International Journal of Academic Engineering Research (IJAER)
ISSN: 2643-9085
Vol. 8 Issue 1 January - 2024, Pages: 1-5

Battery Management System Design with Charge Estimation Algorithm

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Abstract: *The use of fossil fuels, which is one of the causes of global warming, is one of the important problems that humanity deals with due to increasing costs, decreasing resources and other damage to the environment. As a solution to this, interest in electric vehicles (EV) is increasing day by day due to their many benefits in terms of being environmentally friendly, economical and renewable. A lot of research is still being done on EVs. This study presents an analysis on battery health (SOH) and charge (SOC) states, which are one of the most important problems of electric vehicles, and prediction algorithms with machine learning. A comparison was made with the data set prepared in the simulation environment, with the tests in machine learning algorithms and the tests in the literature. The analysis aims to contribute to the development of battery health and charge estimation methods.*

Keywords—Machine learning; SOH; SOC; Regression; Electric Vehicles.

1. INTRODUCTION

Today, there are many scientific studies on the production, use and efficiency of energy obtained from various sources [1-8]. Especially developments in the fields of power electronics and control systems have significantly increased the use of power converters in electric vehicles [9-21].

Many current studies in the field of EA are published in academic literature. In this context, when looking at the studies carried out in the field, there is a lot of information about the types of electric vehicles, charging systems and converters. Charging technologies in hybrid electric vehicles are also becoming widespread [22]. The emphasis is on mechanical powertrains, electric motors, motor drive systems, batteries and charging systems of electric vehicles. In general, charging station standards are new regulations being studied on charging systems [23]. Some studies have also been conducted on the integration of electric vehicles with the smart grid.

The effects of electric vehicle charging stations on the energy distribution network and load flow analysis are also topics worth studying. A comparison of power factor corrected converters used in electric vehicle charging circuits was made, and research was conducted on the efficiency of the intermittent booster type power factor corrected converter compared to the traditional method [24]. Electric vehicle charging station designs based on a multi-port converter that provide features such as power balancing and voltage drop compensation have been studied [25]. Photovoltaic-based smart charging system designs that feature energy flow from the vehicle to the grid using the EV battery storage system have been studied.In another study, a single-ended primary inductor dc-dc converter at the photovoltaic system output, a bidirectional dc-dc converter for EV charging, and a three-level inverter with LCL filter for grid connection and interface were used and the potential of vehicle-to-grid power transfer to increase the fault-riding ability of the distribution grid was used. has been examined [26].

One of the most important research on electric vehicles is battery analysis. Long-range vehicles are produced with the state of health (SOH) and charge estimates (SOC) of the batteries. Increasing battery reliability through longer and regular data collection is important in strengthening battery predictions [27]. In the first stage of the framework in data collection, properties are obtained by analyzing the change patterns of informative parameters such as voltage, capacity, temperature and IR during charge-discharge processes. In this way, SOH and SOC prediction algorithms are expected to work with battery data used in different areas [28]. In current studies, the SOH estimation approach of the battery is recommended by using the sampling entropy feature of the discharge voltage [29]. It can be used as a battery SOH indicator by using algorithms to calculate the predictability of a time series and measure the regularity of a data set. Two ML algorithms are developed, support vector machine (SVM) and corresponding vector machine (RVM), where time series is the input and SOH is the target vector that needs to be predicted. Both SVM and RVM were found to perform well in terms of SOH prediction. In one study, four regression methods were used to estimate SOH and SOC and the results were analyzed. These are auxiliary vector machine (SVM), random forest regression (ROR), K-nearest neighbor (KNN) and decision tree regression (KAR) methods.

