# Energy Management System for Hydrogen Vehicles Considering State of Health of Fuel Cells and Lithium Batteries

## - State of Health Integration Using LSTM and ANN-based ECMS for Improved Hydrogen Consumption-

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**ABSTRACT**: This paper proposed a new method to define and to evaluate the State of Health (SOH) of fuel cells (FC) in hydrogen-powered vehicles. The proposed SOH estimation uses Long Short-Term Memory (LSTM) networks to monitor FC voltage degradation, while lithium battery SOH is based on electric capacity loss. To optimize energy management, an advanced Energy Management System (EMS) is developed by combining an Artificial Neural Network (ANN) with the Equivalent Consumption Minimization Strategy (ECMS). This EMS considers both SOHs for FCs and batteries in order to extending battery life and improving vehicle mileage. A rule-based control strategy is also provided for comparison. Simulations are under two scenarios: (1) at FC SOH is high (100%) and battery SOH is low (80%), ECMS and ANN-ECMS reduce hydrogen consumption by about 37% and 32%, respectively, which are compared to the baseline cases; (2) at FC SOH is low (80%) and battery SOH remains high (100%), these methods achieve reductions of approximately 39% and 32%, respectively.

**KEY WORDS**: Artificial Neural Network, equivalent consumption minimization strategy, State of Heath estimation, energy management, fuel cell, fuel cell electric vehicles

## 1. INTRODUCTION

The evaluation of the State of Health (SOH) of fuel cells is a critical topic in fuel cell lifecycle management. Numerous studies have investigated voltage degradation, increased hydrogen consumption, and cumulative power generation, providing a foundation and inspiration for this research. For example, Barbir, in his work, described in detail the characteristics of fuel cell performance degradation, particularly the trend of voltage declines with usage over time, and explored the effects of pressure and humidity on the V-I curve [1]. This serves as theoretical support for the voltage degradation evaluation model in this study. Several studies have highlighted how the degradation of the V-I curve leads to reduced fuel cell lifespan. For instance, research in [2] demonstrated that after conducting a 640-hour cyclic test at 100A current, the total voltage decreased by approximately 4V, representing a stack voltage drop of 6.9% over time. Meanwhile, reference [3] analyzed the performance degradation of proton exchange membrane fuel cells (PEMFCs) under dynamic load cycles, showing that the time-variant voltage curve during driving cycles reflects the cell's performance. Periodic measurements of polarization curves revealed variations in degradation rates at different operational stages, with significant performance decline after 280 hours of operation. In [4], the steady-state performance and transient responses of PEMFC under various load cycles and operational conditions were investigated. Critical parameters such as polarization curves, gas flow rates, temperatures, pressure drop, and relative humidity were controlled and measured to analyze their effects on the V-I curve. This study utilized the test data provided by [5] to establish a model for assessing the impacts of pressure, humidity, and time on SOH aging. Additionally, Kahia et al. proposed a hybrid method combining electrochemical impedance spectroscopy (EIS), polarization curve parameters, and artificial neural networks to estimate and diagnose the SOH of PEM fuel cells [6]. Their model effectively identifies parameter changes under varying humidity conditions, aiding in water management and SOH definition. In our research on fuel cell health management using neural networks, we demonstrate that pressure, humidity, and voltage data can effectively train a LSTM model to predict SOH and estimate voltage degradation rates.

## 2. VEHICLE CONFIGURARTION

This study drew on the Honda CR-V e:FCEV as a reference for modeling [7]. It consists of a lithium battery, a fuel cell, and an electric motor to develop an FCEV model. The configuration of the FCEV is illustrated in Fig. 1, with the corresponding parameters detailed in Table 1.

