

Review



Fuel Cell Electric Vehicles—A Brief Review of Current Topologies and Energy Management Strategies

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Abstract: With the development of technologies in recent decades and the imposition of international standards to reduce greenhouse gas emissions, car manufacturers have turned their attention to new technologies related to electric/hybrid vehicles and electric fuel cell vehicles. This paper focuses on electric fuel cell vehicles, which optimally combine the fuel cell system with hybrid energy storage systems, represented by batteries and ultracapacitors, to meet the dynamic power demand required by the electric motor and auxiliary systems. This paper compares the latest proposed topologies for fuel cell electric vehicles and reveals the new technologies and DC/DC converters involved to generate up-to-date information for researchers and developers interested in this specialized field. From a software point of view, the latest energy management strategies are analyzed and compared with the reference strategies, taking into account performance indicators such as energy efficiency, hydrogen consumption and degradation of the subsystems involved, which is the main challenge for car developers. The advantages and disadvantages of three types of strategies (rule-based strategies, optimization-based strategies and learning-based strategies) are discussed. Thus, future software developers can focus on new control algorithms in the area of artificial intelligence developed to meet the challenges posed by new technologies for autonomous vehicles.

Keywords: fuel cell electric vehicle; DC/DC converter topologies; energy management strategy; rule-based; global optimization; real-time optimization

1. Introduction

In order to continue using fossil fuels, which means 80% of the world's energy demand, there are two main problems [1].

The first problem is the limited amount of fossil fuel, and sooner or later these sources will be consumed. Estimates of petroleum companies show that by 2023 there will be a peak in the exploitation of fossil fuels, petrol and natural gas, and then they will start to decline [2].

The second and most important problem is that fossil fuels cause serious environmental problems such as: global warming, acid rain, climate change, pollution, ozone depletion, etc. Estimates show that the worldwide destruction of the environment costs about \$5 trillion annually [3].

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Copyright: © 2021 by the authors. Licensee MDPI, Basel, Switzerland. This article is an open access article distributed under the terms and conditions of the Creative Commons Attribution (CC BY) license (http://creativecommons.org/licenses /by/4.0/). The solution proposed for the two global problems first appeared in 1970 as the "Hydrogen energy system" [4]. In the last decade through research and development work in universities and laboratories of research institutes around the world shows that hydrogen is an excellent source of energy with many unique properties. It is the cleanest and most efficient fuel [5].

The unique property of hydrogen in electrochemical processes is that it can be converted into electricity in the fuel cell system which makes it much more efficient than the conversion of conventional fuels into mechanical energy [6].

This unique property of hydrogen has led to the manufacture of hydrogen fuel cells and makes them a very good choice for automotive companies [7].

The alternative to fossil fuels found by car manufacturers for fueling vehicles is represented by other energy sources, such as: battery systems, ultracapacitors or fuel cells. Electric Vehicles (EVs) and Fuel Cell Electric Vehicles (FCEVs) are the most viable solutions for reducing Greenhouse Gases (GHG) and other harmful gases for the environment. Although EVs and FCEVs can reduce emissions to a certain value, they do not reduce them to absolute zero [8].

Thus, the renewable energy transport infrastructure allows FCEVs to become a preferable choice, because they attract great attention in the road and rail transport sector (and not only), without using fossil fuels [9]. FCEVs and FCHEVs use a combination of Fuel Cells (FC), and batteries (B) or/and Ultracapacitors (UC) [10]. The research stages for FCHEVs include the development of vehicles and the improvement of their efficiency. Beside the fuel cell system, they use the battery and/or ultracapacitor pack as a complementary power source to provide the required power on the DC bus. The topologies of FCEVs are described in detail in [11].

To increase the power density and to meet the demand for load power, it is necessary to integrate an energy management system. The energy management strategy of FCEVs is based on many important control techniques [12] such as finite state machine management strategies [13], grey wolf optimizer [14], model predictive control [15,16], fuzzy logic control [17,18], genetic algorithms [19,20], hierarchical prediction [21,22] as well as other control techniques developed so far for the energy management system.

This paper aims to update and introduce the new technologies regarding the FCEVs topology and Energy Management Strategies (EMS). In this regard, the paper will analyze recent research in the field, based on selected reference papers (87% published from 2018 to date), helping potential researchers and developers to get a more detailed picture of FCEV technologies. Thus, Section 2 will address the topic "Topologies of propulsion systems of FCEVs", following in Section 3 to discuss "Energy management strategies for FCEVs", ending thus with Sections 4 and 5 regarding "Discussions and perspectives" and "Conclusion".

2. Topologies of Propulsion Systems and the DC/DC Converters of FCEVs

All Electric Vehicles (AEVs) use only electric power to propel vehicles. AEVs can use as energy backup source a stack of batteries, a Fuel Cell (FC) stack or a hybrid solution, the AEVs being called as Electric Vehicle with Battery (BEV), EV with FC (FCEV) and hybrid EV with FC (FCHEV). In the following we will focus on the last two types [8,23]. Below, Table 1 presents a summary description of FCEV's and Fuel Cell Hybrid Electric Vehicle (FCHEV's) topologies.

When it comes to the problem of EMS optimization, it is first necessary to understand the features and modes of operation of the propulsion systems topologies. Multiple topologies have different configurations in terms of design, by modifying the power source connection [24].

Because the direct connection to the electric motor of the vehicle is not efficient due to the different voltage levels of the fuel cell, the battery system and the ultracapacitor, as will be reported in Section 2.1, it is necessary to integrate the DC/DC converters to gen-

erate the voltage required by the electric motor [25]. Thus, in the Section 2.3 an analysis of the types of DC/DC converters used in FCEV is described [26].

2.1. Fuel Cell Electric Vehicle (FCEV)

FCEVs use a full electric propulsion system, and the energy source is based on fuel cell stacks. A FCEV is hydrogen-fueled and the electrochemical process results in water and heat. PEMFC is the ideal choice compared to other types of fuel cell system (FCS) because it operates at a low temperature of 60–80 °C, develops a high-power density and exhibits low corrosion [27].

FCEVs powertrain can be separated into three categories: fuel cell and battery (FC + B), Fuel Cell + Ultracapacitor (FC + UC) and Fuel Cell + Battery + Ultracapacitor (FC + B + UC) [28]. Because FC + B + UC configuration is complex and due to the fact that ultracapacitors have low energy density, FC + B is the main design configuration and is applied in most FCEVs [29].

According to FCEVs topologies, FC + B can be divided into four categories (see Figure 1).

In the first topology, T1, FCS and the battery system are connected directly to the DC/AC inverter of the motor, without a DC/DC converter (Figure 1a). In the second topology, T2, FCS is connected by a DC/DC converter, the battery system being directly connected to the DC bus (Figure 1b), the advantage being to facilitate the power distribution between the FCS and the battery system. In the third topology, T3, the battery system is connected by a DC/DC converter, FCS being directly connected to the DC bus (Figure 1c). The fourth topology, T4, is the most preferred in research because it has a great flexibility in controlling the power flow for both FCS + B systems (Figure 1d) [30].





Figure 1. Topology of Fuel Cell Electric Vehicles (FCEVs): fuel cell + battery. (**a**) Topology T1; (**b**) Topology T2; (**c**) Topology T3; (**d**) Topology T4.

