Performance Degradation Evaluation of a Lithium-Ion Battery from Multiple SoC Measurements

Riza Hadi Saputra, Adi Mahmud Jaya Marindra*, Muhammad Agung Nursyeha, and Dwi Kurnia Agung Fariyani

Electrical Engineering, Institut Teknologi Kalimantan
Jl. Soekarno-Hatta Km. 15, Karang Joang, Balikpapan, Kalimantan Timur, 76127, Indonesia

**Corresponding author. Email: adi.marindra@lecturer.itk.ac.id*

Abstract— Lithium-Ion (Li-ion) battery is essential in today's energy systems and electric vehicles (EVs). Although Li-ion battery can be charged quickly and have a high energy density, it has several drawbacks, including the rapid degradation of battery performance, especially in terms of battery capacity. Therefore, evaluating its performance degradation is necessary to understand its characteristics. In this paper, the performance degradation of a Li-ion battery is monitored and evaluated from multiple SoC measurements. A simple and low-cost experimental setup consisting of sensors, a microcontroller, and a PC is developed to measure and record the real-time data of Li-ion battery voltage and current. Then, the battery state of charge (SoC) is determined using the Coulomb Counting method, which is based on the incoming and outgoing currents of the battery. As a result, this study derives three parameters that indicate the performance degradation of a Li-ion battery, i.e., SoC, battery capacity, and discharge time. From multiple direct measurements with constant load and C20 discharge process, the minimum SoC value increases from 11% to 18%, while battery capacity decreases from 8.8Ah to 8.3 Ah and, discharge time decreases from 16.9 hours to 16.4 hours. All of those parameters indicate a degradation of around 7% in battery performance. Therefore, this research paves the way for finding a solution to mitigate the quick performance degradation of Li-ion batteries.

Keywords— battery; battery capacity; discharge time; lithium-ion; state of charge

I. Introduction

Batteries play an important role as energy storage in many applications, from power generation systems to mobile electronic systems [1]. With the recent development of electric vehicles (EVs), research in batteries has drawn enormous global attention and will be followed by an increase in battery demands by 2035 [2]. One of the battery types popular for EVs is Lithium-ion (Li-ion) battery, mainly because it can be charged quickly and relatively compact, thus suitable for use in systems with mobility. In other words, Li-ion battery has higher energy density than the other types. Although the physical size of Li-ion battery is smaller than other types of batteries, it can store the same amount of energy as other types of batteries, such as valve-regulated lead acid (VRLA) battery [3].

In EVs and electronics, batteries used as energy sources and storage at once and thus frequently undergo charging and discharging cycles [4]. Charging and discharging are practically arbitrary processes, as batteries flow by different electric currents depending on the charger settings and load characteristics. As different type of battery has unique characteristics and applications, the charging and discharging cycles are critical to the battery's capacity and health. While a battery operates, it is important to understand its performance through its capacity and other parameters [5], [6]. Without knowing the battery capacity, we cannot estimate how far the electric vehicle can go. More severely, the battery could be damaged due to the user's incomprehension. One of parameter used to determine the battery capacity and the charge/discharge state is called the state of charge (SoC). SoC measures the remaining energy in a battery compared to the energy when the battery is fully charged [7].

By understanding the SoC and its dynamics, the charge and discharge cycles of the battery can be monitored and planned so that it can be used more precisely [8]. Monitoring the SoC prevents unwanted issues that can damage the battery, such as over-charge, under-charge, or over-discharge. Several researchers have researched the SoC estimation of VRLA battery to study its performance [9], [10]. Evaluating battery performance through SoC and other parameters is necessary to understand the characteristics of battery.

Performance degradation has been a vital issue in Li-ion batteries [11], [12]. Performance evaluation of Lithium-Sulfur (Li-S) battery on EVs was conducted using the Adaptive Neuro-Fuzzy Inference System (ANFIS) [13]. The average error of SoC estimation was 4%, with a maximum error of 7% when the tested EV was running. The Peukert effect was studied to estimate the SoC of Li-ion battery by measuring temperature variable, even though the Peukert effect is usually used for VRLA battery. SoC estimation of Li-ion battery using the fuzzy logic method in Simulink was discussed [14]. Furthermore, SoC estimation of Li-ion battery with indirect measurements has also been reported [15]. In the other work, the effective discharge time decreases with the power rate increase when it is more than 100%. For example, when the power rate is over 100%, the effective discharge time is very close to the nominal discharging time. On the other hand, it can destroy the battery more [16]. Nevertheless, the performance evaluation of Li-ion battery with direct measurements while providing an in-depth analysis with several quantitative parameters is still lacking in the literature.

In this work, the performance of a Li-ion battery is evaluated to reveal the performance degradation using three quantitative parameters, that is SoC, battery capacity, and

Received 18 December 2022, Accepted 28 February 2023, Published 10 March 2023.
DOI: https://doi.org/10.15294/jte.v14i2.40226

discharge time. The performance degradation is evaluated from multiple measurements, which are the measured voltage, current, and temperature are observed and recorded over five charge/discharge cycles. The contributions of this research are multifold. First, we demonstrate a simple, low-cost, effective setup to log and evaluate battery's performance. Second, this work introduces three parameters to evaluate performance degradation: SoC, battery capacity, and discharging time [17]. Third, this research reveals the performance degradation of a generic Li-ion battery, which occurs after the first charging and discharging cycle [18].

