Reliable Energy Management Optimization in Consideration of Battery Deterioration for Plug-In Intelligent Hybrid Vehicle

Elkhatib Kamal[1,2(✉)] and Lounis Adouane[2]

[1] Department of Industrial Electronics and Control Engineering, Faculty of Electronic Engineering, Menoufia University, Menouf 32952, Menoufia, Egypt
elkhateb.ibrahim@el-eng.menofia.edu.eg; elkateb.kamal@gmail.com
[2] Institut Pascal/Innovative Mobility: Smart and Sustainable Solutions, UCA/SIGMA, UMR CNRS 6602, 63000 Clermont-Ferrand, France
Lounis.Adouane@uca.fr

Abstract. This chapter proposes an intelligent energy management for hydraulic-electric hybrid vehicle in order to minimize its total energy consumption while ensuring a better battery life. It proposes first to model the total energy consumption of the vehicle and investigate the minimization of an expended energy function, formulated as the sum of electrical energy provided by on-board batteries and consumed fuel. More precisely, it is proposed in this chapter an intelligent hierarchical controller system which shows its capabilities of increasing the overall vehicle energy efficiency and therefore minimizing total energy consumption, permitting to increase the distance between refueling. The proposed strategy consists of fuzzy supervisory fault management at the highest level (third), that can detect and compensate the battery faults, regulate all of the possible vehicles operation modes. In the second level, an optimal controller is developed based on artificial intelligence to manage power distribution between electric motor and engine. Then, in the first level, there are local fuzzy tuning proportional-integral-derivative controllers to regulate the set points of each vehicle subsystems to reach the best operational performance. TruckMaker/MATLAB simulation results confirm that the proposed architecture can satisfy the power requirement for any unknown driving cycles and compensate battery faults effects.

Keywords: Artificial intelligence · Battery management system · Fuzzy observer · Hybrid electric vehicles · Power management strategy · Sensor faults · Takagi-Sugeno fuzzy model

1 Introduction

Growing environmental concerns coupled to the decreasing of fossil fuel energy sources stimulate highly research on new vehicle technologies. Electric vehi-

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cles (EVs) and Hybrid Electric Vehicles (HEV) appears to be one of the most promising technologies for reducing fuel consumption and pollutant emissions [1]. Energy management in vehicles is an important issue because it can significantly influence the performances of the vehicles. Improving energy management in vehicles can deliver important benefits such as reducing fuel consumption, decreasing emission, lower running cost, reducing noise pollution, and improving driving performance and ease of use [2]. Several methods for energy management and optimization aiming at the minimization of different cost functions have been published [3–8], such as Dynamic Programming (DP) in [3] to formulate numerically a global optimum for reducing fuel consumption under the assumption of full knowledge of the future driving conditions. Analytical optimization methods, on the other hand, use a mathematical problem formulation to find an analytical solution that makes the obtained solution faster than the purely numerical methods. Within this category, Pontryagin's Minimum Principle (PMP) based energy management strategy is introduced as an optimal control solution [4]. This approach can only generate an optimal solution if implemented offline since in this case the future driving conditions are supposed to be known in prior. For online implementation Rule Based Strategy (RBS) from heuristic ideas have been proposed for HEVs [5] and the Hybrid controller based on rule-based and StateFlow (SF) is given in [6]. The problem of this method is that it needs highly engineering experience, extensive experimental data, etc. to create these rules. In addition, it gives limited benefits for fuel economy. To overcome this problem, the fuzzy system is added to RBS [7] and Artificial Neural Network (ANN) is introduced [8]. One of the main objectives of this chapter is the development and experimental verification of such control framework to minimize the energy consumption based on the merging of the two paradigms (ANN and fuzzy system) to benefit from their advantages and avoids their disadvantages.

Nowadays, there are different blending levels of pure EV and HEV available on the automobile market. According to the blending level, various size, type and number of battery cells are mounted in HEVs and EVs [9]. The battery management system (BMS) is an essential emerging component of both EVs and HEVs alongside with modern power systems. Recently, Lithium-ion batteries can drastically improve the technical characteristics of EVs and HEV for various uses. However, Lithium-ion batteries require very special supervision. Hence, the need to integrate BMS as a supervision system becomes of great interest. Different approaches have been proposed to study battery faults [10–16]. Model based sensor using FDI scheme for a battery pack with a low computational effort is proposed in [10]. To implement the model-based fault diagnosis, a battery model is needed to capture the electrochemical properties [10]. Different battery models were studied by several researchers. The most commonly used models can be summarized as two kinds: the equivalent circuit models and the electrochemical models [11–16]. Recently, energy management optimization in consideration of battery life/degradation for HEV are studied in several works [17–21], in order to improve the total economy in driving process.

According to the previous studies, a reliable battery fault tolerant control to guarantee the battery performance, safety and life while simultaneously minimizing the total energy consumption (summation of electric battery and fuel) for Hybrid Hydraulic-Electric Vehicle (HHEVs) are addressed in this chapter. In order to study and develop an efficient and reliable energy management strategy for HHEV, a precise vehicle modelling is desirable based on [4,15–20]. The studied vehicle is a hybrid bus based on parallel power split hybrid architecture. This hybrid bus is called BUSINOVA and is developed by SAFRA Company (cf. Figs. 1 and 2). BUSINOVA is composed of Electric Motor (EM), Internal Combustion Engine (ICE), Hydraulic Motor (HM), and battery as the propulsion powertrain system of the vehicle. The EM and HM motors are both directly connected to the transmission and can ensure simultaneously or independently the traction of the bus. On the other hand, the ICE is coupled to a Hydraulic Pump (HP) for driving the HM. This gives a big number of working models for the bus which increases the combinations of optimizing its energy management.

In [20], the Energy Management Strategy (EMS) is designed based on two control levels based on neural network, fuzzy logic and rules based optimization. Based on the analysis results of the EMS [20], it is proposed in this chapter an intelligent Robust Hierarchical Hybrid Controller Strategy (IRHHCS), in order to enhance the bus energy efficiency, leading therefore to minimize the total energy consumption (summation of electric energy and fuel energy). The proposed IRHHCS consists of three control levels. An Intelligent Supervisory Switching Mode and Battery Management Controller (ISSMBMC) based on fuzzy logic is developed in the third level (the highest level) that is capable of managing all of the possible bus operation modes, compensate the battery faults, generating optimal mode and SOC set points for second level. In the second level, an Intelligent Power Distribution and Optimization Controller (IPDOC) is proposed. It is based on neural fuzzy logic control to manage and optimize the power distribution between the two different sources. Then, in the first level (the lowest one), there are Local Fuzzy tuning Proportional-Integral-Derivative Controllers (LFPIDC) to regulate the set points of each vehicle sub-systems (EM, battery, ICE, HP, HM) to achieve optimal operational performance. The overall proposed control and energy management strategy is compared with alternative frameworks existing in the literature based on PMP [4] in order to demonstrate the advantages of the proposed methodology (cf. Sect. 4).

The results of this chapter support that the proposed strategy is capable of: (i) being applied to various types of hybrid vehicles; (ii) detect, isolate and compensate the battery voltage sensor faults and battery currant actuator faults; (iii) reducing total energy consumption compared with several traditional methods; (iv) reducing the number of rules needed in fuzzy control; (v) keeping SOC within the range which promotes battery longevity; (vi) being implemented in real time; (vii) it does not require beforehand a-priori knowledge of the driving events. Therefore, this chapter, will provide both a novel model and novel approach for an advanced energy management system of hybrid vehicles.

The chapter is organized as follows. The overall HHEV description and modeling is given in Sect. 2. In Sect. 3, the proposed intelligent robust hierarchical hybrid controller structure is developed. Section 4 shows the experiment model validation and fault effects analysis. Section 5 is devoted to give a conclusion and some prospects.

