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Robust Energy Management Strategy for Fuel Cell Hybrid Electric Vehicles Based on the RPO-DTRN Framework

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ABSTRACT

Fuel Cell Hybrid Electric Vehicles (FCHEVs) present a promising solution for sustainable transportation, but their widespread usage is limited by challenges like fuel cell stack degradation and inefficient power distribution. Conventional energy management strategies have difficulty in balancing power allocation efficiently while maximizing the fuel cell lifespan. To overcome these constraints, this research introduces a novel hybrid methodology-based energy management strategy for FCHEVs to enhance the fuel cell stack's lifetime. The proposed framework integrates the Red Panda Optimization (RPO) algorithm with a Dual Transformer Residual Network (DTRN), referred to as the RPO-DTRN approach. The RPO algorithm optimizes power distribution in hybrid electric vehicles, ensuring efficient energy utilization, while the DTRN model predicts and improves the remaining useful life of the fuel cell stack. The proposed strategy is evaluated using MATLAB environment and compared against existing techniques, including the Soft Actor-Critic algorithm, Twin Delayed Deep Deterministic Policy Gradient algorithm and Harris Hawks Optimization-Sine Cosine algorithm. Results demonstrate that the proposed RPO-DTRN method outperforms the existing methods, attaining a high efficiency of 97% and the lowest error value of 0.148. Additionally, the proposed strategy minimizes hydrogen consumption to 87.28 g, making it a more fuel-efficient approach. Furthermore, it achieves the highest final state of charge at 79.04%, indicating superior battery energy retention and overall system sustainability. These findings suggest the efficiency of the proposed energy management method in improving the reliability, efficiency, and longevity of FCHEVs.

KEYWORDS

Dual transformer residual network; Energy management strategy; Fuel cell stack; Fuel cell; Hybrid electric vehicle; Life span; Red panda optimization

1. INTRODUCTION

1.1 Background

Internal combustion engines and the transportation sector are major contributors to emissions compared to fuel cell hybrid electric vehicles (FCHEVs) which offer advantages such as high efficiency and local pollution-free operation [1]. To lower hydrogen consumption and increase system longevity, an energy management strategy (EMS) is required due to different energy characteristics [2]. Recent trends favor multiple low-power fuel cells over a single high-power fuel cell, improving reliability, durability, and efficiency [3]. However, this requires a multi-agent EMS for efficient power distribution [4, 5]. EMSs for FCHEVs are broadly categorized into optimization-based and rule-based methods [6].

1.2 Challenges

While FCHEVs offer significant advantages, they pose several challenges that need to be addressed [7]. Fuel cell degradation, inefficient power distribution, and the complexity of managing multiple FCSs pose major barriers to achieving optimal efficiency [8]. Conventional EMSs fail to account for individual stack degradation rates leading to suboptimal fuel consumption and reduced lifespan [9].

1.3 Literature Review

There are several study studies in the literature that are based on EMS for a FCHEV. Some of the reviews are as follows:

Ghaderi et al., [10] have suggested a battery pack and three fuel cells in a multi-stack FCHEV that uses a game theory based EMS.

Ebrahim et al., [11] have suggested a hybrid fuel cell-based power system in which the ideal control parameters were found using the new hybrid Harris Hawks Optimization and Sine Cosine Algorithm (HHO-SCA).

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Wang et al., [12] developed an EMS for the fuel cell energy architecture using a twin-delayed deep deterministic policy gradient (TD3) technique.

Chatterjee et al., [13] presented an efficient EMS for FCHEVs by combining Support Vector Machine, K-Nearest Neighbourand the Naive Bayes technique.

Chen et al., [14] presented a beta policy to enhance the standard soft actor critic (SAC) techniques by accounting for hydrogen consumption and power battery health degradation.

Huo et al., [15] applied the SAC algorithm to optimize EMS by incorporating fuel economy and degradation factors.

Leiet al., [16] suggested a hybrid system utilizing solid oxide fuel cells has various benefits, such as quick startup, efficient heat stress reduction, and stable operation.

Huang et al., [17] presented dual deep deterministic policy gradient algorithms to attain the best possible power distribution across energy sources.

