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AN ADAPTIVE AND HYBRID STATE OF CHARGE ESTIMATION METHOD INTEGRATING SEQUENCE-TO-POINT LEARNING AND COULOMB COUNTING FOR LI-ION BASED ENERGY STORAGE SYSTEMS

*** Halil ÇİMEN**

Konya Technical University, Engineering and Natural Sciences Faculty, Electrical-Electronics Engineering Department, Konya, TÜRKİYE
hcimen@ktun.edu.tr

Highlights

- An adaptive and hybrid model has been proposed to achieve high-accuracy SOC estimation
- The estimation process has been improved by integrating sequence-to-point learning with the coulomb counting method, leading to more precise estimations
- Multi-scale CNN-based sequence-to-point learning is used to obtain initial SOC values
- The estimation weights have been adaptively adjusted to optimize estimation performance under various operating conditions, ensuring robust and reliable outcomes

***Corresponding Author:** Halil ÇİMEN, hcimen@ktun.edu.tr

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ABSTRACT: For safe and long-lasting operation of Li-ion batteries used in electric vehicles and electric grid applications, the State of Charge (SOC) of the battery cell must be estimated with high accuracy. However, due to the uncertainty in environmental conditions and the complex nature of battery chemistry, SOC estimation still presents a significant challenge. In this study, an adaptive and hybrid method for SOC estimation of a Li-ion battery cell is proposed. Convolutional Neural Network (CNN) based Sequence-to-point learning architecture is used to estimate the initial SOC values at specific time intervals. In order to increase the estimation accuracy, a multi-scale CNN architecture is designed, and useful features are captured. The obtained estimation values are integrated with the partial coulomb counting method to increase the accuracy. In addition, the proposed model adaptively updates the estimation weights with the help of the estimation error data obtained during the full charging of the batteries. The proposed model is tested on the LG 18650HG2 dataset. The results prove that the proposed model is 23% more accurate than benchmark models at 25°C and 55.5% more accurate at 0°C.

Keywords: *Convolutional Neural Networks, Coulomb Counting, Deep Learning, Li-Ion Batteries, Sequence-to-Point Learning, State of Charge*

1. INTRODUCTION

Today, there is a major revolution in the energy sector due to global warming, the rapid depletion of underground resources, and the increasing share of new energy sources in production. The most important components of this revolution are undoubtedly renewable energy sources and energy storage elements. While cleaner and cheaper electrical energy can be produced with renewable energy sources, the excess energy produced can be stored as a reserve power source. Although there are many different energy storage systems, lithium-ion batteries are the most preferred storage element in power grid applications [1].

Li-ion batteries are preferred in many applications due to their high gravimetric and volumetric energy density, higher cell voltage compared to other batteries, long cycle and calendar lifetime, and low self-discharge. Although batteries have a chemical structure, they are analyzed by modeling them electrically. The characteristics of the battery are modeled using passive circuit elements and detailed information about battery performance is obtained. Parameters such as internal resistance and SOC of the battery are estimated using voltage, current, and temperature measurements, which can be measured by sensors. SOC indicates the instantaneous state of charge of the battery and defines the remaining capacity within the battery cell in percentage terms. Since it cannot be measured directly, it is estimated by various methods. The first of these estimation methods is the Coulomb Counting method. The current drawn (or injected) from the battery cell is measured with a certain sampling frequency and the measured values are accumulated to determine the amount of capacity drawn (or injected) from the battery. However, in order to use this method, the initial SOC value of the battery must be known. However, this value is not always known accurately. In addition, the accuracy of this method is insufficient due to the need to know the coulombic efficiency and the need for recalibration [2]. The second estimation method is the look-up table.

