POSTPRINT VERSION. The final version is published here: Khalatbarisoltani, A., Zhou, H., Tang, X., Kandidayeni, M., Boulon, L. et Hu, X. (2023) Energy Management Strategies for Fuel Cell Vehicles: A Comprehensive Review of the Latest Progress in Modeling, Strategies, and Future Prospects. IEEE Transactions on Intelligent Transportation Systems. https://doi.org/10.1109/TITS.2023.3309052

Energy Management Strategies for Fuel Cell Vehicles: A Comprehensive Review of the Latest Progress in Modeling, Strategies, and Future Prospects

Arash Khalatbarisoltani, *Member, IEEE*, Haitao Zhou, Xiaolin Tang*, *Senior Member*, *IEEE*, Mohsen Kandidayeni*, Member, IEEE*, Loïc Boulon, *Senior Member, IEEE*, and Xiaosong Hu*, *Senior Member*, *IEEE*

[1]***Abstract*--Fuel cell vehicles (FCVs) are considered a promising solution for reducing emissions caused by the transportation sector. An energy management strategy (EMS) is undeniably essential in increasing hydrogen economy, component lifetime, and driving range. While the existing EMSs provide a range of performance levels, they suffer from significant shortcomings in robustness, durability, and adaptability, which prohibit the FCV from reaching its full potential in the vehicle industry. After introducing the fundamental EMS problem, this review article provides a detailed description of the FCV powertrain system modeling, including typical modeling, degradation modeling, and thermal modeling, for designing an EMS. Subsequently, an in-depth analysis of various EMS evolutions, including rule-based and optimization-based, is carried out, along with a thorough review of the recent advances. Unlike similar studies, this paper mainly highlights the significance of the latest contributions, such as advanced control theories, optimization algorithms, artificial intelligence (AI), and multi-stack fuel cell systems (MFCSs). Afterward, the verification methods of EMSs are classified and summarized. Ultimately, this work illuminates future research directions and prospects from multi-disciplinary standpoints for the first time. The overarching goal of this work is to stimulate more innovative thoughts and solutions for improving the operational performance, efficiency, and safety of FCV powertrains.**

***Index Terms*--Energy management strategy (EMS), fuel cell vehicle (FCV), modeling, proton exchange membrane fuel cell (PEMFC).**

I. Introduction

The transportation sector accounted for 29% of total U.S. greenhouse gas emissions in 2019 [1]. The supporters of hydrogen imagine an atmosphere free of air pollution by replacing gasoline with hydrogen. Fuel cells (FCs) use oxygen as an oxidizing agent and hydrogen as a fuel to generate electricity [1]. FCs are employed in transportation, stationary, and portable applications. According to the nature of the electrolyte, FCs can be classified into five types: alkaline fuel cells (AFCs), phosphoric acid fuel cells (PAFCs), molten carbonate fuel cells (MCFCs), solid oxide fuel cells (SOFCs), and proton exchange membrane fuel cells (PEMFCs). AFC was the first type to come into practice. However, interest in AFC technology declined due to some economic factors, such as material issues and the operational shortcomings of electrochemical plants. PAFCs are commonly used in combined heat and power applications. MCFCs and SOFCs are high-temperature FCs used in cogeneration and combined-cycle systems. With the advantages of high-power density, low noise, lightweight, fast start-up, and low corrosion, PEMFCs have been broadly used in fuel cell vehicles (FCVs). FCVs with local zero-emission and long mileage are getting more attention from automobile manufacturers in different countries. A well-to-wheel (WTW) comparison demonstrates that a hydrogen FCV offers 5%-33% lower fossil fuel energy consumption and 15–45% lower greenhouse gas emissions than an ICEV driven by gasoline [2]. FCVs have a higher WTW cost than battery electric vehicles (BEVs), which is the key obstacle to their penetration into the automobile market. If the production costs for hydrogen and FCVs fall, the levelized cost of driving (LCD) for hydrogen and FCVs could be comparable to gasoline ($0.29/km) and BEVs ($0.30/km) by 2030 [3].

Single-stack FCSs (SFCSs) face several challenges: efficiency, availability, durability, and cost. Each cell needs an appropriate distribution of humidity, hydrogen, water, and temperature in the FCS. In malfunctioning cells, uneven heating and variations in cell voltages can happen, so continuing operation under this condition may be impossible. Furthermore, the traction power of buses, trucks, trailers, trains, and ships can reach high levels, so it is necessary to shift to larger FCS, which can generate

This work was supported in part by the Natural Science Foundation of China (No. 52072051 and No. 52222215), in part by the project of basic research funds for central universities (No. 2022CDJDX-006), and in part by the Talent Plan Project of Chongqing (No. cstc2021ycjh-bgzxm0295). The work of L. Boulon is supported in part by the Natural Sciences and Engineering Research Council of Canada (NSERC) and in part by the Canada Research Chairs program. *(Corresponding authors: Xiaolin Tang and Xiaosong Hu)*

A. Khalatbarisoltani, H. Zhou, X. Tang, and X. Hu are with the Department of Mechanical and Vehicle Engineering, Chongqing University, Chongqing, 400044, China (emails: arash.khalatbarisoltani@cqu.edu.cn; htzhou123@163.com; tangxl0923@cqu.edu.cn; xiaosonghu@ieee.org). M. Kandidayeni is with the Department of Electrical and Computer Engineering, Université de Sherbrooke, QC J1K 2R1, Canada (email: mohsen.kandidayeni@usherbrooke.ca). L. Boulon is with the Department of Electrical and Computer Engineering, Université du Québec à Trois-Rivières, QC G8Z 4M3, Canada (email: loic.boulon@uqtr.ca).

more power. However, stacking more cells reduces the reliability of the powertrain systems. Multi-stack FCS (MFCS) is introduced in the literature to address these deficiencies and imperfections of single-stack FCS. In [4], Marx *et al*. provided a survey of MFCSs with different architectures. Thounthong *et al.* [5] reviewed different methods regarding the power-conditioning systems for the SFCS and MFCS. Nevertheless, the PEMFC cannot meet all the requirements of an FCV owing to some operational limitations, such as slow dynamic response, slow-moving electrochemical reaction, and incapability of recovering braking energy [6-8]. Therefore, the powertrains of FCVs are generally composed of at least two different sources: an FC system (FCS) as the primary source and a battery and/or supercapacitor (SC) unit as the auxiliary energy source (AES). The AES can absorb regenerative braking energy and provide peak power, effectively alleviating the deficiencies of the FCS [9]. Since different voltage levels between power sources lead to low efficiency of direct connection to the electric motor, a DC/DC converter is used to convert the output voltage, as shown in Fig. 1. The advantages and disadvantages of FCV topologies are summarized in Table I.

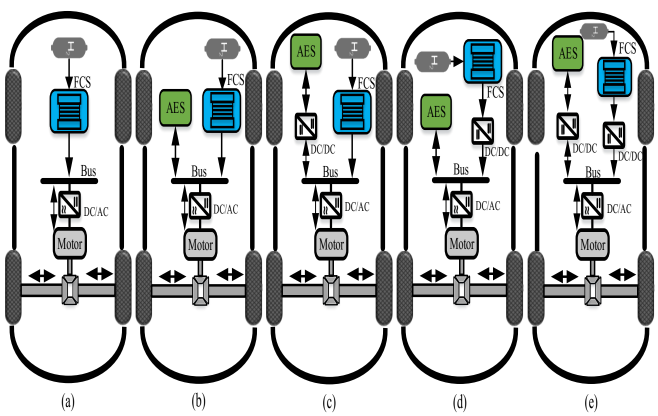

Fig. 1. The classification of FCV powertrain systems: (a) Topology T1, (b) Topology T2, (c) Topology T3, (d) Topology T4, and (e) Topology T5.

An energy management strategy (EMS) distributes the power between the FCS and AES by considering different power sources' characteristics. Developing an efficient EMS in FCVs is a critical technical problem that many academic and industrial scholars have intensively studied over the past few decades. Several review papers have discussed the results and progress of EMSs in FCV applications. For instance, Sulaiman *et al.* [13] provided a review discussion of the different classes of FCV EMSs and their optimization methods. Yue *et al.* [14] discussed the degradation modeling approaches and reviewed various EMSs, considering the degradation phenomenon. Similarly, Lü *et al.* [15] summarized the application of genetic algorithms (GAs) in designing EMSs. Tran *et al.* [16] recently presented a survey of powertrain types, component configurations, and EMS for electric and hybrid vehicles.

The driving cycle has an essential impact on the fuel economy of a vehicle [17]. Typically, a driving cycle can be derived from the field by monitoring the speed of a vehicle. Then, cycle identification and traffic flow modeling can be utilized to determine the cycle [18]. Due to the increasing complexity and uncertainty of traffic conditions, the accuracy of the driving cycle recognition methods is low, and the obtained driving conditions are inconsistent with the actual situation. On the other hand, the traffic flow models can only reflect the route characteristics with solid regularity. The difference between the real and standard driving conditions leads to the fact that the fuel economy of EMS cannot reach the theoretical optimum in practical applications. The rapid development of intelligent transportation systems (ITS), vehicle-to-vehicle (V2V), vehicle-to-everything (V2X), and vehicle-to-infrastructure (V2I) technologies provide more real-time and available traffic data, which offers new ideas for real-time optimization of an EMS design. V2V, V2X, and V2I technologies can accurately quantify traffic flow and driving cycle conditions and effectively improve the overall performance of vehicles, including mobility, safety, and fuel economy. Furthermore, the actual driving process of cars will inevitably be affected by vehicles, pedestrians, traffic jams, traffic lights, and other factors [19, 20], which can be obtained through ITS technology.

Several significant contributions distinguish this review paper from the previous ones. Firstly, the fundamental EMS problem is comprehensively described. Secondly, the modeling of power sources in the EMS of FCV is carefully presented, including typical modeling, degradation modeling, and thermal modeling. Thirdly, the most recently published papers are surveyed, emphasizing covering state-of-the-art approaches. Next, the advanced and new verification methods of EMSs are summarized. Finally, several potential research directions are suggested to overcome the existing critical challenges.

The rest of this review article is organized in the following manner. The fundamental EMS problem is described in detail in Section II. A comprehensive introduction to power source mathematical representations is put forward in Section III. Section IV classifies different EMSs. After Section IV briefly explains the contents of EMS verification methodologies.

Table I
The benefits and drawbacks of various FCV powertrain topologies

Topology	Advantages	Disadvantages	References
T1	Simple structure	Slow dynamic response; cannot recover braking energy; Reduce the powertrain components' lifetime	[8]
T2	High static and dynamic performance, eliminate power loss of electronic hardware	Set the power sources to work in the same voltage range Reduce the powertrain components' lifetime, unable to control the energy buffer	[10]
T3	Soft switching operation minimizes the loss of DC/DC converter under sudden load conditions	High electric power loss	[11]
T4	Widely used topology, power distribution control is easy to implement	Low power flow control flexibility	[12]
T5	Stable DC voltage, high control flexibility in power flow	Complex structure	[11]

Finally, several future trends are provided in Section VI. The conclusions are presented in Section VII.

II. A DESCRIPTION OF THE FUNDAMENTAL PROBLEM OF ENERGY MANAGEMENT IN FUEL CELL VEHICLES

The energy-management problem for FCVs is depicted in Fig. 2. An EMS primarily aims to maximize the efficiency of the onboard energy/power sources by allocating power between them. Control objectives can include one or more criteria, including minimizing hydrogen consumption, extending the FCS life, extending energy storage lifetime, improving driver comfort, ensuring safety, and enhancing mobility. The decision-making problem is usually constrained by three physical constraints: powertrain dynamics, beginning and ultimate values of state variables, and control actions and state variable restrictions. The desired power from each energy/power source and the hydrogen cost can be calculated based on the powertrain dynamics once the inputs (for example, the requested power, the vehicle velocity, and the current values of SOC and SOH for the energy/power sources, and the steering angle speed) for this decision-making problem are provided in advance. The state variables are generally the SOC of the energy/power sources, the position of the gearbox, and the electric motor speed. The output torque of the electric motor, gear shifting, and clutch condition are frequently used as control actions. Limits for these parameters are also required to address this control problem. A mathematical model of the powertrain components is necessary as part of the solution, in addition to the control objective and constraints. The modeling of an FCS can entail calculating hydrogen consumption, estimating efficiency, stack temperature, generated water, and so forth. The energy/power source modeling considers the SOC variation and the link between the open-circuit voltage and internal resistance with the SOC. The rest of this section falls into three parts. Firstly, the mathematical description of the energy management problem is presented, which includes modeling the FCS, battery, and SC based on the overall explanation of the EMS problem. A full assessment of developed energy management systems and strategies is then reviewed. A specific section is offered to investigate the decision-making strategy assessment platforms.

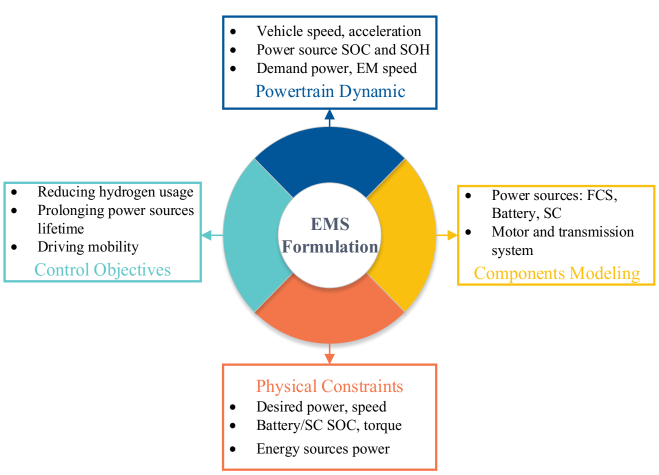

Fig. 2. An overview of general energy management problem for FCVs.

III. MODELING AND MATHEMATICAL REPRESENTATION APPROACHES

Modeling can effectively reflect the performance of power sources with different physical characteristics. This section reviews the suitable modeling approaches in EMS. To gain a deeper understanding of FC, battery, and SC modeling, it is highly recommended to refer to [21], [22], and [23], respectively.

A. PEMFC Modeling

PEMFCs produce electricity and byproducts (heat and water vapor) from the electrochemical reaction of hydrogen and oxygen. A PEMFC stack comprises several single cells, including bipolar plates, gas diffusion layers, micro-porous layers, catalyst layers, and proton exchange membranes.

1) Basic

The characteristics of a PEMFC are usually represented by power, efficiency, and polarization curves, among which the polarization curve is the most representative, as shown in Fig. 3. The polarization curve represents the relationship between current and voltage in the FC stack, where the voltage losses include the activation loss (driving the chemical reaction), ohmic loss (resistance associated with electrodes, electrolytes, and others), and concentration loss (reduction in the concentration of reactants on the electrode surface) [24]. Therefore, the cell voltage can be determined by subtracting the total voltage loss from the open-circuit voltage. The open-circuit voltage expression proposed by Amphlett *et al.* [25] has been widely used. The ohmic voltage loss can be determined using Ohm's law equation. However, the activation voltage and concentration voltage can be expressed differently. For instance, Li *et al.* [26] ignored concentration voltage losses to reduce the computational burden of the model, and the Tafel equation was used to describe the activation loss. Djerioui *et al.* [27] considered the effect of partial oxygen pressure P_{O_2} on concentration loss, and used the Tafel equation to represent the activation loss. Considering that using the Tafel equation to describe the relationship between activation loss and current density is not valid for small current [28], Chen *et al.* [29] employed another model for activation loss, making it reasonable for the entire current range. In this model, the concentration loss is determined by the current density. Furthermore, Fathy *et al.* [30] used a unified expression containing parameter factors ξ_i and oxygen concentration C_{O2} to represent the activation loss at the anode and cathode in an EMS application. An alternative model for concentration loss was proposed using the current density parameter. The above models are summarized in Table II, where R represents the gas constant, F is the Faraday constant, α is the charge transfer coefficient, i is the current of FCS, I_0 is the exchange current density, I_{max} is the maximum current density, S represents the catalyst layer cross-sectional area, N_{cell} is the number of cells, and A, m, n, b, and a are empirical coefficients.

