STATE-OF-HEALTH PREDICTION INTEGRATED WITH STATE-OF-CHARGE MONITORING OF A LITHIUM-ION BATTERY CELL FOR LIFETIME PREDICTION

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STATE-OF-HEALTH PREDICTION INTEGRATED WITH STATE-OF-CHARGE MONITORING OF A LITHIUM-ION BATTERY CELL FOR LIFETIME PREDICTION

by

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This thesis is dedicated to my dearest parents, brother, grandmother

and the memories of my grandfather.

I couldn’t have done this without their love and support.

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LIST OF ABBREVIATIONS

AI	Artificial Intelligence
BMS	Battery Management System
DoD	Depth of Discharge
EKF	Extended Kalman Filter
EIS	Electrochemical Impedance Spectroscopy
EV	Electric Vehicle
FYP	Final Year Project
GHPF	Gauss-Hermite Particle Filter
HEV	Hybrid Electric Vehicle
ICE	Internal Combustion Engine
KF	Kalman Filter
Li	Lithium
mAh	milliAmpere hour
MATLAB	Matrix Laboratory
OCV	Open Circuit Voltage
R&D	Research & Development
RMSE	Root Mean Square Error
RUL	Remaining Useful Life
SEI	Solid-Electrolyte-Interphase
SoC	State-of-Charge
SoH	State-of-Health
SVR	Support Vector Regression

RAMALAN KEADAAN KESIHATAN DIGABUNG DENGAN PANTAUAN KEADAAAN CAJ BAGI BATERI LITIUM-ION UNTUK RAMALAN HAYAT BATERI

ABSTRAK

Dalam FYP ini, bateri litium-ion akan dipantau semasa kitaran caj-dan-nyahcas untuk meramalkan keadaan kesihatan (SoH) dan menganggarkan keadaan caj (SoC) bagi analisis masa hidup bateri. Bateri litium-ion akan mengalami kerosakan yang serius jika terdedah kepada pengecasan yang berlebihan dan penyahcasan yang mendalam dalam masa yang lama, oleh itu anggaran SoC adalah penting untuk membantu pengguna mengawasi SoC bateri, jadi jangka hayat bateri tidak akan dikurang disebabkan oleh pengecasan berlebihan atau penyahcasan yang mendalam. Selain itu, ramalan SoH digunakan untuk menunjukkan keadaan kesihatan bateri sama ada bateri masih boleh beroperasi atau tidak kerana bateri litium-ion mengalami kemerosotan dari masa ke masa. Analisis masa hidup bateri dijalankan untuk meramalkan hayat bateri sebelum kegagalan supaya pengguna dapat mengetahui jumlah kitaran caj-dan-nyahcas sebelum bateri gagal dan membuat persiapan awal terhadap penggantian, ini dapat meningkatkan keandalan sistem. Dalam FYP ini, satu BMS yang ringkas dibinakan. Kemudian, anggaran SoC akan dilakukan melalui kaedah pengiraan Coulomb dan OCV. Pengiraan SoH adalah melalui ukuran kapasiti bateri. Akhir sekali, data yang diperoleh dari anggaran SoH akan digunakan untuk meramalkan hayat bateri yang tinggal.

STATE-OF-HEALTH PREDICTION INTEGRATED WITH STATE-OF-CHARGE MONITORING OF A LITHIUM-ION BATTERY CELL FOR LIFETIME PREDICTION

ABSTRACT

In this FYP, a lithium-ion battery cell was monitored during its charge-and-discharge cycles in order to predict its State-of-Health (SoH) and estimate its State-of-Charge (SoC) for battery lifetime analysis. Lithium-ion battery will experience serious damage if exposed to overcharging and deep discharging for a long time, hence SoC estimation is crucial to help the user monitor the SoC of the battery, so the battery lifetime will not decrease due to overcharging or deep discharging. Besides, SoH prediction is used to indicate the health condition of the battery whether the battery still can operate or not since lithium-ion battery undergoes degradation as time passes. Battery lifetime analysis is performed to predict the remaining useful life of the battery, so the user can know the amount of charge-and-discharge cycles left before failure and then can prepare for the replacement in time, thus improving the system reliability. In this FYP, a simple battery management system (BMS) was developed. Then, SoC estimation was performed via Coulomb counting and OCV methods. SoH prediction was through the measurement of battery capacity. Lastly, the data obtained from SoH prediction was employed to predict the battery remaining useful life.

CHAPTER 1
INTRODUCTION

1.1 Research Background

The rapid developments of portable electronic devices, electric vehicles (EV), hybrid electric vehicles (HEV) and renewable energy technologies have been dominating the technology sector over the past decade. Hence, the demand for lithium-ion battery has been skyrocketed since lithium-ion battery is the core power source for smartphones, electric vehicles and so on, as well as the energy storage for the renewable energy such as wind and solar power [1]. The condition of lithium-ion battery, however, is unable to be examined through the physical appearance. Therefore, in order to monitor the performance and the condition of lithium-ion battery in the applications as aforementioned, battery management system (BMS) is required to display the significant parameters related to the lithium-ion battery during operation. The performance, in terms of power consumption and security, of EV and HEV, as well as the service life of lithium-ion battery can be improved through efficient energy management [2].

There are two crucial battery parameters to be displayed by BMS, namely State-of-Charge (SoC) and State-of-Health (SoH). Both SoC and SoH are parameters expressed in percentage, while the former is to indicate the relative amount of charge (or energy) stored within a battery at certain instant or simply the amount of battery available capacity [3], and the latter is to reveal the battery's ability to store and deliver electrical energy (or power) compared with a new battery [4,5]. SoC is considered as the most important parameter of BMS [3] as it is indispensable in helping the user to identify whether the battery is fully charged and also to predict the remaining discharge time of the battery when it is connected to a load before it needs to be recharged again, since lithium-ion battery will be seriously damaged and its remaining useful life will be decreased if it is overcharged or deep discharged [4]. Typically, a new lithium-ion battery will have SoH of 100% approximately. Lithium-ion battery will undergo degradation (or aging) as time passes, thus SoH will drop during the lifetime of a battery. Once SoH of a battery decreases until a certain percentage, the battery is considered to be “unhealthy” and is unable to perform well, so it should be replaced by a new battery to prevent the overall system failure as it has reached the end of its lifetime.