1.4 Scope of the Study

Building upon these existing approaches, this study aims to:

- Develop a novel EMS framework integrating Red Panda Optimization (RPO) algorithm and Dual Transformer Residual Network (DTRN).
- Optimize power allocation to dynamically distribute energy, reducing fuel cell stress and improving system efficiency.
- Estimate fuel cell lifespan, enabling predictive maintenance and extending operational durability.
- Compare the proposed EMS with existing methods, demonstrating its effectiveness.

By addressing these aspects, the study contributes to the advancement of intelligent and sustainable EMS for FCHEVs.

1.5 Research Gap and Motivation

Despite significant advancements in EMS for FCHEVs, several challenges remain unaddressed, particularly in optimizing power distribution and extending fuel cell lifespan. The SAC algorithm has high computational demands and data requirements, which limit performance. Similarly, HHO-SCA relies on precise parameter tuning, increasing system complexity and the risk of suboptimal results. TD3 suffers from slow convergence and high computational overhead, restricting its applicability in vehicle systems. Furthermore, many approaches fail to dynamically allocate power between fuel cells and batteries, leading to inefficient power distribution and accelerated component degradation. To bridge this gap, this study proposes a novel framework for dynamic power distribution and precise fuel cell lifespan estimation.

1.6 Contributions

The following are the primary contributions of this study:

- Introduces a novel framework, dynamically optimizing power distribution while predicting fuel cell lifespan.
- Unlike conventional strategies, RPO algorithm dynamically allocates power, minimizing stress on components and improving energy utilization.
- The proposed framework enhances the prediction of fuel cell life, enabling a proactive maintenance strategy.
- The proposed EMS outperforms existing approaches in hydrogen consumption and battery energy retention, ensuring a more reliable EMS framework.

1.7 Organization

The rest of the manuscript is as follows: Part 2 clarifies the EMS for FCHEV. The proposed RPO-DTRN based EMS for a FCHEV is shown in Part 3. Part 4 explains the results and discussion. In Part 5, the paper is concluded.

2. CONFIGURATION OF PROPOSED EMS FOR A FUEL CELL HYBRID ELECTRIC VEHICLE

Figure 1 displays the configuration of proposed EMS for a FCHEV. The system integrates fuel cells and a battery, supplying power through DC-DC converters to a common DC bus. The EMS continuously checks the battery's state of charge (SOC) and optimizes power distribution based on demand and component status. Using the RPO-DTRN approach, RPO enhances power allocation, while DTRN estimates fuel cell lifespan.

2.1 Fuel Cell Hybrid Electric Vehicle

The electric motor in an FCHEV is powered by the battery pack and FCS, with an auxiliary energy storage systems (ESS) supporting the fuel cell [18]. Batteries and ultra-capacitors serve as ESS, charging and discharging based on electricity demand [19].

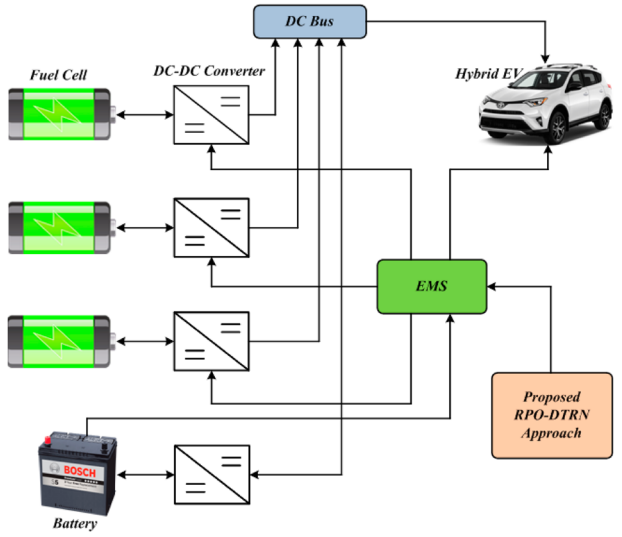


Figure 1: Configuration of proposed EMS for a FCHEV

2.2 Energy Management Strategy

In a multi-stack FCHEV, hydrogen consumption depends on the power split between the battery and fuel cells. This is referred from [10]. The requested power is calculated using Eqn. (1).

$$P_{req} = \eta_{dc-dc}(P_{FC1} + P_{FC2} + P_{FC3} + P_b) \tag{1}$$

here, P_{req} is the requested power, η_{dc-dc} denotes the converter efficiency, P_b is battery power and P_{FC} specifies the fuel cell power.

