

Article

Lithium-Ion Battery State-of-Charge Estimation from the Voltage Discharge Profile Using Gradient Vector and Support Vector Machine

Erwin Sutanto ^{1,*}, Putu Eka Astawa ², Fahmi Fahmi ³, Muhammad Imran Hamid ⁴, Muhammad Yazid ⁵, Wervyan Shalannanda ⁶ and Muhammad Aziz ⁷

¹ Department of Physics, Faculty of Science and Technology, Universitas Airlangga, Kampus C Unair Mulyorejo, Surabaya 60115, Indonesia

² East Java Distribution, Perusahaan Listrik Negara, Surabaya 60271, Indonesia

³ Department of Electrical Engineering, Faculty of Engineering, Universitas Sumatera Utara, Medan 20155, Indonesia

⁴ Department of Electrical Engineering, Universitas Andalas, Padang 25163, Indonesia

⁵ Biomedical Engineering Department, Institut Teknologi Sepuluh Nopember, Surabaya 60111, Indonesia

⁶ School of Electrical Engineering and Informatics, Bandung Institute of Technology, Bandung 40132, Indonesia

⁷ Institute of Industrial Science, The University of Tokyo, Tokyo 153-8550, Japan

* Correspondence: erwin_sutanto@fst.unair.ac.id

Abstract: The battery monitoring system (BMoS) is crucial to monitor the condition of the battery in supplying and absorbing the energy when operating and simultaneously determine the optimal limits for achieving long battery life. All of this can be done by measuring the battery parameters and increasing the state of charge (SoC) and the state of health (SoH) of the battery. The battery dataset from NASA is used for evaluation. In this work, the gradient vector is employed to obtain the trend of the energy supply pattern from the battery. In addition, a support vector machine (SVM) is adopted for an accurate battery accuracy index. This is in line with the use of polynomial regression; hence, points V1 and V2 are obtained as the boundaries of the normal-usage phase. Furthermore, testing of the time length distribution is also carried out on the length of time the battery was successfully extracted from the classification. All these stages can be used to calculate the rate of battery degradation during use so that this strategy can be applied in real situations by continuously comparing values. In this case, using the voltage gradient, SVM method, and the suggested polynomial regression, MAPE (%), MAE, and RMSE can be obtained against the battery value graph with values of 0.3%, 0.0106, and 0.0136, respectively. With this error value, the dynamics of the SoC value of the battery can be obtained, and the SoH problem can be resolved with a shorter usage time by avoiding the voltage-drop phase.

Keywords: battery monitoring system; gradient vector; support vector machine; electric vehicles; affordable and clean energy; responsible consumption and production



Citation: Sutanto, E.; Astawa, P.E.; Fahmi, F.; Hamid, M.I.; Yazid, M.; Shalannanda, W.; Aziz, M.

Lithium-Ion Battery State-of-Charge Estimation from the Voltage Discharge Profile Using Gradient Vector and Support Vector Machine. *Energies* **2023**, *16*, 1083. <https://doi.org/10.3390/en16031083>

Academic Editor: Xianke Lin

Received: 4 December 2022

Revised: 10 January 2023

Accepted: 14 January 2023

Published: 18 January 2023



Copyright: © 2023 by the authors. Licensee MDPI, Basel, Switzerland. This article is an open access article distributed under the terms and conditions of the Creative Commons Attribution (CC BY) license (<https://creativecommons.org/licenses/by/4.0/>).

1. Introduction

The number of electric vehicles (EVs) is significantly increasing [1], and there is an urgent need to monitor the remaining charge from the battery in real time and online. It does not only collect the data, send it remotely, store it in the database, and display the results via the website or mobile applications, but also analyzes the capabilities of the battery, plans a charging or replacement schedule, and evaluates its quality. A battery monitoring system (BMoS) also depends on how the prediction method is performed. The hardware is used to collect data from the vehicle, and simultaneously, it sends it to the server [2]. Moreover, the applications are developed to display the analysis results that may be useful to users. The main focus of this work is on the method of analyzing the condition of lithium-ion batteries to predict their remaining usage time. The importance of

this calculation can be seen from the amount of interest in battery EVs. EV has attracted a lot of interest because of its advantages in terms of driving efficiency and environmental friendliness. However, it is important to know accurately the remaining driving range (RDR). Incorrect estimation of energy stored in the battery can cause the battery to run out its stored energy before the vehicle arrives at its destination and leaves passengers in a precarious situation [3]. Therefore, to increase the passenger's confidence in EVs, the accuracy of RDR estimation is very important [4].

To make EVs to be highly efficient, battery life calculations and prediction are critical. Damage to the battery is also one of the most important variables to be monitored and analyzed when using the battery. Therefore, extending battery life is desirable considering the nature of the battery itself from damage. From a safety point of view, battery damage must be taken into account to avoid explosions or even fatalities [5]. Battery health must be ensured precisely because state of health (SoH) estimation is crucial for user safety and decision-making on when to cut off the battery. Moreover, batteries function by electrochemical reactions and lose capacity over time due to continuous charging and use. As the battery ages, the active ingredients that control the output power and capacity of the battery decrease due to chemical reactions that cause a decrease in performance [6]. Lithium-ion batteries are healthier if their SoH value is higher. It is generally accepted that the battery needs to be replaced when the battery capacity has reached 70–80% of its initial capacity, as this indicates that the end of life (EoL) of the battery has been reached.

SoH is often estimated using designed estimation methods because the devices cannot measure it directly. Model-based and data-driven methods are two main categories of currently available estimation techniques [7]. Remaining useful life (RUL) is also an essential parameter for scheduling the repairs, assessing the battery health, improving the safety, and reducing the accidents by giving an alarm before it reaches a critical level [8]. Accurate RUL estimation is vital for the safety and reliability of lithium-ion battery use because it can provide early warning of the failure of the battery's intended performance [9–11]. This precise prediction model is able to read the degradation trend of the battery to estimate the SoH value. RUL is the remaining service time or battery life at a certain operating point before the capacity reaches an unwanted level [12]. The number of remaining charge and discharge cycles of a battery can be estimated by RUL [13].

If the RDR exceeds the estimated distance and time limit, the battery remaining discharge capacity (Q_{RDC}) rating is the amount of battery capacity. Most of the studies on (Q_{RDC}) estimation have focused on predicting the amount of remaining discharge time under a certain usage profile, for example, in constant current (CC) mode [14]. State of charge (SoC) is determined as the basis of conventional Q_{RDC} estimation methods, and variations in discharge conditions can impact the accuracy of the estimation [4]. If battery health was determined previously by SoH, the amount of battery capacity at the time of use can be estimated by SoC. For SoC estimation of lithium-ion batteries, a number of methods have been suggested, including the use of model-based [15] and directly from the parameters of the battery regardless of the battery model (e.g., using fuzzy logic [16]). The ability to provide a relatively fixed SoC is a major goal in battery management. Most studies provide electrochemical models of lithium-ion batteries and how the average SoC can be estimated [17]. SoC also often refers to a battery's capacity to charge at a certain point during operation, which is often expressed as a percentage value. SoC also cannot be measured directly due to the lithium-ion battery model's structure and its electrochemical's dynamics. Consequently, its value must be calculated through indirect measurements, such as voltage, current, and temperature [18].

This study uses a battery data set from NASA's Prognostic Center of Excellence (PCOE). BAT0005 was selected for several initial trials due to its wide use in both industry and academia [19]. This research aims to develop a method for estimating SoC per battery condition using voltage as the most common parameter. Thus, the remaining battery usage

can also be predicted. Then, by knowing the profile of the battery SoC, the cut-off voltage of the battery can also be determined; hence, the SoH of the battery can be guaranteed. For this reason, the voltage discharge profile from the NASA data set, which shows the profile of the battery parameters when they are being used, was used. As a comparison, several methods of using the data set in previous works [7,13,19,20] were also considered.

To calculate SoC, this study proposes the use of a gradient vector according to the characteristics of the battery usage profile. The support vector machine (SVM) can then be used to predict the various phases of the lithium-ion battery profile by integrating with polynomial regression using machine learning as used for SoH and RUL, as adopted in [21,22]. This method is useful for building the BMoS required for EVs. The proposed approach is applied to the real-life cycle dataset of lithium-ion batteries from NASA. The experimental results demonstrated the effectiveness of SoC calculations and the superiority of the remaining usage time estimation approach, which is useful for estimating the RDR. With the various findings obtained from this method, system efficiency increases; hence, the costs and energy consumption become more efficient. Consistently, there are adjustments in battery use so that responsible consumption from battery and energy production can be achieved properly by limiting battery usage when a certain phase has been reached.

The organization of this paper is structured as follows; Section 2 explains the methods and data sets used in the study, such as the SoC estimation process, battery data set, SVM, and battery modeling. Section 3 presents the findings obtained in the form of discharge profile characteristics, gradient vectors, and time estimation. From the results obtained, comparisons were made with the results of other studies using the NASA data set described in Section 4. Finally, Section 5 concludes the work.

2. Methods

An excellent BMoS is urgently needed to be designed with a framework as an internal control of the charging and discharging of the battery so that it can extend the life of the battery. The battery is an energy storage medium that can be monitored with several parameters, such as SoC and SoH, which provide estimation values that are easier to understand from the condition of the battery. Methodologies, such as SVM, used in realizing this BMoS are discussed. The battery data set from NASA [23] used will also be clarified.

