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# Health-Wise Energy Management Strategies in Fuel Cell Hybrid Electric Vehicles

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The primary objective of an energy management strategy (EMS) in fuel cell (FC) hybrid electric vehicles (HEVs) is twofold: to minimize hydrogen consumption and to extend the lifetime of the power sources. However, these power sources are susceptible to degradation under various operational and ambient conditions, be it from cycling or calendar aging. To achieve optimal performance, the EMS must consider variations in the power sources' characteristics due to degradation. This paper succinctly discusses the necessity of employing a health-wise EMS and the indispensable tools it requires, such as health-monitoring techniques. Subsequently, the study investigates the impact of a health-wise EMS on the total operational cost of a low-speed urban FC-HEV truck through simulations. The simulation results demonstrate that health-wise EMSs can significantly reduce fuel consumption and mitigate FC and battery degradations, resulting in a noteworthy reduction in the total operational cost.

## Introduction

Global warming, the shortage of fossil fuels, and air pollution caused by the transportation sector have motivated governments to legislate on the production of conventional vehicles. For instance, in most European countries, sales of fossil fuel road passenger vehicles will be banned by 2030. In response, car manufacturers have been encouraged to develop new generations of vehicles, ranging from hybrid electric vehicles (HEVs) to fuel cell (FC) and battery electric vehicles (BEVs). Figure 1 depicts the versatility of utilizing the new generation of vehicle types, categorized by their size and travel distance. As shown in the figure, BEVs are highly suitable for compact personal cars utilized on shorter daily commutes. Conversely, hydrogen emerges as a prominent option for vehicles requiring extended range and carrying heavier loads. Despite the automotive industry's rapid increase in the production of BEVs in recent years, the long charging time remains a concern and dissatisfaction for vehicle owners.

To address the mentioned limitations, FC-HEVs have emerged as a promising alternative for eco-friendly transportation, especially in heavy-duty applications or other specific applications (mining, ship transportation, rail, etc.).

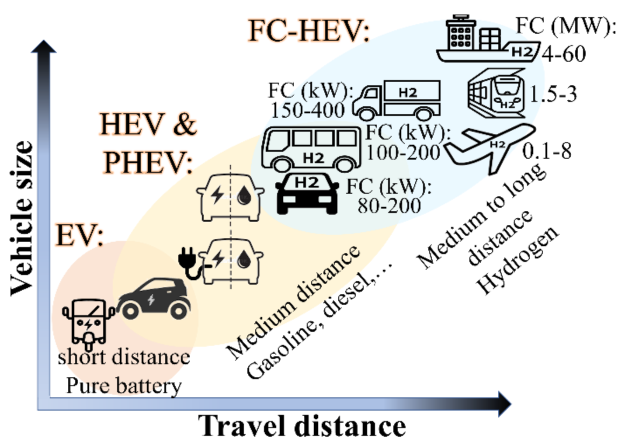


**Figure 1** *The use of different electrified vehicles in transportation.*

While the development of FCs for light-duty vehicles has spanned over two decades, significant focus on heavy-duty applications has emerged only recently. This transition has been prompted by the distinctive scalability of FCs in terms of both power and energy. Scaling up the FC stack or hydrogen tank incurs a relatively minor weight penalty compared to lithium-ion batteries. Moreover, deploying heavy-duty vehicles commercially demands fewer infrastructure investments, as dedicated and more predictable routes necessitate fewer refueling stations.

Nevertheless, certain challenges, such as the lack of infrastructure and high costs, continue to persist. Additionally, the long-term durability of the system, especially concerning the lifetime of the proton exchange membrane FC (PEM-FC) system and the variation of PEM-FC and lithium-ion battery characteristics, remains a significant concern. Consequently, the prediction of performance decay resulting from degradation, induced by cyclic loads, steep power transients, and ineffective control of electrochemical power sources, has been explored and could impede commercial acceptance in specific sectors. Addressing these drawbacks in FC-HEVs imposes the development of a health-wise energy management strategy (EMS) that considers performance decay, system efficiency, and energy distribution in a comprehensive manner.

As the primary decision-maker of an FC-HEV, the EMS plays a crucial role in managing the power split among various power sources, aiming to minimize hydrogen consumption and the maintenance costs of power sources. Given that degradation alters the characteristics of both the battery and FC in a FC-HEV, these variations must be accounted for in the EMS design to achieve optimal performance. This forms the central concept behind a health-oriented EMS, which is currently in the pilot application stage. It utilizes typical measurement methods such as cell voltage monitoring, high-frequency resistance measurement, and total harmonic distortion for adaptation.

