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Comprehensive Review on Algorithms used in Battery Management System for Automotive Applications

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Review Article

Comprehensive Review on Algorithms used in Battery Management System for Automotive Applications

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Abstract

The electric industry has seen a rapid boom over the years and a prominent energy storage device being used is batteries in smart grids and electric vehicles (EV). Apart from developing cells of high energy density and power, performance improvements in the battery management system (BMS) are also equally important. This paper studies the important algorithms essential for a BMS and their estimation techniques. For measuring and predicting the functional status of the battery, the BMS uses accurate algorithms along with state-of-the-art mechanisms to efficiently use and safeguard the battery under all operating conditions.

***Keywords**:* BMS, state of health (SOH), state of charge (SOC), state of power (SOP), remaining useful life (RUL)

INTRODUCTION

While the industry is looking towards electrification of existing systems (transport, lighting, etc.) to reduce dependency on fossil fuels, rechargeable battery packs have gained the spotlight. To enable the supply of the desired range of voltage and current for expected loading conditions, battery packs are used. A battery pack is an assembly of battery cells organized electrically in a matrix configuration. Individuals or a group of cells need to be monitored and controlled to use the battery pack efficiently.

BMS is an embedded system designed for supervising the battery pack. The BMS is used for:

- Monitoring the battery
- Estimating and reporting operational states
- Optimization of performance
- Providing user and battery protection.

So far, the replacement of fossil fuels with their electrical alternatives mainly in terms of battery packs has been successful, but there are challenges to the safety of the system. If operations are performed outside the safe operating area (SOA), a compromise with the battery performance is done or outright failure of the entire system takes place which may also be fatal for the user. There is no fixed set of criteria that a BMS follows but it needs to adhere to safety regulations while providing the utmost utilization of resources.

An efficient BMS for the safe operation of EVs needs an accurate prediction of the battery parameters. These include SOC, SOH, and state of function (SOF) [1].

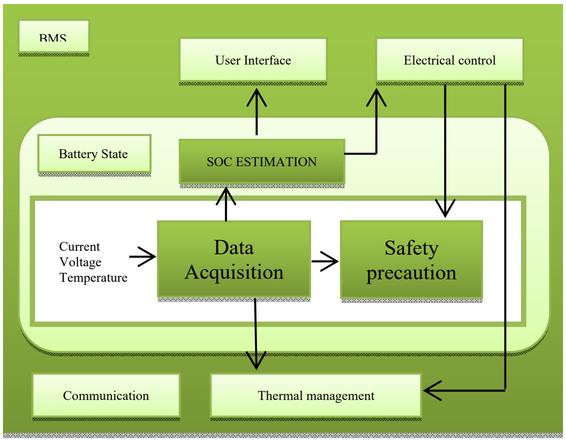

Figure 1: Block diagram of BMS [33]

Battery modeling

An ideal battery model ignores internal parameters and is only a voltage source. The linear model

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shows a battery with an equivalent series resistance (ESR) and an open-circuit voltage (OCV) but it does not account for varying internal impedance with varying SOC. A Thevenin's model consists of OCV, internal resistance (R_i), polarizing resistance (R_d) and capacitance (C_d).

This is one of the most widely used models with several modifications being done to optimize the system [2].

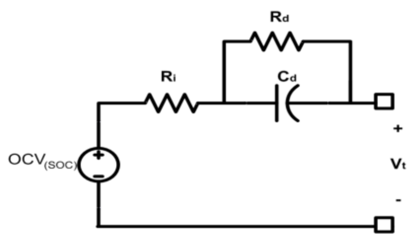

Figure 2: Schematic diagram of Thevenin equivalent circuit [34]

To model a battery, the parameters need to be estimated which is usually done by analyzing the equivalent circuit models. The model consists of resistance (R_i), OCV, and n number of RC pairs. Dynamic characteristics of the battery are determined by the RC pairs. The number of RC pairs needed in the design depends on the type of charging. Genetic algorithm (GA), differential evolution algorithms [3], and particle swarm optimization (PSO) algorithms [4] are used for electrical circuit model (ECM) parameters estimation. But it was observed that the results varied with the number of RC pairs [5]. After the estimation of battery parameters, internal states, time-varying parameters, and SOC of the battery can be determined using the extended Kalman filter (EKF) [4].

