: https://www.sciencedirect.com/science/article/pii/S2214785321058685
[20] R. Smit, J. Whitehead, and S. Washington, "Where are we heading with electric vehicles," *Air Quality climate change*, vol. 52, no. 3, pp. 18–27, 2018. [Online]. Available: https://api.semanticscholar.org/CorpusID:189153029
[21] IEA. (2024). *Electric Car Sales, 2012–2024, IEA, Paris*. Accessed: Nov. 16, 2024. [Online]. Available: https://www.iea.org/data-and-statistics/charts/electric-car-sales-2012-2024
[22] P. Saiteja and B. Ashok, "Critical review on structural architecture, energy control strategies and development process towards optimal energy management in hybrid vehicles," *Renew. Sustain. Energy Rev.*, vol. 157, Apr. 2022, Art. no. 112038. [Online]. Available: https://www.sciencedirect.com/science/article/pii/S1364032121013009
[23] E. Kamal and L. Adouane, "Optimized EMS and a comparative study of hybrid hydrogen fuel cell/battery vehicles," *Energies*, vol. 15, no. 3, p. 738, Jan. 2022. [Online]. Available: https://www.mdpi.com/1996-1073/15/3/738
[24] S. Si, B. Yang, B. Gao, Z. Zhang, B. Zhao, T. Zhang, and H. Xu, "A real-time energy management strategy combining rule and optimization for minimizing energy consumption and emissions of flywheel hybrid electric vehicle (FHEV)," *Appl. Thermal Eng.*, vol. 255, Oct. 2024, Art. no. 124013. [Online]. Available: https://www.sciencedirect.com/science/article/pii/S1359431124016818
[25] R. Huang and H. He, "Naturalistic data-driven and emission reduction-conscious energy management for hybrid electric vehicle based on improved soft actor-critic algorithm," *J. Power Sources*, vol. 559, Mar. 2023, Art. no. 232648. [Online]. Available: https://www.sciencedirect.com/science/article/pii/S037877532300023X
[26] P. G. Anselma, P. Kollmeyer, J. Lempert, Z. Zhao, G. Belingardi, and A. Emadi, "Battery state-of-health sensitive energy management of hybrid electric vehicles: Lifetime prediction and ageing experimental validation," *Appl. Energy*, vol. 285, Mar. 2021, Art. no. 116440. [Online]. Available: https://www.sciencedirect.com/science/article/pii/S0306261921000088
[27] T. Rudolf, T. Schürmann, S. Schwab, and S. Hohmann, "Toward holistic energy management strategies for fuel cell hybrid electric vehicles in heavy-duty applications," *Proc. IEEE*, vol. 109, no. 6, pp. 1094–1114, Jun. 2021.
[28] B. Pang, H. Zhu, Y. Tong, and Z. Dong, "Optimal design and control of battery-ultracapacitor hybrid energy storage system for BEV operating at extreme temperatures," *J. Energy Storage*, vol. 101, Nov. 2024, Art. no. 113963. [Online]. Available: https://www.sciencedirect.com/science/article/pii/S2352152X24035497
[29] D. T. Machacek, N. O. Yasar, T. Huber, and C. H. Onder, "Energy management of hydrogen hybrid electric vehicles—A potential analysis," *Int. J. Hydrogen Energy*, vol. 58, pp. 1–13, Mar. 2024. [Online]. Available: https://www.sciencedirect.com/science/article/pii/S0360319924001277
[30] S. Ferahtia, H. Rezk, R. M. Ghoniem, A. Fathy, R. Alkanhel, and M. M. Ghonem, "Optimal energy management for hydrogen economy in a hybrid electric vehicle," *Sustainability*, vol. 15, no. 4, p. 3267, Feb. 2023. [Online]. Available: https://www.mdpi.com/2071-1050/15/4/3267
[31] J. Yang, X. Xu, Y. Peng, P. Deng, X. Wu, and J. Zhang, "Hierarchical energy management of a hybrid propulsion system considering speed profile optimization," *Energy*, vol. 244, Apr. 2022, Art. no. 123098. [Online]. Available: https://www.sciencedirect.com/science/article/pii/S0360544222000019
[32] Y. Farajpour, H. Chaoui, M. Khayamy, S. Kelouwani, and M. Alzayed, "Novel energy management strategy for electric vehicles to improve driving range," *IEEE Trans. Veh. Technol.*, vol. 72, no. 2, pp. 1735–1747, Feb. 2023.
[33] G. Pierrou, C. Valero-De La Flor, and G. Hug, "Optimal EV charging scheduling at electric railway stations under peak load constraints," *Electric Power Syst. Res.*, vol. 235, Oct. 2024, Art. no. 110612. [Online]. Available: https://www.sciencedirect.com/science/article/pii/S037877962400498X
[34] K. N. Qureshi, A. Alhudhaif, and G. Jeon, "Electric-vehicle energy management and charging scheduling system in sustainable cities and society," *Sustain. Cities Soc.*, vol. 71, Aug. 2021, Art. no. 102990. [Online]. Available: https://www.sciencedirect.com/science/article/pii/S2210670721002766

[35] H. M. Abdullah, A. Gastli, and L. Ben-Brahim, ''Reinforcement learning based EV charging management systems—A review,'' *IEEE Access*, vol. 9, pp. 41506–41531, 2021.

[36] M. Yavuz and Ö. C. Kivanç, ''Optimization of a cluster-based energy management system using deep reinforcement learning without affecting prosumer comfort: V2X technologies and peer-to-peer energy trading,'' *IEEE Access*, vol. 12, pp. 31551–31575, 2024.

[37] S. Ha and H. Lee, ''Energy management strategy based on V2X communications and road information for a connected PHEV and its evaluation using an IDHIL simulator,'' *Appl. Sci.*, vol. 13, no. 16, p. 9208, Aug. 2023. [Online]. Available: https://www.mdpi.com/2076-3417/13/16/9208

[38] H. Dong, W. Zhuang, B. Chen, Y. Wang, Y. Lu, Y. Liu, L. Xu, and G. Yin, ''A comparative study of energy-efficient driving strategy for connected internal combustion engine and electric vehicles at signalized intersections,'' *Appl. Energy*, vol. 310, Mar. 2022, Art. no. 118524. [Online]. Available: https://www.sciencedirect.com/science/article/pii/S0306261922000137

[39] Z. Chen, S. Xiong, Q. Chen, Y. Zhang, J. Yu, J. Jiang, and C. Wu, ''Eco-driving: A scientometric and bibliometric analysis,'' *IEEE Trans. Intell. Transp. Syst.*, vol. 23, no. 12, pp. 22716–22736, Dec. 2022.

[40] S. Sabet and B. Farooq, ''Exploring the combined effects of major fuel technologies, eco-routing, and eco-driving for sustainable traffic decarbonization in downtown Toronto,'' *Transp. Res. A, Policy Pract.*, vol. 192, Feb. 2025, Art. no. 104385.

[41] Y. Zhang, Y. Zhang, Z. Ai, Y. L. Murphey, and J. Zhang, ''Energy optimal control of motor drive system for extending ranges of electric vehicles,'' *IEEE Trans. Ind. Electron.*, vol. 68, no. 2, pp. 1728–1738, Feb. 2021.

[42] S. Wang, X. Wu, X. Zhao, S. Wang, B. Xie, Z. Song, and D. Wang, ''Co-optimization energy management strategy for a novel dual-motor drive system of electric tractor considering efficiency and stability,'' *Energy*, vol. 281, Oct. 2023, Art. no. 128074. [Online]. Available: https://www.sciencedirect.com/science/article/pii/S0360544223014688

[43] Z. Chen, Y. Liu, Y. Zhang, Z. Lei, Z. Chen, and G. Li, ''A neural network-based ECMS for optimized energy management of plug-in hybrid electric vehicles,'' *Energy*, vol. 243, Mar. 2022, Art. no. 122727. [Online]. Available: https://www.sciencedirect.com/science/article/pii/S0360544221029765

[44] M. Passalacqua, D. Lanzarotto, M. Repetto, L. Vaccaro, A. Bonfiglio, and M. Marchesoni, ''Fuel economy and EMS for a series hybrid vehicle based on supercapacitor storage,'' *IEEE Trans. Power Electron.*, vol. 34, no. 10, pp. 9966–9977, Oct. 2019.

[45] D. S. Puma-Benavides, J. Izquierdo-Reyes, J. D. D. Calderon-Najera, and R. A. Ramirez-Mendoza, ''A systematic review of technologies, control methods, and optimization for extended-range electric vehicles,'' *Appl. Sci.*, vol. 11, no. 15, p. 7095, Jul. 2021. [Online]. Available: https://www.mdpi.com/2076-3417/11/15/7095

[46] B. Chen, X. Pan, and S. A. Evangelou, ''Optimal energy management of series hybrid electric vehicles with engine start–stop system,'' *IEEE Trans. Control Syst. Technol.*, vol. 31, no. 2, pp. 660–675, Mar. 2023.

[47] F. Zhang, L. Xiao, S. Coskun, H. Pang, S. Xie, K. Liu, and Y. Cui, ''Comparative study of energy management in parallel hybrid electric vehicles considering battery ageing,'' *Energy*, vol. 264, Feb. 2023, Art. no. 123219. [Online]. Available: https://www.sciencedirect.com/science/article/pii/S0360544222001220

[48] M. Y. Nassar, M. L. Shaltout, and H. A. Hegazi, ''Multi-objective optimum energy management strategies for parallel hybrid electric vehicles: A comparative study,'' *Energy Convers. Manage.*, vol. 277, Feb. 2023, Art. no. 116683. [Online]. Available: https://www.sciencedirect.com/science/article/pii/S0196890423000298

[49] X. Tang, J. Chen, H. Pu, T. Liu, and A. Khajepour, ''Double deep reinforcement learning-based energy management for a parallel hybrid electric vehicle with engine start–stop strategy,'' *IEEE Trans. Transport. Electrific.*, vol. 8, no. 1, pp. 1376–1388, Mar. 2022.

[50] M. Asghar, A. I. Bhatti, Q. Ahmed, and G. Murtaza, ''Energy management strategy for Atkinson cycle engine based parallel hybrid electric vehicle,'' *IEEE Access*, vol. 6, pp. 28008–28018, 2018.

[51] Y. Fu, Z. Fan, Y. Lei, X. Wang, and X. Sun, ''Integrated optimization of component parameters and energy management strategies for a series–parallel hybrid electric vehicle,'' *Automot. Innov.*, vol. 7, no. 3, pp. 492–506, Jul. 2024, doi: 10.1007/s42154-024-00299-8.

[52] W. Pan, Y. Wu, Y. Tong, J. Li, and Y. Liu, ''Optimal rule extraction-based real-time energy management strategy for series-parallel hybrid electric vehicles,'' *Energy Convers. Manage.*, vol. 293, Oct. 2023, Art. no. 117474. [Online]. Available: https://www.sciencedirect.com/science/article/pii/S0196890423008208

[53] L. Zhou, D. Yang, X. Zeng, X. Zhang, and D. Song, ''Multi-objective real-time energy management for series–parallel hybrid electric vehicles considering battery life,'' *Energy Convers. Manage.*, vol. 290, Aug. 2023, Art. no. 117234. [Online]. Available: https://www.sciencedirect.com/science/article/pii/S0196890423005800

[54] K. Yu, S.-Y. Choe, and J. Kim, ''Energy management strategies for series-parallel hybrid electric vehicles considering fuel efficiency and degradation of lithium-ion batteries,'' *SAE Int. J. Electrified Vehicles*, vol. 12, no. 3, pp. 425–448, Jun. 2023, doi: 10.4271/14-12-03-0022.

[55] M. Moghadari, M. Kandidayeni, A. Makhsoos, L. Boulon, and H. Chaoui, ''Integration of water management into the energy management strategy for a fuel cell vehicle,'' *IEEE Trans. Ind. Electron.*, early access, Jun. 20, 2025, doi: 10.1109/TIE.2025.3574537.

[56] A. Lotfy, M. Alzayed, H. Chaoui, and L. Boulon, ''Centralized multi-agent SOC control for battery health using proximal policy optimization in EVs,'' *IEEE Trans. Veh. Technol.*, early access, May 19, 2025, doi: 10.1109/TVT.2025.3571784.

[57] Y. Qiu, T. Zeng, C. Zhang, G. Wang, Y. Wang, Z. Hu, M. Yan, and Z. Wei, ''Progress and challenges in multi-stack fuel cell system for high power applications: Architecture and energy management,'' *Green Energy Intell. Transp.*, vol. 2, no. 2, Apr. 2023, Art. no. 100068.

[58] S. F. Tie and C. W. Tan, ''A review of energy sources and energy management system in electric vehicles,'' *Renew. Sustain. Energy Rev.*, vol. 20, pp. 82–102, Apr. 2013. [Online]. Available: https://www.sciencedirect.com/science/article/pii/S1364032112006910

[59] A. Markel, ''Energy storage system requirements for hybrid fuel cell vehicles,'' in *Proc. 3rd Int. Adv. Automot. Battery Conf.*, 2003, pp. 1–11.

[60] *Doe Hydrogen and Fuel Cells Program Record 20005: Automotive Fuel Cell Targets and Status*. Accessed: Nov. 19, 2024. [Online]. Available: https://www.hydrogen.energy.gov/docs/hydrogenprogramlibraries/pdfs/20005-automotive-fuel-cell-targets-status.pdf?Status=Master

[61] D. De Wolf and Y. Smeers, ''Comparison of battery electric vehicles and fuel cell vehicles,'' *World Electric Vehicle J.*, vol. 14, no. 9, p. 262, Sep. 2023.

[62] M. Waseem, M. Amir, G. S. Lakshmi, S. Harivardhagini, and M. Ahmad, ''Fuel cell-based hybrid electric vehicles: An integrated review of current status, key challenges, recommended policies, and future prospects,'' *Green Energy Intell. Transp.*, vol. 2, no. 6, Dec. 2023, Art. no. 100121. [Online]. Available: https://www.sciencedirect.com/science/article/pii/S2773153723000579

[63] M. A. Hannan, M. M. Hoque, A. Mohamed, and A. Ayob, ''Review of energy storage systems for electric vehicle applications: Issues and challenges,'' *Renew. Sustain. Energy Rev.*, vol. 69, pp. 771–789, Mar. 2017. [Online]. Available: https://www.sciencedirect.com/science/article/pii/S1364032116309182

[64] K. Vidyanandan, ''Overview of electric and hybrid vehicles,'' *Energy Scan*, vol. 3, pp. 7–14, Mar. 2018.

