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Adaptive and Robust Algorithm for Lithium-Ion Battery States Estimation for Application in Electric Vehicles

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Adaptive and Robust Algorithm for Lithium-Ion Battery States Estimation for Application in Electric Vehicles

Van Huan Duong

A thesis submitted as part of the requirements for the award of the degree Doctor of Philosophy from University of Wollongong, Australia

August 2017
Declaration

I, Van Huan Duong, declare that this thesis, submitted in partial fulfilment of the requirements for the award of Doctor of Philosophy, in the Faculty of Engineering and Information Sciences, University of Wollongong, is wholly my own work unless otherwise referenced or acknowledged. The document has not been submitted for qualifications at any other academic institution.

Van Huan Duong
August 2017
Electric vehicles have been well recognized because of their contribution to the promising future of emission-free transportation. The core of electric vehicles is the Li-ion battery storage system, which plays an important role in the safety and price of these vehicles. Therefore, it is necessary to develop an effective battery management system in the field of vehicle electrification. In the management system, real-time access to state of charge and state of health information is crucial, although these states are not directly measurable. Therefore, they are solely obtained by estimation, which is based on a battery model and three measurable parameters, namely, the battery’s voltage, current, and temperature. There are many challenges in conducting estimations of the battery’s states due to both internal and external factors, such as load, temperature, and aging. Various advanced methods have been proposed and applied to cope with these difficulties. There is, however, still a conflict between the simplicity and the accuracy of the reported estimation methods.

Within the scope of this thesis, a comprehensive estimation approach for both the state of charge and the state of health is proposed. This approach has been developed based on experimental results, which take into account three actual crucial factors, namely, dynamic load, variable temperature, and aging. The estimation procedure is based on multiple adaptive forgetting factors recursive least-squares approach, the correlation of the ohmic resistance to the battery capacity, and a model for the relationship of the open circuit voltage to the state of charge, the temperature, and
the state of health. The accuracy and robustness of the developed estimation approach have been validated through various experiments under diverse conditions, including harsh ones. In addition to its low-level complexity, the developed approach is implementable in actual application.
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Chapter 1

Introduction

1.1 Electric Vehicle Introduction

Nowadays, global warming is one of the most concerning issues worldwide. The land-ocean temperature has been significantly increased over the past hundred years. This increase, as shown in Fig. 1-1, has profound consequences for the Earth’s climate, such as rising sea level and extreme weather. It has been reported in a vast number of scientific papers that greenhouse gas emissions are the main reason behind the climate-warming trend [1]. The carbon dioxide (CO$_2$) emissions account for the largest amount of the emissions [2]. The majority of the CO$_2$ emissions are produced by human activities through burning fossil fuel such as in internal combustion engines in the transportation sector. There are many strategies to address this urgent issue such as using cleaner energy and means of transportation with fewer emissions.

Electric vehicles (EVs), in particular, have attracted significant public interest because of their advantages for the future of emission-free transportation. The EVs
basically employ a rechargeable battery storage system as the power source to drive an electric motor through a control unit. The battery is charged from either the power grid or stand-alone charging stations. This provides the capability to use alternative clean forms of energy to eliminate CO\textsubscript{2} emissions from fossil-fuel internal combustion. In the past, the cost and range of the EVs were the biggest hurdles. Thanks to recent developments and mass production, the cost of the battery per kWh has been reduced significantly, which makes EVs much more affordable than ever [3]. In addition, thanks to upgrades in the infrastructure to adapt to the growing number of EVs, many free solar-powered and paid charging stations have been built. As a result, the range of EVs is not a major issue as it was before. EVs are now a reality for an emission-free transportation industry, not only for developed countries, but also for developing ones [4].

![Global Land-Ocean Temperature Index](image)

Fig. 1-1. Global Land-Ocean Temperature Index [5, 6].
1.2 Lithium-ion Battery in Electric Vehicles

There are many types of rechargeable batteries that have been introduced for use in EVs, such as nickel-based batteries, sodium-based batteries, lithium-based batteries, and metal-air batteries, to name a few [7]. Even so, the lithium-based battery, especially the lithium-ion type, has been exclusively used in EVs to date [8]. The Li-ion battery (LIB) is an advanced rechargeable battery, in which the lithium ions move between the positive and negative electrodes during charge and discharge processes. LIB is well known for its high energy density, lack of a memory effect, longevity, maintenance-free nature, and safety compared to other types of batteries. In addition, researchers are still expending much effort on developing better LIB technology from the aspects of energy density, longevity, and lower cost [9, 10]. Because of these outstanding characteristics, the LIB is deemed to be still a solid choice for the EV battery system in the future.

Basically, the LIB is composed of the positive and negative electrodes, the electrolyte and separator, and the current collectors. There are various positive electrode materials for the LIB, such as lithium cobalt oxide (LCO), lithium iron phosphate (LFP), lithium manganese oxide (LMO), and lithium nickel-manganese-cobalt (NMC). To take LFP as an example, a schematic illustration of the principle of the LiFePO$_4$ battery is presented in Fig. 1-2, and its reactions during charge and discharge processes are listed in Eq. (1.1) and Eq. (1.2). With the increasing number of EVs, the overall usage of the LIB in these battery-powered vehicles is expected to increase dramatically, as shown in Fig. 1-3 [11].
Fig. 1-2. General schematic diagram of the LIB, derived from [12].

Charge process: \[ \text{LiFePO}_4 - x\text{Li}^+ + xe^- \rightarrow x\text{FePO}_4 + (1 - x)\text{LiFePO}_4 \]  \hspace{1cm} (1.1)

Discharge process: \[ \text{FePO}_4 + x\text{Li}^+ + xe^- \rightarrow x\text{LiFePO}_4 + (1 - x)\text{FePO}_4 \]  \hspace{1cm} (1.2)

Fig. 1-3. Projected sales growth of LIBs in EVs and for consumer use [11].
Among all the types of cathode materials for the LIB, the battery with LFP as cathode has been increasingly used in EVs in recent years. LFP has several advantages with respect to electric vehicles. The most important characteristic of the LFP is its thermal stability [13]. It has been proven that LFP can endure extreme temperature condition, i.e., 400°C compared to 200°C for the LCO and LMO, approximately. This non-toxic and robust structure of the LFP also makes it a potential candidate for practical application. Safety and longevity are other features of the battery that make it superior for EVs [13]. In terms of cost per kWh, the LFP is more expensive than the other types. Thanks to recent developments, however, it is promising that the cost of the LFP battery is likely to keep on falling in the near future as it has to date. Overall, the LFP battery is considered one of the most suitable battery types for EVs.