2.3 Fuel Cell Model

EMS efficiency depends on fuel cell characteristics, impacting power generation and reliability. A fuel cell converts hydrogen and oxygen into electricity through an electrolyte, cathode, and anode. This is referred from [11]. The cell's output voltage is calculated using Eqn. (2) as follows:

$$V = U_c \circ V_{\text{Nernst}} - V_{\text{act}} - V_{\text{ohm}} \tag{2}$$

where, V_{Nernst} is the Nernst voltage, V_{act} is the voltage loss of activation and V_{ohm} is the ohmic voltage law.

2.4 Battery Model

An auxiliary ESS, especially batteries, helps meet dynamic power demands and stabilize the system by buffering fuel cell output fluctuations. This model is referred from [12].

The battery's output power (P_b) is specified in Eqn. (3) as:

$$P_b = V_b.I_b \tag{3}$$

where, V_b is the voltage output and I_b is the battery's current.

2.5 DC/DC Converter

A DC/DC converter controls power flow between the fuel cell and battery, enabling bidirectional energy transfer. It is referred from [12]. Thus, the following Eqn. (4) isused to depict the DC to DC converter.

$$V_{req}I_{req} = \eta_{dc-dc}V_{FC}I_S \tag{4}$$

Here, V_{req} is the voltage required by the DC bus, I_{req} represent the requested current and I_S represent the stack current.

2.6 Transfer Function of the Proposed System

By combining theDC/DC converter, battery, fuel cell, and electric motor models, the overall system response can be described as:

$$P_{total}(s) = \frac{K_m}{T_m s + 1}\left[\frac{K_{dc}}{T_{dc}s + 1}\left(\alpha\frac{K_{fc}}{T_{fc}s + 1}P_d(s) + (1-\alpha)\frac{1}{C_b s + \frac{1}{R_{\text{int}}}}I_b(s)\right)\right] \tag{5}$$

where, s is the Laplace transform, T and K are the time constant and gain constant, $P_d(s)$ is the power demand of the system, C_b specifies the battery capacity, R_{int} specifies the internal resistance, I_b specifies the battery current and α specifies the power split ratio.

2.7 Problem Formulation

To effectively evaluate and optimize the energy management strategy, a cost-oriented formulation is adopted. This formulation is referred from [10].

$$Cost_{Total} = \left(\sum_{i=1}^{4} Cost_{FCSi}\right) + Cost_{H2} + Cost_{Bat} \tag{6}$$

where, $Cost_{FCSi}$ is the fuel cell degradation cost, $Cost_{H2}$ specifies the fuel consumption cost and $Cost_{Bat}$ specifies the battery degradation cost.

3. PROPOSED EMS FOR FCHEV

This section discusses an EMS for a FCHEV based on the RPO-DTRN technique. The following is a thorough clarification of the proposed method:

