Archives available at journals.mriindia.com

International Journal on Advanced Computer Engineering and Communication Technology

ISSN: 2278-5140

Volume 15 Issue 01, 2026

Energy Management System in Hybrid Electric Vehicle with Hydrogen Fuel Cell

[1]Surekha S., [2]Dr. S. Suthanthira

[1]PG Scholar, Department of EEE, Arunachala College of Engineering for Women, Manavilai, Vellichanthai

[2]ME., Ph.D., Assistant Professor, Arunachala College of Engineering for Women, Manavilai, Vellichanthai

Email: [1]Surekhasukumar2003@gmail.com

Peer Review Information

Submission: 08 March 2026

Revision: 26 March 2026

Acceptance: 05 April 2026

Keywords

Proton Exchange Membrane (PEM), Fuel Cell (FC), Buffer Storage Unit (BSU), Electric Vehicle (EV)

Abstract

The construction of a simulation model for the Energy Management (EM) of an Electric Vehicle (EV) hybrid traction drive based on fuel cells and lithium batteries in the MATLAB Simulink software environment is the focus of this paper. Battery and hybrid traction drive application topologies are taken into consideration. A traction drive model has been developed, where a fuel cell (FC) with a proton exchange membrane (PEM) serves as the primary energy source and a high-power buffer storage unit (BSU) based on a lithium-ion battery smoothens out the uneven transport load. Reduced to a ton of vehicle weight, the reliance of the necessary BSU capacity on the power of the primary source was found. This led to the determination of the ideal range of hybrid power plant characteristics (FC power from 5 to 11 kW/t, Lithium-Ion battery capacity from 6 to 10 Ah/t) when operating in accordance with the WLTC load cycle. In this instance, the period of included state of FC was 94.53%, and the computed fuel consumption was 0.56 kg/km-t.

Introduction

Hybrid drivers do not have to deal with time-consuming charging and a limited driving range. The vehicles refuel at regular fuel stations [1]. The range-extending technology of the car works without the driver even being aware of the continuously occurring changes. This invisible operation, paired with stable automobile performance, increases the acceptance of hybrid vehicles in the consumer marketplace [2]. HEV reduces pollution issues to some extent, but it remains associated with hybrid electric vehicles consisting of ICE and battery. Although the fuel efficiency of HEVs is continuously improving, environmental concerns remain unanswered as long as fossil fuels remain the primary energy source [3-4].

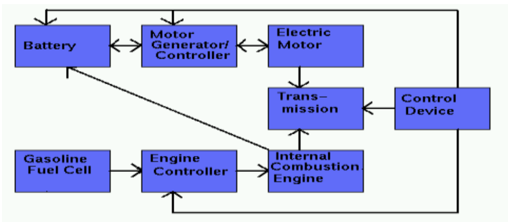

Fig. 1. Hybrid Electric Vehicle

Fuel cell vehicles (FCVs) are those hybrid vehicles that use fuel cells instead of ICE. A fuel cell is an energy conversion device that continuously converts chemical energy in a fuel into electrical energy, as long as both the fuel and oxidant are available [5-6]. It exhibits several advantages over the conventional combustion-based technologies and is currently applied in critical fields, such as electronics, housing power, power plants, passenger vehicles, and military applications [7]. The fuel cell operates at higher energy efficiency (40-60%) than traditional internal combustion engines, which operate at a lower efficiency of 30-40% . The name of the central control programme is “Energy Management”[8-9]. This EMS establishes an interaction link among the each motor and DC-DC Converter for managing power flow across powertrain mechanisms, as well as a communication link between the batteries to regulate the status of charge of each battery pack [10]. The EMS is used in electric vehicles to properly transfer power throughout the powertrain's modules and increase battery life by enhancing thermal stability. Enhanced power control tactics are needed since large super-capacitors are expensive [11].

These are utilised to regulate the performance and norms of the super-charge/discharge capacitor. Here, it is necessary to know the functioning voltage and current of the battery power, the group of battery power system, the super capacitor's initial charging condition, the super capacitor’s charging current, and the performance of the vehicle [12-13]. The strategies for control the speed and current, both of which are dependent on the time of the charging and dis-charging of the supercapacitor [14]. Fuel cells and batteries are energy sources which directly convert chemical energy into electrical energy [15]. Currently, fuel cells are accepted as one of the capable technologies to meet future energy generation requirements. In contrast to batteries, fuel cells generate electric energy instead storing it and continue to deliver it as long as the fuel supply is available. However, fuel cells have some well-known technical restrictions; they have poor efficiency in very low load demand, a slow dynamic response, and a high cost per watt. This is why fuel cells are not suitable alone in the FCEVs to fulfil the load requirements, mostly during start-up and transient conditions., supercapacitors present a higher power density but a lower energy density. In this paper, Energy Management System in Fuel Cell Hybrid Electric vehicle is proposed using fuzzy controller. The contribution of this paper is as follows:

- Fuel cell hybrid electric vehicle is analysed and studied. Based on the study and literature review on the sizing of FCHEV and energy management for FCHEV the following objectives are finalized.
- Develop a generalized methodology for sizing fuel cell and storage systems for fuel cell hybrid electric vehicles by creating design space for optimizing fuel cell and storage requirements.
- Design and simulate energy management algorithm for FCHEV Design and develop practical (dynamic) energy management algorithm for FCHEV and validate for sample route.

This paper's remaining sections are organized as follows. Literature review is explined in section II. The work's component modeling and methodology are provided in Section III. Mathematical modeling of proposed system is explined in section IV. Experiments and simulations are given in Section V and VI concludes with findings.

Literature Review

Panel Raghupathi et. Al. (2025) have presented an advanced energy management strategy for solar-assisted fuel cell hybrid electric vehicles (FCsingle bondHEVs), integrating lithium-ion battery storage, proton exchange membrane fuel cells (PEMFC), and photovoltaic (PV) panels. Furthermore, fuel cell degradation was effectively minimized to 0.04, a substantial reduction from 0.1 observed in suboptimal conditions. These results highlight the potential of integrating statistical modeling with bio-inspired optimization techniques to achieve intelligent, real-time energy management in FCsingle bondHEVs, leading to greater energy utilization, extended driving range, and improved component longevity.

Zhumu Fu et. al. (2025) have developed the Predictive energy management strategies (PEMS) for fuel cell hybrid electric vehicles (FCHEVs) in enhancing safety and energy efficiency. To improve speed prediction accuracy and balance multiple objectives in speed and energy co-optimization, a PEMS based on driving behavior identification is proposed for FCHEVs in car-following scenarios. Firstly, a hybrid model combining support vector machine and recurrent neural network is established to identify driving behavior more accurately. Secondly, considering the strong correlation between driving behavior and speed, a long short-term memory-based model is designed for accurate speed prediction of preceding vehicle. Thirdly, based on prediction results, to achieve a trade-off among multi-objective, multi-objective cost function with weight factors is established into the model predictive control-based PEMS. Simulation results show the proposed strategy reduces speed variation by 1.55%, equivalent fuel consumption cost by 12.16%, and power source degradation cost by 27.1% compared to baseline models.

Shufu Yuan et. al. (2025) have proposed a Q-learning reinforcement learning based adaptive dual MPC (QMPC) for FCHEV energy management and operation improvement. Specifically, Q-learning dynamically adjusts weights for dual MPC framework based on driving information, fuel cell state, and the battery state. Dual MPC comprises an upper-level optimizer for vehicle bus power distribution and a lower-level controller for fuel cell stack working. Simulation results under two standard cycles, compared with three benchmark EMSs, show that QMPC improves hydrogen economy by up to 17.8 % and achieves approximately 45 % fuel cell efficiency, with its practicality validated through real-time simulation.

Zhigen Nie et. al. (2025) have developed a novel predictive energy management architecture, which consists of the Extended Long Short-Term Memory (xLSTM) and Soft Actor-Critic (SAC). Moreover, at SOH = 90 %, the newly designed EMS reduces operational costs by 8.7 % and 10.7 % compared to conventional methods under the New European Driving Cycle and Worldwide Harmonized Light Vehicles Test Procedure, while decreasing FCS degradation costs by 17 % and 51 %, respectively. The innovative approach not only elevates energy efficiency but also prolongs FCS operational longevity via intelligent SOH-aware, which establishes a new paradigm for lifecycle-optimized energy management in FCHEVs.

Haochen Sun et. al., (2025) have presented a health- and behavior-aware two-layer hierarchical energy management framework using an improved adaptive parallel deep deterministic policy gradient (DDPG) learning algorithm for obtaining the optimal EMS of a multi-source FCHEV. In the upper layer, machine learning approaches are employed to recognize the real-time driver's behavior, and Pontryagin's minimum principle is applied to calculate the optimal equivalent factor of each driver's behavior. Simulation results show that, the EMS obtained by the proposed DDPG algorithm can achieve the highest fuel cell (FC) working efficiency (approximate to 56%), apparently reduce the degree of degradation of battery (BAT) from 0.42% to 0.28%, and achieve a reduction of 9.24% in terms of the total cost to use compared with deep Q network (DQN)-based EMS.