Table 1 Main parameter of Honda CR-V e:FCEV

| Parameter | Value/Unit |
|---|---|
| **Vehicle specifications** | |
| Mass | $2{,}023\ kilograms$ |
| Frontal area | $2.25\ m^2$ |
| Aerodynamic drag coefficient | $0.32\ Ns^2m^2$ |
| Rolling resistance coefficient | $0.01$ |
| Air density | $1.225\ kg/m^3$ |
| Radius of the wheel | $0.3511m$ |
| **Gearbox specifications** | |
| Reduction ratio | $10.255{:}1$ |
| **Electric machine specifications** | |
| Maximum power | $129.75kW$ |
| Maximum torque | $310Nm$ |
| **Fuel cell specifications** | |
| Maximum power | $92.2kW$ |
| **Battery specifications** | |
| Nominal voltage | $347.5V$ |
| Capacity | $17.7\ kWh$ |
| Maximum power | $88.5kW$ |

### 2.1. Dynamic modeling

This study developed a MATLAB/SIMULINK model for the EMS of Honda CR-V e:FCEV, simulating key subsystems such as the EMS, electric motor, DC-DC converter, lithium battery, and fuel cell modules, along with SOH estimators for the batteries and fuel cells. The control-oriented system achieves closed-loop energy distribution, validated using the EPA Urban Dynamometer Driving Schedule (UDDS).

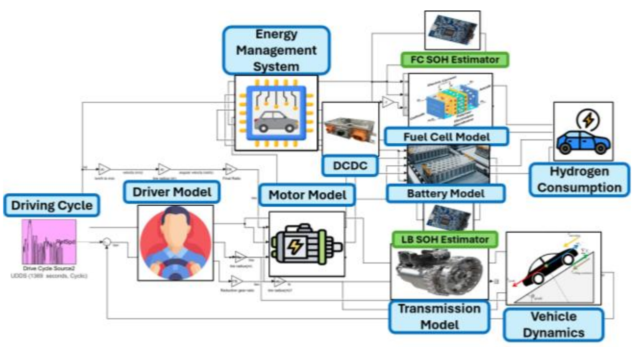


Fig. 1 Fuel cell electric vehicle simulation in SIMULINK

### 2.2. State of Health (SOH) estimation

This study proposed an evaluation metrics to assess the degradation of fuel cell health: voltage degradation rate. Considering practical application needs, we designed an offline update mechanism to reduce unnecessary computational burden and conserve MCU memory resources. Specifically, the voltage degradation rate is updated during vehicle startup (key on) or shutdown (key off), while the total power generation degradation is calculated in real-time based on the cumulative energy consumption of the fuel cell.

#### 2.2.1. SOH estimation model for fuel cells

The evaluation method for the voltage degradation rate was defined by Equation (1), where $V_0$ represents the unaged voltage (ideal voltage) and $V_t$ represents the aged voltage (actual voltage), used to define the voltage degradation SOH based on the voltage differences across the V−I curve, as shown in Figure 2. To estimate SOH, fuel cell pressure, relative humidity, temperature, and cumulative energy are input into an LSTM neural network for training, with voltage as the output. The LSTM architecture, depicted in Figure 3, consists of a single hidden layer with 32 neurons. The network is trained with a batch size of 64 for 25 epochs. LSTM networks are well-suited for time-series prediction, as they can capture long-term dependencies in sequential data. This enables the model to effectively track voltage degradation and assess the fuel cell's SOH over time.

