Battery State of Health and Charge Estimation Using Machine Learning Methods

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Abstract

In this study, state of health (SOH) and state of charge (SOC) estimation of series connected batteries were evaluated for their charge and discharge durations. For this purpose, an ARM-based electronics card module was developed for observing instantaneous batteries voltage, current and temperature values during the charge and discharge process. The implemented microcontroller based card module gathers data from the current, voltage, and temperature sensors and it transfers to the computer environment via serial communication port. A specific human machine interface is designed via app-designer. The obtained variables were used for estimating regression models of the machine-learning toolbox. Random forest, decision tree, polynomial, extreme gradient boosting, linear and gradient boosting regression models were used for instantaneous SOH and SOC estimation for batteries during the charge-discharge period. Root Mean Square Error (RMSE) and R^2 score results were used for performance evaluation of regression models. When the RMSE and R^2 score results were compared, the decision tree regression model was the regression model that made the most accurate SOH and SOC estimation and the results were presented.

Keywords: State of Charge, State of Health, Microprocessor, Machine learning, Regression models.

Makina Öğrenmesi Metotları Kullanılarak Batarya Sağlık ve Şarj Durumunun Kestirimi

Öz

Bu çalışmada, seri bağlı pillerin sağlık durumu (SOH) ve şarj durumu (SOC) tahminleri şarj ve deşarj süreleri boyunca değerlendirilmiştir. Bu amaçla, şarj ve deşarj işlemi sırasında anlık akü voltajı, akım ve sıcaklık değerlerini gözlemlemek için ARM tabanlı bir elektronik kart modülü geliştirilmiştir. Uygulanan mikrodenetleyici tabanlı kart modülü akım, gerilim ve sıcaklık sensörlerinden verileri toplayarak seri haberleşme portu üzerinden bilgisayar ortamına aktarır. App-designer aracılığı ile belirli bir insan makine arayüzü tasarlanmıştır. Elde edilen değişkenler kullanılarak kestirim yapmak için, makine öğrenimi araç kutusunun regresyon modelleri kullanılır. Bataryalar için şarj-deşarj süresi boyunca anlık SOH ve SOC tahminlemesinin yapılması için, rasgele orman, karar ağacı, polinom, aşırı gradyan artırma, doğrusal ve gradyan artırıcı regresyon modelleri kullanıldı. Regresyon modellerinin performans değerlendirmesi için Kök Ortalama Kare Hatası (RMSE) ve R^2 skor sonuçları kullanılmıştır. RMSE ve R^2 skor sonuçları karşılaştırıldığında, karar ağacı regresyon modeli en doğru SOH ve SOC kestirim yapan regresyon modeli olmuştur ve sonuçlar sunulmuştur.

Anahtar Kelimeler: Şarj Durumu, Sağlık Durumu, Mikroişlemci, Makine Öğrenmesi, Regresyon modelleri

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1. Introduction

Series connected battery packs are used as energy storage systems (ESS) for electrical devices such as booster converters, uninterruptible power supply (UPS) and electric vehicle (EV) systems (Yu, 2013), (Badeda, 2018), (Hannan, 2017). In order to fully exploit the potential of the battery in ESS, the system might be properly charged and discharged, which is achieved by accurately measuring the state of charge (SOC) and state of health (SOH) (Cacciato, 2016). After the obtained these variables, regression models of machine learning toolboxes were used to estimate SOH and SOC models. So, these regression models are used to examine the estimated and real SOC and SOH values by using dependent and independent variables (Fahrmeir, 2013).

In this study, SOC and SOH values of series connected batteries were evaluated instantaneously during the charging and discharging periods. The considered serial connected batteries were assessed with 12V-7A lead-acid battery containing 6 lead-acid cells (Gu, 1987), (Yiğit Akü, 2021).. The developed system includes an ARM based development board, sensors, a relay and non-inverting amplifier circuits. To gather the voltage variables of the batteries, the analog to digital converter (ADC) and inter-integrated circuit ports were used. Likewise, to obtain the temperature and current variables of the batteries, universal synchronous asynchronous receiver transmitter (USART) serial communication protocol is used and it also provides transferring the all obtained data to the computer environment (Brown, G.,2012). The obtained data were analyzed using random forest, decision tree, polynomial, extreme gradient boosting, linear and gradient boosting regression models. RMSE and R^2 score results were used for performance evaluation of the estimated regression models. According to the performance evaluation results, the best model was the decision tree regression model. Moreover, a specific human machine interface (HMI) has been designed through App-Designer (Valle, 2017).