III.PROPOSED METHODOLOGY

A typical four-passenger vehicle powered by a polymer electrolyte membrane fuel cell with an energy storage system is considered for the present study. It is assumed that the PEMFC will generate the total energy demand of the electric drive from hydrogen stored onboard. Figure 2 shows the Proposed block diagram of energy management system in Hybrid electric vehicle.

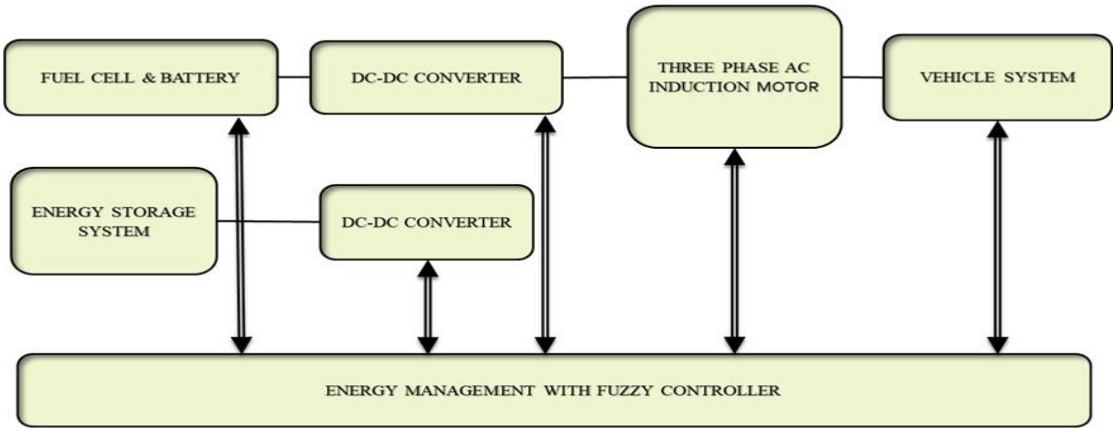

Fig. 2. Proposed block diagram of energy management system in Hybrid electric vehicle

When the power demand by the motor exceeds the nominal capacity of the fuel cell, the energy storage system will meet the deficit in the demand. During regenerative braking, energy is stored in ESS, whereas during acceleration ESS is brought into operation to meet the power demand. An energy management controller regulates the flow of energy from the fuel cell and ESS to maximize the fuel economy of the FCHEV.

Mathematical Modelling Of Proposed System

A. Energy management system

The Energy Management System (EMS) and the batteries which are known as Energy Storage System. For the creation of updated battery packs, advanced composite technologies and sources of energy are needed. Electric automobiles' acceleration and operating range are constrained as hydrocarbon fuel has a higher energy density than battery packs. They must operate on very little power, so an EMS is required to switch the flow of power and keep tolerable energy stores in the storing elements.

Knowing the current and voltage readings of the vehicle's devices allows you to determine the battery's state of charge. The following relationship is used to calculate the battery's state of charge:

$$SOE(t) = SOE(t0)\int_{t0}^{t}(P_e + P_d)dt \qquad (1)$$

Where Pe denotes the instantaneous power transferred from the accumulator to the electric motor, Pd denotes the power drawn by the vehicle's devices, and "t" is the time period during which the devices are operational. The battery pack state of charge (SOC) is defined as a discrete state variable along the distance as follows:

$$SOC(K+1) = SOC(K) - \frac{P(K)}{E_{Battery}}\Delta t(K) \qquad (2)$$

P is battery power, while $E_{battery}$ is the total energy of the battery pack. When the battery is discharging, P is positive (negative) (charging).
Because BEVs are propelled by an electric motor that works on energy deposited in a battery, practically all of the equipment in an EV relies on battery power to operate, as it does not have an internal combustion engine. Figure 3 shows a hierarchical map of the variables that affect how much energy an EV uses. Figure 3 shows an EV energy consumption's impacting aspects are depicted in a hierarchy.

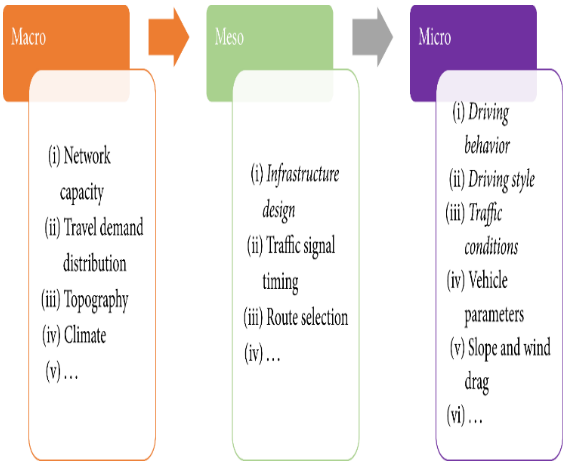

Fig. 3: EV energy consumption's impacting aspects are depicted in a hierarchy.