1.3 Battery Management System

The core of the EV is the Li-ion battery storage system, which plays an important role in the safety and the cost of these vehicles. In order to keep these battery storage systems of the vehicles in a safe, reliable, and high performance condition, the battery has to be constantly monitored. Therefore, the battery management system (BMS) is always a crucial part of the battery system in EVs [14, 15]. The BMS consists of hardware and software which aims to manage the battery system by continuously measuring and monitoring important battery conditions such as the voltage, current, temperature, and internal states. While the first three values are directly obtained from hardware measurements, the battery’s states are currently not measurable. Therefore, estimation techniques are needed to acquire these states and
other unknown internal information from the measurements of the battery’s voltage, current, and temperature.

There has been a tremendous amount of research over last two decades addressing estimation strategies for various parameters in EVs, particularly their battery systems [16-18]. These researches cover a range of parameters and statuses that need to be estimated, such as fault condition of the battery, state of charge (SOC), state of health (SOH), and range of the vehicle. As is shown in Fig. 1-4, the SOC accounts for the largest portion of these efforts, followed by the SOH. These states are considered the most important internal information on the battery. While the SOC provides the remaining charge of the battery, the SOH represents the condition of the battery. There are various approaches have been proposed, which can be applied to many types of LIB or to a specific one due to the electrochemical differences in the battery types.

On the one hand, the estimation methods normally require complicated tasks because of the complexity of their electrochemistry and the nonlinearity in their behaviour, depending on both various internal and external conditions such as their state of degradation and their temperature, current, and SOC. In addition, the requirements for safety of the vehicle also have been upgraded over time, so the number of battery system parameters to be monitored and the number of functions per control unit have increased dramatically [19, 20]. On the other hand, there are still limitations on the development of hardware, particularly microprocessors [19, 20]. Therefore, the estimation methods must be simple, accurate, and reliable for the sake of implementation feasibility [20].
Chapter 1. Introduction

Fig. 1-4. A summary of estimation strategies for EVs, grouped by topics [16].

1.4 Scope and Aim of the Thesis

This thesis covers the development of estimation approaches of most important battery states, namely, SOC and SOH. As the battery characteristics are easily nonlinearly affected by internal factors and external factors, namely, remaining charge, dynamic load current, temperature and degradation status. These factors cause significant difficulties in obtaining the battery states estimation. Various advanced methods have been proposed and applied to cope with the problem. However, there is still a conflict between the simplicity and the accuracy. The broad aim of this thesis is to develop robust estimation approaches that have a low level of complexity but the accuracy is retained under various conditions. The outcome of the thesis will contribute to feasible implementation on actual application and boost the speed of application operation.
In this thesis, after current state-of-art methods for the SOC & the SOH estimations are reviewed, the impacts of aforementioned factors are studied separately. Firstly, the impact the dynamic load on the estimation of the battery’s states is investigated in an ideal case, where the ambient temperature is kept constant throughout operations. Secondly, the effect of ambient temperature is added to the condition. Finally, the influence of battery degradation is studied. This thesis is combined of six chapters and structured is shown as follows:

**Chapter 2** gives a thorough literature review for both the SOC and the SOH estimation of the LIB.

**Chapter 3** discusses the experimental configuration to investigate the battery characteristics and to validate the estimation approach to be developed.

**Chapter 4** provides details on the development of a novel SOC estimation technique under dynamic load conditions. This technique employs a simplified model and multiple adaptive forgetting factors recursive least-squares (MAFF-RLS) estimation to provide capability to accurately capture the real-time variations and the dynamics of the battery parameters while the simplicity in computation is still retained. The accuracy of the proposed approach is verified through standard driving experiments.

**Chapter 5** focuses on the impact of the temperature on the battery SOC estimation. A simple approach to address the effects of dynamic loads and variable temperature on the battery is proposed. This original
model-based approach employs a highly adaptive algorithm to estimate the open circuit voltage (OCV) of the battery in addition to a simple model of the OCV-SOC-Temperature relationship based on a new term, namely $\text{SOC}_F$, which is proposed based on experimental findings to take into account the battery capacity recovery due to temperature variations. The developed approach is validated through a range of experiments conducted under both constant and time-varying temperatures.

**Chapter 6** proposes a comprehensive method for both the SOC and the SOH estimation, which utilizes the advantages of the proposed approaches in Chapter 4 and Chapter 5. The estimation approach for the SOH is based on the correlation of the ohmic resistance and the capacity with respect to aging. The SOC estimation of a degraded battery is obtained through the OCV-SOC-Temperature-SOH model. The accuracy and robustness of the comprehensive estimation approach are validated through multiple experiments.

**Chapter 7** presents the general conclusion and perspectives on future work to further develop this approach.
Chapter 2

Literature Review

2.1 Introduction

For the last decade, tremendous research efforts have been made to develop effective estimation methods for the BMS of the LIB in EVs. The majority of reported research has been focused on the estimation of battery’s states. This literature review covers the estimation methodologies of the most important states, namely, the state of charge (SOC) and the state of health (SOH). This chapter also covers the battery modeling process for EV utilization, which are crucial for these state estimations.

2.2 Battery Modeling in EV Application

The SOC and the SOH of the battery are unknown information and are currently not directly assessable. Meanwhile, the only measurable parameters of the battery are the battery’s voltage, current, and temperature. Thus, different battery models have been employed in the majority of reported estimation methods in order to
connect the gaugeable parameters to these unknown SOC, SOH, and other internal information of the battery. There are several types of battery models that have been used, which can be generally categorized into two major types, namely, the electrochemical model (ECM) and the electrical equivalent circuit model (EECM). In following sub-sections, each type of battery model will be discussed in detail.

2.2.1 Electrochemical Model

The ECM is constructed based on actual electrochemical dynamics and the transport equations of the battery. Among several choices of the ECM, the pseudo-two-dimensional (P2D) model is one of the most widely used battery models for LIBs [21]. It was developed by the Newman group [22] and is mainly based on theories of porous electrodes and concentrated solutions [23]. A schematic illustration of the LIB is presented in Fig. 2-1(a). This model includes a group of governing equations that are expressed in the form of partial differential equations (PDE) and algebraic equations. The details and a summary of these equations can be found in [24] and [21], respectively. The P2D is able to describe accurately not only the battery voltage, but also the reaction kinetics and transport within the battery. However, this model is highly sophisticated and requires major computational resources. Therefore, it is not applicable for real time applications such as BMS in EVs [25]. Alternatively, several simplified variants of P2D, namely, the reduced order model variants of the P2D model, have been proposed [26, 27]. The single particle model (SPM) is considered the simplest one among those models [28]. The SPM, shown in Fig. 2-1(b), is achieved by assuming that the electrolyte does not vary with time and space and that the same distribution of molar flux is applied
along the cell thickness. The SPM requires only low computational effort compared to the P2D model and can be applied in real time applications. The model has a significant drawback, however, if the battery has a thick electrode or operates under a high discharge current rate. The validation of the model for some applications operating at low current rate has been reported in a number of research papers [29-31]. In order to improve the accuracy of the SPM under high current rate, the Extended SPM model was proposed in [32]. In comparison with the SPM, the Extended SPM involves variation of the electrolyte. The electrolyte potential and electrolyte concentration are approximated by polynomial functions. By doing so, the Extended SPM is able to accurately predict the cell voltage with 1% error at a 5 C charge-discharge current rate [32].

