Energy Management System for Fuel Cell-Battery Vehicles Using Multi-Objective Online Optimization

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ABSTRACT An Energy Management system for fuel cell/battery vehicles manages and controls the fuel consumption and affects the lifetime of the powertrain system. This paper proposes a new Energy Management System that is based on a multi-objective online optimization technique. The proposed Energy Management System objective is to minimize a cost function that is composed of four terms: actual fuel consumption, two terms representing the stresses on the lifetimes of the powertrain system components (the fuel cell and the battery), and a fourth term representing a penalty on the deviation from a desired SOC of the battery. This minimization is performed with no need for prior knowledge of the driving cycle. The proposed Energy Management System couples fuel consumption minimization with a frequency-decoupling-based technique to split the power demand among available power sources to relieve the stresses on those sources. The proposed Energy Management System shows flexibility to address multiple objectives and can simply be deployed as a real-time strategy. An analytical derivation is given, and simulation results show the effectiveness of the proposed approach. A comparison is performed between the proposed Energy Management System and a Dynamic-Programming-based Energy Management System. The comparison shows that the proposed Energy Management System achieves a near-optimal solution without the need for prior knowledge of the driving cycle.

INDEX TERMS Fuel cell Vehicle, Energy Management System, Multi-objective Online optimization

I. INTRODUCTION

Nowadays, governments are keen to switch to cleaner vehicles which helps in reducing carbon emissions and air pollutants. It is expected that Electric vehicle (EV) sales will be more than 40 Million Cars by 2040 [1]. The primary power source of EVs can be a battery or a fuel cell. Although Battery-based Electric Vehicles (BEVs) are considered one of the key trends these days, they still face a lot of challenges. One of these challenges is the battery’s charging time. Charging times of less than 20 minutes for level-3 DC charging is achievable [2]. Driving ranges for BEVs can be extended through the addition of heavy batteries, but this increases the total vehicle’s mass and affects the energy economy of the overall system. Fuel-Cell-based Vehicles (FCVs) avoid BEVs’ disadvantages as the driving range of FCVs can be increased without additional weight. Although additional volume is needed for hydrogen, it is not considered a significant increase in the weight of the vehicle [3]. Moreover, the refueling time range is relatively short; typically between 3 to 5 minutes [3]. FCVs numbers are expected to increase by 1784% by the year 2030 [4]. However, FCVs are slower in response compared to battery vehicles. Thus, there is a need for combining the fuel cell with an auxiliary power source. This is essential to support the DC-bus voltage inside FCVs, improve the overall system efficiency, response time, and capture the lost regenerative braking energy. Supercapacitors and batteries are considered as main candidates for auxiliary power sources used in FCVs. The combination of the fuel cell with an auxiliary power source raises the challenge of managing the power share between the fuel cell and the auxiliary power source(s). Such a challenge needs an Energy Management System (EMS). The EMS can be considered as a supervisory controller for the requested power from each power source. Several EMSs are proposed in the literature for controlling FCVs. Operation modes, also called state machine, is considered one of the most commonly used EMSs [5]-[6]. Although it is widely used, it has the disadvantage of heavily relying on the manufacturer’s knowledge of all of the system’s modes. Moreover, switching from one mode to another increases the stress on the power sources. Many other EMS techniques are proposed in the literature. It can be divided into non-optimization techniques and
optimization techniques. Non-optimization techniques are proposed such as PI [7], adaptive control [8], Fuzzy logic [9], and neural network [10]. Traditional simple PI controllers are applied for real-time systems with straightforward implementation [7]. However, PI controllers cannot optimize the fuel consumption nor save the powertrain lifetime. Adaptive controllers are proposed to deal with system uncertainties [8]. It requires a detailed mathematical model of the system. Fuzzy logic-based control is considered a development of the state machine technique [9]. However, it suffers the same need of the manufacturer’s experience with the system, but with lower stress over the system. In [10], neural networks are proposed since they can adapt to new information, but this only gives an acceptable response after an exhaustive training procedure that includes all conditions. Optimization-based EMS can be categorized as being global or local optimizers. Dynamic programming is used for global offline optimization which requires prior knowledge of the driving cycle [11]. Hence, the global problem is non-causal and can’t be implemented for real-time systems. It also needs complex computation which is not suitable for limited resources of the Electronic Control Units (ECUs). Thus, dynamic programming can be used as a reference for the comparison of the implementation of online optimization techniques. In [12], a multi-objective optimization EMS is proposed which includes three factors a) energy consumption cost b) instantaneous fuel cell degradation cost c) instantaneous battery degradation cost. This EMS shows near-optimal results (considering Dynamic programming as a reference). It achieved 95.26 % optimality compared to Dynamic Programming (DP). Under unknown conditions, it achieved around 88.1 % optimality compared to DP. In addition, the instantaneous fuel cell degradation model has some parameters estimated using Proton Exchange Membrane Fuel Cell (PEMFC) degradation tests. For online local optimization, an Equivalent Consumption Minimization Strategy (ECMS) has been proposed [13]. It optimizes the equivalent fuel consumption at each instant which can work for real-time systems without any information of the driving cycle. The cost function used is a sum of the fuel consumption and the equivalent fuel consumption due to SOC variation. Several other online EMSs try to minimize fuel consumption and extend the lifetime of the powertrain system. The drawback with extending the powertrain system lifetime is that performing the optimization is done using a cost function which is driven after obtaining experimental results to get degradation models [14]- [15]. For components’ lifetime optimization, frequency decoupling techniques are proposed in [16], where extending the powertrain lifetime is done by splitting power demand based on the time constant of each power source. Fuel cells need the hydrogen supply system to respond to changes in the power demand. However, increased power demand without sufficient reactants may take the fuel cell through a fuel starvation phenomenon. Hence, fuel cells are assigned to supply the low-time constant component of the power demand. On the other hand, batteries can withstand faster dynamics than fuel cells but slower than supercapacitors as batteries are chemically dependent [17]. Wavelet decomposition in [18], an extension to frequency decoupling, is only concerned with extending the lifetime of the powertrain system. In [19], a wavelet transform is used for training a neural network offline. The trained neural network is then combined with fuzzy logic to work online. Wavelet decomposition is mainly used to extract the low-frequency power data to train the neural network. Lifetime-extension-based EMS doesn’t optimize fuel consumption or regulate the State of Charge (SOC) of the battery. In [20], an optimal power distribution strategy between a fuel cell and a supercapacitor is proposed. This distribution strategy takes into consideration maximum efficiency and maximum FC power points. The system’s degree of degradation is included in the optimization function. This degree of degradation is based on some estimated parameters obtained from an adaptive recursive least square algorithm. In [21], a two-layer strategy is proposed that offers efficient and stable control over systems using PEMFC. The upper optimization layer considers the oxygen starvation and oxygen saturation phenomenon. While the lower optimization layer considers the PEMFC system nonlinearities and uncertainties. However, this strategy considers only one power source. It also needs experimental results for better guidance for the design of the controller.

