

Modelling & Design of Hybrid Energy Storage System for Light Electric Vehicle with Hybrid Artificial Neural Network based Energy Management System

¹Vankadari Praveen and ²Dr. Kotni Sri Kumar

¹Department of Electrical & Electronics Engineering, University College of Engineering (A), JNTU Kakinada, India

²Department of Electrical & Electronics Engineering, University College of Engineering (A), JNTU Kakinada, India

E-mail: ¹praveenvankadari@gmail.com, ²kotni.77@gmail.com

ABSTRACT

The rising air pollution and finite oil supplies, motivated the transportation sector in transitioning from IC engine vehicles (ICEV) to EV (Electric Vehicle). Because of the limits imposed by energy storage, there are still some concerns regarding the performance and reliability of EVs. In this paper, a comprehensive analysis has been carried out on modelling of a Light Electric Vehicle (LEV) driven by a BLDC motor which is powered by Hybrid Energy Storage System (HESS) consisting of Battery pack and Supercapacitors. Later parts of this study are dedicated in examining the EV's energy and power flow management issues during its acceleration and deceleration phases. To enhance optimality in power flow, a Hybrid Artificial Neural Network (ANN) based Energy Management System (HANN-EMS) with a cascaded Adaptive sharing rule-PI controller and ANN current controller is implemented such that high-demand occasions are met by supercapacitors, while the low load demand is met by batteries hence decreasing overall battery stress. The proposed model efficacy is then investigated using MATLAB/SIMULINK and compared with existing Proportional Integral control Energy Management System (PI-EMS).

Keywords: Light Electric Vehicle (LEV), BLDC motor, Hybrid Energy Storage System, Hybrid ANN, Adaptive Sharing Rule (ASR), Energy Management System (EMS).

I. INTRODUCTION

Due to global warming and other related environmental issues, whole world started imposing strict laws on ICEV emissions in order to reduce CO₂ emissions per km by ratifying pollution regulations (i.e., a high tax will be levied on vehicles emitting more than 95 g/km of CO₂). The regulation requires the automotive industries to develop new ICEVs in order to comply with this rule. However, conventional vehicles powered by Internal Combustion Engine (ICE) technology may not meet this requirement. In fact, ICE technology has reached to the point of saturation and the only way ICE vehicles can be improved is by reducing their weight and drag force.[2]

This prompted government authorities to prioritize EV's as an alternative to ICEV's in heavily polluted cities, launching programmes like "Faster Adoption and Manufacturing of electrical and Hybrid Vehicles in India (FAME)," which can provide subsidies for the production units of electrical buses, scooters, bikes, taxis, and e-rickshaws [3].

As a result, interest in electric vehicles has increased in cities where their limited range and charging time aren't a detriment. Niti Aayog published a study titled "India's Electric Mobility Transformation" in April 2019, forecasting EV penetration in India at 70% for commercial vehicles, 30% for personal automobiles, 40% for buses, and 80% for two- and three-wheelers by 2030 [3]. This gave entrepreneurs and academicians an enormous boost to their efforts in exploring novel solutions and platforms for EV development, particularly Light Electric Vehicles.

In recent times, Light Electric Vehicles or LEV's (i.e., Vehicles with power to mass ratio less than 22 W/kg) which includes anything in the range of scooters to low-speed cars are getting a tremendous interest from daily commuters due to their attractive features like simple to drive, operate even in heavy traffic conditions and most of them don't require a license to operate. From Manufacturers point of view, LEV's appeal stems partially from their minimal initial investment still as their low operational and maintenance expenses.

Due to these qualities, they're accessible to a large portion of the world population, including those in emerging economies like India. LEV's even have the advantage of being easy to charge on the regular facility/home and most critically, they meet an increasing number of zero-emissions standards. Despite their recent success and potential future, Light electric vehicle (LEV) applications confront variety of design problems like small space available, battery range and power scaling are limited, only cost-effective solutions needed etc.

This paper involves in addressing the problems above by reducing capacity "battery pack" by conjunction of "supercapacitors" and hence increasing range with effective regenerative braking, better battery health and also decreased charging time. In electrical engineering, any Hybrid storage needs an effective control algorithm and a power electronic converter. [7],[10],[11]

To produce optimality in power and energy flow during various phases of vehicle operation, we are going to design a non-Isolated type Bi-directional DC-DC converter with a novel Energy Management system topology of cascaded Adaptive

sharing rule-based voltage controller with ANN current controller.

II. MATHEMATICAL MODELLING WITH SIMULINK

The mathematical and simulation prerequisites needed for analysis, design and control of electric vehicle are presented in this section. It also consists of critical parameters and dynamics for each Electric Vehicle component, which will be essential for control and monitoring with their SIMULINK model. Electrical Vehicle is a combination of various devices that belong to different domains. So, we need to analyze each component to develop familiarity about their parameters and importance. For ease of modelling, whole EV is divided into atomic units like EV mechanical model, BLDC motor, Li-ion battery, Supercapacitor and DC-DC converters.

a. Vehicle Mechanical System Model:

In the early phases of vehicle modelling, a series of equations is developed to determine "Tractive effort" [1]-[2], which is the force that propels the vehicle forward. Consider a Light Electric Vehicle (two-wheeler) as illustrated in Fig. 1 to get an idea of components that needed to be studied while understanding tractive effort.

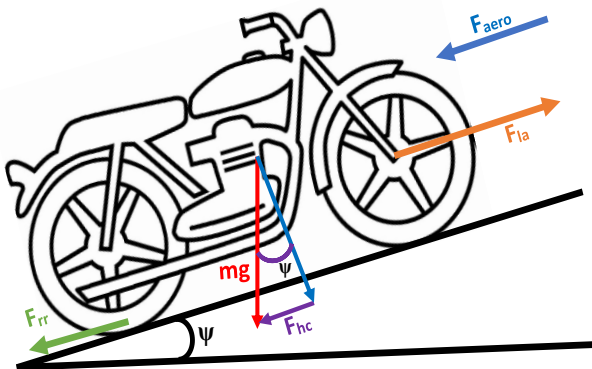


Fig. 1. Forces Acting on EV

The tractive effort, or power driving the vehicle, must provide force to:

- i. Overcome the rolling resistance:

$$F_{rr} = C_{rr} W \quad \text{-----(1)}$$

Where;

- F_{rr} = rolling resistance or rolling friction (N)
- C_{rr} = rolling resistance coefficient - dimensionless
- $W = mg$ = Effective Weight of the vehicle & rider (N)
- m = mass of the vehicle + rider (kg)
- g = acceleration of gravity (~ 9.81 m/s²)

- ii. Overcome the aerodynamic drag:

$$F_{aero} = \frac{1}{2} C_{ad} \rho v^2 A \quad \text{-----(2)}$$

Where;

- F_{aero} = Vehicle Aerodynamic drag force (N)
- C_{ad} = Aerodynamic drag coefficient - dimensionless
- ρ = density of air (~1.21 kg/m³)
- v = flow velocity (m/s)
- A = effective frontal area of the vehicle + rider (m²)

