Power Allocation based on ANN for Hybrid Battery and Supercapacitor Storage System in EV

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***Abstract*— The paper focuses on presented an Artificial Neural Network (ANN) approach to allocate power for a hybrid energy storage system (HESS) in an Electric Vehicle (EV). Batteries are typically used to store excess energy. The high-energy density of batteries can cause increased stress and reduced lifespan when they are exposed to sudden changes in irradiation and load. However, by combining them with supercapacitors, which have a high-power density, the stress on the battery can be reduced and the battery's lifespan extended. The HESS comprises a battery and supercapacitor, and the ANN algorithm aims to optimize power allocation between these two energy storage devices. While optimization can often take high computational resources and time, it is expected that a well-trained ANN can allocate power for the EV HESS more quickly. In this research, the inputs to the ANN are the required power derived from the drive cycle, energy and power capacity of the battery and supercapacitor, and state of charge (SOC) of the battery and supercapacitor. The ANN testing result in case SOC battery 85% and supercapacitor 30% RMSE 3088.2 watt and the time simulation 0.006392 seconds. Case SOC battery 75% and supercapacitor 65% RMSE 3689.3 watt and the time simulation 0.006780 seconds. Case SOC battery 45% and supercapacitor 50% RMSE 2985.2 watt and the time simulation 0.007100 seconds**

Keywords*— *artificial neural network, battery, hybrid energy storage system, power allocation, supercapacitor.

I. INTRODUCTION

The automotive industry undergoes a transformative shift towards sustainable and eco-friendly transportation solutions, electric vehicles (EVs) have emerged as a key player in reducing greenhouse gas emissions and dependence on fossil fuels. Batteries are commonly used in EVs due to their high energy density and long cycle life, despite having a low power density. In the high current and high-frequency load profiles, the service life of lithium-ion batteries will be significantly shortened[1].To solve this problem, supercapacitor with high power density is introduced to form a hybrid energy storage system (HESS) with lithium-ion batteries. HESS has better power performance, durability, and stability. The instantaneous power output of lithium-ion batteries and supercapacitors is affected by the power allocation strategy [2].

An optimal power allocation strategy improves EV performance and efficiency, and prolongs battery life, reducing storage costs [3]. To achieve the optimal power allocation of HESS, various power allocation strategies have been proposed, such as fuzzy logic [4], frequency-based [5], optimization-based power allocation strategies[6], and rule-based [7]. Power-level-based methods for allocating power loads to batteries and supercapacitors quantitatively play a crucial role based on their state of charge (SOC), power demand, and other relevant parameters [8].

Recently, machine learning algorithms, such as ANN have been used to estimate power allocation. Load forecasting can be accurately performed using ANN, an artificial intelligence (AI) technique that does not require human expertise [9]

Therefore, To better evaluate HESS performance, this paper proposes optimal power allocation for energy storage systems using the ANN method [10]. ANN offers several advantages over traditional mathematical models[11]. They can handle complex and nonlinear systems without the need for a pre-defined mathematical model[12][13] However, ANNs also have some challenges. One of the tasks is to identify the most important features, select the appropriate activation function, determine the optimal number of neurons in the hidden layer, and set the appropriate learning rate. Unfortunately, this process can be quite time-consuming.

The referenced [14] study explored power optimization in a battery-supercapacitor hybrid energy storage system integrated with a standalone PV system. The research utilized Mixed-Integer Linear Programming (MILP) and compared it with a rule-based approach to achieve efficient power distribution. The results demonstrated the cost-effectiveness of MILP methods over the rule-based strategy. However, it was noted that MILP methods had longer simulation times.

This paper proposes a battery-supercapacitor hybrid energy storage management system using neural network-based methodologies to address a challenge. The system is simulated using MATLAB alongside electric vehicle setups. The aim is to accelerate output prediction compared

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to a filtering-based method utilizing MILP optimization. Additionally, the simulation considers the variation in state of charge (SOC) from both storage components, a consideration not addressed in the referenced research. The paper is intended to improve output prediction compared to referenced research and accommodate SOC variation.

This paper is split into several sections. Section II discusses ANN model and Section III presents the results and discussion of the research. Lastly, Section IV provides the conclusion.

II. Materials and Methods

This section explains the system configuration, outlines the design of the ANN, and details of the data used in the research.

A. System Configuration

System modeling is carried out to be able to visualize the electric vehicle system will become research material. The visualization is in the form of an SLD (Single Line) configuration Diagram) electric vehicle hybrid storage system. However, the SLD is just that visual representation and does not consider it based on the limitations each component. Additionally, system modeling also includes the simulation process of electric vehicles without hybrid energy storage systems to obtain load profile power that will later be used for HESS optimization.The converters link the parts to the DC buses. This configuration uses full active topology.

