A Brief Overview: Intelligent Battery Management System for Lithium-Ion Battery in Electric Vehicle

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***Abstract*— Green energy generation has experienced a rapid increment in recent year because of the energy demands and rising concern on environmental awareness around the world. Therefore, one of the alternatives to undergo this issue is by using electrical vehicles (EVs) in terms of public and personal transportation. Despite the constant efforts to development EVs by both the scientific research and industrial communities, there are still many obstacles hindering the mass commercialization of EVs. One of the obstacles recognizes was the battery system, the new energy storage component in EVs. As vehicular battery must consist of a large number of cells to provide the necessary energy and current density, lithium-ion batteries are the best option to be used in electric vehicles. Unfortunately, lithium-ion batteries can be dangerous if they are not operated within their safety operation area (SOA) as it can cause fire and other risks. Furthermore, BMS also works to indicate the remaining energy in the battery thru state of charge (SOC) estimation beside balancing the usage of all batteries in the system to avoid over used or under usage. Thus, an intelligent battery management system (BMS) is needed to ensure lithium-ion batteries function safely and effectively.**

Keywords—Electric vehicle; Lithium-ion battery; Battery management system; State of charge

I. Introduction

Global warming, rising crude oil price and greenhouse gas (GHG) emission that caused by diesel and petrol used in a vehicle have encouraged people to find a clean, safe and efficient solution for their mobility [1].

Realizing the problems, the implementation of EVs concerning public and personal transportation has gained huge attention and become attractive choices for researchers due to their promising features in reducing GHG [2].

The transition of fuel vehicle to battery electric vehicle with an intention to reduce the GHG emission can be seen in figure 1. However, despite the constant efforts to development EVs by both the scientific research and industrial communities, there are still many obstacles hindering the mass commercialization of EVs.

The automotive industry has set a goal of achieving 20 million EVs on worldwide roads by the year of 2020. However, they have to overcome the public's reservations about electromobility that caused by the higher cost of EVs, a reluctance to accept new technologies, and a slew of high-profile media cases that depict burning EVs and hint at inherit safety problem [3]. Besides that, limited mileage that EVs could go due to low power density and long charging hour also one of the reasons why these vehicles are not favorable to be used [4], [5].

There are significant growth in the implementation of secondary (rechargeable) battery in EVs application. A good battery is vital for a successful EVs implementation. Various rechargeable batteries have been used in EVs, such as lead-acid, Nickel-cadmium (NiCd), nickel–metal hydride, lithium-ion, lithium-ion polymer, and less commonly, zinc-air and molten-salt batteries [6]. A fair study of various energy storage device has been done as reported in table 1 [7].

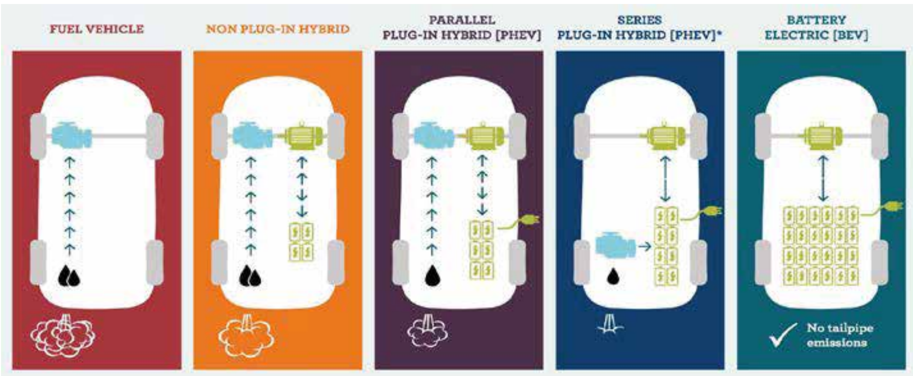

Fig. 1. Types of vehicles [49].