An algorithm to automate the parameter estimation process by using the pulse charging technique is also available for the study of battery performance. For various orders of RC pairs, a comparative analysis is done between model parameters and SOC and observed that the parameters were SOC dependent and were independent of T_{amb} [6].

SOC

It is the amount of charge presently available in a battery compared to its full capacity. SOC estimation is desirable not only for better management of smart grids and EVs but also for the protection of the battery from being overcharged or deep discharged which can cause battery life degradation and also fatal accidents.

Since SOC cannot be measured directly, algorithms are developed. These estimates are categorized into five groups:

1. *Look-up table method*

Experimental data studying characterized behaviour of batteries in laboratories are tabulated and a direct relationship between parameters such as OCV, impedance, and SOC is mapped. The only drawback of using this method is that the battery needs to be in a static state and sufficient rest time is allowed to achieve equilibrium.

2. *Coulomb counting method*

One of the most extensively used methods; SOC is estimated by integrating over time the measured discharge current [7]. This method is fairly accurate given that the initial SOC is known, accurately calibrated current sensors are used, and battery capacity must be accurately calibrated regarding ageing and operating conditions. Due to its open-loop nature, errors are inevitable. Hence, this method is mostly used in combination with other estimation algorithms. SOC by this method is counted by the given equation:

$$SOC(t) = SOC(t_o) - \frac{\eta}{C_n}\int_{t_o}^{t} I(t)dt$$

Where,

η is the columbic efficiency,

SOC(t_o) is the initial state of charge,

I(t) is the instantaneous discharge current,and C_n

is the rated capacity.

3. *Model-based estimation*

ECM method along with adaptive filter algorithms (e.g., Kalman filter) is used to calculate the SOC [8]. If the battery modelling is accurate, then the SOC estimation by this method is highly precise. The only drawback is the complexity involved in battery modelling and the time required to identify all important components that make a good model.

4. *Data-driven estimation*

Self-learning algorithms using machine learning (ML) help determine network parameters in this method [9, 10]. Compared to all other methods neural network provides the highest accuracy of about 97.9% [11].

5. Hybrid method

For improving the accuracy and precision of SOC estimations, this method is used where different algorithms are used in conjunction. Optimization techniques are employed in data-driven and model-based methods to bring forth performance enhancements [12]. Genetic algorithm, PSO, radial basis function neural network (RBFNN) along with EKF [13] are a few such methods employed.

The key challenge faced in SOC estimation is to achieve an enhanced, accurate, effective, and robust algorithm at minimum computational complexity so that it can be applied to low-cost BMS hardware.

SOT

Li-ion batteries (LIB) have a long-life cycle, high working voltage, low self-discharge rate, and specific energy and density, making them the most ideal source of power in EV applications. But due to thermal runaway (TR), the functional safety of battery usage becomes a question as LIBs are sensitive to working temperature. As the temperature goes above critical levels and an avalanche chemical reaction occurs in the battery, composition TR occurs. The temperature rises close to 400°C causing the battery to fire up [14]. Internal short-circuit, external short-circuit, and rapid charging, discharging, and overcharging are some of the known causes. Thus, accurate monitoring is indispensable.

Models for temperature estimation are mainly divided into two:

1. Numerical method models

Finite element analysis (FEA) is used to study the temperature distribution. Even though this model is highly accurate, real-time usage is difficult due to the computational burden and accurate internal structure and material of the cell have to be well known in advance which may not be readily available, and also battery parameters are known to change with ageing.

2. Lumped thermal models

These are used for surface and core temperature estimations. Its simplicity finds applications in onboard automotive control of temperatures.

