SSRG International Journal of Electrical and Electronics Engineering
ISSN: 2348-8379/ https://doi.org/10.14445/23488379/IJEEE-V10I1P120

Volume 10 Issue 1, 209-218, January 2023

Original Article

Deep Learning-Based State-of-Charge Assessment Model for Hybrid Electric Vehicles Energy Management Systems

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Received: 13 December 2022 Revised: 14 January 2023 Accepted: 21 January 2023 Published: 29 January 2023

Abstract - *Promoting the use of Electric Vehicles (EVs) is a practical way to encourage carbon impartiality and thwart the environmental problem. Government regulations and user experiences directly correlate with EV batteries and battery management improvements. Alternative engine technologies have become increasingly important in addressing issues with traditional automobiles in recent years. To decarbonize the transportation industry, electric vehicles are practical solutions. It also becomes crucial to switch from conventional to smart homes and from traditional to EV or HEV vehicles. One of the most vital parts of electric vehicles is the battery. When dealing with larger capacity and high-power needs, high-power providing battery packs—which are made up of many batteries—are necessary. These large battery packs are prone to overheating while being charged and discharged, which can lead to a lot of problems. Consequently, it is imperative to employ a battery management system. It is in charge of optimizing the battery pack so that it functions more effectively and safely. This essay's primary goals are to simulate a Battery Management System (BMS) model and examine several approaches to parameter estimation for a battery management system. It also offers suggestions for the BMS's most effective and economical implementation strategies. An efficient battery management system (BMS), primarily used for signaling the battery level of charge, is still a key component among the numerous HEV technologies (SOC). Since excessive charging and discharging always cause damage to the batteries, the BMS must provide an accurate SOC estimation. Although several SOC prediction strategies are available to control battery cell SOC, HEVs require improved SOC estimation capability. The construction of a unique deep learning with SOC estimate model for safe energy management technique for this is the main emphasis of this paper from this perspective. The proposed model uses a hybrid convolution neural network with long short-term memory (HCL) model to precisely estimate SOC. The HCL model is used to facilitate modeling and provides an accurate representation of the input and output association of the battery model. A detailed experimental investigation showed that the proposed model was superior to other current methods in several ways.*

Keywords - *Electric Vehicle, HCL, Battery Management System, SOC, Deep Learning.*

1. Introduction

Energy scarcity and environmental damage have recently become significant worldwide challenges, particularly as vehicle engineering requirements have become more stringent. Few new energy cars, such as electric vehicles, have been introduced to replace conventional gasoline-powered vehicles to reduce waste gas emissions and reproduce energy in driving activities (HEVs). The HEV now outperforms the EV in terms of high speed and long-distance travel and is a highly viable alternate propulsion technology [1]. Since the development of electricity, researchers from all over the ecosphere have been looking into ways to store liveliness and practice it when needed. As a result, the energy storage (ES) sector was established and has since developed [3]. The development of numerous industries can be aided by growing the precision and efficacy of battery models, which is a hot area of investigation. These industries include electric vehicles (EVs), which also incorporate ES, are thought of as green energy sources, and are of interest to many academics. Using energy storage devices is becoming more common due to the emphasis on lowering greenhouse emissions like carbon dioxide (CO2) and the goal to power transportation with clean, renewable energy [4].

The ecology has been harmed, and the quality of the world's air has significantly declined due to coal-fired power plants with inadequate after-treatment. Internal combustion engine (ICE) automobiles and industrial gas emissions have worsened urban air pollution. Different electric vehicles

(EVs) are being systematically established in a worldwide situation due to the ever-worsening state of the environment. The rise in popularity of EVs has several benefits, including reducing gas emissions and oil reliance, lowering carbon footprints and encouraging carbon neutrality, inciting a green transportation revolution, and making promises to halt climate change [2]. The expansion of electric vehicles (EVs) toward globalization is acknowledged as the most effective alternative, despite being highly reliant on the foundation of electricity.

Using batteries makes it possible to improve the consistency and dependability of microgrids with a high penetration of renewable energy [5]. Out of all the different kinds of batteries that are currently available, the lithium-ions variety is the one that works the best in electrical systems. This is because these batteries have a high liveliness and power compactness, a wide working temperature range, a long lifespan, the capability to charge quickly, and a low rate of self-discharge [6]. The primary objective of battery management systems, often known as BMSs, is to protect batteries from various dangers, including internal and external short circuits, excessive current and voltage, and other threats. Even though the past decade saw the creation of a large number of studies and patents about BMSs and the uses they found, the majority of these resources are still open to further investigation [7–9].

An approximation of the SOC for Li-ion batteries can be calculated using one of three methods: the classic approach, a model-based approach, or a machine learning (ML) approach. Traditional models may be easier to understand but cannot be employed in an online environment [10]. In addition, the model-based approaches are highly good at properly simulating the features of the Li-ion battery. On the other hand, they have a difficult time developing a model that accurately predicts the SOC of lithium-ion batteries [11]. On the other hand, the ML-based SOC estimation algorithms utilize the influx of data and effects processors to estimate the SOC with less prior information on the interesting elements of the battery and biochemical reaction [12]. This allows for a more accurate calculation of the SOC.

On the other hand, the effectiveness of machine learning models is heavily dependent on the quantity and quality of the training data. On the other hand, the SOC estimate that uses recently developed models of deep learning (DL) is accurate. The battery needs to have a sufficiently lengthy life to prevent having to replace over the vehicle's lifetime. Lithium-ion batteries are commonly utilized in electric cars. Therefore understanding how they degrade over time is crucial to this endeavour. As a battery is used to store or discharge energy, its current capacity, measured in terms of the state of charge (SoC), declines. The range of an electric vehicle is directly related to the battery's charge level. Therefore, a battery management system, also known as a BMS, is essential to ensure that the battery is operated within the safety parameters defined for it [13]. The capability of the BMS to correctly estimate the state of care is among its most crucial responsibilities. The state of charge (SOC) offers a percentage of the battery's remaining charge. The SOC can be determined based on 3 different factors of the battery, including the voltage, the current, and the temperature. We can determine when the battery desires to be revitalized and how far the car may be determined before the battery needs to be recharged by using the state of charge [31].