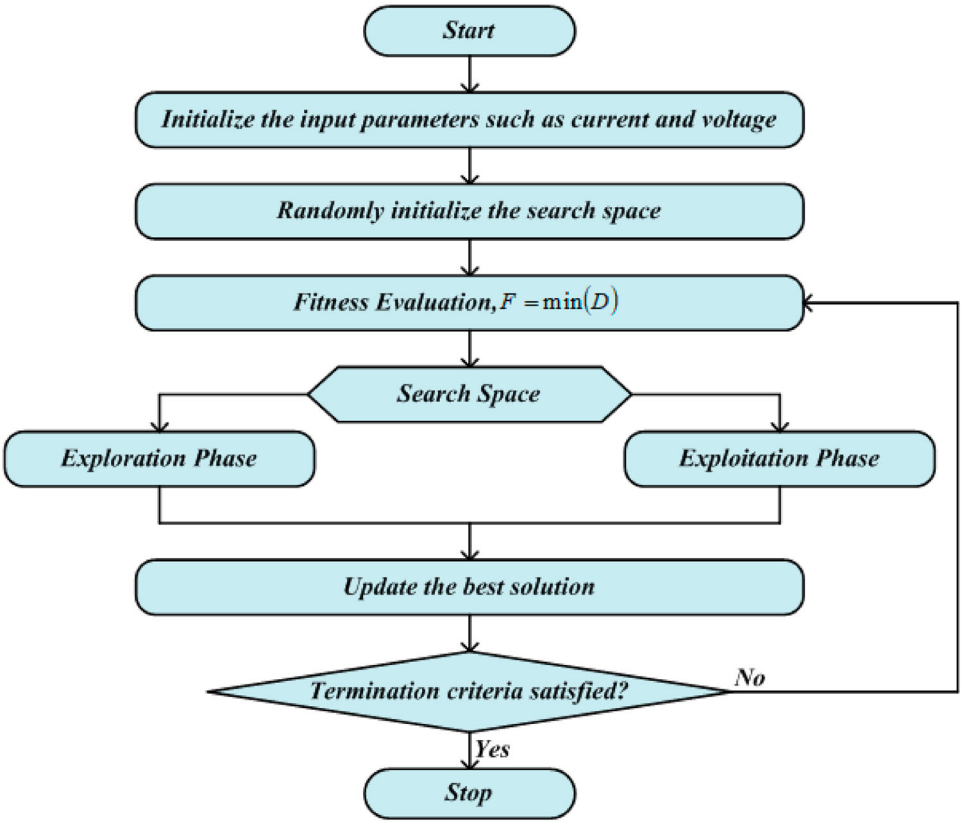


Figure 2: Flowchart of RPO algorithm

3.1 Red Panda Optimization Algorithm

The RPO algorithm is a nature-inspired metaheuristic optimization technique modelled after the foraging and movement behaviour of red pandas [20]. The goal of RPO is to optimize power distribution. The RPO algorithm flowchart is shown in Figure 2.

Step 1: Initialization

Begin by initializing varaiables, such as input voltage, current settings, population size, and bounds for each dimension of the solution space.

Step 2: Random Generation

A population of red pandas is initialized, each indicating a candidate solution

Step 3: Fitness Evaluation

The fitness of each candidate solution is evaluated using the total cost function:

$$F = \min(Cost_{Total}) \tag{7}$$

Step 4: Exploration Phase

The algorithm evaluates a wide range of possible power distribution scenarios under simulated driving conditions. This phase enables global search to avoid local optima. The candidate solution updates during this phase are modeled by:

$$x_i^{p1} : x_{i,j}^{p1} = x_{i,j} + r.(SFS_{i,j} - I..x_{i,j}) \tag{8}$$

here, x_i^{p1} is the i^{th} panda's new position, $SFS_{i,j}$ is the food source chosen, r specifies a random number in [0, 1], and I is an arbitrary from 1, 2.

These candidate strategies are then evaluated using the cost function, ensuring that only economically efficient configurations are promoted.

Step 5: Exploitation Phase

Once promising power allocation strategies are identified, the algorithm shifts to fine-tuning specific parameters. This phase focuses on minimizing total cost by refining candidate solutions.

$$x_{i,j}^{p2} = x_{i,j} + \frac{lb_j + r.(ub_j - lb_j)}{t} \tag{9}$$

here, t specifies the iteration counter, T specifies the maximum iteration, x_i^{p2} specifies the new location of the i^{th} red panda, lb and ub specifies the lower and upper bounds. This phase targets a local search to optimize specific variables affecting cost, such as power split ratio and fuel cell utilization.

Step 6: Update the Best Solution

After each iteration, the best solution found so far is retained and updated if a better solution with a lower cost emerges.

Step 7: Termination

Steps 3 through 6 are repeated until convergence is attained or the highest number of iterations is completed.

3.2 Dual Transformer Residual Network

While the RPO algorithm optimizes power distribution, an accurate prediction of fuel cell lifespan is equally crucial. To address this, the DTRN [21] is integrated into the EMSto accurately predict fuel cell lifespan. The token embedding module includes normalization, cascaded convolutions, and reshaping operations. Mathematically, the token embedding module's output is as Eqn. (10):

$$E_{out} = LN(\text{Re shape}(\text{Conv}(E_{in})), \tag{10}$$

here, the embedding's input and output are denoted by E_{in} and E_{out}, respectively and LN is layer normalization. Lastly, the operators for convolution and reshape are indicated by Re $shape$(.) and $Conv$(.).

The voltage imbalance's anticipated output is represented as Eqn. (11):

$$VI_{out} = Conv(c(Conv(VI_{in}))) \times S + VI_{in}, \tag{11}$$

where, VI_{out} and VI_{in} specifies the voltage imbalance's output and input, respectively. Moreover, $ReLu$ specifies the $ReLu$ activation function, and S is the residual scale.