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2. Battery Prediction Algorithm With Machine Learning

Battery charge status estimation; It is important in many applications involving batteries, including electric vehicles, renewable energy systems and portable electronic devices. Charge status is the instantaneous capacity of the battery, rated It is calculated by its ratio to its capacity [30]. Rated capacity values in ampere-hours (Ah) are stated in the data sheets of the batteries. In equation number 1, instantaneous capacity value is defined as $Q(t)$ and rated capacity value is defined as C_n. Predicting battery status is a very important method used to predict the energy levels of batteries in the future. These predictions are used to optimize the usage time and performance of batteries, to improve energy management and to provide safe information to the user, and to improve usage by taking into account the user experience. Therefore, battery prediction algorithms are being developed to produce accurate and reliable predictions, and research continues in this field.

$$SoC(t) = \frac{Q(t)}{C_n} \quad (1)$$

The state of charge of lithium-ion batteries is a quantity that cannot be measured directly. It also has a non-linear relationship with parameters such as voltage, current and temperature. This creates difficulties in the applicability of lithium-ion batteries. Unless this difficulty caused by its chemical structure is overcome, battery failures and capacity losses are inevitable in applications. Check that the remaining capacity in the batteries is correct.

Predictability protects the battery, prevents over-discharge and extends battery life allows it to extend. In addition, smart control by saving energy and power allows the creation of a strategy. Therefore, the charging status is correct. Estimation is an important output of the battery management system. The most well-known of the widely used charge state estimation methods are; open circuit voltage method, load counting method, model-based filtering algorithms are listed as. Additionally, by combining several methods, the accuracy of charge state estimation can be improved. [31].

The main purpose of battery prediction algorithms is to predict future energy levels based on the current state of the battery. These predictions are made by taking into account the charge and discharge change rates of the battery. It also uses special algorithms that analyze real-time data. These algorithms model the battery's behavior based on historical data and use statistical and machine learning techniques to predict future energy levels. The development of battery prediction algorithms involves a number of challenges and factors. These include factors such as the characteristics of the battery, environmental factors, usage patterns and even the aging process of the battery. Therefore, in battery estimation studies, it is important to produce reliable and precise estimates by using correct data collection and modeling techniques. All machine learning algorithms used in this study were implemented using the Matlab/Simulink environment. The algorithm scheme used is given in Figure 1.

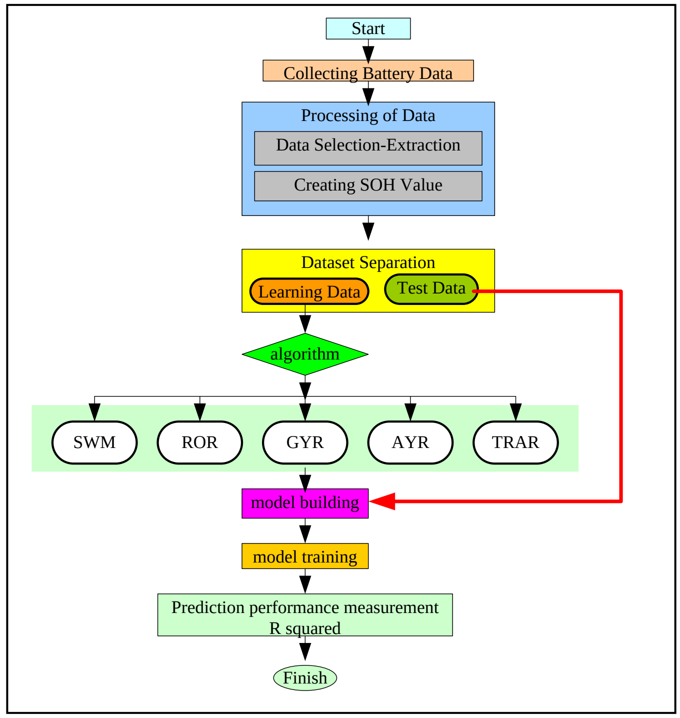

Fig. 1. *Algorithm*

2.1 Parameter Estimation and SoC-OCV Mathematical Equation

In this study, C/30 discharge test data was used for the mathematical equation of charge state - open circuit voltage. Open circuit voltages matching each charge value gradually decreasing by 20% in the test data. Charge state - open circuit voltage mathematical equation transferred to the MATLAB environment has been found. Table 1 shows the open circuit voltages of the battery cell at the relevant state of charge.