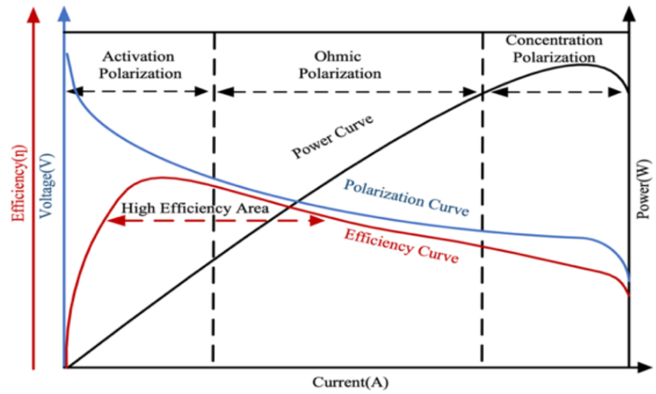

Fig. 3. Different voltage loss regions, along with power, efficiency, and polarization curves.

2) Degradation

Changes in output voltage, internal resistance, and output power are considered indicators of FCS degradation. Most of the researchers use FCS voltage to estimate the degradation. The degradation of the MEA performance comes from the following sources: catalyst layer degradation, PEM degradation, and gas diffusion layer degradation [31, 32]. A detailed description of MEA degradation is provided in [31-33], and the main degradation mechanisms concerning the loading of the PEMFC are shown in Fig. 4.

Pei *et al.* [34] proposed a quantitative description of the relationship between the PEMFC's available lifetime and the load variation, start/stop, idling, and high power load. In this model, output voltage decay is used as an indicator of degradation, and a ten-percent voltage decline is considered the end of life. In this model, t_1, n_1, t_2, and t_3 are idle time, start/stop cycles, heavy load duration, and heavy load time, respectively. The corresponding degradation coefficients are k_1, k_2, k_3, and k_4. Jiang *et al.* [35] applied the voltage decay formula of the previous model for designing an EMS. Then, Hu *et al.* [36] added natural decay β to the voltage decay formula. Fletcher *et al.* [33] evaluated FCS degradation by establishing degradation functions for high and low power ranges between 0 and 1, transient operation, and start-stop cycles. Moreover, Li *et al.* [37] constructed an online model for assessing the degradation of PEMFC in an EMS application. Among open-circuit voltage E_0, total resistance R, exchange current i_0, and limiting current i_L, only R and i_L change linearly with time. Therefore, the degradation parameter $\alpha(t)$ is chosen to represent the degradation of R and i_L. The above-discussed models are summarized in Table II.

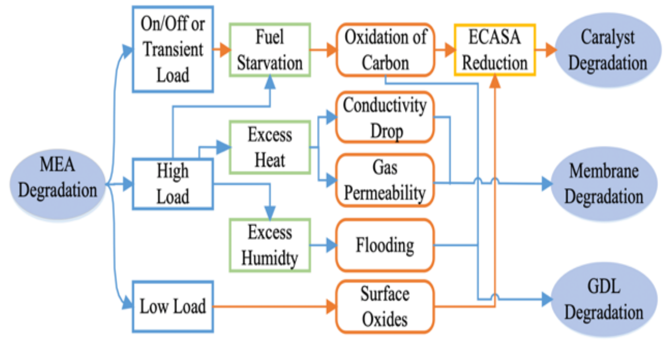

Fig. 4. The main degradation mechanisms of MEA associated with PEMFC loading, adopted from [31].

3) Thermal

Excessive heat generated during the electrochemical reaction of PEMFC is not conducive to its safe and efficient operation. Therefore, it is necessary to build a thermal model of PEMFC to manage the heat to operate safely and efficiently within the appropriate temperature range (340–350 K) [41]. Olivier *et al.* [38] developed a dynamic thermal model for an EMS, in which the heat source P_{src} is produced due to the electrochemical reaction. The heat dissipation happens in the FC channel P_{ab} through the air velocity, the liquid-vapor phase change of the water generated by the electrochemical reaction P_{stm}, the natural convection P_{nat}, and the forced convection generated by the blower P_{cb}. Moreover, He *et al.* [40] developed a temperature dynamic system equilibrium model for a water-cooled PEMFC, in which the total generated heat is the difference between the energy produced by the electrochemical reaction $\dot{H}_{rea}$ and the power induced by PEMFC $\dot{Q}_{ele}$, the

Table II
The summary of PEMFC modeling

Model	Equation	Ref
Basic	$V_{stack} = N_{cell}(E_0 - \frac{RT}{2aF}\ln(\frac{i}{I_0 S}) - i \cdot R)$	[26]
	$V_{stack} = N_{cell}(E_0 - A\ln(i/i_0) - iR - (me^{(ni)} + b\ln(P_{o_2}/a)))\frac{1}{2}$	[27]
	$V_{stack} = N_{cell}((E_0 - (v_0 + v_a(1-e^{-C_1 i})) - i(C_2 i/i_{\max})^{C_3} - iR))$	[29]
	$V_{stack} = N_{cell}(E_0 - (\xi_1 + \xi_2 T + \xi_3 T\ln(C_{o_2}) + \xi_4 T\ln(i)) - iR - b\ln(1 - \frac{i/S}{I_{\max}}))$	[30]
Degradation	$T_f = \Delta P \div (k_p(K_1 t_1 + K_2 n_1 + K_3 t_2 + K_4 t_3))$	[34]
	$D_{FC} = Kp(k_1 t_1 + k_2 n_1 + k_3 t_2 + k_4 t_3)$	[35]
	$D_{FC} = Kp(k_1 t_1 + k_2 n_1 + k_3 t_2 + k_4 t_3 + \beta)$	[36]
	$D_{FC} = D_{power} + D_{tran} + D_{cycle}$	[33]
	$V_{st} = n(E_0 - R_0(1+\alpha(t))i - AT\ln(\frac{i}{i_0}) - BT\ln(1 - \frac{i}{i_{L0}(1-\alpha(t))}))$	[37]
Thermal	$m_{st}C_{st}dT_{st}/dt = P_{src} - Q_{ab} - Q_{stm} - Q_{nat} - Q_{cb}$	[38]
	$m_{st}C_{st}dT_{st}/dt = P_{loss} - Q_{Nat} - Q_{Forced}$	[39]
	$m_{fc}C_{fc}\frac{dT_{fc}}{dt} = \dot{H}_{rea} - \dot{Q}_{ele} - \dot{Q}_{rad} - \dot{Q}_{cool}$	[40]

power dissipated by thermal radiation $\dot{Q}_{rad}$, and the power dissipated by the cooling system $\dot{Q}_{cool}$. The above models are summarized in Table II, where m_{fc} and C_{fc} are the mass and specific heat capacity of PEMFC, respectively.

B. Battery Modeling

The most common rechargeable batteries are Lead-acid, Nickel-metal hydride (NiMH), and Lithium-ion [42]. Lead-acid batteries are inexpensive and reliable but have disadvantages, such as high maintenance and heavy metal pollution problems. NiMH batteries have reliable cycling but relatively low energy density, low cycle life, and high self-discharge rates. As a result, lithium-ion batteries with a better power density and cycle life are more suitable for FCV applications [43].

1) Basic

As the most widely used battery model, the equivalent circuit models (ECMs) mainly use multiple circuit elements to simulate the charge and discharge characteristics of the battery [44]. For example, these models include R_{int} [45], Thevenin [46], PNGV [47], and dual-polarization [48]. The R_{int} model consists of an ideal voltage source and resistance, ignoring battery polarization effects and changes in internal resistance. It is often used for system-level energy management optimization. The Thevenin model is also called the resistance-capacitance (RC) ECM, which adds an RC network to describe the polarization effect of the battery based on the R_{int} model. The PNGV model adds a capacitor to consider the change of open-circuit voltage based on the Thevenin model, effectively solving the problem of open-circuit voltage changing with battery SOC. The dual-polarization model is an improved model of the Thevenin model, which takes into account the charging and discharging process more accurately and is considered to be the best model for the lithium-ion battery simulation [44]. Although the ECM models are simple and the efficiency calculation is high, they cannot reflect the mechanism of reaction that occurs inside the battery. Therefore, the reduced-order electrochemical models that can directly reflect the internal micromechanical reaction process of the battery have been extensively studied [49]. However, the electrochemical model involves numbers coupled with partial differential equations, and the calculation is too large. To reduce the computational burden complexity, some order reduction techniques are used. Although developing the reduced-order electrochemical battery models can be time-consuming, it can be done once, and the results can be generalized into different models with the same essential features. for the reduction of complex electrochemical models, such as the Galerkin projection [50], the ε-embedding method [49], and domain decomposition and polynomial approximation methods [51], etc. Since many key parameters of the electrochemical model cannot be directly measured, parameter identification methods are used to identify the key parameters. Standard parameter identification methods include the genetic algorithm [52], Fisher information matrix [53], homotopy algorithm [49], etc. Amir *et al.* [54] used the reduced-order electrochemical model proposed by Masoudi *et al.* [49] in the EMS of the plug-in HEV. Therefore, applying the reduced-order electrochemical model to EMS has good prospects. The above ECMs are summarized in Table III, where V is the terminal voltage, V_{oc} is the open-circuit voltage, I_{bat} is the battery current, R_0 is the internal resistance, V_p is the polarization voltage and V_{cp} is the capacitance-voltage.

2) Degradation

Despite the discussed advantages of lithium-ion batteries in FCV applications, battery aging remains a barrier to their full penetration in the market. As an AES, the battery pack has the advantages of high power density and long life cycle [55, 56]. However, the lifetime of the battery declines due to the number of charging/discharging cycles and the temperature variation [57]. Battery degradation is a complex process influenced by many factors, such as battery SOC, depth of discharge (DOC), temperature, and charge/discharge rates [58]. The degradation mechanism of lithium-ion batteries comes from mechanical and chemical degradation mechanisms. The mechanical degradation mechanism is related to the volume change and stress generated when lithium-ion is repeatedly intercalated into the active material. In contrast, the chemical degradation mechanism is connected to the reactions, such as solid electrolyte interphase formation, electrolyte decomposition/reduction, and active material dissolution [59]. Moreover, battery aging can be divided into two types: cycle aging and calendar aging. Cycle aging occurs when the battery is charged/discharged due to the battery's current rate (C_{rate}), utilization mode, temperature conditions, SOC, and DOD [60]. Wang *et al.* [61] established a cycle aging model by studying the relationship between DOD, temperature, and C_{rate}, and the aging of lithium-ion batteries. Then, Hu *et al.* [31] applied it to an EMS problem of an FCV. Suri *et al.* [62] replaced the pre-exponential coefficient in the previous model with a function of the SOC variable and applied it to the EMS of HEVs. On the other hand, calendar aging refers to the aging of the battery over time in storage mode, which is mainly concerned with battery temperature and SOC [63]. Sarasketa-Zabala *et al.* [63] analyzed the effect of temperature and SOC on calendar life and built a calendar life model under static and dynamic operating conditions. Zhang *et al.* [64] took cycle and calendar aging in EMS and applied this model to evaluate calendar aging. In another work, Song *et al.* [65] discretized the model and used it for designing an EMS. The above models are summarized in Table III, where E_a is the activation energy, η is the compensation factor for C_{rate}, A_h is the accumulated Ah-throughput, and α, β, α_1, β_1, α_2, β_2, a, b, c, and d are the fitting coefficients.

3) Thermal

The performance of the lithium-ion battery is strongly linked to temperature [66]. To study the effect of battery temperature on hydrogen consumption of FCV, Zheng *et al.* [67] built a lumped capacitance thermal model based on the energy balance among the generated heat Q_{gen}, the heat loss Q_{loss}, the mass m_{bat}, and the service time *T*. In addition, Tang *et al.* [68] studied the EMS of PHEV by a control-oriented thermal model. The heat generated by the internal resistance r and temperature influence coefficients dE_{oc}/dT is considered, and the heat loss is neglected. The above models are summarized in Table III, where C_p, I, and T are the heat capacity, current, and temperature of the battery, respectively. In addition to thermal modeling efforts based on a single state, thermal distributions inside a power pack are also modeled. To better comprehend the thermodynamic properties of battery cells in a pack during simulated drive cycles, a three-dimensional thermal model has been constructed [69]. Using the porous electrode and concentrated solution concept in [70], a thermal model for lithium-ion battery packs has been constructed. During the discharging and charging operation, rechargeable batteries' temperature fluctuates as a result of internal heat generation; a full investigation of battery heat generation considering many contributing elements is conducted in [71].

Table III
The summary of Lithium-ion battery modeling

Model	Equation	Ref
Basic	$V = V_{OC} - I_{bat}R_0$	[46]
	$V = V_{OC} - I_{bat}R_0 - V_{p_1}$	[47]
	$V = V_{OC} - I_{bat}R_0 - V_{p_1} - V_{p_2}$	[48]
Degradation	$Q_{loss} = B(c)\cdot\exp\left(\frac{-E_a(c)}{RT}\right)A_h(c)^z$	[31, 61]
	$Q_{loss} = (\alpha\cdot SOC+\beta)\cdot\exp\left(\frac{-E_a+\eta\cdot I_c}{R\cdot(273.15+T)}\right)A_h^z$	[62]
	$Q_{loss} = \alpha_1\cdot\exp(\beta_1\cdot T^{-1})\cdot\alpha_2\cdot\exp(\beta_2\cdot SOC)\cdot t^{0.5}$	[63, 64]
	$Q_{loss} = \exp^{(a(T)\times I)}\cdot\exp\left(\frac{c\cdot SOC}{a}\right)\cdot\exp\left(\frac{d}{a}\right)\cdot\exp\left(\frac{-b}{aT}\right)$	[65, 72]
Thermal	$m_{bat}C_p dT/dt = Q_{gen} - Q_{loss}$	[67]
	$m_{bat}C_p dT/dt = I(Ir + T\frac{dE_{oc}}{dT})$	[68]

C. SC Modeling

The SC is mainly composed of an electrode, a separator, and an electrolyte, which separate positive and negative charges to store the energy [73]. Table IV presents the SC model presented in this section.

1) Basic

Like lithium-ion batteries, SCs are modeled using ECM. Among various ECMs, the simple RC model is suitable for simulating the energy behavior of an SC [74]. To improve the accuracy of the model, a series resistance, R_s, is used to mimic the charge and discharge resistance behaviors, and a parallel resistance, R_p, represents the self-discharge loss [75].

2) Degradation

Therefore, with the advantages of a long life cycle, high-power density, temperature independence, and unlimited charging/discharging cycles, the SC can replace or work with the battery to provide peak power for the FCV [76, 77]. Despite the superior performance of SCs, degradation is still an important issue. The two leading indicators of SC degradation are an increase in equivalent series resistance (ESR) and a decrease in capacitance [78]. Since an increase in voltage and temperature may accelerate the decomposition of SC electrolytes and the side reactions within the electrode, voltage, and temperature are the two main factors affecting the aging of SCs [79]. In the EMS, Lhomme *et al.* [80] assumed that the expected service life of SCs under normal operating conditions is continuous, and the degradation model of SCs can be expressed by the ratio of service time t_{use} to the expected lifetime L_{SC}. This model cannot reflect the internal mechanism of SC degradation. Therefore, the application of SCs' aging models for energy management needs to be further studied.

3) Thermal

SCs operate at a high circulation rate and generate much heat inside, which can significantly impact the performance and lifetime of the SC [23]. Studies on SC thermal models can be divided into two categories: some are based on geometric and compositional differential equations, while others propose comprehensive models to describe SC thermal dynamics [81]. However, there are few studies on the effect of the heat generated by SC on the performance of an EMS. Therefore, it would be interesting to integrate SC thermal management into an EMS design.