- iii. Overcome a Slope/Gradient:

$$F_{hc} = mg \sin \psi \quad \text{-----(3)}$$

Where;

- F_{hc} = Hill Climbing force (N)
- ψ = slope angle (deg or rad)

- iv. Force to Accelerate the vehicle:

$$F_{la} = ma \quad \text{-----(4)}$$

Where;

- F_{la} = Linear Acceleration force (N)
- a = acceleration (m/s²)

The total tractive effort (F_t) is the sum of all these forces, i.e;

$$F_t = F_{rr} + F_{aero} + F_{hc} + F_{la} \quad \text{-----(5)}$$

Torque required to propel the vehicle (T_v) is given by,

$$T_v = F_t * R \quad \text{-----(6)}$$

Where;

- R = Radius of the tyre (m)

Power required to propel the vehicle (P_v) is given by,

$$P_v = T_v * \omega \quad \text{-----(7)}$$

Where;

- ω = Angular Velocity of the tyre (rad/sec)

The final Simulink model of combined vehicle dynamic developed from the equations (1-7) with an ideal simple gear is shown in Fig. 2 with its expanded subsystem view presented in Fig. 3.

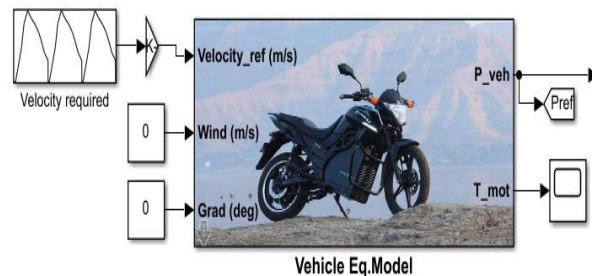


Fig. 2. Vehicle Model in SIMULINK

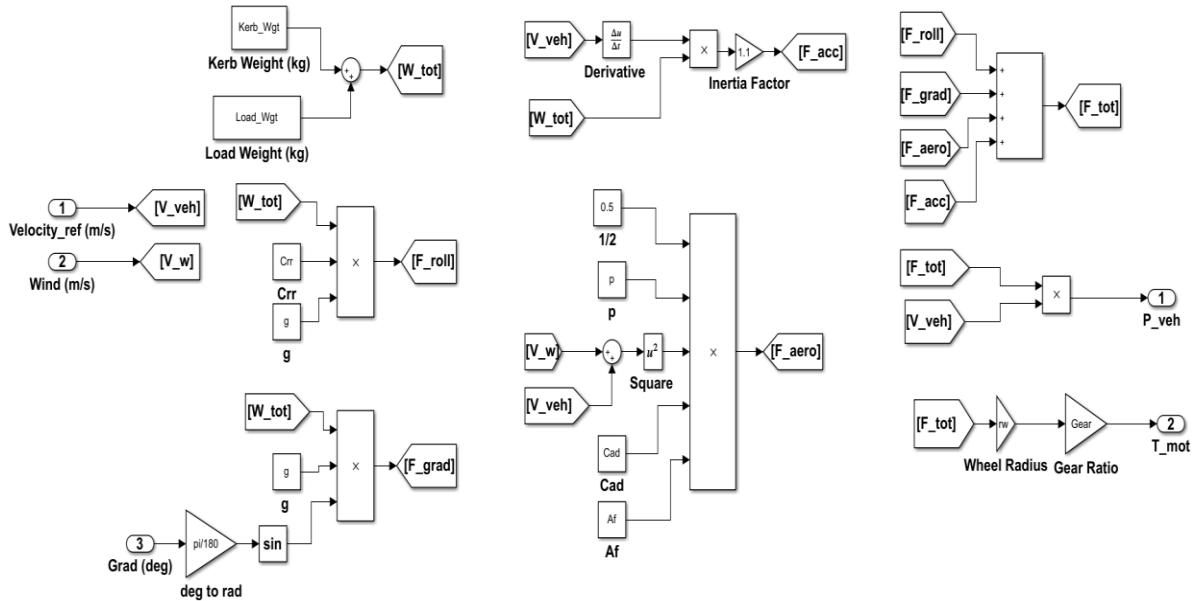


Fig. 3. Expanded Subsystem of Vehicle Equivalent model

The corresponding parameters of the proposed Light Electric Vehicle (LEV) are tabulated in Table 1.

Table 1. Vehicle Parameters

Parameters	Value
Kerb + Driver Mass (m)	150 kg
Acceleration due to gravity (g)	9.81 m/s ²
Frontal Area (A)	0.75 m ²
Air Density (p)	1.21 kg/m ³
Air Drag Coefficient (C _{ad})	0.22
Rolling Resistance (C _{rr})	0.0015
Road Gradient (ψ)	0 °
Tire Radius (r)	0.3 m
Gear Ratio (G)	7.8

b. Modelling of BLDC Motor:

In this section, mathematical model of a three-phase BLDC motor along with its corresponding SIMULINK model is implemented. Here we considered BLDC motor as “star connected” and the internal impedances of stator as symmetric under rotor saliency and magnetic alignment assumed to be ideal & uniform [4],[8]. The electrical and mechanical equations for a BLDC motor are as follows:

$$V_{ab} = R (i_a - i_b) + L \frac{di}{dt} (i_a - i_b) + e_a - e_b \text{ ----- (8)}$$

$$V_{bc} = R (i_b - i_c) + L \frac{di}{dt} (i_b - i_c) + e_b - e_c \text{ ----- (9)}$$

$$V_{ca} = R (i_c - i_a) + L \frac{di}{dt} (i_c - i_a) + e_c - e_a \text{ ----- (10)}$$

$$T_e = B \omega_m + J \frac{d\omega_m}{dt} + T_m \text{ ----- (11)}$$

Where V_{ab} , V_{bc} & V_{ca} are line voltages (Volt), i_a , i_b & i_c are phase currents (A) and e_a , e_b & e_c are phase to neutral Back-EMF's. R and L are resistance (Ω) and inductance (H) per phase respectively. T_e is electrical torque (N-m), T_m is load torque (N-m), J is rotor inertia (kg/m²), B is friction constant (N-m-sec/rad), ω_m is rotor speed (rad/sec).

The Back-EMF's can be expressed as,

$$e_a = \frac{K_e}{2} \omega_m \text{ Trap} (\theta_e) \text{ ----- (12)}$$

$$e_b = \frac{K_e}{2} \omega_m \text{ Trap} (\theta_e - \frac{2\pi}{3}) \text{ ----- (13)}$$

$$e_c = \frac{K_e}{2} \omega_m \text{ Trap} (\theta_e - \frac{4\pi}{3}) \text{ ----- (14)}$$

Where, K_e is back-emf constant & Trap represents ‘Trapezoidal Waveform’ function with respect to θ_e which is represented as follows:

$$\begin{aligned} \text{Trap}(\theta_e) &= 1, & 0 \leq \theta_e \leq 2\pi/3 \\ &1 - \frac{6}{\pi} (\theta_e - \frac{2\pi}{3}), & 2\pi/3 \leq \theta_e \leq \pi \\ &-1, & \pi \leq \theta_e \leq 5\pi/3 \\ &-1 + \frac{6}{\pi} (\theta_e - \frac{5\pi}{3}), & 5\pi/3 \leq \theta_e \leq 2\pi \end{aligned} \text{ ---(15)}$$

The equations (8-15) are enough to develop BLDC motor in SIMULINK as shown in Fig 4 for electrical model & Fig. 5 for mechanical subsystem.