In this work, a new real-time energy management system is proposed to help extend the lifetime of the vehicle’s fuel cell and the battery with the ability to minimize fuel consumption. This proposed system minimizes terms representing stresses on the powertrain system’s components lifetime using analytical relations. The proposed system does not rely on any experimental results to get powertrain system lifetime degradation models. This system minimizes fuel consumption in combination with splitting the power demand among the available power sources to decrease the stresses on the powertrain components. The splitting of the power demand among the available power sources is performed using a frequency decoupling technique.

This paper is organized as follows: the structure of the powertrain system is given in Section II. Section III presents the optimization problem formulation, objectives, and proposed solution. Section IV discusses simulation results obtained for the system with the proposed optimization. A comparison between the proposed solution and dynamic programming is given. Finally, conclusions are provided in Section V.

II. STRUCTURE AND POWER FLOW OF THE POWERTRAIN SYSTEM

The structure of the model used to simulate the performance of the powertrain system along with the proposed EMS is shown in Figure 1. The fuel cell is connected to the DC bus through a DC-DC Converter. The Converter is unidirectional
as the fuel cell can’t capture the regenerative braking energy. The battery is directly coupled to the DC bus to provide more robustness for the system even in the case of any urgent condition in the fuel cell system or any misfiring of the converter. The Battery Management System (BMS) is responsible for estimating the SOC and providing it to the EMS [22]. The battery used in this model is a lithium-ion battery. Lithium-ion batteries have the advantages of high capacity, large number of charge-discharge cycles, and reasonable cost [8]. Interior Permanent Magnet Synchronous Motor (IPMSM) is used in this work. It has 8 salient-type poles with a 100 kW rating. The Machine acts as a motor if the pedal position requests positive torque, while it acts as a generator if the pedal position is reversed. The regenerative braking energy is captured by the battery. The motor drives the vehicle’s wheels through an axle and a gearbox and it is supplied electrically through a DC/AC inverter [23]. The inverter seeks to achieve the desired torque using Field Oriented Control Technique (FOC). FOC is based on Park Clark transformation which decouples the direct and quadrature current components (ID and IQ) [23], [24]. The needed ID and IQ components are generated corresponding to the required machine flux. The required machine flux is calculated using a ‘machine optimal operation lookup table’. This table uses the requested torque and the current vehicle’s speed. The speed is measured from the rotor, while the requested torque is obtained from the ‘Torque/Speed Lookup table’ based on the pedal position. For simulation purposes, a driver model is used to simulate the driver behavior. It provides the needed pedal position required to track a given driving cycle. Under any condition, the motor’s power demand should be fulfilled by the fuel cell and the battery as follows,

\[ P_{motor_k} = P_{FC_k} + P_{batt_k} \]  

where \((\star)_k\) denotes a variable \((\star)\) defined at sample time \(k\), where \(k\) is the discrete time index. \(P_{motor}\) is the motor’s power demand, \(P_{FC}\) is the fuel cell output power, and \(P_{batt}\) is the battery’s output power. The machine works as a motor when \(P_{motor} > 0\), while the machine works as a generator when \(P_{motor} < 0\). The battery supports the motor with power when \(P_{batt} > 0\). If the battery’s power is negative, it means that the battery is charging.

