IEEE Access
Multidisciplinary ⋮ Rapid Review ⋮ Open Access Journal

Received 8 June 2024, accepted 22 June 2024, date of publication 24 June 2024, date of current version 2 July 2024.

Digital Object Identifier 10.1109/ACCESS.2024.3418909

RESEARCH ARTICLE

Battery Management System for Electric Garbage Compactor Trucks

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ABSTRACT When garbage trucks perform garbage collection and compression operations, it is common to keep the engine idling and even increase the engine speed during garbage compression, which can lead to noise, air pollution, increased fuel consumption, and carbon emissions. Adopting an electric compression system can effectively reduce these issues. The battery pack used in electric garbage trucks is the core energy source of the vehicle, making proper battery management system crucial for the overall safety and performance of the vehicle. This study aims to utilize NUVOTON's Cortex-M4 chip to develop a battery management system specifically designed for electric garbage trucks. By real-time online estimation of the battery state, optimal performance of the battery pack can be achieved. Battery health is assessed based on capacity cycle counting for parameter weighting evaluation of battery voltage drop. By comparing the capacities of battery modules to track and calibrate the open-circuit voltage, the capacity error is primarily estimated using a combination of Coulomb counting method and open-circuit voltage method to assess the battery's state of charge and evaluate its lifespan. The proposed method is validated by integrating the battery state estimation technique into the microcontroller of the battery management system, and compared with the conventional Coulomb counting method. The real-time online battery estimation method adjusts the initial value check of SoC by tracking the variation of battery module capacity and adjusting the OCV lookup table, thereby enhancing the accuracy of SoC estimation and reducing errors. This method can be effectively applied to electric garbage compressors to improve battery utilization efficiency and maximize battery lifespan.

INDEX TERMS Battery management system (BMS), Coulomb counting method (CCM), state of charge (SoC).

NOMENCLATURE

BMS	Battery management system.
SoC	State of charge.
RDE	Remaining Discharge Energy.
SoH	State of health.
CCM	Coulomb counting method.
MBM	Model-based method.
DDM	Data-driven method.
HM	Hybrid method.
OCV	Open-circuit voltage.
KF	Kalman filter.
EKF	Extended Kalman filter.
UKF	Unscented Kalman filter.
MCU	Microcontroller Unit.
MPU	Micro-processor Unit.
CPU	Central Processing Unit.
BUBM	bottom-up-based method.
LKF	Linear Kalman Filter.
RAM	Random-access memory.
BMC	Battery monitoring circuit.
BCU	Battery control unit.
CAN	Controller area network.
ADC	analog-to-digital converter.
HMI	Human–machine interface.
EEPROM	Electrically-Erasable Programmable Read-Only Memory.

The associate editor coordinating the review of this manuscript and approving it for publication was Ilaria De Munari.

RTC	Real-time clock.
GPIO	General-purpose input/output.
UART	Universal Asynchronous Receiver/Transmitter.
SPI	Serial Peripheral Interface Bus.
EADC	Enhanced Analog-to-Digital Converter.
OVP	Over voltage protection.
UVP	Under voltage protection.
OTP	Over temperature protection.
UTP	Under temperature protection.
UBL	Unbalanced.
CV	Constant voltage.
V_{oc}	OCV Voltage.

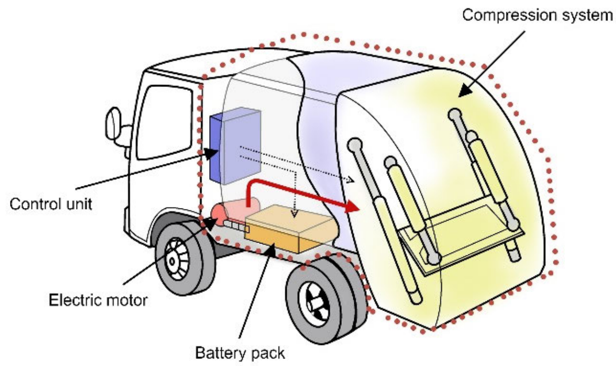

FIGURE 1. Architecture of an electric garbage compactor truck.

I. INTRODUCTION

A. BACKGROUND

Climate change and rising energy-saving and carbon reduction awareness have led to governments around the world investing heavily in resources to actively develop and promote various energy-saving and carbon reduction technologies. The electrification of garbage trucks is particularly noteworthy.

Compared to Japan's electric compression technology, the European and American regions are moving towards full vehicle electrification or hybrid chassis. Taiwan's relevant industries can support the components required for electric compact garbage trucks. Electric garbage compactor trucks use electric motors to replace traditional engine-driven compression devices, with the same garbage collection capacity, and can be mounted on different forms of chassis vehicles. The main components of these vehicles include battery packs, electric motors, and motor control systems, as shown in Figure 1. The development of this technology is expected to improve collection efficiency while reducing carbon emissions, in line with environmental protection trends, and is worth further promotion.

The electric garbage compactor trucks has the following main advantages:

- ➢ The compaction chamber operates at zero idle speed and zero carbon emissions when used at a fixed location, effectively saving fuel consumption and reducing air pollution.
- ➢ Low noise during compaction operations helps reduce urban environmental noise pollution.
- ➢ The motor has high energy conversion efficiency, far exceeding that of a diesel engine.
- ➢ Achievable with existing industry technologies, with a relatively low technical threshold.

The battery pack used in electric garbage compactor trucks is the core power source for the entire vehicle. However, the overall performance of the battery pack will degrade over time due to repeated charging and discharging cycles. Therefore, it is crucial to equip the system with a targeted battery management system (BMS) to monitor, protect, balance the energy, and improve the efficiency and lifespan of the batteries. The BMS is responsible for controlling battery conditions to extend battery life and ensure safe operation, while also providing accurate state of charge (SoC) and state of health (SoH) estimation. Extending battery life and fault diagnosis are the core functions of the BMS. During the charging and discharging process, accurately tracking the SoC is critical to prevent overcharging or over-discharging, improving safety.

The battery cells within the pack may use different materials and operate in different environments, connected in series to meet the power requirements. This often results in uneven battery capacities within the pack, leading to complex non-linear dynamic behavior. This can cause over-charging or over-discharging of individual cells, resulting in inconsistent battery life and aging, as well as potential risks of unexpected power failures. Therefore, accurate estimation of battery status is crucial when considering battery capacity differences, with the aim of extending battery life and ensuring safe operation.