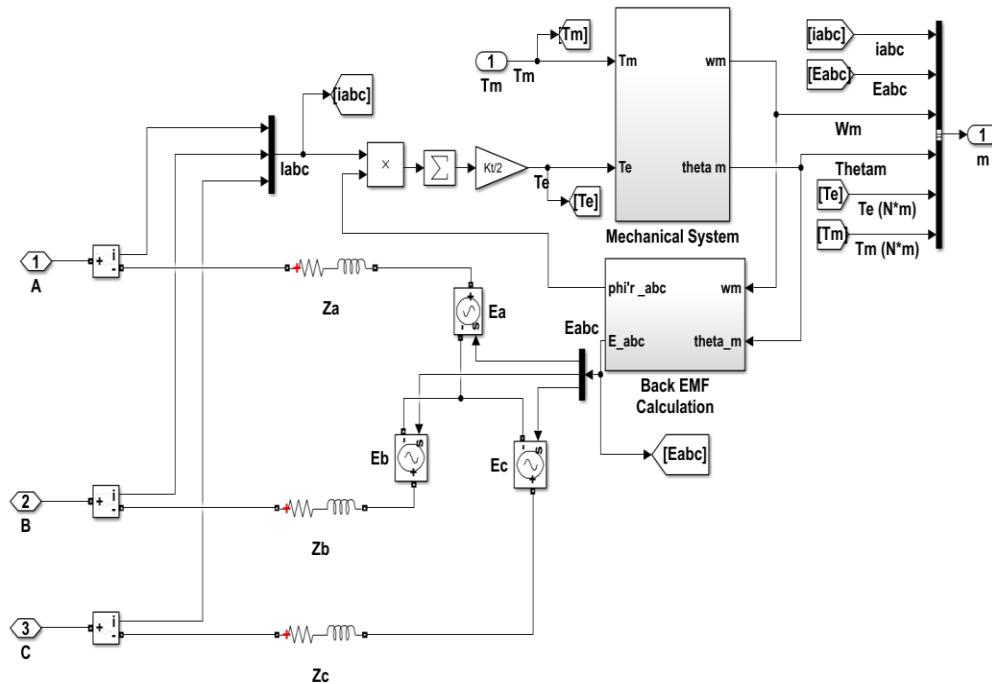


Fig. 4. Three Phase BLDC Motor Electrical Model in SIMULINK

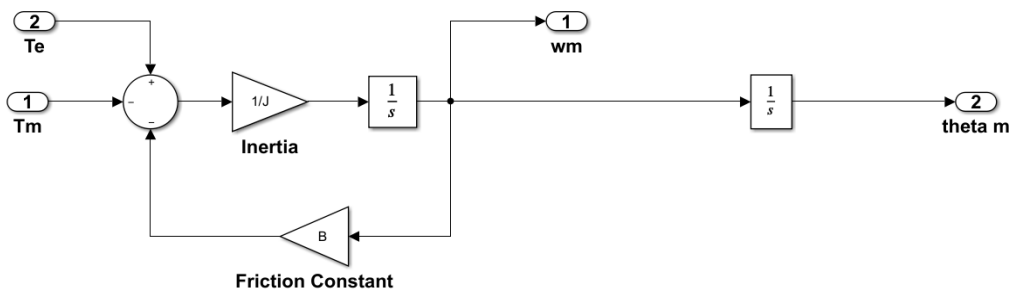


Fig. 5. BLDC Motor Mechanical Model in SIMULINK

The parameters of BLDC motor used in the proposed LEV are presented in Table 2.

Table 2. BLDC Motor Parameters

Parameters	Value
Motor Rated Power (P)	5 kW
Motor Rated Voltage (V)	72 V
Rated Torque (T_n)	14 N-m
Maximum Torque (T_{max})	25 N-m
Rated Speed (N_r)	3700 RPM
Rated Flux Linkages (ψ)	0.01953 Wb
Flat area in Back EMF	120 °
Stator Resistance (R_s)	6.2 mΩ
Stator Inductance (L_s)	77 μH
Friction Coefficient (B)	0.15×10^{-3}
Inertia (J)	0.2 m kg-m ²

c. Modelling of Li-ion Battery with Parameter estimation:

Lithium-Ion (Li-Ion) batteries are high-capacity batteries that can be developed for high energy or high-power applications [5]. A model that can depict battery behaviour with a range of battery factors such as SOC, temperature, loading conditions and their magnitude, and so on is required for optimal use or design. The widely used grey box modelling technique especially for a battery is ‘Thevenin battery model’.

In Thevenin equivalent battery model, Li-ion battery is considered to be a dependent voltage source series with an internal resistance & one or three RC parallel branches depending on the level of dynamic accuracy needed for a model design. For its simplicity and faster simulation time, a simple First-Order (one RC) Model shown in Fig. 6 is considered optimal for a LiFePO₄ Battery.

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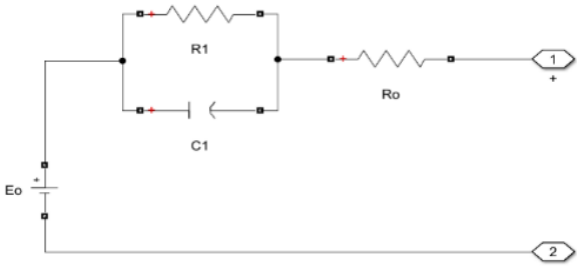


Fig. 6. First-Order (one RC) Model for a LiFePO₄ Battery

In this paper, data from a 3.2 V, 6 Ah is gathered using MATLAB/SIMULINK for constructing its corresponding lookup table-based one-RC model [6],[9]. Initially, random look up tables are created for the battery model after which the parameter estimation process begins. The un-converging waveforms are shown in Fig. 7.a & after parameter estimation, the converged results shown in Fig. 7.b.