The following sections are as follows; in the second section, the developed module, obtained data results and regression models are explained. In the third section, the estimation results of the data are compared using models. In the last section, the results are presented.

2. Material and Method

2.1. Developed Module

The developed module consists of 3 ARM-based microprocessors, 3 serially connected batteries, 1 relay, 1 current sensor, 3 temperature sensors, 3 non-inverting amplifier circuits, 7 USB-TTL modules and 1 computer (Fig.1). The primary microprocessor as master processor is connected to the relay circuit for controlling the charge and discharge processes of the ESS. The primary microprocessor receives the measured voltage, current and temperature variables values. The received these data is sent to the computer environment by using the USART protocol with the related module.
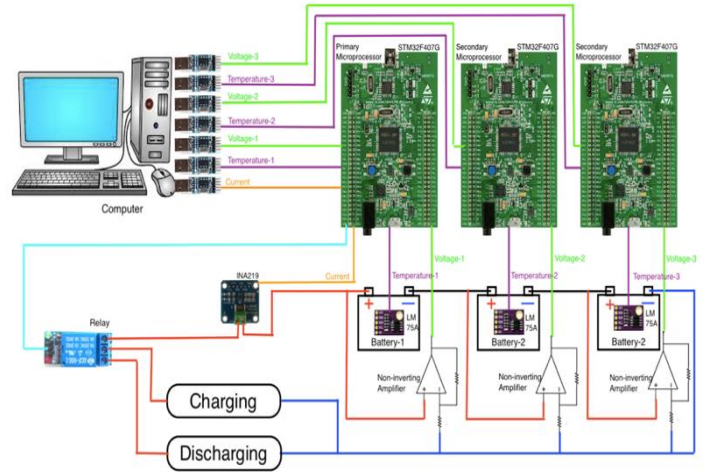

Figure 1. The developed module

The developed module is implemented in Fig.2 where INA219 current sensor is used with the I^2C communication protocol. The current value is determined as in the range of ± 3.2A with 1% accuracy (El Hadi, 2021). LM75A temperature sensor is used for the range of -55°C~125°C with an accuracy of ± 0.125°C (Stanimirescu, 2020). The voltages values are gathered with ADC ports and voltage scaling circuit implementing with non-inverting amplifiers for the 32bit ARM microcontroller (Brown, G.,2012). The flow chart of the developed system is given in Fig.3 where the voltage, current, and temperature values are obtained and they are sent to the computer environment. In Fig.4, the designed HMI displays SOH and SOC estimation results, along with graphs of data received from microprocessors (Valle, 2017).
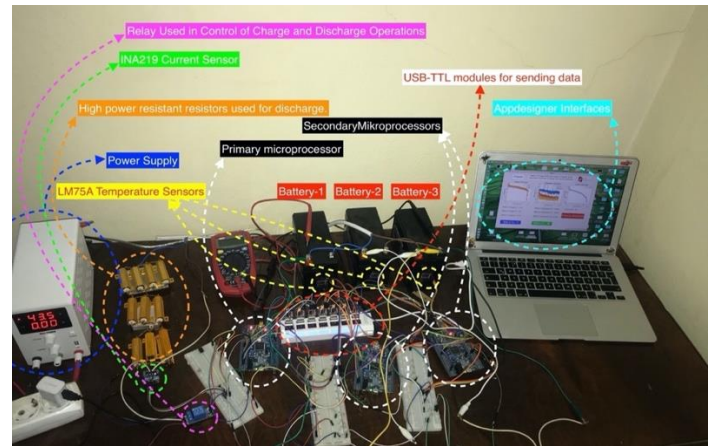

