Bidirectional Long Short Term Memory Controller for Energy Management in Hybrid Electric Vehicles

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Abstract - Energy management is an essential feature in hybrid electric vehicles (HEVs) to maximize efficiency, fuel economy, and range while lowering pollutant emissions. Likewise, Bidirectional Long Short Term Memory (Bi-LSTM) has developed into a valuable and successful tool for developing energy-management strategies for HEVs. The relationship between fuel cells (FC), batteries, and ultracapacitors (UC) for HEV applications is presented in this paper. This technique is used to divide the HEV's energy need between the UC and the FC. The bidirectional buck-boost converter links the UC to the dc-bus, while a boost converter links the FC to the dc-bus. In order to accelerate and brake, an electric motor is used to drive the asynchronous machine. The primary contribution of this research focuses on energy management utilizing Bi-LSTM controller technique, which is based on neural network-based controller strategy. Through a few simulations and practical tests specifically designed for HEV applications, the performance of the suggested control mechanism is assessed.

IndexTerms - Electric vehicle, energy management, Bidirectional Long Short Term Memory Controller, fuel cell, and the bidirectional buck-boost converter

I. INTRODUCTION

Energy is essential for maintaining daily life of people and advancing technology. Fossil fuels are widely employed to supply the increasing demand for energy, which is causing greenhouse gas emissions to continuously rise [1-2]. According to reports, the production of electricity accounts for 28% of all global greenhouse gas emissions, particularly in developing nations. 25% of the global CO2 emissions are caused by fossil fuel-powered engines, such as those powered by petrol, diesel, and other fuels. Internal combustion engines (ICEs), which run on fossil fuel and have the lowest energy conversion efficiency at 20%, are also dangerous [3-4]. Manufacturers of electric vehicles (EVs) release a variety of models, including plug-in hybrid electric vehicles (PHEVs), hybrid electric vehicles (HEVs), battery-powered electric vehicles (BEVs), fuel cell electric vehicles (FCEVs), and photovoltaic EVs, as advantageous economic conditions prevail. BEV appears to be a promising technology that is paving the way for the environment's decarbonization in recent years [5].

BEV is anticipated to have a significant market penetration in the near future due to a slow social acceptance. Its performance is heavily influenced by the choice of energy storage systems (ESS), control tactics, and energy management (EM) strategies [6]. This transport has promising future prospects. As a result, the effectiveness of various energy storage systems has been evaluated, together with their forms, traits, and features with regard to EV applications [7-8]. Any BEV needs an energy management system (EMS) in order to achieve greater performance and control as the mode of transportation of the future. Its primary duty is to maintain the energy flow from the ESS to the wheels of the vehicle as needed. Additionally, an effective EMS might help to increase the EV drive range [9]. Additionally, it controls quick discharge that happens during acceleration or a sudden change in speed. The best choice for sustaining such transitions is found to be ESS paired with an ultra-capacitor (UC). Furthermore, such EVs need an effective EMS to handle problems with the hybridization of energy sources. Combinations of high-power density (battery) and high energy density (UC) or fuel cells are a few examples of hybridization sources [10-11].

Rule-based approach and optimization-based approach are two of the techniques that have been put forth so far in recent studies for EM implementation in HEVs, PHEVs, or HESS in EVs. The majority of the earlier mentioned techniques are recommended for battery/UC and FC/battery/UC combinations [12]. This section explains many EM control strategies for battery/UC combinations that have been discussed in the literature, along with the benefits and drawbacks of each strategy. A NN-based control technique for EV batteries and UC HESS has recently been suggested [13-14]. However, in order to reduce battery peak currents and achieve optimal UC current, NN for HESS powered EV requires a significant quantity of training data sets from historical information. This method determines the optimal battery and UC power split. Power demand and various driving cycle sets are also used as input and output data for NN, respectively [15]. The following benefits are provided by this approach: (a) a large degree of freedom; (b) sharp reasoning and adaptability; (c) the ability to tackle nonlinear control issues; and (d) fault tolerance. The main contribution of the work is as follows:

- Fuel Cell and Ultra-capacitor are hybridized with respective converters to generate DC voltage.
- The Bidirectional-Long Short term Memory (Bi-LSTM) network is developed for predicting the Electric Vehicle (EV) on/off with the goal to improve the quality of energy management.
- To keep the battery state of charge (SOC) within the allowable ranges to extend the life of the batteries.
- An effective battery management system (BMS) is able to accomplish this. A control over the ideal power flow between the battery, converters, and other components of a vehicle should be included in addition to the BMS.
- Simulink/MATLAB is used to model and simulate the suggested EV.

This article is structured as Section II describes the literature survey. Section III details the process of proposed methodology. Section IV describes the simulation analysis, result and discussion. Finally, Section V concludes the proposed system.

II. LITERATURE SURVEY

PEVs, or plug-in electric vehicles, have attracted users' interest with their innovative, economical, and environmentally beneficial services. For PEVs, a wide range of algorithms, machine learning and deep learning solutions, and artificial intelligence solutions have been suggested. For the administration of charging stations and PEVs, Qureshi et al. [16] suggested Electric Vehicle-Intelligent Energy administration and Charging Scheduling System. The suggested system uses battery control units and communicates with charging stations to deliver practical energy management services.

The design of an energy management strategy is the area of research that is most important for extending the fuel cell's lifespan. The fuel cell is the primary power source and the battery is the auxiliary power source for a fuel cell hybrid electric vehicle, according to Min et al. [17]. A new algorithm is suggested and existing studies are compiled. The presented work suggests Neural Network Optimized by Genetic Algorithm as an efficient method for the system under study. The neural network may be trained effectively by genetic algorithm, and the trained network can consciously avoid certain outputs in accordance with the requirements.

An energy management technique based on deep reinforcement learning was put out by Li et al. [18] for an electric car hybrid battery system made up of a high-energy and high-power battery pack. Aiming to reduce energy loss and raise the electrical and thermal safety level of the entire system, the energy management strategy for the hybrid battery system was created based on the electrical and thermal evaluation of the battery cells. The deep Q-learning model was trained using a random combination of different load profiles, which prevented the over fitting issue. In terms of computation time and energy loss reduction of the hybrid battery system, the proposed energy management strategy has shown to be superior to reinforcement learning-based methods, underscoring the relevance of such a strategy in future energy management systems.

