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Evaluation of lightweight battery management system with field test of electric bus in campus transit system

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ABSTRACT

A battery management system is a crucial part of a battery-powered electric vehicle, which functions as a monitoring system, state estimation, and protection for the vehicle. Among these functions, the state estimation, i.e., state of charge and remaining battery life estimation, is widely researched in order to find an accuracy estimation methodology. Most of the recent researches are based on the study of the battery cell level and the complex algorithm. In practice, there is a statement that the method should be simple and robust. Therefore, this research work is focused on the study of lightweight methodology for state estimation based on the battery pack. The discrete Coulomb counting method and the data-driven approach, based on the Palmgren-Miner method, are proposed for the estimation of the state of charge and remaining battery life, respectively. The proposed methods are evaluated through a battery-powered electric bus under real scenario-based circumstances in the campus transit system. In addition, the battery life-cycle cost analysis is also investigated. The tested bus has currently been in operation in the transit system for more than one year.

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1. INTRODUCTION

Moving toward a new direction of transportation, in terms of sustainability and low impact to the environment, electric vehicles (EVs) are the trend and drive the change in the transportation market in recent years. One of the key factors of the development in EVs is the impressive achievement in battery technology. Among many types of batteries, the Lithium-ion battery is dominant in EV application nowadays regarding high energy density, high power density, and longer battery life [1]. However, this battery type is sensitive. It requires an additional apparatus, i.e., a battery management system (BMS), to ensure the reliability of the battery system.

The BMS's functionalities of a Lithium-ion battery are a monitoring system, battery state estimation, battery cell balancing, and a protection system [2]. Among these functionalities, battery state estimation, i.e., battery state of charge (SoC) and battery state of health (SoH), are important parameters of battery packs, which is required by the driver [3, 4]. To estimate the battery SoC, various calculation approaches are classified as follows. The direct measurement method-open-circuit voltage [5], the booking keeping method-coulomb counting [6], the adaptive method-Kalman filter [7], and the hybrid method-the combination of Coulomb counting and a Kalman filter [8]. Based on these four methods, [9] it has been investigated and summarized that the hybrid method is the most potent method for SoC estimation. Consequently, this hybrid method results in a complex algorithm. On the other hand, when the lightweight algorithm, real-time calculations, and less complex hardware are considered for the SoC estimation, the Coulomb counting method is commonly applied [6, 10, 11]. In addition to the conventional Continuous coulomb counting method, the author's concern is that the algorithm has to be executed under discrete operation [12]. Thus, this paper expresses the mathematics of Coulomb counting based on discrete formulation. Moreover, the battery efficiency is involved in the proposed equation. The battery efficiency can be used to correct the accumulative error of the current sensor, the error between the charging and discharging processes [13], and the error due to battery aging.

In the term of SoH, the remaining battery life estimation can be classified into two main approaches, i.e., a model-based approach and data-driven approach [14]. The model-based approach is a physical model. Thus, it can be stated that the model-based approach requires the information of internal parameters for the battery, which are resistance and capacitance [15]. For instance, [16] has examined SoH via the electrochemical impedance spectroscopy, and [17] has monitored the SoH through a capacitance. Unfortunately, those internal parameters of the battery are difficult to determine and not suitable for the practice. In contrast, the data-driven approach uses statistic information for the remaining battery life estimation. Therefore, the data-driven approach has recently been considered more often in industrial applications [18, 19]. According to the estimate for the remaining battery life based on the data-driven approach, this paper proposes the Palmgren-Miner (PM) method. Originally, the PM method is applied in fatigue analysis of a mechanical system [20]. Nevertheless, the PM method can be effectively applied for a chemical system in a battery as well [21]. Furthermore, the PM supports the stochastic charge/discharge cycle of an electric vehicle. As the concept of the PM method is to accumulate the damage of battery, hence this paper proposes a model based on the relationship between battery cycle life and battery depth of discharge (DoD). This relationship can be used to estimate the battery damage for each cycle of use.

In addition to the proposed lightweight algorithm for BMS, this paper also analyses the life cycle cost in order to compare the usage between a Lithium-ion battery and a Lead-acid battery, based on the battery-powered electric bus transit of Chiang Mai University. To assess the economic benefit of the battery, the economic costs of the Lithium-ion battery can be designed by battery charging profiles [22]. This paper proposes a multi-objective optimization to achieve battery charging management from the viewpoint of EV users, which considered the total charging cost and caused by the battery aging and electrical energy loss. A practical solution to reduce the life cycle costs of compacted Lithium-ion batteries have been presented in [23] to analyze the total cost of batteries under the adoption of an opportunity charging strategy. However, the case analysis is focused on motive-power batteries for facilities with laser guided vehicle (LGV) by the simulation model. A life cycle cost analysis for the operation of electric city buses in different operating routes and charging methods have been studied in [24]. The results in this paper show that energy consumption depends on the weight of the bus, weather conditions, and the operating route. This economic analysis part is important for the system operator, who always needs this information [25].

To summarize, the contributions in this research work are: 1) determining the lightweight algorithms to estimate battery SoC and remaining battery life, which the algorithms consume less computational time and are able to operate in real-time, 2) implementing the onboard BMS in the battery-electric bus and evaluating the proposed algorithms, and 3) conducting an economic analysis of a Lithium-ion battery under real scenario-based battery-powered electric bus transit.

The paper is organized as follow: Section 2 presents the overview of the field test area and the modified electric bus, section 3 describes the mathematic description of the proposed lightweight algorithm of battery SoC estimation and remaining battery life estimation, including their working processes. The explanation of the life-cycle cost analysis approach is given in section 4. The field test results and their validation are discussed in section 5. Lastly, the conclusions are drawn.

