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Development of equivalent circuit model for state of power estimation of NMC-based Li-ion cell

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Summary

In this paper, the state of power (SoP) estimation of 43Ah nickel-manganese-cobalt oxide-based lithium-ion cell used in vehicle applications is presented. One of the main reasons for the need of a battery management system having integrated with SoP estimation functions is the need for a safe operation system. Therefore, considering the effect of internal resistance increase throughout the cycle life of the cells, the SoP estimation model is developed. The developed SoP model is validated with static and dynamic validation profiles and promising result is found with root mean square error of 1% and 2% respectively.

Keywords: State of power, State of charge, Nickel-manganese-cobalt oxide, Battery management system, Battery aging

1. Introduction

With the consistent increment of power density and specific energy of lithium-ion batteries, the intensive use of these battery types becomes common practice in the automotive application sector [1-3]. This contributes to have a matured battery management system (BMS) utilized in Li-ion batteries having high charges and discharge current rates and high energy density [4-6]. The state of charge (SoC) and also the state of power (SoP) are most important parameters in the safe operation of the battery system where the BMS is needed. Therefore, for the safe operation of the battery system used in EV applications, an accurate estimation of battery SoP is essential which is commonly expressed as a function of load current, terminal voltage and SoC [7]. Various methods are used for the estimation of SoC and SoP, where Xiong et al. [8] have used the method of Kalman filter joint estimator to estimate SoC and predicted the SoP output. The study provides an SoP estimation model using the SoC result as an input without considering the resistance increase of the cells.

A recursive extended least squares (RELS) algorithm is used to estimate SoP using an online equivalent-circuit model parameters identification technique with an assumption of constant current as input. However, the study didn't consider the use of discharging current and power for effective determination of the desired SoP [9]. Gao et al. [10] have used a coupled equivalent circuit model to estimate SoC and SoP, where as, Jia et al. [11] have made a comparative analysis between compared EKF, strong tracking EKF (STEKF), and multirate strong tracking EKF (MRSTEKF) and proved the MRSTEKF has faster computation time during estimation of SoC and SoP. However, these methods are found to be relatively complex for utilization purposes. Moreover, Esfandyari et al. [12] and Sun et al. [13] analyzed the effect of aging status using combined reference mode of constant-current and constant-voltage method for estimation of fresh cell SoP where the various aging states are adapted. In this case, the authors tried to analyze the aging effect which is limited to the beginning of life (BoL) state of health (SoH) data, which might be insufficient resulting inaccurate SoP determination.

The SoP estimation techniques mentioned above have their advantages and limitations in terms of complexity, accuracy, and computational time. To mitigate the gaps observed from the above reviews, in this paper, an SoP model coupled with dual polarization-equivalent circuit model (DP-ECM) based SoC estimation model is used to predict the dynamic behavior of a battery cell and internal resistance increase until end of life of the battery cell. The SoP estimation is provided as a function of internal resistance of the battery cell. The developed SoP model is validated using a dynamic Worldwide Harmonized Light vehicles Test Cycles (WLTC) and Static profiles and promising results are found.

2. Experimental Setup

The experimental test was performed using an efficient characterization methodology of 43 Ah large capacity nickel-manganese-cobalt oxide (NMC) based lithium-ion cells. The cells used for experimenting is prismatic cells consisted up of NMC/C based cathode and graphite-based anode. The cell has a nominal voltage of 3.6 V, 840 g weight, and high-power density of 1200 W/kg which makes the cell suitable to be used in automotive applications. In addition, the operating voltage region of the cell is 3 to 4.2V with internal resistance of ≤ 2 mΩ. PEC manufactured testers and CTS customed climate chambers for ambient temperature control were used during the test campaign.