B. PREVIOUS WORK

State of Charge (SoC) and Remaining Discharge Energy (RDE) are two important parameters related to the energy status of a battery. The estimation of SoC is mainly focused on monitoring the remaining capacity of the battery in charge-discharge cycles to avoid overcharging and over-discharging, thus extending the battery's effective lifespan. On the other hand, Remaining Discharge Energy (RDE) refers to the available energy remaining within a specific timeframe, which helps in more accurately estimating the battery's SoC [1]. The SoC varies over time during the charging and discharging process, and it is a crucial factor for further predicting the state of health (SoH). The estimation of SoH aims to predict the remaining useful life or remaining charge-discharge cycle count of the battery, to determine if battery replacement is necessary [2], [3]. Due to the availability of different algorithms for estimating the SoC of batteries, various methods for estimating SoC have been extensively researched in recent years. These methods have been categorized based on their advantages and disadvantages [4], [5], [6], [7], [8], [9], [10], [11], [12].

SoC estimation methods are primarily divided into five categories: direct measurement method, CCM, MBM, DDM, and HM. These methods are detailed as follows.

1) DIRECT MEASUREMENT

Direct measurement method primarily involve using the battery voltage and impedance to determine the SoC. The two main direct measurement methods are described in the following text.

a: METHOD BASED ON OPEN-CIRCUIT VOLTAGE

In method based on the OCV, the OCV at different SoC levels is measured to determine the relationship between OCV and SoC. Subsequently, this relationship is used to obtain the SoC for different OCV values. This method is only applicable when the battery's internal state is stable and is thus unsuitable for analyzing the nonlinear characteristics of battery systems. Moreover, the method cannot be executed online and requires the battery to be at rest for a sufficiently long time before SoC monitoring. To achieve internal balance, the battery must be disconnected from any load and left to rest for a substantial period, after which the OCV can be measured under these conditions [13]. Various improved OCV-based methods with enhanced accuracy and shortened processing time have been proposed [14].

b: IMPEDANCE-BASED ESTIMATION METHOD

In methods based on the Faradaic impedance, which refers to an electrode surface's resistance or capacitance in an electrochemical system, a small sinusoidal potential wave is applied under varying frequencies to calculate the impedance values. These values are then used to estimate the SoC.

Impedance values are usually measured using electrochemical impedance spectroscopes, which are generally designed for laboratory use and fairly expensive. Moreover, the use of these spectroscopes is further complicated by the difficulty of online measurements and variations in battery types and experimental conditions [15].

2) COULOMB COUNTING METHOD

In CCM, the discharge current is measured and integrated over time to determine the SoC. Because the CCM involves estimating the SoC on the basis of the accumulated current, a small initial current error can lead to large cumulative errors. In the CCM, incorrect data on initial battery capacity can critically affect the accuracy of the determined SoC over time. Therefore, the Coulomb counting method is usually combined with model-based or data-driven methods to improve reliability. Combining the SoC-OCV lookup table is also a good way to complement the shortcomings of CCM [16]. In addition, a method called Enhanced Coulomb Counting (ECC) has been studied by applying OCV and CCM [17], [18] as well as a numerical iteration-based method [19]. Besides combining with OCV, an enhanced Coulomb counting (ECC) method for SoC estimation has also been proposed by combining Peukert's law for the discharge process and Coulombic efficiency for the charging process [20].

3) MODEL-BASED METHOD

MBM involve using measurements of battery signals (voltage, current, and temperature), battery models, and filtering algorithms to estimate a battery's SoC. The Kalman filter (KF) has been successfully used in battery state estimation. The main characteristic of the KF is its self-correcting nature, which enables it to produce accurate estimations even under high current variations. However, the KF generates relatively inaccurate estimates in nonlinear scenarios. To overcome this limitation, various KF-based algorithms have been proposed for SoC estimation [21], such as the extended KF (EKF) [22], [23], unscented KF (UKF) [24], adaptive EKF [25], and square root UKF [26] algorithms. These algorithms are more robust and accurate relative to the KF algorithm. The accuracy of MBMs, such as those involving the use of the aforementioned algorithms, has been validated by comparing them with methods based on seven nonlinear filters [27]. Although MBMs achieve high accuracy in SoC estimation, they require precise battery models and are computationally expensive. The internal parameters of a battery vary during charging and discharging, and a sufficiently accurate yet lightweight model that accounts for all external battery characteristics is challenging to establish.

4) DATA-DRIVEN METHOD

Advances in computer technology have led to the rapid development of DDM. Data-driven method are often referred to as black-box models because they can directly map the nonlinear relationship between an output (e.g., SoC) and multiple inputs (e.g., voltage, current, and temperature) without previous relevant knowledge (e.g., battery-related data). These algorithms can be easily transferred to a hardware platform after offline training without the need for underlying physical or chemical representations. Data-driven algorithms are trained using voltage, current, and temperature measurements for accurate estimates of a battery's SoC and SoH.

Data-driven method that can be used to estimate a battery's SoC include convolutional neural networks [28], deep neural networks [29], fuzzy logic [30], support vector machines [31], support vector regression [32], extreme learning machines [33], and genetic algorithms [34]. However, these algorithms require large empirical datasets to understand and accurately predict system behavior, and they are also time-consuming and computationally expensive to train. Therefore, data-driven algorithms must be trained offline for them to capture nonlinear relationships.

5) HYBRID METHOD

Due to the inherent strengths and weaknesses of different methods, multiple SoC estimation methods can be combined to form a hybrid approach. Some studies and literature have shown that compared to individual SoC estimation methods,

TABLE 1. Core chip comparison.

	MCU	MPU	CPU
Power Consumption	Small	Large	Large
Operating Frequency	Less than 300MHz	Greater than 300MHz	Greater than 300MHz
Memory Space	Built-in Memory	External memory required	External memory required
Cost	Low	Medium	High

the HM typically enhances the accuracy and robustness of SoC estimation. This is achieved by combining two or more SoC estimation methods to achieve optimal estimation performance. Authors in the literature have proposed a battery state estimation method that combines hybrid and adaptive characteristics. This method integrates Coulomb counting, Kalman Filter (KF), and Unscented Kalman Filter (UKF) techniques for SoC estimation [35].

In another study [36], a novel real-time hybrid SoC estimation algorithm for lithium-ion batteries in electric vehicles was proposed. It combines an improved CCM, MBM, and BUBM. The algorithm was validated through multiple actual driving cycle tests on the 2012 Nissan Leaf model. Another approach combines the advantages of CCM, Linear Kalman Filter (LKF), and OCV-based SoC estimation methods for real-time applications in lithium-ion batteries that require fast response and accurate SoC estimation [37].