There are various works that presented the classification of SoC estimation methods of lithium-ion battery in a diverse manner [6]. Generally, SoC estimation methods can be divided into conventional [6], adaptive [7] and hybrid [6,7] methods. The conventional methods consist of Coulomb counting and open circuit voltage (OCV) methods [6], while the adaptive methods comprise neural network, fuzzy logic and Kalman filter [7]. The hybrid method is the mix of both conventional and adaptive methods, it involves two to three algorithms, greatly increasing the efficiency and accuracy of the SoC estimation [6]. Most of the works have employed the Kalman filter method [2,8] and artificial neural network [9] to estimate the SoC of lithium-ion battery for solely HEV and EV application. Despite being real-time and high accuracy [8], the degree of complexity of the mathematical modelling for these methods has prohibited them to be implemented in low-cost microcontrollers [10].

The prediction of SoH is closely related to battery capacity and internal resistance since the aging of lithium-ion battery is associated with capacity fade [11]. In the literature, majority of the SoH prediction methods are based on Kalman filer, neural networks, fuzzy identification and so on, which are designed for HEV and EV application [10]. Thus, the stated methods are too complicated for being executed in low-cost microcontrollers [10].

Battery lifetime analysis is about predicting the remaining useful life (RUL) of lithium-ion battery which means the available service time left before the capacity fade achieves an intolerable level [12] and hence the battery should be replaced. In the literature, battery lifetime analysis is linked to battery capacity [12] and internal resistance [13] which is similar to the SoH prediction as aforementioned. An integrated method, employing the Gauss-Hermite particle filter (GHPF) technique to predict the capacity as well as the remaining useful life, has been proposed and it is particularly for lithium-ion battery in implantable medical devices [12]. Besides, the battery lifetime can be evaluated through the determination of battery internal resistance via the identification algorithm [13].

In this Final Year Project (FYP), lithium-ion battery is the main research target. A lithium-ion battery is monitored during its charge-and-discharge cycles in order to predict its State-of-Health (SoH) and estimate its State-of-Charge (SoC) for battery lifetime analysis. The proposed methods for the SoC estimation are Coulomb counting and open circuit voltage (OCV) methods. On the other hand, SoH is predicted through the measurement of battery capacity. Hence, the SoH data obtained is used for battery lifetime analysis to predict the remaining useful life of the battery, so the number of cycles left before the battery failure can be known by the user in order to prepare for battery replacement.

1.2 Problem Statements

Lithium-ion batteries have been widely used in many applications such as hybrid electric vehicles (HEV), electric vehicles (EV), laptops, smartphones and so on [4]. However, overcharging and deep discharging are the critical issue faced by lithium-ion battery. This is because the internal structure of the battery may be permanently damaged if the battery is exposed to overcharging and deep discharging frequently [4]. Hence, the lifetime of the battery will be cut short drastically.

Besides, lithium-ion battery also encounters the problem of degradation (or aging). Over the lifetime of a lithium-ion battery, the chemical reaction within the battery will cause the degradation to occur and hence the battery's capacity will decrease (capacity fade), no matter the battery is used regularly or at rest [1]. Therefore, the performance of the battery will be greatly reduced due to the capacity fade and the battery will fail eventually.

In order to solve the problems of overcharging and deep discharging, precise SoC estimation is an essential solution. Through SoC estimation, the user will know the remaining available charges in a battery which expressed as a percentage of its maximum capacity [2]. Hence, the user will recognize the right moment to recharge the battery, as well as unplug the battery from the charger. Therefore, the battery lifetime will be extended. There are many previous works based on Kalman filter [2,8] and artificial neural network [9] to estimate solely SoC. Those previous works are successful in estimating SoC with high degree of accuracy. However, those works do have a common limitation. The drawback is that those works only consider SoC estimation, while SoH prediction and battery lifetime prediction are neglected. Hence, the user only knows when to recharge the battery, but unable to identify the battery condition due to aging, as well as unable to prepare battery replacement timely which may lead to the failure of overall system.

On the other hand, since the degradation of lithium-ion battery is inevitable, so it is crucial to predict SoH of a battery in order for the user to know whether battery replacement is required. As aforementioned, there are various approaches based on Kalman filer, neural networks, fuzzy identification and so forth, for the SoH prediction of lithium-ion battery in HEV and EV application [10]. For instance, SoH prediction based on neural network [14] is highly accurate with low computation cost and low memory requirement. However, the limitation is that SoC estimation is neglected. Hence, overcharging and deep discharging may occur since the user is unable to identify the charge percentage of the battery without SoC estimation, causing severe damage to the battery and decreasing the battery lifetime.

Furthermore, there is a previous work about remaining useful life (RUL) prediction of lithium-ion battery which based on discrete wavelet transform [15]. Since both RUL and SoH are crucial to BMS to guarantee the safety and reliability of EV application, the proposed method is able achieve high accuracy of RUL prediction [15]. However, the limitation is that SoC estimation is neglected. As the aging of lithium-ion battery is affected by the depth of discharge, thus SoC estimation is also critical to improve the accuracy of RUL prediction.

Referring to the literature, there are diverse works done to either estimate SoC [2,3,7,8,9], predict SoH [5,10,14] or battery lifetime [15], but it is uncommon to find a work which is the combination of SoC estimation and SoH prediction and the battery lifetime prediction. Hence, this FYP will focus on SoC estimation and SoH prediction, as well as the battery lifetime analysis for lithium-ion battery cell in order to overcome the limitations.

Since the SoC value of a battery only indicates its current capacity in percentage and does not reflect the health status of the battery. Hence, a battery with SoC of 100% may perform poorly (supply power to the load for a short time) and cause interruption to the overall system connected. Moreover, the SoH data can be used for the battery lifetime analysis, so the remaining useful life of the battery can be estimated and the user will know the remaining period of the battery before failure, hence the user has sufficient time to prepare for the replacement. Therefore, SoC estimation and SoH prediction for battery lifetime analysis is able to improve the reliability and efficiency of lithium-ion battery, as well as to ensure the safe operation of lithium ion battery [11].

1.3 Objectives of the Research

- To estimate the State-of-Charge (SoC) of a lithium-ion battery through the Coulomb counting and open circuit voltage (OCV) methods.
- To predict the State-of-Health (SoH) of a lithium-ion battery through the battery capacity.
- To perform battery lifetime analysis with the obtained SoH data.