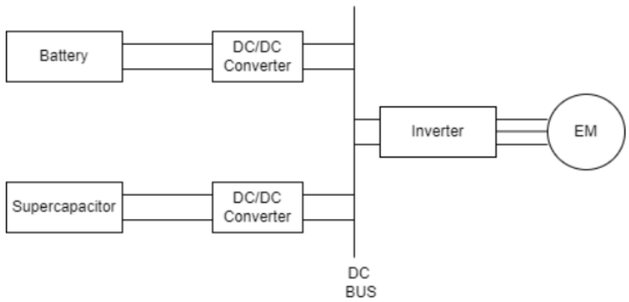

Fig. 1. Hybrid energy storage configuration system

In this configuration, each battery and supercapacitor system has a control module in the form of a DC/DC converter so that the charging and discharging of each e can be regulated. Each battery and supercapacitor system is connected to the DC Bus which is then connected to an inverter that will change the DC current into AC as input from the motor.

The specification of the EV selected for this research is shown in TABLE I. To obtain the power and energy requirements of the EV specified in the research, we used the ADVISOR program in MATLAB. In the ADVISOR, the inputs needed are the specification of the vehicles and the driving cycle, from which the power and energy graphs can be obtained and used as the data. The driving cycle used in this research is the urban dynamometer driving schedule (UDDS) in Fig. 2. In general, electric vehicles only use a battery energy storage system (BES). However, one thing that needs to be paid attention to, it can be seen that the power released by BES is very fluctuates in each unit of time. One of them is to prevent the power released by the battery from being too low fluctuates by adjusting supercapacitor energy storage system to meet power requirements that exceed limits BES maximum discharge .

TABLE I. Electric Vehicle Parameter

Parameter	Value/Type
Nominal Range	384 km
Battery Type	Liquid Cooled Lithium-ion
Battery Capacity	58 kWh
Rated Voltage	522,7 V
Drive Layout	Rear Wheel Drive (RWD)
Drive Motor	125 kW AC Permanent Magnet Synchronous Motor (PMSM)
Charging Time (10%-100%)	1 kW AC
Weight	1830 Kg

B. Data for ANN

The process starts with the inputs and targets. These inputs and targets are processed by the ANN to predict the power allocation hybrid energy storage shown in Fig. 3. The ANN constructed for this study comprises 7 inputs and 2 targets.

The first input is the required power based on driving cycle, as explained in the previous section. The second and third inputs are SOC of the battery and supercapacitor. The fourth and fifth inputs are the energy capacity of the battery and supercapacitor. This data is taken from the specifications of the car type. And the last input is battery and supercapacitor power capacity. Input parameter data shown in Table II

The targets are the power allocation for the battery and supercapacitor, which used the data based on the mixed-integer linear programming optimization[14], which were applied for the renewable energy application, and are applied for the EV application in this research. Datasets comprising input and target variables have been meticulously prepared for analysis. These datasets have not been trained, but rather, are the direct results of MILP optimization procedures. Neural network testing has been conducted across three distinct dataset scenarios to make a comprehensive comparison between the target and output, specifically with regard to battery and supercapacitor.

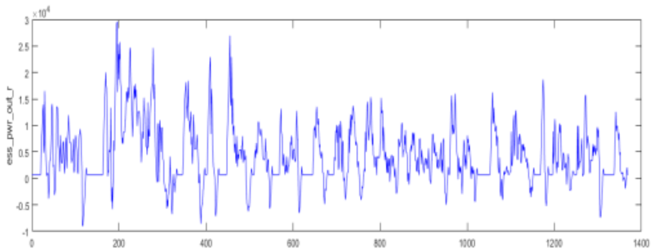

Fig. 2. Required Power vs Time

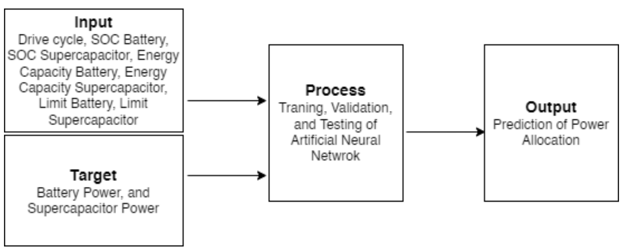

Fig. 3. Conceptual Framework

TABLE II. INPUT PARAMETER

Parameter	Value
Drive Cycle (UDDS)	1360 s
SOC Battery	22 Variations (%)
SOC Supercapacitor	22 Variations (%)
Battery Energy Capacity	208800 (kWs)
Supercapacitors Energy Capacity	2318 (kWs)
Battery Power Capacity	75 (kW)
Supercapacitor Power Capacity	750 (kW)