II. Method

A. Battery Performance Evaluation

In modern battery-powered electrical systems, such as EVs, batteries are installed with a management system or additional circuitry that measures several battery parameters. Despite being an energy source and storage, batteries need a data acquisition system to evaluate the batteries performance. Figure 1 illustrates the batteries performance evaluation in EVs to determine the SoC, which comprises the battery-powered system, data acquisition, and data analysis. The data acquisition collects several battery parameters, including the voltage (*V*), current (*I*), and timestep (*t*) for analysis. The data acquisition is accomplished through direct measurement, meaning the parameters are collected directly from the battery while used. The three measured quantities are necessary to determine the SoC, battery capacity, and discharging time. The data analysis process is required to derive the battery performance. For instance, the data of current and time is used to analyze the SoC through the Coulomb Counting method. Therefore, the last step is to analyze the performance degradation of a Li-ion battery with three parameters, such as SoC, battery capacity, and discharge time.

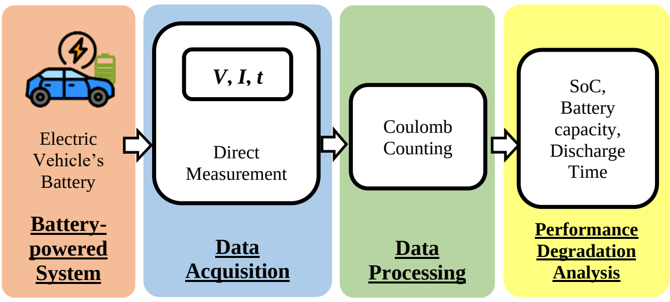

Figure 1. Principle of battery performance evaluation

One of the useful parameter to evaluate battery performance is SoC, which measures the remaining stored energy compared to it in fully charged condition. The SoC is estimated using the Coulomb Counting method while the battery capacity and discharge time are taken from multiple measurements and analysis. The performance parameters are compared, and the degradation is calculated and concluded. Determining the value of the SoC sometimes involves complex calculations depending on the battery type and the application. A simple yet accurate method widely used for estimating SoC in batteries is Coulomb Counting [19]. The advantages of this method are precision, ease of application, and accuracy. The possible error is only from the sensors. Moreover, the Coulomb Counting method can measure SoC while the battery is charging and discharging [20]. This method utilizes the value of the current consumption and total capacity of the battery. The Coulomb Counting method calculates the battery capacity value in Ah units, which later can be used to determine the SoC. Mathematically, The calculation of battery capacity using the Coulomb Counting method can be written as [21]:

$$C_c = \sum_0^n i\ t \tag{1}$$

where *n* is the amount of data taken, *i* is the current flowing to or from the battery, and *t* is the sampling time for data collection. The *n* depends on the data sampling and measurement period. The battery capacity can be determined by recording and updating *n*, *i*, and *t* over time. From the data, the Coulomb Counting method can accurately measure the battery capacity and SoC. After the battery capacity value is obtained using the Coulomb Counting method, the SoC value can be calculated using:

$$SoC = \frac{C_0 - C_c}{C_0} \times 100\% \tag{2}$$

where C_0 is the reference battery capacity value in Ah. The reference capacity value can be obtained from the battery datasheet. The parameter C_c is the battery capacity value calculated using Coulomb Counting according to the ratio of incoming and outgoing currents to the battery [22].

For the continuity of this research, the flowchart of this research is shown in Figure 2. The first step is to prepare an experimental setup for a direct measurement system. The experimental setup records and collects real-time data on the battery for repeated charging and discharging cycles. The collected data are voltage, current, and time used in the Coulomb Counting method to find the battery capacity changes over time. After recording the data, manual data selection and filtering are necessary to remove false data and outliers. Then, data processing through the Coulomb Counting method is applied to estimate SoC, battery capacity, and discharging time. The three parameters are used for analyzing the battery performance degradation.

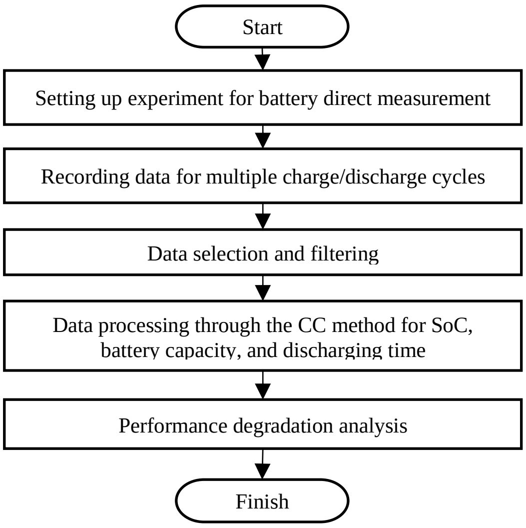

Figure 2. Research flowchart

B. Experimental Setup

In order to evaluate a battery's performance, the voltage and current can be acquired through direct measurement [23]. Figure 3 depicts the connection diagram of direct measurement to evaluate the performance of a Li-ion battery [24]. Several components used in the direct measurement include a Li-ion battery, a load, a microcontroller, i.e., Arduino Uno, a voltage sensor, a current sensor ACS-712, and a PC with data-logging software [25]. The current sensor is connected in series between the battery and load. The voltage sensor is connected in parallel to the battery. The outputs of the current and voltage sensors are connected to the microcontroller's analog-to-digital converter (ADC) pins. In direct measurement, the microcontroller is responsible for reading the measured current and voltage and sending it to the PC through USB serial connection. A data logging software, i.e., The Parallax Data Acquisition Tool (PLX-DAQ), will record the timestamp, measured current, and measured voltage periodically in real time. In this research, a light bulb is used as a load. Although batteries are used in various applications, including EVs, a stable light bulb load is preferred to examine the battery's ideal characteristics. In this research, the discharging process uses the standard "C20" with 0.5A. The issue with using dynamic or variable load is that the actual battery capacity would be affected by many unexpected factors which complicate the analysis.

