Prediction of State of Charge of Battery in Electric Vehicles Using Artificial Neural Network

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***Abstract*—The trajectory of today's world is towards emission-free energy sources. The result is a huge growth in the number of Electric Vehicles (EVs) experienced around the world. However, the batteries in EVs must be properly operated to extend their lifetime for which an accurate estimation of the State of Charge (SOC) of the cell is crucial. The conventional methods of SOC estimation are either less accurate or computationally complex. This paper presents a method of estimating the SOC of a Li-ion cell used in EVs employing an Artificial Neural Network (ANN) model which is tested in a 1-RC Equivalent Circuit Model (ECM) of a cell in MATLAB, SIMULINK. The model uses the measured current, voltage, and temperature, and predicts SOC based on these quantities. The first input feature for the ANN model is the power, which is calculated by multiplying the current and voltage. The average voltage and current over 600 timestep intervals are used as the second and third features, respectively. Additionally, the fourth input feature is the temperature. The performance of the model is tested against experimental data.**

***Key words*—Artificial Neural Network, Electric Vehicles, Equivalent Circuit Model, Lithium-ion Battery, State of Charge**

I. Introduction

The world of fossil fuels and automobiles is gradually shifting towards an era of alternative renewable resources [1]. The world is demanding carbon and pollution-free vehicles that eventually reduce the use of petroleum products and contribute to building a pollution-free environment. Electric Vehicles (EVs) and Hybrid Electric Vehicles (HEVs), with the potential integration with renewable smart power grids, hold a great prospect toward a sustainable future [2]. Hence, the demand for EVs has been increasing day by day. Since, people rely on EVs, without long-lasting and reliable battery sources, EVs are not supposed to fulfill people's demands. Therefore, batteries in EVs must possess high power and energy densities [3]. To compete with the mileage of IC engines, batteries in EVs cannot be heavy enough to affect their overall performance [4]. So, Li-ion batteries are used due to their luring characteristics of stable performance, less self-discharge rate, higher energy density, and long life cycle [5].

Batteries are supposed to be used in a way that may optimize their ability [6]. Although Li-ion batteries have a longer life cycle than many battery types, it has a shorter lifespan compared to other vehicle components [2]. So, battery degradation is considered a significant issue EVs. It also raises concerns about the vehicle's reliability and economy [7].

State of charge (SOC) is one of the important parameters that hold significant importance in a Battery Management System (BMS) for a battery's safe and efficient operation [8]. SOC refers to the available battery capacity expressed as a percentage of its rated capacity where 100% implies a full battery state [9]. It indicates how much longer a battery continues to perform before it requires recharging. Over-discharging a battery can cause voltage drops, and reduced performance [2]. Similarly, they are prone to being overcharged which may lead to irreversible damage, reduced performance, and shorter battery life [1]. By maintaining the SOC within safe operating limits, the risk of battery-related accidents can be minimized and the degradation period of the battery can be extended [6].

An ideal battery cell during a simulation process tends to omit the electrochemical properties, a battery possesses.

Different types of equivalent circuits are used to include the effects due to the electrochemical properties of a cell [10]. One of which is the Equivalent Circuit Model (ECM) of a cell containing RC branches [3]. The RC branches add the non-linear transient property of a cell [11].

There are various techniques for the estimation of SOC of a cell. The Coulomb Counting Method [12], Kalman Filter method [13], OCV method [14], and EIS method [15] are the popular ones. However, none of these methods are perfect in terms of complexity, accuracy, or both. The growing advancement of Machine Learning (ML) technologies has opened a path for the prediction of SOC of battery in EVs using ML.

This paper introduces a method for predicting the SOC by integrating an Artificial Neural Network (ANN) with a 1-RC ECM. The study includes a detailed process for estimating ECM parameters and validates the proposed model through rigorous comparison with experimental data. This work provides a robust and optimized solution for SOC prediction, offering an effective alternative to traditional methods.

II. Dataset Description and Data Preparation

The open-source dataset obtained from the tests performed on a Panasonic 18650PF cell, having a rated capacity of 2.9 amp-hours, at the University of Wisconsin-Madison by Dr. Phillip Kollmeyer [16] is used in this paper. The dataset consists of experimental data at five ambient temperatures of -20°C, -10°C, 0°C, 10°C and 25°C. The data of the drive cycles were recorded with a time step of 0.1 seconds.