In [19], an intelligent EMS for HEV is derived using a deep reinforcement learning (DRL) method called TD3. Within the DRL loop, a heuristic rule-based local controller is integrated to prevent irrational torque allocation while taking into account the properties of powertrain components. A mixed experience buffer (MEB) made up of offline computed optimal experience and online learning experience is the foundation of the hybrid experience replay (HER) method, which is suggested as a means of resolving the impact of environmental disruption. In comparison to standard value-based and policy-based DRL EMSs, the results show that improved TD3 based EMS obtained the best fuel optimality, fastest convergence speed, and highest robustness under diverse driving cycles.

In [20], an innovative co-optimization technique is created to optimize: i) cabin heating using combined engine heat assist and electrical resistance heating, ii) multi-mode powertrain operation during charge depletion, and iii) exhaust after treatment system thermal management to minimize catalyst light-off fuel penalty. In order to do this, a framework for model-based cabin heating and powertrain optimization is developed and put to the test utilizing a plug-in hybrid electric vehicle's vast trial data. The test findings for the United States Urban Dynamometer Driving Schedule and one real-world drive cycle with variable elevations demonstrate the proposed integrated cabin and powertrain thermal management can result in 10% to 26% vehicle energy savings.

Without the aid of the state of charge reference, Chen et al. [21] Proposed intelligent equivalent consumption minimal technique based on dual neural networks and a unique equivalent factor correction which may adaptively regulate the equivalent factor to attain the close to ideal fuel economy. The backpropagation neural network is created to forecast the engine on/off with the purpose of improving the quality of equivalent factor prediction, whilst the Bayesian regularization neural network is built to predict the nearly optimal equivalent factor online. Additionally, the unique equivalent factor adjustment can ensure that the battery's terminal state of charge complies with the predetermined limitations and that electrical energy is gradually utilized along the journey.

For the fuel-saving optimization of a PHEV, Qi et al. [22] developed a self-supervised reinforcement learning method based on a Deep Q-learning methodology. First, a thorough model of the Prius engine is constructed. Second, they enhanced the reward function using the self-supervised learning model. There are two components to the reward function: internal rewards and external rewards. Finally, a reinforcement learning calibration strategy is suggested to stop the self-supervised model from entering the "self-good" condition. The enhancement of the reward function makes the vehicle exploring approach more efficient. Results reveal that the self-supervised and learning calibration-based deep reinforcement learning approach achieves faster training convergence and less fuel consumption than the conventional approach, and that under our new driving cycle, its fuel economy can roughly reach the global optimum.

An ideal hybrid energy sources size methodology for hybrid electric vehicles made up of UC and FC with battery units was put forth by Prasanthi et al. [23]. Dynamic-source models are used to design a multi-objective problem that evaluates the system's starting cost, weight, running cost, and source degradation cost. Additionally, a brand-new adaptive energy management approach (AEMS) that emphasizes driving cycle power demand and dynamic-source features is put forth as a solution to the optimization issue. Finally, the butterfly optimization algorithm (BOA) is enhanced by using the quantum wave notion to more effectively explore the search space in order to solve the hybrid energy source optimization problem. Furthermore, the proposed AEMS performs better and could reduce the system relative cost and weight for the BU-UC-FC configuration by 16% and 10%, respectively, when compared to a traditional discrete wavelet transform power-splitting approach used in the optimization process.

With the objective of reducing fuel usage while satisfying the constraint on the terminal battery State-of-Charge (SoC), Climent et al. [24] presented an EMS for a PHEV. In order to gather data regarding the practical operating circumstances during the driving cycle, the proposed technique assumes that the route has already been travelled by the vehicle multiple times. With the driving cycle estimated, the Equivalent Consumption Minimization Strategy (ECMS) is used to address the torque-split issue in parallel hybrid powertrains. The associated boundary value problem of determining the weighting factor between battery and fuel costs that drives the SoC to the desired level at the end of the estimated cycle is solved, and the solution is then applied to the system. The outcomes show that the online ECMS performs better than the other online useful approaches. In order to maximize the fuel efficiency of HEVs, to enhance the engine's operating conditions, and to advance DRL research in the field of EMSs, Tang et al. [25] initially proposed a DRL-based EMS coupled with a rule-based engine start-stop approach. Additionally, taking into account that both the engine and the gearbox are controlled components, this article developed a novel double DRL (DDRL)-based EMS. The DDRL-based EMS realizes multi-objective synchronization control by using various learning algorithms and a deep Q-network (DQN) to learn the gear-shifting strategy and a deep deterministic policy gradient (DDPG) to control the engine throttle opening.

The electrification makes it possible for vehicles to recover baking energy and adds an additional degree of control over power-flow distribution. This is made possible by invertible energy storage devices and electric motors. The comparable consumption minimum strategy is often viewed as a battery state of charge reference tracking method for plug-in hybrid electric vehicles. Thus, the quality of state of charge reference production has a significant impact on the corresponding control performance. Using a DC/DC converter with a high current rating increases converter size when compared to a battery-UC active architecture. The system's degree of controllable freedom is limited during acceleration, and the DC bus voltage varies widely. Moreover, the sophisticated control techniques needed to maintain the energy balance between two sources. The newly proposed energy management system can address these issues.

II. PROPOSED SYSTEM

A battery pack, electric motor, ultra capacitor, fuel cell, DC-DC converter, inverter, and electric vehicle (EV) are all included in the schematic layout. The fuel cell and ultra-capacitor provide the input power. The inverter fed ac motor drive operates in two modes: propulsion mode and regenerative braking. The DC-DC converter transforms battery voltage into the high-voltage DC needed to power the motor drives. Power is delivered from the battery to the electric motor during propulsion mode, and during regenerative braking, it is reversed. Bidirectional DC-DC converters help with the reverse power flow. The DC motor drive, which functions similarly, is managed by DC-DC converters. The functioning EMS units continuously check the battery's condition, produce control commands for the suggested Bi-LSTM controller, and maintain battery charge over a longer distance. Additionally, EMS controls how electricity is distributed from the battery to other parts like the load.