The datasets are recommended to be split into a training set, validation set, and testing set. The data used for training, validation, and testing were divided in the ratio of 70%, 15%, and 15% respectively. During the training of the model in MATLAB, only the training data was utilized. The validation data was used to monitor the progress of the training, while the testing data was kept aside to evaluate the performance of the trained model.

C. Neural Network Configuration

A feed-forward backpropagation neural network was used in the study. In a feedforward neural network, information flows from input to output layers through hidden layers using the Levenberg-Marquardt backpropagation training function (TRAINLM) in MATLAB R2018a. The model takes input from 7 parameters. There is one hidden layer in the neural network. This layer is an intermediate layer between the input and output layers and plays a crucial role in capturing complex patterns in the data.The hidden layer contains 20 nodes (neurons). Each node in the hidden layer processes the input data and contributes to the model's ability to learn and generalize. The tangent function (tansig) serves as the activation function in the hidden layer. The choice of activation function influences the non-linearity of the model and its capacity to learn complex relationships. The model produces predictions for 2 target parameters. These could represent the output or outcome variables that the model is designed to predict. Its shown in Fig. 4

The training parameters used to derive the model were specified in Table 3, and the neural network model was trained until the validation test achieved the lowest possible MSE. This training function is known for updating weight and bias values more efficiently compared to other backpropagation training functions. The Levenberg-Marquardt algorithm is often used for quickly converging to a solution in optimization problems. The activation function used during artificial neural network (ANN) training was the hyperbolic tangent function (tansig). The tansig function generates output values in the range of +1 to -1. It is commonly used in hidden layers of neural networks for introducing non-linearity and enabling the network to learn complex patterns.

$$\tan sig = \frac{e^{x} - e^{-x}}{e^{x} + e^{-x}} \tag{1}$$

TABLE III. TRAINING PARAMETER

Parameter	Value
Epoch	1000
Time	Infinite
Goal	0
Min Gradient	$1x10^{-7}$
Max fail	10000
mu	0.001
mu_dec	0.1
mu_inc	10
mu_max	$1.0x10^{10}$

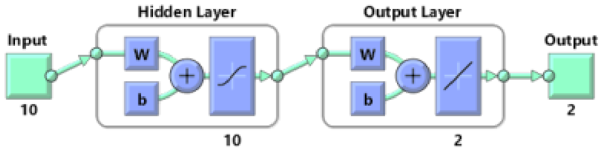

Fig. 4. Neural Network Setup Architecture

The input and output data resulting from MILP optimization, using 20,30%,40%,50%,60%,70%,80%,90% battery SOC and supercapacitor SOC, were utilized as data for training. The primary goal of this approach is to improve the neural network's ability to distinguish between dynamic power distribution in the two storage units during both the charging and discharging phases.

Following that, the neural network goes through a testing phase using early state of charge (SOC) values that have never been used for training before. This is done to evaluate the effectiveness and accuracy of the neural network. The results are then compared with those of MILP (Mixed Integer Linear Programming) optimization, with the evaluation being conducted using mean square error (MSE) and root mean square error (RMSE) values.

III. RESULTS AND DISCUSSION

To evaluate the effectiveness of the neural network, it is important to compare it with the MILP optimization discussed in the previous section. In this section, we will compare the target data obtained from MILP optimization with the output data produced by the neural network for each battery-supercapacitor case.

A. ANN Training Result

In this session, the initial SOC for battery and supercapacitor is set to 50%. Fig. 5 shows the comparison between target and the battery output, while Fig. 6 shows the comparison for supercapacitor between target and the battery output

In Fig. 5 the power battery are quite good, battery output has reached the target. Fig.6 while The result of supercapacitor power is that the supercapacitor output cannot reach the desired target

B. ANN Testing Result

In these test results, datasets containing input and target variables have been carefully prepared, but not trained, and are now ready for analysis.These datasets are the direct results of MILP optimization procedures. Through neural network testing, conducted across distinct dataset scenarios, a comprehensive comparison between the target and output Is undertaken, specifically concerning battery and supercapacitor. MSE and RMSE values for the neural network testing results are presented in the table below. These metrics are used to assess the model's accuracy in predicting target values. MSE calculates the average squared difference between predicted and actual values, while RMSE measures this difference in the original units of the data, providing insight into the magnitude of prediction errors.

