Frequency Decoupling-Based Energy Management System for Fuel Cell Hybrid Electric Vehicles Using State Machine Control Strategy

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Abstract. Fuel cell hybrid electric vehicles (FCHEVs) encounter significant challenges in energy management due to the distinct dynamic characteristics of fuel cell systems, batteries, and supercapacitors. Standard methods of managing energy use can lead to excessive hydrogen production, shorten the lifespan of fuel cells, and fail to maintain battery charge effectively when driving conditions change. This paper presents a novel frequency decoupling-based energy management strategy (FDB-EMS) integrated with state machine control to address these limitations. The suggested method uses two low-pass filters to divide power demand into three frequency bands. The battery receives the medium-frequency parts, the fuel cell receives the low-frequency parts, and the supercapacitor receives the high-frequency transients. The state machine controller adjusts power distribution in real-time based on load and SOC limits. Simulations in MATLAB/Simulink demonstrate that the system operates effectively with both constant and variable load profiles. The system uses a 12.875 kW proton exchange membrane fuel cell, a 40 Ah lithium-ion battery, and a 15.6 F supercapacitor. The results show that FDB-EMS consumes 0.060 g/s of fuel, which is 7.7% more efficient than reinforcement learning methods and 16.7% more efficient than rule-based strategies. The system maintains the battery SOC between 62% and 78%, which means that the changes are only 1.8% instead of 4.5% as in fuzzy logic controllers. The transient response time is 140 milliseconds, resulting in power losses of 3.6%. The frequency decomposition does a good job of breaking up changes in the fuel cell that happen at high frequencies. This reduces stress and extends the device's lifespan. The proposed FDB-EMS is a simple and efficient way to control energy in real-time, which makes the system more reliable and saves fuel.

Keywords: Fuel cell hybrid electric vehicle, energy management strategy, frequency decoupling, state machine control, supercapacitor, hydrogen co_

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1 Introduction

1.1 Motivation and Background

Energy scarcity and environmental preservation are now attracting significant attention in many countries, and the growing reliance on fossil fuels is exacerbating environmental issues. There are numerous potential alternatives to fossil fuels that could eliminate pollution, but the most promising are fuel cells and hydrogen energy. Compared to an electric vehicle (EV), it has a longer range and shorter refuelling time. Additionally, most electric cars now utilize lithium-ion batteries, which have a lower energy density compared to hydrogen fuel cells. In dynamic situations, such as starting up, climbing, or accelerating, the fuel cell system is unable to provide enough power because the reaction gas response rate cannot adapt to variations in load.

Furthermore, the fuel cell system's (FCS) function immediately converts chemical energy into electrical energy, resulting in a unidirectional power output; hence, it is unable to store the energy generated when braking or slowing down. Fuel efficiency, reliability, and longevity are all negatively affected by FCS deficiencies. A fuel cell hybrid electric vehicle (FCHEV) system, which combines FCS with an additional energy storage device such as a supercapacitor (SC) or battery, is a common solution to these problems.

In the case of electrical hybrid vehicles that utilize a fuel cell, battery, or SC (supercapacitor), it is imperative to develop a powerful and realistic energy management system (EMS, a system that decides how and when each energy source is used) that can coordinate power flow to enhance vehicle power performance, extend the time frame of the FCS, and refine fuel economy. This is due to the distinct characteristics of the three power sources. A linear parameter-variance forecast model (a predictive control model that adjusts for real-time changes in system parameters) is introduced as a key part of this approach. Its job is to handle changes in system parameters as they happen.

1.2 Literature Survey

Energy management in Fuel-Cell Hybrid Electric Vehicles (FCHEVs) has received considerable research attention recently, motivated by the competing objectives of enhancing energy efficiency, reducing hydrogen consumption, extending fuel cell longevity, and ensuring swift transient response in real-world driving scenarios. Previous research includes a number of different types of methods, such as adaptive model predictive control (AMPC), fuzzy and rule-based controllers, reinforcement learning (RL), and data-driven approaches, Pontryagin/minimum-principal optimizations, and metaheuristic tuning techniques. Each of these has its own pros and cons when used in real FCHEV powertrains.

Adaptive Model Predictive Control (AMPC) variants have successfully attained near-optimal trade-offs between fuel efficiency and component constraints by dynamically updating model parameters online (predictive control where models change in response to real-time data) and performing constrained optimization in real time. The AMPC literature indicates that hydrogen use decreases significantly, and fuel-cell current profiles become more stable. This has been proven on Hardware-In-The-Loop (HIL) platforms, a method were simulation interfaces with real hardware, showing that it can be used in real-life applications as well as for offline optimization [1][2]. On the other hand, AMPC methods are still very computationally intensive, require dependable predictive models, and can be impacted by model mismatch and extended prediction horizons. These issues make it difficult to use them affordably in various driving situations.