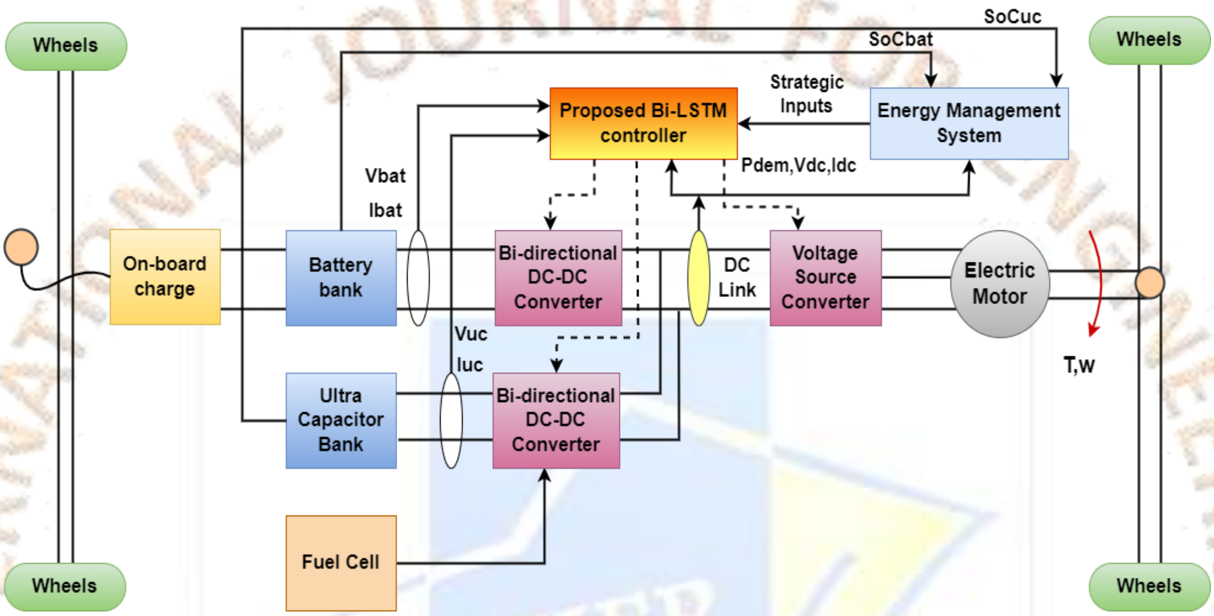


Fig.1 Block diagram of proposed method

ULTRA-CAPACITOR

An electrical component capable of retaining several times more electrical charge than a regular capacitor is referred to as an ultra-capacitor (UC), sometimes known as a super capacitor. An UC can occasionally take the place of a rechargeable low-voltage electrochemical battery. Although the operation of UC is similar to that of conversional kinds, it produces double capacitance and has a higher ability to store energy while simultaneously releasing more power than a conventional capacitor. The current flow through the capacitor is denoted as $I_{SC} = \frac{dQ}{dt} =$ and the storage capacity of the capacitor is $Q = \int I_{SC} dt$ with the capacitance value and resistance of $C_{SC} = \frac{dQ}{dV_{SC}}$ & $R_{ESR} = \frac{dV}{dt}$, respectively. Here, R_{ESR} is the equivalent series resistance. The circuit diagram for an ultra-capacitor, which combines capacitance and resistance, is shown in figure 2 below.

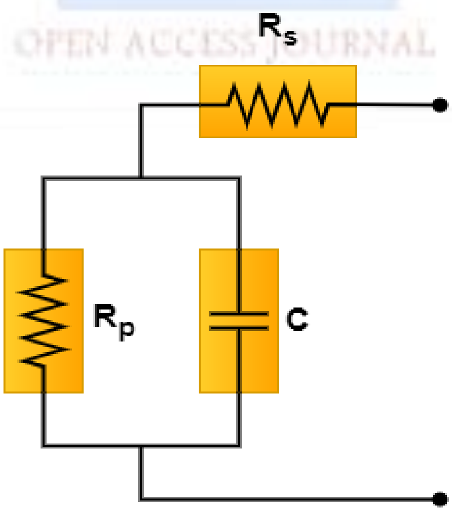


Fig.2 UC circuit diagram

The voltage of the capacitor can be computed by utilizing the accompanying equation,

$$E_{UC} = E_{nom} + \frac{1}{C}\int_{t=0}^{1} I_{UC} dt \qquad (1)$$

In the above condition, Enom (or Vnom) is the supposed voltage level and C signifies the capacitor which is associated in parallel with the resistor RP.

FUEL CELL

A chemical reaction within a fuel cell generates power without burning. It produces power while converting hydrogen and oxygen into water. It is an electrochemical energy conversion system that generates heat, water, and electricity. Similar to batteries in operation, fuel cells do not need an electrical supply to recharge. All of the chemicals in a battery are kept within where they are converted into power. The battery dies when those chemicals are depleted. On the other hand, a fuel cell doesn't run out of the chemicals it needs because it gets them from the outside. As long as there is fuel available, fuel cells can produce electricity practically endlessly. The electrodes are where the electric reactions take place. Every fuel cell contains two electrodes: an anode, which is a positive electrode, and a cathode, which is a negative electrode. A barrier made of electrolyte separates these. While oxygen (or plain air) travels to the cathode side, fuel goes to the anode side. Both of these substances react, divide their electrons apart, and produce an electric current when they come into contact with the electrolyte barrier.

Fuel cell chemical reaction of anode & cathode $H_2 \rightarrow 2H^+ + 2e^-$ (2)

$\frac{1}{2}O_2 + 2H^+ + 2e^- \rightarrow H_2O$ (3)

$H_2 + \frac{1}{2}O_2 \leftrightarrow H_2O + Heat$ (4)

Fuel cell voltage equation $E_{FC} = V - R_{FC} - I_D - Wh(A.I_D + B)$ (5)

Fuel cell current equation $I_{FC} = \frac{V_{FC}}{R_{FC}}$ (6)

Fuel cell power equation $P_{FC-Max} = E_{FC}I_{FC}$ (7)

The power of fuel cell generated by using equations (2) & (3) and which (4) is represented as,

$P_{FC\_max} = E_{FC}I_{FC}$ (8)

BATTERY BANK

The most developed form of commercially available storage alternatives on the market is electrochemical storage in the form of batteries. They can be used for many different applications, ranging from electric vehicles to backup reserves, as they are available in a wide range of features. The positive and negative electrodes in a battery's structure interact with the electrolyte to create a circulating current. The amount of energy absorbed by or discharged from the battery determines the frequency and kind of these chemical reactions. Individual battery cells are connected to create arrays to create larger battery systems. To increase the desired voltage, battery cells are connected in series, and the Ampere-hour (Ah) capacity can be raised by connecting those cells in parallel. Every battery has an energy rating that indicates the amount of energy it can store based on the mass and volume of the electrolyte. However, the contact area and reaction surface area between the electrolyte and electrodes will determine the battery's power rating.

