IEEE Access
Multidisciplinary : Rapid Review : Open Access Journal

Received 6 October 2022, accepted 23 October 2022, date of publication 28 October 2022, date of current version 23 November 2022.

Digital Object Identifier 10.1109/ACCESS.2022.3217771

RESEARCH ARTICLE

Hybrid Sources Powered Electric Vehicle Configuration and Integrated Optimal Power Management Strategy

ABHINAV K. GAUTAM[1], MOHD TARIQ[2,3], (Senior Member, IEEE), J. P. PANDEY[1], (Senior Member, IEEE), K. S. VERMA[1], (Senior Member, IEEE), AND SHABANA UROOJ[4], (Senior Member, IEEE)

[1]Department of Electrical Engineering, Kamla Nehru Institute of Technology, Sultanpur, Uttar Pradesh 228118, India
[2]Department of Electrical Engineering, ZHCET, Aligarh Muslim University, Aligarh 202002, India
[3]Department of Electrical and Computer Engineering, Florida International University, Miami, FL 33174, USA
[4]Department of Electrical Engineering, College of Engineering, Princess Nourah bint Abdul Rahman University, P.O. Box 84428, Riyadh 11671, Saudi Arabia

Corresponding authors: Mohd Tariq (tariq.ee@zhcet.ac.in) and Shabana Urooj (smurooj@pnu.edu.sa)

This research is funded by Princess Nourah bint Abdulrahman University Researchers Supporting Project number (PNURSP2022R79), Princess Nourah bint Abdulrahman University, Riyadh, Saudi Arabia.

ABSTRACT Internal Combustion Engine based transportation rapidly increases the impact on the environment. The burning of fossil fuels in the industries and transportation sector breadth of global warming. However, Hybrid Electric Vehicle is not a permanent solution for emission-less road vehicles. Therefore, electric vehicles are the most feasible technologies to attain the goals of energy savings and zero-emission road vehicles. This paper sequentially surveys the key point of vehicles like; Powertrain strategy, configuration, fuel economy, reduced emission, and control strategy expounds in terms of its basic principles, pros, and cons. These key points make the energy management strategy more conclusive for the more efficient vehicle. In addition, this paper review systematically qualitative and quantitative algorithm in all type of EMS used in HEV and compare them with existing approaches in terms of pros & cons through a comprehensive analysis. Furthermore, addressed the potential research gap and provide the directives for further development in power train and ems in every respect.

INDEX TERMS Full electric vehicle, hybrid electric vehicle, architecture, online EMS, offline EMS, optimization-based EMS, fuel economy, vehicle performance, optimal control strategy, real-time optimal power management, intelligent transportation.

I. INTRODUCTION

This Concern over air contamination, the hydrocarbon-based conveyance has been raising worldwide concerns. International Energy Agency (IEA) estimated 298 Mtoe biofuel consumption in the transportation sector by 2030. This sector consumes 49% of the oil resources and it seems that world resources depleted by 2038 [1], and the U.S. EPA (Environmental Protection Agency) reported that 29% of greenhouse gas emissions (CO_2, NO_2, CO, NO) from the burning of fossil fuel in transportation activities.

Around 28% of all carbon dioxide (CO2) emissions are attributed to the transportation industry, with road transport responsible for more than 70% of those emissions, according to studies by the European Union and other sources. In which main contribution of light commercial vehicles 59%, intermediate and heavy commercial trucks 23%, aircraft 9%, ships & boats 3 %, rail 2% other 4%.

Therefore, the governments of the majority of developed nations are encouraging the use of electric cars in order to minimize the concentration of air pollutants, including CO2 and other greenhouse gases [2]. These days, public consciousness of weather variation and importation of the power savings is increasing the development of innovative technologies for the green vehicle to the utilization of

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

Plug-in Hybrid Electric Vehicle (HEV) and full electric vehicles (FEV), which is a possible eco-friendly and economical solution [3]. A wide range of automakers are working hard to create new EVs [4]:

- General Motors intends to switch to all-electric vehicles by 2023
- Ford will offer seven electrified and customized plug-in hybrids in the future
- Mazda, Denso, and Toyota are working together to develop technologies for EVs
- Renault, Nissan, and Mitsubishi are working to create pure electric vehicles with the goal of releasing 12 EVs by 2023
- 300 vehicles from the Volkswagen group, which also owns the brands Audi and Porsche, will be available in electric and hybrid versions by 2030.

At present HEV has thrived as a solution [5] due to the discontinuity of renewable energy and battery life span. There are some reluctances for public interest in Electric Vehicles (EVs) as: the cost of EVs is higher than fossil-fueled vehicles, EVs do not have much range, refueling of the fossil-fueled vehicle is easy in comparison to EVs, and reluctant to spend in current EVs technology while much-advanced technology may be available in next 2-3 Years.

Existing electric vehicles having more than a single source of power, hybrid powertrains provide a large design space for the system and increase the complexity of the control algorithm [6]. The objective function of the Energy Management Strategy (EMS) optimization problem is generally coupled with powertrain topology collection, while technology and the size of components are treated as optimization constraints. Power management strategy will play a vital role in the expansion of the new generation of green vehicles. The highest challenges of a power management strategy are to power split in optimum mode to provide intended performance under system limitations.

A significant amount of research into energy management strategy has been directed over the last era, not only for HEV [7], [5] but also for FEV. However, with the improvement and introduction of novel approaches in automotive technology, the author perceives EMS for HEV and FEV as a constantly developing area that will continue to draw fresh ideas for many upcoming years.

The major goals of this review work are to contribute to an emergent point of discussion about the latest EMS approaches, as well as to provide an inclusive outline of EMS generated for controlling power management in HEV or FEV.

This research paper is structured as follows: a collection of data sources in section 2, the architecture of the vehicle and a range of powertrain systems & electric alignment of HESS in FEV in section 3, and classification of optimization techniques in power management represent in section 4, latest developing trends & prospective opportunities for future research trends in energy management strategies discussed in Section 5 and some remarkable conclusion in section 6.

II. SOURCES OF DATA COLLECTIONS

All documents employed in this review paper were from the database of reputed journals and conference papers in which we found energy management strategies have been used in the past and current. There was a total of article 267 in this review paper have been used. The contribution of articles is given in Fig.1.

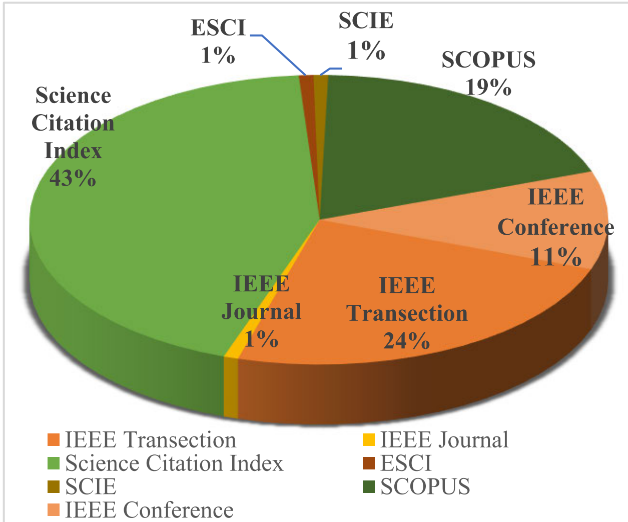


FIGURE 1. Paper contribution in this article.

III. ARCHITECTURE OF HYBRID ELECTRIC VEHICLE

The primary powertrain-controlled structures fo HEV and FEV HEV and FEV are discussed in this segment, along with their main properties. The functional mode of a powertrain topology is necessary to understand before expressing an EMS optimization issue. There is numerous topology on the powertrain of various competencies that can be implemented via modification of the power source connections. These connections may be mechanical or electrical links. HEV powertrain has three major configurations, (1) Series Connection; (2) Parallel Connection, and (3) Series-Parallel, although FEV is further divided into three parts according to the source of energy, battery, and solar-based or fuel cell-based [3]. The Vehicle power train strategy of HEV and FEV is given below in Fig.2.

A. HYBRID ELECTRIC VEHICLES

In the HEV, engine power is transferred across the ring gear which is mechanically joined through the drive shaft while another part of engine power is converted into electrical power to drive the motor, which is hinged with gear, connected into mechanical power again. The prior arrangement is called as a parallel path and the second is called as a series path [8]. The primary aim for HEVs development is to decrease fuel intake and tailpipe emission [5]. According to vehicle powertrain arrangement, HEV can be separated into series, parallel, power-split/ series-parallel HEV, and Plug-in HEV, which can make energy more efficient and relatively high fuel economy [9], [10]. The vehicle configuration and

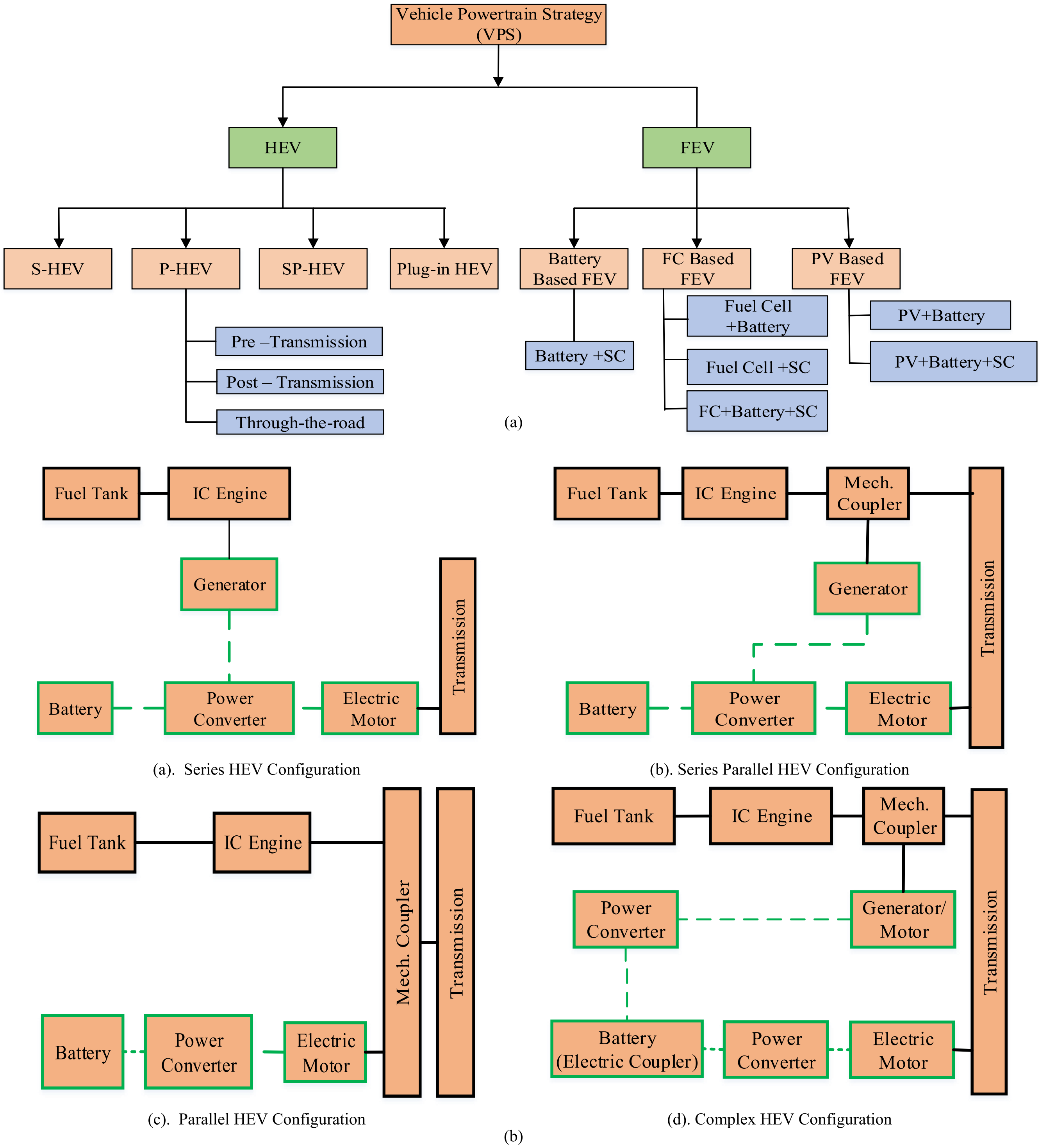


FIGURE 2. **(a) Classification of vehicle powertrain strategy. (b) Various configuration of a hybrid electric vehicle.**

architecture are shown in Fig.2 (a & b)., while the summary of HEV& FEV, and their application are shown in Table 1.

1) SERIES HYBRID ELECTRIC VEHICLES (S-HEV)

A series-HEV topology gives the best performance in a stop-and-go driving pattern. There, ICE and wheels don't have a mechanical connection. The ICE is basically used to generate the electrical power by driving the generator, which is combined with an output power of electrical storage and transmits that power by DC bus to an electric motor to drive the wheels [3]. In this strategy, the engine runs efficiently in varying vehicle speeds [6]. S-HEV are suitable for urban and buses for highway only, while buses are not suitable for urban area driving due to high conversion loss [7].

TABLE 1. Summary of hybrid electric vehicle architecture and their application.

Sr. No.	Vehicle Configuration	Complexity/ Efficiency	Advantages	Disadvantages	Application	Example
1.	**Series Hybrid**	Low	• Enhanced traction driveline efficiency • Flexible power plant options • Longer service life • Probable to operate without emissions.	• Traction drive system having a larger capacity • Energy transformations at several levels	• In Heavy Vehicles for example buses, trucks, and locomotives	• Renault Kangoo
2.	**Parallel Hybrid**	Medium	• Zero-emission operation possible • Economic gain at a high cost	• Required high voltages for better efficiency • Composite space packing	• Cars for inner-city use	• Honda Civic • BMW 7 Series
3.	**Series-Parallel Hybrid**	High	• Zero-emission operation possible • Maximum Flexibility	• High costly system • Control Complexity • Composite space packing	• Light commercial vehicles	• Volvo C30 • Toyota Prius, Auris • Citroen C4 HDi • BMW 1 Series

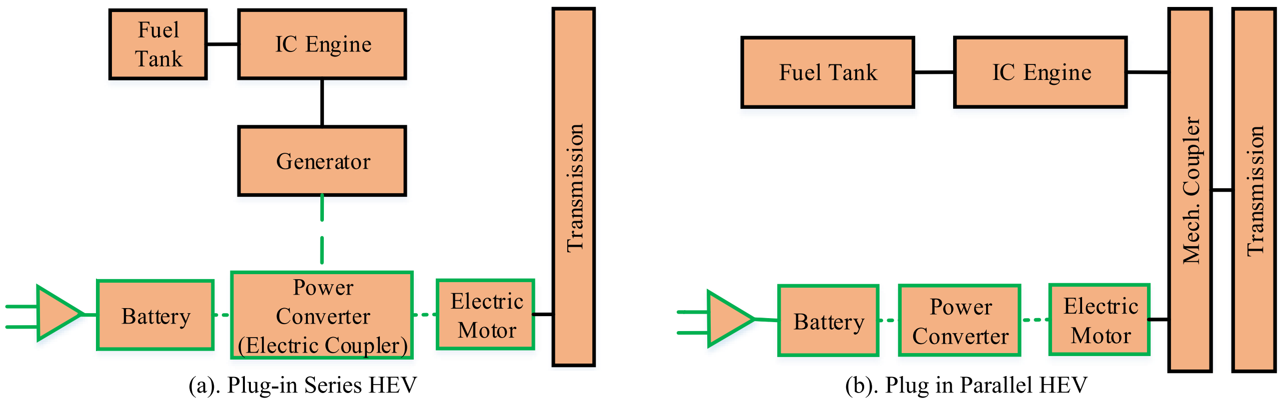


FIGURE 3. Plug-in HEV Configuration.

2) PARALLEL HYBRID ELECTRIC VEHICLES (P-HEV)

In Parallel HEVs, an electric motor is used alone at low speeds while the engine and wheels are mechanically connected directly [11], such that their combined torque is transferred to the wheels via a standard moving shaft and probably a different gear. In this method energy loss is minimum but they are less suitable for quick change stop-and-go traffic in compared to the series HEV topology [6], [12], [3].

3) SERIES-PARALLEL HYBRID ELECTRIC VEHICLES (SP-HEVS)

A Series-Parallel HEVs, as well power-split HEV, have an additional mechanical connection in between the motor and generator through the transmission. This arrangement provides the complementary benefits of series and parallel HEVs [3], [6]. As a result, one of the main problems of SP-HEV is power flow regulation of splitting power because it combines functioning components from both series and parallel systems, increasing the system's complexity [13].

4) PLUG-IN HYBRID ELECTRIC VEHICLES (P-HEV)

Plug-in HEVs differ from conventional HEVs but have the same configuration with additional electric charging plug, and higher capacity electrical components shown in Fig.3. In this way, the Energy Storage System (ESS) is considered as the prime source, which provided a new dimension to the EMS method in PHEV for a superior fuel economy by operating in two modes as charge depleting (CD) and charge sustaining(CS) modes [5]. PHEV can be run in full-electric mode for a long time period due to high capacity electrical components [1]. The plug-in HEV is a good initiative towards reducing worldwide emissions, by which it proposed high performance and fuel efficiency in both electric and hybrid mode [3], [12]. In 2011, Nissan introduced, the company's first plug-in electric vehicle 'Nissan Leaf', while A Ford Fusion Energi is a plug-in hybrid car that debuted in 2013.

B. FULL ELECTRIC VEHICLE

Presently, FEV has seven types of power transfer topology as shown in Fig.4, in which only three types of topologies are prominent for use via an auto-industrialist [14]. The comparative configuration of various HESS is shown in Table 2.

In general, fully electric vehicles are divided into two categories based on the energy source, it may be a fuel cell or battery. Now a day, PV-based vehicle has captured a considerable amount of interest from researcher to enhance

TABLE 2. Comparison of various configurations of HESS [154].

Sr. No.	Configuration	Advantages	Disadvantages
1.	Passive cascaded battery/UC Configuration	• Galvanic isolation is High • Voltage Conversion Ratios is High	• Higher Electro Magnetic Isolation • Voltage Stress is high across the control switches • Magnetic Core is Bulky, Weighty, and Expensive
2.	Active cascaded UC/battery Configuration		
3.	Active Cascaded battery/UC Configuration		
4.	Multiple DC/DC converter configuration	• Input and output current ripples are reduced	• High transfer capacitor voltage rating two inductors
5.	Active Cascaded configuration with two DC/DC Converters	• Transfer capacitor voltage rating is low	• Two big inductor • Irregular output Current • A big output capacitor
6.	Multi-Input DC/DC Converter Configuration	• One Small inductor no transfer capacitor voltage, • Low diode voltage ratings, • Low conduction losses	• Irregular output Current

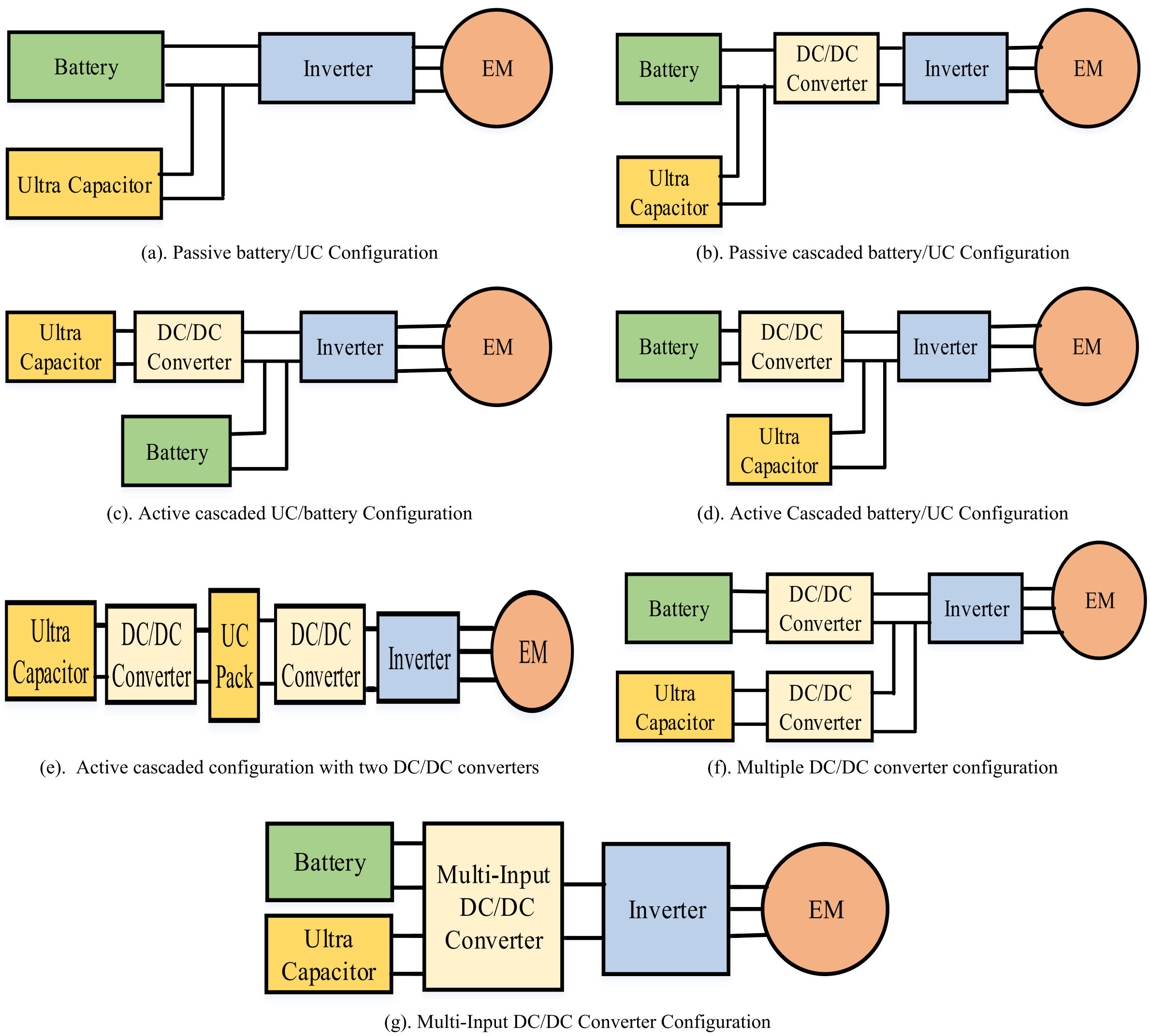


FIGURE 4. Various Possible configurations of UC and battery.

the utilization of renewable resources which are available in abundant amount in nature. The PV-based vehicle was also used in my research project.

