ANN-based State of Charge Estimation of Li-ion Batteries for Embedded Applications

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ABSTRACT — The conventional state of charge (SOC) estimation model has several concerns, such as accuracy and reliability. In order to realize robust SOC estimation for embedded applications, this study focuses on three concerns of the existing SOC estimation model: accuracy, robustness, and practicality. In improving the estimation accuracy and robustness, this study took into account the dynamic of the actual SOC caused by the dynamic charging and discharging process. In practice, the charging and discharging processes have characteristics that must be considered to realize robust SOC estimation. The model-based SOC estimation developed based on the virtual battery model causes difficulties for real-time applications. Additionally, model-based SOC estimation cannot be reliably extrapolated to different battery types. In defining the behavior of various types of batteries, the model-based SOC estimation must be updated. Hence, this study utilized data-driven SOC estimation based on an artificial neural network (ANN) and measurable battery data. The ANN model, which has excellent adaptability to nonlinear systems, is utilized to increase accuracy. Additionally, using measurable battery data such as voltage and current signals, the SOC estimation model is suitable for embedded applications. Results indicate that estimating SOC with the proposed model reduced errors with respect to actual datasets. In order to verify the feasibility of the proposed model, an online estimation was out on the embedded system with the use of C2000 real-time microcontrollers. Results show that the proposed model can be executed in an embedded system using measurable battery data.

KEYWORDS — ANN, BMS, Embedded Systems, Lithium Battery, State of Charge.

I. INTRODUCTION

Lithium-ion (Li-ion) battery has been widely applied in various electronic devices [1]. A battery must be managed immediately to ensure its safe operation and possibly increase its longevity. The task of managing and monitoring the battery can be done by employing a battery management system (BMS) [2]. The important tasks of a BMS are state of charge (SOC) estimation. Battery SOC estimation is used as the main battery health indicator [3]. Battery SOC provides information on how many charge cycles remain in the battery and provides an estimation of how long the battery will need to be charged. SOC is a measure of the capacity that is still usable at the maximum available capacity. In practice, the SOC function is similar to the fuel gauge in an electric vehicle (EV) which is an important function in monitoring the battery state [4]. Hence, for electric vehicles EVs and other equipment that use batteries as a power source, a precise SOC estimation approach is necessary.

An accurate SOC estimation is still an open issue because the internal dynamics of the battery are often poorly estimated. Moreover, various operating conditions such as battery temperature, dynamic capacity regeneration, and inevitable battery aging remain difficult tasks in achieving accurate SOC estimation. Several SOC estimation methods have been presented with various approaches [3]–[5]. SOC estimation methods can be classified into three groups: basic methods, model-based methods, and data-driven estimation methods.

The basic methods of the SOC estimation utilize basic computation and simple modeling to estimate actual battery SOC. Basic methods include the looking-up table and ampere–hour integral methods [5]. These methods rely on initial and maximum available capacity. In practice, these data are not always available when the battery has aged. Model-based SOC estimations are developed based on the virtual battery model, then an observer generates a set of state estimates that are carefully commensurate with the actual SOC of the battery. Model-based SOC estimation methods include electrochemical models (EMs) [6], and equivalent circuit models (ECMs) [7]. EMs consists of several partial differential equations (PDEs) that are used to describe electrochemical reactions [7]. However, some EM parameters cannot be directly retrieved without assistance from battery manufacturers. In terms of computation charges during inference, solving PDEs is also a costly task. Real-time applications are hampered by these shortcomings. Furthermore, model-based SOC estimations utilize observers such as the Luenberger observer [8], and the sliding mode observer [9] to estimate battery SOC based on the virtual battery models.

A data-driven SOC estimation method has attracted considerable attention. This method is less susceptible to changes in battery characteristics and adapts well to different types of batteries. Data-driven estimation methods for SOC estimation rely on black-box models. This method includes the data fusion method, neural network (NN) [10], and support vector machine (SVM) [11]. In particular, NN models are known for their ability to learn complex nonlinear relationships, making them well-suited for accurate and robust modeling of battery SOC behavior [10]. NN-based and SVM-based methods estimate SOC using battery parameters (the signals measured from a Li-ion battery). These methods learn the non-linear relationship between the measured parameter and SOC. The relationship between measured data is used to create the SOC estimation model. SOC can be estimated using an artificial neural network (ANN) at various battery aging levels [12]. Recently, ANN-based approaches have received more and more interest from the scientific community as the