2 Overall HHEV Modeling and Description

This section presents modelling and analysis of the studied HHEV based on [4], [16,18] with its different operations modes. TruckMaker/MATLAB software is used to simulate precisely the studied hybrid vehicle.

2.1 HHEV Description and Modelling

The studied vehicle corresponds to BUSINOVA bus shown in Fig. 1 [20]. The parameters used for the vehicle modeling is presented in [18]. This bus has three actuations: electric, hydraulic and thermal. The principle source of the propulsion in the vehicle is an EM which may be supplemented by the HM via ICE. The hydraulic system block consists of variable-displacement of HM, and an ICE driven fixed-displacement of HP. The ICE is directly connected to a fixed displacement pump, which converts engine mechanical power into hydraulic power as shown in the vehicle configuration and power flow diagram (cf. Fig. 2 [20]). The BUSINOVA is equipped with electric, hydrostatic and dissipative braking capabilities. The dissipative brake is a mechanical brake which dissipates energy as heat through friction. Electric and hydrostatic brakes are linked to the hydraulic motor in a regenerative braking system that is capable of recovering a portion of the kinetic energy of braking that would otherwise be dissipated. An Electrical Junction (EJ) exists between the battery, accessories (Access) and dual converter as well as a Mechanical Junction (MJ) between the HM and EM.

Fig. 1. BUSINOVA a Hydraulic-Electric Hybrid bus.

2.2 Motoring Models

HM model through ICE and the EM models based on [3,4] are given in this section as the following.

Hydraulic Motor Coupled to Internal Combustion Engine. In this chapter, ICE torque versus ICE speed is directly derived from the ICE fuel consumption model. The fuel flow rate $\dot{m}_f$ of the ICE is defined based on [20],

$$\dot{m}_f = f_{ICE}(T_{ICE}, \omega_{ICE}) \tag{1}$$

where ω_{ICE} is the ICE rotational speed. The function f_{ICE} is obtained from the ICE bench tests. The power consumed by the ICE (P_{ICE}) is given by P_{ICE}=$\dot{m}_f(T_{ICE}, \omega_{ICE})Q$ [3], (i.e., P_{ICE} is the instantaneous power of the fuel expressed in terms of $\dot{m}_f$ and the lower heating value of the fuel ($Q = 43\text{MJ/kg}$)). Figure 3 (left) shows the relationship between HM speed, HM torque and HM consumed power. Developing an accurate fuel consumption model is very important for addressing energy consumption optimization problems.

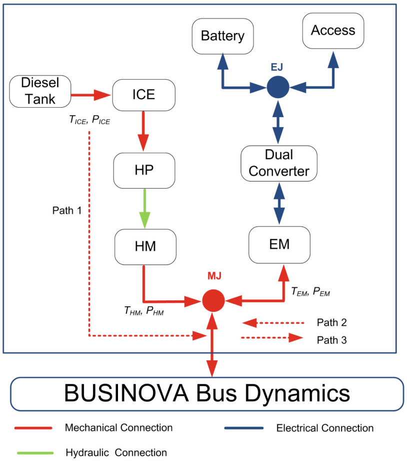

Fig. 2. BUSINOVA bus configuration and power flow. T_{ICE}, T_{HM}, T_{EM} and P_{ICE}, P_{HM}, P_{EM} are the produced torque and power for the ICE, HM and EM, respectively.

Electric Motor. The studied hybrid bus uses a 103 KW permanent magnet synchronous machine as EM. The powers required for the EM were calculated from the known EM torque and speed by using EM efficiency curve as shown in Fig. 3 (right). The output torque T_{EM} of the EM is defined based on [20],

$$T_{EM} = f_{EM}(P_{EM}, \omega_{EM}) \tag{2}$$

where P_{EM} is the EM input power, ω_{EM} is the EM current speed. The function f_{EM} is also obtained from the EM bench test. The EM can operate in motor or generator mode. In generator mode, the electric motor converts the kinetic energy from vehicle regenerative braking into electrical energy stored in the battery. In the motor mode, the electric motor converts electrical energy into kinetic energy to move the vehicle. The efficiency characteristics data of the EM, and HM coupled to the ICE given in Fig. 3 are implemented in IPG automotive TruckMaker software.

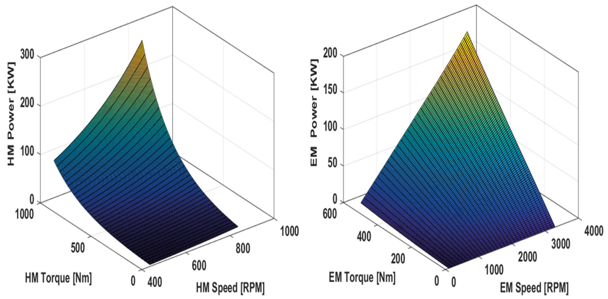

Fig. 3. Power consumption mapping; (left) efficiency characteristics of the HM coupled to ICE; (right) efficiency characteristics of the EM.

2.3 BUSINOVA Lithium-Ion Battery Modeling

The battery model is necessary for its SOC estimation. Different Lithium-ion battery models are developed in the literatures [11–16]. The equivalent electrical circuit models and the electrochemical models are the most widely used in EV studies. The electrical circuit models use equivalent electrical circuits to show current-voltage characteristics of batteries by using voltage and current sources, capacitors, and resistors. For the BUSINOVA bus battery, its model is based on [14,16] (cf. Fig. 4 [20]). Using Kirchhoff's voltage law, the dynamics of the nonlinear battery behavior can be characterized by the following equations [20],

$$\begin{aligned} \dot{x}(t) &= Ax(t) + Bu(t) \\ y(t) &= C(x)x(t) \end{aligned} \tag{3}$$

Where $x(t) = \begin{bmatrix} V_1(t) \\ V_2(t) \\ SOC \end{bmatrix}$, V_{bat} is the battery terminal voltage, V_{oc} is the battery open circuit voltage (OCV), I_{bat} is the battery input current, t is the time varying, V_1, V_2 are the voltages across $R_1//C_1$ and $R_2//C_2$, where R_1 and C_1 are the electrochemical polarisation resistance, capacitance, respectively, R_2 and C_2 are the concentration polarisation resistance, capacitance, respectively and R_o is the internal resistance which consists to the bulk resistance and surface layer impedance, $A = \begin{bmatrix} \frac{1}{R_1C_1} & 0 & 0 \\ 0 & \frac{1}{R_2C_2} & 0 \\ 0 & 0 & 0 \end{bmatrix}$, $B = \begin{bmatrix} \frac{1}{C_1} \\ \frac{1}{C_2} \\ \frac{\eta}{C_n} \end{bmatrix}$, $C(x) = \begin{bmatrix} q_1(x) \\ 1 \\ q_2(x) \end{bmatrix}^T$, $u(t) = I_{bat}$, $y(t) = V_{bat}$, SOC_i is the initial value of the SOC, C_n is the nominal capacity in Ampere-hours ($A{-}s$) and η_{co} is the efficiency of the Coulombic. The tested cells are done always between 10% and 95% of the SOC, which corresponds to the imposed operational work of the bus. In addition, V_1 and V_2 are assumed to be not zero conditions.

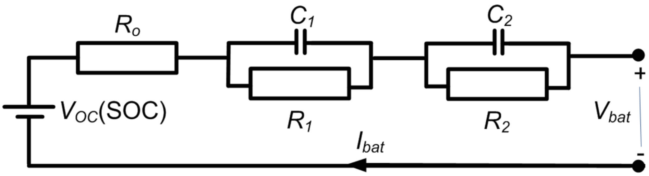

Fig. 4. BUSINOVA Lithium-ion battery equivalent electrical model.

where $q_1(x) = \frac{(I_{bat}R_o + V_1(t))}{V_1(t)}$ and $q_2(x) = \frac{V_{oc}}{SOC}$. Due to the nonlinearity in V_{oc}, the output of the battery system is nonlinear.

