ARTIFICIAL NEURAL NETWORK-BASED ENERGY MANAGEMENT FOR BATTERY–ULTRACAPACITOR HYBRID ENERGY STORAGE SYSTEM CONSIDERING BATTERY DEGRADATION IN ELECTRIC VEHICLES

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Abstract: As the demand for electric automobiles continues to rise, more advanced hybrid energy storage systems will be required to meet peak power demands while preserving battery life. Investigations on the effects of battery degradation provide helpful direction for improving energy management in hybrid systems using both batteries and ultracapacitors. An artificial neural network-based controller dynamically manages the power transfer between the battery and ultracapacitor based on signals related to age, state-of-charge, and load need. The architecture of ultracapacitors allows them to withstand high-frequency power fluctuations, which reduces pressure on the battery current and depth-of-discharge variations. Capability fading may be accurately predicted using an ageing model that accounts for degradation and incorporates several C-rate profiles obtained from driving cycles. This energy management system outperforms conventional ones in terms of efficiency, battery current ripple, and runtime under real-world EV driving conditions, according to the simulation results. Consequently, it is more suited for use in real-time electric vehicle applications.

***Keywords*_** Power quality, electric vehicle management systems (EMS), driving cycles, power distribution, capacity fading, energy efficiency, artificial neural networks (ANN), hybrid energy storage systems (HESS), and electric cars (EVs).

I.INTRODUCTION

Governments throughout the world have lately made sustainable development a top priority. There has been a meteoric rise in research on electrifying transportation in response to the critical need to reduce carbon emissions and dependence on fossil fuels. The automotive industry is now undergoing a paradigm shift, with gas-powered hybrids being replaced by plug-in hybrids and, eventually, electric automobiles. To that purpose, electric vehicles (EVs) are being considered as a green mode of transportation. However, the specifications of electric cars' power storage systems greatly affect the overall performance, reliability, and efficiency of the vehicles. Among electric car battery options, lithium-ion batteries (LIBs) stand out for their efficiency, longevity, and high energy density. But there is a cost to these advantages as well; batteries have a finite lifespan. Reason being, batteries' complex electrochemical processes cause their capacity and output to progressively decline. Several variables, including as operational circumstances, temperature fluctuations, depth of discharge (DoD), and fast charge/discharge rates (C-rate), may contribute to the degradation of batteries. As a consequence of these natural ageing processes, the reliability of electric car systems declines, maintenance costs increase, and battery life diminishes.To address these issues, we looked at HESSs, which combine UCs with batteries, as a possible option. Due to their exceptional charge-discharge characteristics, long cycle life, and high power density, ultracapacitors are ideal for addressing temporary power demands. By integrating the battery's steady-state energy with the UC's ability to regulate high-frequency power fluctuations, a battery-UC HESS may improve system performance while reducing stress on the battery. However, an efficient EMS that allows power to flow directly from the battery to the UC is necessary for HESS to

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function.

Optimisation, rule-based, and model predictive control (MPC) techniques are some of the more conventional EMS methods that have been the subject of many research. Although these methods have their uses, they aren't usually flexible enough to account for variations in driving styles or battery degradation. Assuming a constant C-rate for battery operation, most of the existing research also disregards the reality that load demand changes continually under real-world driving conditions. Oversimplification causes inaccurate evaluations of battery capacity loss and makes degradation-aware management methods useless. The ability to handle nonlinearities and system uncertainties has led to the rise in popularity of intelligent and learning-based EMS techniques. A few ways that artificial neural networks (ANNs) might improve complicated systems like electric cars include adaptive control and real-time decision-making. Tragically, studies examining the integration of ANN-based EMS with all-encompassing models of battery degradation that account for different C-rate profiles derived from real driving cycles are few. This research introduces a smart energy management strategy for battery-ultracapacitor HESSs that is ANN-controlled, with potential applicability in electric vehicle (EV) applications. A proposed controller dynamically allocates power between the battery and UC based on criteria such as age, load demand, and state-of-charge (SOC). By integrating a degradation-aware model of battery ageing with changing C-rate profiles generated from typical driving cycles, capacity fade estimates are improved. By using high-frequency power components in the ultracapacitor, the proposed approach effectively reduces ripple in battery current and depth-of-discharge variations. The simulation findings demonstrate that the proposed approach surpasses current EMS methods in terms of energy efficiency, reduction of battery stress, and extension of battery life under real electric vehicle (EV) operating conditions. These features prove that the proposed technology may be used successfully for EV real-time applications. The following fields are primarily aided by this endeavour:

A battery-UC HESS intelligent energy management system (EMS) developed using ANNs.

Including different C-rate profiles in a model that takes the decrease in battery lifespan into consideration.

A technique that reduces the strain on batteries by distributing electricity effectively and dynamically.

After being put through their paces under realistic driving conditions, the system and batteries proved to be superior.

II.PROPOSED SYSTEM

Several topologies in the literature have used the HESS. There are four possible topologies for operating the battery/UC-based HESS: semiactive, parallel, cascaded, or disabled. You can see the active design that was employed for this experiment in Figure 1. An electric motor receives power from a dc-ac inverter via a direct current connection that connects two BDDCs. Two sources of enhanced dc power are sent into the motor using an inverter. The following is the form of the power balance equation for the system:

$$P_d = \eta_{\text{bat}} P_{\text{bat}} + \eta_{\text{uc}} P_{\text{uc}} \tag{1}$$

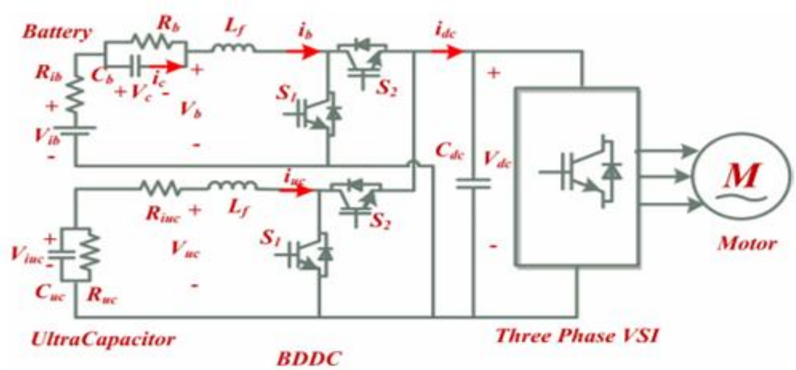


Fig.1. System configuration for the battery- and UC-based HESS.