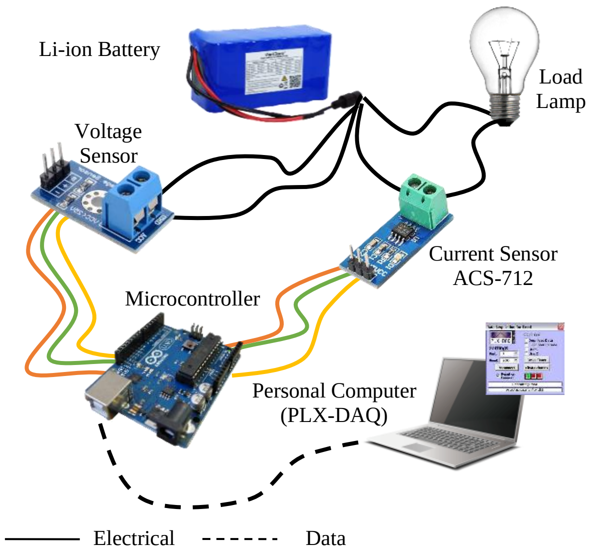

Figure 3. Connection diagram of direct measurement for battery performance evaluation

The selection of sensors and other components considers their specifications. The selected current sensor, ACS712, has a high reading accuracy since it contains a low-offset linear Hall-effect circuit with a single track made of copper. The accuracy is optimized by virtue of components between the conductors that produce a magnetic field and the hall-effect transducer nearby. The electric current from the battery to the load flows through the copper wires. It produces a magnetic field captured by the integrated Hall-effect IC and converts it into a proportional voltage [26]. The specifications of the current sensors, ACS712, are detailed in Table I.

The voltage sensor works based on the voltage divider circuit, which has an input range of 0-25V. Since the microcontroller Arduino Uno can only receive a maximum DC voltage of 5V, the voltage sensor increases the range of the voltage reading. With the voltage divider, the sensor reads a large voltage up to 25V and reduces it to 5 times smaller voltage, no greater than 5V, which is compatible with the microcontroller. The specifications of the voltage sensor are shown in Table II. The two sensors and microcontroller send the data to the PC via the PLX-DAQ data logging software. The data are received and recorded in Ms. Excel file. PLX-DAQ software add-in for Ms. Excel can acquire up to 26 channels of data and arranges the arriving numbers into columns. PLX-DAQ provides a simple spreadsheet analysis of data collected in the field, lab analysis of sensors, and real-time device monitoring [27].

TABLE I. CURRENT SENSOR ACS712 SPECIFICATIONS

No.	Specification	Value
1	Supply voltage	8 V
2	Reverse supply voltage	-0.1 V
3	Output voltage	8 V
4	Reverse output voltage	-0.1 V
5	Output current source	3 A
6	Output Current Sink	10 A
7	Ambient Temperature	-40 to 85 ^{0}C
8	Maximum Temperature	165 ^{0}C
9	Storage Temperature	-65 to 170 ^{0}C

TABLE II. VOLTAGE SENSOR SPECIFICATIONS

No	Specification	Value
1	Input voltage	0 – 25 VDC
2	Detection voltage	0.02445 – 25 VDC
3	Measurement accuracy	0.00489 V
4	Size	25 x 13 mm

Figure 4 shows the experimental setup for the performance evaluation of a Li-ion battery. The experiment was conducted in a laboratory environment with the setup following the connection diagram in Figure 3. A Li-ion battery with the capacity of 10Ah is used as a sample and tested with a direct measurement method. The Li-ion battery used in this study is assembled from 18650 batteries installed in series and parallel with a total capacity of approximately 10Ah. The detailed specification of the Li-ion battery under test is listed in Table III. The battery has a minimum voltage of 9 V and a maximum voltage of 12.6 V. The battery is connected to the load, which is a DC light bulb 6W, to perform the discharging process. In order to perform one cycle of the experiment, the battery is charged using a battery charger and discharged [27].

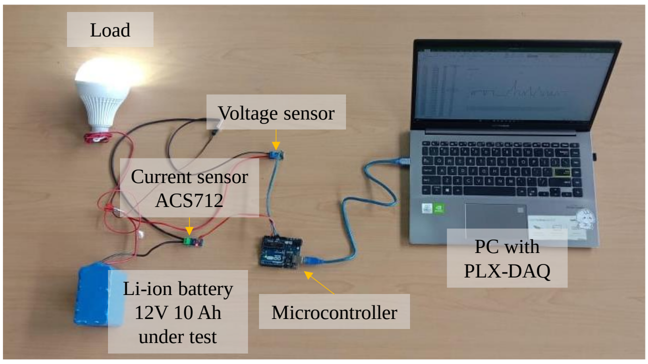

Figure 4. Experimental setup for performance evaluation of a Li-ion battery

TABLE III. BATTERY SPECIFICATIONS

No.	Specification	Value
1	Battery type	Lithium – ion
2	Configuration	3s4p (BMS3s40A)
3	Nominal voltage	11.1 V
4	Maximum voltage	12.6 V
5	Minimum voltage	9 V
6	Maximum charge current	20 A
7	Maximum discharge current	40 A
8	Discharge continuous current	20 A
9	Charger voltage	12,6 V
10	Nominal capacity	Approximately 10 Ah

