Journal of New Materials for Electrochemical Systems
Vol. 28, No. 1, January 2025, pp 55-66
Journal homepage: https://www.newmaterials.ca/

Fractional order Adaptive Integral Hierarchical Sliding Mode Controller for Energy Management System in Electric Vehicles

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https://doi.org/10.18280/jnmes.v28i1.a06

Received: April 09-2024
Accepted: December 20-2024

Keywords:

Energy management, Electric vehicle, Electric motor, Battery pack, FOAIHSM .

ABSTRACT

Transportation is a major source of energy consumption and pollution in today's globe. Although electric vehicles appear to be viable solutions to these issues, their energy management systems are complex and need to be improved before they can be used widely. One of the major and most complicated concerns the globe has ever faced is reducing global warming gases produced by burning gasoline for transportation in vehicles. Electric vehicles, which are power-driven by an electric motor that runs on energy stored in a battery pack, were introduced in order to alleviate the environmental catastrophe caused by global warming. In this research, we have proposed the energy management system for electric vehicles (EMSEV) to stable the energy from the battery pack optimally. Moreover, a Fractional Order Adaptive Integral Hierarchical Sliding Mode Controller (FOAIHSM) has been designed for the smooth execution and energy management of EV in terms of output voltage regulation, reference generation, and smooth tracking of current. The proposed methodology incorporates total power inflow and state of charge of the power sources to satisfy load demands. Simulation results on MATLAB/Simulink have been used to verify the proposed controller's effectiveness. EMS based on Fractional Order Adaptive Integral Hierarchical Sliding Mode (FOAIHSM) Controller reaches 95% efficiency, resulting in smooth electric car performance of 94%. Experiments have been carried out more effectively to compare the results obtained with those of simulations.
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1. INTRODUCTION

The majority of the world's 1 billion passenger automobiles are powered by crude oil-derived fuel. By 2025, the population will have risen to 1.2 billion. To meet India's transportation demands, around 90 lakh liters of petrol and 4 lakh 50 thousand gallons of diesel are consumed annually [1]. Fossil fuel energy is the major source of greenhouse gas emissions, which has a significant impact on people and ecosystems all over the world. Automobiles are a big contributor to global warming, which has a negative influence on the planet's ecosystem [1]. Electric vehicles have piqued the interest of automakers and researchers in recent decades due to its efficiency in terms of power maintenance and emission reduction.

Electric vehicles (EV) depend heavily on energy management systems (EMS) to maximise fuel efficiency (energy optimisation control), increase battery life, and increase range. The energy management system, in general, tries to reduce power consumption while functioning inside the system without affecting driving compatibility. Traditional energy management techniques can result in a variety of pollution. Acid rain, greenhouse gases, and air pollution are a few of the more prevalent ones. Chemicals and particles are discharged into the atmosphere during the burning of fossil fuels. In electric vehicles, the accumulator is serious in distributing the essential energy to the electric motor for transit. The online monitoring and assessment of battery states is critical for the harmless and consistent functioning of batteries in electric cars. A Battery Management System can help with this (BMS). Aside from the BMS, the proper power flow between the converters, battery and other sections of the vehicle should be controlled. Energy Management System is the name of this control (EMS).

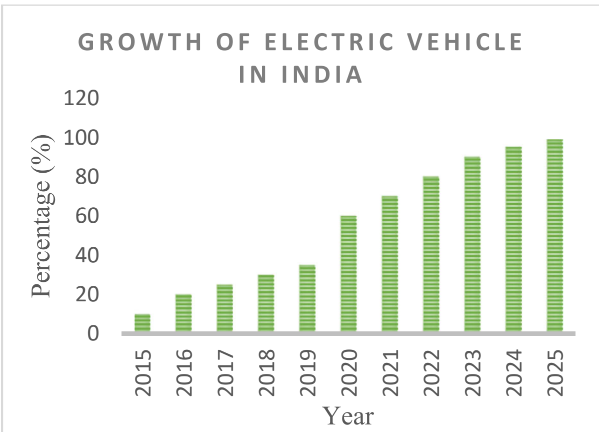

Figure 1: Growth of electric vehicle in India

Figure 1 depicts the growth of electric vehicles in India. The EMS' primary job is to connect with exterior mechanisms such as a power charger/inverter, environment-controlling devices, and controllers of systems. Among these interaction interfaces give users admittance to EMS data about the state and diagnostics, as well as the ability to change switching constraints. Apart from future developments in battery substantial and strategy, on-board energy management takes a critical role in achieving the intended cost, safety, performance, and trustworthiness standards. This contributes to electric vehicles' profitable achievement. An acceptable energy management system was proposed by C. Kothai Andal et al. [1] and integrated into a suitable platform. A significant benefit of this work is energy management in relation to IoT, including real-time device monitoring and control data processing. This project is using the Internet of Things to construct a smart control system that will remotely monitor power generated and consumed in order to manage produced energy across many Nano grids. A collection of multi-purpose sensors collect real-time data wirelessly, and they also transfer that data over a "Internet Connection" to numerous cloud servers where they are formatted appropriately. Achikkulath Prasanthi and coworkers[2], A non-inverted buck-boost H-bridge is suggested as the source side converter for effectively recovering the braking energy when connecting a parallel arranged multi-source system. For effective control of the EV, a detailed control design for the traction motor and converter is also offered. Additionally, the total control system incorporates an adaptive energy management method that takes into account power profile and dynamic source characteristics.

A real-time energy management system and electric vehicle optimisation technique based on deep long-term and short-term memory neural networks are proposed by Wenqi Zhu [3]. To manage large-scale electric vehicles in layers and regions, a three-tier architecture consisting of the power grid layer, regional energy management systems, and charging station energy management systems is first built. Next, a region station interaction strategy based on deep long-term and short-term memory neural networks is then proposed. A multi-criteria framework is created by Moein Moeini-Aghtaie et al. [4] to coordinate the charging habits of PHEVs on an energy hub platform. In this case, the ideal charging profiles are first noted and reported to the PHEVs Coordinator Entity (PCE) from the perspectives of both hub managers and PHEV owners. The PCE then employs an optimisation framework that considers a number of factors, such as the comfort of PHEV owners, the financial success of the energy hub, and the technical performance of the distribution grid, to produce the PHEVs' ideal charging schedules. When all the typical aspects of vehicle operation are incorporated to the reinforcement learning algorithm, the model will have a certain degree of generalizability, according to the initial analysis.