TABLE I
VEHICLE PARAMETERS

PARAMETER	VALUE
Vehicle mass (m_v)	1325 kg
Air density (ρ)	1.29 kg/m^3
Frontal area (A_f)	2.57 m^2
Drag coefficient (C_d)	0.26
Rolling resistance (μ_{rr})	0.0048
Road gradient (θ)	0.175

The power of the battery is denoted by Pbat, whereas the UC is represented by Puc. The charge current and discharge current have an impact on the converter efficiencies, ηbat and ηd, respectively. To find out how much juice the engine requires, use this formula:

$$P_d = \tau\,(\omega/\eta) \tag{2}$$

Here, η stands for efficiency and ó = (vGr)/rw for the rotational speed of the motor. In order to determine the torque generated at the wheels in relation to the resistive force and the vehicle's speed, one may conduct the following:

$$\tau = \left(F_{\text{Total}} + M\frac{dv}{dt}\right)(r_w/Gr) \tag{3}$$

where Gr is the gear ratio and rw is the wheel radius. The fundamental longitudinal dynamics model of the vehicle is used to calculate the total resistive force (FTotal), which is a function of both the vehicle's velocity (v) and the road gradient (θ).

$$F_{\text{Total}} = A_f\rho C_d v^2 + m_v\mu_{rr}g\cos\theta + m_v g\sin\theta \tag{4}$$

This vehicle's frontal area (Cd), air density (ρ), drag coefficient (Af), acceleration due to gravity (g), rolling resistance coefficient (μrr), and mass (mv) are the important elements. The gearbox's function is to transfer mechanical energy from the engine to the wheels. The research vehicle's specs are shown in Table I.

A) Unit Cell and Battery Simulation

Figure 1 shows the results of the HESS evaluation using a first-order RC circuit to mimic the UC and battery. The polarisation components (RC) are arranged in parallel with the internal resistance, and a voltage source is connected to it in series in this battery configuration.

Power for the battery's storage cells is provided by

$$V_b = V_{ib} - R_{ib}i_b - V_c \tag{5}$$

$$i_c = C_b\frac{dVc}{dt} \tag{6}$$

in where Vb is the voltage across the open terminals of the battery, which is set by the system on a chip and is thus dependent on

$$\text{SoC} = 1/Q_n\left[Q_n - \int i_b dt\right] \tag{7}$$

When the RC circuit is modelled in relation to the UC, the resulting cell voltage is:

$$V_{\text{uc}} = V_{i\text{uc}} - i_{\text{uc}}R_{i\text{uc}} \tag{8}$$

$$\frac{dV_{i\text{uc}}}{dt} = \frac{i_{\text{uc}}}{C_{\text{uc}}} - \frac{V_{i\text{uc}}}{R_{\text{uc}}C_{\text{uc}}} \tag{9}$$

The voltage at the output terminals is Vuc, whereas the voltage acting against the polarisation components is Viuc. To find the UC's SoC, one has to follow these steps:

$$\text{SoC} = 1/Q_n\left[Q_n\text{SoC}_o - \int i_{\text{uc}}dt\right] \tag{10}$$

B) Battery and UC Sizing

The components of the research traction battery are 48-volt modules with 110-ampere-hour capacity. Once all of the batteries have been used up, the HESS voltage hits 360 V. In order to get the voltage down from its maximum rating (Vucmax) to half of its minimum rating (Vucmin), the UC pack consumes around 75% of the bank's stored energy [28]. A charge from the UC battery pack is

$$E = k\left[\frac{1}{2}C_{\text{eq}}\ V_{\text{uc}\max}^2 - \frac{1}{2}C_{\text{eq}}\ V_{\text{uc}\min}^2\right] \tag{11}$$

If we know the voltage Vuc, we can calculate the energy stored in the UC as

$$E = \frac{1}{2} C_{\text{eq}} \; V_{\text{uc}}^2 = \; \frac{1}{2} \frac{N_P}{N_S} C_{\text{uc}} \; V_{\text{uc}}^2 \tag{12}$$

The Indian drive cycle (IDC) [29] produces Ceq = 250 F and Vuc = 300 V under regenerative circumstances and with 10 MJ of energy. With respect to the beginning voltage of the UC pack, Ns= 108 and Np= 9.