2.1. HPPC Testing Methodology

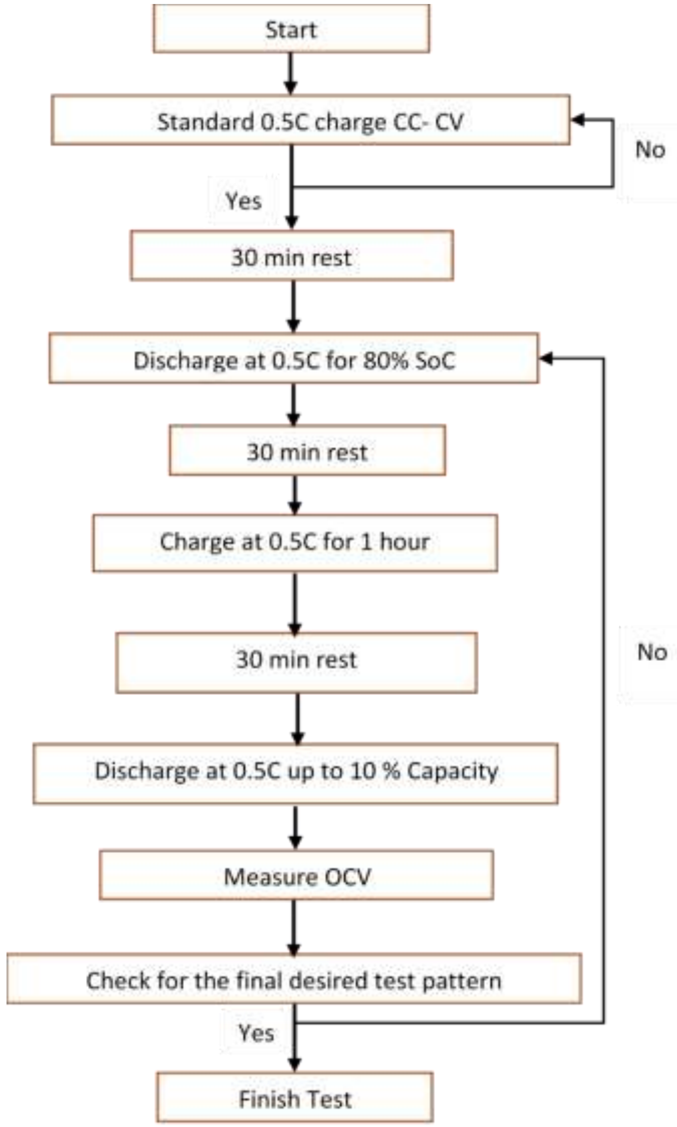


Figure 1 : The HPPC test procedure used for SoC and SoP estimation.

Using the procedure of Fig. 1, HPPC tests with 800 full equivalent cycles (FECs) long duration were accomplished for all the four representative cells considered for the SoP estimation. The characterization of batteries at various environmental and battery state conditions, such as at different temperatures, state-of-charge, and current rates have been performed. The development process of battery modeling consists of a series of standard testing procedures used to capture the electrical and thermal behaviours efficiently. The electro-thermal characterization procedure mainly incorporates the Capacity, open-circuit voltage (OCV), quasi-open-circuit voltage (qOCV), HPPC, and validation tests. Based on these characterization results, an electro-thermal model is parametrized and developed for the determination of the cells' SoC and dynamic behaviours. The charge and discharge cycles are performed using predetermined current rate (C-rate) values with constant current-constant voltage (CC-CV) standard charging of cells. In addition, to the HPPC, the open circuit voltage (OCV) data is measured.

This paper is mainly focused on the Hybrid pulse power characterization (HPPC) used to extract the required internal resistance parameters. The test is performed at three different HPPC_SoC points (80%, 50%, and 20%) [14]. Accordingly, internal resistance (Ri) is calculated using the actual and the nominal value.

2.2. Equivalent Circuit Model Parameters Extraction

The SoC of the battery cells is the most crucial parameters which need accurate determination for effective operation and control of the BMS on the overall system [15-18]. The total SoC is the sum of the state of charge due to both voltage and current effect. Primarily, the SoC can also be determined by using the coulomb-counting method defined by [19]:

$$SoC = SoC_0 - \frac{1}{C_{init}} \int I_{batt} dt \quad (1)$$

Where SoC_0 is the initial state-of-charge of the cell and I_{batt} is the battery current.

With the combined use of the coulomb counting and EKF methods, the total SoC can be estimated by considering the sum of SoC with Voltage and SoC with the current. Both algorithms considered the current input while the EKF considers both voltage and current as input. So, total SoC at K_{th} time step is given by:

$$SoC_k = SoC_{I,k} + SoC_{V,k} \quad (2)$$

Where k stands for the time step, I stands for the current in (A) and V stands for the voltage in (V).