The EMS is responsible for deciding the power share between the battery and the fuel cell. This sharing is controlled actively through the only available degree of freedom using the DC-DC converter’s duty cycle. As shown in Figure 1, the actual fuel cell current is measured. A PI controller is used to control the actual fuel cell to track the requested fuel cell current by the EMS. The battery’s power is controlled passively depending on the fuel cell power assuming an ideal converter. The battery’s actual current is measured for estimating the battery’s SOC. The SOC increases if the fuel cell power is higher than the motor power demand \(P_{motor} < P_{FC}\), as the battery will charge, and vice versa. Hence, SOC regulation is also achievable by controlling the fuel cell output power.

The stresses on the fuel cell and the battery are directly related to the rate of change of their output powers. The more the stress on each power source the more is the reduction of its lifetime [25]. Reducing the high-frequency power component of any power source, fuel cell or battery, will extend its lifetime.

The proposed EMS (via controlling the fuel cell power) aims to control:
- The hydrogen consumption.
- The SOC of the battery.
- The stresses on the fuel cell and the battery which affect the lifetimes of both power sources.

The Fuel cell, the battery, and the motor are modeled using MATLAB/Simulink. The converter is modeled using the average value model where the switching losses of the power

**Figure 1** Structure of the model used to simulate the performance of the Proposed Energy Management System along with the powertrain system.
III. THE PROPOSED MULTI-OBJECTIVE EMS

A. Overview

In this work, the target is to find a multi-objective optimization cost function that can be used online without the prior knowledge of the driving cycle nor the need for any experimental results needed to drive degradation models for each power source. The proposed multi-objective optimization cost function is the sum of four terms: actual fuel consumption \( J_1 \), a term representing stress on the fuel \( J_2 \), a third term representing stress on the battery \( J_3 \), and a fourth term representing a penalty on the deviation from a desired battery’s state of charge. The first three terms are shown to be functions of the fuel cell power (as given in Sections III.B, C, and D). Thus, minimizing the cost function is performed by controlling the fuel cell power. The fourth term is used to force the battery SOC to operate around the maximum efficiency point (50%).

The first term (actual fuel consumption) can be directly computed from the fuel cell power. The fuel cell and battery stresses are hard to estimate. A frequency decoupling-based technique is used to compute the second and third terms of the cost function. In this technique, the load demand is divided into components with different frequency ranges. The fuel cell gets the load demand component within the low-frequency range while the battery supports the load demand component within the high-frequency range. In the case of the existence of a supercapacitor in the system, the supercapacitor supports the load demand component with very high-frequency. To apply this approach online, a set of filters are designed to penalize the different components in the cost function as demonstrated in Figure 2. In this paper, the vehicle only has a fuel cell and a battery. Thus, only two filters are used. The first filter is used to define the fuel cell power. This high-pass filter is used to apply a low penalty on the low-frequency range (less stressful range for the fuel cell) and a high penalty on the high-frequency range (stressful range for the fuel cell). The second filter is used to define the battery’s power. It is a band-stop filter that introduces a high penalty on low and high-frequency ranges and a low penalty on the frequencies of mid-ranges as the latter range is the “less stressful” range for the battery. The filter frequency used for the fuel cell is extracted from [27] while the filter frequencies for the battery are extracted from [28].

The optimization is subject to three constraints. These constraints are used to express the rated limitation of the fuel cell and the battery. In the following subsections, each term of the cost function is driven and the final cost function is given with the constraints.

B. Fuel Consumption

For the fuel consumption, the fuel flow rate depends on the fuel cell current [6] as follows,

\[
M_{H_2} = \left( \frac{N}{F} \right) I_{FC}
\]

(2)

where \( M_{H_2} \) is the fuel flow rate, \( N \) is the number of cells, \( F \) is the Faraday's constant \((A.s/mol)\), and \( I_{FC} \) is the fuel cell current. The relation between the fuel cell power and its current is obtained from the polarization curve, shown in Figure 3 [6]. Neglecting fuel cell losses, the instantaneous fuel consumption can be expressed by polynomial fitting of a second order polynomial in fuel cell power as follows,

\[
J_1 = M_{H_2} = a_{12} P_{FC}^2 + a_{11} P_{FC} + a_{10}
\]

(3)

where \( M_{H_2} \) is the instantaneous fuel (hydrogen) consumption, and \( a_{12}, a_{11}, a_{10} \) are coefficients defining the relation between the instantaneous hydrogen consumption and the instantaneous fuel cell power; which can be obtained by polynomial fitting of the polarization curve.

Figure 2 Penalty on each power source based on Frequency Decoupling Concept

Figure 3 Fuel Cell polarization curve.
C. Fuel Cell Stress

The fuel cell lifetime is mainly affected by the high stresses it is subjected to. A Frequency decoupling technique is used to reduce the fast changes over the fuel cell or the battery. A high pass filter is used to identify the high-frequency component of the fuel cell power $\alpha_{FC}(t)$ as shown in Figure 2. This component is then used to find the cost function term $J_2$. An analytical relation between the high-frequency component of the fuel cell power $\alpha_{FC}(t)$ and the actual fuel cell power is derived as follows using a high pass filter $H(s)$,

$$H(s) = \frac{\alpha_{FC}(s)}{P_{FC}(s)} = \frac{s}{s + \omega_c}$$  \hspace{1cm} (4)

where $\alpha_{FC}$ is the output filter (the high-frequency component of the fuel cell power), $\omega_c = 2\pi f_c$ is the filter corner angular frequency. Using inverse Laplace transform, and Euler backward differentiation; i.e. $(\ast) = \{(\ast)_{k+1} - (\ast)_{k-1}\}/T_s$ where $T_s$ is the sampling interval; leads to,

$$\dot{\alpha}_{FC}(t) + \omega_c \alpha_{FC}(t) = \dot{P}_{FC}(t)$$  \hspace{1cm} (5)

$$\alpha_{FC}(k) = \alpha_{FC}(k-1) - T_s \omega_c \alpha_{FC}(k-1) + P_{FC}(k) - P_{FC}(k-1)$$  \hspace{1cm} (6)