The Executive Suite: A Model for Evaluating Battery Life

Based on the original Arrhenius degradation equation, the dynamic capacity fade model may be used to estimate the capacity loss of the LFP battery, which is mainly influenced by the C-rate and the DoD. An approximation of the capacity decrease is shown here:

$$Q_{\text{loss}} = B.\exp\left(\frac{-Ea + \alpha \times C_{\text{rate}}}{R \times T}\right)(Ah)^{0.55} \tag{13}$$

The sum of the cell's capacity and the number of cycles is used to determine Ah:

$$Ah = n_{\text{cyc}} \times \text{DoD} \times Ah_{\text{cell}} \tag{14}$$

Therefore, by differentiating the original expression with regard to time, we get the following expression, which may be used to assess the minute change in capacity induced by ageing:

$$\frac{dQ_{\text{loss}}}{dt} = \frac{|I|}{3600} z.B.\exp\left(\frac{-Ea + \alpha \times |I|}{R \times T}\right) \times \left(\frac{Q_{\text{loss}}}{B.\exp(\frac{-Ea+\alpha\times|I|}{R\times T})}\right)^{1-\frac{1}{z}} \tag{15}$$

Where

A battery consists of the following components: the Risthegas constant, the power factor zi, and the rate of discharge Qloss. The exact temperature, however, is a point of contention.Current acceleration coefficient, activation energy, and pre-exponential factor are all provided.

III. ENERGYMANAGEMENTSTRATEGY

The system's performance may be evaluated using MPC serving as the EMS. To function, MPC projects the system's future output across a prediction horizon using a linearized model of the system. Under constrained conditions, the control minimises the goal function while precisely anticipating the system's response. Using MPC, we predict the UC's system on a chip in this case. By improving the target function, the EMS lowers battery current variations and maintains the SoCat at the right level.The objective function won't work until the UC reduces battery stress by meeting an unforeseenly large current demand and improves power supply to the load. The limitations of the goal function are determined by the maximum allowable current via the battery and the current level of the UC.You can't do MPC in the MATLAB/Simulink environment without the MPC toolkit.The system's data, such as the goal function, measured and unmeasured outputs, related limitations, and controlled variable, are all stored in the toolbox.To include the decreased battery and UC models, we develop and linearize a HESS continuous state-space model using the MPC toolbox. The discretized goal function is defined as follows by time k.

$$J = \sum_{j=1}^{P_H} w_1[\text{SoC}_{\text{uc}}^*(k+j/k) - \text{SoC}_{\text{uc}}(k+j/k)]^2 + \sum_{j=1}^{C_H} w_2[i_b^*(k+j/k) - i_b(k+j/k)]^2 \tag{16}$$

With the following limitations in mind:

$$\text{SoC}_{\min} \leq \text{SoC}_{\text{uc}}\,(\text{k}+\text{j}/\text{k}) \leq \text{SoC}_{\max} \tag{17}$$

$$i_{b\,\min} \leq i_b\,(k+j/k) \leq i_{b\,\max} \tag{18}$$

When both w1 and w2 are positive integers, it indicates that the objective function's components are essential in that particular order. While increasing w2 increases the chances of keeping the battery current constant, it may cause a SoC violation, hence w1 is much less important. When selecting the weights, it is important to keep in mind that w1 is less than w2, denoted as w1<< w2. Since the discretized system model was used, the UC's So C could be predicted.

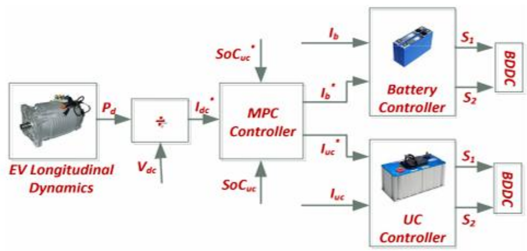


Fig2. Flow diagram for HESS control.

How to Use Battery Age to Evaluate EMS Systems While the battery maintains a constant power supply, the UC may quickly surge power thanks to the reference currents generated by the computer controller. In order to keep the battery current from fluctuating, the objective function puts a high value on weight w2, and the current-corresponding C-rate is restricted for a particular driving cycle.The relationship between C-rate and range arises from the fact that the battery current fluctuates over the driving cycle in response to variations in power consumption.A single C-rate is not a viable basis for estimating the capacity loss of a battery across a driving cycle.By sampling the battery current mathematically throughout a specific driving cycle, one may get a C-rate that is consistent with the real battery current.System assessment in this case is carried out using the IDC[30].

IV. PROPOSED ANN CONTROLLER

To manage the current and voltage output of the converter system, this project uses an ANN-based controller instead of the more conventional Proportional-Integral (PI) controller. By comparing and contrasting input-output data from systems with different loads and grid configurations during training, artificial neural network (ANN) controllers may adapt to non-linear dynamics, setting them apart from traditional PI controllers. The system's control accuracy, responsiveness to changes in conditions, and power factor correction are all enhanced by this repair, which furthermore significantly lowers total harmonic distortion (THD). Using an ANN-based approach improves control of dual-battery charging, power sharing equity, and robust operating in short-term scenarios. To make the compensating device work better, an ANN controller with several back propagation layers is employed. We train the ANN using the MATLAB toolbox. Training the ANN controller using Levenberg-Marquardt-Backpropagation yields better results than using gradient-degressive or Gauss-Newton methods. The Levenberg-Marquardt back propagation method has several advantages, such as faster convergence, reduced memory requirements, and competent learning [9]. The standard PI controller's data set is the only one used to train the ANN. It is proposed that artificial neural networks be controlled using a controller with one output layer, 10 hidden layers, and two input levels. The ANN controller receives both the initial and revised error signals, which measure the difference between the actual and reference values in the d and q coordinate systems. The goal of an ANN controller should be to reduce error as much as possible without sacrificing precision. The ANN controller is responsible for transforming the dqo data into the ABC format. As shown in Figure 3, the mean square error, which is the discrepancy between the input and target values, is used to evaluate the performance of the ANN controller.