2. HARDWARE CONFIGURATION OF MODIFIED ELECTRIC BUS

The utilized electric bus is the bus, which is currently operated in the campus transit system. The electric bus is equipped with a 7.5kW AC motor. The maximum speed is 50 km/h. The Lead-acid battery is used. The battery pack capacity is 220Ah. The battery pack voltage is 72Vdc (12x6Vdc). To assessment the proposed onboard BMS algorithm, the conventional electric bus has to be modified. There are two modified items, i.e., battery and the BMS. Firstly, the new lithium iron phosphate (LFP) battery is used instead of the Lead-acid battery. To obtain a similar specification with the Lead-acid battery, the Lithium-ion battery pack is designed according to the specification of the Lithium-ion battery cell, as shown in Table 1. As a result, the 24 cells of Lithium-ion batteries have to connect in a series, and that battery string has to connect with another string in a parallel. Then, the LFP battery pack capacity and voltage are rated at 166Ah and 76.8V, respectively. The overview of the battery pack is shown in Figure 1.

Table 1. The specification of lithium-ion battery cell

Items	Technical parameters
Rated capacity	83 Ah
Rated voltage	3.2 V
Cut-off voltage	V
Max. charge voltage	3.65 V
Max. continuous charge current	160 A (2C)
Max. continuous discharge current	240 A (3C)
Max. instantaneous discharge current	400 A (5C)
Life cycle (80%DoD)	3000+
Cell impedance	<1m□

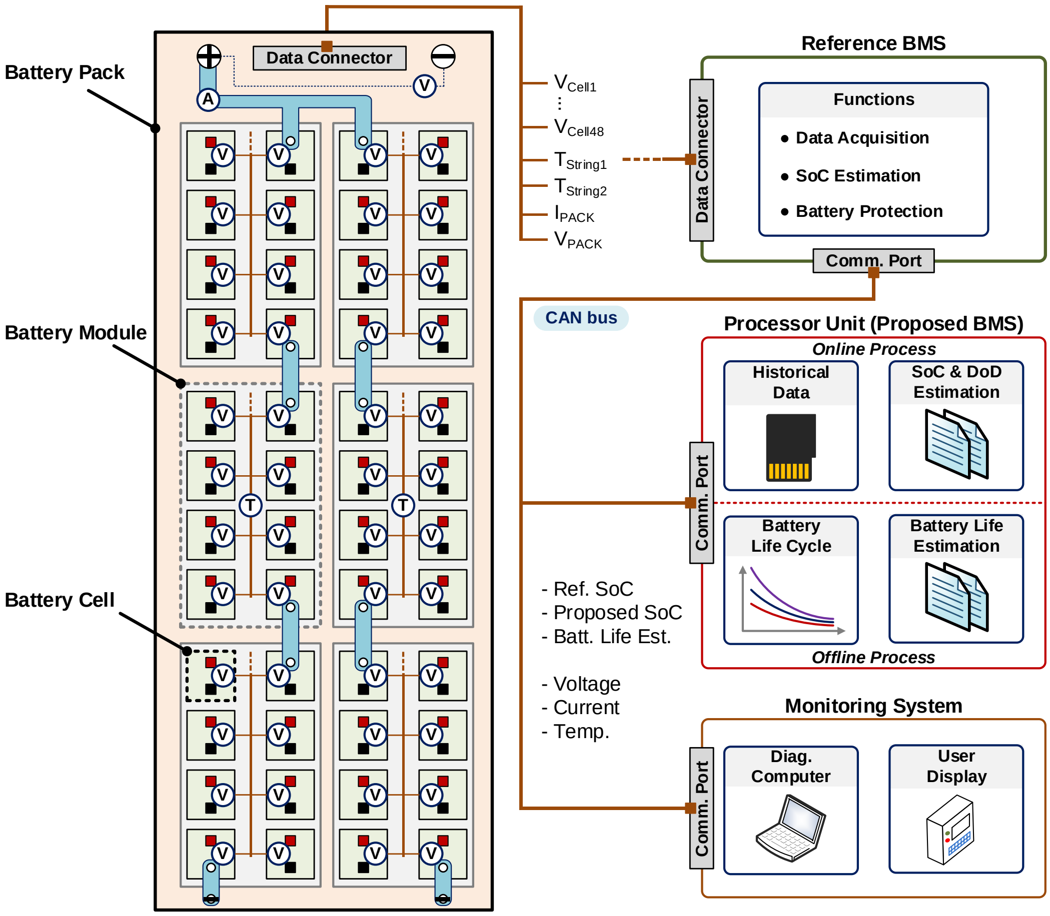


Figure 1. Overview of lithium-ion battery and BMS of modified electric bus

In addition to Figure 1, the sensor positions are pointed out. The voltage is measured in every battery cell and the total voltage of the battery pack. There is one current sensor, which measures the current of the battery pack. There are two temperature sensors. The sensors are equipped at the second battery module of each battery string. All the measured data were logged with a sampling time at 1 sec, which is sent to the reference BMS. The reference BMS is in charge of data acquisition, battery protection, and battery SoC estimation. The value of battery SoC estimation from reference BMS is used as a benchmark for proposed SoC estimation, which is calculated by the Coulomb counting method. Remarks, the reference BMS is provided and configured by the battery supplier.

In the part of proposed BMS, the battery voltage, current, and temperature are received through reference BMS in a real-time via controller area network (CAN) communication protocol with the four decimal places data resolution. In the processing unit, the SoC estimation is examined in an online process. Meanwhile, battery life estimation is observed in an offline process. Regarding the monitoring system, there are two opportunities. The diagnosis computer is designed for engineering purposes, and the user display is for the bus driver. Both are able to observe the data in real-time.