Table IV
The summary of SC modeling

Model	Equations	Ref
Basic	$V = V_C - I_{sc}R_s$	[74]
	$V = R_s\cdot I_{sc} + \frac{1}{C}\int\left(I_{sc} - V_C/R_p\right)$	[75]
Degradation	$D_{SC} = \frac{t_{use}}{L_{SC}}$	[80]

IV. The Latest Development in Energy Management Strategies and Methods for Fuel Cell Vehicles

A comprehensive review of recent advances in EMSs for FCVs is performed in this section. In addition, a detailed analysis of the advantages and disadvantages of EMSs is

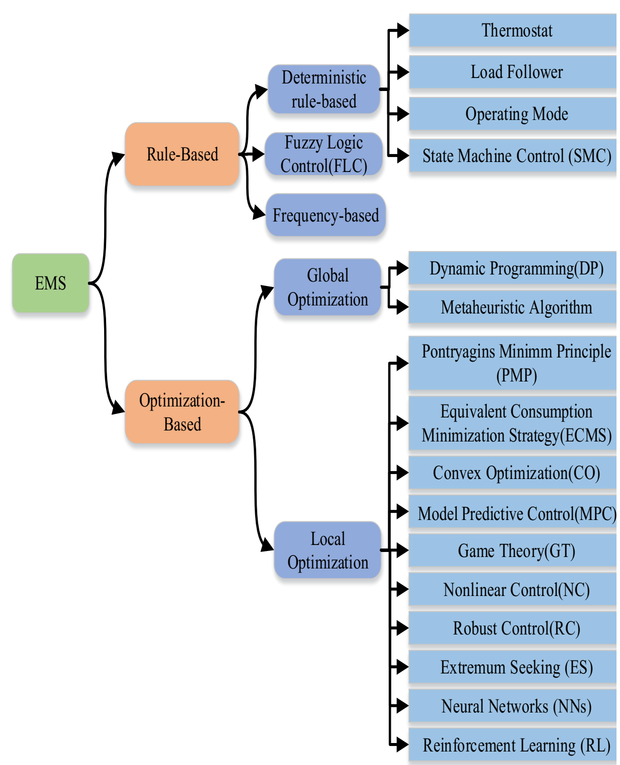

Fig. 5. The classification of EMSs for an FCV.

provided. These strategies are rule-based and optimization-based, as shown in Fig. 5.

A. Rule-based

The rule-based EMSs are generally determined based on expert knowledge and without prior knowledge of a drive cycle. These strategies are classified into deterministic, fuzzy logic control (FLC), and frequency-based approaches. The deterministic approaches can be generally classified into the thermostat, load follower, operating mode, and state machine control (SMC). Li *et al.* [82] developed an EMS based on a combination of FLC and Haar wavelet transform for a tramway. Chen *et al.* [83] suggested an adaptive EMS with FLC parameter tuning to guarantee an acceptable performance in different driving conditions. Zhou *et al.* [84] put forward an online EMS according to a combination of obtained parameters from offline optimized FLCs utilizing a data fusion method. Zhang *et al.* [85] developed an adaptive FLC-based EMS. Driving pattern recognition is performed using the features extracted from the historical velocity window with a multilayer perceptron NN (MLPNN). Generally, the frequency-based EMS breaks down the requested power into high and low frequencies. Fu *et al.* [86] designed a hierarchical EMS based on a low-pass filter and the equivalent consumption minimization strategy (ECMS) to enhance the energy sources' lifetime, performance, and hydrogen economy. An optimized frequency decoupling EMS via the FLC approach was introduced by Fu *et al.* [87] to prolong the FCS lifetime and ameliorate hydrogen economy.

B. Optimization-Based EMSs

The optimization-based strategies are classified into global and local methods. According to the main features and objectives of the optimization-based EMSs, the related papers are summarized in Table V.

1) Global Optimization

Global optimization strategies need traffic and road conditions knowledge in advance to calculate the optimal operation trajectory of power sources. However, precise road information is challenging to get in real-time, and the computation burden is high, making it challenging for the FCV real-time application.

a) Dynamic Programming (DP)

DP is one of the most vital approaches for computing global optimal solutions in an FCV. It is often used as a benchmark solution for other EMSs. For instance, Ansarey *et al.* [88] offered an optimal solution for the hydrogen economy using a multi-dimensional DP. After introducing a model to estimate the effect of EMS on the FC degradation phenomena, Fletcher *et al.* [33] proposed an optimal EMS by using stochastic DP to improve the hydrogen economy and lifespan of the powertrain. Li *et al.* [89] developed an optimal EMS based on a multi-objective DP method to match the hydrogen consumption and the battery SOH in a range-extended bus. Zhou et al. [90] focused on developing a unified DP algorithm to solve the EMS problem. Ali *et al.* [91] introduced an advisory DP for a real-time optimal EMS. A state space is defined as driver-dependent and driver-independent states, and then a statistical model is developed for FCV state prediction. Peng *et al.* [92] introduced a scalable and adaptive rule-based EMS. The rules are determined by the results of a two-dimensional DP under different driving profiles.

b) Metaheuristic Algorithm

As one of the most-famous metaheuristic algorithms, GA is often combined with other approaches to improve overall performance. Zhang and Tao [93] offered a combination of FLC with a low pass filter to extend the FCS lifetime and enhance the hydrogen economy. A modified GA is used to seek the best parameters of the FLC membership functions and fuzzy rules. Another popular metaheuristic algorithm is the particle swarm optimization (PSO) algorithm. Geng *et al.* [94] investigated a constrained multi-objective PSO algorithm to solve an EMS problem for an FC/Battery PHEV. Koubaa *et al.* [95] suggested an online EMS integrated with a derivative-free algorithm. In this work, a set of rules is defined to restrict the search space of the PSO algorithm. Ahmed Fathy *et al.* [96] proposed a metaheuristic-based EMS for a hybrid electric power system that uses a coyote optimization method.

2) Local Optimization

A local optimization strategy replaces the global cost function with an instantaneous cost function to calculate the optimal power split among different power sources.

a) Pontryagin's Minimum Principle (PMP)

PMP-based EMS simplifies the constrained global optimization problem into the local Hamiltonian minimization problem. To take the operating conditions of the FCS into account, an adaptive PMP-based EMS was developed by Ettihir *et al.* [97], suggested the integration of an online identification approach to allocate the requested power between the FCS and the battery unit. Jiang *et al.* [35] developed a real-time EMS based on a two-dimensional PMP for a hydrogen-powered bus with an FC/battery/SC powertrain. Li *et al.* [98] suggested an adaptive PMP-based for an FC/Battery vehicle, in which the co-state estimation is implemented by Markov-based driving cycle prediction. Song *et al.* [65] proposed an adaptive EMS employing PMP, considering both hydrogen consumption and power source durability.

b) Equivalent Consumption Minimization Strategies (ECMSs)

ECMS is a local optimization method derived from PMP optimality conditions. ECMS adds an "equivalent factor" (EF) that has the same effect as the co-state factor of PMP, which is highly dependent on driving cycle information and powertrain constraints. Xu *et al.* [99] suggested an adaptive ECMS-based EMS for a city bus to meet complex and changeable road conditions. Due to uncertainties in a driving profile, there is no guarantee for the battery SOC charge-sustenance and local optimality of ECMS unless the EF is optimally corrected in real-time. For example, Han et *al.* [100] proposed an EF adaptation approach for extracting the optimal global EF based on the DP optimization result. Li *et al.* [37] designed an online adaptive ECMS for an FCV to update EF and FCS dynamic power variation according to the SOH of powertrain sources.

c) Convex Optimization (CO)

Due to the complexity of powertrain components' models, EMS approaches have to cope with various challenges, such as nonlinear mathematical models, equality and inequality constraints, and implementation issues. Convex optimization (CO) can effectively solve the above issues. The CO-based approach needs the EMS optimization problem to be formulated strictly convex. The performance of optimal results is strongly related to the fidelity of the approximated models. For instance, to deal with sub-optimality and computational time burden, Hu *et al.* [101] introduced a CO-based approach to optimize both EMS and component dimensioning problems rapidly. In another work, Hu *et al.* [102] suggested an optimal EMS and battery and SC sizing using the CO method. Wu *et al.* [103] proposed a CO method for EMS and component dimensioning in a logistics plug-in FCV to optimize the total energy and power source costs while fulfilling the determined requirements. Caux *et al.* [104] formulated an EMS problem as a piecewise linearization model. Chen *et al.* [105] proposed an alternating direction method of multipliers (ADMM) approach to solve a QP-based EMS problem.

d) Model Predictive Control (MPC)

MPC-based EMSs are mainly based on predictive models where trip information and future driving data can be integrated into different EMS approaches. The performance of this method depends on powertrain and system modeling, driving cycle and external disturbance prediction, prediction horizon, and sampling time. In general, MPC techniques are dependent on a specified model and parameters. Hence, they lack adaptability. Luna *et al.* [106] proposed a nonlinear MPC to extend the FCS lifespan and augment efficiency and performance by taking into account the local operating constraints of the powertrain sources. Liu *et al.* [107] put forward a hierarchical MPC-based EMS to enhance the efficiency of FCS while considering the safe operational zone of the compressor system. Hu *et al.* [31] established a multi-objective and cost-optimal MPC approach to optimize the total running cost of an electric bus, including the costs of hydrogen consumption and powertrain component degradation. A multi-objective MPC is investigated by Pereira *et al.* [108], where they recommended the integration of a nonlinear MPC with a recurrent NN as a nonlinear dynamic model. To effectively distribute the requested power under changeable driving conditions and multiple driving patterns, Zhou *et al.* [45] introduced adaptive EMS, including a Markov driving pattern recognizer and a multi-mode MPC. Another type of MPC is based on explicit model predictive control (EMPC). In this approach, the non-linear system cost function can be optimized in an offline process, and the computational burden is effectively reduced. Arce *et al.* [109] used EMPC for an FCV to monitor motor power requirements, maintain the SOC of the battery near its optimal value, and improve performance and durability. Using EMPC in the upper layer to allocate the power demand among the different power sources,

e) Game Theory (GT)

Generally, GT involves decision-makers, playing policies, and payoff functions. In a GT problem, Nash equilibrium is a steady-state situation where no decision-maker has an incentive to change its state. GT can be categorized into two main groups: non-cooperative and cooperative. In the former, the decision-makers make individual decisions to maximize their payoff functions with self-centeredness. In the latter, the objectives of all decision-makers should be achieved as far as possible. To improve the EMS robustness in the case of complex driving profiles, Sun *et al.* [110] proposed an EMS based on GT. This strategy incorporates future driving patterns into a prediction window. Since the optimized answers for a given driving profile cannot take different possible driving patterns into account, Zhang *et al.* [111] suggested a non-cooperative GT-based EMS with an adaptive utility function.

f) Nonlinear Control (NC)

Nonlinear control (NC) approaches are robust against external disturbances, parameter changes, and model uncertainty. Moreover, they can efficiently work with time-variant powertrain systems. In [112], El Fadil *et al.* proposed a solution to the EMS problem to satisfy the stability of the closed-loop powertrain system while tracking the SC current and DC voltage fluctuation. To deal with complex driving conditions, in [113], an EMS is proposed by Mane *et al.* to control a hybrid powertrain system properly. In [48], an adaptive EMS was suggested by Zhang *et al.* to split the power between FCS and battery under different driving conditions.

g) Robust Control (RC)

Previous research studies concentrated on ideal FCSs and neglected the uncertainty concept. However, operation conditions change over time, and the approximated modeling brings numerous sources of inaccuracies. From this perspective, Nwesaty *et al.* [114] proposed a disturbance-rejection EMS using the $H\infty$ approach. The system is formulated as a linear parameter-varying system. Wu *et al.* [115] provided an analysis based on a Lyapunov function and singular perturbation theory with local closed-loop stability. The suggested adaptive EMS is model-free and does not require an observer to estimate the SOC level.

h) Extremum Seeking (ES)

Extremum Seeking (ES) framework, as an online adaptive local optimization technique, can be successfully applied to find the optimal operating point of a static nonlinear system. Zhou *et al.* [151] provided a survey of online ES-based strategies and classified them as first-order, band-pass, and high-pass filter-based methods. Zhou *et al.* [137] proposed an online adaptive EMS based on a fractional-order ES algorithm to improve convergence speed and robustness. Additionally, the proposed approach strengthens the durability of the system. Wang *et al.* [136] suggested a data-driven-based ES approach based on a forgetting factor recursive least square (RLS) online identification algorithm. [136] presented an online ES framework based on RLS identification with a forgetting factor to enhance the estimation accuracy.

i) Neural Networks (NNs)

The applications of NNs in FCVs are explained in several examples. In most cases, the NN applications focus on their combinations with other approaches to improve their performance. For instance, Song *et al.* [142] developed a multi-mode EMS based on a learning vector quantization NN as a driving pattern recognition method. According to the NN results, this EMS automatically switches to the GA-optimized thermostat strategy. Liu *et al.* [144] suggested a multi-objective hierarchical prediction EMS where a backpropagation NN is used to predict speed on a prediction horizon. Zhang *et al.* [85] presented a multilayer perceptron NN regarding driving pattern recognition. After developing the model, an adaptive fuzzy EMS is proposed for allocating the power according to the requested profile. In [108], a recurrent NN model is trained to model the behavior of a PEMFC, and then a nonlinear MPC is developed for the EMS of an FCV.

j) Reinforcement Learning (RL)

For the first time, radial-basis NNs were suggested by Lin *et al.* [138] to achieve adaptive optimal control for the FCV EMS through RL theory without prior knowledge of future driving cycle profiles. Yuan *et al.* [147] put forward a hierarchical RL-based EMS. This work combined short-term and long-term speed predictions with a rolling optimization technique. Lin *et al.* [149] offered an online recursive RL-based method to minimize the final cost of a plug-in FCV to deal with various driving conditions. Sun *et al.* [148] developed a hierarchical multi-objective RL using ECMS and a transition probability matrix. Furthermore, an adaptive fuzzy filter was suggested for addressing high-dimensional state-action space to decrease computational time.

C. Component Sizing and Optimization-Based

The most challenging aspect of component sizing in FCVs is proper sizing of the battery and electric motor to modify the whole vehicle's weight to achieve a more excellent full-electric range. Table VI summarizes the design details for several FCVs in the literature. Kim *et al.* [152] proposed a pseudo-SDP controller based on stochastic DP for optimizing the compressor size in an FCS and hydrogen consumption. Hu *et al.* [153] introduced CO to optimize hydrogen consumption and component sizing and improve the durability of PEMFCs. In [101], Hu *et al.* developed a CO framework for optimizing power distribution and component sizing and studied the effect of driving patterns on different actual bus routes. Hu *et al.* also dealt with optimal EMS and sizing of battery and SC utilizing a CO method in [102]. A dynamic battery SOH model was integrated to quantitatively examine the impact of the battery replacement strategy on the studied system performance. Xu *et al.* [117] proposed a multi-objective problem that integrated DP into the component sizing problem and used a two-loop frame to select the best component size. Therefore, Hu *et al.* [36] used the obtained DP results for real-time soft-running strategies to achieve a good hydrogen economy, system durability, and

Table V
The summary of optimization-based EMSs' key features and objectives

Methods	Advantages	Disadvantages	Hydrogen consumption	PEMFC lifetime	Battery lifetime
DP	Global optimal; benchmark	High computing burden; dimension disaster	[88-92, 116, 117]	[33, 92, 117]	[89, 117]
GA	Global stochastic optimal;	Depending on the initial population and parameter tuning	[93, 118]	[93]	—
PSO	Simple; good robust; fast convergence; few parameters	Relying on initial conditions and search speed;	[94, 95]	[95]	—
PMP	Near global optimum; relatively small computational burden	Real time implementation difficult; complex mathematics	[35, 65, 98, 119, 120]	[35, 65, 97, 98]	[65]
ECMS	Real-time implementation	Local optimization; driving cycle sensitivity	[37, 99, 100, 121, 122]	[37, 99, 122]	[37, 122]
CO	Low computational burden; easy to implement	Must be convex form;	[101-105]	—	[102, 103]
MPC	High real-time implementation; good optimization effect	Predicted horizontal sensitivity; poor adaptability, the computational time dependents on the optimization window	[31, 40, 45, 107, 108, 123-126]	[31][40, 41, 45, 106, 108, 124, 127, 128]	[31, 124]
GT	Trade-off of conflicting goals	Dimensionality curse; instantaneous optimization	[110, 111, 129]	[110]	[111, 129]
NC	Real time implementation; robustness	Mathematical complexity	[48, 113, 130, 131]	[48, 131]	[131]
RC	System Robustness; real-time control	Complex robust controllers	[115, 132, 133]	[114, 115]	[114, 115]
ES	Real time implementation, good optimization effect	Only static systems are available	[134-136]	[136, 137]	—
NN	Learning and adaptive; low computational burden	Black-box model; relying on available data	[85, 108, 138-145]	[108, 141, 144]	—
RL	self-learning; adaptive	Dimension disaster; local optimum	[146-149]	[147, 148]	[150]

battery sizing. Furthermore, Wu *et al.* [103] suggested a CO framework for EMS and component sizing for a plug-in FC urban logistics vehicle.