1.4 Scope of the Research

This FYP is concerned on the SoC estimation via the Coulomb counting and open ciruict voltage (OCV) methods, while the SoH prediction via the measurement of battery capacity. Therefore, there are two vital physical quantities that must be measured and recorded – voltage and current – in order to estimate SoC and predict SoH of the battery. Data logger system which was built with Arduino Uno and current sensor was employed to measure the voltage and current during the discharging of the battery and then transferring the data to the computer for SoC estimation and SoH predition. Moreover, the SoH data obtained was employed for the battery lifetime analysis via MATLAB and the prediction of remaining useful life was displayed on the computer. The type of lithium-ion battery used was Panasonic 18650B with capacity of 3350mAh. The load connected to the battery is power resistor of 2Ω with discharging rate of 0.5C at around room temperature.

1.5 Thesis Outline

This thesis comprises five main chapters – introduction, literature review, methodology, results and discussion, as well as conclusion. In the chapter of introduction, the background, problem statements, objectives and scope of the research for this FYP are clearly explained.

Chapter 2 is the literature review of previous works related to this FYP. In this chapter, theoretical concepts of lithium-ion battery are reviewed. Moreover, the methods for SoC estimation and SoH prediction, as well as the battery lifetime analysis proposed in the latest previous works are discussed.

Next, chapter 3 is the methodology of the research. The system overview is first explained, followed by the Coulomb counting and open circuit voltage (OCV) methods to estimate SoC and subsequently the SoH prediction method, then the battery lifetime analysis. In addition, all the hardware, coding and mathematical equations involved in this FYP are presented.

Chapter 4 is the section for the results of this FYP. The results for SoC estimation via the Coulomb counting and open circuit voltage (OCV) methods are depicted, along with the results for SoH prediction and battery lifetime prediction. The results are presented in the form of graphs and tables. Furthermore, the results obtained are compared with the datasheet, followed by discussion.

The final chapter is about the conclusion of the research. It covers the summary and the contribution of this FYP, in addition to the recommendation for the future work to improve the weaknesses.

CHAPTER 2
LITERATURE REVIEW

2.1 Introduction

This chapter begins with the general classification of batteries to provide insight to the types of batteries in the market. In section 2.3, development of lithium-ion batteries is briefly discussed to study the marketing potential of lithium-ion battery. Next, the applications of lithium-ion batteries in different sectors are explained. Section 2.5 introduces battery management system. Then, the methods for SoC estimation and SoH prediction from previous works are reviewed briefly. The review of battery lifetime analysis is presented in section 2.8. Lastly, all the contents are summarized in section 2.9.

2.2 General Classification of Batteries

Batteries can be categorized into two, namely primary (non-rechargeable) and secondary (rechargeable) batteries. Primary batteries are handy for applications that draw intermittent power since they are cheap and readily available in the market. Regulated under IEC 60086 Standard, primary batteries are employed in heart pacemakers, tire pressure gauges, smart meters, clocks, wristwatches, remote controls, toys and so on [16]. However, the cost of continuous usage of primary batteries will be high and the worldwide disposal of primary batteries has caused severe environmental pollution issues.

Therefore, secondary (rechargeable) batteries have been invented to overcome the drawback of primary batteries. The most common rechargeable batteries available in the market are lead acid, nickel-cadmium, nickel-metal-hydride and lithium-ion batteries [16]. The growth in the industry of portable electronic device since the past two decades has stimulated the demand for high reliable and performance power sources. Thus, rechargeable batteries that can provide longer lifetime and higher power has become the better choice for consumers [1]. The main concern in this FYP is lithium-ion battery.

2.3 Development of Lithium-Ion Batteries

In 1980s, lithium-ion battery was developed under the cooperation between Asahi Chemicals and Sony, then first released to the market in 1991 [17]. During that time, lithium-ion battery was competing with the other two types of rechargeable battery, nickel-cadmium and nickel-metal-hydride, as aforementioned in section 2.2. Both, however, were limited in the aspects of gravimetric and volumetric energy density as compared to lithium-ion battery [17].

Since 1991, the technology of lithium-ion battery has been developed from time to time, thus its market share also has been skyrocketed [17]. Nowadays, lithium-ion battery is taking the lead in the consumer market compared to the other battery technologies [18]. In 2013, five billion lithium-ion cells were sold globally just for powering of portable electronic devices [18]. The worldwide market for lithium-ion batteries has been escalating swiftly and is predicted to cross 30 billion USD by 2020 [19]. The market size of lithium-ion batteries for the phase between 2008 and 2013, in addition to the predicted market size for the phase between 2014 and 2020 are shown in Fig. 2.1 [19]. Presently, numerous companies in Japan (Panasonic, Sony, Hitachi, Toshiba and Mitsubishi Electric), South Korea (Samsung and LG), China (BYD) and the United States (A123) compete with each other intensely in the lithium-ion battery market [19].

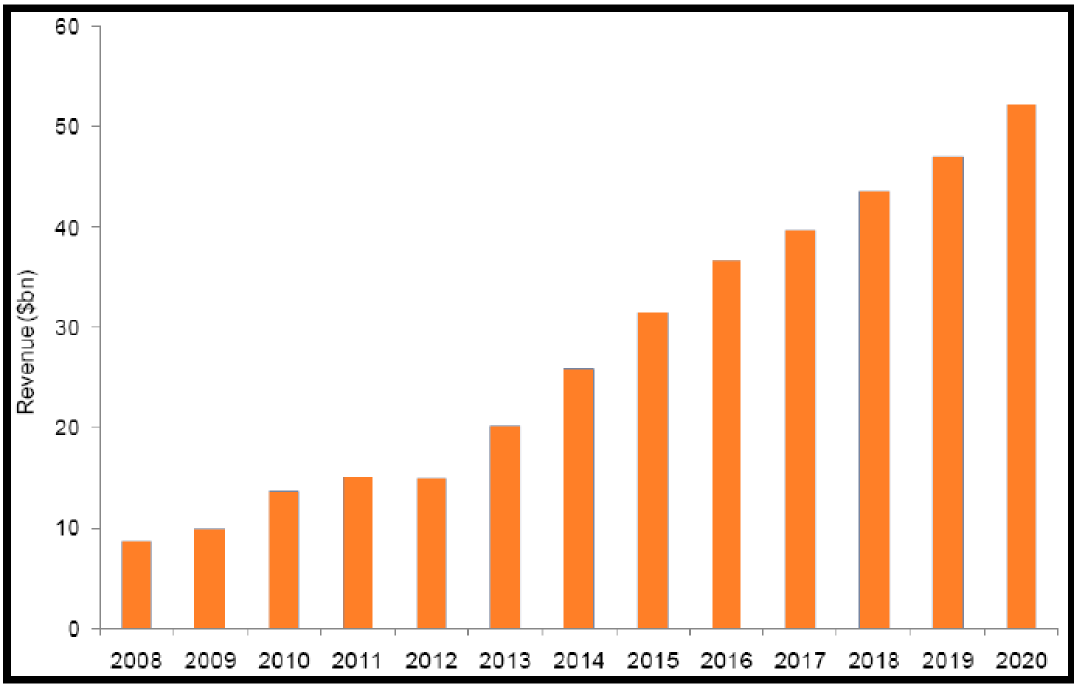

Fig. 2.1. Revenues of the universal lithium-ion battery market in USD Billion, from 2008 to 2020 [19]