3. PROPOSED MATHEMATICAL DESCRIPTION OF BATTERY SOC AND REMAINING BATTERY LIFE ESTIMATION

To determine the proposed battery SoC and the remaining battery life estimation, there are three discussed sections: i.e., the mathematical description of the SoC method, the determination of the initial SoC, and the battery damage model based on PM. Moreover, the complete working process of the SoC estimation and remaining battery life estimation is summarized.

3.1. Proposed battery SoC estimation method

As mentioned before, the SoC estimation method in this application requires a lightweight algorithm and operated under discontinuous time. After investigation, the discrete Coulomb counting method is proposed in this paper. To understand the mathematical description of this method, the relationship between SoC and the discharge capacity (*it*) in Figure 2 needs to be discussed. In the figure, a linear function is used for describing the between SoC and discharge capacity, when the time interval (Δt) is considered as a small difference. As a result, a small-time interval of SoC (SoC_k) and discharge capacity (it_k) based on discrete-time are changed in linear characteristics. The change of SoC in a function of discharge capacity during the time interval (ΔSoC_k) and the small change of discharge capacity (Δit_k) are included in the effect of battery chemistry and electrical non-idealities. Therefore, the proposed discrete battery SoC estimation equation based on Coulomb counting is given as

$$SoC_k = SoC_{k-1} + \left[\frac{i_k \times \Delta t \times \mu}{3600 \times it_{k-1}} \times \left(1 - SoC_{k-1}\right) \right] \tag{1}$$

where SoC_k and SoC_{k-1} are batteries state at different instants of time, k is an index of discrete-time, i_k is the battery current for both charging and discharging processes, Δt is calculated step-time interval, and μ is the battery round trip efficiency.

As a remark, the battery round trip efficiency in (1) is able to adjust for the correction of SoC estimation error due to battery aging. In a short conclusion, the proposed discrete battery SoC estimation algorithm described is based on a linear function. This linear character is perfectly harmonized with the Lithium-ion battery character. However, in some battery types, the linear function cannot be used for relating the battery SoC and discharge capacity.

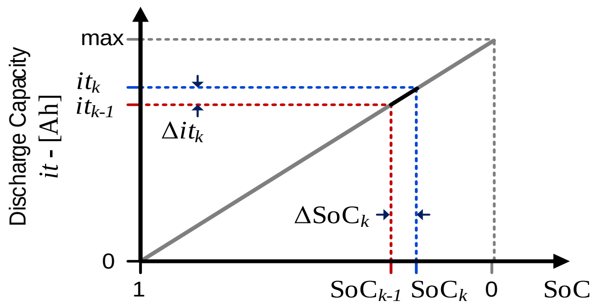


Figure 2. The relation between SoC and discharge capacity

3.2. Initial SoC determination

The initial battery SoC is a key parameter to define a preliminary state of battery SoC. If the determination of initial SoC does not correct, the SoC estimation process will result in an error as well [26]. Typically, the initial SoC can be determined by three methods [6], i.e., charging voltage method, discharging voltage method, and open-circuit voltage method. However, these three methods are typically used in a laboratory investigation.

In practicality, the initial SoC should be directly analyzed when the battery is fully charged. Because at this point, the charging current will be zero. Thus, it can be assured that the initial SoC, or rather a battery SoC, is 100%. In addition to this method, the open-circuit voltage method is also applied. When the charging current is zero, the open-circuit voltage is measured and compared with the information in Figure 3. Regarding the driving cycle of the electric bus in the field test, as mentioned before, the bus driver will charge the battery during the 1-hour breaks. Within this period, the battery will be fully charged. Therefore, the proposed initial SoC determination is flawlessly matched with the schedule of the bus driver.

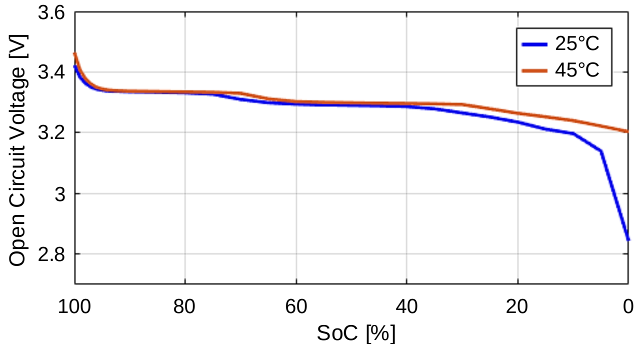


Figure 3. The relation between SoC and open-circuit voltage of used battery cell, providing by the manufacturer

3.3. Proposed battery damage model based on the PM method

Since the charge cycle and the discharge cycle of the electric bus are non-uniform, then the data-driven approach is taken into account in order to estimate the remaining battery life. To accomplish this, the accumulation of system fatigue analysis based on PM is considered. Normally, the PM is used for the analysis of mechanical systems fatigue. However, this method can be effectively applied for the battery as well. Applying the PM method for remaining battery life estimation, the accumulation of battery damage (D_{cu}) is formulated based on the relationship between battery life cycle (L) and battery DoD. As a result, it can be written as (2).

$$D_{cu}\left(n\right)=\sum_{i=1}^{n}\frac{1}{L_i} \tag{2}$$

where n is the driving cycle of the electric vehicle.

To assign the battery life end of life, this paper assumes that the battery will end at 80% of rated capacity. According to this percentage, the battery capacity linearly fades away regarding the accumulation of damage [27]. Since the damage accumulation based on PM is a linear function, the remaining battery life ($Q_{\max}$) can be modeled in the mathematic equation, as in (3).

$$Q_{\max}\left(n\right)=Q_{\max,0}\times\left[1-df\times D_{CU}\left(n\right)\right] \tag{3}$$

where df is the damage factor.

