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Research Article

THE ESTIMATION OF THE STATE OF CHARGE OF A LITHIUM-ION AND SUPERCAPACITOR HYBRID BATTERY MODEL BASED ON K-NEAREST NEIGHBOURS A MACHINE LEARNING APPROACH

Muhammed İkbal KAKECİ[1], Zülfikar ASLAN[2], Mehmet Ali ÖZÇELİK[3]

[1]Department Optical Engineering Gaziantep University, Institute of Science, Universite Bulvari, Gaziantep, Türkiye Orcid[1]:https://orcid.org/0009-0000-4207-6597
[2]Dept.of Electrical-Electronics Eng., Gaziantep Islamic University of Science and Technology, Faculty of Engineering, Gaziantep, Türkiye Orcid[2]:https://orcid.org/0002-2706-5715-0000
[3]Dept.of Electrical-Electronics Eng., Gaziantep Islamic University of Science and Technology, Faculty of Engineering, Gaziantep, Türkiye Orcid[3]:https://orcid.org/0000-0003-0984-5707
[*] Corresponding author; mehmet.ozcelik@gibtu.edu.tr

Abstract: *The Hybrid Energy Storage System signifies a substantial advancement in the domain of energy storage technology, particularly within the context of electric vehicles. The system integrates batteries and supercapacitors, offering a combination that is regarded as one of the most crucial technologies in this domain. The primary advantage of Hybrid Energy Storage System lies in its ability to provide high efficiency in terms of storage capacity and the immediate availability of power when it is required. The estimation of the state of charge is of paramount importance, given its impact on enhancing the performance, efficiency, and safety of vehicles. The estimation of the state of charge is a considerable challenge due to the variable charging and discharging currents present in both the battery and the supercapacitor. In response to this challenge, researchers have developed numerous methods to estimate the state of charge. The present study proposes a novel approach to charge state estimation, underpinned by a sophisticated algorithm that aims to minimize complexity and enhance accuracy. The K-Nearest Neighbors algorithm is utilized in this study due to its simplicity and interpretability, rendering it well-suited for prediction tasks in complex and non-linear systems, such as those found in battery and supercapacitor technologies. The experimental results demonstrated an average absolute error of 0.0021 and a mean square error of 0.0031. These figures are indicative of the model's high degree of accuracy and its capacity to closely mirror the true values. The supercapacitor also demonstrates robust performance. The correlation coefficient was measured at 0.9864. This finding suggests a strong correlation between the independent variables and the dependent variable, as well as a high degree of model fidelity. This high correlation indicates that the model predictions are consistent with the true values. The proposed study calculated the mean absolute error to be 0.0075 and the root mean square error to be 0.0835. These findings suggest that the model predictions are in close proximity to the true values, thereby demonstrating the model's overall high performance.*

Keywords: *KNN neural network, Electric vehicle, hybrid energy storage systems, lithium-ion batteries, supercapacitors, state of charge.*

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1. Introduction

In the context of international forums dedicated to the preservation of our planet, the identification of solutions to mitigate global warming has emerged as a pivotal agenda item. A pivotal solution under consideration is the increased reliance on electric vehicles, which are regarded as a more environmentally sustainable option when compared with diesel-powered vehicles in the land transportation sector. This sector is recognized as a primary contributor to climate change, accounting for approximately 23% of total harmful emissions [1-3]. Nevertheless, concerns regarding the viability of electric vehicles (EVs) as a viable public transportation solution persist. These concerns encompass economic factors and the limited range of EV batteries, which is a salient issue given its impact on the lifespan of the batteries. The maximum battery capacity is pivotal in determining the driving range of the electric vehicle. However, enhancing the driving range necessitates an increase in battery capacity, which, in turn, increases vehicle prices and the size of the battery [6].Despite the utilization of lithium batteries in electric vehicles, which are characterized by their high energy, relatively low cost per watt-hour, and environmental friendliness [7], their power density remains inadequate to satisfy the maximum energy demand during acceleration. This deficiency, when compounded by the consequences of sudden changes, results in elevated battery temperatures, which, in turn, diminishes the battery's lifespan and performance efficiency [8]. The aforementioned factors have resulted in the advent of the hybrid energy storage system (HESS) [9-10], which incorporates lithium batteries and supercapacitors, representing a significant advancement in this domain [11-12].Furthermore, hybrid renewable energy systems offer a dynamic solution to the challenge of achieving sustainable electricity generation by seamlessly integrating hydroelectric power, geothermal, wind turbines and solar energy conversion systems [13-15].

In HESS, the battery and the capacitor perform complementary functions, each exhibiting its own unique characteristics. Supercapacitors exhibit superior characteristics in comparison to conventional batteries, including higher power density, enhanced performance efficiency, extended cycle life, expedited charging speed, and a broader temperature range. However, they are also accompanied by lower power density and discharge rate. The implementation of a HESS system, characterized by its enhanced energy efficiency, reduced voltage, and elevated cost per watt-hour [16-17], is poised to enhance the vehicle's acceleration, augment its driving range, and mitigate the impact on battery modules and weight. This integration is projected to reduce the overall cost of the vehicle, thereby enhancing its economic viability. The life cycle of the battery has been shown to be an environmentally friendly system [18]. In order to facilitate the operation of the HESS system with optimal capacity and efficiency, this article proposes a contemporary method for estimating the state of charge (SoC). This technology is of paramount importance in enhancing the dynamic performance of electric vehicles, particularly in anticipation of the anticipated widespread adoption of HESS [19-20]. The accurate estimation of the SOC is pivotal in optimizing energy management through effective utilization of the battery and supercapacitor capacity. This, in turn, mitigates the deleterious effects of excessive charging and discharging, thereby extending the lifespan of the battery and ensuring the sustainability of the HESS system during the operational period. It is evident that the implementation of this system will result in enhanced safety measures, as the inaccurate estimation of temperature can precipitate a heightened risk of thermal runaway, in addition to the potential for conflagrations or detonations. These factors will have a detrimental effect on the reliability of electric vehicles and will serve to reduce their cost. Consequently, this field has become increasingly prominent on the global stage [21-22].