2.3. Table-Based Linear Interpolation (TBLI) Parameter Extraction

The ECM parameters, including R_0, R_1, C_1, R_2, and C_2, are extracted at SoC_HPPC points of 20%, 50%, and 80% intervals using TBLI method in account of the varying SoC values and C-rates. The temperature considered for this scenario is limited to 0 ºC, 10 ºC, 25 ºC, and 45 ºC. The electrochemical reactions response during a current pulse are shown in Fig. 2.

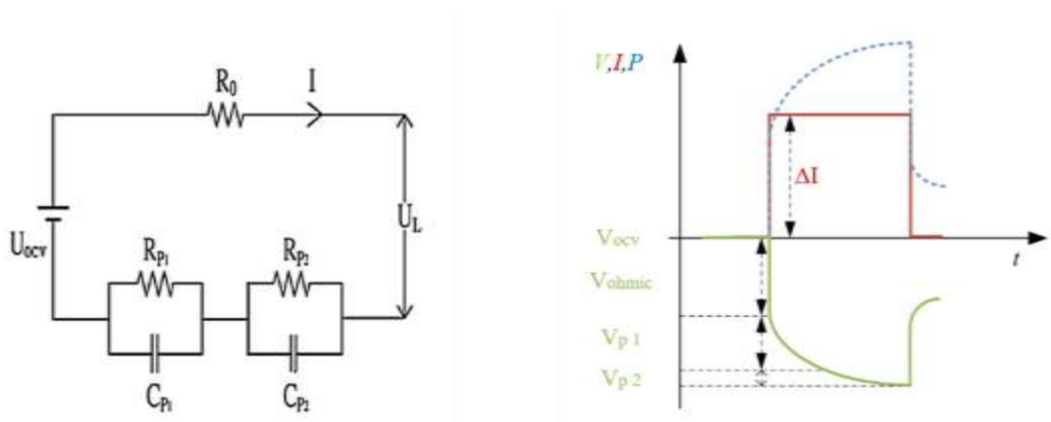


Figure 2: The corresponding region of the pulse and the schematics of the electrical model.

The extracted ECM parameters of R_0, R_1, C_1, R_2, C_2, versus SoC points at different temperatures are analyzed and presented from Fig. 3 to Fig. 5.

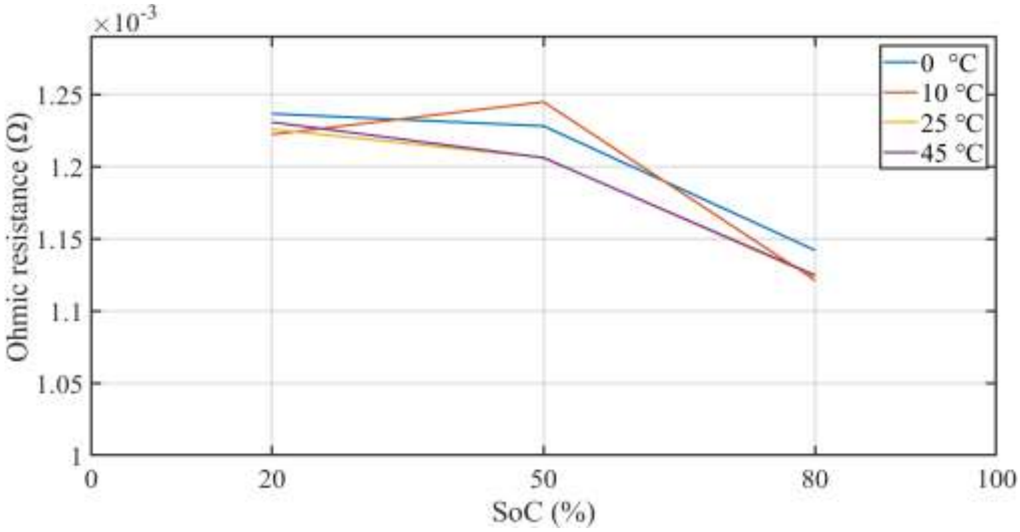
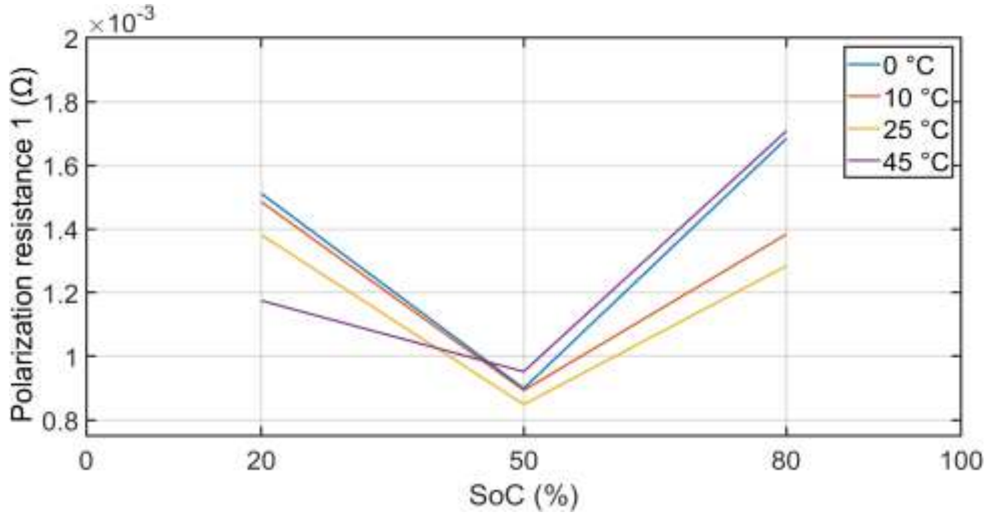