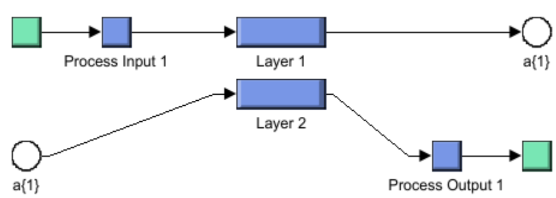


Fig.3 Typical Structure of ANN control

V.SIMULATION RESULTS

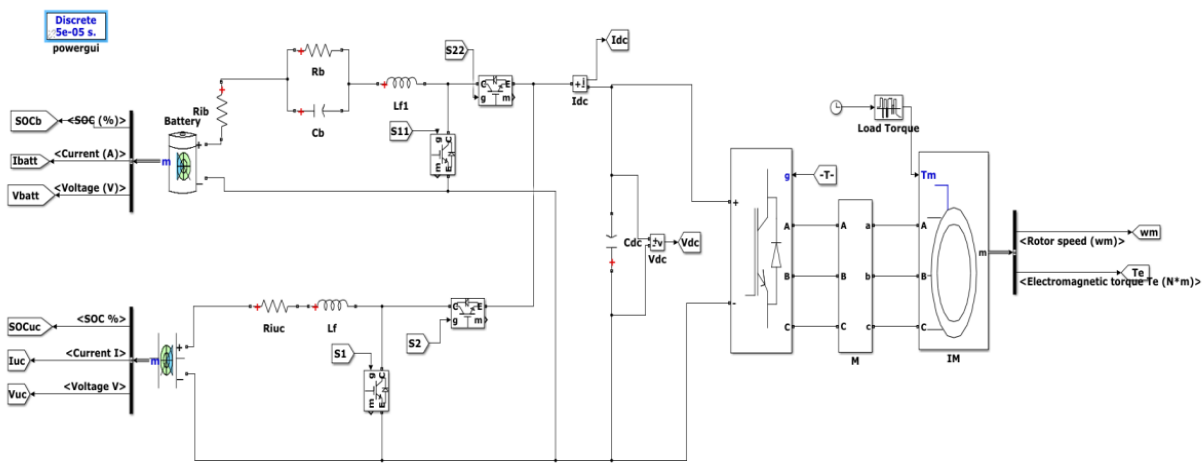


Fig. 4. MATLAB/SIMULINK circuit of the system

A) EXISTING RESULTS

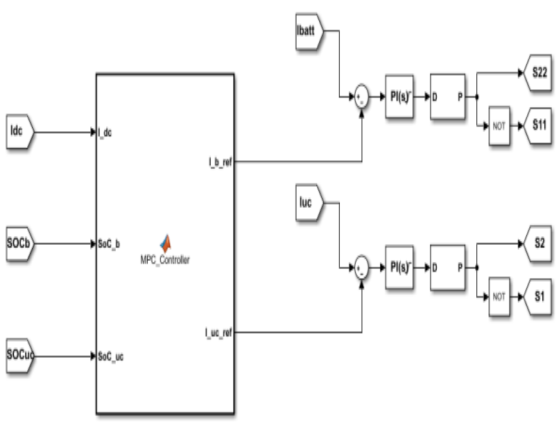
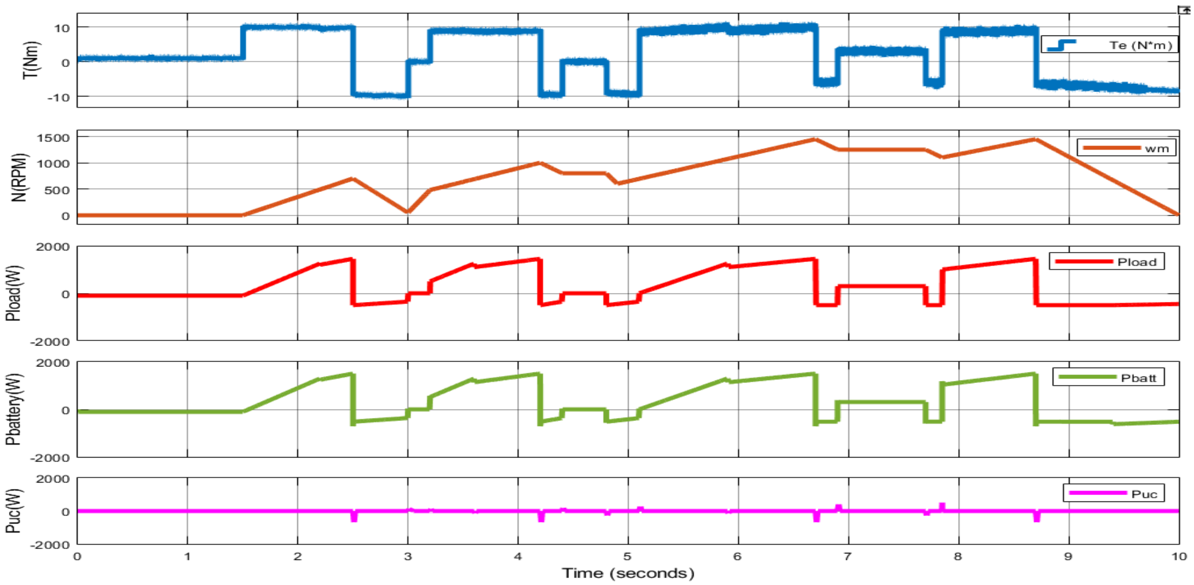