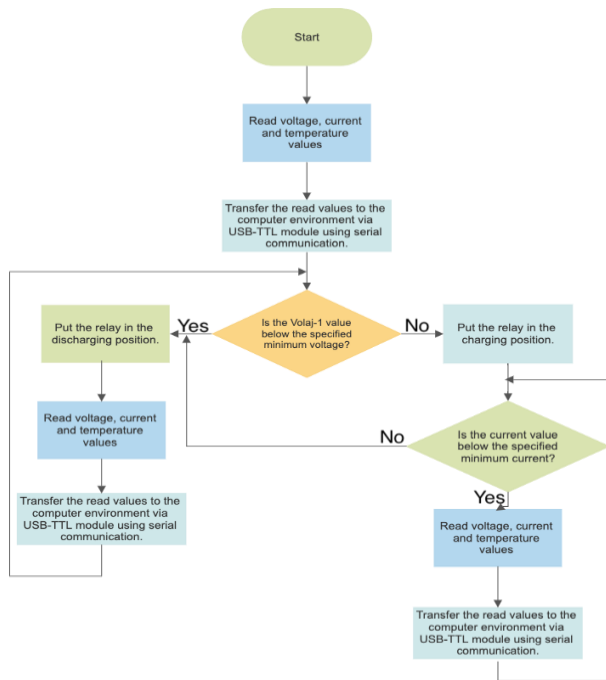Figure. 2. The implemented system overview
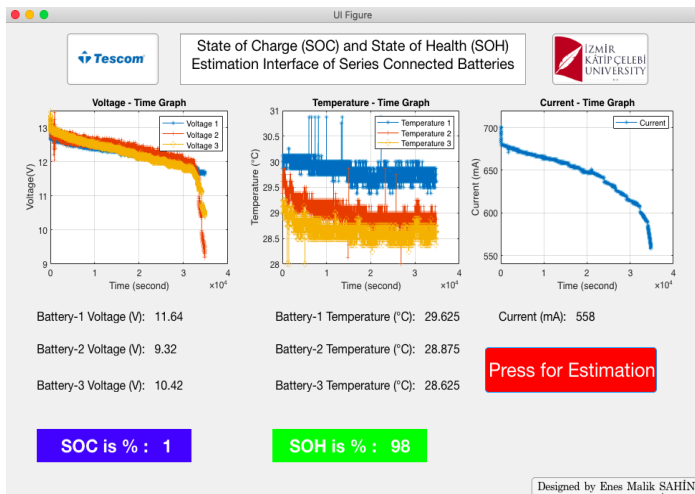
Figure 3. Flow chart of the algorithm

Figure 4. The designed HMI

(a)   (b)

(c)

Figure 5. Charge voltage for a)battery-1, b)battery-2, c)battery-3

(a)   (b)

(c)   (d)

Figure 6. During charging process a) battery-1temperature, b) battery-2 temperature, c) battery-3 temperature, d) current