The energy consumed, E_{cons} is intended as a unit of distance (Wh/m) using the output power of (P_{bat})

$$E_{cons} = \frac{E_{bat}}{d} \qquad (3)$$

$$E_{bat} = \left(P_{b_{out}}(\tau)dr - P_{b_{in}}(\tau)dr\right).\frac{1}{3600} \qquad (4)$$

$$P_{b_{out}} = \frac{R_{Total}.V_{vehicle}}{\eta_{powertrain}} \text{ and } P_{b_{in}} = \alpha.P_{regan} \qquad (3.5)$$

where R_{Total} is the total resistance to vehicle motion in (N), $V_{vehicle}$ is the vehicle speed in (m/s), Distance travelled in meter is denoted by d, and E_{bat} is the battery energy output in (Wh). Powertrain efficiency, which includes the electrical motor, transmission, and power electronics, is the proportion of braking energy that can be recovered ($0 < a < 1$).

$$T_{Br-demanded} = \frac{X_{Bregan}.r_d}{G.\eta_G} \qquad (5)$$

$$P_{Br-demanded} = T_{Br-demanded}.\omega_{motor}(s) \qquad (6)$$

$P_{b_{out}}$ *and* $P_{b_{in}}$ are the power delivered by the battery for vehicle movement and the electricity reproduced to energize the battery in generator mode, taking into account electric motor braking capabilities.
The output power of battery (P_{bat}) is split into two parts:

- Vehicle propulsion power ($P_{b_{out}}$): In order to overcome resistance and any losses of power throughout the motor vehicle system, the battery must supply this power (Power out).
- Regenerative braking power ($P_{b_{in}}$): regenerative braking can recover some of the braking energy by running charging the battery while operating in generator mode (Power in).

B. Battery Model

Electric motor must generate driving force (FM) to overcome resistive force (Fv) and parallel component of weight on inclination (Fg) to cause movement. Equations describing force and speed of vehicle are

$$F_{M,k+1} + F_{v,k+1} + F_{Brk,k+1} + F_{G,k+1} = ma_{k+1} \qquad (7)$$

$$v_{k+1} = v_k + \Delta Ta_{k+1} \qquad (8)$$

$$v_{ref,k+1} + \Delta v_{k+1} = v_{k+1} \qquad (9)$$

State of charge of battery (SoC_B) can be estimated from current over time increment:

$$SoC_{B,K+1} = SoC_{B,K} + \frac{\Delta T}{Q_{B,Max}} I_{B,k+1} \qquad (10)$$

Depth of charge (DSC_B) is limited to 85%, and maximum discharge and charge rates are 6 and 2 times of specific capacity ($Q_{B,Max}$), respectively.

C. Motor driver model

DC machine is used to represent electric drive for the sake of simplicity. Motor voltage is a function of current and speed:

$$U_{M,k+1} = R_M I_{M,K+1} + \frac{K_w}{Nr_{wheel}} v_{k+1} \qquad (11)$$

where k is back-EMF constant, r_{wheel} is effective wheel radius and N is a gear ratio.
Propulsive force is expressed in term of current, linear speed and acceleration:

$$F_{M,k+1} = \frac{N}{r_{wheel}} M_{M,k+1} \quad (12)$$

$$F_{M,k+1} = \frac{N}{r_{wheel}} (K_M I_{M,k+1} - \frac{J_M N}{r_{wheel}} a_{k+1} - \frac{d_M N}{r_{wheel}} v_{k+1} \quad (13)$$

where k_m is torque constant which equals $k\omega$, J_m is inertia, d_M is damping value. Motor voltage is automatically limited by speed limit of EV on optimization level and saturated to maximum voltage ($U_{M,max}$) on component level. Maximum motor current on component level equals the ratio of maximum torque to torque constant ($M_{M,Max}/k_m$).

C. Hydrogen Fuel Cell (HFC) Model

Anode flow, cathode flow, power demand, and FC output-voltage are used as input-output data to determine and optimize the parameters of this HFC model.