***Corresponding Author:** Halil ÇİMEN, hcimen@ktun.edu.tr

Here, a table is created by determining the open circuit voltage value of the battery against the SOC value with the help of experiments. The SOC value corresponding to the voltage value measured during operation is selected from the table. However, the open circuit voltage of the battery can only be measured after a long relaxation time. For this reason, the SOC value cannot be determined accurately. In addition, the open circuit voltage-SOC table may change due to effects such as temperature and aging. The most important disadvantage of the method is that the SOC curve has a flat structure for some battery chemistries, which significantly reduces the estimation accuracy [3]. Model-based and model-free methods are used to overcome the disadvantages of the above-mentioned methods. Model-based methods such as Kalman filter [4], Adaptive Lyapunov observer [5], Fractional-order observer [6] use a battery model and create a closed-loop system for SOC estimation. In this way, the estimation accuracy is increased with feedback. However, this model relies on high model accuracy. The estimation accuracy may decrease due to incorrect determination of model parameters and changes in parameters due to aging. Model-free methods are used to eliminate the need for models in model-based methods. Machine learning and deep learning are the most used model-free SOC estimation methods [7, 8]. Artificial Neural Networks [9], Recurrent Neural Networks (RNNs) [10], CNNs [11] are the most commonly used SOC estimation methods. [12] presents a self-attention assisted Long Short-Term Memory model that can analyze batteries under different operating conditions and aging levels. This allows the model to capture the dependencies in the sequence in more detail. In [13], a CNN-based multi-task learning mechanism is designed to predict the SOC, state of energy and Future temperature of a lithium-ion battery. In [14], it is aimed to increase the SOC estimation accuracy by extracting more features with 2-D time–frequency domain spectrogram analysis. The generalization performance of the estimations is increased with a CNN-based model. The advantage of neural network-based methods is that there is no need for any battery model. Networks are trained using battery cell data obtained as a result of experiments conducted at different temperatures in the laboratory environment. The models trained with voltage, current, and temperature data predict SOC with the data obtained during operation. However, the biggest disadvantage of deep learning is the generalization capacity of the models. Generalization is defined as the accuracy of deep learning models when tested with data not used during training. The distribution of training data and test data may be different. In addition, data distribution shifts may occur due to the aging of the battery cell over time. Due to these factors, the estimations made by deep learning models can be significantly inaccurate.

This paper presents an adaptive and hybrid SOC prediction model that mitigates the disadvantages of the above-mentioned methods. The model is developed by integrating deep learning and coulomb counting methods. Using a CNN-based sequence-to-point learning approach, an initial SOC estimation is performed using voltage, current, and temperature data measured from the cell. This estimate value is processed with the coulomb counting method to obtain a final estimate. The estimates obtained by coulomb counting and sequence-to-point learning are made adaptive by the weighted average method. Main contributions of the paper:

- An adaptive and hybrid model has been proposed to achieve high-accuracy SOC estimation.
- Multi-scale CNN-based sequence-to-point learning is used to obtain highly accurate initial SOC values.
- The estimation process has been improved by integrating sequence-to-point learning with the coulomb counting method, leading to more precise estimations.
- The estimation weights have been adaptively adjusted to optimize estimation performance under various operating conditions, ensuring robust and reliable outcomes.

2. METHODOLOGY

2.1. Problem Formulation

The SOC value of Li-ion batteries cannot be measured directly and must be estimated. Especially in applications such as electric vehicles where the remaining range is important, it is vital to accurately determine the SOC. It can be formulated as follows using the measurable values of voltage, current and temperature of the battery:

$$SOC(t) = f\big(v(t), i(t), T(t)\big) \quad (1)$$

where v is voltage, i is current and T is battery surface temperature. Since SOC is an unmeasurable quantity, it is estimated. Therefore, the estimation value can be expressed by the formula $\widehat{SOC}(t) = f\big(v(t), i(t), T(t)\big) + \epsilon$. Different approaches such as coulomb counting, look-up tables, neural networks can be used for the function *f* here. The coulomb counting method uses only the value of *i(t)* for prediction, while the look-up table method uses the value of *v(t)*.

2.2. Sequence to Point Learning

Deep learning models have the capacity to model time dependencies such as time series. Time dependencies in data divided into sequences with sliding windows can be detected with different deep-learning architectures. Modified versions of RNNs such as Long-short Term Memory (LSTM) [15] and Gated Recurrent Units [16] have the capacity to analyze long-time series. In addition, Temporal CNN [11] architectures have the capacity to capture long-term dependencies and make better predictions. When performing time series analysis, data can be organized in two different ways. The first is when the input and output are sequential. This approach is called Sequence-to-Sequence (seq2seq).

The seq2seq approach considers a sequence of length w, $X(t{:}t{+}w{-}1)$ as input and estimates $Y(t{:}t{+}w{-}1)$ corresponding to the same time period or a future time period sequence $Y(t{+}w{:}t{+}2w)$ as output. Here X represents input data and Y represents output data. A neural network that maps input data to output data can be defined as $f_N(X(t{:}t{+}w{-}1))=Y(t{:}t{+}w{-}1)$. In this approach, multiple predictions are made for each output, and the final prediction is obtained as the average of all predictions. Forecasting by averaging affects the success of the forecasting results as it causes smoothing of the edges. Another disadvantage is that while more accurate predictions can be made for the nodes in the middle of the sequence (midpoint), the predictions for the nodes in the corners may be less accurate. This is because the midpoint output prediction can be predicted with more information using both past and future data [17]. Sequence-to-Point (seq2point) approach is used to overcome this problem. The seq2point accepts a sequence of length w, $X(t{:}t{+}w{-}1)$ as input and predicts a single point $Y(t{+}w/2)$ corresponding to the midpoint of the same time period as output. The neural network can be defined as $f_N(X(t{:}t{+}w{-}1))=Y(t{+}w/2)$. In this way, there is no need for averaging, and more accurate predictions can be made with a non-causal approach. The seq2seq and seq2point architectures are visualized in Figure 1.