In the domain of research, a plethora of methodologies have been proposed for the estimation of the SoC. These include the Coulomb calculation method, the Kalman filter and the voltage method. Despite the success of these methods, there are many disadvantages to each. For instance, the Coulomb calculation method relies on the calculation of charges to estimate SOC by multiplying the current by the time the charge takes to move. This method is regarded as straightforward and uncomplicated to implement; however, it is vulnerable to cumulative errors and imprecise calculations that frequently arise from fluctuations in temperature and capacity. Consequently, it is deemed inappropriate for sophisticated applications, such as electric vehicles [23]. Recently, several enhanced methodologies for the Coulomb method have been proposed, some of which are predicated on recalibrating the maximum variable releasable capacity of the battery during operation. In this context, SoC is defined as the percentage of the releasable capacity in comparison to the rated capacity of the battery. The employment of this algorithm will facilitate a more accurate and reliable estimation of SoC. This approach was developed to address the shortcomings of the traditional coulomb calculation method. The algorithm is regarded as straightforward and efficacious in its implementation, with a wide range of devices, including electric cars, being compatible with its application. It exhibits a minimal estimation error of 1%, a figure that is noteworthy in the field [24]. The voltage method is predicated on the premise that the SoC can be estimated through the measurement of the open circuit voltage (OCV). The relationship between SoC and OCV is a linear relationship that is easily implemented, which has contributed to the overcoming of uncertainty in estimating the value of SoC and reducing the resulting cumulative errors. Concerning the imprecision of sensors. Notwithstanding the aforementioned advantages, it is important to note that estimating SoC is not without its potential disadvantages, primarily due to its sensitivity to temperature and the dynamic nature of battery life. In order to achieve this objective, three distinct strategies were put forward with the intention of reconstructing the OCV to estimate the SoC. These strategies comprised the utilization of the recursive least squares (RLS) algorithm, the employment of the extended Kalman filter (EKF) as a control for the estimation condition, and the gradual reconstruction of the OCV curve from high SoC to low SoC. In the course of the offloading process, it is imperative to achieve a substantial enhancement in the accuracy of the SoC [25]. The Kalman filter (KF) is an algorithm that operates in two stages: the prediction stage and the correction stage. It employs a reliable mathematical model to describe the dynamic voltage behavior of the system under different load conditions. This method is regarded as reliable, but it is known to consume a significant amount of computation time. Consequently, the extended Kalman filter (EKF) and the scented Kalman filter (UKF) were utilized in conjunction with the conventional Kalman filter in complex nonlinear systems. This method is considered appropriate for applications where high estimation accuracy is imperative, with an estimated error margin of only 1% being a key strength [26].However, it should be noted that the aforementioned methods generally exhibit computational flaws arising from modified operating conditions. Consequently, researchers have proposed data-driven state-of-charge estimation methods as a solution. The efficacy of these methodologies is contingent upon the availability of key parameter data, including current, voltage, and temperature, with the potential to yield precise estimations in a reduced development timeframe. However, it should be noted that these methods necessitate substantial data volumes for their implementation. It is possible to circumvent the disadvantages that have been observed in the aforementioned models. In their paper, E. Chemali and his colleagues set out a methodology for the accurate estimation of the state of charge of lithium-ion batteries. This methodology employs a recurrent neural network (RNN) with long short-term memory (LSTM). The method demonstrated a low mean absolute error (MAE) of 0.573% at a constant ambient temperature. Another study adopted a novel approach by employing deep feedforward neural networks (DNNs). This study attained a mean absolute error (MAE) of 1.10% and 2.17% for a range of data and temperature variations. Consequently, the neural network algorithm is regarded as a novel approach for estimating the SOC based on deep learning for the super/lithium-ion battery in electric vehicles. These models are regarded as optimal for predicting complex and non-invasive systems. Linear ones, including batteries and supercapacitors, are also employed [27]. In the present study, the K-Nearest Neighbors (KNN) algorithm will be utilized. This algorithm is regarded as straightforward to implement and comprehend; however, it is also robust and does not presuppose any assumptions concerning the distribution of the underlying data. The work of the system is dependent on a number of stages, including the training stage and the prediction stages (classification and transformation) [28]. The primary contribution of this study is the development of an estimation model for the SOC of a battery/supercapacitor system, with the objective of reducing complexity and achieving a minimal estimation error. Furthermore, the study aims to ascertain the practical application of this model in electric vehicles [29-30]. The proposed model was simulated in a MATLAB environment, with a lithium battery and a super capacitor connected in parallel.

The values for the HESS system are obtained, stored, and subsequently utilized in the proposed K-Nearest Neighbours (KNN) model [31-32]. The contributions of this paper can be enumerated as follows:

- The model for estimating the SoC for the HESS system based on the KNN algorithm has been presented in this study. This model offered a straightforward and efficient solution, characterized by its minimal errors and complexity. It was instrumental in analyzing a substantial volume of data, thereby facilitating the generation of precise estimates regarding the state of charge.

-The KNN approach was utilized for the first time in the performance evaluation of the HESS system, yielding results with minimal error rates.

-A comparison was made between the present method and traditional methods for estimating the state of charge. The KNN algorithm has been demonstrated to provide accuracy in evaluation and response, and work on developing this algorithm will be useful in the early detection of potential problems in the HESS system. Consequently, reliance on KNN can be regarded as a predictive and analytical instrument in future applications.

2. Proposed System

As illustrated in Figure 1, the proposed system uses a HESS [29]. In this configuration, voltage and current data are collected and analyzed. The data are then characterised and evaluated. The KNN model is then trained on the data and its performance evaluated. If performance is deemed satisfactory, an SoC estimate is provided. If not, the data preparation phase is repeated.

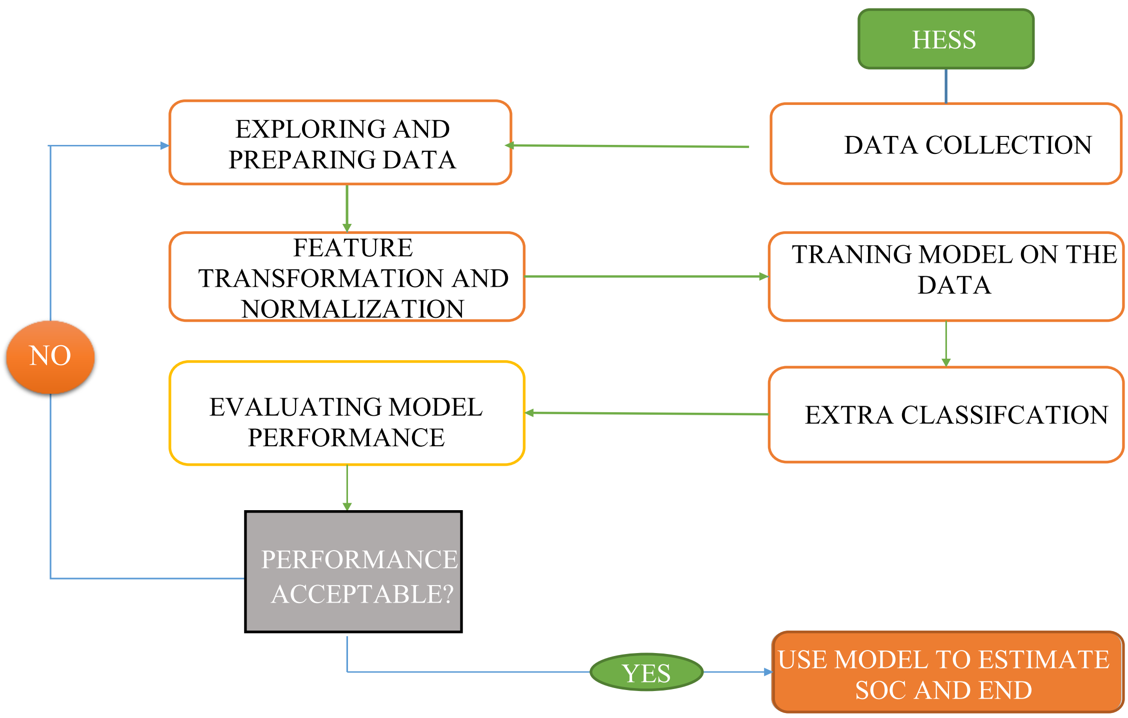

Figure 1. Flowchart of the proposed SoC estimation using KNN for HESS

Figure 1 shows the model for estimating the SoC. The actual voltage and current data collected from the battery and supercapacitor during charging and discharging are used separately in Step 1. These data are then used as input variables for the model. In step 2, the data are prepared and divided into training and testing sets. Further properties are then explored and important patterns are transformed into the model in step 3. The training sets are then used to train the KNN model, determining the number of nearest neighbours in step (4). In step 5, future battery and supercapacitor states are classified. The model's performance is evaluated using metrics such as precision and recall in the final step. If the performance evaluation shows that the performance is acceptable, the SOC estimate for the system is approved and the process is completed. Otherwise, we return to the data exploration and preparation phase. Additionally, a study of the actual system components and the SOC estimation method using KNN has been conducted. The physical components of the system and the method of estimating SOC using KNN have been reviewed.