1) BATTERY-BASED FEVS

In this FEV, the battery is used as a primary source that has high-energy content. It is combined with another

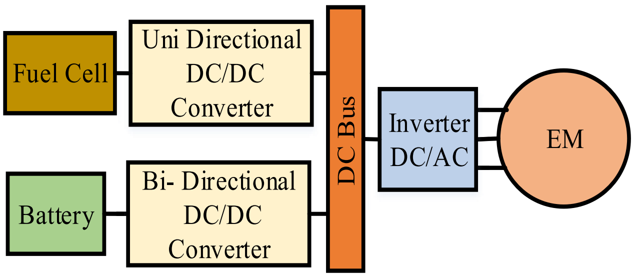


FIGURE 5. FC- based FEV.

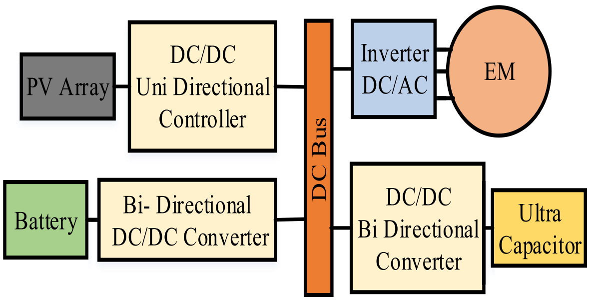


FIGURE 6. PV based FEV structured.

high-density power device like, Supercapacitor, known as ultra-capacitor also to form the HESS. It is also known as an electric double-layer capacitor (EDLC) [15]. In comparison--to a supercapacitor, batteries have a high energy density but a poor power density. So, HESS store enough energy to satisfy abrupt power demands to achieve the required vehicle performance. H. He et al., presented the seven battery model with enough precision and less complexity and provide the optimal performance on experimental results [16]. An FEV can be divided into two categories.

2) FUEL CELL-BASED FEVS

In this FEV, FC worked as a primary source, which uses H_2 and O_2 to produce electricity. The FC's specific energy and power are similar, but not identical to the gasoline [3]. Fuel cells have a slow response due to chemical reactions, so it's not good to provide the frequent changing load. To mitigate this problem, it has hybridized with battery /UC. The FC-based FEVs configuration are shown in Fig.5

3) PV BASED FEV

The architecture of a solar power-based FEVs (PV-FEV) is similar to the Plug-in HEV except for an additional photovoltaic (PV) panel, which provides the current for battery charging in a day time. And the maximum power point tracking (MPPT) control algorithms are applied to achieve the maximum power through PV Panels. The PV-based FEV configuration is shown in Fig.6.

IV. ENERGY MANAGEMENT STRATEGIES FOR VEHICLE

FEV and (P)HEVs are complex electro-mechanical drive systems. The choice of the circuit configuration and EMS have decided the flow of power, fuel economy, and emission reduction [17]. The main purpose of an EMS is to control the power flow for obtaining the improved fuel economy, emissions reduction, ensured drivability, and maintain the state of charge (SOC) and life span of the ESS via advertent the restrictions. A general outline of the objectives of EMS for both FEV and HEVs is shown in Fig.7.

In the past, lots of diversity of research are available for the usage of EMS in Hybrid-EV, Fully-EV, and Plug-in HEV applications. Even though lots of classification can be found in the literature, mainly divided into three parts: rule-based, optimization-based, and learning-based algorithms, and these are further divided into subparts. The taxonomy of the primary parts and subparts are shown in Fig.8 for HEV and FEV technologies. In this article optimization algorithms which are used in Intelligent Transportation System (ITS), additionally included besides of EMS categorization shown in fig.8.

A. RULE-BASED CONTROL METHOD

Rule-Based (RB) control techniques are heuristic control techniques in which the control method well-defined as a set of "if-then" procedures to regulate the control action [18]. The rules-based method is determined by using humanoid intelligence, intuitions, or mathematical models and mostly without pre-information of a drive cycle. They are required low computation so that they are commonly used in many commercial vehicles like Honda Insight and the Toyota Prius [7]. Peng et al. [19] recalibrated the rule-based EMS results to locate the optimum power train by applying dynamic programming (DP) and reduced the fuel consumption by about 10.45 % as well as the electricity consumption up to 4.75%. Ceraolo et al. [20] discussed the optimal energy consumption technique to resolve the energy problem occurring in the designing process. Ali et al. [21] presented an optimized situation-based power management strategy for multi-source EVs. Here proposed methodology obtained the optimal results and improve the energy efficiency 11.9-18.98% while prediction accuracy about 63.9-65.2% respectively dynamic programming and rule-based algorithm. Even though a rule-based EMS may not provide the best result; it has attracted interest due to its ease of deployment in real-time. This strategy is more classified into fuzzy and deterministic rule-based EMSs.

1) DETERMINISTIC RULE-BASED METHODS

The Deterministic Rules-Based (RB) methods are developed with the support of fuel economy or emission data, power split, operating point of ICE, and power flow in the drive train. Rules execution is performed on the basis of a lookup table to share the power in between IC Engine and motor. Hofman et al. [18] discussed an RB-ECMS, in which the control strategies are defined based on "if-then" rules for control action, compared these results with dynamic programming, and increase the accuracy of 1%.

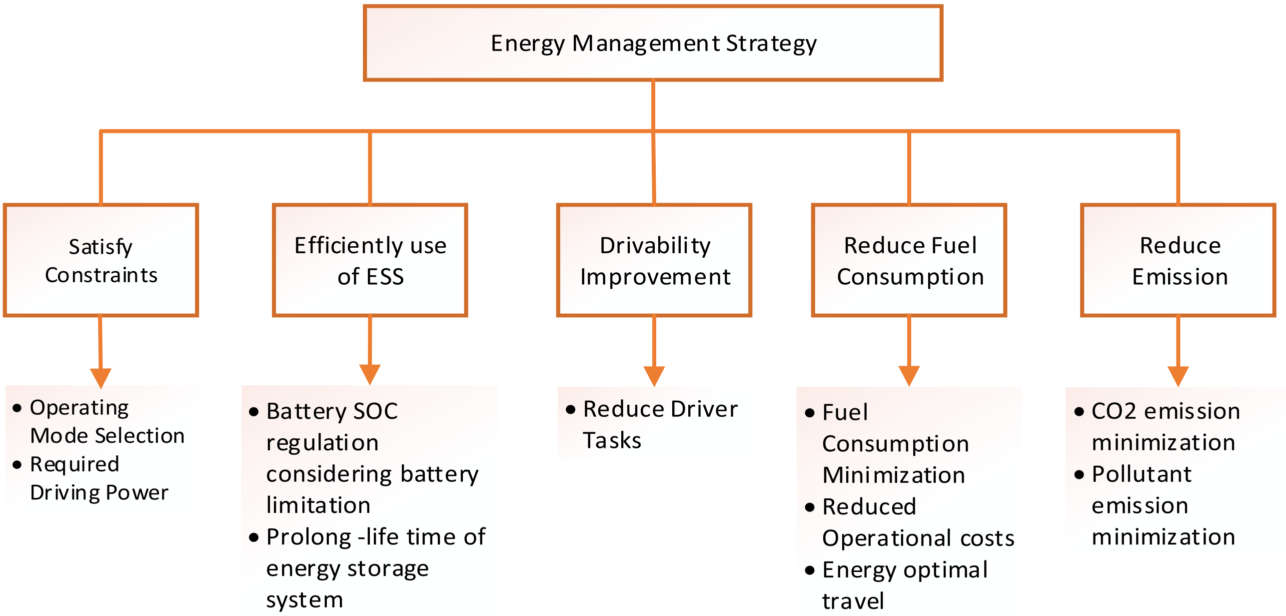


FIGURE 7. General Objective of EMS.

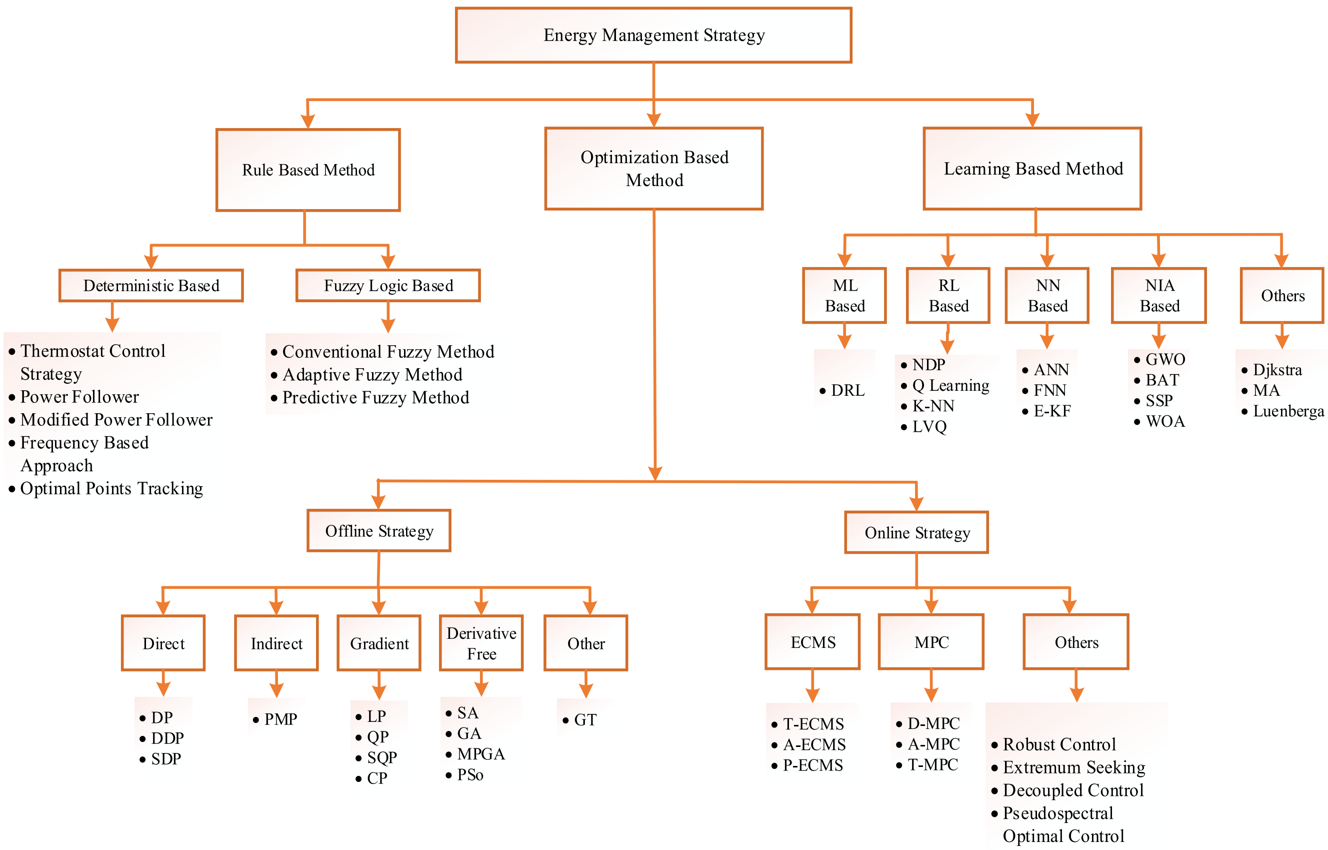


FIGURE 8. Classification of energy management system.

a: THERMOSTAT CONTROL STRATEGY

This control method uses the ICE and generator to produce electrical energy via vehicle. ICE works at its maximum efficiency point when it starts, although the SOC of the battery is always maintained in between its pre-defined upper and lower levels by simply turning on or off ICE.

Ali et al. [22] implemented an RB energy management optimization technique to activate the ICE at optimal fuel saving mode during different standard drive cycles, to improve the vehicle efficiency then it reduces the total trip estimated cost by around 46%. Jalil et al. [23] applied an RB scheme to control the split power among the battery and ICE for a series HEV, in which the 'Thermostat' strategy improved the fuel economy up to 11% in the urban driving cycle and 6% in the highway driving cycle. The parameter designing optimization is proposed [24] to improve the vehicle economy and transmission ratio of the vehicle. Badjate et al. [25] developed a split power-based efficient control strategy in which fuzzy logic (FL) was applied to the interpretation of driver command and driving situations. Gao et al. [26] proposed an equivalent fuel consumption optimal control of a series (EFCOCS) type of power split management strategy [27], the combination of traction control system (TCS) and power factor correction (PFC), in which TCS offer the highest efficiency in the engine generator set while PFC improves the battery durability by controlling SOC. Kim et al. [28] proposed based on equivalent specific fuel consumption (ESFC) with the continuously varying transmission. They determine the maximum system efficiency with optimal values of parameters. These methods are generally used in Series HEV.

b: POWER FOLLOWER (Baseline) CONTROL STRATEGY

This control strategy is reformulated on/off control algorithm to deliver the added power and sustain battery SOC. In this strategy, ICE is taken as the main Source. This strategy is appropriate for both parallel and series-parallel HEVs. Luo et al. [29] uses a combination of two control strategies power follower control and DC-link voltage control to minimize the fuel economy of Series HEV. This method gives better performance than individual control strategies.

c: MODIFIED POWER FOLLOWER-ADAPTIVE RB (ARB)

In order to improve the thermostat and power follower technique, proposed an adaptive rule-based strategy. In this method, a decision is performed stepwise. Johnson et al. [30] proposed the adaptive-based real-time control method to optimize the efficiency and discharges of a parallel HEV. This strategy reduced the 23% NOx and 13% particulate matter (PM) discharges at an expense of 1.4% in fuel economy. Wipke et al. [31] proposed a modified baseline controller to focus on its combination of forwarding and backward-facing methodologies, and evaluates the model in terms of its design objectives.

d: FREQUENCY-BASED APPROACH

Frequency-based strategy approaches for split power requirement at low and high-level frequency components to fulfill the load demand. Kim et al. [32] proposed a frequency-domain power distribution (FDPD) method to improve the fuel budget via 5.9% and shrinkage the shoot emission via 62.7% for the engine and also reduced 23 % ineffective Ah for improving the life span of the battery. Tani et al. [33] focused on power management according to the dynamics performance of the hybrid sources using polynomial correctors to mitigate the transients of dynamic load.

e: OPTIMAL POINTS TRACKING

This method corresponds to the baseline control methods in which the functioning point of the IC engine can be adjusted easily. So that engine optimal functioning point, operation line, efficiency portion, and system optimal operation point are projected for series-parallel HEVs. Park et al. [8] applied the direct search method to optimize the losses in power flow and select the optimal power flow [34] point according to the efficiency and emission. This strategy has the advantage to control the battery power since the maps take charging or discharging power, which is used as one input data. Ahn et al. [35] formulated power-split architectures and applied two control strategies, power split configuration and mode switching configuration [36], for improving the efficiency of series-parallel HEV. They compare the results and verify them by simulation [37]. Andriollo et al. [38] present the optimum design of an electrodynamic suspension magnetic levitation (EDS-MAGLEV) transport system by using global objective function at an analytical aspect of system performance. The new definition is based on possible object oriented language (OOL) transition in HEV during a simulation. The power-split solution gives qualitative fuel depletion improvement in comparison to the conventional line tracking scheme.

2) FUZZY RULE-BASED METHOD

The fuzzy Rule-based control method is presented to energy management in HEV. This strategy is more advantageous due to its toughness to inaccurate dimension and component modeling inconsistency besides its adoption. This strategy is more applicable to multi-domain, non-linear time-changing systems for example HEVs. Fuzzy logic has decision-making properties, it is accepted to the analysis of a real-time & suboptimal split power [39]. Basically, this is the addition of deterministic RB-EMS. For example, Won et al. [40], implemented fuzzy rule bases control strategies for torque distribution and charge sustained in traffic situations for intelligent energy management. Hannoun et al. [41] designed a fuzzy controller [42], [43] according to the energy demand by vehicle speed and SOC of the battery optimize the energy consumption and condensed the pollutant emission. Mohan et al. [44] worked on a fuzzy proportional differential controller with respectably two input velocity & acceleration and single output for incremental control effort. This FL strategy is further divided as follows:

3) CONVENTIONAL FUZZY METHOD

In this method, the FL controller is used to perform basic steps of fuzzy logic. These are tuned via an optimization algorithm to full fill the control purposes for power management like reduced fuel consumption, emission reduction, and maintaining the state of charge of ESS to enhance the driving performance. For example, Lee et al. [45] Implemented FL control through the driving cycle strategy to accelerate the pedal stroke and reduced the hydrogen up to 22% in FCHEV [46]. While, Farrall et al. [47] control the powertrain through legislation in the heat engine used in the hybrid vehicle. Montazeri-Gh et al. [48] improve the fuel economy and reduced its consumption upto 21% by using multi-input FL control strategies. Pan et al. [49] and [50] applied a wavelet-based FLC for multi-input EMS in a hybrid system for a tracked bulldozer and verified the result in real-time. Yuan et al. [51] proposed the power management through stochasticity and fuzziness in solar power generation as well as ship power load demand in his research and improve the solar performance by reducing fuel consumption and CO_2 emission. Chen et al. [52] proposed an FLC in EMS for a certain driving cycle and applied the multi-objective optimization evolutionary algorithm to optimize the parameter [53] of fuzzy function trims and semi-trapmf to improve the FLC efficiency. Wu et al. [54] recognize driving cycle patterns to improve the fuel economy through FL-based EMS. This pattern is recognized by the learning vector quantization method. Schouten et al. [42] and Baumann et al. [55] proposed a novel control strategy for FLC-based power management [56], [57] in HEV and optimize all its components related to the efficiency of the vehicle and also show that the strategy justify the highly nonlinear multi-domain and time-varying plant.

4) ADAPTIVE FUZZY METHOD

The performance of the conventional fuzzy method can be further improved if the control parameters are adaptive for the present operating point. Regarding the HEV, Tong, et al. [58] applied adaptive fuzzy decentralized control technique to estimate the unmeasurable non-linear function, which is designed by back stepping technique and, the Lyapunov function and average dwell time method are used for stability. Chen et al. [59] considered the problem observer-based adaptive fuzzy control for non-linear time-delay system and the signals in closed-loop system are uniformly bounded. Tian et al. [60] proposed adaptive FL used to adhere to the deviation of SOC online and speed of the vehicle to find out the degree of the engine's output powers. Bathaee et al. [61] proposed an FL-based torque controller [62] and optimize the energy flow, generation, and conversion in the individual component [56] of the parallel hybrid vehicle. Li et al. [63] proposed strategy combined the logic threshold and fuzzy control in which fuzzy control design based on Improve Quantum Genetic Algorithm (IQGA) optimization technique to improve the fuel efficiency. Fuel consumption is decreased by 5.17 % by applying IQGA which gives a better response than GA and QGA. Wang et al. [64] implemented a novel real-time evolutionary FL-based EMS then applied the GA for fine-tuning and optimization same. Wu et al. [65] described a method to Optimize control strategy and fuel economies of HEV using multi-objective self-adaptive differential evolution. Wang et al. [66] used a fuzzy control method and DP method for reducing the time period of cold start and energy consumption of warm-up process respectively. Li and Liu [67] show overall efficiency of an FC/battery hybrid vehicle is maximum for given driving cycles and results show that optimally controlled HEV which can provide better fuel economy and enhance system efficiency.

5) PREDICTIVE FUZZY METHOD

Predictive Fuzzy Logic controller works on prior knowledge of driving a trip on a planned route to perform in real-time but mainly drawback of its incapability to accomplish real-time control task. Hajimiri et al. [68] used predictive and protective algorithm (PPA) with FLC to extend the battery life. Montazeri-Gh et al. [54] described a predictive optimized intelligent fuzzy control strategy based on traffic condition recognition for fuel consumption and emission. Niu et al. [69] presented a machine learning framework for real-time driving cycle and trends, which is named as neural network standard driving cycle (NN-SDC) and neural network driving trends (NN-DT). It is developed an intelligent FLC strategy based on micro-controller frame in HEV for determining the power consumption and emission to improve the efficiency. To extend the battery range of BEV here, Mohd et al. [70] applied integrated multimode driving using FL enabled the adapting driving, which select the parameter automatically through speed and reduced the energy consumption by about 32.25%, and increase the driving range up to 4.21%. Yin et al. [71], analyzed a power split mechanism and transmission efficiency of the EV based on control strategies. Where torque distribution is realized by FLC which is optimized by PSO. Ippolito et al. [72] design a fuzzy clustering criterion-based controller with GA to reduce the computational effort and improve efficiency in energy management. Kamal et al. [73] investigated a robust FLC tuned with NN for energy management with battery fault detection and power distribution management. Tao and Taur [74] designed a flexible difficulty-reduced PID-like fuzzy controller which reduced complexity by reducing the number of input variables. Chen et al. [75] developed a machine learning (ML) algorithm ''LOPPS'' to study optimal power combination in an EVs load variation then applied FL according to LOPPS results to reduce power losses.