Fig. 2-1. Schematic illustration of ECM for the LIB battery: (a) P2D (b) SPM [21].
2.2.2 **Electrical Equivalent Circuit Model**

The EECM is a well-known alternative to the ECM. This type of battery model has been widely used in battery’s states estimation. Compared to the ECM, the circuit model requires less computational effort, yet it still yields high accuracy in the SOC estimation. Among the various types of the equivalent circuit model, the Thevenin-based model is popularly used. The most basic equivalent circuit model, namely the zero-order Thevenin model, is shown in Fig. 2-2(a), which consists of only a voltage source and an internal resistance (ohmic resistance), $R_0$ [33, 34]. The voltage source represents the battery terminal voltage under equilibrium conditions which is defined as the equilibrium voltage ($E_{eq}$) or open circuit voltage (OCV). In the schematic diagram, $I$ is the battery current, and $v$ is the battery terminal voltage. This model, however, is not sufficiently accurate for a real-time battery monitoring system under dynamic working conditions. To enhance the accuracy of the battery modeling, one or more resistance-capacitance parallel (RC) networks are added in series to the basic one. The first-order Thevenin-based model, which contains one $RC$ network, is shown in Fig. 2-2(b) [35, 36]. Fig. 2-3 shows the second order model employing two parallel networks [37]. These two RC networks represent the charge-transfer phenomenon and the diffusion phenomenon of the battery, respectively. Even though, the second order model is considered adequately accurate for EV application, several research groups have claimed that these models are not sufficient for modeling the LIB. Therefore, more complicated or higher-order variants of the Thevenin model have been proposed, such as the $n^{th}$-order Thevenin circuit model that uses a series of $RC$ networks, as depicted in Fig. 2-4. The higher the order that the battery model requires, the heavier the computation demands will be.
There is another EECM that has been used in SOC estimation for EV application, as shown in Fig. 2-5 [38]. In this model, $R_t$ represents the terminal resistance, and two sets of series circuit, namely, $R_s$-$C_{\text{surface}}$ and $R_e$-$C_{\text{bulk}}$, represent the battery phenomena in the surface and the bulk layer, respectively. The battery currents in these two layers are denoted as $I_s$ and $I_b$, respectively.
Other than the EECMs mentioned above, impedance-based equivalent circuit models also have been used [39, 40]. This type of model is constructed based on electrochemical impedance spectroscopy (EIS) of the battery. An example of the impedance-based models is shown in Fig. 2-6. In this model, the charge transfer and the diffusion phenomena are represented by the ZARC and the Warburg elements, respectively. The ZARC element consists of a parallel circuit of a resistance and a constant phase element (CPE). The impedance-based models in general are more complicated and require higher computational resources compared to the Thevenin-based models. Because of their complexity, the impedance-based models have not been widely used in EV application.

Fig. 2-5. Another type of equivalent circuit battery models [38, 41].

Fig. 2-6. An example of the impedance based model [40].
It should be noted that, in these EECMs, the parameters such as resistances are proven to be varying in accordance with different factors such as the load current, the SOC, and the status of the battery [42]. Therefore, modified variants of the Thevenin-based models have been proposed, e.g., in [43, 44], the battery resistance in the basic Thevenin-based models is represented by a parallel circuit consisting of a charge resistance and a discharge resistance to address the difference in the resistance during charge and discharge operations.

One of the important aspects of the battery modeling is its parameter identification. The parameters are obtained offline from laboratory experiments. Based on the experimental data, nonlinear functions of these parameters, the SOC, and temperature are built [37, 45]. The aging effect is taken into account in the parameter functions in [46]. In order to investigate all parameter variations, these methods with parameters obtained offline require a large number of experiments. Online parameter identification methods can be employed so as to avoid conducting extensive experiments. By doing this, the battery model parameters are kept up to date, and therefore, the accuracy of the model is retained.

2.3 SOC Estimation Methodology

The SOC of the battery is a descriptive value that indicates the current charge level remaining in the battery. The battery is considered fully charged if the SOC is 100% and fully discharged when the SOC is 0%. As the SOC is not directly measurable, estimation approaches are required to obtain its estimated value. Estimation of the SOC faces fundamental challenges because of the LIB
characteristics and the impact of dynamic working conditions, such as frequently changing current load at different levels of charge, and especially temperature. Therefore, a vast amount of research has been conducted to address these difficulties. Most of the reported approaches for SOC estimation in this research can be categorized into three major groups, namely, conventional methods, model-based adaptive methods, and machine learning methods, which are reviewed in the following subsections. It should be noted that, the literature review for the temperature-focused methods is covered in a separate section because of its significant impact on SOC estimation.

2.3.1 Conventional Methods

There are two conventional methods to estimate the SOC, namely, offline open-circuit-voltage-based estimation and Coulomb counting method. The offline open circuit voltage (OCV) method utilizes the unique OCV-SOC correlation to estimate SOC value from the rested OCV value. This estimation is feasible because the electric vehicle is subjected to rest for many hours during the day. Yet the estimation can only be done in an offline manner. The Coulomb counting technique simply employs current integration. The calculation in this method can be seen in Eq. (2.1) where \( I(A) \) is the battery current (positive for charge, negative for discharge), \( C(Ah) \) is the battery capacity, \( t(s) \) is the step time, and \( \eta \) is the Coulombic efficiency. The battery capacity is to be referred as either the nominal capacity or the current usable capacity in different reports in the literature.

\[
SOC = SOC(0) + \int_{t_0}^{t} \frac{\eta \cdot I(\tau)}{3600 \cdot C} d\tau \quad (2.1)
\]
In order to have a precise SOC estimation, this approach requires accurate knowledge of the battery’s capacity and the initial SOC. It is normally done by fully charging or discharging the battery. Error accumulation, however, might occur over a long period due to several factors such as measurement errors, temperature, and lack of self-correction. To address these issues, some methods have been proposed to accurately detect the initial SOC \cite{47-49}, obtain the efficiency based on various conditions \cite{47, 49}, and self-correct the estimation \cite{47, 48}. Overall, these conventional methods require simple computations and are applicable for low-cost hardware.