1) Case 1 SOCbat =85%, SOCsc=30%

In this case, testing was conducted with 85% battery SOC and 30% supercapacitor SOC, considering the maximum condition of these two components. Fig. 7 illustrates the comparison between the target and battery output, while Fig. 8 depicts the comparison in the supercapacitor. The power distribution graphic shows that both components tested effectively based on the neural network model that was used. However, The test results on the power battery are quite good. while supercapacitor power is that the supercapacitor output cannot reach the desired target. Table IV displays the RMSE value in case 1 with an error of 3088.2 watt and a simulation time of 0.006392 seconds

2) Case 2 SOCbat=75%, SOCsc=65%

In this case, testing was conducted with 85% battery SOC and 30% supercapacitor SOC, considering the maximum condition of these two components. Fig. 9 illustrates the comparison between the target and battery output, while Fig. 10 depicts the comparison in the supercapacitor. The power distribution graphic shows that both components tested effectively based on the neural network model that was used. However, The test results on the power battery are quite good. while supercapacitor power is that the supercapacitor output cannot reach the desired target. Table IV displays the RMSE value in case 1 with an error of 3689.3 watt and a simulation time of 0.006780 seconds

3) Case 3 SOCbat=45%, SOCsc50%

In this case, testing was conducted with 85% battery SOC and 30% supercapacitor SOC, considering the maximum condition of these two components. Fig. 11 illustrates the comparison between the target and battery output, while figure 12 depicts the comparison in the supercapacitor. The power distribution graphic shows that both components tested effectively based on the neural network model that was used however, The test results on the power battery are quite good. while supercapacitor power is that the supercapacitor output does not meet the supercapacitor target. Table IV displays the RMSE value in case 1 with an error of 2985.2 Watt and a simulation time of 0.007100 seconds