Finding the $Q_{\max}$, the relationship between battery life cycle and battery DoD is needed. From the information in Table 2, the relationship in the term of the mathematic equation has to be modeled. For the Lithium-ion battery, an exponential function [28] or a power function [29] can be used for the relationship expression. To select the best curve fitting, the R-squared index is analyzed by the curve fitting tool in MATLAB. The R-squared is a regression analysis based on the statistical measurement of how close the data are to the fitted curve. The best fit curve will result in a high value of R-squared.

Table 2. Lithium-ion battery life cycle, providing by the manufacturer

Temperature	DoD				
	100%	80%	60%	40%	20%
25ºC	2500	4375	7500	15000	30000
35ºC	2000	3500	6000	12000	24000
45ºC	1500	2625	4500	9000	18000

The R-squared results of the exponential function and the power function are 99.89% and 98.29%, respectively. Therefore, the exponential function is selected. To find the coefficient of the exponential function, the information in Table 2 is processed through the curve fitting tool in MATLAB. As a result, the mathematic equation of the battery life cycle is written in (4)-(6).

$$L_{25} \;=\; 5.85\times10^{4}\times e^{(-0.336\times DoD)} \tag{4}$$

$$L_{35} = 4.68\times10^{4}\times e^{(-0.336\times DoD)} \quad (5)$$

$$L_{45} = 3.51\times10^{4}\times e^{(-0.336\times DoD)} \quad (6)$$

The exponential equations in (4)-(6) are plotted and displayed in Figure 4. It can be obvious that the battery DoD and the temperature are the parameters to indicate the battery life cycle. Additionally, if the temperature does not match with the model in (4)-(6), the interpolation technique can be applied.

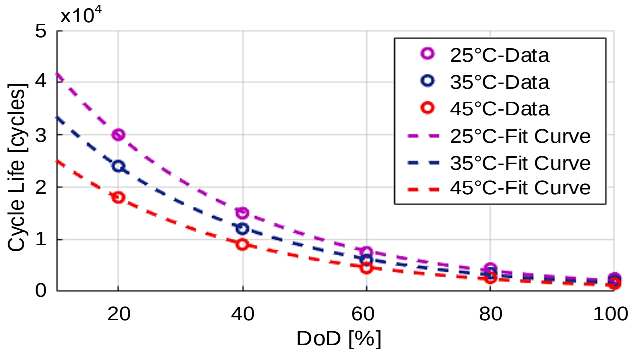


Figure 4. The relation between battery life cycle and battery DoD

3.4. Working process of proposed onboard BMS

According to the SoC estimation method, the working process of the onboard BMS for the electric shuttle bus can be concluded in an algorithm flow chart, as displayed in Figure 5. The algorithm is divided into an initial SoC determination part and the remaining battery life estimation part. The initial algorithm part is the first SoC estimation process. The first step is measuring terminal voltage, current, and temperature of the battery, and the SoC value was estimated by reading historical data of the used battery is retrieved from associated memory. The initial SoC has to be determined every time the bus driver starts the bus. The following step is the initial part. It contains a process that monitoring display and SoC estimation. The discharge current can be estimated using the proposed SoC algorithm, which is an online process. It is active when the battery is operated. Conversely, battery life estimation is an offline process. It is active when the bus driver finishes the driving cycle or, rather, when the battery is charged. This process is determined by the battery damage model based on the PM method. Note that the proposed working process is developed for the battery pack. Then, the monitored parameters for this process are voltage, current, and temperature of the battery pack.

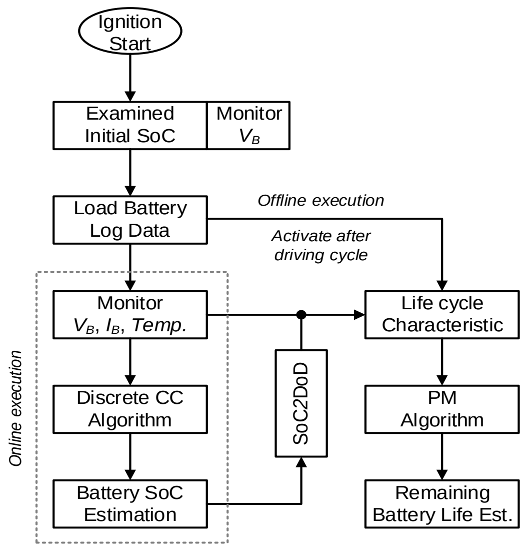


Figure 5. Working process of proposed SoC- and remaining battery life estimation

4. LIFE-CYCLE COST ANALYSIS

In this research, the life-cycle cost of the battery in the electric bus transit is based on the economic modeling analysis. There are four main life-cycle cost types in the analysis, the capacity costs, the replacement costs, the operating and maintenance costs, and the end-of-life cost [30]. The annualized life-cycle costs (c_{lc}) of a battery in the electric bus transit are formulated as follows:

$$c_{\mathrm{lc}} = c_{\mathrm{cap}} + c_{\mathrm{rep}} + c_{\mathrm{o\&m}} + c_{\mathrm{eol}} \tag{7}$$

where c_{cap} weights the capacity costs, which are associated with the acquisition and installation of the battery system, c_{rep} is the replacement costs due to degeneration, $c_{\mathrm{o\&m}}$ is the operating and maintenance costs during the battery's lifetime, and c_{eol} computed the disposal and recycling costs at the end-of-life of the battery.

The capital costs (c_{cap}) in (7) can comprise acquisition and installation costs for a battery system. Thus, the total capital costs are calculated as follows:

$$c_{\mathrm{cap}} = c_{\mathrm{battery}} + c_{\mathrm{charger}} \tag{8}$$

where c_{battery} is the battery cost, and c_{charger} is the charger cost.