TABLE I
CHARGE-DISCHARGE PROFILE OF BEXEL DATASET

Dataset	Charging			Discharging	
	Constant Current (A)	*Upper Voltage (V)*	*Cut-Off Current (mA)*	*Constant Current (A)*	*Cut-Off Voltage (V)*
Cell #7	8	4.2	4.0	8	3.85
Cell #13	8	4.2	4.2	8	3.81

graphics-processing unit's computing capacity has increased. In recent years, researchers have explored different ANN architectures to improve the accuracy of the SOC estimation. The most feedforward neural network (FNN) have been employed to estimate SOC [13]. For instance, an ANN model with a Kalman filter [14], a recurrent neural network model [15], and an exogenous autoregressive with an input-based neural network [16] have been used to estimate SOC. Deep learning is a powerful technique that has been used to estimate SOC hybrid battery and supercapacitor [17].

Although several aforementioned studies [12]–[17] have demonstrated the effectiveness of using NN for the SOC estimation, the practical challenges of applying an NN-based SOC estimation to embedded systems have not been addressed. Existing research has mainly focused on maximizing accuracy without considering practical limitations that may be encountered in embedded applications [18]. This can lead to difficulties when implementing such models in real-time embedded systems, which require not only high accuracy but also robustness, and practicality. This study aims to address the issue by considering the practicality of the proposed model. In this study, the NN model that could capture the uncertainty of battery SOC while prioritizing the practicality of implementation in embedded systems was used.

In this paper, The ANN-based SOC estimation model is presented, which takes into account the concerns related to existing SOC estimation models. To realize a robust and accurate SOC estimation model, this study took into account the dynamic of actual SOC caused by the dynamic charging and discharging process that affect actual SOC. The estimation accuracy is often reduced due to the dynamic of actual SOC charging and discharging. That is, if the SOC estimation model assumes that charging and discharging will always be the same, which did not happen in actual implementation. This assumption would result in high errors. By incorporating this dynamic battery SOC behavior into the proposed model, it can reduce estimation errors compared to existing methods. Furthermore, the ANN model, which has strong adaptability to nonlinear systems, is used as the SOC estimation method. It enables complex and nonlinear relationships between inputs (current and voltage signals) and outputs (battery SOC) to be captured more accurately than model-based SOC estimation methods that commonly assume a simple linear relationship. Using ANN models also avoids the need for complex mathematical models and parameter tuning, which are time-consuming and error prone.

In terms of practicality to achieve a real-time system in an embedded application, the proposed model utilized measurable battery data and employed ANN. The measurable battery, such as current and voltage, was commonly measured in BMS. Using these signals, SOC can be estimated in real-time without the need for additional sensors, thus reducing cost and complexity. Also, this study was simulated in a real-time application. The experiment was carried out using an embedded system and given actual battery data.

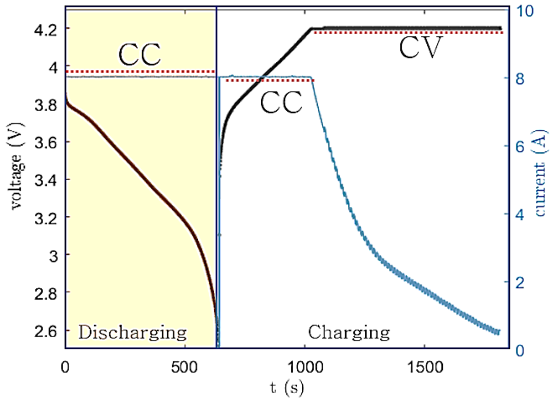


Figure 1. The CCCV charging method is used to avoid over charging.

II. DATASET STRUCTURE

This study utilized the battery dataset provided by BEXEL, a leading battery company, for research and development purposes only [19]. The dataset was collected from the battery testing facility at BEXEL using Li-ion batteries and consisted of more than 50,000 data points for each battery dataset which was recorded for six months. These datasets include the voltage, current, and capacity measurements. They consist of three different operating profiles charging, discharging, and breaking time. This study used two different battery datasets: BEXEL cell #7 and #13. To identify the cells, BEXEL assigns these numbers as cell IDs. The charge-discharge profile of two battery datasets is listed in Table I.

As listed in the table, BEXEL cell #7 and #13 have constant current values in the charging and discharging process. It occurs because the method used to measure the dataset during charging is the constant current constant voltage (CCCV) method, while during discharging is the constant current (CC) method. Specifically, in the charging phase, the charger will first start charging the battery using CC mode. When the battery voltage reaches an upper voltage value, the charger automatically shifts to constant voltage mode, and will continue charging until the battery cut-off current is reached. In discharging phase, the battery is discharged using CC mode. The CCCV charging method is used to avoid overcharging [20]. The CCCV mode in charging phase and CC mode in the discharging phase are presented in Figure 1.