These studies demonstrate that the hybrid method balances cost and effectiveness, making it an ideal SoC estimation technique compared to traditional methods. While it better serves the needs of battery management systems, the challenging task of combining two or three methods requires high computational capabilities and may increase the computational burden on chips, which should be considered as a drawback [38].

Due to the limitations of space and circuit cost in the battery management system (BMS) used in electric garbage compactor trucks, the computational capability and time required for MBM, DDM, and hybrid methods to achieve accurate SoC and SoH estimation are relatively long. However, these techniques are not suitable for low-cost energy storage and vehicle applications. Therefore, Table 1 compares the current control chips, and selects low-power, low-cost microcontroller (MCU) to be applied in the BMS of electric garbage compactor trucks.

The battery management system (BMS) of electric garbage compactor trucks must fulfill various functions, including battery charging and discharging balancing, protection, and control systems, as well as enabling communication among multiple battery module strings and parallel connections. As the system relies on microcontrollers for multiple functions and necessitates sufficient RAM to support related algorithms, the selection of battery state estimation methods must strike a balance between simplicity and efficiency, considering the system's cost and performance requirements [39]. Hence, the fusion of Coulomb counting and OCV is chosen and implemented in the BMS of electric garbage compactor trucks for the following reasons:

- ➢ The Coulomb counting method provides accurate energy estimation by counting the charge and discharge cycles, while combining it with OCV enhances the estimation accuracy.
- ➢ Combining the linear performance of Coulomb counting with the adaptiveness of OCV can enhance estimation accuracy and robustness.
- ➢ By effectively leveraging the strengths of different methods, it is possible to save computational costs and time, thereby achieving more accurate battery state estimation.
- ➢ Provide essential information and reduce reliance on complex circuits and expensive devices within limited space and cost constraints.

In summary, the combination of the Coulomb counting method and OCV can enhance the accuracy of SoC estimation, while providing real-time performance, cost-effectiveness, and stable execution.

Therefore, this paper focuses on the development of a battery management system (BMS) for electric garbage compactor trucks, using the NUVOTON Cortex-M4 chip as the control core. This BMS uses real-time online estimates of battery state to ensure the optimal performance of the battery pack of electric garbage trucks. A battery's health is mainly evaluated according to the weighted assessment of the battery voltage drop through capacity cycle counting. Moreover, battery module capacities are compared to track and correct the OCV of the battery. The capacity error is primarily estimated through the combined use of the CCM and OCV method (OCVM) to accurately determine the battery's remaining capacity.

The contribution of this paper lies in the application of battery state estimation methods based on voltage and capacity cycle counts, integrating CCM and OCV method (OCVM) into a microcontroller. This implementation aims to achieve high precision with minimized errors, making the proposed method suitable for online applications. The system operates in the battery management system of an electric garbage compaction truck. Comparisons and validations against traditional CCM reveal that the accumulated errors of CCM lead to inaccuracies in SoC estimation over extended system operation periods. In contrast, the real-time online battery estimation method adjusts the OCV lookup table by tracking changes in battery module capacities for the initial SoC value checking, enhancing SoC estimation accuracy and reducing errors. Experimental results verify the effectiveness and accuracy of the proposed real-time online battery estimation method.

The rest of this paper is structured as follows. Section II explains the hardware architecture of the proposed BMS for

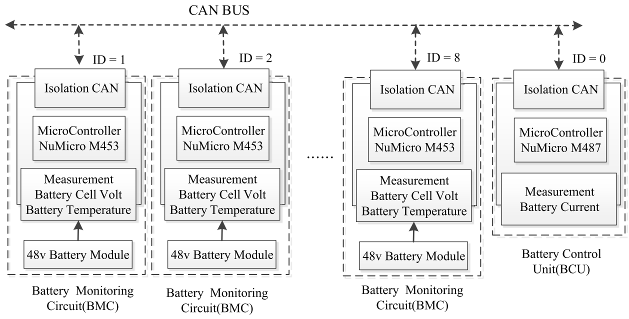

FIGURE 2. Hardware architecture of the proposed BMS for an electric garbage compaction truck.

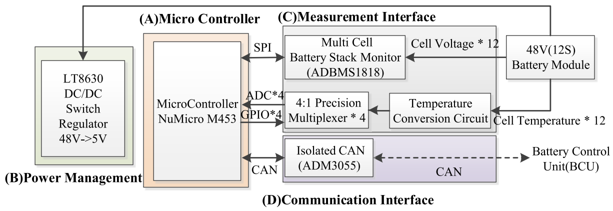

FIGURE 3. Architecture of the BMC.

electric garbage compactor trucks. Section III introduces the software and firmware architectures of the proposed BMS as well as the algorithm used in this system for the real-time online estimation of battery status. Section IV presents the results of experiments performed using the proposed BMS. Finally, Section V provides the conclusion of this study.

II. HARDWARE ARCHITECTURE

The hardware of the proposed BMS mainly comprises a series connection of eight sets of 48-V battery modules to achieve a voltage of 384 V for an electric garbage compaction truck. The hardware architecture of this system is displayed in Figure 2.

The hardware circuit of the BMS consists of two main modules: a battery monitoring circuit (BMC) and battery control unit (BCU). These modules are explained in detail in the following text.

A. BATTERY MONITORING CIRCUIT

Figure 3 depicts the architecture of the BMC. This circuit performs the following functions:

- ➢ It measures the voltage and temperature of each of the 12 individual battery cells used in an electric garbage compaction truck.
- ➢ It transmits battery data to the BCU through internal controller area network (CAN) communication by using a fixed polling process.

Each part of the BMC is detailed as follows.

The BMC comprises four sections, namely sections A–D. Section A contains the core chip of the BMC, namely an M453 microcontroller with a Nuvoton ARM Cortex-M4 core, and section B comprises the overall power supply. When supplying power to the BMC, the power supply effectively steps

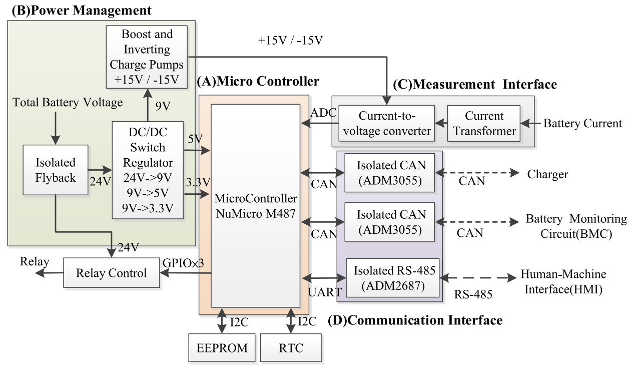

FIGURE 4. Architecture of the BCU.

down the battery module voltage from 48 to 5 V by using an Analog Devices LT8630 step-down DC/DC converter.