Figure 3: Ohmic resistance as a function of temperature and state of charge.



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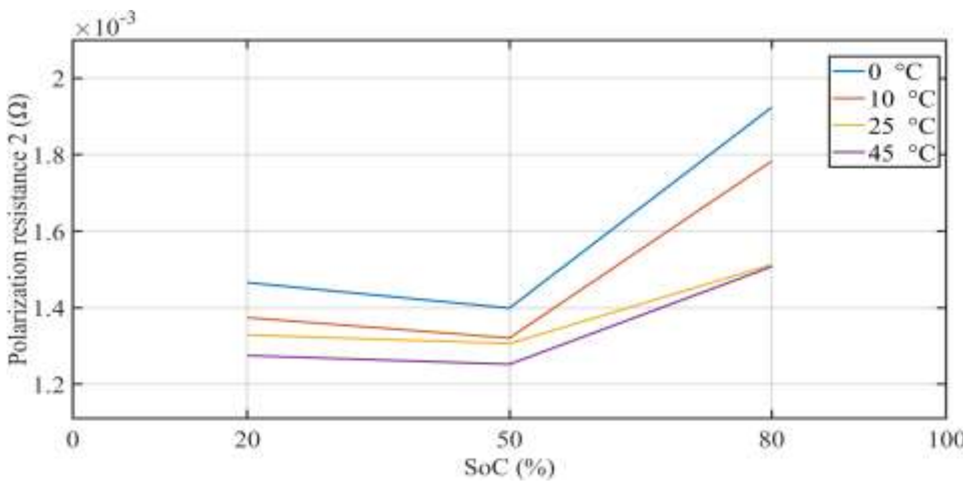
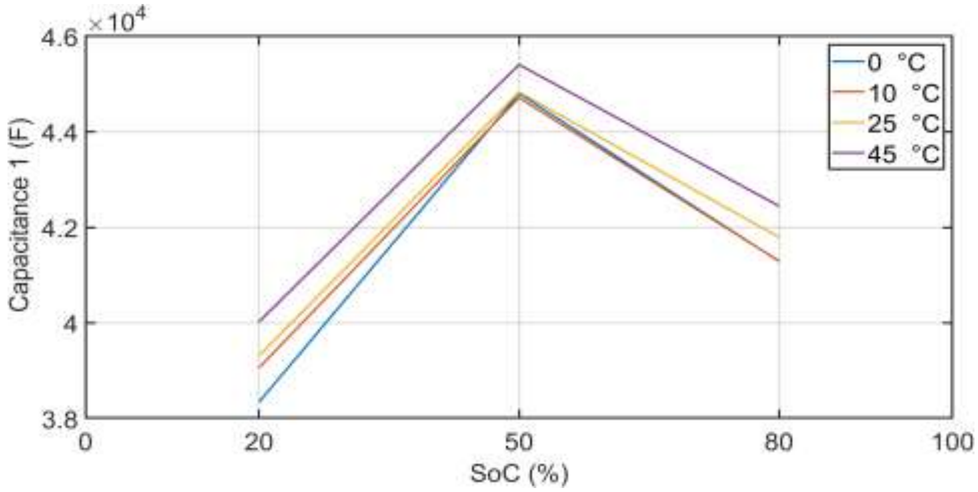