In terms of dataset configuration during model training, 149,278 samples of BEXEL cell #7 are used, which was randomly divided into three sets: 70% (104,494 samples) for training, 15% (22,392 samples) for validating, and 15% (22392 samples) for testing. The remaining data of BEXEL cell #7 data were used for testing in the online SOC estimation process. This scheme was carried out again using BEXEL cell #13.

III. ANN-BASED SOC ESTIMATION MODEL

This study aims to develop the SOC estimation for embedded applications using only current and voltage measurements without relying on direct SOC measurements. This is because direct measurement of SOC can be expensive and difficult to obtain in embedded applications. Therefore, in embedded applications, it is advantageous to estimate SOC using indirect measurements such as current and voltage signals that are easy to obtain using an embedded application.

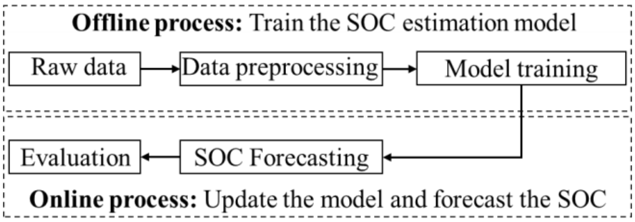


Figure 2. Flowchart of ANN based SOC estimation.

In developing the SOC estimation model, a mathematical-based model with lower computational complexity was tested to model the signal of SOC following. The charging and discharging process were tested using exponential growth and linear decay. Results show that the mathematical solution was only suitable for a specific time period. However, as the battery ages, the SOC signal may change periodically, making it difficult to find a closed-form mathematical model for this kind of signal. Hence, the mathematical-based SOC estimation would not be applicable for other time periods or battery conditions, and a different mathematical model would need to be developed for those scenarios.

In contrast to mathematical models, an ANN model is a more flexible approach that can be adapted to different scenarios and conditions. This study used the ANN model to estimate the SOC. The overall process is illustrated in Figure 2. The proposed model is divided into two main processes: 1) offline processes which focus on training the SOC estimation model and 2) online processes which forecast the SOC using the trained model and embedded system. The offline processes include data gathering, data preprocessing, and model training. All steps in the offline processes were carried out only one time. At the same time, the online processes include the SOC forecasting with new actual battery data and performance evaluation. To validate the accuracy and reliability of the proposed SOC estimation, the measured SOC values from the BEXEL dataset were used as the ground truth (y) and compared with the SOC values predicted from the model.

A. DATA PREPROCESSING

The collected raw data such as voltage, current, and capacity are transformed into a useful and efficient data format. To do preprocessing, collected capacity data were first used to compute the actual SOC. The actual SOC is defined as the ratio of the remaining capacity over the maximum capacity or initial capacity [21], that is expressed as in (1).

$$SOC = \left[\frac{Q(t)-minQ}{maxQ-minQ}\right] \times 100\% \quad (1)$$

where Q is the capacity (Ah), $minQ$ is the minimum capacity (Ah), $maxQ$ is the maximum capacity (Ah), and t is time (s). The total number of cycles obtained in this process is 434 cycles. The obtained actual SOC was used in training and testing the SOC estimation. Voltage, current, and actual SOC were used in data cleansing and normalization. To avoid underfitting, outliers were removed from the data using data cleansing, and the data were scaled to values between 0 and 1 through normalization [22]. Thus, the result of data preprocessing is an efficient format of voltage, current, and actual SOC data. That is, there are no outliers within these data and their values are between 0 and 1.

The input and target data must be defined to train the SOC estimation model. In this study, current and voltage data were chosen as input training data while actual SOC data were chosen as target data. Unlike actual SOC data, voltage and current are directly measurable during inference. To improve accuracy, the SOC estimation model was trained with charging and discharging separately. The training process of the SOC estimation model was conducted for two SOC estimation models, namely the SOC estimation during charging and discharging. At the end of the process, the result of charging and discharging was combined to have a full cycle result.

TABLE II
CORRELATION COEFFICIENTS BETWEEN SOC AND VOLTAGE

SOC	Voltage	Correlation Coefficients
All	All	0.3703
Charging only	Charging only	0.8891
Discharging only	Discharging only	0.7276

Voltage data during discharging were used to estimate SOC during discharging, while voltage data during charging were used to estimate SOC charging. The voltage data are not the only feature used in the charging phase. The current data are also used as a feature along with voltage data since the actual battery dataset used the CCCV charging method which varies current and voltage data in the charging process. While in the charging process, only voltage data change over time. This scheme enables the model to reduce the error estimation due to the different profiles of charging and discharging. It also reduces memory consumption by utilizing only the important features.