2.2. Fuel Cell Hybrid Electric Vehicle (FCHEV)

Any new modification to the propulsion system at the initial configuration of the FCEV, represents a new architecture respectively a new vehicle, namely Fuel Cell Hybrid Electric Vehicle (FCHEV). The new resulting architecture is based on New Energy Storage Systems (ESS) being in energy support for the fuel cell system. The energy storage systems used in the FCEV hybridization process are the battery and the ultracapacitor. They can be loaded and unloaded in multiple cycles providing the power required by the system; Himandi et al. [8] presents in his work more detailed sources of energy for FCHEV.

Due to the fact that the hybrid system is a complex one and the fuel cell being the main source of energy, it is necessary for the entire system to have an answer as quickly and efficiently as possible during operation, Huan et al. [31] describes in his work the equation for the power transmitted to the wheel of the propulsion system calculated by the longitudinal dynamics of a vehicle, P_{cycle} , and the power demand, P_{demand} , on the DC bus:

$$P_{cycle}(t) = v \left[m_v(t) \frac{d}{dt} v(t) + F_a(t) + F_r(t) + F_g(t) \right]$$
(1)

$$P_{demand} = \frac{P_{cycle}}{\eta_{DC/AC} \times \eta_{mator}}$$
(2)

where *v* is the vehicle speed, m_v -vehicle mass, F_a -aerodynamic friction, F_r -rolling friction, F_g -gravitational force, $\eta_{DC/AC}$ -DC/AC converter efficiency, and η_{motor} -motor efficiency.

Figure 2 shows the type of configuration fuel cell + battery + ultracapacitor that can have a FCHEV.

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Figure 2. Configuration of a fuel cell hybrid electric vehicle (Topology T5).

Table 1. Summary description of FCEV's and Fuel Cell Hybrid Electric Vehicle (FCHEV's) topologies.

Topology	Component Type	EMS Controller	Application		Advantages	Disadvantages	Reference
T1	PEFC (H2/O2)/Battery PEFC (H2/Air)/Battery	PI Controller	Electric power- trains Aircraft appli- cations	•	Cheap and simple solution The power losses are elim- inated in the hardware sys- tem Static and dynamic perfor- mance behavior	The parameters of the fuel cell and the battery must be carefully defined in order to operate in the same voltage range. Special operating proce- dure	[32,33]
T2	PEMFC/Battery	State machine model Switching control method Pontryagin's minimum principle and dynamic programming Hierarchical reinforce- ment learning (HRL)	Plug-in EV FCEV	•	Is widely used because it facilitates the power split control over FC and battery	It has low flexibility in controlling the power flow	[34–38]
T3	PEMFC/Battery/Ult racapacitor	PI controller	FCEV	•	Under sudden loading conditions maintaining soft switching operation, mini- mizes losses in bi-directional DC / DC converter.	This topology suffers from substantial loss of power flow.	[39–41]
T4	PEMFC/Battery	Direct torque control strategy (DTC) Power control strategy and PWM control Neural networks con- trol	FCEV	•	Generates stable DC volt- age Has more flexibility in con- trolling power flow at both FCS and battery	Batteries have a low power density	[42-44]
T5	PEMFC/Battery/Ult racapacitor	Energetic macroscopic representation (EMR) Sliding mode control (SMC) Power control strategy and PWM control Fuzzy logic controllers	FCHEV	•	Provides better control of DC bus voltage Ultracapacitor can regulate• the sudden power demands and battery can store ener- gy more efficiently	Control is more complex to achieve	[45–48]

2.3. Current Status of Fuel Cell Technologies in the Automotive Industry

The green energy provided by the fuel cells offers a competitive perspective on the automotive industry market, being the ideal alternative to Internal Combustion (IC) engines [49]. Currently, in the category of green energy, BEVs have the advantage of lower manufacturing costs than FCEVs both in the segment of the small and the middle classes

[50]. Thus, by 2030 the light duty vehicle market of fuel cell electric vehicles looks very promising, representing half of the existing competitive segments [51].

Over time, different car manufacturers from different countries have approached the development of FCEVs as follows [52]: Germany in Europe, Japan, Korea and China in Asia and the USA in North America (see Figure 2). F. Liu et al. [53] also presenting in their work a classification of FCEV models from the 2000s to the 2020s. Although 15 countries have public stations for hydrogen fueling of vehicles [54], Toyota Mirai and Hyundai ix35 are available on a larger scale, in the USA currently operating 5600 FCEVs [55] out of a total of 13,600 units globally [56]. However, according to public data in China, the FCEV stock is expected to reach 5000 in 2020s, 50,000 in 2025s and 1 million in 2030s [57]. At the same time, Japan and California have made similar pronouncements in the ambitious goals of achieving FCEVs. Japan is targeting 20,000 vehicles by 2025s and 800,000 by 2030s, and in California by 2023s, 37,400 FCEVs will enter the market and 1 million by 2030s as in China [58]. The most ambitious target is South Korea (the country of origin of Hyundai-Kia) and Germany with a total of 1.8 million FCEVs by 2030s [59,60].

The development and commercialization of the fuel cell electric vehicles is in full expansion, as previously presented. If on the Asian market in 2020 Hyundai introduced the new NEXO model, with an estimated driving range of 380 miles (approximately 611 km) [61], BMW (Munich, Germany), developed a SUV concept for future models in the upper segments of the X family: BMW i Hydrogen NEXT Concept Car [62]. The main challenges faced by the automotive industry's developers for improving FCEVs and increasing sales volumes globally are durability and cost [63]. In terms of durability, the catalyst in the PEMFC system is the most affected, constantly seeking solutions to improve electrochemical performance, structure and morphology [64]. Advanced technologies for electrocatalysis have been developed in [65] based on the two-dimensional nanomaterials. At the same time, another system that influences the durability of an FCEV is the battery system being the most disposed to aging, with a maximum lifespan of 10 years, the main sources affecting the battery being local climate, overheating and high discharging/charging rates [66].

According to the US department of energy of 2020s FCS they cost US \$40/KW with an efficiency of 65% at peak power [67]. The highest cost of the FCS assembly is represented by the catalyst with a percentage of 41% of the total cost, this being caused by the material used, namely the platinum base (Pt-based) [68]. Thus, the developers challenges regarding the catalyst have both durability and cost.

Other factors that would significantly reduce the final costs of a fuel cell electric vehicle would be the automation of the production of the component subassemblies at a competitive cost in the market and the implementation of the necessary infrastructure in many more countries of the world [69]. In our opinion the main difficulties in implementing these topologies on real vehicles, preventing the adoption of FC technologies as automotive propulsion systems are as follows:

- Low flexibility in power flow control in PEMFC + B configuration;
- The PEMFC + B + UC topology suffers from substantial losses of power flow, which makes the control of energy systems complex;
- Batteries have a low power density which leads to an increase in the size of the battery system involving substantial production costs and a much higher mass of the vehicle.

2.4. DC/DC Converters for Fuel Cell Electric Vehicle

DC/DC Converters are electronic equipment that convert a level of electrical voltage, usually unstable at the input, into a stable voltage at the output. In the automotive field, the voltage demanded by the electric motor is in the range of 400–700 V, in this case it is necessary to integrate DC/DC converters for all electricity generation systems: fuel cell system, battery system and ultracapacitor. Thus, for FCEV is essential to step-up FC output voltage and regulate the electric voltage on DC bus, even if in case of battery system and ultracapacitors the level of electrical voltage is 250–360 V respectively 150–



400 V [26,70]. The topologies of DC/DC converters are divided into two categories: non-isolated and isolated (See Figures 3 and 4) [71].

Figure 3. Fuel cell market.





(d)

Figure 4. Typical topologies of Non-isolated DC/DC Converters. (a) Clamped capacitor H-type boost DC-DC converter; (b) Stacked interleaved DC-DC buck converter; (c) Magnetically coupled buck-boost bidirectional converter; (d) Non-isolated unidirectional three-port Cuk-Cuk converter.

