Research on a Multi-Objective Hierarchical Prediction Energy Management Strategy for Range Extended Fuel Cell Vehicles

Yonggang Liu^{1,*}, Jie Li¹, Zheng Chen^{2,**}, Datong Qin¹, Yi Zhang³

¹State Key Laboratory of Mechanical Transmissions & School of Automotive Engineering, Chongqing University 400044, Chongqing China

²Faculty of Transportation Engineering, Kunming University of Science and Technology 650500, Kunming China

³Department of Mechanical Engineering, University of Michigan-Dearborn, Dearborn MI 48128, USA
Corresponding author. Email: andyliuyg@cqu.edu.cn (Y. Liu), chen@kmust.edu.cn (Z. Chen)

Abstract: In this paper, a multi-objective hierarchical prediction energy management strategy is proposed to achieve optimal fuel cell life economy and energy consumption economy for a range extended fuel cell vehicle. First, a global state of charge rapid planning method is proposed based only on the expected driving distance. Then, the vehicle speed information in the prediction horizon is estimated by a vehicle speed prediction module based on the back propagation neural network. According to the predicted speed and state of charge reference, a novel fusion algorithm that combines the direct configuration method and sequential quadratic programming is proposed to achieve optimal fuel cell life economy and energy consumption economy in the prediction horizon. Simulation results validate that the proposed strategy can effectively reduce the operating costs compared with that of the charge depletion-charge sustaining strategy and the equivalent consumption minimization strategy, thereby proving the feasibility of the proposed strategy.

Key words: Range extended fuel cell vehicles, hierarchical prediction energy management, state of charge reference trajectory, direct collocation method, speed prediction.

I. INTRODUCTION

Nowadays, global warming, environmental pollution and energy concerns are becoming more and more serious. Fortunately, developing alternative fuel vehicles can mitigate air pollution and oil consumption. Hybrid electric vehicles (HEVs), battery electric vehicles (BEVs) and fuel cell vehicles (FCVs) represent a developing trend in the realm of alternative fuel vehicles [1, 2]. Due to unsatisfactory limitations of the long battery charging time, range anxiety, and insufficient number of charging facilities for BEVs, plug-in HEVs (PHEVs) have attracted much attention, as they combine the advantages of BEVs and HEVs [3]. They not only can supply a certain so-called all electric range (AER), but can also work in a blended mode to further improve their operating

efficiency and meanwhile extend their driving range. Currently, most PHEV powertrain systems are powered by internal combustion engines (ICEs) and lithium-ion batteries. With rapid development of hydrogen technology, however, proton exchange membrane fuel cells (PEMFCs), as an environmentally friendly technology, can replace ICEs in PHEVs to constitute range extended FCVs that exhibit high efficiency and zero greenhouse gas (GHG) emissions [4, 5].

For a range extended FCV, the battery can be charged from the power grid or by the fuel cell. The battery and fuel cell can directly power the vehicle, and thus the vehicle can work in different operation modes, leading to complexity when selecting the operation mode and controlling the energy distribution. An efficient energy management strategy (EMS) is imperative for the vehicle controller to properly manage the energy allocation with the promise of satisfying the driving demand while achieving different optimization targets, such as reducing hydrogen consumption and extending the PEMFCs' lifespan. Currently, EMSs of hybrid vehicles can be mainly divided into two categories, i.e., rule-based and optimization-based [6-9].

Rule-based strategies mainly include deterministic rules control strategies [10, 11] and fuzzy logic control strategies [12,13]. These kinds of strategies often need to design the operating modes and energy distribution rules of HEVs based on experience with consideration for each component's characteristics. A fixed rule table can be constructed to achieve control among different energy sources. These strategies have the advantages of stability, robustness, and easy application, but also bring the disadvantages of poor adaptivity when faced with different road conditions and difficulties of finding optimal management solutions [14]. Fuzzy logic based strategies are realized by adding the fuzzification process based on insight experience or neural network (NN) training [15], whereas the EMS based on fuzzy rules is complex and requires developers to take into full consideration all the possible operating conditions.

Essentially, the energy management of hybrid vehicles is an optimal control problem. Consequently, typical optimization algorithms, such as dynamic programming (DP) [16], convex optimization [17], quadratic programming (QP) [18] and Pontryagin's minimum principle (PMP) [19, 20], have been widely employed to find optimal solutions with different targets. DP, as a straightforward and easy implementation method, is effective for finding an optimal solution to a deterministic problem; however, the price to pay is the enormous computational intensity, i.e., the so-called curse of dimensionality, when solving energy management problems with a long driving duration. As such, DP is undoubtedly limited for online applications [21]. Instead, it can be treated as a benchmark to evaluate other methods' performance. As for convex optimization, this method

requires that the object and model are convex, and it is difficult to satisfy the requirement all the time. Meanwhile, PMP is generally treated as the theoretical basis for the equivalent consumption minimization strategy (ECMS) [22]. When applying the PMP algorithm, the equivalent factor is a variable related to the driving conditions as well as the battery parameters [23]; therefore, properly determining the equivalent factor remains challenging [24, 25]. A common approach to this method is that researchers usually assume the battery parameters to be unchanged, calculate the optimal equivalent factor offline, identify the driving conditions online, and finally regulate the appropriate equivalent factor in real time [26]. However, when the driving condition is complex, the ECMS usually cannot achieve satisfactory performance. In order to avoid the shortcomings of DP and PMP, this paper attempts to solve the energy management problem based on the direct method, which can transform the optimal control problem into a nonlinear programming problem. The direct method mainly includes the direct shooting method [27], pseudo-spectral method [28] and direct collocation method [29], among which the direct collocation method is not sensitive to the initial values and shows strong convergence capability. The direct method has been widely used in aircraft guidance and control [30-32], but to the authors' best knowledge, there has not been any research released pertaining to its application in the energy management of hybrid vehicles.

Recently, wide development and application of the global positioning system (GPS), intelligent transportation system (ITS), geographic information system (GIS), and internet of vehicles (IOV) technologies have made it possible to acquire global driving information when a vehicle operates. As a result, more and more research regarding energy management has gradually taken driving information into account. In [33], GPS, GIS, and ITS are applied together to obtain the speed curve information for each section in advance, and a real-time EMS is proposed based on the state of charge (SOC) reference and rolling control. In [34], a hierarchical predictive EMS with traffic awareness is leveraged by combining long-term SOC planning and short-term condition prediction. The predicted driving conditions and planned SOC trajectory can be referred to for real-time control. Nevertheless, this hierarchical EMS strongly relies on the designed global SOC reference trajectory. At the current research stage, precise acquisition of global driving information is quite difficult, due to the complex variation of real-time driving conditions. Hence, the challenge of how to obtain the SOC reference trajectory without relying on global driving information needs to be carefully dealt with in further research.

With fast development of the model predictive control (MPC) theory, more and more energy management research based on MPC has attracted wide attention. In terms of MPC, the future power demand can be predicted

in a receding horizon based on the built model, and short-term energy management can be resolved by an optimization algorithm, thereby finding a near-optimal solution. When MPC is applied in the energy management of HEVs, a critical condition is to predict the future speed in a certain horizon, which can directly influence its control performance. Currently, the vehicle speed prediction models commonly employed in research include exponential prediction models [35, 36], Markov prediction models [37, 38] and NN models [34, 39-41]. Among them, the NN model is the most popular. In [34], an NN based speed predictor is firstly introduced and incorporated into the MPC algorithm, thus characterizing it as having a simple design and reliable prediction. In [39], a vehicle prediction model is proposed based on the radial basis function (RBF)-NN to supply the short-term speed prediction for the MPC application. In [40], an updated NN predictor with a wavelet transformation is put forward, in which the signal that is inputted into the RBF-NN is preprocessed by the wavelet transformation. In this manner, the well-trained prediction model can sufficiently consider the driving characteristics. In [41], the vehicle to vehicle (V2V) and vehicle to internet (V2I) communication are simulated under VISSIM, and the obtained transportation information can be applied to the velocity prediction model built based on the chaining NN (CNN).