The cost function term $J_2$ is expressed in quadratic form as,

$$J_2 = \alpha_{FC}^2(k) = a_{22} P_{FC}^2(k) + a_{21} P_{FC}(k) + a_{20}$$  \hspace{1cm} (7)

where,

$$a_{22} = \frac{1}{(1 + T_s \omega_c)^2}$$

$$a_{21} = 2 \left( \frac{1}{1 + T_s \omega_c} \right) \left( \frac{-P_{FC}(k-1) + \alpha_{FC}(k-1)}{1 + T_s \omega_c} + \frac{\alpha_{FC}(k-1)}{1 + T_s \omega_c} \right)$$

$$a_{20} = \frac{-P_{FC}(k-1) + \alpha_{FC}(k-1)}{1 + T_s \omega_c} \frac{\alpha_{FC}(k-1)}{1 + T_s \omega_c}$$

These coefficients are calculated online for each sample and used to define the relation between the undesired (high) frequency component of the fuel cell power and the actual fuel cell power. As $\alpha_{FC_k}$ represents the undesired frequency component of fuel cell power, the square of $\alpha_{FC_k}$ represents $J_2$ to be minimized by optimization. Minimizing $J_2$ reduces fast transition of fuel cell power and extends the lifetime of the fuel cell, as mentioned in [6], [25], [29].

D. Battery Stress

Similar to the approach used for the fuel cell stress term $J_2$ in Section C, a relation is derived between the undesired frequency component of the battery power and the actual fuel cell required power to minimize it.

According to Figure 2, the mid-range of frequencies is the best to be covered by the battery. To introduce a penalty for the other ranges, a band-stop filter is used. This filter’s transfer function is,

$$H(s) = \frac{\alpha_{Batt}(s)}{P_{Batt}(s)} = \frac{s^2 + \omega_0^2}{s^2 + 2\omega_c s + \omega_0^2}$$  \hspace{1cm} (8)

where $\alpha_{Batt}$ is the undesired frequency component of the battery (low frequencies and very high frequencies) power, $\omega_c = 2\pi f_c$ band-stop angular frequency, $\omega_0 = 2\pi f_0$ central stop angular frequency as shown in Figure 2.

$$\dot{\alpha}_{Batt}(t) + 2\omega_c \alpha_{Batt}(t) + \omega_0^2 \alpha_{Batt}(t) = (\dot{P}_{batt}(t) + \omega_0^2 P_{batt}(t))$$  \hspace{1cm} (9)

Applying Euler backward differentiation and substitute by,

$$P_{motor_k} = P_{FC_k} + P_{batt_k}$$

leads to the following quadratic formula,

$$J_3 = \alpha_{Batt}^2(k) = \left( \beta P_{FC(k)} + \gamma \right)^2$$  \hspace{1cm} (10)

where,

$$\delta = 1 + 2\omega_c T_s + \omega_0^2 T_s^2$$

$$\beta = \frac{1}{\delta} (1 + \omega_0 T_s^2) \left\{ (1 + \omega_0 T_s^2) P_{L(k)} + (2 + 2\omega_2 T_s) \alpha_{Batt}(k-1) - \alpha_{Batt}(k-2) \right\}$$

$$\gamma = \frac{1}{\delta} \left\{ -2P_{L(k-1)} + 2P_{FC(k-1)} + P_{L(k-2)} - P_{FC(k-2)} \right\}$$

and,

$$a_{32} = \beta^2 , \hspace{0.5cm} a_{31} = 2 \beta \gamma , \hspace{0.5cm} a_{30} = \gamma^2$$

These coefficients define the relation between the undesired frequency component of the battery power and the actual fuel cell power. The square of $\alpha_{Batt_k}$ represents $J_3$ which is the third term in the cost function representing the stress on the battery. It is to be noted that the band-stop filter is used to have the ability to extend this EMS to other FCVs topologies, as in the case of employing a supercapacitor as a third power source. In such a case, a new term should be added to the cost function representing the stress on the supercapacitor. This term can be formulated similarly using a low pass filter, as shown in Figure 2.