### 2.3.2 Model-based Adaptive Methods

To date, the model-based approach has attracted significant interest from many researchers for the battery monitoring system. The model-based approach employs advanced estimation algorithms applied to a battery model to cope with difficulties in the simultaneous online management of the internal states of the battery. Different battery models, such as the ECM and the EECM, have been discussed above in Section 2.2. The majority of the model-based methods utilize the EECM; on the other hand, only a few studies employ the ECM due to its complexity. The backbone of the EECM-based approach is to estimate the OCV or SOC from measurements of the battery’s current, voltage, and temperature by applying these to the model equations and one or more advanced estimation algorithms such as the Kalman filter (KF) and its variants \cite{50, 51}, H\(_\infty\) \cite{52}, the particle filter (PF) \cite{53}, state observers \cite{54}, or recursive least-squares (RLS) \cite{55}.
In KF-based estimation, the SOC is normally one of the variables of the state vector to be estimated, and the error between the modeled and measured battery terminal voltages becomes the closed-loop feedback to correct the estimation. The original KF is only suitable for a linear system under the assumption that process noise and measurement noise are known Gaussian white noise \([50]\). When the battery model is nonlinear, other variants of KF that include a linearization process are employed, such as extended KF (EKF) \([56-61]\) and unscented KF (UKF) \([62-65]\). While the linearization technique of EKF is based on the Taylor series, UKF utilizes the statistical linearization method. UKF’s linearization process is claimed to have better reliability and a better approximation compared to EKF, which results in more accurate estimation results, especially with a highly nonlinear system \([66]\). Nevertheless, both UKF and EKF rely on the above-mentioned assumption concerning the system noise. Without accurate information on the measurement noise and the process noise, divergence or slow convergence of the estimation might occur. To address this problem, adaptive versions of the variants, namely, adaptive EKF (AEKF) \([67-72]\) and adaptive UKF (AUKF) \([38, 73, 74]\), have been used to estimate these sources of noise along with the state vector. Both approaches have achieved more accurate estimations, although the computations are more complicated. There is a quite noticeable issue in the majority of the KF-based algorithms, which is that the accuracy of SOC estimation relies significantly on the accuracy of the model, yet the battery model parameters are constantly subject to change due to the working conditions and aging \([20, 42]\). Therefore, these algorithms and their improved variants, e.g. dual extended Kalman filter (DEKF) \([75-77]\) and joint extended Kalman filter (JEKF) \([57]\), are also adopted to keep the model
parameters updated over time. These variants require heavy computational resource due to their complexities, which is an issue for a real-time application such as in a BMS employed in EVs [18, 20]. A large number of laboratory experiments may also be deployed to obtain the variation and sensitivity of the parameters offline, but it is a demanding and time-consuming task.

There are other alternatives to KF-based algorithms for optimal SOC estimation, namely, the $H_\infty$, the PF, and the state observer. The most advantageous characteristic of the $H_\infty$ is its robustness against uncertainties in the battery model parameters [52, 78]. This has been also proven in [79], where the SOC estimation is accurate for all the different types of battery models that have been used with a $H_\infty$-based state observer. Similarly, the observer-based approaches also possess robust characteristics towards handling the uncertainties of the battery model. Among the observer-based methods, the sliding mode observer (SMO) and its variants are the most popular [54, 80-85]. Other types of observers can be found in the literature, such as the proportional-integral observer [86] and the adaptive Luenberger observer [87]. Unlike the KF-based estimation, the PF is applicable for both Gaussian white noise and non-Gaussian white noise systems, which helps to avoid the KF's convergence problem [53, 88, 89].

The RLS algorithm has been employed in the literature to address changes in the battery model parameters and the complexity of the estimation computation [55, 90-93]. This approach makes significantly lower demands on computation because there are no heavy calculations required such as matrix inversion, which is considered as an advantage of RLS over KF and its variants [55]. Most importantly, RLS
simultaneously estimates not only the OCV but also the battery model parameters and can adapt to their actual changes over the lifetime of the battery and its working conditions. In order to do that, the conventional RLS has been used with a single forgetting factor [55, 90, 91]. The parameters to be estimated for the battery model vary at different rates during the battery operation. Hence, assigning a single forgetting factor for all the parameters may not provide an accurate estimation for each battery model parameter. Furthermore, the performance of RLS relies significantly on the forgetting factor value in terms of convergence and stability. Basically, the value of this in the conventional algorithm is fixed in the range between 0 and 1, but there is a trade-off that should be considered when selecting this value [90-95]. It is well known that the higher the value is, the better the stability and convergence speed of the estimation algorithm will be, but at the expense of lower tracking capability.

To improve the tracking capability, the value needs to be low, although this reduces the stability and pace of convergence of the algorithm [94, 95]. Therefore, to improve the accuracy and the adaptability of the RLS-based SOC estimation method, the dynamics of the system and each model parameter should be addressed. Besides the stand-alone SOC estimation, the RLS has been used in many joint methods with other algorithms because of its ability to identify parameters online. These include the EKF [96], the AEKF [91], the AUKF [97], the DEKF [98], the state observer [99], and the EKF in combination with the PF [100]. Other than the RLS-based joint estimation method, combinations of other algorithms, such as the UKF and the $H_\infty$ [101], are also utilized to retain the accuracy of the model parameters and the SOC estimation. These online parameter adaptation approaches have improved the
accuracy and reliability of the estimation, although they require heavier computational efforts.

In the ECM-based estimation methods, the surface SOC and bulk SOC can be predicted from the states of the electrochemical model by using a state estimator [102]. The surface SOC is determined by the ratio between the lithium concentration at the surface of the particles and that in the bulk, The SOC is the average utilization of the entry electrode. The P2D model has been combined with the modified particle filter [89] and the EKF [103, 104] for SOC estimation. To reduce the high computational demands of these approaches, other researchers have employed simplified models, namely, the reduced order model variant of the P2D [26, 27, 105] or the SPM [29, 106-109]. Generally, these approaches also have well-known adaptive filters as their estimation algorithms, such as the EKF and state observers. There are a number of approaches that have been proposed to further simplify the SPM-based methods, such as a simplified finite-dimensional SPM and nonlinear robust observers in [110]. With such simplified methods applied, the ECM-based estimation methods discussed above still require notable computational efforts compared to the EECM-based SOC estimation.