Section C is the interface for measuring the voltage and temperature of each cell. The cell voltage is primarily measured using an Analog Devices ADBMS1818 battery stack monitor, which allows simultaneous voltage measurements for 12 cells. The cell temperature is measured using the MCU's ADC combined with a multiplexer switch to read the thermistor for measurement, mainly measuring the temperature of 12 cells.

Section D is the user interface that presents voltage and temperature information for the 12 cells of the BMC. This information is transmitted to the BCU through internal CAN communication by using a fixed polling process. The transmitted information is then used by the BCU to calculate the SoC and SoH for each battery module.

B. BATTERY CONTROL UNIT

Figure 4 shows the architecture of the BCU.

The main functions of the BCU are as follows:

- ➢ It performs comprehensive current measurement.
- ➢ It communicates with eight sets of BMCs.
- ➢ It communicates battery-related information with a HMI.
- ➢ It performs input/output timing control.
- ➢ It communicates with the charger.
- ➢ SoC/ SoH calculation.

Each part of the BCU is explained in detail in the following text.

The BCU contains four sections, namely sections A–D. Section A contains the core chip of this circuit, namely the M487 microcontroller with a Nuvoton ARM Cortex-M4 core; this microcontroller is responsible for battery pack control. Section B comprises the overall power circuit. The total voltage of 384V is mainly achieved by serially connecting eight battery modules, with this voltage being stepped down to 24V using an external Isolated Flyback circuit. In addition to supplying power to the positive and negative terminals and the pre-charge relay, it also provides power for DC/DC conversion into 9V, 5V, and 3.3V. The 5V and 3.3V are used for the circuit. As the input voltage of the comparator needs to

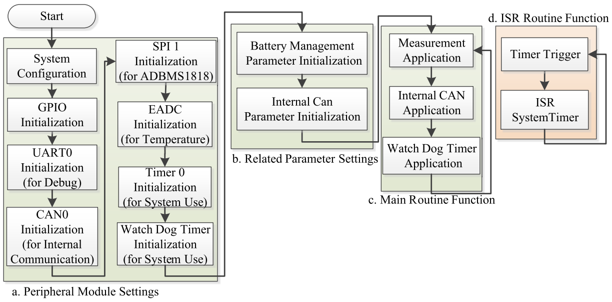

FIGURE 5. Firmware architecture of the BMC.

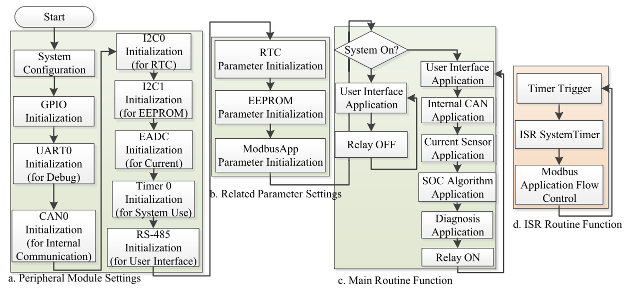

FIGURE 6. Firmware architecture of the BCU.

be ±15V, the 9V is further converted into ±15V using Analog Devices' LTC3265 voltage regulator to supply the current for the voltage converter. Section C can measure the total current of the entire series-connected battery module.

Section D is the communication interface, which consists of three main components, namely two CAN interfaces and an RS-485 interface. One CAN interface is primarily used for communication with the charger, whereas the other CAN interface is used for communication with the eight sets of BMCs. All battery voltage, total current, SoC, SoH, and temperature values are transmitted to the HMI through the RS-485 interface for real-time information display. When abnormalities are detected in battery voltage, total current, SoC, SoH, or temperature, the external relay signal is disconnected to issue a warning notification, thereby facilitating battery monitoring.

Data on all events, relevant protection points, and initial SoC and SoH values are recorded in the EEPROM, and the system time is primarily calculated accurately by sampling once per second through the external RTC.

III. SOFTWARE AND FIRMWARE ARCHITECTURES OF THE PROPOSED BMS AND ALGORITHM FOR THE REAL-TIME ONLINE ESTIMATION OF BATTERY STATUS

The SoC and SoH estimation algorithm is executed in the BCU of the proposed BMS. This algorithm involves four main steps: 1) initialize various system modules, 2) set the relevant parameters, 3) implement main program control, and 4) execute the interrupt service subroutine. The following text details the firmware architectures of the BMC and BCU and the algorithm for the real-time online estimation of battery status.

A. BATTERY MONITORING CIRCUIT

Figure 5 displays the firmware architecture of the BMC. The M453 microcontroller of the BMC enables floating-point operations and optimal peripheral output control.

During the startup of each system module, peripheral modules such as the Clock, GPIO, ADC, CAN, UART, SPI, Timer, and Watchdog modules are initialized. After the system is powered on, it initializes each module. The system communicates with the ADBMS1818 battery stack monitor through the SPI interface to read the voltage information of each cell. Moreover, the system uses the MCU's GPIO to switch the multiplexer and read the battery module's temperature data from the EADC interface. The system samples various important parameters of the battery module at a sampling frequency of 800 ms through interrupt service subroutines. After each round of sampling is completed, the flag is changed to notify the main program. After the entire sampling process is completed, the collected data are sorted and packaged into a packet for transmission. For subsequent processing, the data are then transmitted to the BCU through CAN communication by using a fixed polling process. Therefore, the BMC acts as a battery data collector and transmits relevant information, such as cell voltage and cell temperature, to the BCU.

B. BATTERY CONTROL UNIT

Figure 6 depicts the firmware architecture of the BCU.

The M487 microcontroller, which is the control core of the BCU, is an efficient, low-power microcontroller with a DSP instruction set. This microcontroller can operate at a frequency of up to 192 MHz, and it enables floating-point calculations and optimal peripheral output control. Therefore, the proposed SoC and SoH estimation methods are executed on the aforementioned microcontroller.