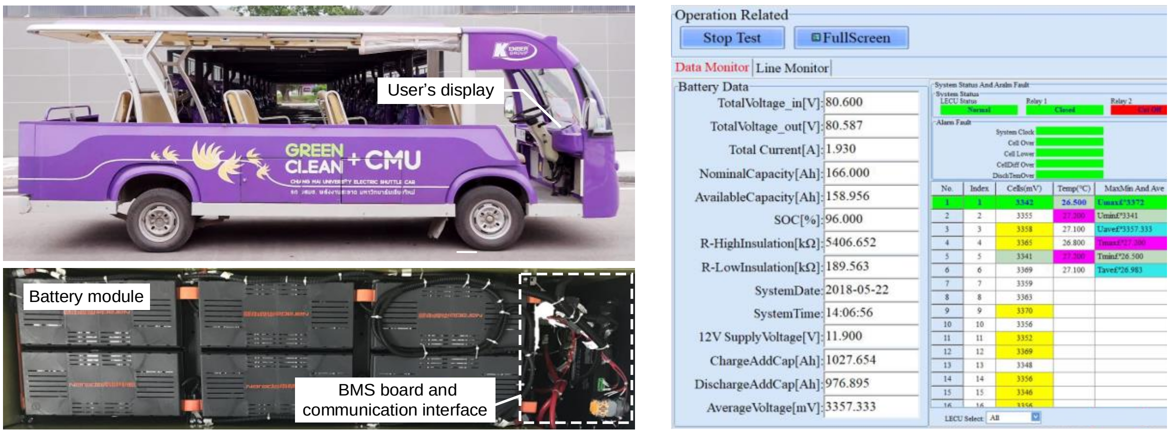
The technology replacement costs refer to the essential replacement of battery due to degeneration. The calculation of annualized technology replacement costs (c_{rep}) can be formulated as follows:

$$c_{\mathrm{rep}} = \sum_{j=0}^{T} \left[c_{\mathrm{battery}} \, f_r N_{cycle} \left(1 - d_{rate}^{-j}\right)\right] \tag{9}$$

where f_r is the replacement function, which has a value of 0 or 1 indicating battery replacement, N_{cycle} is the battery life as a number of deep cycles, d_{rate} is a yearly discount rate, and T is the time period for the life cycle analysis. The end-of-life battery life in terms of the total driving cycle is calculated based on the proposed battery life estimation method, according to the result in Section 5.3. Note that the estimated costs of a battery are dependent on the experience rates and the archetypal sigmoid function (S-curve) of energy storage technologies under a hundred percent market share assumed for each technology.

5. FIELD TEST RESULTS AND ALGORITHM VALIDATION

In this section, the proposed algorithms in section 3 are applied and validated in the field test. The SoC estimation results and battery life evaluation for the battery pack and battery life-cycle costs analysis are shown in detail. The electric bus and Lithium-ion battery pack in the field test are shown in Figure 6(a). The communication interface converts the battery state information voltage, current, and temperature into the CAN bus signal to be displayed on the user's screen and monitoring system, as shown in Figure 6(b). The test condition is under a real scenario in the campus transits system. Every day, the operation service time is from 7:00 am to 10:00 pm, 15 hours per day. Each driving cycle takes around 3 hours. The bus operator has a 1-hour break after each driving cycle. The tested bus is operated three driving cycles per day. The battery of the electric bus is charged three times per day.



(a) (b)

Figure 6. Electric bus and battery system

5.1. Validation of the SoC estimation method

The field test results of the bus service operate, and the validation of proposed SoC estimation are shown in Figure 7. Figure 7(a) to Figure 7(c) shows the velocity, terminal battery voltage, and high and low temperature of the battery cell. From the results in Figure 7(a), one route of the service takes around 33 min. The average speed is approximately 14.9 km/h. In Figure 7(b), the terminal battery voltage is in the operating range 60-87.6 V. The cell temperature in the battery pack is maintained between 25-26ºC, under maximum temperature (35ºC) operation, as shown in Figure 7(c). It can be concluded that the Lithium-ion battery is functioning properly.

Figure 7(d) to Figure 7(f) shows the battery current and battery SoC during the field test. The maximum current is around 255 A, which is lower than the maximum instantaneous discharge current (400 A), as shown in Figure 7(d). The proposed SoC estimation result is shown in Figure 7(e). It can be seen that the result of the SoC of the proposed method is shown along with the SoC from the reference BMS. The corresponding error of battery SoC is shown in Figure 7(f). The percentage difference between the reference and the proposed estimated SoC results remains below 1. Referring to the reference, the SoC estimation method achieves good results. The reference BMS for the SoC validation is provided by the battery manufacturer.