B. OPTIMIZATION BASED POWER MANAGEMENT CONTROL METHOD

The main goal of the optimization-based power management method is to find the optimal control consequences to minimize the process cost above the particular time period. The optimization-based methods can be divided into two categories: offline mode method and online mode method. Earlier bibliometric expose that Optimization Based (OB) methods clasp additional courtesy in the research field with a 56.7% in compared to Rule-Based (RB) methods 32.9% [7]. More details about each category are given below.

TABLE 3. Taxonomy of rule based energy management strategies.

Rule Based Energy Management Classification			References	Advantages	Main Challenges/ Disadvantages
Deterministic	Optimal Working Condition	Thermostat Control Strategy	[22], [23], [24], [25], [26], [27], [28]	• Maintain the working of the engine, electric motor, and battery in specified operating ranges	• Low fuel economy
		Power Follower	[29]	• Sustain the battery SOC	• Overall fuel economy not optimized
		Modified Power Follower	[30], [31]	• Reduced the NOx emissions	• Small Computation Load
	Frequency Based Approach		[32], [33]	• Mitigate the transients of dynamic load • Improve the life span of the battery	• Mostly Suitable in dynamic load Condition
	Optimal Points Tracking		[34], [35], [36], [37], [38]	• To control the battery power	• Performed at a higher hierarchical level
Fuzzy Logic Based	Conventional		[41], [42],[44],[45],[46],[47],[48], [49],[50],[51],[55], [52], [53], [54], [55], [56], [57]	• Robustness, adaptability, and predictability	• Calibration is required for control parameters related to various drive cycles.
	Adaptive		[58], [54], [59], [60], [61], [62] , [63], [64], [65], [66], [67]		
	Predictive		[54], [53], [67], [68], [69], [70], [71], [72], [73], [74], [75]		

1) OFFLINE MODE METHOD

An offline Optimization-based method is belonging to the non-causal and worldwide optimization-based method because it needs a pre-information of upcoming driving cycles. The significance of this type of strategy is that the optimal solution is providing a standard solution for another causal method compared to the other modified online strategies. The offline strategies based on the problem- solving approach can be distributed into four parts: direct algorithm, indirect algorithm, gradient, and derivative-free Algorithms.

a: DIRECT ALGORITHM

The direct algorithm is used to solve the static optimization problems by discretization. The commonly used algorithm to solve the problem of energy management in the offline strategy is dynamic programming (DP), which is originated via Bellman in the 1950s. It is also called deterministic dynamic programming (DDP) because it required prior knowledge of the driving cycle.

b: DYNAMIC PROGRAMMING

Dynamic programming is proposed to resolve optimal control problems in a non-linear system. It decays dynamic optimization problems in an order of sub-problems by discretizing original optimization time. DP applied by Pei et al. [76] to find the equivalent marginal cost factor in ECMS. Zahraeia et al. [77] considered temperature noise factor for optimal EMS and improve fuel efficiency [78] and emission. Sinoquet et al. [79] presented a real-time control strategy in HEV to minimize fuel consumption and reduction in pollutant emission. Marano et al. [80] and Tulpule et al. [81] reduced the 1% fuel consumption in PHEV through DP in comparison to ECMS. Skugor et al. [82] use fleet charging method and show the DP optimization more successfully by reducing the charging cost by more than 10 %. Pan et al. [83] applied two methods RB projection partition method for system efficiency and DP based optimization method to explore the energy-saving factor in HEV. In which RB strategy reduced 13.4 % while DP reduced 17.6 % energy consumption. Zhang et al. [84] applied dynamic programming in distribution to utilize all power users at variable load requirement. The author also shows a 20 % improvement in fuel economy by DP [85]. Chen et al. [86] applied DP for design standards and real-time implementation strategy in power management to evaluate fuel-energy-loss-oriented (FE-LO) and battery-energy-loss-oriented (BE-LO) in which battery protection and fuel economy are used as a cost function. Lin et al. [87] proposed a novel battery model and dynamic programming-based energy management (EM) algorithm for reconfigurable battery packs and optimal power distribution to increase the battery lifetime in BEV [88]. Kessels et al. [89] reduce the mathematical complexity and prior information of driving cycle in DP and produce the optimal solution without using prior road information, and improve the fuel economy up to 25 %. Wu et al. [90] proposed the driving cycle-based DP optimization technique for energy flow in range-extended electric buses (REEB). It reduced the computation time by 96.85 % but power consumption is 0.47% greater than the traditional DP. Asus et al. [91] applied to optimize the control parameter and found an operating point of the engine to achieve longer durability. Sundstrom et al. [92] discussed the hybridization ratio in torque assist and fuel consumption is obtained by using DP for different hybridization ratios.

c: DETERMINISTIC DYNAMIC PROGRAMMING

Deterministic dynamic programming algorithm is based on the concept of subdividing a non-linear dynamic optimization problem into a discrete temporal sub problem, where a cost go function is created at every step time. And the sub-problems solve via a backward recursive technique or a forward DP method to find the best control policy. Vinot et al. [93] developed a global optimum design method for parameters and component sizing in EV by discrete dynamic programming. Extracting DP for optimal energy management [94] design strategy to reduce the fuel consumption [95] and optimal speed and power split strategy [96], [97] in HEV. Wang et al. [85] proposed an optimal control method in PHEV and develop a mechanism based on discretization resolution variables and boundary issues and found 20% development in fuel economy in comparison to the traditional control strategy. Lin et al. [98] applied to extract DP rules to design the power management control strategy in HEV for optimal fuel consumption, reduction in emission and battery constraint for SOC and provide the 45% higher fuel economy than ICE truck.

The main issues of DDP are the high computation required due to the quantization of conditions and control variables, the essential expletive of dimensionality, and the reliance on the driving cycle. These disadvantages make DDP incapable of real-time application.

d: STOCHASTIC DYNAMIC PROGRAMMING (SDP)

The DDP-derived control law can only function as a detailed driving cycle, and it may not assurance a degree of optimality or a constant charge in different driving cycles. Additionally, they advised that DDP is not implemented directly and the rule extracting is a time taking process. To reduce these problems C.C. Lin et al. [99] applied SDD to model for Markov chain process and optimal control firstly and Zeng et al. [100] solved the formulated problem as a finite-horizon Markov decision. Romans et al. [101] optimize the size of the storage system & reduced the power distribution losses up to 24%. Wegmann et al. [102] found 2.4 - 3.4% less battery energy losses calculated in SDP than EECMS. Moura et al. [103] applying the SDP for optimal power management in PHEV to sustain the battery charging and configure the charging station equipments as queuing theory based technique [104] to improve the engine efficiency and reduce charging time. Lust [105] approach iterative dynamic programming for a relatively coarse grid for optimum and vector controls to find the optimal policies for the next iteration. Gao et al. [106] presented the direct heuristic DP with filtered tracking error, to provide a solution for the optimum tracking control problem in the Henon Mapping chaotic system. Tate et al. [107] optimize the consumption of fuel and tailpipe emission for furnished HEV with a dual-mode electric variable transmission (EVT) and a catalytic converter. The SP-SDP controller was capable to provide significantly better performance and trade-offs between emission and fuel consumption [108]. Liu et al. [109] presented an optimal control strategy in Hybrid electric high mobility multipurpose wheeled vehicle (HMMWV) by using SDP, implemented in engine-in-loop setup, to analyze the effect of transient on engine emission. Opila et al. [110] developed a real-time energy management controller to optimal performance in between fuel efficiency and drivability for HEV. The SP-SDP-based controller is 11% additional efficient in comparison to other controllers.

e: INDIRECT ALGORITHM

Pontryagin's Minimum Principle (PMP) is known as an indirect algorithm to solve the optimum control issues, which is derived by Russian mathematician Lev Pontrygain in 1956 to resolve the global optimization problem. It is the expansion of calculus and the Euler Lagrange equation. The main advantage of PMP is that the starting costate is the only calibration parameter for a given driving cycle, which has a significant impact on battery condition. But, it is not suitable in real-time implementation because of starting costate is linked to the driving cycle, and different driving cycles necessitate different optimal initial costate values by which the size of the look-up table grows exponentially and increase the high computational load [111]. Lee et al. [112] developed a control strategy based on PMP and found the best output result in total energy consumption. Later revised Pontryagin's minimum principle algorithm was applied by T. Wu et al. [113] for optimal control in minimizing fuel consumption to prolong the life of lithium-ion batteries. Pérez et al. [114] discuss the finite-dimensional optimization problem to solve the driving cycle equation by PMP and resolve by a programming tool the direct transcription approaches. The size of the table is depending on the dimensions. Therefore, Hou et al. [115] introduced the approximate PMP algorithm based on engine fuel consumption rate, streamlining the Hamiltonian optimization problem into convex optimization problem which applied in-vehicle controller. Onori et al. [9] applied PMP based adaptive supervisory control strategy in less driving information to resolve the energy management problem and improve the fuel consumption by about 20 % in comparison to Optimal PMP, A-PMP, and CD/CS in the vehicle. Rousseau et al. [116] presented the PMP-based heuristic method in the free state for optimal control optimization, which provide the approximately same result as DP in less time. Zhang et al. [117] applied model predictive control (MPC) scheme for real-time optimization in receding horizon optimal problem. Kim et al. [118], describe the mathematical analysis for inequality state constraints in necessary conditions and provide a unique solution for HEV. In [119], PMP algorithms based on instantaneous minimization of the Hamiltonian are applied for real-time optimal control. And provide the closely optimal power solution in HEV via prior knowledge of future driving conditions and suggest to keep proper costate in SOC of battery at desired and predefined level [120]. Stockar et al. [121], minimize the CO_2 emission and utilize the optimal energy in PHEV by PMP. Chasse & Sciarretta [122], presented a chain of tools to develop the

EMS for hybrid power trains, to optimize the energy consumption in a real-time environment. Xiao et al. [123] studied the comparison of different energy management methods for a parallel P-HEV and control methods are inferred at different initial SOC of the battery. In terms of computing efficiency, PMP-MPC approach shows a sizable advantage over DP-MPC. In contrast to dynamic programming, PMP-MPC generates solutions with total costs that are equivalent to those of the globally optimum solutions (6.1% and 6.6% departures from DP and PMP, respectively). In light of this, the suggested PMP-MPC by Xie et al. [124] emerges as a practical and appealing substitute for online predictive energy management of plug-in HEVs.

Xie et al. [125] proposed an integrated control strategy for optimizing power distribution in between the auxiliary power unit (APU) and the battery. It is also compared with different techniques to measure its performance in terms of time efficiency and computational accuracy.

f: GRADIENT ALGORITHM

The gradient algorithm is to decreases the calculation time and increases the toughness of the vehicle. This algorithm is more sophisticated with a non-linear model of EVs and HEVs. This algorithm is used as a derivative analytical approach for an objective function. It solves the optimization problem under mathematical conditions, for example by satisfying the Lipschitz condition.

g: LINEAR PROGRAMMING(LP)

In the Linear Programming structure, the algorithms provide the key to optimizing the problems with linear objectives functions, and constraints. Ripaccioli et al. [126] developed a linear and piece-wise affine identification methods-based hybrid dynamical model to illustrate the use of hybrid modeling and MPC for advanced powertrain-based vehicles. Wu et al. [127], proposed mixed-integer linear programming (MILP) based EMS, which synthesized the velocity trajectory via prior knowledge of the real-time traffic condition for optimizing the fuel consumption. In this strategy fuel saved around 10-15% over the binary mode strategy. The MILP is a powerful tool for modeling and resolving problems with continuous and integer variables [128].

h: QUADRATIC PROGRAMMING (QP)

A Quadratic Programming (QP) based EMS is also used to approximate the powertrain model, resulting in a QP structure that is determined by a quadratic cost criterion subject to linear restrictions. It also starts in a quadratically constrained multiple instance learning (MIL) algorithm. The quadratic programming is applied in energy management over DP to reduce the processing time and global solution in a large driving cycle [129]. It is tested on Urban Dynamometer Driving Schedule (UDDS) and Highway Fuel Economy Test (HWFET) driving cycle via Zhou et al. [130] and found better vehicle performance through optimal power management. Constraint QP is applied by Gonsrang et al. [131] to solve the power management problem and found its performance based on nonlinear MPC in power management. Xia et al. [132] presented a quadratic performance index-based control approach in split power HEV to reduce the fuel consumption and it is also restricting the fluctuation of battery SOC.

i: SEQUENTIAL QUADRATIC PROGRAMMING (SQP)

SQP is an iterative approach for nonlinear controlled optimization. SQP tactics on mathematical problems on which the objective function and constraints can be separated twice regularly. Oh et al. [133], design an SQP based control strategy for multi variable optimization to find optimal value in control parameters. The solution of the embedded optimal control problem offers the non-linear characteristics solved via a Sequential quadratic programming algorithm [134].

j: CONVEX PROGRAMMING (CP)

The optimization problem, which includes a function of cost and inequity restrictions, may be addressed in both convex and affinity forms. The optimization of fuel economy is seen as a nonlinear convex problem (CP) to find the fuel efficiency and analysis the system capabilities [135]. Said et al. [136] described the CP and PMP for the energy management and validate the analytical solution [137] by comparing the obtained results by DP-based original model. Lu et al. [138], proposes the multi-objective optimization problem to solve the device power loss, battery current ripples, and quick charge /discharge ability of ultra-capacitor to stable the dc connection voltage by weighted method and no-preference approach into a convex optimization problem with Karush-Kuhn-Tucker (KKT) conditions.

k: DERIVATIVE-FREE ALGORITHM (DFA)

DFA algorithm applied to solve the optimization problem in which derivative information is unavailable for optimal power management. It can cover the global solution in comparison with the gradient algorithm. The DFA for EMS found in the literature is described below, which is mostly a metaheuristic algorithm.

l: SIMULATING ANNEALING (SA)

SA emerged in 1983 via Kirkpatrick, influenced by the method of annealing the metal. This algorithm uses the stochastic search method to provide a better solution, in which it selects the parameters after changing the objective function. There is very little security to find the global solution. Furthermore, repetitive annealing is exceedingly sluggish, especially when dealing with computationally expensive objective functions. Therefore, this algorithm is used with the combination of another corresponding algorithm to overcome these disadvantages. Delprat et al. discuss the drawback of SA and DP and design an algorithm to reduce the drawback of this optimization technique based on parameter control for the powertrain of HEV [139]. Hui et al. [140] presented an adaptable Simulated Annealing-Genetic

Algorithm (SA-GA) to boost the performance of the vehicle's with enhancing fuel efficiency.

m: GENETIC ALGORITHM (GA)

GA is a metaheuristic technique stimulated by the dynamics of evolution. As the first population, it firstly suggests a set of solutions (chromosomes). The results achieved from this first population are evaluated against an objective fitness function. The finest solutions are required more time to develop. Deb et al. [141] proposed the mutation and crossover-based non dominated sorting genetic algorithm applied to find the optimal solution in a computationally complex problem. The sorting mechanism subpopulation of parents Pi & Offspring Qi are evaluated via rank which indicates the conjunction to the crowding distance and optimal Pareto set, which reflects the diversification in solution [142]. The power tracking via GA was adopted in the ADVISOR simulator to optimize the fuel consumption and reduced 17.6% and 9.7% under UDDS and HWFET driving cycle [143]. It provides the solution precisely and avoids to trapped in a local abscissa. In [144], GA optimized the component size of PHEV and reduced the fuel consumption up to 24.38 %. The equivalent fuel consumption minimization tactic discussed to find proper value of conversion factor [122], Optimization in the propagation of abrupt power fluctuation [145] and component size [146], and parameter in EV [93], while data optimize for charging station [147] for the entire region by GA to reduce the problem of excess driving distance. Li et al. [148], proposed the combination of GA with ACA (Ant Colony Algorithm) to acquire the optimal control parameters exactly and efficiently remains an unresolved problem. Ma et al. [149], proposed a robust optimization method for distribution path in EVs to reduce the computational time [150] by GA, which resolves the problem associated with the uncertainty factor in battery charging and distribution of power in EVs.

n: MULTI-OBJECTIVE GENETIC ALGORITHM(MOGA)

The GA with an optimal Pareto result like MOGA can be used to resolve the multi-objective optimization problems. A MOGA was applied to design parameters with respect to fuel consumption, driving cycle performance [151], and operating cost [152], [153]. The fuzzy clustering condition with GA is applied to reduce the computational effort and improve efficiency [72] and electric-assist control strategy (EACS) to curtail fuel utilization and emission, with maintaining the vehicle performance requirement [154]. Poursamad et al. [155] minimize the fuel uses and discharge as well as enhance the driving performance of the vehicle by applying genetic fuzzy control strategy and performed on New European Driving Cycle (NEDC), Federal Test Procedure (FTP), and the car driving cycle. Shahi et al. [156], design a method for optimal control hybridization via Pareto set pursuing (PSP) multi-objective optimization algorithm and powertrain system analysis toolkit (PSAT) on a Toyota Prius PHEV. This algorithm's key advantage is that it takes much less time than an exhaustive search.

o: PARTICLE SWARM OPTIMISATION(PSO)

PSO was developed in 1995 by Kennedy and Eberhart and is concerned with the behavior of community creatures that travel in clusters, for example, ant colonies and flocks of birds in the wild. Participants of this group will exchange knowledge and communicate with all others nearby, reviewing their final finest location and the preeminent solution for the group to achieve an optimal solution. Rule-based control strategies are applied to optimize the fuel consumption for the decision of driving torque demand by a DCWPSO based algorithm and improve the fuel economy by 15.8% European driving cycle while 14.5% worldwide [157]. The effectiveness of Unified PSO justifies by comparing the result with the standard PSO algorithm [158]. Wu et al. [159] proposed a Learning Vector Quantization (LVQ) method based on driving cycle recognition for fuzzy energy management controller optimized by PSO. It is also used to optimize the power-sharing in between the source and component sizing [160] and optimal design variables on a multi-route environment to wireless charging for EV [161]. The fuzzy membership function and fuzzy rules are optimized by PSO in torque distribution in EV for split power management [71]. The various parameter of HEV optimizes to perform a case study on the smaller size of engine & motor, which provide the 22% improvement in fuel economy [162]. Chen et al. optimize the threshold parameter by PSO and reduce up to 1.76% energy loss in uncertain driving cycles [163]. A predictive EMS is applied for EVs to optimize the problems i.e. the minimization of battery consumption, maximizing the temperature comfortable for the driver cabin, and minimizing the travel time by PSO [164]. PSO provides the optimal solution for different cycles in the revised RB strategy [165]. It is a faster, easy, inexpensive, and robust stochastic global optimization technique [166]. The extension of PSO is deal with a multi-objective optimization problem, this method uses the concept of Pareto Dominance and gives effective results as compared to another existing multi-objective optimization [167].

p: OTHER ALGORITHM

The Game Theory (GT) method is used for economic energy management by Dextreit et al. [168]. This method depends on human nature for learning, understanding then action. Yin et al. [169] proposed control strategies based on Game Theory because the energy management is formulated as a non-cooperative current control game, so the Nash Equilibrium analytical method originate for a stable solution to reduce the challenges in energy management by multi-source hybrid energy system (HES). Younis et al. [170] proposed a spreading sampling point-based SEUMRE method to explore the optimal global solution. This method is faster to get the solution in the highly nonlinear problem than GA.

C. ON-LINE BASED STRATEGIES

The offline optimization-based method is not applied in a straightforward way for an online (real-time) control strategy.

The online control strategy is also called causal and local optimization for the reason that these are not required pre-information of the driving cycle. EMS strategies for real-time optimization problems are simply because of limited computation costs and memory resources. In addition, you can avoid manual adjustment of control parameters. The realization of an EMS for real-time optimization can be accomplished in numerous ways. The ECMS and MPC are the famous EMSs for real-time analysis and these have been widely used in various applications.

1) EQUIVALENT CONSUMPTION MINIMIZATION STRATEGIES (ECMS)

Paganelli et al. propose the renowned real-time optimization EMSs known as ECMS which is the realization of offline PMP. The global optimization problem reformulated into limited optimization issues by decreasing the total fuel consumption. The equivalent fuel factor was evaluated by ECMS for the analysis of the fuel consumption to charge the batteries. The EF in ECMS has a similar character as costate in offline PMP. EF is the main key point of ECMS because the control performance of HEV is dependent on it.