The objective of this paper is to introduce the fundamental principle of a health-wise EMS. Subsequently, the required tools, such as health monitoring and state estimation techniques, for designing such EMS are concisely discussed. Finally, the impact of designing a health-wise EMS on the total trip cost of a FC-HEV using a hardware-in-the-loop setup is investigated, and a conclusion is given.

**Health-wise EMS in FC-HEVs**

EMS exploits a hierarchical supervisory control scheme to determine the reference power demand signals for the power source components. Each power source incorporates its own control loop to achieve the desired reference using feedback from the model parameters or the response variables.

Some of the main parameters of the FC and battery employed in the EMS design in the automotive industry are summarized below.

- Terminal Voltage: Measured in both FC and battery.

- Current: Measured in both FC and battery.

- Open Circuit Voltage: Estimated in both power sources while the vehicle is operating. It can be measured but not under operation.

- State of Charge (SOC): Estimated in batteries.

- Ohmic Resistance: Estimated while in operation and measured with specific protocols in both power sources.

- Power: Measured in FCs and state of power is estimated in batteries.

- Maximum Power: Estimated in FCs.

- Efficiency: Estimated in FCs.

Some of the required variables are measured, and some of them are estimated as they are not measurable or are tough to be measured. Therefore, state estimation is essential for both EMS and power sources' health monitoring purposes. In addition to the estimation, prediction is also highly important for determining some parameters known as health index (HI). For instance, voltage and power decay are two important HIs that can be useful for designing an EMS. State estimation and HI prediction typically rely on a model. However, if the parameters of the employed model are unknown or time-varying, the estimation/prediction may not be very reliable, and the EMS based on the false estimation/prediction may not yield the desired performance. The main reasons for the variation of the model's parameters are degradation and changes in operating conditions. Since developing a comprehensive model that includes all phenomena, degradation, and operating conditions is highly difficult, estimation and prediction techniques assume a crucial role in ensuring accurate results.

To address variations in the EMS due to model uncertainties, health-wise EMSs have been introduced by Kandidayeni et al. in a manuscript published in 2022. Figure 2 provides a schematic overview of the health-wise EMSs in FC vehicles. One of the key characteristics of the health-wise EMS is its capability for online health monitoring. This allows not only the estimation of required state variables but also the estimation or prediction of the health condition of power source elements. Online state monitoring and health estimation in FC vehicles are categorized as prognostic or diagnostic. In the prognostic-based EMS, which relies on prognostic health monitoring, a degradation model is employed and calibrated to capture the degradation of power sources and predict corresponding variations in the parameters affecting the EMS.

In the diagnostic-based EMS, as depicted in Figure 2, the approach revolves around directly monitoring the actual health condition of the power sources and making decisions accordingly. Unlike the prognostic-based EMS, there is no prediction involved using a degradation model; instead, the health of the power sources is continuously monitored in real time. When utilizing a diagnostic-based EMS, the control actions are dependent on the designed strategy and the specific situation at hand. This may include implementing fault-tolerant control actions or updating preset values, such as maximum power or efficiency of the FC system, battery capacity, and so on, based on the information gathered from condition monitoring. Furthermore, if the situation is beyond controllable limits, the diagnostic-based EMS can trigger a maintenance request to address the identified issues promptly.