Concerning the Coulomb Counting method, the direct measurement collects the data on how much electric current is used during the discharging process. The discharging process uses "C20", which refers to the data collection for 20 hours, where the number "20" in the word "C20" means time in hours. There are also C1, C5, C10, and C20 with different purposes and objectives. The C20 method is used because it has been proved by the researchers as the ideal time to prove the battery's capacity under test. In addition, the C20 method is also the ideal method of determining the actual or close to the original SoC value [28]. After calculating the battery capacity value using Coulomb Counting formula (1), it is converted into a percentage form using the formula (2) to estimate the SoC value. Since the battery capacity is 10Ah and the measurement uses C20, the load current that should be used is calculated as:

$$I = \frac{C}{t} \tag{3}$$

where C is the capacity of the Li-ion battery, and t is the time of the data collection using the C20 method, which is 20 hours. I is the load current used in this study.

From the calculation using formula(3), the ideal electric current for C20 and the used battery is 0.5A. Therefore, a DC incandescent light bulb with a power specification of 6W is used [29]. After that, direct data collection is carried out to measure the voltage and current values in real-time. In order to evaluate the performance of a Li-ion battery, multiple measurements were conducted. The number of measurement cycles was five times. Each measurement cycle took approximately 16 hours with the C20 data collection method. The temperature when data were collected is around 25°C (a normal room temperature), which is very important in the data collection process, especially on the battery [30].

III. Results And Discussion

The experiment was conducted five times, meaning the data of battery parameters, i.e., current and voltage were measured for five charging and discharging cycles with around 20 hours for each cycle. The SoC value was calculated from the discharge current and sampling time in each experiment. The calculation uses formula (1) to find C_c, which was then compared to C_0 obtained from the battery specification as in formula (2) to estimate the SoC value. The experimental results of the calculated SoC against the measured voltage from five measurements are depicted in Figure 5. The graph shown in Figure 5 is the results of the discharging processes, in which the SoC goes from 100% to the lower states. Thus, the graphs should be seen from right to left. The initial voltage is around 12.6V, while the final voltage after discharge is 9.38V. During the data recording, the measured parameters, i.e., voltage and current, from sensors are compared with the ones using a multimeter. The sensors have been calibrated so that the sensors reading is the same as the multimeter reading. The initial and final voltages are similar for all experiments. However, the SoC values are different for five experiments. The SoC reduces significantly after the first experiment. It implies that the battery experiences capacity fading, as shown in the grey box in Figure 5.

The SoC value in experiment 1 changes from 100% to 11%, while experiments 2, 3, 4, and 5 have a similar SoC value range, which changes from 100% to roughly 18%. The data shown in Figure 5 is plotted from a very large dataset containing 12,000 data for one cycle with a total of 5 data measurement cycles. For further explanation, it is important to look into the grey box to analyze the battery's performance. The grey box in Figure 5 shows the gap between the first experiment with the second and so on. The results of zooming in, the value into the grey box, and the critical area in the graph are given in Figure 6 and Figure 7. The total data in Figure 6 and Figure 7 are more than 1500, where the data are taken from the lowest value. In Figure 5, the data are taken from row 1238, while the data are taken from row 1262 in Figure 6.

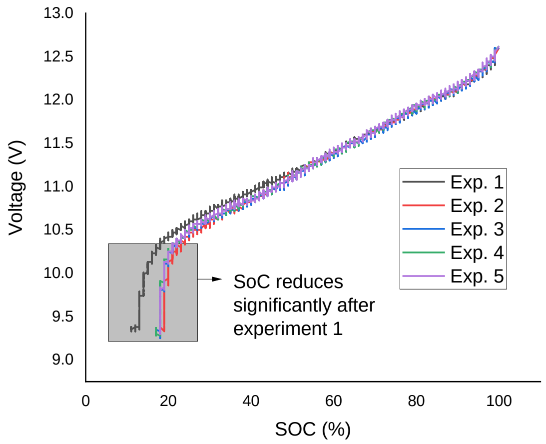

Figure 5. Comparison of SoC and voltage from multiple measurements

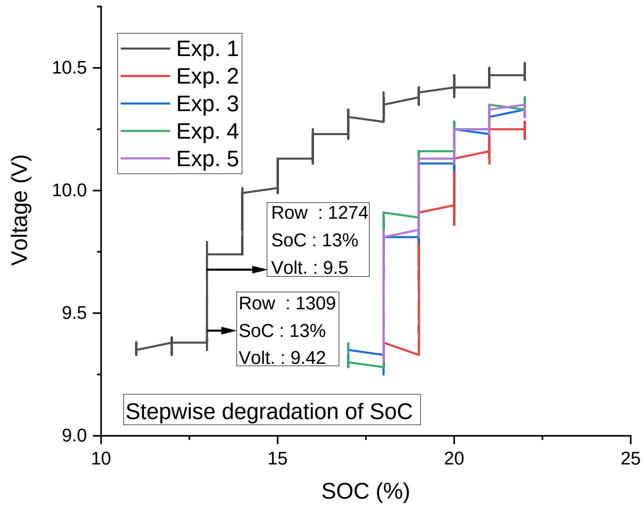

Figure 6. Detailed data of SoC against voltage showing the stepwise degradation of SoC