In this research, we provide an actual deep learning (DL)-based SOC assessment model as part of a renewable energy management strategy for hybrid and electric vehicles (HEVs). In the described model, an accurate SOC estimation is accomplished by creating a hybrid convolution neural network supported by a long short-term memory (HCL) based forecast model. In addition, the barnacles mating optimizer (BMO) is utilized to ensure that the hyper-parameters of the HCL model are properly tuned to ensure that an exact estimation of SOC can be obtained.

The residual parts of the study are prepared as shown below. Section 2 presents a comprehensive analysis of the various SOC estimating methodologies currently in use. The HCL method is then broken down into its component parts in Section 3, an explanation of the experimental design in Section 4, and an evaluation of the findings in Section 5. The final part of the study, Section 6, consists of some reflections on what was learned.

2. Related Works

Zhang et al. [15] developed a particle filter–based fusion filtering method for determining the SOC of Li-ion units in EVs, combining the optical flow with the classic Median filter and the KF as a suggestion dispersion makes it feasible to regain the filter's accuracy and speed. Zahid et al. [16] developed a novel SOC estimation strategy based on a subtractive clustering-enabled neuro-fuzzy system [18] and an advanced vehicle simulator linked to backpropagation neural networks (BPNN). Lai et al. [17] developed a highly credible SOC estimation approach that accounts for huge sensor and model errors using the SOC increment. As a first step, we investigated the features of the SOC error increase while using the ampere-hour counting (AHC) and extended Kalman filter (EKF) methods. Then we estimated the SOC addition with high confidence. Then, an approach that utilized AHC and EKF to calculate SOC was developed. Figure 1 depicts the most important results from this study, which examine the prevalence of Li-ion battery use across nations.

The regionalization of the electrical energy group is a vital step in transitioning away from fossil fuels and toward

RESs [32]. Wind power has increased by 7% and solar photovoltaics by 4% during the previous several years on a worldwide scale. Wind energy output has increased by 13% on average over the past five years, while solar PV-based energy generation has increased by 27% over the same time period [19,20]. RES are difficult to estimate due to their reliance on environmental factors, have limited capacity, and are often difficult to install and maintain. High vigorous and responsive power fatalities, voltage profile balancing, and network dependability are only a few of the problems that these features generate in traditional power systems [21,22]. Researchers investigate the effects of RES on the system using hybrid holdup energy source models and improved incorporation methodologies. Batteries and electric cars are two of the most popular forms of emergency power. They contribute to the grid's reliability by supplying power during peak and emergency periods.

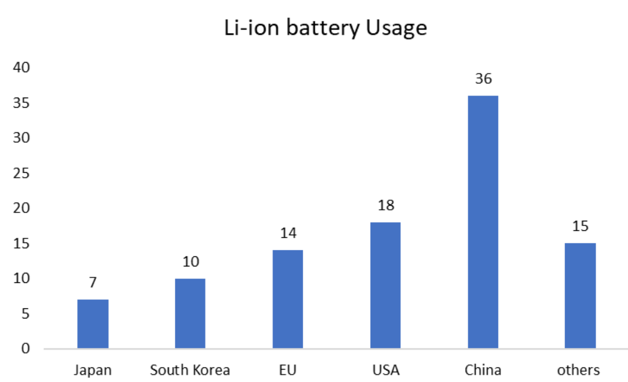


Fig. 1 Li-on Battery usage by a different country

Researchers have shown that including battery banks in the design of a system makes it more robust. Almost no academic work has focused on the possibility of employing electric cars for this function. E-vehicle grid integration is essential when overcoming electric restrictions.

Standard optimization approaches will not be effective for optimizing the HESS systems that are currently in use. For this reason, a large number of academics are doing research and studies on control systems. Controlling the energy flow between the standard battery and the supercapacitor by Chatzakis et al. [23] by applying algorithmic procedures based on rules[24]. In order to determine which rule should be implemented, the threshold values of the various parameters (such as load demand and battery output current, for example) are compared with one another. A lithium-ion is used in the construction of the HESS and is maintained utilizing the practices described before. The data are associated and analyzed in detail by Piao et al. [33]. First-order filtering is outperformed by the rule-based technique commonly referred to as the "amplitude sharing algorithm." The authors in [14],[25] and [26] found that power allocation could be efficiently handled with the use of a fuzzy logic organization whenever a rechargeable battery and biofuel cell or a battery and superconducting magnet were employed as energy storage media. In both cases, the power storage systems were used as batteries.

Veerendra et al. [34] assessed the feasibility of improving the gas mileage and performance of an energy-electric traction electric vehicle equipped with a supercapacitor by employing an electric hybrid management strategy. It is possible to guess the SOC by using both the EKF and traditional Coulomb counting. Chandran et al. [28] established an accurate state-of-charge (SOC) prediction model for Li-ion batteries using six distinct machine-learning models. The models used were artificial neural networks, support vector machines, logistic regression, collaborative bagging, and ensemble boosting. An intensive error investigation of the method was performed to optimize the battery recital parameter. Utilizing a refined DNN model, How et al. [29] developed a practical approach to calculating the SOC of a Li-ion pack for use in EVs[30]. It was found during training that a DNN with an appropriate hidden layer count can predict the SOC of unknown driving cycles with high accuracy. The training procedure was evaluated using several different driving scenarios, and a standard set of DNN approaches was validated with a predetermined amount of hidden layers.

[18] proposed a method for calculating RUL and future capacity that took advantage of uncertainty quantification methodology. Experts have developed cutting-edge machine learning algorithms that use a reliable uncertainty management strategy to provide accurate predictions regarding the storage capacity and lithium-ion (Li-ion) batteries. The next step is to utilize the empirical mode decomposition approach, which is exploited to thoroughly dissect the battery size into the intrinsic mode function and the residual value. We can identify the uncertainty in the mean (IMF) and the residual by making use of Long short-term memory (LSTM).

3. Methodology

In this subsection, a convolutional neural network and the long short-term memory system hybrid is presented as a way of simulating the extremely nonlinear dynamics of lithium-ion batteries and calculating battery SOC from observable voltage, power, and ambient temperature. The convolutional neural network (CNN) layer emphasises real-time data entry and may derive geographical information from battery records. Next, these details are put together to form more complex traits. The LSTM is better suited for processing time-series data because it uses a hidden cell memory to remember the inputs it has already seen. The following explains the parts that make up the CNN and LSTM networks in more in-depth.