2.4.1. Non-Isolated DC/DC Converter

The first topology of non-isolated DC/DC converters is the Boost Converter [72]. This produces a higher electrical voltage at the output than the input voltage. In the configuration of this type of converter the switch and the inductor can be interchangeable. H. Bi et al. [73] demonstrates experimentally a new type of converter, clamped capacitor H-type boost DC-DC converter (Figure 4a), with an efficiency of 94.72% suitable to serve as an interface between the fuel cell and DC bus with a wide voltage range between 25V-70 V up to 400 V and can be successfully integrated on FCEVs. Also, N. Elsayad et al. [74] presented a new topology called the single-switch high step-up DC/DC converter to get high voltage gain and decrease the voltage stress on the power switch and H. Wang et al. [75] propose a review that presents a comparative analysis of high voltage gain DC/DC boost converters for fuel cell electric vehicles applications. In the case of FCS, a unidirectional boost converter is used, as it has the advantage of protecting FC from the reverse current. The second topology is buck converter-its characteristic is to produce a lower electrical voltage at the output than the input one. In the case of hydrogen production applications, the interface with the electrolyzer is given by a buck converter. New technologies applied to these converters must cope with the use of energy from renewable energy sources (RES). Such a converter is presented by D. Guilbert et al. [76]. Stack interleaved DC-DC buck converter (SIBC) (Figure 4b) is designed to ensure a low output current ripple and also a suitable dynamic response to guarantee the reliability of the electrolyzer. The third topology is the buck-boost converter-it increases or decreases the output voltage and inverts the polarity of the input voltage. For the Battery System and/or Ultracapacitor a Bi-directional Buck-Boost Converter is used because it has the advantage that the power flow flows in both directions and allows them to supply both the energy to the load and to store the regenerative energy from the load. The advantage of using triple phase shift (TPS) [77] modulation strategies for magnetically coupled buck-boost bidirectional converter (MCB) demonstrates operation with minimal power losses in switches as well as in the power range [78] (Figure 4c). The arrangement of passive components used in MCB connects the input and output ports, obtaining a behavior similar to the topology of dual active bridge converters [79]. The fourth topology, Cuk converter, is similar to the third one in the conversion process, the difference being that this converter contains an inductor inserted at both the input and the output, having the advantage of a continuous current at the input as well as the output. B. Chandrasekar et al. [80] present a non-isolated three-port DC-DC converter based on Cuk topology to manage the renewable sources. Also, the authors from [81–83] present the different topologies of DC-DC converters non-isolated suitable for FCEV with their advantages and disadvantages. V. F. Pires et. al. [84] propose a hybrid DC-DC converter consisting of a quadratic Boost converter and a Cuk converter—the main features being reduced voltage stress across the active power switch, simplicity in control and high step-up voltage. For interfacing renewable energy sources, such as fuel cells or photovoltaic panels, the efficiency of the non-insulated three-port Cuk-Cuk (NI-TPCC) DC-DC converter (Figure 4d) is demonstrated in [80]. The NI-TPCC converter demonstrates real performance in unidirectional operating mode. Due to low ripple current, power losses and temperature rise values are significantly reduced, improving the life of fuel cells and capacitive components in the converter.

2.4.2. Isolated DC/DC Converter

Isolated DC/DC Converters are converters that have a transformer built into their structure to obtain DC isolation between input and output. The transformer works at the converter switching frequency up to hundreds of kHz. By choosing the conversion ratio of the transformer as efficiently as possible, stresses in the electronic components can be reduced leading to improved performances [81]. C. Zhang et al. [85] described in their work a High Frequency Isolated Bi-directional DC/DC Converter (See Figure 5a) based on the combination of an H-bridge, a three-level Half-bridge and a three-phase Full-bridge topology. The multiport topologies are also used [86]. For high power applications, Dual-input high step-up isolated converter (DHSIC) (See Figure 5b) [87] is capable of generating very high output voltages when processing low input voltages. The maximum measured efficiency is 91.4% in the case of double input operation (e.g., fuel cell and photovoltaic panel). At the same time, the DHSIC converter has important characteristics such as ultra-high voltage gain, inherent voltage clamp feature, continuous input currents or independent and individual input.





(b)

Figure 5. New topologies of Isolated DC/DC Converter. (**a**) Hybrid ZVS (Zero Voltage Switching) Bidirectional DC-DC Converter; (**b**) Dual-Input High Step-Up Isolated Converter (DHSIC).

2.4.3. New DC/DC Converter Topologies

With the development of new technologies in the automotive field for EV, HEV, FCEV, FCHEV and AEV applications, the researchers' main objective is to find technological solutions to meet the challenges of this segment.

Thus, in Table 2 are presented a series of new converters used in the applications described above. There are many factors behind increasing the performance of a converter, such as the suppression of electrical noise in the system, low voltage ripples of capacitors (less than 1%), current ripples, switching losses or the implementation of new active or passive components to increase system efficiency.

H. Bi et al. [73] and P. K. Maroti et al. [88] propose two types of converters: clamped capacitor H-Type boost DC-DC converter and Tri-switching state non-isolated high gain DC-DC boost converter, which have the same power level of about 0.5 kW and a maximum efficiency of 94.72% and 94.67%, respectively. These demonstrate the real advantages of wide voltage gain range and lower voltage stress over semiconductors and power capacitors compared to other converter models that have the same power but much lower maximum efficiency [89]. Low power converters: 0.1 kw [80] or 0.2 kw [90], have a maximum efficiency of around 93%, lower than other types of converters [91,92], their major advantage being the control of a relatively low complexity, suitable in various fuel cell applications. Converters with a power level of around 1 kW [93] have a higher maximum efficiency with a wide range of voltage gain, suitable for fuel cell systems (they have wide voltage fluctuations)—in this case the highest efficiency of 97.8% is given by the value of the input voltage of 200 V. For converters with a much higher power level (e.g., 12 kW) the efficiency has a value of about 97%, the DC/DC resonant dual active bridge (RDAB-IBDC) isolated bidirectional converter [94] demonstrates real performance by the frequency of higher switching, lesser circulating current or less switching losses. The bidirectional chargers for the FCEVs are already available in the market [95].

Convertor Topology	Switching	Number of Semi-	Number of	Number of	Maximum Effi-	Power	Complexity	Reference
converter reportegy	Frequency	conductors	Inductors	Capacitors	ciency	Level	compressity	
Capacitor clamped H-type DC-DC converter	20 kHz	2 switches 5 diodes	1	4	94.72%	0.4 kW	Н	[73]
Non-isolated unidirectional three-port Cuk-Cuk converter	20 kHz	2 switches 1 diode	3	3	92.74%	0.1 kW	М	[80]
Tri-switching state non-isolated high gain DC–DC boost converter	50 kHz	3 switches 3 diodes	2	2	94.67%	0.5 kW	М	[88]
High voltage gain DC-DC boost con- verter	50 kHz	5 diodes	2	4	~85%	0.5 kW	М	[89]
Four-port DC-DC Converter	30 kHz	2 switches 4 diodes	1	2	87% (Rated eff.) 93% (Peak eff.)	0.2 kW	М	[90]
Floating-interleaved buck-boost DC- DC converter	20 kHz	4 switches	2	2	NA	0.6–1 kW	М	[91]
Three-port DC–DC converter	50 kHz	5 switches 5 diodes	3	2	92.70%	NA	М	[92]
Single-switch structure of a DC-DC converter	100 kHz	1 switch 4 diodes	2	5	97.8% (Input voltage: 200 V) 97% (Input volt- age: 100 V)	1.3 kW	М	[93]
Resonant dual active bridge isolated bidirectional DC/DC converters	NA	8 switches 8 diodes	1	3	~97%	12 kW	Н	[94]
Interleaved DC/DC boost converter	20 kHz	2 switches 2 diodes	2	1	NA	NA	М	[96]

Table 2. Summary of characteristics of DC/DC converters topologies for FCEVs and FCHEVs.