2.4 HHEV Torque Distribution and Operation Modes

During the bus displacement, its optimal control depends on the accurate knowledge of torque required to propel the bus and charge the battery. One of the objective of the control strategy is to split the total torque between the HM via ICE and EM to optimize the efficiency of the main components (cf. section III.B). Figure 2 shows the torque paths between HM via ICE and the EM as the following [20]: Mode 1: EM only (path 2); Mode 2: HM via ICE only (path 1); Mode 3: EM assisted by HM via ICE (path 1 and 2); Mode 4: charging mode (path 1 and 3); Mode 5: regenerative braking mode (path 3). As far as possible, each component of the TruckMaker simulator should correspond to an actual component of the actual studied HHEV.

3 Proposed Intelligent Robust Hierarchical Hybrid Controller Strategy (IRHHCS)

The aim of this section is to make the focus on the proposed IRHHCS, embedded in the bus in order to minimize its total energy consumption while maximizing the global vehicle efficiency and compensate the battery faults. Therefore, in this section, an IRHHCS structure is proposed which is capable of meeting various objectives including optimized power flow management, maintaining high operational efficiency of the ICE, and balancing EM and battery charge to maximize the global vehicle efficiency and detect and compensate the effect of the battery faults. The first block of the proposed IRHHCS (cf. Fig. 5) corresponds to a driver command interpreter which converts the driver inputs from the brake and accelerator pedals to required torque to apply at the wheels level in order to follow, as accurate as possible, the desired velocity profile.

This proposed strategy consists of three control levels (cf. Fig. 5). The third level has been developed by fuzzy strategy and fuzzy observer which decide which operating mode or combination of modes would be most efficient based on a healthy SOC (cf. Sect. 3.1). This level consist of two blocks, the first block of this level is Battery Management Fuzzy Fault Tolerant Controller (BMFFTC) to detect and the compensate the battery faults and generate the healthy SOC (the healthy SOC means SOC value determination without faults) for the Fuzzy Switching Mode Controller (FSMC) which selects the optimal mode for the second level. At the second level (cf. Sect. 3.2), an advanced IPDOC (Intelligent Power Distribution and Optimization Controller) has been developed for power splitting which decide the optimal combination of power sharing between different energy sources to maximize the overall vehicle efficiency. In Sect. 3.3, an LFPIDC (Local Fuzzy tuning Proportional-Integral-Derivative Controllers) is described and used to track the set points of EM and HM via the ICE generated at the second level, in order to reach peak performance and acceptable operation indexes while taken in consideration of the dynamic behavior of EM, ICE and HM. The proposed strategy can be used for both offline and online scenarios. Offline scenario implies that the information about the future driving cycle and the environment (road profile, vehicle weight, etc.) is fully known, whereas for the online scenarios this information is obtained in real time. In this chapter, we will focus more on level 3 and level 2 (cf. respectively, Sects. 3.1 and 3.2).

3.1 Intelligent Supervisory Switching Mode and Battery Management Controller (Level 3: ISSMBMC)

The objective of this section is to optimize the selection mode and detect and compensate the battery sensor fault (battery terminal voltage sensor) and the actuator fault (battery input current actuator). This level consists of BMFFTC and FSMC blocks to generate the selected mode and the SOC set point for the second level. Figure 6 shows the block diagram of the proposed level 3 block.

Fuzzy Switching Mode Controller (FSMC). As mentioned in Sect. 2.4, there are five modes of operations. In order to improve the studied HHEV operation, the proposed FSMC based on fuzzy logic and rule based, has to decide which operating mode (or combination of them) is appropriate. Many parameters (such as the value of SOC for the battery, required vehicle power, vehicle speed and maximum power supplied by the battery, etc.) must be considered to choose the most efficient operation mode to manage and optimize the power flow. FSMC is formed by replacing Boolean logic and fixed parameters with fuzzy logic and fuzzy parameters. The basic idea of a fuzzy logic controller is to formulate human knowledge and reasoning, which can be represented as conditional

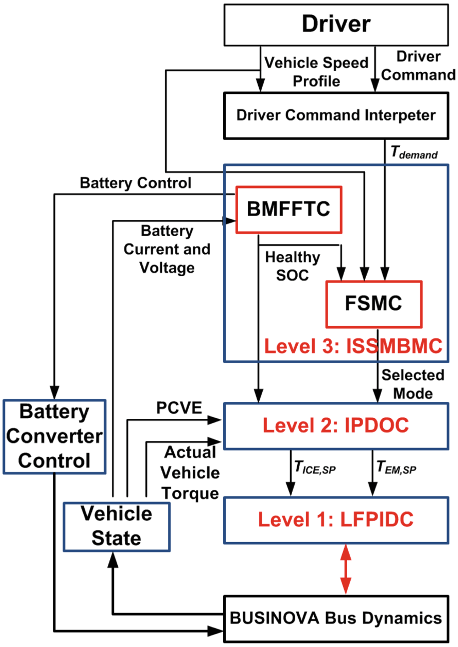

Fig. 5. Developed IRHHCS for BUSINOVA bus. In this figure the following acronyms are used: PCVE (Produced and Consumed Vehicle Energy); T_{demand} (Torque Demand) which is required to drive the vehicle and is defined by the global torque set point; $T_{ICE,SP}$ is the ICE torque set point and $T_{EM,SP}$ is the EM torque set point.

statements with broader application than explicitly stated, in a tractable way for computers. Based on the available output torque, the pedal position is converted into torque demand (T_{demand}). If $T_{demand} < 0$, the driver intends to decelerate the vehicle therefore regenerative braking mode is chosen. But, if $T_{demand} > 0$, the requiring torque is split between EM or/and HM via ICE. In the proposed algorithm, modes 1, 2, 3, and 4 are selected by fuzzy logic and mode 5 is selected by traditional logic. Fuzzy logic is well suited for selecting between modes 1, 2, 3 and 4. The ISSMBMC input variables are Vehicle Speed (VS), T_{demand} and SOC, and its output variable is the operation mode (Mode). We use Gaussian Membership Functions (GMF) and Center of Gravity (COG) defuzzification to calculate the output fuzzy signal, the advantage of this method is its simplicity in reducing the calculations complexity. The fuzzy rule is constructed from 27 individual fuzzy rules based on [20].

Battery Management Fuzzy Fault Tolerant Controller (BMFFTC). The main objective for the BMFFTC is to mange and control the battery faults and generate the healthy SOC point for FSMC and the second level which affects the studied HHEV power optimization. The general configuration of BMFFTC is given in Fig. 6. This section presents a systematic fault diagnosis and con-

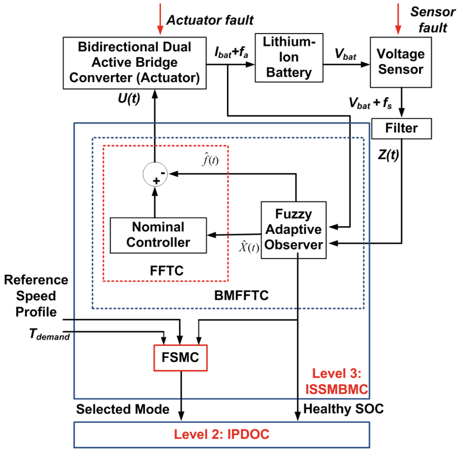

Fig. 6. Schematic of the proposed level 3.

trol scheme for a battery cell to detect current and/or voltage sensor faults, and compensate its effect. For the diagnostic and control scheme implementation, new Fuzzy Fault Tolerant Control (FFTC) based on fuzzy adaptive observer is proposed, to estimate and compensate the effect of the battery faults (current sensor faults, and/or voltage sensor faults). The concept of PDC (Parallel Distributed Compensation) [22] is employed to design fuzzy control and fuzzy adaptive observer from the TS fuzzy models. Sufficient conditions are derived for robust stabilization in the sense of Lyapunov stability, for voltage sensor fault, current actuator fault and state variables unavailable for measurements. The sufficient conditions are formulated in the format of LMI (Linear Matrix Inequalities).