2.1. SoC Estimation Process

The proposed SoC measurement method experiment for this BMoS is depicted in Figure 1. This framework approaches the analysis and prediction of the battery when it is implemented. The battery data passes through the analysis block simultaneously; hence, the prediction and analysis can be conducted in real time manner.

Then, when the system has some changes in operational parameters, such as voltage (V), current (I), and temperature (T), the condition of the charge capacity in the battery associated with the SoC is estimated by following Equation (1).

$$SoC = \frac{E_{Left}}{E_{Nominal}} \simeq \frac{Q_{Left}}{Q_{Nominal}} \quad (1)$$

SoC is a percentage that represents the battery status, with 100% indicating a fully-charged battery and 0% indicating a fully-depleted battery. Meanwhile, E_{Left} is the energy remaining at the time of measurement and $E_{Nominal}$ is the nominal energy amount of the battery when it is in new condition. Then, Q_{Left} is the remaining charge capacity and $Q_{Nominal}$ is the nominal charge capacity stated in the battery specifications. Apart from the SoC, the characteristic profile of the battery can be indicated by three different parameters: the capacity (Q), the nominal voltage (V_{nom}), and the rated maximum voltage (V_{max}). From a fully-charged state to a fully-depleted state, the battery can supply a load with a maximum charge (Q). Although the charge is represented by the letter Q, amp-hours (Ah) is more often used for measurement than Coulombs. V_{max} is

the maximum voltage that can be generated when the battery is fully charged, while V_{nom} is the average voltage when the battery is discharged with a constant current from a fully-charged state to a fully-depleted state [24]. With these four parameters, it is possible to observe how the discharge profile of the battery can be divided into several phases. However, this study had only proof of its potential usage with the variance of a single cell from the same model but not as a battery pack. Meanwhile, practically an EV comes only with a battery pack in order to reach a certain voltage level. To reach the required higher voltage level, it is common to design the cells to be connected in series.

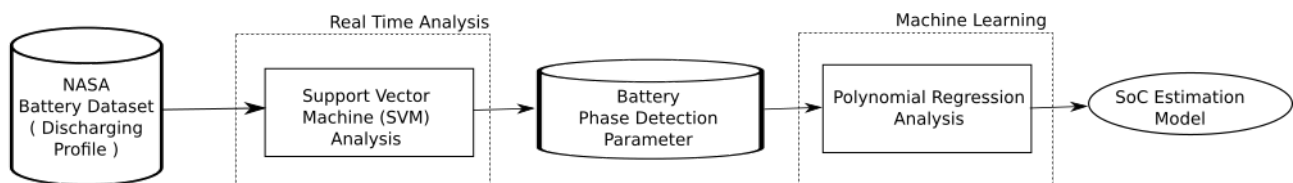


Figure 1. Experiment Setup.

2.2. Four Individual Lithium Battery Data Set

Lithium-ion batteries should not be assumed to be in the same conditions they behave in general in terms of material. The BMoS needs to check the battery pack voltage effectively and perform an occasional cut-off when the cells are suddenly at their limits so that the cells in the battery pack are not fully depleted [25]. When the battery cells are connected back to the load, and each battery is balanced to be reconnected, the control of the battery, including cut-off voltage, depends on the measurement parameters of the battery. This condition can be seen in four different batteries from the NASA battery data set, as shown in Figure 2.

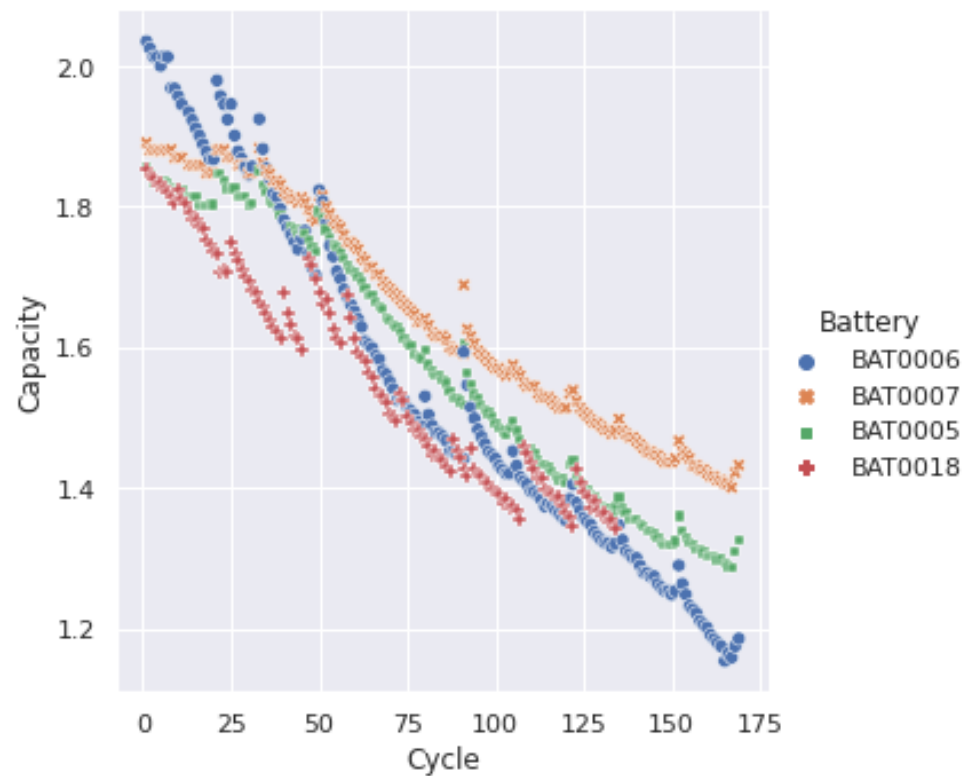


Figure 2. Different capacity behaviour from the same battery model.

The four batteries in Figure 2 come from the same battery model. Also, it goes through the charge and discharge processes which are almost similar to the NASA Prognostics Center of Excellence Data Repository. However, in the testing process, it turns out that the

capacity of each battery is different. Batteries BAT0006 have the greatest storage power in fresh conditions, but they experience the greatest degradation in the next cycles. Meanwhile, the BAT0007 battery is in the second place at the beginning and able to maintain its position until the end with the highest power capability. Batteries BAT0005 and BAT0018 have the same value in the initial conditions but also experience different capabilities in the next charge/discharge cycles. The general parameters of lithium-ion batteries are listed in Table 1.

Table 1. Battery parameter.

Parameter	Value	Unit
Nominal Capacity	2	Ah
EoL Capacity	1.4	Ah
Charging (CC) Constant Current	1.5	A
Charging (CC) Voltage Limit	4.2	V
Charging (CV) Current Limit	20	mA
Discharging (CC) Nominal Current	2	A
Discharging Cut-Off	2.2–2.7	V

Table 1 lists general parameters of the battery testing process carried out in this study. The four lithium-ion batteries (BAT0005, BAT0006, BAT0007 and BAT0018) undergo three characterization processes. The first stage is battery charge. This is done at the first time with constant current (CC) mode with a value of 1.5 A until the battery voltage reaches 4.2 V. Next, the process is continued in constant voltage (CV) mode until the supply current drops to 20 mA. The second stage is loading (discharge). At this stage, the battery is loaded with the constant current (CC) mode with the same value of 2 A until the battery voltage falls to 2.2–2.7 V. This is considered normal considering that the possible maximum capacity from the battery, as defined in Table 1 as nominal capacity, is 2 Ah. In addition, it is also commonly used to see the conformity of each battery treatment as it would be conducted in many cycles. The charge/discharge processes are repeated until the battery reaches its end-of-life (EoL), where about 30% of its power is lost (1.4 Ah). This data set can be used to predict the remaining battery charge with the existing discharge cycle and also the RUL. Batteries need to be adjusted to the condition of whether the battery cells are in a state of exhaustion and this certainly cannot be deceived by the indicated Ah potential value. The dynamic adjustment of the cell is accomplished by giving the time to the battery to readjust under less loading conditions to return it to its Ah equivalent value under charging conditions. Lithium-cell batteries may be of interest in some high power applications with very large charging capabilities. On the other hand, it is also followed by temperatures that become too hot, which have the potential to reduce battery capabilities and cause some negative issues, such as explosion and fire [5].

First, in considering the battery profile, the battery also needs to be estimated in terms of how long the battery will run out and when it needs to be recharged. Battery charge and discharge currents are often expressed in terms of C-rate rather than the current (I), which is discussed below.

$$C_r = \frac{I}{n} \sum_{i=1}^n \frac{1}{E_r} \quad (2)$$

With each sampling i , C_r is the C-rate of the battery, I is the charge/discharge current of the battery in Amps and E_r is the rated energy of the battery, and n is the total number of sampling points. The pace of time in which the battery charges or discharges energy determines its C-rate value. The C-rate can be increased or decreased as it will affect how long it takes the battery to charge and discharge. As an example of a change from C-rate, it can be seen by changing the following numbers; 1C is equivalent to one hour, 0.5 C to 120 min and 2 C rating is equivalent to 30 min.