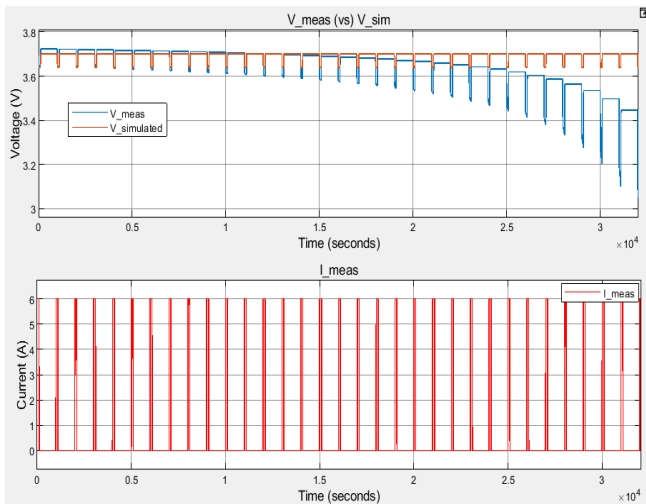


Fig. 7(a). Battery Voltage and Current waveforms before parameter estimation under pulse loading

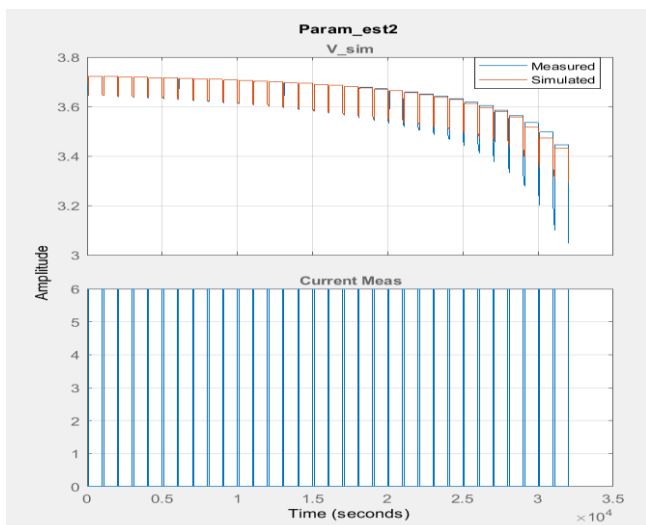


Fig. 7 (a & b). Voltage & Current waveforms of Battery after parameter estimation

The Final converged battery lookup tables with SOC as variable is shown in Table 3.

Table 3. Final Estimated Look-up Table with SOC as Variable for a single cell

SOC	0.1	0.2	0.3	0.4	0.5	0.6	0.7	0.8	0.9	1.0
E _o (V)	3.4352	3.5757	3.63	3.6623	3.6819	3.6959	3.7058	3.7135	3.7195	3.7245
R _o (Ω)	0.0568	0.0354	0.027	0.02196	0.01883	0.01675	0.0151	0.01397	0.01309	0.1218
R ₁ (μΩ)	95.53	98.73	100.5	104.48	98.84	101.81	99.11	104.45	105.56	99.97
T ₁ (sec)	10.61	11.7	9.77	10.4	10.23	10.03	8.8	9.9	9.51	9.986

The Final SIMULINK model of one-RC Thevenin equivalent of a single LiFePO₄ battery equivalent is shown in Fig. 8.

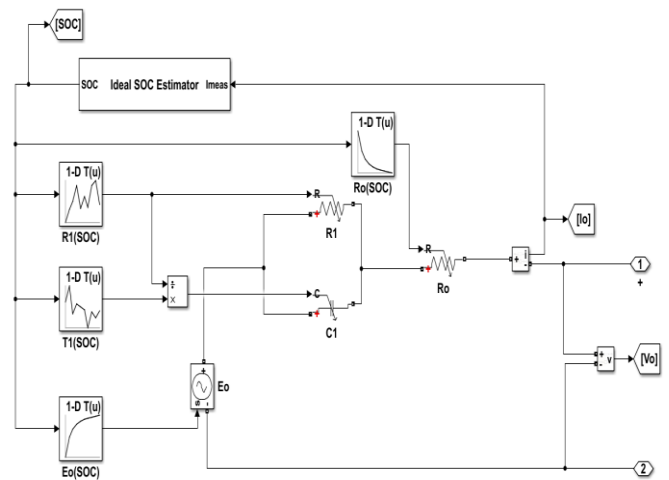


Fig.8. Final SIMULINK model of one-RC Thevenin battery equivalent

In this paper, a 48 V, 18 Ah battery pack made up of 15 series cells (i.e., N_s = 15) & 3 parallel strings (i.e., N_p = 3) with estimated/modelled cell is considered for final simulation.

d. Modelling of Supercapacitor:

Today's low-cost batteries perform horribly in applications requiring large (dis)charge currents. Adequately constructed supercapacitors (SC) in theory allow high energy density batteries to be used successfully, since the supercapacitors take on the temporary load of large (dis)charge currents [4].

In order to get the best result, we need an adequate model of supercapacitor. The supercapacitor model proposed in this paper uses the 'Stern model' where EDLC is described as nonlinear capacitance. Here we consider that electrochemical model reproduces the double layer capacitance (C_{EDLC}) related to the nonlinear diffusion dynamics. These equations are as follows:

$$C_{EDLC} = \frac{Np}{Ns} * \left(\frac{1}{C_{eq}} + \frac{1}{CGC} \right)^{-1} \text{ ----- (eqn 16)}$$

Where;

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the accurate control signals required for outer voltage loop due to fast transients in voltage output during the simulation. To tackle this limitation, a PI controller with an Adaptive sharing rule is thus proposed as outer loop controller.

The algorithm of Adaptive sharing rule which takes current reference and splits them according to battery and supercapacitor SOC is shown in Fig. 11.

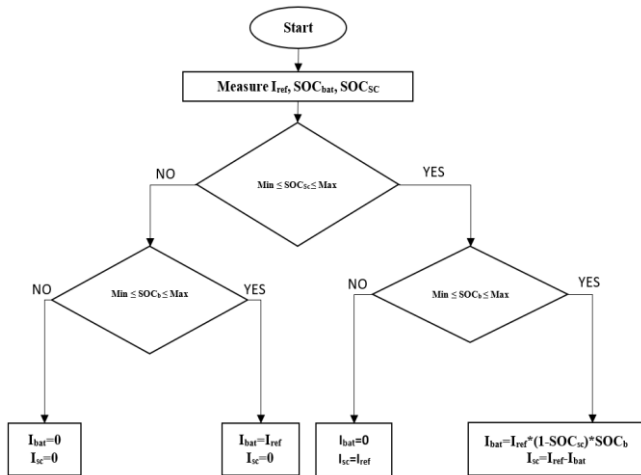


Fig. 11. Flow Chart of Adaptive Sharing Rule

b. Inner Current Loop ANN controllers:

Artificial Neural Networks (ANN's) are one of the most optimal control which consists of equivalent neurons that mimic our biological neuron to get accurate results in optimization problems. There are many types of neural network architectures like Feed Forward Neural Networks, Recurrent Neural Networks, Convolution Neural Networks, Deep Neural Networks (i.e., having more than two hidden layers)

Based on the converter's control problem, a Feed Forward Neural Network with one hidden layer best in terms of control response with less memory. As my current control needs to generate derivative modes of compensation, the layout of proposed ANN is modified as shown in Fig. 12 with its SIMULINK block shown in Fig. 13.