E. Battery’s State of Charge

The fourth term of the cost function is introduced to penalize the deviation from the desired SOC of the battery. This is to keep the battery working around the maximum efficiency point to minimize the battery’s losses. The penalty term can be represented as a quadratic form of the SOC deviation as,

$$\Phi(\Delta SOC) = (SOC_k - SOC_{ref})^2$$  \hspace{1cm} (11)

where $\Phi(\Delta SOC)$ denotes the SOC deviation penalty in the cost function. The quadratic form penalizes the deviation from the
\( \text{SOC}_{\text{ref}} \) regardless if the SOC is higher or lower than \( \text{SOC}_{\text{ref}} \). \( \text{SOC}_{\text{ref}} \) is the reference SOC, which is chosen to be at the maximum efficiency point of the battery. The SOC is usually not a measurable value; although, it can be estimated online as,

\[
\text{SOC}_k = \text{SOC}_{\text{int}} - \sum_{j=1}^{k} \frac{l_{\text{batt},j} \cdot T_s}{3600 \cdot Q} \tag{12}
\]

where \( \text{SOC}_k \) is the estimated SOC at instant \( k \) based on Coulomb’s counting method [30]. \( \text{SOC}_{\text{int}} \) is the initial state of charge, \( Q \) is the battery capacity (Ah), and \( l_{\text{batt}} \) is the battery current which can be calculated from,

\[
l_{\text{batt},k} = \frac{P_{\text{load},k} - P_{\text{FC},k}}{V_{\text{DC},k}} \tag{13}
\]

where \( V_{\text{DC},k} \) is the DC bus voltage at instant \( k \) which is measurable. The state of charge can be estimated regressively as,

\[
\text{SOC}_k = \text{SOC}_{k-1} - \frac{l_{\text{batt},k} \cdot T_s}{3600 \cdot Q} \tag{14}
\]

### F. The Proposed multi-objective cost Function

The proposed multi-objective cost function is the summation of the four terms given in Eqs (3), (7), (10), and (11). The objective function is thus a quadratic function with linear constraints in \( P_{\text{FC}} \) that is solved using the Hildreth algorithm which is based on Active Set method optimization. Two sets of tuning parameters are incorporated in the cost function for two purposes. The first set represents a set of weights for each term of the cost function to facilitate the tuning of the proposed scheme. The second set represents parameters used to make the summation of the different terms of the cost function more meaningful. Both sets of parameters are given and interpreted later in this section.

The optimization problem is given as,

\[
\min_{P_{\text{FC}}} \{ f = \beta k_1 j_1 + (1 - \beta)(c_2 j_2 + c_3 k_3 j_3) \}
\]

\[
+ k_4 \phi(\Delta \text{SOC})
\]

s.t. 

\[
P_{\text{motor}} = P_{\text{FC}} + P_{\text{batt}}
\]

\[
P_{\text{FC},\text{min}} \leq P_{\text{FC}} \leq P_{\text{FC},\text{max}}
\]

\[
P_{\text{batt},\text{min}} \leq P_{\text{batt}} \leq P_{\text{batt},\text{max}}
\]

where,

- \( f \) is the optimization cost function. The target is to minimize the cost function using the controlled variable \( P_{\text{FC}} \).
- \( j_1, j_2, j_3 \) are the instantaneous hydrogen consumption of the fuel cell, fuel-cell stress term, and battery stress term, respectively.
- \( \phi(\Delta \text{SOC}) \) is added as a penalty used to regulate the SOC around a desired value.
- \( k_1, k_2, k_3, k_4 \) are weighting tunable parameters. These parameters are used to increase/decrease the weight of each term for the overall optimization. The tuning of these parameters is discussed in the simulation results section to show the flexibility of the proposed approach.
- \( \beta \) is a weighting factor to reflect the ratio between fuel minimization and power train (FC and battery) system lifetime maximization. As stated in [31], 88% of the vehicle’s running cost is the fuel and 12% is the cost of the power train. Based on this, \( \beta \) is chosen to be 0.88.
- \( c_2, c_3 \) are the ratio between the fuel cell and the battery costs from total power source cost.
- \( P_{\text{FC},\text{min}} \) and \( P_{\text{FC},\text{max}} \) are the minimum and maximum fuel cell load values, respectively. As stated in [14], it is desired to set minimum fuel cell output power during the idle condition as this extends the lifetime of the powertrain system. So, the fuel cell is assumed to operate at its minimum output power during the idle condition to meet the constraint.
- \( P_{\text{batt},\text{min}} \) and \( P_{\text{batt},\text{max}} \) are the minimum and maximum battery load values allowed by the manufacturer, respectively.

The cost function terms are all expressed in terms of the current fuel cell power \( P_{\text{FC}} \). The objective is to minimize the cost function \( f \) using the controlled variable \( P_{\text{FC}} \) to obtain the best performance through the vehicle’s lifetime using Eq. (15).

### IV. SIMULATION RESULTS

The MATLAB Simulink model of Honda FCX Clarity [26], [32] is used to check the validity and the flexibility of the proposed Energy management system. The powertrain system sizing is given in Table 1. For a fair comparison, all simulation scenarios are run for the same driving cycle. The used driving cycle is the New European Driving Cycle (NEDC) [14], [33]. It is considered as a combined driving cycle between urban and highway driving. It is shown in Figure 4 for 10 minutes. US06 driving cycle is also used for the comparison of the hydrogen consumption in Section IV.B. A virtual driver model is developed to simulate a driver’s behavior. All simulation scenarios should fulfill the load by achieving the same speed profile and should begin from the same initial SOC.