This study computes the Pearson correlation coefficient of these variables to highlight the relationship between the separating input voltage and the target SOC. The Pearson correlation coefficient represents the linear correlation between two feature voltage and target SOC data. It is obtained using the ratio between the covariance of both voltage and SOC data and the product of their standard deviations. In other words, it is generally a normalized measurement of the covariance. The Pearson correlation coefficient between voltage and SOC data is presented in Table II. As stated in the table, the correlation coefficient of all SOC and all voltage is 0.3703. At the same time, the Pearson correlation coefficient result of separating the SOC and voltage was 0.8891 and 0.7276 for charging and discharging, respectively. It shows that the feature quality can be improved by dividing SOC and voltage into two phases in the whole cycle, namely charging and discharging. The improved features can positively impact the performance of the ANN model used in this study. By incorporating these high-quality features into the model, the models are able to more accurately predict SOC values during each phase of the battery cycle, leading to an improved overall performance.

B. MODEL TRAINING

ANN model was used to model actual SOC trajectories and to predict the actual SOC given voltage and current as input data. In selecting input and target data, voltage data served as input while SOC data served as output for the SOC estimation model during discharge. At the same time, voltage and current data served as input and SOC data served as output for the SOC estimation model during charging. Since using a high number of hidden neurons increases the model's complexity, one hidden neuron of ANN was used to build the SOC estimation model considering real-time application requirements.

The network architecture of the ANN model is shown in Figure 3. The table shows that a two-layer feedforward network

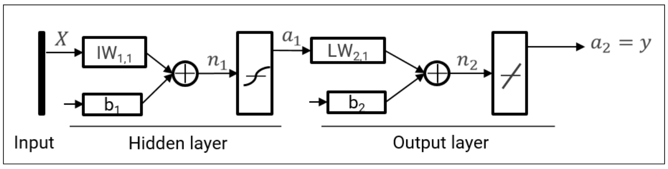


Figure 3. Network architecture of ANN model.

with a sigmoid transfer function in the hidden layer and a linear transfer function in the output layer builds the ANN's network design. The layer weight matrix and input weight matrix were used to connect each LW layer. The X input represents the voltage and current, while b1 and b2 represent values of bias for layer 1 in the (Nx1) array and layer 2 in the (1×1) array. N is the number of hidden layers. The output value ($a2$) represents the estimated SOC. Equations (2), (3), and (4) represents the network architecture of the ANN.

$$a_1 = tansig(IW * X + b1) \tag{2}$$

$$y = LW * \left(tansig(IW * X + b1)\right) + b2 \tag{3}$$

$$a_2 = y = \left(\left(\frac{2}{1+exp\left(-2*(B*X+b1)\right)}\right) - 1\right) + b2. \tag{4}$$

The model parameters in (4) were obtained during the training process, where the input data X represents the voltage and current data while the target data y represents the actual SOC. During the training process, the proposed model learnt to map the input data to the target data by adjusting its parameters to minimize the prediction error on a training set. Once trained, the proposed model could be used to estimate the SOC in real-time by simply inputting the voltage and current measurements.

In the SOC estimation model training, the Levenberg-Marquardt training algorithm was utilized. This training algorithm considers the generalization results in the training process [23]. Specifically, when generalization reaches a plateau, the training process ends automatically. The rise in mean square error (MSE) of the validation samples can be used to illustrate a generalization improvement. A rise in MSE on the validation set during training can be a sign that the model is becoming more generalizable and less prone to overfitting. The sum of squared differences between the actual and projected SOC is known as MSE, and it is defined as in (5).

$$MSE = \frac{1}{N}\sum_{i=1}^{N}(y_i - \hat{y}_i)^2 \tag{5}$$

where y_i and $\hat{y}_i$ are the actual SOC and the predicted SOC, respectively, and N is the total number of samples. MSE and regression R values are the performance metrics used to evaluate training results. Calculating the average squared difference between outputs and targets yields MSE, as seen in (5). Regression R values refer to the correlation between outputs and targets.