2.3. Support Vector Machine

This research uses two techniques to measure SoC. First, by using a statistical-based method using the SVM as in battery application in [21,22]. The second is to use optimization based on linear regression as shown in Figure 1.

$$v \in \mathbb{R}^D \quad (3)$$

$$\phi : \mathbb{R}^D \rightarrow \mathbb{R}^M, \phi(v) \in \mathbb{R}^D \quad (4)$$

The clustering method is applied by mapping the battery voltage data (v) from the discharge profile of the battery to the $\mathbb{R}^D$ coordinate system in the time domain with a gradient function. By using $\phi(v)$, the phase categories of the batteries are grouped, which is discussed later. The SVM is used in the first process, where, based on the value, it will be grouped into the simplest division with the target of the normal usage phase of the battery.

$$\mathcal{H} : w^\top \phi(v) + c = 0 \quad (5)$$

The above equation will be the limit of the phase division of the processed data. The $w^\top$ matrix is a load array to determine whether the gradient enters the normal usage phase. Meanwhile, c is a constant value from the support equation above. Then, we also obtain the d_H distance value using Equation (6).

$$d_H(\phi(v)) = \frac{w^\top \phi(v) + c}{\|w\|^2} \quad (6)$$

The greater the distance between this dividing line and the data in each divided phase, the value will correspond to Equation (5). The distance will either be negative ($d_H < 0$) or positive ($d_H > 0$) or it will lie on the line ($d_H = 0$); a separation line L can be defined using polynomial kernel K at Equation (7).

$$K(\phi, \phi') = (1 + \phi(v)^\top \phi'(v))^2 \quad (7)$$

Basically, by determining the support vector of the boundary line, each datum will enter a certain cluster according to the value of each point. Ideal conditions at a certain stress limit can be obtained by finding a value by determining the loading w^* that follows this condition:

$$w^* = \underset{w}{\operatorname{argmax}} \left[\min_n (d_H(\phi(v_n))) \right] \quad (8)$$

The solution is to replace Equation (6) with Equation (8) above. The above solution can only be used for ideal conditions assuming there is no intersection between each successive phase.

$$w^* = \underset{w}{\operatorname{argmax}} \left[\min_n \frac{p_n [w^\top \phi(v_n) + c]}{\|w\|^2} \right] \quad (9)$$

where p_n is the output of Equation (5). Optimization of determining the best limit of the real system can be obtained by simplifying it to Equation (10).

$$w^* = \underset{w}{\operatorname{argmax}} \frac{1}{\|w\|^2} \quad (10)$$

$$s.t. : \min_n \left(p_n [w^\top \phi(v_n) + c] \right) = 1 \quad (11)$$

In fact, intersections often occur between two successive phases, so the error value ξ needs to be included in the calculation.

$$w^* \rightarrow \min_{w, c, (\xi_n)} \frac{1}{2} \|w\|^2 + C \sum_{n=1}^n \xi_n \quad (12)$$

$$s.t. : \min_n \left(p_n \left[w^\top \phi(v_n) + c \right] \right) \geq 1 - \xi_n \forall n, \xi_n \geq 0 \forall n \quad (13)$$

Next, it will be translated into Algorithm 1 for optimization of the search for the boundaries between phases of the battery. This algorithm also shows the program we used to test with the NASA data set. Starting by determining the limit by using the battery data in the initial condition, fresh cell.

Algorithm 1 Li-ion battery SVM of this study

Input: Time Records $\hat{V} = [v_1, v_2, \dots, v_n]$. Label data set $Phase = [p_1, p_2, \dots, p_n]^T$.

Output: The optimized value $\hat{W}$, and Separation Value L.

Require: sklearn, seaborn, scipy

- 1: Collecting Discharge Data from specific battery
 - 2: Calculate gradient value from the voltage for defined time period
 - 3: Initialize $\phi(v)$ and c
 - 4: **while** not convergence **do**
 - 5: Calculate $w^* \rightarrow \frac{1}{2} \|w\|^2$
 - 6: **if** success **then**
 - 7: Calculate Separation Line L using Kernel Function K
 - 8: Exit
 - 9: **else**
 - 10: n = n + 1
 - 11: **end if**
 - 12: **end while**
 - 13: Run Polynomial Regression for normal usage phase
-

The value limit of each phase obtained will then be used to process the normal usage phase of the battery so that the SoC model of the battery can be obtained. Finally, with the same CC usage mode conditions, the battery run-out time can also be predicted. Additionally, the separation line of L from each phase that will be obtained can basically also be correlated with the battery model.

2.4. Battery Modelling

Different battery diagnostic techniques, including discharge to a fixed cut-off voltage, open circuit voltage, voltage under load, electrochemical impedance spectrometry (EIS) [26], and incorporating conductance technology with other measured parameters, such as battery temperature/differential information and the amount of float charge [27], have all been evaluated for application by NASA. The battery profile can be adjusted according to the cell size scale, when characterizing a full-size battery pack. It has been discussed in [28] that changes in the internal characteristics of the battery as seen through a shift in the EIS data plot can be used to determine battery capacity degradation.

The initial stage in making the model is to retrieve sensor data, which includes readings of voltage, current, power, impedance from EIS, frequency and temperature, and extract features from it. The estimation of the internal parameters of the battery model using the sensor data is depicted in the battery Figure 3. The double-layer capacitance C_{DL} , the charge transfer resistance R_{CT} , the Warburg impedance R_W and the electrolyte resistance R_E are the parameters obtained. Although the nomenclature of the parameters may vary between studies, all variations of the lumped parameter battery model consist essentially of a resistance and a capacitance in parallel with another resistance connected in series [29].

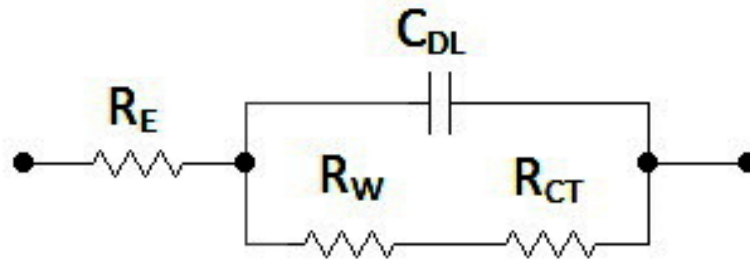


Figure 3. Battery cell model.

The model in Figure 3 is able to anticipate a faster level of capacity degradation related to internal faults. From EIS measurement data, this model is made to characterize fault effects. For example, R_E for effects that come from activation of polarization, and R_W to accommodate the IR drop due to mass transfer resistance from li-ion, as well as R_{CT} that follow concentration of polarization [28]. The voltage drop known as the IR drop itself can also be seen in any impedance resistive component. It occurs by the existence of an electric potential difference between the two ends of the conducting phase during the current flow. The product of the current (I) flowing through the resistance and its magnitude determines the voltage drop across any resistance (R) so the two combine to become IR . The function of the battery is defined in a structural and functional model, which help to build a form of the “physics of failure mechanisms” with internal parameter approach.

The lumped-parameter battery model in Figure 3 uses features taken from sensor data, such as voltage, current, power, impedance, frequency, and temperature, to predict internal parameters, such as C_{DL} , R_{CT} , R_W , and R_E . However, this model should be accompanied with the experimental data set, which has been described previously in Section 2.2. The characteristic profile extracted would be expressed in this model correspondingly. The combination between this model and the profile would help us to understand the phase classification, which will be used in this method. With various ageing and fault processes, such as plate sulfation, passivation, and corrosion, the characteristic values of components might change but the model will be still the same [28].

As a representative error index, we use the mean absolute percentage error (MAPE) to assess the estimation accuracy as follows [6]:

$$MAPE(\%) = \frac{100}{N} \sum_{n=1}^N \frac{|y(n) - \hat{y}(n)|}{y(n)} \quad (14)$$

where N is the number of cycles, $\hat{y}(n)$ represents the estimated capacity, and $y(n)$ represents the actual value. In addition, we calculate the root mean square error (RMSE) and the mean absolute error (MAE) as follows:

$$MAE = \frac{1}{N} \sum_{n=1}^N |y(n) - \hat{y}(n)| \quad (15)$$

$$RMSE = \sqrt{\frac{1}{N} \sum_{n=1}^N (y(n) - \hat{y}(n))^2} \quad (16)$$

3. Results

To estimate the capacity of the battery accurately, machine learning can be used to always update the phase parameters of the battery. Here, the gradient vector is also used as an initial indication of the battery phase in each cycle. Then, we will try to see its characteristics from each cycle. Finally, the results of machine learning will show

what percentage of confidence the phase determination is. The charge–discharge cycle will continue like the existing data set, so the algorithm that is built is also made for this approach.

3.1. Discharge Profile

C-Rate represents both the internal and external battery regarding its ability to supply energy. For example, C20 can also be said to guarantee battery capacity in 20 h of discharge while taking into account the SoH of the battery. With reference to the C-Rate, other battery usage limits can be neglected. This is very valuable in operational conditions where it is only related to run times, operational voltage ranges, and SoH movements [30].