4. RESULT AND DISCUSSION

The proposed EMS framework is evaluated through simulations in a MATLAB environment, assessing its impact on power distribution, energy efficiency, and fuel cell health.

As shown in Figure 3, the current applied reaches 23.5 A during 600–800 sec which was the highest before it peaks at 25 A after 3000 sec. Analysis of voltage is displayedin Figure 4. The measured voltage shown in Figure 4(a) peaks at 1800 sec going over 25 V. The estimated voltage as displayedin Figure 4(b) has a similar curve peaking at 1800 sec with a voltage touch above 25 V. Figure 5 presents the temperature analyses, showing an increase in measured temperature with applied current, reaching a peak of 47°C after 3000 sec. The estimated temperature follows a similar trend. Figure 6 illustrates hydrogen flow analyses, where flow increases with current, peaking at 5.1 SLPM between 600 and 800 sec and 5.4 SLPM after 3000 sec. Both measured and estimated hydrogen flow curves align closely.

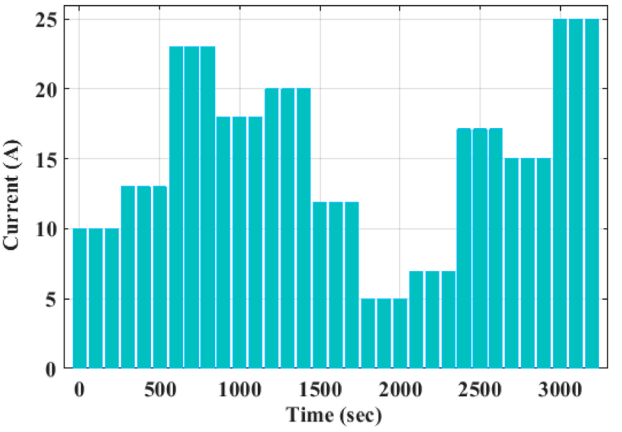


Figure 3: Analyses of current profile

Figure 7 presents the FCS model analyses. The applied current exhibits an initial peak of 16 A at 75 sec, as shown in Figure 7(a). The estimated voltage in Figure 7(b) shows an initial spike of 30 V at 0 sec, followed by a gradual decrease, eventually stabilizing around 25 V for the remaining duration. Figure 8 presents the highway fuel economy test, with speed rising from 6 m/s to 8 m/s with fluctuations. Requested power peaks at 2500 W at 300 sec but remains mostly below 1500 W. Figure 9 shows the supplied power in the proposed method, where FCS1 provides a maximum of 500 W within the first five minutes, and FCS2 supplies 300–500 W as needed. Figure 10 analyses the power supplied by FCS3 and FCS4. FCS3 is made to supply 400 W regularly with theoccasional requirement of 500 as depicted on Figure 10(a). Figure 10(b) depicts that following the initial delivery, no power is drawn from the FCS4. As shown in Figure 11, the proposed method convergesquickly 32 iterations, highlighting its better accuracy and efficiency in reducing error analysed to the existing techniques.