A hybrid energy storage system combines two elements to effectively store energy. These elements may be physical, chemical or electromagnetic energy devices. Among the most advanced energy storage technologies are lithium batteries and supercapacitors. Batteries have high energy density and capacity, as well as low self-discharge, so they are used to store energy over long periods. However, they have a low voltage, and their performance deteriorates after several charging and discharging cycles. In contrast, the capacitor has a high-power density and a longer cycle life than a battery and is therefore used to improve overall performance by providing immediate power in cases of sudden demand. However, it has a low energy density and a high self-discharge rate, meaning the supercapacitor cannot be used as the main energy storage device. The HESS system was developed to address the weaknesses of these two components and combine their advantages. It is a typical and effective solution for energy management, providing high energy capacity and density. The aim of implementing an effective HESS system is to extend battery life and reduce unnecessary charging and discharging cycles, while also considering battery size to reduce mass and consumption. This system will be commonly used in electric vehicles and renewable energy applications. There are several ways to connect the battery and capacitor. In this research, the two elements are connected in parallel, with each connected to a boost converter with the required load. Accurately estimating the SoC is important for improving the system's performance and ensuring its efficient and effective sustainability. The SoC generally refers to the current percentage of charge in the battery or capacitor (Q(t)), compared to its nominal capacity (Q(n)). Nominal capacity indicates the maximum charge that an item can store. This is indicated by the working Equation in (1).

$$\mathrm{SOC(t)} = \frac{\mathrm{Q(t)}}{\mathrm{Q(n)}} \tag{1}$$

A battery is a rechargeable energy storage device that converts chemical energy into electrical energy. One of the most popular types of battery in recent years is the lithium battery, which has transformed portable and stationary energy applications and is primarily used in electric vehicles and renewable energy systems. The benefits of lithium batteries are clear: they have high specific energy and endurance capabilities, a long cycle and shelf life, and high capacity. However, accurately and effectively estimating the state of charge (SoC) is crucial for optimizing the performance, efficiency and longevity of the battery, as well as for addressing risks related to use and sudden malfunctions. There are several methods to estimate the SoC in a battery, which expresses the amount of energy remaining in the battery compared to the total energy stored by the battery. Some of these methods rely on direct mathematical equations, while others, such as calculation methods using neural networks, are more accurate. We use the current and voltage of the battery in the necessary laws. Table 1 provides the specific values for lithium-ion battery data represented by the HESS model. Utilizing this data is instrumental in achieving the ultimate energy objective. The data signifies the battery's complete charge status and encompasses current and voltage measurement ranges.

Table 1. Battery Parameters in HESS Model [33]

Battery Parameters	Charging Status
Nominal Voltage (V)	26.4
Rated Capacity (Ah)	6.6
Battery Response Time (s):	30
Initial State-of-Charge (%)	100

The nominal voltage (V) is defined as the standard voltage that the battery can provide under normal operating conditions. The nominal capacity (Ah) is defined as the maximum amount of charge that the battery can store. Battery response time (s) is defined as the time it takes for the battery to respond to changes in current and voltage.

2.1. Supercapacitor:

Despite the prevalence of battery technology in energy storage, there are certain drawbacks to its use, including its weight, size and inadequate energy density. These limitations have given rise to concerns regarding the potential environmental impact of the project. In view of the advances witnessed in associated technologies, researchers have been prompted to explore alternative solutions, including the integration of batteries with other technologies via specific connection processes. In this regard, supercapacitors are particularly promising and are considered a significant contender in the field of energy storage devices. Supercapacitors are large-capacity capacitors that combine the characteristics of batteries and capacitors in a single device. The following features are of particular significance: high power density; rapid charging and discharging; environmental friendliness; an absence of emissions; a long operational lifespan; and low internal resistance. As shown in Table 2, a comparison is made of the performance of a lithium battery and a supercapacitor.

Table 2. Comparison between the performance of a lithium battery and supercapacitor [34]

Storage device characteristics	Super capacitor	Battery
Charging time	1- 30 S	$1 < t < 5$ h
Discharging time	1 - 30 S	$T > 0.3$ h
Energy density (Wh/kg)	1 – 10	10 - 100
Life time (Cycle number)	10^6	1000
Power density (W/kg)	10.000	< 1000
Charge / discharge efficiency	0.85-0.98	0.7 – 0.85

The subsequent table illustrates the specific values of the supercapacitor data represented by the HESS model. The utilization of these data will facilitate the realization of the desired energy target. The data presented herein signifies the 100% charge state of the supercapacitor, incorporating current and voltage measurement ranges.

Table 3. Super capacitor Parameters in HESS Model

Super capacitor Parameters	Charging Status
Rated Capacitance (F)	500
Rated Voltage (V)	16
Number of Series Capacitors	16
Number of Parallel Capacitors	1
Initial Voltage (V)	16

The quantities stipulated in the Table 3 are the fundamental criteria for determining the performance of the super capacitor and accurately estimating its state of charge. The term 'nominal' is used to denote the amount of electrical charge at a specified voltage. The maximum voltage that can be applied to the capacitor is referred to as the 'nominal voltage' of the super capacitor.

2.2. SoC Estimation:

The specific capacity of a battery or super capacitor is denoted by the SoC ratio, which is defined as the ratio of the charging current to the maximum capacity. The quantity of charge remaining in a battery or super capacitor is typically expressed as a percentage. Mathematically, the SoC can be expressed as follows: t is the current passing through the battery or super capacitor. Cn is defined as the nominal capacity of the battery or super capacitor, representing the maximum charge capacity.

$$\mathrm{SOC}(t) = 100\,\% - \frac{1}{C_n}\int_0^t I(t)\,dt \qquad (2)$$

The state of charge percentage (SOC) at a given moment in time is denoted by the term "SOC (t)". This concept is applicable to both batteries and supercapacitors. This formula demonstrates how the specific gravity of the solution (SOC) decreases over time during the process of discharge and current flow. It has been hypothesized that the device is completely discharged when the SOC approaches zero.

3. KNN Learning Algorithm

KNN is a simple yet powerful algorithm that can be used to classify new points based on the classification of nearby points in the dataset [35]. This process is known as the weighting method, which indicates the extent to which each of the nearest neighbours influences the prediction. In the weighting function, when a new point is received for classification, the distance between this new point and all points in the dataset is calculated [36]. The K nearest neighbours are then identified, and their classification is based on the classification of these proximate points. This algorithm has a multitude of applications, including the estimation of the state of charge of a battery or supercapacitor. The simplicity and efficiency of the algorithm render it a highly useful tool in a variety of contexts. However, challenges pertaining to performance are to be noted, insofar as the necessity of a substantial data set is requisite for effective operation. In order to successfully apply the KNN algorithm, it is necessary to connect the battery and the super capacitor in parallel, and to collect the data extracted from these devices using MATLAB. A total of 5,000 data units of charging current and voltage are collected for the purpose of charging estimation. The subsequent stage of the process is the selection of the objective of estimating the state of charge. Following this, the data is divided into training and testing sets, with the number of neighbours K being tested. The determination of the optimal K value is a crucial factor in the management of the KNN algorithm. In this model, K was tested within the range of 2 to 100 to ascertain the optimal performance of the algorithm. The prevailing consensus in the relevant literature is that low

K values are indicative of heightened sensitivity to noise, while high values are suggestive of the converse. The optimum value for K is determined by cross-validation, which is regarded as the most reliable method for determining the value. The model is trained on the basis of the proposed data. Subsequent to this training stage, the model progresses to the evaluation or rating stage, where the performance is then assessed for acceptability. Should the performance prove satisfactory, an estimation is made of the state of charge of both the battery and the super capacitor. The implementation of the KNN algorithm is contingent upon the adherence to a series of mathematical principles. The distance measure is utilized to calculate the distance between the unknown element and each element in the data set. The data point from the dataset is denoted by xi, the query point by x_q, the feature values of the points by x, and the predicted class for the query point by y_q. In this study, the number of nearest neighbours considered is denoted by K, the class label of the I nearest neighbour is denoted by y_i, the indicator function that accounts for how many neighbours belong to class y_i is denoted by $\delta(y_i\text{-}y)$, and the weight function that assigns importance to each neighbour is denoted by ω(I). The weight function is defined in Equations 3, 4 and 5.

