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TOPICAL REVIEW

Energy Management Systems for Electric Vehicles: A Comprehensive Review of Technologies and Trends

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ABSTRACT As the demand for electric vehicles (EVs) continues to surge, improvements to energy management systems (EMS) prove essential for improving their efficiency, performance, and sustainability. This paper covers the distinctive challenges in designing EMS for a range of electric vehicles, such as electrically powered automobiles, split drive cars, and P-HEVs. It also covers significant achievements and proposed solutions to these issues. The powertrain concept for series, parallel, series-parallel, and complex hybrid electric cars is also disclosed in this study. Much of this analysis is dedicated to investigating the various control strategies used in EMS for various electric vehicle types, which include global-optimization approaches, fuzzy rule-based, and real-time optimization-oriented strategies. The study thoroughly evaluates the strengths and shortcomings of various electric vehicle strategies, offering valuable insights into their practical implementation and effectiveness across different EV models, such as BEVs, HEVs, and PHEVs.

INDEX TERMS HEV, PHEV, power train, EMS, fuzzy based EMS, SoC, Deep RL.

I. INTRODUCTION

The energy problem and global warming are undoubtedly the most severe issues today. The excessive usage of non-renewable energy continues to bring the planet to a catastrophic event [1]. Using conventional energy sources is the main contributor to greenhouse gas emissions [2], [3]. These energy resources are limited and consumed daily due to rising energy consumption demands.

According to the EPA, the average passenger vehicle generates approximately 400 grams of carbon dioxide per mile and approximately 4.6 metric tons of carbon dioxide (CO2) annually. This assumes that the average gasoline vehicle on the road today gets 22.2 miles per gallon and travels 11,500 miles per year. Every gallon of gasoline burned emits approximately 8,887 grams of greenhouse gases [4]. According to the IEA report, the transportation sector contributed 7.98 gigatons (Gt) of carbon dioxide (CO2) emissions in 2022, constituting roughly 23% of total emissions. Figure 1 represents the percentage of global total emissions in different sectors [5].

The California Air Resources Board adopted guidelines in October 1990 requiring that 2% of all vehicles sold in the state between 1998 and 2002 be emission-free and that 10% of vehicles placed on the market have zero emissions by 2003 [6]. Since there is no potential for increasing the fuel efficiency of typical vehicles and all suggested strategies will be detrimental to the growth of the manufacturing sector, creating new energy vehicles has been considered one of the most probable and realistic options [7]. As a result, the entirety of the world is moving toward the usage of clean energy. EVs are sustainable, have minimal gasoline use, are pollutant-free, and are an innovative urban transportation alternative [8]. Chargeable battery sets, which frequently use lithium-ion, also known as Li-ion, batteries, are the main source of energy needed by either one or several motors powered by electricity (EMs) for propulsion in electric vehicles (EVs) [9]. However, two critical challenges to commercializing EVs exist low driving range and high initial cost. The present EV energy source technologies

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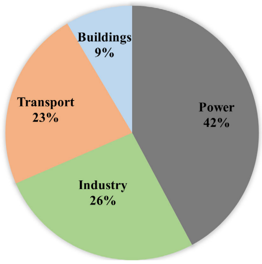

FIGURE 1. Worldwide carbon dioxide (CO2) emissions (2022).

cannot readily overcome these challenges. Regardless of how environmentally friendly it is, people may not purchase an EV if its range between charges is 100-200 km [6].

Abbreviation	Description.
CD	Charge Depleting.
CI	Compression Ignition.
CS	Charge Sustaining.
CVT	Continuously Variable Transmission.
DP	Dynamic Programming.
ECMS	Equivalent Consumption Minimization Strategy.
EF	Equivalent Factor.
EM	Electric Machine.
EMS	Energy Management Strategy.
EPA	Environmental Protection Agency.
EV	Electric Vehicle.
ESS	Energy Storage System.
FC	Fuel Cell.
FLC	Fuzzy Logic Controller.
GA	Genetic Algorithm.
HEV	Hybrid Electric Vehicle.
ICE	Internal Combustion Engine.
IEA	International Energy Agency.
IM	Induction Motor.
ISE	Integral Squared Error.
LP	Linear Programming.
M/G	Motor/Generator.
PG	Planetary Gear.
PHEV	Plug-in Hybrid Electric Vehicle.
PSD	Power Split Device.
RL	Reinforcement Learning.
SOH	State of Health.
SoC	State of Charge.
SUV	Sports Utility Vehicle.
UC	Ultra Capacitor.

To address the challenges associated with electromobile, HEVs have been introduced. A combination of an electricity-powered motor, battery pack, and gasoline engine powers an electric hybrid vehicle. The wheels can be powered by the electricity stored in the battery unit, independently or in association with the combustion engine [9]. HEVs feature distinct advantages, which include greatly extending the initial EV driving range by two to four times and enabling the ease of quick refilling. Another advantage is that HEVs require minimum changes to the current energy infrastructure, and they release much less pollution and consume less fuel than typical vehicle engines while providing a comparable driving range. The fundamental limitations of HEVs are the loss of the zero-emission principle and increased complexity. Despite this, HEVs serve as a bridge to zero-emission vehicles and a feasible strategy for commercializing super-ultra-low-emission vehicles [6].

Plug-in hybrid electric vehicles (PHEVs) are electrically powered automobiles that can be recharged by connecting them to an external power source [10]. This feature allows a PHEV to operate entirely on electricity until the IC engine turns on when the state of the charge (SoC) of the battery drops reduced to a predetermined lower threshold. PHEVs are distinguished from standard HEVs in that they prioritize the primary power source as the energy kept in the ESS while offering a novel approach to the electric motor system (EMS) that improves fuel efficiency [11], [12]. Two types of vehicles from this category have been attainable in the marketplace: blended and extended-range (EREVs) PHEVs. EREVs usually utilize a series framework, in which the conventional engine solely provides energy, and the induction motor moves the drive train. One such instance is the i3 from BMW with an extension of range that operates in this manner, using the engine only when the battery is completely drained. In contrast, blended PHEVs often have the engine directly powering the car, with an electric motor acting as either a motor or generator depending on power demands and the battery's SoC, as demonstrated in the Chevrolet Volt [13].

The paper outlines its contributions in the following manner:

- First, the investigation commences with an examination of the emergence of HEVs, with particular emphasis placed on the factors driving their development, the distinctions among various electric vehicles, their industrial revolution, and the associated advantages and disadvantages.
- An in-depth discussion of various HEV configurations is presented, encompassing their specific design features, limitations, and potential applications.
- A concise overview of HEV mathematical modeling techniques is provided, supplemented by their corresponding electrical equivalent circuit diagrams.
- HEV control strategies are extensively examined across two primary levels: rule-based and optimization-based. This thorough evaluation seeks to emphasize the advantages and disadvantages of each strategy, their uniqueness, variations among different approaches, trends in Energy Management Systems (EMS), and their contributions toward fulfilling multiple optimization goals.
- Finally, provide a summary of the control strategies examined in this study.

The remaining tasks are structured in the following manner: section II contains the power train configurations, section III deals with HEV's modes of functioning, Section IV represents the mathematical modeling of HEV, section V describes the various approaches to energy management that electric vehicles employ, section VI reviews the literatures based on EMS, and section VII contains the conclusion part of this work.

II. POWER TRAIN CONFIGURATIONS

The primary issue when developing dual-power vehicles is appropriately controlling energy transfer from sources to loads while avoiding energy losses, a factor heavily influenced by driving patterns. It contains various electrical components, including embedded power-train controllers, power electronics, continuously variable transmissions, and electric machinery [13]. Three powertrain configurations are recognized for modern electric vehicles: parallel, series, and power-split (series-parallel) [14]. The customer's preferences usually determine the configuration used. As a result, the critical difficulty in HEV development lies in finding the most effective approach to distribute power while attaining the needed performance within the system's limits [7].

A. SERIES HEVS

In series HEVs, the primary mode of propulsion is provided by traction motors, with the reciprocating engine (ICE) serving as a generator, and these motors draw power from the battery [9]. In this configuration, no direct mechanical link is enclosed by the ICE and the propelling axle of the automobile. As a consequence, the traditional fuel-engine can run in its most efficient range despite the speed and the required power, which makes the series hybrid powertrain more straightforward in terms of both its configuration and energy management [15]. Additionally, the new configuration boasts a broader operational area and greater effectiveness than the typical one. Figure 2 shows the Series Hybrid Electric Vehicle schematic. However, they can experience significant energy conversion losses because All the power generated by the ICE needs to be initially changed through electric power [16]. The battery reserves a part of the energy, while the rest drives the M/G and runs the vehicle. Despite the relatively enhanced effectiveness of the Electric Motors (EMs) and the high efficiency of the ICE, several transformations in generated power lead to a reduction in performance overall [17]. Furthermore, the aforementioned arrangement demands a larger induction machine to meet the torque requirements since it is the sole source of traction [13]. Various automobile manufacturers, including Mitsubishi, Volvo, and BMW, have delved into the potential development of series HEVs. However, even with extensive research, the practical adoption of series HEVs remains largely confined to extremely durable cars. While this configuration generally offers the advantage of optimal engine functioning with exceptional efficiency, that benefit is often counterbalanced by the necessity for robust and expensive accumulative sources exhibiting a significant energy concentration. Robust storage devices are essential since, in many situations, the electric driver may need to provide 50% of the required power on its own [18], [19].