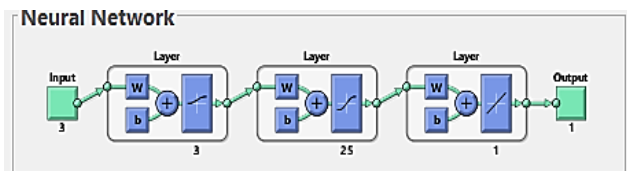


Fig. 12. ANN Schematic Layout

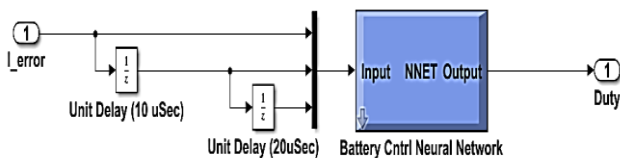


Fig. 13. ANN Current Controller SIMULINK Block

Mathematically, ANN is a collection of linear transformations (Weight Matrices) with a positive offset (biases) and non-linear transformations (Activation Functions) which are needed to be tuned perfectly to fit/map the values of input and output. So this tuning process is known as "Training". Hence to get good results with minimal training time, two ANN current controllers are used instead of a single ANN.

To get optimal fit/control, we use Levenberg-Marquardt Backpropagation Algorithm which has high efficacy for fitting Multi-Input and Single-Output control problems. The final training process using MATLAB is shown in Fig. 14. The same training process is repeated to design Battery and Supercapacitor ANN current controllers.

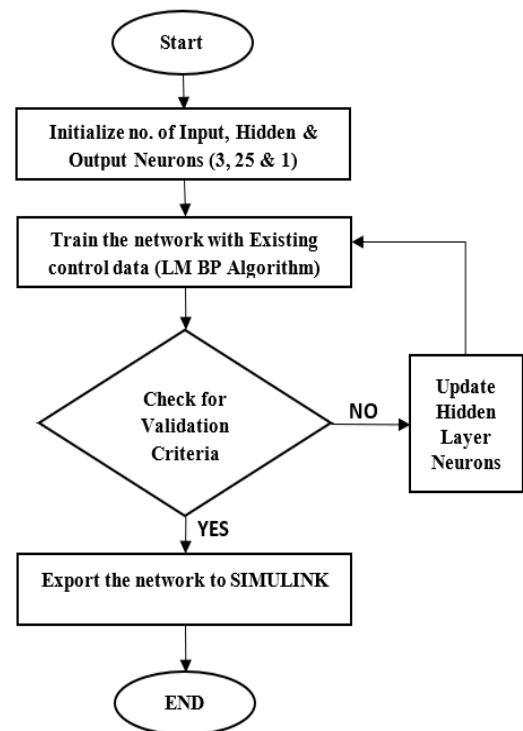


Fig. 14. Flow Chart of ANN Training using MATLAB

The final overview of parameters common for both ANN controllers are presented in Table 6.

Table 6. ANN Current Controller Final Parameters

Parameters	Value
No of Input Neurons	3
Input Layer Activation Function	Sigmoid
No of Hidden Layer Neurons	25
Hidden Layer Activation Function	Sigmoid
No of Output Neurons	1
Output Layer Activation Function	Linear

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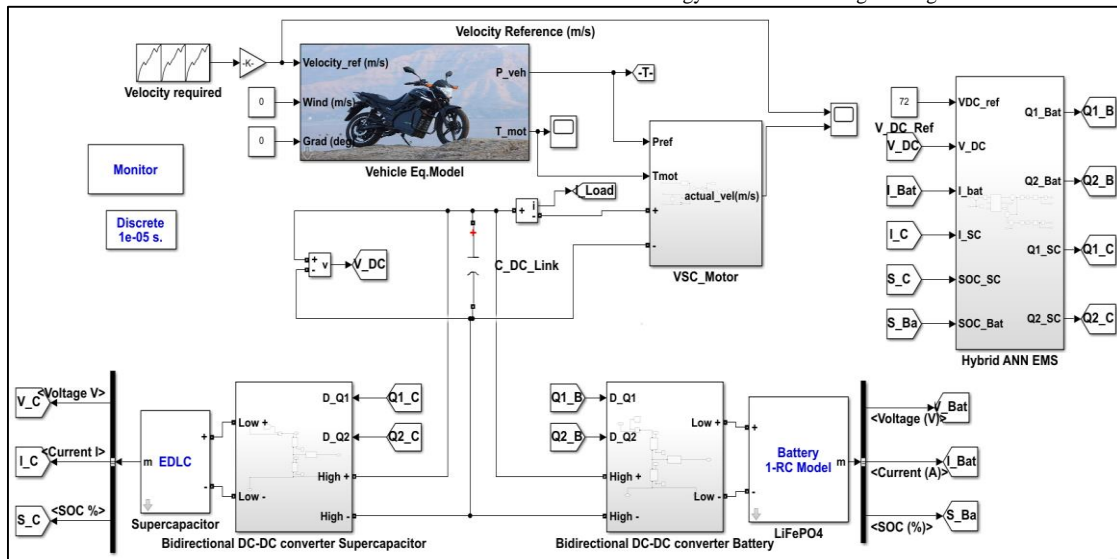


Fig. 15. Final SIMULINK Model of HESS based LEV with Hybrid ANN EMS

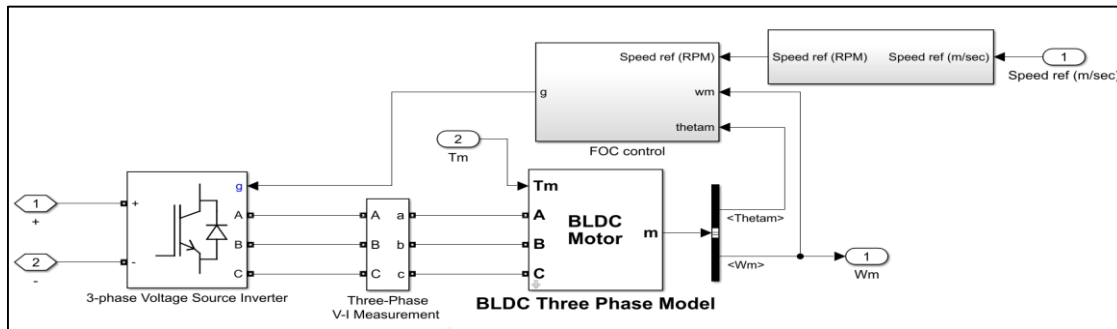


Fig. 16. FOC control of BLDC Motor

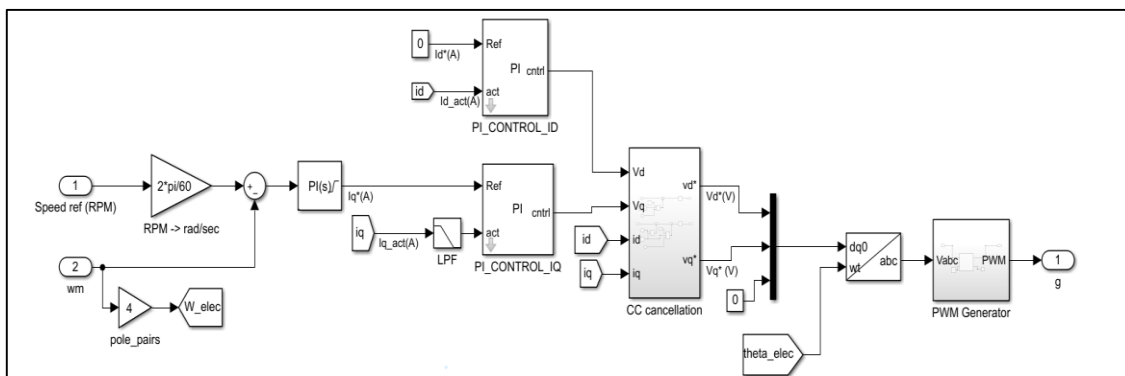


Fig. 17. FOC control subsystem

IV. PROPOSED MODEL

The final SIMULINK model of proposed HESS based LEV with Hybrid ANN EMS is shown in Fig. 15. The total functions to be performed by the proposed system can be listed below:

a. Speed control of BLDC motor:

The Final Speed control unit of the proposed EV using BLDC FOC controller is shown in Fig. 16.