$$\mathrm{d}\left(\mathrm{x_i}.\mathrm{x_q}\right) \equiv \sqrt{\left(\Sigma_{\mathrm{k}=1}^{\mathrm{n}}(X_i - X_q\right)^2} \tag{3}$$

The principle of the nearest neighbour rule dictates that the classification of an unknown element is determined by the categorization of its nearest neighbours.

$$\mathrm{Y_q} = \mathrm{arg_y max} \sum_{\mathrm{\imath}=1}^{\mathrm{K}} \delta(\mathrm{y_\imath} - \mathrm{y}) \tag{4}$$

The number of neighbours, denoted by K, is a crucial factor in determining the number of neighbours to be utilized. The neighbour weight rule is utilized in order to ensure that a proportion of neighbours are able to exert a greater influence on the classification. As demonstrated in the following example, the weight function w(i) can be utilized and incorporated into the ultimate classification.

$$\mathrm{y_q} = \mathrm{arg_y max} \sum_{\mathrm{\imath}=1}^{\mathrm{K}} \omega(\mathrm{i})\delta(\mathrm{y_\imath} \cdot \mathrm{y}) \tag{5}$$

Prior to the initiation of the KNN algorithm, it is imperative to establish a set of requisite hyper-parameters, as these parameters remain constant throughout the training period. Conversely, normal parameters can be ascertained following the initiation of the training process. A crucial aspect that necessitates adjustment in KNN training pertains to the battery and the super capacitor, as evidenced by Tables 4 and 5, respectively.

Table. 4. Battery and Super capacitor hyper parameters used in KNN algorithm

Batch Size	100
The nearest neighbors search algorithm	LineerNNSearch
Distance Function	Euclidean Distance
Cross Validation	10

It is imperative to acknowledge the pivotal role of these hyperparameters in enhancing model performance and ensuring the precision of predictions. The term 'SoC(T)' is used to denote the actual SoC value, whereas 'SoC(p)' is the predicted SoC by KNN. RSS is defined as the sum of squared errors, whereas TSS is expressed as the total sum of squares.

In order to evaluate the accuracy of the model in estimating the state of charge, the KNN algorithm is employed, with mathematical error metrics such as mean absolute error (MAE), root mean square error (RMSE) and R^2 being utilized.

$$RMSE = \sqrt{\frac{1}{N}\sum_{i=1}^{N}(\mathrm{SoC(T)} - \mathrm{SoC(p)})^2} \tag{6}$$

$$MAE = \frac{1}{N}\sum_{i=1}^{N}|SoC(T) - SoC(p)| \tag{7}$$

$$R^2 = \frac{\mathrm{RSS}}{\mathrm{TSS}} \tag{8}$$

4. Simulation Model and Results

The HESS model consists of a lithium battery and a supercapacitor. It is anticipated that the model will be utilised during charging and discharging operations in electric vehicles. As demonstrated in Figure 2, the HESS system consists of a lithium battery and a super capacitor connected in parallel.

The battery is connected to a step-up transformer, while the super capacitor is connected to a step-up/step-down transformer. It is evident that this configuration guarantees that the system is capable of meeting the necessary electrical load. Furthermore, the system incorporates a pulse-width modulation (PWM) control system. The model under consideration was designed using MATLAB simulation software. The collection of the current and voltage values from the model was achieved by utilising the (to workspace) block feature. These values were then employed in KNN algorithms to estimate the SoC value, which constitutes the objective of the research. The HESS system that employs the MATLAB software is illustrated in Figure 2.

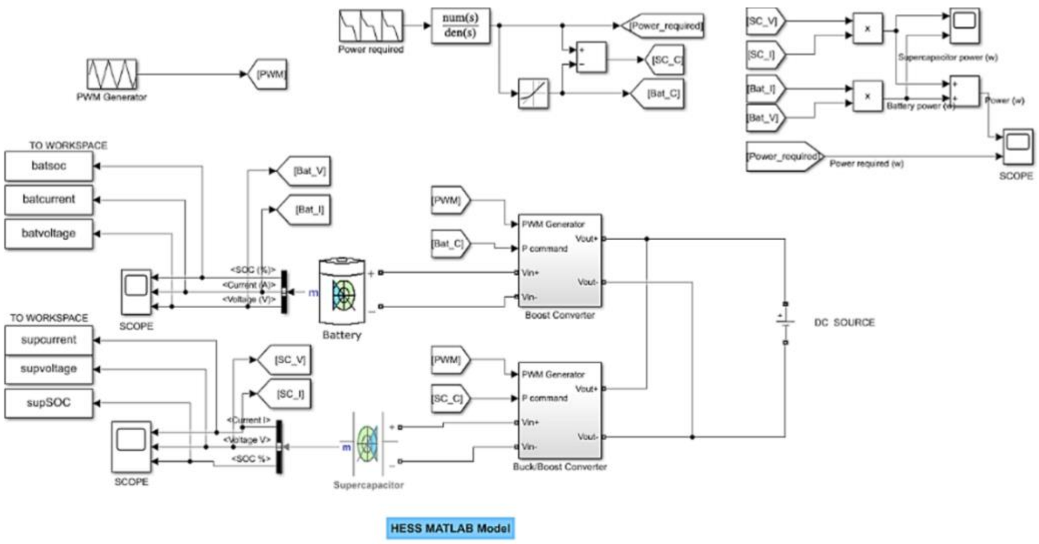

Figure 2. HESS MATLAB Simulink Model [29]

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4.1. Battery Results:

This section is dedicated to the examination of battery results in relation to current, voltage, and SoC charge state. The results obtained from the MATLAB are represented by means of curves.

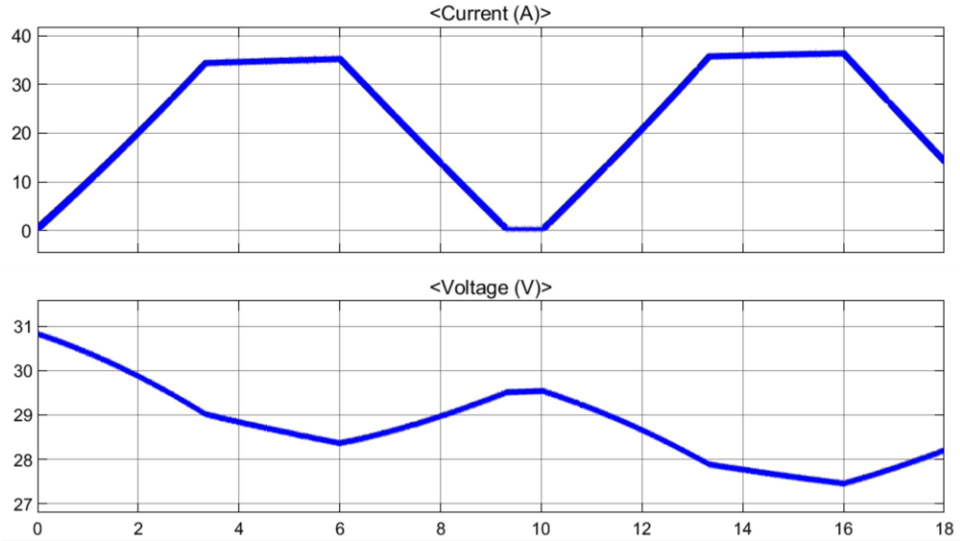


Figure 3. Output Current and voltage of battery (discharging)

In Figure 3, the output voltage and current of the battery in the HESS system are shown. The battery starts working when it is 100% charged. The voltage starts at 26.4 volts and the current starts at zero.