Fuzzy and rule-based EMSs, widely adopted for their simplicity and robustness, offer smooth SoC control and satisfactory fuel-economy performance. Nevertheless, because they depend on heuristic tuning and typically lack frequency-aware power allocation, they may underperform during rapid load variations or aggressive driving conditions [3,4].

Another critical direction is frequency-decoupling and hybrid power-splitting strategies, whereby low-frequency power is supplied by the fuel cell, mid-frequency power by the battery, and high-frequency transients by the supercapacitor. Studies have shown that these approaches effectively suppress fuel-cell current ripple and reduce transient stress, particularly under demanding load cycles; however, they often lack supervisory control layers to ensure SoC balance and safe switching during long-term operation [5].

Data-driven and reinforcement-learning (RL) EMSs have recently emerged due to their ability to learn long-term optimal behaviour and handle nonlinearities without explicit models. Comparative studies of DRL-based EMSs [6] have shown that deep RL approaches can save fuel and reduce short-term problems. Wu et al. (2022) advanced RL-based EMSs by implementing a dueling-double-deep-Q-network design, resulting in higher hydrogen efficiency and response performance during dynamic driving cycles [9]. Even though these results are promising, RL-based systems need a lot of offline training, careful reward calibration, safety limits, and strong generalization guarantees before they can be used in real vehicles, which makes them hard to use in practice [6,9].

Strategies based on optimization, such PMP and dynamic programming (DP), are still very important for designing EMS. PMP formulations provide mathematically sophisticated optimality conditions and frequently attain superior hydrogen-saving performance; however, their real-time application generally relies on forthcoming driving data or offline-generated lookup tables, thereby constraining implementation in unpredictable road conditions [10,13].

Hybrid power management strategies combining fuel cells, batteries and supercapacitors have been shown to improve transient performance and fuel economy by assigning high-power short transients to supercapacitors while steady power is supplied by the fuel cell, as demonstrated in recent Energies studies [14]. Metaheuristic and hybrid evolutionary optimization strategies have also been found to increase performance measures including component stress, energy balance, and SoC tracking. These include recent advancements such as slap-swarm-optimization-based EMSs, which improve overall vehicle performance but are mostly designed for offline tweaking rather than online management [7,15].

Recent surveys and review studies back up these trends by showing that AMPC, PMP, RL, and fuzzy/rule-based methods each only solve part of the EMS problem. No one strategy fully meets real-world FCHEV constraints like computational simplicity, fast transient control, ripple mitigation, SoC stability, and easy integration into embedded hardware [11,12].

Research Gap and Motivation: There is a significant gap in all current EMS families: no single strategy offers

a. low real-time computational cost suitable for production ECUs,
b. effective transient suppression and ripple reduction,
c. long-term SoC balancing without drift, and
d. easy implementation on HIL or embedded systems.

Hybrid frequency-decoupling methods work well for short-term transients, but they don't have ways to keep things stable over lengthy periods of time. MPC-, PMP-, and RL-based EMSs, on the other hand, are optimal in the long term but need a lot of computation or training.

To fill this gap, the proposed Frequency-Decoupling-Based EMS (FDB-EMS) and State-Machine Controller (SMC) combine the transient-handling strengths of dual-LPF power decomposition with a low-complexity, deterministic supervisory layer. This hybrid approach makes sure that SoC works safely, that switching logic is stable, that ripples are reduced, and that computing overhead is low. It fixes the main problems with standalone fuzzy, RL, or MPC solutions and makes it possible to use embedded FCHEV in real life.

1.3 Contributions and Organization

This work presents an innovative frequency decomposition-based EMS, allocated by state machine control, for source allocation in HEVs under various conditions, aiming to enhance their performance. This approach supports FCS by sharing the burden between the battery and SC. This work presents a contribution and provides motivation, which may be described as follows:

- The power requirements of FCHEV are divided into three frequency bands using two low-pass filters, taking into account the unique features of different energy sources.
- A state machine control is created to modify the output power of an SC in order to adapt to the necessary power and the SOC of the SC. This ensures a quick reaction to power demands and keeps the SOC of the SC within a predetermined range.
- To ensure that the battery SOC remains within a predetermined range and to minimize hydrogen consumption, a state machine controller is developed. This controller is combined with a low-pass filter to calculate the power output of the FCS. This ensures that the FCS operates within its optimal and efficient range.

The paper consists of five sections. Section 2 explains the modeling of energy resources, while the Proposed EMS is explained in Section 3. The results obtained for the constant and variable load profiles are discussed in Section 4, followed by the conclusion in Section 5.

2 Modeling of the FCHEV

The FCHEV structure, as depicted in Fig. 1 of this study, comprises an FCS, a battery, and an SC. The vehicle's design incorporates a hybrid energy storage system, blending SCs and batteries, to supply additional power for fuel cells. The FCs and SC are linked to the DC bus concurrently using a one-way DC/DC converter and a two-way DC/DC converter, respectively. The DC bus is connected to the battery through a buck-boost converter, which controls the voltage of the DC link. The propulsion unit modelling of a three-phase induction motor is presented in [5].