2.4 Applications of Lithium-Ion Batteries

At the moment, lithium-ion batteries are widely employed in the fields of portable electronic devices, hybrid electric vehicles (HEV) and electric vehicles (EV), unmanned aerial vehicles, standby units in uninterrupted power supplies and storage of excess energy from renewable energy sources (wind and solar) [1]. Among the stated applications, lithium-ion batteries are extensively used in portable electronic devices, such as smartphones, cameras and laptops [19]. This is because lithium-ion batteries have higher energy density with lighter weight than the other battery technologies to support the features like high definition displays, powerful processors and wireless communication which consume enormous portion of energy [18].

The issues of high carbon dioxide emission and global warming are triggered by the excessive amount of fossil-fuelled vehicles [20]. Moreover, the automobile industry is intimidated by the limited crude oil resource [6]. Thus, the issues have prompted the development of EV and HEV with the aim to replace the internal combustion engine (ICE) vehicles with an environmentally friendly alternative. Since the early 2010s, HEV and EV have become more feasible and commonly available in the market [17]. For instance, Nissan Leaf, Tesla Model S and X, BMW i3 and Chevrolet Spark [17]. In HEV and EV, batteries are a vital element to allow sustainable, clean and electrified movement [21]. Despite the variety of battery technologies available, lithium-ion battery is considered as the most potential option which can effectively guarantee the progressive propulsion of HEV and EV [15]. Hence, the research and development (R&D) projects for lithium-ion battery have been sprouted worldwide.

The limited supply of fossil fuels has also initiated the persistent shift to renewable intermittent energy sources, such as wind and solar power [17]. Thus, electrical energy storage system will become crucial gradually to manage the variable energy demand efficiently, since the supply of renewable energy is unstable and subjected to the changes of weather and occasion [17]. Besides, the electricity supply problems arise from the eastern Japan earthquake and the international determinations to adopt smart grids have caused energy storage system to gain the attention [19]. In the context of battery energy storage system, lithium-ion battery has come into the spotlight due to high density, long lifespan and high efficiency [6].

2.5 Battery Management System (BMS)

The operating condition of lithium-ion battery is relatively critical in large-scale applications like HEV, EV and energy storage system. The failure of lithium-ion battery will lead to the failure of overall system [23]. Thus, BMS is necessary to monitor the battery condition to increase the overall system reliability [17]. In order to improve the favourable performance and reliability of lithium-ion battery, battery management system (BMS) is used to monitor the battery and provide accurate battery information for the user [2]. Moreover, battery monitoring also helps to facilitate maintenance and operational-based decisions [1]. There are two important parameters which are the main concerns in battery monitoring, namely State-of-Charge (SoC) and State-of-Health (SoH). SoC indicates the remaining capacity in a battery which expressed as a percentage of the battery's maximum capacity. SoH is defined as the battery's ability to store and deliver electrical energy (or power) compared with a new battery.

Both SoC and SoH are indirectly measured parameters due to the lack of sensors for electrochemical phenomena within the battery [11], which means they are unable to be measured directly like physical quantities such as voltage, current and power. Hence, they can only be estimated through relative quantities, such as battery's voltage, current, temperature and so on [2].

2.6 State-of-Charge (SoC) Estimation Methods

State-of-Charge (SoC) is a parameter which expresses how much charge can be discharged from a battery in its present state as a percentage of the battery capacity [17], which is shown as follows:

$$SoC = \frac{Q_{remaining}}{Q_{maximum}} \times 100\% \tag{2.1}$$

$$Q_{remaining} = Q_{initial} + Q_{charged} \tag{2.2}$$

$$Q_{remaining} = Q_{initial} - Q_{discharged} \tag{2.3}$$

$$Q_{remaining} = Q_{initial} \tag{2.4}$$

where $Q_{remaining}$ represents the amount of remaining charges in the battery, $Q_{maximum}$ represents the battery capacity which is the maximum amount of charges that can be stored in the battery, $Q_{initial}$ represents the initial charges in the battery before charging or discharging, $Q_{charged}$ represents the amount of charges charged to the battery and $Q_{discharged}$ represents the amount of charges discharged from the battery. SoC can be defined mathematically as shown in equation (2.1). Since a battery can be charged and discharged, thus when it is charging, $Q_{remaining}$ is expressed as depicted in equation (2.2), and when it is discharging, $Q_{remaining}$ is expressed as equation (2.3). If the battery is at rest, $Q_{remaining}$ is expressed as equation (2.4) since no charge is discharged or charged when the battery is at rest. Hence, this implies that SoC is increased when a battery is charging or vice versa when the battery is discharging and SoC is fixed when the battery is at rest.

Since it is impossible to calculate the amount of charges directly, thus SoC can only be estimated to prevent overcharging and deep discharging which is fatal to lithium-ion battery. There are many methods have been proposed to estimate SoC such that each method has its own advantages and disadvantages [11]. In the literature, most of the SoC estimation methods proposed are for the application in HEV and EV. As aforementioned, SoC estimation methods can be categorised into conventional, adaptive and hybrid methods.