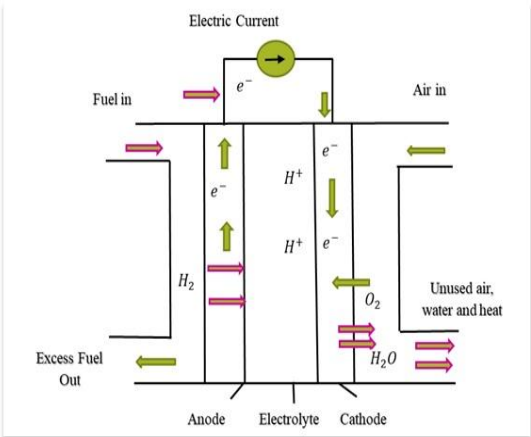

Fig. 4. HFC Model

Figure 4 shows the HFC Model. Activation, ohmic, and concentration overpotentials are taken into account in fuel cell designs as opposed to the voltage losses brought on by things like gas crossover. The suggested model, however, treats the partial voltage loss's impact on overall power conversion efficiency as a separate voltage loss.

By deducting various voltage losses from the thermodynamically predicted voltage, it is possible to derive the actual output voltage of. Consequently, the output voltage can be stated as:

$$E = E_{oc} - E_{ohm} - E_{act} - E_{con} - E_{leak} \quad (14)$$

where E = output voltage of the FC, E_{ohm} = ohmic overpotential, E_{act} = activation overpotential, E_{oc} = open-circuit voltage (OCV), E_{con} = concentration overpotential, and E_{leak} = voltage loss caused by the current leakage and so on.

The Gibbs free energy can be transformed into electrical energy to produce the reversible voltage E_{rev}:

$$E_{rev} = 1.229 - 0.9 \times 10^{-3}(T - 298.15) \quad (15)$$

Consequently, the Nernst equation can be used to determine the OCV:

$$E_{oc} = E_{rev} + \frac{RT}{2F} \ln\left(\frac{P_{H_2} \cdot \sqrt{P_{O_2}}}{P_{H_2O}}\right) \quad (16)$$

The electron conduction resistance $R_{electron}$ of the electrode and end plate and the ion conduction resistance R_{pro} in the membrane make up the majority of the ohmic overpotential E_{ohm}.

$$E_{ohm} = iR_{ohm} = i(R_{electron} + R_{pro}) \quad (17)$$

where i is the density of current. As seen below, the resistance can be computed:

$$R_{electron} = \rho \frac{l}{s} \quad (18)$$

wherein ρ is the efficient resistivity, l *and* s are the effective conductive path length and area, correspondingly. Based on the concept of a parallel circuit, it is possible to determine the total resistance of the electrode component:

$$\frac{1}{R_e} = \sum_{1}^{4\phi k} \frac{1}{R_O} \quad (19)$$

The overall electron conduction resistance can be further simplified to if the anode and cathode's structures and properties are equivalent:

$$R_{electron} = 2(R_e + R_r + R_p) \quad (20)$$

The membrane's ion conduction resistance, R_{pro} is:

$$R_{pro} = \int_0^{\delta_m} \frac{1}{\sigma_m(T)} dz = \frac{\delta_m}{\sigma_m(T)} \quad (21)$$

Where $\sigma_m(T)$ *is* the membrane's ionic conductivity as a function of temperature, is represented as,

$$\sigma_m(T) = \sigma_O \exp\left[1268\left(\frac{1}{303} - \frac{1}{T}\right)\right] \quad (22)$$

Where $\sigma_O = 0.005139\lambda - 0.00326$ *for* $\lambda > 1$. λ is the content of water in the membrane.

$$\lambda = 0.043 + 17.81a - 39.85a^2 + 36a^3 \quad (23)$$

$$\lambda = 14 + 1.4(a - 1), for\ 1 < a \leq 3 \quad (24)$$

Where a is the activity of water

$$a = \frac{X_{H_2O}P}{P_{sat}} \quad (25)$$

The voltage loss caused by current leakage and other factors is taken into account in the model that is being given. This voltage loss is especially noticeable in the low-current density range, especially as the current density gets closer to zero. Based on the thermodynamically ideal voltage, the voltage loss greatly lowers the OCV. Typically, the loss is around 0.15 V.

Results And Discussion

The energy manangent of an EV is developed with fuel cell systems using MATLAB Simulink software. Table I represents parameter specification of proposed work.

Table 1: Parameter Specification

Parameter	Specifications
Capacity of battery(Q)	77.75kWh
Capacity of vehicle (C)	200 units
Consumption rate of charge (h)	1 KWh/m
Charging rate of energy (g)	0.39s/kWh
Average driving speed	1m/s
Total gear box (g)	175.0914W
Wheel radius (R)	72
Vehicle mass (M)	43.99V
Vehicle frontal area (A)	$3.48m^2$
Motor traction torque (T)	247Nm