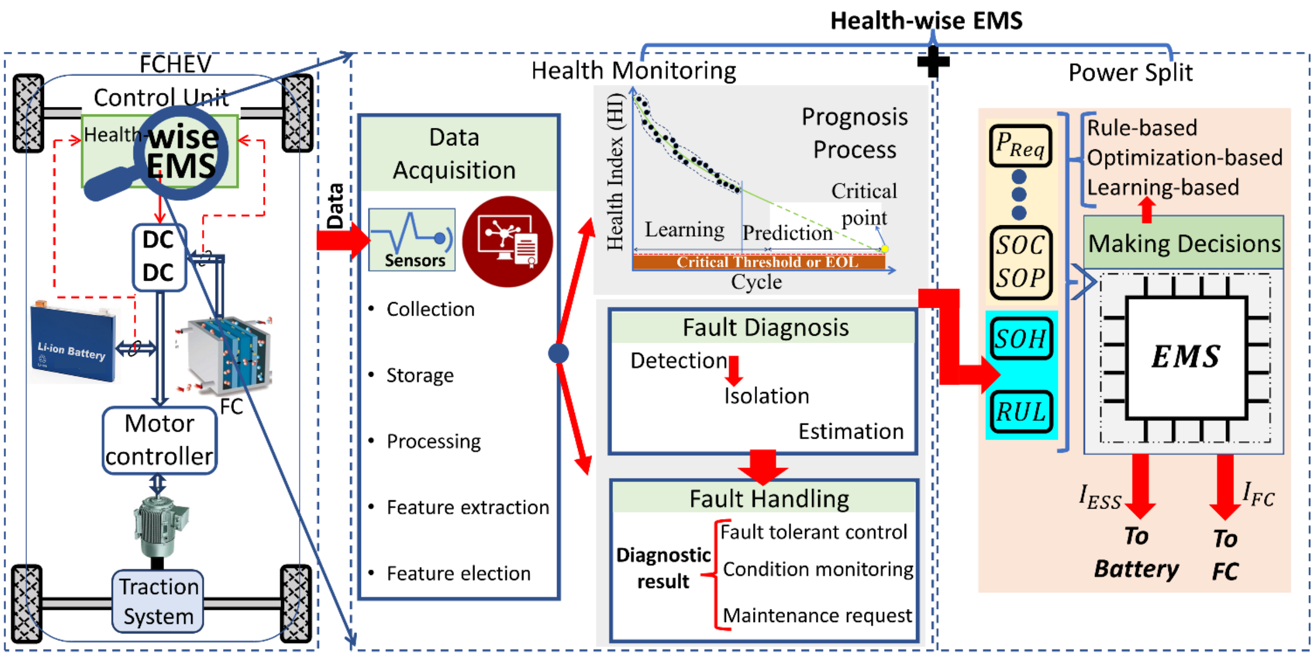


**Figure 2** *Demonstration of steps for developing a health-wise EMS*

**Health monitoring in fuel cells and batteries:**

Health monitoring techniques are crucial in extending the lifetime and enhancing the performance of FCs and batteries while minimizing repair needs. In fact, FC and batteries used in automotive applications experience performance attenuation over time. Despite being preferred power sources for vehicular application, dynamic conditions in automotive use have led to reduced energetic performance in these power sources.

Given the multivariate nature of these electrochemical devices and their distinct conditions, diagnostic and prognostic actions become vital for fault handling and predicting remaining useful life (RUL).

*Prognostics:*

The elementary concept of prognostics involves predicting the RUL of a system based on its current State of Health (SOH) before it experiences failure. This process comprises two main steps: learning and prediction. Precise prognostics for PEM-FCs and batteries necessitate the use of appropriate HIs.

For PEM-FCs, HIs fall into two main groups: measurement-based indexes (e.g., voltage, power, polarization curves, Electrochemical Impedance Spectroscopy (EIS) based indexes, and degradation model parameters) and component indexes (e.g., PEM indexes, electrode indexes, Bipolar plate indexes, GDL indexes, and sealing gasket indexes). Among these, voltage, power, and polarization curves are the most applicable HIs for PEM-FCs in EMS design as they indicate the macro-scale health states. The most commonly used HI for FC systems in energy management applications is the voltage failure threshold, which sets a target of 5000 to 8000 hours with less than a 10% voltage drop for the durability of a FC stack in a passenger vehicle. For heavy-duty vehicles like trucks, the target shifts to 25000 hours while maintaining less than a 10% voltage reduction. In batteries, the main HIs are capacity and internal resistance, and commonly used failure thresholds include reaching 80% of the initial capacity or a 1.3-time to 2-time increase in resistance value.

Prognostic methods for PEM-FCs and batteries in automotive applications generally fall into three categories: model-based, data-driven, and hybrid methods.

Model-based methods rely on mechanistic models, semi-empirical models (including equivalent circuit models), or fused models. Developing mechanistic multi-physics FC models necessitates a thorough understanding of the fundamental principles at play, resulting in a high level of accuracy, albeit with significant computational requirements. Semi-empirical models can be considered as less complex variants of white-box models, wherein certain intricate mathematical equations are replaced by empirical formulas or even mapping tables. The polarization curve-based models are a more prevalent form of semi-empirical models used for FCs, whereas equivalent circuit models find greater application in the context of batteries. Concerning fused models, their primary objective is to amalgamate different model-based approaches to extract a more comprehensive set of information.

Data-driven methods utilize historical data to forecast degradation trends instead of delving into the details of analyzing mechanisms for model development. These methodologies harness intelligent approaches such as Artificial Neural Networks (ANNs), statistical examination, and signal processing to formulate degradation models and project patterns of device aging. A significant advantage is that they only require a substantial amount of raw data for accurate predictions. However, their robustness may be limited when encountering new conditions that were not present during their training phase.

Hybrid methods combine the physical properties of model-based approaches with experimental data, often utilizing intelligent or adaptive techniques to leverage the advantages of both methods while overcoming their weaknesses. Therefore, various hybrid methods can be devised by combining the aforementioned approaches for PEM-FC and battery prognostics.