In this chapter, we consider the sensor faults or the actuator faults can occur at the same time or only one sensor fault can occur at a time. Most of the HEV battery sensors (current sensor and voltage sensor) are Hall effect sensors, which are subject to bias (offset) and gain fault (scaling) [23]. Bias fault is a constant offset from the nominal statistics of the sensor signal, while gain fault is a time-varying offset. The current and the voltage sensor are usually abrupt changes [23]. The bias and gain faults are considered additive faults in industrial applications and they are modeled as the following [24].

$$\delta_m = \delta + E_x f_x(t) \tag{4}$$

where δ_m is the current or voltage sensor measurement, δ is the battery input current (I_{bat}) or terminal voltage (V_{bat}), f_x is the fault value and E_x is the fault matrix. In order to design BMFFTC, we need to represent the battery model based on TS fuzzy model, design fault estimation based on the fuzzy adaptive observer and design FFTC as the following.

Takagi-Sugenos Fuzzy Plant Model with Sensor and/or Actuator Faults Consider the overall fuzzy model achieved by fuzzy blending of each individual plant rule is given by,

$$\begin{aligned} \dot{x}(t) &= \sum_{i=1}^{p} \mu_i(q(t))[A_i x(t) + B_i u(t) + E_{ai} f_a(t)] \\ y(t) &= \sum_{i=1}^{p} \mu_i(q(t))[C_i x(t) + E_{si} f_s(t)] \end{aligned} \tag{5}$$

where $x(t)$ is the state vector, $u(t)$ is the control input vector, $y(t)$ is the output vector, $(j = 1, 2, \ldots, \psi)$ and h_{ij} $(i = 1, 2, \ldots, p; j = 1, 2, \ldots, \psi)$ are the premise variable and the fuzzy sets that are characterized by the membership function, ψ is the number of the premise variable, p is the number of rules of the TS fuzzy model $A_i \in \kappa^{n\times n}$, $B_i \in \kappa^{n\times m}$ and $C_i \in \kappa^{g\times n}$ are system, input and output matrices, respectively, $f_a(t)$, $f_s(t)$ are the actuator faults, sensor faults, E_{si} is the sensor fault matrix, E_{ai} is the actuator fault matrix and $q_1(t)$,..., $q_\psi(t)$ are assumed measurable variables and do not depend on the sensor faults and the actuator faults, $Q_i(q(t)) = \prod_{j=1}^{\psi} h_{ij}(q_j(t))$, $\mu_i(q(t)) = \frac{Q_i(q(t))}{\sum_{i=1}^{p} Q_i(q(t))}$ in which $h_{ij}(q_j(t))$ is the grade of membership of $q_j(t)$ in h_{ij}. Some basic properties of $Q_i(q(t))$ are given by, $Q_i(q(t)) \geq 0$, $\sum_{i=1}^{p} Q_i(q(t)) > 0$, $i = 1, 2, \ldots, p$. It is known that $\mu_i(q(t)) \geq 0$, $\sum_{i=1}^{p} \mu_i(q(t)) = 1$, writing $\mu_i(q(t))$ as μ_i for simplicity. Considering also the state $Z \in \kappa^{g\times 1}$ that is a filtered version of the output $y(t)$ [25]. This state is given by:

$$\dot{Z}(t) = \sum_{i=1}^{p} \mu_i[-A_{zi} Z(t) + A_{zi} C_i x(t) + A_{zi} E_{si} f_s(t)] \tag{6}$$

where $-A_{zi}\kappa^{r\times r}$ is the stable matrix, from the (5) and (6), one can obtain the augmented system:

$$\dot{X}(t) = \sum_{i=1}^{p} \mu_i[\bar{A}_i X(t) + \bar{B}_i U(t) + \bar{E}_i f(t)] \qquad Y(t) = \sum_{i=1}^{p} \mu_i \bar{C}_i X(t) \tag{7}$$

where $X(t) = \begin{bmatrix} x(t) \\ Z(t) \end{bmatrix}$, $U(t) = \begin{bmatrix} u(t) \\ 0 \end{bmatrix}$, $f(t) = \begin{bmatrix} f_a(t) \\ f_s(t) \end{bmatrix}$, $\bar{A}_i = \begin{bmatrix} A_i & 0 \\ A_{zi} C_i & -A_{zi} \end{bmatrix}$, $\bar{B}_i = \begin{bmatrix} B_i & 0 \\ 0 & 0 \end{bmatrix}$, $\bar{E}_i = \begin{bmatrix} E_{ai} & 0 \\ 0 & A_{zi} E_{si} \end{bmatrix}$ and $\bar{C}_i = \begin{bmatrix} 0 & I \end{bmatrix}$.

Fuzzy Adaptive Observer In order to estimate the state and the fault of the battery (3), the following fuzzy adaptive observer is proposed based on [26],

$$\dot{\hat{X}}(t) = \sum_{i=1}^{p} \mu_i[\bar{A}_i X(t) + \bar{B}_i U(t) + \hat{E}_i \hat{f}(t) + K_i(Y(t) - \hat{Y}(t))] \tag{8}$$

$$e_x(t) = X(t) - \hat{X}(t), \qquad e_y(t) = Y(t) - \hat{Y}(t) = \bar{C}_i e_x(t) \tag{9}$$

$$\dot{\hat{f}}(t) = \sum_{i=1}^{p} \mu_i L_i(\dot{e}_y(t) + e_y(t)) = \sum_{i=1}^{p} \mu_i L_i \bar{C}_i(\dot{e}_x(t) + e_x(t)) \tag{10}$$

$$\hat{Y}(t) = \sum_{i=1}^{p} \mu_i \bar{C}_i \hat{X}(t) \tag{11}$$

where $\hat{X}(t)$ is the observer state, $\hat{Y}(t)$ is the observer output vector, $\hat{f}(t)$ is an estimation of the sensor and actuator fault $f(t)$, K_i and L_i are the observer gains to be designed.

Proposed Fuzzy Fault Tolerant Control In this section, the FFTC synthesis procedure is developed to deal with a wide range of sensor faults, and actuator faults while maintaining the stability of the closed loop battery system. For simplicity, we make $\bar{E}_j = \bar{B}_j E_j$, where, E_j are known matrix. For the fuzzy model (5), we construct the following FFTC via the PDC [22]. It is assumed that the fuzzy system (5) is locally controllable. A state-feedback with LMIs is used to design a controller for each subsystem. The final output of the FFTC based on online fault estimation is defined and is based on [26],

$$U(t) = \sum_{j=1}^{p} \mu_j [G_j \hat{X}(t) - E_j \hat{f}(t)] \tag{12}$$

where, G_i are the controller gain to be designed, the sensor and the actuator fault vectors are assumed to be bounded. The main result for the global asymptotic stability of a TS fuzzy model with sensor and actuator faults are summarized by the following Theorem 1.

Theorem 1: The TS fuzzy system (7) is asymptotically stabilizable if there exist symmetric and positive definite matrix $P(P > 0)$, some matrices L_i, K_i, and G_j (*i=1,2,...,p; j=1,2,...,q*), such that the following LMIs are satisfied,

$$O\,A_i^T + A_i O - (B_i\,W_j)^T - (B_i\,W_j) < 0 \tag{13}$$

$$H_{bi}^T\,P_2 + P_2\,H_{bi} - (D_i\,C_i)^T - (D_i\,C_i) < 0 \tag{14}$$

where $P = diag(P_1, P_2)$, $O = P_1^{-1}$, $G_j = W_j O^{-1}$, $\bar{K}_i = P_2^{-1} D_i$, $\bar{K}_i = \begin{bmatrix} K_i \\ L_i \end{bmatrix}$.