B. PARALLEL HEVS

In the case of parallel HEVs, the gasoline-powered engine and the induction machine are mechanically linked to the vehicle's output shaft, enabling them to contribute power to propel the vehicle simultaneously [7]. The ICE connects to a mechanical path, while the energy storage system path is termed the electrical path, permitting bidirectional power transmission [9]. The available EM optimizes engine performance by adjusting its operational parameters to a range that enhances efficiency. When there is little need for energy, it operates as a generator; when more power is demanded, it acts as an electric motor [20]. Figure3 shows the power train connection for Parallel-HEV. When the Energy storage packs reach the whole power level, the IC engine and the EM may operate the car separately or simultaneously, depending on the riding circumstances. During periods of minimal SoC, a portion of the rotational force produced by the heat engine is redirected to propel the electric motor, which functions as a generator to replenish the battery pack [9]. This design's primary advantage lies in its versatility in selecting the capacity of the ESS and EM to be installed, as the highest angular motion for the automobile is supplied in coordination with the internal combustion engine, which can be operated

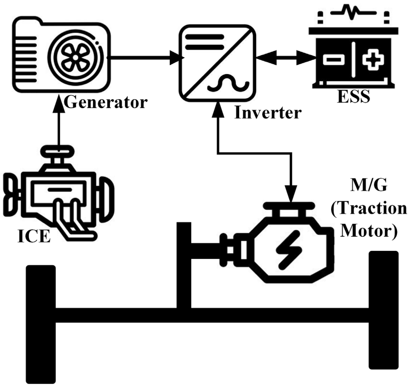

FIGURE 2. Schematic for a series hybrid electric drive.

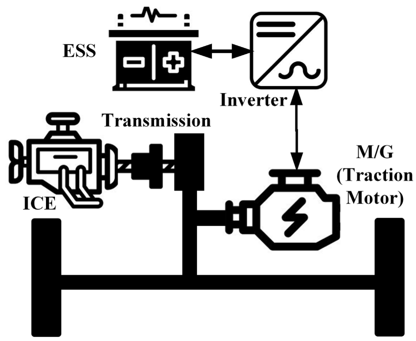

FIGURE 3. Diagram illustrating a parallel hybrid electric vehicle.

at a greater degree of performance compared to a traditional vehicle [13].

However, this configuration may not be the most efficient because of the persistent coupling that is mechanical across the internal combustion driver and the output spindle [21]. Moreover, the electric power drive is unable to both refuel the battery and contribute to propelling the transport concurrently. To maintain a balance between power assistance and EV operations and avoid battery depletion, careful control is required [6]. This issue becomes more pronounced during city driving, where frequent start-and-stop cycles can deplete the battery and lead the engine to operate in its less efficient range. Consequently, parallel HEVs have a relatively minor market share despite the availability of various models [13]. The Insight model, which Honda launched and is categorized as a parallel-configured HEV, is one particular example of a hybrid electric vehicle.

C. POWER SPLIT (SERIES-PARALLEL) CONFIGURATION

The setup resembles a parallel HEV, essentially resembling a vehicle utilizing a Parallel structure with a smaller series configuration integrated inside its layout [19]. Such a combination effectively brought the benefits of the other two architectures to mitigate its drawbacks. As an illustration, the challenge of appropriately selecting the Energy Storage System and Electric Motor in series configuration is resolved as this design's underlying principle is compatible with parallel structure [22]. Simultaneously, the difficulty of driving in constantly changing traffic, which is disadvantageous to parallel HEVs, is addressed by the capability to continue recharging the power source even though the car idles [23]. Those achievements become achievable because of an energy splitter, for instance, the planetary distribution installed in the Prius car made by Toyota. As a result of these characteristics, the series-parallel HEV has become the option preference for numerous automakers in modern times [19]. Figure 4 represents the schematic of the above-discussed arrangement.

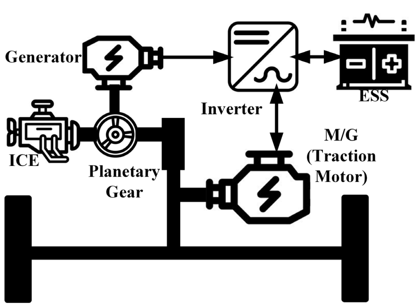

FIGURE 4. Schematic of power split hybrid electric vehicle.

One or more gear pairs are commonly employed in this arrangement to connect the driveshaft, two electric power units, and the CI machine [24]. The power-split hybrid powertrain, also known as a power split device (PSD), is centered around these PG sets. The PSD functions as a CVT, severing the ICE's connection to the vehicle's speed and guaranteeing effective engine performance. Therefore, the term "electronic-CVT" (E-CVT) is occasionally used to refer to the PSD cars [13]. Compared to both series and parallel HEVs, power-split HEVs can often achieve higher fuel economy because of this decoupling capability, especially when traveling in urban situations [25].

The power-splitting apparatus makes energy sent to the transmission from the engine easier via the electrical or mechanical paths [26]. Like a series HEV, the PSD functions in the electrical path by first converting some of the internal combustion engine's power into electrical potential using a converter. This potential is subsequently applied to power the motor or charge the battery. The PSD enables the framework to function in the mechanical path as a parallel HEV, letting the ICE send power straight to the driveshaft. As a result, the benefits of the other two configurations are combined in power-split HEVs [27], [28].

However, the electrical route experiences higher energy loss compared to the mechanical pathway due to additional energy conversions taking place. More ICE power is transmitted across the electrical channel, which results in increased energy loss brought on by the PSD [24]. Energy transfer is most effective when the speed of either EM is zero, which results in zero power transmission along the engine-generator-motor path. This state is referred to as the mechanical point. Power-split HEVs can occasionally show greater energy losses than parallel HEVs due to the release of power inside the electrical network, especially while cruising at high speeds [13].

The Hybrid Synergy Drive (HSD) is an outstanding representation of an input-split power-split hybrid system [13].

III. HEV'S METHOD OF FUNCTIONING

The energy-storage system's SoC fluctuates over time, influenced by the energy source that supplies the power for propulsion. The SoC's behavior is employed to indicate the specific mode in which the energy-storage system operates, such as charge-depleting (CD), electric vehicle (EV), and charge-sustaining (CS) modes [29], [30].

The electric vehicle (EV) mode involves running the vehicle exclusively on electricity from the electric machine till attains a predefined level of charge or completes a specified session. In this mode, the battery depletes quickly but can be replenished by regenerative energy during braking. If the electric machine cannot meet the vehicle's power requirements, it will trigger a mode change, causing the engine to start [31].

In Charge Depleting (CD) mode, the car could be run by the combustion chamber and motor simultaneously, and the engine also recharges the battery. However, the SoC of the battery will gradually decrease. If needed, cars running in this mode can switch to the CS option to charge the ESS [32].

Charge-sustaining (CS) mode bears similarities to CD mode; the primary distinction lies in the preservation of the

State of Charge (SOC) of the Energy Storage System. This means that the ICE supplies the typical force required for shifting the vehicle while the battery provides the extra power needed for acceleration and other dynamic demands [33].

IV. MATHEMATICAL MODELING OF HEV

A. STATE OF CHARGE (SoC)

It is specified as a measure of its residual charge relative to its total capabilities [34]. Efficient battery usage is reflected in a better SoC profile. Maintaining a high SoC is always preferable [35]. The performance of a battery is significantly influenced by its SoC, which is mathematically expressed as [36]:

$$SoC_{bat} = \frac{V_{OCV} - \sqrt{V_{OCV}^2 - 4R_{inter}P_{bat}}}{2C_{initial}R_{inter}} \tag{1}$$

In this equation (1), V_{OCV} is the battery's voltage in an open circuit, $C_{initial}$ represents initial charge volume, R_{inter} denotes the inner resistance of the storage systems, while P_{bat} stands for the output power of the battery.

B. BATTERY MODEL

There are many ways to model batteries, from simple schematics to intricate ones [37]. A resistor and a constant voltage source are coupled in series in the most basic model. More complex models include extra parts to capture additional characteristics of batteries, like capacity and discharge rate. Rather than analyzing the battery itself, these models are primarily employed to evaluate the operation of circuits coupled to the battery [38].

In a broader context, there are three fundamental categories of battery models: those based on runtime, impedance, and Thevenin principles. Impedance-based Models are particularly effective since they accurately capture the active behavior of energy storage systems. These models leverage the relationship between battery impedance and its state, which is influenced by factors like state of charge (SoC), temperature, life cycle, and charge/discharge current [39]. An illustration of the improved battery cell model's equivalent circuit is presented in figure 5 [37].