Despite considerable progress in prognostic techniques, there are several challenges that remain untouched. Researchers often use laboratory data instead of field-based data, and there is a need for FC and battery degradation data under realistic working conditions and dynamic load profiles. Moreover, there is a demand for algorithms capable of generating preliminary forecasts with limited measured data, considering that current techniques frequently necessitate a significant portion of lifecycle data for parameter calibration or model training purposes.

*Diagnostics*:

The main concept behind diagnostic procedures is to continuously monitor the State of Health (SOH) to promptly detect and isolate any malfunctions or faults before the system experiences a complete failure. The diagnostic process, depicted in Figure 2, involves several steps. Initially, data acquisition captures and stores various information like voltage, current, and temperature from experimental measurements or high-fidelity simulation models. After processing, this data becomes available for model identification, fault characterization, and algorithm verification. Next, essential features are extracted through data preprocessing, feature representation, extraction, and selection. These extracted features form the basis for fault diagnosis. In the context of FC/battery fault diagnosis, the tasks are divided into three categories: fault detection (identifying if a fault has occurred), fault isolation (determining the type and/or location of the fault), and fault estimation (evaluating the magnitude/intensity of the fault). Finally, the fault-handling module assesses the results from the fault diagnosis and makes decisions accordingly.

These decisions may include issuing alarms, initiating fault-tolerant control mechanisms, isolating faulty components, or even disconnecting the power supply if necessary. The significance of effective diagnosis and fault handling has been evident in various situations.

Diagnostic methods in FCs and batteries can be categorized into two main groups: model-free and model-based methods.

Model-free methods can be further divided into two subgroups: measurement-based and data-driven approaches. Measurement-based methods utilize regular measured variables (such as stack/cell voltage, flow rate, stack temperature, etc.) and special measurements (polarization curve, Electrochemical Impedance Spectroscopy (EIS), cyclic voltammetry (CV), current interruption) to accomplish diagnosis. Data-driven methods, on the other hand, leverage machine learning techniques (such as ANN, support vector machine, etc.), fusion methods, fuzzy logic, and signal processing to carry out the diagnostic process.

Model-based diagnostic methods encompass parameter identification, observer-based techniques, and structural analysis. Parameter identification techniques frequently utilize analytical or semi-empirical models to pinpoint precise anomalies or performance discrepancies through the scrutiny of specific parameter values. Observers act as virtual sensors, relying on models, peripheral signals, and algorithms, to estimate internal states that are challenging or impossible to directly measure in the hermetic structures of PEM-FC and batteries. Structural analysis, on the other hand, uses parity relations to generate residuals, which help detect and isolate faults like flooding, drying, and compressor over-voltage.

Among the discussed methods, parameter identification and observer-based techniques from the model-based category are the most widely used in EMS design due to their straightforward implementation process.

However, despite the progress in diagnostic methods, there are several challenges that remain concerning FCs and batteries diagnosis:

1-The intrinsic internal mechanisms and their relationships with outputs or operational parameters require careful examination, as different conditions can lead to the same fault. Understanding the coupling or interrelation between these mechanisms in FCs and batteries is still not well-established.

2-Developing a comprehensive mathematical model that can simulate fault behavior from the micro time to macro system level remains an open problem in the field of FCs and batteries.

3-The conventional measured parameters derived from batteries and FCs, encompassing variables like voltage, current, and temperature, do not yield a comprehensive comprehension of the intrinsic electrochemical processes. Consequently, the identification of pertinent attributes for articulating the inner states of electrochemical power sources persists as a daunting undertaking.

To summarize, health-monitoring techniques, including prognostic and diagnostic methods, play a crucial role in tracking, estimating, or predicting specific time-varying FC/battery parameters. Parameters such as the maximum power and efficiency points of the FC system or battery SOC are essential for designing any type of EMS. Certain parameters require even a combination of estimation and prediction techniques (a mix of diagnostic and prognostic methods). For instance, battery SOC itself is typically obtained through estimation techniques like the Kalman filter, and its value is affected by the battery capacity fade or degradation.

To exemplify the potential ramifications arising from the oversight of this updating mechanism, the subsequent section presents an illustrative case study assessing the profound influence of health state awareness on the operational cost of a FC-HEV.

**Comparison of health-wise and non-health-wise strategies**

To indicate the impact of the power sources' health-state on the operating cost of an FCV, a brief yet precise study is carried out in this section. The employed vehicle model in this study is based on a low-speed electric urban truck (golf cart). This vehicle is equipped with a single ratio gearbox, a 5.6-kW induction machine, a 4-kW PEM-FC that is linked to the DC bus through a DC-DC converter, and a 72-V (40 Ah) lithium-ion battery which is directly connected to the DC bus.