After the system is started up, the control chip initializes various system modules. Initially, the control chip updates the system time through the RTC-based calculation and communicates with the EEPROM to verify whether updated protection parameters and initial values for battery status are available. If these values are not available, the system directly uses the original parameter values. The system continues to monitor whether the power button is pressed. When the power button is pressed, the BCU polls and samples the battery voltage and temperature information for each battery module through the CAN bus with the eight BMCs, with a sampling time of around 900ms. The EADC module of the BCU will sample the total battery current every 250ms. After all the battery voltage, temperature, and current data have been sampled, real-time battery status estimation is performed. Moreover, relevant information is used to detect any abnormalities in the voltage, current, or temperature data. If abnormalities exist, external relay signals are controlled to perform disconnection actions, and abnormal information is written in the EEPROM. All information is then transmitted to the HMI via RS-485 every 5 seconds.

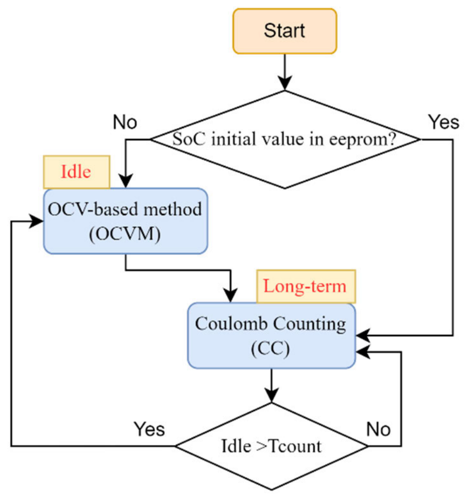

FIGURE 7. Flowchart of the proposed algorithm for the real-time online estimation of battery status.

C. REAL-TIME ONLINE ESTIMATION OF BATTERY STATUS

The battery management system designed in this paper has its main control core and battery state estimation performed by the BCU inside the main control cabinet. In addition to the need for extensive data communication with the BMC within 8 battery modules, considering low-cost and online application requirements, the battery estimation algorithms must be implemented within the microcontroller. The CCM is a commonly used method for SoC estimation. Moreover, this method can be conveniently implemented in a microcontroller. However, the CCM has the following drawbacks that can cause errors in SoC estimation:

- ➢ Any small errors in the calculation process will be accumulated, leading to a drift in the SoC estimation.
- ➢ As time and the number of charge-discharge cycles increase, the battery capacity will gradually degrade. If this capacity change is not considered, it may lead to inaccurate SoC estimation.
- ➢ Estimating SoC solely based on the calculation of charge variation cannot account for factors such as the internal battery chemical state, which may limit the estimation accuracy.
- ➢ The application of the Coulomb Counting Method is limited to specific types of batteries. It may have poorer adaptability for batteries with different chemical characteristics.

Due to the reasons mentioned above, the CCM and the Open Circuit Voltage Method (OCVM) are combined in application to complement the shortcomings of each individual method, thereby improving the estimation precision and accuracy of the battery. This paper focuses primarily on the Coulomb Counting Method, performing calculations every 2.5 second, tracking through the comparison of battery module capacity, and using the open-circuit voltage to calibrate the initial SoC, thereby estimating the battery's SoC, as shown in Figure 7.

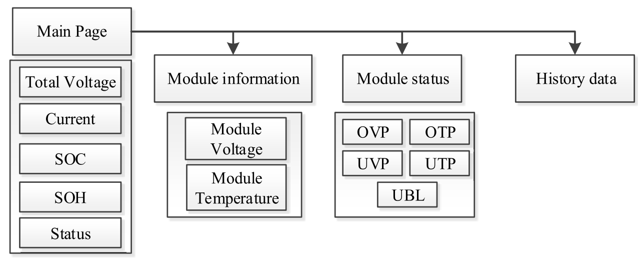

FIGURE 8. Software architecture of the HMI.

When the system starts, it first checks whether data on initial battery capacity are stored in the EEPROM. If such data are available, the system directly uses the initial capacity value obtained from the CCM for capacity calculation. If such data are unavailable, the system uses an OCV lookup table to find the initial capacity value on the basis of voltage readouts and incorporates this value into the CCM for battery capacity calculation. Moreover, the system continuously tracks the changes in the battery module capacity. If the battery capacity remains unchanged for a certain time (T_{count}), the system adjusts the initial capacity value according to the OCV lookup table. This real-time online capacity estimation method helps to reduce capacity estimation errors.

In addition, the SoH is primarily processed through linear degradation lookup tables based on experimental results obtained from the Coulomb counting method.

D. SOFTWARE ARCHITECTURE OF THE HMI

The Delta DOP-107BV monitoring interface is used as the HMI of the proposed BMS. This interface communicates with the BCU through the RS-485 interface to display system information.

Figure 8 depicts the architecture of the HMI. The Main Page displays the total voltage, current, SoC, SoH, and charging/discharging status of the entire system. The Module Information page shows the voltage and temperature information for each cell in every battery module. The Module Status page depicts system warning statuses, including OVP, UVP, OTP, UTP, and UBL. Finally, the History page presents the current recorded data.

IV. RESULTS AND DISCUSSION

This section presents the results of experiments where the proposed BMS was evaluated. The following experiments were conducted in this study:

1) Actual measurements are conducted on the batteries used in the battery management system of the electric garbage compaction truck, ranging from individual cells to assembled battery modules. Through charge/discharge equipment, cyclic charge and discharge tests are carried out under various testing conditions to confirm the capacity and aging status of the batteries used. The test results will be compiled into reports for offline analysis.

TABLE 2. Specifications of the battery cells used in the proposed BMS.

Parameter	Value
Manufacturer	Panasonic
Nominal capacity	3450mAh
Nominal voltage	3.6V
Charging current (standard)	1675mA
Charging voltage	4.20V
Charging time	240min
Operating temperature (charge/discharge)	10-45°C / -20-60 °C
initial internal resistance	<38mΩ
Weight (max.)	48.0g

TABLE 3. Conditions in the single-cell cycling tests.

Item	CV	Current	End Current	Time
Charging Current	4.2V	0.5C	0.5A	
Rest				60min
Discharge Current	2.5V	1C		
Rest				60min

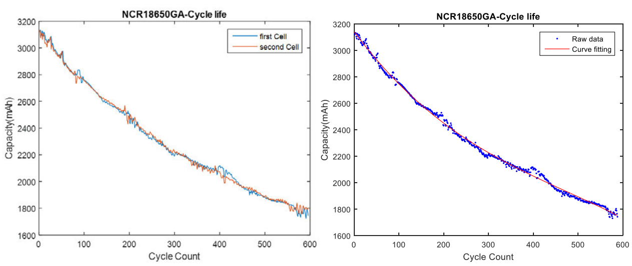

FIGURE 9. Plot of cell capacity versus cycle count.