Table VI
The information on the sizes and weights of FCVs

EMS	Weight	FCS	Battery	SC	References
SDP	-	78.5kW	4.87 Ah	-	[152]
CO	14.5 t	100 kW	6.5 kWh	0.6kWh	[102]
DP	1.10 t	40 kW	150 Ah	-	[117]
DP	2.235 t	40 kW	10 Ah	-	[36]
CO	6.40 t	54 kW	29 kWh	-	[103]

D. Multi-level-based

Due to the increasing complexity of powertrains and the requirement to accomplish various objectives, multi-level control architectures are gaining attention. Generally, a high-level powertrain controller manages the hybrid powertrain system's functions. The high-level powertrain controller also transmits orders to each subsystem module and receives measurement signals and diagnostic status from each subsystem at each sample period. The low-level control systems change local-level inputs to carry out the high-level powertrain controller's commands [154].

E. Multi-Stack Fuel Cell System

The literature introduces multi-stack FCS (MFCS) to solve the shortcomings and weaknesses of single-stack FCS. Herr *et al.* [155] proposed an EMS based on the MILP method to prolong the powertrain systems' useful life through a prognostics and health management (PHM) approach. Fernandez *et al.* [156] introduced an EMS based on an adaptive state machine to improve hydrogen consumption and lifespan. The suggested system was integrated with a Kalman filter identification method to determine each FCS's maximum power and efficiency points. Yan *et al.* [157] presented a hierarchical control method based on an equivalent fitting circle strategy in another study. Zhang *et al.* [158] proposed a hysteresis-based EMS to make activation time evenly distributed and decrease the number of switches over a three-stack MFCS. Khalatbarisoltani *et al.* [159] proposed a decentralized convex optimization framework to solve the multi-objective power distribution problem for modular FCVs.

V. Platforms for Validation

To further verify the effectiveness of the EMS approaches, researchers usually use several verification methods to analyze and test the developed EMSs under various driving conditions. These verification methods can be divided into model-in-the-loop, software-in-the-loop, hardware-in-the-loop, small-scale test bench, and real-vehicle on-road test. The characteristics of the EMS validation methods are summarized in Table VII.

A. Model-In-the-Loop

Model-in-the-loop (MIL) designs the FCV model and EMS controller on the MATLAB/Simulink platform, is the most common verification method. For instance, Li *et al.* [141] verified the feasibility and validity of the proposed MPC-based EMS in the MATLAB/Simulink environment.

B. Software-In-the-Loop

Software-in-the-loop (SIL) platform refers to designing and testing a controller using a vehicle simulator. The EMS is often verified using a MATLAB/Simulink environment. For instance, Ahmadi *et al.* [160] examined the proposed EMS over different driving cycles via Advanced Vehicle Simulator (Advisor) software. Another well-known MATLAB-based software is Autonomie. This software provides several modular and plug-and-play powertrain models to develop a simulation environment for evaluating different EMSs and improving overall system efficiency through virtual design and analysis.

C. Hardware-In-the-Loop

In a typical real-time Hardware-In-the-Loop (HIL) simulator, a virtual mathematical model inside a real-time processor can replace the physical powertrain system. This simulator imitates the FCV behavior and a dedicated electronic control unit (ECU), as shown in Fig. 6. Several vital points should be considered in the implementation process of a HIL simulator, such as the dynamic behavior of components (FCS, battery, sensors, and actuators), numerical solver stability, time-step, and latency jitter. A compromise between the desired control simulation precision, computational time, and behavior of the FCV system should be considered. To improve the performance of computational time, several model reduction techniques can be employed before the implementation step, e.g., linearization, space reduction, and discretization. To select an appropriate iterative method (e.g., Euler, Runge-Kutta, Pantelides), desired model accuracy, processor unit computational performance, and solver stability should be considered comprehensively. Owing to limited computation capabilities in real-time simulators, the formulated powertrain model should be implemented efficiently via the C, Java, and VHDL languages [161, 162]. A real-time system can generate accurate outputs from the computations based on the logical results and the physical time when those results are generated [163]. When a controller responds to a request, its response time typically falls into a variation interval, also known as latency jitter. A powertrain system can only allow a certain amount of latency without damage or failure. In order to provide a reliable automation solution, the latency of a control unit should be at least five times smaller than the latency of the process the controller is meant to control. For appropriate hardware selection, requirements should include handling the processor interrupts in real-time and providing a software environment that can handle the required elapsed time and latency jitter. Various commercial platforms can be found on the market, e.g., RT-Lab, Typhoon, Speedgoat, and dSPACE. For instance, Li *et al.* [164] utilized the RT-LAB real-time simulation platform to verify the SMC EMS. Song *et al.* [165] demonstrated the validity of the proposed EMS by establishing a real-time HIL simulation system using Typhoon HIL 602. Moreover, Zhou *et al.* [151] compared the performance of different extremum-seeking algorithms based on a dSPACE HIL real-time simulation platform.

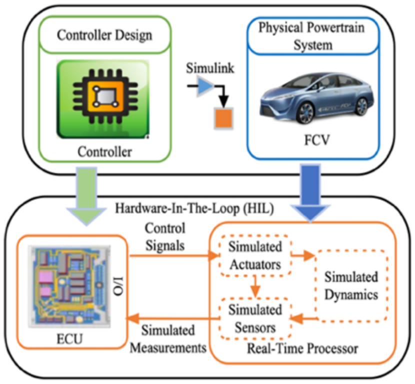

Fig. 6. Hardware-in-the-loop (HIL) simulator test system for the powertrain of an FCV.

Table VII
The characteristics of EMS validation methods

Methods	Ref	Advantages	Disadvantages
MIL	[141]	Simple and easy to implement	Ideal scenario and simple vehicle model
SIL	[160]	High-fidelity plant modeling and user-friendly	Ideal scenario and the powertrain models are based on quasi-static
HIL	[151, 161-165]	Fast; precise; safe; reliable and improved EMS controller development efficiency	Cannot meet the requirement of high accuracy in real time
Small-scale test bench	[74, 166]	Near real vehicle testing and easy to change vehicle structure	High cost; fragile components
Real-Vehicle On-Road Test	[36, 167-169]	The most effective verification method	High costs; difficulty in changing vehicle structure

D. Small-Scale Test Bench

A small-scale test bench is an excellent choice to verify the implementation feasibility of an EMS. This test bench typically consists of a controller, real powertrain components, such as FCS, a battery and/or SC unit, and a converter. For example, Carignano *et al.* [74] verified the economy and durability of an EMS in a hybrid FCS/SC test bench. Moreover, Ou *et al.* [166] validated an adaptive PMP on an FC/battery experimental platform.

E. Real-Vehicle On-Road Test

On-road testing is the most accurate way to investigate the feasibility of an EMS. However, it is not suggested in many situations due to the high expense and operational challenges. In this approach, an EMS is deployed in an experimental vehicle to verify the controller's performance under real-world road conditions. To evaluate the performance of an FLC, Gao *et al.* [167] conducted some tests on a regular bus route in Beijing. After a 3-month demonstration run of an FC hybrid urban bus, Hu *et al.* [36] showed that the proposed EMS could strike a good balance between hydrogen economy and system durability. In [168], Bae *et al.* proposed a plug-in HEV ecological adaptive cruise controller and tested it in Southern California. In a study conducted with a fleet of four autonomous cars, Rama *et al.* [169] developed a route-optimized EMS.

VI. Outlook and Future Trends

With the development of communication technologies, advanced optimization algorithms, AI, and intelligent transportation systems, many forward-looking and revolutionary approaches are expected to emerge in the upcoming research fields of the FCV EMS. This section presents a vision of the future of EMSs from several emerging perspectives.

A. Precise representation

Accurate modeling methods of the powertrain components are essential for enhancing the efficiency of the FCVs' EMS. Several advanced modeling methods based on data-driven approaches have been recently introduced to improve power source modeling using measured and recorded data. For instance, Eddahech *et al.* [170] used the NN to build a highly accurate SC model. Vichard *et al.* [171] applied echo state NN to the PEMFC degradation model. However, few pieces of literature have applied these advanced modeling methods to the EMS of FCVs. Therefore, the combination of advanced modeling methods needs to be further investigated. Auxiliary systems of the FCVs, such as air conditioning and cooling systems, power conditioning systems, power steering, and electronic boards, consume energy during FCV operation. In addition, the auxiliary components of the FCS, such as compressors, fans, and pumps, consume some of the generated power. However, in the modeling and designing process of the EMSs, these power consumption and losses are usually ignored or treated as constants. This ignorance can lead to inaccuracies, specifically for heavy-duty FCV applications. In this regard, taking these losses into account is vital, and the effect on the FCV performance is an area for further research.

B. Fault Diagnosis and Fault-Tolerant Control

From a control point of view, faults and failure modes in an FCS can be categorized into stack, actuator, and sensor faults. The FC stack is the most expensive component of FCS because of its limited lifetime. The most frequent faults in the FC stack are fuel or air starvation, electrode poisoning, flooding, and drying. The actuator faults are the cooling system, controller area network (CAN) bus, terminal connector, fuse, and high-voltage cables. These Faults can result in performance decline and severe safety concerns. In the literature, Fault-tolerant control (FTC) is proposed to satisfy the performance desires and keep the operation safe in case of a fault occurrence [172]. Several diagnoses and prognosis apparatuses have been offered [173-175]. Integrating advanced fault diagnosis techniques and FTC approaches is critical for future FCV applications. For instance, a fault-tolerant MPC-based EMS is proposed for a microgrid application in [176]. Another work suggests a reliable and robust EMS for a hybrid hydraulic-electric vehicle based on fuzzy logic and a neural network in [177].

C. Modular Energy System

With all the promising characteristics of SFCS in the FCVs, it is necessary to advance them regarding efficiency, reliability, modularity, durability, and cost to penetrate this highly competitive automotive market. One of the sustainable solutions is to introduce a modular FCS [178]. Considering the detailed fluidic and electric characteristics, this modular FCS provides better outcomes concerning the hydrogen economy and efficiency than an SFCS. Additionally, thanks to the modular FCS's inherent redundancy, this system's reliability is increased under FCS and converter fault conditions. This modular-based system also benefits from the more flexible implementation characteristic of the FCVs. Thus, this new concept is a forward-looking solution compared to the previous approaches.

D. Advanced Optimization

A transition from single objective (hydrogen consumption) to multi-objective and CO-optimization is another gradually increasing potential research trend in the future FCV EMSs. These multiple objectives can be formulated either with a weighted cost function or several constraints. These advanced objectives for both FCS and battery pack of the FCV include health condition and degradation [31], thermal monitoring and management [39], safety, driver comfort, scheduling and refueling time, and path planning. For instance, a combination of prognostics-enabled decision-making approaches with EMSs has become an exciting research trend that aims to amalgamate health information as part of the management system [179]. Integrating thermal management objectives into the EMS-algorithms is vital to keep the FCS safe and efficient during operation. For instance, in [180], a pseudo-spectral optimization approach is used to determine the ideal power split while considering FCS's thermal dynamics to prevent stack overheating and reduce hydrogen consumption. Co-optimizing drivetrain operation with vehicle dynamics has been suggested by [181] to increase energy efficiency. Since terrain information is predictable, a hierarchical EMS is recommended [182]. [183] proposes a suitable control technique for simultaneous speed planning and energy economy to address different influences from complex traffic environments. [184] suggests a bi-level convex method for eco-driving a connected FCV through signalized intersections. One of the future trends could be the combination of advanced techniques with complementary characteristics. The main challenge is that these methods may no longer be appropriate for real-time EMS applications in the FCVs due to the computational burden issue. Distributed/Decentralized optimization algorithms (DOAs) have been suggested to address this problem [159]. One of the future research trends of the FCV EMS lies in integrating advanced AI and machine learning methods. Among these approaches, the RL methods are essential subjects that attract much attention from academic researchers [185]. Integrating these approaches into the FCV EMSs should be addressed in future trends. Generally, the EMS optimization problems are solved under a single driving profile or a set of standard cycles for a relatively short time window in a single FCV. However, as shown in Fig. 7, considering a trip-ahead EMS and other facilities is necessary for the scheduling problem. This concept inspires shifting from a short timescale with a small space to a longer timescale with a bigger space.

FCV automation may be a new research hotspot in the upcoming industry. It will provide higher degrees of automation by using new technologies, e.g., adaptive cruise control, advanced driver assistance systems, advanced emergency braking, lane-keeping assist, parking assistance, blind spot assist, cross-traffic alerts, and forward-collision warning in automated (L3) FCVs with a driver and fully automated (L4) FCVs without a driver.

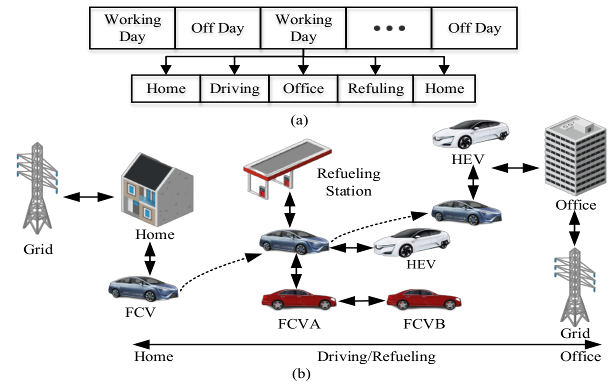

Fig. 7. The scheme of multi-scale EMS: (a) trip-ahead information, (b) a long timescale for EMS in a working day.

E. Integrating Connected Vehicles Technologies and Cyber-Physical Systems

The next generation of FCVs will employ higher levels of connectivity technology, e.g., V2V, V2I, V2X, and ITSs, to improve the performance of EMSs. These upcoming trends can set valuable structures to direct FCV technology toward a more coordinated, autonomous, intelligent, and safer system. Additionally, from the powertrain point of view, these trends will improve driving quality, overall efficiency, powertrain lifetime, and road capacity [186]. Different types of data, such as GPS and GIS information, requested power profiles, velocities, SOC levels, remaining distances, drivers' behaviors, and prices, can be shared by considering information provided by other vehicles and infrastructures. For instance, HomChaudhuri *et al.* [187] developed a multilayer method for a group of HEVs. The higher-level control system established optimal velocity trajectories in the presence of traffic lights, and the lower-level controller was in charge of power distribution employing ECMS. Turri *et al.* [188] introduced a multi-control scheme for a platoon of three conventional heavy trucks in which the velocity trajectories are planned centrally. Generally, in the platooning concept, the longitudinal dynamics of a fleet of connected heavy-duty vehicles are regulated to minimize inter-vehicular distances [189], as shown in Fig. 8. The FCV platooning technique will be developed in the next generation of EMS, along with real-time data sharing between FCVs and the cloud-based networks via V2V communication systems. This can increase safety and control during maneuvers and reduce air resistance to decrease hydrogen consumption and final cost. From an energy perspective, the central idea of eco-driving is to find the best way to reduce energy consumption by optimizing the velocity trajectory [190], as shown in Fig. 9. Fleming *et al.* [191] presented an eco-driving control problem that considered the driver's preferences. Zhao *et al.* [192] proposed an eco-driving model of mixed traffic flow with the V2X technology. A receding horizon MPC is applied to minimize fuel consumption. Several studies have sought to alleviate the computation time in this problem [181, 184]. Additionally, coordinated control strategies are devised with terrain and traffic considerations [182, 183].

A cyber-physical system (CPS) embeds cyber processes into physical devices to link the cyber and physical layers. Sensors and actuators provide the interface between the physical and cyber layers. As shown in Fig. 10, future EMS problems can be considered with this emerging perception where each connected FCV examines other vehicles' behavior with different powertrains and objectives.