2.3.3 Machine Learning Methods

There are various machine learning algorithms that have been employed in the SOC estimation of LIBs. Among these algorithms, the artificial neural network (ANN), the support vector machine (SVM), and their variants are well integrated in the estimation. The general idea of these ANN-based methods is to use the
identification system, which is pre-trained by extensive experimental training data, to predict the SOC value online. The ANN-based methods are constructed by a number of layers, namely, an input layer, one or more hidden layers, and an output layer. Compared to the above-mentioned model-based methods, the ANN and its variants do not require a good understanding of the battery characteristics, although an extensive amount of training data in the memory is required. A three-layer feed-forward neural network (NN) is proposed in [111]. In this approach, the input layer consists of the battery’s voltage, the first and second derivatives of the voltage, its current, and its temperature, and the output layer is the SOC. To improve the dynamic adaptation of the conventional feed-forward neural network, the time-delayed NN, is proposed in [112]. The radial basis function NN (RBFNN) also has been employed to improve the performance of the NN model [113]. The RBFNN is also used in a joint close-loop SOC estimation, to overcome the uncertainties of the battery model, with the adaptive SMO [114, 115], the EKF [116, 117], or the UKF [118].

The SVM is a kernel function-based machine learning algorithm that has been employed in various domains of pattern recognition including SOC estimation. The benefit of the SVM is its capability to deal with nonlinear and high-dimensional models. In the SVM-based SOC estimation, the battery’s voltage, current, and temperature are the inputs of the model [119]. The training data are obtained from experiments with different profiles of these inputs. The SOC can be rapidly and accurately predicted if the training data is suitably chosen. The SVM-based approaches are open-loop estimations and require significant amounts of training data [120]. When the SVM is applied to other estimation algorithms, namely, the KF
and the UKF [121], the AUKF [122], joint closed-loop estimation approaches are established which yield higher accuracy and more reliable performance of the estimation.

In order to enhance the flexibility of the ANN-based and the SVM-based methods, the fuzzy logic-based algorithm has been employed. The combined methods includes a stochastic fuzzy NN in [123], a merged fuzzy NN [124], and the fuzzy SVM in [125]. Fuzzy logic has also been used as the sole estimation algorithm for the SOC of different battery types [126-128]. Overall, even though significant training data and heavy computation are required, the machine learning estimation methods, when combined with adaptive filters, provide the most advantageous capability in addressing the uncertainties in the nonlinear models and enhancing the estimation results.

2.4 Temperature-focused SOC Estimation Methods

Due to the steady growth of the EV industry around the world for the last decade, the EV battery pack has to operate under various dynamic loads and temperature conditions [129]. Hence, it has become a major challenge to maintain the accuracy of the monitoring system [16, 20, 42]. On the one hand, there are an extensive number of reported studies on improving the accuracy of SOC estimation under dynamic load profiles, as discussed in Section 2.3. On the other hand, there are only a limited number of studies that have addressed the temperature effect, despite its profound impact on the SOC estimation [130-137]. These studies mainly employ the same model-based approach, yet they consider the temperature effect in one or more
aspects of the battery. The temperature is included in the third-order polynomial function models of the rated and non-rated OCV-SOC relationships in [130]. Both the models are nonlinear and complicated because all the model parameters in each are also second-order polynomial functions of temperature. The SOC estimation is achieved by applying the model to the Coulomb counting method. In [131], the temperature is also taken into account in the OCV, where an adaptive joint EKF is employed to estimate the OCV and other model parameters online. To retain the accuracy of the SOC estimation from the estimated OCV over a wide range of operating temperatures, the proposed approach employs a large-size, 201 × 41 point, lookup table (LUT) of the OCV, SOC, and temperature relationship. A LUT is also employed with the UKF algorithm in [132]. The estimation algorithm updates the OCV and other model parameters with online measurements. Even though the LUT plays an important role in the SOC estimation, its modeling is still not clearly explained. In [133], the SOC is estimated based on a combination of the Coulomb counting method and a model-based method. The former method involves normalized current integration with respect to the battery capacity, and the latter employs a low-pass filter and a nonlinear LUT for the OCV-SOC relationship. The influence of temperature on the OCV and the battery capacity, however, are not discussed. In [134], the battery parameters are estimated online by a sophisticated algorithm, dual spherical UKF, to avoid the battery model inaccuracy due to the working conditions. However, the OCV is modeled as a temperature-independent seventh-order polynomial function of the SOC thanks to the NCR18650GA battery characteristic. This method is not applicable to the LiFePO₄ battery due to its different characteristics. The impacts of temperature on the Coulombic efficiency,
the battery capacity, and the OCV-SOC relationship were studied with reference to PF-based SOC estimation in [135]. The OCV is modeled by a combined electrochemical model, but the temperature is not present in the model equations and there is a lack of any explicit relevant discussion. In [136], a validation procedure for the different methods for SOC estimation was developed. Numerous different working conditions, including temperature, were examined. By analyzing the results, an optimized algorithm was suggested for better estimation accuracy and temperature stability. Another simple method is proposed in [137], where the resistance of the battery model is assumed to be a simple offline function of temperature only, and the estimation does not take into consideration several other factors that could affect the model parameters, such as different SOC values or current magnitudes.

Although temperature-related approaches offer more comprehensive estimation results, they have some common drawbacks that need to be addressed before actual implementation in EV application. Firstly, most of these methods reported in the literature overlook the dynamic working conditions, where factors such as current and temperature simultaneously vary. Their experimental results are merely obtained under conditions that have either dynamic current at different constant temperatures [130-134], time-varying temperature with constant current [135], or no-load with temperature variations [136]. Secondly, the proposed comprehensive approaches are mostly bedeviled by considerable complexity in attempting to deal with all impacts and therefore require heavy computational resources. The complexity is caused by high-computational-demand algorithms such as in [131, 134] and/or complicated models, e.g., the OCV models in [130, 131]. Therefore, there is a necessity to
develop an accurate adaptive estimation method which does not require heavy computational efforts. The to-be-developed method also needs to be further investigated to test its capability to cope with highly dynamic load conditions, as in an actual EV application, where current and temperature are time-varying simultaneously.

2.5 SOH Estimation Methodology

Battery degradation is inevitable for the LIB over time. The aging phenomenon has profound impacts on the safety and the performance of the EV. Accurate information on the battery status, which is represented by the SOH, is vital. There are various factors that cause degradation to occur, such as high-rate cycling, over-charge, over-discharge, and low and high temperature conditions, as can be seen in Fig. 2-7. Capacity depletion and increasing impedance are the most obvious effects of the degradation of the battery [138], and therefore, they can be used to define the SOH. It is widely acknowledged that the battery is at the end of life (EOL) when the SOH is reduced to 80%. In [139], however, the authors claim that the battery still meets working requirements if the SOH goes below that threshold. In this research, when the SOH is reduced to 75%, the battery is considered to be at the EOL. There are various approaches that have been proposed to obtain an accurate SOH, which can be categorized into two major groups, namely, the direct measurement method and the online adaptive estimation method. The details for each group are discussed in following subsections.
Fig. 2-7. Causes of the aging mechanism in the LIB [140, 141].

