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HYBRID BATTERY SYSTEM FOR ELECTRIC VEHICLES: DEEP NEURAL NETWORKS APPROACH FOR EFFECTIVE ENERGY MANAGEMENT

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ABSTRACT

The rising popularity of electric vehicles (EVs) gained the development of efficient energy management systems for hybrid battery systems. A hybrid battery system, which combines various storage devices types like supercapacitors, batteries and fuel cells to improve the energy efficiency and EVs performance. However, efficient energy management is crucial for hybrid battery systems to attain best efficiency, battery lifespan, and reduce the environmental impact. This study presents effectively managing energy for hybrid battery systems in electric vehicles by utilizing DNNs. This integrates a fuel cell, battery, and supercapacitors to satisfy variable power requirements of the electric vehicle. The battery management system is modeled using PI controllers and machine controllers, while the fuel cell control is performed using a DNN. DNNs are capable of handling complicated and nonlinear interactions between the system's inputs and outputs, making them suitable for energy management in EVs. This can be adapted in changing driving situations and optimize the energy flow between different energy storage devices. The study provides insights into the effectiveness of DNNs for controlling fuel cells in electric vehicles, and the proposed control model can be used to improve the power and efficiency of EV's.

Keywords: Hybrid Battery Systems, Deep Neural Networks, Fuel Cells, Energy Storage Devices, Battery, Supercapacitors

1. INTRODUCTION

Hybrid battery systems in recent years, became attention seeking due to their potential to improve the power and efficacy of EV's. EVs have emerged as a sustainable alternative to conventional gasoline-powered vehicles, offering numerous environmental and economic benefits. However, the limited driving range and long charging times of EVs have hindered their widespread adoption. Hybrid battery systems have been proposed as a solution to these challenges, allowing for the efficient use of various storage devices types like fuel cells, supercapacitors and batteries. Batteries, the primary energy storage device in EVs, providing the necessary power for propulsion. However, batteries have limited energy density, which limits the driving range of EVs. Fuel cells offer high energy density and longer driving range, but their performance is affected by varying power demands and environmental conditions. Supercapacitors provide high power density and fast charging capabilities, but they have limited energy density. Hybrid battery systems integrate these different energy storage devices to provide an efficient and flexible energy management system for EVs. The management of effective power is crucial to the efficiency and longevity of hybrid battery systems. The energy management system must optimize the use of different energy storage devices, ensuring that they are used in the most efficient and effective way. The energy management system should also consider the varying power demands of EVs, which can change rapidly depending on driving conditions and terrain. DNNs that can learn complex relationships between inputs and outputs, making them suitable for modeling and controlling the behavior of energy storage devices in EVs. The use of DNNs can lead to more efficient and accurate energy management systems, improving the energy efficiency and performance of hybrid battery systems in EVs. Many researches based on power management in hybrid battery systems were studied. A plug-in hybrid EV power managing approach that consider battery's ideal depth of discharge to increase fuel efficacy [1]. Pontryagin's minimum principle and Dynamic programming were used in a hierarchical power managing for energy devices in hybrid EVs to maximize energy efficiency [2]. For Power storages in EVs, a real-time power managing method has been developed that reduces energy usage by using Pontryagin's minimal principle [3]. Hybrid energy storage systems in EVs might benefit from a reinforcement learning-based power managing method to increase efficiency and battery lifespan [4]. A DDPG method is used in an managing power technique for HEV to balance battery life and fuel efficiency [5]. A battery and ultracapacitor-based fuel-cell HEV with an improved energy management [6]. To maximize efficiency and cut emissions, a plug-in HEV has been designed with an adaptive hierarchical power managing methods [7]. Hybrid energy storage device with a semi-active battery and supercapacitor for use in EVs that increases energy efficiency and lessens battery deterioration [8]. For electric automobiles with plug-in hybrid system, a naturalistic data-driven predictive energy management approach is being developed that uses machine learning to anticipate future driving conditions and maximize energy efficiency [9]. Connectivity and damping assignment passivity-based control, a revolutionary energy management strategy for hybrid electric cars that leverages to lessen battery deterioration [10]. For storage devices in HEV, a DDRL based HEM technique has also proposed [11].

2. LITERATURE SURVEY

Li, W. et.al (2021) to meet the power and energy requirements of battery EV, an HBS with a HE and HP battery pack is needed. A multi-objective energy management method based on cloud system using a DDPG was developed by the researchers for this hybrid architecture. The energy managing as a primary objective to improve the system's electrical and thermal safety while lowering energy loss and ageing expenses.

Hu, X. et.al (2019) three velocity prediction algorithms that were used inside a framework for model predictive control were fully compared and analysed. The predicted velocities were used to optimise the fuel cost of a power-split HEV. Each vanishing horizon was subject to the prediction approach.