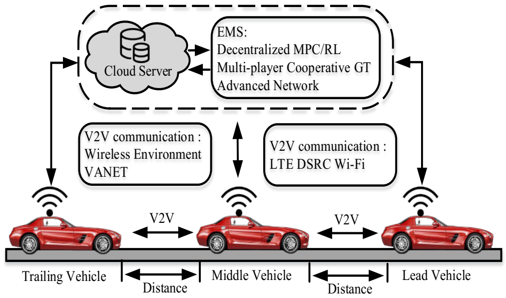

Fig. 8. The platooning technology for designing an EMS.

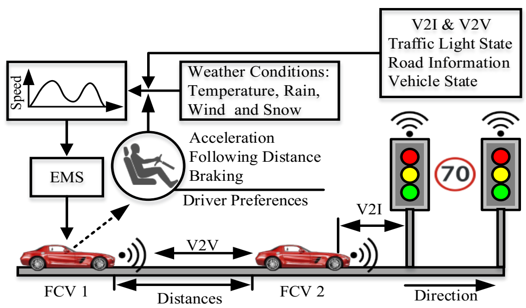

Fig. 9. The eco-driving for developing an EMS.

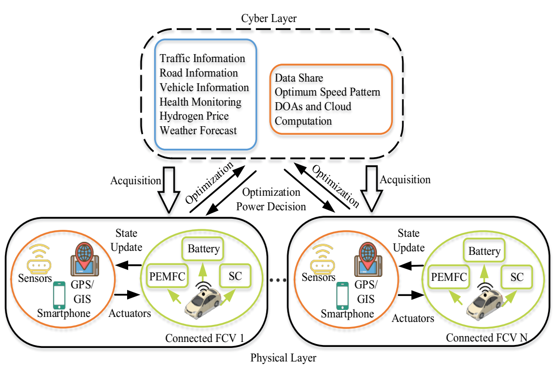

Fig. 10. The scheme of CPS for an energy management design.

F. Vehicle-to-Grid

As shown in Fig. 11, V2G is a systemic framework where a fleet of plug-in FCVs, PHEVs, and EVs, as distributed power systems, could be linked with the grid. Furthermore, as a flexible energy storage system, they can help flatten the generated power of sustainable energy and balance their extra power. Fernandes *et al.* [193] developed an FCV parking lot with the capacity to generate electricity, heat, and hydrogen. Garcia-Torres *et al.* [194] studied the importance of day-ahead optimal scheduling for EV/FCV.

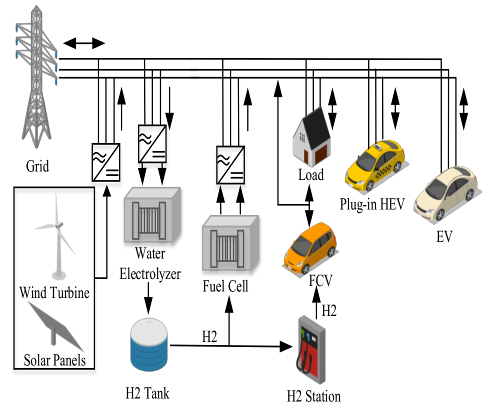

Fig. 11. The scheme of V2G, adopted from [194].

VII. Conclusion

This paper summarizes almost all the existing EMS approaches for FCVs in the open literature. Considering the application of modeling methods in EMS, three kinds of power source modeling are first summed up from the existing literature, including typical modeling, degradation modeling, and thermal modeling. Then, the recent advances in FCV EMSs are comprehensively reviewed regarding rule-based and optimization-based methods. The basic principles, characteristics, and main objectives of each approach are discussed. Furthermore, the verification methods of EMSs are classified into five aspects: MIL, SIL, HIL, small-scale bench test, and real-vehicle on-road test. Finally, a broad and detailed vision of the future direction of EMS for FCV is presented based on current research hotspots, such as artificial intelligence algorithms, intelligent transportation systems, automated driving, and advanced optimization algorithms.

References

[1] J.-H. Wee, "Applications of proton exchange membrane fuel cell systems," *Renewable and Sustainable Energy Reviews,* vol. 11, no. 8, pp. 1720-1738, 2007/10/01/ 2007, doi: https://doi.org/10.1016/j.rser.2006.01.005.

[2] X. Liu, K. Reddi, A. Elgowainy, H. Lohse-Busch, M. Wang, and N. Rustagi, "Comparison of well-to-wheels energy use and emissions of a hydrogen fuel cell electric vehicle relative to a conventional gasoline-powered internal combustion engine vehicle," *International Journal of Hydrogen Energy,* vol. 45, no. 1, pp. 972-983, 2020.

[3] X. He *et al.*, "Well-to-wheels emissions, costs, and feedstock potentials for light-duty hydrogen fuel cell vehicles in China in 2017 and 2030," *Renewable and Sustainable Energy Reviews,* vol. 137, p. 110477, 2021.

[4] N. Marx, L. Boulon, F. Gustin, D. Hissel, and K. Agbossou, "A review of multi-stack and modular fuel cell systems: Interests, application areas and on-going research activities," *International Journal of Hydrogen Energy,* vol. 39, no. 23, pp. 12101-12111, 2014.

[5] P. Thounthong, B. Davat, S. Rael, and P. Sethakul, "Fuel cell high-power applications," *IEEE Industrial Electronics Magazine,* vol. 3, no. 1, pp. 32-46, 2009, doi: 10.1109/MIE.2008.930365.

[6] S. Jiang, C. Wang, C. Zhang, H. Bai, and L. Xu, "Adaptive estimation of road slope and vehicle mass of fuel cell vehicle," *eTransportation,* vol. 2, p. 100023, 2019/11/01/ 2019, doi:

https://doi.org/10.1016/j.etran.2019.100023.

[7] S. Kang and K. J. A. E. Min, "Dynamic simulation of a fuel cell hybrid vehicle during the federal test procedure-75 driving cycle," vol. 161, pp. 181-196, 2016.

[8] M. İnci, M. Büyük, M. H. Demir, and G. İlbey, "A review and research on fuel cell electric vehicles: Topologies, power electronic converters, energy management methods, technical challenges, marketing and future aspects," *Renewable and Sustainable Energy Reviews,* vol. 137, p. 110648, 2021/03/01/ 2021, doi: https://doi.org/10.1016/j.rser.2020.110648.

[9] A. Emadi, S. S. Williamson, and A. Khaligh, "Power electronics intensive solutions for advanced electric, hybrid electric, and fuel cell vehicular power systems," *IEEE Transactions on Power Electronics,* vol. 21, no. 3, pp. 567-577, 2006, doi: 10.1109/TPEL.2006.872378.

[10] J. Bernard *et al.*, "Fuel cell/battery passive hybrid power source for electric powertrains," *Journal of Power Sources,* vol. 196, no. 14, pp. 5867-5872, 2011/07/15/ 2011, doi: https://doi.org/10.1016/j.jpowsour.2011.03.015.

[11] I.-S. Sorlei *et al.*, "Fuel Cell Electric Vehicles—A Brief Review of Current Topologies and Energy Management Strategies," *Energies,* vol. 14, no. 1, 2021, doi: 10.3390/en14010252.

[12] R. Á. Fernández, F. B. Cilleruelo, and I. V. Martínez, "A new approach to battery powered electric vehicles: A hydrogen fuel-cell-based range extender system," *Int J Hydrogen Energ,* vol. 41, no. 8, pp. 4808-4819, 2016/03/02/ 2016, doi: https://doi.org/10.1016/j.ijhydene.2016.01.035.

[13] N. Sulaiman, M. A. Hannan, A. Mohamed, P. J. Ker, E. H. Majlan, and W. R. Wan Daud, "Optimization of energy management system for fuel-cell hybrid electric vehicles: Issues and recommendations," *Applied Energy,* vol. 228, pp. 2061-2079, 2018, doi: 10.1016/j.apenergy.2018.07.087.

[14] M. Yue, S. Jemei, R. Gouriveau, and N. Zerhouni, "Review on health-conscious energy management strategies for fuel cell hybrid electric vehicles: Degradation models and strategies," *International Journal of Hydrogen Energy,* vol. 44, no. 13, pp. 6844-6861, 2019, doi: 10.1016/j.ijhydene.2019.01.190.

[15] X. Lü *et al.*, "Energy management of hybrid electric vehicles: A review of energy optimization of fuel cell hybrid power system based on genetic algorithm," *Energy Conversion and Management,* vol. 205, 2020, doi: 10.1016/j.enconman.2020.112474.

[16] 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," *Renewable and Sustainable Energy Reviews,* vol. 119, p. 109596, 2020/03/01/ 2020, doi: https://doi.org/10.1016/j.rser.2019.109596.

[17] F. Zhang, J. Xi, and R. Langari, "Real-Time Energy Management Strategy Based on Velocity Forecasts Using V2V and V2I Communications," *IEEE Transactions on Intelligent Transportation Systems,* vol. 18, no. 2, pp. 416-430, 2017, doi: 10.1109/TITS.2016.2580318.

[18] C. Yang, M. Zha, W. Wang, K. Liu, and C. Xiang, "Efficient energy management strategy for hybrid electric vehicles/plug-in hybrid electric vehicles: review and recent advances under intelligent transportation system," *IET Intelligent Transport Systems,* vol. 14, no. 7, pp. 702-711, 2020, doi: https://doi.org/10.1049/iet-its.2019.0606.

[19] Y. Gu, M. Liu, J. Naoum-Sawaya, E. Crisostomi, G. Russo, and R. Shorten, "Pedestrian-Aware Engine Management Strategies for Plug-In Hybrid Electric Vehicles," *IEEE Transactions on Intelligent Transportation Systems,* vol. 19, no. 1, pp. 92-101, 2018, doi: 10.1109/TITS.2017.2697044.

[20] L. Guo, B. Gao, Y. Gao, and H. Chen, "Optimal Energy Management for HEVs in Eco-Driving Applications Using Bi-Level MPC," *IEEE Transactions on Intelligent Transportation Systems,* vol. 18, no. 8, pp. 2153-2162, 2017, doi: 10.1109/TITS.2016.2634019.

[21] A. Faghri and Z. Guo, "Challenges and opportunities of thermal management issues related to fuel cell technology and modeling," *International journal of heat and mass transfer,* vol. 48, no. 19-20, pp. 3891-3920, 2005.

[22] W. Wu, S. Wang, W. Wu, K. Chen, S. Hong, and Y. Lai, "A critical review of battery thermal performance and liquid based battery thermal management," *Energy conversion and management,* vol. 182, pp. 262-281, 2019.

[23] L. Zhang, X. Hu, Z. Wang, F. Sun, and D. G. Dorrell, "A review of supercapacitor modeling, estimation, and applications: A control/management perspective," *Renewable and Sustainable Energy Reviews,* vol. 81, pp. 1868-1878, 2018.

[24] Z. Li, Z. Zheng, L. Xu, and X. Lu, "A review of the applications of fuel cells in microgrids: opportunities and challenges," *BMC Energy,* vol. 1, no. 1, p. 8, 2019/10/29 2019, doi: 10.1186/s42500-019-0008-3.

[25] J. C. Amphlett, R. M. Baumert, R. F. Mann, B. A. Peppley, P. R. Roberge, and T. J. Harris, "Performance Modeling of the Ballard Mark IV Solid Polymer Electrolyte Fuel Cell: I . Mechanistic Model Development," *Journal of The Electrochemical Society,* vol. 142, no. 1, pp. 1-8, 1995/01/01 1995, doi: 10.1149/1.2043866.

[26] H. Li, A. Ravey, A. N'Diaye, and A. Djerdir, "A novel equivalent consumption minimization strategy for hybrid electric vehicle powered by fuel cell, battery and supercapacitor," *Journal of Power Sources,* vol. 395, pp. 262-270, 2018/08/15/ 2018, doi: https://doi.org/10.1016/j.jpowsour.2018.05.078.

[27] A. Djerioui *et al.*, "Energy management strategy of Supercapacitor/Fuel Cell energy storage devices for vehicle applications," *International Journal of Hydrogen Energy,* vol. 44, no. 41, pp. 23416-23428, 2019/08/30/ 2019, doi: https://doi.org/10.1016/j.ijhydene.2019.07.060.

[28] J. T. Pukrushpan, "Modeling and control of fuel cell systems and fuel processors," 2003.

[29] X. Chen, G. Hu, F. Guo, M. Ye, and J. Huang, "Switched Energy Management Strategy for Fuel Cell Hybrid Vehicle Based on Switch Network," vol. 13, no. 1, p. 247, 2020. [Online]. Available: https://www.mdpi.com/1996-1073/13/1/247.

[30] A. Fathy, H. Rezk, and A. M. Nassef, "Robust hydrogen-consumption-minimization strategy based salp swarm algorithm for energy management of fuel cell/supercapacitor/batteries in highly fluctuated load condition," *Renewable Energy,* vol. 139, pp. 147-160, 2019/08/01/ 2019, doi: https://doi.org/10.1016/j.renene.2019.02.076.

[31] X. Hu, C. Zou, X. Tang, T. Liu, and L. J. I. T. o. P. E. Hu, "Cost-optimal energy management of hybrid electric vehicles using fuel cell/battery health-aware predictive control," vol. 35, no. 1, pp. 382-392, 2019.

[32] J. Zhao and X. Li, "A review of polymer electrolyte membrane fuel

cell durability for vehicular applications: Degradation modes and experimental techniques," *Energy Conversion and Management,* vol. 199, p. 112022, 2019/11/01/ 2019, doi: https://doi.org/10.1016/j.enconman.2019.112022.

[33] T. Fletcher, R. Thring, and M. Watkinson, "An Energy Management Strategy to concurrently optimise fuel consumption & PEM fuel cell lifetime in a hybrid vehicle," *International Journal of Hydrogen Energy,* vol. 41, no. 46, pp. 21503-21515, 2016/12/14/ 2016, doi: https://doi.org/10.1016/j.ijhydene.2016.08.157.

[34] P. Pei, Q. Chang, and T. Tang, "A quick evaluating method for automotive fuel cell lifetime," *International Journal of Hydrogen Energy,* vol. 33, no. 14, pp. 3829-3836, 2008/07/01/ 2008, doi: https://doi.org/10.1016/j.ijhydene.2008.04.048.

[35] H. Jiang, L. Xu, J. Li, Z. Hu, and M. J. E. Ouyang, "Energy management and component sizing for a fuel cell/battery/supercapacitor hybrid powertrain based on two-dimensional optimization algorithms," vol. 177, pp. 386-396, 2019.

[36] Z. Hu *et al.*, "Multi-objective energy management optimization and parameter sizing for proton exchange membrane hybrid fuel cell vehicles," *Energy Conversion and Management,* vol. 129, pp. 108-121, 2016/12/01/ 2016, doi: https://doi.org/10.1016/j.enconman.2016.09.082.

[37] H. Li, A. Ravey, A. N'Diaye, and A. Djerdir, "Online adaptive equivalent consumption minimization strategy for fuel cell hybrid electric vehicle considering power sources degradation," *Energy Conversion and Management,* vol. 192, pp. 133-149, 2019/07/15/ 2019, doi: https://doi.org/10.1016/j.enconman.2019.03.090.

[38] J.-C. Olivier *et al.*, "Multiphysics modeling and optimization of the driving strategy of a light duty fuel cell vehicle," vol. 42, no. 43, pp. 26943-26955, 2017.

[39] M. Kandidayeni, A. Macias, L. Boulon, and S. Kelouwani, "Investigating the impact of ageing and thermal management of a fuel cell system on energy management strategies," *Applied Energy,* vol. 274, p. 115293, 2020/09/15/ 2020, doi: https://doi.org/10.1016/j.apenergy.2020.115293.

[40] H. He, S. Quan, F. Sun, and Y.-X. J. I. T. o. I. E. Wang, "Model Predictive Control with Lifetime Constraints Based Energy Management Strategy for Proton Exchange Membrane Fuel Cell Hybrid Power Systems," 2020.

[41] L. Yang, A. Karnik, B. Pence, M. T. B. Waez, and N. Ozay, "Fuel Cell Thermal Management: Modeling, Specifications, and Correct-by-Construction Control Synthesis," *IEEE Transactions on Control Systems Technology,* vol. 28, no. 5, pp. 1638-1651, 2020, doi: 10.1109/TCST.2019.2918747.