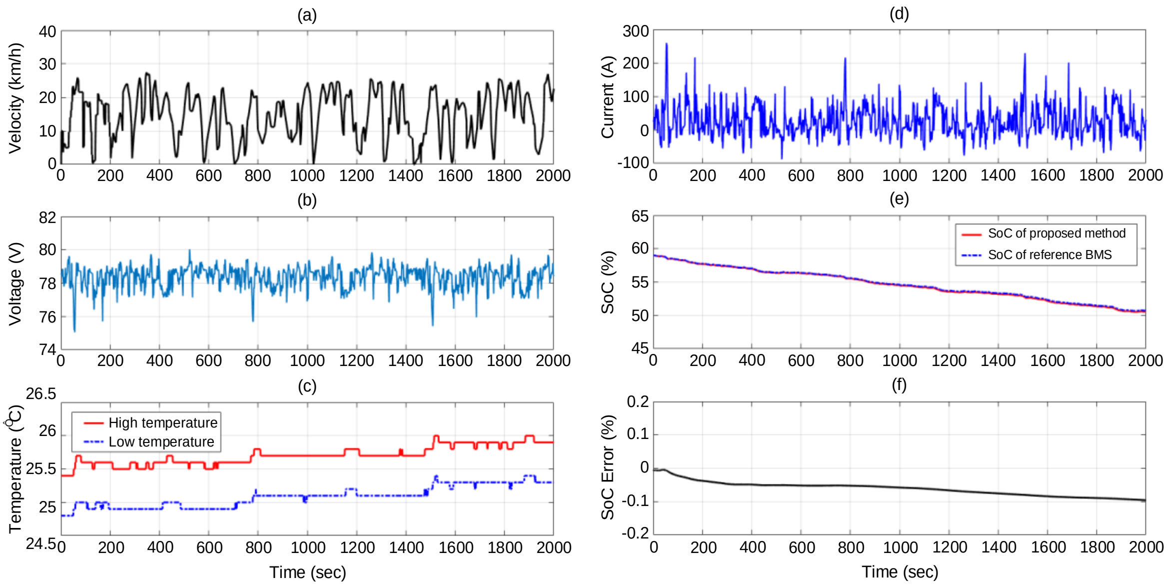


Figure 7. Experimental results of the monitoring parameter from the field test, (a) velocity, (b) voltage, (c) temperature, (d) current, (e) SoC, (f) Error of SoC

Regarding the sampling time, the data logger is randomly delivered data between 1 sec and 2 sec. Even with this inconsistency, the proposed SoC algorithm is able to handle it. The sampling time can be substituted directly in the calculation formulation. This is one of the reasons why the proposed SoC estimation method functioned properly. Currently, the battery round trip efficiency in SoC estimation is set to 0.88 constant value, in which this value is received from the battery manufacturer.

5.2. Remaining battery life estimation

As mentioned, this paper proposes a data-driven approach with the accumulative damage based on the PM method to estimate the remaining battery life. Resulting in accumulative damage, battery temperature, and battery DoD all being input parameters, see (2), and (4)-(6). and the consequent faded battery capacity is estimated through (3). As an experiment, Figure 8 shows the data collection of the remaining battery life estimation in which the electric bus has been operating in the transit system for one year, about 1,000 cycles. It can be seen that the faded battery capacity data from the field test is marked with the dotted line.

Based on the data, the degree of one polynomial is applied to fit the estimation curve, and the faded battery capacity equation (Q_n) is rolled out in (10). With this field test data, the end of battery life is at 2,888 cycles.

$$Q(n) = (-0.006868n) + 99.84 \tag{10}$$

In this research, the linear assumption is used for the estimation, when the end of life is set to 80% of initial battery capacity. Based on the current driving cycle, the battery will be ended after 2,228 cycles. According to this driving cycle, it can be implied for 2.6 years. Thus, the validation of (10) or battery life estimation and the knee point of battery degradation aging need probably 3 years for the investigation. However, it is noteworthy to mention that the linear assumption is a good choice for battery life estimation when the observation is started with a new battery.

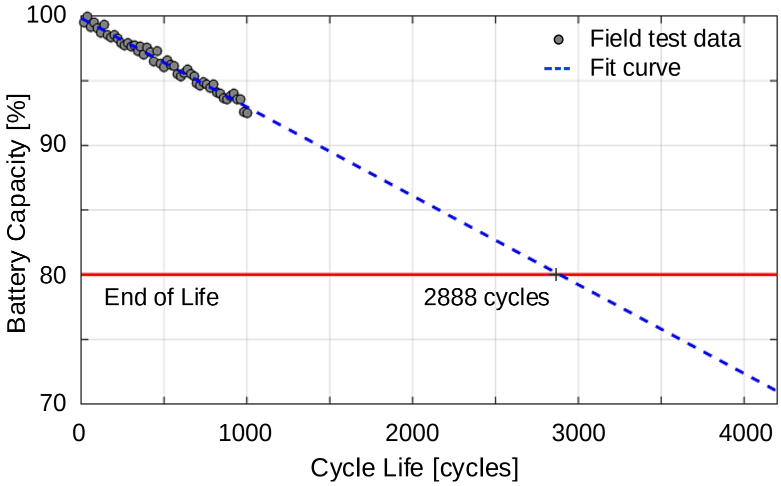


Figure 8. Remaining battery life estimation

5.3. Life-cycle cost results

This section presents an application of the life-cycle cost analysis. The objective of the study is to compare the annual cost of the Lithium-ion battery with a battery management system and the original Lead-acid battery. The cost parameters for this evaluation are defined based on the cost in Table 3. This information is provided by the operator of the transit system.

The operating and maintenance costs include electricity consumption, general repairs, and regular maintenance costs. The replacement costs include the periodic replacement of batteries and the maintenance of the charging devices. The disposal and recycling costs are based on the buyer's market. All costs are considered in the current price data of the USD, based on the average price in 2018. The yearly discount rate was assumed to be 3% of the initial costs. Finally, the maximum calendar life was estimated to be 2.5 years and 0.677 years (8 months) for the Lithium-ion and the Lead-acid batteries, respectively.

Table 3. The battery cost parameters and analyzed in the proposed study

Descriptions	Lithium-ion Battery	Lead-acid Battery
Battery costs (c_{battery})	\$8,320	\$3,072
Charger costs (c_{charger})	\$2,688	\$640
Maintenance costs ($c_{\text{o\&m}}$)	\$160 /year	\$160 /year
(+) Disposal and (-) recycling costs (c_{eol})	\$-268.80	\$320
Discount rate (d_{rate})	3%	3%
Battery life-cycle time (N_{cycle})	2.5 year	0.667 year

After the calculation, according to (7), Figure 9 presents the life-cycle cost analysis for a battery-powered transit bus, using driving cycles from the field test. Figure 9(a) shows the development of the total costs in individual years of life-cycle during the use of the Lead-acid battery and the Lithium-ion battery for a concession period longer than five years. Considering the maximum calendar life, the results show that the Lithium-ion battery has the highest capital cost over the Lead-acid battery in the first year. However, the total costs in other years were decreased. It can be concluded that the replacement cost of the battery, naturally, has a significant effect on the life-cycle costs.