*Hardware-in-the-Loop Platform*

A HIL set-up, as shown in Figure 3, is developed to assess the performance of the EMS in different scenarios. The real component of this set-up is a Horizon 500-W PEM-FC, and the other components are mathematical models. In this set-up, the FC is connected to a National Instrument CompactRIO through its controller. The FC controller controls the hydrogen valve, the purge valve, and the axial fan which has a dual role of cooling down the stack and supplying the required oxygen for the reaction. As mentioned earlier, the utilized electric truck vehicle model requires a 4-kW FC system to run. In this context, the output power of the FC within the HIL configuration is amplified after the converter to fulfil the desired power demand.

To highlight the importance of having awareness about the health state of the power sources while designing an EMS, two 500-W Horizon PEM-FCs with different degradation levels are deployed in this work.

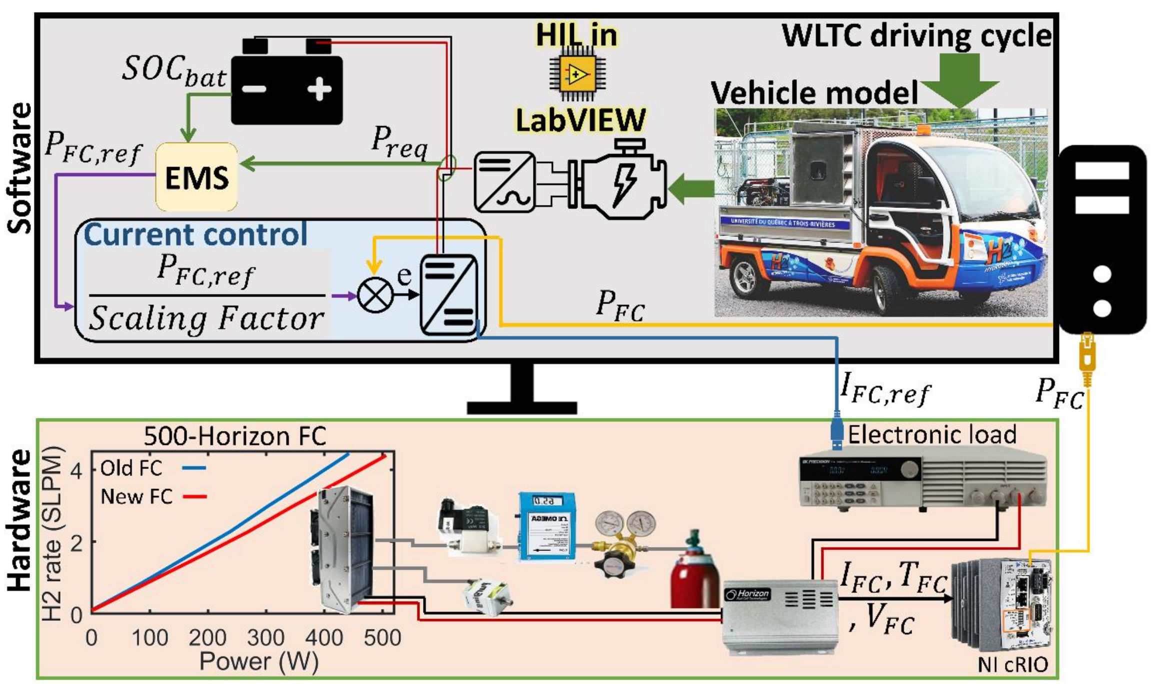


***Figure 3*** The developed HIL platform for testing the health-awareness influence over the EMS performance. Variables shown in the figure: $I_{FC}$, $T_{FC}$, $P_{FC}$, $V_{FC}$ (FC current, temperature, power, and voltage).

*Energy management strategy*

The requested power ($P_{req}$) from the electric motor side is supplied by both of PEM-FC system and battery pack. Therefore, the relationship of $P_{req}$, FC power ($P_{FC}$), and battery power ($P_B$) can be defined as follows in which $\eta_{DC-DC}$ is the efficiency of the converter.

$$P_{req} = P_{FC} \times \eta_{DC-DC} + P_B \tag{1}$$

The energy management problem in a FC-HEV is in essence a nonlinear optimization problem. It can be solved by sequential quadratic programming (SQP), which has reached optimal/sub-optimal results for a wide range of engineering optimization problems. In this work, SQP is utilized to minimize the trip cost, which is formulated using the following multi-objective cost function, at each step.