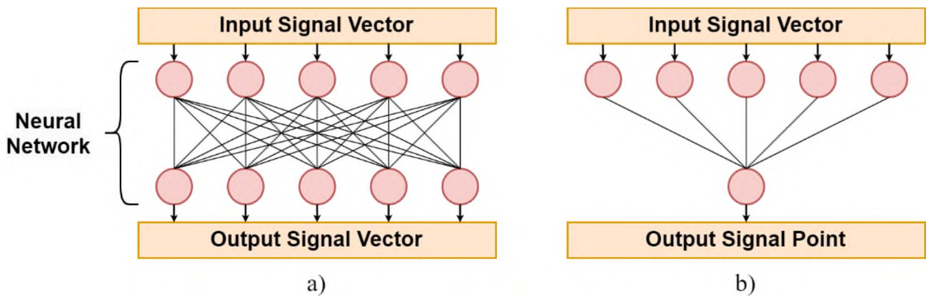


Figure 1. Different types of learning schemes, a) Sequence-to-sequence learning, b) Sequence-to-point learning

2.3. Coulomb Counting

The other name of this method is Ampere-hour counting method. It is a method used to estimate the SOC of a battery cell. By integrating the current injected or withdrawn from the battery over time, it tries to determine the current capacity of the battery with the following formula:

$$SOC_{Coulomb}(t) = SOC(t_0) + \frac{1}{Q_{total}} \int_{t_0}^{t} i(\tau).\eta.d\tau \tag{2}$$

where Q_{total} is the total capacity of the battery cell, i is the battery current, η is the coulombic efficiency of the battery. Since the computational power required is small, it is often preferred in practical applications. As can be seen from (1), the initial SOC value and η value must be known. In addition, the estimates need to be calibrated due to the measurement error of the current sensor. The constant current-constant voltage (CC-CV) curve during charging can be used for calibration.

3. PROPOSED SYSTEM

3.1. System Definition

The architecture of the adaptive and hybrid SOC estimation model proposed in this study is shown in Figure 2.

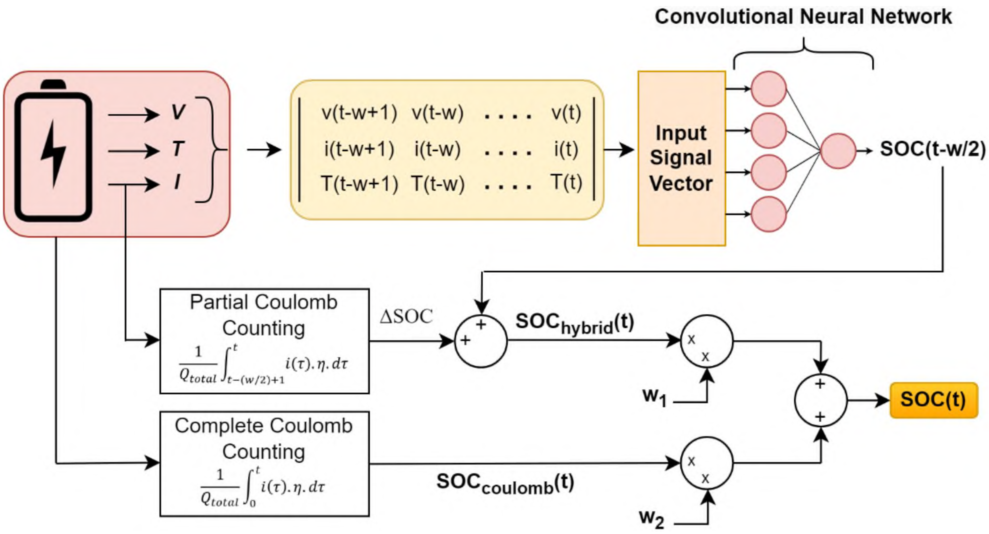


Figure 2. Proposed SOC estimation architecture

Two different forecasts are realized in the model. The first one is the $SOC_{hybrid}(t)$ estimation obtained with the hybrid approach. In the hybrid structure, it is first aimed to accurately determine the initial SOC value required for the coulomb counting method with the help of CNN-based seq2point learning. The seq2point method estimates the midpoint SOC value $SOC(t\text{-}w/2)$ against the input data $X(t\text{-}w\text{+}1\text{:}t)$. However, SOC estimation should be done for time t. For this purpose, the $SOC_{hybrid}(t)$ value was obtained by summing the estimation value obtained from the seq2point method for time $(t\text{-}w/2)$ with the SOC value calculated by partial coulomb counting. The hybrid SOC estimate can be formulated as follows:

$$SOC_{hybrid}(t) = f_{CNN}\big(v, i, T(t - w + 1{:}\,t)\big) + \frac{1}{Q_{total}} \int_{t-\left(\frac{w}{2}\right)+1}^{t} i(\tau).\eta.d\tau \tag{3}$$