For the purpose of the battery life-cycle costs, a relation of 5 years was used, based on which, it is possible to declare that the life-cycle costs are $3,182.38/year and $5,371.83/year for the Lithium-ion battery and Lead-acid battery, respectively. The life-cycle costs of a Lead-acid battery showed that the total costs are higher than the Lithium-ion battery, as shown in Figure 9(b). The difference in the battery life-cycle costs between analyzed alternatives is the sum of $2,189.45/year. Based on the parameter assumption, the payback has been set to 2 years.

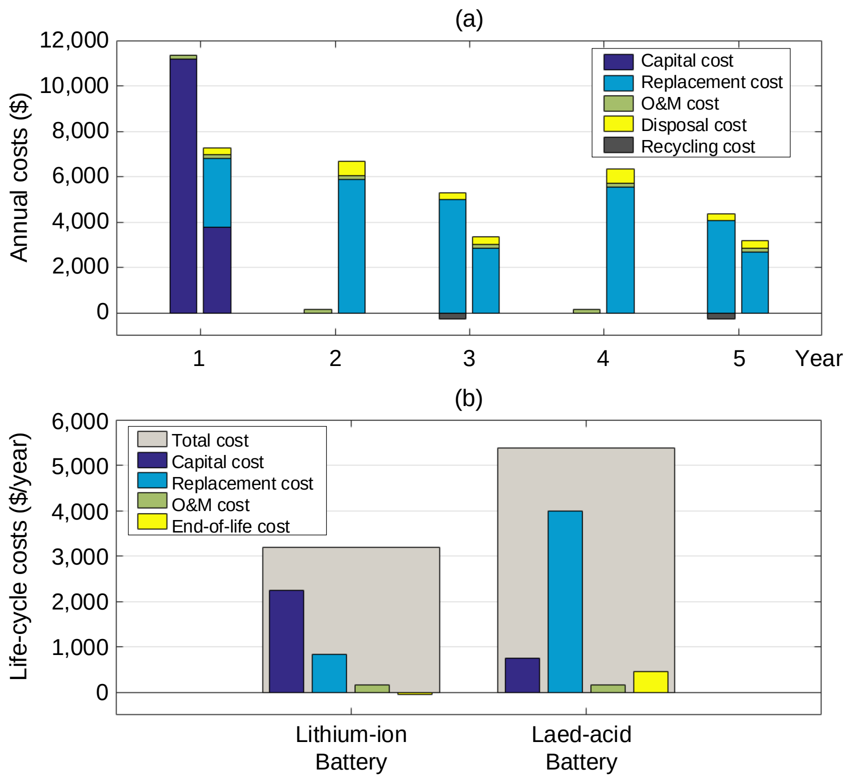


Figure 9. Results of life-cycle costs analysis, (a) annual costs, (b) life-cycle costs

6. CONCLUSION

This research work is aimed to develop and evaluate the lightweight algorithms for BMS. The proposed algorithms are the discrete Coulomb counting method, and the accumulative damage should be based on PM, for the estimation of battery state of charge and remaining battery life, respectively. For the economic aspect, the life cycle cost analysis is also taken into account in this paper. This information will answer the common question from the transit system operator.

The discrete Coulomb counting method is formulated based on linear function, which is proper for the character of the Lithium-ion battery. Furthermore, the battery round trip efficiency is also included in the formulation in order to correct the error, which can be caused by battery aging. The remaining battery life is estimated based on the relationship between battery life and battery DoD. Then, the accumulative damage is collected, once the battery is charged. The proposed PM method is developed based on the data-driven approach to overcome the complexity of the model-based approach, for which the internal battery parameters have to be measured. In addition, the PM method is appropriate for the non-uniform charge and discharge cycle of the electric vehicle. To complete the BMS, the protection system is obviously implemented. The observed parameters are cut-off voltage, maximum voltage, and temperature.

The battery-powered electric bus under the real operation of the Chiang Mai University transit system is used for the evaluation. The result from the field test proves that the proposed discrete Coulomb counting method works correctly. The comparative error with the benchmark BMS is 0.1%. The result of the remaining battery life estimation is that the battery should be replaced after 2,888 cycles. Presently, the battery end-of-life is set to 80% of the initial capacity. With this range, the remaining capacity of a Lithium-ion battery is linearly faded.

Lastly, the life cycle cost analysis of a Lithium-ion battery with a battery management system, and the original Lead-acid battery is calculated. It is found that the use of a Lithium-ion battery can reduce the total cost by 20%. With this amount of cost reduction, it would attract the transit system operator to replace the Lead-acid battery with the Lithium-ion battery.

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REFERENCES

[1] K. Young, et al., "Electric Vehicle Battery Technologies," in R. Garcia-Valle and J. A. P. Lopes (eds), *Electric Vehicle Integration into Modern Power Networks*, Springer, New York, pp. 15-56, 2013.

[2] D. Linden and T. Reddy, "Handbook of Batteries," 3rd edition, New York, *McGraw-Hill*, 2001.

[3] R. Zhang, et al., "State of the Art of Lithium-Ion Battery SOC Estimation for Electrical Vehicles," *Energies*, vol. 11, no. 7, p. 1820, 2018.

[4] S. M. Rezvanizaniani, et al., "Review and Recent Advances in Battery Health Monitoring and Prognostics Technologies for Electric Vehicle (EV) Safety and Mobility," *Journal of Power Sources*, vol. 256, pp. 110-124, 2014.

