International Journal of Engineering, Management, Humanities and Social Sciences Paradigms (IJEMHS)
(Volume 28, Issue 03) Publishing Month: August 2017
An Indexed and Referred Journal with Impact Factor: 2.75
ISSN: 2347-601X
www.ijemhs.com

Evaluation of the Campus Transit System's Lightweight Battery Control System and Field Testing of the Electric Bus

[1]Rashmi Ranjan Sethy
Gandhi Institute of Excellent Technocrats, Bhubaneswar, India
[2]Santosh Kumar Senapati
Vikash Institute of Technology, Bargarh, Odisha, India

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.

Keywords: *Battery management system Discrete coulomb counting method Electric vehicle Lithium-ion battery Palmgren-miner method*

Date of Submission: xx-xx-xxxx Date of acceptance: xx-xx-xxxx

---

I. 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, 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, 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.

II. 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. 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.

III. 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.

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 (□*t*) is considered as a small difference. As a result, a small-time interval of SoC (*SoCk*) and discharge capacity (*itk*) based on discrete-time are changed in linear characteristics. The change of SoC in a function of discharge capacity during the time interval (□*SoCk*) and the small change of discharge capacity (□*itk*) 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 where *SoCk* and *SoCk*-1 are batteries state at different instants of time, *k* is an index of discrete-time, *ik* is the battery current for both charging and discharging processes, □*t* is calculated step-time interval, and □ 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.

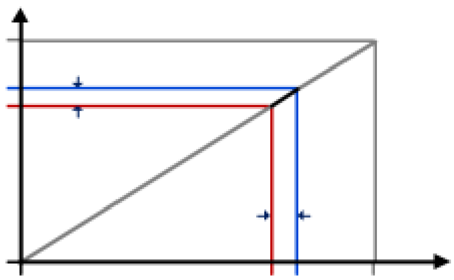

Figure 2. The relation between SoC and discharge capacity

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

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).

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).

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

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

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.

IV. 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.

Figure 6. Electric bus and battery system

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 25-26^{o}C, under maximum temperature (35^{o}C) operation, as shown in Figure 7(c). It can be concluded that the Lithium-ion battery is functioning properly.

V. 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.

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.