Regression R values show the proportionate amount of variation in the response's real SOC that is explained by the provided input voltage and current data. The amount of variability between the given input and the actual SOC that the linear regression model can explain increases as regression R values increase. In other words, an R value of 1 indicates a strong association, whereas 0 indicates a random relationship. R values for the regression are defined as follow.

$$R^2 = \frac{SSR}{SST} = 1 - \frac{SSE}{SST} \tag{6}$$

TABLE III
ANN CONSTANTS PARAMETERS OF THE PROPOSED SOC ESTIMATION MODEL

Parameters	Charging	Discharging
b1	3.0559	-2.1176
IW_1	[0.1775 -2.9987]	2.7579
b2	0.7396	0.2770
LW2_1	-2.1208	1.2974

where R^2 is regression R values, SSE is the sum of squared error, SSR is the sum of squared regression, and SST is the sum of squared total. The MSE and R values between the given input and actual SOC (target) for training, validation, and testing were less than 2.2 and 0.9, respectively. It demonstrates that the trained SOC estimate model is generally accurate for all datasets, with R values of 0.9 in each case. The final output of the training process is a function along with parameters that are used to estimate SOC. The generated ANN constants of the proposed SOC estimation model are shown in Table III. These parameters include the bias value for layer 1 and layer 2, the input weight, and the layer weight for both charging and discharging. These optimized values of these parameters were used as a function to estimate the SOC of the battery.

IV. PERFORMANCE EVALUATION

The proposed model was performed in simulation-based (offline) and online estimation. The offline SOC estimation was carried on MATLAB and online SOC estimation was executed on MATLAB Simulink and edge device C2000 F28379D.

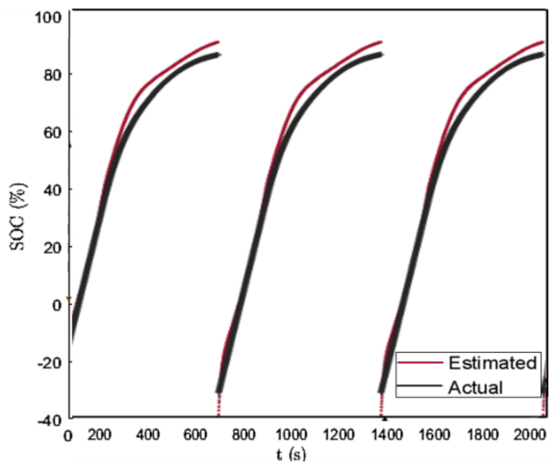
The C2000 is a microcontroller board that can be used for a variety of applications. The C2000 board is used to perform two tasks, namely data acquisition and processing. The data acquisition is the process of sampling an analog signal that attempts to measure the actual physical form of the battery and it also converts the sample of analog signal into digital numerical values that can be processed by a computer. In this study, the data acquisition was performed to measure and gather voltage and current values for the charging and discharging process. Another task of the C2000 board is data processing which includes SOC estimation.

A. SIMULATION-BASED MODEL TESTING RESULTS

The result of the proposed SOC estimation during charging is shown in Figure 4(a). The x-axis represents time, and the y-axis represents the SOC percentage. As shown in Figure 4(a), the black line is the actual SOC, while the red line is the estimated SOC. The figure shows that the proposed model can capture the actual SOC during charging. The proposed model was able to estimate the actual SOC with high accuracy at the beginning of the charging process. The accuracy is reduced when the battery is almost fully charged. The decreasing accuracy is caused by the dynamic SOC curve in the near-end charging process.

Furthermore, the SOC estimation results during discharging are shown in Figure 4(b). The proposed model was able to estimate the trajectory of the actual SOC. The accuracies of the proposed model at the beginning of discharging were smaller than those in the middle of discharging. It occurs because the battery is discharged with a dynamic constant current profile, unlike the result of the SOC estimation during charging (which has the highest accuracy at the beginning of charging).

In the experiment, this study also performed the SOC estimation based on ANN with combined input charging and



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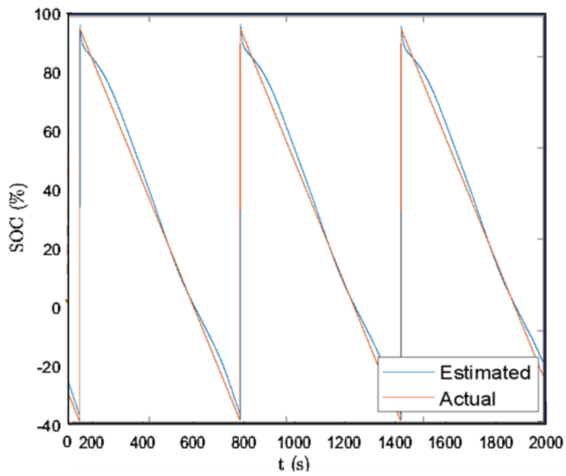
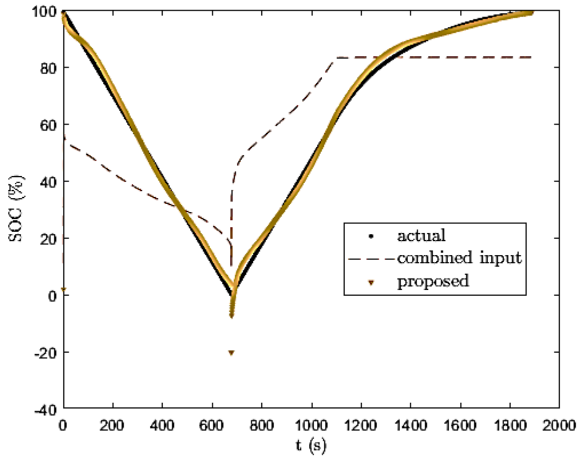