Data from five-pulse Hybrid Power Pulse Characterization (HPPC) tests at all five ambient temperatures are used for the parameter estimation process of the ECM of the cell. Similarly, drive cycles HWFET, US06, UDDS, NN, Cycle 1, Cycle 2, Cycle 3, and Cycle 4, are used as the training datasets for the ANN model, and the LA92 drive cycle is used for testing the performance of the proposed model at 10°C, and 25°C.

The Ampere-hour (Ah) data in the dataset are converted to SOC using (1).

$$\dot{SOC}_{bat} = \begin{cases} \frac{-1}{\eta_{Coul}} * \frac{i_{bat(t)}}{Q_{norm}} & \text{if } i_{bat}(t) < 0 \\ \\ -\eta_{Coul} * \frac{i_{bat(t)}}{Q_{norm}} & \text{if } i_{bat}(t) > 0 \end{cases} \tag{1}$$

where, i_{bat} is the current through the cell, η_{coul} is the coulombic efficiency, which accounts for charge losses, and Q_{norm} is the nominal capacity of the battery [17].

Although SOC cannot be measured directly, it can be deduced by its measured current, voltage, and temperature [8]. The ML method establishes a non-linear relationship between the measured variables and SOC through training [8]. So, the data of voltage, current, temperature, and SOC are used for the training of the ANN model. The voltage and current are multiplied to obtain the power while the temperature is converted from degrees Celsius to Kelvin and the moving average for voltage and current is also calculated for 600 steps. An input matrix consisting of the data of power, temperature, average voltage, and average current, and another matrix of the target values i.e. experimental SOC, is created.

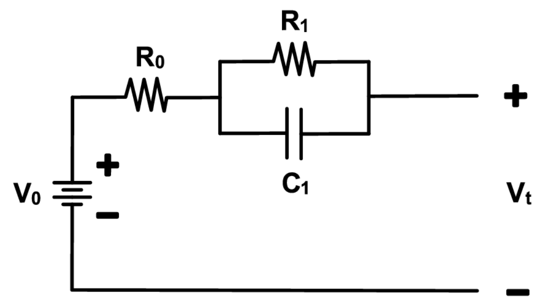

Fig. 1. 1-RC Equivalent Circuit Model

III. RC-branch Equivalent Circuit Model

ECM of a cell is used to replicate the electrochemical phenomena illustrated by a physical battery [6]. In this paper, 1st order ECM model is used which is represented in Fig. 1. The ECM model consists of a single series resistor, R_0, a parallel RC pair, R_1, and C_1, and a voltage source, V_0, which represents the cell's Open Circuit Voltage (OCV). The increase in the number of RC branches increases the accuracy of the simulation model of a physical cell but the rise in the number of RC branches increases the complexity of the model and demands more computing power from the simulation device [10]. The parameters of the ECM of the cell: V_0, R_0, R_1, and C_1 are dynamic and vary with the varying SOC and temperature of the cell [6].

IV. Estimation of the Dynamic Parameters of the ECM

A Simulink model is developed to determine the dynamic parameters of the ECM of the cell. The block diagram of the parameter estimator is shown in Fig. 2.

The discharging current of the HPPC dataset is supplied to the ECM. The lookup table of dynamic parameters contains a matrix consisting of SOC from 0 to 1 in the row and temperature from 253K to 298K in the column which are supplied with initial guesses at the beginning.

The parameter estimator tool of Simulink is used to iterate several times, changing the values of dynamic variables with each iteration and comparing the simulated voltage with the experimental Voltage. The iteration is carried out until the sum of the squared error between the simulated Voltage and the experimental voltage reaches a very minimum. This process is repeated for HPPC datasets at all ambient temperatures. This process is represented in the flowchart in Fig. 3.

V. Training and Selection of Architecture of ANN Model

A suitable architecture of the ANN model is required to predict the battery's SOC accurately. The input matrix is used as input features, and the matrix of experimental SOC is used as the target during the training process of the ANN model.

The training process is performed with the help of Adaptive Moment Estimation (Adam) optimizer with the maximum number of epochs set to 5100. The initial learning rate is set to 0.01 with a drop factor of 0.1 at every thousand iterations. The model is trained using the trainNetwork function in MATLAB.

Several models are trained to select the architecture of the ANN model where each model has an input layer with 4 neurons, an output layer with one neuron using a clippedRelu activation function, and a variable number of hidden layers, each containing 55 neurons. The last hidden neurons consist of a leakyRelu activation function and the remaining hidden layers have a hyperbolic tangent activation function. Primarily, a model with two hidden layers is trained and the number of hidden layers is incrementally increased to six. All the models are tested for 25°C data of LA92 drive cycle in the ECM of the cell and the architecture with the best performance, based on Mean Absolute Error (MAE) is selected.