where f_{CNN} represents a CNN-based deep learning model. This model uses data windows of length w as input. These windows are obtained with sliding windows. The CNN model uses voltage, current and temperature data from time $t\text{-}w\text{+}1$ to time t to estimate the point $t\text{-}w/2$. The partial coulomb counting method obtains a ΔSOC value by summing the current data read from point $t\text{-}(w/2)\text{+}1$ to point t. By summing the obtained SOC values, the $SOC_{hybrid}(t)$ value at t is determined. The estimated value can be used as the final SOC value. However, it should be kept in mind that the deep learning model cannot always make accurate predictions. If the prediction made by CNN is inaccurate, the final *SOC(t)* estimation will also be inaccurate. For this reason, a parallel estimation method is added to the hybrid estimation.

The second estimation method is complete coulomb counting. In this method, the initial SOC value is set to 1 when the full charge condition defined by the manufacturer is reached during charging. From this moment on, the $SOC_{coulomb}(t)$ value is calculated by calculating the Ah value withdrawn/injected from the battery with the traditional coulomb counting method. Each time the battery is fully charged, the initial SOC value is set to 1 again.

Using the values obtained with both estimation methods, the final SOC value is calculated as weighted average as follows:

$$SOC(t) = w_1.SOC_{hybrid}(t) + w_2.SOC_{coulomb}(t) \tag{4}$$

where w_1 and w_2 are weighting factors that weight two different estimations and allow the proposed system to be adaptive. The estimation accuracy of the two estimation methods mentioned above may vary depending on factors such as noise of current sensors, operating conditions, ambient temperature, etc. For this reason, considering the variable conditions, giving more weight to the method with higher estimation accuracy and lower error rate will increase the success of the final SOC estimation. Adaptivity is based on continuously updating the weights. These weights are updated based on the error rate of the two different estimations methods. Therefore, the weight value of the method with low error rate will be higher and the weight value of the method with high error rate will be lower. The process of updating the weights is explained in detail below.

In electric vehicle applications, batteries can be charged up to 100% SOC with the CC-CV method. During charging, CC is used until the battery voltage is equal to the charging cut-off voltage, and after equality is achieved, CV is used until the charging current reaches a certain level. The CC-CV charging curve obtained under 25°C temperature from the LG 18650HG2 dataset shared by MacMaster University in 2020 is shown in Figure 3 [18].

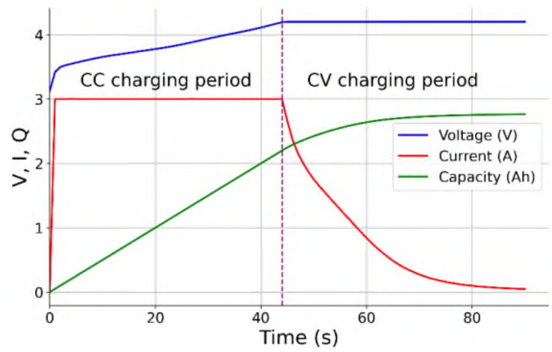


Figure 3. CC-CV charging characteristic

As seen in Figure 3, the capacity curve (green) shows a linear change during CC and a non-linear change during CV. In this study, the capacity increase curve during charging is used to determine the True SOC value. To determine the True SOC value, the battery must be fully charged. The $TrueSOC(t_{plug\text{-}in})$ value at the time the battery is plugged in can be determined by the time until the battery is fully charged. The True SOC value is calculated mathematically by converting the linear/non-linear variation of the CC-CV charging periods into a function with the curve fitting method. According to the obtained $TrueSOC(t_{plug\text{-}in})$ value, the weights w_1 and w_2 are updated as follows:

$$w_h = \frac{1}{\left|1 - \frac{SOC_{hybrid}(t_{plug-in})}{TrueSOC(t_{plug-in})}\right|}, \quad w_c = \frac{1}{\left|1 - \frac{SOC_{coulomb}(t_{plug-in})}{TrueSOC(t_{plug-in})}\right|} \tag{5}$$

$$w_1 = \frac{\alpha . w_h}{\alpha . w_h + w_c}, \quad w_2 = \frac{w_c}{\alpha . w_h + w_c} \tag{6}$$

where α is a coefficient greater than 1. The coefficient α acts as a balancing parameter between the two approaches. If α is increased, the weight of the Hybrid method becomes larger and the weight of the Coulomb method decreases accordingly. Adjusting the α coefficient helps to optimize the performance of the model under different operating conditions.