Nowadays, the primary goal of an EMS is to find the optimal energy savings. For extended range FCVs, since fuel cells are costly and their lifespan is relatively short at current levels, it is equally important to extend the operation durability of the fuel cells by properly designing the EMS [42-44]. One common solution is to manually limit the operating state of the fuel cell, such as the maximum current and the on/off frequency. In [45], the electric energy generated by the fuel cell should be more than the predetermined minimum value at each startup, and the on/off frequency of the fuel cell can be reduced. In this way, the fuel cell life can be extended. In [46], the decay rate of the fuel cell is reduced by artificially limiting the current variation rate to a smaller range; however, this limiting effect can sometimes be restricted. In [47], considering the battery SOC and the fuel cell lifetime function, a fuzzy controller is designed to determine the energy supplied by the battery, the fuel cell, or both in real time. Nonetheless, it is quite difficult to develop appropriate and comprehensive fuzzy rules. Consequently, related multi-objective co-optimization research has moved forward by integrating the fuel cell life economy into the EMS design. In [48], by adding fuel cell life economy indicators to the objective function, the fuel economy and system durability can simultaneously be optimized based on DP. In [49], a multi-optimization model is established to estimate the impact of the EMS in terms of fuel cell degradation. Then, a stochastic DP algorithm is adopted to reduce the fuel cell degradation. In [50], a

hierarchical reinforcement learning (RL) algorithm is leveraged to find the approximate global optimal solution, and the upper confidence tree search method is harnessed to optimize the fuel cell working state, thereby extending its lifespan. In addition, more and more research has been conducted to consider co-optimization of the FCV powertrain design and control strategy determination. In [51], a two-loop control framework based on Pareto optimization is proposed. In the inner loop, DP is employed to optimize the hydrogen consumption economy and fuel cell lifespan under the Chinese city bus cycle; and in the outer loop, the component sizing is optimized by comparing the different objective functions. In [52], according to the built state of health (SOH) model of the battery, a convex objective function is constructed considering the lifespan cost of the fuel cell and hydrogen consumption. A convex algorithm is then employed to find the optimal parameters for the main powertrain components and control strategy simultaneously, given a typical driving cycle. Ref. [53] proposes a co-optimization algorithm, which optimizes the vehicle's overall economy by selecting the powertrain parameters and meanwhile determining the energy management strategy. Ref. [54] builds the electrochemical surface area (ECSA) model of the fuel cell to quantify the degradation rate, considers it associated with the hydrogen consumption in a uniform objective function, and adopts a deterministic DP algorithm to solve the co-optimization problem with the premise of knowing the global driving conditions. That said, global optimization methods that consider optimization of the life economy of the fuel cell are only theoretically attainable and can be considered as a benchmark or optimal samples for building a rule-based optimization strategy. How to design a multi-objective EMS with consideration for the life economy and without global driving information still needs to be widely investigated.

To solve the problems discussed above, this paper proposes a multi-objective hierarchical prediction EMS that divides the whole control framework into two layers. In the upper layer, a rapid SOC planning method is proposed based only on the expected driving distance and without knowing the global driving information. Then, the vehicle speed information in the prediction horizon is estimated by a vehicle speed prediction module based on genetic algorithm (GA) and back propagation neural network (BPNN). In the bottom layer, according to the SOC reference trajectory and vehicle speed information in the prediction horizon, the direct collocation method is applied to transform the optimization control problem into a nonlinear programming problem, which can be solved by the sequential quadratic programming (SQP) method to achieve optimal control performance in the prediction horizon, thereby achieving the multi-objective optimization target, which includes the improvement of both energy consumption economy and fuel cell life economy. Finally, simulation results show that the

proposed multi-objective hierarchical prediction EMS can reduce the operating costs by 8.6% and 13.5%, compared with those of the charge depletion-charge sustaining (CD-CS) strategy and ECMS, respectively.

The main contributions of this paper are attributed to the following three aspects: 1) a multi-objective EMS is proposed with consideration for energy consumption economy and fuel cell life economy. It effectively promotes economical energy consumption and meanwhile prolongs the lifespan of the fuel cell; 2) a method of obtaining the global SOC reference trajectory is proposed, which relies only on the expected travel distance; and 3) the direct collocation method and SQP method are harnessed to solve the multi-objective energy management problem in the prediction horizon.

The remainder of the paper is structured as follows. In Section II, the configuration of a hybrid powertrain system is modeled, and the mathematical analysis is conducted. A detailed introduction to the multi-objective hierarchical prediction strategy is elaborated on in Section III. In Section IV, simulation validation is carried out. The performance of the proposed multi-objective hierarchical prediction strategy is compared with that of the traditional CD-CS strategy and the ECMS. Section V draws main conclusions of the paper.

II. POWERTRAIN STRUCTURE AND SYSTEM MODEL

A. Powertrain System Model

In order to establish the proposed multi-objective hierarchical prediction EMS, it is necessary to model the vehicle dynamic system. The structure of the studied FCV is shown in Fig. 1. The fuel cell stack is connected to the power bus through a DC/DC converter, and the motor is driven by the fuel cell and battery together. It is necessary to mention that there exists a clutch between the motor and gearbox, whose main function is to reduce the inertia introduced by the motor when the vehicle coasts. However, it does not affect the modeling of the vehicle, and we did not consider the clutch control for ease of building the energy management algorithm. Table I lists the main powertrain parameters.

Fig. 1. Range extended FCV configuration.

Table I System parameters

Characteristic	Value
Air drag coefficient	0.32
Frontal projected area	2.82 m ²
Roll resistance coefficient	0.0135
Mass	1350 kg
Battery type	Lithium-ion battery
Rated voltage	320 V
Rated capacity	40 Ah
Fuel cell type	Proton exchange membrane fuel cell
Active area	120 cm ²
Maximum power of fuel cell	30 kw

The vehicle dynamic force can be formulated as the sum of the slope resistance, rolling resistance, air resistance, and inertial resistance. The power required at wheel P_{wheel} can be computed as:

$$P_{wheel} = (mgf_r \cos \theta + mg \sin \theta) \times v(t) + \delta ma(t) \times v(t) + \frac{1}{2} C_D A \rho v^3(t) \quad (1)$$

where C_D expresses the windward resistance coefficient, A means the windward area, $v(t)$ is the vehicle speed, f_r is the rolling resistance coefficient, m is the mass of the vehicle, g is the gravitational acceleration, δ is the rotating mass coefficient, and $a(t)$ denotes the acceleration of the vehicle.

The power bus P_{BUS} , expressed in (2), provides power to the drive motor:

$$P_{BUS} = \frac{P_{wheel}}{\eta_{GB} \times \eta_M \times \eta_{DC/AC}} \quad (2)$$

where η_{GB} , η_M , and $\eta_{DC/AC}$ denote the efficiency of the gear transmission path, motor and DC/AC converter, respectively. The fuel cell and lithium-ion battery are connected to the power bus, and the relationship between the fuel cell power P_{fc} , battery power P_{bat} and bus power P_{BUS} can be expressed as:

$$P_{BUS} = P_{fc} \times \eta_{DC/DC} + P_{bat} \quad (3)$$

where $\eta_{DC/DC}$ denotes the DC/DC converter efficiency.

B. Fuel Cell System Model

A typical modeling manner for fuel cells can be expressed as a semi-rational formula of a polarization curve, according to experimental and mathematical derivation found in previous research [55], such that:

$$V = E_{nest} - \Delta V_{ohm} - \Delta V_{act} - \Delta V_{trans} = E_{OC} - \frac{I_{fc}}{Area} r - A_{Tafel} \ln\left(\frac{I_{fc}}{Area}\right) + m \exp\left(\frac{nI_{fc}}{Area}\right) \quad (4)$$

where E_{OC} means the reversible open circuit voltage, A_{Tafel} is the slope of the Tafel line, r denotes the area-specific resistance, m and n are constants in the mass-transfer overvoltage equation, $Area$ expresses the active area of the PEMFC, and I_{fc} is the output current of the PEMFC. The hydrogen consumption of the PEMFC $\dot{m}_{fc}$ can be calculated as:

$$\dot{m}_{fc} = \frac{N_{cell} I_{fc} M_{H_2}}{2F} \quad (5)$$

where N_{cell} is the number of cells in the fuel cell stack, M_{H_2} is the molar mass of hydrogen, and F is the Faraday constant. The fuel cell system includes not only the fuel cell stack, but also air compressors, solenoid valves, and cooling systems. These subsystems also consume a portion of the power from the fuel cell stack, and the power output from the fuel cell system can be written as:

$$P_{FC} = VI_{FC} - P_{AUX} \quad (6)$$

where P_{AUX} is the fuel cell power consumed by the auxiliary system. According to (5) and (6), the efficiency of the fuel cell system η_{fc} can be calculated as:

$$\eta_{fc} = \frac{VI_{fc} - P_{AUX}}{\dot{m}_{fc} H_{LHV}} \quad (7)$$

where H_{LHV} is the lower heating value of hydrogen. According to (4) and (7), the polarization curve and efficiency curve of the PEMFC in this paper can be plotted as shown in Fig. 2. It can be found that the maximum efficiency is 0.43, and the voltage drops with an increase in current.

