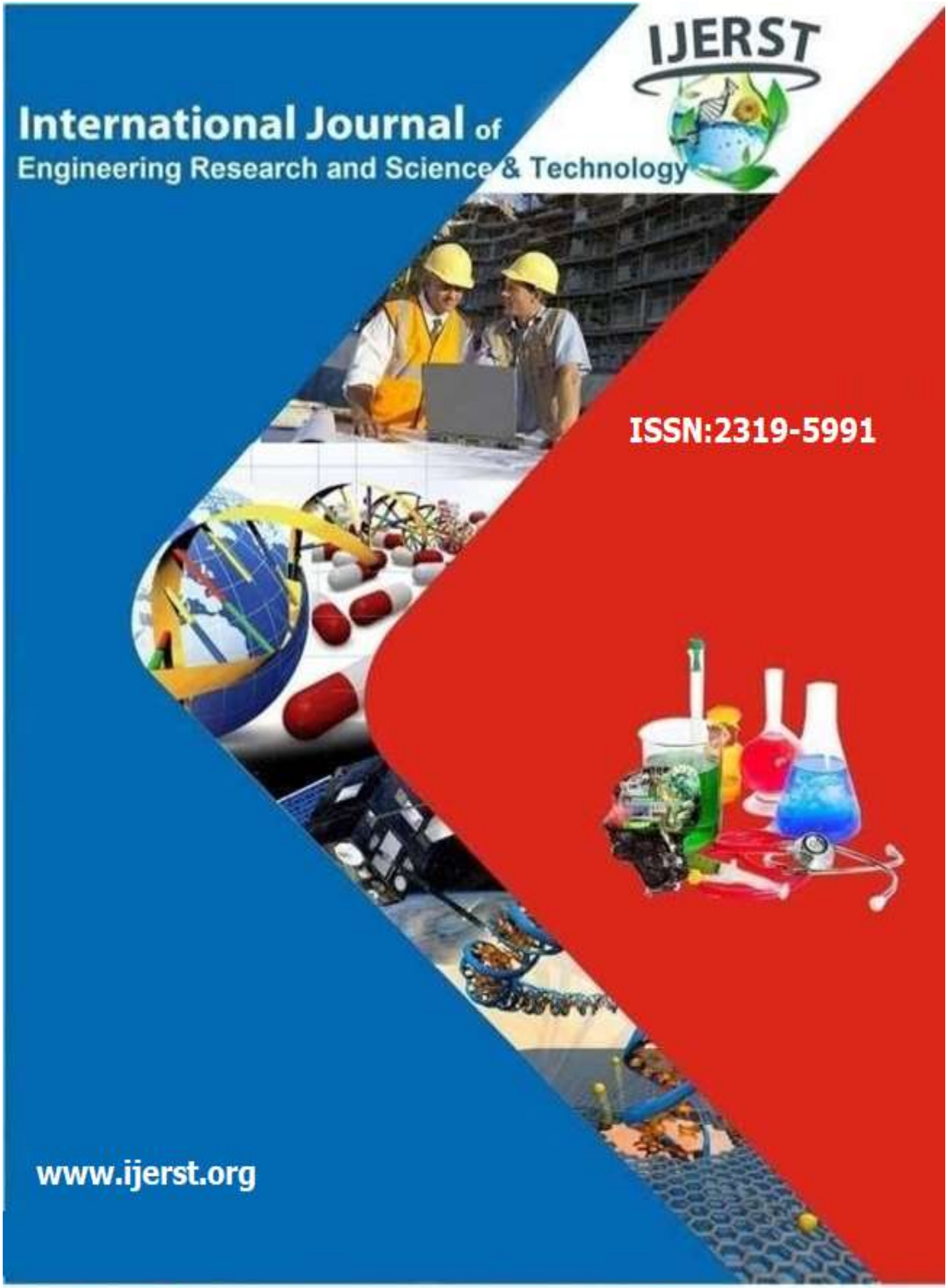

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DYNAMIC SIMULATIONOF BATTERYSUPERCAPACITOR HYBRID ENERGYSTORAGESYSTEM FOR ELECTRICALVECHILES