### 2.5.1 Direct Measurement Methods

There are several offline measurement approaches to obtain the SOH. The simplest way is acquired the current actual capacity, $C$, by completely discharge the fully charged battery. Once the current capacity is observed and the capacity of the battery in the fresh condition, in other words, at the beginning of life (BOL), is known, $C_{\text{BOL}}$, the SOH can be obtained from Eq. (2.2). To measure an accurate SOH, the conditions for experiments, such as temperature, to obtain the battery capacity in different states should be the same.

$$\text{SOH} = \frac{C}{C_{\text{BOL}}} \cdot 100(\%) \quad (2.2)$$

Another method is to obtain the increased battery resistance by using a constant current pulse (CCP). The current battery resistance is calculated by Ohm’s law, the
applied current magnitude, and the corresponding voltage drop. If the resistance at the BOL, $R_{\text{BOL}}$, and the EOL, $R_{\text{EOL}}$, are known, the SOH can be defined as written in Eq. (2.3). The battery resistance is dependent on the SOC, temperature, and current magnitude; therefore, in order to obtain an accurate SOH, the resistance under all aging conditions has to be measured under the same circumstances.

$$\text{SOH} = \frac{R - R_{\text{BOL}}}{R_{\text{EOL}} - R_{\text{BOL}}} \cdot 100(\%)$$ (2.3)

The measurement of the battery impedance can also be done by the electrochemical impedance spectroscopy (EIS) method. This is normally done by EIS measurement instruments with built-in fitting functions to obtain the battery model parameters such as resistance. Consequently, the SOH can be obtained. The measurement methods mentioned above require special instruments, so the measurement is normally conducted in a laboratory. In addition, it is not suitable for an online monitoring system that requires the information on the SOH to be continuously available. Therefore, adaptive approaches are preferable in the EV application.

### 2.5.2 Capacity-based Estimation Methods

In order to have real-time information on the SOH, various methods have been proposed to estimate the actual capacity online. The majority of the capacity estimation methods are adaptive filter-based estimation methods, which typically combine estimation algorithms in either a joint form or a dual form. These combined filter-based approaches generally aim to estimate both the SOC and the capacity. The capacity is estimated by the recursive approximate weighted total least squares
method, as in [142] or by the Gauss–Hermite PF in [143], which is incorporated with
the SOC estimated by another algorithm such as the EKF. Two support vector
regression-PF (SVR-PF) algorithms were used in a joint estimation method in [144].
The first SVR-PF estimates the battery resistances, which are used in the capacity
estimation by the second SVR-PF. The SOC and the capacity are variables of the
state vectors to be estimated by the dual SMO [145] or the DEKF methods [75, 77],
which both demand high computational resources. Some other methods have been
proposed to deal with this issue, such as simplified DEKF [57] or multiple time-scale
DEKF [98]. In [57], the capacity is not included in the state vector, instead, the
capacity has its own simple model. In this method, the first EKF is used to estimate
the SOC, and the second one is for the capacity estimation. A similar method was
used in [53] with parallel particle filters for the SOC & SOH estimations. In [98,
146, 147], a different approach, namely, the multiple time scales technique, was
proposed based on the rapid changes of the SOC and the slow variations of the
capacity and the battery model parameters. The capacity is included in the state
parameter vector along with other model parameters. Micro-EKF was used for the
SOC estimation, and macro-EKF for the capacity and the parameters. By doing this,
the computational effort for the estimation is reduced significantly. Similarly, the
capacity and the SOC are estimated by multi-time-scale dual H\(_\infty\) filters in [148] and
dual multi-time-scale nonlinear predictive filters in [149].

Estimation of the current battery capacity has also been done by voltage-based
methods. In [150], a table for the charge-transfer matrix is constructed based on the
charging voltage profile. The capacity is estimated by calculation from the two SOC
values and the charge transfer, extracted from the table, between these values. The
changes in the charging voltage curves due to the degradation are studied in [151]. By analyzing these changes, the uniform voltage curve hypothesis is introduced, and then, the battery capacity is estimated by mapping the measured voltage curve using the transformation method based on the generic algorithm. The charging profiles of the voltage and the current were also investigated in [152]. These profiles are split into five segments, and at each segment, the capacity is calculated. Then, based on the calculated capacities and the \( k \)-nearest neighbour regression, a pattern recognition algorithm, the current capacity is estimated. In [153], the SOH is estimated by a probabilistic neural network that has been trained with the following inputs: the measured data of the charging time in constant current (CC) mode, the voltage drop at the start of discharge, and the fully-discharged OCV after rest time. Similarly, sparse Bayesian learning is employed in [154]. In this approach, the training data are the initial charge battery voltage, the charge capacities in CC mode and constant voltage (CV) mode, and the voltage and current at the final charge.

The incremental capacity (IC) phenomenon during degradation over time also has been analysed for SOH estimation in the literature [155, 156]. The relationship curves of the IC vs. the battery voltage and battery capacity at different states of aging were studied. Then, the distance between two IC curves’ peaks can be used for the capacity estimation. In [156], support vector regression is used to enhance the robustness of the SOH estimation.
2.5.3 Resistance-based Estimation Methods

The battery resistance is one of the most reliable indicators for the SOH, and therefore, various resistance-based SOH estimation approaches have been introduced. In [157], an adaptive ohmic resistance estimator method has been proposed. The SOH is calculated based on the observed resistance to the reference values at the BOL and the EOL. The diffusion resistance has been used for the SOH estimation instead of the ohmic resistance in [60]. In this approach, the diffusion resistance and the SOC are included in the state vector, which is estimated by the EKF. The calculation method for the SOH is similar to the one in [60]. The RLS is employed to estimate the resistance online in [158]. The impact of temperature on the battery resistance has been taken into account in this approach. The SOH is defined as a function of the resistance in [159]. Then, the joint central difference KF is employed to estimate the state vector, which includes the SOC and SOH.