Fig. 2. Single cell polarization voltage curve and efficiency curve of the fuel cell system.

Many studies have shown that start-stop, load cycling and idling operations directly affect the lifespan of fuel cells [56]. In order to consider the life economy of PEMFCs, the impact of these actions on fuel cells should

be quantified. There has already been much research conducted on the decay model of fuel cells, so this paper selects an empirical formula proposed in [57] and widely adopted in [49, 58, 59], written as:

$$T_f = \frac{\Delta P}{k_p(P_1 n_1 + P_2 n_1 + P_3 t_3 + P_4 t_4)} \quad (8)$$

where ΔP refers to the maximum allowable value of the fuel cell voltage degradation in a vehicle. In this paper, ΔP is set to 10%. P_1 , P_2 , P_3 and P_4 are the performance degradation rates caused by load change, start-stop, idling and heavy load conditions; n_1 , n_2 , t_3 , and t_4 are the number of load change cycles, number of start and stop cycles, idling time, and heavy load time in the driving cycle, respectively. k_p is the correction factor for different fuel cell systems. Table II lists all the parameters' values.

Table II Degradation parameters of the PEMFCs

Coefficient	Value
P_1	0.0000593%
P_2	0.00196%
P_3	0.00126%
P_4	0.00147%
k_p	1

In order to calculate the total operating costs of a fuel cell, the amount of fuel cell degradation needs to be converted into equivalent hydrogen consumption based on the fuel cell stack price and hydrogen price:

$$\dot{m}_{life} = \frac{(P_1 n_1 + P_2 n_1 + P_3 t_3 + P_4 t_4) \alpha_{FC}}{10\% \alpha_{H_2}} \quad (9)$$

where Δm_{life} is the equivalent hydrogen consumption relative to the fuel cell degradation, $\alpha_{FC} = \$11400$ is the fuel cell stack price, and $\alpha_{H_2} = \$10 / kg$ is the price per kilogram of hydrogen.

C. Battery Model

For the lithium-ion battery, an R-int model, which is simple but effective, is employed to characterize its electric performance [60]. The model consists of an internal resistor and an open circuit voltage source that are connected in series. According to Kirchhoff's law, the battery current can be calculated as:

$$I_{bat} = \frac{E - \sqrt{E^2 + 4RP_{bat}}}{2R} \quad (10)$$

where I_{bat} , E , and R denote the current, open circuit voltage and internal resistance of the battery, respectively. The battery SOC, as a key variable when designing the EMS, is calculated based on the coulomb

counting method,

$$SOC(t) = SOC_{\text{int}} - \frac{\eta_b \int_{t_0}^t I_{\text{bat}}(t) dt}{Q_0} \quad (11)$$

where Q_0 is the battery capacity, SOC_{int} denotes the initial SOC value of the battery, and η_b means the charging and discharging efficiency. Here, in order to calculate the total operating cost of the fuel cell, the equivalent hydrogen consumption with respect to the battery is calculated as:

$$\dot{m}_{\text{bat}} = \frac{P_{\text{bat}} \alpha_{\text{ele}}}{3600 \eta_{\text{bat}} \alpha_{H_2}} \quad (12)$$

where $\dot{m}_{\text{bat}}$ is the equivalent hydrogen consumption of the battery, η_{bat} denotes the energy conversion efficiency of the battery, and α_{ele} expresses the electricity price per kilowatt-hour.

Now the total operating costs of the FCV $\dot{m}_w$ can be obtained by summing the hydrogen fuel cell consumption, the equivalent hydrogen consumption relative to the fuel cell degradation, and the equivalent hydrogen consumption of the battery:

$$\dot{m}_w = \dot{m}_{\text{fc}} + \dot{m}_{\text{life}} + \dot{m}_{\text{bat}} \quad (13)$$

Based on the established equivalent hydrogen consumption rate model, in the next step, the proposed multi-objective hierarchical prediction EMS will be discussed in detail.

III. HIERARCHICAL PREDICTION ENERGY MANAGEMENT STRATEGY

As discussed above, the energy management problem of the range extended FCV is a typical multi-objective nonlinear optimization problem. The proposed hierarchical prediction EMS can transform the global optimization problem into a local optimization subproblem that is guided by the global design and local prediction. The structure of the multi-objective hierarchical prediction EMS proposed in this study is shown in Fig. 3. It mainly consists of three parts: 1) SOC trajectory planning, 2) vehicle speed prediction and 3) rolling optimization. Its implementation process is detailed as follows.

Fig. 3. Control framework of the multi-objective hierarchical prediction EMS.

- (1) Ahead of departure, the total driving distance is acquired from the navigation system or driver. Based on the estimated distance, the SOC trajectory planning module optimizes the global SOC reference curve.
- (2) The vehicle speed prediction module predicts the expected speed based on the historical speed.
- (3) According to the expected vehicle speed vector and SOC reference value at the end of the prediction horizon, the rolling optimization algorithm is applied to find the optimal solutions within the predicted range.
- (4) Repeat steps (2) through (3) until the vehicle reaches its destination.

A. Planning of the Global SOC Reference Trajectory

Currently, prevalent methods utilized to obtain the global SOC trajectory is to assume that the global driving speed profile can be acquired in advance and the global SOC reference trajectory can be solved through an optimization algorithm such as DP. However, under real conditions, since vehicle speed can be easily influenced by traffic, pedestrians, and vehicles ahead, the global speed information is difficult to precisely predict, leading to the infeasibility of applying the optimal algorithm online. To overcome this limitation, this paper proposes a rapid planning method for the SOC reference trajectory based only on the expected driving distance.

Generally, the ending SOC is assumed to be its lower limit. The task of the EMS is to find an SOC trajectory that drops, beginning from the initial value and ending at the final value. The power required by the vehicle during the driving process can be expressed based on (1):

$$W = (mgf_r \cos \theta + mg \sin \theta) \times S + \int_0^t (\delta m a(t) v(t)) dt + \frac{1}{2} \int_0^t (C_D A \rho \delta v^3(t)) dt \quad (14)$$

During the driving process, a simple assumption is herein made that when the vehicle speed is low, the magnitude of the air resistance is small, and thus the air resistance can be neglected. Simultaneously, the average value of the acceleration is adopted to simplify the power calculation, and as such, equation (14) can be simplified as

$$W = \left[(mgf_r \cos \theta + mg \sin \theta) + \delta m \bar{a} \right] \times S \quad (15)$$

According to (15), it can be observed that under this assumption, the vehicle demand power increases linearly with the driving distance; thus it can be concluded that the SOC variation can be approximated as a linear function of the driving distance, which can be formulated as:

$$S(k+p) = S(k) + \int_{t_k}^{t_{k+p}} V(k) dt \quad (16)$$

$$SOC(k+p) = SOC_0 - \frac{S(k+p)}{S_{cyc}} (SOC_0 - SOC_{\min}) \quad (17)$$

where S_{cyc} is the entire travel distance, which is obtained at the beginning of each trip, $SOC(k+p)$ is the ending value of the SOC at the end of the prediction horizon at time $k+p$, and $S(k)$ is the driving distance at time k . In this manner, the SOC reference trajectory can be quickly determined.

B. Short-Term Speed Prediction

The main purpose of the vehicle speed prediction module is to predict the vehicle dynamic state in a future period based on historical vehicle speed information and current vehicle status. The predicted information is to be considered as inputs of the rolling optimization module. This paper employs the BPNN to finalize the prediction, of which the training parameters are optimized by GA to predict the speed of the vehicle. The historical vehicle speed vector $V_{history}$ is selected as the input of the NN, and the output $V_{predict}$ can be expressed as:

$$[V_{k+1}, V_{k+2}, \dots, V_{k+p}] = f_n[V_{k-h}, V_{k-h+1}, \dots, V_k] \quad (18)$$

where h expresses the length of the historical vehicle speed vector, f_n means the nonlinear mapping function of the NN, and p is the length of the predicted vehicle speed vector.