[65] *Useable Battery Capacity of Full Electric Vehicles Cheatsheet–EV Database*. Accessed: Nov. 20, 2024. [Online]. Available: https://ev-database.org/cheatsheet/useable-battery-capacity-electric-car

[66] *What is the Difference Between Micro, Mild, Full and Plug-in Hybrid Electric Vehicles—X-Engineer.org*. Accessed: Nov. 20, 2024. [Online]. Available: https://x-engineer.org/micro-mild-full-hybrid-electric-vehicle/

[67] *The Rise of the Mild Hybrid—A Steppingstone Technology or Greenwash—Regen*. Accessed: Nov. 20, 2024. [Online]. Available: https://www.regen.co.uk/the-rise-of-the-mild-hybrid-a-steppingstone-technology-or-greenwash/

[68] *These Are the Top 12 Hybrids in Order of Electric Range | Top Gear*. Accessed: Nov. 20, 2024. [Online]. Available: https://www.topgear.com/car-news/list/these-are-top-12-hybrids-order-electric-range

[69] I.-S. Sorlei, N. Bizon, P. Thounthong, M. Varlam, E. Carcadea, M. Culcer, M. Iliescu, and M. Raceanu, ''Fuel cell electric vehicles—A brief review of current topologies and energy management strategies,'' *Energies*, vol. 14, no. 1, p. 252, Jan. 2021.

[70] A. Urooj and A. Nasir, ''Review of intelligent energy management techniques for hybrid electric vehicles,'' *J. Energy Storage*, vol. 92, Jul. 2024, Art. no. 112132.

[71] H. He, Y. Shou, and J. Song, ''An improved A-ECMS energy management for plug-in hybrid electric vehicles considering transient characteristics of engine,'' *Energy Rep.*, vol. 10, pp. 2006–2016, Nov. 2023. [Online]. Available: https://www.sciencedirect.com/science/article/pii/S2352484723012283

[72] X. Sun, J. Fu, H. Yang, M. Xie, and J. Liu, "An energy management strategy for plug-in hybrid electric vehicles based on deep learning and improved model predictive control," *Energy*, vol. 269, Apr. 2023, Art. no. 126772. [Online]. Available: https://www.sciencedirect.com/science/article/pii/S0360544223001664

[73] A. Alyakhni, L. Boulon, J.-M. Vinassa, and O. Briat, "A comprehensive review on energy management strategies for electric vehicles considering degradation using aging models," *IEEE Access*, vol. 9, pp. 143922–143940, 2021.

[74] Y. Farajpour, "A comprehensive energy management framework for electric vehicle driving range extension considering battery aging," Ph.D. dissertation, Dept. Electron., Carleton Univ., Ottawa, ON, Canada, 2024.

[75] V.-B. Vu, J. M. González-González, V. Pickert, M. Dahidah, and A. Triviño, "A hybrid charger of conductive and inductive modes for electric vehicles," *IEEE Trans. Ind. Electron.*, vol. 68, no. 12, pp. 12021–12033, Dec. 2021.

[76] S. S. G. Acharige, M. E. Haque, M. T. Arif, N. Hosseinzadeh, K. N. Hasan, and A. M. T. Oo, "Review of electric vehicle charging technologies, standards, architectures, and converter configurations," *IEEE Access*, vol. 11, pp. 41218–41255, 2023.

[77] M. Safayatullah, M. T. Elrais, S. Ghosh, R. Rezaii, and I. Batarseh, "A comprehensive review of power converter topologies and control methods for electric vehicle fast charging applications," *IEEE Access*, vol. 10, pp. 40753–40793, 2022.

[78] M. Shahjalal, T. Shams, M. N. Tasnim, M. R. Ahmed, M. Ahsan, and J. Haider, "A critical review on charging technologies of electric vehicles," *Energies*, vol. 15, no. 21, p. 8239, Nov. 2022. [Online]. Available: https://www.mdpi.com/1996-1073/15/21/8239

[79] S. Bamati and H. Chaoui, "Lithium-ion batteries long horizon health prognostic using machine learning," *IEEE Trans. Energy Convers.*, vol. 37, no. 2, pp. 1176–1186, Jun. 2022.

[80] C. She, Y. Shen, G. Bin, J. Hong, and Y. Peng, "Accurate state of health estimation of battery system based on multistage constant current charging and behavior analysis in real-world electric vehicles," *IEEE Trans. Transport. Electrific.*, vol. 11, no. 1, pp. 97–108, Feb. 2025.

[81] C. Yang, M. Zha, W. Wang, K. Liu, and C. Xiang, "Efficient energy management strategy for hybrid electric vehicles/plug-in hybrid electric vehicles: Review and recent advances under intelligent transportation system," *IET Intell. Transp. Syst.*, vol. 14, no. 7, pp. 702–711, Jul. 2020. [Online]. Available: https://ietresearch.onlinelibrary.wiley.com/doi/abs/10.1049/iet-its.2019.0606

[82] F. Zhang, L. Wang, S. Coskun, H. Pang, Y. Cui, and J. Xi, "Energy management strategies for hybrid electric vehicles: Review, classification, comparison, and outlook," *Energies*, vol. 13, no. 13, p. 3352, Jun. 2020. [Online]. Available: https://www.mdpi.com/1996-1073/13/13/3352

[83] M. S. Munsi and H. Chaoui, "Energy management systems for electric vehicles: A comprehensive review of technologies and trends," *IEEE Access*, vol. 12, pp. 60385–60403, 2024.

[84] A. Alsharif, C. W. Tan, R. Ayop, A. Dobi, and K. Y. Lau, "A comprehensive review of energy management strategy in vehicle-to-grid technology integrated with renewable energy sources," *Sustain. Energy Technol. Assessments*, vol. 47, Oct. 2021, Art. no. 101439. [Online]. Available: https://www.sciencedirect.com/science/article/pii/S2213138821004495

[85] H. Maghfiroh, O. Wahyunggoro, and A. I. Cahyadi, "Energy management in hybrid electric and hybrid energy storage system vehicles: A fuzzy logic controller review," *IEEE Access*, vol. 12, pp. 56097–56109, 2024.

[86] M. Ehsani, K. V. Singh, H. O. Bansal, and R. T. Mehrjardi, "State of the art and trends in electric and hybrid electric vehicles," *Proc. IEEE*, vol. 109, no. 6, pp. 967–984, Jun. 2021.

[87] V. Chandra Tella, M. Alzayed, and H. Chaoui, "A comprehensive review of energy management strategies in hybrid electric vehicles: Comparative analysis and challenges," *IEEE Access*, vol. 12, pp. 181858–181878, 2024.

[88] C. Jia, W. Qiao, and L. Qu, "Modeling and control of hybrid electric vehicles: A case study for agricultural tractors," in *Proc. IEEE Vehicle Power Propuls. Conf. (VPPC)*, Aug. 2018, pp. 1–6.

[89] N. Azim Mohseni, N. Bayati, and T. Ebel, "Energy management strategies of hybrid electric vehicles: A comparative review," *IET Smart Grid*, vol. 7, no. 3, pp. 191–220, Jun. 2024. [Online]. Available: https://ietresearch.onlinelibrary.wiley.com/doi/abs/10.1049/stg2.12133

[90] Q. Xue, X. Zhang, T. Teng, J. Zhang, Z. Feng, and Q. Lv, "A comprehensive review on classification, energy management strategy, and control algorithm for hybrid electric vehicles," *Energies*, vol. 13, no. 20, p. 5355, Oct. 2020. [Online]. Available: https://www.mdpi.com/1996-1073/13/20/5355

[91] C. Kök and S. O. Mert, "Comparison of energy and exergy analysis of fuzzy logic and power follower control strategies in fuel cell electric vehicles," *J. Power Sources*, vol. 614, Sep. 2024, Art. no. 235033. [Online]. Available: https://www.sciencedirect.com/science/article/pii/S0378775324009856

[92] A. Ali and D. Söffker, "Towards optimal power management of hybrid electric vehicles in real-time: A review on methods, challenges, and state-of-the-art solutions," *Energies*, vol. 11, no. 3, p. 476, Feb. 2018. [Online]. Available: https://www.mdpi.com/1996-1073/11/3/476

[93] B. Kanouni, A. E. Badoud, S. Mekhilef, M. Bajaj, and I. Zaitsev, "Advanced efficient energy management strategy based on state machine control for multi-sources PV-PEMFC-batteries system," *Sci. Rep.*, vol. 14, no. 1, p. 7996, Apr. 2024.

[94] K. Song, F. Li, X. Hu, L. He, W. Niu, S. Lu, and T. Zhang, "Multi-mode energy management strategy for fuel cell electric vehicles based on driving pattern identification using learning vector quantization neural network algorithm," *J. Power Sources.*, vol. 389, pp. 230–239, Jun. 2018. [Online]. Available: https://www.sciencedirect.com/science/article/pii/S0378775318303677

[95] A. Benhammou, M. A. Hartani, H. Tedjini, Y. Guettaf, and M. A. Soumeur, "Breaking new ground in HEV energy management: Kinetic energy utilization and systematic EMS approaches based on robust drive control," *ISA Trans.*, vol. 147, pp. 288–303, Apr. 2024. [Online]. Available: https://www.sciencedirect.com/science/article/pii/S0019057824000478

[96] S. Kaushik, K. Rachananjali, and V. Nath, "A novel LSTM-based EMS and interleaved DC–DC boost converter topology for real-time driving conditions in HEVs," *Electr. Eng.*, vol. 106, no. 5, pp. 5523–5542, Mar. 2024, doi: 10.1007/s00202-024-02259-1.

[97] D. Zhong, B. Liu, L. Liu, W. Fan, and J. Tang, "Artificial intelligence algorithms for hybrid electric powertrain system control: A review," *Energies*, vol. 18, no. 8, p. 2018, Apr. 2025.

[98] L. A. Zadeh, "Fuzzy logic," in *Granular, Fuzzy, and Soft Computing*. Cham, Switzerland: Springer, 2023, pp. 19–49.

[99] S. Boumediene, A. Nasri, T. Hamza, C. Hicham, K. Kayisli, and H. Garg, "Fuzzy logic-based energy management system (EMS) of hybrid power sources: Battery/Super capacitor for electric scooter supply," *J. Eng. Res.*, vol. 12, no. 1, pp. 148–159, Mar. 2024. [Online]. Available: https://www.sciencedirect.com/science/article/pii/S2307187723001682

[100] K. V. Singh, H. O. Bansal, and D. Singh, "Feed-forward modeling and real-time implementation of an intelligent fuzzy logic-based energy management strategy in a series–parallel hybrid electric vehicle to improve fuel economy," *Electr. Eng.*, vol. 102, no. 2, pp. 967–987, Jan. 2020, doi: 10.1007/s00202-019-00914-6.

[101] K. Keskin and B. Urazel, "Fuzzy control of dual storage system of an electric drive vehicle considering battery degradation," *Int. J. Optim. Control, Theories Appl.*, vol. 11, no. 1, pp. 30–40, Dec. 2020. [Online]. Available: https://ijocta.org/index.php/files/article/view/848

[102] S. Mehdi Rakhtala Rostami and Z. Al-Shibaany, "Intelligent energy management for full-active hybrid energy storage systems in electric vehicles using teaching–learning-based optimization in fuzzy logic algorithms," *IEEE Access*, vol. 12, pp. 67665–67680, 2024.

[103] M. Kamoona, o. C. Kvanc, and O. A. Ahmed, "Intelligent energy management system evaluation of hybrid electric vehicle based on recurrent wavelet neural network and PSO algorithm," *Int. J. Intell. Eng. Syst.*, vol. 16, no. 1, pp. 1–14, Dec. 2022.

[104] J. E. Valdez-Resendiz, J. C. Rosas-Caro, J. C. Mayo-Maldonado, A. Claudio-Sanchez, O. Ruiz-Martinez, and V. M. Sanchez, "Improvement of ultracapacitors-energy usage in fuel cell based hybrid electric vehicle," *Int. J. Hydrogen Energy*, vol. 45, no. 26, pp. 13746–13756, May 2020. [Online]. Available: https://www.sciencedirect.com/science/article/pii/S0360319920300045

[105] A. U. Rahman, S. S. Zehra, I. Ahmad, and H. Armghan, "Fuzzy super-twisting sliding mode-based energy management and control of hybrid energy storage system in electric vehicle considering fuel economy," *J. Energy Storage*, vol. 37, May 2021, Art. no. 102468. [Online]. Available: https://www.sciencedirect.com/science/article/pii/S2352152X21002152

[106] M. Sellali, S. Abdeddaim, A. Betka, A. Djerdir, S. Drid, and M. Tiar, "Fuzzy-super twisting control implementation of battery/super capacitor for electric vehicles," *ISA Trans.*, vol. 95, pp. 243–253, Dec. 2019. [Online]. Available: https://www.sciencedirect.com/science/article/pii/S0019057819302034

[107] N. Feng, T. Ma, and C. Chen, "Fuzzy energy management strategy for hybrid electric vehicles on battery state-of-charge estimation by particle filter," *Social Netw. Appl. Sci.*, vol. 4, no. 10, p. 256, Oct. 2022.