Voltage, current and temperature during both charging and discharging situations can be seen in Figure 4a. From Figure 4b, it can be seen that there is a decrease in C-Rate with an increase in cycle. The reduction in C-Rate can be seen in the faster discharge time under the same conditions from a new cell to Cycle 85 and then to 169. The stress factor is usually taken into account when the battery value decreases, which also affects its temperature, SoC, C-Rate, and depth of discharge (DoD) [31]. Temperature and SoC are the two most visible variables from the long test. This battery cycle shows the need for DoD calculations to energy throughput and C-Rate [32].

$$DoD = \frac{E_{Discharged}}{E_{Total}} \quad (17)$$

DoD becomes the basic component of the calculation of the discharge cycle, which will form the battery model. To implement this methodology, machine learning will be used to represent the DoD for the remaining battery SoC with the release of the real data.

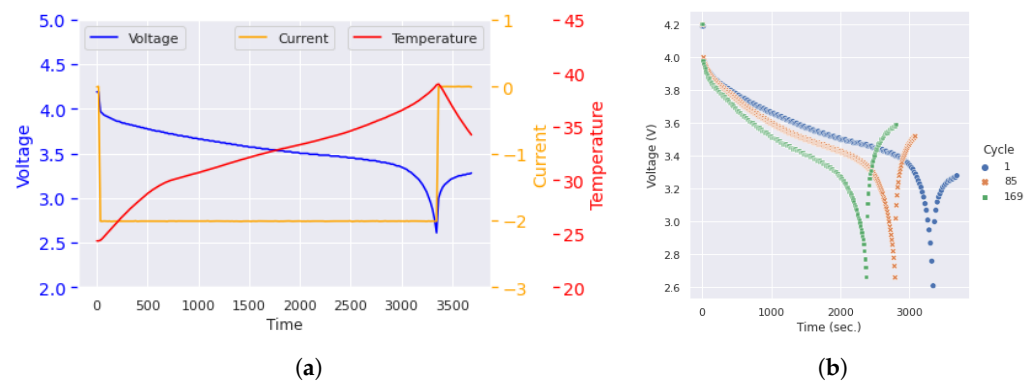


Figure 4. All possible parameters. (a) Discharge voltage, current and temperature profile from fresh cell. (b) Voltage discharge profile at different cycles from BAT0005.

The battery capacity is shown in blue, which could be seen from the condition of the fresh cell (1st cycle) to the last cycle (169th cycle) in a decreasing trend from around 1.8 to 1.3 Ah. This trend is also followed by the red line, which is for discharge time, which moves from a little over 60 min to a bit under 50 min. However, there is a slight difference in the yellow line for charge voltage. It shows the voltage used when charging the battery. Basically, the voltage should be at the same number around 4.2 V. However, from the data, it is found that there is a difference at the 85th cycle, where the measured voltage reached around 8 V as shown in Figure. Overall, it could be seen that the weight and C-rate of the battery would diminish along with the trend of capacity and time in Figure 5. For this reason, when using batteries, it is necessary to arrange them simultaneously, either in parallel or in series, so that the ongoing adequacy that may occur randomly from any battery would be covered by another battery [30]. Meaning that we had calculated the possibility of any powerless batteries that might be present among the battery packs. For this reason, in this experiment we will also see the possible differences from other batteries, such as BAT0006, BAT0007,

and BAT0018, even though the analysis method at the beginning will only use BAT0005 for the explanation.

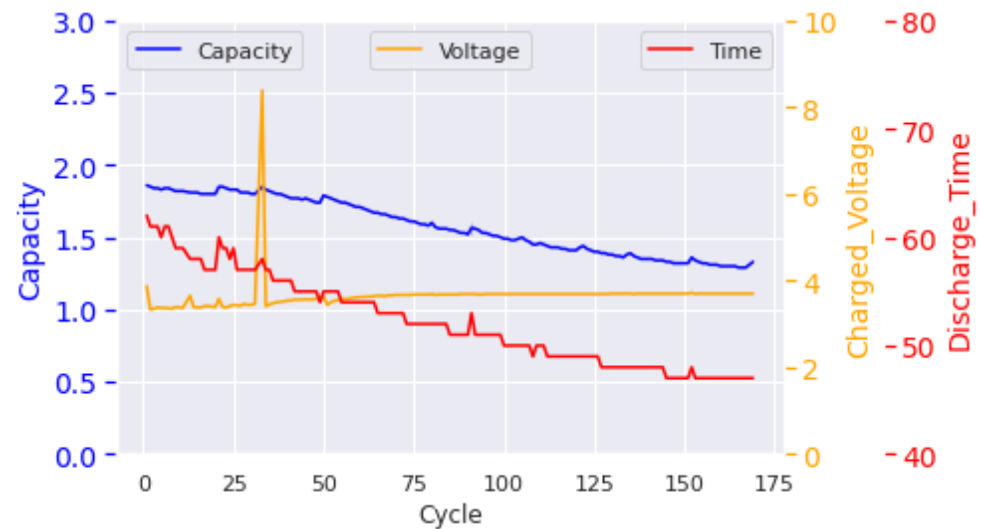


Figure 5. Discharge profile in capacity change.

3.2. The Gradient Vector

The amount of data from fresh cycle on BAT0005 is 197 with information in the form of voltage, current, and temperature from the battery in each time period. With these data we can calculate the magnitude of the gradient from each point. Then from the gradient values obtained easily we can see that there are several regions between the data patterns. To separate this data scientifically, we can use SVM Analysis. Among these regions, we can see that there are regions whose average value is smaller than the others. The data distribution that is carried out in this study is shown in Figure 6.

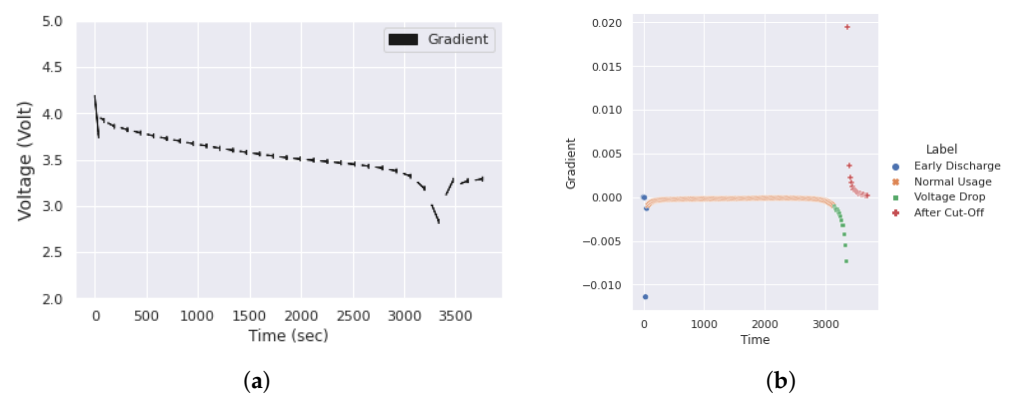


Figure 6. Fresh cell of BAT0005. (a) Vectors' position at the curve. (b) Gradient value over time.

The DoD can also be analyzed by the obtained gradient vector as in Figure 6. By deriving the $V(t)$ function, we can find how far DoD had entered in the battery. The representation of each vector follows Equation (18).

$$V'(t) = \frac{dV}{dt} \quad (18)$$

From the magnitude of this gradient value, as shown in Figure 6, and also between cycles, as in Figure 4b, as a whole can be divided into four phases, which have their own characteristics. This should be referred to as the phase of the battery discharge process. Phase 1 is the part where the battery energy is first used. This can be referred to as the

early discharge phase. The charge voltage around 4.2 V is unstable and looks like it has dropped drastically to a more stable value. The vector in this area looks quite steep down. The next second phase is the phase where the battery has reached a more stable voltage. In this phase, the battery is in normal usage phase. The voltage no longer drops drastically and is represented by a more sloping sideways vector. The third phase is the stage where the battery voltage drops drastically again, indicated by a downward steep vector. In this phase, there is also a point where it starts to be cut off following the previous battery operational parameters in Table 1.

If connected to battery modeling at Section 2.4, the first drop is caused by the Warburg impedance R_W . After that, there is an IR drop caused by the mass transfer resistance of the electrochemical battery. Furthermore, the electrolyte resistance, R_E , also increases due to polarization activation. Finally, the charge transfer resistance, R_{CT} , which is caused by concentration polarization. With the R_W and R_{CT} values together with the C_{DL} , the double layer capacitance can determine the time constant (τ) of the circuit, as shown in Equation (19). This is the time constant required for the circuit response to decay by a factor of $1/e$ or 36.8% of its initial value. A large τ value will decay longer and a small τ value will cause a faster decay. When there is no external source of excitation, the natural response of the circuit refers to the behavior (in terms of voltage and current) of the battery model circuit itself according to Equation (20).

$$\tau = (R_W + R_{CT})C_{DL} \quad (19)$$

$$v(t) = V_0 e^{-\frac{t}{\tau}} \quad (20)$$

However, this equation only exists in the normal usage phase, where the battery charge is modeled by C_{DL} . However, there are several curves in the discharge profile graph as shown in the voltage discharge profile in Figure 4b. By comparing each gradient value and its voltage range statistically, Figure 7 showed the phase classification for each cycle of 1, 85, 169, respectively from right to left.