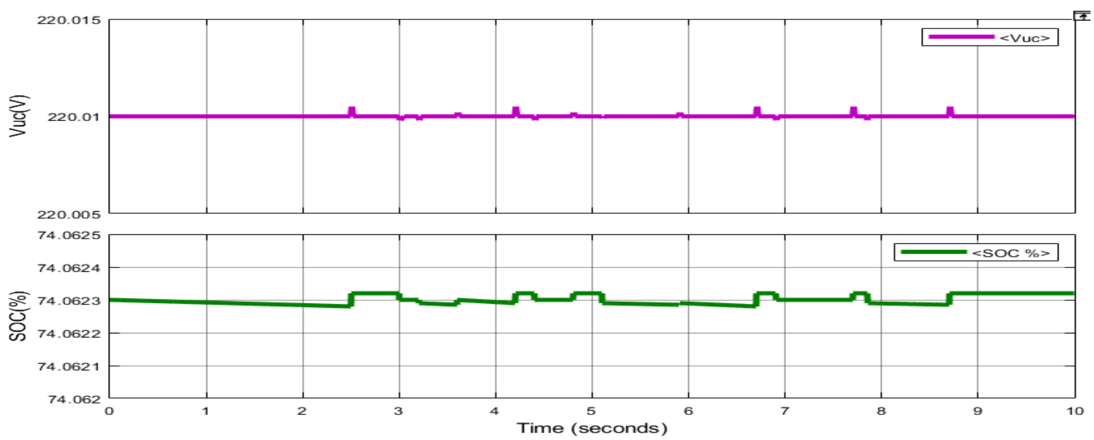
Fig.5 Control system for HESS

We may assess the performance of the Hybrid Energy Storage System (HESS) by simulating it in MATLAB/Simulink using the Indian Driving Cycle (IDC). The power requirements, traction torque requirements, and velocity profile of an electric vehicle are determined by the driving cycle, which in turn is determined by the vehicle's longitudinal dynamics. Figure 6(a) shows that the load's whole power need is satisfied by using the battery in conjunction with the ultracapacitor (UC). Because of its rapid dynamic reaction and high power density, the UC is an ideal backup power source in the event of an unexpected drop or surge in power demand. Additional evidence of the UC's potential for quick refuelling via regenerative braking is shown in Figure 6(a).

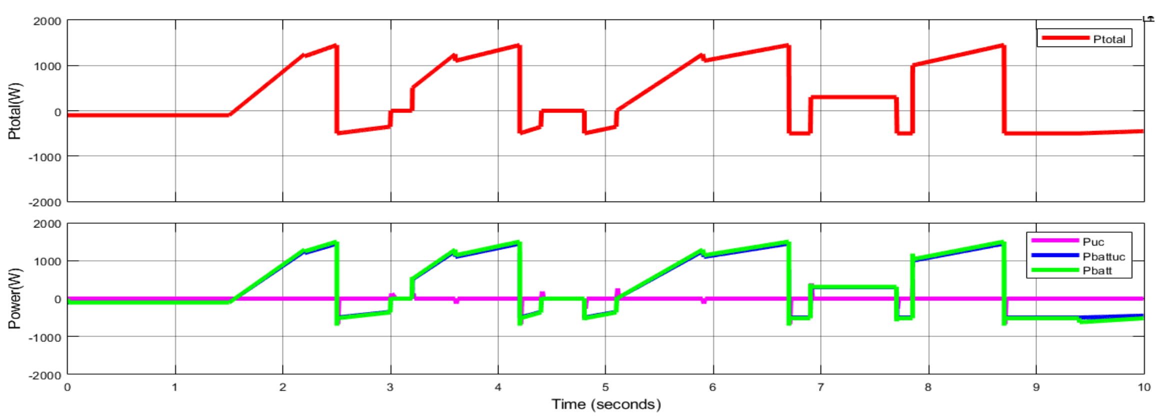
Throughout the whole driving cycle, the UC voltage and state of charge (SoC) remain within their operating limits, as seen in Figure 6(b). Together, the battery and UC provide the necessary traction power, as seen in Figure 6(c). By mimicking operational scenarios with transient spikes, the UC power system aids the battery in handling abrupt changes in demand. According to the numbers, the combined output of the battery and UC is the same as their respective outputs.



(a)

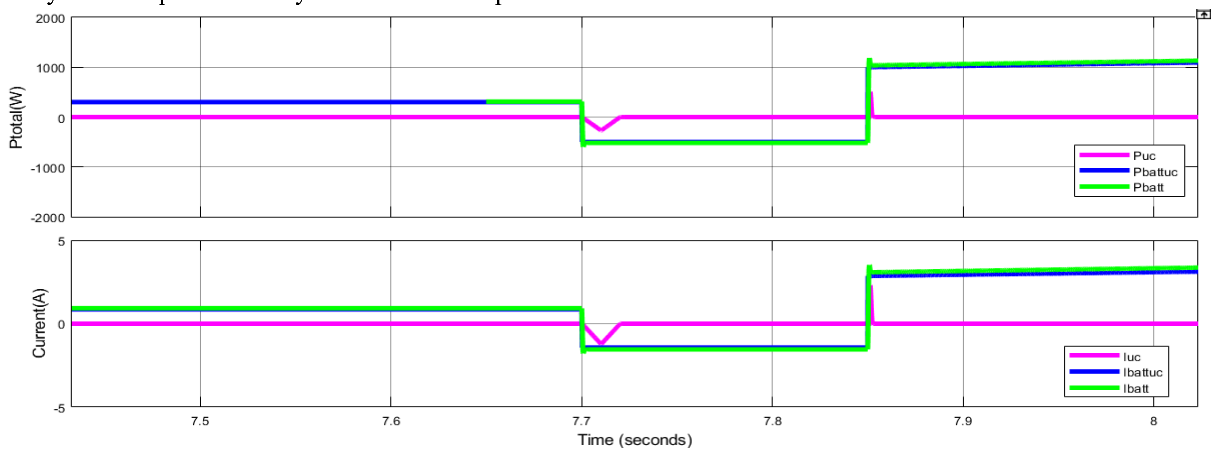


(b)