So the researcher has focused on the estimation of EF in EVs, dependent randomly on three factors: (i) SOC limits of Battery, (ii) Information of driving cycle (iii) ESS Charging and discharging. Paganelli et al. [171], presented the ECMS for PHEV, which provides the instantaneous power split strategy to optimize the fuel consumption in between ICE and electric machine by charge sustaining mode [172]. This is a real-time minimization strategy for estimating the future driving conditions and can be improved the fuel economy by up to 1% [173]. Pisu et al. [174], analyzed two different energy sources by power split algorithm in modified instantaneous ECMS for a Series Hybrid Vehicle. The comparative result analysis between ECMS and DP-based control strategy discussed by Marano et al. [80], that ECMS algorithm gives the results on Blended Mode control strategy at known driving distance. Musardo et al. [175], proposed a real-time energy management control strategy by adding the fly algorithm on the ECMS framework, known as Adaptive-ECMS. It updates the controlling parameter periodically as per the situation of road traffic and situation. Velocity forecasting is also having a vital role in A-ECMS to optimize the equivalence factor [176], by which it can improve the 3% fuel economy [177]. Won et al. [178], converted the multi-objective nonlinear optimum torque delivery problem into a single objective linear optimization problem by describing an equivalent energy consumption rate for fuel flow frequency and battery charging. Onori et al. [179], design feedback corrected strategies in the A-ECMS controller, which is capable to generate a solution robust and quasi-optimal. It consumes 1-2% more fuel in comparison to another method. Li et al. [180], proposed ECMS based Markov chain model to predict the future driving condition. Sun et al. [181] forecast the velocity by neural network and combined with adaptive ECMS, by this strategies fuel consumption reduced up to 3%. The chaining neural network (CNN) based velocity forecast discussed by Zhang et al. [182] and reduced the fuel consumption up to 5%. Payri et al. [183] describe a unique control approach for optimum power management in HEV, in which the eminent ECMS method upgraded by a stochastic estimation based on past power demand in the vehicles for future driving patterns and applied the S-ECMS method to obtain S parameters for battery energy via log-likelihood ratio. Sciarretta [36] define the equivalent factor for battery charging and discharging on current energy depletion without knowing future driving condition.

2) MODEL PREDICTIVE CONTROL (MPC) BASED STRATEGIES

MPC is a famous technique used in industry to address multi-dimensional constrained control problems. The main purpose of its introduction is to address the DP algorithm issues. When all future information is known ahead of time, the DP's global optimal control can be obtained. For real-time applications, obtaining such conditions in advance is not practical. Therefore, MPC ordinarily consists of three core stages: (i) Measure the optimal control sequence in a predictive horizon which minimizes the cost function subject to constraints; (ii) Apply the first part of the derived optimal control sequence for the physical plant; and (iii) Moving the entire predictive horizon one step forward and repeat step 1. Cairano et al. [184], applied an automatic control via learning of driver behavior through stochastic model predictive control with learning (SMPCL) method in power management. Gomozov et al. [185], applied a computational rate in MPC to provide control of dynamical parameters and horizon prediction. Chaudhuri et al. [186], discussed a hierarchical control strategy in which a higher-level controller is considered to apply traffic signal information and the lower-level controller provides the optimum velocity in an MPC framework. Huang et al. [187], proposed a unique anti-idling system for a service vehicle, where coordination in between the different sources is compulsory for efficient operation. In this strategy prior information is unavailable of driving cycle [188], so it will work on the ordinary concept. Here, MPC applies to increase the efficiency of the regenerative auxiliary power system (RAPS). MPC algorithm applied by Johannesson et al. [189], which use the feedback of vehicle position and single nominal drive cycle. It improves the performance by 0.3% over minimum attainable fuel consumption at the studied route. Siampis et al. [190], design the three MPC strategies (Linear MPC, nonlinear MPC- Real Time Iteration (RTI), nonlinear MPC- Primal-Dual Interior-Point (PDIP) for handling the different levels of complexity and compare these strategies on different aspects then found it NMPC-PDIP is the best control strategies in comparison to other. Guo et al. [191], discussed a new formulation of MPC for a continuous-time non-linear system. In the real-time optimization, the GPM combined with MPC, and finite horizon non-linear optimum control problem converted into a linear problem, which is solved by SQP algorithm. The accuracy of the proposed method is higher than the Euler method. Borhan et al. [192], proposed MPC-based full minimization strategy, where the power management problem is divided into two parts. The first part is based on linear time-varying MPC with a quadratic cost function to calculate future control sequence, for minimizing a performance index then applied for the implementation in the computed control sequence. Trovao et al. [193], proposed an EMR approach model for an effective EMS in EV. The joint optimization technique for speed of vehicle and power management is a large-scale non-linear problem [131] discussed by Chen et al. [194] and improves the fuel economy by 6%-14%. Stroe et al. [195] proposed a generic parameterization under the certain assumption to control the energy flow for power management, it is controlled by MPC strategy. Optimal EMS is analyzed for plug-in HEV and reduces the average consumption of fuel [196].

3) OTHER ALGORITHMS

a: EXTREMUM SEEKING (ES)

ES is a real-time adaptive optimization algorithm. ES method may be used in a stationary non-linear system to find the real-time extreme value efficiently. It is also called a derivative-free algorithm, which is used to find the optimal functional level in the output function. The objective function is mandatory, to express a sliding surface for following a time-accumulative function and the optimization parameter is chosen by a discontinuous switching function. Bizon [197], proposed the Global Extremum Seeking (GES) algorithm for real-time optimization. GES operation improves the energy efficiency up to 1-2.1% in comparison to Static Feed-Forward (SFF) approach. The application of ESS is studied by using a first-order high-pass & band-pass filter to control the charging/discharging policy of the battery. The band pass filter has the better ability to reduce the load dynamics and improve the durability of ESS [198]. D. Zhou et al. [199], proposed the fractional-order extremum seeking a method to increase the fuel efficiency and durability. It is a more rapid convergence speed and advanced robustness [198].

b: ROBUST CONTROL (RC)

Robust control (RC) aims at determining an output feedback controller which minimizes fuel consumption. In estimation, RC can handle parametric uncertainties, sensor noises, and defects, assuring stability and toughness. However, RC can only produce a sub-optimum result due to the translation of a nonlinear time-variant system into a linear time-invariant. P. Pisu et al. [200], discussed the comparative analysis of four different techniques (Finite State Machine, H-Infinity Control, Adaptive Equivalent Consumption Minimization, and Dynamic Programming) for Energy Management in a sports vehicle. Zaher et al. [201], design optimal robust control for real-time EMS. In this strategy, mechanical wastage is used to regenerate the energy for the energy storage device for later usage. This hybrid configuration reduces the fuel consumption on the machine by 20-30% at different drive cycles.

c: DECOUPLED CONTROL METHOD

Decoupled Control (DC) is a model-based control approach, which applied to resolve competing performance targets, for example, fuel efficiency, regulation, and drivability SOC. By developing the dynamic model powertrain arrangement, the battery regulator and drivability control decoupled by using the constraint on power demand and vice-versa. Chen et al. [202], investigated problems regarding fuel economy and vehicle speed in HEV. Besides this, it also analyses the energy management strategy for the electric power train. Here author separately analyses the optimization problem for power train losses and the speed characteristics. Two sliding mode controllers detached the DC strategy's control operations. In which, the first-order sliding mode precisely regulates the dc-bus voltage with the modest voltage drip caused by rapid load fluctuations, while the second-order sliding mode produces less chatter and recovers earlier from voltage losses.

d: PSEUDO SPECTRAL OPTIMAL METHOD

A pseudospectral control method is an additional modern optimization-based mathematical method stretched to an energy management system. A direct method resolves the optimum control issues. In which PSOC set down an optimum control problem into a nonlinear problem (NLP) by parameterizing the state and control variables in a series of collocation nodes using global polynomials. Li [203], studied a low-temperature characteristic of HESS and its structure for better utilization of power density of UC by applying a logic threshold control strategy to decrease the power loss. The pseudo spectral method has a better control effect than the LTCS and has good real-time, high reliability, and high-efficiency characteristics. Dosthosseini et al. [204], proposed direct method (Legendre, Chebyshev, and Haar Wavelets polynomials) to reduce the optimal control problem with inequality constraints by orthogonal function. This method does not require discretization of the control problem. The PSOC was engaged in seeking the best global results integrated into a logic threshold management approach.

D. LEARNING BASED ENERGY MANAGEMENT STRATEGY

Learning-based EMS works on sophisticated schemes of data mining for broad real-time and historical knowledge to extract the maximum control legislation. The exact model information is not required in the LB-EMS to decide on the control. It is conversely challenging and time taking to establish an exact database whose configuration and size directly influence the controller performance. Machine learning and data-driven approaches are versatile and capable handle massive data sets under varying driving environments and drivers outside.

1) MACHINE LEARNING BASED EMSS

ML-based EMS is used widespread in Intelligent Transport Systems. Boyah et al. [205], designed a neuro-dynamic programming-based real-time controller to get the optimum result in power distribution while computational complexity and the resulting burden are very critical. The Quality(Q)-learning-based vehicle learning system combined with neuro-dynamic programming (NDP) discussed by Liu et al. [206] to estimate expected energy costs in near future. Yanqing et al. [207], developed an instance-based machine learning algorithm to learn the rolling driving condition that can be predicted by the k-Nearest Neighbor (k-NN) algorithm. Venditti [208], addressed the performance of cluster optimization & rule extraction (CORE) and cluster extraction & rule optimization (CERO) and compare with DP, and provide the almost same result with the small discrepancy about 1.84% and 4.85 %. Langari et al. [209] implemented an intelligent energy management agent (IEMA) whose role is to assess the driving environment, by which learning vector quantization (LVQ) network can efficiently determine the driving condition within a limited time period of driving data.

2) REINFORCEMENT LEARNING (RL) METHOD

A RL framework contains two modules: a learning agent, and an environment in which the learning agent communicates with the environment continuously. At every point in time, the learning agent obtains an assessment of the status of the world. After that, the learning agent takes an action to perform, which is later implemented in the environment. The environment then shifts to a new state as a result of the action, and the reward connected with the shift is calculated and communicated back to the learner. The agent receives an immediate reward along with each state change, to establish a strategy of control that records the existing state to the appropriate control decision on a particular place. Deep Reinforcement Learning (DRL) based EMS associate as a deep NN with a conservative RL, called a deep Q-network. Recently, some RL-based EMSs have been recorded. Lin et al. [210], proposed RL technique for optimal power management in HEV, without prior knowledge of driving cycle. It improves the fuel economy up to 42%, while Lee et al. [211]obtain that the RL-based approach is more suitable for a time-variant controller with boundary value limitations. He and Cao [212], proposed a restructured algorithm framework based on Deep Q-learning (DQN) to obtain a better pedal's control strategy. The deficiencies in traditional approaches are discussed by Liessner et al. [213] and offered a deep reinforcement learning framework to overcome these deficiencies. Deep RL is capable to achieve optimal fuel consumption [214]. The prior route information is not required as DP, so it can apply to line vehicles [215]. Wu et al. [216], applied DP for split power optimization, FLC for dynamically adjusting coefficient α, and reinforcement learning applied as an online correction algorithm to resolve the optimal control problem and obtain 4% improvement in fuel economy. Liu et al. [217], proposed an energy management strategy based on a Dyna agent of RL approach for optimizing fuel efficiency and improving fuel economies. Here, the author made a relative analysis of the one-step Q-learning, Dyna, and Dyna-H algorithms. Xia et al. [218], proposed a real-world driving data-based energy management to recover the energy consumption in PHEV and reduce the computational complexity of the optimization method, while the K-means Clustering method is used to calculate the sensitivity of new factor to the energy consumption.

a: NEURAL NETWORK BASED LEARNING METHOD

The learning approach based on neural networks is modeled after human brain neurons. As with a real neuron, which contains a plethora of connections, A neural network's nodes are objects with numerous inputs and outputs. Various kinds of behaviors would be modeled by involving multiple neurons in layers that make a network. The three-layer neural network optimization controller was designed for energy management issues by Xie [219]. Raj et al. [220], proposed the loss model control (LMC) and search control (SC) method for optimal control and also discussed the different optimization techniques such as ANN, FL, GA, Nature Inspired Algorithm (NIA), an evolutionary algorithm.

The evolutionary algorithm discussed by Potvin [221] addresses difficult vehicle routing problems in many different ways in which branch cut and price algorithms are used to resolve the capacitated vehicle routing problem [222] Baldacci et al. [223], discussed an innovative approach to solve the vehicle routing problem and retract performance and comparison analysis of a different exact algorithm for the time window [224] with VRP and Capacitated VRP. Huang et al. [225], designed an intelligent vehicle control system, which is based on both membership functions and control rule base neural fuzzy network tuned by mixed genetic/gradient parameter algorithm to obtain an optimum control performance in the vehicle. This technique is also used in the load-leveling strategy, which consists of fuel economy and reduced emission for a different driving pattern [226]. Rubaai et al. [227], presented a training set for Fuzzy NN, which included different methods such as back- propagation (BP), extended Kalman filter (EKF), Genetic (GEN), PSO, and found the EKF is the best learning method in pattern matching. Lee et al. [228], define the ANN-based fuel economy as much better than others and Power Split Ratio (PSR) technique is very simple and robust. Wang et al. [229] applied an Elman neural network (NN) in an optimal EMS, and reduced the fuel consumption by 9.1% & 24.6% in comparison to logic threshold & conventional ICE bus. Park et al. [230] developed an ML algorithm to learn the efficiency of different road types and traffic jamming levels, as well as a neural learning algorithm for learning the NN to forecast the road type traffic jamming levels. These are all things processed by the University of Michigan-Dearborn intelligent power controller (UMD_IPC). Murphey et al. [231] developed an

TABLE 4. Taxonomy of optimization based energy management strategies.

Optimization Based Energy Management Classification			References	Advantages	Main Challenges/ Disadvantages
Offline Strategy	Direct	DP	[76], [77], [78], [79], [80], [81], [82], [83], [84], [85], [86], [87], [88], [89], [90], [91], [92]	• Globally Optimal • Standard for other EMSs • No requirement of objective function's derivative • No need to identify the starting position	• The driving cycle is required ahead of time. • High computational cost • Slow convergence to true global optimum when reaching a global optimal region
		DDP	[93], [94], [95], [85], [96], [97], [98]		
		SDP	[99], [100], [101], [102], [103], [104], [105], [106], [107], [108], [109], [110]		
	Indirect	PMP	[111],[112], [9], [113], [114], [115], [116], [117], [118], [119], [120], [121], [122], [123], [124], [125]	• Globally trajectory optimum control	• Required estimate of modeling to decrease computation power
	Gradient	LP	[126], [127], [128]	• Helps in re-evaluation of a basic plan for changing conditions	• Model parameters assumed as constant
		QP	[129],	• Easy to implement • Effective for solving continuous and smoothing problems	• Assumptions are required on objective function to obtain derivative • Only obtain local optimum
		SQP	[133], [134]		
		CP	[135], [136],	• Faster, simpler, and less computationally intensive • one optimal solution	• Challenges to identified convex or non-convex function
	Derivative-free	SA	[139], [140]	• Find global optimum without covering the entire design space.	• The performance depends on tuning parameters.
		GA	[141],[122],[142],[143],[144], [150] [145], [146], [147], [148], [149],	• Has strong capability of global search • Has a strong universality	• Has weak capability of local search.
		MOGA	[72], [151], [152], [153], [154], [155], [156],		
		PSO	[157], [158], [159], [160], [161] [162], [163], [164], [165], [166], [167]	• Easy to understand and implement • Has a stronger capability of local search compared to GA.	• Easy to get trapped in local optimum; • Has weaker capability of global search compared to GA.
	Other	GT	[168], [169]	• Comprehensive trade-off of conflicting objectives • Analysing decision making	• All competitive problems cannot be Analysed • Involved mixed strategies
		SEUMRE	[170]	• It is faster to get the solution in highly nonlinear problem	• Greater computation effort is required to achieve the accuracy
Online Strategy	ECMS	T- ECMS	[171], [172], [173], [174]	• Maintenance requirements are lower • Engineering clarification of one cost function	• Sensitivity of driving cycle for equivalence factor
		A-ECMS	[175], [176], [177]		
		P- ECMS	[178], [179], [180], [181][182], [183]		
	MPC	D-MPC	[184], [185], [186]	• Nearest Solutions to global optimum point	• Preview driving pattern, as well as terrain and prospective driving data • Prediction the horizon sensitivity
		A-MPC	[187], [188], [189],[190], [191]		
		T-MPC	[192], [193], [194], [195],[196]		
	Others	Robust Control	[200], [201]	• Robustness with parametric uncertainties and sensor noises	• Complexity in mathematics
		Extremum Seeking	[197], [198], [199]	• Improvement in performance and durability of ESS	• Its convergence speed and robustness for energy management
		Decoupled Control	[202]	• Faster dynamic response • To balance the control and operation of HES	• Model uncertainties • Robust stability
		Pseudospectral Optimal Control	[203], [204]	• No requirement of discretization of control problem	• The feasibility and convergence

energy optimization technique with ML framework tuned all three online intellectual controllers, IEC_HEV_SISE, IEC_HEV_MIME & IEC_HEV_MISE integrate into ford escape hybrid vehicle for real-time performance calculation and found IEC_HEV_MISE give the best performance by saving the fuel consumption from 5% to 19% as compared to ford escape controller. Long [232], studied the EKF for estimation of the SOC [233] of the battery based on Stochastic FNN. This model is used for the non-linear dynamic model of battery and filter the effect of noise at the input. The online SOC estimation of the Li-ion battery [234] is operated by the adaptive Luenberger observer method and the function parameter are optimized by the least square algorithm [235] which are giving the better result in comparison others.

b: PATTERN RECOGNITION BASED EMSS

This method is based on driving cycle behavior which is part of the Intelligent Transportation System (ITS). GPS has a big role to identify the traffic condition and road map. Driving behavior-based EMS have been reported. Marano et al. [236], discuss the intelligent transport system, in which information is given by different vehicles to everything, enables the power management system for small & long distance power splitting for improved fuel efficiency. The prediction mechanism for a piece of prior knowledge about future driving cycles is discussed on the ML framework with the combination of DP [237]. Fan et al. [238], proposed a map-based approach for optimal energy management to decrease consumption and enhance the economies of parallel plug-in HEV. Wu et al. [239],parallel chaos optimization algorithms are used to optimize control strategy, instability of torsional [240] as well as to minimize the cost, while an intellectual multi-dimensional statistical method is used to discriminate automatically the driving condition of HEV [241].

3) NATURE INSPIRED ALGORITHM BASED EMSS

Some nature-inspired new algorithms applied to EMS in which the author discusses the results and application in HEV/FEV. Hmidi et al. [242] presented the meta-heuristic-based grey wolf optimization (GWO) algorithm for optimal energy management on fuel consumption, CO_2 emissionand optimal gain absorb in the urban cycle is 13.9 % in comparison to simple rule-based strategy. Improved binary GWO and give the better experimental result in comparison to the GA and PSO [243]. Multi-objective GWO is used to minimize the power loss and voltage abnormality in the supply system [244]. Ullah et al. [245] proposed the bio-inspired Grasshopper-Optimization Algorithm and Cuckoo Search Algorithm to reduce the energy consumption budget, peak-to-normal power ratio, and quick time responses because of different loads. Preetha et al. [246] proposed ALO (Ant Lion Optimizer) to solve the energy management problem and also compare with GA, PSO, BAT algorithm, while the Salp Swarm Algorithm is used to optimize the energy consumption and cost [247]. Kayalvizhi et al. [248] applied the firefly algorithm to optimize the power consumption from the battery and devices automatically switching by dynamic EDF based on allocated priority. Liu et al. [249] optimize the real-time constraint to charge completion strategy by the grey wolf optimizer method. Mohseni et al. [250] proposed the Whale Optimization Algorithm (WOA) to reduce the computational burden on microgrids for energy management which is required lower iterations in comparison to PSO and GA. This is also coordinate to energy management in PV-BES units and electric vehicles [251]. Trovao et al. [252], presented a technological approach for simultaneous optimization by simulating an annealing metaheuristic for power and energy management, for a supercapacitor and battery, in the electric vehicle. Bagherzadeh et al. [253] proposed Salp Swarm Algorithm (SSA) to decrease the objective function of the problem to determine the optimal location and capacity of RES.SSA optimizer showed its preeminence with great attitude and correctness in problem-solving of renewable distributed generators (RDGs) and shunt capacitor banks (SCBs) [254]. Deb et al. [255] proposed the Chicken Swarm Optimization (CSO) with Ant Lion Optimization (ALO) for efectively resolve the and efciently coping with the charger placement problem.

4) OTHER ALGORITHM FOR EMSs

a: NEURO-FUZZY METHOD

Neuro-fuzzy is a term used in artificial intelligence to describe a method that combines fuzzy logic and artificial neural networks. Mascioli et al. [256], proposed a control technique to optimize the energetic flows via a neuro-fuzzy approach with the vehicle state especially of their energy consumption in HEV.

b: ACTION-DEPENDENT HEURISTIC DYNAMIC PROGRAMMING (ADHDP)

An algorithm for approximative dynamic programming is action-dependent heuristic dynamic programming. It is not necessary to have a system model that is explicit. use the Action and Critic, two neural networks. Over a predetermined period of time, this plan can minimise a specific Utility Function. Hui et al. [257] examined issues regarding lowering average cost over a period of time for electric vehicles by proposing a strategy to optimally control vehicles in a heterogeneous vehicular network. An ecological adaptive cruise control for HEV in the car, following scenario to optimize the fuel consumption. As well as ADH-DP in adaptive cruise control (ACC) is used to optimize and maintain the velocity and inter-vehicle distance in normal driving conditions [258].

c: SHUFFLED COMPLEX EVOLUTION (SCE) ALGORITHM

This algorithm developed by Duan et al. is useful for calibrating hydrological models. This approach, a type of differential evolution (DE), is effective because it uses geometric operations to look for potential optimal solutions to space parameter problems. Chen et al. [259], studied an adaptive tracking control, for nonlinear stochastic systems.

TABLE 5. Taxonomy learning based energy management strategies.