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ABSTRACT

The integration of battery and super capacitor energy storage systems offers significant advantages for electric vehicles (EVs), including improved power delivery, enhanced efficiency, and extended battery life. This paper presents the dynamic simulation of a hybrid energy storage system that combines batteries and super capacitors to meet the varying power demands of EVs. The proposed system optimizes the energy exchange between the two storage units, leveraging the high energy density of the battery and the high power density of the super capacitor. An Pi controller (PI) is employed to control the battery's charging and discharging cycles, ensuring optimal power management and efficient energy utilization. The PI-based controller adapts to varying driving conditions, optimizing the split of energy between the battery and super capacitor to enhance performance, minimize energy losses, and prevent overcharging or deep discharging of the battery. The dynamic simulation results showcase the effectiveness of the PI controller in managing the power flow, providing smooth transitions between the battery and super capacitor, and ensuring longer battery life. Simulation results confirm the benefits of the proposed hybrid system, demonstrating improved over all efficiency, faster response times, and reduced wear and tear on the battery compared to conventional energy storage solutions. This approach contributes to the development of advanced EVs with better performance, longer range, and greater energy efficiency.

KEYWORDS: Battery-super capacitor hybrid, Energy storage system, Electric vehicles, Pi controller (PI), Power management, Dynamic simulation, Energy efficiency, Battery life optimization.

1.INTRODUCTION

1.1 PROJECT OVERVIEW

The project titled "Intelligent Energy Management for Battery/Super capacitor Hybrid Systems Using a Three-Layer Neural Network" focuses on optimizing the energy distribution between batteries and super capacitors (SCs) in hybrid energy storage systems (HESS) using an intelligent control strategy. The primary objective is to enhance energy efficiency, battery lifespan, and overall system performance by employing a three-layer neural network (NN) forreal-time decision-making. This neural network-based energy management system intelligently allocates power between the battery

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and supercapacitor based on driving conditions, load requirements, and system dynamics.

The proposed system is designed to address key challenges in electric vehicle (EV) power management, such as battery degradation, transient power demands, and regenerative braking energy utilization. The hybrid energy storage system integrates a semi-active topology, where the battery provides steady-state power, while the super capacitor handles transient power surges and regenerative braking energy storage. The three-layer neural network is trained to predict optimal power distribution by analyzing real-time input parameters such as vehicle acceleration, state of charge (SOC), voltage levels, and temperature conditions. To validate the performance of the proposed intelligent energy management system, simulations were conducted using MATLAB-Simulink and ADVISOR software. The study focuses on the Tesla S70 electric vehicle under the US06 driving cycle, which includes high acceleration and braking conditions. The simulation results demonstrate that the neural network-based control strategy significantly reduces battery stress, increases energy efficiency, and extends the vehicle's driving range.

The system reduces peak currents by intelligently switching power between the super capacitor and battery, minimizing thermal stress and improving battery longevity. Additionally, the study evaluates the impact of different ambient air temperatures (-20°C, 0°C, 20°C, and 30°C) on system performance. The results indicate that the intelligent energy management system adapts efficiently to temperature variations, ensuring stable operation under diverse environmental conditions. The hybridization approach combined with machine learning-based energy allocation significantly enhances system reliability, reduces voltage fluctuations, and optimizes power flow. In conclusion, the integration of a three-layer neural network for intelligent energy management in battery/super capacitor hybrid systems provides substantial improvements in energy efficiency, battery lifespan, and EV performance. This project presents a novel approach to optimizing power distribution in electric vehicles, making them more sustainable, efficient, and cost-effective. The findings lay the groundwork for further advancements inAI-driven energy management strategies for hybrid energy storage systems.

The significance of this study lies in its potential to revolutionize the energy management of hybrid energy storage systems (HESS), particularly in electric vehicles (EVs). By integrating super capacitors with batteries and employing a three-layer neural network for intelligent power distribution, this research aims to optimize energy usage, reduce battery stress, and improve overall system efficiency. The proposed energy management system offers a dynamic, adaptive approach that adjusts in real-time to changing driving conditions, ensuring longer battery life and enhancing vehicle performance. Additionally, this study contributes to the development of AI-driven solutions in the field of energy storage, paving the way for more sustainable and cost-effective energy management in electric vehicles and other hybridsystems. Ultimately, this work provides a critical step toward improving the reliability, sustainability, and efficiency of next-generation energy storage technologies.