2.6.1 Coulomb Counting and Open Circuit Voltage (OCV) Methods

Both Coulomb counting [24] and open circuit voltage (OCV) methods [3,25] are the conventional ways for SoC estimation as aforementioned. The principle of Coulomb counting method is related to equations (2.1) to (2.3), such that SoC is estimated by accumulating the charge that transferred in or out of the battery [4]. For instance, when a lithium-ion battery is discharging, the amount of charges that discharged out from the battery can be determined by integrating the discharge current over the duration of discharge as shown in equation (2.5):

$$Q_{discharged} = \int_0^t I_{discharge}\, dt \tag{2.5}$$

where $I_{discharge}$ is the discharge current and t is the duration of discharge. For the case of charging, the amount of charges that charged into the battery is shown in equation (2.6):

$$Q_{charged} = \int_0^t I_{charge}\, dt \tag{2.6}$$

where I_{charge} is the charging current and t is the duration of charging. Then, SoC of the battery can be estimated online by employing equations (2.1) to (2.3). It should be noted that the battery capacity ($Q_{maximum}$) and the initial charges ($Q_{initial}$) before discharging must be known when using the Coulomb counting method. The easiest way of finding $Q_{maximum}$ is by measuring the total transferred charges during a full discharge of a fully charged battery [17], while $Q_{initial}$ can be determined via OCV method.

The principle of OCV method is related to the battery discharge curve. It has been proven that there is relationship between OCV and SoC of lithium-ion battery. Thus, the discharge curve is a graph of OCV against SoC. Hence, by measuring the open circuit voltage (OCV) of a battery, SoC can be estimated by referring to the discharge curve. Although this method is easy to be implemented, it is an offline method which means the battery must be at rest when using this method to estimate SoC. Moreover, this method is employed to determine the initial SoC or $Q_{initial}$ for the Coulomb counting method.

Both methods are easy and less complex to be implemented as well as fast in computation, but the Coulomb counting method extremely relies on the accuracy of current sensor and it is sensitive to the initial SoC value and accumulation errors, while the open circuit voltage method is not effective for battery with flat open circuit voltage characteristic curve [2,11]. Moreover, an enhanced Coulomb counting method [26] has been proposed to overcome the weakness of typical Coulomb counting method through the correction of the operating efficiency and the evaluation of SoH.

2.6.2 Kalman Filter (KF) Method

Besides, there are also artificial intelligent (AI) based methods have been proposed to establish black-box SoC estimation models, such as neural network[9], fuzzy logic and support vector regression (SVR) models [11]. Moreover, the Kalman filter (KF), extended Kalman filter (EKF) [2,8,17] and sliding mode observer have also been employed for SoC estimation, which are model-based, closed-loop, and thus can use output feedback to keep better robustness than non-feedback methods [11]. Those mentioned methods are adaptive methods which are algorithm-based and suitable for online application [17].

Among the stated adaptive methods, both Kalman filter (KF) and extended Kalman filter (EKF) methods are the most common [17]. Generally, KF is a recursive state estimator which is used to estimate a time-dependent and indirect-measured parameter in the presence of noises from measureable parameters. In other words, KF is an algorithm or a set of mathematical equations which predicts and corrects a new state repeatedly while the system is operating.

The general principle of KF is illustrated in Fig. 2.2 [4]. The most crucial element in KF is the model that represents the actual system. The model refers to mathematical equations which used to describe the system and deriving the model is the first step in KF. The general equations involved are as follows [4,6]:

$$\hat{x}_{k+1} = A_k\hat{x}_k + B_k u_k + w_k \tag{2.7}$$

$$\hat{y}_k = C_k\hat{x}_k + D_k u_k + v_k \tag{2.8}$$

$$\hat{x}_{k+1} = \hat{x}_{k+1} + K_{k+1}(y_{k+1} - \hat{y}_{k+1}) \tag{2.9}$$

where x is the system state (parameter to be estimated), u is the control input, w is the process noise, y is the measurement output, v is the measurement noise, K is the Kalman gain, k is the time step, while A, B, C and D are the covariance matrices which are time dependent and depict the dynamics of the system. Equation (2.7) is the state equation which is to estimate the current system state from the earlier state and control input, while equation (2.8) is the measurement equation which is to estimate the measureable parameter from the system state and control input. Then, equation (2.9) is the update/correction equation which is to minimize, in real time, the error between the estimated and the measured outputs in order to update/correct the estimated state. The correction is governed by K, the Kalman gain, which is calculated at each iteration from noises and prediction errors. KF can be applied to any system that can be modelled by the general equations.

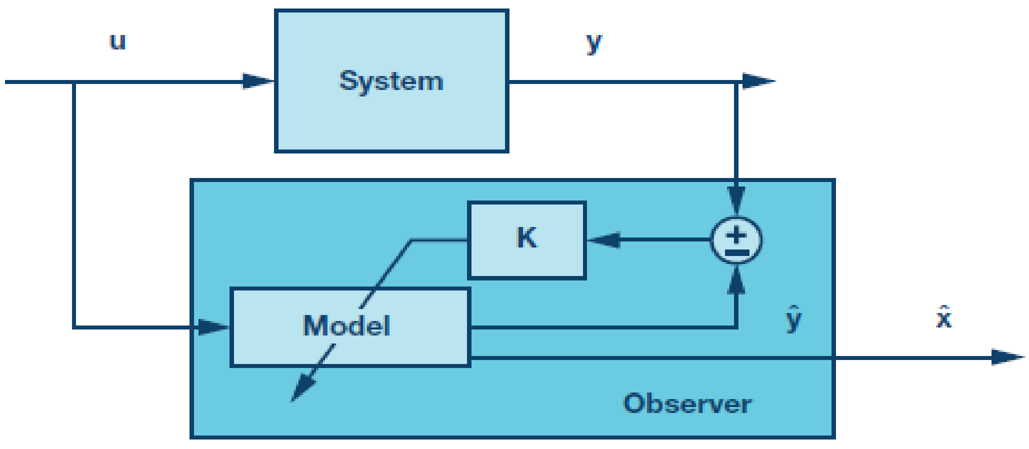

Fig. 2.2. The general principle of Kalman filter [4]

After the equations are derived, the KF algorithm can be constructed. The algorithm works by estimating the values of present state, output and error covariance first after the initialization process. Then, the algorithm corrects the estimated state and error covariance by using the measurement of the physical system output [4]. Although the estimation via KF method is highly accurate, KF is not applicable to a non-linear system such as battery system [6]. Hence, extended Kalman filter (EKF) method is employed to overcome the non-linear characteristic of battery system [8]. The general principle of EKF is similar to that of KF, but partial derivatives and first order Taylor series expansion are used in EKF to linearize the battery model [6].