[42] A. Väyrynen and J. Salminen, "Lithium ion battery production," *The Journal of Chemical Thermodynamics,* vol. 46, pp. 80-85, 2012/03/01/ 2012, doi: https://doi.org/10.1016/j.jct.2011.09.005.

[43] G. Zubi, R. Dufo-López, M. Carvalho, and G. Pasaoglu, "The lithium-ion battery: State of the art and future perspectives," *Renewable and Sustainable Energy Reviews,* vol. 89, pp. 292-308, 2018/06/01/ 2018, doi: https://doi.org/10.1016/j.rser.2018.03.002.

[44] 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 Conversion and Management,* vol. 64, pp. 113-121, 2012/12/01/ 2012, doi: https://doi.org/10.1016/j.enconman.2012.04.014.

[45] Y. Zhou, A. Ravey, and M.-C. Péra, "Multi-mode predictive energy management for fuel cell hybrid electric vehicles using Markov driving pattern recognizer," *Applied Energy,* vol. 258, p. 114057, 2020/01/15/ 2020, doi: https://doi.org/10.1016/j.apenergy.2019.114057.

[46] Y. Wang, Z. Sun, and Z. Chen, "Energy management strategy for battery/supercapacitor/fuel cell hybrid source vehicles based on finite state machine," *Applied Energy,* vol. 254, p. 113707, 2019/11/15/ 2019, doi: https://doi.org/10.1016/j.apenergy.2019.113707.

[47] F. Zhou, F. Xiao, C. Chang, Y. Shao, and C. Song, "Adaptive Model Predictive Control-Based Energy Management for Semi-Active Hybrid Energy Storage Systems on Electric Vehicles," *Energies,* vol. 10, no. 7, p. 1063, 2017. [Online]. Available: https://www.mdpi.com/1996-1073/10/7/1063.

[48] Y. Zhang, C. Zhang, Z. Huang, L. Xu, Z. Liu, and M. Liu, "Real-Time Energy Management Strategy for Fuel Cell Range Extender Vehicles Based on Nonlinear Control," *IEEE Transactions on Transportation Electrification,* vol. 5, no. 4, pp. 1294-1305, 2019, doi: 10.1109/TTE.2019.2958038.

[49] R. Masoudi, T. Uchida, and J. McPhee, "Parameter estimation of an electrochemistry-based lithium-ion battery model," *Journal of Power Sources,* vol. 291, pp. 215-224, 2015/09/30/ 2015, doi: https://doi.org/10.1016/j.jpowsour.2015.04.154.

[50] T.-S. Dao, C. P. Vyasarayani, and J. McPhee, "Simplification and order reduction of lithium-ion battery model based on porous-electrode theory," *Journal of Power Sources,* vol. 198, pp. 329-337, 2012/01/15/ 2012, doi: https://doi.org/10.1016/j.jpowsour.2011.09.034.

[51] C. Li, N. Cui, C. Wang, and C. Zhang, "Reduced-order electrochemical model for lithium-ion battery with domain decomposition and polynomial approximation methods," *Energy,* vol. 221, p. 119662, 2021/04/15/ 2021, doi: https://doi.org/10.1016/j.energy.2020.119662.

[52] J. C. Forman, S. J. Moura, J. L. Stein, and H. K. Fathy, "Genetic identification and fisher identifiability analysis of the Doyle–Fuller–Newman model from experimental cycling of a LiFePO4 cell," *Journal of Power Sources,* vol. 210, pp. 263-275, 2012/07/15/ 2012, doi: https://doi.org/10.1016/j.jpowsour.2012.03.009.

[53] Z. Deng, H. Deng, L. Yang, Y. Cai, and X. Zhao, "Implementation of reduced-order physics-based model and multi-parameters identification strategy for lithium-ion battery," *Energy,* vol. 138, pp. 509-519, 2017/11/01/ 2017, doi: https://doi.org/10.1016/j.energy.2017.07.069.

[54] A. Taghavipour and S. Moghadasi, "A Real-Time Nonlinear CRPE Predictive PHEV Energy Management System Design and HIL Evaluation," *IEEE Transactions on Vehicular Technology,* vol. 70, no. 1, pp. 49-58, 2021, doi: 10.1109/TVT.2020.3045489.

[55] Z. P. Cano *et al.*, "Batteries and fuel cells for emerging electric vehicle markets," vol. 3, no. 4, pp. 279-289, 2018.

[56] N. Nitta, F. Wu, J. T. Lee, and G. J. M. t. Yushin, "Li-ion battery materials: present and future," vol. 18, no. 5, pp. 252-264, 2015.

[57] Y. Gao, J. Jiang, C. Zhang, W. Zhang, Z. Ma, and Y. Jiang, "Lithium-ion battery aging mechanisms and life model under different charging stresses," *Journal of Power Sources,* vol. 356, pp. 103-114, 2017/07/15/ 2017, doi: https://doi.org/10.1016/j.jpowsour.2017.04.084.

[58] M. Woody, M. Arbabzadeh, G. M. Lewis, G. A. Keoleian, and A. Stefanopoulou, "Strategies to limit degradation and maximize Li-ion battery service lifetime - Critical review and guidance for

stakeholders," *Journal of Energy Storage,* vol. 28, p. 101231, 2020/04/01/ 2020, doi: https://doi.org/10.1016/j.est.2020.101231.

[59] M. M. Kabir and D. E. Demirocak, "Degradation mechanisms in Li-ion batteries: a state-of-the-art review," *Int. J. Energy Res.,* vol. 41, no. 14, pp. 1963-1986, 2017/11/01 2017, doi: 10.1002/er.3762.

[60] A. Barré, B. Deguilhem, S. Grolleau, M. Gérard, F. Suard, and D. Riu, "A review on lithium-ion battery ageing mechanisms and estimations for automotive applications," *Journal of Power Sources,* vol. 241, pp. 680-689, 2013/11/01/ 2013, doi: https://doi.org/10.1016/j.jpowsour.2013.05.040.

[61] J. Wang *et al.*, "Cycle-life model for graphite-LiFePO4 cells," *J Power Sources,* vol. 196, no. 8, pp. 3942-3948, 2011/04/15/ 2011, doi: https://doi.org/10.1016/j.jpowsour.2010.11.134.

[62] G. Suri and S. Onori, "A control-oriented cycle-life model for hybrid electric vehicle lithium-ion batteries," *Energy,* vol. 96, pp. 644-653, 2016/02/01/ 2016, doi: https://doi.org/10.1016/j.energy.2015.11.075.

[63] E. Sarasketa-Zabala, I. Gandiaga, L. M. Rodriguez-Martinez, and I. Villarreal, "Calendar ageing analysis of a LiFePO4/graphite cell with dynamic model validations: Towards realistic lifetime predictions," *Journal of Power Sources,* vol. 272, pp. 45-57, 2014/12/25/ 2014, doi: https://doi.org/10.1016/j.jpowsour.2014.08.051.

[64] S. Zhang, X. Hu, S. Xie, Z. Song, L. Hu, and C. J. A. E. Hou, "Adaptively coordinated optimization of battery aging and energy management in plug-in hybrid electric buses," vol. 256, p. 113891, 2019.

[65] K. Song, X. Wang, F. Li, M. Sorrentino, and B. Zheng, "Pontryagin's minimum principle-based real-time energy management strategy for fuel cell hybrid electric vehicle considering both fuel economy and power source durability," *Energy,* vol. 205, p. 118064, 2020/08/15/ 2020, doi: https://doi.org/10.1016/j.energy.2020.118064.

[66] G. Xia, L. Cao, and G. Bi, "A review on battery thermal management in electric vehicle application," *Journal of Power Sources,* vol. 367, pp. 90-105, 2017/11/01/ 2017, doi: https://doi.org/10.1016/j.jpowsour.2017.09.046.

[67] C. Zheng, N. Kim, Y. Park, W. Lim, S. Cha, and G. J. I. j. o. h. e. Xu, "The effect of battery temperature on total fuel consumption of fuel cell hybrid vehicles," vol. 38, no. 13, pp. 5192-5200, 2013.

[68] X. Tang, T. Jia, X. Hu, Y. Huang, Z. Deng, and H. Pu, "Naturalistic Data-Driven Predictive Energy Management for Plug-in Hybrid Electric Vehicles," *IEEE Transactions on Transportation Electrification,* pp. 1-1, 2020, doi: 10.1109/TTE.2020.3025352.

[69] H. Sun, X. Wang, B. Tossan, and R. Dixon, "Three-dimensional thermal modeling of a lithium-ion battery pack," *Journal of Power Sources,* vol. 206, pp. 349-356, 2012/05/15/ 2012, doi: https://doi.org/10.1016/j.jpowsour.2012.01.081.

[70] C. Zhu, X. Li, L. Song, and L. Xiang, "Development of a theoretically based thermal model for lithium ion battery pack," *Journal of Power Sources,* vol. 223, pp. 155-164, 2013/02/01/ 2013, doi: https://doi.org/10.1016/j.jpowsour.2012.09.035.

[71] G. Liu, M. Ouyang, L. Lu, J. Li, and X. Han, "Analysis of the heat generation of lithium-ion battery during charging and discharging considering different influencing factors," *Journal of Thermal Analysis and Calorimetry,* vol. 116, no. 2, pp. 1001-1010, 2014/05/01 2014, doi: 10.1007/s10973-013-3599-9.

[72] I. Baghdadi, O. Briat, J.-Y. Delétage, P. Gyan, and J.-M. Vinassa, "Lithium battery aging model based on Dakin's degradation approach," *Journal of Power Sources,* vol. 325, pp. 273-285, 2016/09/01/ 2016, doi: https://doi.org/10.1016/j.jpowsour.2016.06.036.

[73] A. Khaligh and Z. Li, "Battery, Ultracapacitor, Fuel Cell, and Hybrid Energy Storage Systems for Electric, Hybrid Electric, Fuel Cell, and Plug-In Hybrid Electric Vehicles: State of the Art," *IEEE Transactions on Vehicular Technology,* vol. 59, no. 6, pp. 2806-2814, 2010, doi: 10.1109/TVT.2010.2047877.

[74] M. G. Carignano, R. Costa-Castelló, V. Roda, N. M. Nigro, S. Junco, and D. Feroldi, "Energy management strategy for fuel cell-supercapacitor hybrid vehicles based on prediction of energy demand," *Journal of Power Sources,* vol. 360, pp. 419-433, 2017/08/31/ 2017, doi: https://doi.org/10.1016/j.jpowsour.2017.06.016.

[75] I. Lachhab and L. J. I. j. o. h. e. Krichen, "An improved energy management strategy for FC/UC hybrid electric vehicles propelled by motor-wheels," vol. 39, no. 1, pp. 571-581, 2014.

[76] A. Muzaffar, M. B. Ahamed, K. Deshmukh, and J. Thirumalai, "A review on recent advances in hybrid supercapacitors: Design, fabrication and applications," *Renewable and Sustainable Energy Reviews,* vol. 101, pp. 123-145, 2019/03/01/ 2019, doi: https://doi.org/10.1016/j.rser.2018.10.026.

[77] A. Tahri *et al.*, "Management of fuel cell power and supercapacitor state-of-charge for electric vehicles," *Electric Power Systems Research,* vol. 160, pp. 89-98, 2018/07/01/ 2018, doi: https://doi.org/10.1016/j.epsr.2018.02.003.

[78] N. Rizoug, P. Bartholomeus, and P. L. Moigne, "Study of the Ageing Process of a Supercapacitor Module Using Direct Method of Characterization," *IEEE Transactions on Energy Conversion,* vol. 27, no. 2, pp. 220-228, 2012, doi: 10.1109/TEC.2012.2186814.

[79] A. M. Bittner *et al.*, "Ageing of electrochemical double layer capacitors," *Journal of Power Sources,* vol. 203, pp. 262-273, 2012/04/01/ 2012, doi: https://doi.org/10.1016/j.jpowsour.2011.10.083.

[80] W. Lhomme *et al.*, "IEEE VTS motor vehicles challenge 2019-Energy management of a dual-mode locomotive," in *2018 IEEE Vehicle Power and Propulsion Conference (VPPC)*, 2018: IEEE, pp. 1-6.

[81] A. Berrueta, I. San Martín, A. Hernández, A. Ursúa, and P. Sanchis, "Electro-thermal modelling of a supercapacitor and experimental validation," *Journal of Power Sources,* vol. 259, pp. 154-165, 2014/08/01/ 2014, doi: https://doi.org/10.1016/j.jpowsour.2014.02.089.

[82] Q. Li, W. Chen, Z. Liu, M. Li, and L. J. J. o. P. S. Ma, "Development of energy management system based on a power sharing strategy for a fuel cell-battery-supercapacitor hybrid tramway," vol. 279, pp. 267-280, 2015.

[83] J. Chen, C. Xu, C. Wu, and W. J. I. T. o. I. I. Xu, "Adaptive fuzzy logic control of fuel-cell-battery hybrid systems for electric vehicles," vol. 14, no. 1, pp. 292-300, 2016.

[84] D. Zhou, A. Al-Durra, F. Gao, A. Ravey, I. Matraji, and M. G. J. J. o. p. s. Simões, "Online energy management strategy of fuel cell hybrid electric vehicles based on data fusion approach," vol. 366, pp. 278-291, 2017.

[85] R. Zhang, J. Tao, and H. Zhou, "Fuzzy Optimal Energy Management for Fuel Cell and Supercapacitor Systems Using Neural Network Based Driving Pattern Recognition," *IEEE Transactions on Fuzzy Systems,* vol. 27, no. 1, pp. 45-57, 2019, doi:

10.1109/TFUZZ.2018.2856086.
[86] Z. Fu, Z. Li, P. Si, and F. J. I. J. o. H. E. Tao, "A hierarchical energy management strategy for fuel cell/battery/supercapacitor hybrid electric vehicles," vol. 44, no. 39, pp. 22146-22159, 2019.
[87] Z. Fu, L. Zhu, F. Tao, P. Si, and L. Sun, "Optimization based energy management strategy for fuel cell/battery/ultracapacitor hybrid vehicle considering fuel economy and fuel cell lifespan," *International Journal of Hydrogen Energy,* vol. 45, no. 15, pp. 8875-8886, 2020, doi: 10.1016/j.ijhydene.2020.01.017.
[88] M. Ansarey, M. S. Panahi, H. Ziarati, and M. J. J. o. P. S. Mahjoob, "Optimal energy management in a dual-storage fuel-cell hybrid vehicle using multi-dimensional dynamic programming," vol. 250, pp. 359-371, 2014.
[89] J. Li, X. Jin, and R. J. A. e. Xiong, "Multi-objective optimization study of energy management strategy and economic analysis for a range-extended electric bus," vol. 194, pp. 798-807, 2017.
[90] W. Zhou, L. Yang, Y. Cai, and T. J. J. o. P. S. Ying, "Dynamic programming for new energy vehicles based on their work modes Part II: Fuel cell electric vehicles," vol. 407, pp. 92-104, 2018.
[91] A. M. Ali, A. Ghanbar, and D. Söffker, "Optimal Control of Multi-Source Electric Vehicles in Real Time Using Advisory Dynamic Programming," *IEEE Transactions on Vehicular Technology,* vol. 68, no. 11, pp. 10394-10405, 2019, doi: 10.1109/TVT.2019.2941523.
[92] H. Peng *et al.*, "A scalable, causal, adaptive rule-based energy management for fuel cell hybrid railway vehicles learned from results of dynamic programming," *eTransportation,* vol. 4, p. 100057, 2020/05/01/ 2020, doi: https://doi.org/10.1016/j.etran.2020.100057.
[93] R. Zhang and J. Tao, "GA-Based Fuzzy Energy Management System for FC/SC-Powered HEV Considering H2 Consumption and Load Variation," *IEEE Transactions on Fuzzy Systems,* vol. 26, no. 4, pp. 1833-1843, 2018, doi: 10.1109/TFUZZ.2017.2779424.
[94] B. Geng, J. K. Mills, and D. Sun, "Combined power management/design optimization for a fuel cell/battery plug-in hybrid electric vehicle using multi-objective particle swarm optimization," *International Journal of Automotive Technology,* vol. 15, no. 4, pp. 645-654, 2014/06/01 2014, doi: 10.1007/s12239-014-0067-x.
[95] R. Koubaa and L. krichen, "Double layer metaheuristic based energy management strategy for a Fuel Cell/Ultra-Capacitor hybrid electric vehicle," *Energy,* vol. 133, pp. 1079-1093, 2017/08/15/ 2017, doi: https://doi.org/10.1016/j.energy.2017.04.070.
[96] 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.
[97] K. Ettihir, L. Boulon, and K. Agbossou, "Optimization-based energy management strategy for a fuel cell/battery hybrid power system," *Applied Energy,* vol. 163, pp. 142-153, 2016/02/01/ 2016, doi: https://doi.org/10.1016/j.apenergy.2015.10.176.
[98] X. Li, Y. Wang, D. Yang, and Z. Chen, "Adaptive energy management strategy for fuel cell/battery hybrid vehicles using Pontryagin's Minimal Principle," *Journal of Power Sources,* vol. 440, p. 227105, 2019/11/15/ 2019, doi: https://doi.org/10.1016/j.jpowsour.2019.227105.
[99] L. Xu, J. Li, J. Hua, X. Li, and M. Ouyang, "Adaptive supervisory control strategy of a fuel cell/battery-powered city bus," *Journal of Power Sources,* vol. 194, no. 1, pp. 360-368, 2009/10/20/ 2009, doi: https://doi.org/10.1016/j.jpowsour.2009.04.074.
[100] J. Han, Y. Park, and D. Kum, "Optimal adaptation of equivalent factor of equivalent consumption minimization strategy for fuel cell hybrid electric vehicles under active state inequality constraints," *Journal of Power Sources,* vol. 267, pp. 491-502, 2014/12/01/ 2014, doi: https://doi.org/10.1016/j.jpowsour.2014.05.067.
[101] X. Hu, N. Murgovski, L. M. Johannesson, and B. Egardt, "Optimal Dimensioning and Power Management of a Fuel Cell/Battery Hybrid Bus via Convex Programming," *IEEE/ASME Transactions on Mechatronics,* vol. 20, no. 1, pp. 457-468, 2015, doi: 10.1109/tmech.2014.2336264.
[102] X. Hu, L. Johannesson, N. Murgovski, and B. J. A. E. Egardt, "Longevity-conscious dimensioning and power management of the hybrid energy storage system in a fuel cell hybrid electric bus," vol. 137, pp. 913-924, 2015.
[103] X. Wu, X. Hu, X. Yin, L. Li, Z. Zeng, and V. J. J. o. P. S. Pickert, "Convex programming energy management and components sizing of a plug-in fuel cell urban logistics vehicle," vol. 423, pp. 358-366, 2019.
[104] S. Caux, Y. Gaoua, and P. J. E. Lopez, "A combinatorial optimisation approach to energy management strategy for a hybrid fuel cell vehicle," vol. 133, pp. 219-230, 2017.
[105] H. Chen, J. Chen, Z. Liu, and H. J. A. J. o. C. Lu, "Real‐time optimal energy management for a fuel cell/battery hybrid system," vol. 21, no. 4, pp. 1847-1856, 2019.
[106] J. Luna, E. Usai, A. Husar, and M. Serra, "Enhancing the efficiency and lifetime of a proton exchange membrane fuel cell using nonlinear model-predictive control with nonlinear observation," *IEEE transactions on Industrial Electronics,* vol. 64, no. 8, pp. 6649-6659, 2017.
[107] S. Liu, Y. Bin, Y. Li, and B. Scheppat, "Hierarchical MPC Control Scheme for Fuel Cell Hybrid Electric Vehicles," *IFAC-PapersOnLine,* vol. 51, no. 31, pp. 646-652, 2018/01/01/ 2018, doi: https://doi.org/10.1016/j.ifacol.2018.10.151.
[108] D. F. Pereira, F. D. C. Lopes, and E. H. Watanabe, "Nonlinear Model Predictive Control for the Energy Management of Fuel Cell Hybrid Electric Vehicles in Real-Time," *IEEE Transactions on Industrial Electronics,* pp. 1-1, 2020, doi: 10.1109/TIE.2020.2979528.
[109] A. Arce, A. J. d. Real, and C. Bordons, "Explicit MPC for battery performance improvement in hybrid PEM fuel cell vehicles," in *2009 European Control Conference (ECC)*, 23-26 Aug. 2009 2009, pp. 4852-4857, doi: 10.23919/ECC.2009.7075168.
[110] Z. Sun, Y. Wang, Z. Chen, and X. Li, "Min-max game based energy management strategy for fuel cell/supercapacitor hybrid electric vehicles," *Applied Energy,* vol. 267, p. 115086, 2020/06/01/ 2020, doi: https://doi.org/10.1016/j.apenergy.2020.115086.
[111] Q. Zhang, J. Han, G. Li, and Y. J. I. J. E. S. Liu, "An Adaptive Energy Management Strategy for Fuel Cell/Battery/Supercapacitor Hybrid Energy Storage Systems of Electric Vehicles," vol. 15, pp. 3410-3433, 2020.
[112] H. E. Fadil, F. Giri, J. M. Guerrero, and A. Tahri, "Modeling and Nonlinear Control of a Fuel Cell/Supercapacitor Hybrid Energy Storage System for Electric Vehicles," *IEEE Transactions on Vehicular Technology,* vol. 63, no. 7, pp. 3011-3018, 2014, doi: 10.1109/TVT.2014.2323181.
[113] S. Mane, M. Mejari, F. Kazi, and N. Singh, "Improving Lifetime of Fuel Cell in Hybrid Energy Management System by Lure–Lyapunov-Based Control Formulation," *IEEE Transactions on*

Industrial Electronics, vol. 64, no. 8, pp. 6671-6679, 2017, doi: 10.1109/TIE.2017.2696500.

[114] J.-M. Nwesaty, A. I. Bratcu, A. Ravey, D. Bouquain, and O. Sename, "Robust Energy Management System for Multi-Source DC Energy Systems--Real-Time Setup and Validation," *IEEE Transactions on Control Systems Technology,* 2019.

[115] C. Wu, J. Chen, C. Xu, and Z. Liu, "Real-time adaptive control of a fuel cell/battery hybrid power system with guaranteed stability," *IEEE Transactions on Control Systems Technology,* vol. 25, no. 4, pp. 1394-1405, 2016.

[116] D. Fares, R. Chedid, F. Panik, S. Karaki, and R. J. I. J. o. H. E. Jabr, "Dynamic programming technique for optimizing fuel cell hybrid vehicles," vol. 40, no. 24, pp. 7777-7790, 2015.

[117] L. Xu, C. D. Mueller, J. Li, M. Ouyang, and Z. J. A. e. Hu, "Multi-objective component sizing based on optimal energy management strategy of fuel cell electric vehicles," vol. 157, pp. 664-674, 2015.

[118] S. Ahmadi and S. M. T. Bathaee, "Multi-objective genetic optimization of the fuel cell hybrid vehicle supervisory system: Fuzzy logic and operating mode control strategies," *International Journal of Hydrogen Energy,* vol. 40, no. 36, pp. 12512-12521, 2015/09/28/ 2015, doi: https://doi.org/10.1016/j.ijhydene.2015.06.160.

[119] L. Xu, M. Ouyang, J. Li, F. Yang, L. Lu, and J. Hua, "Application of Pontryagin's Minimal Principle to the energy management strategy of plugin fuel cell electric vehicles," *International Journal of Hydrogen Energy,* vol. 38, no. 24, pp. 10104-10115, 2013/08/12/ 2013, doi: https://doi.org/10.1016/j.ijhydene.2013.05.125.

[120] H. Hemi, J. Ghouili, and A. Cheriti, "Combination of Markov chain and optimal control solved by Pontryagin's Minimum Principle for a fuel cell/supercapacitor vehicle," *Energy Conversion and Management,* vol. 91, pp. 387-393, 2015/02/01/ 2015, doi: https://doi.org/10.1016/j.enconman.2014.12.035.

[121] J. P. Torreglosa, F. Jurado, P. García, and L. M. Fernández, "Hybrid fuel cell and battery tramway control based on an equivalent consumption minimization strategy," *Control Engineering Practice,* vol. 19, no. 10, pp. 1182-1194, 2011/10/01/ 2011, doi: https://doi.org/10.1016/j.conengprac.2011.06.008.

[122] W. Zhang, J. Li, L. Xu, and M. Ouyang, "Optimization for a fuel cell/battery/capacity tram with equivalent consumption minimization strategy," *Energy Conversion and Management,* vol. 134, pp. 59-69, 2017/02/15/ 2017, doi: https://doi.org/10.1016/j.enconman.2016.11.007.

[123] B. Geng, J. K. Mills, and D. Sun, "Two-Stage Energy Management Control of Fuel Cell Plug-In Hybrid Electric Vehicles Considering Fuel Cell Longevity," *IEEE Transactions on Vehicular Technology,* vol. 61, no. 2, pp. 498-508, 2012, doi: 10.1109/TVT.2011.2177483.

[124] Amin, R. T. Bambang, A. S. Rohman, C. J. Dronkers, R. Ortega, and A. Sasongko, "Energy Management of Fuel Cell/Battery/Supercapacitor Hybrid Power Sources Using Model Predictive Control," *IEEE Transactions on Industrial Informatics,* vol. 10, no. 4, pp. 1992-2002, 2014, doi: 10.1109/TII.2014.2333873.

[125] H. Zheng, J. Wu, W. Wu, and Y. Wang, "Integrated Motion and Powertrain Predictive Control of Intelligent Fuel Cell/Battery Hybrid Vehicles," *IEEE Transactions on Industrial Informatics,* vol. 16, no. 5, pp. 3397-3406, 2020, doi: 10.1109/TII.2019.2956209.

[126] H. Chen, J. Chen, H. Lu, C. Yan, and Z. Liu, "A Modified MPC-based Optimal Strategy of Power Management for Fuel Cell Hybrid Vehicles," *IEEE/ASME Transactions on Mechatronics,* pp. 1-1, 2020, doi: 10.1109/TMECH.2020.2993811.

[127] A. Vahidi, A. Stefanopoulou, and H. Peng, "Current management in a hybrid fuel cell power system: A model-predictive control approach," *IEEE Transactions on control systems technology,* vol. 14, no. 6, pp. 1047-1057, 2006.

[128] W. Greenwell and A. Vahidi, "Predictive control of voltage and current in a fuel cell–ultracapacitor hybrid," *IEEE Transactions on Industrial Electronics,* vol. 57, no. 6, pp. 1954-1963, 2009.

[129] Q. Zhang and G. Li, "A Game Theory Energy Management Strategy for a Fuel Cell/Battery Hybrid Energy Storage System," *Mathematical Problems in Engineering,* vol. 2019, p. 7860214, 2019/01/09 2019, doi: 10.1155/2019/7860214.

[130] C. Dépature, W. Lhomme, P. Sicard, A. Bouscayrol, and L. Boulon, "Real-time backstepping control for fuel cell vehicle using supercapacitors," *IEEE Transactions on Vehicular Technology,* vol. 67, no. 1, pp. 306-314, 2017.

[131] D. Xu, Q. Liu, W. Yan, and W. Yang, "Adaptive Terminal Sliding Mode Control for Hybrid Energy Storage Systems of Fuel Cell, Battery and Supercapacitor," *IEEE Access,* vol. 7, pp. 29295-29303, 2019, doi: 10.1109/ACCESS.2019.2897015.

[132] S. N. Motapon, L. Dessaint, and K. Al-Haddad, "A Robust $\hbox{H}_{2}$-Consumption-Minimization-Based Energy Management Strategy for a Fuel Cell Hybrid Emergency Power System of More Electric Aircraft," *IEEE Transactions on Industrial Electronics,* vol. 61, no. 11, pp. 6148-6156, 2014, doi: 10.1109/TIE.2014.2308148.

[133] J. Morales-Morales, I. Cervantes, and U. Cano-Castillo, "On the design of robust energy management strategies for FCHEV," *IEEE Transactions on Vehicular Technology,* vol. 64, no. 5, pp. 1716-1728, 2014.

[134] M. H. Cano, M. I. A. Mousli, S. Kelouwani, K. Agbossou, M. Hammoudi, and Y. Dubé, "Improving a free air breathing proton exchange membrane fuel cell through the Maximum Efficiency Point Tracking method," *Journal of Power Sources,* vol. 345, pp. 264-274, 2017.

[135] N. Bizon, "Energy optimization of fuel cell system by using global extremum seeking algorithm," *Applied Energy,* vol. 206, pp. 458-474, 2017.

[136] T. Wang, Q. Li, Y. Qiu, L. Yin, L. Liu, and W. Chen, "Efficiency Extreme Point Tracking Strategy Based on FFRLS Online Identification for PEMFC System," *IEEE Transactions on Energy Conversion,* vol. 34, no. 2, pp. 952-963, 2019, doi: 10.1109/TEC.2018.2872861.

[137] 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 Transactions on Industrial Electronics,* vol. 65, no. 8, pp. 6787-6799, 2018.

[138] W.-S. Lin and C.-H. Zheng, "Energy management of a fuel cell/ultracapacitor hybrid power system using an adaptive optimal-control method," *Journal of Power Sources,* vol. 196, no. 6, pp. 3280-3289, 2011/03/15/ 2011, doi: https://doi.org/10.1016/j.jpowsour.2010.11.127.

[139] Y. Ates, O. Erdinc, M. Uzunoglu, and B. Vural, "Energy management of an FC/UC hybrid vehicular power system using a combined neural network-wavelet transform based strategy," *International Journal of Hydrogen Energy,* vol. 35, no. 2, pp. 774-783, 2010/01/01/ 2010, doi: https://doi.org/10.1016/j.ijhydene.2009.11.021.

[140] P. M. Muñoz, G. Correa, M. E. Gaudiano, and D. Fernández, "Energy management control design for fuel cell hybrid electric vehicles using neural networks," *International Journal of Hydrogen Energy,* vol. 42, no. 48, pp. 28932-28944, 2017/11/30/ 2017, doi: https://doi.org/10.1016/j.ijhydene.2017.09.169.

[141] T. Li, H. Liu, and D. Ding, "Predictive energy management of fuel cell supercapacitor hybrid construction equipment," *Energy,* vol. 149, pp. 718-729, 2018/04/15/ 2018, doi: https://doi.org/10.1016/j.energy.2018.02.101.

[142] K. Song *et al.*, "Multi-mode energy management strategy for fuel cell electric vehicles based on driving pattern identification using learning vector quantization neural network algorithm," *Journal of Power Sources,* vol. 389, pp. 230-239, 2018/06/15/ 2018, doi: https://doi.org/10.1016/j.jpowsour.2018.04.024.

[143] T. Zeng *et al.*, "Modelling and predicting energy consumption of a range extender fuel cell hybrid vehicle," *Energy,* vol. 165, pp. 187-197, 2018/12/15/ 2018, doi: https://doi.org/10.1016/j.energy.2018.09.086.

[144] Y. Liu, J. Li, Z. Chen, D. Qin, and Y. Zhang, "Research on a multi-objective hierarchical prediction energy management strategy for range extended fuel cell vehicles," *Journal of Power Sources,* vol. 429, pp. 55-66, 2019/07/31/ 2019, doi: https://doi.org/10.1016/j.jpowsour.2019.04.118.

[145] G. Yao *et al.*, "Traffic-Condition-Prediction-Based HMA-FIS Energy-Management Strategy for Fuel-Cell Electric Vehicles," vol. 12, no. 23, p. 4426, 2019.

[146] R. C. Hsu, S. Chen, W. Chen, and C. Liu, "A Reinforcement Learning Based Dynamic Power Management for Fuel Cell Hybrid Electric Vehicle," in *2016 Joint 8th International Conference on Soft Computing and Intelligent Systems (SCIS) and 17th International Symposium on Advanced Intelligent Systems (ISIS)*, 25-28 Aug. 2016 2016, pp. 460-464, doi: 10.1109/SCIS-ISIS.2016.0104.

[147] J. Yuan, L. Yang, and Q. Chen, "Intelligent energy management strategy based on hierarchical approximate global optimization for plug-in fuel cell hybrid electric vehicles," *International Journal of Hydrogen Energy,* vol. 43, no. 16, pp. 8063-8078, 2018/04/19/ 2018, doi: https://doi.org/10.1016/j.ijhydene.2018.03.033.