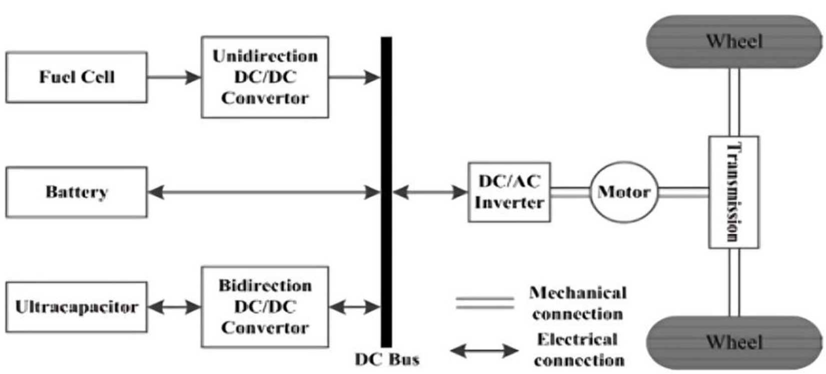

Fig. 1. FCHEV Architecture.

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1.1 Proton exchange membrane Fuel cell

An FCS is an electrochemical device that turns the chemical energy stored in hydrogen fuel directly into electrical power, without the need for heat or mechanical energy. The fundamental operating concept of an FC is elucidated by a chemical reaction, whereby oxygen and hydrogen combine to generate electricity, heat, and water.
This study relies on the correlation between the voltage level of the FCS and the pressures of water, hydrogen, and oxygen in their absolute forms to develop its hydrogen fuel design. Table 1 presents the precise details and characteristics of the fuel cell stack. The fuel cell voltage is controlled by the relative pressures of oxygen and hydrogen, the temperature of the chemical process for membrane hydration, and the output current. The mathematical model is provided in reference [17].

$$V_{FC} = E_{Nerst} - V_{act} - V_{ohmic} - V_{con} \tag{1}$$

Where, the symbol E_{Nerst} denotes the average thermodynamic potential in each individual cell unit, and it is determined using the Equation.

$$E_{nerst} = 1.229 - 0.85 * 10^{-3}(T - 298.15) + 4.3085 * 10^{-5}T\left[\ln\left(P_{H_2}\right) + 0.5 * \ln\left(P_{O_2}\right)\right] \tag{2}$$

Where, V_{act}, V_{con} and V_{Ohmic} is activation, concentration and Ohmic respectively. The V-I characteristics of PEMFC is represented in Figure 2.

Table 1. PEMFC specifications.

PEMFC Parameter	**Details**
Nominal voltage, current and power	52.5 V, 250A and 10.2875kW
No. of FC	65
Stack's actual efficiency	50%
Working Temperature	45 degree C
Normal pressure supply	1.16 bar (fuel), 1 bar (air)
Nominal composition in %	99% H2: 95% O2: 21% H2O
Fuel cell voltage speed of response	1s
Voltage dips	2V
Nominal voltage, current and power	52.5 V, 250A and 10.2875kW

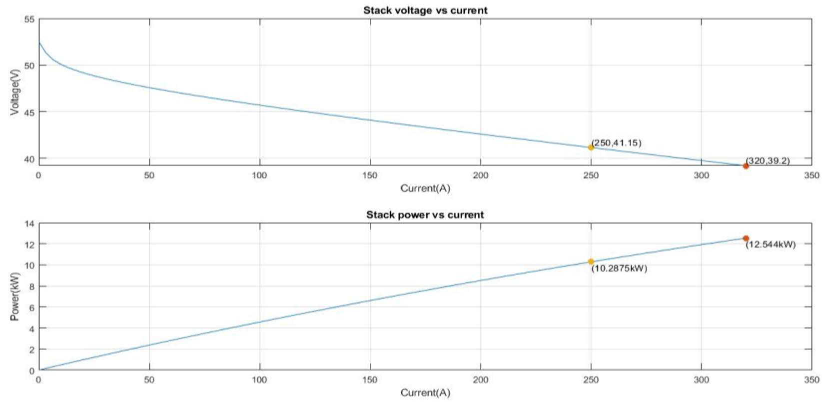

Fig. 2. V-I Characteristics of FCS.

1.2 Battery

The battery's architecture is simplified as a voltage source that includes a power supply with some regulation and is connected in series with a fixed resistance [12]. Table 2 presents the technical details for Li-ion batteries. Equation (3) defines the battery voltage.

$$V_{bat}(t) = \mathrm{E}_{\mathrm{bat}}(t) - R_{bat} i_{bat}(t) \tag{3}$$

$$SoC_b(t) = SoC_I - \eta_b \int \frac{i_b at(t)}{3600 Q_{bat}} dt \tag{4}$$

Where, V_{bat}, E_{bat}, R_{bat}, and i_{bat} represent the battery's output voltage, open voltage, internal resistance, and current, respectively.