The controller and simulation parameters are listed in Table 2. Table 2 shows the selection of the parameters \( c_2 \) and \( c_3 \) based on the price ratio between the FC and the battery. It also shows the filters’ corner frequencies used to define the frequencies used by the decoupling technique employed in this work. As shown in Table 3, there are 6 different scenarios used to show the effectiveness of the proposed Multi-objective EMS. The difference between these scenarios is the choice of the cost function parameters. Case 1 objective is to minimize the actual fuel consumption during the driving cycle. Case 2 works to balance fuel cell stress and battery stress. Cases 3 and 4 seek to minimize fuel cell stress and Battery stress, respectively. While Case 5 regulates the battery SOC regardless of the power sources’ stresses or the actual hydrogen consumption. Finally, Case 6 works to achieve reasonable fuel consumption and minimize fuel cell and
battery stresses using the relative cost coefficients presented in Eq. (15). The power share results of all cases are plotted in Figures 5-10. The SOC during the simulation time is plotted for all cases in Figure 11. The performance indices are calculated for comparison and discussion purposes. These performance indices are listed in Table 4. The main performance index is chosen to be the fuel consumption of the vehicle along the driving cycle. Other performance indices are the stresses on the vehicle’s power sources. These stresses have a direct relation to the high-frequency component of the output power of each power source as the fast power transitions of the fuel cell or the battery shorten their lifetimes severely [34]. The stresses indices are obtained using Fast Fourier Transform (FFT) of the output power of each power source [35], [36]. Finally, the mean and the standard deviation of the battery’s SOC are used to show the effectiveness of the added penalty term for regulating the SOC of the battery around the desired value.

A. Different Cases’ Results
In Case 1 (target is to minimize fuel consumption), the fuel cell outputs minimum power possible (most of the time) to minimize fuel consumption. The fuel cell only supports the battery when the demand exceeds the battery’s limitations. Simulation results of case 1 are shown in Figure 5. As depicted, whenever the load can be covered with the battery only, the EMS instructs the fuel cell to output its minimum power as “fast” as possible to achieve minimum fuel consumption as is clearly shown in the (530, 550) seconds period. These fast sharp changes happen regardless of the high stress over the fuel cell. These sharp changes don’t happen in Case 3, which is explained later, where the fuel cell power returns to minimum power with a lower slope to decrease the stress over the fuel cell. In addition, the battery is more loaded as it is clear from its final SOC of 27.3% which is far from its maximum efficiency point. In summary, minimum fuel consumption is achieved in case 1 regardless of the SOC or any fast transitions in the output power of the fuel cell.

In Case 2, the parameters are tuned to minimize the stresses over the fuel cell and the battery. No weight is imposed on the fuel consumption or the SOC regulation in this case. The results are illustrated in Figure 6. In comparison with Case 1, the output-power rate of change of both sources is reduced achieving less stress on both sources.

![Figure 4 New European Driving Cycle](image)

| Table 1 | VEHICLE POWERTRAIN SIZING |
|---------|---------------------------|
| Powertrain Component | Type | PEMFC |
| Fuel Cell | Max. Power | 100 kw |
| | Max. Current | 347.3 A |
| | Cells Number | 400 |
| Battery | Type | Lithium-ion |
| | Max. Power | 27 kw |
| | Capacity | 13.9 Ah |
| | Nominal Voltage | 288 V |
| Motor | Type | PMSM |
| | Poles | 8 |
| | Max. Power | 100 kw |

| Table 2 | CONTROLLER AND SIMULATION PARAMETERS |
|---------|-------------------------------------|
| Parameter | Value |
| Fuel Cell Power Cut off Freq. (f₁) | 0.5 Hz [37] |
| Battery Power Band-Stop Freq. (f₂) | 2.25 Hz |
| Battery Power Central Freq. (f₃) | 2.75 Hz |
| Fuel Cell Cost | $28000 [38] |
| Battery Cost | $1441 [38] |
| Fuel Cell Cost Percentage (c₂) | 0.951 |
| Battery Cost Percentage (c₃) | 0.049 |
| Sampling Time (Ts) | 15 ms |
| Initial State of Charge (SOCint %) | 50 |
| Simulation Duration (minutes) | 10 |
| Distance (Meter) | 7494 |

| Table 3 | SIMULATION CASES |
|---------|------------------|
| Case | Tuned-Parameters’ values | Targeted Objective(s) |
| 1 | k₁ = 1 k₂ = 0 k₃ = 0 | Minimize fuel consumption |
| 2 | k₁ = 0 k₂ = 0.5 k₃ = 0.5 | Minimize fuel cell stress and battery stress |
| 3 | k₁ = 0 k₂ = 0.99 k₃ = 0.01 | Minimize fuel cell stress |
| 4 | k₁ = 0 k₂ = 0.01 k₃ = 0.99 | Minimize battery stress |
| 5 | k₁ = 0 k₂ = 0 k₃ = 1 | Regulate battery SOC |
| 6 | k₁ = 0.25 k₂ = 0.25 k₃ = 0.25 | Achieve reasonable performance -all indices |

In Case 3 and Case 4, the parameters are tuned to minimize the stress over one supply source at a time; the fuel cell and the battery, respectively. The parameters used are given in Table 3 and the power share results are shown in Figure 7 and Figure 8. In Case 3, it is clear from Figure 7 that the battery takes sharper changes than the fuel cell. The EMS is able to reduce the changes over the fuel cell specifically after the second 500 as shown in Figure 7. On the other hand, in Case 4, the fuel cell takes sharper transitions than the battery’s power as shown in Figure 8. From Cases 2, 3, and 4, it can be
stated that increasing the parameter $k_2$ results in reducing the stresses over the fuel cell. Besides, increasing the parameter $k_3$ (relative to $k_2$) reduces the battery’s stress. This defines a tuning tradeoff, as the shifted power goes from one power source to the other.