3.1. Battery Management System

As an alternative to other kinds of chemistry, lithium-ion batteries have found widespread usage in the industry for various applications, such as electric cars, due to the one-of-a-kind characteristics discussed earlier. Therefore, it might be difficult to implement monitoring and control systems (BMS) to lengthen the battery's lifespan and prevent unanticipated catastrophic events. To effectively deploy BMS, its numerous parts must be dissected into their constituent aspects and analyzed in depth. Then alternative solutions must be investigated to solve their deficiencies and boost their overall performance. The primary components of the BMS are broken down in Fig. 2, which may be used as a reference for discussions and inquiries.

As a result of the multiple problems posed by the battery packs, electric vehicles (EVs) require constant monitoring of the battery status, both under normal and abnormal operating situations.

Monitoring of individual battery cells comprises providing signals of battery state and functioning. To prevent harm to the battery cells from high current or voltage, keeping an eye on both the current and the temperature is essential. To analyze EV spending patterns and predict the battery's future health, data-driven methodologies and edge detection can be employed. To do this, sensors and a data-collecting system are used to keep track of the battery cells' energy, power, and temperature. When in charging or discharging mode, often known as when an electric vehicle is being driven on public roads or when it is linked to the power grid, the batteries of electric cars need to be safeguarded from excessive current or voltage. As a result, battery management in various modes is essential if one wants to safeguard the battery and extend the battery's life cycle successfully.

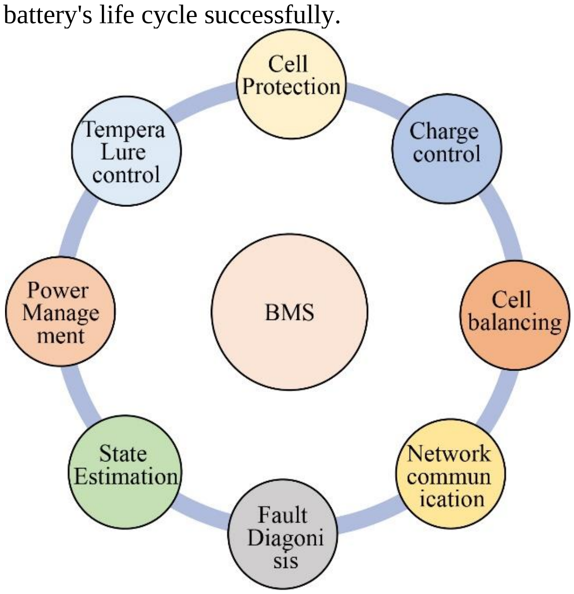


Fig. 2 The Battery Management System Overview

3.2. BMS Hardware Structure

Electric vehicles' power systems consist of the BMS, start charging circuit, and battery stack. Managing the batteries is the job of the Battery Management System (BMS). For this purpose, it employs CAN communication to talk to the ECU and relays A, B, and C to regulate the charge and discharge circuit. The electric vehicle receives power from the battery tower when relays A and B are connected; the battery pile is recharged when relays A and C are activated.

The battery stack supplies power to the electric car when relays A and C are connected. The BMS makes use of a wide variety of measuring units. The thermal sampling device keeps tabs on the charge lane's internal temperature by means of a sensor. The battery management system (BMS) will shut down the entire circuit if the battery stack's temperature goes beyond the safe threshold due to overcurrent or any other problems in the system. This is done to protect the battery stack from being permanently damaged or even exploding. The voltage sampling device monitors the voltage of each cell as well as the overall voltage of the battery stack. The BMS uses voltage information to execute over-charge/over-discharge protection and charge balance. By measuring this current, the current sampling device determines how much current flows through the Hall sensor in the charge/discharge circuit. The current information is the maximum significant signal for determining a battery stack's charge state.

3.3. Proposed Model

Within the scope of this article, an efficient tactic for accurate SOC estimation in HEVs has been devised. The proposed method contains two primary processes, namely, HCL-based forecast and hyperparameter modification. Both of these processes are described in more detail below. At this point in the process, it is possible to ascertain both the proposed approach's input and output. The SOC selection mechanism occurs at step n. Hence the $SOC(n)$ value can be considered a benchmark input representing the current battery health. This is because NN is conceptually grounded on neural networks. A change in external factors, like the battery's voltage level, does not have a linear effect on it. The battery terminal voltage $Vl(n)$ is understood to be the input, whereas the straight restriction current $In(n)$, which may be represented as the output, is considered the input. It is also possible to use $Vl(n-1)$ (the final voltage at sampling step $n-1$) as the third input to the suggested approach. The terminal state of a battery is represented by the value $v(n-1)$ and serves as an indication of the battery's former operational condition.

The terminal voltage measured at step n is represented by the notation.

$$Vl(nr) = V(SOC(nr)) + IR_s(nr) + C_{RC}(nr) \quad (1)$$

IR_s indicates the battery's internal confrontation and C_{RC} represents the RC circuit voltage.

$$Vl(nr) = f(v(nr-1), In(nr), SOC(nr)) \quad (2)$$

The battery’s input and output vectors are represented as

$$A(nr) = [V(nr-1) In\, SOC(nr)]^T \quad (3)$$

$Vl(nr)$ is the output route of the battery.

$$F(A(nr)) = Vl(nr) \quad (4)$$

3.4. HCL Model

For the purpose of determining the SOC of the HEVs in this investigation, the HCL model was applied. The CNN layer is utilized within the HCL model to carry out the process of automatically extracting the patterns. The LSTM layer is used to learn the sequence of characteristics once more. The CNN and LSTM learning processes provide results fed into the HCL model, which then uses those results to make ongoing adjustments to the hyperparameters. The CNN technique is applied to derive variables essential to the organization process, which may be carried out by the class activation map, and extract correlations present in the data. This is done so that the CNN method can be used for data analysis. Figure 3 shows the overall architecture of the HCL model.