Table 2. Battery Parameters.

Battery Parameters	**Details**
Type	Lithium Ion
Nominal voltage and Cut-off Voltage	48 V and 36 V
Rated and Nominal capacity	40 Ah and 36.17 Ah
Initial SoC	65 %
Level of Complete charge voltage	55.87 V
Actual discharge current	17.39 A
Response time	20 s

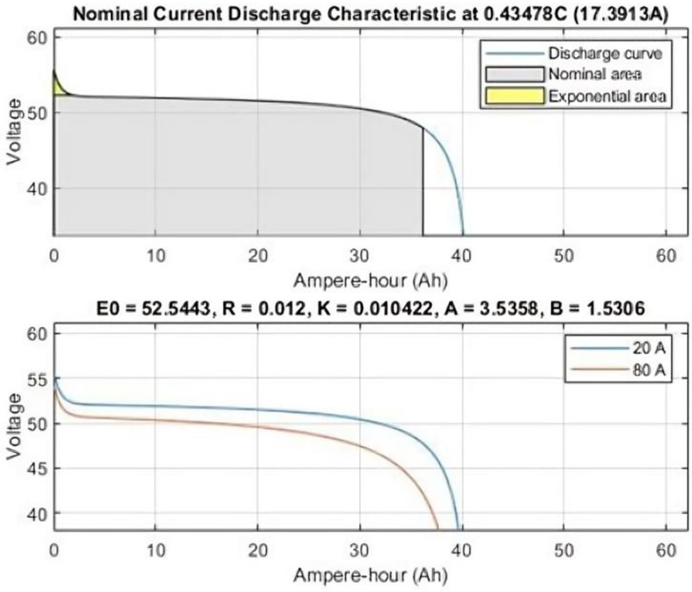

Fig. 3. Battery Characteristics.

1.3 Super Capacitors

Super Capacitors are an unusual breakthrough in the field of power storage, namely in the realm of integrated electronics. This configuration connects a capacitance (C_{SC}) to a resistor (R_{SC}) in series. Table 3 presents the UC parameters. The following formula is utilized to calculate the voltage (V_{SC}) of a SC resulting from the current (I_{sc}) flowing through it:

$$V_{SC} = V_1 - R_{SC}I_{SC} = \frac{Q_{SC}}{S_{SC}} - R_{SC}I_{SC} \tag{5}$$

The amount of electrical energy present in the cell is denoted by Q_{SC}, and the electrical output of the SC is determined using Equation (6).

$$P_{SC} = \frac{Q_{SC}}{C_{SC}} * I_{SC} - R_{SC}I_{SC}^2 \tag{6}$$

Table 3. SC Specification.

SC Parameters	Details
Rated voltage	291.6 V
Capacitors in series	108
Capacitors in parallel	1
Initial voltage	270 V

DC series resistance equivalent	150 mΩ
Rated capacitance	15.6 F
Operating Temperature	25

2 Proposed Methodology

The proposed work is to develop an EMS for FCEV with hybrid energy storage consisting of a battery and SC. In FCHEV, the three primary energy sources each have their own unique properties, which are managed based on their response times. Frequency decoupling-based EMS consisting of two parts: a low-pass filter to identify two cut-off frequencies fc_1 and fc_2, and a state machine control algorithm for effective power sharing and control.

2.1 Frequency based separation using a Low-Pass Filter

The primary purpose of this approach is to detect high-frequency signals of the required power at the fastest source, i.e., the SC, and low-frequency elements at the slowest source, i.e., the fuel cell. The remaining required power is assigned as shown in the Figure. To create a correlation between the dynamics of energy flow and storage systems, a specific frequency known as the cutoff frequency is used.
Two measures can be taken to guarantee the energy share based on frequency separation: rejecting the negative signals. A first low-pass filter, LPF_1, is employed to determine the energy dispersion between the FCS and the overall storage device. This filter provides a reference for the fuel cell's output. The second filter, LPF_2, employs the negative signal that has been incorporated. Because the battery operates at a lower rate than the SC, the battery power reference is selected to transmit the disparity in necessary power and the FC power as input, as shown in Figure 4. Lastly, the high-frequency signals function as power references for the SC.