Du, R. et.al (2020) a temperature and battery aging-aware predictive managing of energy technique for parallel HEV. In urban bus transportation, the model predictive control (MPC)-based technique was designed and assessed.

Li, L. et.al (2019) vehicle speed and controlling power prediction was created for situations when hybrid automobiles' lateral dynamics are crucial. Building a speed of the vehicle prediction controller with the concept of using less frictional brakes and more regen braking included calculating the vehicle's maximum cornering speed using the tire-road frictional force and the GPS signal.

Anselma, P. G. et.al (2021) a number of SOH sensitive approaches have been put forward, but there hasn't been any experimental confirmation. The purpose of the work was to close this gap by presenting an off-line, multi-objective, and optimum HEV management strategy that is sensitive to battery SOH. To verify the method's capacity to forecast battery longevity, dynamic programming (DP) was performed.

Hu, J. et.al (2020) an AWTFL control power manging technique to regulate power distribution in HESS for EV that include batteries and supercapacitors. Driving cycle was known to have a substantial influence on the operation of EMS, thus the technique was created to be based on DPR. By adjusting to variations in driving patterns, the strategy aimed to achieve optimum power distribution in the HESS, which would increase the electric vehicle's performance and efficiency.

Podder, A. et.al (2021) selecting a suitable control strategy for HEV applications may be difficult since these systems, when combined with various control techniques, produced a diversity of HEV kinds. An extensive assessment of significant data about the energy storage technologies utilised in HEVs was presented in a publication. Moreover, the article discussed several optimization topologies that were accessible depending on various control schemes and vehicle advancements.

Xiong, R. et.al (2018) studied the distribution of optimal power between ultracapacitor and the battery may be achieved by using a Real-Time managing energy method based on RL, which was suggested as a solution to this problem. A stationary Markov chain was utilized for determining the power transition probability matrices after choosing a lengthy driving cycle with a variety of speed fluctuations. A control technique that attempted to reduce HESS's energy loss was subsequently developed using an RL algorithm.

Uebel, S. et.al (2019) AEMS, which was a crucial component of the optimization issue, was proposed. The features of dynamic sources and drive cycle power demand was considered. By more efficiently using the quantum wave notion to explore the search space, the Butterfly Optimization Algorithm (BOA) was modified to address the hybrid energy source optimization issue.

Zhang, Q. et.al (2020) a two-level Model Predictive Control (MPC) strategy was introduced to alleviate the load capacitence. The method utilised a Sequential Quadratic Program (SQP) to calculate a target set for a lower layer, which then used Pontryagin's Maximum Principle and Discrete State-Space Dynamic Programming to establish the best control for a short horizon.

Zhao, B. et.al (2019) a real-time EM control approach that could accomplish particular targets was studied. WT, NN, and FL were used to create the technique. In order to successfully match the properties of the battery and supercapacitor, the wavelet transform was used to extract different frequency components of the load power requirement.

East, S. et.al (2018) a novel 3-D model of stochastic Markov chain based online driving cycle prediction approach for hybrid electric vehicles (HEV). A driving-cycle-aware energy management approach was then developed

Tan, H. et.al (2019) a convex design of the MPC optimization for EMS in HEV was proposed, along with a method for its resolution called the ADMM.

Torres-Moreno, J. L. et.al (2018) Actor-Critic, a novel EM approach with a DRL framework, was introduced. Actor-Critic used a DNN called the actor network for continuous control signals outputs, by increasing the EMS's effectiveness.

Du, G. et.al (2019) the effects of PV systems on microgrid storing and EV use. More research was considered required due to the growing use of these systems in the home sector and the creation of new technology, like more effective solar panels. According to the research, the systems were particularly intriguing in profitable because of their more predictable daily patterns of power use, which often took place during the hours of maximum solar radiation.

Drawbacks of these energy management strategies include their high computational complexity, limited real-time adaptability, and limited applicability to specific types of vehicles or driving scenarios[27]. These strategies also rely heavily on accurate models of the vehicle and its components, which can be difficult to obtain and maintain in practice. Additionally, some strategies may require additional sensors, hardware, or software, adding to the overall cost of the vehicle or energy management system[28].

To overcome all these challenges, we propose an efficient EMS for hybrid battery systems in EVs using DNNs. We demonstrate the effectiveness of this approach in controlling fuel cells in EVs, and we highlight the advantages and contributions of the proposed system. This study contributes to the development of advanced energy management systems for EVs and promotes the use of sustainable and efficient transportation systems.

3. PROPOSED METHODOLOGY

The methodology involves data collection and preprocessing, development and training of a DNN model, and real-time energy management using the trained model. The approach includes the integration of different types of storage energy devices, like fuel cells, supercapacitors, and batteries, to optimize energy flow and improve the performance and efficiency of electric vehicles. The overall methodology is shown in flow chart in figure 1.