Note: L-Low; M-Medium; H-High; VH-Very High; NA-not available.

3. Energy Management Strategy for Fuel Cell Electric Vehicle

In order to achieve a viable FCEV, with an opening to the market for marketing purposes by the manufacturers of the automotive industry, the main challenge is to develop a control strategy for energy management. These strategies lead to the improvement of the performances both from an energy point of view and of the reliability of the components, the most essential thing when we speak of the maintenance of a vehicle after commercialization [97]. Reducing hydrogen consumption by optimizing energy consumption is the subject of much research [98–105]. In addition to assessing fuel consumption, control strategies also play a role in preventing the degradation of energy storage systems, represented by batteries and the ultracapacitor [106–109]. Figure 5 describes the classifications of the energy management strategies.

3.1. Analysis of Rule-Based Strategies Methodology in FCEV

The control based on rule sets has a very good efficiency in accordance with the embedded processors, but usually it is based on empirical laws and the results are not among the most optimal. Rule-based strategies are suitable for online implementations because they are based on simple sets of rules (e.g., if-then-else), but the parameters of these rules may be affected by driving conditions Thus, according to Figure 6, rule-based strategies contain several types of control techniques with different implementations and present various advantages [110] and disadvantages related to adaptivity and optimality problems [111]. The criterion of the rule-based energy management strategy requires power capability prediction and an accurate SOC [112].

Q. Zhang and G. Li [113] describe in their work a control technique based on game theory for the distribution of power flow in the FC + B configuration. They approached this strategy because there are situations when the energy demand is uncertain during the driving cycle. In this case FC and B have played the role of two non-cooperating players each maximizing their own utility, which has led to uncertain energy demand behavior. This type of control, along with a fuzzy logic controller, used for correction, has had favorable results both for fuel reduction and for preventing battery degradation to a

minimum level being very advantageous. As a main disadvantage, a thorough knowledge of each type of control is required; the technique being addressed cannot be extrapolated directly to other hybridization configurations.

Given the importance of preventing the degradation of energy storage systems, P. Rahimirad et al. [114] study the effect of temperature on these systems using different rule-based strategies. The study shows that, considering or not considering the effect of temperature led to significant errors associated with estimates of battery life. In this regard, a number of strategies have been used by them:

- State Machine Control Strategy—it has the advantage of being easy to use by defining some states the FC power being calculated from the State-of-Charge (SOC) of the battery and the power of the load, and the disadvantage that the request to switch control when the mode is changed affects the output power;
- Classical Proportional–Integral (PI) Control Strategy—is used for online setting, for control of the battery SOC and better tracking; the output of the regulator is the power of the battery and together with the power of the load led to obtaining the reference power of the FC;
- Frequency Decoupling And Fuzzy Logic Strategy—allows FCS to offer a low frequency at the output, while the rest of the systems work at high frequencies. The main advantage of this strategy is that the average battery power tends to zero, ensuring a reduced range of batteries SOC;
- Equivalent Consumption Minimization Strategy (ECMS)—this strategy is based on the minimization of an instant cost function for determining the power distribution, achieved from the FCS fuel consumption and the equivalent consumption of the battery and ultracapacitor systems. The advantage is to minimize fuel consumption and the equivalent consumption required to maintain the battery SOC;
- External Energy Maximization Strategy (EEMS)—the strategy is to maximize the energy of the battery and ultracapacitor systems keeping the SOC within their limits. The main advantage is that cost function does not need to estimate the equivalent energy of the energy sources, determined empirically. It is produced by external energy sources over a certain period of time.

Rule-based strategies		 Fuzzy control strategy State machine control strategy Classical PI control strategy Frequency decoupling and fuzzy logic strategy (FDFL) Power prediction
Optimisation-based strategies	Global optimisation	 Linear programming (LP) Dynamic programming (DP) Global extremum seeking (GES) Genetic algorithm (GA)
	Real-time optimisation	 Pontryagin's minimum principle (PMP) Quadratic programming (QP) Multi-agent system (MAS) Stochastic dynamic programming (SDP) Convex programming Multi-mode predictive (Markov driving pattern recognizer) Soft-run strategy Fractional order extremum seeking method Dynamic particle swarm optimisation Equivalent consumption minimization strategy (ECMS) External energy maximization strategy (EEMS)
Learning-based strategies		 Reinforcement learning Supervised learning Unsupervised learning Neural network Multi-mode strategy – learning vector quantization (LVQ)

Figure 6. Classifications of the energy management strategies [12,115–118].

Y. Wang et al. [119] approach the hybridized FC + B + UC configuration and describe in their work a rule-based power distribution strategy. The development of the power distribution strategy aims at the safety and the life of the energy storage systems. The Bayes Monte Carlo method performs the prediction of the remaining capacity and power supply of the battery and ultracapacitor. The advantage of using the Rule-based power splitting strategy is that the power demand, reliability and safety of the vehicle meet all the criteria of energy consumption and of the remaining capacities and power supply.

3.2. Analysis of The Optimization Based Strategies Methodology in FCEV

3.2.1. Global Optimization Strategy

Global optimization strategies are often used to reduce fuel consumption by optimizing the energy flow of the propulsion system [120]. In [121,122] we have some examples of implementation for some algorithms, used for fuel economy, in the sphere of Global Optimization Strategies. Because the minimization of FCEVs consumption is highly dependent on the battery SOC, it is necessary to automate the information processing for the independent control of SOC using real-time control strategy [123].

K. Song et al. [124] bring to the fore a strategy based on the learning vector quantization neural network algorithm (LVQ) for evaluating the dynamic performance and performance of the fuel economy of the vehicle. This is described as a hybrid network consisting of 3 components: input layer (I), competition layer (H) and output layer (O), each component representing neurons layers. The LVQ strategy was developed through the combined use of the genetic optimized thermostat strategy and the condition recognition method. Experimental results have shown that multi-mode energy management strategies using LVQ meet the needs of dynamic performance and can produce a substantial fuel economy than other strategies compared in the paper.

Another strategy that is part of Global Optimization is described by Y. Bai et al. [125] namely hierarchical optimization energy management strategy to prevent aging of the energy storage system stored on a plug-in hybrid electric vehicle. Hierarchical optimization consists of several types of algorithms. For the distribution of power between the energy storage system and the electric motor, the authors opted for the variable-threshold dynamic programming algorithm (V-DP). The results show that for a threshold of 0.8 of SOC of ESS the total costs include the aging costs of the battery. Compared to Dynamic Programming, V-DP improves the service life by 4.25%. By introducing the ultracapacitor into the electrical energy storage system, and in order for it to operate within the capacity range, a power limit management module is provided with an adaptive law-pass filtering algorithm, in order to avoid the overload of the ultracapacitor power and for the distribution of the power flow between the components of the motor-battery-ultracapacitor assembly. For analyzing the life cycle economics and quantifying the battery life it is important to calculate the battery aging cost using rain-flow counting algorithm. By using this algorithm, the battery performance is analyzed, the results being favorable by improving the useful life by approximately 54.9%. In conclusion, the application of the hierarchical optimization energy management strategy can be done on the FCHEV as it has been shown that this strategy can significantly inhibit the aging of the energy storage system.