[108] M. M. Ferdaus, M. Pratama, S. G. Anavatti, M. A. Garratt, and E. Lughofer, ''PAC: A novel self-adaptive neuro-fuzzy controller for micro aerial vehicles,'' *Inf. Sci.*, vol. 512, pp. 481–505, Feb. 2020.
[109] N. Guler, Z. M. Ismail, Z. B. Hazem, and N. Naik, ''Adaptive fuzzy logic controller-based intelligent energy management system scheme for hybrid electric vehicles,'' *IEEE Access*, vol. 12, pp. 173441–173454, 2024.
[110] C. Lin, W. Luo, H. Lan, and C. Hu, ''Research on multi-objective compound energy management strategy based on fuzzy control for FCHEV,'' *Energies*, vol. 15, no. 5, p. 1721, Feb. 2022. [Online]. Available: https://www.mdpi.com/1996-1073/15/5/1721
[111] S. Siddula, ''Efficiency enhancement of electric vehicles with ANFIS-based energy management,'' in *Proc. Int. Conf. Intell. Algorithms Comput. Intell. Syst. (IACIS)*, Aug. 2024, pp. 1–6.
[112] A. Beheshtikhoo, M. Pourgholi, and I. Khazaee, ''Design of type-2 fuzzy logic controller in a smart home energy management system with a combination of renewable energy and an electric vehicle,'' *J. Building Eng.*, vol. 68, Jun. 2023, Art. no. 106097. [Online]. Available: https://www.sciencedirect.com/science/article/pii/S2352710223002760
[113] F. Gao and X. Gao, ''Hyper-spherical search optimized fuzzy logic control considering operating conditions for hybrid tram,'' *IEEE Access*, vol. 10, pp. 65925–65935, 2022.
[114] A. Beşkardeş and Y. Hameş, ''Data-driven-based fuzzy control system design for a hybrid electric vehicle,'' *Electr. Eng.*, vol. 105, no. 4, pp. 1971–1991, Mar. 2023, doi: 10.1007/s00202-023-01776-9.
[115] T. Sadeq, C. K. Wai, E. Morris, Q. A. Tarbosh, and Ö. Aydogdu, ''Optimal control strategy to maximize the performance of hybrid energy storage system for electric vehicle considering topography information,'' *IEEE Access*, vol. 8, pp. 216994–217007, 2020.
[116] Q. Zhang and X. Fu, ''A neural network fuzzy energy management strategy for hybrid electric vehicles based on driving cycle recognition,'' *Appl. Sci.*, vol. 10, no. 2, p. 696, Jan. 2020. [Online]. Available: https://www.mdpi.com/2076-3417/10/2/696
[117] R. Zhang, J. Tao, and H. Zhou, ''Fuzzy optimal energy management for fuel cell and supercapacitor systems using neural network based driving pattern recognition,'' *IEEE Trans. Fuzzy Syst.*, vol. 27, no. 1, pp. 45–57, Jan. 2019.
[118] C. Wei, X. Wang, Y. Chen, H. Wu, and Y. Chen, ''Adaptive fuzzy power management strategy for extended-range electric logistics vehicles based on driving pattern recognition,'' *Actuators*, vol. 12, no. 11, p. 410, Nov. 2023. [Online]. Available: https://www.mdpi.com/2076-0825/12/11/410
[119] S. F. Da Silva, J. J. Eckert, F. C. Corrêa, F. L. Silva, L. C. A. Silva, and F. G. Dedini, ''Dual HESS electric vehicle powertrain design and fuzzy control based on multi-objective optimization to increase driving range and battery life cycle,'' *Appl. Energy*, vol. 324, Oct. 2022, Art. no. 119723. [Online]. Available: https://www.sciencedirect.com/science/article/pii/S0306261922010121
[120] K. Kakouche, T. Rekioua, S. Mezani, A. Oubelaid, D. Rekioua, V. Blazek, L. Prokop, S. Misak, M. Bajaj, and S. S. M. Ghoneim, ''Model predictive direct torque control and fuzzy logic energy management for multi power source electric vehicles,'' *Sensors*, vol. 22, no. 15, p. 5669, Jul. 2022. [Online]. Available: https://www.mdpi.com/1424-8220/22/15/5669
[121] M. Devi, S. S. Sreedhar P, S. G. Priya, M. Amutha, D. Kanagajothi, and R. K. Sri, ''Optimizing energy efficiency in electric vehicles through fuzzy logic and neural network algorithms,'' in *Proc. Int. Conf. Distrib. Comput. Optim. Techn. (ICDCOT)*, Mar. 2024, pp. 1–6.
[122] C. Pan, Y. Tao, L. Wang, H. Li, and J. Yang, ''Fuzzy energy management strategy for electric vehicle combining driving cycle construction and air-conditioning load identification,'' *Adv. Mech. Eng.*, vol. 13, no. 2, Feb. 2021, Art. no. 1687814021994381, doi: 10.1177/1687814021994381.
[123] Y. Cao, M. Yao, and X. Sun, ''An overview of modelling and energy management strategies for hybrid electric vehicles,'' *Appl. Sci.*, vol. 13, no. 10, p. 5947, May 2023.
[124] J.-P. Gao, G.-M.-G. Zhu, E. G. Strangas, and F.-C. Sun, ''Equivalent fuel consumption optimal control of a series hybrid electric vehicle,'' *Proc. Inst. Mech. Eng., D, J. Automobile Eng.*, vol. 223, no. 8, pp. 1003–1018, Aug. 2009.
[125] P. Polverino, I. Arsie, and C. Pianese, ''Optimal energy management for hybrid electric vehicles based on dynamic programming and receding horizon,'' *Energies*, vol. 14, no. 12, p. 3502, Jun. 2021.
[126] H. Zhou, Z. Yu, X. Wu, Z. Fan, X. Yin, and L. Zhou, ''Dynamic programming improved online fuzzy power distribution in a demonstration fuel cell hybrid bus,'' *Energy*, vol. 284, Dec. 2023, Art. no. 128549. [Online]. Available: https://www.sciencedirect.com/science/article/pii/S0360544223019436
[127] S. Wu, Z. Chen, S. Shen, G. Liu, Y. Liu, Y. Zhang, and G. Li, ''Co-optimization of velocity planning and energy management for intelligent plug-in hybrid electric vehicles based on adaptive dynamic programming,'' *IEEE Trans. Veh. Technol.*, vol. 73, no. 7, pp. 9812–9824, Jul. 2024.
[128] H. Lee, C. Song, N. Kim, and S. W. Cha, ''Comparative analysis of energy management strategies for HEV: Dynamic programming and reinforcement learning,'' *IEEE Access*, vol. 8, pp. 67112–67123, 2020.
[129] Y. Wang and X. Jiao, ''Dual heuristic dynamic programming based energy management control for hybrid electric vehicles,'' *Energies*, vol. 15, no. 9, p. 3235, Apr. 2022. [Online]. Available: https://www.mdpi.com/1996-1073/15/9/3235
[130] W. Tang, Y. Wang, X. Jiao, and L. Ren, ''Hierarchical energy management strategy based on adaptive dynamic programming for hybrid electric vehicles in car-following scenarios,'' *Energy*, vol. 265, Feb. 2023, Art. no. 126264. [Online]. Available: https://www.sciencedirect.com/science/article/pii/S0360544222031504
[131] J. Liu, Y. Chen, J. Zhan, and F. Shang, ''Heuristic dynamic programming based online energy management strategy for plug-in hybrid electric vehicles,'' *IEEE Trans. Veh. Technol.*, vol. 68, no. 5, pp. 4479–4493, May 2019.
[132] J. Liu, Y. Chen, W. Li, F. Shang, and J. Zhan, ''Hybrid-trip-model-based energy management of a PHEV with computation-optimized dynamic programming,'' *IEEE Trans. Veh. Technol.*, vol. 67, no. 1, pp. 338–353, Jan. 2018.
[133] K. Deb, A. Pratap, S. Agarwal, and T. Meyarivan, ''A fast and elitist multi-objective genetic algorithm: NSGA-II,'' *IEEE Trans. Evol. Comput.*, vol. 6, no. 2, pp. 182–197, Apr. 2002.
[134] H. Ma, Y. Zhang, S. Sun, T. Liu, and Y. Shan, ''A comprehensive survey on NSGA-II for multi-objective optimization and applications,'' *Artif. Intell. Rev.*, vol. 56, no. 12, pp. 15217–15270, Jun. 2023, doi: 10.1007/s10462-023-10526-z.
[135] X. Lü, Y. Wu, J. Lian, Y. Zhang, C. Chen, P. Wang, and L. Meng, ''Energy management of hybrid electric vehicles: A review of energy optimization of fuel cell hybrid power system based on genetic algorithm,'' *Energy Convers. Manage.*, vol. 205, Feb. 2020, Art. no. 112474. [Online]. Available: https://www.sciencedirect.com/science/article/pii/S0196890420300108
[136] S. Zhou, Z. Wen, X. Zhi, J. Jin, and S. Zhou, ''Genetic algorithm-based parameter optimization of energy management strategy and its analysis for fuel cell hybrid electric vehicles,'' in *Proc. SAE Tech. Paper Ser.*, Apr. 2019, pp. 1–12, doi: 10.4271/2019-01-0358.
[137] H. Yu, ''Fuzzy logic energy management strategy based on genetic algorithm for plug-in hybrid electric vehicles,'' in *Proc. 3rd Conf. Vehicle Control Intell. (CVCI)*, Sep. 2019, pp. 1–5.
[138] A. Mazouzi, N. Hadroug, W. Alayed, A. Hafaifa, A. Iratni, and A. Kouzou, ''Comprehensive optimization of fuzzy logic-based energy management system for fuel-cell hybrid electric vehicle using genetic algorithm,'' *Int. J. Hydrogen Energy*, vol. 81, pp. 889–905, Sep. 2024. [Online]. Available: https://www.sciencedirect.com/science/article/pii/S0360319924029112
[139] R. Gao, J. Tao, J. Zhang, L. Ma, and M. Xu, ''NSGA-III-SD based fuzzy energy management system optimization for lithium battery/supercapacitor HEV,'' *Appl. Soft Comput.*, vol. 142, Jul. 2023, Art. no. 110280. [Online]. Available: https://www.sciencedirect.com/science/article/pii/S1568494623002983
[140] Y. Li, Y. Luo, and X. Lu, ''PHEV energy management optimization based on multi-island genetic algorithm,'' Wuhan Univ. Technol., Wuhan, Hubei, China, Paper 2022-01-0739, 2022, doi: 10.4271/2022-01-0739.
[141] Y. Farajpour, H. Chaoui, and S. Kelouwani, ''Machine learning-enhanced aging-aware energy management strategy for electric vehicles,'' in *Proc. IEEE Vehicle Power Propuls. Conf. (VPPC)*, Oct. 2024, pp. 1–6.
[142] T. Liu, X. Tang, H. Wang, H. Yu, and X. Hu, ''Adaptive hierarchical energy management design for a plug-in hybrid electric vehicle,'' *IEEE Trans. Veh. Technol.*, vol. 68, no. 12, pp. 11513–11522, Dec. 2019.
[143] J. K. Maherchandani, N. Jain, and N. K. Garg, ''Optimal genetic algorithm-pontryagin minimum principle approach for equivalent fuel consumption minimization in hybrid electric vehicle,'' *J. Electr. Syst.*, vol. 17, no. 2, p. 182, 2021.
[144] S. J. Ankar and K. P. Pinkymol, ''Optimal sizing and energy management of electric vehicle hybrid energy storage systems with multi-objective optimization criterion,'' *IEEE Trans. Veh. Technol.*, vol. 73, no. 8, pp. 11082–11096, Aug. 2024.
[145] H. H. Eldeeb, A. T. Elsayed, C. R. Lashway, and O. Mohammed, ''Hybrid energy storage sizing and power splitting optimization for plug-in electric vehicles,'' *IEEE Trans. Ind. Appl.*, vol. 55, no. 3, pp. 2252–2262, May 2019.