Chunyang Qi et al. [5] proposed from the state values of reinforcement learning in the state selection. Then, with the aid of the auxiliary agent, KL-divergence can be used to increase the reinforcement learning's reward value. Zhou, Huayanran, and others [6], This research proposes a machine learning approach based on a long short-term memory (LSTM) recurrent neural network (RNN) to arrange the charging and discharging of many EVs in prosumers of commercial buildings. The suggested system control structure allows for the separation of the offline and online stages of the LSTM algorithm. The LSTM is used to map states (inputs) to decisions (outputs) based on network training during the offline stage. Arian Zahedmanesh and colleagues [7], It is proposed to operate an integrated system as a virtual energy hub (VEH) that includes an electric transportation system with a battery-powered bus [electric bus (eBus)] charging station and an EV parking lot, integrated with solar photovoltaic (PV) generation, combined with a battery storage system (BSS), and powered by solar energy. A novel three-stage cooperative control system is used to schedule the active and reactive power flows as well as the economic functioning of the VEH in a cooperative decision-making (CDM) strategy. Agents are used in the development of a supervisory control system to implement the VEH's scheduled CDM and assign control parameters for the delivery of ancillary services. Based on the existing research, this paper examines the development of electric vehicles, batteries and energy management systems, different anode and cathode compounds being used battery packs, the parts of the powertrain and how they work, as well as a potential energy management system with Fractional Order Adaptive Integral Hierarchical Sliding Mode Controller (FOAIHSM).

The contribution of the paper includes:

i) To develop a better energy management system to assure a maximum lifetime of the battery.
ii) The energy management system involves the close monitoring of the individual battery modules of the battery pack to assure appropriate charging and discharging conditions.
iii) Demonstrate that the suggested controller responds quickly and robustly even when there is model uncertainty.
iv) Using MATLAB/Simulink to validate the proposed controller.

Paper is organized as follows, The first section explains why this project is needed and introduces the topic. The second section contains proposed method of this paper. Third section explains about mathematical modeling of Energy Management System. Section 4 contains the results of simulation studies as well as a discussion of the findings. Finally, Section 5 has the conclusion.

2. PROPOSED FRACTIONAL ORDER ADAPTIVE INTEGRAL HIERARCHICAL SLIDING MODE CONTROLLER (FOAIHSM) BASED ENERGY MANAGEMENT SYSTEM:

Electric vehicle energy management systems (EMS) are created to optimise power distribution across the propulsion parts and increase thermal stability, hence extending battery performance. Electric vehicle supplied equipment loads are controlled by joining, removing, raising, or decreasing the electric power to the grid using a devices for communication, a timers, a regulators, a monitors and other suitable device (s). An electrochemical capacitor is referred to as a ultra-capacitor or super-capacitor with extraordinarily high energy storage capacity contrasted to its volume when compared to other capacitor designs.

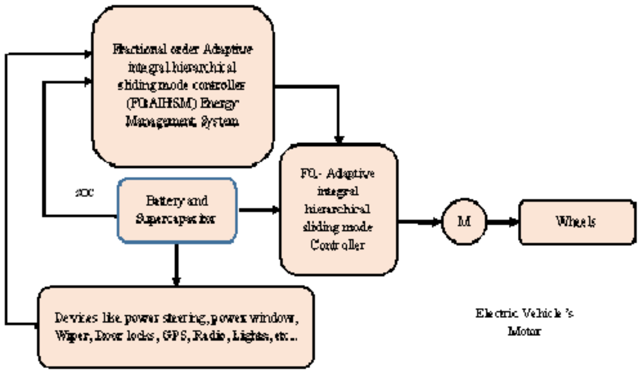

Figure 2: Proposed Fractional order Adaptive integral hierarchical sliding mode (FOAIHSM) Controller based EMS

The "power battery and super-capacitor" technology—which comprises a battery power assembly, power converter of capacitor, DC link, Ultra-capacitor, power converter of motor and traction motor—is the subject of this research. The total load capacity used by EV chargers is controlled by an EVEMS, allowing for maximum charging speeds without risking overloading the conductors or distribution equipment. When it comes to selecting an EVEMS, there are numerous alternatives. Some work mechanically, while others permit a user to control, monitor, and manage loads manually. Figure 2 represents the Proposed Fractional order Adaptive Integral Hierarchical Sliding Mode (FOAIHSM) Controller based Energy Management system. The battery is the ultimate source of power for the devices. Obviously, battery power will be reduced because these devices consume electricity when the car is in motion. To implement an efficient EM in electric vehicles, prior information of the devices' power usage is essential. The battery's state of charge (SOC) must be understood because it is one of the inputs used by the controller to determine which devices should be turned on utilising scheduling.

2.1 Proposed Fractional Order Adaptive Integral Hierarchical Sliding Mode Controller (FOAIHSM) Algorithm:

The goal of fractional order is to provide the control system's time and frequency responses greater flexibility, enabling it to deliver better and more reliable performance. Additionally, the fractional order prevents a deterioration in tracking accuracy. The adapters connected to the charging unit need to be correctly handled in effort to accomplish voltage stability at the transitional DC bus. The suggested adaptive integral hierarchical sliding mode controller keeps both integral hierarchical and sliding mode control capabilities (SMC). Integral hierarchical is a recursive technique to steady-state error minimization. SMC, on the other hand, is used to reduce a signal's convergence time and provide strength compared to transients in terms of load changes and circumscribed uncertainties. A nonlinear control technique known as sliding mode control (SMC) compels a nonlinear system to "slide" over a cross-section of its typical behaviour by delivering a discontinuous control signal (or, more precisely, a set-valued control signal). Table1 represents the parameters of SMC Controller.