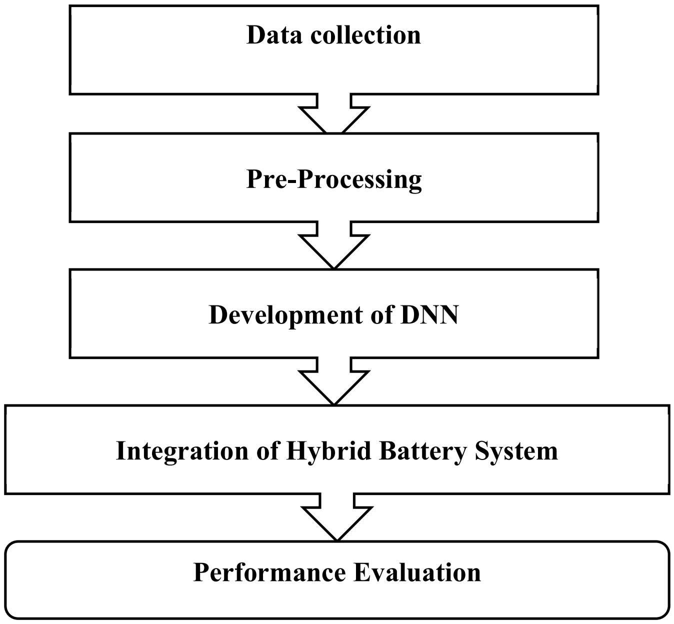

Figure 1: Flow Diagram

3.1 Data Collection

The first step in developing an efficient energy management system using deep neural networks (DNNs) for hybrid battery systems in electric vehicles (EVs) is to collect the data required for the development of the model[29]. The data collected will include the power requirements of the EV under different driving conditions, the characteristics of the different energy storage devices used, and the environmental conditions.

3.2 Data Pre-Processing

Once the data has been collected, the next step is to preprocess it. Data preprocessing involves cleaning, transforming, and preparing the data so that it is suitable for use in the DNN model[30]. The collected data may contain errors, missing values, or outliers, which can adversely affect the performance of the DNN model. Therefore, it is important to preprocess the data to remove any noise or anomalies. The preprocessing of the data will involve the following steps:

3.2.1 Data Cleaning:

In this process the determining and rectifying any errors or inconsistencies in the data takes place. For instance, missing data can be imputed using techniques such as mean imputation, median imputation, or interpolation. Outliers can also be removed using statistical techniques such as z-score or interquartile range (IQR).

3.2.2 Feature Scaling:

The data may contain features with different scales. Scaling of features improve the DNN model performance. Common techniques for feature scaling include normalization, min-max scaling, and standardization.

3.2.3 Data Normalization:

Normalization is a technique used to transform the data so that it has a Gaussian distribution. This can improve the convergence of the DNN model and make it less sensitive to the initial values of the weights.

3.3 DNN Model Development:

The next step in the process is to develop a DNN model that can efficiently manage the energy flow between different energy storage devices in the hybrid battery system. The DNN model will consider the power requirements of the EV, the characteristics of the different energy storage devices, and the environmental conditions. The model will be trained using the preprocessed data[31-32]. The DNN model takes input features as its input and produces an output that determines the power flow between different energy storage devices. The input features may include the power demand, the battery SOC, the temperature, and other relevant parameters. The DNN model include a layer structure with input layers, a fully connected layer, and a regression output layer. The output from the model will be the control signal for the fuel cell, which is a time-based output. In this case, only three layers will be used for the DNN. The layer construction of the DNN model is as follows:

Input Layer
|
Hidden Layer
|
Output/Regression Layer

Figure 2: Layer Structure of DNN

Input layer: The input layer is responsible for taking in the input features, such as the power demand, battery SOC, and other relevant parameters.

Fully connected layer: The fully connected layer is responsible for computing a weighted sum of the input features and passing the result through an activation function. The output size of this layer is 1, as the DNN model is used to control the fuel cell.

Regression output layer: The regression output layer is responsible for computing the final output of the DNN model. This layer takes the fully connected layer's output and produces the control signal for the fuel cell, which is a time-based output. The mathematical representation of the DNN model can be expressed as follows:

Let A be the input feature vector of the DNN model Z, which includes the PD, SOC of the battery, and other relevant parameters. The output of the DNN model, C, is the control signal for the fuel cell.

$$C = Z(A) - - - - - (1)$$

where Z represents the deep neural network with the layer structure described above.

During the training process, the weights of the neurons in the fully connected layer are adjusted to error reduction between the predicted output and the actual output. The optimization algorithm used for training the DNN model could be stochastic gradient descent (SGD) or Adam.