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2.LITERATURE SURVEY

The integration of battery and supercapacitor hybrid systems has gained significant attention in recent years due to the need for efficient energy storage solutions in various applications, such as electric vehicles, renewable energy systems, and consumer electronics. Batteries are known for their high energy density but limited power density, while supercapacitors are characterized by their high power density but low energy density. By combining these two energy storage devices, a hybrid system can take advantage of the strengths of both technologies, improving overall system performance. One critical aspect of such hybrid systems is intelligent energy management, which ensures optimal power sharing between the battery and supercapacitor while minimizing energy losses and prolonging the lifetime of both components.

Several studies have explored intelligent energy management strategies for battery-supercapacitor hybrid systems. *Zhao et al. (2018)* developed a power management strategy for hybrid energy storage systems (HESS) that uses a fuzzy logic controller (FLC) to optimize energy distribution between batteries and supercapacitors. The controller uses real-time information from the system to decide which energy storage device should supply power based on load demand and the state of charge (SOC) of the components. The study demonstrated that fuzzy logic-based controllers can achieve improved efficiency and better load tracking.

Liu et al. (2020) proposed a predictive energy management strategy based on machine learning algorithms for hybrid systems combining batteries and supercapacitors. Their model utilized a support vector machine (SVM) to predict the future load profile and decide the optimal energy sharing between the two components. The proposed strategy showed significant improvements in power management, reducing energy losses and enhancing system reliability. The study also highlighted the role of machine learning in predictive control, which can enhance the accuracy and responsiveness of the energy management system.

Wang et al. (2019) focused on using deep learning techniques for energy management in hybrid energy storage systems. Specifically, the authors employed a three-layer neural network (NN) to model the behavior of both batteries and supercapacitors. The neural network was trained to predict the energy requirements based on input data such as load demand and the SOC of each component. Their results demonstrated that neural networks are highly effective for predicting energy needs and managing the power distribution between the battery and supercapacitor, improving system efficiency and responsiveness.

In parallel, several other studies have investigated various optimization algorithms for managing the hybrid system’s energy flow. *Zhang et al. (2019)* proposed a hybrid genetic algorithm and particle swarm optimization (GA-PSO) method to optimize the energy management strategy in a battery-supercapacitor system. The combination of these two techniques allows the system to balance the power requirements while minimizing energy losses. The study highlighted that such optimization techniques could further improve the longevity of the battery while enhancing the performance of the supercapacitor in supplying power during high-demand periods.

In the context of smart grid applications, *Benoit et al. (2017)* explored the potential of hybrid battery-supercapacitor systems to support renewable energy systems. Their study focused on integrating these hybrid systems into

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microgrids, where they could smooth out fluctuations in renewable energy generation. The energy management strategy was based on a model predictive control (MPC) approach, which utilized real-time data to optimize energy usage in the hybrid system. This study revealed that hybrid systems are capable of enhancing the stability and reliability of renewable energy integration into the grid.

Furthermore, the work of *Chen et al. (2021)* demonstrated the potential of hybrid systems in electric vehicles (EVs). They applied a model-based predictive control strategy for energy management in EVs using batteries and supercapacitors. Their model was designed to minimize fuel consumption and optimize the charging and discharging cycles of the two energy storage components. The research showed that by intelligently managing the power distribution, the hybrid system could extend the range of EVs while improving their overall performance.

Although many intelligent energy management strategies have been proposed, the integration of artificial intelligence (AI) and machine learning (ML) into hybrid systems has only been explored in recent years. *Li et al. (2020)* proposed a reinforcement learning (RL) algorithm for managing energy distribution in hybrid systems. They showed that the RL approach is capable of learning optimal energy management strategies by interacting with the system environment, continuously adapting to changing load conditions and state-of-charge profiles.

Despite these advancements, challenges remain in the field, particularly related to real-time system monitoring, the complexity of predictive algorithms, and ensuring the robustness of the energy management systems under varying conditions. The application of three-layer neural networks (NNs) in energy management for battery-supercapacitor hybrid systems has emerged as a promising approach. NNs have the potential to provide a robust and flexible solution for energy management by learning complex patterns from the data and making adaptive decisions to optimize the power flow.