To increase the performance of the fuel cell system and maintain the super capacitor's good operation, battery is used as a buffer energy source. It is important to note that the battery's energy comes from the fuel cell technology. Therefore, the amount of energy in the battery should remain within safe bounds. The SOC is defined as the ratio of the battery's maximum charge capacity to its stored charge, and it can be explained as follows.

$$SOC_b(t) = SOC_b^0 - \frac{\eta_b.\int_0^t I_b(t).dt}{E_b^{max}} \quad (9)$$

BIDIRECTIONAL DC-DC CONVERTER

The Bi buck-boost converter is comprised of one inductor L, two MOSFETs (or IGBTs) Q1, Q2, two diodes D1, D2, two capacitors C1, C2, and two MOSFETs Q1, Q2. Only MOSFETs are employed as switching devices in this investigation; if IGBTs were used, the outcomes would be comparable. This converter can operate in both buck and boost modes to achieve energy flow in both directions. The following is a detailed explanation of how these two modes operate.

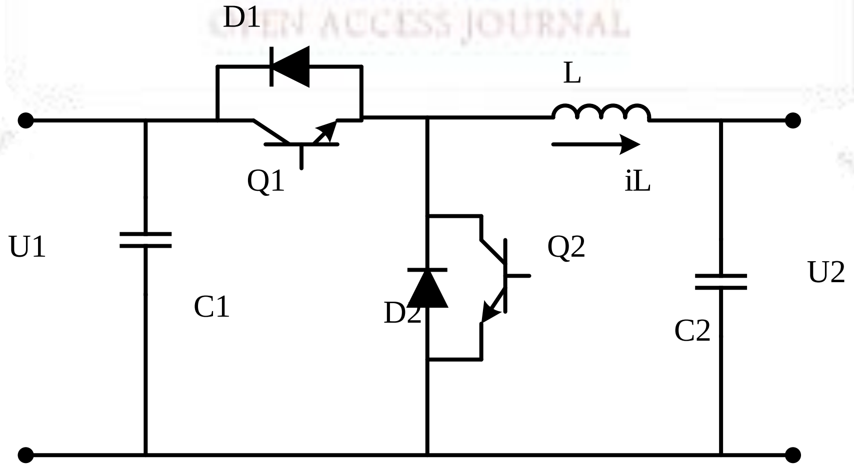


Fig.3 Bi buck-boost converter

Buck Mode

Assuming the converter is operating in continuous conduction mode (CCM), the input voltage U1 and output voltage U2 have a relationship of KD1 ¼ U2=U1, where KD1 is the duty cycle. The inductor's current, iL, runs from left to right. While Q1 is on and Q2 is off, iL is increasing while KD1Ts is on and iL is dropping when KD1Ts is on and Q1 is off. The energy from the source V1 is transmitted to the load on the V2 side in the buck mode. Fig. 4(a) and (b)depicts the process' present path overall.

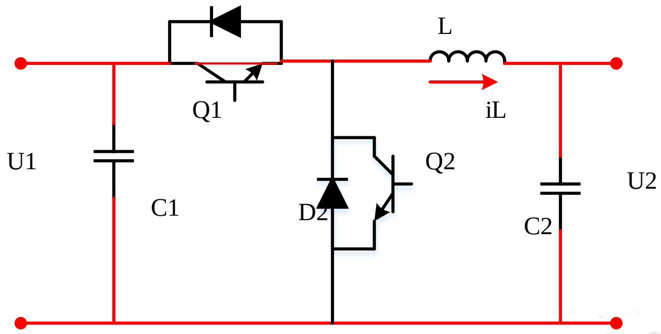


Fig.4(a) Buck mode operation (0≤t≤$K_{D1}T_s$)

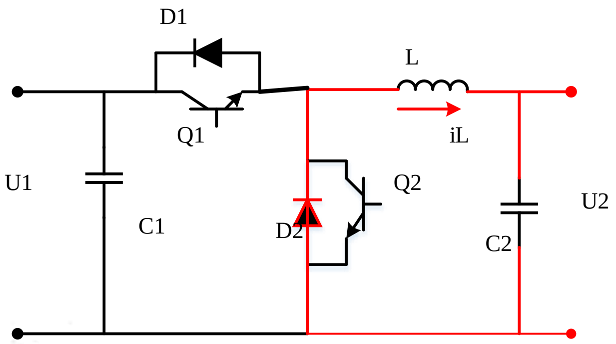
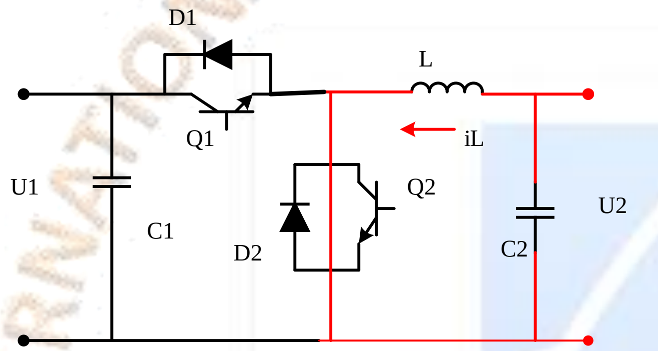


Fig.4(b) Buck mode operation ($K_{D1}T_s$≤t≤T_s)

Boost Mode

It is assumed that the converter is in the CCM mode too. The relationship between the input voltage U2 and output voltage U1 is U1=U2 ¼ 1=ð1 KD2Þ, where KD2 is duty cycle. The current in the inductor iL flows from right to left, when 0 6 t 6 KD2Ts, Q1 is off and Q2 is on and iL is increasing; when KD2Ts 6 t 6 Ts, Q1 is on and Q2 is off and iL is decreasing. The energy stored in the inductor together with DC power V2 supplies to the load in V1 side. The current path in the whole process is shown in Fig. 5 (a) and (b).