3.2. CNN Model Definition

CNNs are a deep learning model frequently used in areas such as image recognition and segmentation [19]. In this study, a CNN-based multi-scale deep learning model is used to implement seq2point learning. Multi-scale is an approach that processes sequence inputs at different scales to extract different features from the same data. Deep learning models such as U-Net [20] can extract different features from different layers by combining low-layer features with high-layer features with skip-connections. In addition, different filter sizes and different dilation rates are used for multi-scale [21]. In this study, it is aimed to extract more features and capture different dependencies over time by using different dilation rates. The developed model is shown in Figure 4.

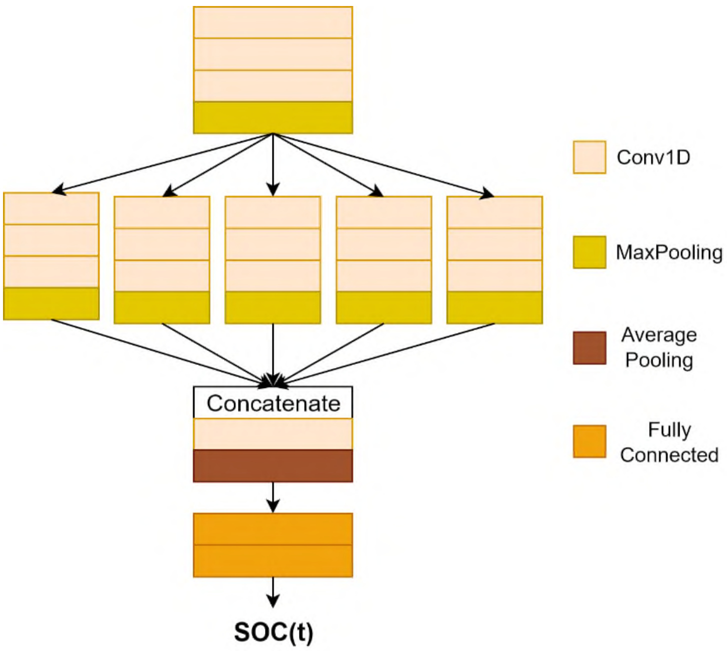


Figure 4. Proposed sequence-to-point CNN architecture

First, low-level features are extracted using three convolution layers and one maxpooling layer. Then, the model was divided into five parallel branches. In each arm, multi-scale feature extraction was performed using different dilation rates. The features collected from these branches were then concatenated and passed through a convolution and average pooling layer. In order to perform SOC estimation, the last two layers of the model are chosen to be fully connected.

4. RESULTS AND ANALYSIS

4.1. Implementation Details

Dataset: This study used the LG 18650HG2 (Nickel Manganese Cobalt-NMC) dataset shared by MacMaster University in 2020 [18]. The most important reason for choosing this dataset is that the open access datasets created by Dr. Phillip Kollmeyer are frequently used in SOC estimation publications shared in the literature [10, 11, 22-24]. Li-ion battery cells were tested at six different temperatures and different values of the battery were recorded. Data from the tests performed at temperatures between -20°C and 40°C were collected with a sampling frequency of 10Hz. The CC-CV method was used for the full charge of the battery. For discharge, four different drive cycles and eight drive cycles consisting of a mixture of these drive cycles, 12 different drive cycles in total, were used. During discharge, voltage, current, cell surface temperature and capacity data were recorded.

CNN Model Details: Since the main objective of this study is to demonstrate the success of the designed adaptive and hybrid SOC prediction system, the hyperparameter selections of the deep learning model are adapted from [17]. In the designed deep learning model, the number of filters in the first three convolution layers are 30, 30 and 40, and the filter sizes are 10, 8 and 6, respectively. After the convolution layer, a maxpooling layer with a pool value of 3 was used to increase the learning capacity of the network and reduce the risk of overfitting. The number of filters of each convolution layer in parallel branches was set to 50, the filter size was set to 10, and the pool value of each maxpooling layer was set to 3. In order to perform multi-scale feature extraction, dilation rates of 1, 2, 4, 6 and 8 were used in parallel arms respectively. After the concatenate process, a convolution layer with a filter number of 64 and a filter size of 1 was used. The pool size of the averagepooling layer was set to 3. The number of nodes of the last two fully connected layers were chosen as 512 and 1, respectively. ReLU function was used as activation function in all layers. Experiments were performed with sliding windows by selecting the window size w 512 for splitting the data. The data were normalized with z-score and the models were trained with Adam optimizer. Mean squared error function was used as the loss function during training. The models were created using the Tensorflow-Keras library and were run on Google Colab.

For the hybrid approach, the SOC estimator was updated every five minutes using the outputs from the seq2point model. The coulombic efficiency of the battery cell was set as 0.998 based on the values in the dataset. The SOC estimation weights are updated when the battery is fully charged. In the final SOC estimation, the α value was set to 3.

4.2. Experimental Results

The experimental results will be evaluated in two different ways. First, the results obtained with CNN-based seq2point learning are shared.