[146] C. Wang, R. Liu, and A. Tang, "Energy management strategy of hybrid energy storage system for electric vehicles based on genetic algorithm optimization and temperature effect," *J. Energy Storage*, vol. 51, Jul. 2022, Art. no. 104314. [Online]. Available: https://www.sciencedirect.com/science/article/pii/S2352152X22003395
[147] L. Fan, Y. Wang, H. Wei, Y. Zhang, P. Zheng, T. Huang, and W. Li, "A GA-based online real-time optimized energy management strategy for plug-in hybrid electric vehicles," *Energy*, vol. 241, Feb. 2022, Art. no. 122811. [Online]. Available: https://www.sciencedirect.com/science/article/pii/S0360544221030607
[148] A. G. Gad, "Particle swarm optimization algorithm and its applications: A systematic review," *Arch. Comput. Methods Eng.*, vol. 29, no. 5, pp. 2531–2561, Apr. 2022, doi: 10.1007/s11831-021-09694-4.
[149] T. M. Shami, A. A. El-Saleh, M. Alswaitti, Q. Al-Tashi, M. A. Summakieh, and S. Mirjalili, "Particle swarm optimization: A comprehensive survey," *IEEE Access*, vol. 10, pp. 10031–10061, 2022.
[150] J. Gim, M. Kim, and C. Ahn, "Energy management control strategy for saving trip costs of fuel cell/battery electric vehicles," *Energies*, vol. 15, no. 6, p. 2131, Mar. 2022. [Online]. Available: https://www.mdpi.com/1996-1073/15/6/2131
[151] H. Gu, B. Yin, Y. Yu, and Y. Sun, "Energy management strategy considering fuel economy and life of fuel cell for fuel cell electric vehicles," *J. Energy Eng.*, vol. 149, no. 1, Feb. 2023, Art. no. 04022054, doi: 10.1061/(asce)ey.1943-7897.0000871.
[152] S. Ankar and K. P. Pinkymol, "Optimal energy management strategy for electric vehicles based on fuzzy logic controller integrated with PSO-NM optimization approach," in *Proc. IEEE Int. Conf. Power Electron., Smart Grid, Renew. Energy (PESGRE)*, Dec. 2023, pp. 1–6.
[153] B. Tifour, M. Boukhnifer, A. Hafaifa, and C. Tanougast, "An optimal fuzzy logic control for a fuel cell hybrid electric vehicle based on particle swarm and advisor," in *Proc. IEEE Green Technol. Conf. (GreenTech)*, Apr. 2021, pp. 148–154.
[154] S. Abd-Elhaleem, W. Shoeib, and A. A. Sobaih, "Improved power management under uncertain driving conditions for plug-in hybrid electric vehicles via intelligent controller," *IEEE Trans. Intell. Transp. Syst.*, vol. 24, no. 12, pp. 13698–13712, Dec. 2023.
[155] O. Perez-Dávila and R. Álvarez Fernández, "Optimization algorithm applied to extended range fuel cell hybrid vehicles. Contribution to road transport decarbonization," *Energy*, vol. 267, Mar. 2023, Art. no. 126519. [Online]. Available: https://www.sciencedirect.com/science/article/pii/S0360544222034053
[156] I. M. Abdelqawee, A. W. Emam, M. S. ElBages, and M. A. Ebrahim, "An improved energy management strategy for fuel cell/battery/supercapacitor system using a novel hybrid jellyfish/particle swarm/BAT optimizers," *J. Energy Storage*, vol. 57, Jan. 2023, Art. no. 106276. [Online]. Available: https://www.sciencedirect.com/science/article/pii/S2352152X22022654
[157] J. Omakor, M. Alzayed, and H. Chaoui, "Particle swarm-optimized fuzzy logic energy management of hybrid energy storage in electric vehicles," *Energies*, vol. 17, no. 9, p. 2163, Apr. 2024. [Online]. Available: https://www.mdpi.com/1996-1073/17/9/2163
[158] M. Spano, P. G. Anselma, D. A. Misul, and G. Belingardi, "Exploitation of a particle swarm optimization algorithm for designing a lightweight parallel hybrid electric vehicle," *Appl. Sci.*, vol. 11, no. 15, p. 6833, Jul. 2021. [Online]. Available: https://www.mdpi.com/2076-3417/11/15/6833
[159] A. Djouahi, B. Negrou, B. Rouabah, A. Mahboub, and M. M. Samy, "Optimal sizing of battery and super-capacitor based on the MOPSO technique via a new FC-HEV application," *Energies*, vol. 16, no. 9, p. 3902, May 2023. [Online]. Available: https://www.mdpi.com/1996-1073/16/9/3902
[160] Z. Yuan, L. Teng, S. Fengchun, and H. Peng, "Comparative study of dynamic programming and Pontryagin's minimum principle on energy management for a parallel hybrid electric vehicle," *Energies*, vol. 6, no. 4, pp. 2305–2318, Apr. 2013. [Online]. Available: https://www.mdpi.com/1996-1073/6/4/2305
[161] S. Xie, X. Hu, Z. Xin, and J. Brighton, "Pontryagin's minimum principle based model predictive control of energy management for a plug-in hybrid electric bus," *Appl. Energy*, vol. 236, pp. 893–905, Feb. 2019. [Online]. Available: https://www.sciencedirect.com/science/article/pii/S0306261918318518
[162] X. Liu, H. Guo, X. Cheng, J. Du, and J. Ma, "A robust design of the model-free-adaptive-control-based energy management for plug-in hybrid electric vehicle," *Energies*, vol. 15, no. 20, p. 7467, Oct. 2022. [Online]. Available: https://www.mdpi.com/1996-1073/15/20/7467
[163] P. Nambisan and M. Khanra, "Optimal power-split of hybrid energy storage system using Pontryagin's minimum principle and deep reinforcement learning approach for electric vehicle application," *Eng. Appl. Artif. Intell.*, vol. 135, Sep. 2024, Art. no. 108769. [Online]. Available: https://www.sciencedirect.com/science/article/pii/S0952197624009278
[164] K. Song, X. Wang, F. Li, M. Sorrentino, and B. Zheng, "Pontryagin's minimum principle-based real-time energy management strategy for fuel cell hybrid electric vehicle considering both fuel economy and power source durability," *Energy*, vol. 205, Aug. 2020, Art. no. 118064.
[165] A. Upadhyaya and C. Mahanta, "Optimal online energy management system for battery-supercapacitor electric vehicles using velocity prediction and Pontryagin's minimum principle," *IEEE Trans. Veh. Technol.*, vol. 74, no. 2, pp. 2652–2666, Feb. 2025.
[166] X. Li, Y. Wang, D. Yang, and Z. Chen, "Adaptive energy management strategy for fuel cell/battery hybrid vehicles using Pontryagin's minimal principle," *J. Power Sources*, vol. 440, Nov. 2019, Art. no. 227105. [Online]. Available: https://www.sciencedirect.com/science/article/pii/S0378775319310985
[167] C. T. P. Nguyen, B.-H. Nguyen, J. P. F. Trovão, and M. C. Ta, "Optimal energy management strategy based on driving pattern recognition for a dual-motor dual-source electric vehicle," *IEEE Trans. Veh. Technol.*, vol. 73, no. 4, pp. 4554–4566, Apr. 2024.
[168] N. Kim, J. Jeong, and C. Zheng, "Adaptive energy management strategy for plug-in hybrid electric vehicles with Pontryagin's minimum principle based on daily driving patterns," *Int. J. Precis. Eng. Manuf.-Green Technol.*, vol. 6, no. 3, pp. 539–548, Mar. 2019, doi: 10.1007/s40684-019-00046-z.
[169] M. Maschler, S. Zamir, and E. Solan, *Game Theory*. Cambridge, U.K.: Cambridge Univ. Press, 2020.
[170] E. N. Barron, *Game Theory: An Introduction*. Hoboken, NJ, USA: Wiley, 2024.
[171] S. Ruan, Y. Ma, Z. Wei, C. Zhang, and C. Xiang, "Data-driven cooperative differential game based energy management strategy for hybrid electric propulsion system of a flying car," *IEEE Trans. Intell. Transp. Syst.*, vol. 25, no. 10, pp. 14770–14784, Oct. 2024.
[172] C. Li, X. Sun, M. Zha, C. Yang, W. Wang, and J. Su, "IGBT thermal model-based predictive energy management strategy for plug-in hybrid electric vehicles using game theory," *IEEE Trans. Transport. Electrific.*, vol. 9, no. 2, pp. 3268–3281, Jun. 2023.
[173] R. Ghaderi, M. Kandidayeni, M. Soleymani, L. Boulon, and J. P. F. Trovão, "Online health-conscious energy management strategy for a hybrid multi-stack fuel cell vehicle based on game theory," *IEEE Trans. Veh. Technol.*, vol. 71, no. 6, pp. 5704–5714, Jun. 2022.
[174] W. Liu, C. Yang, W. Wang, Y. Ma, L. Yang, and X. Du, "Efficient energy management for a plug-in hybrid electric vehicle considering motor current alert mechanism," *J. Cleaner Prod.*, vol. 406, Jun. 2023, Art. no. 137072. [Online]. Available: https://www.sciencedirect.com/science/article/pii/S0959652623012301
[175] Z. Sun, Y. Wang, Z. Chen, and X. Li, "Min-max game based energy management strategy for fuel cell/supercapacitor hybrid electric vehicles," *Appl. Energy*, vol. 267, Jun. 2020, Art. no. 115086. [Online]. Available: https://www.sciencedirect.com/science/article/pii/S0306261920305985
[176] W. Zou, J. Li, Q. Yang, X. Wan, Y. He, and H. Lan, "A real-time energy management approach with fuel cell and battery competition-synergy control for the fuel cell vehicle," *Appl. Energy*, vol. 334, Mar. 2023, Art. no. 120667. [Online]. Available: https://www.sciencedirect.com/science/article/pii/S0306261923000314
[177] Y. Huang, J. Chen, L. Huang, and Q. Zhu, "Dynamic games for secure and resilient control system design," *Nat. Sci. Rev.*, vol. 7, no. 7, pp. 1125–1141, Jul. 2020.
[178] Z. Chen, C. C. Mi, B. Xia, and C. You, "Energy management of power-split plug-in hybrid electric vehicles based on simulated annealing and Pontryagin's minimum principle," *J. Power Sources*, vol. 272, pp. 160–168, Dec. 2014. [Online]. Available: https://www.sciencedirect.com/science/article/pii/S0378775314013123
[179] C. Yang, X. Wang, J. Zhao, and L. He, "Optimization of the energy management system in hybrid electric vehicles considering cabin temperature," *Appl. Thermal Eng.*, vol. 242, Apr. 2024, Art. no. 122504. [Online]. Available: https://www.sciencedirect.com/science/article/pii/S1359431124001728
[180] F. Machado, J. P. F. Trovão, and C. H. Antunes, "Effectiveness of supercapacitors in pure electric vehicles using a hybrid metaheuristic approach," *IEEE Trans. Veh. Technol.*, vol. 65, no. 1, pp. 29–36, Jan. 2016.

[181] B. Wang, J. Xu, B. Cao, and B. Ning, "Adaptive mode switch strategy based on simulated annealing optimization of a multi-mode hybrid energy storage system for electric vehicles," *Appl. Energy*, vol. 194, pp. 596–608, May 2017. [Online]. Available: https://www.sciencedirect.com/science/article/pii/S0306261916306249
[182] P. M. Pardalos and T. D. Mavridou, *Simulated Annealing*. Cham, Switzerland: Springer, 2024, pp. 1–3, doi: 10.1007/978-3-030-54621-2.
[183] Q. Zhang, L. Song, Y. Zeng, Y. Liu, S. Liu, and N. Wang, "Real-time power optimization strategy for fuel cell ships based on improved genetic simulated annealing algorithm," *Electr. Power Syst. Res.*, vol. 245, Aug. 2025, Art. no. 111647.
[184] D. Delahaye, S. Chaimatanan, and M. Mongeau, *Simulated Annealing: From Basics to Applications*. Cham, Switzerland: Springer, Sep. 2018, pp. 1–35, doi: 10.1007/978-3-319-91086-4.
[185] H. Karloff, *Linear Programming*. Cham, Switzerland: Springer, 2008.
[186] A. B. Siddique and H. A. Gabbar, "Adaptive mixed-integer linear programming-based energy management system of fast charging station with nuclear–renewable hybrid energy system," *Energies*, vol. 16, no. 2, p. 685, Jan. 2023. [Online]. Available: https://www.mdpi.com/1996-1073/16/2/685
[187] S. Umetani, Y. Fukushima, and H. Morita, "A linear programming based heuristic algorithm for charge and discharge scheduling of electric vehicles in a building energy management system," *Omega*, vol. 67, pp. 115–122, Mar. 2017. [Online]. Available: https://www.sciencedirect.com/science/article/pii/S0305048316301189
[188] S. Pirouzi, M. A. Latify, and G. R. Yousefi, "Conjugate active and reactive power management in a smart distribution network through electric vehicles: A mixed integer-linear programming model," *Sustain. Energy, Grids Netw.*, vol. 22, Jun. 2020, Art. no. 100344. [Online]. Available: https://www.sciencedirect.com/science/article/pii/S2352467719304643
[189] A. K. Venkitaraman and V. S. R. Kosuru, "Electric vehicle charging network optimization using multi-variable linear programming and Bayesian principles," in *Proc. 3rd Int. Conf. Smart Technol. Comput., Electr. Electron. (ICSTCEE)*, Dec. 2022, pp. 1–5.
[190] J. Wu, N. Zhang, D. Tan, J. Chang, and W. Shi, "A robust online energy management strategy for fuel cell/battery hybrid electric vehicles," *Int. J. Hydrogen Energy*, vol. 45, no. 27, pp. 14093–14107, May 2020. [Online]. Available: https://www.sciencedirect.com/science/article/pii/S0360319920310284
[191] T. Ghandriz, B. Jacobson, N. Murgovski, P. Nilsson, and L. Laine, "Real-time predictive energy management of hybrid electric heavy vehicles by sequential programming," *IEEE Trans. Veh. Technol.*, vol. 70, no. 5, pp. 4113–4128, May 2021.
[192] J. Feng, Z. Han, Z. Wu, and M. Li, "A dynamic ECMS method considering vehicle speed pattern and minimum engine operation time for a range-extender electric vehicle (Jan. 2022)," *IEEE Trans. Veh. Technol.*, vol. 71, no. 5, pp. 4788–4800, May 2022.
[193] S. Li, L. Chu, J. Hu, S. Pu, J. Li, Z. Hou, and W. Sun, "A novel A-ECMS energy management strategy based on dragonfly algorithm for plug-in FCEVs," *Sensors*, vol. 23, no. 3, p. 1192, Jan. 2023. [Online]. Available: https://www.mdpi.com/1424-8220/23/3/1192
[194] K. Choi, J. Byun, S. Lee, and I. G. Jang, "Adaptive equivalent consumption minimization strategy (A-ECMS) for the HEVs with a near-optimal equivalent factor considering driving conditions," *IEEE Trans. Veh. Technol.*, vol. 71, no. 3, pp. 2538–2549, Mar. 2022.
[195] M. Moghadari, M. Kandidayeni, L. Boulon, and H. Chaoui, "Operating cost comparison of a single-stack and a multi-stack hybrid fuel cell vehicle through an online hierarchical strategy," *IEEE Trans. Veh. Technol.*, vol. 72, no. 1, pp. 267–279, Jan. 2023.
[196] X. Zhang, L. Yang, X. Sun, Z. Jin, and M. Xue, "ECMS-MPC energy management strategy for plug-in hybrid electric buses considering motor temperature rise effect," *IEEE Trans. Transport. Electrific.*, vol. 9, no. 1, pp. 210–221, Mar. 2023.
[197] X. Sun, Z. Chen, S. Han, X. Tian, Z. Jin, Y. Cao, and M. Xue, "Adaptive real-time ECMS with equivalent factor optimization for plug-in hybrid electric buses," *Energy*, vol. 304, Jan. 2024, Art. no. 132014. [Online]. Available: https://www.sciencedirect.com/science/article/pii/S0360544224017882
[198] X. Sun, M. Xue, Y. Cai, X. Tian, Z. Jin, and L. Chen, "Adaptive ECMS based on EF optimization by model predictive control for plug-in hybrid electric buses," *IEEE Trans. Transport. Electrific.*, vol. 9, no. 2, pp. 2153–2163, Jun. 2023.
[199] X. Sun, Z. Jin, M. Xue, and X. Tian, "Adaptive ECMS with gear shift control by grey wolf optimization algorithm and neural network for plug-in hybrid electric buses," *IEEE Trans. Ind. Electron.*, vol. 71, no. 1, pp. 667–677, Jan. 2024.
[200] G. R. Guercioni, E. Galvagno, A. Tota, and A. Vigliani, "Adaptive equivalent consumption minimization strategy with rule-based gear selection for the energy management of hybrid electric vehicles equipped with dual clutch transmissions," *IEEE Access*, vol. 8, pp. 190017–190038, 2020.
[201] B. Gao, B. Yang, H. Zhang, X. Liu, S. Si, B. Zhao, and T. Zhang, "Adaptive real-time ECMS based on optimal SOC path following for flywheel hybrid electric vehicle," 2024. [Online]. Available: https://ssrn.com/abstract=4974140 or http://dx.doi.org/10.2139/ssrn.4974140
[202] T. Abdelhalim, L. Kouider, H. Rezk, R. Abdelkader, and H. M. Amine, "Optimal energy management based equivalent hydrogen consumption minimization strategy of DC microgrid," *Int. J. Hydrogen Energy*, vol. 83, pp. 355–366, Sep. 2024. [Online]. Available: https://www.sciencedirect.com/science/article/pii/S0360319924032464
[203] X. Chen, G. Hu, F. Guo, M. Ye, and J. Huang, "Switched energy management strategy for fuel cell hybrid vehicle based on switch network," *Energies*, vol. 13, no. 1, p. 247, 2020.
[204] C. Lin, J. Yi, X. Yu, and H. Liu, "Gearshift control in engagement process of dual-motor coaxial propulsion system for electric bus," *IEEE Access*, vol. 10, pp. 43351–43366, 2022.
[205] B. Yang, J. Wang, X. Zhang, J. Wang, H. Shu, S. Li, T. He, C. Lan, and T. Yu, "Applications of battery/supercapacitor hybrid energy storage systems for electric vehicles using perturbation observer based robust control," *J. Power Sources*, vol. 448, Feb. 2020, Art. no. 227444. [Online]. Available: https://www.sciencedirect.com/science/article/pii/S0378775319314375
[206] M. Babazadeh and H. Karimi, "A robust two-degree-of-freedom control strategy for an islanded microgrid," *IEEE Trans. Power Del.*, vol. 28, no. 3, pp. 1339–1347, Jul. 2013.
[207] J. Morales-Morales, I. Cervantes, and U. Cano-Castillo, "On the design of robust energy management strategies for FCHEV," *IEEE Trans. Veh. Technol.*, vol. 64, no. 5, pp. 1716–1728, May 2015.
[208] P. Muthyala, M. Mayank, B. Ünver, S. E. Han, B. Uzunoğlu, A. B. Kaydeci, F. Toğuş, J. Schaub, L. Virnich, and S. Pischinger, "Comparative study of real-time A-ECMS and rule-based energy management strategies in long haul heavy-duty PHEVs," *Energy Convers. Manag., X*, vol. 23, Jul. 2024, Art. no. 100679.
[209] S. N. Motapon, Louis-A. Dessaint, and K. Al-Haddad, "A robust H_2-consumption-minimization-based energy management strategy for a fuel cell hybrid emergency power system of more electric aircraft," *IEEE Trans. Ind. Electron.*, vol. 61, no. 11, pp. 6148–6156, Nov. 2014.
[210] R. Koubaa, S. Bacha, M. Smaoui, and L. Krichen, "Robust optimization based energy management of a fuel cell/ultra-capacitor hybrid electric vehicle under uncertainty," *Energy*, vol. 200, Jun. 2020, Art. no. 117530.
[211] J. Arroyo, C. Manna, F. Spiessens, and L. Helsen, "Reinforced model predictive control (RL-MPC) for building energy management," *Appl. Energy*, vol. 309, Mar. 2022, Art. no. 118346. [Online]. Available: https://www.sciencedirect.com/science/article/pii/S0306261921015932
[212] L. Guo, B. Yang, and J. Ye, "Predictive energy management for dual-motor BEVs considering temperature-dependent traction inverter loss," *IEEE Trans. Transport. Electrific.*, vol. 8, no. 1, pp. 1501–1515, Mar. 2022.
[213] E. Bøhn, S. Gros, S. Moe, and T. A. Johansen, "Reinforcement learning of the prediction horizon in model predictive control," *IFAC-PapersOnLine*, vol. 54, no. 6, pp. 314–320, 2021. [Online]. Available: https://www.sciencedirect.com/science/article/pii/S2405896321013380
[214] E. González-Rivera, P. García-Triviño, R. Sarrias-Mena, J. P. Torreglosa, F. Jurado, and L. M. Fernández-Ramírez, "Model predictive control-based optimized operation of a hybrid charging station for electric vehicles," *IEEE Access*, vol. 9, pp. 115766–115776, 2021.
[215] H. Chen, R. Xiong, C. Lin, and W. Shen, "Model predictive control based real-time energy management for hybrid energy storage system," *CSEE J. Power Energy Syst.*, vol. 7, no. 4, pp. 862–874, Jul. 2021.
[216] M. Moghadari, M. Kandidayeni, L. Boulon, and H. Chaoui, "Predictive health-conscious energy management strategy of a hybrid multi-stack fuel cell vehicle," *IEEE Trans. Veh. Technol.*, vol. 74, no. 4, pp. 5542–5557, Apr. 2025.
[217] S. Shen, S. Gao, Y. Liu, Y. Zhang, J. Shen, Z. Chen, and Z. Lei, "Real-time energy management for plug-in hybrid electric vehicles via incorporating double-delay Q-learning and model prediction control," *IEEE Access*, vol. 10, pp. 131076–131089, 2022.