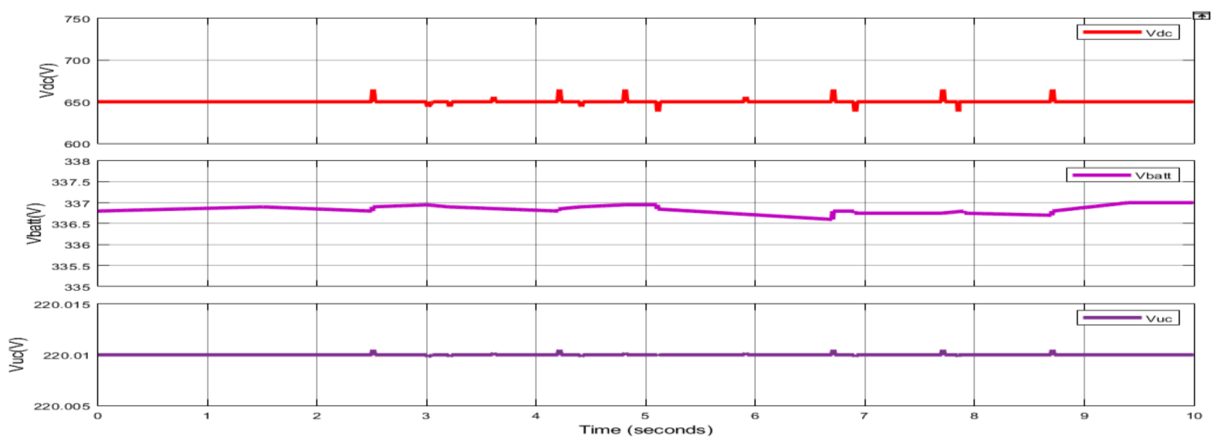


(c) You can see torque, speed, load power, battery power, and UC power in Figure 6, which provides a number of parameters throughout the whole driving cycle. The picture also displays the voltage of the UC and SoC, the power of the load, and the power of the battery both with and without UC.

Highlighting the power and current profiles of the battery and the UC, Figure 7 depicts the dynamic behaviour of the HESS during acceleration, cruising, and deceleration modes. Having only the battery results in increased stress and faster deterioration in a system when the load requirement is met. But the battery-UC setup deliberately uses the UC to power the high-frequency components, so the battery doesn't have to work as hard. The data shows that at 76 seconds, the UC can absorb a maximum of 710 W of regenerative power and at 78 seconds, it can output a high of 1190 W of power.



(a)



(b)

Fig 7. The results display (a) a magnified picture of the current and power coming from the UC and battery, and (b) the voltages that the dc bus, battery, and battery all experience over the whole driving cycle.

B) EXTENSION RESULTS

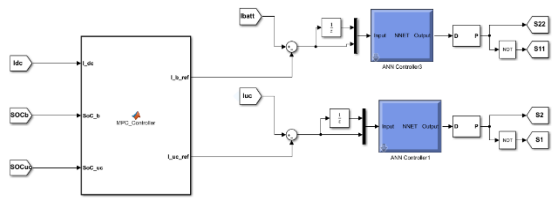
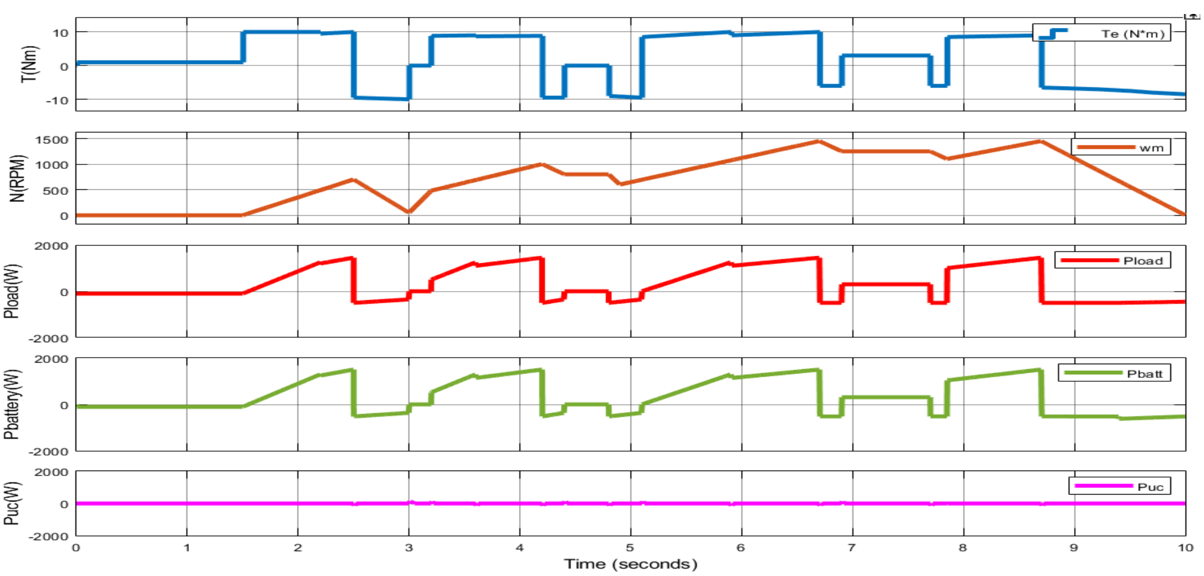
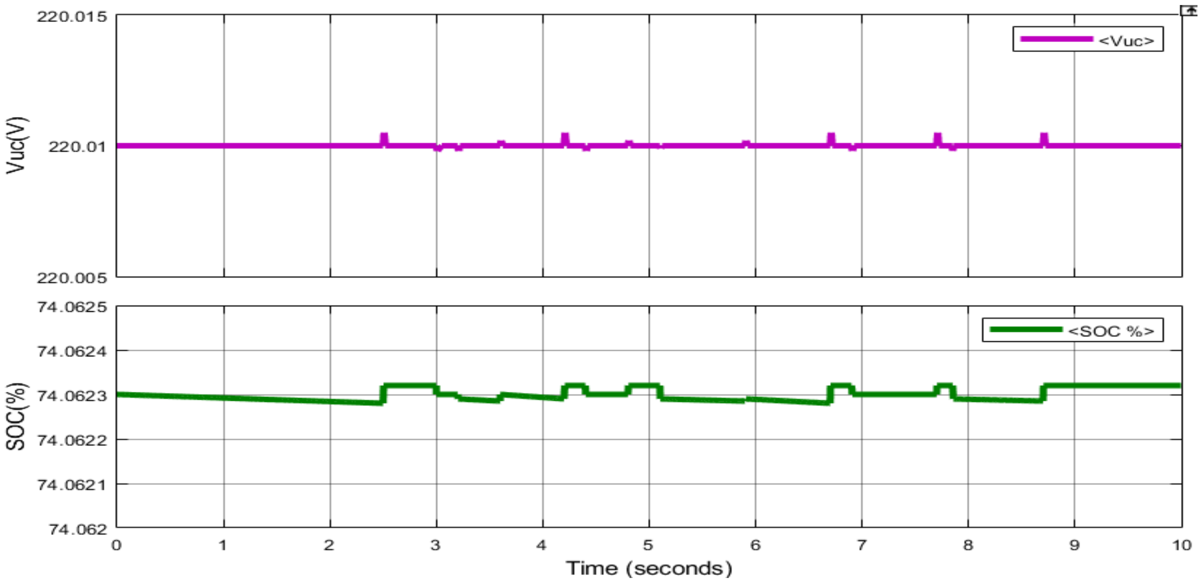