The LG 18650HG2 dataset contains experimental data under temperatures of -20°C, -10°C, 0°C, 10°C and 25°C. The proposed CNN model is trained and tested first for positive temperatures and then for all temperatures. US06, HWFET, Mixed1-8 drive cycle data were used for training and LA92 and UDDS drive cycle data were used for testing. 20% of the training data was reserved as a validation set. The values obtained for positive temperatures are shown in Tables 1 and 2. LSTM [25] and CNN [22] models were used as benchmark models. For comparison purposes, the model is designed to predict last point instead of midpoint with the proposed model and the results are compared in the tables. Mean absolute error (MAE) and mean squared error (MSE) metrics were used to evaluate the results. MAE is used to assess the error magnitude of a model by measuring the mean absolute difference between predicted values and true values. The most important advantage is that it is easy to interpret as the unit is the same as the unit of the predicted value. MSE squares the errors between predicted and true values and calculates their average. This metric is an important indicator for detecting noise in the predictions. Noise increases the variance of errors in the time series forecasts, which leads to a higher MSE.

Table 1. MAE results obtained for positive temperatures

	0°C		10°C		25°C		Average	
	LA92	UDDS	LA92	UDDS	LA92	UDDS	LA92	UDDS
LSTM [25]	1,3362	1,6929	1,2725	1,0898	0,874	1,0577	1,1609	1,2801
CNN [22]	1,444	1,0745	1,6666	1,3205	0,9832	1,209	1,3646	1,2013
Seq2last	0,7951	**1,0017**	1,2312	1,0474	0,6161	0,7411	0,8808	0,9301
Proposed	**0,6288**	1,0589	**1,1737**	**0,9938**	**0,5305**	**0,656**	**0,7777**	**0,9029**

Table 2. MSE results obtained for positive temperatures

	0°C		10°C		25°C	
	LA92	UDDS	LA92	UDDS	LA92	UDDS
LSTM [25]	0,0293	0,044	0,0255	0,0199	0,0137	0,0193
CNN [22]	0,0324	0,0211	0,0385	0,0268	0,0152	0,0225
Seq2last	0,0113	**0,0192**	0,0209	0,0169	0,0062	0,0094
Proposed	**0,0077**	0,0212	**0,0183**	**0,0159**	**0,0049**	**0,0073**

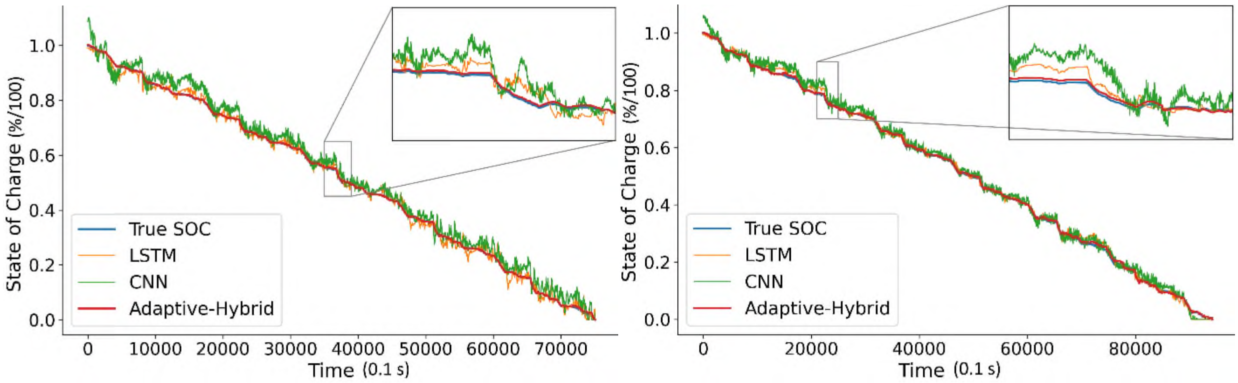
When the results obtained are analyzed, the proposed model achieves more accurate estimations than the benchmark models. Comparable results are obtained for the 0°C test data for the UDDS drive cycle. The average MAE values of the predictions are shared in the last column of Table 1. According to these values, the proposed model is 33% more accurate for LA92 and 29% more accurate for UDDS than LSTM. When the MSE results in Table 2 are analyzed, it is observed that the proposed model makes less noisy predictions than the benchmark models.

Secondly, the results obtained using the adaptive and hybrid SOC prediction model are analyzed. Three different scenarios are created considering different measurement errors of the current sensor, and they are listed in Table 3.