The output of the input layer, h_0, is a vector of input features A:

$$h_0 = A - - - - - (2)$$

The output of the hidden layer, h_1, is obtained by computing a weighted sum of the input features, applying an activation function, and adding a bias term:

$$h_1 = f\ (W_1 \times h_0 + b_1) - - - - - (3)$$

where *f* is the function of activation, the weight matrix is W_1 for the hidden layer, and bias vector b_1 for the hidden layer.

The output of the output layer, C, is obtained by computing a weighted total output of the hidden layer and adding a bias term:

$$C = W_2 \times h_1 + b_2 ------ (4)$$

where the weight matrix W_2 for the output layer, and b_2 is the bias vector for the output layer The activation function used in the hidden layer is typically a nonlinear function such as the rectified linear unit (ReLU) function:

$$f(C) = max\,(0, C) ------ (5)$$

The output of the output layer is a single value that represents the control signal for the fuel cell:

$$C = fc ------ (6)$$

The input features x may include variables such as power demand PD, state of charge (SOC) of the battery, and environmental conditions such as temperature T and humidity H:

$$A = [PD + SOC + T + H] ------ (7)$$

The weight matrix W_1 and bias vector b_1 are learned during training to optimize the performance of the DNN model:

$$W_1, b_1 = Arg_{min}\,(\theta) ------ (8)$$

where θ loss is the objective function that measures the predicted output difference of the DNN model and the actual output.

The weight matrix W_2 and bias vector b_2 are also learned during training:

$$W_2, b_2 = Arg_{min}\,(\theta) ------ (9)$$

The loss function θ may be a mean squared error (MSE) loss or another appropriate loss function:

$$\theta = MSE\left(C_{true}, C_{pred}\right) ------ (10)$$

where C_{true} is the actual output and C_{pred} is the predicted output.

During training, the weights and biases of the DNN model are updated using backpropagation and gradient descent:

$$W, b = \begin{matrix} W - \varphi \times \partial W, \\ b - \varphi \times \partial b \end{matrix} ------ (11)$$

where W and b represent the weight matrices and bias vectors for all layers in the DNN model, Z and ∂W and ∂b represent the gradient loss function regarding W and b, respectively. The learning rate is a hyperparameter that determines the size of the updates to the weights and biases during training.

The power requirements of the EV can be represented by:

$$T_P = T_{Pdrive} + T_{Paux} ------ (12)$$

where T_P is the total power requirement, T_{Pdrive} is the power required to drive the vehicle, and T_{Paux} is the power required for auxiliary systems.

The energy stored in the battery can be represented by:

$$E_t = \int_{dt}^{t} P_t + E_{initial} ------ (13)$$

where T_E is the battery energy storage in the and supercapacitor at time t, P_t is the power requirement at time t, and $E_{initial}$ is the initial energy of battery and supercapacitor.

The output power in the fuel cell can be represented by:

$$Pfc_t = Z(Pdrive_t, E_{initial}, E_{temp}) - - - - - (14)$$

where Pfc_t is the power output of the fuel cell at time t, $Pdrive_t$ is the power required to drive the vehicle at time t, $E_{initial}$ is the initial energy stored in the battery, and E_{temp} is the environmental temperature.

Algorithm for the DNN model
Input: Preprocessed data containing feature values and target values Output: Control signal of fuel cell to manage the energy flow in the hybrid battery system Step 1: Initialize the DNN model with the specified number of layers, neurons per layer, and activation functions Step 2: Split the preprocessed data for train and test sets Step 3: Train the DNN model using the training set with a specified number of power requirements and optimization algorithm Step 4: Evaluate the DNN performance of the trained model on the testing set Step 5: If the performance is satisfactory, save the trained model for future use Step 6: Otherwise, adjust the hyperparameters and repeat steps 2-5 until satisfactory performance is achieved Step 7: In real-time, collect data on the necessities of power in electric vehicle, the characteristics of the energy storage devices, and the environmental conditions Step 8: Preprocess the collected data by cleaning, scaling, and normalizing it to a suitable format for use in the DNN model Step 9: Feed the preprocessed data into the trained DNN model to obtain the control signal for the fuel cell Step 10: Use the control signal to manage the flow of energy between the different energy storage devices in the hybrid battery system Step 11: Repeat steps 7-10 continuously to adjust to driving conditions changes and optimize the energy flow in the hybrid battery system.