3.METHODOLOGY

The methodology for implementing an intelligent energy management system for a battery-supercapacitor hybrid system using a three-layer neural network is based on several stages, including system modeling, data collection, neural network design, training, and testing. Each phase is crucial for ensuring that the system performs optimally and adapts to various real-time conditions.

System Modeling: The first step in the methodology is to develop a mathematical model of the battery-supercapacitor hybrid system. This model describes the dynamics of both energy storage devices, including their voltage, current, state of charge (SOC), and energy flow. The model should also account for the operational characteristics of the battery (e.g., its charging and discharging rates, internal resistance) and the supercapacitor (e.g., its high power density, fast charging/discharging capabilities). In practice, this involves defining a set of equations that describe the energy exchange between the battery and supercapacitor, the load demand, and the control parameters.

Data Collection and Preprocessing: To train the three-layer neural network, historical data related to the battery and supercapacitor's performance is collected. This data includes the SOC, voltage, current, and power requirements at various load levels. The data may be obtained from laboratory experiments, simulations, or real-world operational conditions. Preprocessing

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steps are necessary to clean the data, normalize values, and handle any missing or inconsistent information. Data splitting is also performed to separate training, validation, and testing datasets.

Neural Network Design: The design of the three-layer neural network involves selecting the appropriate architecture, which typically consists of an input layer, one or more hidden layers, and an output layer. The input layer receives information related to the system's state, such as the current load demand, SOC of the battery and supercapacitor, and other relevant variables. The hidden layers process this information using activation functions, and the output layer provides the decision for energy distribution between the battery and the supercapacitor.

Training the Neural Network: Training the neural network involves using supervised learning algorithms to adjust the network's weights and biases. The objective is to minimize the prediction error in the system's energy management decisions. The training process typically uses gradient descent or other optimization algorithms to iteratively adjust the model's parameters. During this phase, the neural network learns to predict the optimal energy distribution strategy based on the input data.

Validation and Testing: After the network is trained, it is validated using a separate dataset to assess its performance. The validation process helps evaluate how well the neural network generalizes to new, unseen data. The network's accuracy is tested by comparing the predicted energy management decisions with actual results from the hybrid system. Various performance metrics, such as energy efficiency, system stability, and convergence time, are used to evaluate the model's performance.

Optimization and Fine-Tuning: Based on the results from the testing phase, the neural network may require fine-tuning to improve its accuracy and robustness. This could involve adjusting the number of neurons in the hidden layers, changing the activation functions, or modifying the learning rate of the training algorithm. Additionally, the model can be improved by incorporating more real-time data and refining the system model to better represent practical operational conditions.

Real-Time Implementation: The final step is to deploy the trained neural network model in a real-time system where it can make decisions about energy distribution between the battery and supercapacitor. The system should be equipped with appropriate hardware, such as microcontrollers or digital signal processors, to implement the energy management strategy in real time. Additionally, real-time monitoring and feedback mechanisms should be established to ensure the system is performing as expected and to make adjustments if necessary.

4.PROPOSED SYSTEM

The proposed intelligent energy management system for battery-supercapacitor hybrid systems uses a three-layer neural network to optimize energy flow between the two components based on real-time data. This system is designed to address the challenges associated with the efficient management of hybrid energy storage systems, particularly in applications like electric vehicles, renewable energy storage, and industrial power supplies.

The proposed system consists of several key components:

Hybrid Energy Storage: The system integrates a lithium-ion battery and a supercapacitor to combine the advantages of both technologies. The battery is responsible for providing energy during low-power demand, while the supercapacitor handles high-power demand or short bursts of energy.

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Three-Layer Neural Network: The core of the proposed system is a three-layer neural network, which is trained to predict the optimal energy sharing between the battery and the supercapacitor. The neural network considers inputs such as load demand, SOC of the battery and supercapacitor, and other operating conditions. The network adjusts its output based on these factors to optimize energy flow.