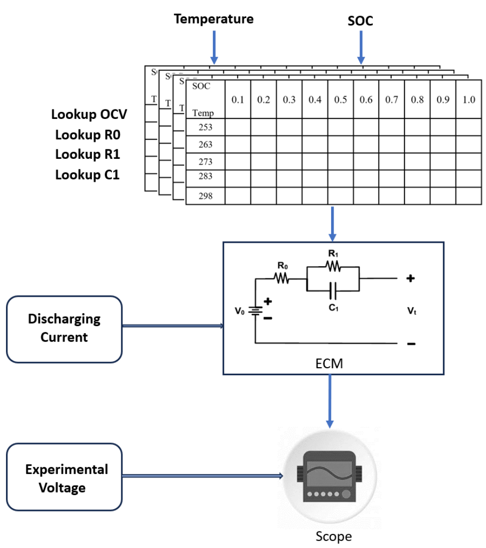

Fig. 2. Block Diagram of Parameter Estimator

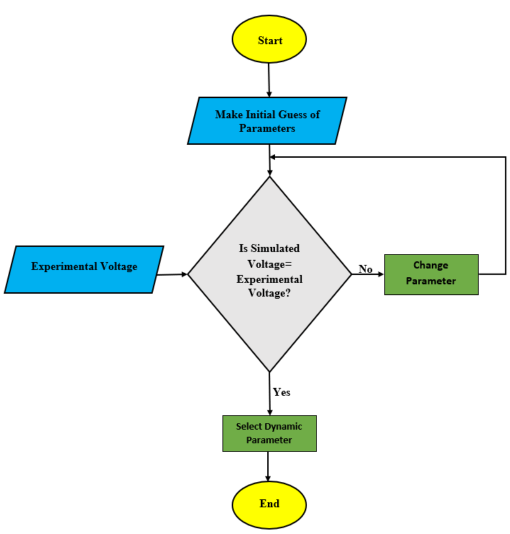

Fig. 3. Flowchart of Parameter Estimation Process

TABLE I
ACCURACY OF DIFFERENT ARCHITECTURE OF ANN MODEL

No. of hidden layer	MAE of SOC	% Accuracy
2	0.0183	98.17
3	0.0198	98.02
4	0.0173	98.27
5	0.0198	98.02
6	0.0244	97.56

The accuracy of different architectures of the ANN model is presented in Table I which indicates that the model with four hidden layers achieves the highest accuracy. Hence, the selected model has four hidden layers: three with hyperbolic tangent activation, one with leakyRelu activation, and an output layer with a clippedRelu activation function. The selected architecture of ANN model is represented in Fig. 4.

VI. PROPOSED MODEL

The ANN model for the prediction of SOC is integrated with the ECM of the cell. Then, the ECM is discharged with the current profiles of the LA92 drive cycle displayed in Fig. 6 and Fig. 7 for temperatures 10°C and 25°C respectively. The voltage across the ECM and the current through it are measured and multiplied using a product block to obtain the power. The measured current and voltage are passed through the moving average block to obtain the average voltage and average current of 600 timesteps measured every 0.1 seconds. Power, average voltage, and average current are then supplied to the ANN model. Similarly, the temperature data available in the dataset is directly fed to the ANN model. The ANN model predicts the SOC which is subsequently filtered through a moving average block of 600 timesteps. The filtered SOC is then compared with experimental data, and the MAE as well as the Maximum Error (ME) of the predictions are computed. The measured terminal voltage of the cell is also compared with the experimental data and the corresponding MAE and ME are calculated. The block diagram of the proposed model is shown in Fig. 5.