Table 1: Parameters of SMC Controller

S.No	SMC Parameters	Value
1	K_D	0.9803
2	δ	1.6027
3	λ	2.334

The SMC method is made up of two parts: an analogous control portion that specifies how the system behaves if the trajectories continue to move over the sliding surface, and a adjustable erection regulator factor that drives the trajectories to influence the sliding surface and stay there forever. When the system is in the sliding mode, the following equation is satisfied:

$$s(t) = 0 \tag{1}$$

Therefore, when $S_{n-i} = 0$ is first reached at t_i^s, then

$$S_{n-i}(t) = D^{\alpha} S_{n-i-1} + D^{\alpha-1} \times \left(\beta_{n-i}^{1} S_{n-i-1} + \beta_{n-i}^{2} |S_{n-i-1}|^{\rho}\, sgn(S_{n-i-1})\right) = 0 \tag{2}$$

$$D^{\alpha} S_{n-i-1} = -D^{\alpha-1} \times \left(\beta_{n-i}^{1} S_{n-i-1} + \beta_{n-i}^{2} |S_{n-i-1}|^{\rho}\, sgn(S_{n-i-1})\right) \tag{3}$$

After simple calculations, we have

$$dt \le -\frac{d|S_{n-i-1}|}{\beta_{n-i}(|S_{n-i-1}| + |S_{n-i-1}|^{\rho})} = -\frac{|S_{n-i-1}|^{-\rho} d|S_{n-i-1}|}{\beta_{n-i}(|S_{n-i-1}|^{1-\rho} + 1)} = -\frac{1}{\beta_{n-i}(1-\rho)} \cdot \frac{d|S_{n-i-1}|^{1-\rho}}{(|S_{n-i-1}|^{1-\rho} + 1)}$$

Taking integral of both sides in above equation from t_i^s to t_{i-1}^s and knowing $S_{n-i-1}(t_{i-1}^s)$, we have

$$t_{i-1}^s - t_i^s \le -\frac{1}{\beta_{n-i}(1-\rho)} \int_{S_{n-i-1}(t_i^s)}^{S_{n-i-1}(t_{i-1}^s)} \frac{d|S_{n-i-1}|^{1-\rho}}{|S_{n-i-1}|^{1-\rho} + 1} = -\frac{1}{\beta_{n-i}(1-\rho)} \ln(|S_{n-i-1}|^{1-\rho} + 1) = \frac{1}{\beta_{n-i}(1-\rho)} \ln(|S_{n-i}(t_i^s)|^{1-\rho} + 1 \tag{4}$$

Therefore the variable S_{n-i-1} will converge to zero in the finite time

$$T_{i-1} \le \frac{1}{\beta_{n-i}\,(1-\rho)} \ln(|S_{n-i}(t_i^s)|^{1-\rho} + 1) + t_i^s \tag{5}$$

The stability of the Lyapunov function can be ensured by using algebraic simplifications if $|\sigma| \ge |\gamma|$:

$$v_1 = \emptyset S_1^2 \tag{6}$$

The Lyapunov function's stability ensures precise voltage controller on the DC bus. Moreover, the signum function utilised causes excessive chattering, so a different function, namely the saturation function, is used. The rationale for the sat function's specific use is its steadily rising reaction, which is defined as:

$$sgn(S_1) = \frac{S_1}{|S_1| + \mu_1} \tag{7}$$

where 1 denotes the EV's isolated operating territory. Furthermore, the Lyapunov function is only stable if the errors related with supercapacitor and battery current are kept to a minimum. Here are the errors that correspond to them:

$$e_3 = x_4 - x_{4ref} \tag{8}$$

$$e_4 = x_5 x_{5ref} \tag{9}$$

The following PI controllers are utilised to reduce errors e_3 *and* e_4 to zero and provide current monitoring of the power sources:

$$U_{23} = k\rho_1 e_3 + ki1 \int e_3 dt \tag{10}$$

$$U_{45} = k\rho 2 e_4 + ki2 \int e_4 dt \tag{11}$$

$$x_4 = -\frac{V_{sc}}{V_{bat}} x_5 + \frac{x_6}{V_{bat}} I_o - \frac{x_6 C_{dc}}{V_{bat}} \varphi S_3 - \frac{x_6 C_{dc}}{V_{bat}} \beta_2 - \sigma \frac{S_3}{|S_3| + \mu_3} \tag{12}$$

Finally, the battery current reference can be obtained with a reliable integral backstepping controller and is reported by Equation (12). Furthermore, because the state variables x4 and x5 may be observed directly utilizing physical equipment, an observer is not required for simulation training. Furthermore, state observers will be developed to eliminate human error, but at the penalty of greater computing cost.

3. MATHEMATICAL MODELLING OF PROPOSED SYSTEM

3.1 Battery Model:

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. There will be tactics used for the processes of creation, preservation, dissemination, and consumption of electric power. Since deep-cycle batteries are designed to supply electricity for longer durations, electric vehicle battery packs differ from beginning, lights, and ignition (SLI) packs. Lighter and smaller batteries are favoured because they reduce vehicle mass and hence improve efficiency; Electric car batteries stand out thanks to their ratio between power and mass, greater specific energy and high - power density. Modern battery topologies often have a lower specific energy than liquid fuels, which affects the possible all-electric range of the vehicles. An electric car is powered by a battery. If the battery is entirely discharged without being charged, the vehicle's performance suffers. Although EVs have battery monitoring systems, and just keep track of the battery's ability and do not optimise power utilisation. This research tries to reduce the amount of electricity used by the battery to power all of the vehicle's components.

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:

$$SOE(t) = SOE(t0) \int_{t0}^{t} (P_e + P_d) \tag{13}$$

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:

$$SOC(K+1) = SOC(K) - \frac{P(K)}{E_{Battery}} \Delta t(K) \tag{14}$$

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. Several factors influence vehicle energy consumption, which can be categorized into two groups [7, 8]: (a) inner factors related to the vehicle and (b) external factors related to driving conditions. The impact of all elements must be thoroughly investigated in order to construct an exact EV energy consumption estimation model, because slope of road, for example, has a significant effect. External factors show a wide range of variability when it comes to real-world driving situations. Based on their both uncertainty and flexibility, they are categorised into three groups: stable, dynamic but forecastable, and tough to anticipate. Figure 3 shows a hierarchical map of the variables that affect how much energy an EV uses.