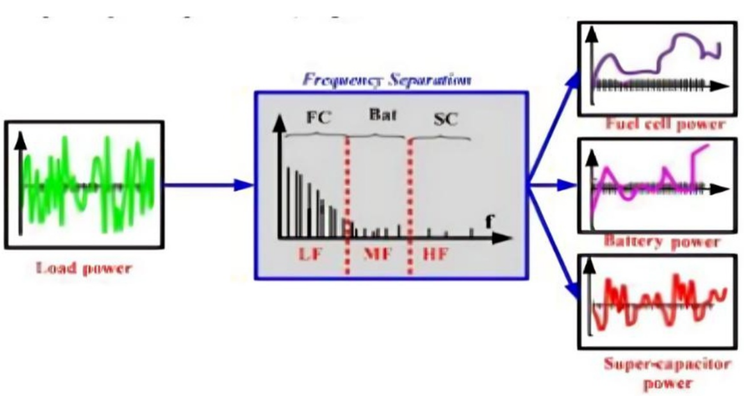

Fig. 4. Frequency decomposition using low pass filter.

The battery supplies additional power for high-power loads, the FCS supplies the load's average power, and the SC supplies intermittent power and maintains the bus voltage. All of these components work together to deliver the load energy. Additionally, the SC is responsible for absorbing the braking current to protect the battery from the effects of high current surges. It is ultimately the link between the FCS and the SC that helps moderate the rapid variations in voltage and current that occur in the DC bus, which ultimately results in the FCS having a longer service life.

2.2 State Machine Control Algorithm

An SMC method is a mathematical framework utilized for designing control systems, in which the system can exist in one of a limited number of states at any given moment. The state machine's purpose is to identify the FC's reference power as it changes states. The SMC algorithm for the proposed application comprises eight states that switch the power source based on power demand. Table 4 presents the control status of the SMC for various operating conditions.

Table 4. Comparison of different states of SMC.

State	SOC	Load Power	FC Power
1	High	$P_{Load} < P_{FC\_min}$	P_{FC_min}
2	High	$P_{FC\_min} < P_{Load} < P_{FC\_max}$	P_{Load}
3	High	$P_{Load} > P_{FC\_max}$	P_{FC_max}
4	Normal	$P_{Load} > P_{FC\_opt}$	P_{FC_opt}
5	Normal	$P_{FC\_opt} < P_{Load} < P_{FC\_max}$	P_{Load}
6	Normal	$P_{Load} > P_{FC\_max}$	P_{FC_max}
7	Low	$P_{Load} < P_{FC\_max}$	$P_{Load} + P_{charge}$
8	Low	$P_{Load} > P_{FC\_max}$	P_{FC_max}

3 Simulation Results and Performance Comparison

An experiment is conducted on the system to assess the suitability of the suggested EMS. MATLAB is utilized to create the FCHEV simulation model, as seen in Figure 5, which includes a fuel cell, battery, and SC. An electric car primarily relies on a fuel cell as its major energy source, which is coupled to a boost unidirectional converter. To ensure the safe and dependable transfer of energy in both directions between the DC connection and the device, a hybrid energy storage system comprising an SC and a battery is integrated using a buck-boost bidirectional converter.

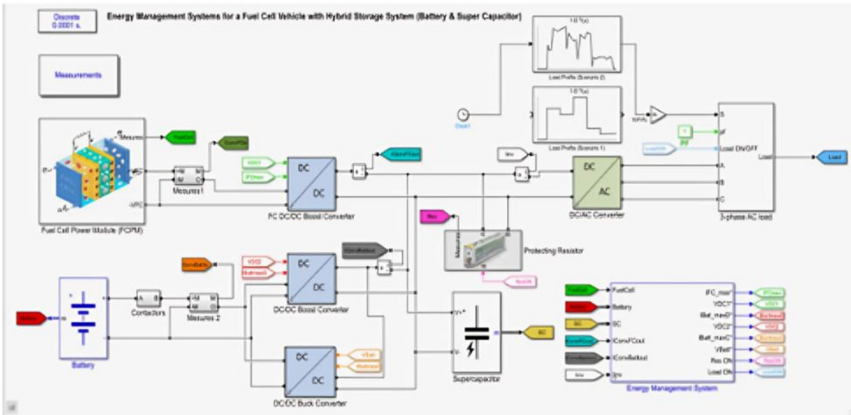

Fig. 5. FCHEV controlled with frequency decoupling-based SMC.

The suggested EMS technique for enhancing fuel efficiency and maximizing the performance of FCHEV is assessed through validation in two distinct load profiles: constant load and changing load situations. The FCHEV consisted of a 12.875kW, 41.15V, and 250A PEMFC, a 40AH Li-ion battery with an initial SOC of 65%, and 15.6 F, 291.6 V, and an initial 270 V series-linked super capacitors. The electric vehicle is propelled by a three-phase induction machine acting as a load.