GA is employed to optimize the initial parameters of the BPNN, and the whole process of network training is divided into two parts. First, GA is applied to optimize the initial parameters of the NN; then the training data is entered into the NN. The basic elements of the GA consist of the choice of chromosome coding, selection of

the fitness function, and genetic operations, including selection, crossover and mutation. The selection of these operational parameters needs to be carefully dealt with. They include the population size M , genetic algebra G , crossover probability P_c and mutation probability P_m . After a variety of trial-and-error iterations, the population size is set to 100, the genetic algebra is also set to 100, according to the variation of the fitness value, the crossover probability is set to 0.7, and the mutation probability is set to 0.02. The specific process is shown in Fig. 4 (a).

In this paper, h and p are set to 5 and 10, respectively, and the hidden structure of the NN is one layer with 20 nodes. The training data is a combined driving cycle, which consists of different standard driving cycles, including the New York City Cycle (NYCC), New York Bus Cycle, Economic Commission of Europe Extra Urban Driving Cycle Low (ECE_EUDC_LOW), Highway Fuel Economy Test (HWFET), US06 Supplemental Federal Test Procedure (US06_SFTP), New European Driving Cycle (NEDC), Indian Highway Sample Cycle (INDIA_HWY) and Indian Urban Sample Cycle (INDIA_URBAN). These cycles represent all possible driving conditions, and the total time of the combined driving cycle is 10209 s.

Fig. 4. Vehicle speed prediction. (a) NN parameters optimized by GA; and (b) Comprehensive driving cycle.

C. Multi-Objective Rolling Optimization Algorithm

The goal of multi-objective optimization energy management for the range extended FCV is to control the output current of the fuel cell to achieve optimal balance between the fuel cell life and energy consumption. In this paper, SOC is considered the state $x(t)$, and the fuel cell stack current I_{FC} is considered the control variable $u(t)$. The objective function can be obtained in the prediction horizon as:

$$J = \int_{t_k}^{t_{k+p}} (m_{fc}(t) + m_{bat}(t) + m_{life}(t)) dt \quad (19)$$

In addition, the system control variables and state variables should be subject to the following constraints [46]:

$$\begin{cases} SOC \in [SOC_{\min}, SOC_{\max}] \\ I_{FC} \in [I_{FC_min}, I_{FC_max}] \\ I_{FC}(t+1) - I_{FC}(t) \in [-1, 1] \end{cases} \quad (20)$$

where $SOC_{\min} = 0.3$, $SOC_{\max} = 0.9$, $I_{FC_min} = 2$ A, and $I_{FC_max} = 45$ A. It is necessary to note that the initial value and ending value of the SOC during the rolling optimization process should be respectively equal to $SOC(t_k)$ and $SOC(t_{k+p})$, given by the SOC reference trajectory:

$$\begin{cases} SOC_{\text{int}} = SOC(t_k) \\ SOC_{\text{end}} = SOC(t_{k+p}) \end{cases} \quad (21)$$

Here, the direct collocation method is employed to solve the optimal control problem of the energy management, which can transform the optimal control problem into a nonlinear optimization problem. It uses a piecewise polynomial equation to approximate the trajectory of the state variable, and then transforms the original problem into a nonlinear programming problem with multiple optimization variables and constraints. To apply the direct collocation method, the time period $[t_0, t_f]$ in the prediction horizon needs to be equally divided into n subintervals with $n+1$ nodes. Thus, each segment duration Δt is equal to $(t_f - t_0) / (n+1)$, and the discrete time points can be described as $t_0 = t_1 < t_2 < \dots < t_{n+1} = t_f$. The state variables and control variables at time t_i are $x_i = x(t_i)$ and $u_i = u(t_i)$. The optimization parameters are composed of all the state variables x_i and control variables u_i ; therefore, the decision vector of the nonlinear programming problem can be expressed as:

$$Z = [x_1^T, u_1^T, x_2^T, u_2^T, \dots, x_{n+1}^T, u_{n+1}^T] \quad (22)$$

In this paper, when $t \in [t_i, t_{i+1}]$, according to the Hermite-Simpson method, the state variables can be

represented by a cubic Hermite polynomial equation:

$$x = c_0 + c_1 s + c_2 s^2 + c_3 s^3 \quad (23)$$

where $s = (t - t_i) / \Delta t$ and $s \in [0, 1]$. The state variable at the midpoint x_m and its derivation $\dot{x}_m$ can be calculated as:

$$\begin{cases} x_m = (x_i + x_{i+1})/2 + \Delta t(f_i - f_{i+1})/8 \\ \dot{x}_m = [-3 / (2\Delta t)](x_i + x_{i+1}) - (f_i + f_{i+1})/4 \end{cases} \quad (24)$$

The control variable at the midpoint u_m can be calculated by the linear interpolation, such that $u_m = (u_i + u_{i+1}) / 2$. According to (10), f_m corresponds to the state variable at the midpoint and can be calculated as:

$$f_m = f(x_m, u_m, t) \quad (25)$$

To determine the extent to which the polynomial approximates the differential equation, the deviation at the midpoint is defined as:

$$\Delta = f_m - \dot{x}_m = f_m + [3 / (2\Delta t)](x_i + x_{i+1}) + (f_i + f_{i+1})/4 \quad (26)$$

We then find that if x_i , x_{i+1} , u_i and u_{i+1} are selected with appropriate values that make the deviation small enough, the polynomial at the midpoint can be approximated to the system's motion differential equation. In this manner, the optimal control problem can be transformed into a nonlinear sequential optimization problem, of which the state variables and control quantities need to be optimized for $n + 1$ nodes. Certainly, it can be solved by the SQP method.

When $\Delta t = 1s$, equation (19) can be transformed into (27) by the direct collocation method:

$$O(Z) = \sum_{i=1}^{p+1} (m_{fc}(i) + m_{bat}(i) + m_{life}(i)) \quad (27)$$

in which the parameters to be optimized include:

$$Z = [x_1^T, u_1^T, x_2^T, u_2^T, \dots, x_{p+1}^T, u_{p+1}^T] \quad (28)$$

Similarly, the equality constraints of the nonlinear programming problem can be expressed as:

$$\begin{cases} h_{i1} = SOC_{int} - SOC(t_k) = 0 \\ h_{i2} = f_m - \dot{x}_m = 0 \end{cases} \quad (29)$$

In order to avoid a situation that cannot be solved due to some erroneous prediction speeds that do not satisfy the SOC change, it is necessary to relax the terminal condition of the state variable. By converting the equality

constraint to a soft constraint and adding it to (27) as a penalty function, we can attain:

$$P(Z) = 10^{12} \times (SOC_{end} - SOC(t_{k+p}))^2 \quad (30)$$

The inequality constraints of the optimization problem are summarized as follows:

$$\begin{cases} g_{i1} = SOC_{\min} - SOC \leq 0 \\ g_{i2} = SOC - SOC_{\max} \leq 0 \\ g_{i3} = I_{FC_min} - I_{FC} \leq 0 \\ g_{i4} = I_{FC} - I_{FC_max} \leq 0 \\ g_{i5} = |I_{FC}(t+1) - I_{FC}(t)| - 1 \leq 0 \end{cases} \quad (31)$$

According to (27) to (31), the objective function and constraints of the multi-objective optimization can be transformed into a nonlinear programming problem, as:

$$\begin{cases} \min J = F(Z) = O(Z) + P(Z) \\ s.t. \ h_{ij}(Z) = 0; i = 1, 2, \dots, p+1; j = 1, 2 \\ \quad g_{it}(Z) \leq 0; t = 1, 2, 3, 4, 5 \end{cases} \quad (32)$$

In this paper, the SQP method is employed to solve this problem, which is achieved through a series of QP subproblems. The basic structure of SQP includes the main iteration and QP subproblems. The main iteration gradually converges to the optimal solution of the problem, and the QP subproblem in the main iteration produces the search direction for the next main iteration. Based on (32), its Lagrange multiplier function can be expressed as:

$$L(Z, \lambda, \mu) = F(Z) + \sum_{i=1}^{p+1} \sum_{j=1}^2 \lambda_{ij} h_{ij}(Z) + \sum_{i=1}^{p+1} \sum_{t=1}^5 \mu_{it} g_{it}(Z) \quad (33)$$