[5] J. Chiasson and B. Vairamohan, "Estimating the State of Charge of a Battery," *IEEE Transactions on Control Systems Technology*, vol. 13, no. 3, pp. 465-470, 2005.

[6] K. S. Ng, et al., "Enhanced Coulomb Counting Method for Estimating State-of-charge and State-of-health of Lithium-ion Batteries," *Applied Energy*, vol. 86, no. 9, pp. 1506-1511, 2009.

[7] L. Xu, et al., "Kalman Filtering State of Charge Estimation for Battery Management System based on a Stochastic Fuzzy Neural Network Battery Model," *Energy Conversion and Management*, vol. 53, no. 1, pp. 33-39, 2012.

[8] J. Wang, et al., "Combined State of Charge Estimator for Electric Vehicle Battery Pack," *Control Engineering Practice*, vol. 15, no. 12, pp. 1569-1576, 2007.

[9] Y. Zheng, et al., "Investigating the Error Sources of the Online State of Charge Estimation Methods for Lithium-ion Batteries in Electric Vehicles," *Journal of Power Sources*, vol. 377, pp. 161-188, 2018.

[10] M. Murnane and A. Ghazel, "A Closer Look at State of Charge (SOC) and State of Health (SOH) Estimation Technique for Batteries," *Technical Article Analog Device*, 2017.

[11] B. Xiao, et al., "A Universal State-of-Charge Algorithm for Batteries," *in Design Automation Conference*, pp. 687-692, 2010.

[12] S. Yuan, et al., "Stability Analysis for Li-Ion Battery Model Parameters and State of Charge Estimation by Measurement Uncertainty Consideration," *Energies*, vol. 8, no. 8, pp. 7729-7751, 2015.

[13] F. D´ıaz Gonzalez, et al., "Energy Storage in Power Systems," *John Wiley & Sons*, Ltd., 2016.

[14] R. Xiong, and W. Shen, "Advanced Battery Management Technologies for Electric Vehicles," *John Wiley & Sons Ltd.*, 2019.

[15] W. Waag and D. U. Sauer, "Secondary Battery Lead –acid system — State-of-charge/health," *Reference Module in Chemistry, Molecular Sciences and Chemical Engineering Encyclopedia of Electrochemical Power Sources*, *Elsevier*, pp. 793-804, 2009.

[16] A. Eddahech, et al., "Behavior and State-of-health Monitoring of Li-ion Batteries using Impedance Spec-troscopy and Recurrent Neural Networks," *International Journal of Electrical Power & Energy Systems*, vol. 42, no. 1, pp. 487-494, 2012.

[17] P. Leijen, et al., "Use of Effective Capacitance Variation as a Measure of State-of-Health in a Series-Connected Automotive Battery Pack," *IEEE Transactions on vehicular technology*, vol. 67, no. 3, pp. 1961-1968, 2018.

[18] C. Kunlong, et al., "SOH Estimation for Lithium-ion Batteries: A Cointegration and Error Correction Approach," in *Proceedings of IEEE International Conference on Prognostics and Health Management*, pp. 1-6, 2016.

[19] A. Nuhic, et al., "Health Diagnosis and Remaining Useful Life Prognostics of Lithium-ion Batteries using Data-driven Methods," *Journal of Power Sources*, vol. 239, pp. 680-688, 2013.

[20] M. Ciavarella, et al., "On the Connection between Palmgren-Miner Rule and Crack Propagation Laws," *Fatigue & Fracture of Engineering Materials & Structures*, vol. 41, no. 7, pp. 1469-1475, 2018.

[21] M. Safari, M. Morcrette, et al., "Life-Prediction Methods for Lithium-Ion Batteries Derived from a Fatigue Approach - I. Introduction: Capacity-Loss Prediction Based on Damage Accumulation," *Journal of the Electrochemical Society*, vol. 157, pp. A892-A898, 2010.

[22] K. Liu, et al., "Lithium-ion Battery Charging Management Considering Economic Costs of Electrical Energy Loss and Battery Degradation," *Energy Conversion and Management*, vol. 195, pp. 167-179, 2019.

[23] P. Cicconi, et al., "A life cycle costing of compacted lithium titanium oxide batteries for industrial applications," *Journal of Power Sources*, vol. 436, p. 226837, 2019.

[24] A. Lajunen, "Lifecycle Costs and Charging Requirements of Electric Buses with Different Charging Methods," *Journal of Cleaner Production*, vol. 172, pp. 56-67, 2017.

[25] M. Singer, "Consumer Views on Plug-in Electric Vehicles National Benchmark Report," *National Renewable Energy Laboratory*, pp. 1-38, 2016.

[26] J. Meng, et al., "An Overview and Comparison of Online Implementable SOC Estimation Methods for Lithium-Ion Battery," *IEEE Transactions on Industry Applications*, vol. 54, no. 2, pp. 1583-1591, 2018.

[27] K. Tseng, et al., "Regression Models Using Fully Discharged Voltage and Internal Resistance for State of Health Estimation of Lithium-Ion Batteries," *Energies*, vol. 8, pp. 2889-2907, 2015.

[28] K. R. Mallon, et al., "Analysis of On-Board Photovoltaics for a Battery Electric Bus and Their Impact on Battery Lifespan," *Energies*, vol. 10, no. 7, pp. 1-31, 2017.

[29] C. Zhou, et al., "Modeling of the Cost of EV Battery Wear Due to V2G Application in Power Systems," *IEEE Transactions on Energy Conversion*, vol. 26, pp. 1041-1050, 2011.

[30] A. Lajunen and T. Lipman, "Lifecycle Cost Assessment and Carbon Dioxide Emissions of Diesel, Natural Gas, Hybrid Electric, Fuel Cell Hybrid and Electric Transit Buses," *Energies*, vol. 106, pp. 329-342, 2016.

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