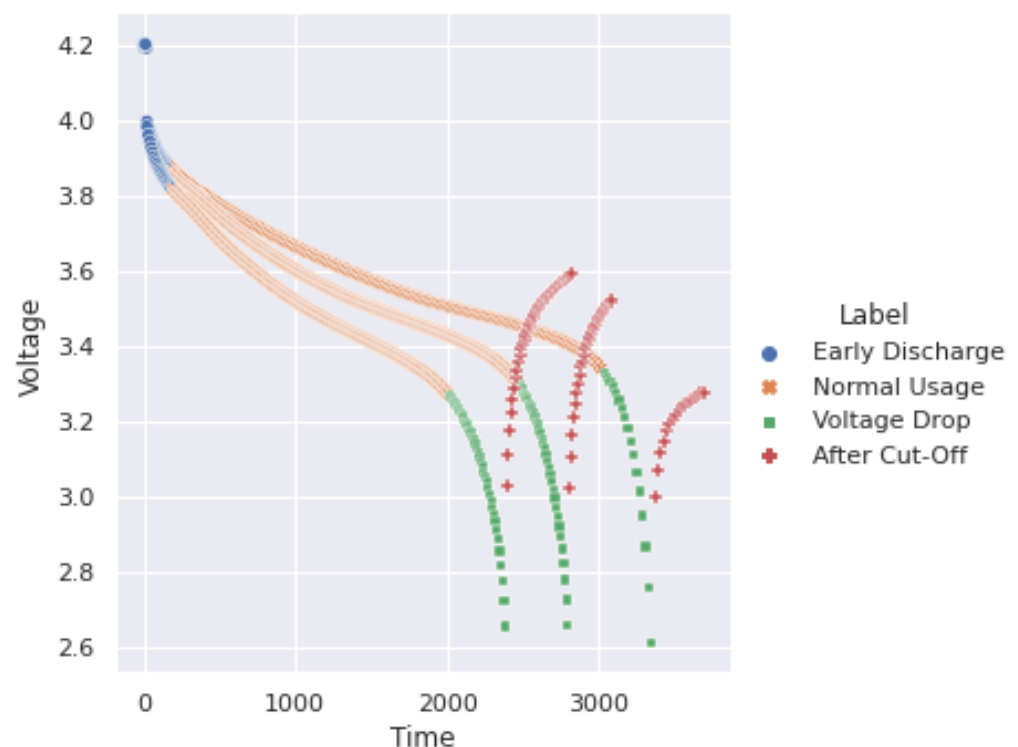


Figure 7. Comparison of voltage discharge profile at Cycle 1, 85, 169 of BAT0005 Cf. Figure 4b.

By mapping each phase of the NASA battery data set, we can also find out the statistical value based on the magnitude of the gradient vector. Each of the batteries, BAT0005, BAT0006, BAT0007 and BAT0018, will be broken down sequentially from their minimum, average, and maximum values, as shown in Table 2. This may be necessary if we look at the possible categories intuitively to determine the limits of each phase. Namely, the L value, which is the boundary between the two successive phases, and the normal usage phase will be the main goals of the SoC measurement method with this method.

In general there are several characteristics of each phase. For example, only the early discharge and after cut-off phases have positive gradient values. This can also be seen in Figure 6, with the vector pointing up. However, here we do not need to pay attention to the last phase, after cut-off phase. This is because the ultimate goal is to calculate the SoC and predict the end time of the battery on a single charge. In other words, use is only present in the initial three phases starting from early discharge phase to voltage drop phase, after the battery is disconnected we will no longer use it for various reasons, as discussed earlier in Section 2.2. Even if possible, the battery has begun to be reduced in use or is disconnected when entering the voltage drop phase. This can be seen by looking at the characteristic curve of battery usage in Figure 7, where the phase does not contribute a long time and the value will drop drastically, until finally it has to be forcibly disconnected because it has reached the voltage threshold of the battery.

When viewed in detail, there are differences between each battery. The value that should be the same for each battery is the maximum value at the early discharge phase before the battery discharging test is carried out is charging with a full charge voltage of 4.2 V. However, here, the voltage in the measurements of each battery obtained a tolerance value of around 0.02 V. The minimum value is BAT0006 with a value of 4.18 V and mostly 4.19 V on the BAT0005 and BAT0018 batteries. The same voltage value can only be obtained on BAT0007, which is 4.2 V. Then what is interesting is that there is a minimum value during normal usage phase that is slightly smaller or more positive than the maximum value of “Voltage Drop.” With a difference of about 0.11, 0.16, 0.12 and 0.05 mV/sec for BAT0005, BAT0006, BAT0007, and BAT0018, respectively.

Table 2. Statistical data from gradient vector region.

Data Set	Phase	Measured Voltage(V)			Gradient		
		Min.	Avg.	Max.	Min.	Avg.	Max.
BAT0005	Early Discharge	3.89	3.98	4.19	−0.01141	−0.00181	0.00000
	Normal Usage	3.25	3.57	3.88	−0.00099	−0.00021	−0.00009
	Voltage Drop	2.61	3.01	3.23	−0.00735	−0.00297	−0.00110
	After Cut–Off	3.00	3.20	3.28	0.00019	0.00196	0.01943
BAT0006	Early Discharge	3.90	3.99	4.18	−0.01127	−0.00189	0.00000
	Normal Usage	3.24	3.57	3.89	−0.00100	−0.00020	−0.00008
	Voltage Drop	2.48	2.96	3.21	−0.00891	−0.00340	−0.00116
BAT0007	Early Discharge	3.90	4.00	4.20	−0.01130	−0.00177	0.00001
	Normal Usage	3.25	3.58	3.89	−0.00098	−0.00021	−0.00009
	Voltage Drop	2.15	2.88	3.23	−0.01035	−0.00425	−0.00110
	After Cut–Off	2.77	2.97	3.06	0.00051	0.00452	0.03094
BAT0018	Early Discharge	3.88	3.96	4.19	−0.02075	−0.00208	0.00001
	Normal Usage	3.25	3.56	3.87	−0.00095	−0.00021	−0.00008
	Voltage Drop	2.47	3.00	3.24	−0.01031	−0.00340	−0.00100
	After Cut–Off	2.86	2.98	3.05	0.00145	0.00754	0.04047

3.3. Time Estimation

Then, by following the predictions from the regression model, it is possible to obtain the beginning of the voltage drop phase. To find out all the dropping points from each cycle of each battery, the model is used together with the gradient value. The difference in dropping point values from different cycles from BAT0005 can be seen in Figure 7.

However, here we are trying to predict the time of the normal usage phase. For this reason, the comparison between this phase and the total phase up to the voltage drop phase is attempted to be visualized as shown in Figure 8.

To understand the time estimation, a comparison between normal usage vs. total usage time before cut-off is used to check the difference ratio. From the existing data set, Figure 7 is formed using data of 167 for each of BAT005, BAT006, and BAT0007. Meanwhile, BAT0018 only consists of 132 data. Plots of the data are shown in the bar chart at Figure 8, where the average ratio between normal usage phase time and total usage time before cut-off is 85%. In other words, the ratio between the difference between the two to the total phase value of early discharge and voltage drop phases is only about 15% of the total. Whereas, the cut-off limit of the battery is about 2.2–2.7 V, as noted in Table 1. However, as shown in Figure 8, there is a time span difference between the four batteries. This difference can also be seen in the average length of time from the total time and also from the difference. The average total time is around 47 min with a slight difference in seconds for BAT005, BAT006 and BAT0018, respectively, and 50 min for BAT0007. Meanwhile, the average normal usage time is about the same for 40 battery sequences with a slight difference in seconds, and 43 min for BAT0007 only. Also, the difference between the two values is about 7 for each of the three batteries with a slight difference in seconds, and 8 min for the BAT0007. With the previous cut-off voltages of 2.7, 2.5, 2.2, and 2.5 V for batteries BAT005, BAT006, BAT0007, and BAT0018, respectively; with this method, the battery is in a critical state when it enters its voltage drop phase. Of course it varies more and can be in a voltage range greater than 3 V. The possible values are quite large compared to those in absence of this method. This voltage is represented by V2 in Table 3.