In the main iteration process, the search direction d is determined by the QP:

$$\begin{cases} \min \frac{1}{2} d^T H_c d + (\nabla F(Z_c))^T d \\ s.t. (\nabla h_{ij}(Z_c))^T d + h_{ij}(Z_c) = 0 \\ \quad (\nabla g_{it}(Z_c))^T d + g_{it}(Z_c) = 0 \end{cases} \quad (34)$$

According to the solution of the QP, a one-dimensional search equation can then be obtained:

$$Z_{c+1} = Z_c + \alpha_c d_c \quad (35)$$

where α_c is the step size of the search in the main iteration process. H_c , defined in (36), is the approximate Hessian matrix of the Lagrange multiplier function, which is corrected by the Broyden–Fletcher–Goldfarb–Shanno (BFGS) algorithm [61]:

$$H_{c+1} = H_c - \frac{H_c s_c s_c^T H_c}{s_c^T H_c s_c} + \frac{y_c y_c^T}{y_c^T s_c} \quad (36)$$

where $s_c = Z_{c+1} - Z_c$ and $y_c = G_{c+1} - G_c$. Here, G_c is the first derivative of the Lagrange multiplier function. In the next section, simulation is performed to verify the feasibility of the proposed strategy.

IV. SIMULATION AND DISCUSSIONS

In order to verify effectiveness of the proposed multi-objective hierarchical prediction EMS, simulation is conducted based on Matlab/Simulink. We divide the whole simulation into four parts. First, the global SOC reference trajectory calculated by the proposed planning method is compared with that calculated by DP with global driving information, and the reliability and robustness of the proposed method is discussed. Second, we compare two predictors, of which one is the suggested simple model with no change in the next step and the other is our prediction model. Third, the energy consumption economy of the proposed multi-objective rolling optimization algorithm is analyzed. Finally, the economy of the proposed strategy is analyzed under the condition that the global driving information is unknown. Moreover, the computational effort with respect to the proposed strategy and optimization-based control algorithm is analyzed and compared.

A. Reliability Analysis of the Global SOC Reference Trajectory Method

The speed trajectories of three different standard driving cycles, including the Urban Dynamometer Driving Schedule (UDDS), NEDC and Manhattan cycle, are shown in Fig. 5 (a). These three cycles can typically represent common driving conditions. The SOC reference trajectory is calculated using DP with the global speed information under three standard driving cycles, and its solution output is the optimal SOC trajectory, which can be considered as a benchmark. The objective function and restrictions of DP are described as:

$$J = \int_{t_0}^{t_f} (m_{fc}(t) + m_{bat}(t)) dt \quad (37)$$

$$\begin{aligned} s. t. \quad & SOC_{\min} \leq SOC \leq SOC_{\max} \\ & I_{FC_min} \leq I_{FC} \leq I_{FC_max} \end{aligned} \quad (38)$$

The main parameters used to realize DP are specified as $SOC_{\min} = 0.3$, $SOC_{\max} = 0.9$, $I_{\min} = 2$ and $I_{\max} = 45$.

The simulation starts with $SOC_{int} = 0.4$. The global SOC reference trajectory calculated by the proposed method with the expected driving distance and by DP with global speed information are shown in Fig. 5 (b). It can be found that both methods can ensure the SOC converges to the setting ending value. When comparing the calculation result for the NEDC cycle, there exist obvious differences between the two SOC trajectories; while

for the UDDS cycle and Manhattan cycle, they are almost the same and only show slight differences.

In order to evaluate the reliability of the proposed method, the R-square method is calculated by the SOC reference trajectory of the two methods, as furnished in (39), and the final results are listed in Table III.

$$R^2 = 1 - \frac{SSE}{SST} = 1 - \frac{\sum_{i=1}^n (y_i - \hat{y}_i)^2}{\sum_{i=1}^n (y_i - \bar{y}_i)^2} \quad (39)$$

Fig. 5. Speed profiles and SOC calculation. (a) Speed curve of three standard driving cycles; (b) Comparison of the SOC reference trajectory. DP-SOC denotes the SOC reference trajectory based on DP with global speed information. Dis-SOC means the SOC reference trajectory of the proposed method with expected driving distance.

Table III Correlation coefficient of the two methods

Drive cycle	Drive distance	Drive time	R-square
UDDS	11990m	1370s	0.9322
NEDC	10931m	1186s	0.3502
3*MANHATTAN	9973m	3270s	0.9925

According to Fig. 5 and Table III, when the simulation is carried out under the UDDS cycle and Manhattan cycle, the SOC reference trajectories calculated by the proposed method are quite close to the optimal SOC reference trajectories obtained by DP, and the R-square of the SOC reference trajectories obtained by these two methods is close to one. However, for the NEDC, the SOC reference trajectory obtained by the proposed method is obviously different from that based on DP, which proves that the assumption made in Section III is correct at low vehicle speeds. The lower the vehicle speed, the more similar the SOC trajectories based on the two methods become. Under this condition, the reference trajectory calculated by the proposed method is more reliable.

B. Performance Analysis of the Speed Prediction Model

When analyzing the performance of the speed prediction model, it is necessary to obtain the global SOC reference trajectory and train the short-term vehicle speed prediction model. In order to avoid the impact of obtaining the global SOC reference trajectory using different algorithms, here we have applied DP, introduced previously, to calculate the global SOC reference trajectory for the UDDS, as shown in Fig. 6 (a). The short-term vehicle speed prediction model uses the BPNN prediction model built in Section III B. The predicted driving cycle is the UDDS, and the predicted result is shown in Fig. 6 (b). The root-mean-square error (RMSE) is harnessed to quantify the difference between the predicted vehicle speed and expected value. After calculation, it equals 2.29, proving the proposed algorithm can predict the speed satisfactorily after comparing the results with those shown in similar research [62]. In addition, we also employed a simple speed prediction algorithm to evaluate the effect of the proposed BPNN predictor. Here, the simple speed prediction model assumes that the vehicle speed will not change in the next time step. The corresponding prediction result is shown in Fig. 6 (c). On the premise of ensuring the SOC reference trajectory and receding optimization algorithm unchanged, two different velocity predictors are implemented to achieve the simulation. Related simulation results in terms of the SOC trajectory and fuel cell current are plotted in Fig. 6 (d) and Fig. 6 (e). Table IV compares the operating costs under the two vehicle speed predictors.

Fig. 6. Simulation results of two vehicle speed predictors. (a) The global SOC reference trajectory; (b) BPNN prediction under the UDDS; (c) Simple speed prediction under the UDDS; (d) The SOC variation trajectories; (e) The fuel cell current.

Table IV Comparison of operating costs under two vehicle speed predictors

	$m_{fc}(g)$	$m_{bat}(g)$	$m_{life}(g)$	$Total(g)$
Simple predictor	94.7477 (-5.9%)	91.5376 (+0.64%)	79.5561 (-10.9%)	265.8413 (-5.2%)
BPNN predictor	89.0719	92.1250	70.8977	252.0946

Note: +: Increment; -: Reduction

As can be seen in Fig. 6 (d), since two velocity predictors can estimate the future speed profiles differently, the final SOC shows certain differences; however, both algorithms can effectively track the global SOC reference curve. From Fig. 6 (e), we can find that the BPNN based predictor can regulate the fuel cell current more actively when faced with variations in the driving condition, such as the acceleration process from 165 s to 240 s. Before the acceleration occurs, the BPNN predictor can anticipate the acceleration, and the built algorithm can regulate the fuel cell current increase earlier; similarly, toward the end of the acceleration process, the BPNN predictor can foresee the action and correspondingly, the strategy will reduce the fuel cell current faster. In this manner, a lower fuel cell current can be better controlled by the BPNN predictor in comparison with the simple predictor. As a result, the hydrogen consumption can be obviously reduced. By comparing the

hydrogen consumption in Table IV, we can find that our proposed prediction algorithm is more effective than the simple prediction algorithm, and the operating costs based on the proposed prediction model can be reduced by 5.2%. Therefore, we can conclude that the BPNN predictor is more suitable for the proposed EMS than the simple predictor.