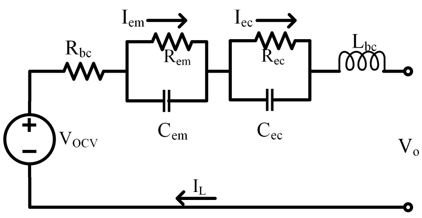

FIGURE 5. Schematic of improved battery cell.

The voltage measured in a battery unit without a load connected is represented by V_{OCV}, while R_{bc} denotes the cell's internal resistance. The electromagnetic short-term double-layer effect is characterized by two parameters: resistance (R_{em}) and capacitance (C_{em}). The electro-chemical long-term mass transport effect is also characterized by two parameters: resistance (R_{ec}) and capacitance (C_{ec}). The battery cell's inductance and resistance are denoted by L_{bc} and R_{bc}, respectively. The load current is represented by I_L [40]. The battery cell's terminal voltage (V_o) can be calculated using the following equation:

$$\begin{aligned} V_o = V_{OCV} - I_L \times R_{bc} - \frac{1}{C_{em}} \int (I - I_{em})dt \\ - \frac{1}{C_{ec}} \int (I - I_{ec})dt - L_{bc}\frac{\mathrm{d}I_L}{\mathrm{d}t} \end{aligned} \tag{2}$$

where, $I_{em} = V_{em}/R_{em}$, and $I_{ec} = V_{ec}/R_{ec}$.

C. THE FUEL CELL

The electrical circuit model that represents the fuel cell (FC) is shown by the following mathematical equation. In this model, $\tilde{E}_{OCV}$ is the voltage of the FC when no current is flowing, $\tilde{V}_{tr}$ represents the voltage loss during transfer, $\tilde{R}_{la}$ and $\tilde{R}_{tr}$ are the resistances of the FC layers and the restriction during transfer. $\tilde{C}_{la}$ is the capacitance of the double layer. $\tilde{V}_{out}$ and $\tilde{I}_{fc}$ represent the output voltage and current of the fuel cell, respectively [41], [42].

$$\begin{cases} \tilde{V}_{out} = \tilde{E}_{OCV} - \tilde{V}_{tr} - \tilde{R}_{la}\tilde{I}_{fc} \\ \tilde{I}_{fc} = \tilde{C}_{la}\frac{\mathrm{d}\tilde{V}_{tr}}{\mathrm{d}t} + \tilde{V}_{tr}/\tilde{R}_{tr} \end{cases} \tag{3}$$

D. THE ULTRACAPACITOR

There are several ways to model ultracapacitors (UCs) in the scientific literature. Three standard models are the distributed constant model, the localized constant model, and the behavioral model with two branches [43], [44]. The generalized model consists of a capacitance, $\tilde{C}_{uc}$, and a series resistance, $\tilde{R}_{uc}$. The mathematical equation that describes this model is shown below:

$$\begin{cases} \tilde{V}_{uc} = \tilde{V}_{uc0} - \tilde{R}_{uc}\tilde{I}_{uc} \\ \tilde{I}_{uc} = \tilde{C}_{uc}\frac{\mathrm{d}\tilde{V}_{uc0}}{\mathrm{d}t} \end{cases} \tag{4}$$

In this equation 4, $\tilde{V}_{uc}$ and $\tilde{V}_{uc0}$ represent the obtained voltage from the ultra-capacitor and the initial voltage, respectively. $\tilde{I}_{uc}$ denotes the output current of the Ultra-capacitor.

E. THE MODELING OF POWER DEMAND

In the event that the velocity of the vehicle is known beforehand, one can compute the necessary power for its propulsion by applying the subsequent formula [45]:

$$P_{req} = (\delta_m\tilde{m}\tilde{a} + \frac{\tilde{C}_{ad}A_f}{21.15}\tilde{v}^2 + \tilde{m}g\tilde{f}_r)\tilde{v} \tag{5}$$

The representation of the equivalent inertia from the revolving components of the axles and transmission system is indicated by δ_m, the weight of the vehicle is represented by $\tilde{m}$, $\tilde{a}$ denotes the acceleration, the coefficient of the aerodynamic is $\tilde{C}_{ad}$, the transport's anterior area is A_f, g is the force of gravity, $\tilde{v}$ is the vehicle's speed, and the coefficient of traction resistivity is $\tilde{f}_r$.

HEVs utilize a combination of mechanical and electrical powertrains, which can be used together or separately to power the driving shaft [46]. The formula for the overall power delivered to the car is:

$$\tilde{P}_{demand} = (\tilde{P}_{eng} + \tilde{P}_{bat}\tilde{\eta}_m)\tilde{\eta}_T \quad (6)$$

In this context, $\tilde{P}_{eng}$ stands for the generated power by the engine, $\tilde{P}_{bat}$ represents the potential delivered by the ESS, and $\tilde{\eta}_m$ signifies the effectiveness of the induction M/G, and $\tilde{\eta}_T$ indicates the axle's and transmission's capacity [45].

V. ENERGY MANAGEMENT STRATEGIES FOR HEV

Efficient power distribution in electric vehicles relies heavily on executing successful approaches for Energy Management. It plays a central role in both meeting the vehicle's power requirements and optimizing its power system. The EMS dictates how each energy source responds to power demands, facilitating the efficient distribution of power [47]. The key objectives of energy management strategies encompass ensuring satisfactory performance in terms of acceleration, noise, range, and handling, as well as meeting power demands, maximizing fuel efficiency, reducing emissions, and minimizing the overall cost of the propulsion system [48]. These objectives act as guiding principles while developing energy-saving maneuvers for hybridized automobiles. Consequently, an effective EMS is critical for achieving efficient power distribution and improving the overall functionality of electric vehicles. This EMS is integrated into the vehicle's central controller, which continuously monitors operating conditions and makes decisions to control components and adjust their operational parameters accordingly [49]. Different types of control approaches have been used for electric vehicles. Figure 6 indicates the trends and advancements in Electric Vehicle energy management strategies over time [50].

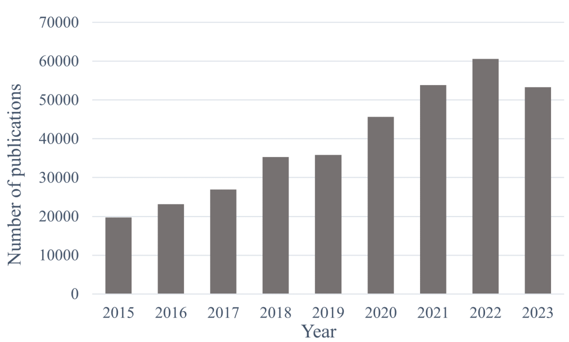

FIGURE 6. Evolution of scientific literature based on electric vehicle powertrain control systems.

Traditional actions to control the power flow in electrified SUVs are focused on the same basic principle of adjusting intake information to generate resultant signals [51]. This uniformity carries both advantages and disadvantages. On the one hand, it makes these strategies very reliable. On the other hand, due to this fixed nature, they are less able to adjust to modifications in the drivetrain specifications of the car. As a result, traditional strategies are unable to handle the uncertainties, which leads to inefficient use of power and poor fuel economy [31]. In the past few years, a selection of new energy management strategies for PHEVs have been created that rely on locally known vehicle variables and are optimized for real-world and real-time driving conditions. However, most of these strategies have only been evaluated using standard driving cycles, such as the U.S. EPA's city and highway cycles, which are used for fuel economy testing. Therefore, their effectiveness under real-world driving conditions is not well suited [52].

A. THE CLASSIFICATION OF EMS

Several control schemes have been implemented to maximize HEVs and PHEVs' functioning. These fall into two categories, commonly referred to as rule-based and optimization-based techniques. These two primary groups encompass all additional subcategories [49]. An in-depth analysis of several electric car control schemes, including their contributions and shortcomings, is given in the following section. Figure 7 symbolizes a cluster of energy-saving measures in hybrid electric car systems.

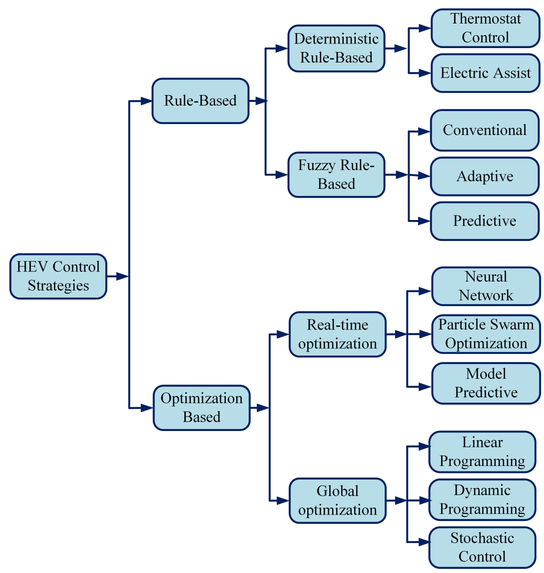

FIGURE 7. Classification of the energy management strategies for HEV system.