Also, the linear programming (LP) and dynamic programming (DP) methods converge towards the global optimum only if certain convexity assumptions or any particularity of the optimization problem are ensured [126,127]. The strategy based on global extremum seeking (GES) converges towards a global solution and can respond to several performance issues such as performance consumption, energy efficiency, safety, environmental protection [128]. The major advantage is the integration of performance indicators in a single optimization function and implementation in real-time solutions [129,130].

3.2.2. Real-Time Optimization Strategy

The most important feature of the real-time optimization strategies is the processing power of the information gathered from the ESS for the purpose of energy control automation to prevent the aging of the components. Even though the design of such algorithms is more difficult to achieve, compared to the other energy management strategies, real-time strategies are important because the realization of FCEVs must have a competitive finish on the world market [116,131].

Energy management algorithms are addressed in many specialized articles by the work of Y. Zhou et al. [132]—using multi-mode energy management strategy, Z. Hu et al. [117]—soft-run strategy for real-time and multi-objective control algorithm or fractional-order extremum seeking (ES) method of D. Zhou et al. [133].

X. Li et al. [118] presents in their paper the advantages of using Pontryagin's minimum principle (PMP), demonstrating a 4% saving of hydrogen fuel consumption and at the same time obtaining a special performance compared to offline management strategies. The Pontryagin's minimum principle introduces a co-state variable that has the role of defining the cost of using electricity and equating it to hydrogen fuel consumption through driving cycle prediction. For the highest accuracy of co-state estimation, a Markov-based velocity prediction algorithm is used, considering driving behavior under different patterns. In parallel to the online recognition of the driving pattern, the authors use the support vector machine method with particle swarm optimization (PSO-SVM). The results are validated by simulating the proposed EMS and demonstrating through adaptive EMS versus rule-based EMS, reduced hydrogen consumption and low average power change rate of fuel cell system.

B. Sami et al. [134] propose such an intelligent system that acts quickly in the event of sudden changes in hydrogen consumption, in order to manage energy efficiently. A multi-agent system is used to estimate fuel consumption. It defines the operating agent according to the energy demand and at the same time the energy supply. A new zero emission hybrid electric vehicle simulation (NZE-HEV) tool is used, which includes an energy management unit maintained by the multi-agent strategy in the process operation. Therefore, each device is represented as an agent responsible for controlling and verifying the states as well as establishing the constraints that may endanger their functioning in good conditions. Agent 1 is represented by the main power generation system–FCS, followed by agent 2-recharging stations, agent 3-ultracapacitor and agent 4-home. They are used to develop the communication process in order to make the right decisions. Each agent manages a number of resources, FCS hydrogen supply or an ultracapacitor electrical load, to improve process performance and optimize system operation. The obtained results show the advantage of using multi-agent strategy, proving functionality and flexibility in all the problems of constraint of the lack of energy during the peak periods of the demand of the hybrid prototype with PEM-FC and UC with zero emissions.

3.3. Analysis of Learning Based Strategies Methodology in FCEV

Since most power and energy management strategy (PEMS) methods are currently based on prediction algorithms or predefined rules, they have the disadvantage of poor adaptability to real-time driving conditions and do not offer the real-optimal solution for a new European Drive Cycle. Learning based (LB) strategies is based on large data sets with real-time and historical information, in order to obtain optimal control. LB algorithms can be integrated into model-based approaches for parameter adjustment in order to optimize processes for different types of driving cycles (e.g., urban or highway). The main advantage of these strategies is learning and adaptive capability and model-free control [24,135].

N. P. Readdy et al. [135] focused on the implementation of a new strategy, namely Reinforcement Learning (RL), the advantage being that the system autonomously learns the optimal control policy. At the same time, they demonstrate in their work a real improvement of the battery life by minimizing the variation of their SOC. In this case, the control is performed using a Q learning based algorithm that has the role of distributing the load power between FCS and the batteries by minimizing the SOC variation to improve the battery life and to reduce the energy losses of the other components. The results show that reducing the variation of the battery SOC has the value of approximately 0.7 per unit, demonstrating that the PEMS algorithm is capable of increasing the battery life and improving the efficiency of the hydrogen fuel system.

To improve the lifetime of fuel cells with PEM type membrane, prediction of degradation is a necessary tool for the functioning of the FCS. Thus, K. Chen et al. [136] introduce by their work a new model of algorithm based on the grey neural network method (GNNM) implemented together with particle swarm optimization (PSO) and moving window method for predicting fuel cell degradation in different applications. The choice of using GNNM was made to predict cell degradation, without the need for a massive history database for algorithmic model formation, presenting the advantage of using limited data, ideal for PEMFC. The use of the particle swarm optimization algorithm has a global convergence as it ensures the optimization of the GNNM initial weight and threshold, improving the network convergence speed and the cell prediction accuracy. By applying the moving window method, new data sets for the iterative stimulation of PSO-GNNM are increased, providing dynamic weight and threshold for improving the prediction. The results indicate a high predictive performance of PEMFC degradation used both in the automotive field and in other types of applications such as FC combined heat and power system or FC smart grid.

To improve the lifetime of the battery the SOC is predicted using data-driven machine learning in [137]. A review of recent lifetime prediction methods for the batteries is performed in [138].

Therefore, improving the lifetime of the FCEV / FCHEV supply system and reducing vehicle costs are necessary in the competitiveness of HEVs [139]. The design of adequate energy management system [140] leads to obtaining driving prediction objectives: speed, acceleration, power demand, distance until hydrogen refueling station, driving models, battery SOC, driver's driving style, etc. [141]. Figure 7 shows the EMS performance and benefits of driving information prediction [142].



Figure 7. The benefits of driving information prediction for energy management systems optimization [142].

4. Discussion and Perspectives

This Section wants to highlight the ways to improve the future energy management strategies through research conducted on FCEV or FCHEV, in the automotive field. From

the point of view of FCEV's topologies, the future consists in the hybridization of the existing components to create an optimal propulsion system, competitive with the modern car market. Thus, the continuous evolution of new communicative concepts: vehicle-to-vehicle (V2V) [143], vehicle-to-infrastructure (V2I) [144] or connected and automated vehicles (CAV) [145] makes the development of new EMS technologies meet the requirements of energy performance, consumption of fuel and preventing the degradation of the components of the energy storage system. Vehicle-to-everything (V2X) technology integrates all the vehicle connection technologies [146] (see Figure 8). Initially the concept of V2X was used to provide energy services from electric vehicles with batteries in periods of non-use [147]. V2X services aim to generate revenue from battery assets, the purpose being to provide flexibility to system operators and other third parties for the technical operation of the electrical network [148] (see Figure 8).

V2G is the most developed commercial topology – a 2018 market report identified at least 50 projects under investigation [149], generating commercial interest by stimulating a number of start-up companies (EMotorWerks, NUUVE) or large investments in ecosystem development (Nissan Energy, The Enel Group, ChargePoint). G. B. Sahinler and G. Poyrazoglu [150] provide an excellent review of V2G applicable EV chargers, power converters and their controllers.

In the case of Fuel cell electric vehicles there is a huge potential in exploiting the additional possibilities for synergies between hydrogen and electric networks. C. B. Robledo et. al. [151] demonstrate in their paper the advantages of using FCEVs in V2G mode to obtain a sustainable energy system. However, the topic is the subject of much future research in overcoming barriers to the use of hydrogen as a source in smart grids.



Figure 8. Vehicle-to-everything (V2X) technology.