Table 3. List of scenarios

	Measurement Error	Sensor Bias (A)	Mean of Sensor Noise (A)	Standard Deviation of Sensor Noise (A)
Scenario 1	×	×	×	×
Scenario 2	✓	+0.1	0	0.01
Scenario 3	✓	+0.2	0	0.1

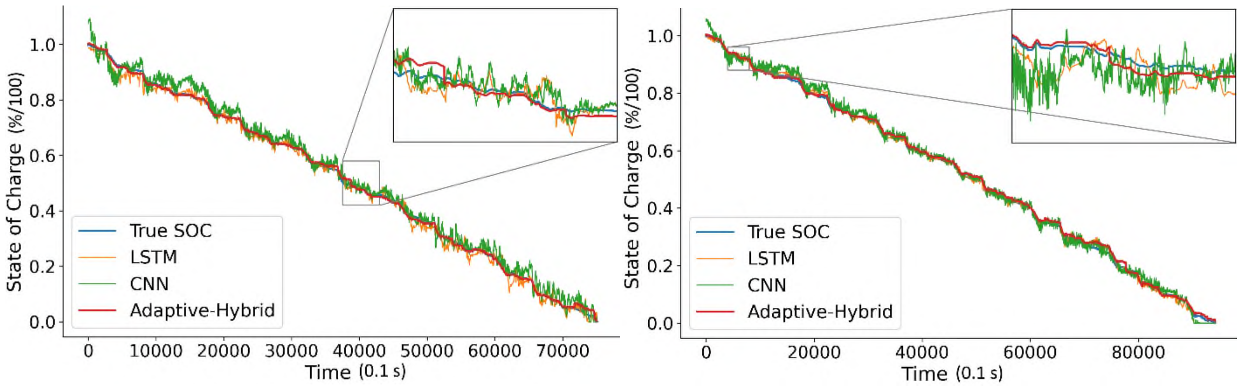
Scenario 1–Error-Free Measurement: In this scenario, although it is not possible in real-world applications, the analysis will be performed assuming that the current sensor measurements are accurate and error-free. The obtained results are shown in Figure 5, where the performance of the proposed model and two different deep learning models , LSTM and CNN, are visually compared. Figures 5.a and 5.b show the SOC values obtained using the LA92 driving cycle at 0°C and 25°C respectively. When the obtained results are analyzed, it is seen that the proposed model significantly outperforms the deep learning models and makes more accurate predictions. This is an expected situation, and the reason is quite clear. Because the proposed model makes adaptive predictions using both deep learning and current sensor data. Since the values read from the current sensor are error-free, the model significantly increases the prediction success by increasing the value of the w_2 weight. Coulomb counting is undoubtedly a practical and useful method if the data read from the sensor is accurate. Since the problem of not knowing the initial SOC value, which is the biggest disadvantage of the Coulomb counting method, is solved with the sequence to point learning approach, the predictions are quite successful. If the predictions visualized in Figure 5 are evaluated with numerical metrics, the MAE value obtained by the proposed model for the LA92 driving cycle at 0°C is 0.1266. The minimum MAE value achieved by the LSTM model is 1.3364 and the CNN model is 2.5115. The MAE values obtained by the proposed model, LSTM and CNN for the LA92 drive cycle at 25°C are 0.3198, 0.8738 and 1.4743, respectively. Since MAE is a metric that indicates the prediction error, it can be said that the model with the lowest value performs the most successful predictions. Therefore, the proposed model made more accurate predictions compared to the benchmark models.



a) b)

Figure 5. SOC estimation results for Scenario 1, a) 0°C-LA92 drive cycle, b) 25°C-LA92 drive cycle

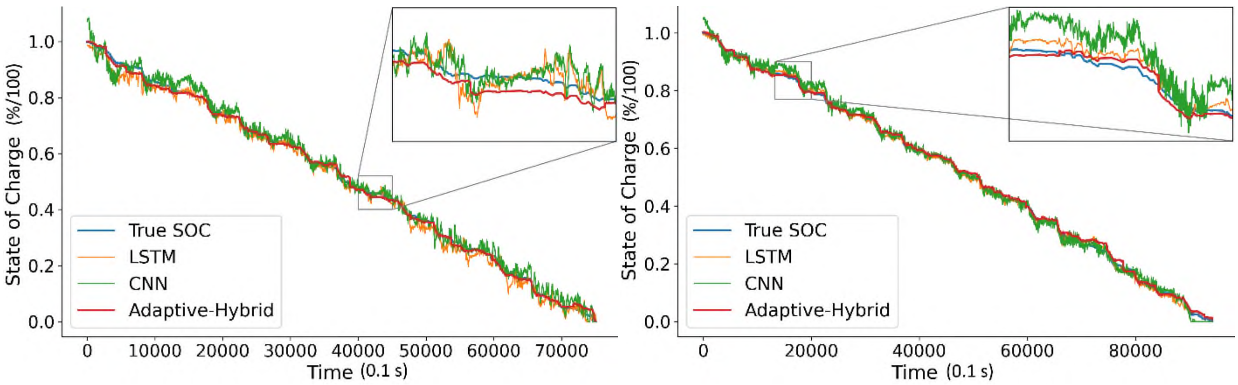
Scenario 2–Measurement with bias=0.1 and std=0.01: In this scenario, it is assumed that the current sensor makes both noisy and biased measurements. The bias value of the current sensor is determined as +0.1A. The noise is added to the current signal with a mean value of 0 and a standard deviation of 0.01. The SOC estimation is performed using the obtained erroneous measurements. The obtained results are shown in Figure 6, where the performance of the proposed model and benchmark models are visually compared. Figures 6.a and 6.b show the SOC values obtained using the LA92 driving cycle at 0°C and 25°C respectively. It is observed that the accuracy of SOC estimation decreases due to inaccurate measurements of the current sensor used in SOC estimation. However, the proposed model adaptively detects the sensor error during charging and increases the value of the weight w_1 and decreases the value of w_2 to achieve better prediction accuracy. The proposed model automatically and adaptively updated the weights using the error rate it determined during charging. The w_1 weight was calculated as 0.9396 and the w_2 weight as 0.0604. The MAE value obtained by the proposed model for the LA92 drive cycle at 25°C is 0.735, 0.8092 for LSTM, and 1.2889 for CNN. The MAE value obtained by the proposed model for the LA92 drive cycle at 0°C is 0.5491, for LSTM it is 1.401, and for CNN it is 2.0612. According to the results obtained, in the experiments at 25°C, the proposed model performed 11.2% more successful predictions than the LSTM model and 43% more successful predictions than the CNN model, respectively. In the experiments at 0C, the proposed model performed 61% and 73.4% more successful predictions than the LSTM and CNN models, respectively.