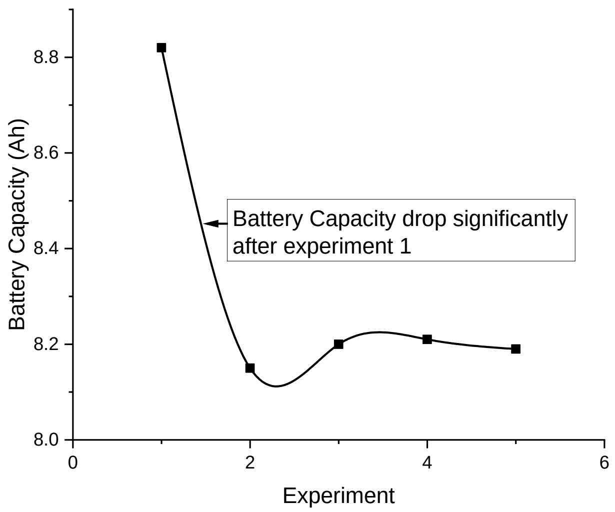

Figure 7. Battery capacity drops in five measurement cycles

The SoC of the Li-ion battery under test can be seen more clearly in Figure 6 and Figure 7. As seen in Figure 5, the SoC values are at the same level, i.e., 13%, while the voltages are at different values, i.e., 9.62V at the 1238th data and 9.55V at the 1262nd data. This proves that the SoC has a fixed value, but the voltage decreases because the battery is in its discharge phase. This phenomenon also makes the graphs in Figure 6 and Figure 7 show spikes for different voltages. It is good for the battery, which indicates that the battery is in a healthy state. When the graph is sloping without spikes, the SoC value changes faster to the next level. However, this is inversely proportional to the SoC value for each experiment. It can be seen again in Figure 5, Figure 6, and Figure 7 that the first experiment (black line) experienced a significant change in the second, third, and so on. Therefore, after the first experiment, the SoC will decrease significantly. A decrease in capacity is a change in the minimum SoC values from 11% to 18%. It implies that the battery experienced a capacity reduction of 7%. Therefore, other variables are needed to prove that performance degradation has occurred in Li-ion battery besides the SoC degradation. The other phenomena that can be observed for evaluating the performance degradation are the battery capacity and discharge time [31].

The capacity fading indicates a degradation of battery performance related to the battery life. Figure 7 shows the changes in battery capacity taken from five measurements denoted with the black rectangular markers. It can be seen that the battery capacity drops significantly after the first experiment. The battery capacity decreases from roughly 8.8Ah to 8.15Ah, which is about 8%. Then, the battery capacity fluctuates in experiments 3, 4, and 5, yet has a declining trend of around 1%. Therefore, a capacity fade occurred due to the battery's repeated use. Another factor causing a decrease in battery capacity is an increase in the battery's internal resistance or the thickening of the resistance in the battery. Hence, the decrease in battery capacity indicates the performance degradation in the Li-ion battery under test. For comparison, a research [32] also reveals the Li-ion battery capacity degradation proved by a similar result as in Figure 7.

The performance degradation also applies to a decrease in battery usage based on the battery discharge time [33]. It can be seen in Figure 8 that the pattern of decline is the same as in Figure 7. This shows that battery capacity and discharge time are interrelated variables and cannot be separated. The result of this pattern is when the battery capacity decreases, the discharge time will also decrease. After experiment 1, the discharge time was significantly reduced from 16.9 hours to 16.3 hours. The significant decrease was proven to represent the decrease in the discharge time after experiment 1. For the next experiments, the degradation happens slowly. Therefore, with the electric current that has been determined using properties of constant current, the ideal temperature for data collection, and the accuracy of the sensor that takes data, it can be concluded that there is a decrease in the SoC, capacity, and discharging time of the battery.

TABLE IV. COMPARISON WITH OTHER RELEVANT WORKS ON BATTERY PERFORMANCE DEGRADATION

Ref. No.	Battery type	Simulation/measurement tool	Analyzed parameters	Results
[31]	Lithium-ion	Equivalent electric circuit models (EECM)	Charging time, temperature, charging cost	Battery capacity degradation is affected by charging cost, temperature, and charging time.
[32]	Lithium-ion	NEWARE BTS 4000 battery tester	Battery capacity	The battery capacity estimation show the capacity degradation over 900 charging and discharging cycles
[33]	lithium-ion battery with Li (NiMn Co) O2 cathode	Multi-channel 5V-100A Arbin battery tester	Battery capacity, impedance	Charge and discharge cycling under 0–20% causes more impedance increase and less capacity loss, cycling under 80%–100% cause more capacity loss.
[34]	Lithium-ion	Battery testing machine (not specified)	SoC	The average estimation error using a neural network under three conditions is less than 3%. The capacity degrades with the number of discharges.
[35]	Lithium-ion	ab initio calculations, kinetic Monte Carlo simulations, software BEST	Battery capacity	Battery performance degradation can be estimated using mechanical and chemical models, which can fit experimental datasets.
[36]	Lithium-ion	MATLAB 2019b	Battery capacity	Anodic failure through the mechano-chemical model causes battery performance degradation shown by the capacity fade.
[37]	Lithium-ion	BTS200-100-10-4 battery testing system, thermostat (DGBELL), MATLAB	Battery capacity	The improved data-driven Coulomb Counting algorithm can accurately estimate SoC with less than a 3.6% error.
[38]	Lithium-ion	NEWARE, BTS-4000	Charging/discharging capacity, temperature, resistance, depth of discharge (DOD)	The battery charging characteristics are nearly independent of the charging temperature ranging from 20 °C to 40 °C, while the battery charging/discharging performance degrades dramatically for the battery temperature lower than 20 °C.
[39]	LiFePO4 / graphite lithium-ion	Scanning electron microscopy (SEM)	Discharge capacity, impedance, cycling cell	Degradation of the LFP/graphite LIBs could progress with an increasing C-rate; however, higher C-rates could mitigate the degradation because of the lowered capacity utilization.
This work	Lithium-ion	Voltage sensors, current sensors, and Arduino microcontroller, PC with PLX-DAQ software	SoC, battery capacity, discharge time	The battery SoC, capacity, and discharge time degrade of about 7% after the first cycle.