TABLE I. PERFORMANCE COMPARISON AMONG VARIOUS ENERGY STORAGE DEVICE [7]

	Temperature [°C]	n (%)	Energy		Power [W/kg]	Voltage [V]	Self-discharge [%/Month]	Cycle life @80%DOD	Cost estimation	
			[Wh/l]	[Wh/kg]					[$/kWh]	[$/kW]
Lead Acid	-30 - 60	85	50 - 70	20 - 40	300	2,1	4 - 8	200	150	10
NiMH	-20 - 50	80	200	40 - 60	1300 -500	1,2	20	> 2500	500	20
Li-ion	-20 -55	93	150 - 250	100 - 200	3000 - 800	~ 3, 6	1 - 5	< 2500	800	50 - 75
EDLC	-30 -65	97	5	5 - 20	15000	~ 2, 5	30	Not applicable	2000	50

Among all, lithium-ion battery dominates the most recent groups of EVs due to its high energy density, long lifespan, and high efficiency. Plus, having the characteristic of no memory effect and small self-discharge as well as being compact and lightweight, they have been used in EVs since 2009 [8]. However, the downsides of traditional lithium-ion batteries include short cycle lives (hundreds to a few thousand charge cycles) and significant degradation with age. The cathode is also somewhat toxic. Moreover, traditional lithium-ion batteries can pose a fire safety risk if punctured or charged improperly [9]. A lot of researchers have been done to enhance the safety, stability, and robustness of lithium-ion battery [10]. Even though of high primary cost, market growth of lithium-ion battery has been increasing steadily and is expected to expand into the future [11].

An advanced and efficient BMS is required to ensure lithium-ion battery can operate safely and reliably. Other than that BMS is also essential to maintain the health of each cell in the battery pack, protecting the cells from damage, handle thermal degradation and cell unbalancing to prolong the life of the battery pack [12]. Moreover, different states of the battery such as state of charge (SOC), state of health (SOH), state of life (SOL) and state of function (SOF) can be assessed through an efficient BMS, which can sense temperature, measure voltage and current, regulate safety alarm to avoid any overcharging or over-discharging. Furthermore, a BMS is essential for controlling and updating data, detecting faults, equalizing battery voltage that are the critical factors for achieving a good accuracy of SOC and SOH value [13].

SOC had been recognized as one of the crucial factors that contribute to the successful operation of BMS. Battery SOC does the similar process of the fuel gauge in a gasoline-driven vehicle which indicates the amount of energy inside a battery to power a vehicle [14], [15]. Accurate estimation of battery states not only helps to provide information about the current and remaining power of the battery but also gives assurance of a reliable and safe operation of the EVs. However, due to non-linear, time-varying characteristics and electrochemical reactions, battery SOC cannot be read directly [16]. Furthermore, the performance of the battery is profoundly affected by aging, temperature variation, charge and discharge cycles which make the task of estimating an accurate SOC very challenging [17].

II. BATTERY MANAGEMENT SYSTEMS (BMS)

Battery is the only power source in pure electric vehicles and it is as a passive component that has no ability to protect itself. As for that, a management system is needed to keep the battery ready to deliver full power when necessary and it can extend the life of the battery.

The most common key operational parameters that BMS record are voltage, current and the internal temperature of the battery during charging and discharging. If any of the parameters exceed the values that been set by the safety zone, the system will provide inputs to the protection devices to generate alarms and disconnect the battery from the load or charger.

However, existing BMS cannot entirely satisfy the requirements in EVs although comprehensive and mature BMS is currently found in portable gadgets, such as laptop and cellular phones. This is because the number of cells in a vehicle's battery is hundreds of times higher than the cells in the portable electronics. Moreover, a vehicle's battery is designed not only to be a long-lasting energy system but also to be a high-power system. Their safety in conditions of high-current or high-power charge and discharge make BMS for EVs much more complicated than those for portable electronics [18]. The currently certain defects of batteries and the strict demands of EVs require a multi-functional, reliable, intelligent and safe BMS.

