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Performance Analysis of Time Capacity and Coulomb Methods for SoC Estimation in VRLA Batteries

Analisis Performa Kapasitas Waktu dan Metode Coulomb untuk Estimasi SoC pada Baterai VRLA

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Abstract

The climate crisis and limited energy availability in remote areas encourage the use of VRLA battery-based off-grid solar energy systems, where accurate state-of-charge (SoC) evaluation is essential for system efficiency. At middle SoC ranges, the VRLA voltage curve's flatness makes voltage-based methods less effective. This research investigates the efficacy of two practical methods, Time Capacity and Coulomb Counting, in estimating the SoC of 12V 10Ah VRLA batteries at varying discharge rates (C20 to C1) using a system that incorporates Arduino Uno and ACS712 sensors. The experimental findings show that Time Capacity is the best strategy, with an inaccuracy of 0-12%. Due to sensor error and temperature sensitivity, Coulomb Counting's error is 30-38.4%. Heatmap imaging proved Time Capacity's stability across all C-rates, making it suitable for remote monitoring. These findings lay the groundwork for reliable and cost-effective renewable energy systems and encourage further research on hybrid algorithms and environmental optimisation.

Keywords: state of charge, VRLA battery, time capacity, coulomb counting, Arduino.

***SDGs*:**

Abstrak

Krisis iklim dan ketersediaan energi yang terbatas di daerah terpencil mendorong penggunaan sistem energi surya off-grid berbasis baterai VRLA, di mana evaluasi state-of-charge (SoC) yang akurat sangat penting untuk efisiensi sistem. Pada rentang SoC menengah, kerataan kurva tegangan VRLA membuat metode berbasis tegangan menjadi kurang efektif. Penelitian ini menyelidiki kemampuan dua metode praktis, yaitu metode *time capacity* dan *counting coulomb*, dalam memperkirakan status pengisian daya (SoC) baterai VRLA 12V 10Ah pada berbagai tingkat pengosongan (C20 hingga C1) menggunakan sistem yang menggabungkan sensor Arduino Uno dan ACS712. Temuan eksperimental menunjukkan bahwa metode *time capacity* adalah metode terbaik, dengan ketidakakuratan 0-12%. Karena kesalahan sensor dan sensitivitas suhu, kesalahan (error) pada metode Coulomb Counting sebesar 30-38,4%. Pencitraan *Heatmap* membuktikan stabilitas Time Capacity di semua C-rate, sehingga cocok untuk pemantauan jarak jauh. Temuan ini menjadi dasar bagi sistem energi terbarukan yang andal dan hemat biaya serta mendorong penelitian lebih lanjut mengenai algoritme hibrida dan optimalisasi lingkungan.

Kata Kunci: *state of charge, VRLA battery, time capacity, coulomb counting, Arduino.*

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1. INTRODUCTION

The climate crisis and the growing global energy consumption have compelled countries worldwide to expedite the transition to renewable energy (Rawal *et al.*, 2019). Solar power generation is one of the most popular technologies because of its low operating costs, flexible installation options, and wide availability (Victoria *et al.*, 2021). Nevertheless, the intermittent nature of solar radiation and its fluctuations necessitate energy storage units to ensure that solar systems can generate electricity continuously, particularly during dark hours or in overcast conditions (Madhusudanan and Padhmanabhaiyappan, 2024; Conde, Demition and Honra, 2025).

Valve-Regulated Lead-Acid (VRLA) batteries remain a popular choice in small to medium-sized solar energy storage systems due to their widespread availability in the market, lack of regular maintenance, and reasonable price (Skyllas-Kazacos, 2010). AGM and gel-type VRLA batteries are commonly used in off-grid systems, UPS, and hospital reserves due to their self-sealing properties and resistance to extreme conditions (Rawal *et al.*, 2019). VRLA batteries continue to be beneficial for solar energy applications due to their ability to withstand temperature fluctuations and maintain consistent performance during low- to medium-level usage (Alshabib and Tural, 2022). Other researcher discovered that over 60% of off-grid photovoltaic systems in developing nations continue to use VRLA batteries owing to their accessibility and ease of installatio (de Almeida, Moura and Quaresma, 2020). VRLA continues to prevail in the cost-effective storage industry, notwithstanding the swift advancement of lithium-ion technology (Bose *et al.*, 2024; Bouchareb *et al.*, 2024).