Proof. The proof can be given directly from [20].
BUSINOVA Lithium-Ion Battery Model Based on TS Fuzzy Model To design the FFTC and the fuzzy adaptive Observer, a fuzzy model that represents the dynamics of the battery is necessary. Therefore, the system is first represented with a TS fuzzy model. The system (3) is described by a TS fuzzy representation. Next, calculate the minimum and maximum values of $q_1(x)$ and $q_2(x)$ under the constraints $q_{1,min} \leq q_1(x) \leq q_{1,max}$ and $q_{2,min} \leq q_2(x) \leq q_{2,max}$. From the

maximum and minimum values $q_1(x)$ and $q_2(x)$, one can obtain the nonlinearity sector as follows

$$\begin{aligned} q_1(x) &= q_{1,max}N_1(q_1(x)) + q_{1,min}N_2(q_1(x)) \\ q_2(x) &= q_{2,max}M_1(q_2(x)) + q_{2,min}M_2(q_2(x)) \end{aligned} \tag{15}$$

where $N_1(q_1(x)) + N_2(q_1(x)) = 1$, $M_1(q_1(x)) + M_2(q_1(x)) = 1$ (as commonly used in the literature [22], [26]), N_{i1} and M_{i2} are a fuzzy term of rule i, $q_1(x)$ and $q_2(x)$ are the premise variables. Referring to (5), the fuzzy plant model given by

$$\begin{aligned} \dot{x}(t) &= \sum_{i=1}^{4} \mu_i[A_i x(t) + B_i u(t) + E_{ai} f_a(t)] \\ y(t) &= \sum_{i=1}^{4} \mu_i[C_i x(t) + E_{si} f_s(t)] \end{aligned} \tag{16}$$

where $x(t) \in \kappa^{3\times1}$, $u(t) \in \kappa^{1\times1}$ and $C_i \in \kappa^{1\times3}$ are the state vectors and the battery control input, respectively, where

$$A_1 = A_2 = A_3 = A_4 = \begin{bmatrix} \frac{1}{R_1C_1} & 0 & 0 \\ 0 & \frac{1}{R_2C_2} & 0 \\ 0 & 0 & 0 \end{bmatrix},\ B_1 = B_2 = B_3 = B_4 = \begin{bmatrix} \frac{1}{C_1} \\ \frac{1}{C_2} \\ \frac{\eta}{C_n} \end{bmatrix},$$

$$C_1 = \begin{bmatrix} q_{1,min} \\ 1 \\ q_{2,min} \end{bmatrix}^T,\ C_2 = \begin{bmatrix} q_{1,min} \\ 1 \\ q_{2,max} \end{bmatrix}^T,\ C_3 = \begin{bmatrix} q_{1,max} \\ 1 \\ q_{2,min} \end{bmatrix}^T \text{ and } C_4 = \begin{bmatrix} q_{1,max} \\ 1 \\ q_{2,max} \end{bmatrix}^T.$$

The choice of E_{ai} and E_{si} depend on the input and the output of the battery system. The sensor fault and actuator fault are considered: battery input current and battery terminal voltage which are modeled up to 25% from the rated value for the current and the voltage of the battery.

3.2 Intelligent Power Distribution and Optimization Controller (Level 2: IPDOC)

Once level 3 has selected the appropriate mode and generated the healthy SOC set point, this level of control manages and optimizes the power distribution between the two different sources based on new proposed formula to update the proposed fuzzy controller. Therefore, the mode of operation and healthy SOC set point are considered as two inputs for the second level of control (cf. Fig. 7). There are six input variables at this control level: PCVE and actual vehicle torque for the Learning Adaptive Algorithm (LAA) block and mode of operation with the same three inputs of the third level (speed of the vehicle, torque demand, SOC) for the Fuzzy Management Controller (FMC) block. The two output variables of level 2 are $T_{ICE,SP}$ and $T_{EM,SP}$. This level consists of three blocks. The FMC block splits the required torque between EM or/and HM via ICE. The proposed LAA block based on a neural network is used to update FMC parameters. The Global Vehicle Actual and Optimal Efficiency Calculation Algorithm (GVAOECA) block is used to calculate the total actual and the optimal efficiency for the vehicle based on the elementary efficiencies of the EM, battery, ICE, HP, HM and transmission. The main contributions of this level are: (i) to find the best combination of power distribution between different energy sources and maximize hybrid vehicle overall efficiency; (ii) to tune the optimal parameters of the fuzzy controller based on neural network optimization; (iii) to generate the set point for the first level.

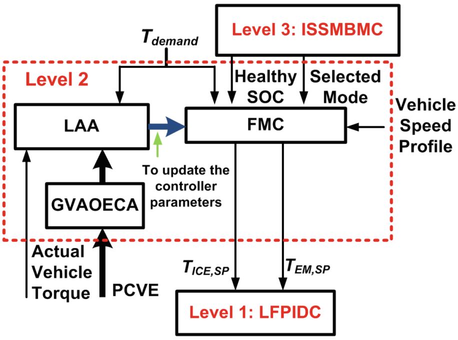

Fig. 7. Block diagram of the proposed level 2.

The two output variables of level 2 are $T_{ICE,SP}$ and $T_{EM,SP}$. The proposed fuzzy management controller inferred output for the ICE torque (T_{ICE}) and EM torque (T_{EM}) are given by [20],

$$T_{ICE} = \frac{\sum_{j=1}^{c} m_{ICE,j}\sigma_{ICE,j1}\sigma_{ICE,j2}}{\sum_{j=1}^{n} m_{ICE,j}\sigma_{ICE,j2}} \tag{17}$$

$$T_{EM} = \frac{\sum_{i=1}^{c} m_{EM,i}\sigma_{EM,i1}\sigma_{EM,i2}}{\sum_{i=1}^{c} m_{EM,i}\sigma_{EM,i2}} \tag{18}$$

where, $\sigma_{ICE,j1}$ and $\sigma_{EM,i1}$, $\sigma_{ICE,j2}$ and $\sigma_{EM,i2}$ are the mean and the standard deviation of the GMF of the output variable for the ICE and the EM, respectively, which are two adjustable parameter, $m_{ICE,j}$ and $m_{EM,i}$ are the inferred weights of the j^{th} and i^{th} output membership function for the ICE and the EM, respectively, c is the number of fuzzy rules. The mean and the standard deviation of the output variable are optimize based on the LAA presented in the following section. In order to optimize the output of the proposed FMC based on Artificial Neural Network (ANN). We first identify the parameter sets involved in the premise and consequence control logic and use the proposed below Theorem 2 to updates the parameters values.

Theorem 2: The parameters required by the FMC, shown in Eqs. (17) and (18) are updated by the proposed LAA, if the mean and the standard deviation of the membership function satisfy the following:

$$\sigma_{ij1}^{k+1} = \sigma_{ij1}^{k} - \zeta^{k} \sum_{k=t+1}^{t+s} \sum_{j=1}^{N} \left(e_{ed}^{k} \mu_{td,ij} + e_{eff}^{k} \mu_{eff,ij} \right) \tag{19}$$

$$\sigma_{ij2}^{k+1} = \sigma_{ij2}^{k} - \zeta^{k} \sum_{k=t+1}^{t+s} \sum_{j=1}^{N} \left(e_{ed}^{k} \mu_{td,ij} + e_{eff}^{k} \mu_{eff,ij} \right) \tag{20}$$

where, σ_{ij1} is $\sigma_{ICE,j1}$ and $\sigma_{EM,i1}$ for (17) and (18), and σ_{ij2} is $\sigma_{ICE,j2}$ and $\sigma_{EM,i2}$ for (17) and (18) which are the mean and the standard deviation of the GMF for ICE and the EM, respectively. e_{td} and e_{eff} are the error functions for the torque demand and the vehicle total efficiency. $\mu_{td,ij}$ and $\mu_{eff,ij}$ are the weights of the i^{th} rule for the j^{th} training pattern, ζ^k is the learning rate, k is the iteration index, t is the trailing edge of the moving time-window over which the prediction error is minimized and s is the window of learning. For off-line learning we select $t = 1$ and $s = P$; where P is the size of the training set, which is usually much larger than the largest multi-step-ahead prediction horizon needed in practice [27]. The prediction accuracy deteriorates very quickly with increasing P. For on-line learning, s can be selected to be sufficiently large so as to include the largest possible prediction horizon [27].