In a vehicle, BMS are considered as one of the complex part and fast-acting power management system. BMS may consist of many kinds of component such as sensors, controller, actuators that been controlled by many models, algorithm and signal. In summary, basic framework of BMS shown in figure 2 where divided into hardware and software component as proposed by Xing et al. [18].

Generally, the hardware consist of various sensor to monitor and measure the battery parameters. All of this data will be store for software analyzation in building a database for system modeling. Meanwhile for safety circuitry in BMS is to prevent over-heating, overcharge and over-discharge. Charge control is necessary to govern the charge-discharge protocol. As batteries are charge by constant voltage/constant current method (CV/CC), a potentiostat and galvanostat are required to balance battery cells. As temperature differences within each cell has an impact on cell imbalance, reliability and performance, a thermal management module are placed in BMS to monitored and ensure each cell operated under proper temperature conditions. Most subsystems in a BMS are stand-alone modules. Hence, controlled transceiver is required to communicate data within the BMS. With the current development of smart batteries, wireless and telecommunication techniques, more data can be collected to communicate with the user and the charger through the microchips incorporated within the battery.

In order to control all hardware operation, robust software is required to make decision and estimates states for all sensors. Other than that, software also control cell balancing control, sample rate monitoring in the sensor system, switch control and safety circuit design. Moreover, the software perform online data processing and analysis for continually updating and controlling battery functions. Each of this information will be shown to the user through a user-friendly interface with appropriate suggestions.

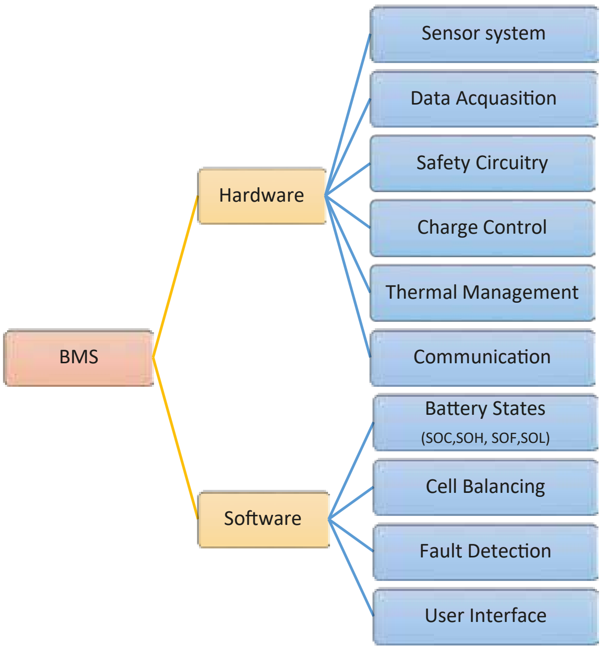

Fig. 2. Basic component of BMS in EVs

Functional block diagram of a typical BMS shows in figure 3 [19]. On the left side of figure 3 are the battery cells, current sensor and data acquisition portion of the BMS. The cell voltage and temperature measurements, and cell balancing consist of various multicell battery monitor internal circuit (IC) that converts the voltage, current and temperature at each point of the battery into a digital signal. These parameters are used to estimate the states (SOC, SOH, SOF, SOL) of battery in the processor. The processor or control functional block also controls the maximum charge/discharge current with the help of a suitable algorithm. The outcome of this block are communicate with the external communication or control functional blocks to limit the battery over-charge/over discharge abnormalities. Normally, a BMS communicates with a system controller, a power inverter/charger, and other components in a larger system. Communication interfaces, such as ethernet, USB, CAN, and UART are usually used for these purposes. A BMS often includes external relays or contactors to connect the battery pack to the external load or to the charger. Relays or contactors are also used to disconnect the battery pack from the rest of the system in the case of cell failures or other safety issues.

Moreover, BMS also can control other system components, such as fans, air conditioner, alarms, and other functions via user controllable general purpose input/output (GPIO) signals to ensure the battery operates in optimal temperature range. A BMS typically requires hardware fail-safe circuitry to protect the hardware and the battery in the case of a failure of the software components, or hardware components internal or external to the BMS.