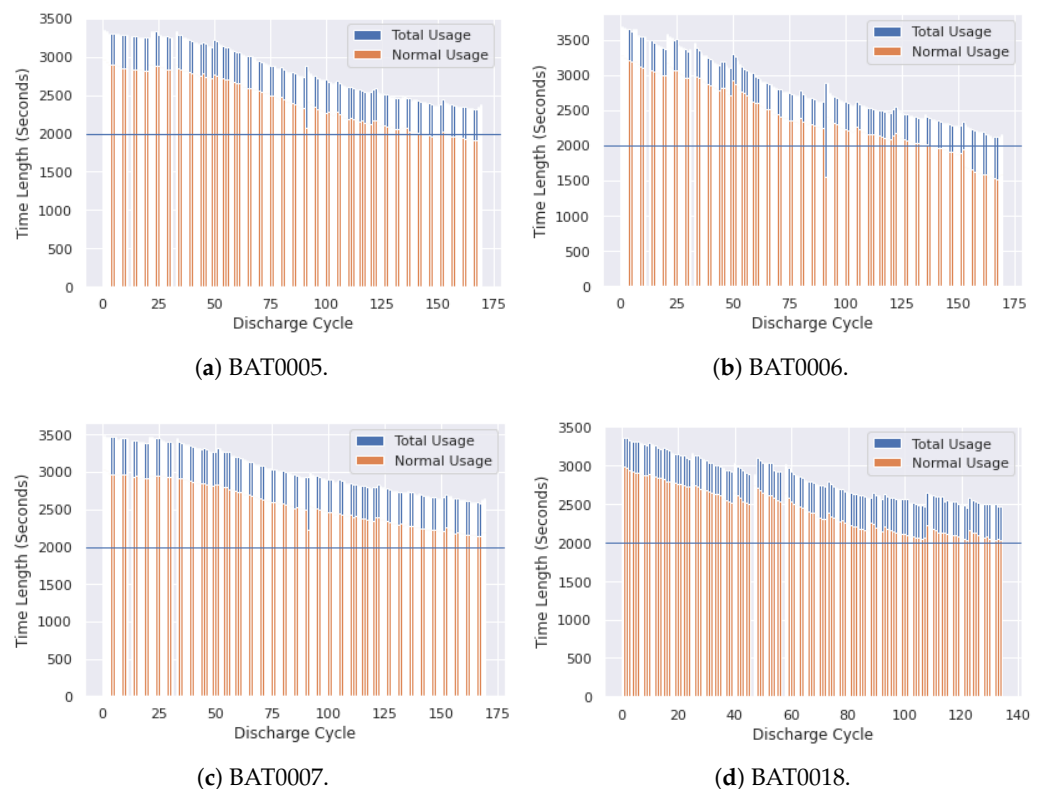


Figure 8. Normal usage phase time vs. total usage time before cut-off.

Table 3. Values of normal usage phase time distribution.

Battery	Time Length (s)			V1 (Volt)			V2 (Volt)		
	Min.	Avg.	Max.	Min.	Avg.	Max.	Min.	Avg.	Max.
BAT0005	1911	2417	2968	3.79	3.85	3.88	3.13	3.23	3.39
BAT0006	1527	2399	3286	3.57	3.79	3.88	3.02	3.14	3.41
BAT0007	2139	2572	3030	3.82	3.87	3.88	3.18	3.25	3.40
BAT0018	2024	2419	2987	3.80	3.85	3.88	3.15	3.22	3.29

From Table 3, we could see that the threshold for each battery has a different range. V1 is the threshold between the early discharge phase and normal usage phase. From the table it can be seen that the upper limit is at the same number at 3.88 V. However, the lower and average limits of V1 still vary with the lowest value being at BAT0006. Meanwhile, V2 is the threshold between the normal usage phase and the voltage drop phase. There is an unequal threshold shift as previously discussed. There are similarities with the threshold on V1, and the lowest and highest values are on BAT0006. The data in the table still shows data from the overall cycle of each battery. Then, there is the time length that shows the variation of the length of the normal usage phase, which is started by V1 and ended by V2. According to the description in Figure 8, even though the number of seconds varies quite a bit, between batteries BAT0005, BAT0006, and BAT0018 it is still around 4200 s or approximately 40 min with a slight difference in seconds. The difference is only in BAT0007 with a difference of about 3 min or 180 s. Basically, the time length distribution of each cycle of each battery is random. The distribution can be seen in Figure 9.

Again at Table 3, we could see also that the V1 and V2 thresholds follow the characteristics of each battery and its usage. Battery use up to a lower cut-off value is followed by an increase in usage time as seen in BAT0007 with a cut-off value of up to 2.2 V. However, the above concept is not always followed by a decrease in the existing value because of the comparison between BAT0005 with cut-off voltage of 2.7 V to BAT0006 and BAT0018 with cut-off voltage of 2.5 V does not show the corresponding data. It may be possible to compare the battery's model from the characteristics of the battery. Meanwhile, there are still other possibilities that come from the division of phases that have been carried out. With this classification, basically we have also divided the existing graph into four different curve sections, as previously discussed in the voltage discharge profile between Figures 4b and 7. Similarly, for the distribution of normal usage phase time, which has been described in Table 3, there are also several possibilities, as described in Equation (21) as the Total Probability.

$$P_{Total} = P(Early \cap Normal) + P(Normal) + P(Normal \cap Drop) \quad (21)$$

With P_{Total} as the total probability of all possible data entering the normal usage phase. From Equation (21), it can be seen that the total is not the same as the probability of that phase alone, which should be represented by $P(Normal)$. However, there is also the addition of the intersection with the previous phase, early discharge phase, which is represented by $P(Early \cap Normal)$. In addition, there is also the addition of a wedge with a phase after "Voltage Drop." This is represented by $P(Normal \cap Drop)$. Thus, the overall probability of normal usage data is formed from these three probability groups. In the real case of this intersection area, it is possible that a certain value comes from the two phases that overlap. Here, we try to minimize the value range because it can confuse the system in determining the initial limit of V1 and the final limit of the phase in V2. At least we know the point where we can classify it as the normal usage phase. Before carrying out cut-off point comparisons as before, it is necessary to get an idea from the existing data. In order to determine a particular intersection point, it is necessary to find a solution to the area of uncertainty. We make the resolution for the previous intersection of the normal phase and the intersecting phase as close to zero

as possible. This can be simplified by assuming the occurrence of uncertainty when approaching the limit values in V1 and V2, as follows:

$$\lim_{V \rightarrow V1^-} P(Early \cap Normal|V) \rightarrow 0 \quad (22)$$

$$\lim_{V \rightarrow V2^+} P(Normal \cap Drop|V) \rightarrow 0 \quad (23)$$

The probability of this slice can be zero, if we follow a normal distribution in which the maximum is usually at the midpoint and decreases as the standard deviation of the limiting stress approaches. The results of the time length distribution from the modeling process with Table 3 can be observed in Figure 9 even though the data distribution does not really follow a normal distribution. By looking at the limit values of each prediction curve, we can define as above, with a limit approaching the threshold in Table 3; the phase slice is expected to be close to zero. The initial threshold voltage as point V1, can be found using the SVM approximation analysis, which is discussed previously in Section 2.3. Next, of course, we return to the process of the best interpretation of the time length. The statistical data shown in Table 3 cannot really represent the percentage of data density for each length of time, be it the existing minimum, maximum and average values. Of course there will be shifts and differences between the curves formed by each battery. For example, by the batteries BAT0005, BAT0006 and BAT0018, all three of which have an average of around 40 min or 2400 s. In other words, it takes an illustration that shows the overall data distribution between the minimum and maximum values. The distribution density for each battery is shown in Figure 9.

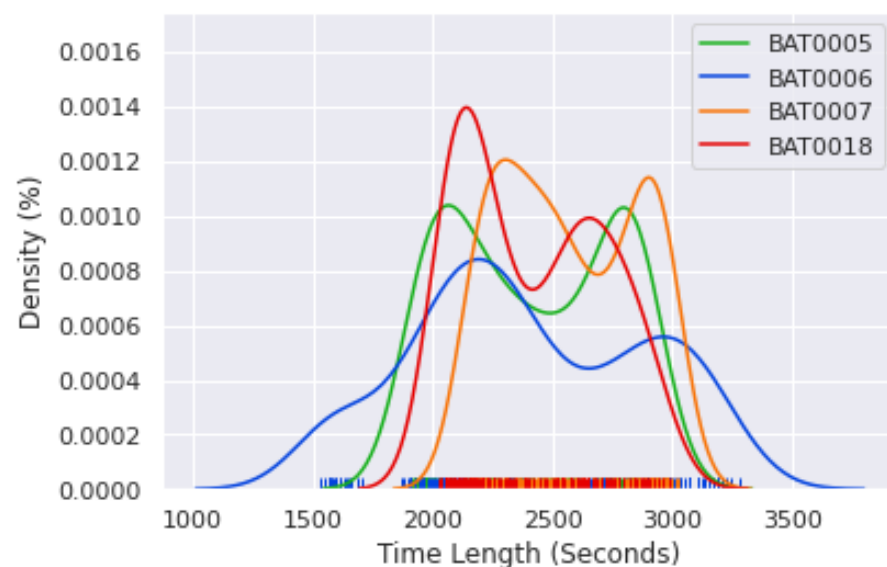


Figure 9. Time length distribution comparison of prediction over all batteries.

Figure 9 shows that the length of time used for each battery varies from cycle to cycle, but there is a length of time that can be used as a guide as a characteristic. Of course, the duration of use has decreased according to Figure 8 but a time limit, such as the 2000 s range, can be the range, as represented as a line in the figure. From the time length distribution, it can be seen that this figure represents almost the entire peak of all batteries.

In general, one might think that battery capacity is simply a matter of the charge number, which is stated as the nominal energy of the battery. Considering that all batteries, BAT0005, BAT0006, BAT0007 and BAT0018, come from the same battery type with a specification of nominal capacity as 2Ah, as shown in Table 1. However, from the results above with CC mode, we conclude that the estimated time limit for battery use that can be guaranteed to the user is the minimum time limit of the various variations in

the characteristics of each battery. The estimation results can also be calculated by taking into account the DoD level profile of each usage cycle and predicting the usage time with C Rate. Because the available data sets are limited, we need to fully exploit them by comparing the values of the available data sets with the polynomial regression models we obtain. Of the four data sets, we iterate in each cycle to calculate the difference according to Equations (14)–(16). Overall, Table 4 shows the statistical data for each parameter of MAPE, MAE and RMSE.