Pseudocode for the DNN model

```
function dnn_energy_management(preprocessed_data):
    // Initialize the DNN model
    model = initialize_dnn_model()

    // Split data into train and test sets
```

```
X_train, X_test, y_train, y_test = split_data(preprocessed_data)

// Train the DNN model
model = train_dnn_model(X_train, y_train)

// Evaluate the performance of the trained DNN model
performance = evaluate_dnn_model(model, X_test, y_test)

// Repeat training and evaluation until satisfactory performance is achieved
while performance < threshold:
    // Adjust hyperparameters
    model = train_dnn_model(X_train, y_train)
    performance = evaluate_dnn_model(model, X_test, y_test)

// Use the trained DNN model for real-time energy management
while True:
    // Collect and preprocess data
    data = collect_data()
    preprocessed_data = preprocess_data(data)

    // Use the DNN model to obtain control signal
    control_signal = model.predict(preprocessed_data)

    // Manage energy flow in the hybrid battery system using the control signal
    manage_energy_flow(control_signal)

    // Repeat for continuous energy management
```

The trained DNN model is used to manage the energy flow between different energy storage devices in the hybrid battery system. The DNN model is adapted in changing driving conditions and optimize the flow of energy between different storage devices of energy to meet the power requirements of the EV.

4. RESULTS AND DISCUSSION

The results of the study show that the use of a deep neural network in managing the energy flow between different energy storage devices in a hybrid battery system can improve the energy management efficiency of electric vehicles. The use of the DNN for fuel cell control resulted in better fuel consumption compared to the use of traditional PI controllers and machine controllers for battery management. The model was able to satisfy variable power requirements, as indicated by the different loads at different speeds, using a combination of battery and supercapacitors. Figure 3 training progress output for the network is as follows

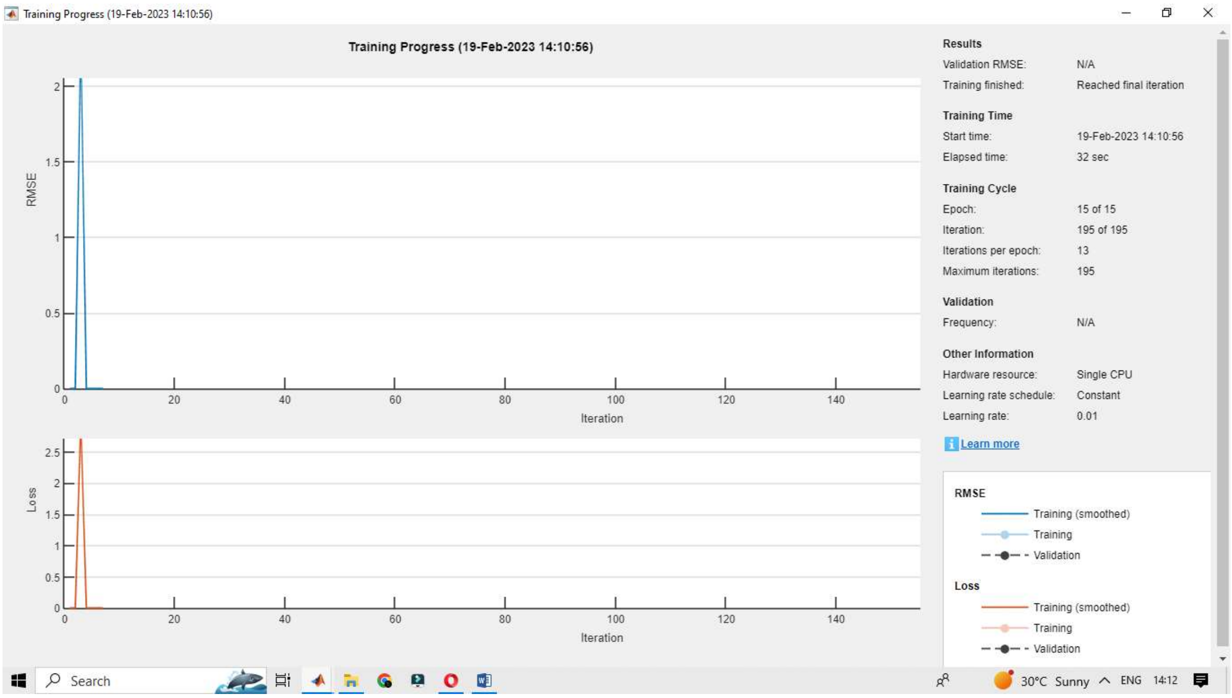

Figure 3: Training Progress

The proposed control model is represented in figure 4.