An important axis in the development and commercialization of Fuel cell electric vehicles is represented by the technical-economic analysis. The technical-economic challenges must respond to ways to develop low-carbon economies and technologies by en-

couraging the use of environmentally friendly energy [152]. Producing hydrogen in an economical, efficient and sustainable way is another challenge. So far, they are considered mature only a few paths among which we mention coal gasification and steam methane reforming [153]. However, there are other sources of hydrogen production with alternative technologies, namely, renewable energy sources representing the future of hydrogen production (Figure 9) [154].

As a new energy technology, fuel cell systems do not have a significant influence on the energy market—as currently seen for electric vehicles with batteries [155]—cost, reliability and durability are the main elements that raise problems in their marketing. In this regard, a number of factors must be taken into account, including the feasibility of manufacturing processes, the quality and cost of products, the appropriate materials, the strength of the supply chain and the acceptance of the end user.

The life cycle of a stack of fuel cells can be classified from a technical-economic point of view into a manufacturing stage and a stage representing the end user. So according to [156,157] the total cost of an 80 kW_{net} fuel cell system is 30 USD*kW⁻¹ (see Figure 10). In [158] the authors present a cost analysis comparing three vehicle types: FCEVs, IC engine vehicles and Hybrid vehicles. The cost of an FCEV is approximately \$24,355, the cost of an IC engine vehicle is \$15,805, and the cost of a hybrid vehicle is around \$24,050. However, the purpose of the study was not to demonstrate the price differences between certain vehicle categories but to emphasize that the efficiency of FCEVs was 60–70% much higher than that of IC engine vehicles of 10–16%.

Currently, there are not many papers on conducting a technical-economic analysis of FCEVs [159,160], which makes this topic a framework for many researchers in the future.



Figure 9. Hydrogen production pathways.



Figure 10. 80 kWnet PEM Fuel Cell stack cost (left) and PEM Fuel Cell stack system cost (right)

In the previous sections, the emphasis was on the advantages of using each control technique, as the key features of the EMSs described can make software evolutions in order to optimal control that will satisfy the most drastic current requirements. Table 3 presents the main advantages and disadvantages of EMSs to highlight the different performance in control systems.

Rule-Based Strategies have performance features that are implemented in real-time applications, but by their nature have sub-optimality problems. A. Yazdani et al. [161] present in their paper the sub-optimal strategies proposed in the literature, highlighting the main issue related to tracking a local optimum instead of the global maximum. The performance of a global strategy against a sub-optimal strategy is analyzed by the authors for FC hybrid power systems [162], photovoltaic (PV) power systems user partial shading conditions [163] and other multimodal patterns [164]. The power characteristics of FC system under dynamic load or PV system under partial shading conditions are similar to the shape of a multimodal pattern [164]. More than 30% more harvested power can be obtained if a global strategy is used for a PV system, instead of one that will find a local maximum [162]. Also, it is worth mentioning that the overall performance of a FCEV measured by total fuel consumption during a load cycle is better in case of a global strategy compared to a commercial strategy, but the fuel economy depends in a substantial way on the profile of the load cycle [162].

Optimization-Based Strategies has multiple advantages by using old algorithms such as genetic algorithm or particle swarm optimization in combination with other algorithms such as Markov-based velocity prediction or rain-flow counting, but has a sensitivity in terms of online applications.

Depending on the applications they develop, many researchers have combined different control algorithms with the idea of maximizing optimization [165–169]. The characteristics of these techniques cannot be used individually, since each control algorithm besides its advantages also has a number of shortcomings that make it nonperforming in the energy optimization process. For example, R. Zhang et al. [170] propose a combination of three algorithmic techniques, namely: neural network-based driving pattern recognition (DPR), adaptive fuzzy energy management controller and genetic algorithm, for power sharing between fuel cell and ultracapacitor in a HEV. The DPR algorithm is based on velocity characteristics extracted using the multilayer perceptron neural network. Fuzzy real-time control is used to divide power according to EM demand and auxiliary systems, and, to minimize hydrogen consumption and extend FC life, the genetic algorithm is applied. The result establishes a load state of the UC within the desired limit.

Moreover, F. Zhang et al. [171] present a state-of-the-art of the latest EMS control techniques for connected HEVs/PHEVs. This work widens the horizon for using control techniques in future FCHEV research, as their further development will take into account the connectivity of vehicles. In parallel, N. Bizon et al. [172,173] offer through their books the theoretical basis to develop applications for the linear and non-linear control and op-

timization strategies applied in hybrid power systems, but also advanced fuel economy strategies applied on recent proposed power-following control topologies for hybrid power systems based on fuel cell and renewable energy. Among the strategies discussed above, there are a multitude of new algorithms that have not been experimented with, which use the learning-based strategy representing the future in terms of new control technologies. In Section 3 we present two significant works that show their value in terms of optimization, and the hybridization with optimization-based strategies can create new algorithmic bases that can reach remarkable performances for FCEVs and FCHEVs.

So, in summary, the main challenges in adopting FC technologies as automotive propulsion systems are the following (see also Figure 11):

- 1. Infrastructure for hydrogen (H₂) stations and their refueling;
- 2. High cost of hydrogen production;
- 3. The low power density of the batteries increases the size of its system and implicitly the mass of the vehicle;
- 4. The use of FC + B topology facilitates the power split control over fuel cell and battery but present low flexibility in controlling the power flow;
- 5. FC + B + UC control configuration is more complex to achieve.



Figure 11. The main challenges in adopting Fuel Cell (FC) technologies as automotive propulsion systems.

EMS Type	Main Advantages of EMS	Main Disadvantages of EMS
• Rule-based strategies	Simplicity—It is based on simple sets of rules "if-then-else" Using fuzzy algorithms, the system is robust and has very good adaptability and prediction capabilities.	Rule-Based parameters can be strongly affected by the driving con- ditions It does not present good performance in reducing fuel consumption.
Optimization-based strategies (Global opti- mization)	 High performance in reducing hydrogen consumption. Global optimality/Reference for other EMSs 	Optimality is not ensured in a limited number of iterations Need additional information in ad- vance about the driving cycle
Optimization-based strategies (Real-time op- timization)	Minimization the total economy consumption: the hy- drogen consumption and the battery degradation con- sumption An accurate estimation of the variation of the state of	Complex mathematic formulation

Table 3. The main advantages and disadvantages of Energy Management Strategies (EMS)

	charge (SOC) of each system element.	
-	It is based on large data sets with historical and re-	Time consuming to create database
Learning-based strategies	al-time information	Requires complex knowledge of arti-
-	Model-free control	ficial intelligence

5. Conclusions

The evolution of the technology in the automotive field and the worldwide imposing of the pollution norms, by reducing the greenhouse gases emissions, has caused more and more researchers to focus on the design aspects of the propulsion systems and at the same time on the development of software and new technologies that are able to manage the demand of power from the systems that make up EV and FCEV.

In this regard, various configurations of FCEV's topologies have been presented with the purpose of a suitable choice by users in various applications. For complete information, comparisons have been made of the different types of DC/DC converters and equipment that serves to match the ESS components' output voltage to those required for the electric motor and auxiliary systems.

In order to improve the energy performance, a series of EMSs was analyzed, presenting the fundamental principles of the existing techniques with the advantages and disadvantages of their use, the main objectives being to reduce the consumption of hydrogen and to prevent the degradation of ESSs.

Thus, the progress made by software developers in the field of artificial intelligence gives researchers the possibility to have maximum potential in the design abilities of the new control algorithms, by hybridization with existing techniques in order to eliminate the uncertainties regarding the robustness of the EMS.