C. Economic Analysis of the Multi-Objective Rolling Optimization Algorithm

To analyze the economic performance of the multi-objective rolling optimization algorithm, simulation was conducted to optimize the energy consumption economy based on it. The global SOC reference trajectory and vehicle speed prediction model are the same as before. Simulation results in terms of the SOC trajectory, the current and operating point of the fuel cell are plotted in Fig. 7. Table V compares the operating costs under two strategies.

Fig. 7. Simulation results of two algorithms. (a) Simulation results of SOC trajectory; (b) Simulation results of fuel cell current; (c) Simulation results of fuel cell operating point.

Table V Comparison of operating costs

	$m_{fc}(g)$	$m_{bat}(g)$	$m_{life}(g)$	$Total(g)$
Comparison algorithm	89.6047 (-0.59%)	92.0010 (+0.13%)	90.1707 (-21.4%)	271.7764 (-7.2%)
Proposed algorithm	89.0719	92.1250	70.8977	252.0946
Note: +: Increment; -: Reduction				

It can be observed from Fig. 7 (a) that the proposed algorithm can track the SOC reference trajectory precisely, proving its effectiveness. As can be seen in Fig. 7 (b), in order to ensure the highest overall efficiency of the fuel cell and battery, large current fluctuation of the fuel cell exists. The proposed multi-objective optimization algorithm can restrict the current fluctuation within a narrow range, thereby reducing the degradation of the fuel cell. In order to ensure the energy consumption economy of the FCV, the proposed algorithm needs to continuously adjust the operating point of the fuel cell to ensure the optimal energy consumption economy. As can be found in Fig. 7 (c), the fuel cell operating points of the proposed multi-objective optimization algorithm are more concentrated in the higher efficiency region. From Table V, the operating costs of the proposed multi-objective optimization algorithm are reduced by 7.2% compared with that of the single-objective optimization algorithm, proving the advanced nature of the proposed algorithm.

D. Results of the Multi-Objective Hierarchical Prediction EMS

In this section, we assume that only the expected driving distance is known and the initial SOC is set to 0.45. A combined driving cycle that consists of two Manhattan cycles and one UDDS, shown in Fig. 8 (a), is simulated based on the proposed EMS. Here we also applied the CD-CS strategy and ECMS to compare their performance with that of the proposed strategy. The results are shown in Fig. 8 and Table VI. Fig. 8 (b) compares the actual SOC based on the proposed strategy with the SOC planning trajectory based on DP and proposed method. Fig. 8 (c), (d), and (e) show the simulation results of the SOC trajectory, fuel cell current, and fuel cell operating point with these three strategies. Table VI provides a quantitative analysis with respect to the hydrogen consumption, equivalent hydrogen consumption of the battery, equivalent hydrogen consumption of the fuel cell degradation, total operating costs and total calculating time. Simulations were conducted on a computer with an Intel Core i7 CPU. The simulation duration for each step based on the two methods is shown in Fig. 8 (f).

Fig. 8. Simulation results of the three strategies in the comprehensive driving cycle. (a) Speed curve of the combined driving cycle; (b) Comparison of the actual SOC trajectory and reference SOC trajectory; (c) Simulation results of the SOC trajectory; (d) Simulation results of the fuel cell current; (e) Simulation results of the fuel cell operating point; (f) Calculation time comparison.

Table VI Economic comparison of different strategies under a combined driving cycle

	$m_{fc}(g)$	$m_{bat}(g)$	$m_{life}(g)$	$Total(g)$	$Calculating\ time(s)$
CD-CS	165.2293 (-4.5%)	137.2172 (+0.35%)	188.4134 (-18.8%)	490.8598 (-8.6%)	0.39
ECMS	147.7922 (+6.8%)	142.7423 (-3.5%)	227.6821 (-32.8%)	518.2166 (-13.5%)	1.83
Proposed EMS	157.8684	137.6949	152.9464	448.5097	434.26

Note: +: Increment; -: Reduction

From Fig. 8 (b), it can be found that the proposed strategy can follow the SOC reference trajectory accurately based on the expected driving distance, with the SOC dropping to 0.3 in the end. From Fig. 8 (c) and Table VI, the SOC trajectory curves based on these three strategies are different at the beginning of the trip. The SOC based on the CD-CS strategy drops to the lower limit of 0.3 at around 1452 s, hence the CD-CS strategy results in the most hydrogen fuel consumption. The ECMS ensures that the battery SOC drops to around 0.3 at the end of the trip by adjusting the equivalent factor; however, it does not take the fuel cell life economy into account, thus, the equivalent hydrogen consumption of the fuel cell degradation is the most among these three strategies. The proposed strategy plans the SOC reference trajectory through the expected driving distance, and then guarantees the energy consumption economy and fuel cell life economy in the prediction horizon through the multi-objective rolling optimization algorithm. It not only ensures that the SOC drops to 0.3 at the end of the trip, but it also lessens the fuel cell degradation. It can be seen from Fig. 8 (d) that the proposed strategy leads to smoother fluctuation of the fuel cell current and achieves multi-objective optimization. As shown in Fig. 8 (e), the operating points of the CD-CS strategy and ECMS are focused in the high efficiency region, thereby improving the energy consumption economy.

In addition, from Fig. 8(a), we can find that the comprehensive driving cycle has the highest speed at 1250 s. Since the battery SOC does not drop to the low threshold based on the CD-CS strategy, the fuel cell current is still zero and the battery SOC decreases fast. Then, in the latter part of the trip, the fuel cell needs to start/stop more frequently to supply enough driving power and maintain the SOC in vicinity of the lower threshold simultaneously. As a result, the CD-CS strategy leads to more hydrogen consumption and faster life degradation of the fuel cell. In contrast, the ECMS can regulate the optimal equivalent factor adaptively, thereby controlling the fuel cell to work in the optimal efficiency region. As can be seen in Fig. 8 (b), the SOC reference curve calculated by the proposed algorithm is located above the optimal trajectory calculated by DP. To track the SOC reference curve, the fuel cell needs to work in the higher power area, which deviates from the optimal efficiency

region and thus leads to more hydrogen consumption compared with that of the ECMS. However, as discussed before, the ECMS needs to acquire the global transportation information in advance, and repetitively regulates the optimal equivalent factor by trial and error, thereby finding the optimal solution. From this point of view, it is quite difficult and even impossible to employ the ECMS in real applications. On the contrary, the proposed algorithm is more feasible for real-time driving conditions due to its simple principle of finding the global solution. From Table VI, the operating costs based on the proposed strategy are reduced by 8.6% and 13.5% compared with those based on the CD-CS strategy and ECMS when the global driving distance is unknown, proving the feasibility of the proposed strategy.

As shown in Fig. 8 (f), the time consumption is around 0.13 s when DP is applied to resolve the global optimal control, and the proposed multi-objective hierarchical strategy only needs 0.2 s to 0.4 s per step. The calculation intensity based on DP is shorter than that based on the built algorithm; however, DP needs to search the optimal solution inversely for the whole driving cycle of 3550 s, demonstrating the infeasibility of its use in real-time application. Moreover, in order to further reduce the calculation effort of the proposed algorithm and avoid unnecessary calculation, preliminary judgement is applied in the algorithm ahead of the rolling optimization. Supposing the current variation rate is 1 A/s, which is the maximum allowable value, the battery SOC can reach the extreme setting threshold at the end of the preceding horizon. If the ending SOC reference is not located within the anticipated region restricted by the extreme thresholds, then the fuel cell current variation is set to 1 A directly without processing by the rolling optimization. In this manner, the total computation time can be further reduced. As shown in Table VI, the built strategy can shorten the total calculation duration to 434.26 s and each step time to 0.122 s, which are much shorter than those of DP. However, they are still longer than those based on the CD-CS strategy and ECMS and still leave room for further improvement. To sum up, the calculation time of the built strategy is acceptable and shows certain feasibility for real-time application.

V. CONCLUSIONS

This paper designs a multi-objective hierarchical prediction EMS to improve the energy consumption economy and fuel cell life economy for a range extended FCV. Two control layers are designed to realize global SOC planning and local rolling control. The vehicle speed prediction is considered based on the BPNN in between. In the upper layer, a rapid planning method for the SOC reference trajectory is proposed only based

on the expected driving distance, independent of the detailed trip information. In the bottom layer, the direct collocation method and SQP method are applied to solve the multi-objective energy management problem in the prediction horizon. Finally, compared with the traditional CD-CS strategy and the ECMS, the operating costs based on the proposed strategy can be reduced by 8.6% and 13.5%, respectively, verifying the effectiveness of the proposed strategy.