2.6.3 Equivalent Circuit Model (ECM) of Lithium-Ion Battery

In order to employ EKF for SoC estimation, battery modelling is the critical first step before proceeding further. Battery modelling is to develop a virtual battery model which is able to satisfy the actual behaviour of the real battery to an adequate degree, along with achieving adequate computational performance [17]. In EKF, a system must be mathematical modelled based on equations (2.7) to (2.9) as aforementioned, thus battery modelling must be performed first to assist in the mathematical modelling.

Typically, the types of battery models can be classified into three, namely pure empirical model, electrochemical model and equivalent circuit model. However, equivalent circuit model (ECM) is the most common and popular model to be applied due to fair accuracy and computational performance [17]. The fundamental concept of ECM is to model the dynamic behaviour of battery with simple hypothetical electric circuit, comprising elements such as resistors, voltage sources and capacitors connected in series and parallel configurations [17]. Hence, the actual physical occurrences in the battery are represented by the elements in ECM. The simplest form of ECM is depicted in Fig. 2.3 [17].

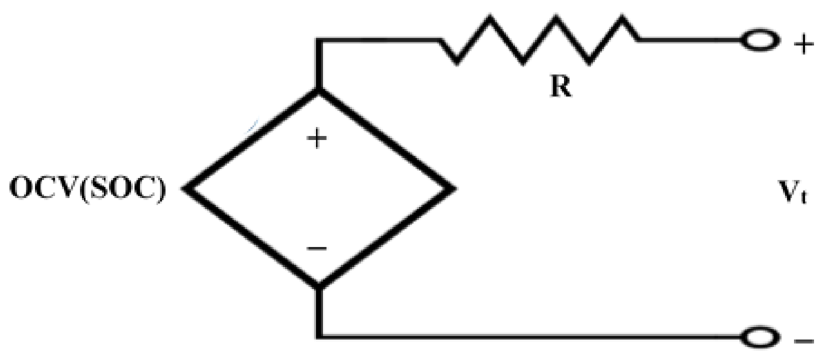

Fig. 2.3. Simplest ECM of a lithium-ion battery [17]

The ECM in Fig. 2.3 represents a battery as a voltage source with internal resistance, such that V_t is the terminal voltage, OCV is the open circuit voltage and R is the internal resistance. Despite its simplicity, it still contains some essential battery behaviour. For instance, the value of OCV is dependent on SoC since it is proven that there is relationship between OCV and SoC as shown in battery discharge curve as aforementioned. Moreover, the terminal voltage will decrease when the battery is loaded due to the presence of internal resistance in the battery according to Ohm's Law and it is shown in equation (2.10).

$$V_t = OCV(SoC) - I \cdot R \tag{2.10}$$

There is another battery behaviour not included in the ECM above – the voltage drop after being loaded is not instantaneous but a decaying behaviour. This implies that an actual battery will not respond immediately to an applied current and the terminal voltage will not increase to OCV instantly after being unloaded. This is because of the diffusion effects within the battery cell. Hence, in order to describe this behaviour, the previous ECM is modified by adding a series of parallel resistor-capacitor (RC) couples and the modified ECM is shown in Fig. 2.4 [17], where C_n and R_n are the capacitance and resistance of the n^{th} parallel pair respectively, and V_n the transient voltage across the n^{th} pair.

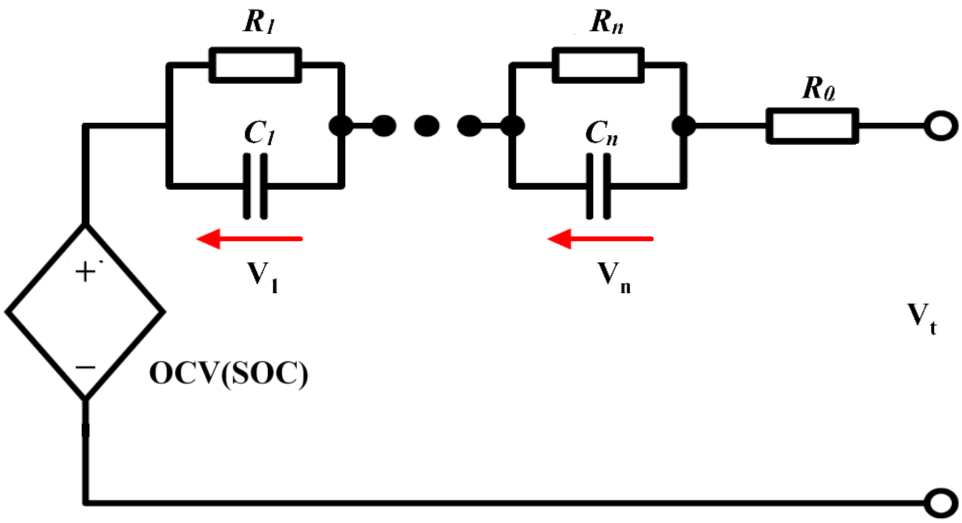

Fig. 2.4. Modified ECM of lithium-ion battery [17]

The purpose of adding the RC pair is to model the non-instantaneous behaviour of voltage drop and the voltage across the RC pair is shown in equation (2.11). Hence, the terminal voltage equation is modified to equation (2.12). Since the voltage across RC pair in equation (2.11) shows non-linear characteristics, thus a linear differential equation can be obtained by applying Kirchhoff's current law as shown in equation (2.13) and then equation (2.14) obtained by rearranging the terms in equation (2.13). Therefore, it can be seen that the significance of ECM is to allow the battery parameters to be mathematical modelled during the process of KF and EKF.

$$V_n = V_0 \cdot e^{-\frac{t}{R_n \cdot C_n}} \tag{2.11}$$

$$V_t = OCV(SoC) - I \cdot R_0 - \sum_{n=1}^{n} V_n \tag{2.12}$$

$$C_n \frac{dV_n}{dt} + \frac{V_n}{R_n} = I \tag{2.13}$$

$$\frac{dV_n}{dt} = -\frac{1}{R_n C_n} \cdot V_n + \frac{1}{C_n} \cdot I \tag{2.14}$$

2.6.4 Comparison of SoC Estimation Methods

All the SoC estimation methods mentioned above are summarized in Table 2.1 for clarification. From the literature, it can be seen that majority of the previous works focus in developing SoC estimation methods with higher accuracy, so most works only cover SoC estimation without SoH prediction and lifetime prediction. Hence, this limitation will cause the user unable to identify the battery condition and prepare the battery replacement in time. In this FYP, Coulomb counting and OCV methods are employed to estimate the SoC of lithium-ion battery since there is limited literature for that particular methods.