$$\text{Min: } \$Trip_j = C_{H_2} H2_{flow,j} + C_{FC}\Delta_{FC,j} + C_{Bat}\Delta_{Bat,j} \;\; j = 1,2,3 \ldots \tag{2}$$

Where $C_{H_2}$ is the cost of hydrogen in US dollars (2.3 $\$/kg$), $H2_{flow}$ is the hydrogen flow ($kg/s$) $C_{FC}$ is the cost of the FC system (40 $\$/kW_{net}$), $\Delta_{FC}$ is the FC power decay owing to degradation (kW), $C_{bat}$ is the battery cost (178.41 $\$/kWh$), and $\Delta_{Bat}$ is the battery degradation ($kWh$). The FC power decay is given by:

$$\Delta_{FC} = P_{FC,max}\left(\frac{k_1 t_1}{3600} + k_2 n_1 + k_3 n_2 + \frac{k_4 t_2}{3600} + \frac{k_5 t_3}{3600}\right) \tag{3}$$

where $P_{FC,max}$ is the FC maximum power, $k_1$ (0.00126 $\%/h$) is the degradation rate caused by operating in low-power condition (less than 5 % of $P_{FC,max}$), $k_2$ (0.00196 $\%/cycle$) is the degradation caused by one on/off cycle, $k_3$ (5.93×10−5 $\%/cycle$) is the degradation caused by violating the fast transient condition (more than 10% of $P_{FC,max}$ per second), $k_4$ is the degradation rate caused by operating in high-power operation (more than 90 % of $P_{FC,max}$), and $k_5$ (0.002 $\%/h$) is the natural performance decay rate. $t_1$, $t_2$, and $t_3$ represent the duration of operations under low-power, high-power, FC activated states, respectively. Meanwhile, $n_1$ refers to the count of on/off cycles, and $n_2$ indicates the quantity of transient load variations. As stated by the US Department of Energy (DOE), the end of life for FCs is characterized by a decrease in maximum power by 10%, with an operational goal of 5000 hours. The battery degradation is formulated as follows:

$$\Delta_{Bat} = E_{Bat}\left(SOH_{Bat,Initial} - \frac{|i_{Bat}|}{2N_{EOL}(C_{rate})Q_{Bat}}\right) \tag{4}$$

$$N_{EOL}(C_{rate}) = \frac{3600\, A_h^{EOL}(C_{rate})}{Q_{Bat}} \tag{5}$$

$$A_h^{EoL}(C_{rate}) = \left[\frac{20}{B(C_{rate}) * exp\left(-\frac{E_a(c_{rate})}{RT}\right)}\right]^{1/0.55} \tag{6}$$

$$E_a(C_{rate}) = 31700 - (370.3\, C_{rate}) \tag{7}$$

Where $E_{Bat}$ is the battery capacity (kWh), $SOH_{Bat,Initial}$ is the battery state-of-health with initial value of 1, $i_{Bat}$ is the battery current, $C_{rate}$ is considered 1, $B$, which is a pre-exponential coefficient, is 25.652, $E_a$ is the activation energy, $R$ is the constant of ideal gas (8.31 J/mol), $T$ is the battery cell temperature (which is considered 298.2 K), $A_h$ is the amount of electric charge delivered by battery. From Arrhenius equation, the percentage loss of battery capacity $\Delta Q_{Bat}$ (%) is obtained by:

$$\Delta Q_{Bat} = B(c_{rate}).\exp\left(\frac{-E_a c_{rate}}{RT}\right)(A_h c_{rate})^{0.55} \tag{8}$$

The battery SOC is calculated by:

$$SOC(t) = SOC(t_0) - \eta_c \frac{\int_{t_0}^{t} I_B dt}{3600\, Q_B} \tag{9}$$

where $\eta_C$ is the coulombic efficiency ($\eta_C = 0.98$ in charging and $\eta_C = 1$ in discharging), $I_B$ is the battery current (A), and $Q_B$ is the battery capacity (Ah).

To ensure the operation of the power sources remains within acceptable limits, the following restrictions are taken into account:

$$SOC_{min} \leq SOC_j \leq SOC_{max} \tag{10}$$
$$P_{FC,min} \leq P_{FC,j} \leq P_{FC,max} \tag{11}$$
$$\Delta P_{Rise,j} - 10\%\ P_{FC,max} \leq 0 \tag{12}$$
$$\Delta P_{Fall,j} - 30\%\ P_{FC,max} \leq 0 \tag{13}$$

Where $SOC_{min}$ is the minimum battery SOC (50%), $SOC_{max}$ is the maximum battery SOC (90%), $P_{FC,min}$ is the minimum Fc power which is zero, $\Delta P_{Rise}$ is the positive FC power variation, and $\Delta P_{Fall}$ is the negative FC power variation. During the optimization process, the utilized EMS attempts to keep the FC power between 0 and 4 kW (or 0 and 500 W in the downscaled system).