1) RULE-BASED ENERGY MANAGEMENT STRATEGY

This strategy is referred to as real-time control tactics that rely on preset rules derived from individual skill, intuition, and the properties of the power line. [49]. These strategies are computationally efficient and easy to implement but lack of mathematical analysis and theoretical basis, making it difficult to define accurate thresholds and rules. A great deal of parameter validation and adjusting is needed to increase performance for specific driving cycles. It does not involve attenuation or maximization, and their solutions cannot be guaranteed to be optimal. In order to maximize rule-based strategies, several techniques have been proposed. These include hybrid energy management strategies, which combine ECMS, and blending strategies, such as instantaneous and rule-based strategies [7]. Using rule-based control strategies, the power generated sources run at their most efficient phases to maximize fuel utilization, reliability, and emissions for a particular driving cycle. However, their ability to determine the global minimum and optimize the vehicle holistically is limited. Figure 10 represents the flow chart of sample rule-based EMS. Subcategories of this kind of methodology include deterministic rule-based and fuzzy rule-based [31]. Figure 9 showcasing the trajectory of two distinct tactics [53].

Deterministic control strategies operate based on predefined rules and state machines, often depicted in flowcharts and control parameter tables, along with real-time inputs. So, prior knowledge of future speed vs. time profiles is optional [54]. State-machine-based control logic is used, with different states representing various vehicle operation modes. These strategies aim to balance the load between the ICE and the traction electric device to maximize fuel economy, efficiency, and emissions. The electric propulsion system adjusts the ICE's operating points to match the power demand, either by providing additional propulsion energy or taking in extra power to replenish the onboard storage [55]. An example of such a controller is the thermostat controller, which uses the SoC of the cells and circulatory force demands to turn the engine on and off. While this approach works for some hybrid vehicles, it may not be suitable for optimizing modern electrified transport systems. The most popular is the widely discussed rule-based strategy known as the "power follower," which is employed by automobiles like the Honda Insight HEV and Toyota Prius. The power follower's primary goal is keeping the ESS charged. It is well-suited for parallel hybrid topologies where the electric motor assists with torque. However, it is not ideal for PHEV applications as it is not adaptable to various drive cycles and cannot handle uncertainties resulting from powertrain model errors [56], [57].

The fuzzy EMS approach, an expansion of the conventional deterministic rule-based strategy, is well-suited for managing energy in dynamic, nonlinear systems like PHEV drivetrains due to its advantages in robustness, adaptability, and ease of fine-tuning. These strategies reduce the complexity of assessing and offer an extra level of abstraction [7]. Nonetheless, they rely on predefined rules and are primarily optimized for specific driving scenarios. This method involves several stages, In the first step, fuzzification is employed to transform the input data into a precise value or a linguistic variable. The precise input could be the vehicle's power demand or the battery's SoC. For the fuzzification process, three main types of fuzzifiers are utilized: Gaussian fuzzifier, Singleton fuzzifier, Triangular/trapezoidal fuzzifier [8]. To simplify calculations and ensure a smooth transition, trapezoidal membership functions (TMFs) are employed for fuzzification instead of Singleton fuzzifier or Gaussian-type functions. This precise value or fuzzy set is then utilized to develop a rule in the inference-making block, emulating the human decision-making process. It is the most crucial part of the fuzzy logic controller, which controls the effectiveness of a fuzzy rule-based EMS. It has two components: the membership function and the fuzzy rule. The formulation of fuzzy logic rules and their associated membership functions is an iterative process that draws upon human knowledge, experience, and intuition that introduce uncertainty into control performance [58]. Figure 8 represents the FLC's fundamental block diagram.

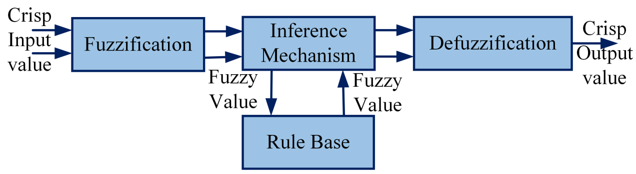

FIGURE 8. Block diagram representation of fuzzy logic controller.

Various optimization techniques, such as proportional factors, genetic algorithms, particle swarm optimization, and bat algorithms, are used to enhance performance. To bolster robustness and adaptability further, the strategy incorporates adaptive neural fuzzy inference systems, machine learning algorithms, and the recognition of driving patterns [59]. The final step, defuzzification or inverse fuzziness, transforms linguistic variables into numerical values or precise outputs. The most widely used method in practice is the center of gravity (COG) approach [60].

2) OPTIMIZATION-BASED CONTROL STRATEGY

Designers have shifted to optimization-based controllers because rule-based approaches are too inflexible. These controllers use a cost function to find the best way to control the PHEV, taking into account the vehicle and component parameters, as well as the desired performance (emissions, fuel consumption, and torque) [31]. Different cost functions lead to different optimization problems, and various techniques based on optimization have been suggested to address these issues [61].

Despite extensive research aimed at enhancing the efficiency of optimization-driven EMS, it is difficult to strike a balance between optimal and implementation [62]. An accessible, pragmatic optimization-driven power distributed method is still not available [7].

Optimization-focused control techniques can be categorized into two primary groups: global and real-time optimization.

Global optimization energy management strategies for HEVs aim to find the best way to use the vehicle's energy sources (e.g., engine, battery, electric motor) to reduce fuel usage and emissions throughout a specified driving pattern. They do this by considering the physical constraints

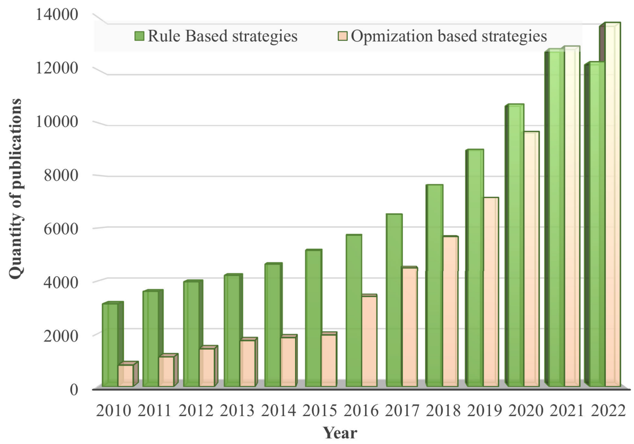

FIGURE 9. Illustrating the evolution of two contrasting strategies.

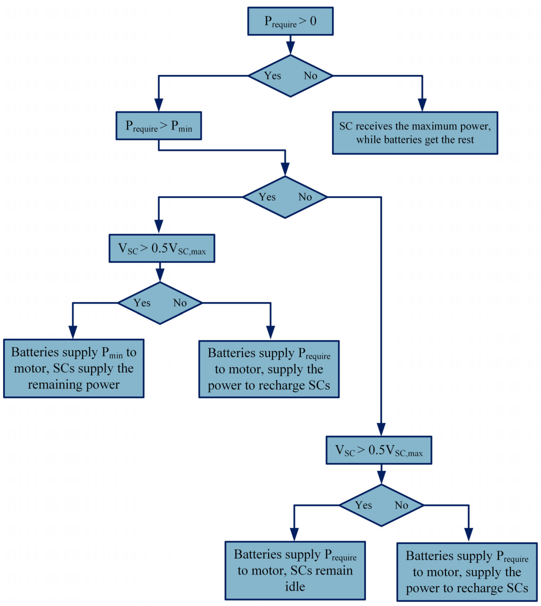

FIGURE 10. Flow chart representation of sample rule-based energy management strategy.

of the vehicle (e.g., engine capacity, battery capacity, electric motor power) as well as driving conditions (e.g., speed, acceleration, traffic) [7]. These approaches necessitate an understanding of the driving cycle in advance [63]. Hence, they are referred to as non-causal control methods. Unless there's an accurate prediction of forthcoming driving conditions, these approaches cannot be directly executed in a practical scenario. Additionally, global optimization energy management strategies are more computationally expensive than rule-based energy management strategies [64]. Despite these challenges, among the various energy management strategies for HEVs, global optimization remains the most extensively researched. Figure 11 proves the progress of global optimization-based strategies throughout time [65]. Common optimization algorithms used for this purpose include linear programming, dynamic programming, and genetic algorithms [66].

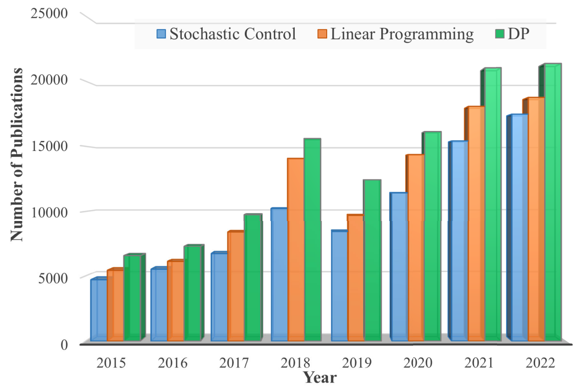

FIGURE 11. Depicting the development of global optimization-based approaches over time.