Table 4. Prediction error between batteries.

Battery	MAPE (%)			MAE			RMSE		
	Min.	Avg.	Max.	Min.	Avg.	Max.	Min.	Avg.	Max.
BAT0005	0.31	0.39	0.44	0.0110	0.0137	0.0151	0.0149	0.0175	0.0190
BAT0006	0.33	0.42	0.77	0.0113	0.0144	0.0275	0.0136	0.0182	0.0276
BAT0007	0.33	0.40	0.44	0.0116	0.0141	0.0153	0.0158	0.0180	0.0194
BAT0018	0.30	0.37	0.42	0.0106	0.0129	0.0145	0.0144	0.0166	0.0181

Furthermore, in Table 4, it can be seen how much error the method has used for each battery. For MAPE, which shows the difference from the average, overall it is in the range of 0.30 to 0.77. With the smallest difference in BAT0018 and the largest in BAT0006. The same happens for MAE, which is the absolute value, but with a different value, between 0.0106 and 0.0275. Finally, for the RMSE, which represents the process with the roots of the square, there is a slight difference with the lowest value 0.0136 and the largest 0.0276 all coming from BAT0006. BAT0006 itself is shown in Figure 8d has a prediction portion of under 2000 s with the largest portion. Additionally, Figure 9 has the largest distribution range and the gentlest peak value compared to other data set batteries. Meanwhile, BAT0018 is the data set that has the highest peak of the figure.

4. Discussion

As a comparison of the methods that have been used, various research data have been compiled, which also use NASA data sets. By comparing the error parameters reported from each study, we can see whether this method yields good enough results as shown in Table 5. The MAE and MAPE(%) values show the lowest numbers even though there are only two articles from MAPE. Meanwhile, MAE is obtained by comparison with four other articles. For the RMSE value, this method is in the second position from the lowest in comparison with the other six articles.

Table 5. Error report from using Nasa battery data set.

Objective	Battery Parameter	Methods	Battery Data Set				Min. Error Parameters		
			5	6	7	18	MAE	RMSE	MAPE (%)
A Deep Learning Approach [20] Estimation Using Partial Data [13]	RUL	ADNN Algorithm	V	V	V	V	-	0.0666	-
	RUL	Long Short-Term Memory Approach	V	V	V	V	0.00222	0.00286	-
A New Hybrid Neural Network Method [7]	SoH	Dilated CNN, BiGRU, CNN-BiGRU, Dilated CNN-GRU, Dilated CNN-BiLSTM, Dilated CNN-BiGRU	V	V	V	V	0.019	0.033	-
Machine Learning-Based Exploiting Multi-Channel Charging Profiles [6]	SoH	FNN, CNN, LSTM	V	V	V	V	0.0246	0.0159	1.032
Health Monitoring Using Dual Filters [19]	SoC	The Kalman filter (KF) and the novel sliding innovation filter (SIF)	V	-	-	-	-	0.0675	-
Estimation from the Voltage Discharging Profile (This Work)	SoC	Gradient and SVM	V	V	V	V	0.0106	0.0144	0.3

Table 5 shows a comparison of several studies using the NASA data set. There are five parameters used as a comparison. The first is the objective of the research, which, in general, can also be seen from the title of the article. The second is the battery parameter, which will generalize the objectives into those specific parameters, such as RUL, SoH and SoC. These three are useful methods for differentiating approaches to the same battery parameters. The fourth is the battery data set used. The last is error parameters, which will be a concern for comparing this method. Of the five comparisons above, this work is closest to health monitoring using dual filters [19]. Where the battery parameter discussed is the SoC. From the use of the Kalman filter (KF) and the novel sliding innovation filter (SIF) on BAT0005, results with an RMSE of 0.0675 or greater than 0.0531 are obtained with the method we use. The RMSE value obtained, as discussed earlier, is the second after the results from estimation using partial data [13] with an RMSE of 0.00286. By using the long- short-term memory approach, the approach for RUL has a smaller error of 0.00838 for MAE and 0.01154 for RMSE, compared to the method we used. However, its objective at battery parameter was different than this study. It was for RUL, while in this study, it is mainly for SoC. In comparison, RUL is common for the calculating the remaining cycle of the battery, while SoC could be used for remaining useful time within the running cycle. After SoC and RUL, there is still error reported on SoH. In that case, there is [6], which shows a better RMSE than [7]. However, not all the studies used NASA data sets. There were still many others that could be listed in Table 5, such as [9,10]. Both also used the data set with objective parameter of RUL with machine-learning-based methods, such as LSTM, PF, GPR and BLS. Here, we listed two articles for each battery parameter were just for references of the study using the data set. They were just for comparison and not all of them can be equally compared, as described before [13].

RUL and SoH are closely related because they show the parameters of the battery's cycle and are related to EoL. However, for real-time analysis, SoC is more widely used and is related to end of discharge (EoD). This is slightly different from SoH, which looks more at the quality of the battery between one cycle and the next. This is also closer to the RUL, which has to do with the EoL of the battery ending at 1.4 Ah for this battery case. In other words, our approach at determining the SoC of a battery also does not directly define the % battery capacity, which starts at 100% when the battery is in full charge (FC) and starts to be used until it drops to 0% when the battery is cut off. This is because what we recommend is the use of a battery from FC to the normal usage phase only or around 85% of battery capacity. This, as discussed in Section 3.3, is the ratio of time between normal usage phase to the total time before cut-off. By avoiding the use of the battery in the voltage drop phase, it is expected that the SoH of the battery gets better, as indicated by BAT0005, with the most balanced peak distribution, as shown in Figure 9. Moreover, the BAT0005 battery is applied with the highest cut-off voltage compared to the other batteries at 2.7 V, and it shows a better distribution of SoH compared to other batteries. However, further research needs to be conducted to ensure the SoH measurement. Next, the processing time would vary across the number of data and the processing unit. For this simulation, we use a PC with CPU having speed of 2.60 GHz and RAM's capacity of 8 GB and frequency of 1333 MHz. It takes less than 100 ms. A custom development using field programmable gate array (FPGA) might increase the speed for its possible implementation. After that, the NASA experiment is run in CC mode. It might be different from the real situation where the battery could be used for changing the current's value and not always in maximum load condition. It is expected that in the next implementation test, it can be conducted in variable discharging current to see if there would be any possibilities of change.

5. Conclusions

A good SoC estimation is crucial to guarantee the usage time of the battery before EoD occurs, especially for EVs. In this work, a new method that utilizes the voltage gradient of

the battery has been proposed to classify the phases of battery usage. The lower limit of the new SoC is also explained with its time estimation, which follows the normal usage phase of the battery. SVM analysis can be used effectively in finding the V1 limit of the normal usage phase. Furthermore, the polynomial regression model of the battery can be used to determine the V2 limit of the phase to become the new cut-off voltage. From the NASA data set testing for BAT0005, BAT0006, BAT0007, and BAT0018, it is consistently found that the normal usage phase ratio is around 85% of the total usage time of the battery. Based on this test, the MAPE, MAE, and RMSE values are 0.3%, 0.0106, and 0.0144, respectively, in the NASA data set. The experimental results show that this classification method can clearly predict the safe usage time of the battery in CC mode by avoiding the voltage drop phase so that it gives more assurance to the SoH value of the battery; therefore, it can support the use of affordable and clean energy and guarantee responsible consumption and production by increasing the SoH and RUL of the battery.

Author Contributions: This particular research was started and coordinated by E.S. as first and corresponding author. The investigation was initiated by P.E.A. Then, overall administration was managed by F.F. Testing and verification has been performed by M.I.H. Machine Learning has been developed by M.Y. and W.S. Finally, M.A. assisted with checking the whole work, editing the manuscript, and proofreading. All authors have read and agreed to the published version of the manuscript.

Funding: This research was funded by Universitas Airlangga with grant number is 1097/UN3.15/PT/2022.

Data Availability Statement: The dataset in this study is available at the NASA Battery Aging Dataset [23] at <https://data.nasa.gov/dataset/Li-ion-Battery-Aging-Datasets/uj5r-zjdb> (accessed on 1 August 2022).

Acknowledgments: This work has been funded by Universitas Airlangga under a research scheme of Riset Kolaborasi Indonesia (RKI) 2022 coordinated with Kemendikbud Ministry of Education of Indonesia. This particular research was started by Erwin Sutanto in Universitas Airlangga in collaboration with five other universities, which are Universitas Sumatera Utara, Universitas Andalas, Institut Teknologi Sepuluh Nopember, Bandung Institute of Technology, and University of Tokyo.

Conflicts of Interest: The authors declare no conflict of interest.