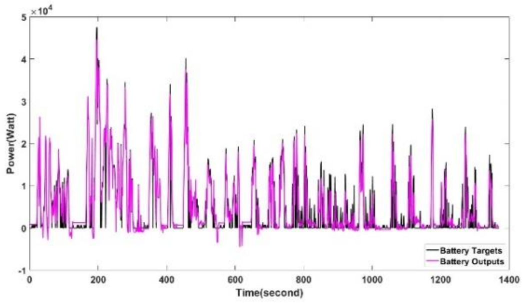

Fig. 5. Targets and outputs battery power sharing for ANN training

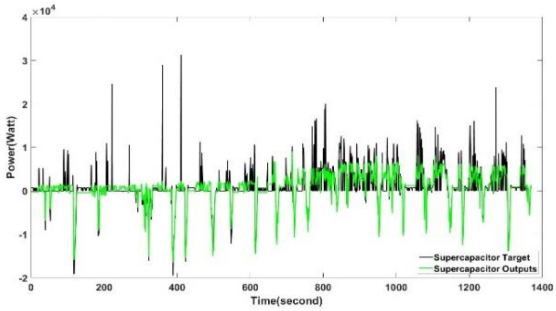

Fig. 6. Targets and outputs supercapacitor power sharing for ANN training

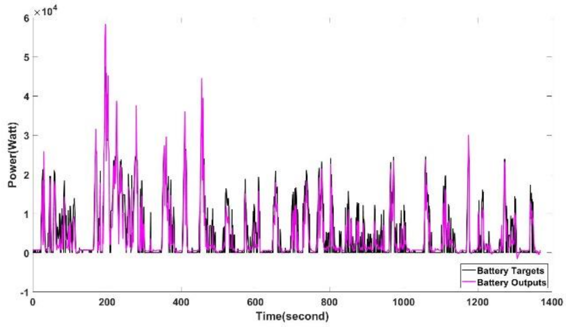

Fig. 7. Targets and outputs battery power sharing for ANN testing case 1

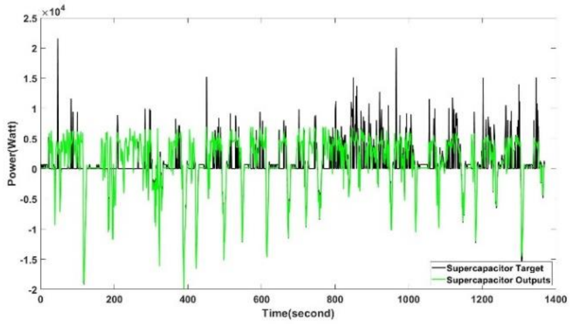

Fig. 8. Targets and outputs supercapacitor power sharing for ANN testing case 1

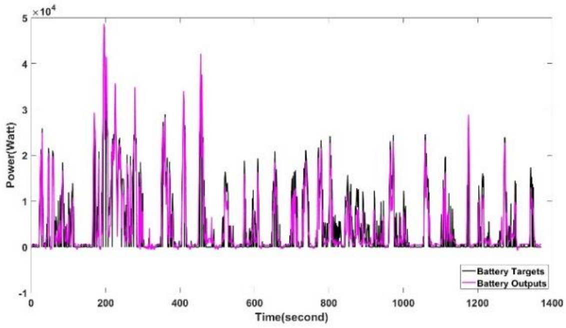

Fig. 9. Targets and outputs battery power sharing for ANN testing case 2

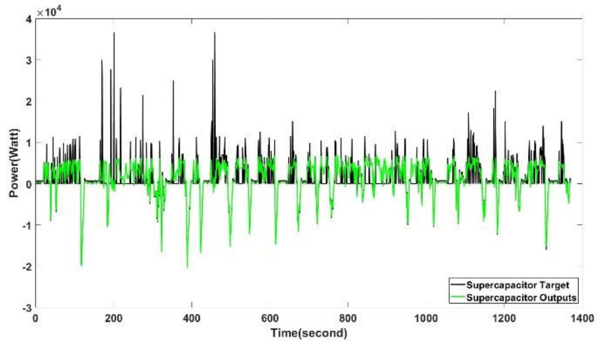

Fig. 10. Targets and outputs supercapacitor power sharing for ANN testing case 2

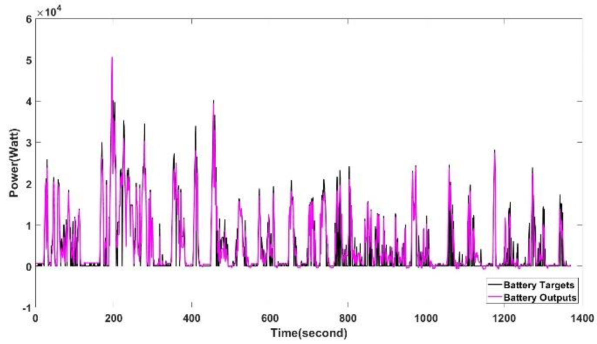

Fig. 11. Targets and outputs battery power sharing for ANN testing case 3

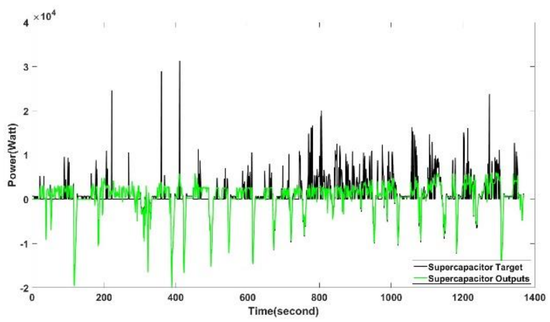

Fig. 12. Targets and outputs supercapacitor power sharing for ANN testing case 3

TABLE IV. MSE-RMSE TESTING RESULT AND TIME SIMULATION

No	SOC		MSE	RMSE	Time Simulation (second)
	Bat	SC			
1	85%	30%	9.5370e+06	3088.2	0.006392
2	75%	65%	1.3611E+07	3689.3	0.006780
3	45%	50%	8.9115e+06	2985.2	0.007100

As observed the previous, the ANN output cannot reach the target supercapacitor in a certain time. It is caused by a rapid transition to the discharge state, where the power load exceeds the power generated by the load, leading to a shift in the charging process. However, in the previous dataset, rapid changes with significant differences from charging to discharging rarely occur. As a result, only during this timeframe, the neural network needs more time to identify the pattern.

IV. CONCLUSION

This paper presents the result of ANN-based power allocation for battery and supercapacitor HESS in an EV. The ANN data training was based on a cost-optimization-based power allocation with various ANN inputs. In the ANN, power can be manange and allocated in less second, where MILP takes 154.101634 seconds. However, differences exist in some intervals, particularly supercapacitors in various scenarios. Despite this, the ANN commonly operates perfectly fine and shows acceptable error differences. This indicates that a well-trained ANN is a promising alternative method to the optimization-based method which typically require high computational cost. There are several future improvement potentials of the presented research, such as directly using driving cycle as the inputs instead of required power, or furthermore using the starting and end location of the EV as the inputs

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