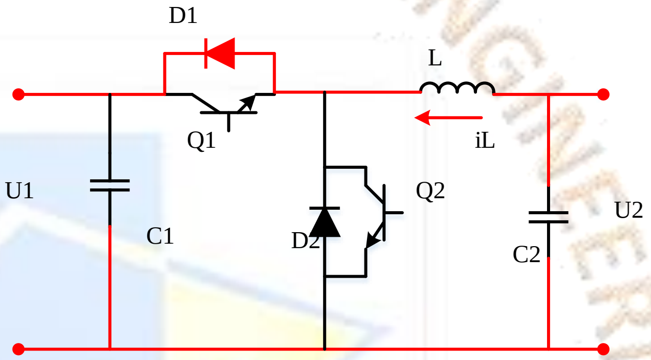


Fig.5 (a) Boost mode operation (0≤t≤$K_{D1}T_s$)Fig. 5(b) Boost mode operation$K_{D2}T_s$≤t≤T_s

PROPOSED Bi-LSTM CONTROLLER

As shown in Figure 6, the neural model reference control architecture employs two neural networks: a controller network and a plant model network. The reference model output is followed by the plant output by first identifying the plant model and then training the controller. Bi-LSTM controller is suggested as a means of controlling the EV energy management system.

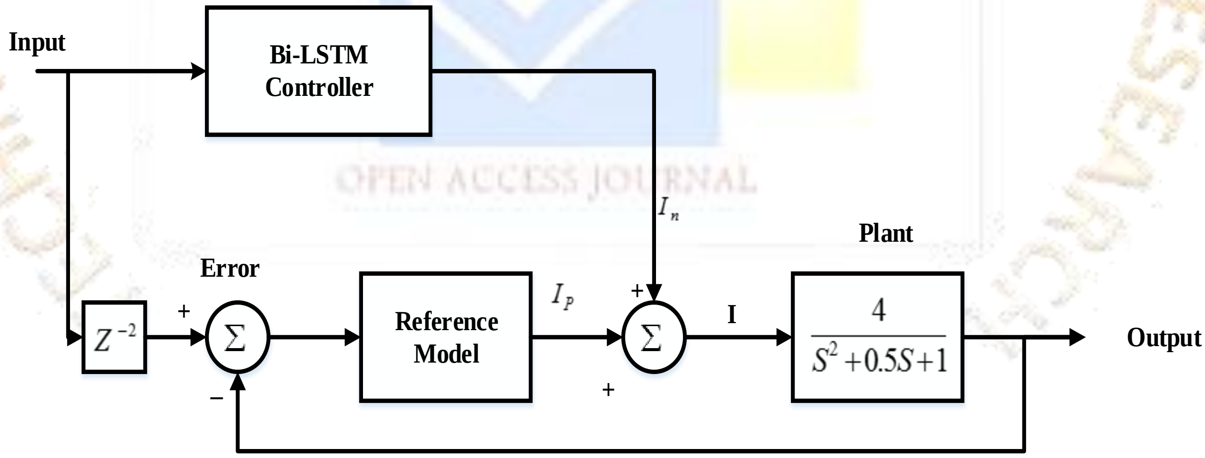


Fig.6 Bi-LSTM controller design model

The Deep Learning Toolbox software incorporates the neural network plant model and the Bi-LSTM neural network controller. There are two layers in each network, and we may choose how many neurons to use in the hidden levels. Three groups of controller inputs are available:

- Delayed reference inputs
- Delayed controller outputs
- Delayed plant outputs

We can choose how many delayed values to utilise for each of these inputs. Usually, the amount of delays rises as the plant is ordered. The neural network plant model has two sets of inputs:

- Delayed controller outputs
- Delayed plant outputs

RNN has been used for applications involving sequential time series and temporal dependencies. An unfurled RNN is capable of processing recent input using historical data. In the meantime, one of the RNN variations can train the long-term dependency data, which is a challenge for RNN. With the help of memory cells, a hidden layer unit that Hochreiter and Schmidhuber predicted will be employed in LSTM, RNN's limitations have been removed.

Three gates—the input gate, output gate, and forget gate—are used by memory cells to manage self-connections that store the network's temporal state. Input and output gates are used to regulate how memory cell inputs and outputs are distributed throughout the rest of the network. Additionally, the memory cell now incorporates a forget gate, which passes output data with large weights from one neuron to the next.

Information that has high activation results is retained in memory cells; if the input unit has high activation, then the information is stored there. Additionally, if the output unit is highly activated, the information will be passed to the following neuron. Otherwise, high weight input data is stored in a memory cell. The input-output mapping function of the LSTM network is used,$X = (X1, X2, \dots, Xn)$and $y = (y1, y2, \dots, yn)$. Calculating by the following equations:

$forget\ gate\ (f_t) = sigmoid(w_{fg}X_t + w_{hfg}h_{t-1} + b_{fg}$ (10)

$input\ gate\ (i_t) = sigmoid(w_{ig}X_t + w_{hig}h_{t-1} + b_{ig}$ (11)

$output\ gate\ (o_t) = sigmoid(w_{og}X_t + w_{hog}h_{t-1} + b_{og}$ (12)

$C_t = C_{t-1} \times f_t + i_t \times (\tanh(w_cX_t + w_{hc}h_{t-1} + b_C)$ (13)

$h_t = o_t \times \tanh(C_{t-1})$ (14)

In Equations, (10), (11), (12) and (13), $w_{ig}, w_{og}, w_{hC}, w_{fg}\ and\ b_{fg}, b_{ig}, b_{og}, b_C$ represent the weights and bias variables respectively of three gates and a memory cell.

Here, h_{t-1}symbolizes the prior hidden layers units that element-wise adding with weights of three gates. After the processing of Eq. (12), $C_t$turns into current memory cell unit. Eq. (13) shows the element wise multiplication of prior hidden unit outputs and previous memory cell unit. Add the non-linearity on top of the three gates in the form of tanh and sigmoid activation functions. Here, $t-1$ and t are previous and current time steps.