In order to investigate the impact of power sources' health state awareness on the trip cost obtained by the EMS, the following scenarios have been tested:

1-New power sources with a health-wise EMS ($New_{Source-HW}$):

In this scenario, the utilized power sources in the optimization process are new and all the constraints and equations are based on the characteristics of these new power sources.

2-Aged power sources with a health-wise EMS ($Aged_{Source-HW}$):

In this scenario, the utilized power sources in the optimization process are aged. That means the old FC which is presented in Figure 3 (10% of decline in the maximum power) is used as the main power source and a battery pack that has experienced a 20% of capacity fade along with a twofold increase in the internal resistance is employed as the secondary source. During this test, the EMS is health-wise which implies that the constraints of the FC system (maximum power and power variation) are based on the characteristics of the old FC and the value of battery capacity in the SOC calculation is adjusted based on the aged battery pack.

3-Aged power sources with a non-health-wise EMS ($Aged_{Source-NHW}$):

Similar to the second scenario, both of power sources are aged in this third attempt. However, the deployed EMS herein is health-unaware which means that the constraints of the FC system and the value of battery capacity for the calculation of the battery SOC are adjusted based on the characteristics of the new power sources while they are aged. This scenario imitates the behaviour of an EMS that has been tuned in the beginning of life of the power sources and its settings have not been updated although the power sources have become degraded.

*Results and discussion*

To assess the performance of the designed EMS, the class 3b of worldwide harmonized light vehicles test cycle (WLTC) is utilized in this work. This driving cycle is 1800 s and has been repeated four times consecutively for the purpose of this study. The driving cycle speed has been scaled down based on the top speed of the employed low-speed electric truck, which is 40 km/h.

Figure 4 presents different achieved results under the WLTC driving cycle. Figure 4a represents the trip cost of each scenario for different battery SOC conditions. From this figure, it is obvious that regardless of the initial and final battery SOCs, $New_{Source-HW}$ scenario reaches the lowest trip cost, followed by the $Aged_{Source-HW}$ and $Aged_{Source-NHW}$ scenarios. Comparison of the achieved trip costs for the initial battery SOC of 70% indicates that when the power sources get aged, the trip cost of the vehicle increases by almost 13%, assuming that the vehicle is equipped with a health-wise EMS (comparing the $New_{Source-HW}$ with $Aged_{Source-HW}$). However, if the vehicle is not equipped with a health-wise EMS, this difference can be increased up to around 25% (comparing the $New_{Source-HW}$ with $Aged_{Source-NHW}$). To dig deeper into the analysis of these results, the variation of battery SOC, the extracted power from the FC system, and the drawn current from the FC system are shown in Figures 4b, 4c, and 4d respectively. From Figure 4b, both $New_{Source-HW}$ and $Aged_{Source-HW}$ scenarios are capable of respecting the defined constraint for the minimum battery SOC. In the $Aged_{Source-HW}$ scenario, the EMS does not discharge the battery a lot in the beginning so that it can comply with the constraint. However, $Aged_{Source-NHW}$ scenario cannot sustain the minimum SOC constraint although the level of degradation in the power sources of this scenario is the same as $Aged_{Source-HW}$. The reason why $Aged_{Source-NHW}$ cannot sustain the minimum SOC constraint is that its settings (battery capacity and maximum power of the FC) are the same as $New_{Source-HW}$ scenario while its power sources are aged and cannot supply the same amount of power. Hence, it tries to follow a similar SOC trend as the $New_{Source-HW}$ (as shown in Figure 4a) but fails to sustain the minimum SOC level. According to Figure 4c, the policy of the EMS in the $Aged_{Source-HW}$ is different with the other two scenarios. It turns on the FC at around 290 s (almost 300 s sooner than the other two strategies) and runs the FC at lower power level at the time peaks (e.g., between 1500 s and 2000 s). Moreover, when the FC operates in a constant power level in other two scenarios (e.g., between 2000 s and 3000 s), the EMS of $Aged_{Source-HW}$ operates the FC in higher power levels in average. Figure 4d indicates that the FC in the $Aged_{Source-NHW}$ is reaching almost the same current level as the one in $New_{Source-HW}$. However, since it is an aged FC, it can achieve the same power level as the scenario with new power sources. Operating the FC in such a high current level is the main reason that the trip cost of the $Aged_{Source-NHW}$ is almost 12% higher than the $Aged_{Source-HW}$ scenario.