[218] M. R. Larijani, S. H. Kia, M. Zolghadri, A. E. Hajjaji, and A. Taghavipour, "Linear parameter-varying model predictive control for intelligent energy management in battery/supercapacitor electric vehicles," *IEEE Access*, vol. 12, pp. 51026–51040, 2024.
[219] F. M. Ali and N. H. Abbas, "Energy management strategy for hybrid electric vehicles based on adaptive equivalent ratio-model predictive control," *Electricity*, vol. 5, no. 4, pp. 972–990, Dec. 2024. [Online]. Available: https://www.mdpi.com/2673-4826/5/4/49
[220] Y. Wu, Z. Huang, H. Hofmann, Y. Liu, J. Huang, X. Hu, J. Peng, and Z. Song, "Hierarchical predictive control for electric vehicles with hybrid energy storage system under vehicle-following scenarios," *Energy*, vol. 251, Jul. 2022, Art. no. 123774. [Online]. Available: https://www.sciencedirect.com/science/article/pii/S0360544222006776
[221] Z. Hou, L. Chu, W. Du, J. Hu, J. Jiang, J. Yang, and Y. Zhang, "A novel dual-model MPC-based energy management strategy for fuel cell electric vehicle," *IEEE Trans. Transport. Electrific.*, vol. 10, no. 4, pp. 8585–8604, Dec. 2024.
[222] T. Zhao, C. Li, Z. Zang, and Y. Wu, "Chebyshev–Legendre pseudo-spectral method for the generalised Burgers–Fisher equation," *Appl. Math. Model.*, vol. 36, no. 3, pp. 1046–1056, Mar. 2012.
[223] H. He, D. Liu, X. Lu, and J. Xu, "ECO driving control for intelligent electric vehicle with real-time energy," *Electronics*, vol. 10, no. 21, p. 2613, Oct. 2021.
[224] J. Wu, Y. Zou, X. Zhang, G. Du, G. Du, and R. Zou, "A hierarchical energy management for hybrid electric tracked vehicle considering velocity planning with pseudospectral method," *IEEE Trans. Transport. Electrific.*, vol. 6, no. 2, pp. 703–716, Jun. 2020.
[225] F. Gao, Y. Han, S. Eben Li, S. Xu, and D. Dang, "Accurate pseudospectral optimization of nonlinear model predictive control for high-performance motion planning," *IEEE Trans. Intell. Vehicles*, vol. 8, no. 2, pp. 1034–1045, Feb. 2023.
[226] K. Zhao, K. He, Z. Liang, and M. Mai, "Global optimization-based energy management strategy for series–parallel hybrid electric vehicles using multi-objective optimization algorithm," *Automot. Innov.*, vol. 6, no. 3, pp. 492–507, Aug. 2023.
[227] W. Wang, J. Li, and F. Sun, "Pseudo-spectral optimisation of smooth shift control strategy for a two-speed transmission for electric vehicles," *Vehicle Syst. Dyn.*, vol. 58, no. 4, pp. 604–629, Mar. 2019, doi: 10.1080/00423114.2019.1594316.
[228] D. Zhang, L. Hu, Q. Tian, and C. Zou, "A research of different energy management strategies of lithium-ion battery-ultracapacitor hybrid energy storage system," in *Proc. Int. Conf. Adv. Construction Machinery Vehicle Eng.*, 2024, pp. 1091–1102.
[229] S. S. Multani, "Pseudospectral collocation method based energy management scheme for a parallel P2 hybrid electric vehicle," M.S. thesis, Dept. Mech. Aerosp. Eng., Ohio State Univ., Columbus, OH, USA, 2020.
[230] S. Ruan, Y. Ma, F. Qi, and H. Zhang, "Segmentation trajectory optimization of nonlinear power components in series HEV," in *Proc. IEEE 8th Data Driven Control Learn. Syst. Conf. (DDCLS)*, May 2019, pp. 800–807.
[231] K. Zhao, J. Bei, Y. Liu, and Z. Liang, "Development of global optimization algorithm for series-parallel PHEV energy management strategy based on Radau pseudospectral knotting method," *Energies*, vol. 12, no. 17, p. 3268, Aug. 2019. [Online]. Available: https://www.mdpi.com/1996-1073/12/17/3268
[232] H. Maghfiroh, O. Wahyunggoro, and A. I. Cahyadi, "Low pass filter as energy management for hybrid energy storage of electric vehicle: A survey," *Automot. Experiences*, vol. 6, no. 3, pp. 466–484, Nov. 2023, doi: 10.31603/ae.9398.
[233] C. Wang, R. Xiong, H. He, Y. Zhang, and W. Shen, "Comparison of decomposition levels for wavelet transform based energy management in a plug-in hybrid electric vehicle," *J. Cleaner Prod.*, vol. 210, pp. 1085–1097, Feb. 2019. [Online]. Available: https://www.sciencedirect.com/science/article/pii/S0959652618334851
[234] Z. Fu, L. Zhu, F. Tao, P. Si, and L. Sun, "Optimization based energy management strategy for fuel cell/battery/ultracapacitor hybrid vehicle considering fuel economy and fuel cell lifespan," *Int. J. Hydrogen Energy*, vol. 45, no. 15, pp. 8875–8886, Mar. 2020. [Online]. Available: https://www.sciencedirect.com/science/article/pii/S0360319920300756
[235] F. Tao, L. Zhu, Z. Fu, P. Si, and L. Sun, "Frequency decoupling-based energy management strategy for fuel cell/battery/ultracapacitor hybrid vehicle using fuzzy control method," *IEEE Access*, vol. 8, pp. 166491–166502, 2020.
[236] B. Samia, A. Toufik, and H. Kamel-Eddine, "Frequency splitting approach using wavelet for energy management strategies in fuel cell ultra-capacitor hybrid system," *J. Meas. Eng.*, vol. 10, no. 1, pp. 15–26, Feb. 2022, doi: 10.21595/jme.2022.22233.
[237] A. Badji, D. O. Abdeslam, M. Becherif, F. Eltoumi, and N. Benamrouche, "Analyze and evaluate of energy management system for fuel cell electric vehicle based on frequency splitting," *Math. Comput. Simul.*, vol. 167, pp. 65–77, Jan. 2020. [Online]. Available: https://www.sciencedirect.com/science/article/pii/S0378475419300722
[238] A. Latorre, W. Martinez, and C. A. Cortes, "Average current control with internal model control and real-time frequency decoupling for hybrid energy storage systems in microgrids," *J. Modern Power Syst. Clean Energy*, vol. 11, no. 2, pp. 511–522, 2023.
[239] Y. Zhou, F. Yang, Y. Guo, B. Chen, W. Jiang, R. Ma, and F. Gao, "Adaptive energy management for fuel cell heavy trucks based on wavelet neural network speed predictor and real-time weight distribution," *IEEE Trans. Transport. Electrific.*, vol. 11, no. 1, pp. 5069–5083, Feb. 2025.
[240] H. Li, J. Kang, and C. Li, "Energy management strategy based on reinforcement learning and frequency decoupling for fuel cell hybrid powertrain," *Energies*, vol. 17, no. 8, p. 1929, Apr. 2024. [Online]. Available: https://www.mdpi.com/1996-1073/17/8/1929
[241] N. Ali, Z. Liu, H. Armghan, and A. Armghan, "Double integral sliding mode controller for wirelessly charging of fuel cell-battery-super capacitor based hybrid electric vehicle," *J. Energy Storage*, vol. 51, Jul. 2022, Art. no. 104288. [Online]. Available: https://www.sciencedirect.com/science/article/pii/S2352152X22003140
[242] G. H. Eddine, B. Said, A. Houari, A. Dieroui, and T. Mesbahi, "Integral sliding mode control of synchronous reluctance machine based electric vehicle powered by battery/supercapacitor hybrid source," in *Proc. 19th Int. Multi-Conference Syst., Signals Devices (SSD)*, May 2022, pp. 2133–2138.
[243] O. A. A. Mohammed, L. Peng, G. H. A. Hamid, A. M. Ishag, and M. A. A. Abdalla, "Effective energy management strategy with model-free DC-bus voltage control for fuel cell/battery/supercapacitor hybrid electric vehicle system," *Machines*, vol. 11, no. 10, p. 944, Oct. 2023. [Online]. Available: https://www.mdpi.com/2075-1702/11/10/944
[244] P. K. Prasad and P. Ramesh Kumar, *A Higher-Order Sliding Mode Observer for SOC Estimation With Higher-Order Sliding Mode Control in Hybrid Electric Vehicle*. Singapore: Springer, 2023, pp. 481–500, doi: 10.1007/978-981-19-8086-2.
[245] A. Hamlat, M. Sekour, M. Mankour, M. Yahiaoui, M. Khalfaoui, and B. Brahmi, "Advanced power management and control using fuzzy backstepping super-twisting controls designed for fuel cell supercapacitors hybrid power systems for traction applications," *J. Control, Autom. Electr. Syst.*, vol. 34, no. 5, pp. 996–1012, Jun. 2023, doi: 10.1007/s40313-023-01014-4.
[246] S. Ullah, R. Hayat, K. Zeb, A. Rasheed, and S. M. Muyeen, "Super-twisting sliding mode controller for energy storage system of a novel multisource hybrid electric vehicle: Simulation and hardware validation," *Int. J. Hydrogen Energy*, vol. 71, pp. 952–963, Jun. 2024. [Online]. Available: https://www.sciencedirect.com/science/article/pii/S0360319924020238
[247] J. Ding, X. Jiao, and J. Zhang, "Robust adaptive control for hybrid electric vehicles using sliding mode control," *Proc. Inst. Mech. Eng., I, J. Syst. Control Eng.*, vol. 238, no. 2, pp. 272–287, Aug. 2023, doi: 10.1177/09596518231188496.
[248] B. Wang, H. Fan, Z. Li, G. Feng, and Y. Han, "An ultra-local model-based control method with the bus voltage supervisor for hybrid energy storage system in electric vehicles," *IEEE J. Emerg. Sel. Topics Power Electron.*, vol. 12, no. 1, pp. 461–471, Feb. 2024.
[249] K. Ariyur and M. Krstic, *Real-Time Optimization by Extremum-Seeking Control*. Nashville, TN, USA: Wiley, 2003.
[250] S. Li, Y. Qiu, L. Yin, R. Li, R. Gan, Q. Li, and Y. Huangfu, "Net power optimization based on extremum search and model-free adaptive control of PEMFC power generation system for high altitude," *IEEE Trans. Transport. Electrific.*, vol. 9, no. 4, pp. 5151–5164, Dec. 2023.
[251] Q. Li, T. Wang, S. Li, W. Chen, H. Liu, E. Breaz, and F. Gao, "Online extremum seeking-based optimized energy management strategy for hybrid electric tram considering fuel cell degradation," *Appl. Energy*, vol. 285, Mar. 2021, Art. no. 116505. [Online]. Available: https://www.sciencedirect.com/science/article/pii/S0306261921000635