Table 2.1. Comparison between proposed methods for SoC estimation [11]

Methods	Advantages	Disadvantages
Coulomb counting method	Simple.	Open-loop, sensitive to the current sensor precision and uncertain to initial SoC.
Terminal voltage method	Simple.	Open-loop, sensitive to the voltage sensor precision and unsuitable for battery with flat OCV-SoC curve.
Neural network	Generic, good nonlinearity mapping approximation.	Sensitive to the amount and quantity of training data.
Fuzzy logic	Generic, good nonlinearity mapping approximation.	Sensitive to the amount and quantity of training data.
Support vector machine	Generic, good nonlinearity mapping.	Sensitive to the amount and quantity of training data.
Kalman filter	Closed-loop, online, and accruate	More computationally expensive than non-feedback methods and highly dependent on the model accuracy.
Sliding mode observer	Closed-loop, online and accurate	More computationally expensive than non-feedback methods and highly dependent on the model accuracy.

2.7 State-of-Health (SoH) Prediction Methods

Since all lithium-ion batteries will undergo degradation throughout their lifetime, so the SoH prediction is important to determine the status of a lithium-ion battery whether it still can function normally or it needs a replacement. In other words, SoH is an indicator of the level of battery performance due to degradation process [17]. The degradation is caused by the chemical mechanisms inside the battery cell and then the growth of a solid electrolyte interface (SEI) layer will increase the internal resistance of the battery and reduce the maximum power output of the battery. Furthermore, the loss of bonding sites in the active material and the loss of active lithium ions will decrease the capacity of the battery [1,5]. SoH is a significant parameter because it can avoid severe battery failure, regulate battery operation and maintenance to boost efficiency and return on investment and it is vital for accurate SoC prediction [17].

Regrettably, SoH does not have a fixed set of definition and numerous different metrics are employed in the industry [17]. Similar to SoC, it is impossible to measure SoH directly [17]. Since both internal resistance and capacity are affected by the degradation, therefore the prediction of SoH can be done by monitoring the internal resistance and capacity of the battery during operation [27]. SoH which is defined in term of internal resistance is shown in equation (2.15), while SoH defined in term of capacity is depicted in equation (2.16), where R_i is the i^{th} measurement of internal resistance, R_0 is the initial value, C_i is the i^{th} measurement of capacity and C_0 is the initial value [5].

$$SoH = \frac{R_i}{R_0} \times 100\% \tag{2.15}$$

$$SoH = \frac{C_i}{C_0} \times 100\% \tag{2.16}$$

2.7.1 Neural Network (NN) Method

In the literature, many approaches are proposed to predict SoH via battery capacity [5,10,20,28] which are based on battery modelling merged with filtering or observer [23] algorithms. Among the methods, neural network (NN) method is suitable for SoH prediction of lithium-ion battery in EV application. This is because NN is adapted to work in non-linear system such as battery system, in addition to online feature which means NN is able to predict SoH while the battery is operating [6].

Neural network (NN) is an intelligent mathematical tool which possesses the flexibility and self-learning feature to describe a complex non-linear system [6]. The general principle is that NN is a type of self-learning algorithm which requires large amount of experimental input data for training in order to obtain ideal results [14]. The structure of a neural network comprises 3 types of layers, namely input layer, output layer and hidden layer [6]. The input layer refers to the training data which is the measurements from the actual system. The hidden layer is the set of mathematical functions which known as neurons. The output layer is the estimation results produced by the hidden layer. Thus, the hidden layer is the vital element of a neural network because the mathematical functions work together to produce the estimation output from the training data. In other words, a neural network can be seen as a black-box model such that input data is fed to the black-box and the estimated data is produced at the output. The black-box model is dependent on the respective system.

Based on the previous work [14], NN method is employed to predict SoH from battery capacity. In that case, the input data is the parameters from first order ECM and the output obtained is predicted SoH data in term of battery capacity. The hidden layer is a set of mathematical equations that represents the battery system. This method is successful to predict SoH with low computation cost and low memory requirement [14].

2.7.2 DC Resistance Method

On the other hand, the battery internal resistance can be determined through DC method [29], AC method, extended Kalman filter and electrochemical impedance spectroscopy (EIS). Since the battery internal resistance is increased as a battery undergoes aging, thus by tracking the battery internal resistance, SoH can be predicted using equation (2.15).

Referring to the previous work [29], EIS method is off-line, time consuming and dependent on expensive apparatus. Thus, DC method is proposed in the work to predict real time SoH in term of internal resistance for a lithium-ion battery used as backup energy supply. Equation (2.17) as shown below is employed to estimate the internal resistance:

$$R_{int} = \frac{U_{ocv} - U_{bat}}{Idesc}\ \Omega \tag{2.17}$$

where R_{int} is the internal resistance, U_{ocv} is the open circuit voltage, U_{bat} is the terminal voltage after discharge current was applied and I_{desc} is the discharge current. In order to obtain the required parameters accurately, certain equipment is required. For instance, electronic load and thermal chamber. Although this method involves simple calculation, the accuracy of results is highly dependent on the measured parameters.

2.7.3 Comparison of SoH Prediction Methods

Table 2.2 depicts the summary of proposed methods for SoH prediction. From the literature, it can be observed that most of the previous works on SoH prediction focus in the improvement of estimation accuracy. However, the significance of SoC estimation has been neglected as a battery will fail prematurely due to overcharging and deep discharging without SoC estimation. In this FYP, SoH prediction is performed with the durability external characteristic method which is by tracking the battery capacity via Coulomb counting.

Table 2.2. Comparison between proposed methods for SoH prediction [11]

Methods	Advantages	Disadvantages
Durability mechanism	Comprehensive understanding	Complex, need accurate input parameters
Durability external characteristic	Simple and easy to predict capacity fade and internal resistance increment	Based on a large number of experiments
DC resistance	Simple	Less accurate and sensitive to disturbances
AC impedance	Accurate	Complex
Extend Kalman filter	Quite easy to implement, accurate	Sensitive to modelling accuracy
Fuzzy logic	Quite easy to implement, accurate	Slow convergence
Sample entropy	Simple	Need large amount of data
Discharge voltage	Easy	Not accurate
Adaptive control system	Online	Sensitive to modelling accuracy

2.8 Battery Lifetime Analysis

Battery lifetime analysis is a fundamental aspect for successful market introduction [30]. As aforementioned, battery lifetime analysis is to predict the remaining useful life of lithium-ion battery which means the available service time left before the capacity fade achieves an intolerable level [12] and hence the battery should be replaced. The lifetime of a battery can be expressed in the unit of time or the amount of charge-and-discharge cycles.