(b)

Figure 4: Resistance as a function of temperature and state of charge, (a) R_{p1}, (b) R_{p2}.

Where, R_{p1} stands for polarization resistance 1, and R_{p2} represents polarization resistance 2.



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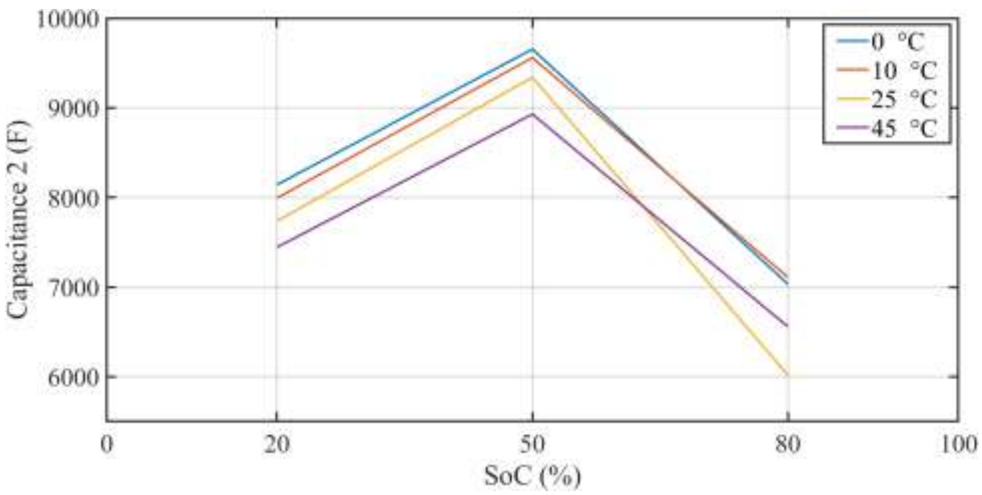


(b)

Figure 5: Capacitance as a function of temperature and state of charge, (a) C_{p1}, (b) C_{p2}.

Where, C_{p1} stands for polarization capacitance 1, and C_{p2} represents polarization capacitance 2.

As shown from Fig. 3 to Fig. 5, the ohmic resistance is higher at lower SoC levels and decreases with the increase in SoC level. Besides, the result shows that in most of the cases, at a lower temperature, the resistance is higher, on the other hand, at higher temperature resistance is found to be lower, which is coherent to the previous report in [20].

3. Mathematical Formulation and Model Representation

To identify the behaviors of the battery cell and find the electrical response, prior to the SoP model development, an electro-thermal model is developed based on the Thevenin model [21] (Fig. 2), which consists of a voltage source with an ohmic resistance and two parallel RC circuits. Based on the equivalent circuit model, the battery output voltage of the Li-ion cell is the voltage drop resulting from the battery open-circuit voltage (OCV), the battery ohmic resistance (R_0), and battery polarization impedances (R_1C_1, R_2C_2 circuits). The output voltage of the cell is given by [21]:

$$V_{cell} = V_{oc} - R_1 I_1 - R_2 I_2 - R_0 I_{batt} \tag{3}$$

Where I_{batt} is the flowing current in the battery (A), I_1 is the current passing in the polarization resistance (A) and I_2 is the current flowing through the charge transfer one (A).