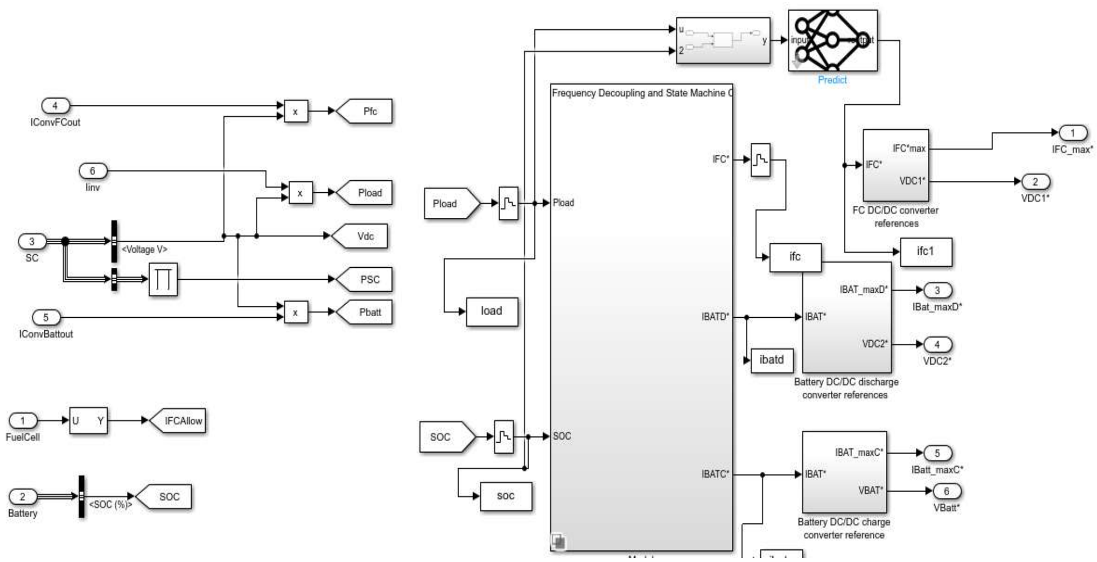

Figure 4: Proposed model

Figure 5 represents the overall all model and power requirements of EV’s for efficient energy management.

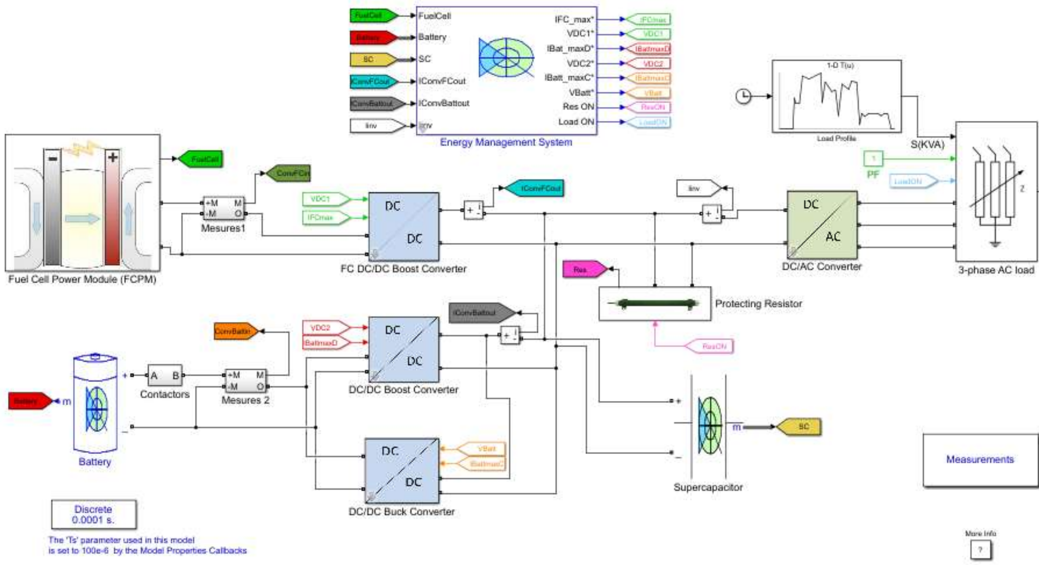

Figure 5: Overall Model

The output results of the system are as follows;