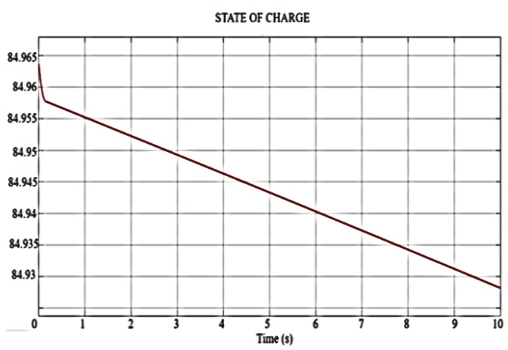

Fig. 5. State of charge waveform

Figure 5 depicts the battery state of charge waveforms, where the values of SOC attain 85% with respect to time. It illustrates Overcharging of the batteries can be avoided by keeping an eye on them while they are being discharged. If the batteries are depleted past the point when 100 percent of their capacity has been eliminated, the battery's life is reduced or the battery's ability to be charged is lost. Although this method is more expensive than the previous one due to the additional components and complexity, the battery life can be greatly extended and the battery can be used more efficiently.

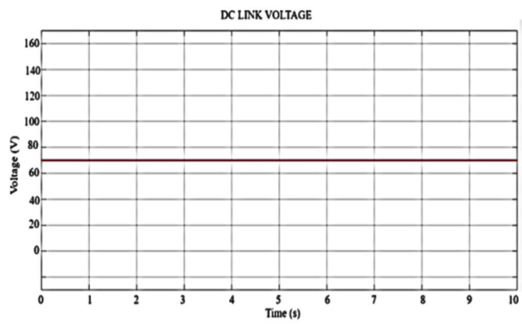

Fig. 6 DC Link Voltage

DC link voltage waveform is represented in figure 6, where the value of voltage is attained 70V with respect to time. The profile of the battery used in EVs directly affects the design features used for the charger. A battery with a big storage capacity necessitates the charger's high-power balancing capabilities. To stabilise the charging current and voltages, a Fuzzy logic Controller has been presented.

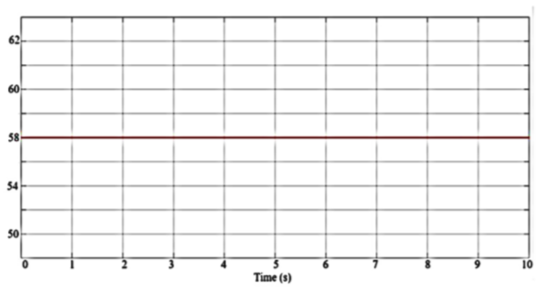

Fig. 7 Super Capacitor current waveform

Figure 7 depicts the supercapacitor current waveform, where the range of current attains 58A during the time period 10s.

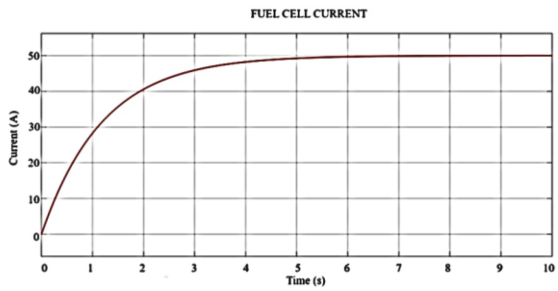

Fig. 8. Fuel cell current

Figure 8 depicts the current of a fuel cell, with the current reaching 50A over time. They don't emit any air pollutants that are harmful to health, and their greenhouse gas emissions are substantially lower. Fuel cells produce just heat and water as a by-product when pure hydrogen is used.

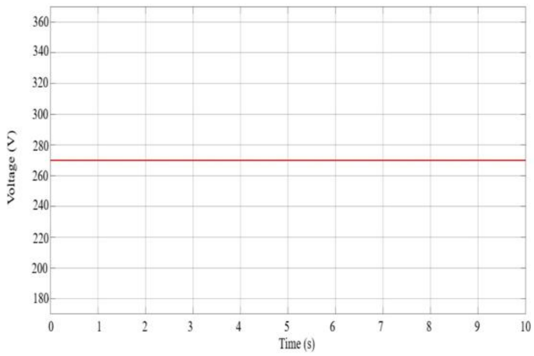

Fig. 9. Battery Voltage waveform

Figure 9 depicts the battery voltage waveform, where the rate is 270V with respect to time.

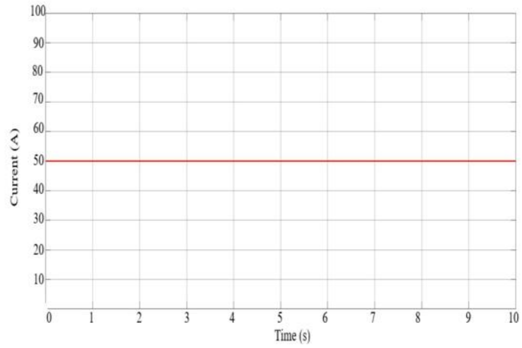

Fig. 10. Maximum battery current waveform

Maximum battery current waveform is represented in Figure 10, where the current is 50A with respect to time. When a rapid charge is required to deliver short-term energy, batteries are the ideal answer.