[252] A. Recalde, R. Cajo, W. Velasquez, and M. S. Alvarez-Alvarado, "Machine learning and optimization in energy management systems for plug-in hybrid electric vehicles: A comprehensive review," *Energies*, vol. 17, no. 13, p. 3059, Jun. 2024. [Online]. Available: https://www.mdpi.com/1996-1073/17/13/3059
[253] A. H. Ganesh and B. Xu, "A review of reinforcement learning based energy management systems for electrified powertrains: Progress, challenge, and potential solution," *Renew. Sustain. Energy Rev.*, vol. 154, Feb. 2022, Art. no. 111833. [Online]. Available: https://www.sciencedirect.com/science/article/pii/S136403212101100X
[254] D. A. Pisner and D. M. Schnyer, "Support vector machine," in *Machine Learning*. New York, NY, USA: Academic, 2020, ch. 6, pp. 101–121. [Online]. Available: https://www.sciencedirect.com/science/article/pii/B9780128157398000067
[255] R. S. Sutton and A. G. Barto, *Reinforcement Learning: An Introduction* (Adaptive Computation and Machine Learning Series). Cambridge, MA, USA: Bradford Books, Nov. 2018.
[256] C. Zheng, D. Zhang, Y. Xiao, and W. Li, "Reinforcement learning-based energy management strategies of fuel cell hybrid vehicles with multi-objective control," *J. Power Sources*, vol. 543, Sep. 2022, Art. no. 231841. [Online]. Available: https://www.sciencedirect.com/science/article/pii/S0378775322008308
[257] Y. Li, H. He, J. Peng, and H. Wang, "Deep reinforcement learning-based energy management for a series hybrid electric vehicle enabled by history cumulative trip information," *IEEE Trans. Veh. Technol.*, vol. 68, no. 8, pp. 7416–7430, Aug. 2019.
[258] H. Zhang, J. Peng, H. Dong, H. Tan, and F. Ding, "Hierarchical reinforcement learning based energy management strategy of plug-in hybrid electric vehicle for ecological car-following process," *Appl. Energy*, vol. 333, Mar. 2023, Art. no. 120599. [Online]. Available: https://www.sciencedirect.com/science/article/pii/S0306261922018566
[259] Z. Wang, H. He, J. Peng, W. Chen, C. Wu, Y. Fan, and J. Zhou, "A comparative study of deep reinforcement learning based energy management strategy for hybrid electric vehicle," *Energy Convers. Manage.*, vol. 293, Feb. 2023, Art. no. 117442. [Online]. Available: https://www.sciencedirect.com/science/article/pii/S0196890423007884
[260] Z. E. Liu, Y. Li, Q. Zhou, B. Shuai, M. Hua, H. Xu, L. Xu, G. Tan, and Y. Li, "Real-time energy management for HEV combining naturalistic driving data and deep reinforcement learning with high generalization," *Appl. Energy*, vol. 377, Jan. 2025, Art. no. 124350. [Online]. Available: https://www.sciencedirect.com/science/article/pii/S0306261924017331
[261] Z. E. Liu, Y. Li, Q. Zhou, Y. Li, B. Shuai, H. Xu, M. Hua, G. Tan, and L. Xu, "Deep reinforcement learning based energy management for heavy duty HEV considering discrete-continuous hybrid action space," *IEEE Trans. Transport. Electrific.*, vol. 10, no. 4, pp. 9864–9876, Dec. 2024.
[262] J. Xu, Z. Li, G. Du, Q. Liu, L. Gao, and Y. Zhao, "A transferable energy management strategy for hybrid electric vehicles via dueling deep deterministic policy gradient," *Green Energy Intell. Transp.*, vol. 1, no. 2, Sep. 2022, Art. no. 100018.
[263] Y. Zhang, C. Zhang, R. Fan, C. Deng, S. Wan, and H. Chaoui, "Energy management strategy for fuel cell vehicles via soft actor-critic-based deep reinforcement learning considering powertrain thermal and durability characteristics," *Energy Convers. Manage.*, vol. 283, May 2023, Art. no. 116921. [Online]. Available: https://www.sciencedirect.com/science/article/pii/S0196890423002674
[264] Z. Zhang, T. Zhang, J. Hong, H. Zhang, and J. Yang, "Energy management strategy of a novel parallel electric-hydraulic hybrid electric vehicle based on deep reinforcement learning and entropy evaluation," *J. Cleaner Prod.*, vol. 403, Jun. 2023, Art. no. 136800. [Online]. Available: https://www.sciencedirect.com/science/article/pii/S0959652623009587
[265] Z. E. Liu, Q. Zhou, Y. Li, S. Shuai, and H. Xu, "Safe deep reinforcement learning-based constrained optimal control scheme for HEV energy management," *IEEE Trans. Transport. Electrific.*, vol. 9, no. 3, pp. 4278–4293, Sep. 2023.
[266] D. Wang, L. Mei, F. Xiao, C. Song, C. Qi, and S. Song, "Energy management strategy for fuel cell electric vehicles based on scalable reinforcement learning in novel environment," *Int. J. Hydrogen Energy*, vol. 59, pp. 668–678, Apr. 2024. [Online]. Available: https://www.sciencedirect.com/science/article/pii/S0360319924003719
[267] A. Zare and M. Boroushaki, "A knowledge-assisted deep reinforcement learning approach for energy management in hybrid electric vehicles," *Energy*, vol. 313, Dec. 2024, Art. no. 134113. [Online]. Available: https://www.sciencedirect.com/science/article/pii/S036054422403891X
[268] A. Lotfy, H. Chaoui, M. Kandidayeni, and L. Boulon, "Enhancing energy management strategy for battery electric vehicles: Incorporating cell balancing and multi-agent twin delayed deep deterministic policy gradient architecture," *IEEE Trans. Veh. Technol.*, vol. 73, no. 11, pp. 16593–16607, Nov. 2024.
[269] P. Chen, S. Liu, H. Chaoui, B. Chen, and L. Yu, "Asynchronous deep reinforcement learning with gradient sharing for state of charge balancing of multiple batteries in cyber–physical electric vehicles," *J. Franklin Inst.*, vol. 361, no. 6, Apr. 2024, Art. no. 106717. [Online]. Available: https://www.sciencedirect.com/science/article/pii/S0016003224001388
[270] P. Kalaivani and C. S. Joice, "Design and modelling of a neural network-based energy management system for solar PV, fuel cell, battery and ultracapacitor-based hybrid electric vehicle," *Electr. Eng.*, vol. 106, no. 1, pp. 689–709, Sep. 2023, doi: 10.1007/s00202-023-02015-x.
[271] F. Millo, L. Rolando, L. Tresca, and L. Pulvirenti, "Development of a neural network-based energy management system for a plug-in hybrid electric vehicle," *Transp. Eng.*, vol. 11, Mar. 2023, Art. no. 100156. [Online]. Available: https://www.sciencedirect.com/science/article/pii/S2666691X22000549
[272] A. N. Ribeiro and D. M. Muñoz, "Neural network controller for hybrid energy management system applied to electric vehicles," *J. Energy Storage*, vol. 104, Dec. 2024, Art. no. 114502. [Online]. Available: https://www.sciencedirect.com/science/article/pii/S2352152X2404088X
[273] A. A. M. Omer, H. Wang, Y. Tian, and L. Peng, "Optimal energy management strategy based on neural network algorithm for fuel cell hybrid vehicle considering fuel cell lifetime and fuel consumption," *Soft Comput.*, vol. 28, no. 19, pp. 11471–11493, Jul. 2024, doi: 10.1007/s00500-024-09883-w.
[274] K. V. Singh, H. O. Bansal, and D. Singh, "Fuzzy logic and Elman neural network tuned energy management strategies for a power-split HEVs," *Energy*, vol. 225, Jun. 2021, Art. no. 120152. [Online]. Available: https://www.sciencedirect.com/science/article/pii/S0360544221004011
[275] A. Nouri, A. Lachheb, and L. El Amraoui, "Optimizing efficiency of vehicle-to-grid system with intelligent management and ANN-PSO algorithm for battery electric vehicles," *Electric Power Syst. Res.*, vol. 226, Jan. 2024, Art. no. 109936. [Online]. Available: https://www.sciencedirect.com/science/article/pii/S0378779623008246
[276] Z. Lu, H. Wang, Z. Zheng, and M. Yao, "Research on multi-objective energy management strategy based on DP algorithm and SVM-ECMS," in *Powertrain Systems for a Sustainable Future*, 1st ed., Boca Raton, FL, USA: CRC Press, 2023, p. 16.
[277] A. Benhammou, H. Tedjini, M. A. Hartani, R. M. Ghoniem, and A. Alahmer, "Accurate and efficient energy management system of fuel cell/battery/supercapacitor/AC and DC generators hybrid electric vehicles," *Sustainability*, vol. 15, no. 13, p. 10102, Jun. 2023. [Online]. Available: https://www.mdpi.com/2071-1050/15/13/10102
[278] M. Li, L. Wang, Y. Wang, and Z. Chen, "Sizing optimization and energy management strategy for hybrid energy storage system using multiobjective optimization and random forests," *IEEE Trans. Power Electron.*, vol. 36, no. 10, pp. 11421–11430, Oct. 2021.
[279] Y. Wu, Z. Huang, R. Zhang, P. Huang, Y. Gao, H. Li, Y. Liu, and J. Peng, "Driving style-aware energy management for battery/supercapacitor electric vehicles using deep reinforcement learning," *J. Energy Storage*, vol. 73, Dec. 2023, Art. no. 109199. [Online]. Available: https://www.sciencedirect.com/science/article/pii/S2352152X23025975
[280] H. Li, Y. Zhou, H. Gualous, H. Chaoui, and L. Boulon, "Optimal cost minimization strategy for fuel cell hybrid electric vehicles based on decision-making framework," *IEEE Trans. Ind. Informat.*, vol. 17, no. 4, pp. 2388–2399, Apr. 2021.
[281] L. Wang, M. Li, Y. Wang, and Z. Chen, "Energy management strategy and optimal sizing for hybrid energy storage systems using an evolutionary algorithm," *IEEE Trans. Intell. Transp. Syst.*, vol. 23, no. 9, pp. 14283–14293, Sep. 2022.
[282] D. Swain, M. Kumar, A. Nour, K. Patel, A. Bhatt, B. Acharya, and A. Bostani, "Remaining useful life predictor for EV batteries using machine learning," *IEEE Access*, vol. 12, pp. 134418–134426, 2024.
[283] Z. Wang, H. Wei, G. Xiao, and Y. Zhang, "Real-time energy management strategy for a plug-in hybrid electric bus considering the battery degradation," *Energy Convers. Manage.*, vol. 268, Sep. 2022, Art. no. 116053. [Online]. Available: https://www.sciencedirect.com/science/article/pii/S0196890422008421

[284] D. Chatterjee, P. K. Biswas, C. Sain, A. Roy, M. M. Islam, and T. S. Ustun, ''SVM classifier based energy management strategy for dual-source fuel cell hybrid electric vehicles,'' *J. Eng.*, vol. 2024, no. 6, May 2024, Art. no. e12392, doi: 10.1049/tje2.12392.

[285] D. Chatterjee, P. K. Biswas, C. Sain, A. Roy, and F. Ahmad, ''Efficient energy management strategy for fuel cell hybrid electric vehicles using classifier fusion technique,'' *IEEE Access*, vol. 11, pp. 97135–97146, 2023.

[286] S. Gao, Y. Zong, F. Ju, Q. Wang, W. Huo, L. Wang, and T. Wang, ''Scenario-oriented adaptive ECMS using speed prediction for fuel cell vehicles in real-world driving,'' *Energy*, vol. 304, Sep. 2024, Art. no. 132028.

[287] J. Pei, Y. Su, D. Zhang, Y. Qi, and Z. Leng, ''Velocity forecasts using a combined deep learning model in hybrid electric vehicles with V2V and V2I communication,'' *Sci. China Technological Sci.*, vol. 63, no. 1, pp. 55–64, Mar. 2019, doi: 10.1007/s11431-018-9396-0.

[288] A. Mesdaghi and M. Mollajafari, ''Improve performance and energy efficiency of plug-in fuel cell vehicles using connected cars with V2V communication,'' *Energy Convers. Manage.*, vol. 306, Apr. 2024, Art. no. 118296. [Online]. Available: https://www.sciencedirect.com/science/article/pii/S0196890424002371

[289] H. Liu, S. E. Shladover, X.-Y. Lu, and X. Kan, ''Freeway vehicle fuel efficiency improvement via cooperative adaptive cruise control,'' *J. Intell. Transp. Syst.*, vol. 25, no. 6, pp. 574–586, Nov. 2021. [Online]. Available: https://www.sciencedirect.com/science/article/pii/S1547245022003176

[290] F. Ma, Y. Yang, J. Wang, Z. Liu, J. Li, J. Nie, Y. Shen, and L. Wu, ''Predictive energy-saving optimization based on nonlinear model predictive control for cooperative connected vehicles platoon with V2V communication,'' *Energy*, vol. 189, Dec. 2019, Art. no. 116120. [Online]. Available: https://www.sciencedirect.com/science/article/pii/S0360544219318158

[291] H. He, Y. Wang, R. Han, M. Han, Y. Bai, and Q. Liu, ''An improved MPC-based energy management strategy for hybrid vehicles using V2V and V2I communications,'' *Energy*, vol. 225, Jun. 2021, Art. no. 120273. [Online]. Available: https://www.sciencedirect.com/science/article/pii/S0360544221005223

[292] L. Zhu, F. Tao, Z. Fu, N. Wang, B. Ji, and Y. Dong, ''Optimization based adaptive cruise control and energy management strategy for connected and automated FCHEV,'' *IEEE Trans. Intell. Transp. Syst.*, vol. 23, no. 11, pp. 21620–21629, Nov. 2022.

[293] Z. Mehraban, A. Y. Zadeh, H. Khayyam, R. Mallipeddi, and A. Jamali, ''Fuzzy adaptive cruise control with model predictive control responding to dynamic traffic conditions for automated driving,'' *Eng. Appl. Artif. Intell.*, vol. 136, Oct. 2024, Art. no. 109008. [Online]. Available: https://www.sciencedirect.com/science/article/pii/S0952197624011667

[294] U. Mittal, P. Chawla, and A. Kumar, ''Smart traffic light management system for heavy vehicles,'' in *Autonomous and Connected Heavy Vehicle Technology*, 2022, pp. 225–244. [Online]. Available: https://www.sciencedirect.com/science/article/pii/B9780323905923000136

[295] M. Cao, V. O. K. Li, and Q. Shuai, ''A gain with no pain: Exploring intelligent traffic signal control for emergency vehicles,'' *IEEE Trans. Intell. Transp. Syst.*, vol. 23, no. 10, pp. 17899–17909, Oct. 2022.

[296] M. S. Shahriar, A. K. Kale, and K. Chang, ''DRL-based intersection traffic efficiency enhancement utilizing 5G-NR-V2I data,'' *ICT Exp.*, vol. 9, no. 6, pp. 1095–1102, Dec. 2023. [Online]. Available: https://www.sciencedirect.com/science/article/pii/S2405959523000954

[297] L. Mauricette, Z. Dong, L. Zhang, X. Zhang, N. Zhang, and G. Strbac, ''Resilience enhancement of urban energy systems via coordinated vehicle-to-grid control strategies,'' *CSEE J. Power Energy Syst.*, vol. 9, no. 2, pp. 433–443, Mar. 2023.

[298] I. Sami, Z. Ullah, K. Salman, I. Hussain, S. M. Ali, B. Khan, C. A. Mehmood, and U. Farid, ''A bidirectional interactive electric vehicles operation modes: Vehicle-to-grid (V2G) and grid-to-vehicle (G2V) variations within smart grid,'' in *Proc. Int. Conf. Eng. Emerg. Technol. (ICEET)*, Feb. 2019, pp. 1–6.

[299] M. Sithambaram, P. Rajesh, F. H. Shajin, and I. Raja Rajeswari, ''Grid connected photovoltaic system powered electric vehicle charging station for energy management using hybrid method,'' *J. Energy Storage*, vol. 108, Feb. 2025, Art. no. 114828. [Online]. Available: https://www.sciencedirect.com/science/article/pii/S2352152X24044141

[300] A. Dik, C. Kutlu, S. Omer, R. Boukhanouf, Y. Su, and S. Riffat, ''An approach for energy management of renewable energy sources using electric vehicles and heat pumps in an integrated electricity grid system,'' *Energy Buildings*, vol. 294, Sep. 2023, Art. no. 113261. [Online]. Available: https://www.sciencedirect.com/science/article/pii/S0378778823004917

[301] A. K. Candan, A. R. Boynuegri, and N. Onat, ''Home energy management system for enhancing grid resiliency in post-disaster recovery period using electric vehicle,'' *Sustain. Energy, Grids Netw.*, vol. 34, Jun. 2023, Art. no. 101015, doi: 10.1016/j.segan.2023.101015.