Upon initiation of the loading process, a decline in voltage is observed, accompanied by an increase in current. This phenomenon can be attributed to the device's response to fluctuating power demands and sudden alterations in the system.

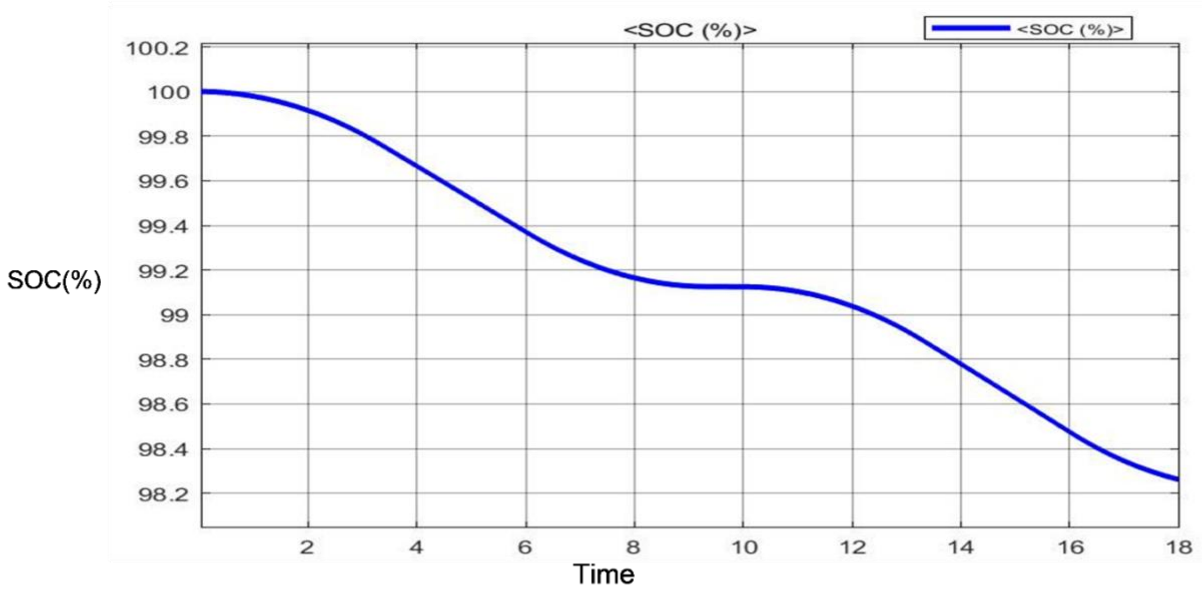


Figure 4. SOC for battery

Figure 4, a graph showing the battery's SoC is displayed to estimate the state of charge. If the battery is fully charged, the SoC percentage is 100%. After startup, the ratio starts to decrease.

4.2. Supercapacitor Results:

In this section, the results of the supercapacitor for the current, voltage and charge state of the SoC obtained from the MATLAB program are examined by representing them with curves.

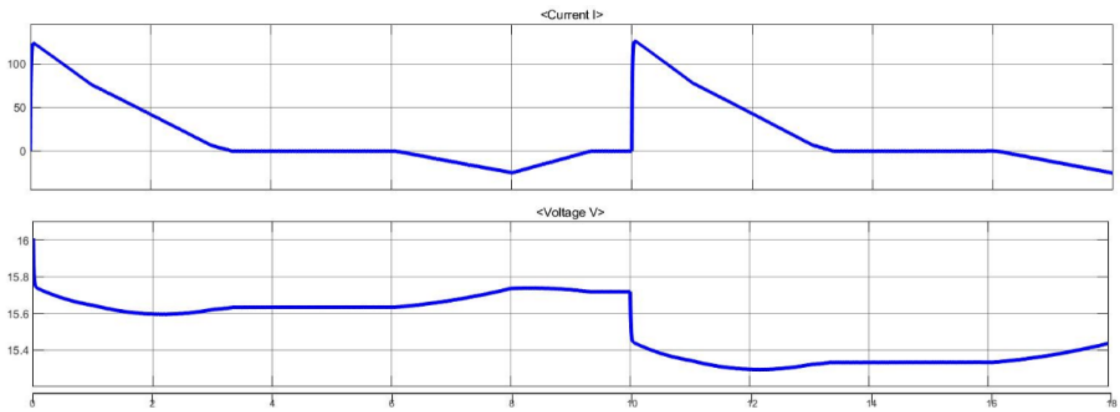


Figure 5. Current and Voltage of Supercapacitor (discharging)

As demonstrated in Figure 5, the output voltage and current of a supercapacitor within a system are shown. The HESS supercapacitor is characterized by its ability to commence operation upon attainment of a complete charge. When a load is applied, the voltage begins to fall and the current peaks. Subsequently, both the voltage and current undergo changes in response to fluctuations in power demand and emergency conditions.

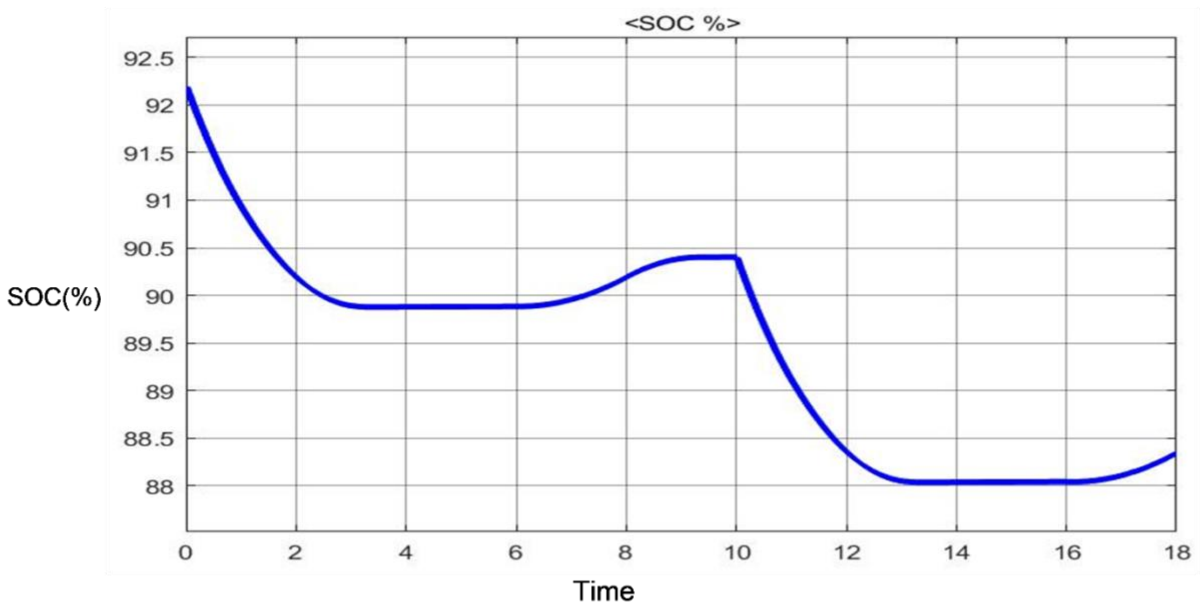


Figure 6. SoC for Supercapacitor

As demonstrated in Figure 6, a graph is provided for the purpose of estimating the SoC of a supercapacitor. During the charging cycle, the SoC ratio is elevated; however, subsequent to startup, a decline in the ratio becomes observable.