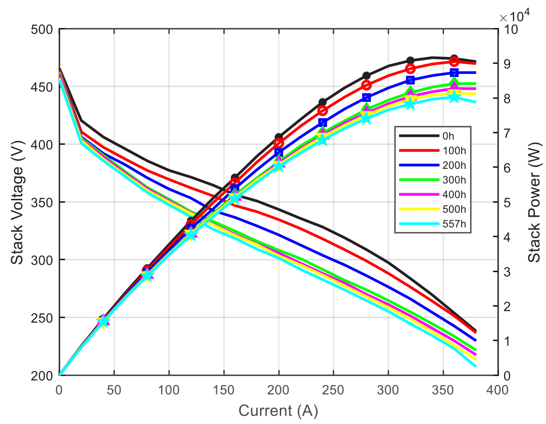


Fig. 2 Fuel cell V−I curve

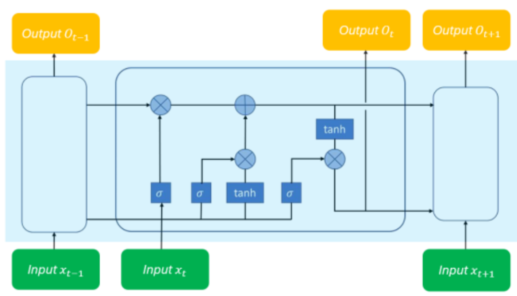


Fig. 3 LSTM architecture of fuel cell SOH estimation

$$SOH_{fc} = 1 - \frac{V_0 - V_t}{V_0} = \frac{V_t}{V_0} \tag{1}$$

### 2.2.1. SOH estimation model for batteries

The evaluation method for total power generation degradation is shown in Equation (2). It calculates $E_{tol}$ based on the lithium battery's total lifespan at the time of manufacture and its rated power. By integrating the power consumed of the lithium battery per second, the total degradation in power generation is obtained and defined as the lithium battery health degradation rate.

$$SOH_E = \frac{E_{tol} - \frac{\int_0^t P_{fc(t)}\,dt}{3600000}}{E_{tol}} \tag{2}$$

## 3. ENERGY MANAGAMENT STRATEGY

### 3.1. Rule-based control (RB)

Energy distribution is managed using a Rule-Based Control (RBC) strategy based on the vehicle speed, battery State of Charge (SOC), and State of Health (SOH) of both the fuel cell and battery. In "High-Speed Mode", power is shared between the fuel cell and battery. A healthier battery leads to a balanced split, while a weaker battery relies more on the fuel cell. In "Hybrid Mode", the battery takes a main role, but power distribution adjusts based on SOH. In "Low-Speed Mode", the battery supplies most of the power, with minimal fuel cell support if needed. In "Battery Charge Mode" (SOC ≤ 30%), the fuel cell prioritizes charging the battery while still powering the vehicle.

Table 2 Rule-based operation modes

| Condition | | Execution | Mode |
|---|---|---|---|
| $V_d > 60$ (km/h) | High SOH | $P_{fc} = 0.5P_d$<br>$P_{bat} = 0.5P_d$ | High-speed mode |
| | Low battery SOH | $P_{fc} = 0.6P_d$<br>$P_{bat} = 0.4P_d$ | |
| | Low FC SOH | $P_{fc} = 0.4P_d$<br>$P_{bat} = 0.6P_d$ | |
| $60 \geq V_d > 30$ (km/h) | High SOH | $P_{fc} = 0.3P_d$<br>$P_{bat} = 0.7P_d$ | Hybrid mode |
| | Low battery SOH | $P_{fc} = 0.6P_d$<br>$P_{bat} = 0.4P_d$ | |
| | Low FC SOH | $P_{fc} = 0.2P_d$<br>$P_{bat} = 0.8P_d$ | |
| $V_d \leq 30$ (km/h) | High SOH | $P_{fc} = 0$<br>$P_{bat} = P_d$ | Low-speed Mode |
| | Low battery SOH | $P_{fc} = 0.1P_d$<br>$P_{bat} = 0.9P_d$ | |
| | Low FC SOH | $P_{fc} = 0$<br>$P_{bat} = P_d$ | |
| SOC ≤ 0.3 | All SOH | $P_{fc} = P_d$<br>$P_{bat} = 0$<br>$P_{fc2b} = P_{fc}(\max)$ - $P_d$ | Battery charge mode |

### 3.1. Equivalent consumption minimization strategy (ECMS)

This study adopted equivalent consumption minimization strategy (ECMS) to optimize energy distribution in the energy management strategy. The algorithm exhaustively computes parameter variations across a defined range using a five-for-loop structure, as shown in Figure 4. A custom cost function, described in Equation (3) and (4), incorporates factors related to SOH of fuel cell, SOC and SOH of battery, as detailed in Equations (5) and (6). The optimal energy distribution ratio, expressed as the power allocation between the fuel cell and the total power demand, is determined using these factors and is illustrated in Equation (7).