Monitoring the SoC is essential for the efficiency, life expectancy, and safety of energy storage devices. SoC is a critical metric that indicates the remaining energy capacity of the battery at any specific moment (Soyoye *et al.*, 2025). Nonetheless, VRLA batteries have a rather flat voltage against SoC curve, particularly within the mid-range (30-70%), hence diminishing the accuracy of voltage-based estimations (Hassan *et al.*, 2022). Inaccuracies in State of Charge assessment may result in overcharging or over-discharging, hence causing battery deterioration, reduced system performance, and potential safety hazards if inadequately managed (Oloyede *et al.*, 2025). Consequently, other methodologies such as time capacity and coulomb counting techniques are extensively employed, particularly in economical microcontroller systems.

The time capacity method determines SoC by comparing the actual discharge time to the theoretical full discharge time (Qian *et al.*, 2019). This technique is straightforward and recommended for applications with consistent loads. In the meantime, Coulomb counting makes use of the battery's cumulative current in and out over a predetermined period (Triawan, Yolanda and Humam, 2024). This method is more flexible, but it can accumulate errors if not compensated regularly. Various techniques, including extended Kalman filters (Azis, Joelianto and Widyotriatmo, 2019), impedance spectroscopy, and machine learning approaches (Sharma and Panigrahi, 2024), have been implemented to enhance the precision of SoC estimation. Nevertheless, these methods require the installation of additional sensors, significant computational resources, and costs that do not align with the characteristics of basic solar photovoltaic systems.

Despite numerous studies examining SoC estimation in lithium-ion batteries through mathematical, simulation, or sophisticated algorithmic methods like the Kalman Filter and machine learning, there is a deficiency of empirical research directly comparing two straightforward and practical techniques—time capacity and coulomb counting—in VRLA batteries under real-time conditions with variations in microcontroller-based discharge rates (C-rate). This method is highly pertinent for the advancement of economical SoC monitoring systems in small-scale solar power installations in remote regions that preclude the use of expensive, advanced equipment.

Another research developed an Arduino-based System on Chip SoC monitoring system; nevertheless, it failed to provide a comparative analysis of estimating methodologies (Kondaveeti *et al.*, 2021). To mitigate overcharging and over-discharging, Maltezo et al., implemented an Arduino Uno-based battery monitoring system that monitored voltage, current, and state-of-charge (Maltezo *et al.*, 2021). The method has been utilised for VRLA batteries in photovoltaic systems, illustrating its effectiveness in calculating battery lifespan and preserving optimal depth-of-discharge parameters (Hassan *et al.*, 2022). Recent implementations of coulomb counting in VRLA batteries for solar systems have demonstrated favourable outcomes in calculating battery longevity and sustaining optimal depth of discharge values (Afif, Aprillia and Priharti, 2020). Simultaneously, the research assessed a singular estimating approach without examining the stability of the estimation in relation to current variations (C-rate) (Hassanzadeh *et al.*, 2022). Consequently, there is a significant research gap in the field of comparative experimental evaluation of microcontroller-based SoC estimation methods for VRLA batteries, which is essential for addressing the practical requirements of renewable energy development.

This research is driven by the absence of experimental studies that directly contrast time capacity and coulomb counting state-of-charge estimation methods for microcontroller-based VRLA batteries across diverse discharge rate (C-rate) conditions, despite the significance of this method for the advancement of economical monitoring systems in off-grid solar power systems. It is hypothesised that the Time Capacity method will provide a more precise and dependable State of Charge estimation than Coulomb Counting, particularly when the battery is discharging fast.

This study presents a novel approach that uses an Arduino Uno system and an ACS712 current sensor to directly verify the accuracy and stability of the Time Capacity and Coulomb Counting methods for measuring the SoC on a 12V 7Ah VRLA battery. The underlying hypothesis is that the Time Capacity method provides a more precise and stable estimate of SoC at high discharge rates than the Coulomb Counting method. The objective of this research is to evaluate the performance of the two methods at a variety of C-rates (C20, C4, C2, C1), analyse error trends, and ascertain the most suitable method for a cost-effective battery monitoring system. The research's primary contribution is the provision of precise comparison data that facilitates the development of a microcontroller-based SoC VRLA monitoring system for renewable energy that is both practical and cost-effective. The research methods consist of the analysis of error trends and the recording of current, voltage, and time data through experimental testing.