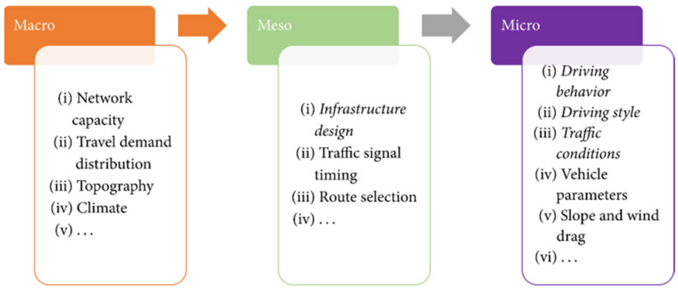

Figure 3: EV energy consumption's impacting aspects are depicted in a hierarchy.

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

$$E_{cons} = \frac{E_{bat}}{d} \tag{15}$$

$$E_{bat} = \left(P_{b_{out}}(\tau)dr - P_{b_{in}}(\tau)dr\right) \cdot \frac{1}{3600} \tag{16}$$

$$P_{b_{out}} = \frac{R_{Total} \cdot V_{vehicle}}{\eta_{powertrain}} \text{ and } P_{b_{in}} = \alpha . P_{regan} \tag{17}$$

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 ($0 < a < 1$).

$$T_{Br-demanded} = \frac{X_{Bregan} \cdot r_d}{G . \eta_G} \tag{18}$$

$$P_{Br-demanded} = T_{Br-demanded} \cdot \omega_{motor}(s) \tag{19}$$

$P_{b_{out}}$ *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).

3.2 Battery Pack 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

$$F_{M,k+1} + F_{v,k+1} + F_{Brk,k+1} + F_{G,k+1} = ma_{k+1} \quad (20)$$
$$v_{k+1} = v_k + \Delta \mathrm{T} a_{k+1} \quad (21)$$
$$v_{ref,k+1} + \Delta v_{k+1} = v_{k+1} \quad (22)$$

Battery voltage can be estimated using equation,

$$U_{B,K+1} = U_{B0} + R_B I_{B,k+1} + A_B e^{-B_B Q_{B,Max}(1-SoC_{B,k+1})} - \frac{K_B}{SoC_{B,k+1}}\left(Q_{B,max}\left(1-SoC_{B,k+1}\right)\right) \quad (23)$$

where U_{B0} is constant voltage, R_B is internal resistance, A_B is amplitude of exponential zone, B_B is the inverse exponential zone time constant, $Q_{B,max}$ is maximum capacity, KB is polarisation constant. As battery charge changes slowly over time it is able to replace $SoC_{B,max}$ in exponential term and in denominator of the last term with $SoC_{B,K}$. State of charge of battery (SoC_B) can be estimated from current over time increment:

$$SoC_{B,K+1} = SoC_{B,K} + \frac{\Delta T}{Q_{B,Max}} I_{B,k+1} \quad (24)$$

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.

3.3 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:

$$U_{M,k+1} = R_M I_{M,K+1} + \frac{K_w}{N r_{wheel}} v_{k+1} \quad (25)$$

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:

$$F_{M,k+1} = \frac{N}{r_{wheel}} M_{M,k+1} \quad (26)$$

$$F_{M,k+1} = \frac{N}{r_{wheel}}(K_M I_{M,k+1} - \frac{J_M N}{r_{wheel}} a_{k+1} - \frac{d_M N}{r_{wheel}} v_{k+1} \quad (27)$$

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 $(M_{M,Max}/k_m)$.

3.4 Energy Management Strategies

A centralized power system is necessary after the expansion of BMS and vehicle motor devices to supply the ratio of a wheel's adhesive friction to its outer layer's motive force, such as it is between the road and vehicle's wheels, and to determine which pack should receive power during regeneration.

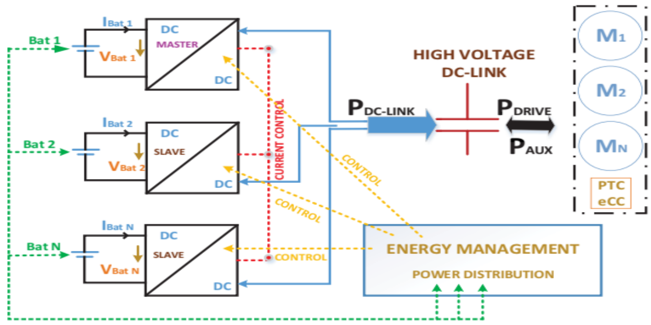

Figure 4: Effective energy transfer between the powertrain elements and the energy management system

The name of the central control programme is "Energy Management". 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. Figure 4 depicts the ideal power flow between the powertrain elements and an EMS. 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. 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. 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 are discussed in the sections that follow.

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3.4.1 Current Restrained Control Strategy

An electric vehicle's load current changes wildly during accelerating, braking, and downgrading. The super-capacitor enhances the battery's working condition and lengthen its operating safety while the load current extends the threshold charging or discharging current that the battery can sustain. The operational current of the battery is:

$$I_b = I_L + I_C \quad (28)$$

I_c is supplied by a supercapacitor through a Buck-Boost converter, whereas I_L is the load current. To restrict the operating current of the power battery, the following requirements must be met:

$$-I_b^N \leq I_b \leq I_b^p \quad (29)$$

Where I_b^N is the power battery's maximum charging current and I_b^b is its maximum discharging current,

$$I_b^N = -K_1 C_n \quad (30)$$

$$I_b^p = K_2 C_n \quad (31)$$

Where C_n is the battery's nominal capacity, A- h is the maximum charging rate of the battery, and k_1 is the maximum dis-charging rate of the battery. Equations (30) and (31) provide the following relationship:

$$-I_b^N - I_L \leq I_c \leq I_b^p - I_L \quad (32)$$

The current limitation control strategy uses the Buck-Boost circuit to maintain I_C within the desirable range.

Table 2: primary attributes of the instance a fluctuating load and a 400 volt-regulated output voltage.