Figure 11, which illustrates the SOC, clearly shows that in Case 1 and Case 3, the SOC drops along the simulation time. Both of these cases’ aims were to “relax” the fuel cell, the first by focusing on the fuel consumption, and the second by focusing on reducing the fuel cell stress.

Also, it is to be noted from Table 4 that the fuel cell stress is minimized using higher values for the tuning parameters $k_1$ and $k_2$. This happens in both Case 1 and Case 3. On the other hand, the battery’s stress is minimum in Case 4, as the parameter $k_3$ is the dominant parameter.

In Case 5, tuning parameters’ values are selected to regulate the battery’s SOC regardless of the other terms of the cost function. To investigate this case, Figure 9 and Figure 11 need to be considered simultaneously. From Figure 11, and at the beginning, the SOC increases over 50 % as the fuel cell operates at its minimum fuel cell output power during the idle condition. The EMS priority is to fulfill the load so at the first 250 seconds the EMS allows the battery (whenever possible) to cover the load as long as the SOC is above $SOC_{ref}$ which is 50 %. At the 250-seconds mark, the SOC returns to 50 % so the load demand is covered by the fuel cell only regardless of the fuel cell power. After that, from 370-550 seconds, the SOC is above 50 % again so the EMS allows the battery to cover the load along with the minimum fuel cell power. After that, from 550 seconds, the SOC is equal to $SOC_{ref}$. At the second 550, there is a sharp deceleration so the motor becomes a generator and there is energy captured by the battery. So, the EMS decides to let the battery SOC increase above 50 %, because capturing the regenerative braking has a higher priority than regulating the SOC. Also note that according to Table 4, it is clear that the SOC is regulated and operated within minimized range in this case. This is reflected in the SOC standard deviation. However, this results in higher fuel consumption due to the need for the fuel cell to supply the load as the SOC reaches its desired value. This shows the capability of the proposed EMS to regulate the SOC, if needed, via proper adjustment of the tuning parameters.
In the final case, Case 6, the tuning parameters are selected to show a situation where all of the cost function terms are addressed. The fuel cell and the battery output powers change smoothly as shown in Figure 10. At the same time, the EMS is forced to regulate the SOC of the battery while achieving reasonable fuel consumption. The stress over the fuel cell is relatively high, but as shown in Section III, \( \beta \) is chosen to be 88% as most of the minimization weight is provided for fuel cell consumption minimization.

In summary, Table 4 gives a detailed comparison between six different tuning strategies (cases). The table’s data can be divided into three sections. The first section shows the values of the first three terms of the cost function \( (J_1, J_2, J_3) \) versus the studied cases. As shown in the table, the values of these terms reflect the priority of the targeted objective of each studied case. In Case 1, the system achieves minimum fuel consumption as expected. While it achieves minimum fuel cell stress in Cases 1 and 3, and minimum battery stress in Case 4. The second section in Table 4 gives the battery’s final SOC, mean and standard deviation versus all studied cases. It is clear that Case 5 gives the best regulation for the battery after the 10 minutes driving cycle. For a fair comparison, the third section of Table 4 gives an “equivalent fuel consumption” comparison for all studied cases. The equivalent fuel consumption is calculated as the sum of the actual fuel consumed by the fuel cell \( (J_1) \) and the equivalent amount of fuel required to recharge the battery back to its initial state at 50% (if needed). The equivalent fuel for recharging the battery is calculated using its parameters and the final SOC value as in [26].
Case 6 represents a proposed tuning strategy that delivers a balanced performance between the different targeted objectives of the other simulation cases as shown in Table 4.

\[\text{Table 4} \quad \text{Simulation Results Comparison}\]

| Index                      | Case 1 Min Fuel Consumption | Case 2 Min Stress FC & Batt. | Case 3 Min FC Stress | Case 4 Min Batt. Stress | Case 5 Regulate SOC | Case 6 Proposed Tuning |
|----------------------------|-----------------------------|-----------------------------|----------------------|------------------------|---------------------|------------------------|
| Fuel consumption (gm) J₁   | 17.94                       | 62.47                       | 35.85                | 63.3                   | 60.81               | 45.79                  |
| FC Stress (σ) J₂           | 3.20                        | 10.33                       | 5.85                 | 10.44                  | 11.08               | 9.13                   |
| Battery Stress (σ) J₃      | 10.39                       | 4.77                        | 7.99                 | 4.68                   | 5.32                | 6.01                   |
| SOC final (%)              | 27.3                        | 54.50                       | 39.47                | 54.95                  | 53.34               | 45.23                  |
| SOC (μ)                    | 44.18                       | 52.02                       | 47.16                | 52.21                  | 50.45               | 47.8                   |
| SOC (σ)                    | 8.36                        | 0.95                        | 4.6                  | 1.02                   | 0.71                | 3.02                   |
| Equivalent Fuel for Battery Recharge (gm) | 13.88              | -2.75                       | 5.74                 | -3.02                  | -1.82               | 2.3                    |
| Total Equivalent Fuel Consumption (gm) | 31.82             | 59.72                       | 41.59                | 60.28                  | 58.99               | 48.09                  |