2. METHODOLOGY

2.1. Research Location

The research study was carried out at the Department of Electrical Engineering, Sriwijaya University, at the Electrical Machinery and Energy Conversion Laboratory. This laboratory was selected due to its capacity for real-time data recording, its incorporation of battery testing equipment, an Arduino microcontroller, and a portable solar system, and its suitableness for SoC monitoring experiments.

2.2. Specifications of Tools and Materials

To facilitate the implementation of the battery SoC monitoring system, this research employs a combination of electronic components, sensors, and microcontroller-based data recording tools. The hardware system is intended to allow for the real-time collection of voltage, current, and time data while a VRLA battery discharges under various load scenarios. The comprehensive specifications of the instruments and materials utilised in this experiment are provided in Table 1.

Figure 1 illustrates the circuit design of the SoC monitoring system, providing clarity on the configuration of the wires and the interrelation of each component inside the experiment. Figure 1 shows a system using an Arduino Uno as the central processing unit with inputs from ACS712, LM35, and ACS712 sensors. During the discharge process, these sensors monitor the real-time status of a 12V 7.3Ah VRLA battery. The data logger module simultaneously stores the data on a microSD card, while the I2C module displays it on a 16x2 LCD. A continuous load 12V DC bulb simulates C-rate discharge scenarios.

Table 1. Equipment and materials specifications.

No	Component/ Material	Technical Specification
1.	VRLA Battery	AGM type, 12 V nominal voltage, 10 Ah capacity
2.	Micro-controller	Arduino Uno R3, 8 bit, 16 Mhz clock, 10-bit ADC, USB and UART communication ports
3.	Current sensors	ACS712, ±20 A range, 100 nV/A sensitivity, analog output, compatible with Arduino
4.	Voltage sensor	Voltage divider circuit: R1 = 10 kΩ, R2=2 kΩ, output to Arduino analog input (<5V)
5.	RTC and SD Card Module	DS3231 RTC, microSD card module (16GB, FAT32 format)
6.	Discharge Resistor Load	Variable resistive load (0.5-3.0 Ohm) for discharge rate (C1, C2, C4, C20)
7.	Digital Multimeter	Used for calibration of voltage and current measurements
8.	Charge and Power Supply	DC charger 13.8V, max current 1.5A, used for full charging of the battery
9.	Laptop and Software	Arduino IDE for Coding, MS Excel and Phyton (Matplotlib, Seaborn) for data visualization
10.	Temperature Sensor	LM35 module

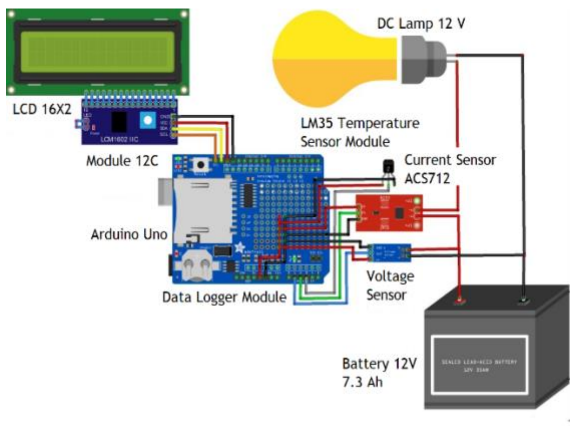


Figure 1. Circuit schematic of the SoC monitoring system.

This configuration allows accurate SoC estimation using time capacity and coulomb measurements.

2.3. Data Collection Technique

The battery was completely charged to around 13.8V (100% State of Charge) utilising a 13.8V DC charger. Discharge testing was performed with four constant current levels corresponding to conventional C-rates: C20 (0.35 A), C4 (1.75 A), C2 (3.5 A), and C1 (7 A) (Catenaro and Onori, 2021). The discharge cycle concluded when the terminal voltage decreased to 10.5V to avert over discharge. Voltage and current were measured with a voltage divider and an ACS712 current sensor interfaced with an Arduino Uno. Data were collected every second (Δt = 1 s), time-stamped with an RTC module (DS3231), and stored on a microSD card through a data logger module for subsequent analysis. The complete research flow can be seen in Figure 2.