In FOC (Field Oriented Control) of AC Machines, we try to align rotor and stator magnetic fields 90° to ensure maximum torque with less ripple in speed. It employs DQO (Park) Transformation that transforms 3-phase measured currents to rotating DC currents separated by 90° each.

By making D-component as zero and only maximizing Q-component, one can achieve speed control objectives with less power ripples. The FOC control subsystem is shown in Fig. 17 which has inner DQO current control loop and outer speed control loop.

b. Energy Management System (EMS):

The proposed EMS algorithm generates appropriate power sharing commands based on the SOC conditions of Battery & Supercapacitor packs respectively. In the flow chart (Fig. 11) the ‘Min’ represents minimum SOC which is taken as 15 % and ‘Max’ represents maximum SOC, taken as 90 %. The SIMULINK model of final control unit of HESS is shown in Fig. 18.

When both battery and supercapacitor packs are at ‘Min’ SOC point and we still have positive reference current that need to be supplied, the EMS terminates the reference call and isolates HESS by making battery and supercapacitor reference currents to zero and thus improving their health. The same functionality gets repeated during regenerative braking, where reference current becomes negative and both sources at

‘Max’ SOC point, EMS isolates HESS and generates a brake signal for mechanical braking.

If there is only one source’s SOC lies between safe operating range, the total reference current signal gets transferred to that source’s converter and it drives the EV alone.

When both sources are intact and lies within the operatable range of SOC, the supercapacitor pack supplies more current with respect to its SOC the battery current simply adapts to the balance reference current, which is a function of both sources’ SOC’s. In each mode of operation, the ANN Current controllers attempt to obtain their respective reference currents in as little time as possible, hence boosting power flow efficiency and thereby keeping DC-Link Voltage within tolerable limits.

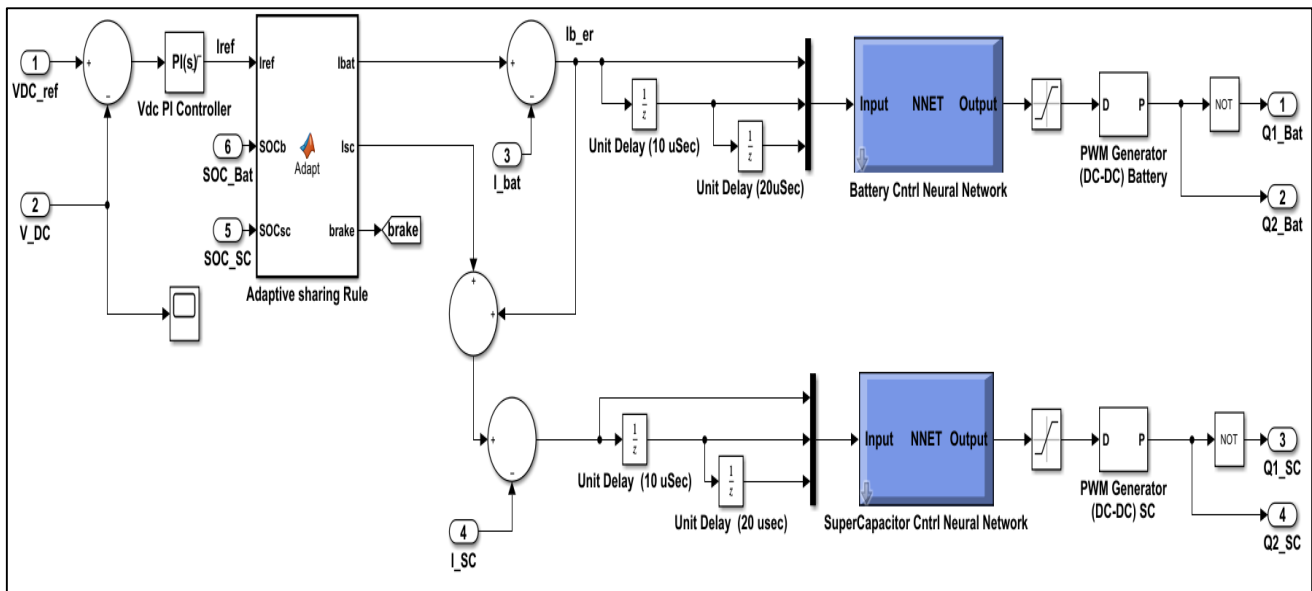


Fig.18. Final Hybrid ANN EMS

V. RESULTS & DISCUSSION

The simulations have been done in MATLAB 2020a. This section presents the final results regarding to DC link voltage, speed, Battery and supercapacitor waveforms with a comparison between existing PI controller-based EMS strategies and proposed Hybrid ANN EMS. The proposed and existing methods are tested for accelerating speed reference input for a simulation time of 33 seconds and the following results are obtained.

A. For Existing PI Controller based EMS:

The following are the output waveform when we operate battery & supercapacitor Hybrid storage with classical PI cascaded control for Bidirectional DC-DC converters.

As depicted in Fig. 19, the hybrid energy storage’s DC link voltage (i.e., voltage applied to motor) has the mean value of 72

V with ± 5.6 V variations which is worse than their stand-alone operations.

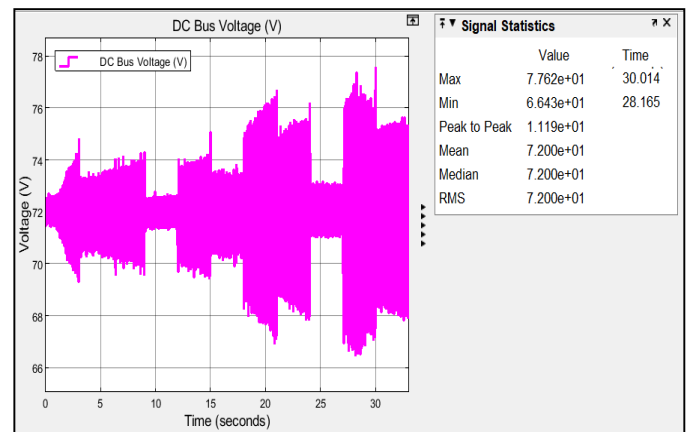


Fig. 19. DC Bus Voltage with Classical PI controlled HESS

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From Fig. 20, when we applied maximum reference velocity of 21.725 m/s (78.2 kmph), the EV max speed attained is 21.05 m/s (75.781) and the velocity tracking Root Mean Square Error (RMSE) is around 0.57 m/s (2.052 kmph) which is very better compared to standalone operations of battery & supercapacitor but not optimal.