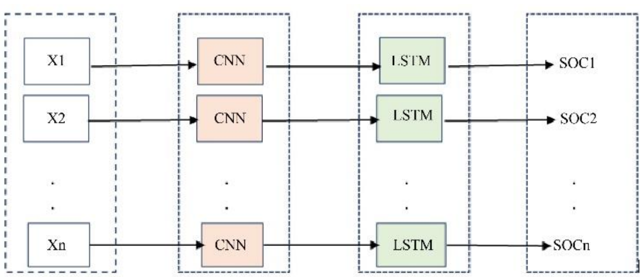


Fig. 3 HCL model structure

The Convolutional Neural Network, or CNN, is useful for pattern acknowledgment and feature abstraction. An input layer, a convolutional layer, a fully connected layer, a pooling layer, and an output layer are the typical layers that make up a typical CNN. These layers are depicted in Figure 4. The CNN starts with a set of filters and then performs layer-by-layer intricacy and combining operations to extract the topological characteristics concealed within the data. The CNN can capture the spatial aspects of the input with very few parameters and then combine those features with others to produce higher-level features. After that, the fully connected layer receives these characteristics for the sake of further classification or regression.

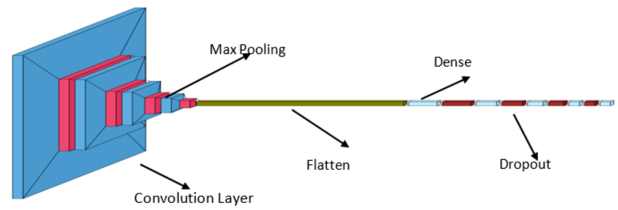


Fig. 4 CNN architecture

To obtain a collection of features, the convolutional operation c is represented by equation (5). The convolution procedure applies a product operation to the dataset that has been trained with the use of a feature map that has the dimensionsfm^{c-1}. During the process of extracting the relevant areas of the feature map, the kernel $kw_{l,n}{}^{c}$ assigns different weights to each individual region. In addition, the correlation between the neighboring characteristics may be determined by the multiplicative operations. In addition, the bias matrix $B\,_l^c$can be applied to modify the weight produced by the NN process. After performing the product operation on the count of feature mappings $fm_1{}^c$, y_l^c is sent on to the succeeding convolution layer.

In Equation (5), $f(a)$ represents an activation function, ReLU, used in layer l. This allows for the creation of a nonlinear decision boundary. Using many layers of the convolution technique accomplishes the extraction of features.

$$I_l^c = Bi_l^c + \sum_{m=1}^{n_1^{c-1}} T_{l,m}^c * X_m^{c-1} \quad (5)$$

$$O_l^c = g_l f(y_l^{c-1}), f(x) = \begin{cases} x & if\ x \geq 0 \\ 0 & if\ x \leq 0 \end{cases} \quad (6)$$

Using the pooling layer to improve the classification result while lowering the computational cost is possible. The pooling layer function provides a reduction in overfitting while also facilitating the efficient derivation of features.

One of the most often used variations of RNN is called an LSTM. When employing a traditional gradient-based training framework, RNNs are unable to resolve long-term dependencies because of phenomena known as gradient vanishing and gradient explosion. The LSTM network, on the other hand, employs hidden memory rather than traditionally hidden nodes to circumvent these limitations. The construction of an LSTM unit is represented in Figure 6.

Input gate I, which determines what fraction of the input signal will be merged into the cell remembrance; forget gate F, which characterises the forgetting rate of the cell recollection given the current input; and Output gate O, which regulates the effect of the cell memory on the node output, make up this structure. Starting at time T, an LSTM unit performs its forward run in the following fashion:

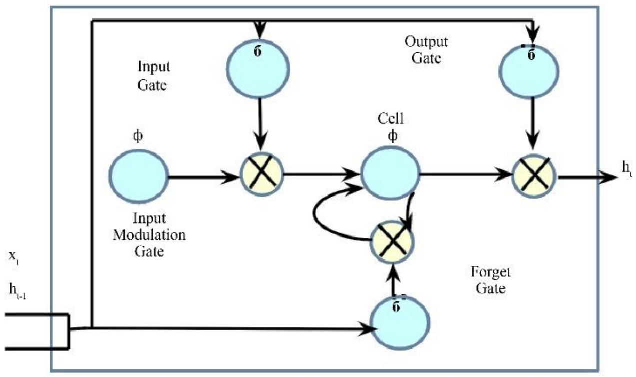


Fig. 5 LSTM architecture

$$F_t = \sigma_F(w_F x_t + V_F hI_{t-1} + b_F \tag{7}$$

$$I_t = \sigma_I(w_I x_t + V_I hI_{t-1} + b_I \tag{8}$$

$$O_t = \sigma_O(w_O x_t + V_O hI_{t-1} + b_O \tag{9}$$

$$M_t = F_t \circ M_{t-1} + I_t \circ \sigma_M(w_M x_t + V_M hI_{t-1} + b_M) \tag{10}$$

$$hI_{t-1} = O_t \circ \sigma_{hl}(M_t) \tag{11}$$

Hadamard product is denoted as $\circ$. and the x_t is the input data, the hidden memory unit is denoted as hI_{t-1}. $\sigma_F, \sigma_I, \sigma_O, \sigma_M$ are the activation functions of all gates.

What follows is an example of the 1D convolutional layer's impact in action. Different features of the data may be extracted and utilised as input to the LSTM layer by adjusting the weight of the convolution and the breadth of the window. Applying a DFT or a wavelet transform to the original data is similar to doing a 1D convolution using the same kernel. So, the characteristics are taken out in the spectral domain. This is due to the fact that 1D convolution is analogous to other signal-processing tasks. The LSTM network is now probing the associations between the current output and the inputs it has received in the past, while the inclusion of CNN forces the network to further capitalise on the linkages existing within the input it is getting at the time. The connection between power, voltage, average current, temperature, and average voltage might help shed light on its sometimes murky or paradoxical manifestations. The acquisition of these features is indicative of the CNN network's training to diminish estimate error. At each forward pass during training, the mean squared error (MSE) is chosen to serve as the aggregate loss function:

$$MSE = \frac{1}{m}\sum_{m=1}^{n}(y_m - \hat{y}_m)^2 \tag{12}$$

The root mean square error (RMSE) and the mean absolute error (MAE) are used in the challenging phase to appraise the recital of the planned network:

$$RMSE = \sqrt{\frac{1}{m}\sum_{m=1}^{n}(y_m - \hat{y}_m)^2} \tag{13}$$

$$MAE = \frac{1}{m}\sum_{m=1}^{n}|y_m - \hat{y}_m| \tag{14}$$

The MAE is a measurement that ignores the sign of the genuine values to determine how near the estimation is to the actual values. In contrast, the root-mean-square error (RMSE) is more sensitive to high mistakes and acts as a characterising measure for error variance.