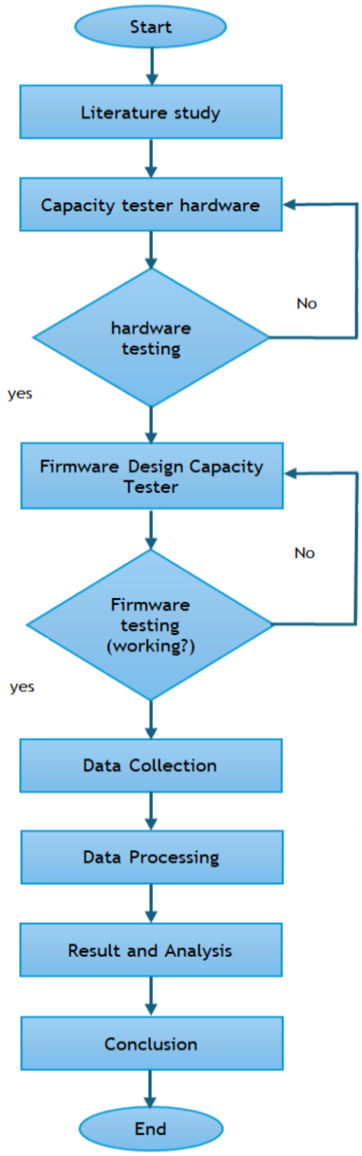


Figure 2. Flowchart of the research.

The research stages of this study are in accordance with the research flow depicted in Figure 2. Initially, this investigation commences with a literature review to acquire a comprehension of the technology and procedures involved in battery capacity testing. The hardware (capacity tester) was subsequently functionally tested to guarantee its performance, following the design and manufacture efforts. The firmware design stage is where the development remains after the hardware is functioning correctly. This stage is responsible for controlling the testing process and data acquisition. Following the testing of the firmware design, the integrated device is employed to conduct the data collection process if it satisfies the established criteria. The collected data is processed to generate information on battery capacity, which is subsequently analysed to assess the device's efficacy and the integrity of the measurements. Ultimately, the research is concluded by formulating conclusions that are derived from the analysis results.

2.4. Data Analysis Technique

The assessment of the battery's SoC was conducted utilizing two methodologies: the Time Capacity Method and the Coulomb Counting Method. Each technique employs a distinct principle to analyse battery depletion behaviour based on the gathered voltage, current, and time data.

2.4.1. Time Capacity Method

This method evaluates the SoC by contrasting the elapsed discharge time with the anticipated full discharge period for a specific C-rate. The equation is (Yang *et al.*, 2020):

$$\mathrm{SoC_{Time}} = \left(\frac{\mathrm{T_{actual}}}{\mathrm{T_{total}}}\right) \mathrm{x100\%} \tag{1}$$

where:

T_{actual} = Actual discharge time, seconds (s) or (hours (h)

T_{total} = Total expected discharge time based on C-rate, seconds (s) or hours (h)

SoC_{time} = Estimated State of Charge/Capacity [%]

This approach is most accurate when the load is steady and assumes a constant discharge profile.

2.4.2. Coulomb Counting Method

This method integrates the discharge current over time to determine the remaining charge. The equation employed is as follows (Lee and Won, 2023):

$$\mathrm{SoC(n)} = \mathrm{Soc(n-1)} + \frac{\mathrm{I(n).\Delta t}}{\mathrm{Q_{nominal}}} \tag{2}$$

where:

SoC(n) = SoC at the current time step (%)

SoC(n-1) = SoC at the prevous time step (%)

I(n) = Current at time step n (Ampere, A)

Δt = Time interval between reading, seconds (s), in this case Δt = 1 s

$Q_{nominal}$ = Nominal capacity of the battery = 7 Ah = 25.200 Coulombs (C)

This method enables more dynamic monitoring in the presence of fluctuating load conditions; however, it is susceptible to cumulative error if it is not periodically recalibrated.