Real-time optimization refers to using controllers that can optimize themselves in real-time, allowing PHEVs to achieve their maximum potential. These controllers use past information to develop a cost function and continuously optimize it in real-time [31]. Consequently, it is directly applicable to real-time control systems [67]. This strategy should be simple enough to be implemented with limited computational resources and avoid manual control parameter tuning. ECMS and MPC are two prominent real-time optimization strategies that have gained significant research attention in energy management applications. ECMS exhibits responsiveness to the driving cycle, whereas MPC necessitates foreknowledge of future driving details [68]. Hence, navigational details are crucial for these approaches. Overall, real-time optimization aims to stabilize the energy distribution in PHEVs while maintaining the ESS charge [69].

VI. OVERVIEW OF THE LITERATURE CONCENTRATING ON ENERGY MANAGEMENT APPLICATIONS

A. RULE-BASED ENERGY MANAGEMENT STRATEGIES

1) FUZZY RULE STRATEGIES

Yu introduced a fuzzy logic and genetic algorithm (GA) based EMS for plug-in hybrid electric cars. This approach takes the torque request and Charge levels as input and calculates the engine torque as output. The GA improved the fuzzy rules to achieve better gasoline consumption. The simulation indicated an improvement in the expenditure of fuel by 4.41% in contrast to its predecessor fuzzy logic approach. The charge level in storage devices was more balanced, with a decrease of 0.062 and 0.035 before and after optimization, respectively. The torque output of the vehicle is also more stable after optimization [70]. Traore et al. implemented an EMS based on fuzzy logic control, Lyapunov control, and frequency separation for an electric vehicle's multi-source system in which Lyapunov controls the total energy flow to keep the DC-bus voltage steady. The approach combines FLC with frequency separation to maximize the use of ESS and ensure effective EMS in the system. Low-pass filters are also incorporated into the plan to protect the fuel cell and batteries from strong current dynamics. The results of the testing demonstrate that the suggested method can maintain a steady DC-bus voltage of 150V and regulate the transmission of electricity [41]. Ishaque *and others* applied a Fuzzy logic controller and the ultra-power transfer algorithm (UPTA) to manage the power supply flow, where UPTA managed the energy transmission within the principal and auxiliary energy storage systems (ESSs). The proposed design was compared to the proportional-integral (PI) controller regarding performance and stability. Numerous metrics, including integral squared error (ISE), integral absolute error (IAE), and integral time-weighted absolute error (ITAE), were used to compare the results. The comparison was carried out at two different SoCs of the battery: 45% and 95%. At 45% battery SoC, the FLC had a better ISE value (0.41) than the PI controller (0.55). Similarly, the IAE and ITAE values for FLC were also better than the PI controller. The same trend was observed at 95% battery SoC. The FLC also had a smaller rise time, response time, and overshoot than the PI controller, except for settling time. Overall, the proposed design with FLC had a better response and stability than the PI controller in the EMS of HEVs [8]. Dawei *and collaborators* proposed a fuzzy logic control strategy for the uniaxial PHEV that uses a method based on genetics to maximize the membership functions and control rules, which improves the strategy's performance compared to the electric auxiliary strategy. Intelligent control approaches optimize the membership functions and regulate algorithms to guarantee that the high-efficiency zone is where the majority of the motor functioning areas are located, which prevents the motor from producing peak torque [71]. Jin et al. suggested an FLC-based energy distribution approach. The strategy limits the battery's power and engages the ultra-capacitor during acceleration and regenerative braking. The resultant data showed that the fuzzy logic control strategy significantly reduces battery degradation by 17%, but the system encounters significant fluctuations in power levels when the vehicle speed is high [72]. Hajimiri and Salmasi introduced a fuzzy logic control strategy that relies on forecasting the future state of a vehicle and the health condition of the batteries to safeguard the battery from severe harm. Their proposed approach, named the Predictive and Protective Algorithm (PPA), regulates the battery's recharge and discharge in accordance with its SOH, aiming to prolong the battery's lifespan. The simulation outcomes revealed that the Predictive Algorithm curtailed fuel consumption, reducing it from 0.202 Lit/mile (PFA) to 0.189 Lit/mile, and mitigated emissions of CO, HC, and NOx [73].

Yin et al. introduced the Adaptive FLC Based Energy Management Strategy (AFEMS) to offer a holistic control solution tailored for congested urban and highway driving scenarios. Simulation findings indicate that, on average, AFEMS outperforms the Limited Tolerance Method (LTM), Thermo-state Method (TM), and Average Load Demand (ALD) method in the case of system efficiency, battery current fluctuation, and the discrepancy in ultracapacitor State of Charge (SoC) [60]. Suhail et al. presented an ANFIS control for PHEVs. The advanced controller adjusts the value of the forward gain, resulting in improved energy management and battery performance in hybrid electric vehicles. The results carried out on the simulation showed that the ANFIS controller with Gaussian membership function was the most energy-efficient, with the highest SoC value at 84% and a smooth SoC curve compared to the ECMS, Adaptive-ECMS, and Fuzzy A- ECMS [35]. Kakouche and other co-authors proposed a novel fuzzy-MPDTC controller to lower the torque and flux ripples of the system by predicting future behavior and optimizing the cost function. The proposed MPDTC method improved the performance of the overall system by reducing torque and flux ripples by 54.54% and 77%, respectively [74].

2) BLENDED RULE BASED ENERGY MANAGEMENT STRATEGIES

Bianchi et al. proposed a blended method to extract rules from dynamic programming to devise a rule-based strategy that can be put into practice. The proposed approach involves analyzing the results of DP to identify recurring formations in its choices and then extracting standards that may be used to create a sub-optimal rule-based controller. Simulation results proved that the SoC profiles are similar in shape to DP programming and have a higher mean value [75]. Chen et al. also used the Dynamic Programming optimization technique to optimize current flow in fuel cells. Additionally, Genetic Algorithms were applied to lower the instantaneous cost [76]. Wang and colleagues developed a rule-based power distribution strategy considering demanded power, residual energy, and power capability. The remaining capacity and power capabilities of the batteries and supercapacitors were calculated using the Bayes Monte Carlo method. Employing this strategy achieves a 6.81% decrease in hydrogen usage relative to the strategy that does not involve SOP estimation and also minimizes the instances of starting and stopping a fuel cell. Additionally, the DEM strategy lowers the power fluctuations of the battery and fuel cell systems [77]. Peng and co-authors introduced an innovative technique to improve rules-driven energy estimation by leveraging optimal solutions derived from the DP algorithm. The key novelty of this approach is its development of a fresh method to fine-tune existing rule-based control strategies using globally optimized outcomes obtained from sophisticated intelligent algorithms. Experiments conducted in hardware-in-loop (HIL) demonstrated a prolonged CD mode and an enlarged engine working spectrum. Moreover, they achieved a 10.45% decrease in diesel consumption and a 4.75% reduction in battery charge consumption per 100 kilometers. [78]. Similarly, Li and collaborators developed a strategy termed Optimal-LTCS using the pseudospectral method, which outperformed the conventional Logic Threshold Control Strategy (LTCS) in simulation studies. The developed Optimal-LTCS effectively utilized the positive aspects of the ultra-capacitor, suppressed battery currents to less than 1C, decreased energy losses, minimized voltage fluctuations, and perhaps increased the driving range [79]. Hofman et al. introduced an EMS which is the combination of Rule-based and Equivalent Consumption Minimization Strategies (RB-ECMS) having various types of driving modes selected from different states and conditions. When evaluating the Toyota Prius model 1998, using the RB-ECMS for fuel economy and control strategy, it was found that the default strategy in ADVISOR could be considerably improved (12%). The RB-ECMS results were also very close to the best possible outcome calculated with DP (within 1%) [80]. Padmarajan et al. introduced an innovative acausal rule-based EMS that effectively manages battery energy usage and engine operation, minimizing energy conversion losses by integrating driving information and estimated trip energy. This strategy, based on the blended charge depletion (BCD) principle, has the potential to be implemented in various plug-in hybrid architectures. The proposed EMS adapts to uncertain trip requirements, resulting in an 18.4% enhancement in fuel efficiency and a substantial decrease in engine stop-and-start instances compared to the typical CS-CD approach [81].

B. OPTIMIZATION-ORIENTED STRATEGIES FOR ENERGY MANAGEMENT

1) REAL TIME OPTIMIZATION BASED APPROACHES

Paganelli and his colleagues present the idea of equivalent gasoline utilization as part of the methodology for the management of energy (ECMS). This notion sees the battery as a supplementary fuel tank that receives charge from the gasoline engine and discharges it to alleviate the ICE workload, thereby economizing fuel. ECMS computes the overall fuel usage by summing the actual ICE energy expenditure and the induction actuator's equivalent fuel usage. Through the use of a unified representation, an instantaneous optimization issue becomes the replacement for the global optimization problem, simplifying its solution and reducing computational complexity [49]. ECMS calculates equivalent fuel consumption dynamically, considering the present system variables, eliminating the need for future predictions, and reducing the number of required control parameters. ECMS can compensate for uncertainties in dynamic programming and provide an immediate optimal resolution for the power distribution plan, making it suitable for operating in actual time. However, this strategy doesn't ensure the long-term sustainability of the system's charge. The equivalent factor (EF) significantly impacts the control strategy's torque distribution and is crucial for achieving the optimization effect of ECMS [82]. Figure 12 exemplifies the fundamental block diagram for ECMS strategy.