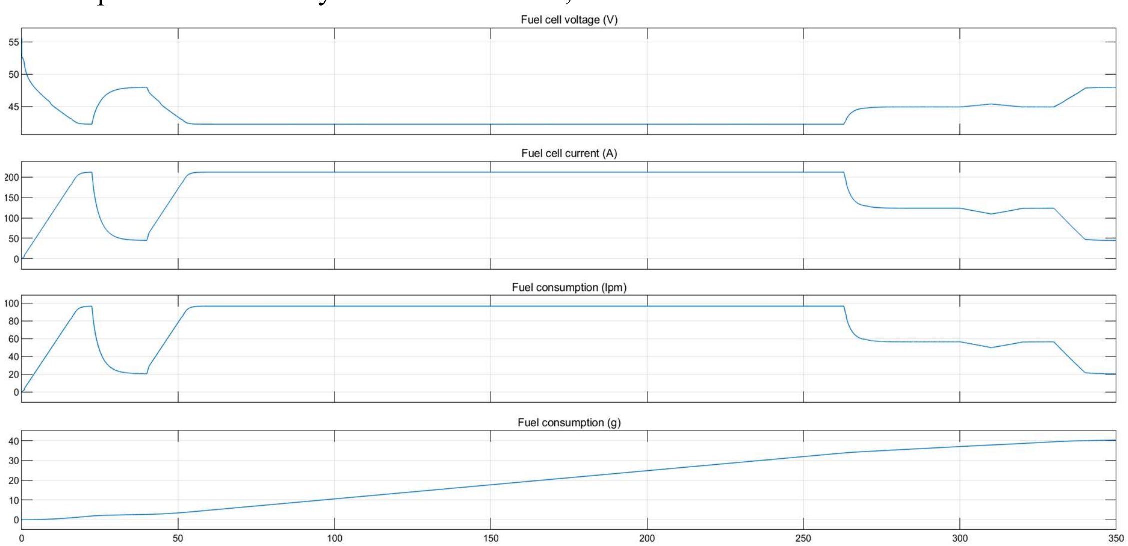

Figure 6: Fuel cell

The overall HBS performance was improved, with the battery, fuel cell, and ultracapacitors all contributing to the power supply.

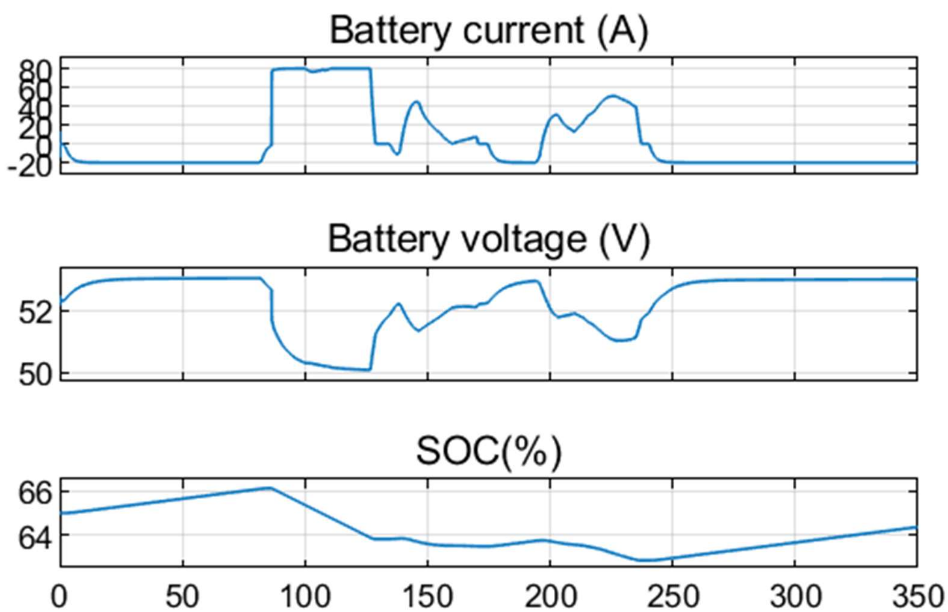

Figure 7: Battery capacity

Figure 7 shows the overall battery capacity of the proposed model. Figure 8, 9, 10 shows the load, ultracapacitor and power capacity management of the proposed system.