A lithium-ion battery is said to reach its end of life when its remaining useful life is zero and this situation occurs when SoH of the battery has attained certain level [17]. Thus, SoH is strongly related to the concept of battery lifetime analysis [17]. For the application of HEV and EV, a lithium-ion battery reaches its end of life if its SoH in term of capacity reaches 80%. While for the application of energy storage system, the limit is 65% [17]. In simpler words, battery lifetime analysis can be performed via simple curve fitting and extrapolation techniques on SoH data over time as depicted in Fig.2.5 [17].

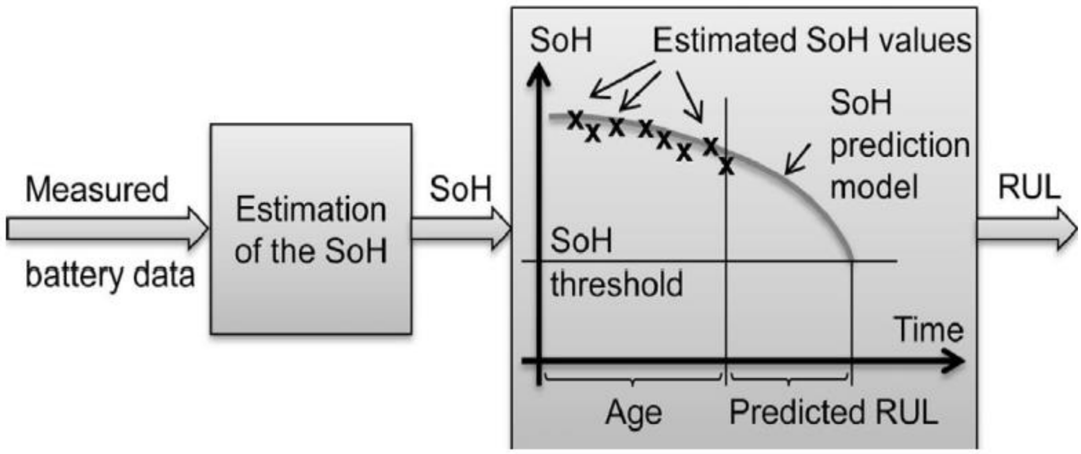

Fig. 2.5. Illustration for battery lifetime analysis [17]

Based on the literature, battery lifetime analysis is linked to battery capacity [12] and internal resistance [13,31] which is correlated to the SoH prediction as aforementioned. An integrated method which employs the Gauss-Hermite particle filter (GHPF) technique to track the capacity fade has been proposed and then the remaining useful life prediction is performed by extrapolating the future capacity values [12]. This method is especially for lithium-ion battery in implantable medical devices [12]. Besides, the battery lifetime can be evaluated through the determination of battery internal resistance via the identification algorithm [13] and the accelerated degradation testing [31]. The general principle of identification algorithm [13] is rather similar to that of KF method. Firstly, ECM of lithium-ion battery is established. Then, all related parameters are expressed in the least square algorithm via mathematical modelling. Hence, the parameters can be identified by using the experimental data. On the other side, the concept of accelerated degradation testing method [31] is about the use of degradation and error models, which are empirical type of battery model, to predict the life of lithium-ion cells via simulation approach.

As mentioned earlier, both SoH prediction and battery lifetime prediction are linked to each other. This is because both of them are related to the aging process of battery. The difference between them is that the aim of SoH prediction is to identify the current battery condition by tracking the capacity fade or the increase of internal resistance, while the purpose of battery lifetime analysis is to predict the remaining useful life of the battery by tracking the capacity fade or the increase of internal resistance so the user can know how long the battery will last before failure. However, the previous work [14] only focus in SoH prediction and the battery lifetime prediction is neglected. Therefore, the previous work only allows the user to identify the present battery condition via SoH prediction, but the user is unable to identify the battery condition in the future without lifetime prediction. Thus, the user may not prepare the battery replacement on time and causing the failure of overall system powered by the battery.

Besides, the previous works [12,13,31] that focus in battery lifetime analysis have ignored the significance of SoC estimation in the remaining useful life prediction. Since a good lifetime prediction is critical to BMS in order to ensure the safety and reliability of the overall system [15], therefore the factors that affect the accuracy of remaining useful life prediction must be considered. It is mentioned that battery lifetime analysis is related to the aging process of lithium-ion battery. Thus, the factors that influence the aging process must be controlled to ensure the accuracy of remaining useful life prediction. For instance, if the aging process was occurring at a faster rate due to the influences of the factors, then the battery might fail prematurely and hence the remaining useful life prediction is not accurate.

Based on the literature, the battery aging is affected by 3 main factors, namely discharge current rate, working temperature and depth of discharge (DoD) [32,33]. It is proven that high discharge current rate is harmful to the battery performance as the battery degrades faster. Moreover, it is shown that the operating temperature has a huge impact on the battery performance and remaining useful life of the battery. For instance, at higher temperature of 40°C, the battery performance is less compared to at 25°C [32].

Furthermore, higher depth of discharge (DoD) will also lead to a faster aging process. Generally, when a battery is discharging, DoD is defined as the percentage of the amount of released charges relative to the battery capacity as shown in equation (2.18) below [4]:

$$DoD = \frac{Q_{released}}{Q_{maximum}} \times 100\% \tag{2.18}$$

where $Q_{released}$ is the amount of charges released from the battery during discharging and $Q_{maximum}$ is the battery capacity. Based on the previous work [34], operating at reduced DoD improves the cycle life of the battery, decreases its capacity fade and slows down the aging process. Besides discharging, DoD can also be applied when a battery is charging.

Due to the influence of DoD to the aging process, thus SoC estimation is critical in battery lifetime analysis because SoC parameter reflects the charge and discharge depth [35] so the DoD can be controlled. For instance, in order to slow down the aging process, the range of SoC is suggested to be 20% to 80% for each charge-discharge cycle. This is because high SoC (overcharging) and low SoC (deep discharging) will lead to battery capacity deterioration [36]. Therefore, SoC estimation is important to control the DoD at certain level so that the remaining useful life prediction is more accurate. This is because if the three factors are not controlled, the aging process may occur at slower or faster rate, hence the remaining useful life prediction will be inaccurate.