[302] O. Almughram, S. Ben Slama, and B. Zafar, ''Model for managing the integration of a vehicle-to-home unit into an intelligent home energy management system,'' *Sensors*, vol. 22, no. 21, p. 8142, Oct. 2022, doi: 10.3390/s22218142.

[303] K. El Harouri, S. El Hani, N. Naseri, E. Elbouchikhi, M. Benbouzid, and S. Skander-Mustapha, ''Hybrid control and energy management of a residential system integrating vehicle-to-home technology,'' *Designs*, vol. 7, no. 2, p. 52, Apr. 2023, doi: 10.3390/designs7020052.

[304] G. Ellemund, M. Fresia, and S. Bracco, ''Energy management system for a prosumer with Vehicle-to-home: A case study in Italy,'' in *Proc. Int. Conf. Smart Energy Syst. Technol. (SEST)*, Sep. 2024, pp. 1–6.

[305] A. T. Tran, A. Kawashima, S. Inagaki, and T. Suzuki, ''Design of a home energy management system integrated with an electric vehicle (V2H-HPWH EMS),'' in *Design and Analysis of Distributed Energy Management Systems: Integration of EMS, EV, and ICT*. Cham, Switzerland: Springer, 2020, pp. 47–66, doi: 10.1007/978-3-030-33672-1.

[306] H. Alkhudhayr and A. Subahi, ''Vehicle-to-home: Implementation and design of an intelligent home energy management system that uses renewable energy,'' *Eng., Technol. Appl. Sci. Res.*, vol. 14, no. 4, pp. 15239–15250, Aug. 2024. [Online]. Available: https://etasr.com/index.php/ETASR/article/view/7273

[307] S. Ben Slama, ''Design and implementation of home energy management system using vehicle to home (H2V) approach,'' *J. Cleaner Prod.*, vol. 312, Aug. 2021, Art. no. 127792, doi: 10.1016/j.jclepro.2021.127792.

[308] Ş. Y. Gelbal, S. Zhu, G. A. Anantharaman, B. A. Güvenç, and L. Güvenç, ''Cooperative collision avoidance in a connected vehicle environment,'' in *Proc. SAE Tech. Paper Ser.*, Apr. 2019, pp. 1–15, doi: 10.4271/2019-01-0488.

[309] F. Oliva, E. Landolfi, G. Salzillo, A. Massa, S. M. D'Onghia, and A. Troiano, ''Implementation and testing of V2I communication strategies for emergency vehicle priority and pedestrian safety in urban environments,'' *Sensors*, vol. 25, no. 2, p. 485, Jan. 2025.

[310] S. Islam, A. Iqbal, M. Marzband, I. Khan, and A. M. A. B. Al-Wahedi, ''State-of-the-art vehicle-to-everything mode of operation of electric vehicles and its future perspectives,'' *Renew. Sustain. Energy Rev.*, vol. 166, Sep. 2022, Art. no. 112574. [Online]. Available: https://www.sciencedirect.com/science/article/pii/S1364032122004701

[311] M. A. Rehman, M. Numan, H. Tahir, U. Rahman, M. W. Khan, and M. Z. Iftikhar, ''A comprehensive overview of vehicle to everything (V2X) technology for sustainable EV adoption,'' *J. Energy Storage*, vol. 74, Dec. 2023, Art. no. 109304. [Online]. Available: https://www.sciencedirect.com/science/article/pii/S2352152X23027020

[312] Z. Xu, J. Xu, Z. Guo, H. Wang, Z. Sun, and X. Mei, ''Design and optimization of a novel microchannel battery thermal management system based on digital twin,'' *Energies*, vol. 15, no. 4, p. 1421, 2022.

[313] W. Wang, J. Wang, J. Tian, J. Lu, and R. Xiong, ''Application of digital twin in smart battery management systems,'' *Chin. J. Mech. Eng.*, vol. 34, no. 1, p. 57, Dec. 2021.

[314] L. D. Tai, K. S. Garud, S.-G. Hwang, and M.-Y. Lee, ''A review on advanced battery thermal management systems for fast charging in electric vehicles,'' *Batteries*, vol. 10, no. 10, p. 372, Oct. 2024.

[315] C. Anamtawach, S. Odngam, and C. Sumpavakup, ''Experimental investigation on affecting air flow against the maximum temperature difference of a lithium-ion battery with heat pipe cooling,'' *World Electric Vehicle J.*, vol. 14, no. 11, p. 306, Nov. 2023.

[316] F. Alanazi, ''Electric vehicles: Benefits, challenges, and potential solutions for widespread adaptation,'' *Appl. Sci.*, vol. 13, no. 10, p. 6016, May 2023. [Online]. Available: https://www.mdpi.com/2076-3417/13/10/6016

[317] V. Sidharthan Panaparambil, Y. Kashyap, and R. Vijay Castelino, ''A review on hybrid source energy management strategies for electric vehicle,'' *Int. J. Energy Res.*, vol. 45, no. 14, pp. 19819–19850, Nov. 2021. [Online]. Available: https://onlinelibrary.wiley.com/doi/abs/10.1002/er.7107

[318] Y. Zhu, X. Li, Q. Liu, S. Li, and Y. Xu, "Review article: A comprehensive review of energy management strategies for hybrid electric vehicles," *Mech. Sci.*, vol. 13, no. 1, pp. 147–188, Mar. 2022. [Online]. Available: https://ms.copernicus.org/articles/13/147/2022/

[319] I. Veza, M. Syaifuddin, M. Idris, S. G. Herawan, A. A. Yusuf, and I. M. R. Fattah, "Electric vehicle (EV) review: Bibliometric analysis of electric vehicle trend, policy, lithium-ion battery, battery management, charging infrastructure, smart charging, and electric vehicle-to-everything (V2X)," *Energies*, vol. 17, no. 15, p. 3786, Jul. 2024. [Online]. Available: https://www.mdpi.com/1996-1073/17/15/3786

[320] P. Arévalo, D. Ochoa-Correa, and E. Villa-Ávila, "A systematic review on the integration of artificial intelligence into energy management systems for electric vehicles: Recent advances and future perspectives," *World Electric Vehicle J.*, vol. 15, no. 8, p. 364, Aug. 2024. [Online]. Available: https://www.mdpi.com/2032-6653/15/8/364

[321] P. S. P. Krishna, N. S. Jayalakshmi, and A. Kedlaya, "Energy management strategies for hybrid energy storage system in electric vehicles: A review," in *Proc. IEEE Int. Conf. Electron., Comput. Commun. Technol. (CONECCT)*, Jul. 2020, pp. 1–7.

[322] Y. M. Prianka, A. Sharma, and C. Biswas, "Integration of renewable energy, microgrids, and EV charging infrastructure: Challenges and solutions," *Control Syst. Optim. Lett.*, vol. 2, no. 3, pp. 317–326, Dec. 2024.

[323] H. Al-Thani, M. Koç, R. J. Isaifan, and Y. Bicer, "A review of the integrated renewable energy systems for sustainable urban mobility," *Sustainability*, vol. 14, no. 17, p. 10517, Aug. 2022. [Online]. Available: https://www.mdpi.com/2071-1050/14/17/10517

[324] P. Sinha, K. Paul, S. Deb, and S. Sachan, "Comprehensive review based on the impact of integrating electric vehicle and renewable energy sources to the grid," *Energies*, vol. 16, no. 6, p. 2924, Mar. 2023. [Online]. Available: https://www.mdpi.com/1996-1073/16/6/2924

[325] P. K. Maroti, S. Padmanaban, M. S. Bhaskar, V. K. Ramachandaramurthy, and F. Blaabjerg, "The state-of-the-art of power electronics converters configurations in electric vehicle technologies," *Power Electron. Devices Compon.*, vol. 1, Mar. 2022, Art. no. 100001. [Online]. Available: https://www.sciencedirect.com/science/article/pii/S2772370421000018

[326] M. Z. Khaneghah, M. Alzayed, and H. Chaoui, "Fault detection and diagnosis of the electric motor drive and battery system of electric vehicles," *Machines*, vol. 11, no. 7, p. 713, Jul. 2023. [Online]. Available: https://www.mdpi.com/2075-1702/11/7/713

[327] K. Zekentes, V. Veliadis, S.-H. Ryu, K. Vasilevskiy, S. Pavlidis, A. Salemi, and Y. Zhang, *SiC and GaN Power Devices*. Cham, Switzerland: Springer, 2023, pp. 47–104, doi: 10.1007/978-3-031-21610-7.

[328] R. Zaino, V. Ahmed, A. M. Alhammadi, and M. Alghoush, "Electric vehicle adoption: A comprehensive systematic review of technological, environmental, organizational and policy impacts," *World Electric Vehicle J.*, vol. 15, no. 8, p. 375, Aug. 2024. [Online]. Available: https://www.mdpi.com/2032-6653/15/8/375

[329] I. Kosmidis, D. Müller-Eie, and A. Delbosc, "Electric cars as a path to sustainable travel behaviour: Insights from Nord–Jæren," *Transp. Res. D, Transp. Environ.*, vol. 125, Dec. 2023, Art. no. 103982. [Online]. Available: https://www.sciencedirect.com/science/article/pii/S1361920923003796

[330] Z. A. Arfeen, R. Hassan, M. K. Azam, and M. P. Abdullah, "Environmental impact of the recycling and disposal of EV batteries," in *Electric Vehicle Integr. a Smart Microgrid Environ.*, 2021, pp. 313–334.

[331] M. Yu, B. Bai, S. Xiong, and X. Liao, "Evaluating environmental impacts and economic performance of remanufacturing electric vehicle lithium-ion batteries," *J. Cleaner Prod.*, vol. 321, Oct. 2021, Art. no. 128935. [Online]. Available: https://www.sciencedirect.com/science/article/pii/S0959652621031280

[332] C. M. Costa, J. C. Barbosa, R. Gonçalves, H. Castro, F. J. D. Campo, and S. Lanceros-Méndez, "Recycling and environmental issues of lithium-ion batteries: Advances, challenges and opportunities," *Energy Storage Mater.*, vol. 37, pp. 433–465, May 2021. [Online]. Available: https://www.sciencedirect.com/science/article/pii/S2405829721000829

[333] M. Slattery, J. Dunn, and A. Kendall, "Transportation of electric vehicle lithium-ion batteries at end-of-life: A literature review," *Resources, Conservation Recycling*, vol. 174, Nov. 2021, Art. no. 105755. [Online]. Available: https://www.sciencedirect.com/science/article/pii/S0921344921003645

[334] S. Shirvani, Y. Baseri, and A. Ghorbani, "Evaluation framework for electric vehicle security risk assessment," *IEEE Trans. Intell. Transp. Syst.*, vol. 25, no. 1, pp. 33–56, Jan. 2024.

[335] S. I. Jeong and D.-H. Choi, "Electric vehicle user data-induced cyber attack on electric vehicle charging station," *IEEE Access*, vol. 10, pp. 55856–55867, 2022.

[336] J. Shi, J. Wu, B. Xu, and Z. Song, "Cybersecurity of hybrid electric city bus with V2C connectivity," *IEEE Trans. Intell. Vehicles*, vol. 9, no. 2, pp. 4070–4084, Feb. 2024.

[337] J. Ye, L. Guo, B. Yang, F. Li, L. Du, L. Guan, and W. Song, "Cyber–physical security of powertrain systems in modern electric vehicles: Vulnerabilities, challenges, and future visions," *IEEE J. Emerg. Sel. Topics Power Electron.*, vol. 9, no. 4, pp. 4639–4657, Aug. 2021.

[338] A. Sanghvi and T. Markel, "Cybersecurity for electric vehicle fast-charging infrastructure," in *Proc. IEEE Transp. Electrific. Conf. Expo (ITEC)*, Jun. 2021, pp. 573–576.

[339] S. Aggarwal, N. Kumar, and P. Gope, "An efficient blockchain-based authentication scheme for energy-trading in V2G networks," *IEEE Trans. Ind. Informat.*, vol. 17, no. 10, pp. 6971–6980, Oct. 2021.

[340] Q. Lai, C. Xiong, J. Chen, W. Wang, J. Chen, T. R. Gadekallu, M. Cai, and X. Hu, "Improved transformer-based privacy-preserving architecture for intrusion detection in secure V2X communications," *IEEE Trans. Consum. Electron.*, vol. 70, no. 1, pp. 1810–1820, Feb. 2024.

[341] S. Yan, M. H. Shah, J. Li, N. O'Connor, and M. Liu, "A review on AI algorithms for energy management in E-mobility services," in *Proc. 7th CAA Int. Conf. Veh. Control Intell. (CVCI)*, Oct. 2023, pp. 1–8.

[342] J. Hu, Y. Lin, J. Li, Z. Hou, L. Chu, D. Zhao, Q. Zhou, J. Jiang, and Y. Zhang, "Performance analysis of AI-based energy management in electric vehicles: A case study on classic reinforcement learning," *Energy Convers. Manage.*, vol. 300, Jan. 2024, Art. no. 117964. [Online]. Available: https://www.sciencedirect.com/science/article/pii/S0196890423013109

[343] Y. Lin, L. Chu, J. Hu, Z. Hou, J. Li, J. Jiang, and Y. Zhang, "Progress and summary of reinforcement learning on energy management of MPS-EV," *Heliyon*, vol. 10, no. 1, Jan. 2024, Art. no. e23014, doi: 10.1016/j.heliyon.2023.e23014.

[344] H. Jondhle, A. B. Nandgaonkar, S. Nalbalwar, and S. Jondhle, "An artificial intelligence and improved optimization-based energy management system of battery-fuel cell-ultracapacitor in hybrid electric vehicles," *J. Energy Storage*, vol. 74, Dec. 2023, Art. no. 109079. [Online]. Available: https://www.sciencedirect.com/science/article/pii/S2352152X23024775

[345] A. Kadechkar and X. Llauradó, "AI-enhanced velocity prediction for efficient EV energy management with hybrid storage," in *Proc. 12th Int. Conf. Smart Grid (icSmartGrid)*, May 2024, pp. 659–665.

[346] Z. Wu, N. N. Manne, J. Harper, B. Chen, and D. Dobrzynski, "A cloud-based simulation and testing framework for large-scale EV charging energy management and charging control," *SAE Int. J. Adv. Current Practices Mobility*, vol. 4, no. 5, pp. 1492–1500, Mar. 2022, doi: 10.4271/2022-01-0169.

[347] Y. Zhang, H. Liu, Z. Zhang, Y. Luo, Q. Guo, and S. Liao, "Cloud computing-based real-time global optimization of battery aging and energy consumption for plug-in hybrid electric vehicles," *J. Power Sources*, vol. 479, May 2020, Art. no. 229069. [Online]. Available: https://www.sciencedirect.com/science/article/pii/S0378775320313641

[348] M. Ismail and R. Ahmed, "A comprehensive review of cloud-based lithium-ion battery management systems for electric vehicle applications," *IEEE Access*, vol. 12, pp. 116259–116273, 2024.