S.No	Description	Value
1	Capacity of battery (Q)	77.75kWh
2	Capacity of vehicle (C)	200 Units
3	Consumption Rate of energy (h)	1 kWh/m
4	Charging Rate of battery (g)	0.39s/kWh
5	Average driving speed	1 m/s
6	Total gear box (a)	10a
7	Wheel radius (R)	0.36m
8	Vehicle mass (M)	3904Kg
9	Vehicle frontal area(A)	3.48m^2
10	Motor traction torque (T)	247Nm

3.4.2 Speed Restrained Control Strategy

The speed of the vehicle is also significant since it has an immediate effect on the super-condition capacitor. The ultra-capacitor should be completely energized and permitted to de-energized when the electric car starts up for greater-performance momentum. The ultra- capacitor should have less energy stored because the electric car is moving quickly in order to acquire regenerative power used when braking. Another crucial signal is the rate of the traction battery. The traction battery can only store so much energy after it is fully charged. Throughout real-world driving, current flow from the regenerative cycle is permitted while the ultra-capacitor is not powered up. The amount of energy deposited in the supercapacitor is comparative to the square of the applied voltage (Uultr), which may be changed using the IGBT PWM regulator.

The goal of the energy management approach is to safeguard the suitable quantities of energy are stored in the super-capacitor and that the ultra-capacitor is constantly operating at the correct level of charge. It works like a solid-state flywheel, delivering and absorbing energy in real time to and from the system. The vehicle's current speed and discharge surface are used in all computations for the control strategy (DOD). The control strategy of speed and current are combined in the integrated control strategy.

4. SIMULATION RESULTS AND DISCUSSIONS

In this section, MATLAB/Simulink has been used to verify the performance of the suggested controller. The goal of the complete arrangement is to guarantee the EV's reliable functioning and effective performance. A genetic gain estimation-based technique was utilised to get the gains needed for fine-tuning the suggested controller. Voltage controller at DC bus, current tracking, profile of vehicle load and SOC of the contributory sources are the outcomes of the simulation study. The simulation is run for 350 seconds.

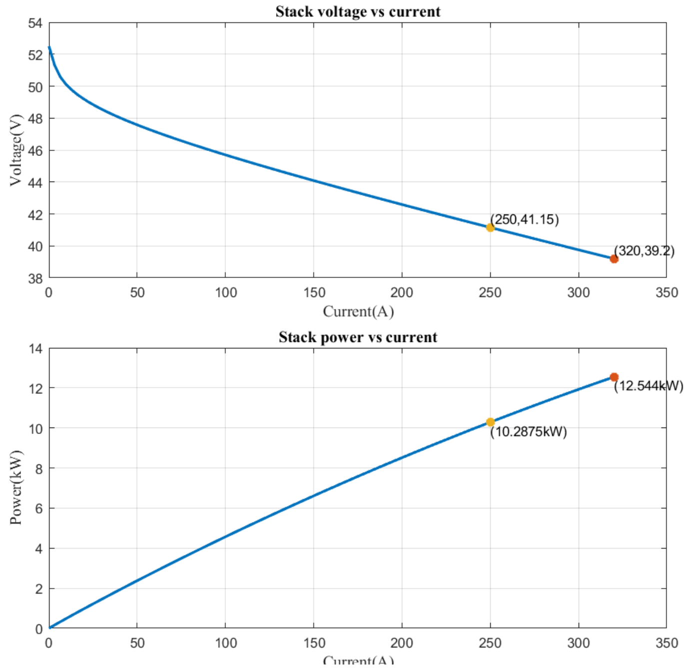
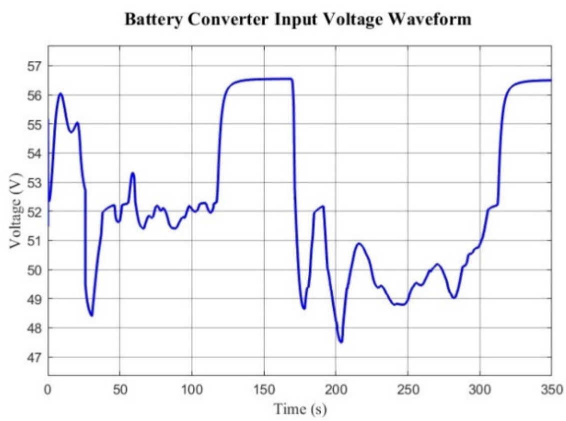


Figure 6: Stack Voltage Vs Current and Stack power Vs Current Waveform

Figure 6 shows the waveforms of stack power and voltage, where the values of power attain 12.544Kw and voltage attain 39V with respect to time. When the voltage of battery reaches its reference value of 48V during the stage of CC, the current of battery stabilises at 10A. At this same moment, the CV stage commences, and the battery current starts to decrease. The battery's internal voltage rises progressively during the stage of CC until it influences its reference value of 48V. After that, it doesn't change for the duration of the CV stage or until the battery is fully energized to a safe level.



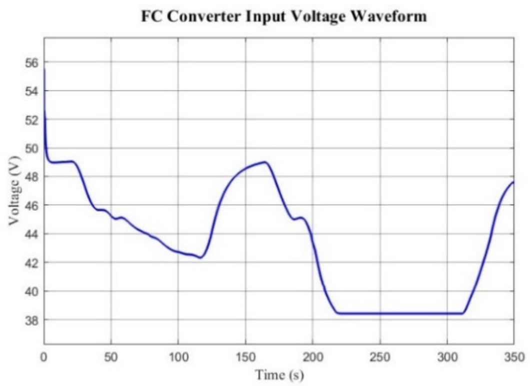
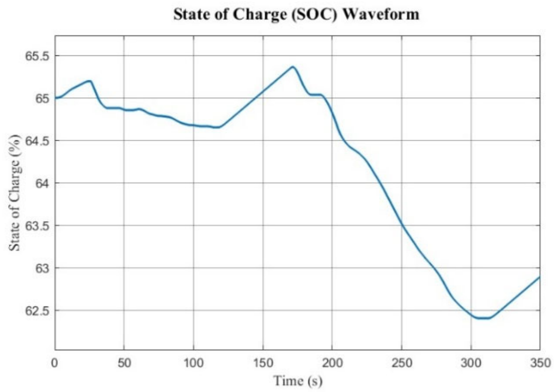
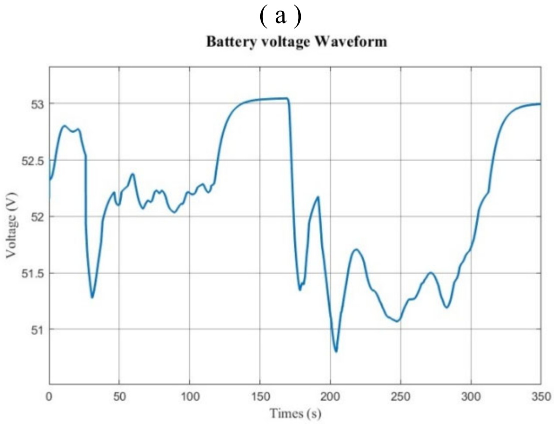


Figure 7 (a,b) : Input voltage waveform for Battery and Fuel cell Converter

Figure 7 (a,b) depicts the battery and fuel converter input voltage waveforms, where the values of voltage attain 56.5V and 39 V 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.