Proof. The proof can be given directly from [18].

3.3 Local Fuzzy Tuning Proportional-Integral-Derivative Controllers (Level 1: LFPIDC)

The objective at this level is to regulate the set points of EM and HM via ICE, to give a good control tracking performance. In this level, it is proposed fuzzy logic tuning PID controller based on [18] for the EM and HM via ICE.

4 Simulation Results and Discussion

In order to develop and to evaluate the performance of the proposed overall energy management strategy called IRHHCS (cf. Sect. 3), a realistic model of the studied Hybrid Hydraulic-Electric bus included an accurate battery model is used (cf. Sect. 2) and implemented. In this section, three simulations and discussions to demonstrate the effectiveness of the proposed IRHHCS are presented. The first simulation validate the battery model at low and high temperature during the charging and discharging phases. In the second simulation, the effectiveness of the proposed strategy to detect and compensate the effect of battery fault and its effect on the SOC estimation are presented. The third simulation validates the overall control architecture for the complete vehicle to illustrate the effectiveness of the proposed technique.

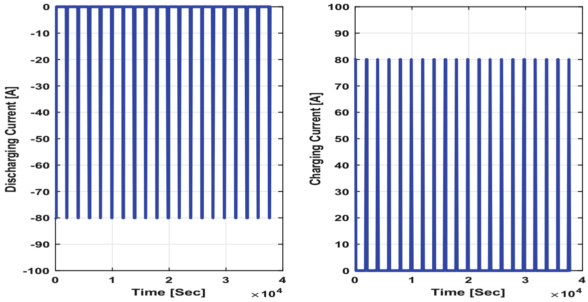

Fig. 8. Battery current profile; (left) battery discharging current profile; (right) battery charging current profile [20].

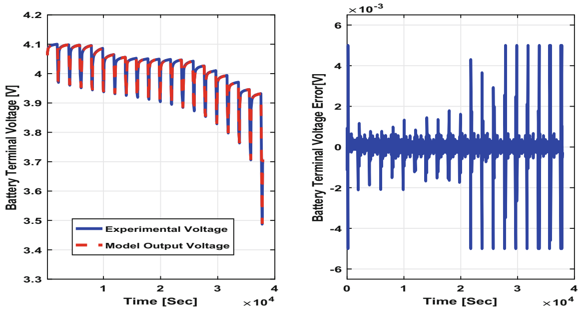

Fig. 9. Comparison of experimental and model output voltages and voltage error at high temperature (40 ^{o}C) and discharge current (80A); (left) experimental and model output voltages; (right) voltage error.

4.1 Simulation 1: BUSINOVA Battery Model Validation

The objective of this section is to validate BUSINOVA bus battery model through experimental tests before implementing the diagnostic scheme. BUSINOVA bus battery cell has rated capacity of 80 Ah and nominal voltage of 4.1 V. Figure 8 (left) shows battery discharging and charging current profiles. Experimental and model output voltage comparison and the voltage error for discharging at high temperature (40 ^{o}C) and low temperature ($-40\,^o$C) are given in Figs. 9 and 10, respectively. Figure 11 shows the comparison of the experimental and model output voltage and the voltage error at thigh temperature (40 ^{o}C) for the pulsating charging current (cf. Fig. 8 (right)). Output voltage and the voltage error comparison at low temperature ($-40\,^o$C) and constant charging current (80A) is given in Fig. 12.

From the simulation results it can be seen that, for low and high temperature the maximum voltage error for discharging and charging are similar to the error found at reference temperature which permit us to conclude that the proposed BUSINOVA battery model is more accurate.

From the Figs. 9, 10, 11 and 12, one can observe that the proposed model of Lithium-ion battery gives a good modeling performance. For the proposed model, between 10% and 95% SOC, the terminal voltage error around 0.2% which corresponds to lower error compared to voltage error of 1.5% [15].

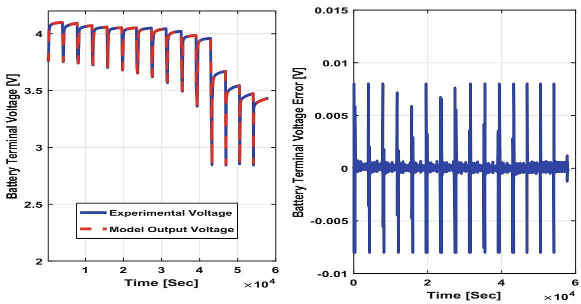

Fig. 10. Comparison of experimental and model output voltages and voltage error at low temperature ($-4\,0^oC$) and discharge current (80A); (left) experimental and model output voltages; (right) voltage error.

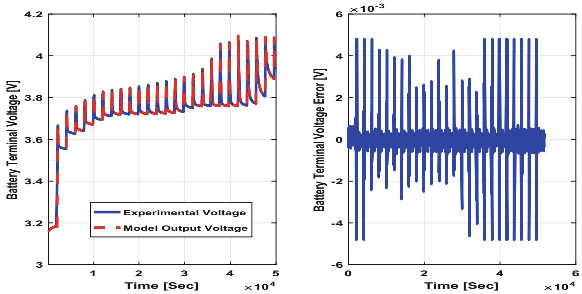

Fig. 11. Comparison of experimental and model output voltages and voltage error at high temperature (40^oC) and charge current (80 A); (left) experimental and model output voltages; (right) voltage error [20].

4.2 Simulation 2: Fault Detection and Its Effects on Battery SOC Estimation

The objective of BMFFTC for the Lithium-ion battery presented in Sect. 3.2 is to ensure that all signals in the closed-loop battery system are bounded during the battery faults. In this section, the effects of current or voltage sensor faults on the battery SOC estimations and compensate its effect are investigated. For the testing purpose, it is required that sensor and/or actuator fail. The current or voltage sensor faults are injected in the battery test bench. The initial value of the fuzzy observer SOC state is 50%. The tested discharging current profile is given in Fig. 13. Figure 14 (left) and (right) show the current sensor fault (+20 A bias fault) and voltage sensor fault (+0.1 V bias fault) (solid lines) and their estimations (dashed lines) based on the fuzzy observer, respectively. To prevent the battery from over-discharge, the lower limit of the battery SOC is taken as 10%. We are considered the ±20 A bias sensor fault occurs at the time 2406 sec. Figure 15 (left) plots the experimental SOC estimation under the current sensor fault with FFTC and without FFTC, while Fig. 15 (right) shows the SOC estimation errors. It can be found from Fig. 15 (left) that the computed SOC in battery management system (observer-estimated SOC) is around 20% at the time 4812 sec when the current sensor has a +20 A bias fault. According to this result, the battery suffering from over-discharge. Therefore, this will accelerate the battery aging and decrease the battery life. For a −20 A bias fault, the estimated SOC will reach to 10% and the battery cannot release the supposed energy. Also with ±0.1 V bias fault occurs at the time of 2406 sec, similar simulation results are obtained in Fig. 16 (left) and (right). The battery may be over-discharged when the voltage sensor has a +0.1 V fault as shown in Fig. 16 (left). The estimation errors are up to 22% with the voltage sensor faulty condition (cf. Fig. 16 (right)). The results show that the battery may be over-discharged in the faulty sensor cases. The simulation results demonstrate the effectiveness of the proposed control approach. The proposed control scheme can guarantee the stability of the closed-loop battery system.