For surface temperature estimation, an impulse response concept is used to predict variations in temperature. The magnitude and width of the current help infer a thermal impulse reference. This reference helps obtain an associated impulse response for several temperature measurements done on cell surfaces. The convolution theorem helps compute variations in temperature associated with the current discharge profile [15]. An enhanced temperature estimation method uses a 1-D model and dual Kalman filter (DKF). Internal resistance and SOC estimation are also done along with the temperature. A comparison between estimated and simulated temperature shows high estimation accuracy [16].

When working with high current and rapid loads, observing the surface temperature alone is not adequate. It has been observed that core temperature is much higher than the surface temperature in such applications [17].

Direct measurement of core temperatures has practical limitations. Hence, estimation strategies use model-based, machine learning-based, and direct impedance measurement-based approaches. Pack level thermal model using thermal state observer (TSO) Kalman filter can be used in BMS. Using TSO [18], limited cell surface measurement allows estimation of the core temperature for the entire battery pack. A cell core temperature estimation using a neural network-based technique is defined for a hybrid ECM with 2D-grid long short-term memory (2D-GLSTM). Total heat generation is estimated from voltage, current, and temperature using ECM and for the evaluation of core temperature, this information is used by the 2D-GLSTM (deep learning) [19].

SOH

SOH indicates the ageing of the battery. A SOH evaluation helps in the timely replacement of battery with reliable operation and increase in life.

The equation defining SOH which is used is:

$$SOH\ \% = \frac{Q_{act}}{Q_R} * 100$$

Where Q_{act} is the actual capacity and Q_R is the rated capacity of the battery.

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Degradation models or direct estimation techniques can be used. Cell parameter modelling is the commonly used method used for estimation as it provides accurate results but the computational time is very high and so is the cost. Ageing is predominated by capacity degradation (capacity fade) and a series of internal resistance changes (power fade) of the battery [20]. Capacity and power fade do not occur simultaneously and are a result of undesirable side reactions [21]. These variations are irreversible and depend on several factors with an increase in temperature, SOH degradation occurs. During fast current discharge, the internal temperature rapidly increases to dangerous levels [22]. Temperature, depth of discharge, and C-rate information assist in the SOH estimation of a battery coupled with a bi-directional DC-DC converter but it is specific to a given system and detailed data on battery capacity and C-rates at different capacities are needed [23].

The data-driven method can also be used for SOH estimation. These include ML approaches like support vector machines (SVM), feed-forward neural network (FNN), regression models, and recurrent neural network (RNN) to name a few [24-27].

RUL

An index used to state the current health of a battery for a new battery is the RUL. Predicting RUL with capacity or impedance data depends on laboratory conditions which are not always practical. To solve this issue, a novel method is developed which combines multiple Gaussian process regression (GPR) model with indirect health indicators for RUL forecast. The process has been validated by using two different life cycle test datasheets [28]. Data-driven approach [29] is also used where an auto-encoder model exhibits battery health degradation and a multi-dimensional feature extraction method working on a deep neural network is used for RUL prediction [30]. Estimating RUL using electrochemical impedance spectroscopy (EIS) can also be done as different frequencies of the small amplitude of AC voltage are applied to the LIB, a change in between the electrodes is observed but the battery has to be disconnected from the system [31]. This is an offline method. An online method to predict the RUL using a mathematical model considering the ageing parameters like temperature and charge or discharge rates is also available. The DC resistance is measured while the battery is in operation by sending a 1C discharge pulse of short duration to monitor the terminal voltage change [32].

CONCLUSION

Battery parameters are the fundamental blocks of BMS and its accurate estimation is essential for its successful estimates of SOC and SOH. This review studies a critical examination of several estimation approaches concerning their fundamentals and accuracy. Some of the important battery indicators have been discussed here like SOC, SOH, RUL, TR, and available estimation techniques have been studied. Conventional methods like model-based techniques are now being replaced or used in conjunction with modern techniques like ML and neural networks to reduce the error rate and increase accuracy. There are challenges like remote BMS upgrade possibilities, atmospheric conditions, and multi-scale developments but the implementation of these methods and advancements in this field is necessary to progress towards a renewable future.

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