Fig .8 ANN Control system for HESS

Figure 9(a) shows the proposed energy management system, which uses an ANN to calculate the optimal ratio of battery to ultracapacitor (UC) power consumption under full load conditions. The UC's high power density and rapid dynamic response make it an excellent backup power source in the event of unanticipated changes in load demand. By continuously assessing inputs such as load power, state of charge (SoC), and system dynamics, the ANN controller distributes high-frequency power components to the UC while reducing the burden on the battery. As shown in Figure 9a, the ANN controller may take advantage of the UC's quick charging capability by using regenerative braking. The ANN-based control kept the UC voltage and SoC within their safe working limits the whole driving cycle, as shown in Figure 9(b). By optimising UC use, the ANN's adaptive nature ensures conformity with power and system-on-chip constraints. The traction power is supplied by a combination of the battery and UC, as shown in Figure 9(c). A change in operating circumstances might cause transient spikes in the UC power profile, which the ANN controller can identify and handle automatically. This means there will be less variation in the power supply and battery current. Evidently, ANN is the way to go for managing the HESS's overall power production, which comprises both battery and UC power.Figure.10 shows the power and current characteristics of the battery and UC; this information may be used to understand the HESS's dynamic performance during cruising, deceleration, and accelerating. If the system could fully fulfil the load requirement, the battery would last longer and incur less current stress. However, the proposed ANN-based battery-UC configuration manages transient and high-frequency power demands by dynamically distributing the UC, which reduces battery stress and increases lifetime. According to the statistics, the ANN controller is also great at catching fleeting occurrences; for instance, the UC drew 710 W of regenerative power at 76 s and sent out 1190 W of power at 78 s. Thanks to this smart power sharing, the system becomes more efficient, the battery life is extended, and reliable functioning is guaranteed even in the most unpredictable driving conditions.



(a)