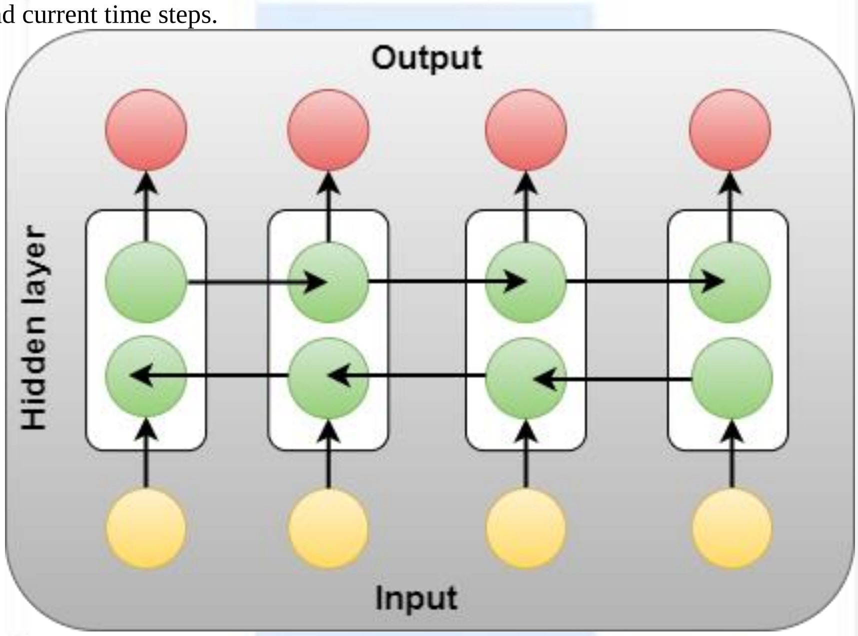


Fig.7 Structure of Bi-LSTM

This is able to work on past content but is unable to use future content to get beyond LSTM cell's constraints. Bidirectional recurrent neural networks (BRNNs), which are made up of two different LSTM hidden layers with comparable output in opposite directions, were proposed by Schuster and Paliwal. With this architecture, the output layer makes use of past and future knowledge.

An input sequence $X = (X1, X2, \dots, Xn)$ in Bi-LSTM is calculated in forward direction as $\overrightarrow{h_t} = \overrightarrow{h_1}, \overrightarrow{h_1}, \dots \overrightarrow{h_n}$and backward directions as $\overleftarrow{h_t} = \overleftarrow{h_1}, \overleftarrow{h_1}, \dots \overleftarrow{h_n}$. The final out of this cell y_t is formed by both $\overrightarrow{h_t} and \overleftarrow{h_t}$ the final sequence of out looks like $y = (y1, y2, \dots yt \dots, yn)$. Fig. 7 displays the single cell of Bi-LSTM.

In the LSTM, each hidden layer cell's input is reliant on the calculations made by the cell processing the data at the preceding time instant. Because it explicitly accommodates memory in a series, LSTM is a very effective method for sequential modelling. Bi-LSTM, in contrast, features a two-way information flow. In this network, two LSTM networks—one trained in forward direction and the other in reverse—train the sequence. The performance of channel equalisation has been increased because to this architecture, which connects both of these networks to the same output layer.

VOLTAGE SOURCE INVERTER

Voltage Source Converters (VSC) are self-commutated converters used to link electric vehicle (EV) systems with components like IGBTs that are appropriate for high power electronic applications. VSCs have the ability to self-commutate, which allows them to produce AC voltages without relying on an AC system. As a result, black start capability and independent rapid control of active and reactive power are both possible. For their constituent parts, such as the 2-level or 3-level converter as well as the so-called 'modules' in an MMC, VSCs maintain a constant polarity of the DC voltage which is shown in Fig 8. By switching the current's direction, the direction of power flow can be changed. As a result, VSCs can be integrated into multi-terminal DC systems more quickly.

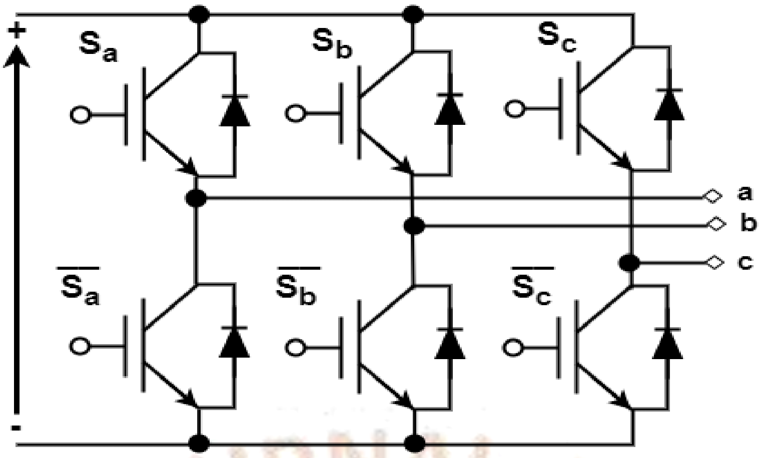


Fig.8 Structure of VSC

An EV's power electronics contain a DC-AC inverter to supply the stator with the AC current required to produce the vital variable RMF because batteries are direct-current (DC) devices. It is important to note that these electric motors are also generators. As a result, the wheels will back-drive the rotor within the stator to induce an RMF in the opposite direction, which feeds power back through the now AC-DC converter to deliver power into the battery. Regenerative braking is the procedure that causes drag and slows the vehicle. Regen is essential for extending the driving range of electric vehicles, but it also plays a crucial role in creating extremely efficient hybrids because it increases the EPA fuel efficiency ratings. However, coasting, which eliminates the losses each time the energy travels through the motor and converter when harvesting kinetic energy, is more effective in the actual world than regen.

EVs that use batteries for storage need to be recharged frequently. For those who use fuel cells to generate electricity, a hydrogen source is required. Batteries are typically used for storage in electric vehicles (EVs), however given their reduced autonomy, hydrogen- or fuel-cell vehicles, solar vehicles, or a combination of FC, SC, and battery banks, may offer a competitive alternative. To make the various energy sources coordinate, power management control is required. In our work, we have opted to begin energy production using a battery bank method. The fuel cell then uses hydrogen to produce energy, and at the very least, the photovoltaic system functions to convert solar radiation into electrical energy delivered to a DC bus. The total power is calculated as

$$P_{load} = P_{batt} + P_{FC} + P_{SC} \qquad (15)$$

IV RESULTS AND DISCUSSION

Here, the simulated outcomes of the proposed EV energy management system are discussed. The proposed system was created using the MATLAB/Simulink platform on an Intel Core i5-based PC with 4 GB of RAM in 2022. The proposed methodology's Simulink model is displayed in Figure 9.