4.3. The Result of Battery and supercapacitor Using KNN:

In the course of the prediction process, the dataset is segmented into two distinct components. 80% of the budget is allocated for training, while the remaining 20% is designated for testing purposes. In the proposed methodology, the dataset was subjected to a KNN algorithm test, with the optimal result calculated for K values ranging from 2 to 100. The issue of under-learning and over-learning is addressed by employing a 10-fold cross-validation approach. As a consequence of the experimental studies, the optimal performance outcomes were obtained for the Li-ion battery at K=5, with an RMSE value of 0.0022618, and for the super capacitor at K=2, with an RMSE value of 0.002986. Following meticulous consideration of the evaluation scale, it is evident that the results obtained are satisfactory.

A comprehensive evaluation of the resulting graphs from the evaluation process for lithium-ion batteries and super capacitors has unequivocally demonstrated the efficacy of the proposed methodology. The K values and metrics for the battery model are illustrated in Figure 7.

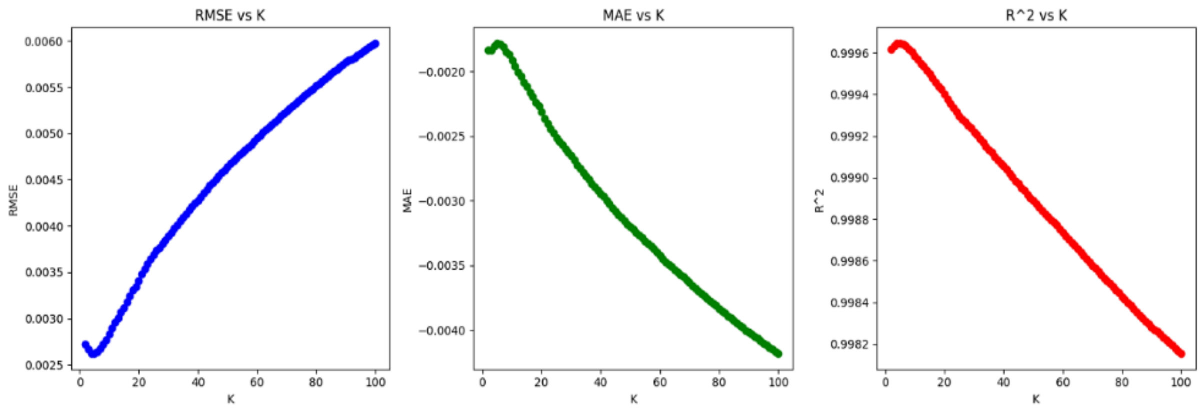


Figure 7. K values and metrics (RMSE, MAE, R^2) for battery

As illustrated in Table V, the most optimal metrics for the battery are presented, along with the respective K values at which these metrics are attained. An experimental study was conducted on the MATLAB platform, with the K value ranging from 2 to 100. The optimal result was obtained, as illustrated in Table 5.

Table 5. The best value for K and metrics for battery

K	RMSE	MAE	R^2
5	0.0022618	-0.00178	0.999646

As demonstrated in Figure 8, a graphical representation of the mathematical error measures (RMSE, MAE, R2) is presented alongside the K values. The graph illustrates the most balanced K value between bias and variance. It is optimal for the root mean square error (RMSE) and the mean absolute error (MAE) to reach their lowest possible values, while the R-squared (R^2) should ideally reach its highest possible value. The findings of this analysis demonstrate that the model exhibits a strong correlation in the absence of noise. The optimality of these values is achieved when K=2 for the super capacitor.

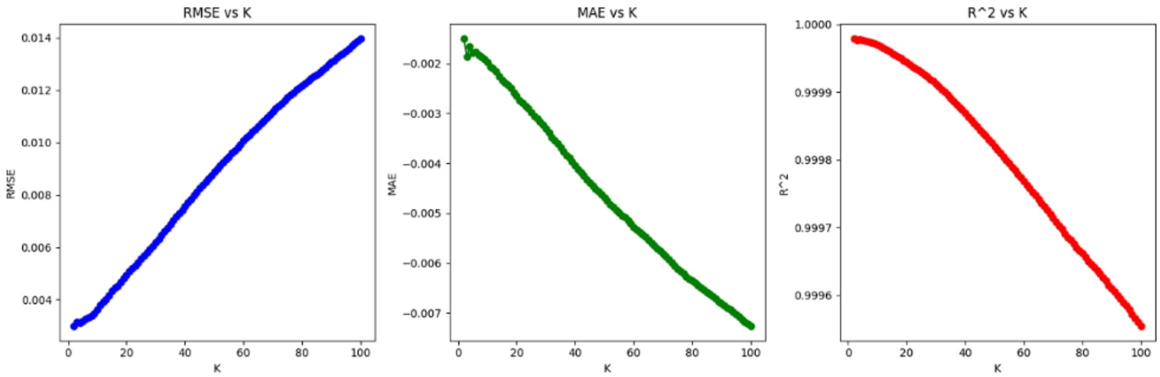


Figure 8. K values and metrics (RMSE, MAE, R^2) for supercapacitor

As illustrated in Table VI, the most optimal metrics for the super capacitor are indicated, along with the K value that was achieved. The experimental studies were conducted on the MATLAB platform for K values ranging from 2 to 100, and the optimal results are presented in Table 6.

Table 6. The best value for K and metrics for super capacitor

K	RMSE	MAE	R^2
2	0.002986	-0.001498	0.999979

Moreover, an analysis of the training curves for the battery and super capacitor demonstrated that the discrepancy between the training and validation error of the proposed model diminished as the data set size increased. This finding approximated the actual value with a high degree of accuracy. The alterations in training error and validation error for the battery at K=5 are illustrated in Fig. 9.

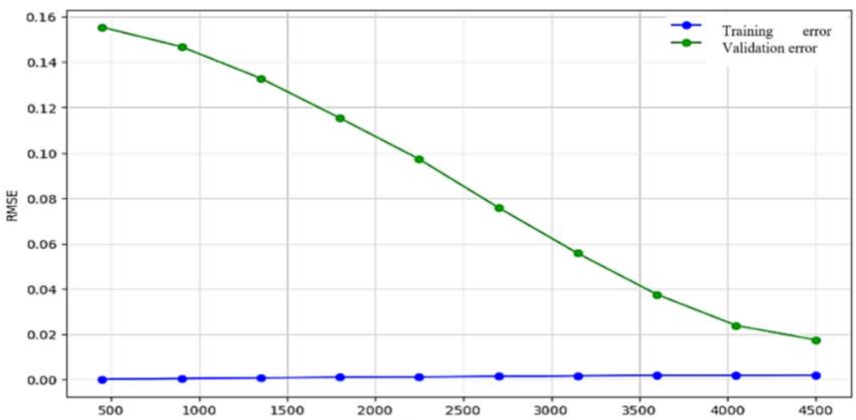


Figure 9. Training error and Validation error for Battery (K=5)

As demonstrated in Figure 10, there is a clear demonstration of the alterations in both training error and validation error for the supercapacitor when K is set at a value of 2.

A comparison of these results with those obtained from a real data set provided by the CALCE Research Group [37] was undertaken. The data was collected using various drive cycles on a cylindrical INR1865020 R LiNiMnCoO2/NMC Li-ion battery cell, using standard charging and discharging protocols. The cell was initially charged in accordance with a constant current/constant voltage protocol, after which it was discharged at three distinct temperatures (0 °C, 25 °C, and 45 °C). The technical specifications of the battery utilised in the present study are detailed in Table 7.