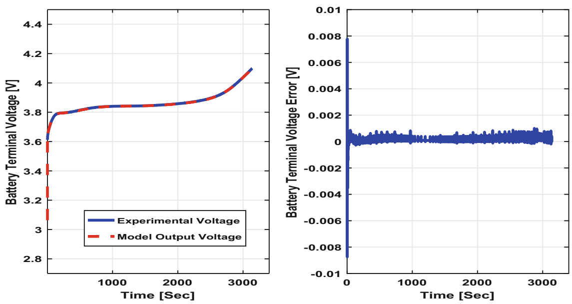

Fig. 12. Comparison of experimental and model output voltages and voltage error at low temperature (-40^oC) and constant charging current (80A); (left) experimental and model output voltages; (right) voltage error.

From the simulation results, it can be seen that without the reconfiguration mechanism, the battery lost performance just after the sensor became faulty, whereas for the same condition and using the proposed FFTC scheme strategy, the battery remains stable in the presence of voltage sensor fault and current actuator fault which demonstrates the effectiveness of the proposed FFTC strategy. In summary, it has been shown that the proposed scheme is able to detect

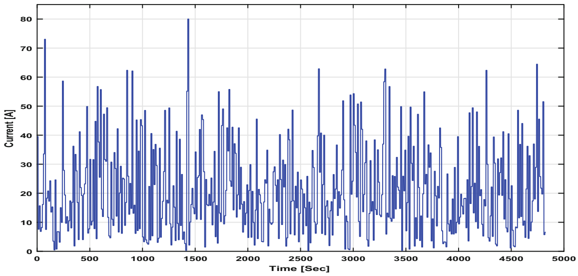

Fig. 13. Battery discharging current profile [20].

and compensate voltage sensor faults and current actuator faults, through a proper and feasible selection of the observed variables.

4.3 Simulation 3: Proposed Overall Strategy Validation

To prove the effectiveness of the proposed overall control architecture for optimal energy management, IRHHCS is compared with Pontryagin's Minimum Principle (PMP) [4] method already existing in the literature. The desired and the actual bus speed profile for the proposed IRHHCS and PMP strategies are shown in Fig. 17. Total energy consumed by the vehicle for these controllers is given in Fig. 18 which shows that the IRHHCS strategy is better w.r.t. to PMP controller for reducing total energy consumed (fuel consumption and battery discharge), which increases the efficiency of the vehicle.

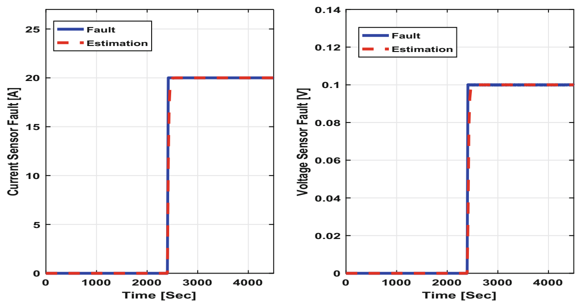

Fig. 14. Battery current and voltage sensor faults and their estimations; (left) battery current sensor fault and its estimation; (right) battery voltage sensor fault and its estimation [20].

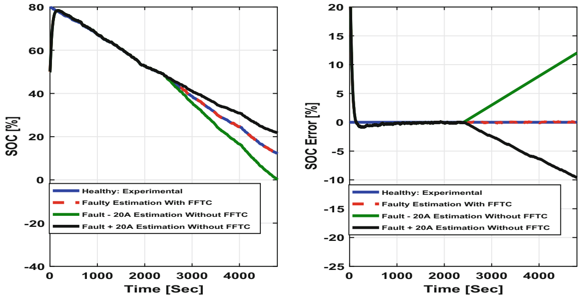

Fig. 15. Effects of current fault on battery SOC estimation; (left) SOC estimation results in the current sensor faulty conditions with FFTC and without FFTC; (right) SOC estimation errors in the current sensor faulty conditions with FFTC and without FFTC [20].

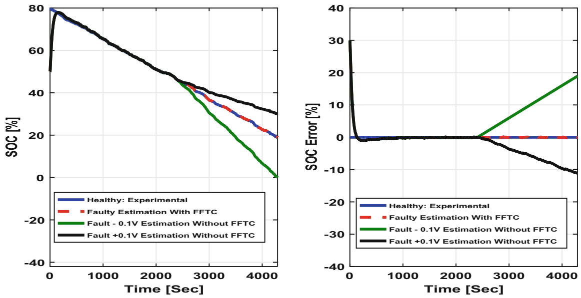

Fig. 16. Effects of voltage fault on battery SOC estimation; (left) SOC estimation results in the voltage sensor faulty conditions with FFTC and without FFTC; (right) SOC estimation errors in the voltage sensor faulty conditions with FFTC and without FFTC [20]

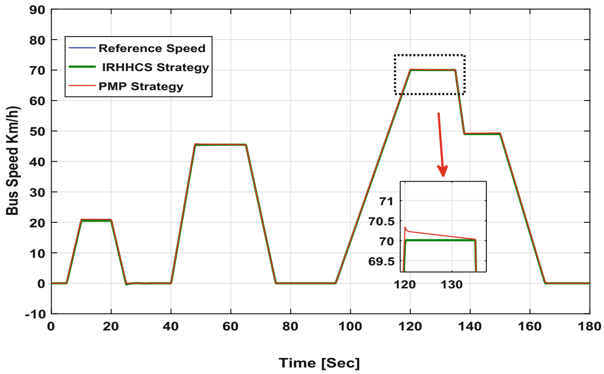

Fig. 17. Comparisons between reference speed and actual vehicle speed [Km/h] for the proposed IRHHCS strategy w.r.t. PMP.

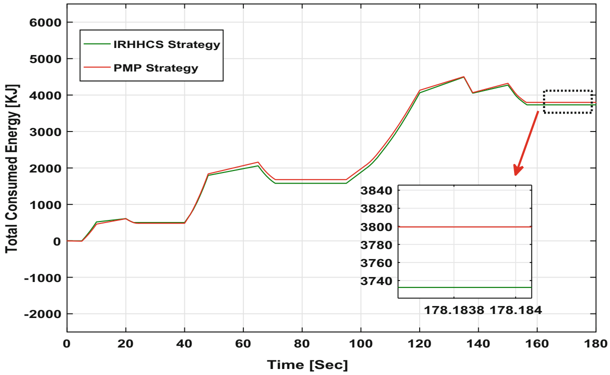

Fig. 18. Total energy consumed by the vehicle in [KJ] for the proposed IRHHCS strategy w.r.t. PMP.

To have a more specific comparative analysis, the total energy consumption for a typical driving cycle are shown in Table 1.

Table 1. Comparison of results for proposed IRHHCS and PMP strategies.

Control strategy	Total energy consumed [KJ]
PMP	3799.341
IRHHCS	3732.384

From Table 1, with the initial SOC, driving cycle, all other parameters and constrains conditions are considered the same. It is seen that the proposed IRHHCS reduces the fuel consumption up to 2% compared to PMP method. In summary, it can be seen that the BUSINOVA bus follows the trajectory of the reference input. In addition, the proposed overall control architecture for optimal energy management is reliable even during current and/or voltage sensor faults (cf. Sect. 4.2). It is amazingly found in Table 1, that the proposed strategy significantly reduce the total energy consumed (in [KJ]), which shows the effectiveness of the strategy applied on the BUSINOVA bus.