According to the ECMS control strategy's fundamental principles, the overall instantaneous equivalent fuel usage can

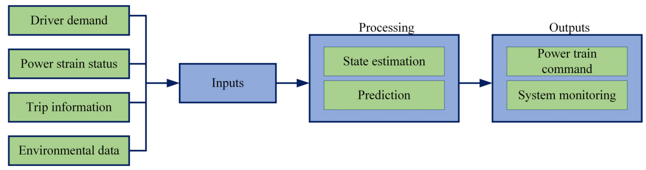

FIGURE 12. Depicting a basic block diagram for the ECMS-based energy management strategy.

be expressed in the following manner:

$$\begin{cases} \tilde{P}_{eqv} = \tilde{P}_{ice} + \tilde{s} \times \tilde{P}_{bat} \\ \tilde{P}_{ice} = \tilde{M}_{ice} \times \tilde{Q}_{lcv} \end{cases} \tag{7}$$

Herein, $\tilde{P}_{eqv}$ represents the total instantaneous equivalent fuel consumption. $\tilde{P}_{ice}$ denotes the power associated with the fuel consumed by the engine, $\tilde{s}$ represents the equivalence factor, $\tilde{P}_{bat}$ represents the power drawn from the battery, $\tilde{M}_{ice}$ represents the engine's fuel consumption, $\tilde{Q}_{lcv}$represents the low calorific value of diesel [82].

ECMS approaches can be categorized based on their EF adaptation strategies. There are two main types of ECMS methodologies: (1) offline design utilizing global optimization algorithms and (2) online adaptation that adjusts EF in real-time.

Offline EF design ECMS, also known as basic ECMS, necessitates prior knowledge of the route to achieve overall efficiency. The best possible efficiency factor remains unchanged throughout the path because there is no mechanism to adjust it. Moreover, the EF needs to be adjusted specifically for every unique driving profile, further complicating the process [83].

Adaptive ECMSs (A-ECMSs) incorporate online EF adaptation capabilities that consider elements like desired and restricted battery charge levels, present SoC readings, and current and upcoming driving circumstances. Firstly, ECMSs must take into account the battery state-of-charge limitations, such as ensuring charge longevity and adhering to higher and lower SoC boundaries. Therefore, EF adjustments are necessary based on SoC-related parameters. To achieve the desired EF adjustments, a variety of control techniques can be implemented, including weighting functions, PID controllers, rule-based techniques, neural network adaptability, and methods based on linear regression [84].

Sciarretta et al. proposed an ECMS strategy that utilized the concept of fuel equivalent for electrical energy to optimize energy management. For the MVEG-A and the ECE urban driving cycle, the suggested approach demonstrated a reduction in fuel consumption that could reach 30% and around 50% compared to conventional methods, respectively. This performance improvement did not affect charge sustainability, as SoC variations remain within 2% for the specified cycles. The robustness of the ECMS was validated under varying energy horizon scenarios. Additionally, introducing an extra cost term to minimize frequent engine status changes resulted in full qualitative agreement [21]. Pisu and Rizzoni compared three strategies for controlling a parallel- SUV:

rule-based control, A-ECMS, and H-infinity control. They discovered that A-ECMS proved to be the most effective approach, closely resembling the optimal solution identified through dynamic programming. A-ECMS is also more robust and more accessible to drive than the other two strategies, but it requires more computation and a hierarchical control structure. Rule-based control and H-infinity control are simpler to implement, but they require more calibration effort and are less efficient [85]. Tulpule et al. recommended the ECMS energy management system in PHEV to minimize the usage of fuel by obtaining the lowest possible battery SoC. Under conditions of extended travel and substantial energy storage, simulations demonstrated that the proposed ECMS achieved outcomes equivalent to those of the DP [86]. Li and his colleagues developed a strategy for optimizing energy usage in FCHEVs using an ECMS, including two other sources (battery and ultracapacitor), where the three sources were taken into the objective function. The suggested ways underwent testing in various driving patterns, and the outcomes showed that ECMS consumed less hydrogen and maintained the fuel cell's most extended durability compared to both the RBCS and the HEOS [87]. Chen and collaborators presented a novel P-ECMS methodology for managing energy distribution in PHEVs, assuming the availability of two levels of traffic information (segmented traffic information and detailed velocity information). To evaluate the strategy, its effectiveness was assessed in comparison to the Adaptive-ECMS approach. The comparative results found that the proposed method reduced fuel consumption (9.7%), provided robust performance, and minimized the standard deviation (96%) in terms of fuel usage when contrasted with the A-ECMS measures [88]. Lee and Cha developed a new strategy that utilizes reinforcement learning (RL) in conjunction with the ECMS, in which the comparable variable was ascertained by the RL substances and the driving situation's interaction. The proposed method was compared to the A-ECMS and found that the recommended system could attain a solution close to optimal, reaching 96.7% similarity to the DP outcome, and it enhanced performance by an average of 4.3% [89]. Wang and others recommended a Fuzzy Adaptive-ECMS dependent energy management system to adjust the proportional element. A comparative result validated the effectiveness and robustness of the proposed controller among other controllers [90]. Zeng et al. offered an optimization-oriented A-ECMS scheme. This strategy used a local optimization process to periodically update the equivalent factor. Simulations reveal that compared to current alternatives, the recommended EMS techniques are more reliable and productive. It can save fuel and extend the battery life [91].

Model predictive control (MPC) is a sophisticated control algorithm designed to enhance the efficiency of a regulated method. The primary concept of this controller is to forecast the forthcoming actions of the system based on its current state and a reference framework of the system to calculate an optimal regulate signal that will minimize a defined function of cost [92]. The cost function usually comprises elements representing the difference between predicted and real system outputs, constrained by the limits of the control signal [2], [93]. Three stages comprise the MPC programs's operation: (i) utilize the system's dynamic model to predict future outputs within the specified horizon of the fine-tuning; (ii) analyze the associated charges for each set of predicted system outcomes; and (iii) implement the initial component of the control tactic that minimizes the predicted cost. Figure 14 represents the block diagram of Model Predictive controller.

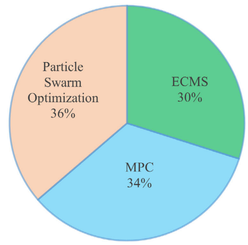

FIGURE 13. The percentage of three real-time optimization-based journals published since 2019.

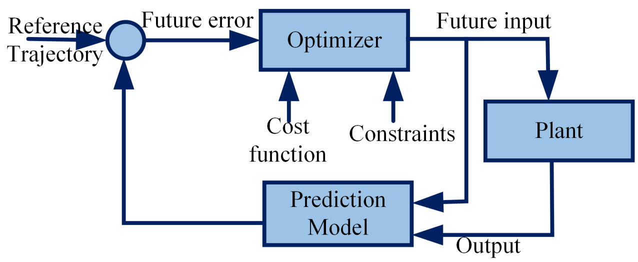

FIGURE 14. Block diagram representation of MPC controller.

Concerning a specific HEV, the comprehensive mathematical representation of its behavior is described by the equation below,

$$\begin{cases} \tilde{x}(m+1) = A(m)\tilde{x}(m) + B(m)\tilde{u}(m) + \tilde{n}(m) \\ \tilde{y}(m) = C(m)\tilde{x}(m) + D(m)\tilde{u}(m) + \tilde{v}(m) \end{cases} \tag{8}$$

In the above equation 8, $\tilde{x}$ represents the system's states at time m, $\tilde{u}$ denotes the inputs of the controller, $\tilde{y}(m)$ presents the outputs of the system at time m, $\tilde{n}(m)$ represents the state noise that affects the system's dynamics, and $\tilde{v}(m)$ represents the disturbance in evaluations that reduce the accuracy the observed outputs [92], [94]. Finally, $A(m)$, $B(m)$, $C(m)$, and $D(m)$ represent the state matrix, input matrix, output matrix, and feedthrough matrix, respectively.