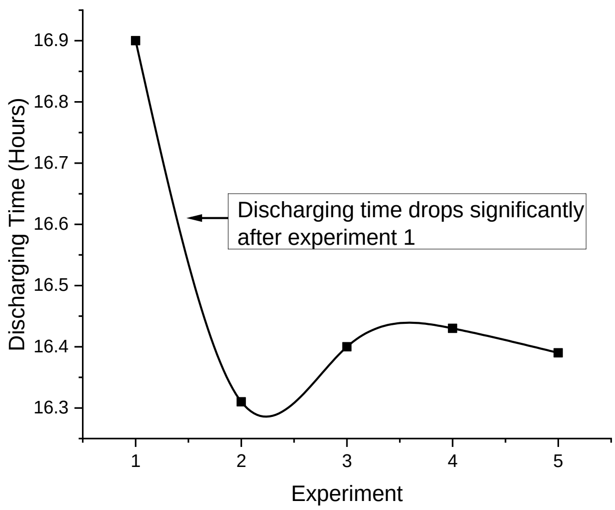

Figure 8. Discharging time (hours) drops in five measurement cycles

After analyzing the SoC, battery capacity, and discharge time, it can be concluded that these three measurements are very influential in determining the evaluation of the performance degradation of Li-ion battery. The degradation that occurs is an average of 7% - 9% for each variable after the first experiment. For the sake of comparison, other relevant works on battery performance degradation are summarized in Table IV based on the battery type, method (simulation or measurement), the analyzed parameters, and the results [34]–[36]. In the battery type, most researchers characterize Li-ion battery. Many of them create battery models and use simulations to study the performance degradation of battery. The other research based on experiments is conducted using costly battery testing and measurement system [37]–[39]. In our work, the measurements are done using a low-cost system employing off-the-shelf sensors, a microcontroller, and open-source data-logging software. Most research works analyzed battery capacity to observe battery performance degradation. In our work, three parameters are derived: SoC, battery capacity, and discharge time. In general, all relevant works agree well that Li-ion battery experience performance degradation. The performance degradation of Li-ion battery is proved in simulation and experimental works with mechanical and chemical models, as well as proved with direct measurements. Future research is expected to pay more attention to the battery monitored by using a Battery Management System (BMS), which can regulate excess voltage, current, and temperature to reduce this performance degradation.

IV. Conclusion

This research has evaluated the performance of a 10Ah Li-ion battery from multiple measurements of the SoC, battery capacity, and discharging time. The three parameters are derived from the direct measurements of voltage, current, and time. The measurements were conducted using a low-cost system employing off-the-shelf sensors, a microcontroller, and the PLX-DAQ data logging software. Results obtained from this study show that the Li-ion battery experienced a significant performance degradation denoted by the increase of minimum SoC value, battery capacity, and discharge time from the first experiment to the next. The change of minimum SoC from 11% to 18% indicates a capacity reduction of 7%. The discharge time is also reduced by 7% with the reduced battery capacity. The decrease in SoC value is related to the reduction of battery capacity and usage time. All the evaluated parameters from the Li-ion battery are related to each other. For the future, the results of this study can be used as a reference for research related to battery life and it is expected to pay more attention for the new battery, which should be monitored by a BMS to mitigate performance degradation.

References

[1] A. Gismero, E. Schaltz, and D. I. Stroe, “Recursive state of charge and state of health estimation method for lithium-ion batteries based on coulomb counting and open circuit voltage,” *Energies*, vol. 13, no. 7, p. 1811, 2020, doi: 10.3390/en13071811.

[2] S. Zhang, X. Guo, X. Dou, and X. Zhang, “A rapid online calculation method for state of health of lithium-ion battery based on coulomb counting method and differential voltage analysis,” *J. Power Sources*, vol. 479, p. 228740, Dec. 2020, doi: 10.1016/J.JPOWSOUR.2020.228740.

[3] S. M. Qaisar, “Event-Driven Coulomb Counting for Effective Online Approximation of Li-Ion Battery State of Charge,” *Energies 2020, Vol. 13, Page 5600*, vol. 13, no. 21, p. 5600, Oct. 2020, doi: 10.3390/EN13215600.

[4] N. Shateri, Z. Shi, D. J. Auger, and A. Fotouhi, “Lithium-Sulfur Cell State of Charge Estimation Using a Classification Technique,” *IEEE Trans. Veh. Technol.*, vol. 70, no. 1, pp. 212–224, 2021, doi: 10.1109/TVT.2020.3045213.