Learning Based Energy Management Classification		References	Advantages	Main Challenges/ Disadvantages
ML&RL Based	DRL	[206], [207], [208], [209], [230], [231], [237]	• To solve the decision making problems	• Agents must deal with long-range time dependencies
	NDP	[206]	• Widely accessible in the context of stochastic control	• Computational burden by efficiently approximating the value function
	Q-Learning	[206]	• Solve the sequentially decision making problems	• Learning process is expensive for the agent
	K- NN	[208]	• It is robust to noisy training data	• Always needs the value of K • Computation cost is high
	LVQ	[209]	• To determine the driving condition effectively with in a limited time period • It is simple and intuitive	• Slow convergence • Possibility of being trapped at locally minimum value
NN Based	ANN	[219], [220], [224], [225]	• Ability to outperform nearly every other ML algorithms	• Neural networks cannot be used if training data is not available
	FNN	[227], [232]	• Self-learning, self-organizing and self-tuning capabilities	• Interpretation of results is difficult
	E-KF	[229], [232], [223]	• Best learning method in pattern matching	• But fail if the functions are highly nonlinear
NIA Based	GWO	[242], [243], [245], [249]	• Reduced number of random parameters and user selected parameters	• Low solving accuracy, • Bad local searching ability • Slow convergence rate
	BAT	[246], [247]	• Has a higher convergence rate than GA	• Easy to get trapped in local optimum.
	WOA	[250], [251]	• To solve unconstrained problem • Power loss reductions	• Slow convergence speed • Low accuracy
	SSA	[252], [253], [254]	• Adaptability, robustness, and scalability	• Suffers from premature convergence
Other Algorithm	Dijkstra	[262]	• To find shortest path • It is a graph searching algorithm	• Consuming a lot of time • It cannot handle negative edges
	MA	[261]	• It is local search technique to reduce premature convergence	• Slow conversion rate
	Queuing Theory	104]	• To predict their behaviour and suggest strategies for mitigating the unpreparedness	• Restricted for real life modelling • Strongly simplified uncertainty assumptions
	Luenberga	[234]	• Steady state performance and low speed operation of LO are the best	• Low accuracy • Much large computation burden
	Coyote	[263]	• To solve boundary constrained global optimization problems with continuous variables	• It has not presented the best results in separable and unimodal
	Chaos	[239], [240]	• Establishes an balance between exploration and exploitation to prevents the algorithm from falling into a local optimum state • To replace random programs	• It is not simplistic to find an immediate and direct application • Highly complex and not always accurate

The shuffled Complex Evolution (SCE) algorithm resolves the waiting time problem in the optimization model of the charging station [260].

d: MEMETIC ALGORITHMS (MA)

Memetic Algorithms are known as evolutionary algorithms that use local search technique rather than global search technique to refine individuals. Memetic Algorithm (MA) is used to reduce fuel consumption and emissions [261].

e: DIJKSTRA's AALGORITHM (DA)

Dijkstra's technique use to determine the shortest path between any two graph vertices. In [262] Tribioli, presented Dijkstra algorithm (DA), which is much more computationally efficient than any other optimization technique.

f: COYOTE OPTIMIZATION ALGORITHM

Pierezan and Coelho debuted a brand-new meta-heuristic Coyote Optimization Algorithm (COA) in 2018. The algorithm is based on how the coyote adapts to its surroundings and exchanges experiences with other coyotes. Fathy et al. [263], discussed the Coyote Optimization Algorithm which moderates hydrogen consumption by 38.8% in comparison to the EEMS technique and got the first ranked in between GWO, SSA, GOA, MVO, GA, PSO, and EEMS based on the lowest hydrogen feeding.

TABLE 6. Pros and cons of various types of energy management strategies and its application.

Strategy type	Advantages	Disadvantages	Applications
Deterministic rule-based energy management strategy	• Effective computation • Easy to implement	• Requires extensive calibration and tuning of the parameters • Cannot guarantee the best results • Non-movability	• Widely used in HEV prototypes • Commercial HEVs
Fuzzy rule-based energy management strategy	• Has the capacity to withstand measurement noise and component variation • Low computation • Easy to implement.	• Cannot guarantee the best results • Necessary to calibrate the membership function and the fuzzy rule • Non-movability.	• Used in HEV prototypes • Commercial HEVs
Real-time optimization energy management strategy	• Has the potential to be used with HEVs • Obtain sub-optimal solution.	• Cannot obtain global optimal solution • Still difficult to be implemented in current vehicle controller	• Used in HEV prototypes.
Global optimization energy management strategy	• Can obtain optimal solution; • Requires no calibration.	• Requires a-priori knowledge of driving cycle; • Computation is the most complex; • Cannot be implemented directly.	• Identify maximal potential performance of specific HEV; • Evaluating the effectiveness of other energy management strategies;
Machine Learning Based EMS	• Support eco driving behavior • Reduce the operating cost	• Possibility of High Error • Data acquisition	• EV Charging Behaviour • Self - Driving Vehicle
Reinforcement Based Learning based EMS	• Control without using a model • Learning ability	• Preparing a database is time-consuming. • Not suitable for simple problem	• Used in HEV prototypes and EVs
Neural Network Based EMS	• Learning and adaptive capability	• Quality and quantity of training data needed to be qualified • Uncertainty outside of the training environment	• Automatic Vehicle Control Application • EVs
Nature Inspired Algorithm Based EMS	• Reduce the distribution system losses as well as total cost • Efficient Energy Utilization	• Running time is Longer	• Used in PV based Electric Vehicle • PHEV

V. DISCUSSION & OUTLOOK

In light of the previous section's analysis, it is clearly seen that researchers have made significant efforts in the field of EMSs for HEV and FEV, with promising outcomes.

However, the recent rapid developments in the application of smart transportation systems, developing innovations in powertrain components, and computational methodologies have created tremendous opportunities to improve EMS performance. With the current evaluation of renewable energy charging systems and new communicative techniques like a vehicle- to- vehicle (V2V), vehicle-to-infrastructure (V2I), and Automated connected vehicle (ACV). Auspicious potential required to unleash for additional development in driving performance and fuel budget. Hence, this segment looks at perspectives that haven't been discussed before and have received little attention but could be expected as future research directions in this field.

To that purpose, an overview of vehicle configuration and their application of HEV has been shown in Table 1 and found that traditional ICE vehicles generate high greenhouse gas emissions and low-efficiency drivetrain. IC Engine also suffered with the inherent and pronounced delay in torque production [264]. Hence IC engine revved-up by torque filling and boosting to achieve maximum power and torque. Electric automobiles are much quicker than their combustion counterparts [265]. This is due to the fact that electric automobiles can create high torque right away, whereas combustion engines must acquire speed to achieve that torque. So that vehicle transmuting in electric vehicles, have an alternate solution [63]. Ever since Lohner Porshe, developed the first HEV in 1901. HEV technology has gotten a lot of attention in terms of research and development, but when people talk about the benefits of HEVs, they typically forget the drawbacks, like; limited range, low power, expensive costs, maintenance costs, batteries. The current state of the HEV power management approach is summarized from the standpoints of real-time implementation and optimum forecast capabilities.

RB-EMS seems to be the only method that has demonstrated successful capabilities in commercially implemented real-time systems, however, it falls short of providing the optimum solution. OB-EMS overcomes the inherent drawback of RB-EMS through an optimization control approach. In the same way that offline OB-EMS are being challenged in terms of their application in online use due to computational burden. Table 6 lists the benefits and drawbacks of the primary EMS under investigation.

It has been observed that none of them can address all of the control objectives' criteria at the same time. Therefore, numerous researchers have used different optimization algorithms to enhance EMS performance by combining their complementing qualities. In terms of optimization, it appears that the majority of the research has emphasized the usage of older algorithms (Eg. PSO, GA, and SA) for OB-EMS control. However, the literature has more than 40 different nature-inspired algorithms [266]. There are a plethora, black widow [267] of novel algorithms that have not been used in the EMS optimization sector among EVs.

In terms of optimization, incorporating more recently developed algorithms into EMS applications, particularly MPPT in solar PV-based FEV, would be a promising field of research. The introduction of a new algorithm will help in the field of computational cost, efficiently handling complex multiple objective cases in the direction of extremely necessary raw data that are received at the input of any intelligent EMS.

The offline EMS aims to reduce worldwide fuel usage. Even though they cannot be directly deployed in real vehicles, they serve as a benchmark for other EMS and receiving modified online EMS. As ITS technology has advanced, driving cycle prediction has become increasingly crucial in predictive EMS. They are more adaptable and perform better than other EMS. In addition, infrastructure that can recognize, save, and combine datasets of traffic paths, vehicles, weather, road signs, preceding cars, speed, and other factors at the same time and use them for forecast purposes should be explored. Finally, EMS can be expanded to include multi-time scalar multi-vehicle interactions as well as several information layers.

The use of the OB-Algorithm in conjunction with machine learning techniques can help speed up the evaluation of larger space out EMS. In this aspect, thanks to the new smart devices, EMS now considers a fleet of vehicles rather than a single vehicle when interacting with the smart grid and optimizing charging rates. The primary goal of these initiatives is to boost road capacity and overall performance in all aspects. These methods are mostly used in heavy-duty applications. like: city buses. It is expected that groups of passenger vehicles would be thriving research topics in the future. Which will be the designing EMS framework for smart and sustainable city concepts.

The discussed item can be summarized in an integrated EMS (i-EMS) concept which included the level of information (like: Data from the server, ITS, V2V, V2G, GPS & Traffic Lights), Time Horizons, and the number of the vehicle (Transportation Level). Integrated EMS can be considered various integration possibilities for future research trends: Waste Heat Recovery (WHR) System. Some dynamic behaviors, including battery temperature, catalyst temperature, engine out temperature, and engine cold start circumstances, can have an impact on the WHR system.

The proposed methods for incorporating the investigated components into an optimal power control problem, previously utilized effective methodologies require the development of high-fidelity models that include the engine and battery's dynamic transient behavior. Self-learning and model-based control systems that can autonomously decide the best control settings on the road would be a solution to the shortcomings of a typical EMS based on quasi-static and map-based models, in the coming years.

The integration of several control layers into a concrete holistic EMS framework will be one of the future research trends. The inclusion of eco-driving into an EMS for the double vehicle level thru an Adaptive/Predictive cruise control approach as at multiple vehicles platooning warrants consideration as a potential field in the coming years with the support of cyber-physical systems.

VI. CONCLUSION

According to the review, many researchers are becoming more interested in the design features of powertrains and EMSs for hybrid and electric vehicles. To address control goals such as decreasing fuel consumption and emissions, preserving ESS charges, and increasing drivability and vehicle performance, many topologies for powertrains and associated EMSs have been suggested. In creating energy management techniques, there is a trade-off between optimality and execution. The advantages and disadvantages of different optimization techniques & algorithms are shown in Table 3, 4 & 5. All energy management techniques are influenced by the driving cycle, and the application of all the optimization methods is shown in Table 6. The first time, focus on intelligent transport systems for improving the vehicle performance and uses the recently originated meta-heuristic algorithm inspired by nature. In light of current advancements in smart and information-based methods, it has been suggested that new frameworks/algorithms, communication ideas, technologies, and infrastructure be incorporated into the design of an EMS to overcome existing uncertainties and attain real-time robustness.

VII. ACKNOWLEDGMENT

Princess Nourah bint Abdulrahman University Researchers Supporting Project number (PNURSP2022R79), Princess Nourah bint Abdulrahman University, Riyadh, Saudi Arabia.

REFERENCES

[1] S. Amjad, S. Neelakrishnan, and R. Rudramoorthy, "Review of design considerations and technological challenges for successful development and deployment of plug-in hybrid electric vehicles," *Renew. Sustain. Energy Rev.*, vol. 14, no. 3, pp. 1104–1110, Apr. 2010.
[2] J. A. Sanguesa, V. Torres-Sanz, P. Garrido, F. J. Martinez, and J. M. Marquez-Barja, "A review on electric vehicles: Technologies and challenges," *Smart Cities*, vol. 4, no. 1, pp. 372–404, Mar. 2021.
[3] D.-D. Tran, M. Vafaeipour, M. El Baghdadi, R. Barrero, J. Van Mierlo, and O. Hegazy, "Thorough state-of-the-art analysis of electric and hybrid vehicle powertrains: Topologies and integrated energy management strategies," *Renew. Sustain. Energy Rev.*, vol. 119, Mar. 2020, Art. no. 109596.
[4] R. Casper and E. Sundin, "Electrification in the automotive industry: Effects in remanufacturing," *J. Remanuf.*, vol. 11, no. 2, pp. 121–136, Jul. 2021.
[5] M. F. M. Sabri, K. A. Danapalasingam, and M. F. Rahmat, "A review on hybrid electric vehicles architecture and energy management strategies," *Renew. Sustain. Energy Rev.*, vol. 53, pp. 1433–1442, Jan. 2016, doi: 10.1016/j.rser.2015.09.036.
[6] E. Silvas, T. Hofman, N. Murgovski, L. F. P. Etman, and M. Steinbuch, "Review of optimization strategies for system-level design in hybrid electric vehicles," *IEEE Trans. Veh. Technol.*, vol. 66, no. 1, pp. 57–70, Jan. 2016.

[7] P. Zhang, F. Yan, and C. Du, "A comprehensive analysis of energy management strategies for hybrid electric vehicles based on bibliometrics," *Renew. Sustain. Energy Rev.*, vol. 48, pp. 88–104, Aug. 2015.

[8] P. Joonyoung, O. Jonghan, P. Youngkug, and L. Kisang, "Optimal power distribution strategy for series-parallel hybrid electric vehicles," in *Proc. 1st Int. Forum Strateg. Technol. e-Vehicle Technol. (IFOST)*, Dec. 2006, pp. 37–42.

[9] S. Onori and L. Tribioli, "Adaptive pontryagin's minimum principle supervisory controller design for the plug-in hybrid GM Chevrolet volt," *Appl. Energy*, vol. 147, pp. 224–234, Jun. 2015.

[10] M. Ehsani, Y. Gao, and J. M. Miller, "Hybrid electric vehicles: Architecture and motor drives," *Proc. IEEE*, vol. 95, no. 4, pp. 719–728, Apr. 2007.

[11] A. Emadi, K. Rajashekara, S. S. Williamson, and S. M. Lukic, "Topological overview of hybrid electric and fuel cell vehicular power system architectures and configurations," *IEEE Trans. Veh. Technol.*, vol. 54, no. 3, pp. 763–770, May 2005.

[12] K. V. Singh, H. O. Bansal, and D. Singh, "A comprehensive review on hybrid electric vehicles: Architectures and components," *J. Mod. Transport.*, vol. 27, pp. 77–107, May 2019.

[13] S. Mahapatra, T. Egel, R. Hassan, R. Shenoy, and M. Carone, "Model-based design for hybrid electric vehicle systems," SAE, Warrendale, PA, USA, Tech. Paper 724, 2008.

[14] 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.

[15] R. E. Drives and D. Y. Ave, "Optimization of hybrid energy storage system for electric vehicles," *Power Electron. Drives*, vol. 1, no. 2, pp. 97–111, 2016.

[16] H. He, R. Xiong, H. Guo, and S. Li, "Comparison study on the battery models used for the energy management of batteries in electric vehicles," *Energy Convers. Manag.*, vol. 64, pp. 113–121, Dec. 2012.

[17] F. Bashir and F. Bakhsh, "Energy management strategies in hybrid electric vehicles (HEVs)," *Int. J. Eng. Res. Electr. Electron. Eng.*, vol. 4, no. 1, pp. 42–45, Jun. 2018.

[18] T. Hofman, R. M. van Druten, A. F. A. Serrarens, and M. Steinbuch, "Rule-based energy management strategies for hybrid vehicles," *Int. J. Electr. Hybrid Veh.*, vol. 1, no. 1, pp. 71–94, 2007.

[19] J. Peng, H. He, and R. Xiong, "Rule based energy management strategy for a series–parallel plug-in hybrid electric bus optimized by dynamic programming," *Appl. Energy*, vol. 185, pp. 1633–1643, Jan. 2017.

[20] M. Ceraolo, A. D. Donato, and G. Franceschi, "A general approach to energy optimization of hybrid electric vehicles," *IEEE Trans. Veh. Technol.*, vol. 57, no. 3, pp. 1433–1441, May 2008.

[21] A. M. Ali, R. Shivapurkar, and D. Soffker, "Optimal situation-based power management and application to state predictive models for multi-source electric vehicles," *IEEE Trans. Veh. Technol.*, vol. 68, no. 12, pp. 11473–11482, Dec. 2019.

[22] A. M. Ali, A. M. Sharaf, H. Kamel, and S. Hegazy, "A theo-practical methodology for series hybrid vehicles evaluation and development," SAE, Warrendale, PA, USA, Tech. Paper 2017-01-1169, Mar. 2017.

[23] N. Jalil and N. A. Kheir, "A rule-based energy management strategy for a series hybrid vehicle," in *Proc. Amer. Control Conf.*, Mar. 1997, pp. 2–6.

[24] J. S. Cao, "Study on parameter matching of drive system in pure electric vehicle based on AVL-CRUISE," *Appl. Mech. Mater.*, vols. 644–650, pp. 446–450, Sep. 2014.

[25] S. Badjate, Z. K. Ali, and R. Kshirsagar, "Energy management of hybrid vehicle using artificial intelligence for optimal fuel efficiency," *Int. J. Soft Comput. Eng.*, vol. 6, no. 3, pp. 2231–2307, 2016.

[26] J.-P. Gao, G.-M. G. Zhu, E. G. Strangas, and F. Sun, "Equivalent fuel consumption optimal control of a series hybrid electric vehicle," *Proc. Inst. Mech. Eng. D, J. Automobile Eng.*, vol. 223, pp. 1003–1018, Aug. 2009.

[27] G. Buccoliero, P. G. Anselma, S. A. Bonab, G. Belingardi, and A. Emadi, "A new energy management strategy for multimode power-split hybrid electric vehicles," *IEEE Trans. Veh. Technol.*, vol. 69, no. 1, pp. 172–181, Jan. 2020.

[28] C. Kim, E. Namgoong, S. Lee, T. Kim, and H. Kim, "Fuel economy optimization for parallel hybrid vehicles with CVT," SAE, Warrendale, PA, USA, Tech. Paper 724, 1999.

[29] C. Luo, Z. Shen, S. Evangelou, G. Xiong, and F.-Y. Wang, "The combination of two control strategies for series hybrid electric vehicles," *IEEE/CAA J. Autom. Sinica*, vol. 6, no. 2, pp. 596–608, Mar. 2019.

[30] V. H. Johnson, K. B. Wipke, and D. J. Rausen, "HEV control strategy for real-time optimization of fuel economy and emissions," SAE, Warrendale, PA, USA, Tech. Paper 724, 2000.

[31] K. B. Wipke, M. R. Cuddy, and S. D. Burch, "ADVISOR 2.1: A user-friendly advanced powertrain simulation using a combined backward/forward approach," *IEEE Trans. Veh. Technol.*, vol. 48, no. 6, pp. 1751–1761, Nov. 1999.

[32] Y. Kim, A. Salvi, J. B. Siegel, Z. S. Filipi, A. G. Stefanopoulou, and T. Ersal, "Hardware-in-the-loop validation of a power management strategy for hybrid powertrains," *Control Eng. Pract.*, vol. 29, pp. 277–286, Aug. 2014.

[33] A. Tani, M. B. Camara, and B. Dakyo, "Energy management based on frequency approach for hybrid electric vehicle applications: Fuel-cell/lithium-battery and ultracapacitors," *IEEE Trans. Veh. Technol.*, vol. 61, no. 8, pp. 3375–3386, Oct. 2012.

[34] R. Gnanadass, P. Venkatesh, and N. P. Padhy, "Evolutionary programming based optimal power flow for units with non-smooth fuel cost functions," *Electr. Power Compon. Syst.*, vol. 33, no. 3, pp. 349–361, Dec. 2004.

[35] K. Ahn and P. Y. Papalambros, "Engine optimal operation lines for power-split hybrid electric vehicles," *Proc. Inst. Mech. Eng., D, J. Automobile Eng.*, vol. 223, no. 9, pp. 1149–1162, Sep. 2009.

[36] A. Sciarretta, M. Back, and L. Guzzella, "A sciarretta optimal control of parallel hybrid electric vehicles," *IEEE Trans. Control Syst. Technol.*, vol. 12, no. 3, pp. 352–363, May 2004.

[37] J. Wu, J. Peng, H. He, and J. Luo, "Comparative analysis on the rule-based control strategy of two typical hybrid electric vehicle powertrain," *Energy Proc.*, vol. 104, pp. 384–389, Dec. 2016.

[38] M. Andriollo, G. Martinelli, A. Morini, and A. Scuttari, "Optimization of the winding configuration in EDS-MAGLEV trains," *IEEE Trans. Magn.*, vol. 32, no. 4, pp. 2393–2398, Jul. 1996.

[39] A. K. Gautam, S. P. Singh, J. P. Pandey, R. P. Payasi, and A. Verma, "Fuzzy logic based MPPT technique for photo-voltaic energy conversion system," in *Proc. IEEE Uttar Pradesh Int. Conf. Electr., Comput. Electron. Eng. (UPCON)*, 2016, pp. 275–281.

[40] J.-S. Won and R. Langari, "Intelligent energy management agent for a parallel hybrid vehicle—Part II: Torque distribution, charge sustenance strategies, and performance results," *IEEE Trans. Veh. Technol.*, vol. 54, no. 3, pp. 935–953, May 2005.