(b)

Figure 4. Results of SOC estimation left (zoom out), right (zoom in) during (a) charging and (b) discharging.



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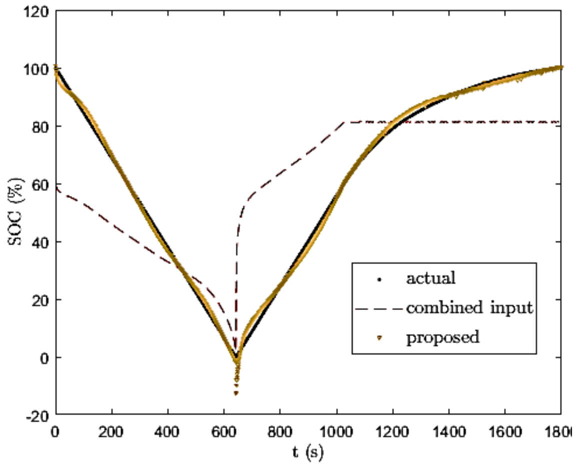


(b)

Figure 5. Results of SOC estimation comparison during (a) BEXEL#7 and (b) BEXEL #13.

discharging, which was denoted as a combined input-based SOC estimation. The result of the proposed method was compared with the combined input-based method. The combined input-based method and the proposed model's sample results are shown in Figure 5(a) and Figure 5(b) using BEXEL cells #7 and #13, respectively. As shown in the figures, the actual SOC, results of combined input, and proposed methods (separated input) are represented using a black dot, red dash, and yellow triangle, respectively. The figures show that the combined input results are far from the actual SOC. At the same time, the proposed model result could estimate the actual SOC for both charging and discharging. It also shows that the proposed method reduces the estimation error, indicating that it is more robust and accurate.

The combined input-based method considers both charging and discharging signals as a single input to the model, which can result in a more complex and less accurate SOC estimation model. On the other hand, the proposed SOC estimation model separates the charging and discharging signals and uses them as separate inputs to the model, which allows for a simpler and more accurate model. Furthermore, the results show that the proposed method can accurately estimate the actual SOC for both the charging and discharging processes. It is important for real-time SOC estimation in embedded applications, as it allows for accurate and reliable SOC estimation during both charging and discharging cycles.

To evaluate the accuracy of the proposed model, this study used mean absolute error (MAE) as the main performance metric, which is commonly used in regression analysis. Additionally, two other widely-used metrics: the root mean square error (RMSE) and mean absolute percentage error (MAPE), are also employed to evaluate the accuracy of the proposed model. RMSE and MAPE are frequently used to evaluate the accuracy of forecasting models [24]. These metrics can provide further insights into the performance of the model [24]. The formulas for MAE, RMSE, and MAPE are as follows.

$$MAE = \frac{1}{N}\sum_{i=1}^{N}|(y_i - \hat{y}_i)| \tag{10}$$

$$RMSE = \sqrt{\frac{1}{N}\sum_{i=1}^{N}(y_i - \hat{y}_i)^2} \tag{11}$$

$$MAPE = \frac{100}{N}\sum_{i=1}^{N}\frac{|y_i - \hat{y}_i|}{y_i} \tag{12}$$

where y_i, $\hat{y}_i$, N denote the actual SOC, the predicted SOC, and the total number of samples, respectively.