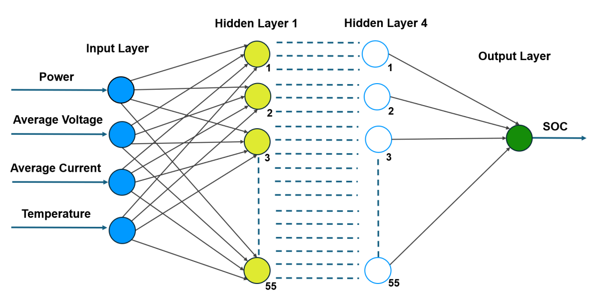

Fig. 4. Selected Architecture of ANN model

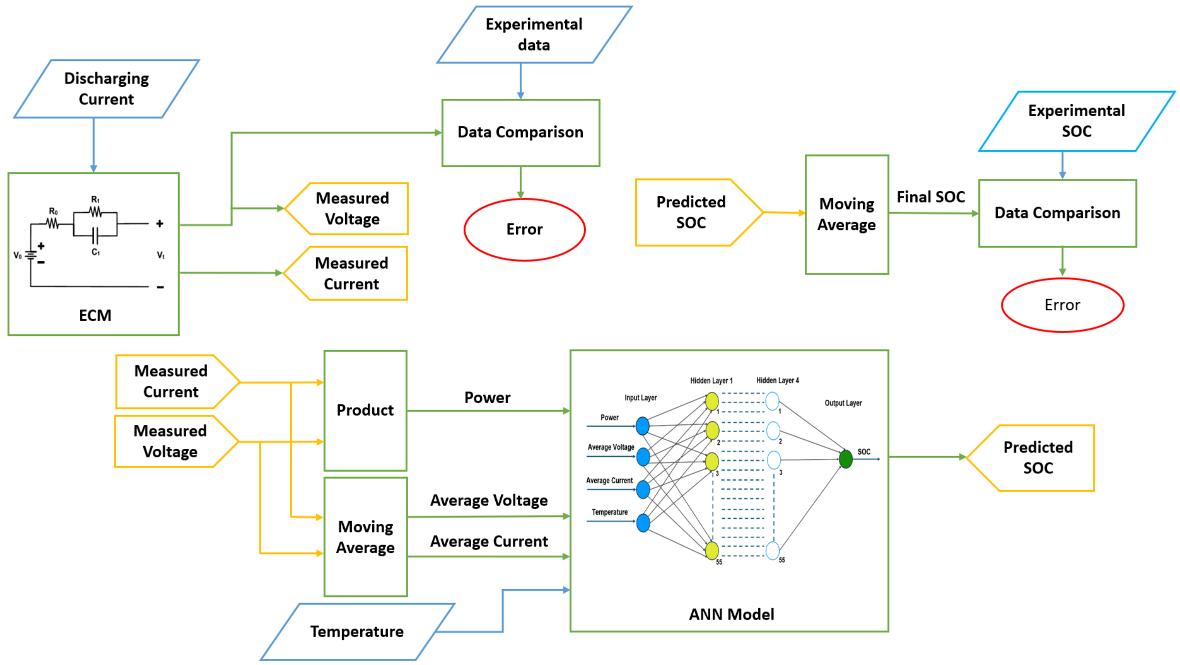

Fig. 5. Block Diagram of the Proposed Model

VII. Results and Discussions

A. Predicted SOC

The predicted SOC curve obtained by discharging the ECM of the cell with the LA92 drive cycle at ambient temperatures 10°C and 25°C along with the experimental data is shown in Fig. 8 and Fig. 9 respectively. The calculation of the MAE and the ME is performed by clipping the initial section of the graph as the current profile begins with a 0 Ampere current resulting in a 0% SOC predicted by the block. At an ambient temperature of 10°C, MAE is obtained to be 0.0258, corresponding to 2.58%, and ME of 0.2, corresponding to 20% is obtained. Similarly, at 25°C, MAE is found to be 0.0173, corresponding to 1.73%, and ME of 0.1111, corresponding to 11.11% is achieved as displayed in Table II.

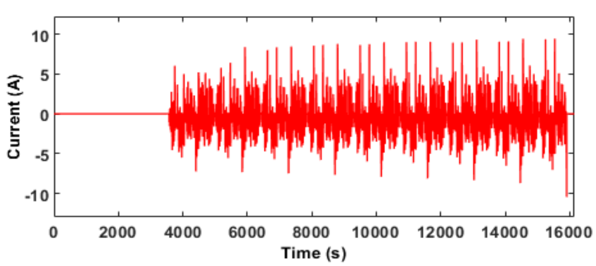

Fig. 6. LA92 Current Profile for 10°C

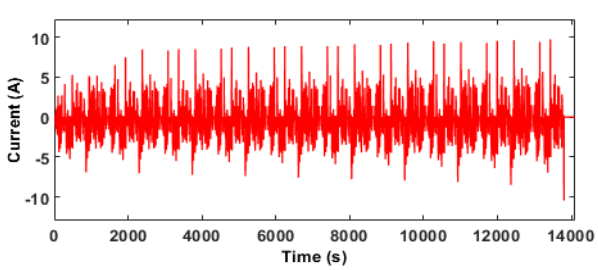

Fig. 7. LA92 Current Profile for 25°C

TABLE II
Errors of Predicted SOC and Terminal Voltage compared to Experimental Data