5 Conclusion

This chapter presented a robust energy management strategy, with battery faults detection and compensation for the studied hydraulic-electric hybrid vehicle. The first part of this work is dedicated to the development and validation of the dynamic model of the BUSINOVA bus, including an accurate battery model. The obtained results given in Sect. 4 confirm the reliability of the model under a variety of operating conditions. In the second part, an appropriate design of systematic BMFFTC (Battery Management Fuzzy Fault Tolerant Controller) scheme is proposed to estimate and compensate the battery faults. Some sufficient conditions for robust stabilization of the TS fuzzy model were derived for a Lithium-ion battery and were formulated in an LMI (Linear Matrix Inequalities) format. The third part of the chapter has been focused on minimizing total energy consumption and thereby on increasing the total distance traversed between refueling of the studied hybrid vehicle. The proposed method has been implemented using real time power management strategy, named Intelligent Robust Hierarchical Hybrid Controller Strategy (IRHHCS). This proposed strategy consists of three control levels. The highest one (the third level) has been developed using fuzzy strategy and fuzzy observer in order to manage all of the possible bus operation modes and to generate SOC set point for second level and compensate the battery faults. At the second level, an advanced IPDOC (Intelligent Power Distribution and Optimization Controller) has been developed for power splitting which decides the optimal combination of power sharing (between different energy sources) to minimize the total bus energy consumption while maximizing the overall vehicle efficiency. In the first level, an LFPIDC (Local Fuzzy tuning Proportional-Integral- Derivative Controllers) is described and used to track the set points of EM (Electric Motor) and HM (Hydraulic Motor) via the ICE (Internal Combustion Engine) generated at the second level, in order to reach peak performance and acceptable operation indexes while taken into consideration the dynamic behavior of EM, ICE and HM. The obtained results confirm that, using the proposed approach: (i) the strategy can be easily implemented in real time because it does not depend on prior information about future driving conditions; (ii) battery faults could be accurately detected and compensated to minimize its aging effects; (iii) minimize total energy consumption. It is planned in near future to implement the overall proposed control strategy on the actual BUSINOVA platform. Among the main future developments, it is targeted to ensure the robustness of the overall proposed control strategy w.r.t. modelling uncertainties.

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References

1. German, J.M.: Hybrid powered vehicles, Society of Automotive Engineers (SAE) publication T-119 (2003)
2. Panday, A., Bansal, H.O.: Energy management strategy implementation for hybrid electric vehicles using genetic algorithm tuned pontryagin's minimum principle controller. Int. J. Veh. Technol. **2016**, 1–13 (2016)
3. Abdrakhamanov, R., Adouane, L.: Dynamic programming resolution and database knowledge for online predictive energy management of hybrid vehicles. In: International Conference on Informatics in Control, Automation and Robotics (ICINCO), Madrid-Spain, 26–28 July 2017

lounis.adouane@uca.fr

4. Ouddah, N., Adouane, L., Abdrakhamanov, R., Kamal, E.: Optimal energy management strategy of plug-in hybrid electric bus in urban conditions. In: International Conference on Informatics in Control, Automation and Robotics (ICINCO), Madrid-Spain, 26–28 July 2017
5. Ying, X.C., Cong, Z.: Real-time optimization power-split strategy for hybrid electric vehicles. Sci. China Tech. Sci. **59**(5), 814–824 (2016)
6. Adel, B., Youtong, Z., Shua, S.: Parallel HEV hybrid controller modeling for power management. World Electr. Veh. J. **4**, 190–196 (2010). ISSN 2032-6653
7. Lihao, Y., Youjun, W., Congmin, Z.: Study on fuzzy energy management strategy of parallel hybrid vehicle based on quantum PSO algorithm. Int. J. Multimed. Ubiquitous Eng. **11**(5), 147–158 (2016)
8. Dai, X., Li, C.K., Rad, A.B.: An approach to tune fuzzy controllers based on reinforcement learning for autonomous vehicle control. IEEE Trans. Intell. Transp. Syst. **6**(3), 285–293 (2005)
9. Zhou, M.L., Lu, D.K., Li, W.M., Xu, H.F.: Optimized fuzzy logic control strategy for parallel hybrid electric vehicle based on genetic algorithm. Appl. Mech. Mater **274**, 345–349 (2013)
10. Zhentong, L., Hongwen, H.: Sensor fault detection and isolation for a lithium-ion battery pack in electric vehicles using adaptive extended Kalman filter. Appl. Energy **185**, 2033–2044 (2017)
11. Chen, M., Rincon-Mora, G.A.: Accurate electrical battery model capable of predicting runtime and I-V performance. IEEE Trans. Energy Convers. **21**(2), 504–511 (2006)
12. Jaguemont, J., Boulon, L., Dub, Y.: Characterization and modeling of a hybrid-electric-vehicle Lithium-Ion battery pack at low temperatures. IEEE Trans. Veh. Technol. **65**(1), 1–14 (2016)
13. He, H., Xiong, R., Guo, H., Li, S.: Comparison study on the battery models used for the energy management of batteries in electric vehicles. Energy Convers. Manag. **64**, 113–121 (2012)
14. Hua, X., Li, S., Peng, H.: A comparative study of equivalent circuit models for Li-ion batteries. J. Power Sources **198**, 359–367 (2012)
15. Sepasi, S., Ghorbani, R., Liaw, B.Y.: Improved extended Kalman filter for state of charge estimation of battery pack. J. Power Sources **255**(1), 368–376 (2014)
16. Kamal, E., El Hajjaji, A., Mabwe, A.M.: State of charge estimation based on extended kalman filter algorithm for lithium-ion battery. In: 23rd Mediterranean Conference on Control and Automation, Spain, June 16–19 2015
17. Mohan, S., Kim, Y., Stefanopoulou, A.G.: Estimating the power capability of li-ion batteries using informationally partitioned estimators. IEEE Trans. Control. Syst. Technol. **24**(5), 1643–1654 (2016)
18. Kamal, E., Adouane, L., Abdrakhmanov, R., Ouddah, N.: Hierarchical and Adaptive neuro-fuzzy control for intelligent energy management in hybrid electric vehicles. In: IFAC World Congress, Toulouse-France, 9–14 July 2017
19. Padovani, T.M., Debert, M., Colin, G., Chamaillard, Y.: Optimal energy management strategy including battery health through thermal management for hybrid vehicles. In: 7th IFAC Symposium on Advances in Automotive Control, vol. 7. Tokyo, Japan, 4–7 Sept 2013
20. Kamal, E., Adouane, L.: Energy optimization strategy based on battery fault management for hydraulic-electric hybrid vehicle. In: International Conference on Informatics in Control, Automation and Robotics (ICINCO), Madrid-Spain, 26–28 July 2017

21. Hu, X., Martinez, C.M., Yang, Y.: Charging, power management and battery degradation mitigation in plug-in hybrid electric vehicles: a unified cost-optimal approach. Mech. Syst. Signal Process. (2016)
22. Kamal, E., Aitouche, A.: Robust scheduler fuzzy controller of DFIG wind energy systems. IEEE Trans. Sustain. Energy **4**(3), 706–715 (2013)
23. Balaban, E., Saxena, A., Bansal, P., Goebel, K.F., Curran, S.: Modeling, detection, and disambiguation of sensor faults for aerospace applications. IEEE Sens. J. **9**, 1907–1917 (2009)
24. Foo, G.H., Zhang, X., Vilathgamuwa, D.M.: A sensor fault detection and isolation method in interior permanent-magnet synchronous motor drives based on an extended kalman filter. IEEE Trans. Ind. Electron. **60**, 3485–3495 (2013)
25. Edwards, C.: A comparison of sliding mode and unknown input observers for fault reconstruction. Eur. J. Control. **12**(3), 245–260 (2006)
26. Kamal, E., Aitouche, A., Ghorbani, R., Bayart, M.: Robust fuzzy fault tolerant control of wind energy conversion systems subject to sensor faults. IEEE Trans. Sustain. Energy **3**(2), 231–241 (2012)
27. Ljung, L.: System Identification: Theory for the Users, 2nd edn. Prentice-Hall, NJ (1999)
28. Hamed, B., Almobaied, M.: Fuzzy PID controllers using FPGA technique for real time dc motor speed control. Intell. Control. Autom. **2**, 233–240 (2011)
29. Rodrguez, O.H., Fernndez, J.M.L.: A Semiotic Reflection on the Didactics of the Chain Rule. In: The Montana Mathematics Enthusiastl, vol. 7, pp. 321–332 (2010)
30. Jain, A.-K., Dubes, R.C.: Algorithms for Clustering Data. Prentice Hall, NJ (1988)