[148] H. Sun, Z. Fu, F. Tao, L. Zhu, and P. J. J. o. P. S. Si, "Data-driven reinforcement-learning-based hierarchical energy management strategy for fuel cell/battery/ultracapacitor hybrid electric vehicles," vol. 455, p. 227964, 2020.

[149] X. Lin, B. Zhou, and Y. Xia, "Online Recursive Power Management Strategy based on the Reinforcement Learning Algorithm with Cosine Similarity and a Forgetting Factor," *IEEE Transactions on Industrial Electronics,* pp. 1-1, 2020, doi: 10.1109/TIE.2020.2988189.

[150] N. P. Reddy, D. Pasdeloup, M. K. Zadeh, and R. Skjetne, "An intelligent power and energy management system for fuel cell/battery hybrid electric vehicle using reinforcement learning," in *2019 IEEE Transportation Electrification Conference and Expo (ITEC)*, 2019: IEEE, pp. 1-6.

[151] 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 Conversion and Management,* vol. 151, pp. 778-790, 2017/11/01/ 2017, doi: https://doi.org/10.1016/j.enconman.2017.08.079.

[152] M.-J. Kim and H. J. J. o. p. s. Peng, "Power management and design optimization of fuel cell/battery hybrid vehicles," vol. 165, no. 2, pp. 819-832, 2007.

[153] X. Hu, C. M. Martinez, B. Egardt, and D. Cao, "Multi-objective optimal sizing and control of fuel cell systems for hybrid vehicle applications," in *2015 European Control Conference (ECC)*, 15-17 July 2015 2015, pp. 2559-2564, doi: 10.1109/ECC.2015.7330923.

[154] C.-C. Lin, H. Peng, J. W. Grizzle, J. Liu, and M. Busdiecker, "Control system development for an advanced-technology medium-duty hybrid electric truck," *SAE transactions,* pp. 105-113, 2003.

[155] N. Herr *et al.*, "Decision process to manage useful life of multi-stacks fuel cell systems under service constraint," *Renewable Energy,* vol. 105, pp. 590-600, 2017/05/01/ 2017, doi: https://doi.org/10.1016/j.renene.2017.01.001.

[156] A. O. M. Fernandez, M. Kandidayeni, L. Boulon, and H. J. I. T. o. V. T. Chaoui, "An Adaptive State Machine Based Energy Management Strategy for a Multi-Stack Fuel Cell Hybrid Electric Vehicle," 2019.

[157] Y. Yan, Q. Li, W. Chen, W. Huang, and J. Liu, "Hierarchical Management Control Based on Equivalent Fitting Circle and Equivalent Energy Consumption Method for Multiple Fuel Cells Hybrid Power System," *IEEE Transactions on Industrial Electronics,* vol. 67, no. 4, pp. 2786-2797, 2019.

[158] H. Zhang, X. Li, X. Liu, and J. Yan, "Enhancing fuel cell durability for fuel cell plug-in hybrid electric vehicles through strategic power management," *Applied Energy,* vol. 241, pp. 483-490, 2019/05/01/ 2019, doi: https://doi.org/10.1016/j.apenergy.2019.02.040.

[159] A. Khalatbarisoltani, M. Kandidayeni, L. Boulon, and X. Hu, "Power Allocation Strategy based on Decentralized Convex Optimization in Modular Fuel Cell Systems for Vehicular Applications," *IEEE Transactions on Vehicular Technology,* pp. 1-1, 2020, doi: 10.1109/TVT.2020.3028089.

[160] S. Ahmadi, S. Bathaee, A. H. J. E. C. Hosseinpour, and Management, "Improving fuel economy and performance of a fuel-cell hybrid electric vehicle (fuel-cell, battery, and ultra-capacitor) using optimized energy management strategy," vol. 160, pp. 74-84, 2018.

[161] E. Breaz, F. Gao, D. Paire, and R. Tirnovan, "Fuel cell modeling With dSPACE and OPAL-RT real time platforms," in *2014 IEEE Transportation Electrification Conference and Expo (ITEC)*, 15-18 June 2014 2014, pp. 1-6, doi: 10.1109/ITEC.2014.6861813.

[162] F. Gao, B. Blunier, M. G. Simões, and A. Miraoui, "PEM Fuel Cell Stack Modeling for Real-Time Emulation in Hardware-in-the-Loop Applications," *IEEE Transactions on Energy Conversion,* vol. 26, no. 1, pp. 184-194, 2011, doi: 10.1109/TEC.2010.2053543.

[163] H. Koptez, "Real-time systems: design principles for distributed embedded applications," ed: Kluwer Academic Publisher, 1997.

[164] Q. Li *et al.*, "A State Machine Control Based on Equivalent Consumption Minimization for Fuel Cell/ Supercapacitor Hybrid Tramway," *IEEE Transactions on Transportation Electrification,* vol. 5, no. 2, pp. 552-564, 2019, doi: 10.1109/TTE.2019.2915689.

[165] Q. Song, L. Wang, and J. Chen, "A Decentralized Energy Management Strategy for a Fuel Cell-Battery Hybrid Electric Vehicle Based on Composite Control," *IEEE Transactions on Industrial Electronics,* pp. 1-1, 2020, doi: 10.1109/TIE.2020.2992964.

[166] K. Ou, W.-W. Yuan, M. Choi, S. Yang, S. Jung, and Y.-B. J. I. J. o. H. E. Kim, "Optimized power management based on adaptive-PMP algorithm for a stationary PEM fuel cell/battery hybrid system," vol. 43, no. 32, pp. 15433-15444, 2018.

[167] D. Gao, Z. Jin, and Q. Lu, "Energy management strategy based on

fuzzy logic for a fuel cell hybrid bus," *Journal of Power Sources,* vol. 185, no. 1, pp. 311-317, 2008, doi: 10.1016/j.jpowsour.2008.06.083.

[168] S. Bae *et al.*, "Ecological Adaptive Cruise Control of Plug-in Hybrid Electric Vehicle with Connected Infrastructure and On-Road Experiments," *Journal of Dynamic Systems, Measurement, and Control,* 2021, doi: 10.1115/1.4053187.

[169] N. Rama, H. Wang, J. Orlando, D. Robinette, and B. Chen, "Route-Optimized Energy Management of Connected and Automated Multi-Mode Plug-In Hybrid Electric Vehicle Using Dynamic Programming," 2019. [Online]. Available: https://doi.org/10.4271/2019-01-1209.

[170] A. Eddahech, O. Briat, M. Ayadi, and J.-M. Vinassa, "Modeling and adaptive control for supercapacitor in automotive applications based on artificial neural networks," *Electric Power Systems Research,* vol. 106, pp. 134-141, 2014/01/01/ 2014, doi: https://doi.org/10.1016/j.epsr.2013.08.016.

[171] L. Vichard, F. Harel, A. Ravey, P. Venet, and D. Hissel, "Degradation prediction of PEM fuel cell based on artificial intelligence," *International Journal of Hydrogen Energy,* vol. 45, no. 29, pp. 14953-14963, 2020/05/26/ 2020, doi: https://doi.org/10.1016/j.ijhydene.2020.03.209.

[172] Z. Donghua and X. Ding, "Theory and applications of fault tolerant control," *Acta Automatica Sinica,* vol. 26, no. 6, pp. 788-797, 2000.

[173] D. Hissel and M.-C. Pera, "Diagnostic & health management of fuel cell systems: Issues and solutions," *Annual Reviews in Control,* vol. 42, pp. 201-211, 2016.

[174] Z. Zheng *et al.*, "A review on non-model based diagnosis methodologies for PEM fuel cell stacks and systems," *International Journal of Hydrogen Energy,* vol. 38, no. 21, pp. 8914-8926, 2013.

[175] R. Petrone *et al.*, "A review on model-based diagnosis methodologies for PEMFCs," *International Journal of Hydrogen Energy,* vol. 38, no. 17, pp. 7077-7091, 2013.

[176] M. M. Morato, P. R. Mendes, J. E. Normey-Rico, and C. Bordons, "LPV-MPC fault-tolerant energy management strategy for renewable microgrids," *International Journal of Electrical Power & Energy Systems,* vol. 117, p. 105644, 2020.

[177] E. Kamal and L. Adouane, "Hierarchical energy optimization strategy and its integrated reliable battery fault management for hybrid hydraulic-electric vehicle," *IEEE Transactions on Vehicular Technology,* vol. 67, no. 5, pp. 3740-3754, 2018.

[178] A. K. Soltani, M. Kandidayeni, L. Boulon, and D. L. St-Pierre, "Modular Energy Systems in Vehicular Applications," *Energy Procedia,* vol. 162, pp. 14-23, 2019/04/01/ 2019, doi: https://doi.org/10.1016/j.egypro.2019.04.003.

[179] M. Yue, S. Jemei, and N. Zerhouni, "Energy management strategy based on prognostics-enabled decision-making for fuel cell hybrid electric vehicles," in *GdR Hydrogène, Systèmes et Piles à Combustible 3652*, Le Croisic, France, 2019-06-11 2019, https://hal.archives-ouvertes.fr/hal-02867829/document. [Online]. Available: https://hal.archives-ouvertes.fr/hal-02867829. [Online]. Available: https://hal.archives-ouvertes.fr/hal-02867829

[180] M. Figueroa-Santos, V. Sulzer, Y. Kim, J. Siegel, A. Stefanopoulou, and D. M. Rizzo, "Airflow and Power-Split Control Strategy for a Fuel Cell Hybrid Powered Robot," *IFAC-PapersOnLine,* vol. 54, no. 20, pp. 387-392, 2021/01/01/ 2021, doi: https://doi.org/10.1016/j.ifacol.2021.11.204.

[181] Y. Kim, M. Figueroa-Santos, N. Prakash, S. Baek, J. B. Siegel, and D. M. Rizzo, "Co-optimization of speed trajectory and power management for a fuel-cell/battery electric vehicle," *Applied Energy,* vol. 260, p. 114254, 2020/02/15/ 2020, doi: https://doi.org/10.1016/j.apenergy.2019.114254.

[182] X. Lin, X. Xu, and H. Lin, "Predictive-ECMS based degradation protective control strategy for a fuel cell hybrid electric vehicle considering uphill condition," *eTransportation,* vol. 12, p. 100168, 2022.

[183] Z. Nie, Y. Jia, W. Wang, Z. Chen, and R. Outbib, "Co-optimization of speed planning and energy management for intelligent fuel cell hybrid vehicle considering complex traffic conditions," *Energy,* vol. 247, p. 123476, 2022.

[184] B. Liu *et al.*, "Bi-level convex optimization of eco-driving for connected Fuel Cell Hybrid Electric Vehicles through signalized intersections," *Energy,* vol. 252, p. 123956, 2022.

[185] X. Hu, T. Liu, X. Qi, and M. J. I. I. E. M. Barth, "Reinforcement Learning for Hybrid and Plug-In Hybrid Electric Vehicle Energy Management: Recent Advances and Prospects," vol. 13, no. 3, pp. 16-25, 2019.

[186] N. Lu, N. Cheng, N. Zhang, X. Shen, and J. W. Mark, "Connected Vehicles: Solutions and Challenges," *IEEE Internet of Things Journal,* vol. 1, no. 4, pp. 289-299, 2014, doi: 10.1109/JIOT.2014.2327587.

[187] B. HomChaudhuri, R. Lin, and P. Pisu, "Hierarchical control strategies for energy management of connected hybrid electric vehicles in urban roads," *Transportation Research Part C: Emerging Technologies,* vol. 62, pp. 70-86, 2016.

[188] V. Turri, B. Besselink, and K. H. Johansson, "Cooperative look-ahead control for fuel-efficient and safe heavy-duty vehicle platooning," *IEEE Transactions on Control Systems Technology,* vol. 25, no. 1, pp. 12-28, 2016.

[189] D. Jia, K. Lu, J. Wang, X. Zhang, and X. Shen, "A Survey on Platoon-Based Vehicular Cyber-Physical Systems," *IEEE Communications Surveys & Tutorials,* vol. 18, no. 1, pp. 263-284, 2016, doi: 10.1109/COMST.2015.2410831.

[190] L. Guo, H. Chen, Q. Liu, B. J. I. T. o. S. Gao, Man,, and C. Systems, "A computationally efficient and hierarchical control strategy for velocity optimization of on-road vehicles," vol. 49, no. 1, pp. 31-41, 2018.

[191] J. Fleming, X. Yan, and R. Lot, "Incorporating Driver Preferences Into Eco-Driving Assistance Systems Using Optimal Control," *IEEE Transactions on Intelligent Transportation Systems,* pp. 1-10, 2020, doi: 10.1109/TITS.2020.2977882.

[192] W. Zhao, D. Ngoduy, S. Shepherd, R. Liu, and M. Papageorgiou, "A platoon based cooperative eco-driving model for mixed automated and human-driven vehicles at a signalised intersection," *Transportation Research Part C: Emerging Technologies,* vol. 95, pp. 802-821, 2018/10/01/ 2018, doi: https://doi.org/10.1016/j.trc.2018.05.025.

[193] A. Fernandes, T. Woudstra, A. Van Wijk, L. Verhoef, and P. Aravind, "Fuel cell electric vehicle as a power plant and SOFC as a natural gas reformer: An exergy analysis of different system designs," *Applied Energy,* vol. 173, pp. 13-28, 2016.

[194] F. Garcia-Torres, D. G. Vilaplana, C. Bordons, P. Roncero-Sanchez, and M. A. J. I. T. o. S. G. Ridao, "Optimal management of microgrids with external agents including battery/fuel cell electric vehicles," vol. 10, no. 4, pp. 4299-4308, 2018.

Arash Khalatbarisoltani (S’18) received a Ph.D. degree in electrical engineering from the Université du Québec à Trois-Rivières (UQTR), Canada, in 2022. He is a Postdoctoral Researcher with the College of Mechanical and Vehicle Engineering, Chongqing University, China. His research interests include fuel cell systems, energy management, renewable energy, and intelligent transport systems.

Haitao Zhou received a B.S. degree in Marine Engineering from Dalian Maritime University, China, in 2019. He is pursuing an M.S. degree in automotive engineering from Chongqing University, China. His current research interests include energy management for fuel cell vehicles.

Xiaolin Tang (M’19) received a B.S. degree in Mechanics engineering and an M.S. in Vehicle Engineering from Chongqing University, China, in 2006 and 2009, respectively. He received his Ph.D. in Mechanical Engineering from Shanghai Jiao Tong University, China, in 2015. He is currently an Associate Professor at the State Key Laboratory of Mechanical Transmissions and the Department of Automotive Engineering, Chongqing University, Chongqing, China. His research focuses on Hybrid Electric Vehicles (HEVs), Vehicle Dynamics, Noise and Vibration, and Transmission Control.

Mohsen Kandidayeni (S’18) received a master’s degree in Mechatronics from Arak University (Iran) in 2014. He joined the Hydrogen Research Institute of the University of Quebec, Trois-Rivières (UQTR), Canada, in 2016 and received his Ph.D. degree in Electrical Engineering from this university in 2020. He is currently a postdoctoral researcher in the Electric-Transport, Energy Storage, and Conversion Lab (e-TESC) at Université de Sherbrooke and a research assistant member in the Hydrogen Research Institute of UQTR.

Loïc Boulon (M'10, SM'15) received a master's degree in electrical and automatic control engineering from the University of Lille in 2006. Then, he obtained a Ph.D. in electrical engineering from the University of Franche-Comté (France). Since 2010, he has been a professor at UQTR (Full Professor since 2016) and works at the Hydrogen Research Institute (Deputy director since 2019). His research interests include hybrid electric vehicles and energy and power sources (fuel cell systems, batteries, and ultracapacitors).

Xiaosong Hu (SM’16) received a Ph.D. in automotive engineering from the Beijing Institute of Technology, China, in 2012. He did scientific research and completed his Ph.D. dissertation in the Automotive Research Center at the University of Michigan, USA, between 2010 and 2012. He is currently a professor at the Department of Mechanical and Vehicle Engineering, Chongqing University, China. His research interests include modeling and controlling alternative powertrains and energy storage systems.