After completing the experiments, the obtained charging voltage values of the ESS batteries are depicted in Fig.5. It is observed that the voltage value of each battery is approximately equal to each other during the charging period. In Fig.6, it is observed that the temperature values are presented during the charging period and their values are nearly same for each battery. According to the Fig.6d, the total current value of the system is observed as 700mA for 2800 seconds. After 3200 seconds, it might be assumed as discharging initial conditions, the voltage value of battery decreases faster than the other two batteries. This situation might be explained that the voltage value of the battery-1 is 11.51 volts, the voltage value of the battery-2 is 9.28 volts and the voltage value of the battery-3 is 10.47 volts (Fig.7). However, in Fig.8 during the discharge period, the temperature values are approximately the same as for each battery. According to Fig. 8d, the current value of the discharge period decreases according to the decrease in battery voltages since constant resistance is used.
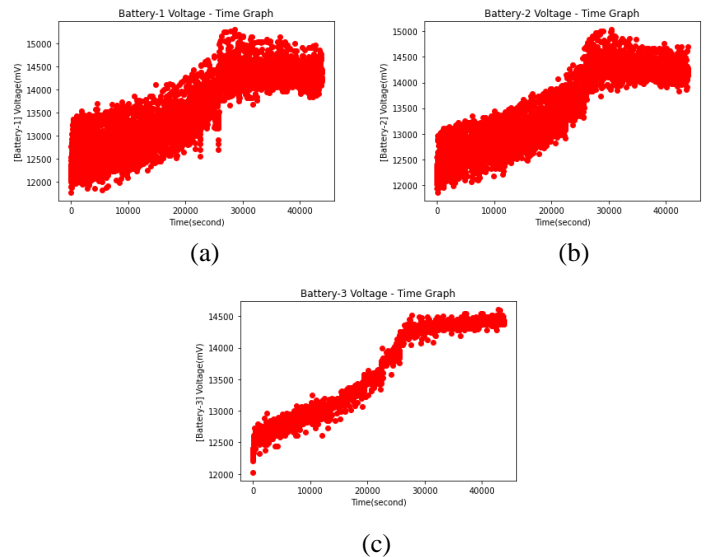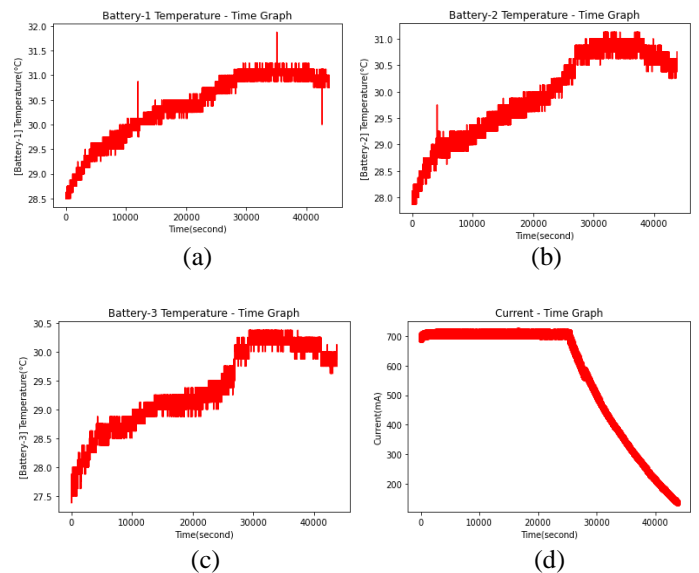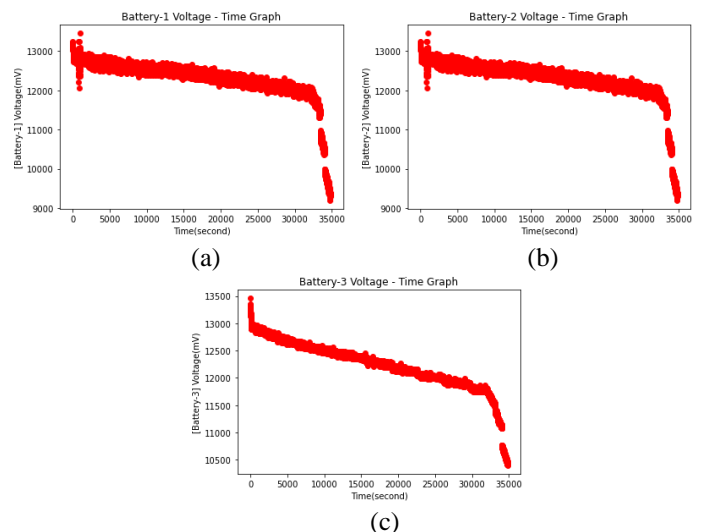

(a)   (b)

(c)

Figure 7. Discharge voltage for a) battery-1, b) battery-2, c) battery-3
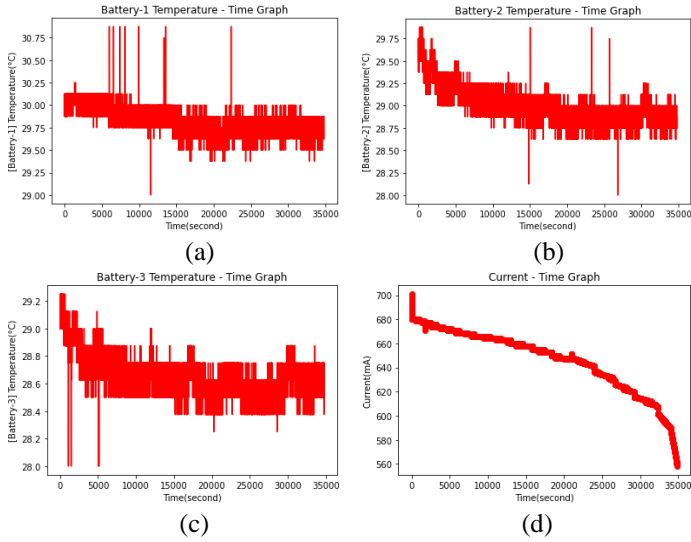
(a)

(b)

(c)

(d)

Figure 8. During discharge process a) battery-1temperature, b) battery-2 temperature, c) battery-3 temperature, d) current

2.2. Regression Models

Machine learning algorithms fall into two groups: supervised learning and unsupervised learning (Freedman, 2009). Regression models are in the supervised learning group and are used to predict the relationship between dependent and independent variables in a function. Regression model analysis provides both predicting and estimating of the variables (Mason, 1991). Random forest regression, decision tree regression, polynomial regression are some of the regression models. In this project, regression models are used to estimate SOC and SOH of series connected batteries.