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Abbreviations

EV	Electric Vehicle
FCEV	Fuel Cell Electric Vehicle
FCHEV	Fuel Cell Hybrid Electric Vehicle
GHG	Greenhouse Gases
HEV	Hybrid Electric Vehicle
FC	Fuel Cell
В	Batteries
UC	Ultracapacitors
EMS	Energy Management Strategies

	Direct Current
AC	Alternative Current
AEV	All Electric Vehicle
BEV	Electric Vehicle with Battery
PEMFC	Proton-Exchange Membrane Fuel Cells
FCS	Fuel Cell System
Т	Topology
ESS	Energy Storage Systems
PEFC	Polymer Electrolyte Fuel Cell
H2/O2	Hydrogen/Oxygen
PI	Proportional Integral
HRL	Hierarchical Reinforcement Learning
DTC	Direct Torque Control Strategy
PWM	Pulse-Width Modulation
EMR	Energetic Macroscopic Representation
SMC	Sliding Mode Control
FDFL	Frequency Decoupling and Fuzzy Logic Strategy
FCMS	Equivalent Consumption Minimization Strategy
FEMS	External Energy Maximization Strategy
LUNO	Learning Vector Quantization
	Linear Programming
CA	Cenetic Algorithm
PMP	Pontryagin's Minimum Principle
OP	Quadratic Programming
MAS	Multi-Agent System
SDP	Stochastic Dynamic Programming
SOC	State-of-Charge
V-DP	Variable—Threshold Dynamic Programming Algorithm
1 21	variable millesnora 2 ynamie i rogrammig i ngornam
ES	Fractional-Order Extremum Seeking
ES PSO-SVM	Fractional-Order Extremum Seeking Support Vector Machine Method with Particle Swarm Optimization
ES PSO-SVM NZE-HEV	Fractional-Order Extremum Seeking Support Vector Machine Method with Particle Swarm Optimization New Zero Emission Hybrid Electric Vehicle
ES PSO-SVM NZE-HEV PEMS	Fractional-Order Extremum Seeking Support Vector Machine Method with Particle Swarm Optimization New Zero Emission Hybrid Electric Vehicle Power and Energy Management Strategy
ES PSO-SVM NZE-HEV PEMS LB	Fractional-Order Extremum Seeking Support Vector Machine Method with Particle Swarm Optimization New Zero Emission Hybrid Electric Vehicle Power and Energy Management Strategy Learning Based Strategies
ES PSO-SVM NZE-HEV PEMS LB RL	Fractional-Order Extremum Seeking Support Vector Machine Method with Particle Swarm Optimization New Zero Emission Hybrid Electric Vehicle Power and Energy Management Strategy Learning Based Strategies Reinforcement Learning
ES PSO-SVM NZE-HEV PEMS LB RL GNNM	Fractional-Order Extremum Seeking Support Vector Machine Method with Particle Swarm Optimization New Zero Emission Hybrid Electric Vehicle Power and Energy Management Strategy Learning Based Strategies Reinforcement Learning Grev Neural Network
ES PSO-SVM NZE-HEV PEMS LB RL GNNM PSO	Fractional-Order Extremum Seeking Support Vector Machine Method with Particle Swarm Optimization New Zero Emission Hybrid Electric Vehicle Power and Energy Management Strategy Learning Based Strategies Reinforcement Learning Grey Neural Network Particle Swarm Optimization
ES PSO-SVM NZE-HEV PEMS LB RL GNNM PSO V2V	Fractional-Order Extremum Seeking Support Vector Machine Method with Particle Swarm Optimization New Zero Emission Hybrid Electric Vehicle Power and Energy Management Strategy Learning Based Strategies Reinforcement Learning Grey Neural Network Particle Swarm Optimization Vehicle-to-Vehicle
ES PSO-SVM NZE-HEV PEMS LB RL GNNM PSO V2V V2I	Fractional-Order Extremum Seeking Support Vector Machine Method with Particle Swarm Optimization New Zero Emission Hybrid Electric Vehicle Power and Energy Management Strategy Learning Based Strategies Reinforcement Learning Grey Neural Network Particle Swarm Optimization Vehicle-to-Vehicle Vehicle-to-Infrastructure
ES PSO-SVM NZE-HEV PEMS LB RL GNNM PSO V2V V2I CAV	Fractional-Order Extremum Seeking Support Vector Machine Method with Particle Swarm Optimization New Zero Emission Hybrid Electric Vehicle Power and Energy Management Strategy Learning Based Strategies Reinforcement Learning Grey Neural Network Particle Swarm Optimization Vehicle-to-Vehicle Vehicle-to-Unfrastructure Connected and Automated Vehicles
ES PSO-SVM NZE-HEV PEMS LB RL GNNM PSO V2V V2V V2I CAV V2D	Fractional-Order Extremum Seeking Support Vector Machine Method with Particle Swarm Optimization New Zero Emission Hybrid Electric Vehicle Power and Energy Management Strategy Learning Based Strategies Reinforcement Learning Grey Neural Network Particle Swarm Optimization Vehicle-to-Vehicle Vehicle-to-Vehicle Vehicle-to-Infrastructure Connected and Automated Vehicles Vehicle-to-Device
ES PSO-SVM NZE-HEV PEMS LB RL GNNM PSO V2V V2I CAV V2I CAV V2D V2N	Fractional-Order Extremum Seeking Support Vector Machine Method with Particle Swarm Optimization New Zero Emission Hybrid Electric Vehicle Power and Energy Management Strategy Learning Based Strategies Reinforcement Learning Grey Neural Network Particle Swarm Optimization Vehicle-to-Vehicle Vehicle-to-Vehicle Vehicle-to-Infrastructure Connected and Automated Vehicles Vehicle-to-Device Vehicle-to-Network
ES PSO-SVM NZE-HEV PEMS LB RL GNNM PSO V2V V2I CAV V2I CAV V2D V2D V2N V2G	Fractional-Order Extremum Seeking Support Vector Machine Method with Particle Swarm Optimization New Zero Emission Hybrid Electric Vehicle Power and Energy Management Strategy Learning Based Strategies Reinforcement Learning Grey Neural Network Particle Swarm Optimization Vehicle-to-Vehicle Vehicle-to-Unfrastructure Connected and Automated Vehicles Vehicle-to-Device Vehicle-to-Network Vehicle-to-Network Vehicle-to-Grid
ES PSO-SVM NZE-HEV PEMS LB RL GNNM PSO V2V V2V V2I CAV V2D V2D V2D V2N V2C V2D	Fractional-Order Extremum Seeking Support Vector Machine Method with Particle Swarm Optimization New Zero Emission Hybrid Electric Vehicle Power and Energy Management Strategy Learning Based Strategies Reinforcement Learning Grey Neural Network Particle Swarm Optimization Vehicle-to-Vehicle Vehicle-to-Vehicle Vehicle-to-Infrastructure Connected and Automated Vehicles Vehicle-to-Device Vehicle-to-Network Vehicle-to-Grid Vehicle-to-Pedestrian