B. Performance comparison between the proposed EMS and the Operation Modes EMS

In this section, the proposed multi-objective optimization strategy performance is compared to the performance of the Operation modes EMS. The operation modes EMS is used as the original EMS for Honda FCX Clarity [26]. Four modes of operation are used as EMS for Honda FCX Clarity:

1. High power demand mode: In this mode, the Li-ion battery supplies the motor if the power demand exceeds the output power of the fuel cell until the fuel cell can cope with the demand.
2. Standard power demand mode: In this mode, as the fuel cell output power can cope with the load demand, the battery output power returns to zero.
3. Regenerative Braking mode: During this method, the battery gets charged and the output power of the fuel cell goes to its minimum value.
4. Low power demand mode: During low power, the demand is covered by the fuel cell and the battery can be charged if its SOC becomes lower than its preset value.

The load is fulfilled at each instant without violating any constraints. However, the operation modes EMS doesn't give any flexibility to the manufacturer or the driver to minimize fuel consumption or extend powertrain lifetime.

Table 5 compares the equivalent fuel consumption for the proposed multi-objective optimization strategy (Tuning parameters’ values used in Case 6) and the operation modes strategy. The table shows that there is a reduction in the equivalent fuel consumption when using the proposed strategy compared to the Operation mode strategy. This is verified through testing using two driving cycles: the New European Driving Cycle (NEDC) and the US06 Supplemental Federal Test Procedure (SFTP). The proposed Multi-objective EMS strategy managed to reduce the equivalent fuel consumption while also considering the fuel cell and the battery stresses which is not considered in the Operations modes EMS.

\[\text{Table 5} \quad \text{Equivalent Fuel Consumption (kg/ 100 km)}\]

| Equivalent Fuel Consumption (kg/ 100 km) | Proposed Operation Modes Strategy | Discrepancy |
|-----------------------------------------|-----------------------------------|-------------|
| NEDC (7.49 km)                          | 0.64                              | 0.8         | 20.1%       |
| US06 (12.8 km)                          | 1.24                              | 1.33        | 6.77%       |

C. Performance comparison between the proposed EMS and Dynamic Programming EMS

A comparison between the performance of the proposed EMS and dynamic programming based EMS is performed. The comparison is performed for three cases of the cases discussed in Section IV. Dynamic Programming (DP) is considered as an optimal offline control algorithm. It is non-causal, as it needs a priori knowledge of the driving cycle. On the other hand, its solution is a global optimum one that can be used as...
a comparison reference. In this work, a DP open-source solver
was used [39]. The compared cases are: Case 1, 3 and 5. In Case 1, the
proposed strategy achieved 99 % of the global optimum
solution as shown in Table 6 and the comparison is illustrated
in Figure 12. Figure 12.a shows that the fuel cell output power
is at its minimum most of the time. In Case 3, the objective is
to minimize the fuel cell stress. Figure 12.b shows that the fuel
cell power transitions are smooth over the driving cycle. The
proposed strategy achieves 66 % of the DP solution. In Case
5, the SOC is regulated most of the time. Figure 12.c shows
that the DP had a prior knowledge of the driving cycle, so it
dissipates some energy from the battery as there it is known
for the algorithm that energy will be captured at the end of the
driving cycle. The proposed strategy achieved 87% from the
DP optimal solution. The average of the 3 cases is 84 % of the DP global optimal
solution as shown in Table 6. This is achieved without any prior
knowledge of the driving cycle.

V. CONCLUSION

In this paper, an online energy management system for fuel
cell–battery vehicles is proposed. The proposed EMS is based
on a multi-objective optimization function that is formulated
in a quadratic form. The terms addressed by the proposed EMS
are: actual fuel consumption, stresses on the lifetime of the
powertrain system components (fuel cell and battery), and the
state of charge of the battery. The proposed EMS performance
is tested by simulation using the Honda FCX clarity model for
two standard driving cycles. The proposed EMS is compared
also to DP as a comparison reference. The proposed EMS
shows on average 84 % near optimality without any prior
knowledge of the driving cycle.

The proposed EMS can address the targeted objectives
separately or in a multi-objective balanced approach
depending on some controlling parameters. Actual fuel
consumption, terms representing fuel cell and battery stresses
as well as Battery’s SOC mean value and standard deviation
are used to evaluate the performance of the proposed EMS.
The proposed EMS comes with some advantages over other
multi-objective optimization strategies. The proposed EMS
has lower computational complexity and it works online with
no prior knowledge of the driving cycle. So, it can be an
optimum solution as a real-time strategy. The proposed EMS
also helps extend the lifetimes of the fuel cell and battery based
on analytical relation based on a frequency decoupling
technique. Thus, eliminating the need for experimental results
to get degradation models for the fuel cell and the battery.
Finally, the proposed EMS manages to merge frequency
decoupling and optimization techniques in a Multi-objective
approach.

| Case  | Proposed EMS (%) | DP (%) |
|-------|------------------|--------|
| 1     | 99               | 100    |
| 3     | 66               | 100    |
| 5     | 87               | 100    |
| Average | 84               | 100    |

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