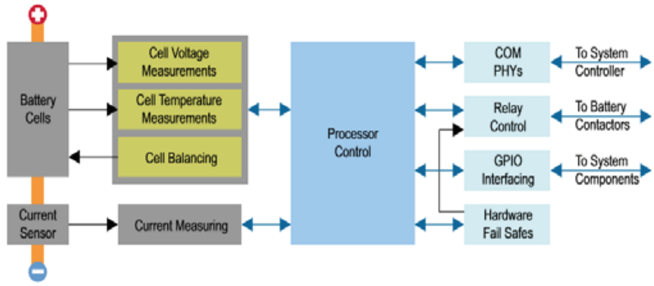

Fig. 3. Block diagram of BMS[19]

However, improvement need to be done on the fault detection instead of detecting over charge, over discharge and over heat only. As BMS should have a function to detect battery that could not perform well anymore before the battery actually totally breakdown based on the SOC trend of each battery.

III. STATE OF CHARGE (SOC)

In conventional vehicles, lightweight materials and advanced combustion engines are continually being improved to increase fuel economy. Concurrently, much attention is being diverted to vehicle electrification as battery technologies become more accessible. Although EVs remain small fraction of the market today, huge increment of research been done globally in recent years based on data recorded in figure 4. Much attention been put on SOC study as both the scientific research and industrial communities realise building and installing lithium-ion battery management with SOC estimation in EVs application has become major challenges due to its complicated electro-chemical reactions, large number of serial-parallel cells and performance degradation over time caused by various internal and external factors.

Furthermore, most of the defined experiments of the battery are conducted in a laboratory environment with standard voltage, current limits, and low-temperature variation. However, very few research have been found on battery operating in different conditions such as heavy rain, hot and cold weather as well as vibration from uneven roads. In addition, the variation in external loads makes an impact on the available capacity of a battery. Therefore, some un-modeled effect adds in the existing models and algorithms, which have not been taken into account yet. Moreover, cell unbalancing, battery aging process, temperature, dynamic hysteresis characteristics, self-discharge, charge-discharge rate are the other factors, which are responsible for declining performance of the battery. The researchers have

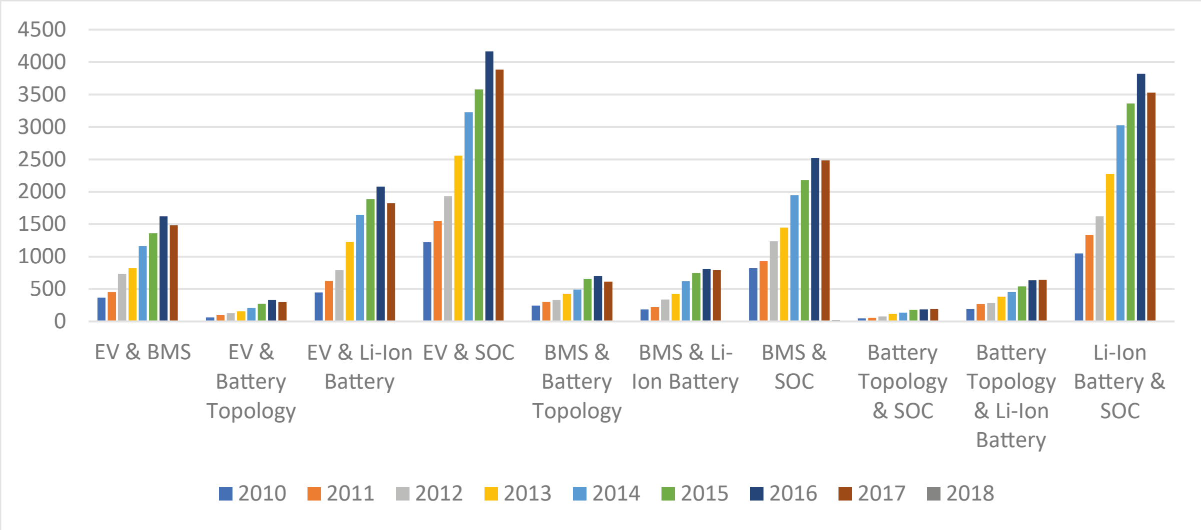

Fig. 4. Number of journal produce base on EVs, BMS, battery topology, lithium ion battery and SOC. (Source from www.ScienceDirect.com)