He et al. mentioned an MPC controller to manage the energy of a PHEV where dynamic programming was employed to fix an issue of optimization and Markov prediction to estimate navigation circumstances. They compared the MPC controller to rule-based and DP controllers and found that the MPC controller performed better and was close to the DP controlling scheme [95]. Bordons and the rest used an MPC to improve energy use in an SUV. The MPC's effectiveness in meeting the power demands of the driver was verified through simulations while minimizing fuel usage and meeting operational constraints [96]. Amin and so on designed an approach to limit the rate of change of current (current slope) in fuel cells and batteries and to stabilize the potential difference in a DC bus at a desired value. They showed that the MPC controller was able to achieve both of these goals effectively [97]. Zhang and so forth applied the model-oriented predictive controller (MPC) with a receding time horizon to determine the battery pack's output power. The advanced controller forecasts the torque requirement for the upcoming ten seconds and employs DP-based programming to determine the optimal battery output current [98]. Xiang et al. identified a new methodology to manage the energy that used a combination of nonlinear model predictive control (NMPC) and proportional-integral-derivative (PID) control. This methodology was created to enhance fuel efficiency, preserve the state of charge of the battery, and accommodate driving needs. The outcomes demonstrated that the suggested EMS surpasses alternative approaches [99]. Wang and others suggested a new way to improve the powertrain efficiency of a tracked bulldozer with a hybrid electric power system using an MPC controller. They compared their MPC controller to two other methods and found that the MPC controller's performance surpassed that of the rule-based controller in achieving the desired outcomes and was almost similar to the DP controller [100]. Guo and collaborators planned a new Hybrid Electric Vehicle energy management algorithm that combines the Gauss pseudospectral method and model predictive control. the new algorithm is more accurate and computationally efficient than the Euler method [101]. Golchoubian and Azad proposed a nonlinear model predictive controller (NMPC) for fast-changing systems like electric vehicles. The NMPC controller outperformed without foreknowledge of the forthcoming trip [102]. Pereira and the rest proposed a nonlinear MPC and an RNN control strategy, which is applied to model the fuel cell accurately. The system was tested on a low-cost development board and showed that it can meet the vehicle's energy needs while operating the fuel cell at its most efficient point. The system also reduces fuel cell degradation and provides better fuel economy than other control systems [103]. Machacek et al.introduces a new online-based MPC controller. The proposed controller demonstrates the capability to recapture 70% of the optimality loss of a state-of-the-art predictive controller, and its performance is nearly indistinguishable from that of dynamic programming optimization [104]. Chen et al. employed a reinforcement learning-driven stochastic Model Predictive Controller to establish the ideal storage power within the anticipated timeframe [105]. Jia et al. considered A-MPC controller to maximize the load current between the Energy storage devices in real-time. The AMPC-centered EMS underwent assessments via hardware-in-the-loop tests, revealing its superior performance in hydrogen consumption, stability in FC current fluctuation, and its minimal optimality gap when juxtaposed with an offline dynamic programming-based optimal EMS [106]. Sun and associates introduced a DL algorithm-driven MPC strategy aimed at enhancing fuel efficiency and resilience. This framework underwent assessment across three distinct driving cycles, showcasing resemblances with the DP-based program [107].

2) GLOBAL OPTIMIZATION BASED ENERGY MANAGEMENT STRATEGIES

Dynamic programming is a mathematical approach to solving optimization problems that involve multiple decision-making steps over time [108]. These problems, known as multi-stage decision problems, can be broken down into a series of interconnected stages, where each stage requires a decision that influences both the immediate outcome and the initial state for the next stage. Dynamic programming aims to identify a sequence of decisions that minimizes the total cost across all stages. The technique was pioneered in the 1950s by Richard Bellman, who originally introduced the concept of the optimality principle [109].

Two methods for implementing Bellman's dynamic programming approach are the forward dynamic programming approach and the backward recursive method. Working from the problem's final state backward to its beginning state is known as the backward recursive technique. This technique is typically applied when the problem can be segmented into a group of interdependent subproblems, where the solution to each sub-problem depends solely on the solutions to the sub-problems that come later in the sequence [110]. Dynamic programming involves working forward from the initial formulation of the problem to its ultimate resolution. This approach is often employed when the methodology can be divided into a series of sub-issues, where the solution to each sub-problem depends solely on the solutions to the sub-problems that come earlier in the sequence [20].

Dynamic programming provides the benefit of being applicable to a wide range of systems, including both non-linear and linear systems, problems with constraints and without constraints [49]. However, it also encounters two limitations: the requirement to have complete information about the entire driving cycle beforehand, the challenge of dealing with a large number of variables, and also a significant workload caused by computation. Hence, the control solutions obtained from dynamic programming are primarily utilized as reference points for assessing other controllers or as building blocks for creating and enhancing alternative optimization-based approaches [20].

The following is the generalized cost function of a HEV for dynamic Programming strategy:

$$
\begin{aligned}
J_{cost} &= \sum_{l=0}^{l=N-1} [\tilde{G}(\tilde{x}(n), \tilde{u}(n))] + \tilde{G}(\tilde{x}(N)) \\
&= \sum_{l=0}^{N-1} [gasoline(n) + \alpha.No_x(n) + \beta.PM(n)_{emi}] \\
&\quad + \gamma(SoC(N)_{ini} - SoC_{final})^2 \qquad (9)
\end{aligned}
$$

To alleviate the computational burden and enhance the tractability of the DP scheme, the vehicle model was simplified by considering only three state variables: speed of the vehicle, no. of gear used for transmission, and battery' SoC. where the state vector at time step n is represented by $\tilde{x}(n)$, control vector is expressed by $\tilde{u}(n)$, comprising the target torque output provided by the engine/motor and instructions for gear shifting in the distribution. In the context where N signifies the length of the transmission route, and $\tilde{G}$ denotes the immediate cost function encompassing gasoline utilization as well as engine-out NOx and PM emissions, SoC_{final} stands for the targeted state of charge after the specified duration. Additionally, α, β, and γ are constructive weighting factors [111].

Chen and his fellows considered driving pattern recognition-based dynamic programming to maximize fuel efficiency and battery protection for range-extended electric vehicles. It was observed that the proposed strategy outperforms conventional thermostat control strategies concerning both ESS protection and fuel savings [112]. Larsson et al. used an approximation of the cost-to-go to find the optimal torque split decision at each point in time and state. This approach did not require quantizing the torque split or interpolating in the cost-to-go. The results suggested that this strategy significantly decreased calculation time and memory storage requirements [113]. Liu and his fellows developed a computationally efficient DP-dependent EMS that can operate in real-time without GPS data. The proposed EMS utilizes a hybrid trip model and a SoC search range optimization algorithm to achieve its objectives [114]. Lee and coworkers evaluated the fuel efficiency of an RL-based dynamic programming strategy against other control algorithms. The comparison revealed that the proposed strategy achieved superior global optimality [115]. Liu et al. submitted an online strategy for the purpose of energy utilization based on heuristic dynamic programming to alleviate the energy absorption of a P-HEV while accounting for the vehicle's nonlinear dynamic behavior. Experimental outcomes proved the superiority of the suggested method in precision and speed tracking accuracy, achieving over 98% accuracy. However, it consumed around 4% more fuel than the offline global optimization energy management technique [116]. Peng and his mates arranged a reconfiguration procedure to fortify the effectiveness of a rule-based system by integrating findings from the DP heuristic. The HIL simulation findings revealed that the adjusted system decreased diesel consumption per 100 kilometers from 25.46 liters to 22.80 liters [78]. Romaus and other collaborators explored the application of SDP to boost the management of power flow in energy storage systems during live operation. They compared the performance of SDP-based control to the optimal strategy determined during system dimensioning [117]. Li and his colleagues proposed an approximate dynamic programming (ADP) oriented plan to design a fuel-optimal control system for vehicles, eliminating the need for prior knowledge of future driving conditions. The control strategy relies solely on real-time system information and optimizes fuel consumption, emissions, and battery charge balance. The ADP-based approach demonstrated superior performance compared to traditional rule-based control strategies [118]. Zhang and Xiong utilized Dynamic Programming to develop optimal control strategies for various driving scenarios, facilitating the implementation of adaptive EMS for real-world driving paths [119]. Chen and other co-authors developed an EMS concentrating on DP controller to increase energy savings. Two NN modules were developed on optimal findings from DP approaches incorporating the length of the trip and time frame. Depending on these two factors, the controller selects the appropriate module from NN to produce efficient battery current instructions for the distribution of energy [108].

Linear programming (LP) is a straightforward and efficient optimization technique that employs first-order polynomial and linear equality or inequality constraints to model and solve issues with minimal computational expense. It is widely used in series HEVs to optimize fuel efficiency. Using LP to formulate the fuel efficiency optimization issue can result in achieving the best possible solution globally [49]. While LP and its variants can solve some fundamental problems, their simple structure cannot handle complex nonlinear systems with nonlinear objective functions such as deviation variance. As a result, they appear to be unsuitable for solving PEV charging optimization problems, and alternative programming techniques must be employed [120]. Figure 15 represents the sequential steps to calculate the linear programming-based EMS. The general linear programming problem is formulated as follows:

$$min \sum_{j=k_0}^{k_f} (\tilde{f}(k)) \tag{10}$$

depending on vehicle dynamics constraints such as

$$\tilde{f}(k) \geq m_i.P_{engine}(k) + n_i \qquad \{i = 1, \ldots, N\} \tag{11}$$

where, the instantaneous fuel consumption is denoted by $\tilde{f}(k)$, and the engine/generator set power output is denoted by $P_{engine}(k)$ [111].

Umetani his fellows designed a novel approach to scheduling the charging and discharging of electric cars using a time-space network model and an LP-based heuristic algorithm. This algorithm enables effective scheduling within a limited computation time. To address the uncertainty in EV demand and departure times, an improved two-stage heuristic algorithm was also developed. Computational experiments demonstrated that the two-stage heuristic algorithm effectively reduces peak load while handling uncertain EV demand and departure times within a limited computation time [121]. Ghandriz and others developed a new method for prophetic EMS using a sequential linear program (SLP). The proposed SLP was faster and simpler than traditional sequential quadratic programming (SQP) methods and provided near-optimal trajectories. The proposed method's performance

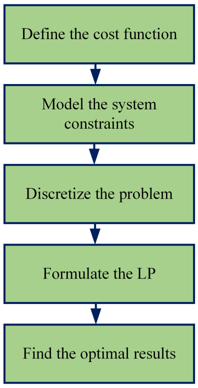

FIGURE 15. Sequential procedure for establishing the optimization-driven (LP) EMS.