3.1. Mathematical Description of SoP Estimation

For estimation of the SoP, first, the maximum discharge current (i_{max}^{dis}) has to be defined, which is given by:

$$i_{max}^{dis} = C_{rate} * Q_{norm} \tag{4}$$

Where C-rate is the current rate of the cell and Q_{norm} stands for the current cell capacity in Ah.

The maximum discharge current due to SoC at k_{th} time step can be expressed as:

$$i_{max,k}^{dis,SoC} = \eta * C_{rate} * Q_{norm} * (SoC_k - SoC_{min}) \tag{5}$$

Where η is cell efficiency commonly taken as 1 at beginning of life (BoL).

On the other hand, the maximum discharge current due to voltage is given as:

$$i_{max,k}^{dis,\ volt} = |i_{0,k}| * (V_{ocv} - V_{min}) * \left(\frac{1}{|V_{ocv} - V_{min}|} + \frac{1}{V_{max} - (V_{ocv} - V_{min})}\right) \tag{6}$$

Where V_{ocv} is the open-circuit voltage (V) at the SoC value of the K_{th} time step, V_{min} is the minimum cell voltage and V_{max} is the maximum cell voltage, $i_{0,k}$ is the load current at the K_{th} time step. For the battery cell under study, the following voltage limits are considered.

Here, V_{max} = 4.2V and V_{min} = 3V, SoC_{min} = 0.1, SoC_{max} = 1, Q_{norm} = 43 Ah, C_{rate} = 1C.

$$i_{max,k}^{dis} = min\left(i_{max}^{dis}, i_{max,k}^{dis,SoC}, i_{max,k}^{dis,volt}\right) \tag{7}$$

The maximum power where the cell could perform is also defined as,

$$P_{max}^{dis} = V_{max} * i_{max}^{dis} \tag{8}$$

Finally, the maximum discharge power $P_{max,k}^{dis}$ is defined as the function of the discharge current, voltage, and discharge resistance parameters.

$$P_{max,k}^{dis} = \min\left(P_{max}^{dis}, i_{max,k}^{dis} * \left(V_{ocv} - i_{max,k}^{dis} * R_{dis}\right)\right) \tag{9}$$

3.2. SoP Model Representation

The overall model is developed based on MATLAB/Simulink environment. The objective of the model development is to determine the SoP of the cell in relation to the internal resistance increase not only at BoL, but also throughout its lifetime for consideration of the aging effects. The model is a coupled model combined with electro-thermal and SoP models. The electro-thermal is used to reproduce the cell's electrical performances/behaviors, whereas the SoP model is used for the estimation of the SoP parameter crucial for the BMS. The SoP estimation model is developed based on Eq. 4 to 9, parameterized using SoC, voltage, temperature, and current experimental data found from the test result.

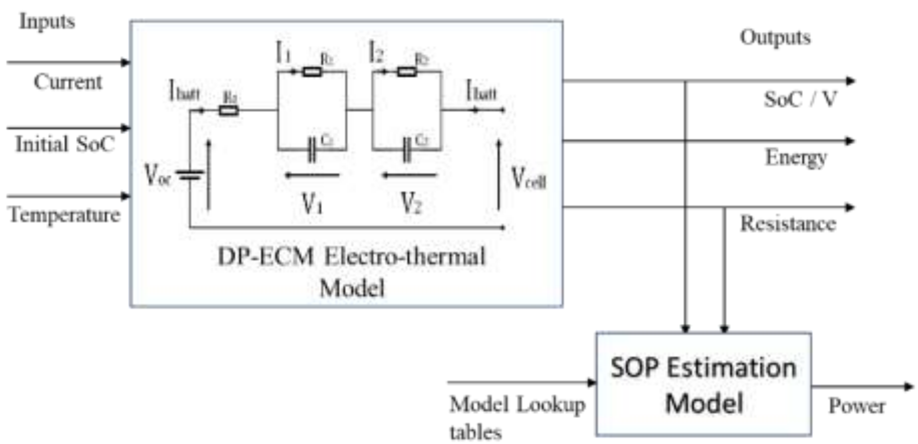


Figure 6: Schematic representation of DP-ECM coupled SoP battery model.