[41] H. Hannoun, D. Diallo, and C. Marchand, "Energy management strategy for a parallel hybrid electric vehicle using fuzzy logic," in *Proc. Int. Symp. Power Electron., Electr. Drives, Autom. Motion, (SPEEDAM)*, Dec. 2006, pp. 229–234.

[42] N. J. Schouten, M. A. Salman, and N. A. Kheir, "Energy management strategies for parallel hybrid vehicles using fuzzy logic," *Control Eng. Pract.*, vol. 11, no. 2, pp. 171–177, Feb. 2003, doi: 10.1016/S0967-0661(02)00072-2.

[43] N. J. Schouten, M. A. Salman, and N. A. Kheir, "Fuzzy logic control for parallel hybrid vehicles," *IEEE Trans. Control Syst. Technol.*, vol. 10, no. 3, pp. 460–468, May 2002.

[44] B. M. Mohan and A. V. Patel, "Analytical structures and analysis of the simplest fuzzy PD controllers," *IEEE Trans. Syst., Man, Cybern. B, Cybern.*, vol. 32, no. 2, Apr. 2002.

[45] H.-D. Lee and S.-K. Sul, "Fuzzy-logic-based torque control strategy for parallel-type hybrid electric vehicle," *IEEE Trans. Ind. Electron.*, vol. 45, no. 4, pp. 625–632, Aug. 1998.

[46] A. Ravey, B. Blunier, and A. Miraoui, "Control strategies for fuel-cell-based hybrid electric vehicles: From offline to online and experimental results," *IEEE Trans. Veh. Technol.*, vol. 61, no. 6, pp. 2452–2457, Jul. 2012.

[47] S. D. Farrall, "Energy management in an automotive electric/heat engine hybrid powertrain using fuzzy decision making," in *Proc. 8th IEEE Int. Symp. Intell. Control*, Aug. 1993, pp. 463–468.

[48] M. Montazeri-Gh and M. Mahmoodi-K, "Development a new power management strategy for power split hybrid electric vehicles," *Transp. Res. D, Transp. Environ.*, vol. 37, pp. 79–96, Jun. 2015.

[49] M. Pan, J. Yan, Q. Tu, and C. Jiang, "Fuzzy control and wavelet transform-based energy management strategy design of a hybrid tracked bulldozer," *J. Intell. Fuzzy Syst.*, vol. 29, no. 6, pp. 2565–2574, Nov. 2015.

[50] M. Pan, J. Yan, Q. Tu, and C. Jiang, "Research on the multi-energy management strategy of the electric drive system of a tracked bulldozer," *Math. Problems Eng.*, vol. 2016, pp. 1–13, Dec. 2016.

[51] Y. Yuan, T. Zhang, B. Shen, X. Yan, and T. Long, "A fuzzy logic energy management strategy for a photovoltaic/diesel/battery hybrid ship based on experimental database," *Energies*, vol. 11, no. 9, p. 2211, Aug. 2018.

[52] W. Chen, Y. Zhang, Y. Liang, L. Chen, and J. Yang, "Multi-objective optimisation of parallel hybrid electric vehicles based on fuzzy logic control," *Int. J. Veh. Auton. Syst.*, vol. 6, nos. 3–4, pp. 236–250, 2008.

[53] B. Zhang, Z. Chen, C. Mi, and Y. L. Murphey, "Multi-objective parameter optimization of a series hybrid electric vehicle using evolutionary algorithms," in *Proc. IEEE Vehicle Power Propuls. Conf.*, Sep. 2009, pp. 921–925.
[54] M. Montazeri-Gh and M. Mahmoodi-K, "Optimized predictive energy management of plug-in hybrid electric vehicle based on traffic condition," *J. Cleaner Prod.*, vol. 139, pp. 935–948, Dec. 2016.
[55] B. M. Baumann, G. Washington, B. C. Glenn, and G. Rizzoni, "Mechatronic design and control of hybrid electric vehicles," *IEEE/ASME Trans. Mechatronics*, vol. 5, no. 1, pp. 58–72, Mar. 2000.
[56] E. Cerruto, A. Consoli, A. Raciti, and A. Testa, "Energy flows management in hybrid vehicles by fuzzy logic controller," in *Proc. 7th Medit. Electrotech. Conf.*, vol. 3, Apr. 1994, pp. 1314–1317.
[57] A. K. Gautam, M. Tariq, J. P. Pandey, and K. S. Verma, "Optimal power management strategy by using fuzzy logic controller for BLDC motor-driven E-Rickshaw," *J. Intell. Fuzzy Syst.*, vol. 42, no. 2, pp. 1089–1098, Jan. 2022.
[58] S. Tong, L. Zhang, and Y. Li, "Observed-based adaptive fuzzy decentralized tracking control for switched uncertain nonlinear large-scale systems with dead zones," *IEEE Trans. Syst., Man, Cybern. Syst.*, vol. 46, no. 1, pp. 37–47, Jan. 2016.
[59] B. Chen, C. Lin, X. P. Liu, and K. Liu, "Observer-based adaptive fuzzy control for a class of nonlinear delayed systems," *IEEE Trans. Syst., Man, Cybern. Syst.*, vol. 46, no. 1, pp. 27–36, Jan. 2016.
[60] H. Tian, X. Wang, Z. Lu, Y. Huang, and G. Tian, "Adaptive fuzzy logic energy management strategy based on reasonable SoC reference curve for online control of plug-in hybrid electric city bus," *IEEE Trans. Intell. Transp. Syst.*, vol. 19, no. 5, pp. 1607–1617, May 2018.
[61] S. M. T. Bathaee, A. H. Gastaj, S. R. Emami, and M. Mohammadian, "A fuzzy-based supervisory robust control for parallel hybrid electric vehicles," in *Proc. IEEE Vehicle Power Propuls. Conf.*, Sep. 2005, pp. 694–700.
[62] J. S. Won and R. Langari, "Fuzzy torque distribution control for a parallel hybrid electric vehicle," in *Proc. ASME Int. Mech. Eng. Congr. Expo.*, vol. 2, 2001, pp. 989–994.
[63] P. Li, J. Yan, Q. Tu, M. Pan, and J. Xue, "A novel energy management strategy for series hybrid electric rescue vehicle," *Math. Problems Eng.*, vol. 2018, pp. 1–15, Oct. 2018.
[64] A. Wang and W. Yang, "Design of energy management strategy in hybrid electric vehicles by evolutionary fuzzy system part II: Tuning fuzzy controller by genetic algorithms," in *Proc. World Congr. Intell. Control Autom.*, vol. 2, May 2006, pp. 8329–8333.
[65] L. Wu, Y. Wang, X. Yuan, and Z. Chen, "Multiobjective optimization of HEV fuel economy and emissions using the self-adaptive differential evolution algorithm," *IEEE Trans. Veh. Technol.*, vol. 60, no. 6, pp. 2458–2470, Jul. 2011.
[66] D. Wang, C. Song, Y. Shao, S. Song, S. Peng, and F. Xiao, "Optimal control strategy for series hybrid electric vehicles in the warm-up process," *Energies*, vol. 11, no. 5, p. 1091, Apr. 2018.
[67] C.-Y. Li and G.-P. Liu, "Optimal fuzzy power control and management of fuel cell/battery hybrid vehicles," *J. Power Sources*, vol. 192, no. 2, pp. 525–533, 2009.
[68] M. H. Hajimiri and F. R. Salmasi, "A fuzzy energy management strategy for series hybrid electric vehicle with predictive control and durability extension of the battery," in *Proc. IEEE Conf. Electric Hybrid Vehicles*, Dec. 2006, pp. 1–5.
[69] L. Niu, H. Yang, and Y. Zhang, "Intelligent HEV fuzzy logic control strategy based on identification and prediction of drive cycle and driving trend," *World J. Eng. Technol.*, vol. 3, no. 3, pp. 215–226, 2015.
[70] T. A. T. Mohd, M. K. Hassan, I. Aris, C. S. Azura, and B. S. K. K. Ibrahim, "Application of fuzzy logic in multi-mode driving for a battery electric vehicle energy management," *Int. J. Adv. Sci. Eng. Inf. Technol.*, vol. 7, no. 1, pp. 284–290, 2017.
[71] C. Yin, S. Wang, C. Yu, and J. Li, "Fuzzy optimization of energy management for power split hybrid electric vehicle based on particle swarm optimization algorithm," *Adv. Mech. Eng.*, vol. 11, no. 2, pp. 1–12, 2019.
[72] L. Ippolito, V. Loia, and P. Siano, "Extended fuzzy C-Means and genetic algorithms to optimize power flow management in hybrid electric vehicles," *Fuzzy Optim. Decis. Making*, vol. 2, no. 4, pp. 359–374, Dec. 2003.
[73] E. Kamal and L. Adouane, "Hierarchical energy optimization strategy and its integrated reliable battery fault management for hybrid hydraulic-electric vehicle," *IEEE Trans. Veh. Technol.*, vol. 67, no. 5, pp. 3740–3754, May 2018.
[74] C. W. Tao and J.-S. Taur, "Flexible complexity reduced PID-like fuzzy controllers," *IEEE Trans. Syst., Man, Cybern. B, Cybern.*, vol. 30, no. 4, pp. 510–516, Aug. 2000.
[75] Z. Chen, M. A. Masrur, and Y. L. Murphey, "Intelligent vehicle power management using machine learning and fuzzy logic," in *Proc. IEEE Int. Conf. Fuzzy Syst. (IEEE World Congr. Comput. Intell.)*, Hong Kong, 2008, pp. 2351–2358, doi: 10.1109/FUZZY.2008.4630697.
[76] D. Pei and M. J. Leamy, "Dynamic programming-informed equivalent cost minimization control strategies for hybrid-electric vehicles," *J. Dyn. Syst., Meas., Control*, vol. 135, no. 5, Sep. 2013.
[77] M. Shams-Zahraei, "Integrated thermal and energy management of plug-in hybrid electric vehicles," *J. Power Sources*, vol. 216, pp. 237–248, Oct. 2012.
[78] X. Gong, H. Wang, M. R. Amini, I. Kolmanovsky, and J. Sun, "Integrated optimization of power split, engine thermal management, and cabin heating for hybrid electric vehicles," in *Proc. IEEE Conf. Control Technol. Appl. (CCTA)*, Aug. 2019, pp. 567–572.
[79] D. Sinoquet, G. Rousseau, and Y. Milhau, "Design optimization and optimal control for hybrid vehicles," *Optim. Eng.*, vol. 12, nos. 1–2, pp. 199–213, Mar. 2011.
[80] V. Marano, P. Tulpule, S. Stockar, S. Onori, and G. Rizzoni, "Comparative study of different control strategies for plug-in hybrid electric vehicles," SAE, Warrendale, PA, USA, Tech. Paper, 2009.
[81] P. Tulpule, V. Marano, and G. Rizzoni, "Energy management for plug-in hybrid electric vehicles using equivalent consumption minimisation strategy," *Int. J. Electr. Hybrid Vehicles*, vol. 2, no. 4, pp. 329–350, Sep. 2010, doi: 10.1504/IJEHV.2010.034985.
[82] B. Škugor and J. Deur, "Dynamic programming-based optimisation of charging an electric vehicle fleet system represented by an aggregate battery model," *Energy*, vol. 92, pp. 456–465, Dec. 2015.
[83] C. Pan, Y. Liang, L. Chen, and L. Chen, "Optimal control for hybrid energy storage electric vehicle to achieve energy saving using dynamic programming approach," *Energies*, vol. 12, no. 4, p. 588, Feb. 2019.
[84] W. Zhang, Y. Xu, S. Li, M. Zhou, W. Liu, and Y. Xu, "A distributed dynamic programming-based solution for load management in smart grids," *IEEE Syst. J.*, vol. 12, no. 1, pp. 402–413, Mar. 2018.
[85] X. Wang, H. He, F. Sun, and J. Zhang, "Application study on the dynamic programming algorithm for energy management of plug-in hybrid electric vehicles," *Energies*, vol. 8, no. 4, pp. 3225–3244, Apr. 2015.
[86] B.-C. Chen, Y.-Y. Wu, and H.-C. Tsai, "Design and analysis of power management strategy for range extended electric vehicle using dynamic programming," *Appl. Energy*, vol. 113, pp. 1764–1774, Jan. 2014.
[87] N. Lin and S. Ci, "Toward dynamic programming-based management in reconfigurable battery packs," in *Proc. IEEE Appl. Power Electron. Conf. Expo. (APEC)*, Mar. 2017, pp. 2136–2140.
[88] B. Sakhdari and N. L. Azad, "An optimal energy management system for battery electric vehicles," *IFAC-PapersOnLine*, vol. 48, no. 15, pp. 86–92, 2015.
[89] J. T. B. A. Kessels, M. W. T. Koot, P. P. J. van den Bosch, and D. B. Kok, "Online energy management for hybrid electric vehicles," *IEEE Trans. Veh. Technol.*, vol. 57, no. 6, pp. 3428–3440, Nov. 2008.
[90] X. Wu, J. Chen, and C. Hu, "Dynamic programming-based energy management system for range-extended electric bus," *Math. Probl. Eng.*, vol. 2015, Sep. 2015, Art. no. 624649.
[91] Z. Asus, E. Aglzim, D. Chrenko, Z. H. C. Daud, and L. Le-Moyne, "Optimization of racing series hybrid," *J. Mek.*, vol. 38, pp. 106–121, Jun. 2015.
[92] O. Sundström, L. Guzzella, and P. Soltic, "Optimal hybridization in two parallel hybrid electric vehicles using dynamic programming," *IFAC Proc. Volumes*, vol. 41, no. 2, pp. 4642–4647, 2008.
[93] E. Vinot, V. Reinbold, and R. Trigui, "Global optimized design of an electric variable transmission for HEVs," *IEEE Trans. Veh. Technol.*, vol. 65, no. 8, pp. 6794–6798, Aug. 2016.
[94] J. Peng, H. He, and R. Xiong, "Study on energy management strategies for series-parallel plug-in hybrid electric buses," *Energy Proc.*, vol. 75, pp. 1926–1931, Aug. 2015.
[95] R. Biasini, S. Onori, and G. Rizzoni, "A near-optimal rule-based energy management strategy for medium duty hybrid truck," *Int. J. Powertrains*, vol. 2, nos. 2–3, p. 232, May 2013.
[96] R. Abdrakhmanov and L. Adouane, "Energy management and powersplit for hybrid electric bus using DP-based optimal profiles database," in *Proc. IEEE Vehicle Power Propuls. Conf. (VPPC)*, Dec. 2017, pp. 1–6.
[97] L. V. Pérez, G. R. Bossio, D. Moitre, and G. O. García, "Optimization of power management in an hybrid electric vehicle using dynamic programming," *Math. Comput. Simul.*, vol. 73, no. 1, pp. 244–254, Jun. 2006.

[98] C.-C. Lin, H. Peng, J. W. Grizzle, and J.-M. Kang, "Power management strategy for a parallel hybrid electric truck," *IEEE Trans. Control Syst. Technol.*, vol. 11, no. 6, pp. 839–849, Nov. 2003.
[99] C.-C. Lin, H. Peng, and J. W. Grizzle, "A stochastic control strategy for hybrid electric vehicles," in *Proc. Amer. Control Conf.*, vol. 5, Jun. 2004, pp. 4710–4715.
[100] X. Zeng and J. Wang, "A parallel hybrid electric vehicle energy management strategy using stochastic model predictive control with road grade preview," *IEEE Trans. Control Syst. Technol.*, vol. 23, no. 6, pp. 2416–2423, Nov. 2015.
[101] C. Romaus, K. Gathmann, and J. Bocker, "Optimal energy management for a hybrid energy storage system for electric vehicles based on stochastic dynamic programming," in *Proc. IEEE Vehicle Power Propuls. Conf.*, Sep. 2010, pp. 1–5.
[102] R. Wegmann, V. Döge, J. Becker, and D. U. Sauer, "Optimized operation of hybrid battery systems for electric vehicles using deterministic and stochastic dynamic programming," *J. Energy Storage*, vol. 14, pp. 22–38, Dec. 2017.
[103] S. J. Moura, H. K. Fathy, D. S. Callaway, and J. L. Stein, "A stochastic optimal control approach for power management in plug-in hybrid electric vehicles," *IEEE Trans. Control Syst. Technol.*, vol. 19, no. 3, pp. 545–555, May 2011.
[104] G. B. Qiu, W. X. Liu, and J. H. Zhang, "Equipment optimization method of electric vehicle fast charging station based on queuing theory," *Appl. Mech. Mater.*, vols. 291–294, pp. 872–877, Feb. 2013.
[105] R. Luus, "Optimal control by dynamic programming using systematic reduction in grid size," *Int. J. Control*, vol. 51, no. 5, pp. 995–1013, Jan. 1990.
[106] Y. Gao and Y. J. Liu, "Adaptive fuzzy optimal control using direct heuristic dynamic programming for chaotic discrete-time system," *J. Vibrat. Control*, vol. 22, no. 2, pp. 595–603, Feb. 2016.
[107] E. D. Tate, J. W. Grizzle, and H. Peng, "SP-SDP for fuel consumption and tailpipe emissions minimization in an EVT hybrid," *IEEE Trans. Control Syst. Technol.*, vol. 18, no. 3, pp. 673–687, May 2010.
[108] E. D. Tate, Jr., J. W. Grizzle, and H. Peng, "Shortest path stochastic control for hybrid electric vehicles," *Int. J. Robust Nonlinear Control*, vol. 18, no. 14, pp. 1409–1429, 2008.
[109] J. Liu, J. Hagena, H. Peng, and Z. S. Filipi, "Engine-in-the-loop study of the stochastic dynamic programming optimal control design for a hybrid electric HMMWV," *Int. J. Heavy Veh. Syst.*, vol. 15, nos. 2–4, pp. 309–326, 2008.
[110] D. F. Opila, X. Wang, R. McGee, R. B. Gillespie, J. A. Cook, and J. W. Grizzle, "An energy management controller to optimally trade off fuel economy and drivability for hybrid vehicles," *IEEE Trans. Control Syst. Technol.*, vol. 20, no. 6, pp. 1490–1505, Nov. 2012.
[111] X. Liu, J. Ma, X. Zhao, Y. Zhang, K. Zhang, and Y. He, "Integrated component optimization and energy management for plug-in hybrid electric buses," *Processes*, vol. 7, no. 8, p. 477, 2019.
[112] W. Lee, H. Jeoung, D. Park, and N. Kim, "An adaptive concept of PMP-based control for saving operating costs of extended-range electric vehicles," *IEEE Trans. Veh. Technol.*, vol. 68, no. 12, pp. 11505–11512, Dec. 2019.
[113] T. Wu, Y. Ding, and Y. Xu, "Energy optimal control strategy of PHEV based on PMP algorithm," *J. Control Sci. Eng.*, vol. 2017, pp. 1–11, May 2017.
[114] L. V. Pérez and G. O. García, "Commande optimale avec restrictions d'états appliquẽe á la supervision de l'énergie de véhicules hybrides," *Oil Gas Sci. Technol.*, vol. 65, no. 1, pp. 191–201, 2010.
[115] C. Hou, M. Ouyang, L. Xu, and H. Wang, "Approximate Pontryagin's minimum principle applied to the energy management of plug-in hybrid electric vehicles," *Appl. Energy*, vol. 115, pp. 174–189, Feb. 2014.
[116] G. Rousseau, D. Sinoquet, and P. Rouchon, "Constrained optimization of energy management for a mild-hybrid vehicle," *Oil Gas Sci. Technol., Rev. IFP*, vol. 62, no. 4, pp. 623–634, 2007.
[117] J. Zhang and T. Shen, "Real-time fuel economy optimization with nonlinear MPC for PHEVs," *IEEE Trans. Control Syst. Technol.*, vol. 24, no. 6, pp. 2167–2175, Nov. 2016.
[118] N. Kim, A. Rousseau, and D. Lee, "A jump condition of PMP-based control for PHEVs," *J. Power Sources*, vol. 196, pp. 10380–10386, Dec. 2011.
[119] N. Kim, S. Cha, and H. Peng, "Optimal control of hybrid electric vehicles based on Pontryagin's minimum principle," *IEEE Trans. Control Syst. Technol.*, vol. 19, no. 5, pp. 1279–1287, Sep. 2011.
[120] N. Kim, S. W. Cha, and H. Peng, "Optimal equivalent fuel consumption for hybrid electric vehicles," *IEEE Trans. Control Syst. Technol.*, vol. 20, no. 3, pp. 817–825, May 2012.
[121] S. Stockar, V. Marano, M. Canova, G. Rizzoni, and L. Guzzella, "Energy-optimal control of plug-in hybrid electric vehicles for real-world driving cycles," *IEEE Trans. Veh. Technol.*, vol. 60, no. 7, pp. 2949–2962, Sep. 2011.
[122] A. Chasse and A. Sciarretta, "Supervisory control of hybrid powertrains: An experimental benchmark of offline optimization and online energy management," *Control Eng. Pract.*, vol. 19, no. 11, pp. 1253–1265, 2011.
[123] R. Xiao, B. Liu, J. Shen, N. Guo, W. Yan, and Z. Chen, "Comparisons of energy management methods for a parallel plug-in hybrid electric vehicle between the convex optimization and dynamic programming," *Appl. Sci.*, vol. 8, no. 2, pp. 16–19, 2018.
[124] 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.
[125] S. Xie, X. Hu, K. Lang, S. Qi, and T. Liu, "Powering mode-integrated energy management strategy for a plug-in hybrid electric truck with an automatic mechanical transmission based on Pontryagin's minimum principle," *Sustainability*, vol. 10, no. 10, p. 3758, Oct. 2018.
[126] G. Ripaccioli, A. Bemporad, F. Assadian, C. Dextreit, S. Di Cairano, and I. V. Kolmanovsky, "Hybrid modeling, identification, and predictive control: An application to hybrid electric vehicle energy management," in *Proc. Int. Workshop Hybrid Syst., Comput. Control* (Lecture Notes in Computer Science), vol. 5469, 2009, pp. 321–335.
[127] G. Wu, K. Boriboonsomsin, and M. J. Barth, "Development and evaluation of an intelligent energy-management strategy for plug-in hybrid electric vehicles," *IEEE Trans. Intell. Transp. Syst.*, vol. 15, no. 3, pp. 1091–1100, Jun. 2014.
[128] N. V. Sahinidis, "Mixed-integer nonlinear programming 2018," *Optim. Eng.*, vol. 20, no. 2, pp. 301–306, 2019.
[129] M. Koot, J. T. B. A. Kessels, B. de Jager, W. P. M. H. Heemels, P. P. J. van den Bosch, and M. Steinbuch, "Energy management strategies for vehicular electric power systems," *IEEE Trans. Veh. Technol.*, vol. 54, no. 3, pp. 771–782, May 2005.
[130] Z. Zhou and C. Mi, "Power management of PHEV using quadratic programming," *Int. J. Electr. Hybrid Veh.*, vol. 3, no. 3, pp. 246–258, 2011.
[131] S. Gonsrang and R. Kasper, "Optimisation-based power management system for an electric vehicle with a hybrid energy storage system," *Int. J. Automot. Mech. Eng.*, vol. 15, no. 4, pp. 5729–5747, Dec. 2018.
[132] C. Xia, Z. Du, and C. Zhang, "A single-degree-of-freedom energy optimization strategy for power-split hybrid electric vehicles," *Energies*, vol. 10, no. 7, p. 896, Jul. 2017.
[133] K. Oh, J. Min, D. Choi, and H. Kim, "Optimization of control strategy for a single-shaft parallel hybrid electric vehicle," *Proc. Inst. Mech. Eng., D, J. Automobile Eng.*, vol. 221, no. 5, pp. 555–565, May 2007.
[134] K. Uthaichana, R. DeCarlo, S. Bengea, M. Žefran, and S. Pekarek, "Hybrid optimal theory and predictive control for power management in hybrid electric vehicle," 2018, *arXiv:1804.00757*.
[135] E. D. Tate and S. P. Boyd, "Finding ultimate limits of performance for hybrid electric vehicles," SAE, Warrendale, PA, USA, Tech. Paper 724, 2000.
[136] S. Hadj-Said, G. Colin, A. Ketfi-Cherif, and Y. Chamaillard, "Convex optimization for energy management of parallel hybrid electric vehicles," *IFAC-PapersOnLine*, vol. 49, no. 11, pp. 271–276, 2016.
[137] S. Hadj-Said, G. Colin, A. Ketfi-Cherif, and Y. Chamaillard, "Energy management of a parallel hybrid electric vehicle equipped with a voltage booster," *IFAC-PapersOnLine*, vol. 51, no. 31, pp. 606–611, 2018.
[138] X. Lu, Y. Chen, M. Fu, and H. Wang, "Multi-objective optimization-based real-time control strategy for battery/ultracapacitor hybrid energy management systems," *IEEE Access*, vol. 7, pp. 11640–11650, 2019.
[139] S. Delprat, J. Lauber, T. M. Guerra, and J. Rimaux, "Control of a parallel hybrid powertrain: Optimal control," *IEEE Trans. Veh. Technol.*, vol. 53, no. 3, pp. 872–881, May 2004.
[140] G. Jungmeier, "The biorefinery fact sheet," IEA Bioenergy Task 42 Biorefining, Int. Energy Agency, Paris, France, Sep. 2014, pp. 1–48, vol. 1.
[141] K. Deb, A. Pratap, S. Agarwal, and T. Meyarivan, "A fast and elitist multiobjective genetic algorithm: NSGA-II," *IEEE Trans. Evol. Comput.*, vol. 6, no. 2, pp. 182–197, Jan. 2002.