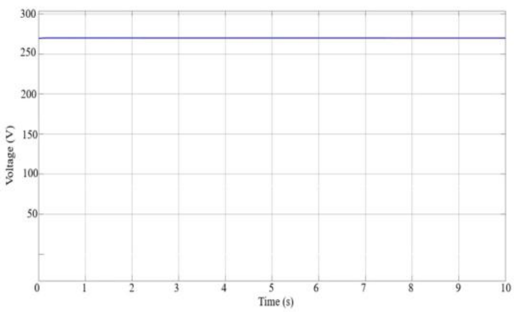

Fig. 11. Fuel cell voltage waveforms

Figure 11 depicts the Fuel cell voltage waveforms of Fuel cell a, where the magnitude of voltage attain 270V with respect to time.

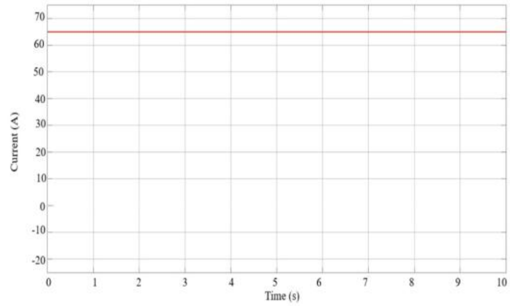

Fig. 12. Maximum Fuel cell current

Figure 12 depicts the maximum Fuel cell current waveforms of Fuel cell a, where the magnitude of current attain 65A with respect to time.

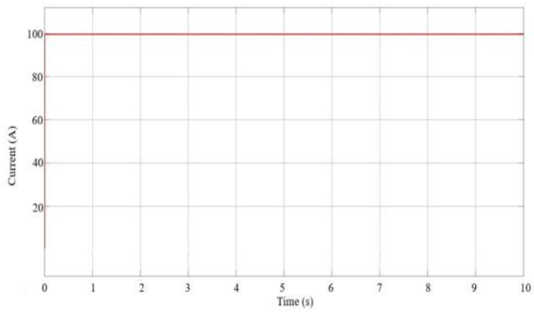

Fig. 13. Load current waveforms

Figure 13 depicts the Load current waveforms, where the magnitude of current attains 100A with respect to time.

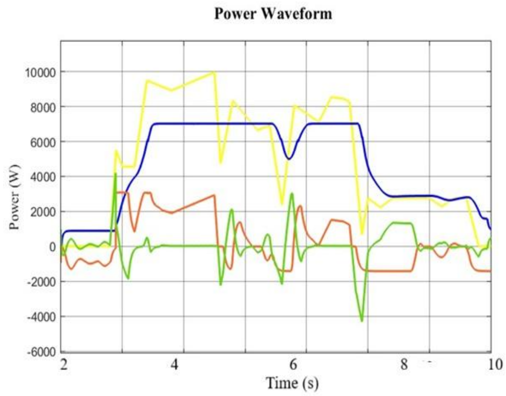

Fig. 14. Real and reactive power waveform

Power of load, Fuel cell, battery and ultra-capacitor are represented in figure 14 where the rate load power attain 9 Kw, power of fuel cell attain 7Kw, power of battery attain 3Kw, and the power of supercapacitor attain 1Kw.

Conclusion

To improve the power consumption of the gadgets from the battery, an optimal energy management system for electric vehicles with fractional order adaptive integral hierarchical sliding mode controller is proposed in this work. The battery power is used efficiently and appropriately through this method. EV cruised economically and had the lowest specific consumption under Fuzzy Logic Controller based EMS. The advantage of FLC Controller-based EMS over competing strategies is that optimal velocity is always established, resulting in minimal loss. This is significant on a worldwide scale since EVs will reduce CO2 and NOX emissions, lessening the environmental effect of vehicles. EV's Energy Management System is also important since it extends battery life, improves battery thermal stability, and improves powertrain component reliability and functional safety. MATLAB is used to acquire device simulation results in order to minimise battery power and to construct a controller area network channel for communicating device power usage. As a result, Fractional Order Adaptive Fuzzy Logic Controller based EMS achieves 95 percent efficiency, resulting in 94 % smooth electric car performance. Furthermore, this system can be made to work with different kinds of hybrid batteries that may be used in the future EV by simple modifications