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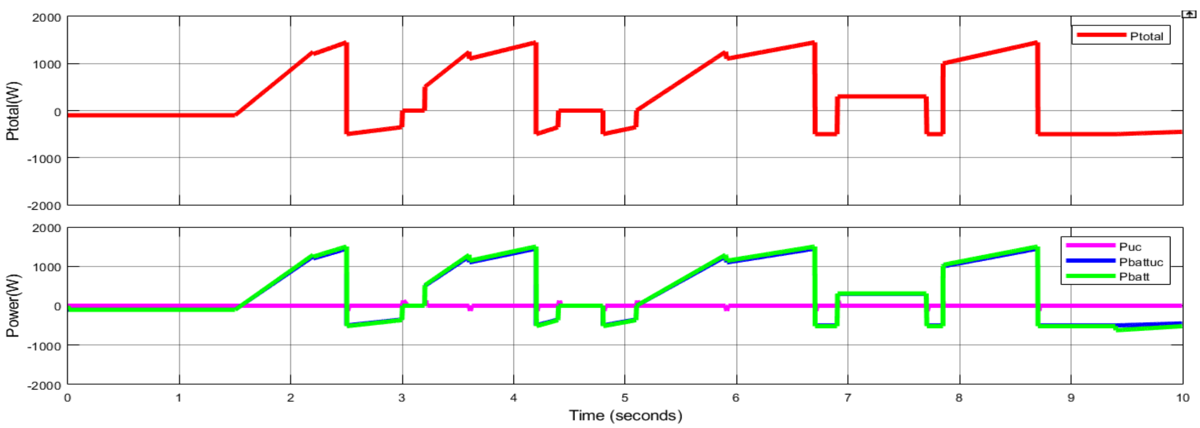
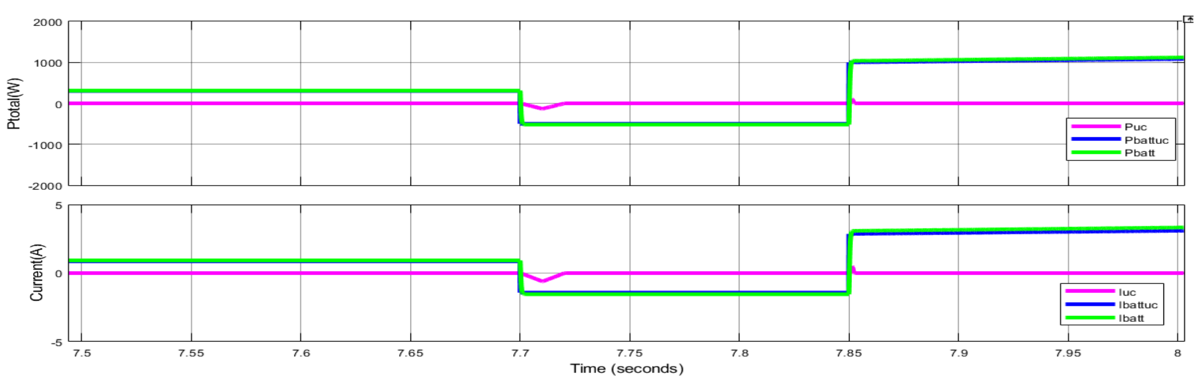
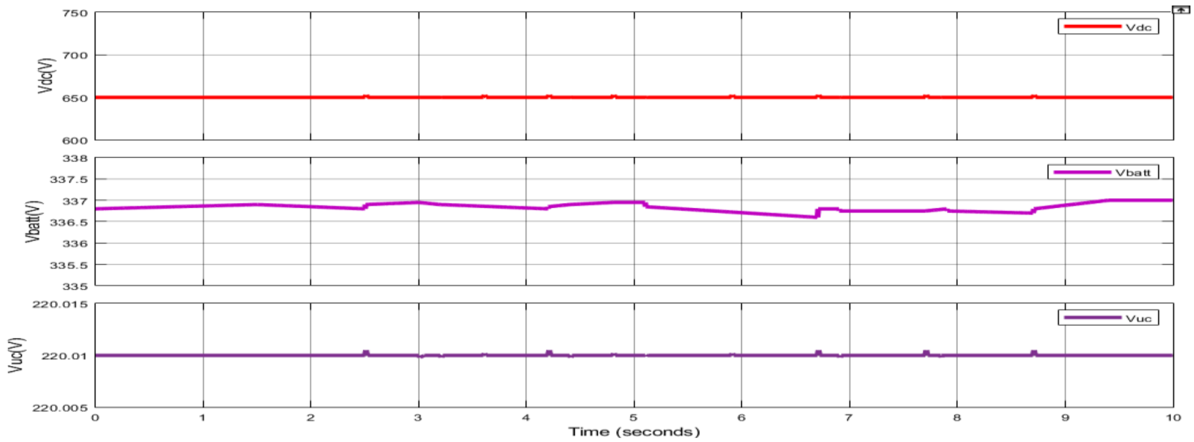


(c)Fig.9 Complete driving cycle data include (a) torque, speed, load power, battery power, and UC power; (b) UC and SoC voltage; and (c) battery and load power with and without UC.



(a)



(b) The outcomes for the whole driving cycle are shown in Figure 10, which includes (a) a magnified view of the current and power from the battery and UC, and (b) the voltages of the dc bus, your battery, and the UC.

COMPARSION TABLE

Parameter	Existing System (Conventional PI Controller)	Proposed System (ANN Controller)
Voltage Ripple (%)	8 %	2 %
Battery Current (A)	High peaks (±80 A)	Reduced peaks (±40 A)
Battery Stress	High	Low
Battery Power Variation (kW)	2 – 5 kW (irregular)	1 – 3 kW (smooth)
Ultracapacitor Power Contribution (kW)	Limited (~1 kW)	Enhanced (2 – 4 kW)
State of Charge (SoC) Variation (%)	60 – 85 % (large variation)	70 – 80 % (controlled)
Response Time (ms)	150 – 200 ms	50 – 100 ms
Load Power Tracking	Moderate accuracy	High accuracy
Torque Ripple (%)	15 %	6 %
Speed Stability	Slight oscillations	Smooth and stable
Energy Efficiency (%)	85 %	95 %
Battery Life Impact	Reduced (due to stress)	Improved (less stress)
Power Sharing (Battery–UC)	Poor coordination	Intelligent sharing
Transient Performance	Slower response	Faster response

CONCLUSION

An electric vehicle's battery life may be increased with the use of a UC-assisted battery-based HESS by supplying surge power during sudden changes in load. Using an ANN-based energy management technique, this work optimises the performance of the battery and ultracapacitor. In real-time, the ANN controller decides the power split based on a number of factors, including operational conditions, load demand, and state of charge (SoC). This guarantees the system's adaptability and efficiency. With the sole purpose of studying battery ageing, we analyse the impact of both fixed and changing C-rates. While it's often believed that C-rates remain constant throughout the driving cycle, the actual capacity fade at the end is determined by shifting C-rate profiles. In order to decrease battery ageing, power is routed to the UC by artificial neural networks (ANNs) in order to fulfil the high-frequency and transient power demands in battery-UC operation (HESS). If the battery degradation model employed the actual C-rate rather than the unreasonable assumption of a constant C-rate, it may provide a more accurate evaluation of capacity loss. Because the ANN-controlled HESS reduces power consumption, the battery lasts longer and has less degradation. Intelligent ANN-based power management and shifting C-rate profiles allow for more precise assessment of battery capacity loss for a given driving cycle, and the results demonstrate that the system performs better overall.

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