Although this paper proposes a rapid planning method for the SOC reference trajectory, this method is more precise under low speed conditions on the plain area. Our next step work will focus on extending the model application under different road conditions, including mountain terrain. How to establish a more universal global SOC planning method without global driving information remains to be further investigated. In addition, the proposed algorithm still needs a relatively long calculation time, so how to further improve its computation efficiency for real-time control in real vehicle applications still needs to be further studied.

ACKNOWLEDGEMENTS

The work presented in this paper is funded by the National Natural Science Foundation (No. 51775063 and No. 61763021) in part, the National Key R&D Program of China (2018YFB0105402 and 2018YFB0104000) in part, the Special Funding for Postdoctoral Research Projects in Chongqing, China (No. XM2017009) in part, the Fundamental Research Funds for the Central Universities (No. 2018CDQYQC0035) in part, and the EU-funded Marie Skłodowska-Curie Individual Fellowships Project under Grant 845102-HOEMEV-H2020-MSCA-IF-2018 in part.

REFERENCE

- [1] K. Ç. Bayindir, M. A. Gözükcük, and A. Teke, "A Comprehensive Overview of Hybrid Electric Vehicle: Powertrain Configurations, Powertrain Control Techniques and Electronic Control Units," *Energy Conversion & Management*, vol. 52, no. 2, pp. 1305-1313, 2011.
- [2] S. S. Williamson, *Hybrid Electric and Fuel Cell Hybrid Electric Vehicles*. Springer New York, 2013, pp. 31-63.
- [3] H. He, J. Fan, Y. Li, and J. Li, "When to Switch to A Hybrid Electric Vehicle: A Replacement Optimisation Decision," *Journal of Cleaner Production*, vol. 148, pp. 295-303, 2017.
- [4] H. S. Das, C. W. Tan, and A. H. M. Yatim, "Fuel Cell Hybrid Electric Vehicles: A Review on Power Conditioning Units and Topologies," *Renewable & Sustainable Energy Reviews*, vol. 76, pp. 268-291, 2017.
- [5] V. Das, S. Padmanaban, K. Venkitesamy, R. Selvamuthukumar, F. Blaabjerg, and P. Siano, "Recent Advances and Challenges of Fuel Cell Based Power System Architectures and Control - A Review," *Renewable & Sustainable Energy Reviews*, Review vol. 73, pp. 10-18, Jun 2017.
- [6] S. G. Wirasingha and A. Emadi, "Classification and Review of Control Strategies for Plug-in Hybrid Electric Vehicles," *IEEE Transactions on Vehicular Technology*, vol. 60, no. 1, pp. 111-122, 2011.
- [7] K. Ettahir, 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.
- [8] J. Peng, H. He, and R. Xiong, "Rule Based Energy Management Strategy for a Series-Parallel Plug-In Hybrid Electric Bus Optimized by Dynamic Programming," *Applied Energy*, vol. 185, 2016.

- [9] Z. Chen, R. Xiong, and J. Cao, "Particle Swarm Optimization-Based Optimal Power Management of Plug-in Hybrid Electric Vehicles Considering Uncertain Driving Conditions," *Energy*, vol. 96, pp. 197-208, 2016.
- [10] T. Yi, Z. Xin, Z. Liang, and X. Zhang, "Intelligent Energy Management Based on Driving Cycle Identification Using Fuzzy Neural Network," in *International Symposium on Computational Intelligence and Design*, 2009, pp. 501-504.
- [11] S. F. Tie and C. W. Tan, "A Review of Energy Sources and Energy Management System in Electric Vehicles," *Renewable and Sustainable Energy Reviews*, vol. 20, no. 4, pp. 82-102, 2013.
- [12] S. Ahmadi, S. M. T. Bathaee, and A. H. Hosseinpour, "Improving Fuel Economy and Performance of A Fuel-Cell Hybrid Electric Vehicle (Fuel-Cell, Battery, And Ultra-Capacitor) Using Optimized Energy Management Strategy," *Energy Conversion & Management*, vol. 160, pp. 74-84, 2018.
- [13] H. Yin, W. Zhou, M. Li, C. Ma, and C. Zhao, "An Adaptive Fuzzy Logic-Based Energy Management Strategy on Battery/Ultracapacitor Hybrid Electric Vehicles," in *IEEE transactions on transportation electrification*, 2016, vol. 2, no. 3, pp. 300-311.
- [14] C. M. Martínez, X. Hu, D. Cao, E. Velenis, and M. Wellers, "Energy Management in Plug-in Hybrid Electric Vehicles: Recent Progress and a Connected Vehicles Perspective," *IEEE Transactions on Vehicular Technology*, vol. 66, no. 6, pp. 4534-4549, 2017.
- [15] L. I. Qi, W. Chen, L. I. Yankun, S. Liu, and J. Huang, "Energy Management Strategy for Fuel Cell/Battery/Ultracapacitor Hybrid Vehicle Based on Fuzzy Logic," *International Journal of Electrical Power & Energy Systems*, vol. 43, no. 1, pp. 514-525, 2012.
- [16] C. Zheng, C. C. Mi, J. Xu, X. Gong, and C. You, "Energy Management for a Power-Split Plug-in Hybrid Electric Vehicle Based on Dynamic Programming and Neural Networks," *IEEE Transactions on Vehicular Technology*, vol. 63, no. 4, pp. 1567-1580, 2014.
- [17] X. Hu, S. J. Moura, N. Murgovski, E. Bo, and D. Cao, "Integrated Optimization of Battery Sizing, Charging, and Power Management in Plug-In Hybrid Electric Vehicles," *IEEE Transactions on Control Systems Technology*, vol. 24, no. 3, pp. 1036-1043, 2016.
- [18] C. Zheng, C. C. Mi, X. Rui, J. Xu, and C. You, "Energy Management of a Power-Split Plug-in Hybrid Electric Vehicle Based on Genetic Algorithm and Quadratic Programming," *Journal of Power Sources*, vol. 248, no. 7, pp. 416-426, 2014.
- [19] L. Tribioli, R. Cozzolino, D. Chiappini, and P. Iora, "Energy Management of a Plug-in Fuel Cell/Battery Hybrid Vehicle with On-Board Fuel Processing," *Applied Energy*, vol. 184, pp. 140-154, 2016.
- [20] S. Onori, L. Serrao, and G. Rizzoni, "Hybrid Electric Vehicles: Energy Management Strategies," *Encyclopedia of Energy*, vol. 277, no. 4, pp. 197-213, 2016.
- [21] M. Ansarey, M. S. Panahi, H. Ziarati, and M. J. Mahjoob, "Optimal Energy Management in a Dual-Storage Fuel-Cell Hybrid Vehicle Using Multi-Dimensional Dynamic Programming," *Journal of Power Sources*, vol. 250, pp. 359-371, 2014.
- [22] Z. Hong, Q. Li, Y. Han, W. Shang, Y. Zhu, and W. Chen, "An Energy Management Strategy Based on Dynamic Power Factor for Fuel Cell/Battery Hybrid Locomotive," *International Journal of Hydrogen Energy*, vol. 43, no. 6, pp. 3261-3272, 2018.
- [23] 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 Plug-in Fuel Cell Electric Vehicles," *International Journal of Hydrogen Energy*, vol. 38, no. 24, pp. 10104-10115, 2013.
- [24] K. Ettihir, M. H. Cano, L. Boulon, and K. Agbossou, "Design of An Adaptive EMS for Fuel Cell Vehicles," *International Journal of Hydrogen Energy*, 2016.
- [25] K. Ou, W. Yuan, M. Choi, S. Yang, S. Jung, and Y. Kim, "Optimized Power Management Based on Adaptive-PMP Algorithm for a Stationary PEM Fuel Cell/Battery Hybrid System," *International Journal of Hydrogen Energy*, vol. 43, no. 32, pp. 15433-15444, 2018.
- [26] C. Sun, F. Sun, and H. He, "Investigating Adaptive-ECMS With Velocity Forecast Ability for Hybrid Electric Vehicles," *Applied Energy*, vol. 185, pp. 1644-1653, 2017.
- [27] G. Boyarko, O. A. Yakimenko, and M. Romano, "Optimal Rendezvous Trajectories of a Controlled Spacecraft and a Tumbling Object," *Journal of Guidance Control and Dynamics*, vol. 34, no. 4, pp. 1239-1252, 2011.
- [28] X. Chu, J. Zhang, L. Shan, Z. Yao, and S. Yue, "Optimised Collision Avoidance for an Ultra-Close Rendezvous with a Failed Satellite Based on the Gauss Pseudospectral Method," *Acta Astronautica*, vol. 128, pp. 363-376, 2016.
- [29] R. Zhong and Z. H. Zhu, "Optimal Current Switching Control of Electrodynamics Tethers for Fast Deorbit," *Journal of Guidance Control & Dynamics*, vol. 37, no. 5, pp. 1501-1511, 2014.
- [30] J. T. Betts, "Survey of Numerical Methods for Trajectory Optimization," *Journal of Guidance Control and Dynamics*, vol. 21, no. 2, pp. 193-207, 1998.
- [31] S. Jain and P. Tsotras, "Trajectory Optimization Using Multiresolution Techniques," *Journal of Guidance Control & Dynamics*, vol. 31, no. 5, pp. 1424-1436, 2008.
- [32] O. A. Yakimenko, "Direct Method for Rapid Prototyping of Near-Optimal Aircraft Trajectories," *Journal of Guidance Control and Dynamics*, vol. 23, no. 5, pp. 865-875, 2000.
- [33] Y. Zhao, M. L. Kuang, A. M. Phillips, and J. G. Kristinsson, "Path-Forecasting for HEV Optimal Energy Management (POEM)," in *advances in computing and communications*, 2016, pp. 1518-1523.