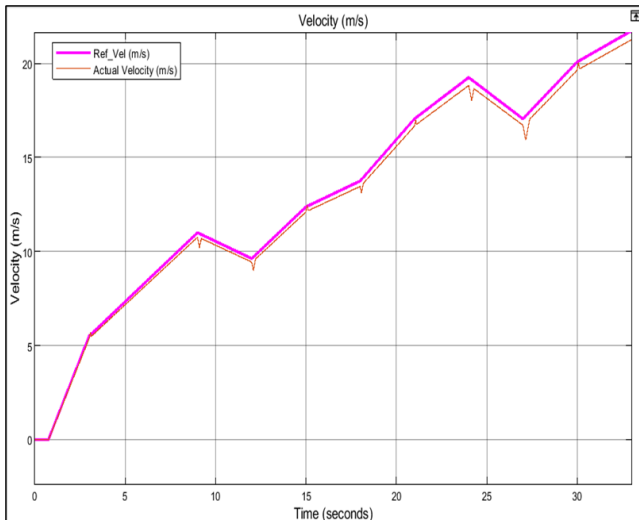


Fig. 20. Reference & Actual Velocity with Classical PI controlled HESS

From Fig. 21, it is observed that the initial SOC of battery is 60 % and the end SOC is 59.4373 %. The max. Current supplied by the battery is 30 A which equals 1.67 C (where 'C' means rated charge of battery) discharge rate which is very optimal for health of battery pack. Maximum Regenerative current is observed to be -30.9 A which is acceptable but not optimal.

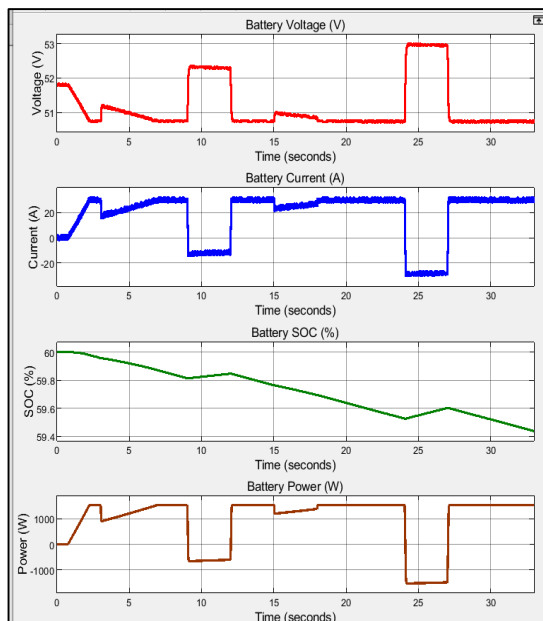


Fig. 21. Battery Voltage, Current, SOC & Power waveforms with Classical PI controlled HESS

From Fig. 22, the initial SOC of supercapacitor is observed to be 99.3 % and the end SOC is 90.86 %. The max. Current supplied by the supercapacitor is 70.21 A. Maximum Regenerative current observed is -3.11 A which means it is not charging.

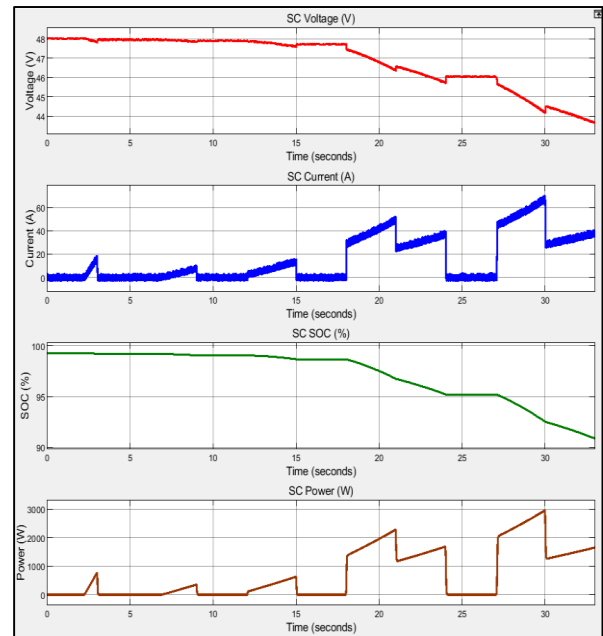


Fig. 22. Supercapacitor Voltage, Current, SOC & Power waveforms with Classical PI controlled HESS

B. Proposed Hybrid ANN EMS:

The proposed Hybrid ANN EMS based LEV results are as follows:

The Fig.23 depicts that the DC link voltage varied around ± 1.63 V with mean value maintained at reference point of 72V which characterizes its superior bus power control i.e., HESS with the Hybrid ANN Controller supplies and absorbs required power during acceleration and braking phases vehicle operation making the voltage fluctuations minimal.

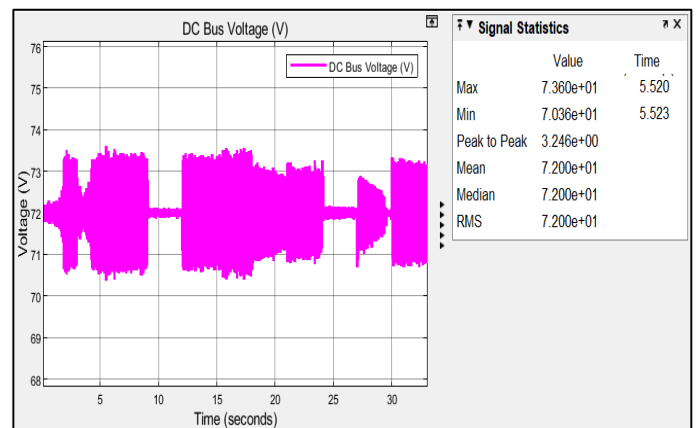


Fig. 23. DC Bus Voltage for Proposed EMS strategy

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In Fig. 24, when the maximum reference velocity of 21.725 m/s (78.2 kmph) has been applied, the LEV attained the maximum speed of 21.4952 m/s (77.38271 kmph) such that the velocity tracking Root Mean Square Error (RMSE) is around 0.1844 m/s (0.663 kmph) which is optimal.