[349] A. Fehrle, F. Teske, F. Dorscht, and J. Franke, "Potential analysis of a cloud-based energy management system for the generation of flexibilities," in *Proc. IEEE PES Innov. Smart Grid Technol. Eur. (ISGT Europe)*, Oct. 2021, pp. 1–5.

[350] W. Li, H. Cui, T. Nemeth, J. Jansen, C. Ünlübayir, Z. Wei, X. Feng, X. Han, M. Ouyang, H. Dai, X. Wei, and D. U. Sauer, "Cloud-based health-conscious energy management of hybrid battery systems in electric vehicles with deep reinforcement learning," *Appl. Energy*, vol. 293, Jul. 2021, Art. no. 116977. [Online]. Available: https://www.sciencedirect.com/science/article/pii/S0306261921004499

[351] J. Omakor, M. S. Miah, and H. Chaoui, "Battery reliability assessment in electric vehicles: A state-of-the-art," *IEEE Access*, vol. 12, pp. 77903–77931, 2024.

[352] B. Spoorthi and P. Pradeepa, "Review on battery management system in EV," in *Proc. Int. Conf. Intell. Controller Comput. Smart Power (ICICCSP)*, Jul. 2022, pp. 1–4.

[353] M. S. Ramkumar, C. S. R. Reddy, A. Ramakrishnan, K. Raja, S. Pushpa, S. Jose, and M. Jayakumar, "Review on Li-ion battery with battery management system in electrical vehicle," *Adv. Mater. Sci. Eng.*, vol. 2022, pp. 1–8, May 2022. [Online]. Available: https://onlinelibrary.wiley.com/doi/abs/10.1155/2022/3379574

[354] S. Mishra, S. C. Swain, and R. K. Samantaray, "A review on battery management system and its application in electric vehicle," in *Proc. Int. Conf. Adv. Comput. Commun. (ICACC)*, Oct. 2021, pp. 1–6.
[355] X. Zhang, J. Li, J. Zhou, S. Zhang, J. Wang, Y. Yuan, J. Liu, and J. Li, "Vehicle-to-Everything communication in intelligent connected vehicles: A survey and taxonomy," *Automot. Innov.*, vol. 8, no. 1, pp. 1–33, Feb. 2025.
[356] M. R. R. Razu, S. Mahmud, M. J. Uddin, S. S. Islam, B. Bais, N. Misran, and M. T. Islam, "Wireless charging of electric vehicle while driving," *IEEE Access*, vol. 9, pp. 157973–157983, 2021.
[357] K. Song, Y. Lan, X. Zhang, J. Jiang, C. Sun, G. Yang, F. Yang, and H. Lan, "A review on interoperability of wireless charging systems for electric vehicles," *Energies*, vol. 16, no. 4, p. 1653, Feb. 2023. [Online]. Available: https://www.mdpi.com/1996-1073/16/4/1653
[358] K. Dimitriadou, N. Rigogiannis, S. Fountoukidis, F. Kotarela, A. Kyritsis, and N. Papanikolaou, "Current trends in electric vehicle charging infrastructure; opportunities and challenges in wireless charging integration," *Energies*, vol. 16, no. 4, p. 2057, 2023. [Online]. Available: https://www.mdpi.com/1996-1073/16/4/2057
[359] M. Amjad, M. Farooq-I-Azam, Q. Ni, M. Dong, and E. A. Ansari, "Wireless charging systems for electric vehicles," *Renew. Sustain. Energy Rev.*, vol. 167, Nov. 2022, Art. no. 112730. [Online]. Available: https://www.sciencedirect.com/science/article/pii/S1364032122006190
[360] G. Kumar and S. Mikkili, "Advancements in EV international standards: Charging, safety and grid integration with challenges and impacts," *Int. J. Green Energy*, vol. 21, no. 12, pp. 2672–2698, Mar. 2024, doi: 10.1080/15435075.2024.2323649.
[361] V. M. Macharia, V. K. Garg, and D. Kumar, "A review of electric vehicle technology: Architectures, battery technology and its management system, relevant standards, application of artificial intelligence, cyber security, and interoperability challenges," *IET Electr. Syst. Transp.*, vol. 13, no. 2, p. 12083, Jun. 2023. [Online]. Available: https://ietresearch.onlinelibrary.wiley.com/doi/abs/10.1049/els2.12083
[362] H. S. Das, M. M. Rahman, S. Li, and C. W. Tan, "Electric vehicles standards, charging infrastructure, and impact on grid integration: A technological review," *Renew. Sustain. Energy Rev.*, vol. 120, Mar. 2020, Art. no. 109618. [Online]. Available: https://www.sciencedirect.com/science/article/pii/S1364032119308251
[363] S. R. Kirchner, "OCPP interoperability: A unified future of charging," *World Electric Vehicle J.*, vol. 15, no. 5, p. 191, Apr. 2024. [Online]. Available: https://www.mdpi.com/2032-6653/15/5/191
[364] F. Haneem, N. Kama, R. M. Adam, S. Basri, H. M. Rusli, and H. M. Sarkan, "Data exchange interoperability protocol for electric vehicle charging systems infrastructure," in *Proc. 20th Int. Conf. Smart Technol.*, Jul. 2023, pp. 193–198.
[365] R. Porter, M. Biglari-Abhari, B. Tan, and D. Thrimawithana, "Extending ISO 15118-20 EV charging: Preventing downgrade attacks and enabling new security capabilities," in *Proc. 21st Annu. Int. Conf. Privacy, Secur. Trust (PST)*, Aug. 2024, pp. 1–9.
[366] Z. Xu, C. Wang, T. Jiang, Z. Liu, and N. Zheng, "Impediments to environmental awareness in autonomous driving systems and its effect on user adoption," *IEEE Trans. Intell. Vehicles*, early access, Mar. 8, 2024, doi: 10.1109/TIV.2024.3373773.
[367] P. Hang and X. Chen, "Towards autonomous driving: Review and perspectives on configuration and control of four-wheel independent drive/steering electric vehicles," *Actuators*, vol. 10, no. 8, p. 184, Aug. 2021. [Online]. Available: https://www.mdpi.com/2076-0825/10/8/184
[368] G. Manavaalan, K. Gobikannan, S. Elango, and P. V. Kumar, "Energy saving and speed control in autonomous electric vehicle using enhanced manta ray foraging algorithm optimized intelligent systems," *J. Power Sources*, vol. 619, Nov. 2024, Art. no. 235217. [Online]. Available: https://www.sciencedirect.com/science/article/pii/S0378775324011698
[369] A. Mansour Saatloo, A. Mehrabi, M. Marzband, and N. Aslam, "Hierarchical user-driven trajectory planning and charging scheduling of autonomous electric vehicles," *IEEE Trans. Transport. Electrific.*, vol. 9, no. 1, pp. 1736–1749, Mar. 2023.
[370] V. K. Yanumula, P. Typaldos, D. Troullinos, M. Malekzadeh, I. Papamichail, and M. Papageorgiou, "Optimal trajectory planning for connected and automated vehicles in lane-free traffic with vehicle nudging," *IEEE Trans. Intell. Vehicles*, vol. 8, no. 3, pp. 2385–2399, Mar. 2023.
[371] B. Ma, D. Hu, X. Chen, Y. Wang, and X. Wu, "The vehicle routing problem with speed optimization for shared autonomous electric vehicles service," *Comput. Ind. Eng.*, vol. 161, Nov. 2021, Art. no. 107614. [Online]. Available: https://www.sciencedirect.com/science/article/pii/S0360835221005180
[372] L. Zhang, Z. Liu, L. Yu, K. Fang, B. Yao, and B. Yu, "Routing optimization of shared autonomous electric vehicles under uncertain travel time and uncertain service time," *Transp. Res. E, Logistics Transp. Rev.*, vol. 157, Jan. 2022, Art. no. 102548. [Online]. Available: https://www.sciencedirect.com/science/article/pii/S1366554521003069
[373] C.-J. Huang, K.-W. Hu, H. Y. Ho, B. Z. Xie, C.-C. Feng, and H.-W. Chuang, "A distributed urban traffic congestion prevention mechanism for mixed flow of human-driven and autonomous electric vehicles," *Int. J. Comput. Intell. Syst.*, vol. 14, no. 1, p. 1714, 2021, doi: 10.2991/ijcis.d.210608.001.
[374] C.-J. Huang, K.-W. Hu, and C.-Y. Hsieh, "Congestion-aware rideshare dispatch for shared autonomous electric vehicle fleets," *Electronics*, vol. 11, no. 16, p. 2591, Aug. 2022. [Online]. Available: https://www.mdpi.com/2079-9292/11/16/2591
[375] C.-J. Huang, K.-W. Hu, and C.-Y. Hsieh, "Congestion-avoiding routing and charging scheduling mechanism for shared autonomous electric vehicle networks in urban areas," in *Proc. IEEE Int. Conf. Internet Things Intell. Syst. (IoTaIS)*, Nov. 2022, pp. 76–80.
[376] H. Bang and A. A. Malikopoulos, "Congestion-aware routing, rebalancing, and charging scheduling for electric autonomous mobility-on-demand system," in *Proc. Amer. Control Conf. (ACC)*, Jun. 2022, pp. 3152–3157.
[377] S. Lapardhaja, M. Yang, K. Yagantekin, and X. D. Kan, "Unlocking the potential congestion relief from electric vehicles (EVS)–field experiments, open database, and simulations of EVs WITH adaptive cruise control (ACC)," in *Proc. Forum Innov. Sustain. Transp. Syst. (FISTS)*, Feb. 2024, pp. 1–6.
[378] H. Huang, A. M. Y. M. Ghias, P. Acuna, Z. Dong, J. Zhao, and M. S. Reza, "A fast battery balance method for a modular-reconfigurable battery energy storage system," *Appl. Energy*, vol. 356, Feb. 2024, Art. no. 122470. [Online]. Available: https://www.sciencedirect.com/science/article/pii/S0306261923018342
[379] Z. Wei, H. Cui, X. Liu, Y. Li, and R. Wang, "Real-time reconfiguration-based all-cell flexibility and capacity maximum utilization of second-life batteries," *IEEE Trans. Transport. Electrific.*, vol. 11, no. 1, pp. 1035–1047, Feb. 2025.
[380] A. Farakhor, D. Wu, Y. Wang, and H. Fang, "A novel modular, reconfigurable battery energy storage system: Design, control, and experimentation," *IEEE Trans. Transport. Electrific.*, vol. 9, no. 2, pp. 2878–2890, Jun. 2023.
[381] R. Eskandari, P. Venugopal, and G. Rietveld, "Advanced battery management systems with integrated battery electronics," in *Proc. IEEE 20th Int. Power Electron. Motion Control Conf. (PEMC)*, Sep. 2022, pp. 55–61.
[382] Z. M. Pinter, D. Papageorgiou, G. Rohde, M. Marinelli, and C. Træholt, "Review of control algorithms for reconfigurable battery systems with an industrial example," in *Proc. 56th Int. Universities Power Eng. Conf. (UPEC)*, Aug. 2021, pp. 1–6.

YASHAR FARAJPOUR received the Ph.D. degree in electrical and computer engineering from Carleton University, Ottawa, ON, Canada, in 2024. During his doctoral studies, he made significant contributions to the fields of energy management and optimization for electric vehicles, with a particular focus on driving range extension and battery degradation mitigation. He has published several research articles in internationally recognized publications, where his work has been cited extensively. His research interests include energy management, battery management, optimization, machine learning modeling, motor-drive systems, inverters, and power engineering. With a strong background in theoretical and applied aspects of power systems, he has worked on developing innovative solutions for real-world challenges. He was a recipient of the prestigious Ontario Graduate Scholarship (OGS), in 2021, recognizing his academic excellence and research achievements. His dedication to cutting-edge research and his commitment to sustainability and innovation highlight his contributions to the advancement of electric mobility and renewable energy technologies. He has served as a peer reviewer for prestigious journals.

ARMIN LOTFY (Student Member, IEEE) received the M.Sc. degree in electrical engineering from Iran University of Science and Technology, Tehran, Iran, in 2019, and the Ph.D. degree from the Department of Electronics, Carleton University, Ottawa, Canada, in 2021. He became a member with the Intelligent Robotic and Energy Systems (IRES) Research Group, Department of Electronics, Carleton University. His research is centered on the application of advanced machine learning methodologies—including deep learning and reinforcement learning—to address complex challenges in energy systems. His primary research interests include the development of intelligent energy management strategies for battery electric vehicles (BEVs), optimization of battery and hybrid energy storage systems, and the integration of predictive and adaptive control algorithms to improve the efficiency, reliability, and sustainability of energy-related technologies.

HICHAM CHAOUI (Senior Member, IEEE) received the Ph.D. degree (Hons.) in electrical engineering from the Université du Québec à Trois-Rivières, QC, Canada, in 2011. From 2007 to 2014, he held various engineering and management positions in Canadian industry. He is currently a Professor at Carleton University, Ottawa, ON, Canada. He is a registered Professional Engineer in the Province of Ontario. His career has spanned both academia and industry in the field of control and energy systems. His scholarly work has resulted in more than 250 journal and conference publications leading to more than 6000 citations. He was a recipient of the Best Thesis Award and the Governor General of Canada Gold Medal Award. He was also a recipient of the FED Research Excellence Award, the Early Researcher Award from the Government of Ontario, and the Top Editor Recognition from both the IEEE Vehicular Technology Society and the IEEE Power Electronics Society. He is an Associate Editor of IEEE Transactions on Power Electronics, IEEE Transactions on Vehicular Technology, and several other journals.

SOUSSO KELOUWANI (Senior Member, IEEE) received the Ph.D. degree in robotics systems from the École Polytechnique de Montréal, in 2011. He completed the postdoctoral internship on fuel cell hybrid electric vehicles with the Université du Québec á Trois-Rivières (UQTR), in 2012. Since 2017, he has been a Full Professor of mechatronics with the Department of Mechanical Engineering, UQTR. He holds four patents in the U.S. and Canada. He has published more than 100 scientific articles. His research interests include optimizing energy systems for vehicle applications, advanced driver assistance techniques, and intelligent vehicle navigation taking into account Canadian climatic conditions. He is a member of the Hydrogen Research Institute and the Order of Engineers of Quebec. In 2019, his team received the First Innovation Prize in partnership with DIVEL awarded by the Association des Manufacturiers de la Mauricie et Center-du-Québec for the development of an autonomous and natural navigation systems. In 2017, he received the Environment Prize at the Gala des Grands Prix d'excellence en Transport from the Association Québécoise du Transport (AQTr) for the development of hydrogen range extenders for electric vehicles. He is the winner of Canada General Governor Gold Medal, in 2003. He holds a Canada Research Chair of the Energy Optimization of Intelligent Transport Systems and the Noovelia Research Chair of the Intelligent Navigation of Autonomous Industrial Vehicles. He developed expertise in the optimization and the intelligent control of vehicular applications. He was the Co-President and the President of the technical committee of the IEEE International Conferences on Vehicular Power and Propulsion, in Chicago, IL, USA, in 2018, and Hanoi, Vietnam, in 2019.