4. Experimental Setup

Experiments were performed using cylindrical A123 18650 battery samples and an Arbin BT2000 battery tester. The battery tester was calibrated with a lithium iron phosphate (LFP) cathode and a graphite anode. Mits Pro, a piece of software developed by Arbin, was used to regulate the charge/discharge profile of the battery. Using a temperature chamber manufactured by Votsch, the temperature of the surrounding air around the battery samples was controlled.

The Adam optimizer is chosen to use to realize the goal of minimizing the total loss. This optimizer modifies the weights and biases of the network based on the gradient of the loss function. The starting learning rate is set at 0.01, which is the default. Both of the decay rates are set to their respective default values of 0.999. In the LSTM layer and the fully linked layer, we use a dropout rate of 20% since we are concerned about the possibility of over-training occurring during the training phase.

4.1. Dataset

At room temperature, the DST data, the FUDS data, and the US06 data are used to train the proposed CNN-LSTM network in this section. Overall, 33165 data are used for training and testing purposes, 24815 data are used for testing, and the remaining data are used for testing. Figure 6 shows the data distribution used in our proposed model.

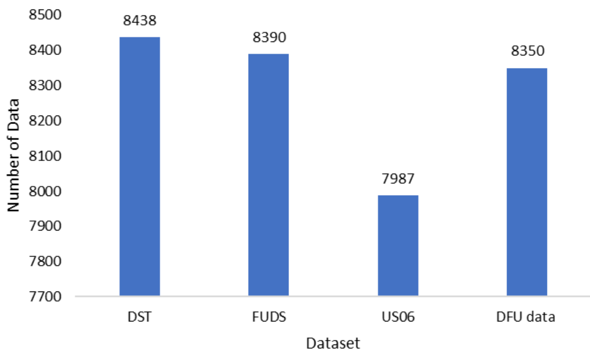


Fig. 6 The number of data used in our HCL model

4.2. SOC initial Value

Data on Lithium-ion open-circuit amplitude and SOC are used in Figure 7 to depict the relationship between these two variables. There is no doubt that the voltage measured with the circuit open at the present moment may be used to compute the SOC value. The link between the SOC value of an electric car during its parking period and the amount of time necessary for the battery to achieve a steady state. The SOC value decreases as time passes, which is the factor that establishes whether or not Figure 7 is suitable for use as the starting point for the SOC value.

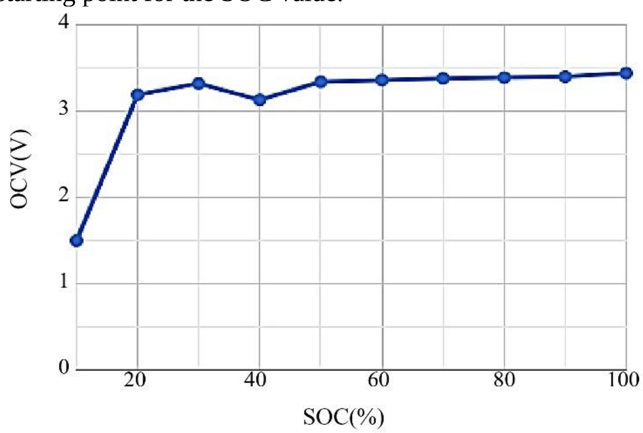


Fig. 7 The link between the open-circuit voltage and the SOC

5. Performance Evaluation

Data from the DFU test is used to evaluate the quality of live SOC estimate, whereas data from the DST test, the FUDS test, and the US06 test are used to train the HCL network described in Section III. In addition, the recital of the network is examined. As seen in Figure 8, the RMSE soon falls below 4% after 2000 epochs, and then after 6200 epochs, it practically remains within 2% of that value. Around epochs 6000–8000 and 11000–12000, fluctuations can be seen in the RMSEs. These fluctuations indicate that the optimization process is jumping from one optimal local state to another. Training and testing errors both reach their lowest point on a global scale between epochs 8000 and 11000. Therefore, 10,000 is an appropriate number to use as the training epoch.

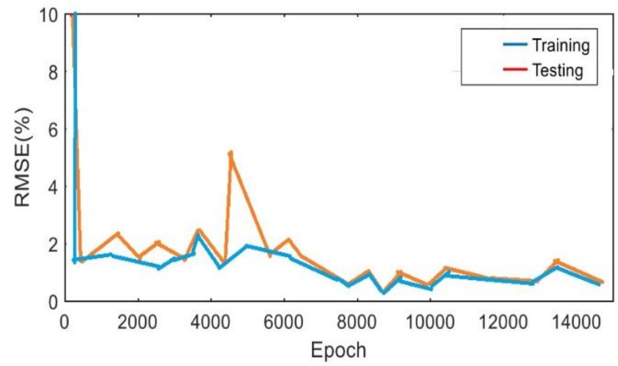


Fig. 8 The root means square errors (RMSEs) of the epoch range is from 1 to 15000

The results of each case's RMSE and MAE are arranged in Table 1, where it can be understood that each case's RMSE is under 2% and each case's MAE is within 1.5%.

Table 1. RMSE and MAE of Initial SOC

SOC	RMSE (%)			MAE (%)		
	CNN	LSTM	HCL	CNN	LSTM	HCL
100	6.32	0.85	0.45	5.42	0.85	0.35
80	6.7	1.52	1.25	5.62	0.85	0.92
60	7.25	3.62	0.85	4.56	1.99	0.52
40	7.89	3.12	1.45	5.6	1.2	0.4
20	6.59	1.2	0.65	6.02	0.95	0.35

It has been found that the RMSEs and MAEs of the estimate are larger within the 42% to 88% range rather than growing with the initial SOC bias. Table 1 contains a tabulation of further statistical findings, which shows that the initial SOC falls from 100% to 20% by a factor of 20%. The RMSEs and MAEs produced by the proposed network are consistently lower than those produced by the LSTM and CNN networks. Figures 9 and 10 show the RMSE and MAE values for the proposed model.