From Fig. 6 it is shown that, the current, initial SoC, and temperature are the inputs for the DP-ECM model and its outputs are SoC, resistance, and energy. The resistance and SoC outputs are fed as an input to the SoP model together with lookup table parameters (cycling resistances and cycle numbers) and power is the output of the SoP model. Using the electro-thermal model output of these parameters, input of lookup table is provided to the SoP model and then maximum discharge current and discharge resistances are calculated.

4. SoP Estimation Results and Model Validation

4.1. SoP Estimation

The estimation of SoP through lifetime until end-of-life (EoL) condition is estimated by defining the range of equivalent cycles and internal resistance increase parameter. The reference resistance increase at EoL has been estimated using the rate of internal resistance (R_i) increase at 50% SoC. The total Ri increase rate is estimated by using the combined effect of the FECs, the resistance cycle (estimated using the difference between two consecutive R_i values), and the cycle test resistance values. To find out the total R_i and hence estimate SoP at EoL condition, first the rate of R_i increase is multiplied with Ri value at BoL condition. Finally, using the respective current rate and total resistance increase, the SoP output of the cell is estimated until its EoL.

With the application of varying SoC values between 0.1 and 1 as input, the SoP output from BoL to EoL of a representative cell is shown in Fig. 7, where, the SoP output is dependent on the internal resistance [20, 22]. The SoP result follows the magnitude of the R_i increase throughout the total FECs.

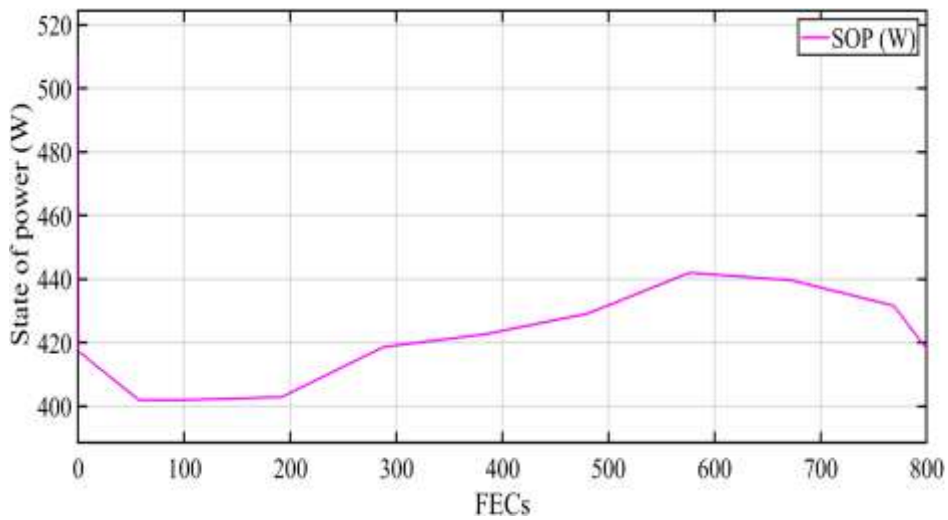
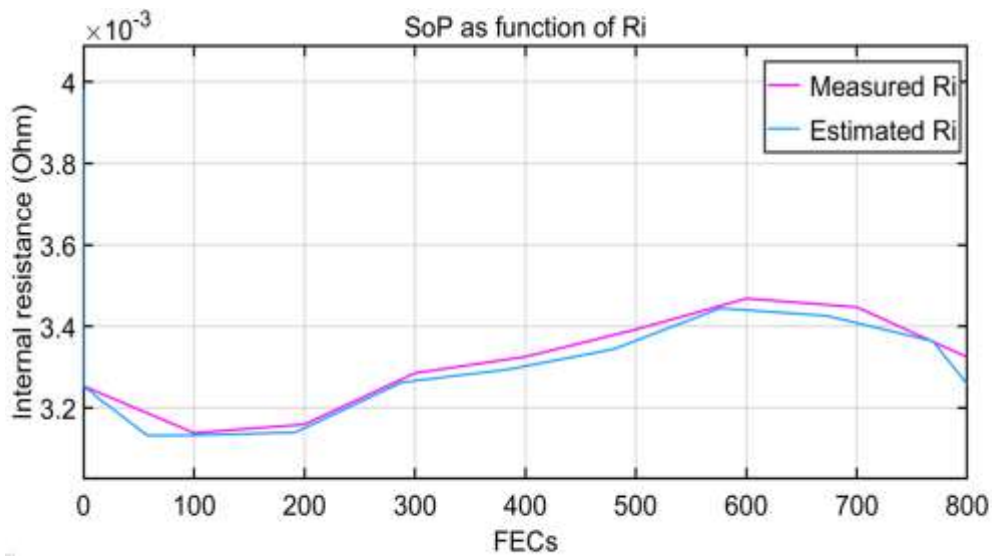


Figure 7: SoP output of the cell through 800 FECs.