2) The relevant parameters obtained from the testing are incorporated into real-time online battery estimation algorithms and implemented into the microcontroller of the BCU. The designed battery management system is actually deployed on the electric garbage compaction truck for real data measurements. A comparison and validation are conducted against traditional CCM to confirm the feasibility of the system.

Table 2 presents the specifications of the battery cells used in the proposed BMS (Panasonic NCR18650GA lithium-ion batteries). Cyclic charge–discharge tests were conducted on individual battery cells to verify their capacity and aging status.

Table 3 presents the conditions in the testing of the cycle life of individual battery cells. The testing was conducted at an ambient temperature of 25°C. Two battery cells were subjected to 600 cycles of charge/discharge testing by using a cycling machine to determine the relationship between cell capacity and cycle count, The measured results were then used to perform curve fitting, as shown in Figure 9, and

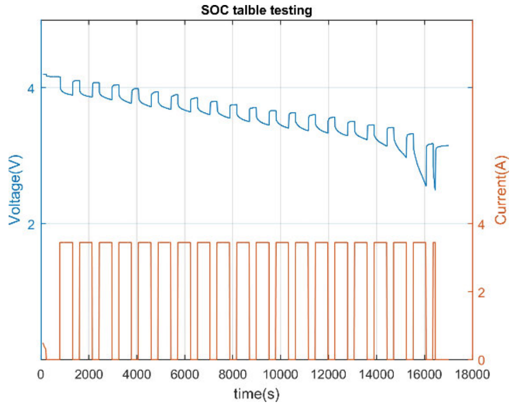

FIGURE 10. Plot of static open circuit voltage correction lookup table test results.

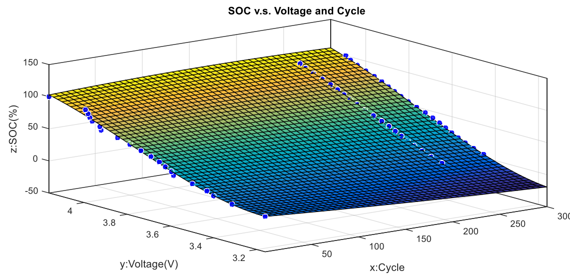

FIGURE 11. Plot of battery cell SoC, voltage, and cycle count.

Equation 1 represents the curve fitting equation.

$$\mathrm{SoC} = 0.01\mathrm{V}_{\mathrm{oc}}^2 - 4.54\mathrm{V}_{\mathrm{oc}} - 3143.25 \tag{1}$$

According to the cell capacity, a static OCV correction lookup table test was conducted. The main conditions for building the table were based on the capacity corresponding to the cycle test count, with the OCV table unit being 5% of the capacity. When the system is at rest for 60 minutes without any load, it will perform OCV-based table correction. The experimental environment temperature was maintained at room temperature of 25 degrees. Figure 10 shows the test results of the static OCV correction lookup table.

Through the lookup table test, the SoC versus voltage and cycle count curves were obtained, and curve fitting was performed, as shown in Figure 11.

Equation 2 represents the curve fitting equation, which can be used to estimate the SoC of the batteries used in the electric compressor cabinet based on the measurement data.

$$\begin{aligned}\mathrm{SoC} = {} & 5678.87 - 0.75 \times \mathrm{Cycle} - 4722.74 \times \mathrm{Voltage} \\ & + 0.24 \times \mathrm{Cycle} \times \mathrm{Voltage} + 1284.34\mathrm{Voltage}^2 \\ & - 0.01 \times \mathrm{Cycle}\times\mathrm{Voltage}^2 - 113.29\end{aligned} \tag{2}$$

After the static OCV correction table was created, battery cells were assembled into a 48-V battery module, and the variations in the SoC of this module with the discharge voltage were investigated at a discharge current of 1 C (Figure 12). The SoC at the beginning of the discharge phase was obtained using the following Equation 3:

$$\mathrm{SoC} = 0.136\mathrm{V}_{\mathrm{oc}}^2 - 1.6821\mathrm{V}_{\mathrm{oc}} - 139.09 \tag{3}$$

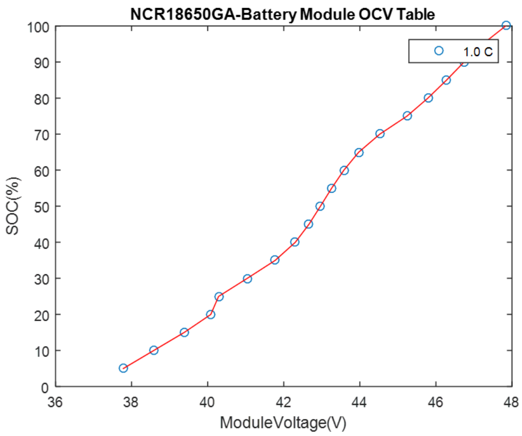

FIGURE 12. Plot of battery module SoC versus voltage.

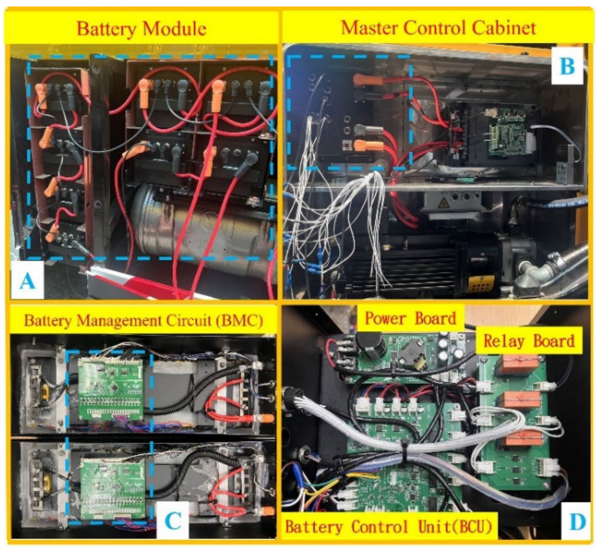

FIGURE 13. Integration of the proposed BMS into an electric garbage compactor truck.