Data Acquisition and Control System: The system continuously monitors the status of the battery and supercapacitor using sensors that measure voltage, current, and SOC. The data is fed into the neural network, which makes real-time decisions about power distribution. The control system is responsible for implementing the decisions made by the neural network, ensuring that the battery and supercapacitor are operated within their optimal ranges.

Energy Efficiency Optimization: The system aims to maximize energy efficiency by ensuring that the battery is used for long-term energy storage, while the supercapacitor handles high-power demand. This reduces the wear and tear on the battery and prolongs its lifespan. The neural network is designed to minimize energy losses during transitions between the two components and ensure that power is supplied from the most efficient source at any given time.

Real-Time Performance and Adaptability: The proposed system is adaptive, meaning it can adjust to changing load conditions and energy demands in real-time. As the system is trained with data from various operating scenarios, it can continuously learn and improve its decision-making process, adapting to the specific needs of the application.

5.EXISTING SYSTEM

In recent years, various energy management strategies have been employed to optimize the use of hybrid energy storage systems, combining batteries and supercapacitors. The goal is to make efficient use of the strengths of both technologies while minimizing their limitations. Existing systems typically focus on power management and the balancing of the energy storage devices to ensure that the battery and supercapacitor work together harmoniously, providing power as needed based on load demand and state-of-charge levels.

One of the most common approaches to energy management in hybrid systems is the use of rule-based controllers. These controllers use predefined rules to make decisions regarding the energy distribution between the battery and supercapacitor. For example, *Kim et al. (2017)* proposed a simple rule-based method for managing energy flow in hybrid energy storage systems. The rules dictate when the supercapacitor should discharge (e.g., during high-demand periods) and when the battery should discharge (e.g., during low-demand periods). While such rule-based systems are relatively easy to implement, they lack the flexibility of more advanced techniques such as machine learning and artificial intelligence.

Another widely used method is the fuzzy logic controller (FLC). *Zhao et al. (2018)* applied FLC to manage the energy flow in a hybrid battery-supercapacitor system. Fuzzy logic offers more flexibility than rule-based systems by allowing for the use of fuzzy sets to model uncertain or imprecise information. This enables the system to make decisions based on a wider range of input data, such as load fluctuations or partial system degradation. FLC has been successfully applied in various hybrid energy storage systems, but it still faces limitations in terms of its ability to handle large datasets or learn from past operational data.

With the advent of machine learning techniques, researchers have moved toward using more

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advanced algorithms for energy management. *Liu et al. (2020)* proposed using a support vector machine (SVM) for predictive energy management in hybrid systems. The SVM model was trained to predict load requirements and the system's state-of-charge, allowing for more accurate energy distribution decisions. However, SVM models require a large amount of labeled training data and can be computationally expensive to train and implement.

A major area of development in hybrid energy storage systems has been the introduction of neural networks. *Wang et al. (2019)* explored the use of deep learning techniques in battery-supercapacitor energy management. The neural network-based approach demonstrated significant improvements in energy management, with the ability to process large datasets and identify complex patterns in the data. However, neural networks also come with challenges, including the need for large amounts of high-quality data and potential overfitting issues. Despite these challenges, neural networks are gaining popularity due to their ability to learn and adapt, making them suitable for real-time applications.

Additionally, some hybrid systems have focused on model predictive control (MPC) for energy management. *Chen et al. (2021)* investigated the use of MPC in hybrid systems to minimize energy consumption and optimize power flow. MPC allows for the prediction of future system behavior based on mathematical models, enabling the system to make decisions in advance, rather than reacting to immediate changes in load demand. This proactive approach helps optimize system efficiency and minimize energy losses. However, MPC is often computationally intensive and requires accurate system modeling, which can be challenging to achieve in dynamic environments.

Overall, the existing systems primarily focus on rule-based methods, fuzzy logic controllers, machine learning models, or model predictive control techniques to manage energy distribution in hybrid energy storage systems. While these methods have demonstrated varying degrees of success, they each have their limitations in terms of flexibility, computational complexity, and adaptability. Many existing systems lack the ability to learn from operational data in real-time and cPIot dynamically adapt to varying conditions, making them less efficient compared to more advanced AI-based solutions.