Table 1: Charge state-open circuit voltage values

SoC (%)	OCV (V)
99	4,205
79	4,015
59	3,902
39	3,710
19	3,525
0	3,102

Charge status - open circuit voltage in MATLAB environment with recorded test data curve is given in Figure 2.

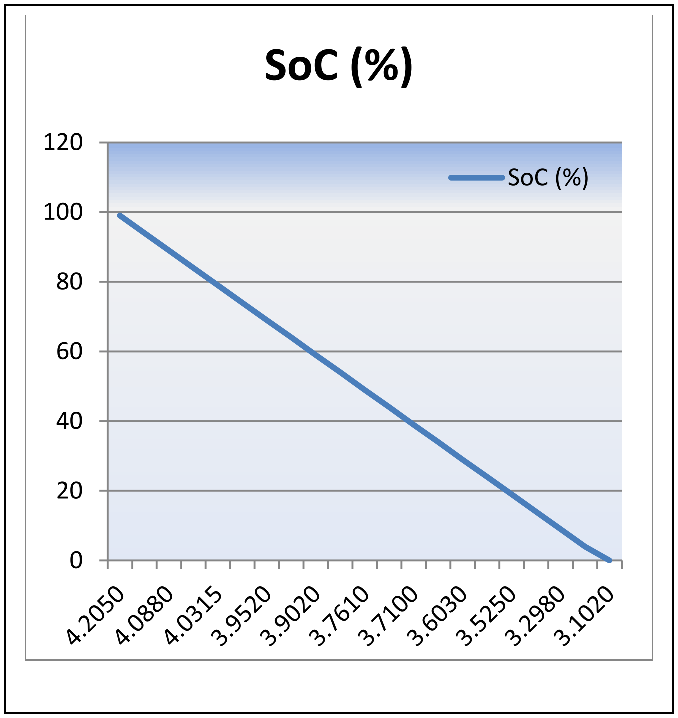

Fig. 2. *State of charge - open circuit curve)*

Python curve fitting for calculating equivalent circuit model parameters library was used. All charging states using HPPC test data for the effect of the rest period on the terminal voltage, equations 2-3 were used. In the equation 3 second-order and first-order Thevenin equivalent circuit model parameters has been calculated.

$$U_T = U_{OC} - \sum_{i=0} U_i - \Delta I_b R_0 \quad (2)$$

$$\Delta U_{last-(last-1)} = U_i = \Delta I_b \sum_{i=0} R_i(\,1 - e^{t/\tau_i}) \quad (3)$$

Using HPPC test data, second-order and first-order Thevenin equivalent circuit model parameters were calculated for all charge states, using equation 3 for the effect of the rest period on the terminal voltage.

While calculating parameters in the software, equation 4 is converted into first order Thevenin equivalent.

The coefficients shown in Figure 3 were calculated by updating equation 5 for the circuit model and equation 6 for the second-order Thevenin equivalent circuit model. It is observed in Figure 3 that the second-order equivalent circuit model converges to the measurement values with higher performance than the first-order equivalent circuit model.

$$\Delta U_{RC2} = \mathrm{a}(1 - e^{-t/b}) \quad (4)$$

$$\Delta U_{RC2} = \mathrm{a}\left(1 - e^{-t/b}\right) + \mathrm{c}(1 - e^{-t/d})$$
(5)

$$C_1 = \frac{a}{\Delta}\mathrm{a}\left(1 - e^{-t/b}\right) + \mathrm{c}(1 - e^{-t/d})$$
(6)