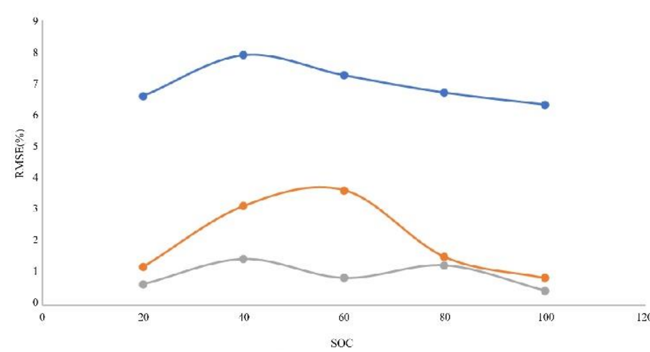


Fig. 9 RMSE of CNN, LSTM and HCL models

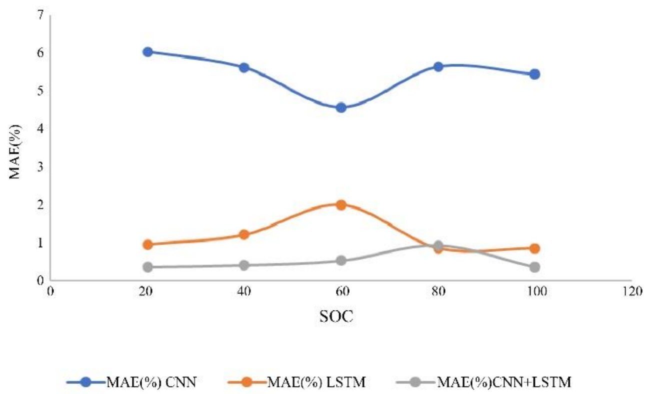
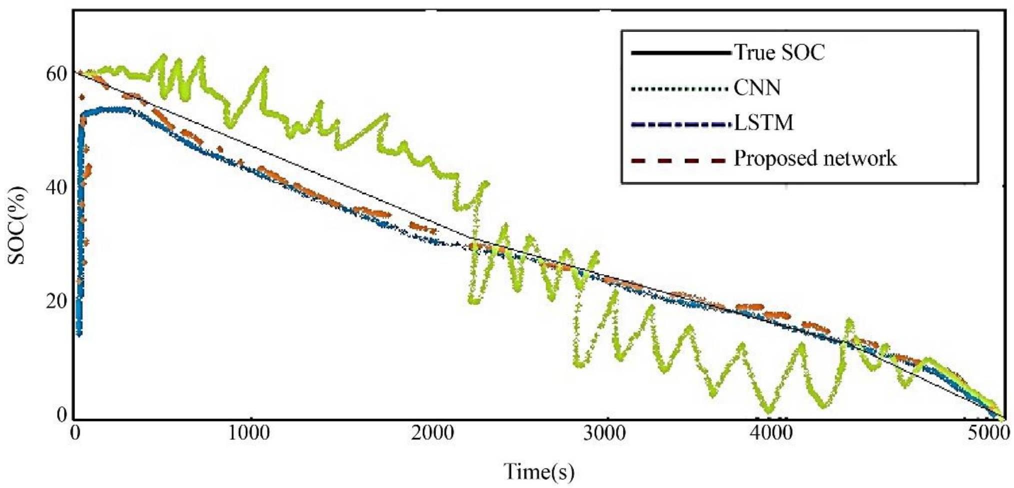


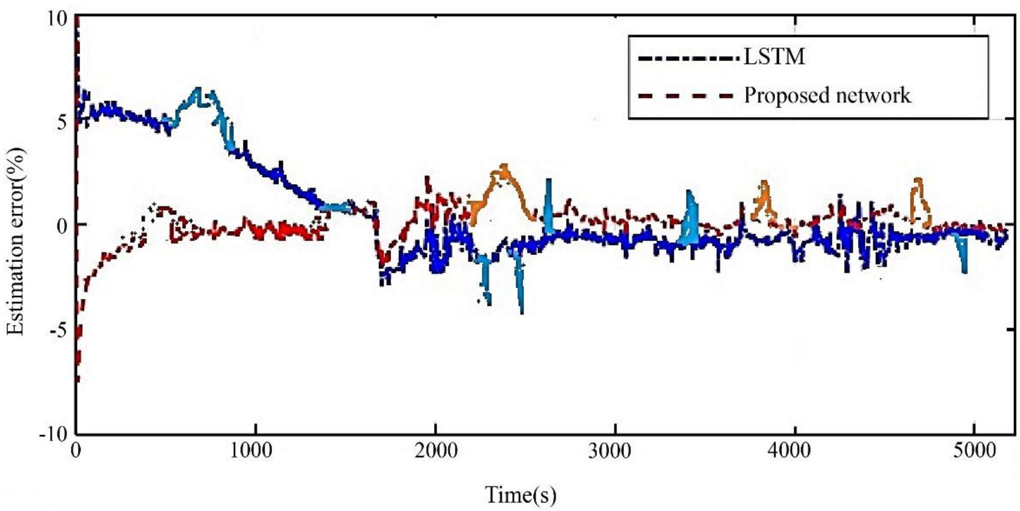
Fig. 10 MAE of CNN, LSTM and HCL models

In addition, the estimation results are shown in Figure 11, with the starting SOC set to 60%. As was to be predicted, the CNN network's estimation results are quite similar. This time around, the proposed network can converge to the actual SOC at a significantly quicker rate than the LSTM network. The planned network is once again more stable and precise once it has gone through the second step.

Compared to the LSTM network, the RMSE and MAE of the planned network come in at 0.95% and 0.39%, respectively, whereas those of the LSTM network comes in at 3.67% and 3.23%, respectively, correspondingly. Even though it has the lowest performance overall, the CNN network is the least affected by variables whose starting points are unknown. Both the LSTM network and the proposed network have the same problem when it comes to SOC approximation: it is initially conquered by an unknown starting SOC. When all of the networks have finally converged on the real SOC, the projected network will have superior recital accuracy and consistency.



(a)



(b)

Fig. 11 Approximation results for SOC assuming a starting value of 60%: (a) estimate inaccuracy; and (b) SOC tracking.

It has been found that the RMSEs and MAEs of the estimate are larger within the 42% to 88% range rather than growing with the initial SOC bias. The appearance of a flat zone in the OCV-SOC curve for the LFP batteries might explain this phenomenon. The area with a SOC between 40% and 80% is quite flat, which indicates that the measured battery physical states are pretty stable throughout this range. This is something that is desired for the battery when it is being used as a power source. On the other hand, because of this trait, it is considerably more difficult to infer the original SOC. This is because even a slight variation in the OCV can lead to a significant variation in SOC estimate.