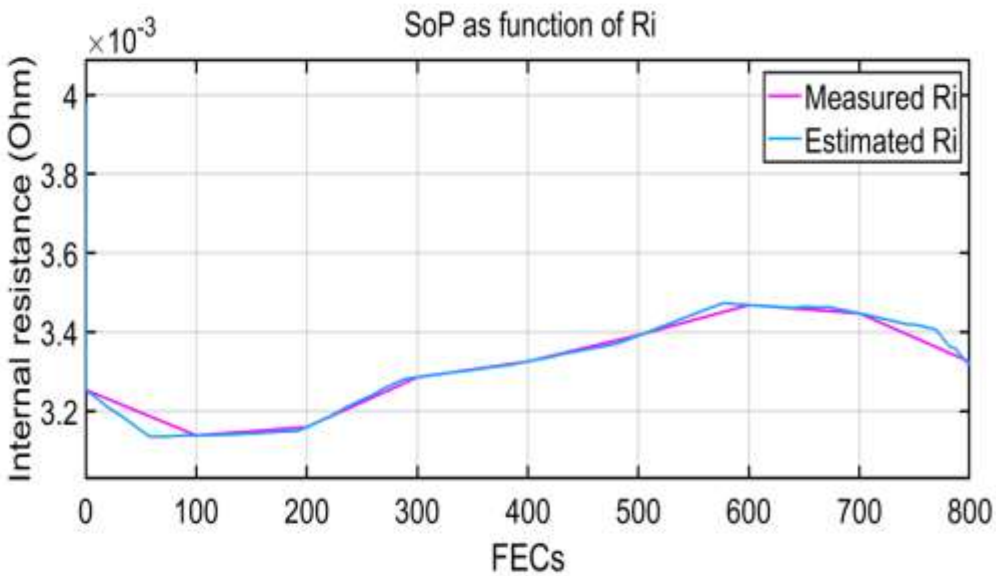
From Fig. 7, it is shown that the SoP did not follow a uniform trend, this is because the measured internal resistance is not increasing monotonically which is resulted from the dynamic current profile used and the inconsistent R_i measured data shows that the resistance change is not dominant for these cells.

4.2. SoP Model Validation

The validation of the SoP model is performed using two types of current profiles. The dynamic WLTC and static load current profiles are used for evaluation of the model performance and its accuracy. From Fig. 8(a), it is shown that the estimated R_i output follows a similar trend to the measured R_i, and the resulting RMSE is found to be around 2 %, which is comparable with the values reported by previous studies [11,12].



(a)



(b)

Figure 8: SoP validation as function of internal resistance using (a) WLTC profile, (b) Static current profile.

From Fig. 8(b), it is shown that the estimated output follows the measured value with better accuracy, showing that the static profile provides a better validation result compared to the dynamic profile. In this case, the RMSE is found to be around 1 %, which is found to be better compared to the results found in previous reports [13, 20].

5. Conclusions

Besides the SoC parameter estimation, the development of accurate SoP estimation model enables to evaluate the cells' behaviours in terms of their state of power output which is considered as an essential parameter in the safe operation of battery and BMS system. In this paper, an efficient method is used to estimate the SoP output of the cells and the RMSE result of the model validation with the dynamic and static profile is found to be 2 % and 1 %, respectively. The maximum error is found with the dynamic WLTC profile, whereas relatively less error is found with static validation profile. The resulting error is mainly caused by the inconsistency of the measured internal resistance value where the resistance change is found as not dominant for the cells under study. In the future, the aspect of pack-level or module-level SoP estimation model development can be further investigated.

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