2.4.3. Assessment of Errors and Accuracy

The inaccuracy is determined by the disparity between the capacity computed by the two methods in equation (3) and (4) (Zhao *et al.*, 2024):

$$Galat_{Ah} = Q_{coulomb} - Q_{time} \tag{3}$$

$$\mathrm{Galat\%} = \frac{\mathrm{Galat_{Ah}}}{\mathrm{Q_{time}}} \mathrm{x100\%} \tag{4}$$

Analyses were performed to assess the method's stability in relation to C-rate fluctuations and its sensitivity to sensor inaccuracies. Both methodologies were implemented on each discharge dataset that was collected at distinct C-rates. The resulting SoC values were analysed in terms of accuracy, error trends, and stability, and subsequently visualised using line plots and heatmaps.

3. RESULTS AND DISCUSSION

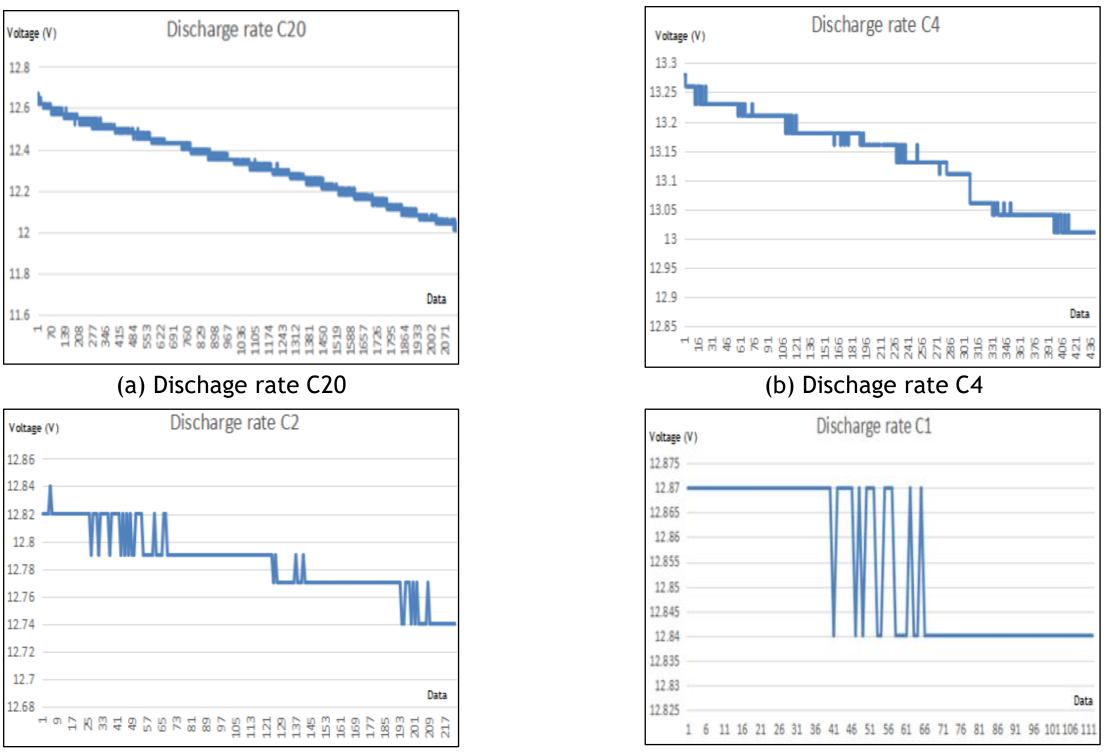
3.1. Sensor Testing and Data Collection

Experiments were conducted on a 12V 7.2Ah VRLA battery utilising four distinct discharge rates: C20 (0.35 A), C4 (1.75 A), C2 (3.5 A), and C1 (7.0 A). The accuracy of the measurements is verified through sensor testing on the Capacity Tester system prior to their implementation in the primary data collection. The sensors evaluated comprise voltage, current, and temperature sensors. Prior to the measurement, the sensors were calibrated at a stable room temperature and with a full battery. Due to an Arduino reference voltage reduction, the voltage sensor's initial and final measurements revealed 12.92V with an average inaccuracy of 0.07739%. Using a 12V 3W DC light, the current sensor showed 0.15A on the multimeter and 0.14A on the tester, resulting in an average inaccuracy of 4.44% due to the ACS712's voltage and temperature sensitivity. In 32°C room settings, the temperature sensor read 30°C before measurement and 27°C after testing, resulting in an average error of 9.375% due to the LM35's high ambient sensitivity.