3. Results and Discussion

The voltage, current and temperature values obtained from series connected batteries were used for regression models. SOC and SOH estimations were assessed with six different regression models. The regression models used in this study; random forest regression (Pal, 2005), decision tree regression, polynomial regression, linear Regression, extreme gradient boosting (XGB) Regression and Gradient Boosting Regression (Freedman, 2009). Using these regression models, the time variable during the charge and discharge application was estimated and SOC and SOH were estimated with this estimation. RMSE score and R^2 score were used to evaluate the regression models.

$$RMSE = \sqrt[2]{\frac{\sum_{i=1}^{n}(y_i-\dot{y})^2}{n}} \qquad (1)$$

$$R^2 = 1 - \left(\frac{\sum_{i=1}^{n}(y_i-\dot{y})^2}{\sum_{i=1}^{n}(y_i-\bar{\bar{y}})^2}\right) \qquad (2)$$

The y_i value in Equations (1) and (2) is the time variable, $\dot{y}$ is the predicted time variable, $\bar{\bar{y}}$ is the average of the time variable, and n is the number of data obtained.

3.1. SOC Estimation

SOC estimation was made by the total power value of the three batteries in order to find the regression models by these power values of the three batteries obtained during the discharge

(Fig.9) and charge (Fig.10) process. The error of the SOC estimation during charging was higher than the error of the SOC estimation during discharge. According to the RMSE score and R^2 score values in Table-1 and Table-2, decision tree regression is the most appropriate model.

Table 1. RMSE and R^2 score values of regression models for discharge.

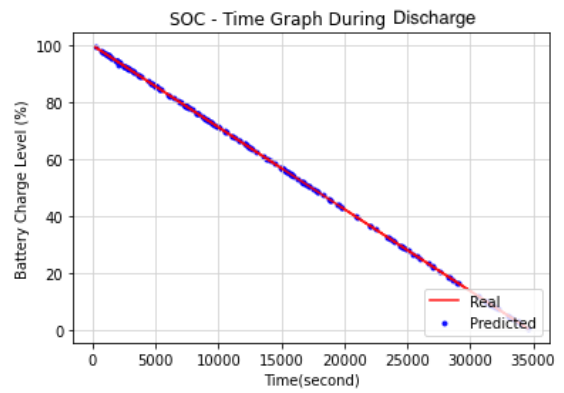| Regression Models	RMSE Score	R^2 Score
Random Forest Regression	388.9697	0.998529
Decision Tree Regression	27.9125	0.999992
Polinomial Regression	474.8788	0.997791
Linear Regression	2980.0720	0.913029
XGB Regression	732.6739	0.994730
Gradient Boosting Regression	708.3919	0.995120

Figure 9. SOC during discharge.

Table 2. RMSE and R^2 score values of regression models for charge

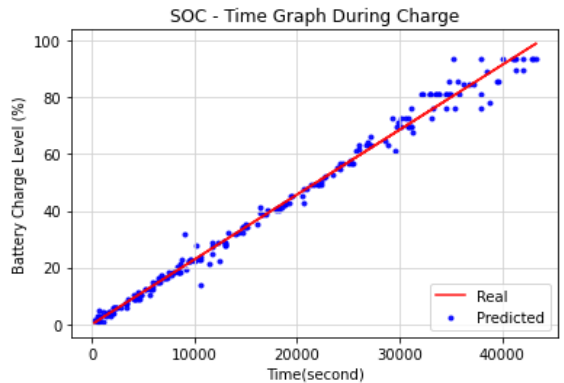| Regression Models	RMSE Score	R^2 Score
Random Forest Regression	1367.8962	0.988368
Decision Tree Regression	1332.2522	0.988972
Polinomial Regression	1598.9724	0.984234
Linear Regression	2619.0182	0.957703
XGB Regression	1379.6596	0.988581
Gradient Boosting Regression	1356.5291	0.988603

Figure 10. SOC during charge.