(a)



(b)

Figure 8 (a,b): Battery voltage and current Waveform

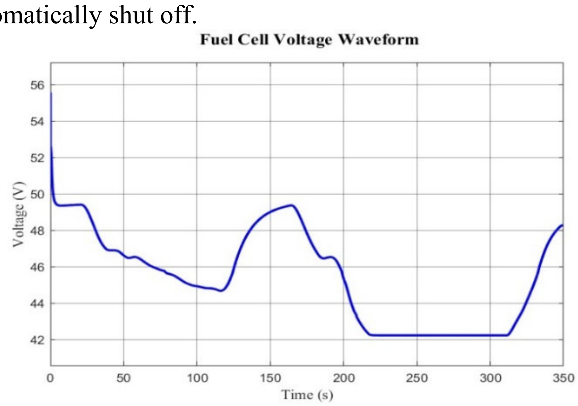
Battery current and voltage waveform is represented in figure 8 (a,b), where the value of current is attained 60A and the value of voltage is attained 53V with respect to time. The profile of the battery used in EVs directly affects the design features used for the charger. A battery with a big storage capacity necessitates the charger's high-power balancing capabilities. To stabilise the charging current and voltages, a FOAIHSM Controller has been presented.

Figure 9 depicts the state of charge, where the range of state of charge is 65.4 % during the time period 150-200s. The defective batteries can be identified when the batteries in the pack are monitored individually. This keeps other good batteries from deteriorating.

Figure 9: Battery State of Charge Waveform

A single defective battery can dramatically reduce the pack's performance. The performance can be enhanced by replacing the problematic batteries with the good ones in the pack. The tracking system allows for the charging and discharging of specific batteries within the pack. Regulated charging provides total charging of each battery in the pack. Individual batteries can be charged and monitored separately, so each battery may be fully charged. Because each battery is handled separately and depends on its state of charge, the charging time for each battery can vary (SOC).

Table 3 shows how long it takes a battery to charge from empty to full which illustrates the batteries were charged separately and in groups (connected in series) to assess the battery performance. The batteries were repeatedly charged and discharged to observe any differences in performance between batteries charged singly and in groups. An initial 7 amps of steady current was used to charge the batteries. H began to charge as a constant voltage charge after the voltage across the battery pack (14 batteries) hit 200 volts. The constant current charge mode began when the current dropped to less than 1 amp. When the batteries were fully charged (just a very small current flowed into the battery), the chargers automatically shut off.



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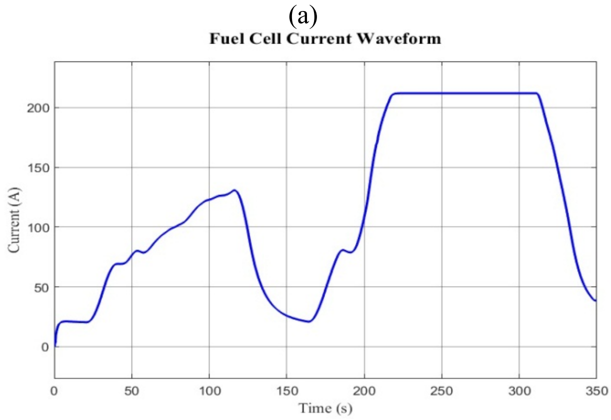


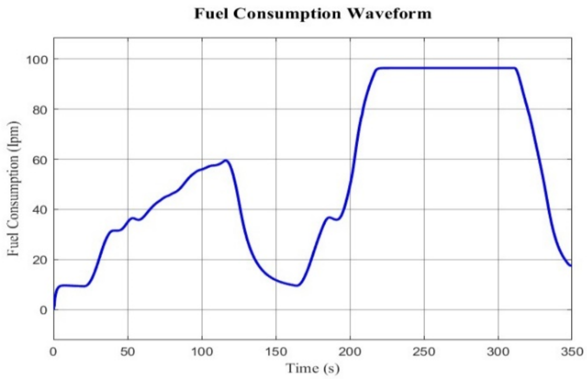
(b)

Figure 10 (a,b): Fuel cell current and Voltage waveform

Figure 10 (a,b) depicts the current and voltage waveforms of a fuel cell, with the current reaching 220A and the voltage reaching 52V 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.

Table 3: Duration of battery charging from empty to full

			Charge duration between empty and full				
S.No	Battery	Range (miles) approx..	3.7kW	7kW	22kW	50kW	150kW
1	90kWh	275	30 hrs	13 hrs	13 hrs	1.5 hrs (0-80%)	45 mins (0-90%)
2	80kWh	270	25 hrs	12 hrs	10 hrs	2 hrs	1.5 hrs
3	75kWh	238	21 hrs	11 hrs	5 hrs	2.5 hrs	1 hr
4	95kWh	235	31 hrs	13.5 hrs	4 hrs	1.5 hrs (0-80%)	30 mins (0-80%)
5	33kWh	146	11 hrs	4.5 hrs	3 hrs	35 mins (0-80%)	N/A
6	40kWh	143	11 hrs	6 hrs	6 hrs	1 hr	N/A