References

Abbas M. Al-Ghaili;Hairoladenan Kasim;Naif M. Al-Hada;Bo Nørregaard Jørgensen; Marini Othman;Jihua Wang, 2021, “Energy Management Systems and Strategies in Buildings Sector: A Scoping Review” IEEE Access, Vol. 9

Achikkulath Prasanthi, Hussain Shareef, Rachid Errouissi, Madathodika Asna, Azah Mohamed, 2022, “Hybridization of battery and ultracapacitor for electric vehicle application with dynamic energy management and non-linear state feedback controller” Energy Conversion and Management: X, Vol. 15

Ahmad Alyakhni;Loïc Boulon;Jean-Michel Vinassa;Olivier Briat, 2021, “A Comprehensive Review on Energy Management Strategies for Electric Vehicles Considering sssssDegradation Using Aging Models” IEEE Access, Vol. 9

Amir Rezaei;Jeffrey B. Burl;Mohammad Rezaei;Bin Zhou, “Catch Energy Saving Opportunity in Charge-Depletion Mode, a Real-Time Controller for Plug-In Hybrid Electric Vehicles” IEEE Transactions on Vehicular Technology, Vol. 67, No. 11, pp. 11234 – 11237, Nov. 2018

Arian Zahedmanesh;Kashem M. Muttaqi;Danny Sutanto, 2021, “A Cooperative Energy Management in a Virtual Energy Hub of an Electric Transportation System Powered by PV Generation and Energy Storage” IEEE Transactions on Transportation Electrification, Vol 7, No. 3, pp. 1123 – 1133

Bo Wang;Payman Dehghanian;Shiyuan Wang;Massimo Mitolo, “Electrical Safety Considerations in Large-Scale Electric Vehicle Charging Stations” IEEE Transactions on Industry Applications, Vol. 55, No. 6, pp. 6603 – 6612, Dec 2019

Bo Zhao;Xiangjin Wang;Da Lin;Madison M. Calvin;Julia C. Morgan;Ruwen Qin;Caisheng Wang, 2018, “Energy Management of Multiple Microgrids Based on a System of Systems Architecture” IEEE Transactions on Power Systems, Vol. 33, No. 6, pp. 6410 - 6421

C. Kothai Andal, R. Jayapal, 2022, “Design and implementation of IoT based intelligent energy management controller for PV/wind/battery system with cost minimization” Renewable Energy Focus, Vol. 43, pp. 255-262

Christoforos Chatzikomis;Aldo Sorniotti;Patrick Gruber;Mattia Zanchetta;Dan Willans;Bryn Balcombe, “Comparison of Path Tracking and Torque-Vectoring Controllers for Autonomous Electric Vehicles”IEEE Transactions on Intelligent Vehicles, Vol. 3, No. 4, 2018

Chunhua Zheng;Weimin Li;Quan Liang, 2018, “An Energy Management Strategy of Hybrid Energy Storage Systems for Electric Vehicle Applications” IEEE Transactions on Sustainable Energy, Vol. 9, No. 4

Chunyang Qi, Chuanxue Song, Feng Xiao, Shixin Song, 2022, “Generalization ability of hybrid electric vehicle energy management strategy based on reinforcement learning method” Energy, Volume 250

Ephrem Chemali;Matthias Preindl;Pawel Malysz;Ali Emadi, 2016, “Electrochemical and Electrostatic Energy Storage and Management Systems for Electric Drive Vehicles: State-of-the-Art Review and Future Trends” IEEE Journal of Emerging and Selected Topics in Power Electronics, Vol. 4, No. 3, pp. 1117 – 1134

Haochen Sun, Jing Li, Chun Cheng, Suzhen Shi, Jing Wang, Jingjing Lin, Yang Liu, 2025, “Health-and behavior-aware energy management strategy for fuel cell hybrid electric vehicles based on parallel deep deterministic policy gradient learning", Engineering Applications of Artificial Intelligence, Volume 158, Part A,

Hiroshi Kikusato;Kohei Mori;Shinya Yoshizawa;Yu Fujimoto;Hiroshi Asano;Yasuhiro Hayashi;Akihiko Kawashima;Shinkichi Inagaki;Tatsuya Suzuki, 2019, "Electric Vehicle ent" IEEE Transactions on Intelligent Transportation Systems, Vol. 20, No. 7, pp. 2715 – 2727

Charge–Discharge Management for Utilization of Photovoltaic by Coordination Between Home and Grid Energy Management Systems" IEEE Transactions on Smart Grid, Vol. 10, No. 3

Hrvoje Novak;Vinko Lešić;Mario Vašak, 2019, "Hierarchical Model Predictive Control for Coordinated Electric Railway Traction System Energy Managem