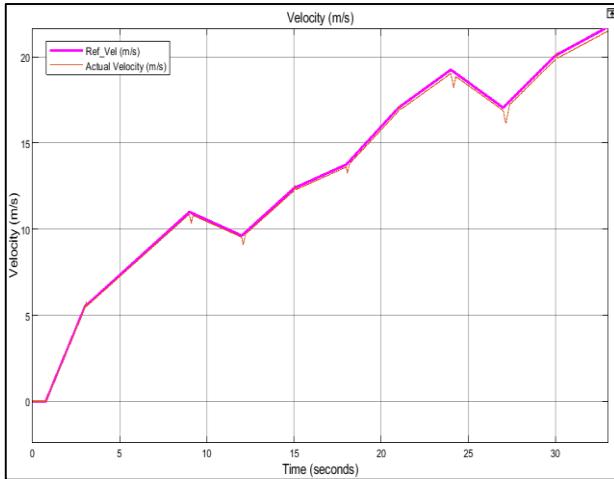


Fig. 24. Reference & Actual Velocity with Proposed EMS

From Fig. 25, the initial SOC of battery is 60 % and the end SOC is 59.9685 %. The peak current supplied by the battery is 15.3912 A which nearly equals 0.8 C discharge rate which is a healthy magnitude for the designed battery pack. Maximum Regenerative current observed is found to be -14.613 A which is an acceptable magnitude.

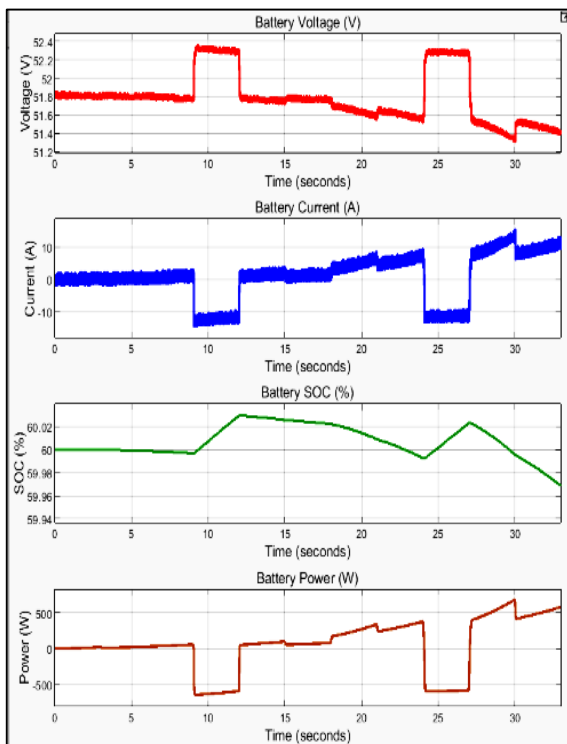


Fig. 25. Battery Voltage, Current, SOC & Power waveforms with Proposed EMS

From Fig. 26, the initial SOC of supercapacitor is 99.3 % and the end SOC is 77.8694 % and hence Supercapacitor is utilized more than battery when its fully available which is effective way in improving battery health and range of EV. The peak current supplied by the supercapacitor is 109.4097 A. Maximum Regenerative current observed is -25.0597 A which means it is taking maximum regenerative current and thus sparing battery deterioration.

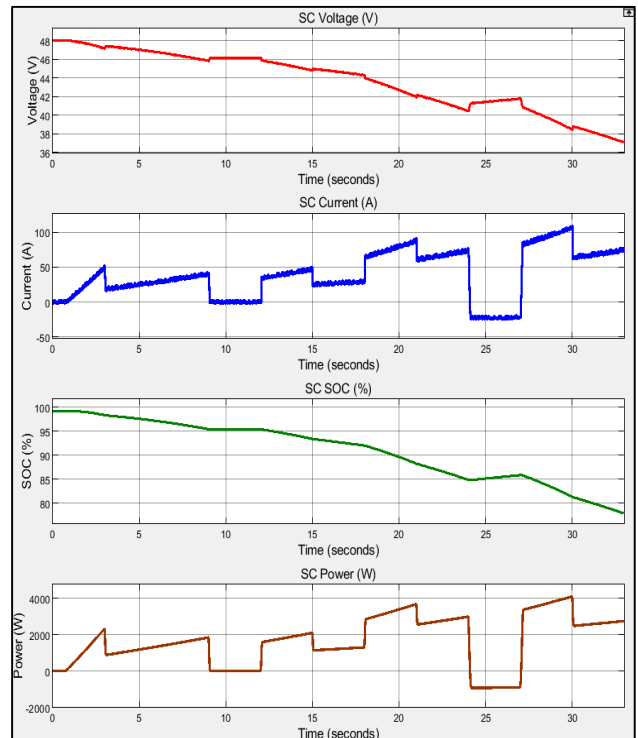


Fig. 26. Supercapacitor Voltage, Current, SOC & Power waveforms with Proposed EMS

In Fig. 27, the load, battery and super capacitor power waveforms are displayed to give a final overview on power flow.

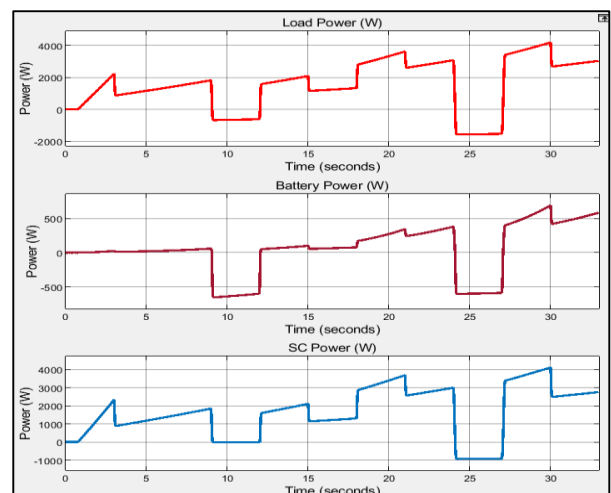


Fig. 27. Final Power Waveforms for proposed HEMS strategy

VI. CONCLUSIONS

In this project, we have developed a novel control approach using Hybrid ANN EMS which has Adaptive sharing rule for outer loop and ANN current control for inner loop to optimize power flow in a battery-supercapacitors Hybrid storage unit for a Light Electrical Vehicle (LEV) application. The goal of stable power control of a bidirectional DC-DC converter is achieved by the use of a Hybrid ANN EMS as it provides a constant DC bus voltage of 72 V with a ripple of ± 1.63 V under continually varying load power and input voltage. The simulation results show that the supercapacitor delivers maximum amount power during acceleration & absorbs major share of regenerative power during deceleration. This avoids deep discharge and quick charge of the battery pack and hence smaller battery sizes can be employed for same power requirements. the adaptive rule-based ANN control has the potential to restrict the battery current magnitude to less than its maximum and thus improve the battery life-cycle. Finally, it can be stated that the proposed management system satisfied optimal power flow objectives thus enhancing efficiency and reliability of hybrid energy storage.

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AUTHOR PROFILES

Vankadari Praveen completed BTech in Electrical & Electronics Engineering (EEE) and now currently pursuing MTech in Advanced Electrical Power Systems (AEPS) from Department of EEE, University College of Engineering Kakinada (A), Jawaharlal Nehru Technological University, Kakinada, Andhra Pradesh, India.

Dr. Kotni Sri Kumar is Professor and Head of the Department of EEE, University College of Engineering Kakinada (A), Jawaharlal Nehru Technological University, Kakinada, Andhra Pradesh. His research interests include Power Electronics, Renewable Energy Systems, Energy Auditing & Energy Conservation.