There are various approaches for the battery resistance estimation, which can be utilized for the SOH estimation, such as adaptive filter-based approaches. Among these approaches, the KF-based methods [57, 160] and the least-squares-based methods [67, 93], are the most well-known online battery model parameter identification systems. On the other hand, on-board EIS measurement methods also have been proposed. In the EIS measurements, the impedance at each frequency is obtained by a mathematical method, and the battery’s sinusoidal voltage and current perturbations are measured at that frequency. This perturbation signal can be applied to battery in either the voltage form or current form. So, in order to measure the EIS online, the perturbation generation and the impedance calculation must be embedded.
on-board. In [161], the perturbation is generated by a digital proportional-integral controller and a ladder converter which is added to the BMS hardware. In [162], a digital controller of the bidirectional dc–dc power converter in EVs is utilized. By adding a small duty-cycle perturbation to the duty cycle of the converter, the perturbation is generated at the output of the converter. This makes the impedance measurement possible without the need for hardware modification. For the EVs that have an on-board battery charger, the impedance measurement can be conducted by utilizing the digital controller or modifying the analog controller of the charger in a similar manner as in [161, 162].
Chapter 3

Experimental Setup for the Investigation of Battery’s Characteristics

3.1 Test Bench Configuration

Lithium-ion batteries (LIBs) are well known for their advantages, yet the battery’s nonlinear characteristics due to working conditions give rise to challenges for monitoring. In order to fully investigate and address the battery characteristics, various experiments have to be conducted. These experiments involve both basic current load profiles, such as constant current (CC) mode, constant current pulse (CCP) mode, and dynamic current load profiles under constant and variable ambient temperature. This needs to be done with the fresh battery and also the degraded battery. To do so, a test bench, as depicted in Fig. 3-1, has been configured, which
includes a battery charging machine, temperature chamber, and a host computer, which are employed with following specifications:

**Bitrode FTV – EV module testing system**: The programmable Bitrode FTV machine, coded FTV4-500/50/5-12, with high accuracy, ±0.1% of full scale (FS), is used to charge/discharge the battery with maximum voltage of 12 V and maximum charge/discharge current of 500 A.

**Temperature and humid chamber – Espec Platinous J Series**: The temperature range of this chamber is from -40°C to 180°C with fast temperature response. This chamber is programmable either manually or digitally.

**Host computer**: The host computer is equipped VisuaLCN client software and the MATLAB platform. The data measurements from the experiments are transferred to and stored in the computer.

Fig. 3-1. Experimental configuration setup.
A number of the prismatic 90 Ah and 200Ah LiFePO$_4$ batteries made by different manufacturers were employed in the experiments. These batteries were kept inside the temperature chamber, which controls the chamber’s temperature as programmed. All the experimental load profiles were programmed in the host computer and then transferred to the Bitrode machine with real-time monitoring. In order to investigate the battery characteristics, the following list of experiments was conducted: Capacity and open circuit voltage – state of charge (OCV-SOC) characteristic curves, dynamic load conditions, variable temperature conditions, and degradation acceleration, to name a few. In this thesis, the impact of humidity on the battery is not addressed; however, the experimental results show its relatively minor influence on battery as can be seen in Appendix B.

3.2 Capacity and OCV-SOC Characteristic Curves

Firstly, it is necessary to obtain the battery capacity under any given conditions. The simple method to determine the capacity is to conduct a constant current (CC) mode experiment. The battery is first fully charged in constant current – constant voltage (CC-CV) mode, and it then is discharged in the CC mode until its voltage reaches the cut-off value, 2.5 V. Then, the battery is fully charged again by CC-CV mode. The battery capacity and the Coulombic efficiency are calculated based on the Coulomb counting method from accurate current measurements. Fig. 3-2 shows an illustration of the voltage and current profiles under the CC, and the CC-CV modes.

Secondly, the vital characteristic curves of the OCV and the SOC are constructed by conducting a CC pulse (CCP) experiment. To begin with, the battery is fully
charged and then left to rest until the battery voltage reaches its equilibrium. Then, a series of CCP with a relaxation time after each pulse, as shown in Fig. 3-3, are applied to the battery. The duration of the CCP is defined based on the obtained capacity for the sake of resolution. The experiment also stops when the battery voltage reaches 2.5 V. The OCV-SOC characteristic curve is then constructed from the measurement voltage and the calculated SOC.

![Constant current and constant current-constant voltage profiles.](image1)

Fig. 3-2. Constant current and constant current-constant voltage profiles.

![Load profile of constant current pulses.](image2)

Fig. 3-3. Load profile of constant current pulses.
3.3 Dynamic Load Conditions: NEDC & UDDS

In actual working conditions, the battery is subjected to a highly dynamic current, which is mixed charge and discharge in different magnitudes. In order to analyze the impact of the dynamic load conditions on the battery and verify the to-be-developed estimation approaches, two highly dynamic standard driving cycles, namely, the Urban Dynamometer Driving Schedule (UDDS) profile [163] and the New European Driving Cycle (NEDC) profile [164], are employed. The velocity profiles of the UDDS and the NEDC are shown in Fig. 3-4 and Fig. 3-5, respectively. In order to convert the velocity into the battery load current, the following equations are employed:

\[ P_t = (M \cdot g \cdot f_r + \frac{1}{2} P_a \cdot C_D \cdot A_f \cdot \nu^2 + M \cdot \delta \cdot \nu + M \cdot g \cdot i) \nu \]  \hspace{1cm} (3.1)

\[ I_b = -\left( \frac{1}{\eta_{hw}} + \frac{1 + sgn(P_t)}{2} \right) + \eta_r \left( \frac{1 - sgn(P_t)}{2} \right) \frac{P_t}{\alpha \cdot N \cdot V_b} \]  \hspace{1cm} (3.2)

In these equations, the load current \( I_b (\text{A}) \) is obtained from the required traction power \( P_t (\text{W}) \) through Eq. (3.2) which takes into account the efficiency of the drive and a laboratory-scaling factor. The traction power is calculated by Eq. (3.1) from the velocity \( \nu (\text{m/s}) \) and other parameters, with reference values, which can be found in Table 3-1 [165-167]. The values shown in the table are extracted from a typical car corresponding to the electric car under investigation. The number of batteries can be different with respect to the battery capacity. The converted current profiles are applied to the battery, which is preferably fully charged for the sake of accurate reference values.
Table 3-1. Reference electric car parameters.