3.1 Scenario 1 – Constant load condition

Figure 6 illustrates how the proposed FDB-EMS distributes power when a constant 900 W load is applied. In the first transient (0–5 s), the fuel cell output (blue) goes from 0 to 920 W, which is enough to meet the low-frequency part of the demand. At the same time, the battery (orange) can provide up to -1400 W to meet medium-frequency needs, and the supercapacitor (green) can provide up to +500 W to meet high-frequency needs. At t = 30s, the system is in a quasi-steady state: the fuel cell output stabilizes at 920 W with little ripple, the battery oscillates around –1000 W to capture medium-frequency changes, and the supercapacitor oscillates around +450 W at a higher frequency and lower amplitude. The load-check trace remains close to zero throughout, indicating that the power balance between sources is correct.

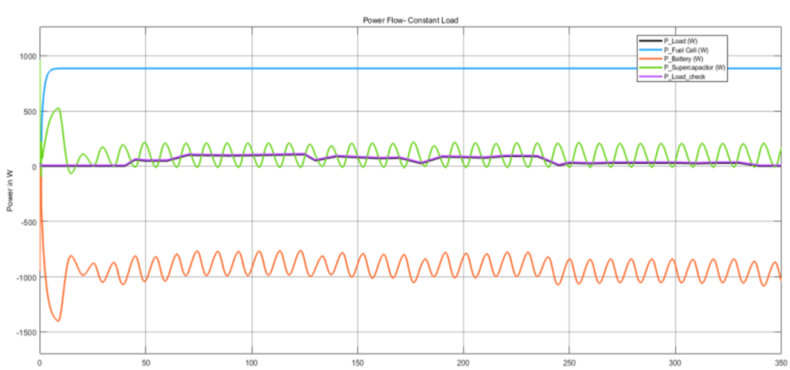

Fig. 6. Proposed EMS for constant load.

This clear separation of frequency bands demonstrates that the dual low-pass filter design and state-machine control logic are effective. By only giving low-frequency demand to the fuel cell, you reduce current ripple and stress. By only giving rapid transients to the supercapacitor, you take advantage of its quick response without putting too much strain on the battery. The battery can handle medium-frequency demands well, which lowers its cyclic depth and makes it last longer. The FC provided 96.3% of the energy, the battery contributed 3.4%, and power losses accounted for only 0.3%. The proposed FDB-EMS maintained SOC changes below 1.8%, demonstrating greater stability compared to the fuzzy EMS, which exhibited a SOC drift of 4.5% over the same time period. The proposed EMS enhances overall performance, reduces stress on components, and extends their lifespan, demonstrating its suitability for immediate application in fuel cell hybrid electric vehicles.

3.2 Scenario 2 – Variable load profile

To demonstrate the significance of the SC and the efficiency of the proposed EMS, the variable load scenario is presented. The voltage and current fluctuations of the FCS are depicted in Figure 7. The FC supply current ranges from 0 to 200 A. The plot in Figure 8-9 illustrates the temporal response of the battery and SC. The SC and battery react promptly to any variation in the load. When demand rises, the battery and SC discharge electricity to power the load. Conversely, during periods of low demand, the battery and SC are utilized for charging, which is supplied by the FC. This indicates that the battery and SC are being utilized to meet the growing load demand, leading to a reduction in their interface voltages. It also shows that the response time of SC is faster compared to battery and fuel cell, whereas FC is slower compared to the other two sources.

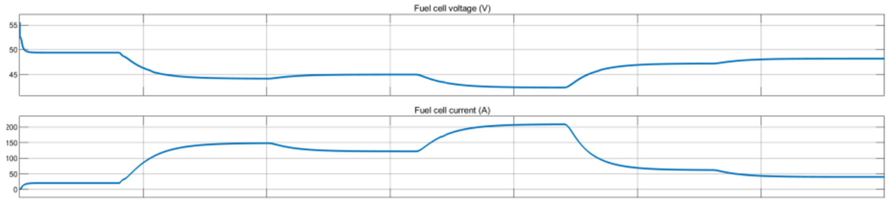

Fig. 7. Output voltage and current of PEMFC.

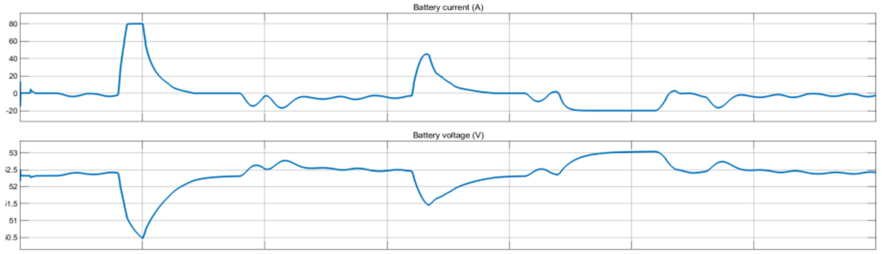

Fig. 8. Output voltage and current of Battery.