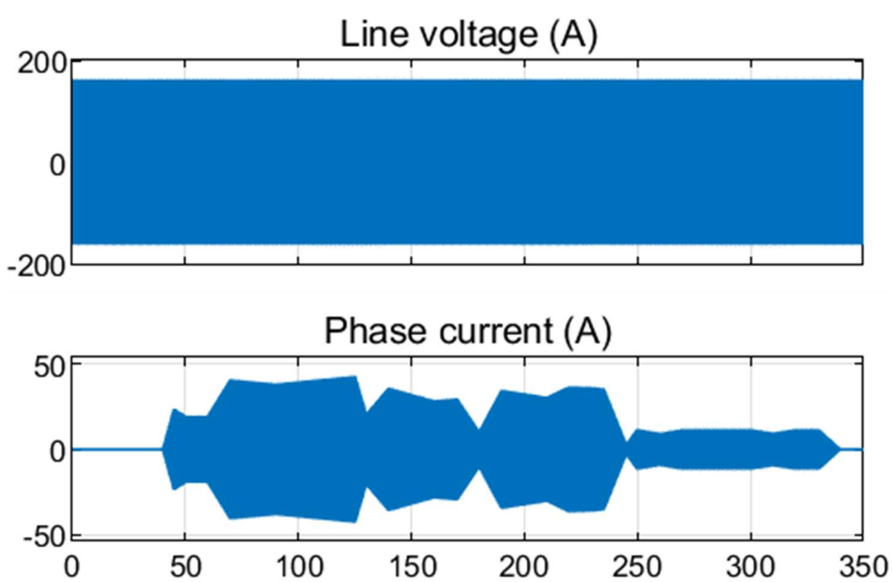

Figure 8: Load

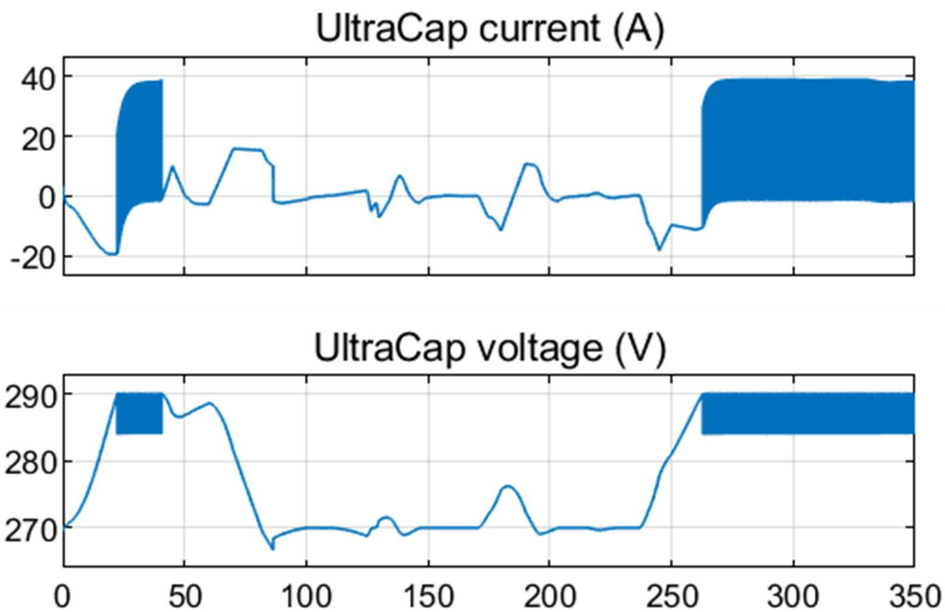

Figure 9: Ultracapacitor

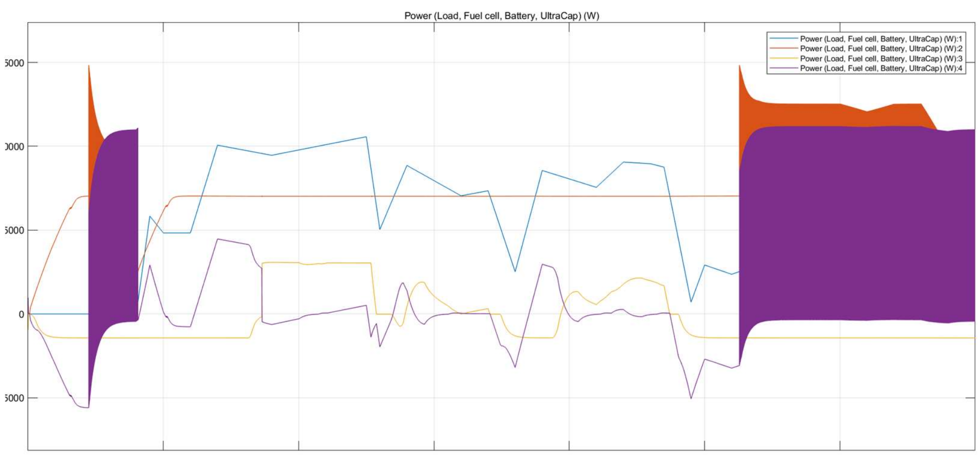

Figure 10: Power

Overall, the study highlights the potential for deep neural networks to improve energy management in electric vehicles and increase their efficiency.

5. CONCLUSION

The study has demonstrated that the use of a DNN can significantly improve energy management efficiency of electric vehicles. The proposed control model, which utilizes a combination of battery, fuel cell, and ultracapacitors, was able to satisfy variable power requirements and optimize energy flow between different energy storage devices. The use of the deep neural network for fuel cell control resulted in better fuel consumption compared to traditional PI controllers and machine controllers for battery management. The overall HBS performance was improved, with the battery, fuel cell, and ultracapacitors all contributing to the power supply. The results suggest that the proposed model can be used for efficient energy management in electric vehicles, which can help in reducing consumption of energy and improving the overall system efficiency. The study highlights the potential for deep neural networks to play a significant role in improving management of energy in EVs and reducing their environmental impact.

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