3.2. Discharge Rate Testing

Discharge rate testing evaluates the battery's discharge rate utilising a constant current load as specified in the battery datasheet corresponding to the battery's rating. The objective of discharge rate testing is to ascertain the rate of voltage decrease over time. The battery capacity calculation is subsequently conducted in accordance with the IEEE 1188-2005 standard after the test data has been obtained. In this investigation, Panasonic's AGM-type VRLA batteries with the serial number LC-V127R2 were employed for discharge rate testing. In accordance with the battery datasheet, the discharge rates employed are C20, C4, C2, and C1. The results of the discharge rate test are shown in Figure 3.

Discharge tests were performed at several C-rates (C20, C4, C2, and C1) utilising a 12V 3W DC lamp load, and observations continued until the voltage declined to 10.5V. Even though the test was scheduled to last for 20 hours, the battery for C20 (Figure 3a) only attained its final voltage after 33 hours, which is inconsistent with the datasheet.



(a) Dischage rate C20 (b) Dischage rate C4

(c) Dischage rate C2 (d) Dischage rate C1

Figure 3. Discharge rate testing.

For C4 (Figure 3b), the discharge persisted for four hours, resulting in a gradual but unstable voltage drop because of the current sensor's sensitivity to temperature and the lamp's heating. The voltage for C2 (Figure 3c) fluctuated between the 14th and 36th minutes, but it did not approach the 10.5V limit. It momentarily climbed in the early minutes. Concurrently, C1 (Figure 3d) exhibited voltage instability from the 21st to the 35th minute because of the high current, which resulted in rapid heating and influenced the sensor readings. In general, current stability, ambient temperature, and sensor limitations under extreme conditions influence voltage fluctuations and deviations from ideal discharge specifications.

The discharge rate tests conducted in this study indicate that the voltage drop characteristics of VRLA batteries are not entirely linear at high discharge rates, particularly at C2 and C1. These voltage fluctuations are a consequence of the high current, temperature, and sensor limitations. This result is consistent with the findings of Xu et al., who concluded that large discharge rates (>C2) in VRLA batteries increase internal resistance, leading to voltage instability and non-linear voltage decay (Xu and Wen, 2021).

3.3. Calculation of Capacity

The efficiency and longevity of energy storage systems are contingent upon the precise estimation of battery capacity. This study tests Time Capacity and Coulomb Counting on a 12V 10Ah VRLA battery with four C-rate changes (C20, C4, C2, and C1). Table 2 below illustrates the comparison between the nominal capacity and the capacity calculation results, which are expressed in Ah and percent. The Table 2 contains the results of the calculations conducted using equations (1)-(4), which were previously discussed in the methodology section.

The outcomes of battery capacity evaluation utilising the Time Capacity and Coulomb Counting methodologies exhibit notable discrepancies, particularly at elevated discharge rates. At a discharge rate of C20, the Time Capacity approach estimated the battery capacity at 10 Ah, representing 100% of the nominal capacity, but Coulomb Counting achieved only 7 Ah, or 70%. This trend persisted in tests C4, C2, and C1, wherein the Time Capacity technique yielded estimates that remained near the expected value, with a slight decline attributed to complications in load disconnection or tiny fluctuations in current. Conversely, the Coulomb Counting approach exhibited a notable decline to 6.16 Ah (61.6%) in test C1, with error rates above 35%.

Table 2. Comparison of capacity calcuation result.

C Rate	Time Capacity (Ah)	Coulomb Counting (Ah)	Error Time (%)	Error Coulomb (%)
C20	10.00	7.00	0.00	30.00
C4	9.75	6.83	2.50	31.70
C2	9.50	6.65	5.00	33.50
C1	8.80	6.16	12.00	38.40

The Coulomb Counting method's accuracy diminishes due to cumulative inaccuracies in the ACS712 current sensor, which are influenced by variations in temperature and input voltage. Elevated discharge rates result in increased system temperature and higher current, causing reading noise that the system cannot mitigate. This method is contingent upon the precision of current calibration and accurate temporal integration. Conversely, time capacity exhibits greater stability, necessitating only a predetermined discharge period and current, irrespective of real-time sensor data.