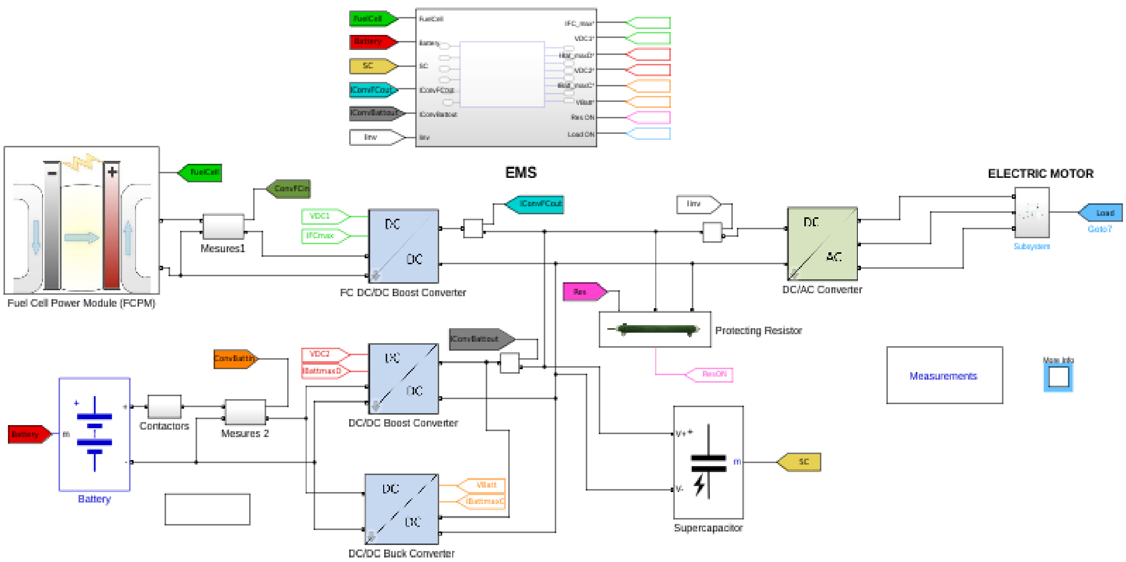


Fig.9 Simulink Model of Proposed Work

Figure 10 displays the voltage, current, and fuel consumption of a fuel cell. The FC voltage is 52.5V and the FC current is 4A, according to the observation. The UC current and voltage waveform are displayed in Figure 11. According to the observation, the UC has a voltage of 269.9V and a current of 3.9A.

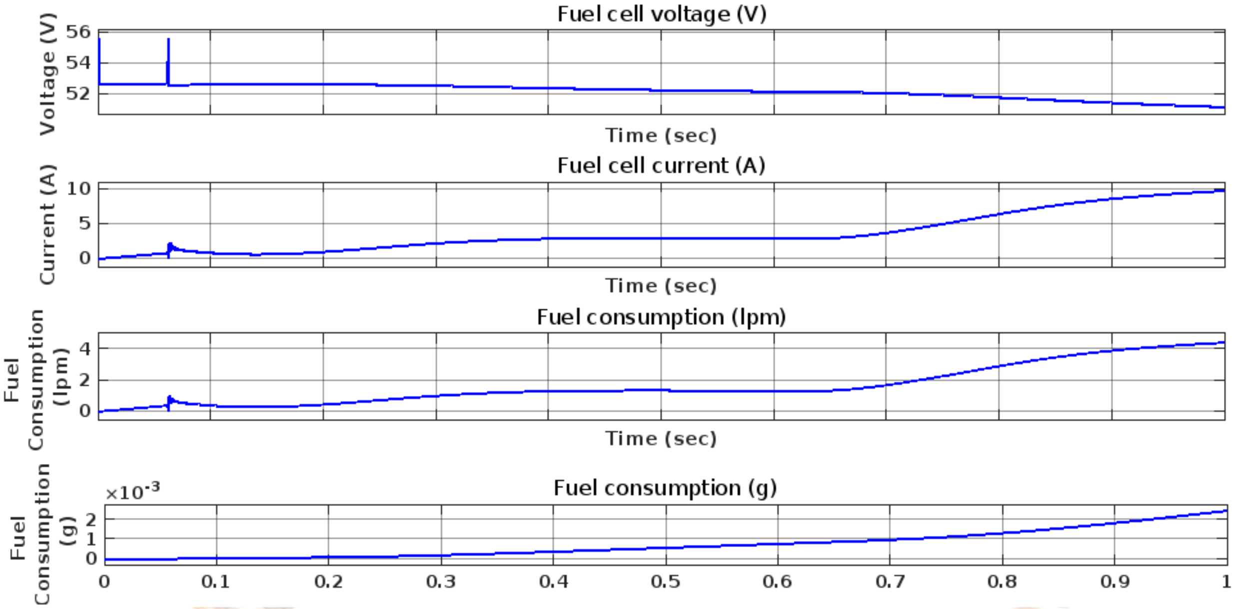


Fig.10 Simulation Output for Fuel Cell

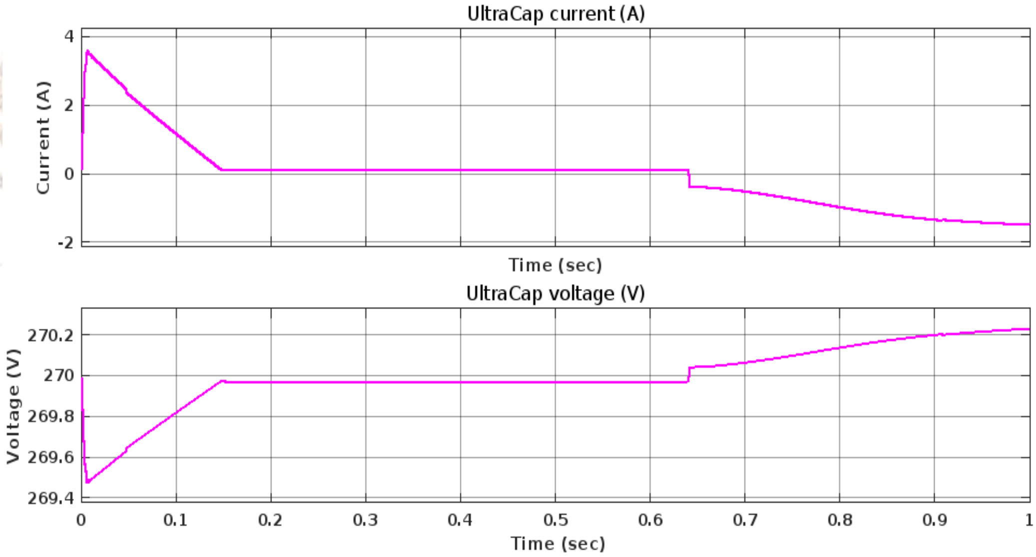


Fig.11 Simulation Output for UC Current & voltage

Figure 12 displays the simulation output for battery and FC converter voltage. A value of 52.4V is observed from the bi-directional converter, and an average of 52V is seen from the FC converter.