Abbreviations

The following abbreviations are used in this manuscript:

ADNN	Autoencoder and DNN models
BMoS	Battery Monitoring System
BLS	Broad Learning System
CNN	Convolutional Neural Network
DoD	Depth of Discharge
EIS	Electrochemical Impedance Spectrometry
EoD	End of Discharge
EoL	End of Life
FC	Full Charge
FPGA	Field Programmable Gate Array
FNN	Feedforward Neural Network
GPR	Gaussian Process Regression
GRU	Gated Recurrent Unit
LSTM	Long Short-Term Memory
MAE	Mean Absolute Error
MAPE	Mean Absolute Percentage Error
PF	Particle Filtering
RDR	Remaining Driving Range
RMSE	Root Mean Square Error
RUL	Remaining Useful Life
SoC	State-of-Charge
SoH	State-of-Health

References

1. Aziz, M.; Huda, M.; Budiman, B.A.; Sutanto, E.; Sambegoro, P.L. Implementation of Electric Vehicle and Grid Integration. In Proceedings of the 2018 5th International Conference on Electric Vehicular Technology (ICEVT), Surakarta, Indonesia, 30–31 October 2018; pp. 9–13.
2. Fahmi, F.; Sutanto, E.; Yazid, M.; Aziz, M. Integrated Car Telemetry System Based On Internet Of Things: Application And Challenges. *J. Eng. Sci. Technol.* **2020**, *15*, 3757–3771.
3. Franke, T.; Krems, J.F. Understanding charging behaviour of electric vehicle users. *Transp. Res. Part F Traffic Psychol. Behav.* **2013**, *21*, 75–89. [\[CrossRef\]](#)
4. Liu, G.; Ouyang, M.; Lu, L.; Li, J.; Han, X. Online estimation of lithium-ion battery remaining discharge capacity through differential voltage analysis. *J. Power Sources* **2015**, *274*, 971–989. [\[CrossRef\]](#)
5. Liu, K.; Hu, X.; Yang, Z.; Xie, Y.; Feng, S. Lithium-ion battery charging management considering economic costs of electrical energy loss and battery degradation. *Energy Convers. Manag.* **2019**, *195*, 167–179. [\[CrossRef\]](#)
6. Choi, Y.; Ryu, S.; Park, K.; Kim, H. Machine learning-based lithium-ion battery capacity estimation exploiting multi-channel charging profiles. *IEEE Access* **2019**, *7*, 75143–75152. [\[CrossRef\]](#)
7. Bao, Z.; Jiang, J.; Zhu, C.; Gao, M. A new hybrid neural network method for state-of-health estimation of lithium-ion battery. *Energies* **2022**, *15*, 4399. [\[CrossRef\]](#)
8. Li, D.; Yang, L. Remaining useful life prediction of lithium battery using convolutional neural network with optimized parameters. In Proceedings of the 2020 5th Asia Conference on Power and Electrical Engineering (ACPEE), Chengdu, China, 4–7 June 2020; pp. 840–844.
9. Zhang, C.; Zhao, S.; He, Y. An Integrated Method of the Future Capacity and RUL Prediction for Lithium-Ion Battery Pack. *IEEE Trans. Veh. Technol.* **2021**, *71*, 2601–2613. [\[CrossRef\]](#)
10. Zhao, S.; Zhang, C.; Wang, Y. Lithium-ion battery capacity and remaining useful life prediction using board learning system and long short-term memory neural network. *J. Energy Storage* **2022**, *52*, 104901. [\[CrossRef\]](#)
11. Zhang, C.; Zhao, S.; Yang, Z.; Chen, Y. A reliable data-driven state-of-health estimation model for lithium-ion batteries in electric vehicles. *Front. Energy Res.* **2022**, *10*. [\[CrossRef\]](#)
12. Chen, L.; Chen, J.; Wang, H.; Wang, Y.; An, J.; Yang, R.; Pan, H. Remaining useful life prediction of battery using a novel indicator and framework with fractional grey model and unscented particle filter. *IEEE Trans. Power Electron.* **2019**, *35*, 5850–5859. [\[CrossRef\]](#)
13. Chinomona, B.; Chung, C.; Chang, L.K.; Su, W.C.; Tsai, M.C. Long short-term memory approach to estimate battery remaining useful life using partial data. *IEEE Access* **2020**, *8*, 165419–165431. [\[CrossRef\]](#)
14. Doerffel, D.; Sharkh, S.A. A critical review of using the Peukert equation for determining the remaining capacity of lead-acid and lithium-ion batteries. *J. Power Sources* **2006**, *155*, 395–400. [\[CrossRef\]](#)
15. Pop, V.; Bergveld, H.J.; het Veld, J.O.; Regtien, P.; Danilov, D.; Notten, P. Modeling battery behavior for accurate state-of-charge indication. *J. Electrochem. Soc.* **2006**, *153*, A2013. [\[CrossRef\]](#)
16. Salkind, A.J.; Fennie, C.; Singh, P.; Atwater, T.; Reisner, D.E. Determination of state-of-charge and state-of-health of batteries by fuzzy logic methodology. *J. Power Sources* **1999**, *80*, 293–300. [\[CrossRef\]](#)
17. Di Domenico, D.; Fiengo, G.; Stefanopoulou, A. Lithium-ion battery state of charge estimation with a Kalman filter based on an electrochemical model. In Proceedings of the 2008 IEEE International Conference on Control Applications, San Antonio, TX, USA, 3–5 September 2008; pp. 702–707.
18. Zhang, S.; Sun, H.; Lyu, C. A method of soc estimation for power li-ion batteries based on equivalent circuit model and extended kalman filter. In Proceedings of the 2018 13th IEEE Conference on Industrial Electronics and Applications (ICIEA), Wuhan, China, 31 May–2 June 2018; pp. 2683–2687.
19. Bustos, R.; Gadsden, S.A.; Malysz, P.; Al-Shabi, M.; Mahmud, S. Health Monitoring of Lithium-Ion Batteries Using Dual Filters. *Energies* **2022**, *15*, 2230. [\[CrossRef\]](#)
20. Ren, L.; Zhao, L.; Hong, S.; Zhao, S.; Wang, H.; Zhang, L. Remaining useful life prediction for lithium-ion battery: A deep learning approach. *IEEE Access* **2018**, *6*, 50587–50598. [\[CrossRef\]](#)
21. Feng, X.; Weng, C.; He, X.; Han, X.; Lu, L.; Ren, D.; Ouyang, M. Online state-of-health estimation for Li-ion battery using partial charging segment based on support vector machine. *IEEE Trans. Veh. Technol.* **2019**, *68*, 8583–8592. [\[CrossRef\]](#)
22. Patil, M.A.; Tagade, P.; Hariharan, K.S.; Kolake, S.M.; Song, T.; Yeo, T.; Doo, S. A novel multistage Support Vector Machine based approach for Li ion battery remaining useful life estimation. *Appl. Energy* **2015**, *159*, 285–297. [\[CrossRef\]](#)
23. Saha, B.; Goebel, K. *Battery Data Set*; NASA Prognostics Data Repository, NASA Ames Research Center: Moffett Field, CA, USA, 2007.
24. Tar, B.; Fayed, A. An overview of the fundamentals of battery chargers. In Proceedings of the 2016 IEEE 59th International Midwest Symposium on Circuits and Systems (MWSCAS), Abu Dhabi, United Arab Emirates, 16–19 October 2016; pp. 1–4.
25. Chitra, A.; Holm-Nielsen, J.B.; Sanjeevikumar, P.; Himavathi, S. *Artificial Intelligent Techniques for Electric and Hybrid Electric Vehicles*; Wiley-Scrivener: Beverly, MA, USA, 2020.
26. Vutetakis, D.; Viswanathan, V. Determining the state-of-health of maintenance-free aircraft batteries. In Proceedings of the Tenth Annual Battery Conference on Applications and Advances, Long Beach, CA, USA, 10–13 January 1995; pp. 13–18.

27. Cox, D.C.; Perez-Kite, R. Battery state of health monitoring, combining conductance technology with other measurement parameters for real-time battery performance analysis. In Proceedings of the INTELEC. Twenty-Second International Telecommunications Energy Conference (Cat. No. 00CH37131), Phoenix, AZ, USA, 10–14 September 2000; pp. 342–347.
28. Goebel, K.; Saha, B.; Saxena, A.; Celaya, J.R.; Christophersen, J.P. Prognostics in battery health management. *IEEE Instrum. Meas. Mag.* **2008**, *11*, 33–40. [[CrossRef](#)]
29. Saha, B.; Goebel, K. Uncertainty management for diagnostics and prognostics of batteries using Bayesian techniques. In Proceedings of the 2008 IEEE Aerospace Conference, Big Sky, MT, USA, 1–8 March 2008; pp. 1–8.
30. Elsayed, A.T.; Lashway, C.R.; Mohammed, O.A. Advanced battery management and diagnostic system for smart grid infrastructure. *IEEE Trans. Smart Grid* **2015**, *7*, 897–905. [[CrossRef](#)]
31. Barré, A.; Deguilhem, B.; Grolleau, S.; Gérard, M.; Suard, F.; Riu, D. A review on lithium-ion battery ageing mechanisms and estimations for automotive applications. *J. Power Sources* **2013**, *241*, 680–689. [[CrossRef](#)]
32. Guo, J.; Yang, J.; Lin, Z.; Serrano, C.; Cortes, A.M. Impact analysis of v2g services on ev battery degradation-a review. In Proceedings of the 2019 IEEE Milan PowerTech, Milan, Italy, 23–27 June 2019; pp. 1–6.

Disclaimer/Publisher’s Note: The statements, opinions and data contained in all publications are solely those of the individual author(s) and contributor(s) and not of MDPI and/or the editor(s). MDPI and/or the editor(s) disclaim responsibility for any injury to people or property resulting from any ideas, methods, instructions or products referred to in the content.