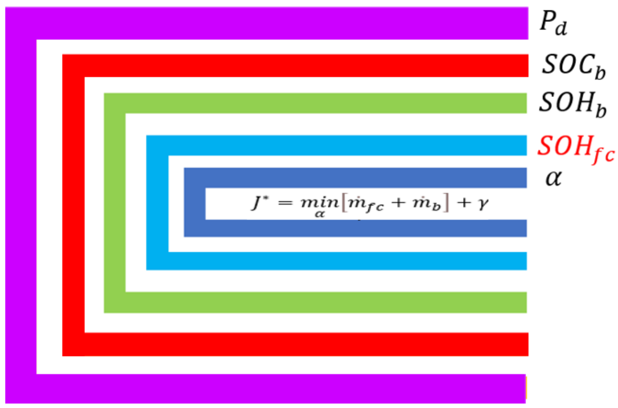


Fig. 4 Five-for-loop structure for ECMS

$$J = \dot{m}_{fc} + \dot{m}_b + \gamma \tag{3}$$

$$J^* = \min_{\alpha}\left[\dot{m}_{fc} + \dot{m}_b\right] + \gamma \tag{4}$$

$$\dot{m}_{fc} = \dot{m}_{fc(dis)} \times \frac{1}{\eta_{fc}(SOH_{fc})} \times f_{fc}(SOH_{fc}) \tag{5}$$

$$\dot{m}_b = \dot{m}_{b(chg)} \times \eta_b(SOH_b) \times x \times f_{b(chg)}(SOH_b) \times f_{b(chg)}(SOC_b)$$
$$+\dot{m}_{b(dis)} \times \frac{1}{\eta_b} \times (1-x) \times f_{b(dis)}(SOH_b) \times f_{b(dis)}(SOC_b) \tag{6}$$

$$\alpha = \frac{P_{fc}}{P_d} \tag{7}$$

The hydrogen-specific consumption for the battery, derived from Equation (8), $\overline{SC_b}$ (gram/kWh), represents the average hydrogen required to store 1 kWh of electrochemical energy in the battery.

$$\overline{SC_b} = \frac{\overline{SC_{fc}}}{\overline{Eff_{pc}} \times \overline{Eff_{ch\_b}}} \tag{8}$$

where $\overline{SC_{fc}}$ represents the fuel cell average specific consumption, converting fuel into electrical energy. $\overline{Eff_{pc}}$ denotes the average efficiency of power converter, while $\overline{Eff_{ch\_b}}$ reflects the average charging efficiency of the battery. When the power is positive (battery currently discharging):

$$\dot{m}_b = \frac{\overline{SC_b} \times P_b}{3600 \times \overline{Eff_{dis\_b}}} \tag{9}$$

When the power is negative (battery currently charging):

$$\dot{m}_b = \frac{\overline{SC_b} \times P_b \times Eff_{ch\_b}}{3600} \tag{10}$$

**3.3. Artificial Neural Network based Equivalent consumption minimization strategy (ANN-ECMS)**

As the dimension of ECMS increases, it becomes increasingly challenging for the VCU to process it efficiently. To implement this control strategy in real-world applications, significant MCU memory saving is required. Therefore, an ANN-based ECMS that leverages artificial neural networks to predict the equivalence factor $\alpha$, enabling efficient power management was proposed.

The ANN takes power demand ($P_d$), battery SOC, fuel cell SOH, and lithium battery SOH as inputs, dynamically adjusting $\alpha$ to optimize energy distribution. This approach reduces memory consumption, enhances computational efficiency, and improves adaptability to varying driving conditions, ensuring real-time feasibility and optimal energy utilization. The architecture is presented in Figure 5.