[5] X. Tang, F. Gao, C. Zou, K. Yao, W. Hu, and T. Wik, “Load-responsive model switching estimation for state of charge of lithium-ion batteries,” *Appl. Energy*, vol. 238, pp. 423–434, 2019, doi: 10.1016/j.apenergy.2019.01.057.

[6] S. Mian Qaisar, “A Proficient Li-Ion Battery State of Charge Estimation Based on Event-Driven Processing,” *J. Electr. Eng. Technol.*, vol. 15, no. 4, pp. 1871–1877, Jul. 2020, doi: 10.1007/s42835-020-00458-x.

[7] T. Zahid, K. Xu, W. Li, C. Li, and H. Li, “State of charge estimation for electric vehicle power battery using advanced machine learning algorithm under diversified drive cycles,” *Energy*, vol. 162, pp. 871–882, 2018, doi: 10.1016/j.energy.2018.08.071.

[8] X. Liu, W. Ai, M. Naylor Marlow, Y. Patel, and B. Wu, “The effect of cell-to-cell variations and thermal gradients on the performance and degradation of lithium-ion battery packs,” *Appl. Energy*, vol. 248, pp. 489–499, 2019, doi: 10.1016/j.apenergy.2019.04.108.

[9] J. Xie, J. Ma, and K. Bai, “Enhanced coulomb counting method for state-of-charge estimation of lithium-ion batteries based on peukert’s law and coulombic efficiency,” *J. Power Electron.*, vol. 18, no. 3, pp. 910–922, 2018, doi: 10.6113/JPE.2018.18.3.910.

[10] M. Fasahat and M. Manthouri, “State of charge estimation of lithium-ion batteries using hybrid autoencoder and Long Short Term Memory neural networks,” *J. Power Sources*, vol. 469, p. 228375, Sep. 2020, doi: 10.1016/J.JPOWSOUR.2020.228375.

[11] X. Han, L. Lu, Y. Zheng, X. Feng, and Z. Li, “A review on the key issues of the lithium ion battery degradation among the whole life cycle,” *eTransportation*, vol. 1. 2019. doi: 10.1016/j.etran.2019.100005.

[12] F. Yang, D. Wang, Y. Zhao, K. L. Tsui, and S. J. Bae, “A study of the relationship between coulombic efficiency and capacity degradation of commercial lithium-ion batteries,” *Energy*, vol. 145, pp. 486–495, 2018, doi: 10.1016/j.energy.2017.12.144.

[13] B. Rente *et al.*, “Lithium-Ion Battery State-of-Charge Estimator Based on FBG-Based Strain Sensor and Employing Machine Learning,” *IEEE Sens. J.*, vol. 21, no. 2, pp. 1453–1460, 2021, doi: 10.1109/JSEN.2020.3016080.

[14] L. Li, C. Wang, S. Yan, and W. Zhao, “A combination state of charge estimation method for ternary polymer lithium battery considering temperature influence,” *J. Power Sources*, vol. 484, p. 229204, Feb. 2021, doi: 10.1016/J.JPOWSOUR.2020.229204.

[15] S. Zhang, X. Guo, X. Dou, and X. Zhang, “A data-driven coulomb counting method for state of charge calibration and estimation of lithium-ion battery,” *Sustain. Energy Technol. Assessments*, vol. 40, p. 100752, Aug. 2020, doi: 10.1016/J.SETA.2020.100752.

[16] Y. Zhang *et al.*, “Performance assessment of retired EV battery modules for echelon use,” *Energy*, vol. 193, p. 116555, Feb. 2020, doi: 10.1016/J.ENERGY.2019.116555.

[17] Z. Huang, F. Yang, F. Xu, X. Song, and K. L. Tsui, “Convolutional Gated Recurrent Unit-Recurrent Neural Network for State-of-Charge Estimation of Lithium-Ion Batteries,” *IEEE Access*, vol. 7, pp. 93139–93149, 2019, doi: 10.1109/ACCESS.2019.2928037.

[18] A. Yang *et al.*, “A comprehensive investigation of lithium-ion battery degradation performance at different discharge rates,” *J. Power Sources*, vol. 443, p. 227108, Dec. 2019, doi: 10.1016/j.jpowsour.2019.227108.

[19] H. Huang *et al.*, “A comprehensively optimized lithium-ion battery state-of-health estimator based on Local Coulomb Counting Curve,” *Appl. Energy*, vol. 322, p. 119469, 2022, doi: 10.1016/j.apenergy.2022.119469.

[20] D. Lee *et al.*, “Modeling the effect of the loss of cyclable lithium on the performance degradation of a lithium-ion battery,” *Energies*, vol. 12, no. 22, p. 4386, Nov. 2019, doi: 10.3390/en12224386.

[21] X. Li, Z. Wang, and L. Zhang, “Co-estimation of capacity and state-of-charge for lithium-ion batteries in electric vehicles,” *Energy*, vol. 174, pp. 33–44, 2019, doi: 10.1016/j.energy.2019.02.147.

[22] J. A. Braun, R. Behmann, D. Schmider, and W. G. Bessler, “State of charge and state of health diagnosis of batteries with voltage-controlled models,” *J. Power Sources*, vol. 544, p. 231828, Oct. 2022, doi: 10.1016/J.JPOWSOUR.2022.231828.