[142] N. Jozefowiez, F. Semet, and E. G. Talbi, "Enhancements of NSGA II and its application to the vehicle routing problem with route balancing," in *Proc. Int. Conf. Artif. Evol. (Evolution Artificielle)* (Lecture Notes in Computer Science), vol. 3871, 2006, pp. 131–142.
[143] S. Z. Su Zhou, Z. Wen, X. Zhi, and J. Jin, "Genetic algorithm-based parameter optimization of energy management strategy and its analysis for fuel cell hybrid electric vehicles," SAE, Warrendale, PA, USA, Tech. Paper 2019-01-0358, 2019.
[144] V. Madanipour, M. Montazeri-Gh, and M. Mahmoodi-k, "Optimization of the component sizing for a plug-in hybrid electric vehicle using a genetic algorithm," *Proc. Inst. Mech. Eng., D, J. Automobile Eng.*, vol. 230, no. 5, pp. 692–708, Apr. 2016.
[145] A. T. Abkenar, A. Nazari, S. D. G. Jayasinghe, A. Kapoor, and M. Negnevitsky, "Fuel cell power management using genetic expression programming in all-electric ships," *IEEE Trans. Energy Convers.*, vol. 32, no. 2, pp. 779–787, Jun. 2017.
[146] M. Montazeri-Gh and A. Poursamad, "Application of genetic algorithm for simultaneous optimisation of HEV component sizing and control strategy," *Int. J. Altern. Propul.*, vol. 1, no. 1, pp. 63–78, 2006.
[147] M. M. Vazifeh, H. Zhang, P. Santi, and C. Ratti, "Optimizing the deployment of electric vehicle charging stations using pervasive mobility data," *Transp. Res. A, Policy Pract.*, vol. 121, pp. 75–91, Mar. 2019.
[148] L. Li, L. Zhou, C. Yang, R. Xiong, S. You, and Z. Han, "A novel combinatorial optimization algorithm for energy management strategy of plug-in hybrid electric vehicle," *J. Franklin Inst.*, vol. 354, no. 15, pp. 6588–6609, Oct. 2017.
[149] C. Ma, "Distribution path robust optimization of electric vehicle with multiple distribution centers," *PLoS ONE*, vol. 13, no. 3, pp. 1–16, 2018.
[150] N. Denis, M. R. Dubois, J. P. F. Trovão, and A. Desrochers, "Power split strategy optimization of a plug-in parallel hybrid electric vehicle," *IEEE Trans. Veh. Technol.*, vol. 67, no. 1, pp. 315–326, Jan. 2018.
[151] T. J. Boehme, M. Rothschuh, B. Frank, M. Schultalbers, M. Schori, and T. Jeinsch, "Multi-objective optimal design of parallel plug-in hybrid powertrain configurations with respect to fuel consumption and driving performance," *SAE Int. J. Alternative Powertrains*, vol. 3, no. 2, pp. 176–192, Apr. 2014.
[152] Y. Li, X. Lu, and N. C. Kar, "Rule-based control strategy with novel parameters optimization using NSGA-II for power-split PHEV operation cost minimization," *IEEE Trans. Veh. Technol.*, vol. 63, no. 7, pp. 3051–3061, Sep. 2014.
[153] R. S. Wimalendra, L. Udawatta, E. M. C. P. Edirisinghe, and S. Karunarathna, "Determination of maximum possible fuel economy of HEV for known drive cycle: Genetic algorithm based approach," in *Proc. 4th Int. Conf. Inf. Autom. Sustainability*, Dec. 2008, pp. 289–294.
[154] M. Montazeri-Gh, A. Poursamad, and B. Ghalichi, "Application of genetic algorithm for optimization of control strategy in parallel hybrid electric vehicles," *J. Franklin Inst.*, vol. 343, nos. 4–5, pp. 420–435, Jul. 2006.
[155] A. Poursamad and M. Montazeri, "Design of genetic-fuzzy control strategy for parallel hybrid electric vehicles," *Control Eng. Pract.*, vol. 16, no. 7, pp. 861–873, Jul. 2008.
[156] S. K. Shahi, G. G. Wang, L. An, E. Bibeau, and Z. Pirmoradi, "Using the Pareto set pursuing multiobjective optimization approach for hybridization of a plug-in hybrid electric vehicle," *J. Mech. Des.*, vol. 134, no. 9, pp. 1–6, Sep. 2012.
[157] P. Shen, Z. Z. Zhao, X. Zhan, and J. Li, "Particle swarm optimization of driving torque demand decision based on fuel economy for plug-in hybrid electric vehicle," *Energy*, vol. 123, pp. 89–107, Mar. 2017.
[158] K. E. Parsopoulos and M. N. Vrahatis, "Unified particle swarm optimization in dynamic environments," *Lect. Notes Comput. Sci.*, vol. 3449, pp. 590–599, Jun. 2005.
[159] J. Wu, C.-H. Zhang, and N.-X. Cui, "Fuzzy energy management strategy for a hybrid electric vehicle based on driving cycle recognition," *Int. J. Automot. Technol.*, vol. 13, no. 7, pp. 1159–1167, 2012.
[160] O. Hegazy and J. Van Mierlo, "Optimal power management and powertrain components sizing of fuel cell/battery hybrid electric vehicles based on particle swarm optimisation," *Int. J. Veh. Des.*, vol. 58, nos. 2–4, pp. 200–222, 2012.
[161] I. Hwang, Y. J. Jang, Y. D. Ko, and M. S. Lee, "System optimization for dynamic wireless charging electric vehicles operating in a multiple-route environment," *IEEE Trans. Intell. Transp. Syst.*, vol. 19, no. 6, pp. 1709–1726, Jun. 2017.
[162] N. Al-Aawar, T. M. Hijazi, and A. A. Arkadan, "Particle swarm optimization of coupled electromechanical systems," *IEEE Trans. Magn.*, vol. 47, no. 5, pp. 1314–1317, May 2011.
[163] Z. Chen, R. Xiong, and J. Cao, "Particle swarm optimization-based optimal power management of plug-in hybrid electric vehicles considering uncertain driving conditions," *Appl. Energy*, vol. 96, pp. 197–208, Feb. 2016.
[164] S. Kachroudi, M. Grossard, and N. Abroug, "Predictive driving guidance of full electric vehicles using particle swarm optimization," *IEEE Trans. Veh. Technol.*, vol. 61, no. 9, pp. 3909–3919, Nov. 2012.
[165] Z. Lei, D. Cheng, Y. Liu, D. Qin, Y. Zhang, and Q. Xie, "A dynamic control strategy for hybrid electric vehicles based on parameter optimization for multiple driving cycles and driving pattern recognition," *Energies*, vol. 10, no. 1, p. 54, Jan. 2017.
[166] R. Eberhart and J. Kennedy, "New optimizer using particle swarm theory," in *Proc. Int. Symp. Micro Mach. Hum. Sci.*, 1995, pp. 39–43.
[167] G. T. Pulido and C. A. Coello Coello, "Using clustering techniques to improve the performance of a multi-objective particle swarm optimizer," in *Proc. Genetic Evol. Comput. Conf.*, (Lecture Notes in Computer Science), vol. 3102, 2004, pp. 225–237.
[168] C. Dextreit and I. V. Kolmanovsky, "Game theory controller for hybrid electric vehicles," *IEEE Trans. Control Syst. Technol.*, vol. 22, no. 2, pp. 652–663, Mar. 2014.
[169] H. Yin, C. Zhao, M. Li, C. Ma, and M. Chow, "A game theory approach to energy management of an engine-generator/battery/ultracapacitor hybrid energy system," *IEEE Trans. Ind. Electron.*, vol. 63, no. 7, pp. 4266–4277, Jul. 2016.
[170] A. Younis, L. Zhou, and Z. Dong, "Application of the new SEUMRE global optimization tool in high efficiency EV/PHEV/EREV electric mode operations," *Int. J. Electr. Hybrid Veh.*, vol. 3, no. 2, pp. 176–190, 2011.
[171] G. Paganelli, G. Ercole, A. Brahma, Y. Guezennec, and G. Rizzoni, "General supervisory control policy for the energy optimization of charge-sustaining hybrid electric vehicles," *JSAE Rev.*, vol. 22, no. 4, pp. 511–518, 2001.
[172] R. Mura, V. Utkin, and S. Onori, "Energy management design in hybrid electric vehicles: A novel optimality and stability framework," *IEEE Trans. Control Syst. Technol.*, vol. 23, no. 4, pp. 1307–1322, Jul. 2015.
[173] C. Zhang and A. Vahidi, "Route preview in energy management of plug-in hybrid vehicles," *IEEE Trans. Control Syst. Technol.*, vol. 20, no. 2, pp. 546–553, Mar. 2012.
[174] P. Pisu and G. Rizzoni, "A supervisory control strategy for series hybrid electric vehicles with two energy storage systems," in *Proc. IEEE Vehicle Power Propuls. Conf.*, May 2005, pp. 65–72.
[175] C. Musardo, G. Rizzoni, Y. Guezennec, and B. Staccia, "A-ECMS: An adaptive algorithm for hybrid electric vehicle energy management," *Eur. J. Control*, vol. 11, no. 4, pp. 509–524, Dec. 2005.
[176] A. Rezaei, J. B. Burl, and B. Zhou, "Estimation of the ECMS equivalent factor bounds for hybrid electric vehicles," *IEEE Trans. Control Syst. Technol.*, vol. 26, no. 6, pp. 2198–2205, Nov. 2018.
[177] C. Sun, H. He, and F. Sun, "The role of velocity forecasting in adaptive-ECMS for hybrid electric vehicles," *Energy Proc.*, vol. 75, pp. 1907–1912, Aug. 2015.
[178] J.-S. Won, R. Langari, and M. Ehsani, "An energy management and charge sustaining strategy for a parallel hybrid vehicle with CVT," *IEEE Trans. Control Syst. Technol.*, vol. 13, no. 2, pp. 313–320, Mar. 2005.
[179] S. Onori and L. Serrao, "On adaptive-ecms strategies for hybrid electric vehicles," in *Proc. Int. Sci. Conf. Hybrid Electr. Vehicles*, Malmaison, France, vol. 67, Dec. 2011, pp. 1–7.
[180] L. Li, S. You, C. Yang, B. Yan, J. Song, and Z. Chen, "Driving-behavior-aware stochastic model predictive control for plug-in hybrid electric buses," *Appl. Energy*, vol. 162, pp. 868–879, Jan. 2016.
[181] C. Sun, F. Sun, and H. He, "Investigating adaptive-ECMS with velocity forecast ability for hybrid electric vehicles," *Appl. Energy*, vol. 185, pp. 1644–1653, Jan. 2017.
[182] F. Zhang, J. Xi, and R. Langari, "Real-time energy management strategy based on velocity forecasts using V2V and V2I communications," *IEEE Trans. Intell. Transp. Syst.*, vol. 18, no. 2, pp. 416–430, Feb. 2017.
[183] F. Payri, C. Guardiola, B. Pla, and D. Blanco-Rodriguez, "On a stochastic approach of the ECMS method for energy management in hybrid electric vehicles," *IFAC Proc. Volumes*, vol. 45, no. 30, pp. 341–348, 2012.
[184] S. Di Cairano, D. Bernardini, A. Bemporad, and I. V. Kolmanovsky, "Stochastic MPC with learning for driver-predictive vehicle control and its application to HEV energy management," *IEEE Trans. Control Syst. Technol.*, vol. 22, no. 3, pp. 1018–1031, May 2014.

[185] O. Gomozov, J. P. F. Trovão, X. Kestelyn, and M. R. Dubois, "Adaptive energy management system based on a real-time model predictive control with nonuniform sampling time for multiple energy storage electric vehicle," *IEEE Trans. Vehicular Technol.*, vol. 66, no. 7, p. 5520–5530, Dec. 2016.
[186] B. HomChaudhuri, R. Lin, and P. Pisu, "Hierarchical control strategies for energy management of connected hybrid electric vehicles in urban roads," *Transp. Res. C, Emerg. Technol.*, vol. 62, pp. 70–86, Jan. 2016.
[187] Y. Huang, A. Khajepour, and H. Wang, "A predictive power management controller for service vehicle anti-idling systems without a priori information," *Appl. Energy*, vol. 182, pp. 548–557, Nov. 2016.
[188] M. J. West, C. M. Bingham, and N. Schofield, "Predictive control for energy management in all/more electric vehicles with multiple energy storage units," in *Proc. IEEE Int. Electr. Mach. Drives Conf. (IEMDC)*, vol. 1, 2003, pp. 222–228.
[189] L. Johannesson, M. Asbogard, and B. Egardt, "Assessing the potential of predictive control for hybrid vehicle powertrains using stochastic dynamic programming," *IEEE Trans. Intell. Transp. Syst.*, vol. 8, no. 1, pp. 71–83, Mar. 2007.
[190] E. Siampis, E. Velenis, S. Gariuolo, and S. Longo, "A real-time nonlinear model predictive control strategy for stabilization of an electric vehicle at the limits of handling," *IEEE Trans. Control Syst. Technol.*, vol. 26, no. 6, pp. 1982–1994, Nov. 2017.
[191] L. Guo, B. Gao, Y. Li, and H. Chen, "A fast algorithm for nonlinear model predictive control applied to HEV energy management systems," *Sci. China Inf. Sci.*, vol. 60, no. 9, Sep. 2017, Art. no. 092201.
[192] H. Borhan, A. Vahidi, A. M. Phillips, M. L. Kuang, I. V. Kolmanovsky, and S. Di Cairano, "MPC-based energy management of a power-split hybrid electric vehicle," *IEEE Trans. Control Syst. Technol.*, vol. 20, no. 3, pp. 593–603, May 2012.
[193] J. P. Trovao, M. R. Dubois, O. Gomozov, X. Kestelyn, and A. Bouscayrol, "A model predictive control with non-uniform sampling times for a hybrid energy storage system in electric vehicle application," in *Proc. IEEE Vehicle Power Propuls. Conf. (VPPC)*, Oct. 2015, pp. 1–6.
[194] B. Chen, S. A. Evangelou, and R. Lot, "Fuel efficiency optimization methodologies for series hybrid electric vehicles," in *Proc. IEEE Vehicle Power Propuls. Conf. (VPPC)*, Aug. 2018, pp. 1–6.
[195] N. Stroe, G. Colin, K. Ben-Cherif, S. Olaru, and Y. Chamaillard, "Towards a generic control-oriented model for HEV predictive energy management," *IFAC-PapersOnLine*, vol. 49, no. 11, pp. 259–264, 2016.
[196] Y. Zhao, Y. Cai, and Q. Song, "Energy control of plug-in hybrid electric vehicles," *IEEE/CAA J. Autom. Sin.*, vol. 8, no. 99, pp. 1–8, Feb. 2018.
[197] N. Bizon, "Energy optimization of fuel cell system by using global extremum seeking algorithm," *Appl. Energy*, vol. 206, pp. 458–474, Nov. 2017.
[198] D. Zhou, A. Ravey, A. Al-Durra, and F. Gao, "A comparative study of extremum seeking methods applied to online energy management strategy of fuel cell hybrid electric vehicles," *Energy Convers. Manag.*, vol. 151, pp. 778–790, Nov. 2017.
[199] D. Zhou, A. Al-Durra, I. Matraji, A. Ravey, and F. Gao, "Online energy management strategy of fuel cell hybrid electric vehicles: A fractional-order extremum seeking method," *IEEE Trans. Ind. Electron.*, vol. 65, no. 8, pp. 6787–6799, Aug. 2018.
[200] P. Pisu and G. Rizzoni, "A comparative study of supervisory control strategies for hybrid electric vehicles," *IEEE Trans. Control Syst. Technol.*, vol. 15, no. 3, pp. 506–518, May 2007.
[201] M. Zaher and S. Cetinkunt, "Real-time energy management control for hybrid electric powertrains," *J. Control Sci. Eng.*, vol. 2013, pp. 1–10, May 2013.
[202] B. Chen, S. A. Evangelou, and R. Lot, "Hybrid electric vehicle two-step fuel efficiency optimization with decoupled energy management and speed control," *IEEE Trans. Veh. Technol.*, vol. 68, no. 12, pp. 11492–11504, Dec. 2019.
[203] J.-Q. Li, Z. Fu, and X. Jin, "Rule based energy management strategy for a Battery/Ultra-capacitor hybrid energy storage system optimized by pseudospectral method," *Energy Proc.*, vol. 105, pp. 2705–2711, May 2017.
[204] R. Dosthosseini, A. Z. Kouzani, and F. Sheikholeslam, "Direct method for optimal power management in hybrid electric vehicles," *Int. J. Automot. Technol.*, vol. 12, no. 6, pp. 943–950, Nov. 2011.
[205] A. Boyali and L. Guvenc, "Real-time controller design for a parallel hybrid electric vehicle using neuro-dynamic programming method," in *Proc. IEEE Int. Conf. Syst., Man, Cybern.*, Oct. 2010, pp. 4318–4324.
[206] C. Liu and Y. L. Murphey, "Optimal power management based on Q-learning and neuro-dynamic programming for plug-in hybrid electric vehicles," *IEEE Trans. Neural Netw. Learn. Syst.*, vol. 31, no. 6, pp. 1942–1954, Jun. 2020.
[207] Y. Hu, L. Yang, B. Yan, T. Yan, and P. Ma, "An online rolling optimal control strategy for commuter hybrid electric vehicles based on driving condition learning and prediction," *IEEE Trans. Veh. Technol.*, vol. 65, no. 6, pp. 4312–4327, Jun. 2016.
[208] M. Venditti, "Analysis of the performance of different machine learning techniques for the definition of rule-based control strategies in a parallel HEV," in *Proc. 71st Conf. Italian Thermal Mach. Eng. Assoc. (ATI)*, vol. 101, Apr. 2016, pp. 685–692.
[209] R. Langari and J.-S. Won, "Intelligent energy management agent for a parallel hybrid vehicle—Part I: System architecture and design of the driving situation identification process," *IEEE Trans. Veh. Technol.*, vol. 54, no. 3, pp. 925–934, May 2005.
[210] X. Lin, Y. Wang, P. Bogdan, N. Chang, and M. Pedram, "Reinforcement learning based power management for hybrid electric vehicles," in *Proc. IEEE/ACM Int. Conf. Comput.-Aided Design (ICCAD)*, Nov. 2014, pp. 32–38.
[211] 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.
[212] H. He, J. Cao, and X. Cui, "Energy optimization of electric vehicle's acceleration process based on reinforcement learning," *J. Clean. Prod.*, vol. 248, Mar. 2020, Art. no. 119302.
[213] R. Liessner, C. Schroer, A. Dietermann, and B. Bäker, "Deep reinforcement learning for advanced energy management of hybrid electric vehicles," in *Proc. 10th Int. Conf. Agents Artif. Intell.*, vol. 2, May 2018, pp. 61–72.
[214] L. Fan, Y. Zhang, H. Dou, and R. Zou, "Design of an integrated energy management strategy for a plug-in hybrid electric bus," *J. Power Sources*, vol. 448, Feb. 2020, Art. no. 227391.
[215] Y. Hu, W. Li, K. Xu, T. Zahid, F. Qin, and C. Li, "Energy management strategy for a hybrid electric vehicle based on deep reinforcement learning," *Appl. Sci.*, vol. 8, no. 2, p. 187, Jan. 2018.
[216] J. Wu, Y. Zou, X. Zhang, T. Liu, Z. Kong, and D. He, "An online correction predictive EMS for a hybrid electric tracked vehicle based on dynamic programming and reinforcement learning," *IEEE Access*, vol. 7, pp. 98252–98266, 2019.
[217] T. Liu, X. Hu, W. Hu, and Y. Zou, "A heuristic planning reinforcement learning-based energy management for power-split plug-in hybrid electric vehicles," *IEEE Trans. Ind. Informat.*, vol. 15, no. 12, pp. 6436–6445, Mar. 2019.
[218] H. Xia, T. Li, B. Wang, P. He, and Y. Chen, "Energy management optimization for plug-in hybrid electric vehicles based on real-world driving data," SAE, Warrendale, PA, USA, Tech. Paper 2019-01-0161, 2019.
[219] C.-J. Xie, S.-H. Quan, and Q.-H. Chen, "Control strategy of hybrid power system for fuel cell electric vehicle based on neural network optimization," in *Proc. IEEE Int. Conf. Autom. Logistics*, Sep. 2008, pp. 753–757.
[220] C. T. Raj, S. P. Srivastava, and P. Agarwal, "Energy efficient control of three-phase induction Motor–A review," *Int. J. Comput. Electr. Eng.*, vol. 1, no. 1, pp. 61–70, 2009.
[221] J.-Y. Potvin, "State-of-the art review—Evolutionary algorithms for vehicle routing," *Informs J. Comput.*, vol. 21, no. 4, pp. 518–548, Nov. 2009.
[222] D. Pecin, A. Pessoa, M. Poggi, and E. Uchoa, "Improved branch-cut-and-price for capacitated vehicle routing," *Math. Program. Comput.*, vol. 9, no. 1, pp. 61–100, 2017.
[223] R. Baldacci, A. Mingozzi, and R. Roberti, "Recent exact algorithms for solving the vehicle routing problem under capacity and time window constraints," *Eur. J. Oper. Res.*, vol. 218, no. 1, pp. 1–6, Apr. 2012.
[224] P. Lebeau, C. De Cauwer, J. Van Mierlo, C. Macharis, W. Verbeke, and T. Coosemans, "Conventional, hybrid, or electric vehicles: Which technology for an urban distribution centre?" *Sci. World J.*, vol. 2015, pp. 1–11, Jun. 2015.
[225] S. Huang and W. Ren, "Use of neural fuzzy networks with mixed genetic/gradient algorithm in automated vehicle control," *IEEE Trans. Ind. Electron.*, vol. 46, no. 6, pp. 1090–1102, Dec. 1999.
[226] B. Baumann, G. Rizzoni, and G. Washington, "Intelligent control of hybrid vehicles using neural networks and fuzzy logic," SAE, Warrendale, PA, USA, Tech. Paper 724, 1998.