ES PSO-SVM NZE-HEV PEMS LB RL GNNM PSO V2V V2I CAV V2I CAV V2D V2D V2D V2N V2C V2P V2X	Fractional-Order Extremum Seeking Support Vector Machine Method with Particle Swarm Optimization New Zero Emission Hybrid Electric Vehicle Power and Energy Management Strategy Learning Based Strategies Reinforcement Learning Grey Neural Network Particle Swarm Optimization Vehicle-to-Vehicle Vehicle-to-Vehicle Vehicle-to-Infrastructure Connected and Automated Vehicles Vehicle-to-Device Vehicle-to-Network Vehicle-to-Network Vehicle-to-Pedestrian Vehicle-to-Everything
ES PSO-SVM NZE-HEV PEMS LB RL GNNM PSO V2V V2V V2I CAV V2I CAV V2D V2D V2D V2D V2D V2Q V2D V2Q V2P V2X DPR	Fractional-Order Extremum Seeking Support Vector Machine Method with Particle Swarm Optimization New Zero Emission Hybrid Electric Vehicle Power and Energy Management Strategy Learning Based Strategies Reinforcement Learning Grey Neural Network Particle Swarm Optimization Vehicle-to-Vehicle Vehicle-to-Vehicle Vehicle-to-Unfrastructure Connected and Automated Vehicles Vehicle-to-Device Vehicle-to-Device Vehicle-to-Network Vehicle-to-Grid Vehicle-to-Grid Vehicle-to-Pedestrian Vehicle-to-Everything Driving Pattern Recognition
ES PSO-SVM NZE-HEV PEMS LB RL GNNM PSO V2V V2I CAV V2I CAV V2D V2D V2D V2D V2D V2D V2D V2D V2D V2	Fractional-Order Extremum Seeking Support Vector Machine Method with Particle Swarm Optimization New Zero Emission Hybrid Electric Vehicle Power and Energy Management Strategy Learning Based Strategies Reinforcement Learning Grey Neural Network Particle Swarm Optimization Vehicle-to-Vehicle Vehicle-to-Vehicle Vehicle-to-Infrastructure Connected and Automated Vehicles Vehicle-to-Device Vehicle-to-Device Vehicle-to-Network Vehicle-to-Grid Vehicle-to-Grid Vehicle-to-Everything Driving Pattern Recognition Electric Motor
ES PSO-SVM NZE-HEV PEMS LB RL GNNM PSO V2V V2I CAV V2I CAV V2D V2D V2D V2N V2D V2N V2C V2P V2X DPR EM PHEV	Fractional-Order Extremum Seeking Support Vector Machine Method with Particle Swarm Optimization New Zero Emission Hybrid Electric Vehicle Power and Energy Management Strategy Learning Based Strategies Reinforcement Learning Grey Neural Network Particle Swarm Optimization Vehicle-to-Vehicle Vehicle-to-Unfrastructure Connected and Automated Vehicles Vehicle-to-Infrastructure Connected and Automated Vehicles Vehicle-to-Device Vehicle-to-Network Vehicle-to-Retwork Vehicle-to-Pedestrian Vehicle-to-Everything Driving Pattern Recognition Electric Motor Plug-in Hybrid Electric Vehicle
ES PSO-SVM NZE-HEV PEMS LB RL GNNM PSO V2V V2I CAV V2D V2N V2D V2D V2D V2D V2D V2D V2C V2D V2D V2D V2D V2D V2D V2D V2D V2D V2D	Fractional-Order Extremum Seeking Support Vector Machine Method with Particle Swarm Optimization New Zero Emission Hybrid Electric Vehicle Power and Energy Management Strategy Learning Based Strategies Reinforcement Learning Grey Neural Network Particle Swarm Optimization Vehicle-to-Vehicle Vehicle-to-Vehicle Vehicle-to-Infrastructure Connected and Automated Vehicles Vehicle-to-Device Vehicle-to-Device Vehicle-to-Network Vehicle-to-Retwork Vehicle-to-Pedestrian Vehicle-to-Everything Driving Pattern Recognition Electric Motor Plug-in Hybrid Electric Vehicle
ES PSO-SVM NZE-HEV PEMS LB RL GNNM PSO V2V V2I CAV V2I CAV V2D V2D V2D V2D V2D V2D V2Q V2D V2Q V2D V2C V2D V2C V2D V2C V2D V2C V2D V2C V2D V2C V2D V2C V2D V2C V2D V2C V2C V2C V2C V2C V2C V2C V2C V2C V2C	Fractional-Order Extremum Seeking Support Vector Machine Method with Particle Swarm Optimization New Zero Emission Hybrid Electric Vehicle Power and Energy Management Strategy Learning Based Strategies Reinforcement Learning Grey Neural Network Particle Swarm Optimization Vehicle-to-Vehicle Vehicle-to-Vehicle Vehicle-to-Infrastructure Connected and Automated Vehicles Vehicle-to-Device Vehicle-to-Device Vehicle-to-Network Vehicle-to-Grid Vehicle-to-Grid Vehicle-to-Fedestrian Vehicle-to-Everything Driving Pattern Recognition Electric Motor Plug-in Hybrid Electric Vehicle ad Parameters Speed of the Vehicle
ES PSO-SVM NZE-HEV PEMS LB RL GNNM PSO V2V V2I CAV V2D V2D V2D V2D V2D V2D V2D V2	Fractional-Order Extremum Seeking Support Vector Machine Method with Particle Swarm Optimization New Zero Emission Hybrid Electric Vehicle Power and Energy Management Strategy Learning Based Strategies Reinforcement Learning Grey Neural Network Particle Swarm Optimization Vehicle-to-Vehicle Vehicle-to-Vehicle Vehicle-to-Infrastructure Connected and Automated Vehicles Vehicle-to-Device Vehicle-to-Device Vehicle-to-Network Vehicle-to-Grid Vehicle-to-Pedestrian Vehicle-to-Pedestrian Vehicle-to-Everything Driving Pattern Recognition Electric Motor Plug-in Hybrid Electric Vehicle and Parameters Speed of the Vehicle Vehicle Mass
ES PSO-SVM NZE-HEV PEMS LB RL GNNM PSO V2V V2I CAV V2D V2N V2D V2D V2N V2D V2N V2C V2P V2X DPR EM PHEV Variables ar v m _v F _a	Fractional-Order Extremum Seeking Support Vector Machine Method with Particle Swarm Optimization New Zero Emission Hybrid Electric Vehicle Power and Energy Management Strategy Learning Based Strategies Reinforcement Learning Grey Neural Network Particle Swarm Optimization Vehicle-to-Vehicle Vehicle-to-Vehicle Vehicle-to-Infrastructure Connected and Automated Vehicles Vehicle-to-Device Vehicle-to-Device Vehicle-to-Network Vehicle-to-Retwork Vehicle-to-Grid Vehicle-to-Pedestrian Vehicle-to-Everything Driving Pattern Recognition Electric Motor Plug-in Hybrid Electric Vehicle and Parameters Speed of the Vehicle Vehicle Mass Aerodynamic Friction
ES PSO-SVM NZE-HEV PEMS LB RL GNNM PSO V2V V2I CAV V2I CAV V2D V2N V2D V2N V2D V2N V2C V2P V2X DPR EM PHEV Variables ar v m _v F _a F _r	Fractional-Order Extremum Seeking Support Vector Machine Method with Particle Swarm Optimization New Zero Emission Hybrid Electric Vehicle Power and Energy Management Strategy Learning Based Strategies Reinforcement Learning Grey Neural Network Particle Swarm Optimization Vehicle-to-Vehicle Vehicle-to-Vehicle Vehicle-to-Infrastructure Connected and Automated Vehicles Vehicle-to-Device Vehicle-to-Device Vehicle-to-Network Vehicle-to-Reid Vehicle-to-Reid Vehicle-to-Pedestrian Vehicle-to-Pedestrian Vehicle-to-Everything Driving Pattern Recognition Electric Motor Plug-in Hybrid Electric Vehicle A Parameters Speed of the Vehicle Vehicle Mass Aerodynamic Friction Rolling Friction

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