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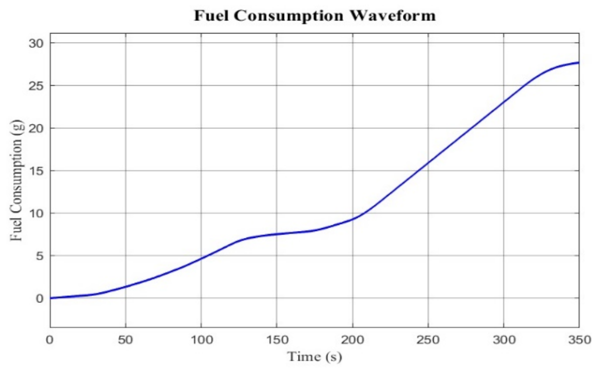
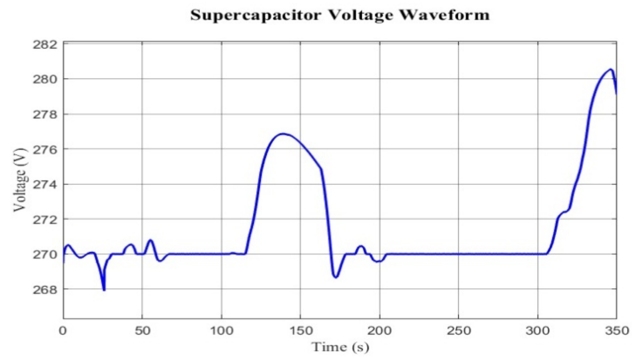


(b)

Figure 11 (a,b): Electric vehicle's fuel consumption Waveform

Figure 11 (a,b) depicts the rate of fuel consumption in an electric vehicle, where the rate is 90 Ipm with respect to time. In a fuel cell vehicle, no gasoline is burned. Because hydrogen is the primary source of energy, no carbon emissions are produced. The tailpipe emits only water and heat. This contributes to environmental protection and the battle against global warming.



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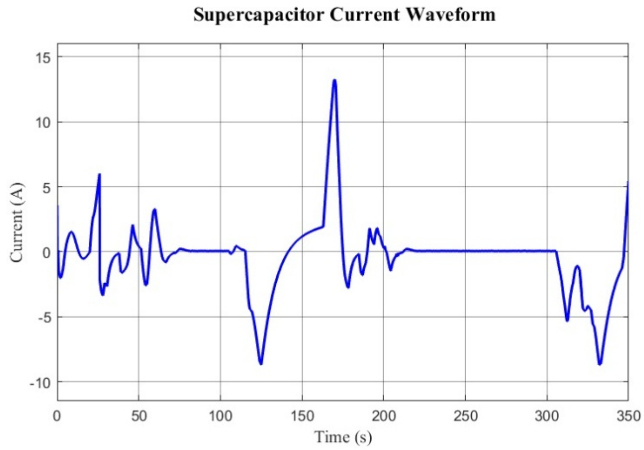

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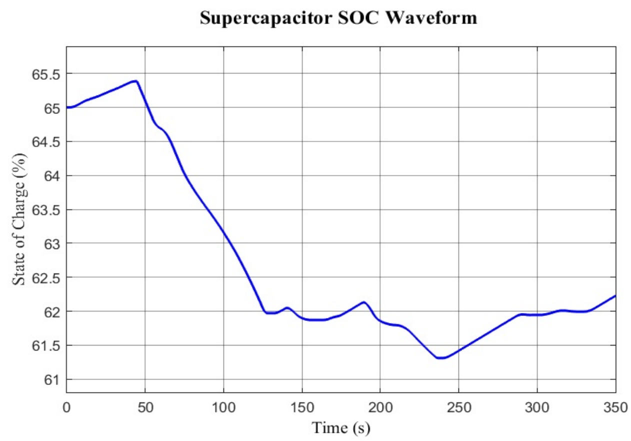


(c)

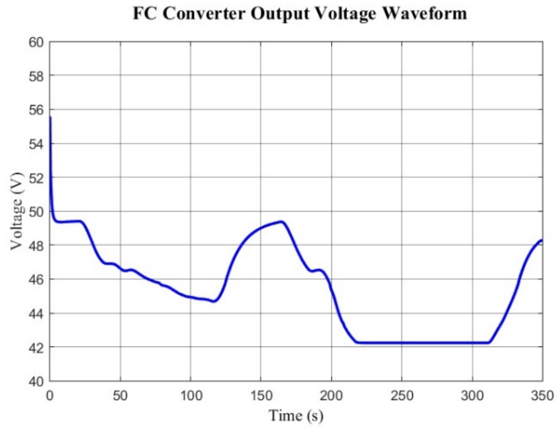
Figure 12(a,b,c): Supercapacitor voltage, current and SOC waveforms

The Supercapacitor voltage, current, and State of Charge waveform is represented in Figure 12 (a,b,c), where the current is 13A, the voltage is 270V, and the percentage state of charge is 65 percent with respect to time. When a rapid charge is required to deliver short-term energy, supercapacitors are the ideal answer. The most significant benefit is the ability to charge at a high rate. Because capacitors charge quickly, range anxiety is no longer an issue.

Table 4: Time required to charge a supercapacitor at various frequencies

S.No	Frequency (Hz)	Charging time (s)	Voltage at Supercapacitor (V)
1	40	0	0
2	47	300	10
3	48	280	11
4	49	230	15
5	50	130	18
6	51	250	12
7	52	310	10
8	53	320	9
9	54	330	8
10	60	0	0

Table 4 shows the charging times for supercapacitors at various frequencies which illustrates the connectors that can carry a high current are necessary due to the supercapacitors' quick charge and discharge cycles. When charging, which frequently begins at 0V, the adapters must operate smoothly in both constant voltage and current (CV and CC) mode.



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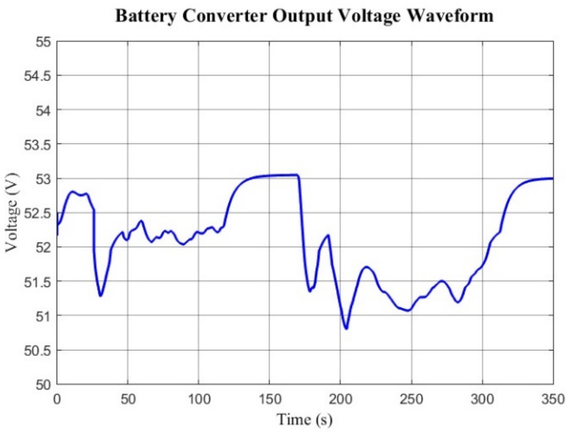

(b)

Figure 13 (a,b): Fuel cell and Battery Converter Output Voltage Waveform

Figure 13 (a,b) depicts the Output voltage waveforms of Fuel cell and battery converter, where the magnitude of voltage attain 42V and 53V with respect to time.