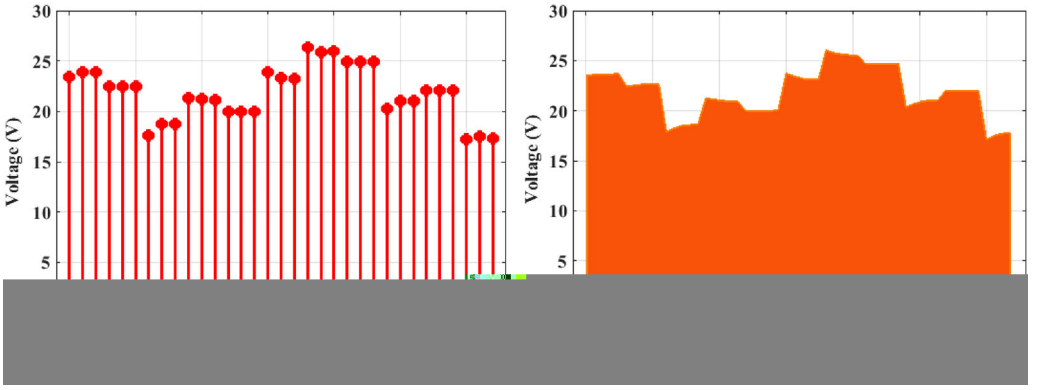


Figure 4: Analyses of voltage (a) measured (b) estimated

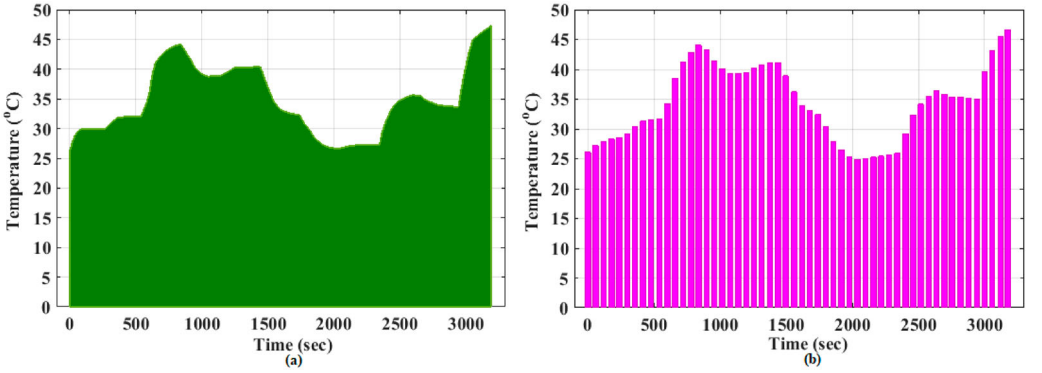


Figure 5: Analysis of temperature (a) measured (b) estimated

As shown in Table 1, the proposed technique achieves 97% efficiency with the lowest error of 0.148. The proposed approach has been comprehensively validated through a comparative study with both contemporary techniques like SAC, HHO-SCA, and TD3 and conventional methods like dynamic programming (DP) and PI Control. As indicated in Table 2, the proposed technique achieves the lowest hydrogen consumption of 87.28 g and the highest final SOC at 79.04%. Table 3 strengthens this superiority by showing that the proposed method also attains the lowest total cost of $0.60, outperforming both contemporary and conventional methods.

5. CONCLUSION

This study presented the RPO-DTRN based EMS to enhance the lifespan of the FCS by optimally managing the power distribution and predicting the remaining life of the fuel cell. The proposed strategy optimizes power distribution among the FCSs and a battery pack using battery SOC, requested power and fuel cell efficiency.