This study took into account the dynamic charging and discharging process, which are unique characteristics of each battery type. By incorporating these dynamic characteristics, the proposed SOC estimation model can more accurately estimate the SOC of the battery, which in turn increases the robustness of the SOC estimation. Additionally, the proposed SOC estimation model utilized data-driven SOC estimation

TABLE IV
PERFORMANCE COMPARISON OF COMBINED INPUT AND PROPOSED SOC ESTIMATION MODEL

Performance Metric	Cell #	Combined Input	Baseline [12]	Proposed Method
MAE	7	18.10	5.49	1.45
	13	28.10		2.23
RMSE	7	21.82	6.87	2.83
	13	22.29		1.49
MAPE	7	43.03	16.5	9.90
	13	32.73		8.87

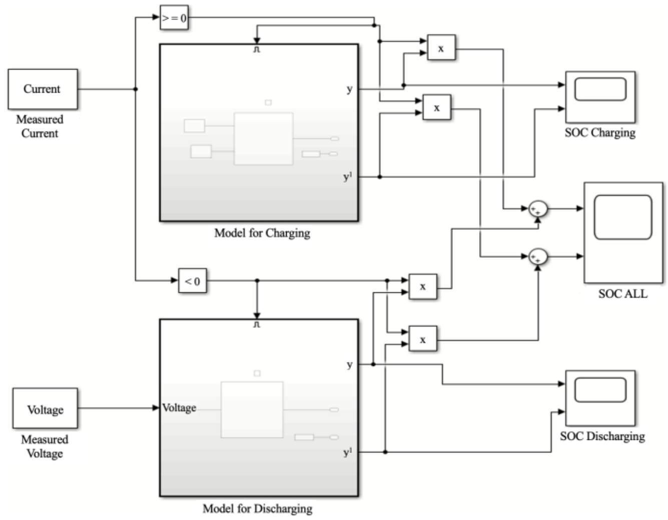
with measurable battery data and ANN, which also contributes to the increased robustness of the model. Data-driven methods are less sensitive to changes in the battery characteristics and are more adaptable to different battery types. In general, the proposed method increases the robustness of SOC estimation by incorporating dynamic characteristics of the battery and using ANN model, which can handle nonlinear relationships and adapt to different battery types.

The result of the computing estimation error using BEXEL cells #7 and #13 is shown in Table IV. The proposed model separating charging and discharging shows substantially better performance than the combined input. The MAE, RMSE, and MAPE values for the combined input method for cell #7 were 18.10, 21.82, and 43.03, respectively; meanwhile, the proposed model reduced these values to 1.45, 2.83, and 9.90. The proposed model has better performance because it has been developed considering the dynamic of charging and discharging. Specifically, the approach ensured that the model relied only on the most relevant features to estimate the SOC. The strong relationship between input and target allows for increased estimation accuracy. The performance comparison using cell #13 shows the same trend as cell #7. The proposed method had lower error than the combined input for all performance metrics MSE, RMSE, and MAPE

This study selected the SOC model suggested in [12] (baseline model) as a benchmark to showcase the accuracy and robustness improvement achieved by the proposed model. The reason behind selecting this model as a baseline is that it also uses an ANN-based model for estimating SOC, which is similar to the proposed model. In contrast to the proposed model, the baseline model disregards the dynamic of charging and discharging profiles and does not emphasize the development of SOC estimation for embedded applications. Furthermore, the baseline model consists of two input layer neurons, nine hidden layer neurons, and one output layer neuron. The input and output layers use the terminal voltage, discharge current, and battery SOC. According to the results presented in Table IV, it can be inferred that the proposed model outperforms the baseline model regarding MAE, RMSE, and MAPE, with lower values indicating an improved accuracy. In particular, the proposed model yields lower MAE, RMSE, and MAPE values for cell #7 (1.45, 2.83, and 9.90) than the combined input method (5.49, 6.82, and 16.5). The performance comparison using cell #13 shows the same trend as cell #7.

B. ONLINE-BASED MODEL TESTING RESULTS

In order to validate the practicality of the proposed model, The online estimation process was run on the target platform C2000. Specifically, the proposed model that had been converted to the Simulink platform, as shown in Figure 6(a), was uploaded to C2000. The online estimation experimental



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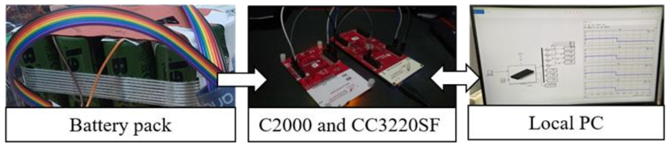


(b)