After the battery cells and modules undergo different cycle tests using the charge and discharge equipment, the designed battery management system is integrated into the electric garbage compaction truck as shown in Figure 13. The components are arranged in sequence as follows: A. eight sets of battery modules, B. main control cabinet, C. BMC inside the battery modules, and D. various circuits inside the main control cabinet, including the BCU, power board, Relay board, and Relay components.

Subsequently, the parameters used for the input into the proposed algorithm for the real-time online estimation of battery status (implemented by the BCU in the main control cabinet) to perform various integrated testing experiments.

Figure 14 shows the workflow of the proposed BMS in the compression chamber of an electric garbage truck.

When the power button on the HMI is pressed, the system verifies whether the main control cabinet is powered by eight sets of battery modules (or a voltage of 24 V) and then waits for the user to insert the key. Upon key insertion,

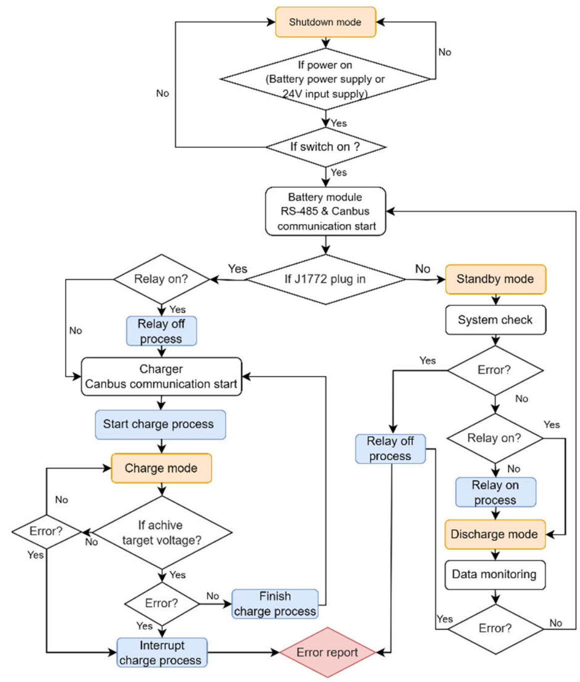

FIGURE 14. Workflow of the proposed BMS in the compression compartment of an electric garbage truck.

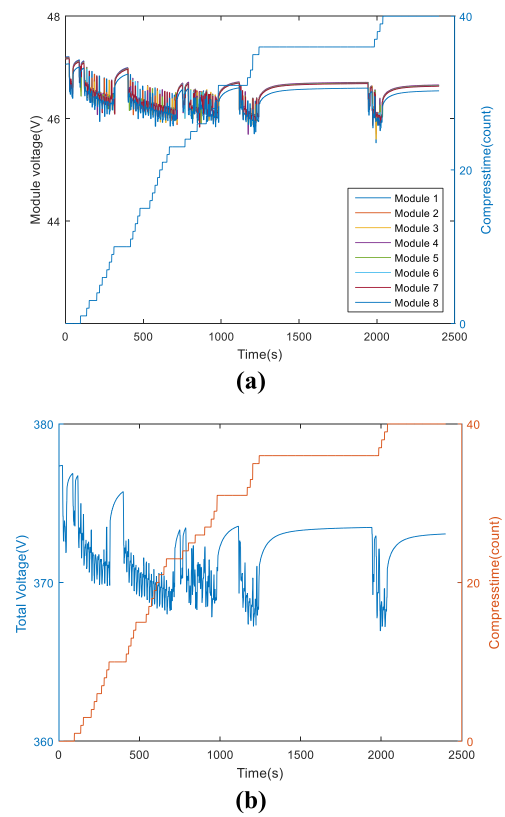

FIGURE 15. Data obtained in the practical testing of the proposed BMS (involving the compression of a full load of garbage) (a) Variation in voltage of individual modules (b) Changes in total system voltage.

communication is initiated between the HMI and the eight sets of battery modules, and the connection of the charging