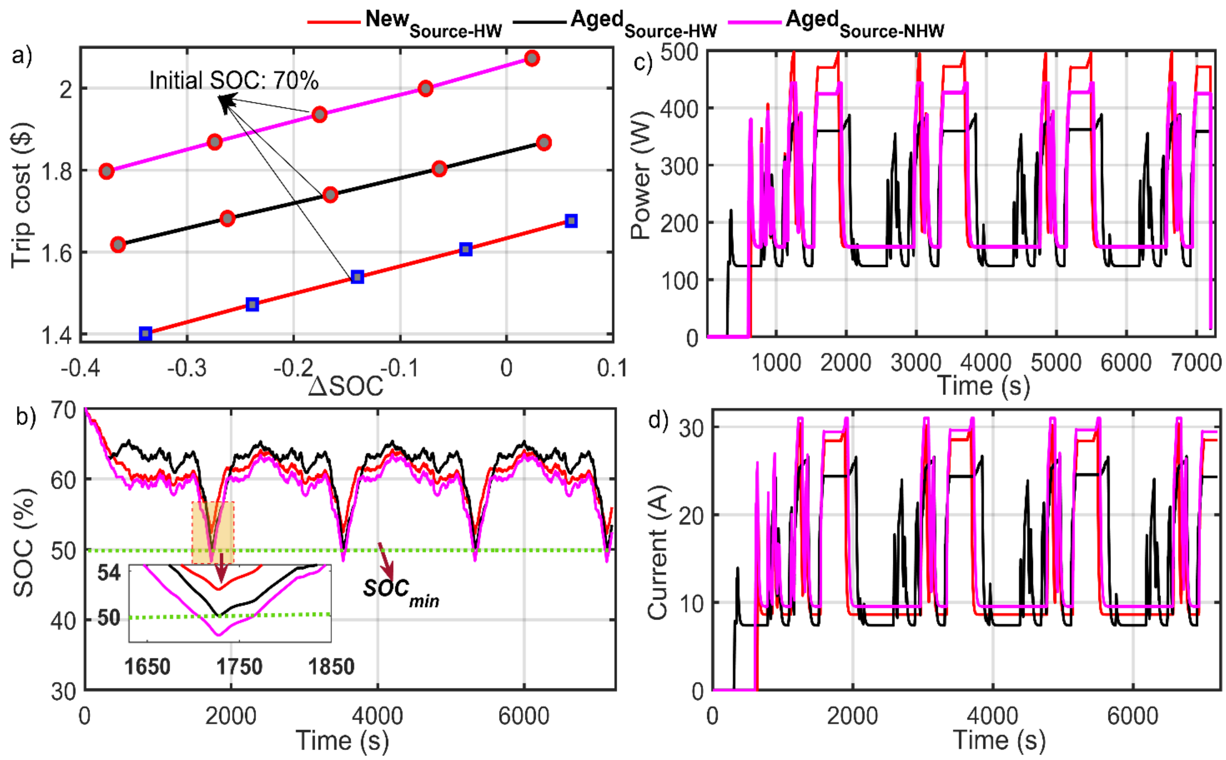


**Figure 4** Performance evaluation of the health-wise (HW) and non- health-wise (NHW) EMSs. a) Trip cost comparison for different battery initial and final SOC levels, b) The variation of the battery SOC in different scenarios, c) The supplied power by the FC system, d) the drawn current from the FC.

## Conclusion

This paper initiates by delineating a comprehensive methodology for infusing health monitoring techniques into EMS design, with a deliberate emphasis on the pivotal parameters and HIs tailored for this application. A subsequent concise survey is conducted, elucidating the prevailing prognostic and diagnostic methodologies for both FCs and batteries. Finally, a comprehensive simulation using a HIL setup is performed. The simulation investigates three scenarios under a standard driving cycle:

-New power sources with a health-wise EMS ($New_{Source-HW}$)

-Aged power sources with a health-wise EMS ($Aged_{Source-HW}$)

-Aged power sources with a non-health-wise EMS ($Aged_{Source-NHW}$)

The simulation results demonstrate that the trip cost of the vehicle increases by almost 13% when equipped with a health-wise EMS (comparing $New_{Source-HW}$ with $Aged_{Source-HW}$). However, the difference can increase up to around 25% if the vehicle is not equipped with a health-wise EMS (comparing $New_{Source-HW}$ with $Aged_{Source-NHW}$). The findings underscore the need for implementing health-wise EMSs to ensure efficient and cost-effective operation of FC-HEVs.

**For Further Reading**

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