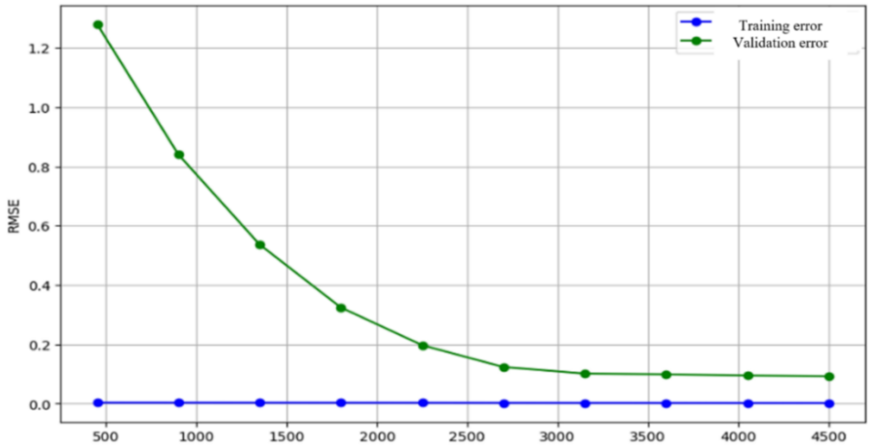


Figure 10. Training error and Validation error for supercapacitor (K=2)

Table 7. The specifications of the battery

Type	Capacity (Ah)	Voltage (V)	Cut-off voltage (V)	Max Current(A)	Life cycle
18.650 NMC	2.0	3.60	2.4/4.2	22	1000-2000

A KNN model was trained on this data to predict SOC based on voltage, current, and temperature. The optimal results were achieved at K=5, as illustrated in Table 8.

Table 8. The best results at K=5

Temperature	RMSE	MAE	R^2
0	0.0188	0.0032	0.9990
25	0.0330	0.0024	0.9937
45	0.0035	0.00025	0.9998

The findings demonstrate a remarkable precision of the model. A comparison of these results with those previously obtained using MATLAB reveals a high degree of similarity, thereby enhancing the reliability of the former results.

4.4. Effect of temperature on SOC mode:

Temperature is a significant factor that has a detrimental effect on the performance of lithium-ion batteries, thus complicating the estimation of the state of charge (SOC). The objective of this section is to analyse the behaviour of the model under different temperatures (0°C, 25°C, and 45°C) in order to evaluate the accuracy of the estimation and the dynamic performance of the model. In this section, two types of lithium-ion batteries were utilised: LiFeMgFo4 (12.8 V, 40 Ah) and LiCoO2 (11.1 V, 6600 mAh). The data collected from these batteries was then evaluated using MATLAB in order to ascertain their performance. The quantity of samples is 1,000 for each individual sample. The purpose of this experiment is twofold: firstly, to demonstrate the differences between the two variables; and secondly, to further clarify the effect of temperature.

As illustrated in Table 9, the results obtained for the LiFeMgFo4 battery are presented. Conversely, Table 10 details the results for the LiCoO2 battery. It is evident that the optimal outcomes were attained when K=2 for both batteries.

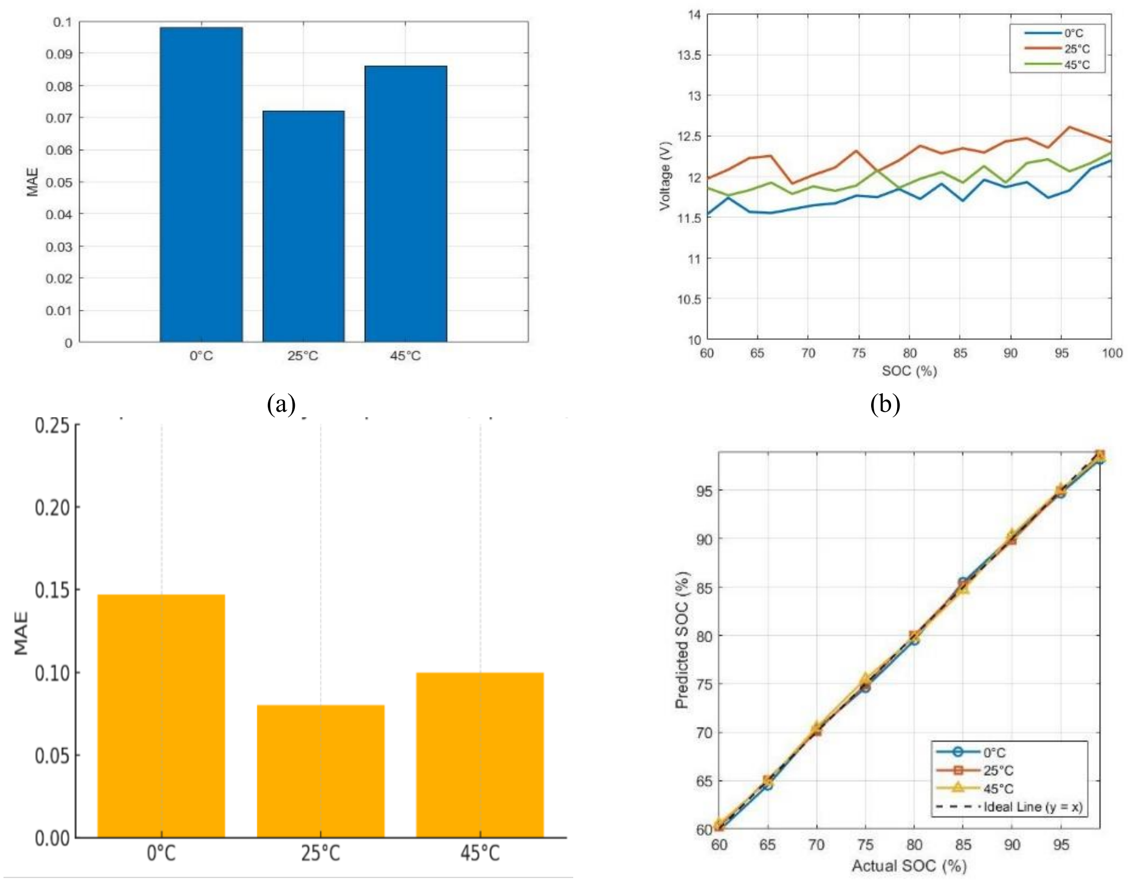
Table 9. The result of battery LiFeMgFo4

TEMPERATURE	MAE	RMSE	R^2
0 °C	0.098	0.221	0.998
25°C	0.072	0.168	0.999
45°C	0.086	0.172	0.999

Table 10. The result for LiCoO2

TEMPERATURE	MAE	RMSE	R^2
0 °C	0.147	0.191	0.998
25°C	0.079	0.122	0.999
45°C	0.098	0.182	0.999

The obtained results display variations in values, thereby demonstrating the direct effect of temperature on the battery dynamic performance. As demonstrated in Figure 11, Panel (a) presents a comparison of MAE as a function of temperature, while Panel (b) offers a comparison between voltage and SoC as a function of temperature for the LiFeMgFo4 battery. The following comparisons should be made: (c) a comparison of MAE by temperature, and (d) a comparison of SoC prediction accuracy at different temperatures.



(a) (b)

(c) (d)

Figure 11: Comparison of (MAE, SoC and voltage, SoC prediction) at different temperature.

The Figure shows how the voltage gradually increases with the SoC. The maximum voltage is observed to be 25 C, indicating that the system is operating at its most efficient level at this temperature. At 0°C, the level is considerably lower, indicative of elevated resistance and diminished efficiency in chemical processes.

The result demonstrates that battery properties are evidently influenced by temperature, with prediction SOC, voltage and current exhibiting enhanced accuracy at 25°C and 45°C in comparison to a lower temperature of 0°C. This discrepancy can be attributed, in part, to the suboptimal accuracy of the battery at low temperatures, as evidenced by the dynamic hysteresis observed in the relationship between voltage and SoC, as depicted in the curves. At a temperature of 25°C, a reduced number of errors were observed in the estimation of voltage and other parameters when compared to a higher temperature of 45°C. This finding indicates that the model performs with greater consistency and exhibits a greater proximity to the actual battery behaviour under these conditions. It is evident that the model, when operating at a temperature of 25°C, demonstrates negligible deviation from the actual data. This observation facilitates enhanced accuracy in the estimation of SoC. Despite the alterations in battery parameters under varying temperatures, operating conditions and battery types, the KNN model exhibited remarkable efficacy in mitigating the impact of these external factors, a feat attributable to its capacity to update parameters in real time. It is evident that the model's adaptive capacity facilitates the estimation of reliable SOC values across a substantial temperature range.