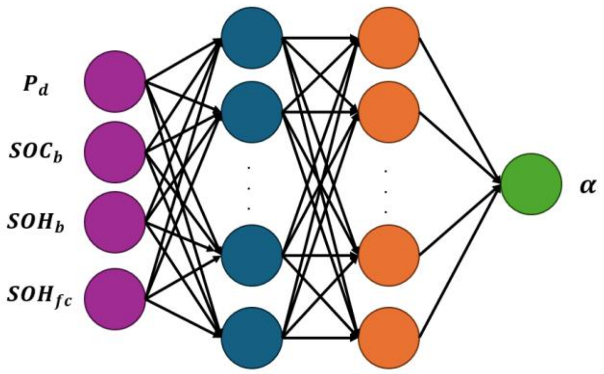


Fig. 5 Acritical neural network architecture of ANN-ECMS

## 4. RESULTS

**4.1. Data analysis of LSTM model of FC SOH**

Figures 6 and 7 illustrate the LSTM model's voltage prediction performance and residual analysis for fuel cell SOH estimation. The predicted voltage closely follows the actual trend in both training and testing phases, with minor deviations. The residual distribution is centered around zero, indicating high prediction accuracy, though slight variations suggest room for refinement. These results confirm the LSTM model's reliability in capturing long-term degradation patterns, making it a useful tool for SOH estimation in fuel cell systems.

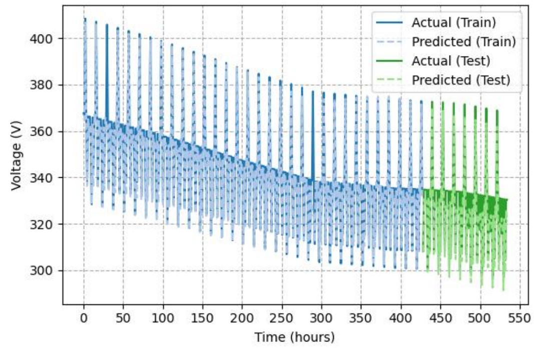


Fig. 6 Voltage estimation of fuel cell

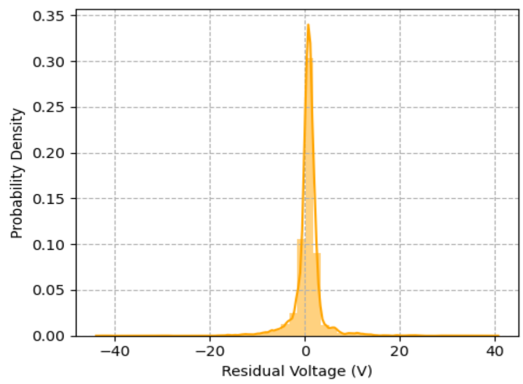


Fig. 7 Residual analysis for fuel cell SOH estimation

**4.2. Comparison of baseline control, ECMS, and ANN-ECMS**

Figures 8 and 9 illustrate the equivalent hydrogen consumption and power split for Case I (high FC SOH, low battery SOH). As shown in Table 4, the baseline RBC is with the highest hydrogen consumption (189.72g). The ANN-ECMS reduces hydrogen consumption by 31.93% (129.15g), while ECMS achieves the best reduction of 36.86% (119.78 g). ANN-ECMS closely follows ECMS and performs significantly better than RBC, demonstrating its efficiency in adapting to SOH variations while optimizing power distribution.