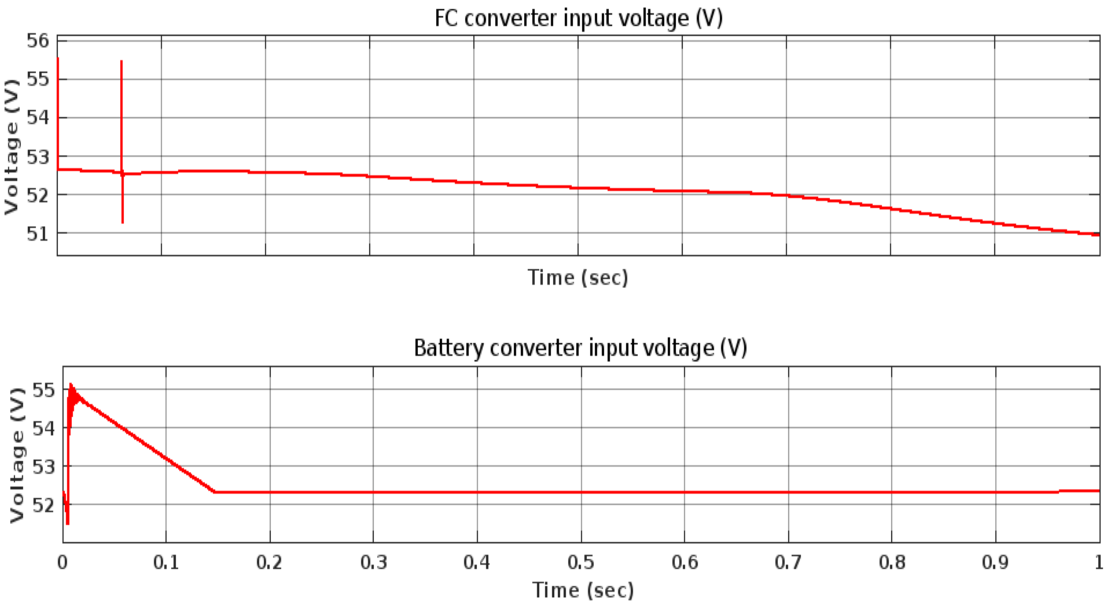


Fig.12 Simulation Output for Converter

Voltage is a straightforward way to measure state-of-charge, but because cell materials and temperature have an impact on the voltage, it can be unreliable. When charging or discharging a battery, the voltage-based SoC makes its most obvious fault. The voltage is distorted as a result of the agitation, and it is no longer a reliable SoC reference. The battery must rest in the open circuit condition for at least four hours in order to obtain good readings; lead acid battery manufacturers advise 24 hours. The voltage-based SoC solution is therefore unworkable for a battery that is actively being used. The battery performance waveforms are displayed in Figure 13. Based on the observation, the system battery that is suggested reaches 65% SoC.

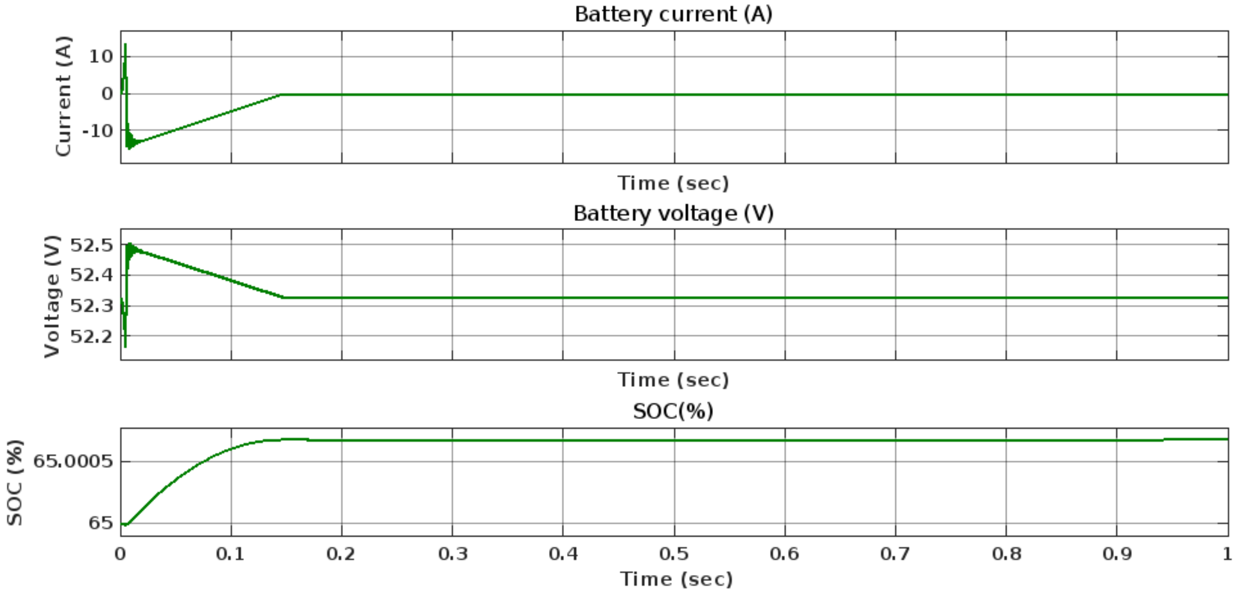


Fig.13 Simulation Output for Battery

The proposed bi-LSTM based EV energy management strategy determines the required power and the energy generation that is available while also setting the reference power values for the storage devices. The proposed control strategy efficiently regulates the load demand by utilising the storage devices when the FC and SC storage devices are unable to supply the appropriate amount of power due to insufficient inputs. It is evident from the findings in this section that the proposed energy management strategy successfully manages the power flow from storage devices and controls the EV and power from storage devices without any shedding.

V. CONCLUSION

In this study, the modelling, control, and power management of a hybrid fuel cell/super capacitor/battery bank system that powers an electric vehicle (EV) are discussed. Bi-LSTM based control technique was introduced to control the SOC and EMS. Whether the initial value of the SOC is low or high, the proposed system with Bi-LSTM controller can maintain the SOC of the battery at a particular level. After first simulating each component of the proposed system separately, the power management control was employed to coordinate the three sources in order to supply the EV. MATLAB/Simulink has been used to create the hybrid system simulation model. The collected results demonstrate the viability of producing a hybrid system for an electric car. A new converter will be developed in the future to enhance the EV EMS system. There are numerous optimization methods that can be used to improve controllers. The performance of the suggested controller can be enhanced by optimizing the weights.

VI. REFERENCES

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