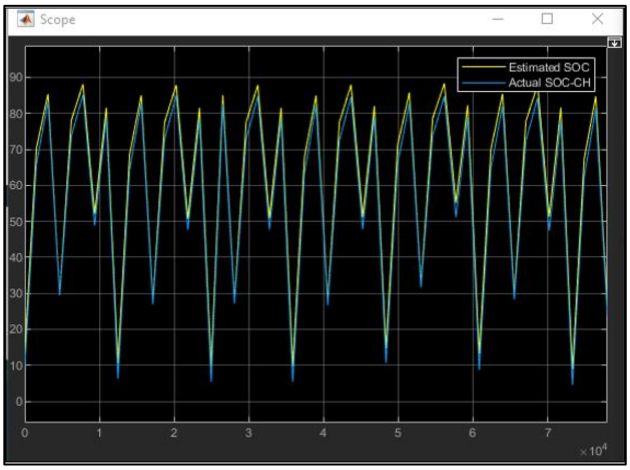
Figure 6. Experimental set-up for online estimation using (a) MATLAB Simulink model and (b) C2000 real-time microcontrollers.

setup is shown in Figure 6(b). The process started with voltage and current data acquisition. The voltage and current as input were collected every second. The C2000 is a microcontroller board that can be used for various applications. It is used to perform two tasks: data acquisition and processing.

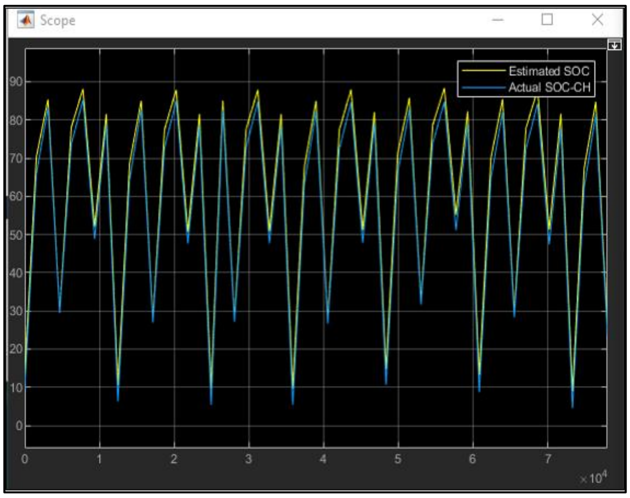
The data acquisition is the process of sampling analog signals in attempt to measure the actual physical battery form. Additionally, it also converts the sample of analog signal into digital numeric values that can be processed by a computer. In this case, the data acquisition is performed to measure and gather voltage and current value for charging and discharging process. Another task of C2000 board is data processing.

The online estimation commenced with voltage and current data acquisition. The voltage and current as input were collected every second. After that, these input data were used to estimate the SOC. To evaluate the performance of the proposed model, the result of online estimation was compared with actual SOC. The online estimation results of the proposed method are shown in Figure 7(a) and Figure 7(b). These figures show samples of the estimated SOC and the actual SOC during charging and discharging. The x-axis and y-axis of the figures represent the time measurement in second and SOC in percentage. As shown in the figures, the proposed model can capture the actual SOC start from the beginning to the end of charging and discharging process.

The results reveal that the proposed model is suitable for real-time application. It is because the proposed method used lower computational complexity model and measurable data, such as current and voltage. The inference time happened every second. It provides evidence that the proposed model can address two main challenges in real-time SOC estimation. First, it eliminates the need for computationally expensive and complex features by using easily measurable battery parameters.



(a)



(b)

Figure 7. Sample of results of real-time SOC estimation during discharging.

Second, it reduces the dependence on specific software. The proposed ANN-based SOC estimation model, which originally relied on MATLAB software, was successfully transformed into a standalone model that only requires the operating system to operate. This accomplishment is particularly essential because it enables the proposed model to be easily implemented on any embedded system without the need for additional software. By eliminating the requirement for specific software, the proposed model becomes more practical and user-friendly. This conversion does not compromise the accuracy and performance of the proposed model as demonstrated by the experiment results. The success of this conversion process confirms the feasibility and practicality of the proposed model for real-time SOC estimation in embedded systems.

V. CONCLUSION

This study proposed an alternative approach to improve the accuracy, robustness, and practicality of SOC estimation for embedded applications. This study shows that taking into account the dynamic charging and discharging process has enhanced estimation accuracy and robustness. Results suggest that the proposed model successfully reduces the values of MSE, RMSE, and MAPE. It indicates that the model has higher accuracy and better performance predicting SOC. An advanced DL algorithm can further employ it to achieve higher accuracy. Regarding practicality, the proposed model utilizes a low computational complexity ANN model and measurable data. This scheme ensures that the proposed system is suitable for real-time application.

CONFLICT OF INTEREST

The author has no conflicts with any parties during the writing and the course of this research. Any information submitted is the original result as obtained when conducting research and is not influenced by personal opinions or interests.

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