	Temperature (°C)	MAE (%)	ME (%)
SOC	10	2.586	20
	25	1.73	11.11
Voltage	10	0.755	8.98
	25	0.425	9.8

B. Simulated Voltage

The simulated voltage is compared with the experimental voltage from the dataset as shown in Fig. 10 and Fig. 11. The MAE of the simulated voltage at 10°C is found to be 0.0272V corresponding to 0.755% regarding its nominal voltage of the cell i.e. 3.6V. Similarly, the MAE of the simulated voltage at 25°C is found to be 0.0153V which corresponds to 0.425% concerning the nominal voltage. The ME of the simulated voltage is found to be 0.3235V which corresponds to 8.98% and 0.3539V corresponding to 9.8% concerning the nominal voltage for 10°C and 25°C respectively.

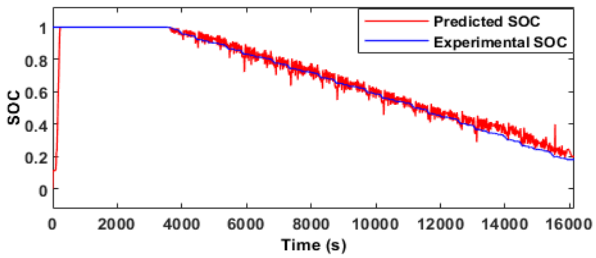

Fig. 8. Predicted SOC Vs Experimental SOC at 10°C

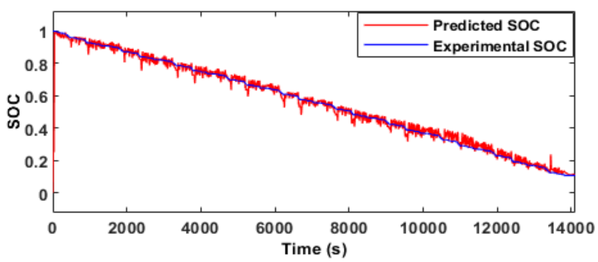

Fig. 9. Predicted SOC Vs Experimental SOC at 25°C

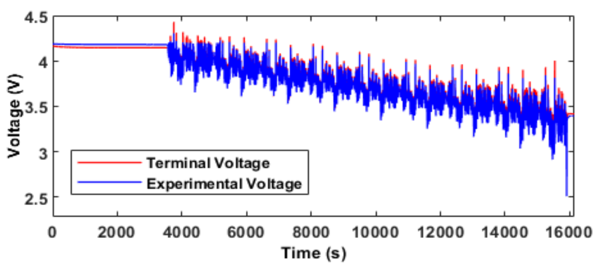

Fig. 10. Simulated Voltage Vs Experimental Voltage at 10°C

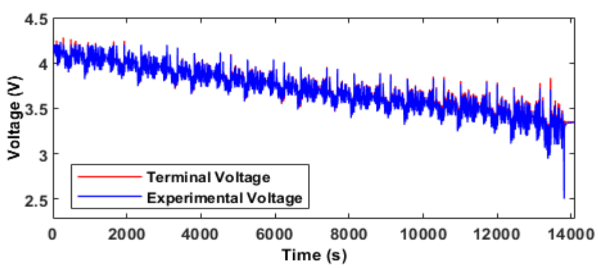

Fig. 11. Simulated Voltage Vs Experimental Voltage at 25°C

VIII. Conclusion

SOC denotes a cell's remaining capacity, which is an important parameter for any BMS to ensure the battery's safe and efficient operation. Thus, an accurate estimation of SOC becomes pivotal. This paper presents a method employing ANN for the prediction of a cell's SOC using measurable quantities i.e. Current, Voltage, and Temperature. A 1-RC ECM of the cell is developed using experimental data. The ANN model for the prediction of SOC is integrated into the ECM when discharged through a discharging current of a drive cycle in MATLAB, Simulink. The predicted SOC and the terminal voltage of the ECM are compared with the experimental data to validate the accuracy of the proposed model at two different temperatures and MAE and ME are calculated as shown in Table II. Overall, the results indicate that the ANN-based approach can satisfactorily predict SOC and can be an alternative to the conventional approaches.

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