proposed various battery models to estimate SOC; however, each model suffers from limited information for real EVs applications. Furthermore, lack of accuracy, complex calculation, and high computation cost have become a major concern to accurately estimate battery states [13]. Summary of SOC estimation error from different SOC method presented in Table 2.

Based on table 2, the conventional method such as OCV, EMF, CC, Resistance, EIS and Modul based are simple and easy to implement. However, the average of SOC error recorded are huge, as these method uses the physical properties of the battery, which includes voltage, discharge current, resistance, and impedance. Meanwhile, KF, EKF, UKF, SPKF, PF, UPF, H∞ Filter and RLS method used various models and algorithms to calculate the SOC. These methods look promising to be develop further as the average error recorded are about 1% to 2.49% As for NN, FL, SVM and GA, it is not attractive for EVs as large amount of training data, complex and heavy computation required to describe the nonlinear characteristics of lithium-ion in estimating the SOC. Whereas for SMO, PIO and NLO is designed to handle with the highly nonlinear system. As for MARS, BI, and IR method, it use extended linear model, two linear interpolations, and linear time invariant system respectively. Recently, more study using hybrid method been done by combining two or three SOC algorithms to obtain optimal performance and improve SOC reading, by taking advantage of different method available.

SOC is similar to the fuel usage indication in gasoline cars. However the battery is inaccessible for measuring and experiences aging, varying environmental conditions, and charge-discharge cycles, will makes it difficult for a BMS to provide an accurate SOC estimation. Nevertheless, SOC estimation with high accuracy is important to evaluate the reliability of batteries and provides an idea about charging/discharging strategies, which have a significant impact on battery application where each cell may have different capacities due to ageing, temperature, self-discharge and manufacture difference. Moreover, accurate SOC estimation is crucial to maximize the performance of the cell by making the safety margin smaller and enable the usable capacity of the cell larger, which leads to lengthier cruising distance and longer battery lifetime as capture in figure 5.

TABLE II. SUMMARY OF SOC ESTIMATION ERROR (PERCENTAGE)

Method	Avg. error	Author
Open circuit voltage (OCV)	Unspecified	[20]
Electro-Motive Force (EMF)	≤ ± 2%	[21]
Coulomb Counting (CC)	≤ ± 4%	[36]
Resistance	Unspecified	[22]
Electrochemical Impedance Spectroscopy (EIS)	Unspecified	[23]
Model-based	≤ ± 5%	[24]
Kalman Filter (KF)	≤ ± 1.76%	[25][26]
Extended Kalman Filter (EKF)	≤ ± 1%	[27]
Unscented Kalman Filter (UKF)	≤ ± 4%	[28][29]
Sigma point Kalman Filter (SPKF)	≤ ± 2%	[30]
Particle Filter (PF)	Unspecified	[31]
H∞ Filter	≤ ± 2.49%	[32]
Recursive Least Square (RLS)	≤ ± 1.03%	[33]
Neural Networking (NN)	≤ ± 4.6%	[34]
Fuzzy Logic (FL)	≤ ± 5%	[35]
Support Vector Machine (SVM)	≤ ± 6%	[37]
Genetic Algorithm (GA)	≤ ± 2%	[38]
Sliding Mode Observer (SMO)	≤ ± 3%	[39]
Proportional-integral Observer (PIO)	≤ ± 1%	[40]
Nonlinear Observer (NLO)	≤ ± 4.5%	[41]
Multivibrate Adaptive Regression Splines (MARS)	≤ ± 1%	[42]
Bi-linear Interpolation (BI)	≤ ± 5%	[43]
Impulse Response (IR)	Unspecified	[44]
Hybrid	≤ ± 2.7%	[45]
	≤ ± 6.5%	[46]
	≤ ± 3.5%	[47]
	≤ ± 3%	[48]