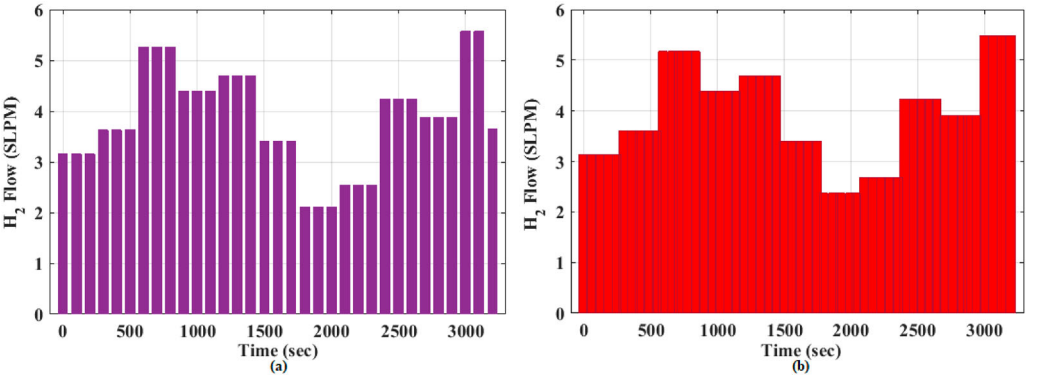


Figure 6: Analysis of hydrogen flow (a) measured (b) estimated

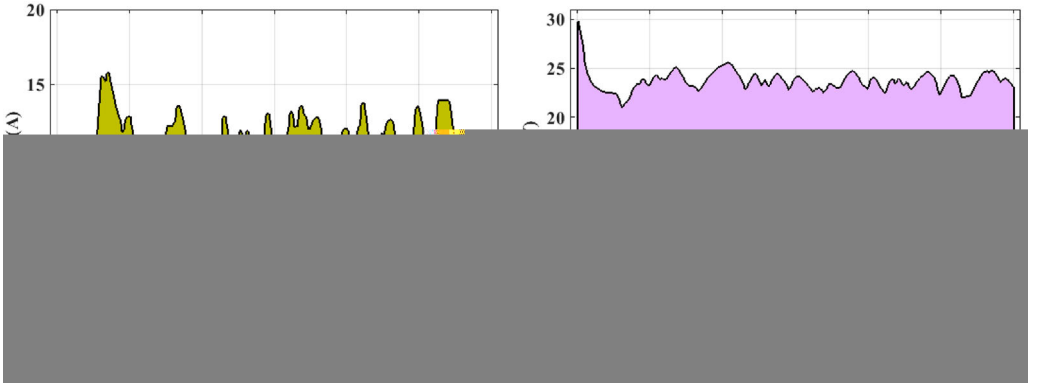


Figure 7: Analyses of FCS model results (a) applied current (b) measured temperature (c) estimated voltage

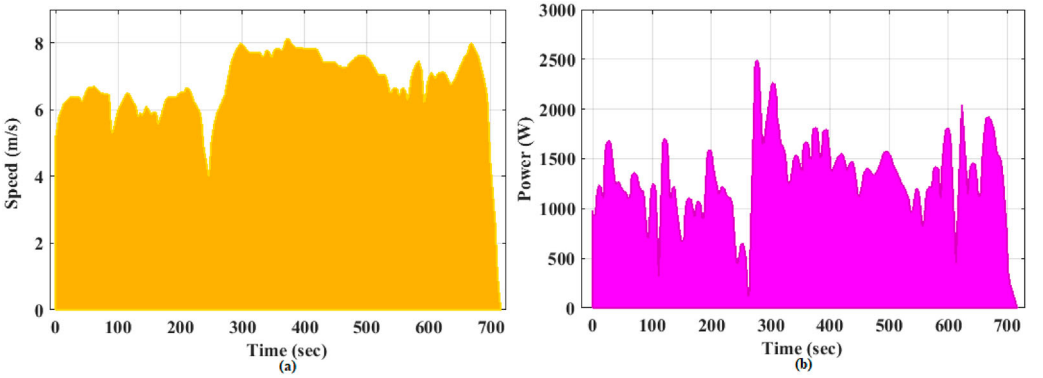


Figure 8: Analyses of highway fuel economy test (a) speed (b) requested power

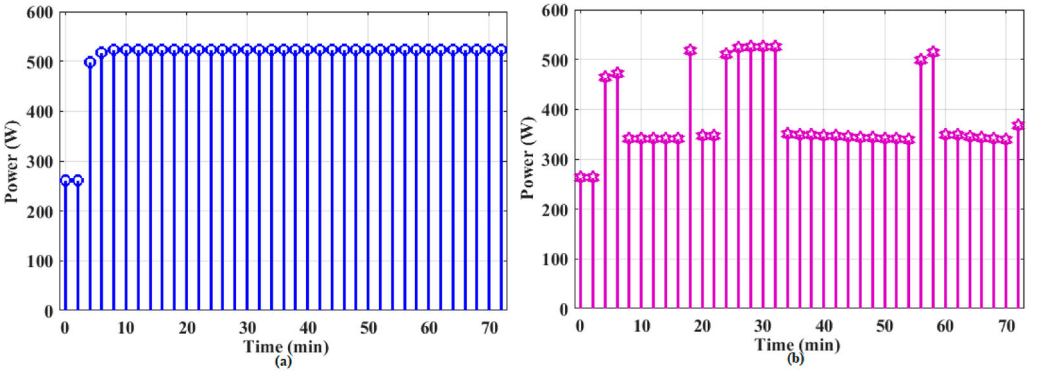


Figure 9: Analyses of supplied power in proposed method (a) FCS1 (b) FCS2

The proposed strategy's performance analysis is compared with various advanced and classical approaches, demonstrating its effectiveness. With an efficiency of 97%, the proposed strategy achieved the lowest H2 consumption of 87.28 g, while advanced methods like SAC consumed 92.61 g and classical PI control consumed 98.62 g. The reduction in H2 consumption reached up to 22.85%. Additionally, the final SOC of the battery pack is achieved to be 79.04% with an improvement up to 37.84% compared to the existing strategies. While the EMS improves fuel efficiency and component longevity, it does not explicitly model degradation dynamics or inter-stack coordination challenges essential to multi-stack FCHEV architectures. Future studies should focus on integrating a detailed aging model to find and mitigate degradation issues in FCHEVs. Additionally, designing a strategy based on control theory specifically for multi-stack FCHEVs can enhance system performance.