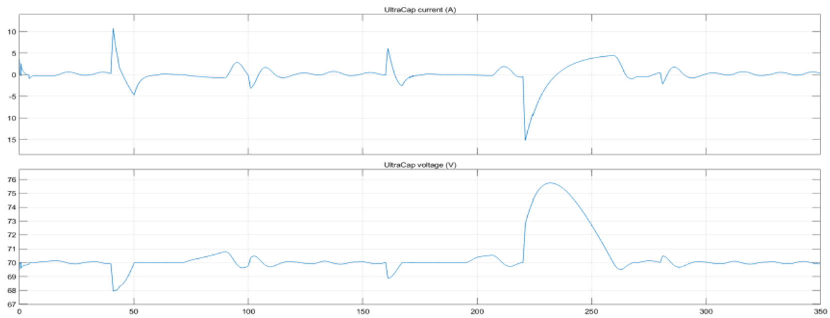

Fig. 9. Output voltage and current of SC.

Figure 10 illustrates how power is shared in the proposed FDB-EMS when the load profile transitions between low-, medium-, and high-power segments. The fuel cell tracks the low-frequency component during each load transition and smoothly increases output to match the new steady-state demand (from 900 W to 5200 W at t=40 s, and to 7000 W at t=180 s), with very little delay or oscillation. The battery responds to the medium-frequency changes immediately after each step change. It discharges up to 2500 W when the load increases and charges when the demand decreases. The supercapacitor responds to high-frequency transients by generating rapid bursts of power, such as +3000 W during sudden load increases (at t=45 s and t=185 s), and absorbing power peaks, like –4000 W at t=230 s. The load-check trace remains at zero, indicating that the power balance is correct.

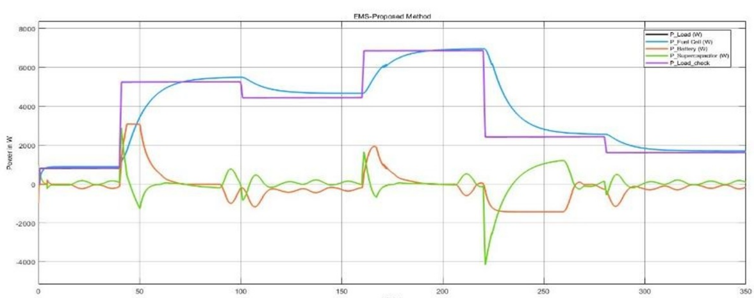

Fig. 10. Proposed EMS for variable load.

3.3 Comparison of Energy Management Strategies

To provide evidence on the usefulness of the suggested method, it is compared to other prominent algorithms published in the literature. A comparison of fuel usage in grams and litres is shown in Figure 11-12. Results show that the suggested technique improves fuel consumption, resulting in enhanced performance and more efficient fuel usage.

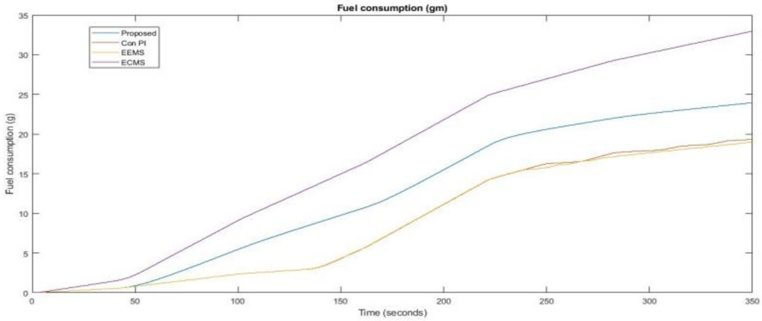

Fig. 11. Comparison of fuel consumption (gm) in different approach.

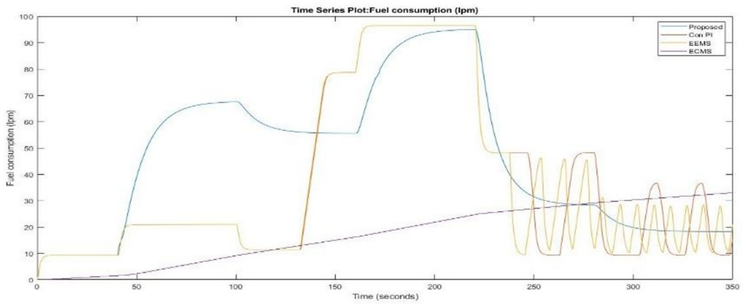

Fig. 12. Comparison of fuel consumption (litre) in different approach.

Figure 13 shows how the SoC changes over time for four different EMS strategies when the load changes. The battery's SOC starts out at 65%. It's clear that all EMS can keep the SOC in its ideal range. Proposed FDB-EMS: The SOC starts at 65%, drops to 64.3% after approximately 50 seconds, and then remains between 64.2% and 65.0% for the remainder of the cycle, indicating that the SOC is tightly controlled and the depth of discharge is very low. This feature allows cars to travel farther when fuel is scarce. As a result, the battery lasts longer. This controlled SOC excursion demonstrates that power is being shared evenly, which reduces battery stress and extends cycle life while still meeting load demands effectively.