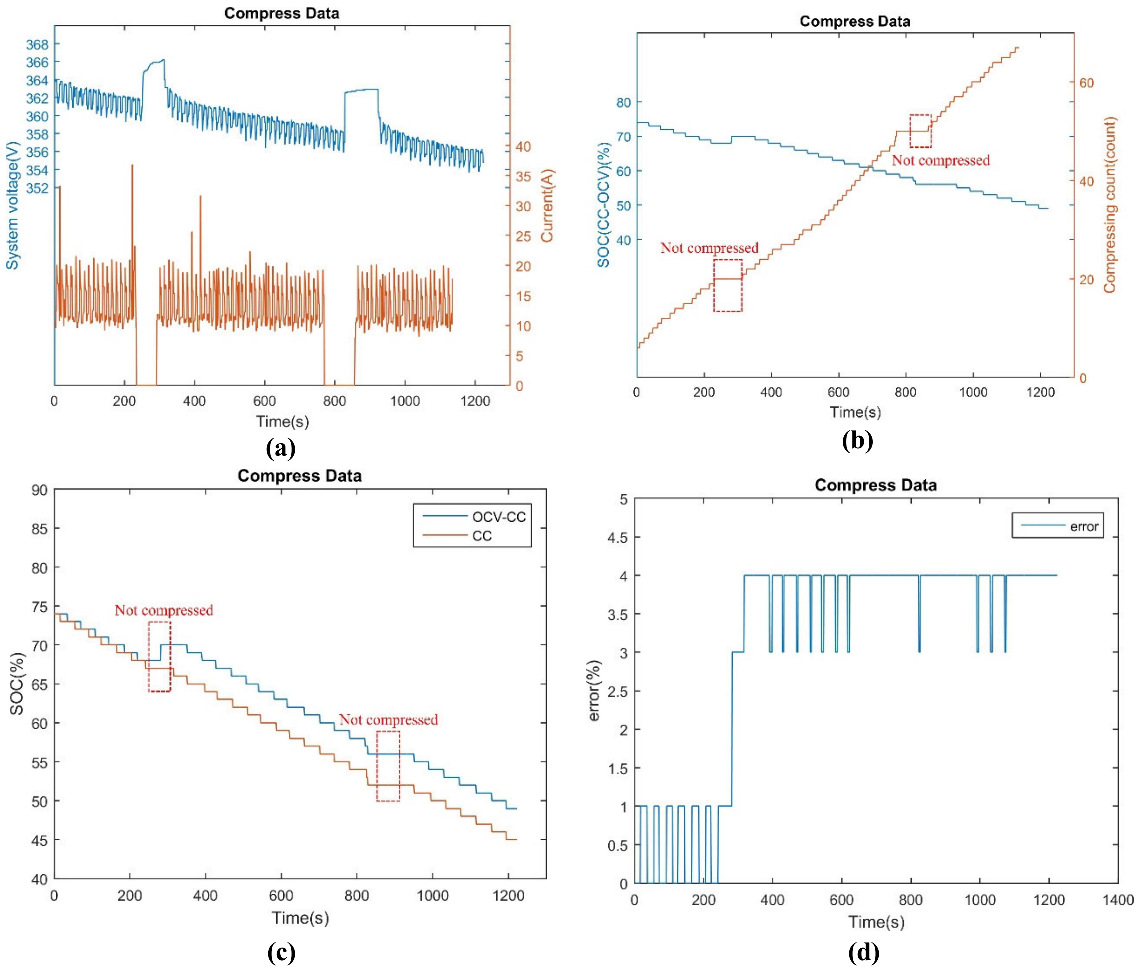

FIGURE 16. Results of the actual 15-Minute battery compression test. (a) Variations in the total voltage and total current. (b) The variation of SoC with compression counts. (c) Comparison of SoC. (d) Comparison of SoC error rates.

gun is checked. Subsequently, the system proceeds in the following two modes:

(1) Charging mode (when the charging gun is connected): The electric compression compartment cannot be operated until the charging process is completed.
(2) Discharging mode (when the charging gun is not connected): The electric compression compartment can be operated in the discharging mode.

The related parameters of the cycle tests are introduced into the real-time online battery estimation algorithm and implemented into the BCU in the main control cabinet for various integration testing experiments. The actual battery state is measured for parameter error verification, validating the feasibility of the real-time online battery estimation. Subsequently, actual garbage compaction tests are conducted using the electric compression garbage truck with a full load of garbage for practical testing. The measurements focus on the voltages of each individual module and the total system voltage used in this system. Figure 15 depicts the test data showing voltage variations.

During the garbage compression test using a truckload of garbage, the voltage of each module remains consistent as observed from the voltage readings. The designed battery management system can stably display and record the voltage status. Subsequent tests focus on the actual back-and-forth compression of the electric compression chamber for 20 minutes to measure voltage, current, and to compare the SoC. Figure 16 shows the battery measurement results of the actual 20-minute back-and-forth compression test.

According to the data from Figure 16, the designed battery management system was installed on an electric garbage compactor truck for actual testing. During the compression process, variations in voltage, current, and SoC decreasing gradually with compression counts can be observed in Figure 16 (a) and Figure 16 (b). Due to system cost and chip memory limitations, the real-time online battery estimation proposed in this paper is compared and validated with the conventional CCM in Figure 16 (c). It was found that when compression stops, the real-time online battery estimation switches to OCV for table lookup to correct the initial SoC value, while the Coulomb counting method continues calculation based on the original SoC value. In Figure 16 (d), the switching between no load and loaded conditions causes the SoC error of approximately 4% between the two methods. This experiment indicates that the cumulative error of the Coulomb counting method over the long term leads to incorrect SoC estimations. On the other hand, the real-time online battery estimation method adjusts the OCV table source by tracking battery module capacity changes for initial SoC verification, thereby improving SoC estimation accuracy and reducing errors.

From the operational test results on the electric garbage compactor truck, battery modules were composed of battery cells. The necessary parameters for the real-time online battery estimation method were calculated through cyclic tests of cells and modules and then introduced into the system. Eight battery modules were connected in series to meet the system requirements of the electric garbage compactor truck. During the actual discharge process in the compression operation, voltage, current, and SoC could be displayed and recorded in real-time, allowing users to clearly understand the battery's usage status.

V. CONCLUSION

This paper proposes a low-cost lithium-ion battery state estimation solution suitable for microcontroller-based applications. The proposed method can be used for fast and accurate lithium-ion battery state estimation, meeting the requirements of real-time online applications. The designed BMS can be applied not only to electric garbage compactor trucks, but also has the following features:

A. FLEXIBLE ADJUSTMENT OF THE NUMBER OF BATTERY STRINGS AND MODULES

The system achieves stacking different battery voltage ranges through a master-slave architecture with a set of BCUs and eight BMCs. The flexibility of the BMCs allows support for applications with up to 18 strings per individual battery module. This design advantage allows the system to flexibly adjust the number of battery strings to accommodate different requirements, and easily replace affected battery modules in the event of a failure.

B. BATTERY TYPE COMPATIBILITY

The proposed method for battery state estimation mainly utilizes voltage and capacity cycle counting, combined with OCV and CCM battery state estimation methods. This approach can quickly and accurately estimate the state of lithium-ion batteries, making it suitable for real-time online applications. As a result, when replacing different battery models, the system can simply adjust the OCV and battery protection point parameters to adapt to different models and brands of batteries, improving the system's adaptability.

C. CROSS-DOMAIN APPLICATION POTENTIAL AND UNIVERSALITY

In addition to electric vehicles, the system can also be applied in domains such as home, industrial, and medical applications, demonstrating the wide range of application prospects and the importance of the battery management system.

D. FLEXIBLE HARDWARE AND SOFTWARE DESIGN

Through simple mechanical adjustments, this system can meet the needs of various battery form factor sizes. On the software side, the system mainly uses Delta's HMI and Modbus communication protocol for communication. In the future, when applying this system to other scenarios, it is easy to connect with different devices to enable diverse applications.

The battery management system designed in this paper adopts a modular architecture concept, connecting to the target voltage through 48V battery modules. Apart from its application in electric garbage compactor trucks, the system can be extended to other vehicles and energy storage applications in the future. If the budget allows, the microcontroller of the BCU can be upgraded to a high-performance CPU or MPU. Additionally, by transmitting battery information over the network, advanced data analysis and machine learning algorithms can be utilized to optimize battery usage, predict maintenance needs, and enhance overall performance. Through flexible adjustments, the designed battery management system can achieve higher efficiency, sustainability, and integration with the evolving electric vehicle and energy storage domains.

ACKNOWLEDGMENT

The authors thank Tongshine Energy (Tainan, Taiwan) for providing the necessary laboratory facilities for testing battery cells and battery modules under various conditions. They also express their gratitude to UL International Taiwan, for its assistance in conducting various verification tests on the proposed BMS and for providing relevant recommendations.

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