[227] A. Rubaai and P. Young, "Hardware/software implementation of fuzzy-neural-network self-learning control methods for brushless DC motor drives," *IEEE Trans. Ind. Appl.*, vol. 52, no. 1, pp. 414–424, Jan./Feb. 2015.

[228] H. Lee, C. Kang, Y.-I. Park, and S. Cha, "Study on power management strategy of HEV using dynamic programming," *World Electr. Vehicle J.*, vol. 8, no. 1, pp. 274–280, Mar. 2016.

[229] L. Wang, Y. Zhang, C. Yin, H. Zhang, and C. Wang, "Hardware-in-the-loop simulation for the design and verification of the control system of a series–parallel hybrid electric city-bus," *Simul. Model. Pract. Theory*, vol. 25, pp. 148–162, Jun. 2012.

[230] J. Park, "Intelligent vehicle power control based on machine learning of optimal control parameters and prediction of road type and traffic congestion," *IEEE Trans. Veh. Technol.*, vol. 58, no. 9, pp. 4741–4756, Feb. 2009.

[231] Y. L. Murphey, J. Park, L. Kiliaris, M. L. Kuang, M. A. Masrur, A. M. Phillips, and Q. Wang, "Intelligent hybrid vehicle power control—Part II: Online intelligent energy management," *IEEE Trans. Veh. Technol.*, vol. 62, no. 1, pp. 69–79, Jan. 2013.

[232] L. Xu, J. Wang, and Q. Chen, "Kalman filtering state of charge estimation for battery management system based on a stochastic fuzzy neural network battery model," *Energy Convers. Manag.*, vol. 53, no. 1, pp. 33–39, 2012.

[233] B. S. Bhangu, P. Bentley, D. A. Stone, and C. M. Bingham, "Nonlinear observers for predicting state-of-charge and state-of-health of lead-acid batteries for hybrid-electric vehicles," *IEEE Trans. Veh. Technol.*, vol. 54, no. 3, pp. 783–794, May 2005.

[234] W. Waag, C. Fleischer, and D. U. Sauer, "On-line estimation of lithium-ion battery impedance parameters using a novel varied-parameters approach," *J. Power Sources*, vol. 237, no. 3, pp. 260–269, Sep. 2013.

[235] X. Hu, F. Sun, and Y. Zou, "Estimation of state of charge of a lithium-ion battery pack for electric vehicles using an adaptive Luenberger observer," *Energies*, vol. 3, no. 9, pp. 1586–1603, 2010, doi: 10.3390/en3091586.

[236] V. Marano, G. Rizzoni, P. Tulpule, Q. Gong, and H. Khayyam, "Intelligent energy management for plug-in hybrid electric vehicles: The role of ITS infrastructure in vehicle electrification," *Oil Gas Sci. Technol., Rev. IFP Energies Nouvelles*, vol. 67, no. 4, pp. 575–587, Jul. 2012.

[237] Y. L. Murphey, J. Park, Z. Chen, M. L. Kuang, M. A. Masrur, and A. M. Phillips, "Intelligent hybrid vehicle power control—Part I: Machine learning of optimal vehicle power," *IEEE Trans. Veh. Technol.*, vol. 61, no. 8, pp. 3519–3530, Oct. 2012.

[238] J. Fan, J. Zhang, and T. Shen, "Map-based power-split strategy design with predictive performance optimization for parallel hybrid electric vehicles," *Energies*, vol. 8, no. 9, pp. 9946–9968, Sep. 2015.

[239] X. Wu, G. Guo, J. Xu, and B. Cao, "Application of parallel chaos optimization algorithm for plug-in hybrid electric vehicle design," *Int. J. Bifurc. Chaos*, vol. 24, no. 1, pp. 1–14, 2014.

[240] D. Hu, L. Hu, and Y. Yan, "Optimization methodology for control strategy of parallel hybrid electric vehicle based on chaos prediction," *AIP Adv.*, vol. 8, no. 11, Nov. 2018, Art. no. 115305.

[241] X. Huang, Y. Tan, and X. He, "An intelligent multifeature statistical approach for the discrimination of driving conditions of a hybrid electric vehicle," *IEEE Trans. Intell. Transp. Syst.*, vol. 12, no. 2, pp. 453–465, Jun. 2011.

[242] M. E. Hmidi, I. Ben Salem, and L. El Amraoui, "An efficient method for energy management optimization control: Minimizing fuel consumption for hybrid vehicle applications," *Trans. Inst. Meas. Control*, vol. 42, no. 1, pp. 69–80, Jan. 2020.

[243] W. Jiang and Y. Zhen, "A real-time ev charging scheduling for parking lots with PV system and energy store system," *IEEE Access*, vol. 7, pp. 86184–86193, 2019.

[244] A. Shukla, K. Verma, and R. Kumar, "Multi-objective synergistic planning of EV fast-charging stations in the distribution system coupled with the transportation network," *IET Gener., Transmiss. Distrib.*, vol. 13, no. 15, pp. 3421–3432, Aug. 2019.

[245] I. Ullah, I. Hussain, and M. Singh, "Exploiting grasshopper and cuckoo search bio-inspired optimization algorithms for industrial energy management system: Smart industries," *Electronics*, vol. 9, no. 1, p. 105, Jan. 2020.

[246] P. S. Preetha and A. Kusagur, *Implementation of Ant-Lion Optimization Algorithm in Energy Management Problem and Comparison*, vol. 2. Cham, Switzerland: Springer, 2020.

[247] R. P. Patel and H. B. Bhadka, "Modified salp swarm algorithm based energy-efficient resource allocation in cloud-computing data centers," *Int. J. Innov. Technol. Exploring Eng.*, vol. 8, no. 12, pp. 3713–3720, Oct. 2019.

[248] E. Kayalvizhi, A. Karthikeyan, and J. Arunarasi, "An optimal energy management system for electric vehicles using firefly optimization algorithm based dynamic EDF scheduling," *Int. J. Eng. Technol.*, vol. 7, no. 4, pp. 1385–1393, 2015.

[249] B. Liu, Z. Pan, Z. Tan, D. Wang, and T. Yu, "A real-time schedule optimization of massive electric vehicles and energy storage system based on grey wolf optimizer," in *Proc. IEEE 8th Annu. Int. Conf. CYBER Technol. Autom., Control, Intell. Syst. (CYBER)*, Jul. 2018, pp. 1160–1165.

[250] S. Mohseni, A. Brent, D. Burmester, and A. Chatterjee, "Optimal sizing of an islanded micro-grid using meta-heuristic optimization algorithms considering demand-side management," in *Proc. Australas. Universities Power Eng. Conf. (AUPEC)*, Nov. 2018, pp. 1–6.

[251] K. Kasturi and M. R. Nayak, "Optimal planning of charging station for EVs with PV-BES unit in distribution system using WOA," in *Proc. 2nd Int. Conf. Man Mach. Interfacing (MAMI)*, Dec. 2017, pp. 1–6.

[252] J. P. Trovão, P. G. Pereirinha, H. M. Jorge, and C. H. Antunes, "A multi-level energy management system for multi-source electric vehicles—An integrated rule-based meta-heuristic approach," *Appl. Energy*, vol. 105, pp. 304–318, May 2013.

[253] L. Bagherzadeh, H. Shayeghi, and S. J. S. Shenava, "Optimal allocation of electric vehicle parking lots and renewable energy sources simultaneously for improving the performance of distribution system," in *Proc. 24th Electr. Power Distrib. Conf. (EPDC)*, Jun. 2019, pp. 87–94.

[254] M. Tolba, H. Rezk, A. A. Z. Diab, and M. Al-Dhaifallah, "A novel robust methodology based Salp swarm algorithm for allocation and capacity of renewable distributed generators on distribution grids," *Energies*, vol. 11, no. 10, pp. 1–36, 2018.

[255] S. Deb and X.-Z. Gao, "A hybrid ant lion optimization chicken swarm optimization algorithm for charger placement problem," *Complex Intell. Syst.*, vol. 8, no. 4, pp. 2791–2808, Aug. 2022.

[256] F. M. F. Mascioli, A. Rizzi, M. Panella, and C. Bettiol, "Optimization of hybrid electric cars by neuro-fuzzy networks," in *Proc. Int. Workshop Fuzzy Logic Appl.* (Lecture Notes in Computer Science), vol. 4578, 2007, pp. 253–260.

[257] Y. Hui, Z. Su, T. H. Luan, and J. Cai, "A game theoretic scheme for optimal access control in heterogeneous vehicular networks," *IEEE Trans. Intell. Transp. Syst.*, vol. 20, no. 12, pp. 4590–4603, Dec. 2019.

[258] G. Li and D. Görges, "Ecological adaptive cruise control and energy management strategy for hybrid electric vehicles based on heuristic dynamic programming," *IEEE Trans. Intell. Transp. Syst.*, vol. 20, no. 9, pp. 3526–3535, Sep. 2019.

[259] C. L. P. Chen, Y.-J. Liu, and G.-X. Wen, "Fuzzy neural network-based adaptive control for a class of uncertain nonlinear stochastic systems," *IEEE Trans. Cybern.*, vol. 44, no. 5, pp. 583–593, May 2014.

[260] Z. Tian, W. Hou, X. Gu, F. Gu, and B. Yao, "The location optimization of electric vehicle charging stations considering charging behavior," *Simulation*, vol. 94, no. 7, pp. 625–636, Jul. 2018.

[261] Y. H. Cheng and C. M. Lai, "Control strategy optimization for parallel hybrid electric vehicles using a memetic algorithm," *Energies*, vol. 10, no. 3, pp. 1–21, May 2017.

[262] L. Tribioli, "Energy-based design of powertrain for a re-engineered post-transmission hybrid electric vehicle," *Energies*, vol. 10, no. 7, p. 918, Jul. 2017.

[263] A. Fathy, M. Al-Dhaifallah, and H. Rezk, "Recent coyote algorithm-based energy management strategy for enhancing fuel economy of hybrid FC/battery/SC system," *IEEE Access*, vol. 7, pp. 179409–179419, 2019.

[264] D. Pavković, M. Cipek, F. Plavac, J. Karlušić, and M. Krznar, "Internal combustion engine starting and torque boosting control system design with vibration active damping features for a P0 mild hybrid vehicle configuration," *Energies*, vol. 15, no. 4, p. 1311, Feb. 2022.

[265] F. Un-Noor, S. Padmanaban, L. Mihet-Popa, M. N. Mollah, and E. Hossain, "A comprehensive study of key electric vehicle (EV) components, technologies, challenges, impacts, and future direction of development," *Energies*, vol. 10, pp. 1–82, Aug. 2017.

[266] Z. Wang, C. Qin, B. Wan, and W. W. Song, "A comparative study of common nature-inspired algorithms for continuous function optimization," *Entropy*, vol. 23, no. 7, pp. 1–40, 2021.

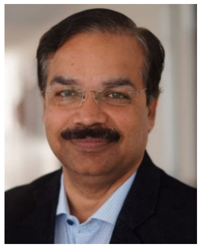
[267] A. K. Gautam, M. Tariq, K. S. Verma, and J. P. Pandey, "An intelligent BWO algorithm-based maximum power extraction from solar-PV-powered BLDC motor-driven light electric vehicles," *J. Intell. Fuzzy Syst.*, vol. 42, no. 2, pp. 767–777, Jan. 2022.

ABHINAV K. GAUTAM received the B.Tech. degree in electrical and electronics engineering from IMS Engineering College, Ghaziabad, India, and the M.Tech. degree in power electronics and drives from Kamla Nehru Institute of Technology, Sultanpur, Uttar Pradesh, India. He is currently pursuing the Ph.D. degree with Dr. A. P. J. Abdul Kalam Technical University, Lucknow, under the Homi Bhabha Research Cum Teaching Fellowship Scheme. His research interests include power converters, energy storage systems, and power management application in electric vehicle.

MOHD TARIQ (Senior Member, IEEE) received the bachelor's degree in electrical engineering from Aligarh Muslim University (AMU), Aligarh, the master's degree in machine drives and power electronics from the Indian Institute of Technology (IIT)-Kharagpur, and the Ph.D. degree in electrical engineering with a focus on power electronics and control from Nanyang Technological University (NTU), Singapore.

He is currently working as a Faculty/Postdoctoral Associate with Florida International University. He is associated with the Energy, Power, Sustainability, and Intelligence (EPSi) Group and working on high penetration renewable systems, grid resiliency, large-scale data analysis, artificial intelligence, and cybersecurity. He is also an Assistant Professor (on-leave) with AMU, where he was directing various international and national sponsored research projects and led a team of multiple researchers in the domain of power converters, energy storage devices, and their optimal control for electrified transportation and renewable energy application. Previously, he has worked as a Researcher at the Rolls-Royce-NTU Corporate Laboratory, Singapore, where he has worked on the design and development of power converters for more electric aircraft. Before joining his Ph.D. degree, he has worked as a Scientist with the National Institute of Ocean Technology, Chennai, under the Ministry of Earth Sciences, Government of India, where he has worked on the design and development of BLDC motors for the underwater remotely operated vehicle application. He also served as an Assistant Professor at the Maulana Azad National Institute of Technology (MANIT), Bhopal, India. He has secured several fundings worth approx. 18 million INR for AMU. He is also the inventor of approx. 25 patents granted/published by the patent offices of USA, Australia, U.K., Europe, India, and China. He has authored more than 200 research papers in international journals/conferences including many articles in IEEE TRANSACTIONS/Journals.

Dr. Tariq was a recipient of the 2019 Premium Award for Best Paper in *IET Electrical Systems in Transportation* Journal for his work on more electric aircraft and the Best Paper Award from the IEEE Industry Applications Society's (IAS) and the Industrial Electronic Society (IES), Malaysia Section-Annual Symposium (ISCAIE-2016), Penang, Malaysia, and many other best paper awards in different international conferences. He is the Young Scientist Scheme Awardee supported by the Department of Science and Technology, Government of India, in 2019, the Young Engineer Awardee by the institution of engineers, India, in 2020, and the Young Researchers Awardee by the Innovation Council, AMU, in 2021. He is also the Founder Chair of IEEE AMU Student Branch and IEEE SIGHT AMU. He is an Associate Editor of IEEE ACCESS journal and the Editorial Board Member of *Scientific Report* (Nature) journal.



J. P. PANDEY (Senior Member, IEEE) received the B.Tech. and M.Tech. degrees in electrical engineering-power systems from the Kamla Nehru Institute of Technology, Sultanpur, Uttar Pradesh, India, and the Ph.D. degree from Uttar Pradesh Technical University, Lucknow, Uttar Pradesh.

He is currently a Professor at the Department of Electrical Engineering, Kamla Nehru Institute of Technology. He is also working as a Vice-Chancellor at the Madan Mohan Malaviya University of Technology, Gorakhpur, India. He has more than 30 years of experience in the field of teaching, industry, and administration. He has published more than 40 technical papers in peer-reviewed journals, including IEEE, and in conference proceedings. His research interests include applications of artificial intelligence techniques to electrical engineering problems in power systems, estate estimation, and power quality.

K. S. VERMA (Senior Member, IEEE) received the B.Tech. and M.Tech. degrees in electrical engineering from the Kamla Nehru Institute of Technology (KNIT), Sultanpur, Uttar Pradesh, India, and the Ph.D. degree from the Indian Institute of Technology, Roorkee. He is currently a Professor with the Department of Electrical Engineering, KNIT Sultanpur. He is also working as the Director of KNIT Sultanpur. He has also worked as the Founder Director of Rajkiya Engineering College, Ambedkar Nagar, Uttar Pradesh, India, and the Director of KNIT Sultanpur. He has published more than 50 research papers in international journals and conferences proceedings. He has guided several M.Tech. and Ph.D. theses in the field of electrical engineering. His research interests include power systems, flexible AC transmission systems, planning and operation of distributed generation, and modeling and simulation of power systems.

SHABANA UROOJ (Senior Member, IEEE) received the B.E. degree in electrical engineering and the M.Tech. degree in instrumentation and control from Aligarh Muslim University, Aligarh, India, in 1998 and 2003, respectively, and the Ph.D. degree from the Department of Electrical Engineering, Jamia Millia Islamia (A Central University), Delhi, India, in 2011. She has nearly three years of industry experience and over 19 years of teaching experience. She is currently working as an Associate Professor with the Department of Electrical Engineering, College of Engineering, Princess Nourah bint Abdul Rahman University, Riyadh, Saudi Arabia. She has guided several Ph.D. and master's thesis and dissertations. She has authored and coauthored more than 150 research papers which are published in high quality international journals and conference proceedings. She was a recipient of the Research Excellence Award from PNU, the Springer's Excellence in Teaching and Research Award, the American Ceramic Society's Young Professional Award, the IEEE Region 10 Award for outstanding contribution in Educational Activities, and several Best Paper Presentation Awards. Recently, she has received the Badge of IEEE STEM Ambassador for her excellent volunteering and efforts in STEM promotional activities. She is holding the responsibility of the Vice Chair of the IEEE Saudi Arabia Section.