6. Conclusion

In this study, we proposed estimating the charge level of lithium iron phosphate batteries with a convolutional neural network (CNN) combined with a long short-term memory (LSTM) network. The network was qualified using information from several diverse discharge profiles. These profiles were the DST, US06, and FUDS. Data from a new collective DFU profile was used to assess the efficacy of the projected network for SOC calculation. The results of the experiments show that the suggested network can successfully capture the nonlinear correlations between the state of charge (SOC) and the input variables of the network, specifically power, voltage, temperature, average power, and average voltage. Within the scope of this work, an efficient deep learning-based approach for precise SOC estimation in HEVs was devised. The HCL method contains two key processes: HCL-based prediction and hyperparameter tuning.

Both of these processes are described here. The use of the HCL model makes the modelling process simpler and delivers an accurate portrayal of the input–output relationship of the battery model. This is made possible by the utilization of the HCL model. In addition, selecting the most appropriate values for the hyperparameters enables a reduction in the error rate and an improvement in the accuracy of the predictions. In order to provide evidence of the technique's superior performance, a number of simulations were run, and the results were analyzed in a number of different ways. An exhaustive comparison study found that this method is superior to more contemporary methods that are considered state-of-the-art in terms of various categories and subcategories. As a result, the proposed approach has the potential to function as an efficient instrument for the precise and speedy estimate of SOC in the electric vehicle. In the not-too-distant future, hybrid optimization algorithms will be able to be built for enhanced SOC estimate results and will be able to be applied in a real-time setting.

It is preferable to account for various uncertainties, such as the noise effect and the various temperature conditions, during the data acquisition process because the Li-ion battery may be subjected to a wide range of environmental conditions in the real world that cannot be replicated in laboratories. More study is needed to determine the best ways to optimize machine learning systems and reduce their computational efficiency. Since the algorithms in realistic real-time systems must be processed at rapid rates, lesser data-based solutions are used to accelerate the learning. In order to meet the challenges of everyday life, this is essential. In addition, parallel computing techniques might be used to hasten the learning and computing phases.

References

[1] Pier Giuseppe Anselma, "Computationally Efficient Evaluation of Fuel and Electrical Energy Economy of Plug-In Hybrid Electric Vehicles with Smooth Driving Constraints," *Applied Energy*, vol. 307, pp. 118247, 2022. *Crossref*, https://doi.org/10.1016/j.apenergy.2021.118247

[2] Chau K.T., *Energy Systems for Electric and Hybrid Vehicles*, Institution of Engineering and Technology, 2016 *Crossref*, https://doi.org/10.1049/PBTR002E

[3] Yury Dvorkin et al., "Ensuring Profitability of Energy Storage," *IEEE Transactions on Power Systems*, vol. 32, no. 1, pp. 611– 623, 2017. *Crossref*, https://doi.org/10.1109/TPWRS.2016.2563259

[4] Ridoy Das et al., "Multi-Objective Technoeconomic-Environmental Optimisation Of Electric Vehicle For Energy Services," *Applied Energy*, vol. 257, pp. 113965, 2020. *Crossref*, https://doi.org/10.1016/j.apenergy.2019.113965

[5] DolfGielen et al., "The Role of Renewable Energy in The Global Energy Transformation," *Energy Strategy Reviews*, vol. 24, pp. 38–50, 2019. *Crossref*, https://doi.org/10.1016/j.esr.2019.01.006

[6] Kailong Liu et al., "A Brief Review on Key Technologies in the Battery Management System of Electric Vehicles," *Frontiers of Mechanical Engineering*, vol. 14, no. 1, pp. 47–64, 2019. *Crossref*, https://doi.org/10.1007/s11465-018-0516-8

[7] Nisha C. Rani, and N Amuthan, "Soft-Switching Integrated Quasi Resonance Buck-Boost Converter for HHO Optimized Grid Connected PV System," *SSRG International Journal of Electrical and Electronics Engineering*, vol. 9, no. 8, pp. 28-39, 2022. *Crossref*, https://doi.org/10.14445/23488379/IJEEE-V9I8P104

[8] R. Venkedesh, R. Anandha Kumar, and G. Renukadevi, "Multilevel Inverter Design with Reduced Switches & THD Using Fuzzy Logic Controller," *SSRG International Journal of Electrical and Electronics Engineering*, vol. 9, no. 12, pp. 1-21, 2022. *Crossref*, https://doi.org/10.14445/23488379/IJEEE-V9I12P101

[9] Farithkhan Abbas Ali, and E. D. Kanmani Ruby, "Clustering Metric Algorithm for Cost-Effective Routing in Flying Ad-hoc Networks," *SSRG International Journal of Electrical and Electronics Engineering*, vol. 9, no. 12, pp. 101-108, 2022. *Crossref*, https://doi.org/10.14445/23488379/IJEEE-V9I12P108

[10] Murali Matcha et al., "Design and Performance Analysis of Multilayer Neural Network-based Battery Energy Storage System for Enhancing Demand Side Management," *SSRG International Journal of Electrical and Electronics Engineering*, vol. 9, no. 10, pp. 7-13, 2022. *Crossref*, https://doi.org/10.14445/23488379/IJEEE-V9I10P102

[11] Xiong, Rui et al., "Co-Estimation of State of Charge and Capacity for Lithium-Ion Batteries with Multi-Stage Model Fusion Method," *Engineering*, vol. 7, no. 10, pp. 1469–1482, 2021. *Crossref*, https://doi.org/10.1016/j.eng.2020.10.022

[12] Chen, Xiaopeng et al., "Robust Adaptive Sliding-Mode Observer Using RBF Neural Network for Lithium-Ion Battery State of Charge Estimation in Electric Vehicles*," IEEE Transactions on Vehicular Technology*, vol. 65, no. 4, pp. 1936–1947, 2015. *Crossref*, https://doi.org/10.1109/TVT.2015.2427659

[13] Thiruvonasundari Duraisamy, and Deepa Kaliyaperumal, "Machine Learning-Based Optimal Cell Balancing Mechanism for Electric Vehicle Battery Management System", *IEEE Access*, vol. 9, pp. 132846-132861, 2021. *Crossref*, https://doi.org/10.1109/ACCESS.2021.3115255