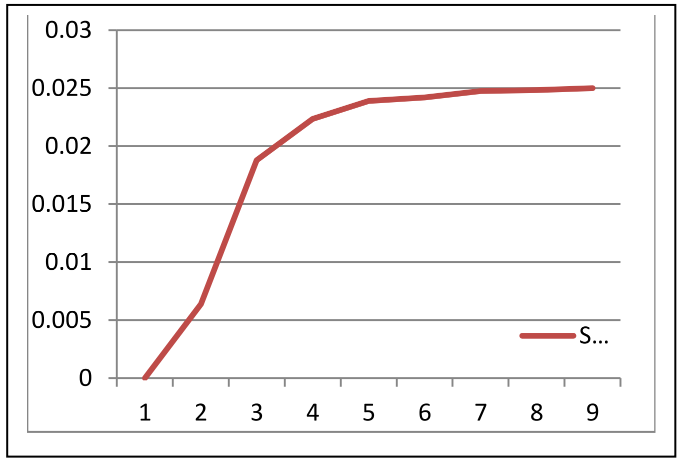

Fig. 3. *Terminal voltage convergence curves*

In Equation 7, $C0$ represents the initial capacity of the battery, while CT represents the current capacity of the battery.

$$RMSE = \sqrt{(\frac{1}{n}\sum\left(y_{prediction} - y_{real}\right)^2)}$$
(7)

Therefore, it is defined as the ratio of the current capacity of the battery to its initial capacity. This formula is a commonly used metric to evaluate the health of a battery. If the SOH value is close to 1, this indicates that the battery is healthy and maintains its full capacity. However, if the SOH value is lower than 1, it means the health of the battery has decreased and its capacity has decreased. Using Equation 7, SOH values are obtained in the battery data. According to this datas, it is possible to examine the effects of each battery data on each other. According to the heat datas, it can be said that the SOH data is 'time' dependent and also has a high relationship in the reverse direction. The ratio of 0.97 indicates that the more 'time' increases, the more the battery's health will decrease.

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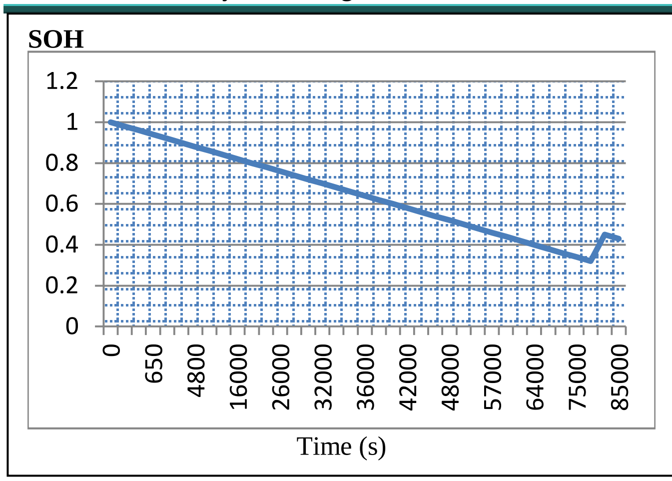

Fig. 4. *Battery Health Graph*

3. Results

In this study, the historical development of electric vehicles, their classification, converter structures used in charging systems, charging standards, electric motor types, battery types and charging technologies used, as well as battery health status and charge status estimation were examined. The production and use of electric vehicles is increasing rapidly. However, with this increase, the services and infrastructure required by Electric Vehicles must also be taken into consideration. It is important to increase the number of EV charging stations and ensure energy efficiency with smart charging systems. Thus, more options can be offered for electric vehicles and more use can be made of renewable energy sources.

Electric vehicles attract attention for reasons such as having a better and more economical mileage cost compared to internal combustion engine vehicles, reduced or no emissions and greenhouse gas emissions, superior performance features, low maintenance costs and energy security. However, some problems such as the high cost of electric vehicles, the lack of widespread use of charging stations, long charging times and limited ranges are also the subject of research.

In this study, a data set was used to test machine learning algorithms on values such as battery temperature, capacity, voltage and current with a large number of battery data. According to the test results, the algorithm for battery SOH predictions was determined as the decision tree regression method. At the same time, regression methods are among the other high-performance algorithms. In other learning algorithms, different results can be obtained with detailed data. It can be evaluated that the results of this study will help to use batteries more effectively and manage energy resources more efficiently. It will also form the basis for further studies on the development of optimized algorithms to increase the reliability and accuracy levels of battery prediction models.

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