The capacity calculation outcomes in this study correspond with trends shown in previous research. The Time Capacity technique provided estimates closely aligned with the expected values for all C-rates (100% at C20, 88% at C1), corroborating the findings of Zine et al., that time-based estimation is effective for VRLA batteries under constant load conditions (Zine *et al.*, 2022). The researcher also observed analogous sensor drift and cumulative errors in ACS712-based systems. This finding is also consistent with Movassagh et al., who emphasised that Coulomb Counting's accuracy declines under dynamic operating conditions when temperature and current compensation are not implemented (Movassagh *et al.*, 2021).

The accuracy of each battery capacity estimation method was visualised using a heatmap graph as a visual analysis tool. This graph illustrates the percentage error of the Time Capacity and Coulomb Counting methods in relation to the nominal battery capacity (10 Ah) in a variety of discharge rate (C-rate) scenarios. The heatmap illustrates patterns and trends in the buildup of estimating mistakes that may not be evident in simple numerical representation, as depicted in Figure 4.

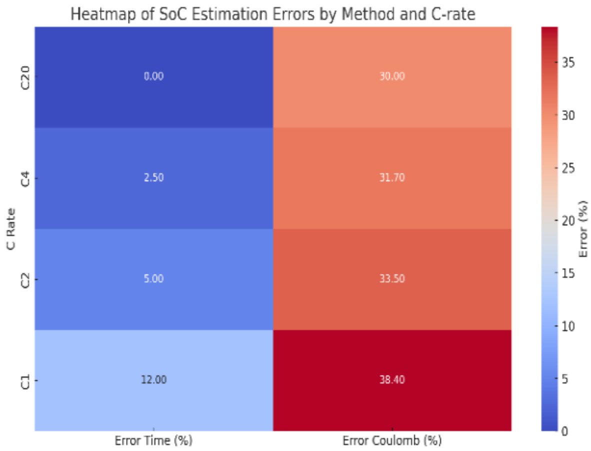


Figure 4. Heatmap of SoC estimation errors by Method and C-rate.

Based on Figure 4, the error rates of battery capacity estimation were visualised using heatmaps at four discharge rate levels (C20, C4, C2, and C1) using two methods: coulomb counting and time capacity. The Time Capacity method exhibits a very low error at C20 (0%), where the colour is vibrant blue. The colour transitions to light green at C4 (2.5%), C2 (5%), and yellowish green at C1 (12%). This evidence indicates that time capacity remains very accurate and consistent, even when the discharge rate increases. Conversely, the Coulomb Counting method exhibits a more striking colour transition, commencing with a dark green colour in C20 (30%), progressing to a dark yellow colour in C4 and C2 (31.7 and 33.5%), and ultimately transitioning to a brilliant orange colour in C1 (38.4%). A substantial increase in error is indicated by this colour change, which is the result of the accumulated error of the current sensor, which is susceptible to fluctuations in voltage and temperature. This visualisation serves as confirmation that the Time Capacity method is more dependable for straightforward battery monitoring applications, particularly in high-load scenarios.

Upon consideration of these findings, it is evident that the time capacity method is more practical for the implementation of battery monitoring systems in remote solar farms, where they are uncomplicated and cost-effective (Simanjuntak *et al.*, 2021). This approach not only estimates capacity more accurately but is also more resilient to less-than-ideal environmental circumstances. The Coulomb Counting method remains dependable when employing high-precision current sensors and more advanced signal processing; however, it necessitates an increase in cost and complexity.

4. CONCLUSION

According to the test results, the Time Capacity approach is more accurate and reliable at calculating VRLA battery capacity (State of Charge or SoC) than Coulomb Counting, especially at significant discharge rate changes. The temporal capacity approach yields findings near to the nominal capacity (10 Ah), but the coulomb counting method loses precision due to current sensor readings that are subject to temperature and voltage changes. Practically, these discoveries are pertinent to the creation of cost-effective and straightforward monitoring systems for solar power plants or reserve power systems in remote regions, where environmental conditions and current stability are not always optimal. The implementation of the Time Capacity method, which necessitates only the recording of current and time, remains more efficient and dependable.

However, this investigation is restricted by the utilisation of a single battery type (VRLA 12V 10Ah) and the execution of the study under fixed load conditions. No assessments were performed under dynamic load or extreme temperature conditions. In the future, it is recommended that this method be tested in real-time Internet of Things (IoT) systems, that it be tested with other battery types such as Li-ion, and that a hybrid approach be investigated that employs both time capacity and coulomb counting to improve the accuracy and reliability of SoC estimation.

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