4.5. Comparison of Battery Types:

Battery technology has witnessed significant advancements over the past decade, driven by the growing need for highly efficient power sources, especially in the electric vehicle (EV) sector. In recent decades, there has been considerable progress in the field of battery technology, primarily driven by the imperative for highly efficient power sources, particularly within the context of electric vehicles (EVs). The operation of these vehicles is contingent upon the utilisation of high-performance batteries in conjunction with effective battery management systems (BMS), thereby ensuring safe and reliable functionality. Lithium-ion (Li-ion) and nickel-metal hydride (NiMH) batteries are among the most widely used types in EV applications due to their high efficiency and distinctive specifications. It has been demonstrated that NiMH batteries exhibit superior specific energy and lifetime performance in comparison to nickel-cadmium batteries, thus positioning them as a more environmentally sustainable alternative [38]. Conversely, Li-ion batteries offer high energy density and high open-circuit voltage, thereby enabling reduced battery pack size and weight, as well as operation over a wide temperature range. The objective of this section is to provide a comparative analysis of the performance characteristics of these two types of batteries, with a particular focus on the impact of temperature on the state of charge (SoC) and open-circuit voltage (OCV). In addition, a review of the fundamental characteristics of different battery types and their implications for the design of storage systems in electric vehicles (EVs) will be conducted.

As illustrated in Table 11, the fundamental requirements for two distinct categories of EV application are outlined. It is evident from the data presented in Table I that the battery parameters under consideration will be identical for both batteries. This observation is indicative of the application conditions being analogous for both batteries.

Table 11. Requirements for NiMH and Li-ion batteries for EV applications:

Requirement	NiMH	Li-ion
Specific energy	40-80 Wh/kg	130-200 Wh/kg
Specific power	900-1600 Wh/kg	1200-4000 Wh/kg
Energy density	90-160 Wh/L	10-320 Wh/L
Charge/discharge efficiency	80-95%	85-96%
Self-discharge rate	8-15% month	<5% month
Cycle durability	800-1200 cycles	1500-2000cycles

The coefficient of determination indicates the extent to which the data aligns with the model, with a strong effect size observed for both Li-ion and NiMH. The Root Mean Square Error (RMSE) was found to be 0.197. The residual measure of the farness of the data points from the regression line is given by MAE=0.103. The Root Mean Square Error (RMSE) values are minimal, thus substantiating the hypothesis that the data is approximately linear.

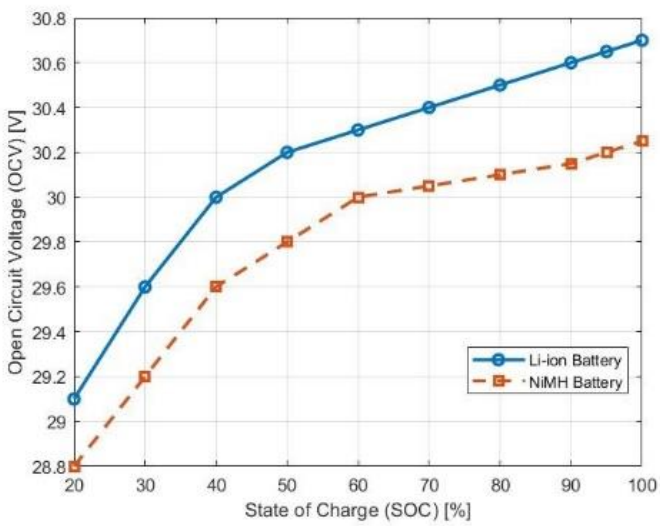


Figure12. Comparison of SoC and OCV for Li-ion and NiMH

A comparison of the SoC and OCV curves reveals that lithium-ion batteries are distinguished by their high voltage, high energy efficiency, and suitability for applications requiring high energy density, such as electric vehicles. This renders them a preferable option in comparison to NiMH batteries, which offer chemical stability but are coupled with lower voltage. The limited use of NiMH batteries in modern high-performance applications is thus explained. However, the extremely flat OCV-SoC curve in lithium-ion batteries poses a challenge for accurate SoC estimation and cell balancing in battery management systems. In order to meet the requirements for high energy density and low internal resistance, as well as to ensure a lifespan, it is essential to adopt well-trained battery models in conjunction with reliable estimation methods as KNN. This will enable independent or joint estimation of the battery's state of charge, internal temperature, and dynamic resistance.

4.6. Reasons for the Success of the KNN Algorithm in SoC Prediction:

The high performance of the KNN algorithm for SoC prediction in the HESS system is based on several key factors. Firstly, the non-parametric nature of KNN renders it independent of any assumptions when modelling the complex and nonlinear behavior of batteries and supercapacitors. This enables the precise capture of the dynamic and non-linear characteristics induced by the variable charging and discharging currents in the HESS system. Secondly, the dataset under consideration provides a substantial training set comprising 5,000 data points (current and voltage measurements) collected from the battery and super capacitor. This substantial data set enhanced the precision of the KNN's neighbor-based prediction mechanism and fortified the model's generalization capabilities.

The low training and validation errors (e.g., RMSE=0.0022618 for battery and RMSE=0.002986 for super capacitor) were achieved by determining the optimal K values of the KNN algorithm (K=5 and K=2) through 10-fold cross-validation. The low K values enabled the model to capture local patterns in the dataset, while cross-validation increased the generalization capacity of the model by minimizing the risks of overfitting and underfitting. As demonstrated in Figures 9 and 10, the training and validation error curves reveal a decline in error rates and an enhancement in the model's proximity to true values as the dataset size is augmented. Furthermore, the straightforward and interpretable structure of KNN reduces the computational complexity, providing a practical advantage in real-time applications such as SoC prediction.

The observation that the performance of KNN offers lower error rates in comparison with conventional methods (e.g. Coulomb counting method or Kalman filter) indicates that the algorithm is suitable for the dynamic conditions specific to the battery and super capacitor/box2>or HESS system. This finding indicates that the KNN model exhibits superior performance in terms of both accuracy and computational efficiency.

5. Conclusion

This research presented a relatively novel approach to estimate the state of charge (SoC) in the HESS system using the KNN algorithm. The KNN is regarded as an accessible and comprehensible algorithm. The approach has been developed to address the complex nonlinear behaviors of the battery and the super capacitor. The proposed approach has been implemented using a real data set for both current and voltage for both components. The hybrid system test results indicated a mean absolute error of 0.0021 and a mean square error rate of 0.0031. The minimal error values indicate a strong correlation between the model predictions and the actual values, thereby substantiating the model's high degree of accuracy. The model exhibited a high degree of precision in predicting the SoC of the two components, particularly in the context of electric vehicle applications. In view of these findings, it is anticipated that this model can play a pivotal role in the future of energy management systems in electric vehicles.

Data Availability:

The data that support the findings of this study are available from corresponding author upon reasonable request.

Conflicts of Interest

The author declares that there are no conflicts of interestregarding the publication of this paper.

Authors' Contributions

M.İ.K: Conceptualization, Methodology, Formal analysis, Writing - Original draft preparation
Z. A.: Conceptualization, Methodology, Resources, Investigation.

M.A.Ö.: Conceptualization, Methodology, Resources, Investigation .
All authors read and approved the final manuscript.

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