[23] K. Hidayat, M. C. Hasani, N. A. Mardiyah, and M. Effendy, “Strategi Pengisian Baterai pada Sistem Panel Surya Standalone Berbasis Kontrol PI Multi-Loop,” *J. Tek. Elektro*, vol. 13, no. 1, pp. 25–33, 2021, doi: 10.15294/jte.v13i1.29765.

[24] J. A. Prakosa, S. Agmal, E. Kurniawan, M. J. Kholili, and C. Astuti, “Performance Evaluation of Two System Models for a MIMO System to Hover the Bicopter Unmanned Aerial Vehicle,” *J. Tek. Elektro*, vol. 14, no. 1, pp. 29–35, 2022, doi: 10.15294/jte.v14i1.35746.

[25] S. Boulmrharj *et al.*, “Online battery state-of-charge estimation methods in micro-grid systems,” *J. Energy Storage*, vol. 30, p. 101518, Aug. 2020, doi: 10.1016/J.EST.2020.101518.

[26] M. F. Ng, J. Zhao, Q. Yan, G. J. Conduit, and Z. W. Seh, “Predicting the state of charge and health of batteries using data-driven machine learning,” *Nature Machine Intelligence*, vol. 2, no. 3. pp. 161–170, 2020. doi: 10.1038/s42256-020-0156-7.

[27] X. Xin, S. L. Wang, C. M. Yu, J. Cong, and J. Coffie-Ken, “A novel state of charge estimation method for ternary lithium batteries based on system function and extended kalman filter,” *Int. J. Electrochem. Sci.*, vol. 15, no. 3, pp. 2226–2242, 2020, doi: 10.20964/2020.03.47.

[28] K. Movassagh, A. Raihan, B. Balasingam, and K. Pattipati, “A critical look at coulomb counting approach for state of charge estimation in batteries,” *Energies*, vol. 14, no. 14, p. 4074, 2021, doi: 10.3390/en14144074.

[29] J. Tian, R. Xiong, W. Shen, and J. Wang, “A Comparative Study of Fractional Order Models on State of Charge Estimation for Lithium Ion Batteries,” *Chinese J. Mech. Eng. (English Ed.*, vol. 33, no. 1, pp. 1–15, Dec. 2020, doi: 10.1186/S10033-020-00467-X/FIGURES/16.

[30] M. U. Ali, A. Zafar, S. H. Nengroo, S. Hussain, M. J. Alvi, and H. J. Kim, “Towards a smarter battery management system for electric vehicle applications: A critical review of lithium-ion battery state of charge estimation,” *Energies*, vol. 12, no. 3. p. 446, 2019. doi: 10.3390/en12030446.

[31] K. Liu, X. Hu, Z. Yang, Y. Xie, and S. Feng, “Lithium-ion battery charging management considering economic costs of electrical energy loss and battery degradation,” *Energy Convers. Manag.*, vol. 195, pp. 167–179, 2019, doi: 10.1016/j.enconman.2019.04.065.

[32] Y. Li, K. Li, X. Liu, Y. Wang, and L. Zhang, “Lithium-ion battery capacity estimation — A pruned convolutional neural network approach assisted with transfer learning,” *Appl. Energy*, vol. 285, p. 116410, Mar. 2021, doi: 10.1016/j.apenergy.2020.116410.

[33] Y. Gao, J. Jiang, C. Zhang, W. Zhang, and Y. Jiang, “Aging mechanisms under different state-of-charge ranges and the multi-indicators system of state-of-health for lithium-ion battery with Li(NiMnCo)O2 cathode,” *J. Power Sources*, vol. 400, pp. 641–651, 2018, doi: 10.1016/j.jpowsour.2018.07.018.

[34] S. Li *et al.*, “State-of-charge estimation of lithium-ion batteries in the battery degradation process based on recurrent neural network,” *Energies*, vol. 14, no. 2, p. 306, Jan. 2021, doi: 10.3390/en14020306.

[35] J. M. Reniers, G. Mulder, and D. A. Howey, “Review and Performance Comparison of Mechanical-Chemical Degradation Models for Lithium-Ion Batteries,” *J. Electrochem. Soc.*, vol. 166, no. 14, pp. A3189–A3200, 2019, doi: 10.1149/2.0281914jes.

[36] A. Sarkar, I. C. Nlebedim, and P. Shrotriya, “Performance degradation due to anodic failure mechanisms in lithium-ion batteries,” *J. Power Sources*, vol. 502, p. 229145, Aug. 2021, doi: 10.1016/J.JPOWSOUR.2020.229145.

[37] S. L. Wang *et al.*, “An improved coulomb counting method based on dual open-circuit voltage and real-time evaluation of battery dischargeable capacity considering temperature and battery aging,” *Int. J. Energy Res.*, vol. 45, no. 12, pp. 17609–17621, 2021, doi: 10.1002/er.7042.

[38] Z. Lu *et al.*, “A comprehensive experimental study on temperature-dependent performance of lithium-ion battery,” *Appl. Therm. Eng.*, vol. 158, p. 113800, Jul. 2019, doi: 10.1016/J.APPLTHERMALENG.2019.113800.

[39] Y. Abe, N. Hori, and S. Kumagai, “Electrochemical impedance spectroscopy on the performance degradation of LiFePO4/graphite lithium-ion battery due to charge-discharge cycling under different c-rates,” *Energies*, vol. 12, no. 23, p. 4507, Nov. 2019, doi: 10.3390/en12234507.