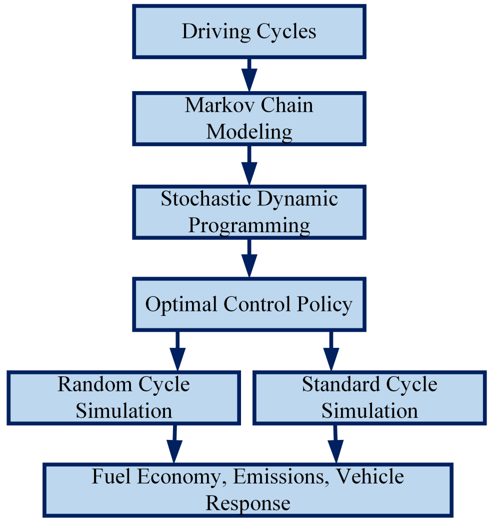

FIGURE 16. Stochastic optimization algorithm.

was tested and compared to SQP approaches [122]. Fanti and collaborators proposed an LP approach to enhance day-ahead energy purchasing and real-time energy consumption. The LP formulation aims to maximize the utilization of day-ahead purchased energy while minimizing real-time additional costs. This approach was implemented in a Demand-Side Energy Management System (DEMS) to achieve the desired optimization goals [123]. Wu and others implied ROEMS to manage FC-HEVs under unpredictable driving conditions effectively. The ROEMS utilizes an offline linear programming-based method to establish a benchmark solution [124]. Pirouzi et al. successfully applied Mixed-Integer Linear Programming (MILP) to three distribution networks of varying sizes: 33-bus, 69-bus, and 133-bus. Their proposed model demonstrated superior performance, achieving the lowest energy cost and energy loss among the alternatives. Additionally, it maintained an optimal voltage profile within a reasonable calculation time. This highlights the effectiveness of MILP in optimizing distribution network operations [125]. Venkitaraman and Kosuru employed linear programming principles and Bayesian theory to optimize the electric vehicle (EV) charging distribution network. Applying these mathematical approaches, the numerical results demonstrated that the proposed strategy effectively minimizes the impact on the power grid while ensuring a safe and cost-efficient EV charging infrastructure [126].

Stochastic control strategies are employed to model and optimize problems involving uncertainty, mainly when input data is probabilistic rather than deterministic. This technique defines the power requirement from the driver as an arbitrary Markov chain and implements it to an infinite-horizon stochastic dynamic optimization problem [127]. This model forecasts forthcoming power requirements by employing probability distributions, eliminating the need for past decision knowledge. Following that, stochastic dynamic programming (SDP) is applied to identify the most suitable approach, resulting in a stationary full-state feedback control law for direct implementation. This method optimizes the control policy across various driving patterns rather than a single deterministic cycle, enhancing adaptability and robustness in uncertain environments [128]. The advantage of SDP in optimizing power split maps lies in its ability to comprehensively and robustly address optimization challenges. Unlike traditional methods that optimize for a single deterministic drive cycle, SDP considers a probabilistic distribution of drive cycles, accounting for real-world driving variability and uncertainty. By modeling driver demand as a discrete-time stochastic dynamic process, SDP generates probability distributions for future power demands. This enables the optimization algorithm to adapt and respond to different driving patterns. SDP's application in power split optimization provides a more realistic and practical solution, improving hybrid vehicle performance and efficiency [31], [129]. Figure 16 represents the steps for optimization using the Stochastic Control Strategy.

Zeng and Wang introduced a stochastic dynamic programming (SDP) algorithm for offline optimization of the energy management strategy, followed by its real-time implementation through a lookup table. The findings indicated that after 24 hours of rides on the defined track, the suggested strategy consumes just 1.8% additional energy compared to the optimal outcome, significantly outperforming alternative casual energy management strategies [130]. Vagg et al. used the same approach (SDP) to implement and test the controller in the real world. They also addressed practical considerations for the robust implementation of the SDP algorithm. This method led to a 13% decrease in strain on the electrical powertrain during dynamometer testing, maintaining fuel savings without compromising performance [131]. Payri and colleagues enhanced the established ECMS technique by incorporating a stochastic assessment of upcoming driving conditions. This involved estimating the future probability distribution of power demands using past power requirements. They determined the parameter necessary to keep the anticipated ESS'charge level at a specified value after

TABLE 1. Overview of the diverse energy management strategies examined in this paper.

Strategy Type	Advantages	Disadvantages	Applications
Rule-Based EMS	Deterministic techniques are simple to use and have high computational efficiency	Difficulties to define accurately due to the absence of mathematical scrutiny and a solid theoretical foundation	Extensively applied in HEV prototypes and commercial HEVs (such as the Toyota Prius and Honda Insight HEV)
	Prior knowledge is optional for the deterministic approach	It is not suitable for optimizing modern electrified transport systems	
	Fuzzy EMS are robust, have high adaptability, and are easy to fine-tune	Fuzzy EMS relies on predefined rules	
Optimization-Based EMS	Global optimization is the EMS that has been studied the most	Global optimization approaches can not be executed directly in a practical scenario since it requires the driving cycle information in advance	Optimization-based EMSs are primarily utilized as reference points for assessing other controllers. These can also be used in online applications, and HEV Prototypes
	Real-time optimization is directly applicable to real-time control systems	They are more computationally expensive	
	ECMS reduces the computational complexity by converting global optimization problems into instantaneous issue	ECMS doesn't ensure the long-term sustainability of the system's charge	
	ECMS eliminates the need for future knowledge	The equivalent factor used in ECMS requires precise calculations	
	MPC predicts the future based on current and reference states	MPC necessitates foreknowledge of future driving details	
	DP can be applied both in linear and non-linear systems	DP requires information about the complete driving cycle beforehand	
	LP can lead to attaining the most optimal solution on a global scale	It cannot handle complex nonlinear systems	
	SDP offers a solution that is both more realistic and practical	Requires driving cycle database	

a given time horizon. Simulations demonstrate that this approach facilitates sustainable charging and yields results close to optimality [132]. Marefat and his co-authors implemented Stochastic Dynamic Programming to predict power demand using Markov chain assumptions and actual driving information. The SDP approach constructed a Transition Probability Matrix (TPM) from training cycles and simulates power demand based on test drive cycles. SDP demonstrated superior performance and substantial computational cost savings compared to existing methods [133]. Liu and his associates suggested a cluster-based SDP to enhance energy recovery through regenerative braking. The strategy involved employing the K-means algorithm to divide driving conditions into clusters and constructing static Markov chains for each cluster to model the probabilities of future braking torque demand changes. Real-time identification of driving conditions was accomplished using a support vector machine (SVM). Both the hardware and software experiments were conducted, and the results revealed that the SDP-based strategy outperforms no-downshifting and rule-based approaches regarding energy recovery during regenerative braking [134]. Chen and the rest implemented an S-MPC approach that relies on reinforcement learning (RL) to optimize the gasoline sustainability of PHEVs. Integrating an RL controller into the stochastic MPC framework determines the efficient battery power for the defined time frame. A number of simulations confirm the efficacy of this method, showcasing fuel economy [105]. Yang et al. applied a novel stochastic predictive-EMS, employing fast rolling optimization to enhance efficiency. Simulations and real-world testing were used to evaluate the proposed approach, comparing its performance against SMPC optimized using DP and ECMS. The proposed controller outperformed ECMS in terms of computational speed and energy consumption [127]. Ripaccioli introduced a stochastic method to address power distribution challenges in series hybrid electric vehicles (HEVs). They modeled the driver's power requirements as the model of the Markov chain, constructed using data from diverse route statistics, and utilized it to construct a set of scenarios within the SMPC framework. The practicality of the proposed stochastic technique was successfully shown by simulation results, even without precise knowledge of future power requirements [135].

VII. CONCLUSION

The increasing popularity of HEVs, driven by the promise of better fuel efficiency and vehicle performance, has attracted significant research interest from both academic and industry experts. Various power management strategies have been developed to address the energy requirements of different HEV configurations. This paper comprehensively reviews all control techniques employed to achieve the best power allocation between main and secondary energy generations in HEVs/PHEVs. This in-depth analysis aims to shed light on the reviewed techniques' control structure, novelty, and contributions. EMS are typically categorized based on their mathematical approach. While easy to implement, rule-based controllers can lead to suboptimal performance; power consumption optimization should encompass the entire trip. Achieving global optimality requires a priori trip information. While optimization-based techniques do not directly allow for real-time energy management, an instantaneous cost function-based approach could allow it. Strategies should prioritize minimal computational time, global optimality, and compatibility with dynamic simulation environments.

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