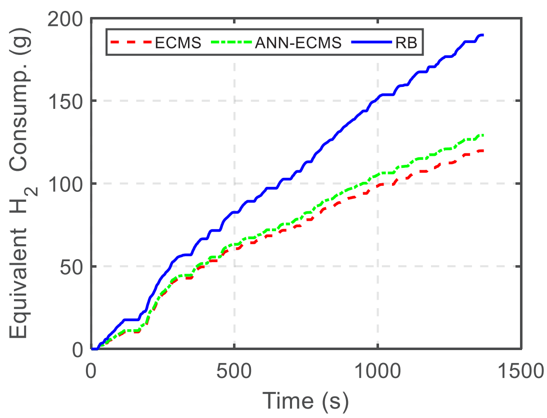


Fig. 8 Equivalent Hydrogen consumption of case I

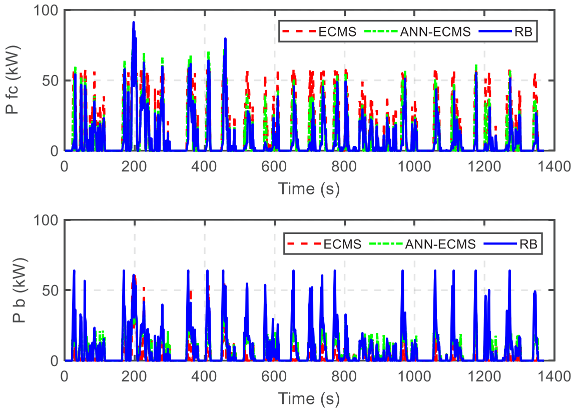


Fig. 9 Power Split of case I

Similarly, Figures 10 and 11 present results for Case II (low FC SOH, high battery SOH). As shown in Table 5, ANN-ECMS continues to follow ECMS closely, achieving a 31.85% reduction in hydrogen consumption, while ECMS reaches 39.22%, both significantly better than that of RBC. These results confirm that ECMS and ANN-ECMS provide major fuel efficiency improvements, with ANN-ECMS serving as a more adaptive and practical alternative to ECMS by integrating SOH considerations into energy management.

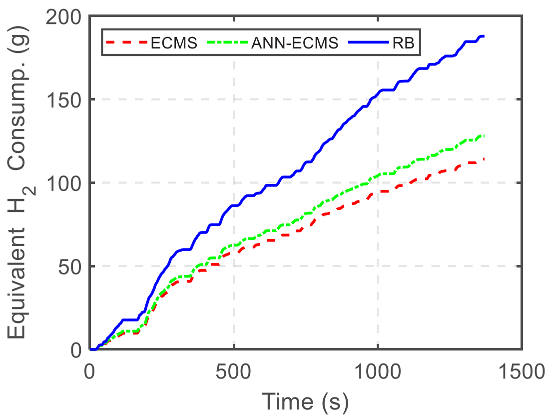


Fig. 10 Equivalent Hydrogen consumption of case II

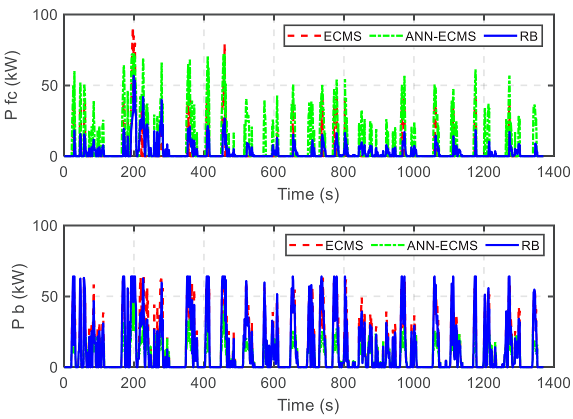


Fig. 11 Power Split of case II

Table 4 Equivalent hydrogen consumption/improvement

| Case I | Equivalent hydrogen consumption (g) | Improvement (%) |
|---|---|---|
| RB | 189.72 | -- |
| ANN-ECMS | 129.15 | 31.92% |
| ECMS | 119.78 | 36.86% |

Table 5 Equivalent hydrogen consumption/improvement

| Case II | Equivalent hydrogen consumption (g) | Improvement (%) |
|---|---|---|
| RB | 187.83 | -- |
| ANN-ECMS | 128.00 | 31.85% |
| ECMS | 114.16 | 39.22% |

## 5. CONCLUSIONS

This study implemented an online optimal control strategy using ECMS for fuel cell electric vehicles. The key contributions are summarized as follows:

(1) Design and define both SOH estimators for fuel cells and lithium batteries:

We defined SOH estimators for fuel cells and lithium batteries, using voltage degradation for fuel cells and capacity performance for lithium batteries to ensure accurate and efficient health monitoring.

(2) Four-mode rule-based control:

The four-mode rule-based control operates in high-speed mode, hybrid mode, low-speed mode, and battery charge mode, depending on the vehicle velocity and battery SOC. It determines two key outputs: the required fuel cell power and battery power.

(3) Hydrogen consumption improvement of ANN-ECMS/ECMS with SOH:

The results indicate that different battery health levels affect energy distribution. The EMS distributes power to extend the lifespan of both the fuel cell and the lithium battery and improve approximately 30 to 40% of equivalent hydrogen consumption.

## ACKNOWLEDGMENT

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