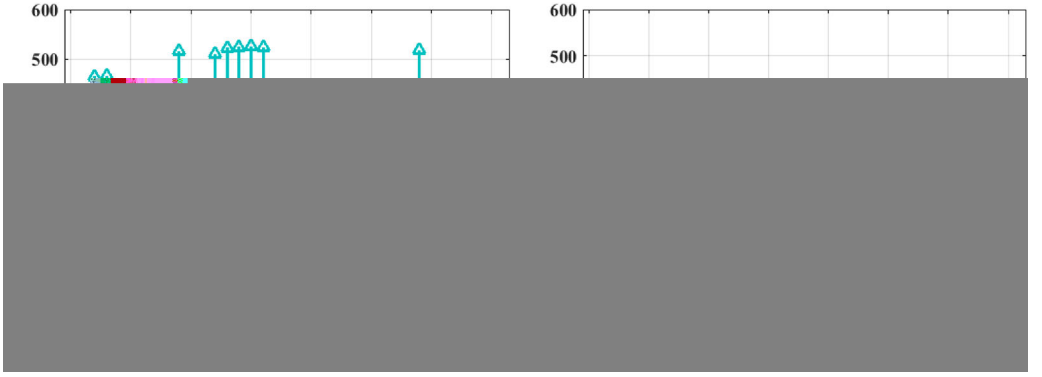


Figure 10: Analyses of supplied power in proposed method (a) FCS3 (b) FCS4

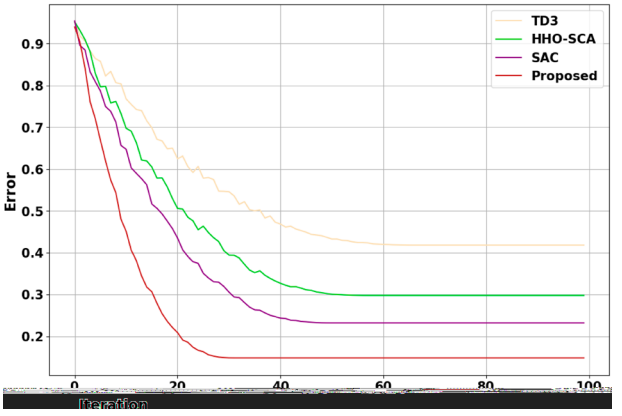


Figure 11: Comparison of convergence

Table 1: Comparison of error of proposed and existing methods

Methods	Efficiency	Error
Proposed	97	0.148
SAC [14]	86	0.232
HHO-SCA [11]	78	0.298
TD3 [12]	68	0.418

Table 2: Comparison of proposed method with advanced and classical methods.

Methods	H2 Consumption (g)	Final SOC
Proposed	87.28	79.04
SAC [14]	92.61	70.28
HHO-SCA [11]	95.22	68.43
TD3 [12]	97.86	61.18
DP	113.13	58
PI Control	98.62	57.34

DISCLOSURE STATEMENT

No potential conflict of interest was reported by the author(s).

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Table 3: Comparative analysis of cost

Work	Total Cost ($)
Proposed	0.60
SAC [14]	0.71
HHO-SCA [11]	0.68
TD3 [12]	0.79
DP	0.73
PI Control	0.94

DATA AVAILABILITY STATEMENT

This research is not eligible for data sharing since it does not generate or analyse any new data.

SUPPLEMENTARY MATERIAL

Supplemental data for this article can be accessed online at https://doi.org/10.1080/03772063.2025.2521671

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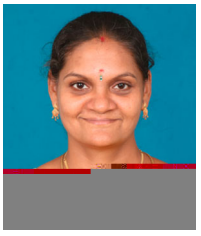
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APPENDIX

PARAMETERS

The fuel cell comprises 36 individual cells, delivering a rated power output of 500 W. It operates within a voltage range of 18–34 V and can support a maximum current of 27 A, ensuring efficient energy conversion and stable power supply. Complementing the fuel cell, the battery features a substantial capacity of 335 Ah and a nominal voltage of 8 V, contributing to energy storage and system reliability. The key parameters for RPO algorithm include a total of 100 iterations, allowing the algorithm to converge effectively, and a population size of 30, ensuring sufficient diversity in the search space.

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