- [34] C. Sun, S. J. Moura, X. Hu, J. K. Hedrick, and F. Sun, "Dynamic Traffic Feedback Data Enabled Energy Management in Plug-in Hybrid Electric Vehicles," *IEEE Transactions on Control Systems and Technology*, vol. 23, no. 3, pp. 1075-1086, 2015.
- [35] H. A. Borhan and A. Vahidi, "Model Predictive Control of A Power-Split Hybrid Electric Vehicle with Combined Battery and Ultracapacitor Energy Storage," in *Proceedings of the 2010 American Control Conference*, Baltimore, MD, USA, 2010, pp. 5031-5036.
- [36] X. Ma, Z. Tao, Y. Wang, H. Yu, and Y. Wang, "Long Short-Term Memory Neural Network for Traffic Speed Prediction Using Remote Microwave Sensor Data," *Transportation Research Part C*, vol. 54, pp. 187-197, 2015.
- [37] S. Xie, H. He, and J. Peng, "An Energy Management Strategy Based on Stochastic Model Predictive Control for Plug-in Hybrid Electric Buses," *Applied Energy*, vol. 196, 2017.
- [38] S. Xie, X. Hu, Z. Xin, and L. Liang, "Time-Efficient Stochastic Model Predictive Energy Management for a Plug-In Hybrid Electric Bus with Adaptive Reference State-of-Charge Advisory," *IEEE Transactions on Vehicular Technology*, vol. PP, no. 99, pp. 1-1, 2018.
- [39] C. Xiang, D. Feng, W. Wang, and H. Wei, "Energy Management of a Dual-Mode Power-Split Hybrid Electric Vehicle Based on Velocity Prediction and Nonlinear Model Predictive Control," *Applied Energy*, vol. 189, pp. 640-653, 2017.
- [40] Z. Chen, N. Guo, J. Shen, R. Xiao, and P. Dong, "A Hierarchical Energy Management Strategy for Power-Split Plug-in Hybrid Electric Vehicles Considering Velocity Prediction," *IEEE Access*, vol. 6, pp. 33261-33274, 2018.
- [41] 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.
- [42] T. H. Kwan, X. Wu, and Q. Yao, "Multi-Objective Genetic Optimization of the Thermoelectric System for Thermal Management of Proton Exchange Membrane Fuel Cells," *Applied Energy*, vol. 217, pp. 314-327, 2018.
- [43] L. Xu *et al.*, "Design of Durability Test Protocol for Vehicular Fuel Cell Systems Operated in Power-Follow Mode Based on Statistical Results of On-Road Data," *Journal of Power Sources*, vol. 377, pp. 59-69, 2018.
- [44] N. Sulaiman, M. A. Hannan, A. Mohamed, P. J. Ker, E. H. Majlan, and W. R. W. Daud, "Optimization of Energy Management System for Fuel-Cell Hybrid Electric Vehicles: Issues and Recommendations," *Applied Energy*, vol. 228, pp. 2061-2079, 2018.
- [45] S. Kelouwani, K. Agbossou, Y. Dube, and L. Boulon, "Fuel Cell Plug-in Hybrid Electric Vehicle Anticipatory and Real-Time Blended-Mode Energy Management for Battery Life Preservation," *Journal of Power Sources*, vol. 221, pp. 406-418, 2013.
- [46] H. Li, A. Ravey, A. Ndiaye, 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.
- [47] K. Ameer, A. Hadjaissa, M. S. A. Cheikh, A. Cheknane, and N. Essounbouli, "Fuzzy Energy Management of Hybrid Renewable Power System with the Aim to Extend Component Lifetime," *International Journal of Energy Research*, vol. 41, no. 13, pp. 1867-1879, 2017.
- [48] 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.
- [49] T. P. Fletcher, R. H. 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.
- [50] 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.
- [51] L. Xu, C. D. Mueller, J. Li, M. Ouyang, and Z. Hu, "Multi-Objective Component Sizing Based on Optimal Energy Management Strategy of Fuel Cell Electric Vehicles," *Applied Energy*, vol. 157, pp. 664-674, 2015.
- [52] X. Wu, X. Hu, X. Yin, L. Li, Z. Zeng, and V. Pickert, "Convex Programming Energy Management and Components Sizing of a Plug-in Fuel Cell Urban Logistics Vehicle," *Journal of Power Sources*, vol. 423, pp. 358-366, 2019.
- [53] M. Sorrentino, V. Cirillo, and L. Nappi, "Development of Flexible Procedures for Co-optimizing Design and Control of Fuel Cell Hybrid Vehicles," *Energy Conversion and Management*, vol. 185, pp. 537-551, 2019.
- [54] Y. Wang, S. J. Moura, S. G. Advani, and A. K. Prasad, "Power Management System for a Fuel Cell/Battery Hybrid Vehicle Incorporating Fuel Cell and Battery Degradation," *International Journal of Hydrogen Energy*, vol. 44, no. 16, pp. 8479-8492, 2019.
- [55] J. Larminie and A. Dicks, "Fuel Cell Systems Explained, 2nd Edition," 2003.
- [56] R. Shimoi, T. Aoyama, and A. Iiyama, "Development of Fuel Cell Stack Durability based on Actual Vehicle Test Data: Current Status and Future Work," *SAE International journal of engines*, vol. 2, no. 1, pp. 960-970, 2009.
- [57] 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.
- [58] Z. Hu, L. Xu, J. Li, M. Ouyang, Z. Song, and H. Huang, "A Reconstructed Fuel Cell Life-Prediction Model for a Fuel Cell Hybrid City Bus," *Energy Conversion & Management*, vol. 156, pp. 723-732, 2018.
- [59] H. Chen, P. Pei, and M. Song, "Lifetime Prediction and the Economic Lifetime Of Proton Exchange Membrane Fuel Cells," *Applied Energy*, vol. 142, pp. 154-163, 2015.

- [60] Y. Zheng, W. Gao, M. Ouyang, L. Lu, Z. Long, and X. Han, "State-of-Charge Inconsistency Estimation of Lithium-ion Battery Pack Using Mean-Difference Model and Extended Kalman Filter," *Journal of Power Sources*, vol. 383, pp. 50-58, 2018.
- [61] R. Fletcher, *Practical Methods of Optimization*. John Wiley & Sons, 2013.
- [62] S. Chao, X. Hu, S. J. Moura, and F. Sun, "Velocity Predictors for Predictive Energy Management in Hybrid Electric Vehicles," *IEEE Transactions on Control Systems Technology*, vol. 23, no. 3, pp. 1197-1204, 2015.