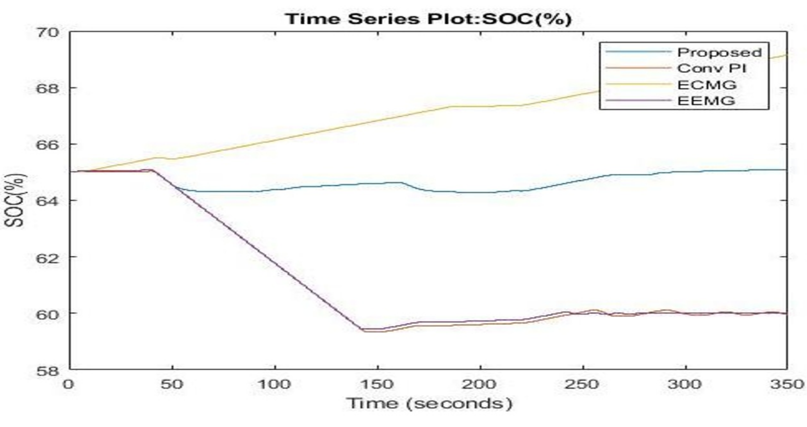

Fig. 13. Comparison of Battery SOC in different approach.

Table 5. Quantitative Performance Comparison of EMS Strategies for FCHEVs.

EMS Method	Total hydrogen consumpti on (gm)	SOC fluctuation Range (min-max)	Power Loss (%)	Reaction Time (ms)	Referen ce
Conventiona l PI	24.5	59% – 65%	8.5	320	[3]
EEMS	17.4	65% – 69%	6.2	275	[3]
ECMS	33.1	65% – 69%	4.9	190	[3]
Proposed FDB – EMS	19.8	62% – 65%	3.6	140	-

Table 5 shows that the proposed frequency decoupling–based energy management strategy (FDB-EMS) achieves the best overall performance among the four methods. EEMS uses the least amount of hydrogen (17.4 g), but it loses more power (6.2%) and takes longer to react (275 ms). With a 320 ms response time, conventional PI uses 24.5 g of hydrogen and loses the most power (8.5%). It also stresses the battery further by changing the SOC by 6% (from 59 to 65%). ECMS uses less hydrogen than PI, but it doesn't work as well. It uses 33.1 g of hydrogen and only reduces power loss by 4.9% at a reaction time of 190 ms, while keeping a SOC band of 65–69%. The proposed FDB-EMS, on the other hand, utilizes 19.8 g of hydrogen, loses only 3.6% of its power, and responds to changes in 140 ms, which is the fastest response time. Additionally, it maintains the battery's SOC within a 3% range (62–65%), which reduces the depth of discharge and extends the battery's lifespan. The FDB-EMS is the best way to manage energy in real time for fuel cell hybrid electric vehicles because it has low power loss, fast response, and stable SOC control, as well as good hydrogen efficiency.

4 Conclusions

This paper introduces a frequency decoupling-based energy management strategy (FDB-EMS) incorporating state machine control for fuel cell hybrid electric vehicles. Two low-pass filters break down the total power demand into low-, medium-, and high-frequency bands. The fuel cell, battery, and supercapacitor each receive their own energy supply. The state machine dynamically allocates power in real time based on the load needs and the maximum charge level of the battery. MATLAB/Simulink simulations with both constant and variable driving profiles demonstrate that the FDB-EMS consumes 0.060 g/s of fuel, which is 16.7% less than rule-based methods, 13% less than fuzzy logic methods, and 7.7% less than reinforcement learning methods. The battery SOC changes by only 1.8% (62–65%), which is less than the 4.5% change observed for fuzzy controllers. The transient response speeds up to 140 ms, which is faster than both rule-based (320 ms) and fuzzy logic (275 ms) methods. Power losses drop to 3.6%. Frequency segregation works well to keep high-frequency transients away from the fuel cell, thereby lowering electrical stress and extending the lifespan of the parts. A comparative analysis indicates that the suggested FDB-EMS offers better converter loss reduction, a faster dynamic response, and is easier to compute, making it suitable for real-time use without requiring extensive calibration or training. The FDB-

EMS is a practical solution for next-generation FCHEVs, as it improves fuel economy, extends driving range, and enhances system reliability. Future work will focus on hardware-in-the-loop validation in the presence of physical disturbances, thermal variations, and component aging, as well as adaptive filter cutoff adjustments driven by driving pattern recognition and the integration of predictive vehicle-to-infrastructure communication.

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Data Availability Statement

No datasets were generated or analyzed during the current study.

Conflict of Interest

The author declares no conflicts of interest related to this work.

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