[14] S. Gopiya Naik et al., "Battery Parameter Monitoring and Control System for Electric Vehicles," *SSRG International Journal of Electrical and Electronics Engineering*, vol. 9, no. 3, pp. 1-6, 2022. *Crossref*, https://doi.org/10.14445/23488379/IJEEE-V9I3P101

[15] Zhang Ming, Wang Kai, and Yan-Ting Zhou, "Online State of Charge Estimation of Lithium-Ion Cells Using Particle Filter-Based Hybrid Filtering Approach," *Complexity*, pp. 1–10, 2020. *Crossref*, https://doi.org/10.1155/2020/8231243

[16] Zahid, Taimoor et al., "State of Charge Estimation for Electric Vehicle Power Batteries Using Advanced Machine Learning Algorithms under Diversified Drive Cycles," *Energy*, vol. 162, no. 1, pp. 871–882, 2018. *Crossref*, https://doi.org/10.1016/j.energy.2018.08.071

[17] Lai, Xin et al., "A Hybrid State-of-Charge Estimation Method Based on Credible Increment for Electric Vehicle Applications with Large Sensor and Model Errors," *Journal of Energy Storage*, vol. 27, pp. 101106, 2020. *Crossref*, https://doi.org/10.1016/j.est.2019.101106

[18] Ravindra Panchariya, and Dr. Poonam Syal, "An Improved Current Control Charging Scheme Using Neuro-fuzzy and Fopid Based Mppt System for EV Charging," *International Journal of Engineering Trends and Technology*, vol. 69, no. 10, pp. 251-257, 2021. *Crossref*, https://doi.org/10.14445/22315381/IJETT-V69I10P232

[19] Eric Paglia, and Charles Parker, "The Intergovernmental Panel on Climate Change: Guardian of Climate Science," *Guardians of Public Value*, pp. 295–321, 2021. *Crossref*, https://doi.org/10.1007/978-3-030-51701-4_12

[20] Wei He et al., "Optimal Analysis of a Hybrid Renewable Power System for a Remote Island," *Renewable Energy*, vol. 179, pp. 96–104, 2021. *Crossref*, https://doi.org/10.1016/j.renene.2021.07.034

[21] Alberto Boretti, and Stefania Castelletto, "Cost and Performance of CSP and PV Plants of Capacity above 100 MW Operating in the United States of America," *Renewable Energy Focus*, vol. 39, pp. 90–98, 2021. *Crossref*, https://doi.org/10.1016/j.ref.2021.07.006

[22] Octavio Alves et al., "Techno-Economic Study For a Gasification Plant Processing Residues of Sewage Sludge and Solid Recovered Fuels," *Waste Management*, vol. 131, pp. 148–162, 2021. *Crossref*, https://doi.org/10.1016/j.wasman.2021.05.026

[23] J. Chatzakis et al., "Designing a New Generalized Battery Management System," *IEEE Transactions on Industrial Electronics*, vol. 50, no. 5, pp. 990–999, 2003. *Crossref*, https://doi.org/10.1109/TIE.2003.817706

[24] R Sivapriyan et al., "Comprehensive Review on State of Charge Estimation in Battery Management System" *International Journal of Engineering Trends and Technology*, vol. 70, no. 7, pp. 169-179, 2022. *Crossref*, https://doi.org/10.14445/22315381/IJETT-V70I7P218

[25] Z. Cheng-Ning et al., "Design on the Dispersed Management System for the Traction Battery Pack in Electric Transmission Vehicle," *Acta Armamentarii*, vol. 28, no. 4, pp. 396–398, 2017.

[26] Min Luo et al., "Online Battery Monitoring System Based on GPRS for Electric Vehicles," *2013 5th International Conference on Intelligent Human-Machine Systems and Cybernetics*, pp. 122-125, 2013. *Crossref*, https://doi.org/10.1109/IHMSC.2013.36

[27] G. Muneeswari et al., "Urban Computing: Recent Developments and Analytics Techniques in Big Data" *International Journal of Engineering Trends and Technology*, vol. 70, no. 7, pp. 158-168, 2022. *Crossref*, https://doi.org/10.14445/22315381/IJETT-V70I7P217

[28] Venkatesan Chandran et al., "State of Charge Estimation of Lithium-Ion Battery for Electric Vehicles Using Machine Learning Algorithms," *World Electric Vehicle Journal*, vol. 12, no. 1, pp. 38, 2021. *Crossref*, https://doi.org/10.3390/wevj12010038

[29] Dickson N.T. How et al., "State-of-Charge Estimation of Li-Ion Battery In Electric Vehicles: A Deep Neural Network Approach," *IEEE Transactions on Industry Applications*. Vol. 56, pp. 5565–5574, 2020. *Crossref*, https://doi.org/10.1109/TIA.2020.3004294

[30] R.Jeyapandi Prathap et al., "A New Resonant Converter Topology for Ev," *SSRG International Journal of Electronics and Communication Engineering*, vol. 9, no. 3, pp. 9-15, 2022. *Crossref*, https://doi.org/10.14445/23488549/IJECE-V9I3P102

[31] Yuanliang Fan et al., "Data-driven State-of-Charge Estimation of Lithium-Ion Batteries," *International Conference on Power Electronics Systems and Application*, pp. 1-5, 2021. *Crossref*, https://doi.org/10.1109/PESA50370.2020.9344017

[32] Kailong Li et al., "A Data-Driven Approach With Uncertainty Quantification for Predicting Future Capacities and Remaining Useful Life of Lithium-ion Battery," *IEEE Transactions On Industrial Electronics*, vol. 68, no. 4, pp. 3170-3180, 2021. *Crossref*, https://doi.org/10.1109/TIE.2020.2973876

[33] Changhao Piao et al., "VRLA Battery Management System Based on LIN bus for electric vehicle," *Advanced Technology in Teaching*, vol. 163, pp. 753–763, 2012. *Crossref*, https://doi.org/10.1007/978-3-642-29458-7_105

[34] Arigela Satya Veerendra et al., "Hybrid Power Management for Fuel Cell/Supercapacitor Series Hybrid Electric Vehicle," *International Journal of Green Energy*, vol. 18, no. 2, pp. 128–143, 2020. *Crossref*, https://doi.org/10.1080/15435075.2020.1831511