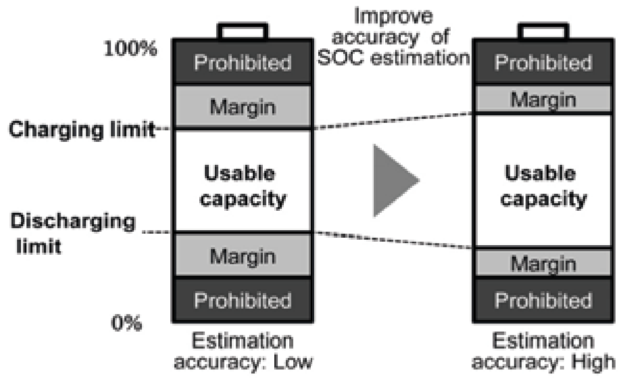

Fig. 5. Image of Battery Capacity [26]

IV. Communication method

SOC of a battery requires a communication mechanism from charging station to the storage device, which is used for charging the battery. BMS enables a battery to communicate with the charger, internal modules, and external environment. At present, most of the manufacturers of EVs use a controlled transceiver to communicate with internal modules. Communication between a charger and a battery is developed through a system management bus (SMBus) which is able to transfer battery data, such charging-discharging current, voltage and SOC. However, different manufacturers have different charging mechanism that been applied, which makes it difficult to develop a standardize charger. Hence, difficulties also with the charger when it applies to different applications.

To address the problem, a uniform communication method should be developed. Wireless technology may be implemented in an EVs not only to transfer information between a battery and a charger but also to predict when the battery will break down and send the data to users based on the battery health trend. Plus this wireless technology also need to be able to record external data such as ambient temperature, humidity and vibration for better energy management.

V. Summary

The penetration of renewables in the power system is expected to significantly increase in near future. Thus, batteries play a crucial role in the reliable and cost-efficient grid integration of intermittent energy sources. The lithium-ion batteries had begun to play a major role in the automotive market. The use of batteries in full electric vehicles is a promising option in order to replace the internal combustion engine car with ideally, zero emissions vehicles. The optimal operation to improve the performance, prolong the life time and prevent damage of the battery are key factors that have to be achieved by the battery management system (BMS). Therefore, a precise real time, reliable, accurate estimation of battery parameters and internal states are highly required. Moreover, from these parameters especially SOC reading, BMS could monitor and predict when a battery would when thru fault beforehand.

As SOC estimation in BMS is one of the most significant and challenging techniques to promote the commercialization of EVs. An accurate estimation result can indicate the amount of remaining energy in a battery to the user, and cooperate with BMS to notify user about the battery fault. Unfortunately, the crucial state cannot be measured directly, fundamentally requiring a soft estimator to calculate it. SOC suffer from various interference in vehicle driving environment and model uncertainties due to the strong time-variant property and inconsistency of batteries. The existing typical SOC estimators such as coulomb counting and extended Kalman filter (EKF) cannot perform their theoretically optimal efficiency in practical applications [15]. Therefore, SOC estimation using new algorithm combination using Electrochemical impedance spectroscopy (EIS) and EKF should be attractive for better efficiency.

As EIS calculation involve more on impedance calculation inside the battery however, linearization error could occur if the system is highly non-linear. So implementing dual EKF in an electrochemical model to estimate battery SOC and capacity may detect the monomer cell with abnormal voltage and effectively predict when and where voltage abnormality happens based on voltage fluctuations in minutes, hour or days in advance.

From the detection, BMS could send data directly to the user with precis detail on which battery is fault so that the user could be prepare, rearrange their journey and save cost. This info also may save user from having breakdown in the middle of the road and avoid user changing the whole battery as fault happened.

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