3.2. SOH Estimation

SOH estimate was calculated using the time dependent change of the SOC estimate for both charge (3) and discharge (4) in the following equations;

$$SOH(\%) = \left(\frac{time_{SOC(initial\ predicted)} - time_{SOC(final\ real)}}{time_{SOC(initial\ predicted)} - time_{SOC(final\ predicted)}} \right) x100 \quad (3)$$

$$SOH(\%) = \left(\frac{time_{SOC(final\ real)} - time_{SOC(initial\ predicted)}}{time_{SOC(final\ predicted)} - time_{SOC(initial\ predicted)}} \right) x100 \quad (4)$$

where $time_{SOC(initial\ predicted)}$ is time(second) of the first predicted SOC value based on the values taken, $time_{SOC(final\ real)}$ is time(second) of the last SOC value calculated based on instant data, and $time_{SOC(final\ predicted)}$ represents the time(second) value of the instantaneous SOC value on the predicted SOC-Time graph for the first charge / discharge period. SOH estimation results for charge and discharge in the first experiment are given in Fig.11 and Fig.12. Minimum time of 20000 seconds is required to calculate the SOH estimate with a minimum error of 5% during the charging process. By using the developed system, 6 charge and discharge experiments have been carried out. The average SOH results calculated as a result of the experiment are given in Table 3.
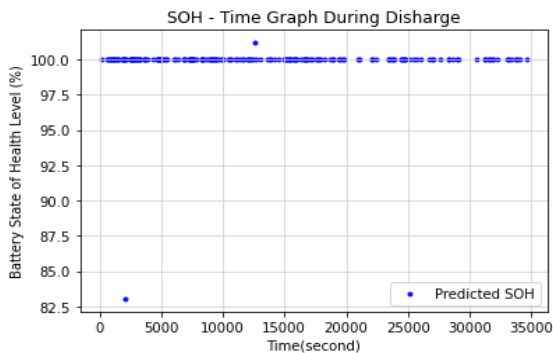

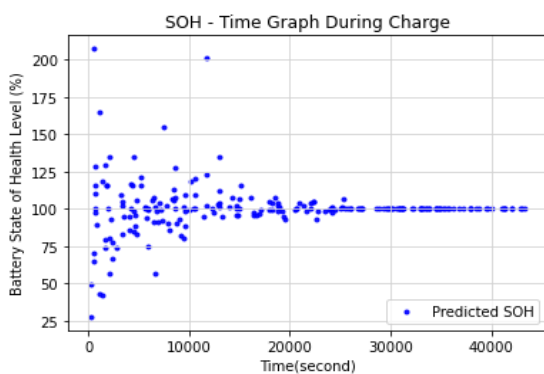
Figure 11. SOH - time graph while discharge

Figure 12. SOH - time graph while charge

Table 3. Average SOH results calculated in charge and discharge experiments

Average SOH Estimation	Exp.1	Exp.2	Exp.3	Exp.4	Exp.5	Exp.6
For Charge	99.9	100.0	99.9	99.8	100.0	99.7
For Disharge	100.3	100.7	100.2	99.1	99.9	100.2

In addition, Equation 5 is used to learn how long after the discharge period will be completed. The SOC and SOH values in this equation are the values estimated instantaneously using the regression model. The $time(second)_{(when\ SOH=\%100)}$ value represents the first discharge time, that is the time calculated when the SOH value is 100% (in this study, the $time(second)_{(when\ SOH=\%100)}$ value was calculated as 34800 seconds).

$$Discharge\ Completion\ Time(second) =$$

$$\frac{SOC}{100} x \frac{SOH}{100} x time(second)_{(when\ SOH=\%100)} \quad (5)$$

4. Conclusions and Recommendations

This study was developed for ECC application where serially connected battery sets are used to ensure the long life of these batteries by using SOC and SOH values during charge and discharge periods. The obtained regression models were made of the voltage, current and temperature measurements. The regression model performances for the SOC estimation were determined by RMSE and R^2 score values, and the decision tree regression model provided the best result.

5. Acknowledge

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