a) b)

Figure 6. SOC estimation results for Scenario 2, a) 0°C-LA92 drive cycle, b) 25°C-LA92 drive cycle

Scenario 3–Measurement with bias=0.2 and std=0.1: In this scenario, the bias value of the current sensor is determined as +0.2A. The noise is added to the current signal with a mean value of 0 and a standard deviation of 0.1. The SOC estimation is performed using the obtained erroneous measurements. Figure 6 illustrates the results, providing a visual comparison between the proposed model and the benchmark models. Specifically, Figures 6.a and 6.b display the SOC estimations under the LA92 driving cycle at temperatures of 0°C and 25°C, respectively. It is evident that inaccuracies in the current sensor's measurements negatively impact the SOC estimation accuracy. Nevertheless, the proposed model effectively adapts by detecting sensor errors during charging phases, dynamically adjusting the weights—by increasing w_1 and reducing w_2 to enhance prediction accuracy. The proposed model adaptively updated the weights using the error rate determined during charging. The w_1 weight is calculated as 0.9674 and the w_2 weight is calculated as 0.0326. The MAE value obtained by the proposed model for the LA92 drive cycle at 0°C is 0.7601, 1.6525 for LSTM, and 1.7586 for CNN. The MAE value obtained by the proposed model for the LA92 drive cycle at 25°C is 0.773, for LSTM it is 0.8799, and for CNN it is 1.1782. According to the results obtained, in the experiments at 25°C, the proposed model performed 12.2% more successful predictions than the LSTM model and 34.4% more successful predictions than the CNN model, respectively. In the experiments at 0°C, the proposed model performed 54% and 56.8% more successful predictions than the LSTM and CNN models, respectively.



a) b)

Figure 7. SOC estimation results for Scenario 3, a) 0°C-LA92 drive cycle, b) 25°C-LA92 drive cycle

5. CONCLUSIONS

In this study, an adaptive and hybrid SOC estimation system for Li-ion battery cells is proposed. A hybrid model is created using CNN-based seq2point learning and coulomb counting methods. Less noisy and more accurate estimations are achieved with seq2point learning. Instantaneous SOC estimation is made by performing forward partial ampere counting from midpoint with coulomb counting. In addition, an adaptive approach is proposed by updating the weights based on the estimation error during charging. Experiments are carried out for battery cells operated at different temperatures. In addition, simulation studies are carried out considering different current sensor errors. The proposed model has achieved more accurate SOC estimation by outperforming deep learning models such as LSTM and CNN. Apart from this, the estimation noise is significantly reduced. For the scenario with the highest current sensor error, 12.2% more accurate estimations are obtained compared to LSTM, 34.4% more accurate estimations are obtained compared to CNN at 25°C, 54% more accurate estimations are obtained compared to LSTM and 56.8% more accurate estimations are obtained compared to CNN at 0°C.

Declaration of Ethical Standards

The author declares that the materials and methods used in this study do not require ethical committee permission and/or legal-special permission.

Credit Authorship Contribution Statement

Author - Conceived and designed the study, analyzed data and interpreted results, drafted and revised the manuscript.

Declaration of Competing Interest

The author declares that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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Data Availability

The datasets analyzed during the current study are available in https://data.mendeley.com/datasets/b5mj79w5w9/2

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