The proposed system, using a three-layer neural network for intelligent energy management, aims to address these limitations by introducing a more adaptive, data-driven approach to hybrid energy storage management. By utilizing a neural network, the system can process complex datasets, learn from past operational conditions, and continuously adapt to changing demands, ultimately improving the efficiency and lifespan of the energy storage components.

In summary, while existing energy management systems for hybrid battery-supercapacitor systems have made significant strides, they still face challenges related to adaptability, data processing, and efficiency. The integration of machine learning and neural networks represents a promising approach to overcoming these challenges, enabling hybrid systems to perform more optimally in dynamic real-world environments.

6.RESULTS & DISCUSSIONS

6.1 SIMULATION

The performance simulation results of the modelled battery/SC HESS are evaluated in this section. As mentioned in Section 2, the dynamic simulations were carried out on a virtual EV(Tesla 70S electric car) after factoring in the

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respective physical and electrical characteristics of the HESS and the vehicle. The study analysed the effects of driving cycle and ambient air temperatures on the system's performance. It also reviewed four different ambient air temperatures (-20, 0, 20 and 30 o C), and one driving cycle (US06) [41, 42] for fresh battery cells for the Tesla EV. Using ADVISOR and taking into account the characteristics of the EVs and driving cycle deployed, an estimation of required load power for virtual EVs was made. Figures 7−12 present the main transient simulation results of speed, power distribution, voltage, state of charge (SOC) and current of the HESS for the Tesla EV. Figures 7 and 8 show the effect of the driving cycle on the power required by the load and the amount of power supplied from each HESS source controlled by the proposed semi-active topology (which is the same for battery-only). As can be seen, the SCs dramatically reduced the peak battery power, while the HESS was able to work with the dynamic requirements of the driving cycle. The SC's consistent energy store supported the electric power emanating from the battery pack throughout acceleration and transience phases.

The SCs provided peak surges of power for short periods, while the battery supplied average power. Deriving from this hybridization, battery stress was reduced. It was deduced that the value of the SC's power enhanced to about 70 kW during the US06 driving cycle on the electric car. On the other hand, the battery pack power within the HESS plate a used to a maximum value of approximately 20kW during the most demanding section in the US06driving cycle, representing about 71% reduction in peak power compared to the battery stand-alone system in the EV. The maximum braking power of the HESS EVs riding on US06is-38 kW. Figures 9−12 present the effect of driving cycle and ambient air temperatures on the electric car terminal voltage, SOC and current amounts supplied by each source of the HESS. The SOC decreases by about 3.25 % during the US06 driving cycle for ambient temperatures between -20 and 30 C o C. It can be seen that the hybridization has a positive effect onimproving the EV HESS performance at low temperatures. The simulation results showed that the decrease in power is only in the range 2.5-3.29% for ambient air temperatures in the range- 20 o C-30 o C. The simulation results disclosed that ambient air temperature has no significant effect on SC voltage, current and SOC, so only the results at ambient temperature of 20 o C, are shown

SIMULATION CIRCUIT:

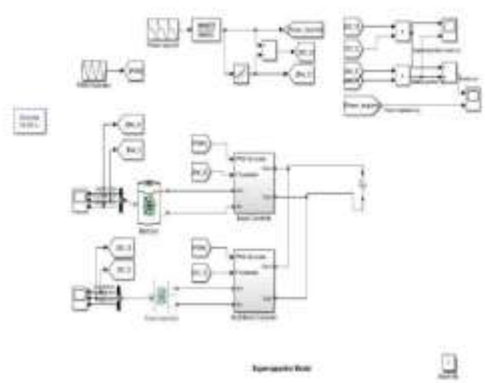

Fig 1: Simulation model in MATLAB - Simulink of the Battery/SC HESS for EV

By using PI controller :

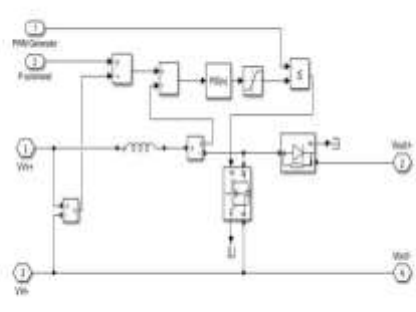

Fig 2 : Boost converter

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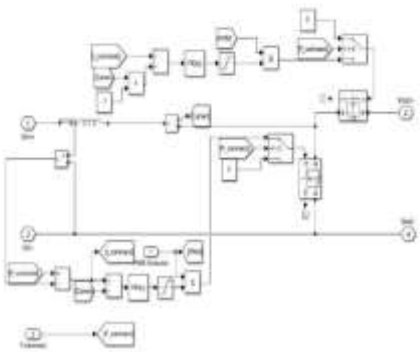