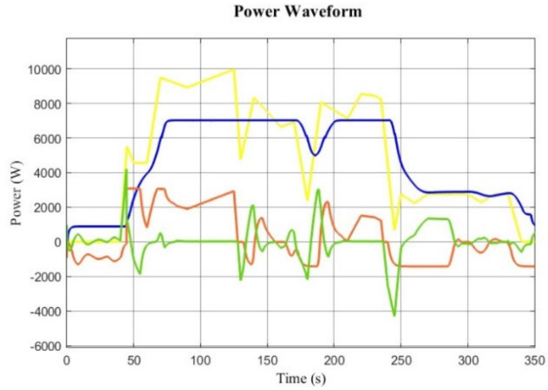

Figure 14: Power Waveform for Load, Fuel Cell, Battery and Supercapacitor

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. When the car started moving with the assumed load current of 30A, the battery and SC both started to discharge in order to meet the high load demands. Take a look at the time period from t = 0 to 200s. As the load current rises from 30A to 45A during the period t = 100–300s, both resources continue to supply the shortfall current. Finally, the load demand drops to 25A throughout the time window of t = 300–350 s, reducing stress on the energy storage device. Additionally, the stress from the primary source is lessened during this time, which causes the SC to start charging from the regenerative braking. Reduced stress and longer power-up source life are benefits of the energy management algorithm.

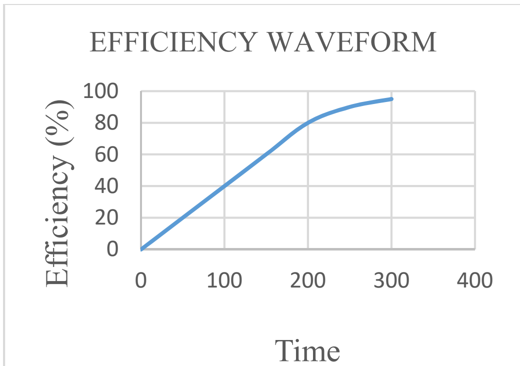

Figure 15: Proposed FOAIHSM Controller based EMS Efficiency Waveform

Figure 15 shows the Efficiency waveform, which shows that the Fractional Order Adaptive Integral Hierarchical Sliding Mode (FOAIHSM) Controller based EMS achieves 95 percent efficiency, resulting in smooth electric car performance. Table 5 shows the comparison of proposed controller with existing SMC Controller.

Table 5: Comparison of proposed controller with existing controller

SI.No	Method	Advantages	Efficiency
1	SMC-Sliding mode Control	➢ Tracking accuracy is high ➢ High performance in non-linear system ➢ Applied for MIMO system	90%
2	FOSMC-Fractional order Sliding mode control	➢ Applied for uncertain systems ➢ Easy to understand ➢ Easy to design	91.12%
3	SMFC-Sliding mode fuzzy control	➢ Rule base is reduced ➢ Chattering effect is reduced ➢ Stability and robustness is increased	92.34%
4	FSMC-Fuzzy Sliding mode control	➢ High robustness ➢ Reduced chattering problem	93%
5	Adaptive FSMC	➢ High robustness ➢ Reduced chattering ➢ Easy to design	94.23%
6	Fractional order adaptive Integral Hierarchical Sliding mode control-FOAIHSM	➢ Reduce Uncertainty ➢ Fast response speed ➢ High Robustness ➢ High performance ➢ Chatter free control inputs ➢ Less overshoot ➢ Faster convergence speed	95%

Table 6: Comparison of various energy management methodology

S.No	**Author Name and year**	**Methodology**	**Outcome**
1	Huan Chen et al, year: 2021	Real-time EMS based on model analytical regulator for hybrid energy storage systems	For a HESS, it achieves greater EMS performance. In comparison to fuzzy logic-based EMS, it reduces energy dissipation by up to 15.3 percent.
2	Huayanran Zhou; Yihong Zhou et al, year: 2021	LSTM-based Energy Management for Commercial-Building Prosumers Charging Electric Vehicles	A machine learning technique based on a long short-term memory (LSTM) recurrent neural network (RNN) is used to arrange the charging and discharging of many EVs in commercial-building prosumers which has 93% efficiency.
3	Arian Zahedmanesh et al, year: 2021	A virtual energy hub for an electric transportation system that is supported by cooperative energy management and PV generation.	The suggested CDM may organise 90% effective energy management (EM) for the VEH at a low operational cost.
4	Chunhua Zheng et al, year: 2018	A Hybrid Energy Storage System Energy Management Approach for Applications with Electric Vehicles	It reduces the EV's electricity use while also extending the battery's life that is 92%. The proposed technique has the effect of extending the life of the battery.
5	Sohaib Rafique et al, year: 2021	Residential Energy Management Systems Using Electric Vehicles and Distributed Energy Resources	When compared to non-optimized energy management methods, the energy management solutions dramatically lower (90%) the amount of energy drawn from the grid.
6	Wei Wang et al, year: 2021	Vehicle-to-grid energy management and optimization for wind power integration	The energy management and optimization solution for V2G systems outperforms benchmark techniques by a significant margin which has 92% efficiency in energy management.
7	Zil e Huma et al, year: 2021	In plug-in hybrid electric vehicles, an effective integral backstepping controller is used for energy management.	In terms of output voltage regulation, reference generation, and 90 % smooth current tracking, it ensures smooth PHEV execution and energy management. The PHEV's asymptotic stability was ensured using Lyapunov stability theory.

8	Proposed	Fractional order adaptive integral hierarchical sliding mode controller for energy management system in electric vehicles.	EV cruised economically and had the lowest specific consumption under Fractional Order Adaptive Integral Hierarchical Sliding Mode (FOAIHSM) Controller based EMS. The advantage of FOAIHSM Controller-based EMS over competing strategies is that optimal velocity is always established, resulting in minimal loss. Experiments have been carried out more effectively (95%) to compare the results obtained with those of simulations.

As a result, in electric vehicles, an energy management system is required to make the best and most efficient use of the battery's energy. The comparison of various energy management methodologies is shown in Table 6.

5. 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 Fractional Order Adaptive Integral Hierarchical Sliding Mode (FOAIHSM) Controller based EMS. The advantage of FOAIHSM 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 Integral Hierarchical Sliding Mode (FOAIHSM) 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

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