Fig 3 : Buck-Boost converter

6.2 Existing System Response Using PI Controller

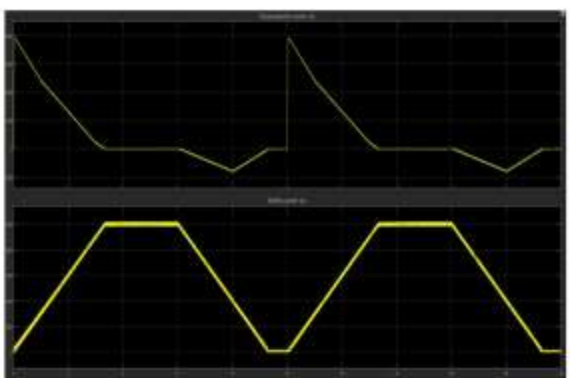

Fig 6.2 : Battery/SC Power vs Time

6.3 Proposed System Response Using Neural Network

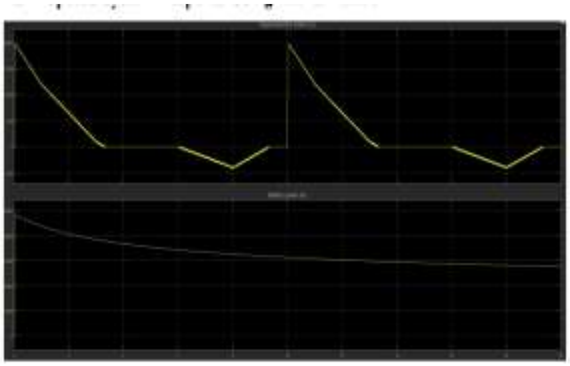

Fig6.3 : Battery/SC Power vs Time

7.CONCLUSION

This study explored the feasibility of using SCs as a power buffer to regulate power fluctuations in and out of the batteries in combination with parallel batteries in EVs taking into account the driving cycle and ambient air temperature for Tesla S70 electric car. Asemi-active hybrid topology, employing only one DC/DC converter was selected. The battery and HESS models validated by data from the literature have shown a good agreement. This implies that the models used in the present study are reliable and can accurately predict the performance of HESS. The key parameters considered in this work were the effects of driving cycle and ambient air temperature on the power, voltage, current, and SOC on the system performance. Different computation cases were run on transient mode to systematically analyse their effects on the HESS performance.

The simulation results indicated that following hybridization, the battery current drawn was reduced, the SC energy storage source supplied the larger proportion of transient current and as a result, the battery stress could be reduced. The results relating to hybridization showed a significant reduction in battery charge. The SC power contribution and the range extension in the HESS was estimated to be in average 21.5% and 80 km for the USC06 driving cycle, respectively. The main benefits of the battery/SC hybridization can be sum marised as follows: The HESS is able to significantly reduce battery stress by supporting with transient currents during acceleration and deceleration (power buffer to smooth rapid power fluctuations in and out of the battery pack).

The battery/SC HESS reduces peak currents and voltage surges, in contrast to the battery-only

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system. This averts the risk of failures caused by overly low voltage, reduces electro magnetic interference, and expands maintenance life spans of the electronic inverter modules. In other words, minimising battery peak currents can result in increased reliability of the battery pack by reducing the risk of a catastrophic failure through short-circuiting or thermal runaway. The battery/SC HESS configuration's overall performance increases substantially, especially in terms of increased vehicle range and reduced number of cycles/year which has a direct impact on battery aging process. In addition, the battery pack will not require heating if operated with SC (auxiliary high-power storage) at very cold ambient air temperatures. This hybridization also enables size reduction of the EV battery primary power source. This model may serve as a valuable performance tool for future simulation, analysis and optimization of HESS for the EVs.

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