<table>
<thead>
<tr>
<th>Symbol</th>
<th>Description</th>
<th>Value</th>
</tr>
</thead>
<tbody>
<tr>
<td>M</td>
<td>Vehicle mass with passengers (kg)</td>
<td>1600</td>
</tr>
<tr>
<td>g</td>
<td>Gravity acceleration (m s(^{-2}))</td>
<td>9.81</td>
</tr>
<tr>
<td>(\rho_a)</td>
<td>Air density (kg m(^{-3}))</td>
<td>1.225</td>
</tr>
<tr>
<td>(A_f)</td>
<td>Front area (m(^{-2}))</td>
<td>2.1</td>
</tr>
<tr>
<td>(C_D)</td>
<td>Aerodynamic drag coefficient</td>
<td>0.3</td>
</tr>
<tr>
<td>(f_r)</td>
<td>Rolling resistance coefficient</td>
<td>0.005</td>
</tr>
<tr>
<td>(\delta)</td>
<td>Rotational inertia factor</td>
<td>1.05</td>
</tr>
<tr>
<td>i</td>
<td>Grade of road</td>
<td>0</td>
</tr>
<tr>
<td>(V_b)</td>
<td>Battery working voltage (V)</td>
<td>3.3</td>
</tr>
<tr>
<td>N</td>
<td>Number of batteries</td>
<td>40</td>
</tr>
<tr>
<td>(\alpha)</td>
<td>Scaling factor</td>
<td>2.5</td>
</tr>
<tr>
<td>(\eta_w)</td>
<td>Efficiency from battery to wheel</td>
<td>0.7</td>
</tr>
<tr>
<td>(\eta_r)</td>
<td>Efficiency from wheel to battery</td>
<td>0.3</td>
</tr>
</tbody>
</table>

Fig. 3-4. UDDS velocity profile.
3.4 Variable Temperature Conditions

To investigate the influence of temperature on the battery performance, a series of experiments were conducted. These experiments also included the fundamental experiments, namely, capacity, the OCV-SOC characteristic curve, and the UDDS profile, which have been discussed in Section 3.2 and Section 3.3. In this series, the experimental sequence is repeatedly applied at multiple constant temperatures (°C): -10, 0, 10, 20, 30, 40, and 50. At each temperature, the battery is kept at that temperature for a sufficient time to enable stabilization before running any experiments. In addition, the UDDS load profile experiments are also conducted under dynamic temperature conditions. These variable-temperature experiments play an important role in validating the developed estimation approach.
3.5 Degradation Acceleration

The impact of degradation on the battery performance is investigated at different stages of aging. As the battery’s life normally lasts for many years, it is therefore necessary to accelerate the degradation progress to save time. There are different approaches to accelerating the degradation progress, but in this research, cycling experiments with high current rate at high temperature were applied to the battery. Each cycle stops after a pre-defined number of cycles or after the battery’s temperature goes over the safe range. At each stage of aging, a series of experiments were conducted, such as: capacity and OCV-SOC characteristic curves, and dynamic load conditions. Due to the time allowance, this research assumes that the temperature effect on the battery continues under various aging conditions of the battery, so no intensive temperature-related experiments were conducted during this degradation process.
Chapter 4

SOC and Model Parameter Estimation under Dynamic Load Conditions

4.1 Introduction

In this chapter, a novel method for the SOC and model parameters estimation of the LiFePO4 battery under dynamic load conditions is developed. The method employs multiple adaptive forgetting factors recursive least-squares (MAFF-RLS), and a simplified model where each parameter is estimated with its own adaptive forgetting factor to accommodate to the highly dynamic operating conditions. This simple yet comprehensive approach provides an effective solution for estimating the SOC and the battery model parameters. Firstly, a simplification of the battery model is discussed and its equations are derived. Secondly, the conventional RLS and the MAFF-RLS are both studied in details. In order to validate the advantages of the proposed method over conventional one, a comparison in the simplicity and the
accuracy of both methods are made. Two standard driving cycles, namely Urban Dynamometer Driving Schedule (UDDS) and the New European Driving Cycle (NEDC) are employed for the experimental verification. The proposed approach address well the contradiction between simplicity and accuracy of the SOC estimation in the battery management system (BMS). The impact of temperature on the battery is neglected in this chapter.

4.2 Battery Modeling Simplification

In EV application, the equivalent electrical battery models are often deployed to obtain desired information of battery from its measurable values, i.e., voltage, current, and temperature. Particularly, to accurately model the LiFePO$_4$ battery, an equivalent circuit, shown in Fig. 4-1(a), consists of an equilibrium voltage source ($E_{eq}$), an internal resistance (ohmic resistance), $R_0$, and at least two $RC$ pairs ($R-RC_{short}-RC_{long}$) connected in series is required [15, 37, 45, 55]. In this two-$RC$ model, $RC_{short}$ network represents the charge-transfer phenomenon which has very short time constant of convergence, while $RC_{long}$ network represents the diffusion phenomenon which causes a second voltage drop on the electrode potential called diffusion over-voltage that varies very slowly [37]. It has been seen that the voltage drop on the $R_0$ and the $RC_{short}$ network vanishes after a couple of minutes (e.g., $t_m$ minutes) whilst the terminal voltage of the battery reaches its equilibrium condition after a couple of hours of relaxation time (e.g., $t_h$ hours).

On one hand, it is clear that the higher the model order is, the more complex the computational procedure becomes. Therefore, for the sake of simplicity in
computation, the battery model has to be as simple as possible to optimize the number of model parameters. In order to do that, the one-RC model is used. On the other hand, in terms of accuracy, the simple one-RC model with conventional OCV \( E_{eq} \) causes larger estimation errors than two-RC model in dynamic load profiles such as UDDS. This happens because the one-RC model with the conventional OCV, in which the diffusion process is neglected, is not suitable for the highly dynamic profiles (e.g., UDDS and NEDC) where long relaxation times infrequently take place. Our simplified model employs a dynamic OCV that is a combination of the \( RC_{long} \) and \( E_{eq} \) to overcome this drawback and retain both computation simplicity and estimation accuracy. The dynamic OCV is SOC and time dependent that adopts a formula combining the open circuit terminal voltages at the time \( t_m \) and \( t_h \) which can be determined through certain lab experiments as suggested in [168, 169]. Then, the battery model can be transformed into the one depicted in Fig. 4-1(c) using the dynamic OCV which compensates for the voltage drop caused by \( RC_{long} \) network and the equilibrium voltage shown in Fig. 4-1(b).

In order to apply the proposed recursive method on the simplified battery model, an auto regressive exogenous (ARX) model is required. Thus, the transfer function of the battery impedance is obtained and expressed in the s-domain as follows:

\[
G(s) = \frac{U_{RRC}(s)}{I(s)} = R_0 + \frac{R_1}{1 + s \cdot R_1 \cdot C_1} \quad (4.1)
\]

To discretize this transfer function, the basic forward Euler transformation method is employed. This method provides a simple yet accurate approximation with small step-size interval [170], i.e., sampling time \( T_s \). Substituting \( s \rightarrow \frac{1-z^{-1}}{T_s \cdot z^{-1}} \) into Eq. (4.1), yields:
Fig. 4-1. LiFePO₄ battery modeling: (a) Equivalent electrical model, (b) Dynamic OCV concept, (c) Simplified model.

\[ G(z) = \frac{b_0 + b_1 \cdot z^{-1}}{1 + a_1 \cdot z^{-1}} \]  
\[ y_k = I_k \cdot b_0 + I_{k-1} \cdot b_1 + a_1 (OCV_{k-1} - y_{k-1}) + OCV_k \]  

Eventually, the ARX form of the battery is acquired by rewriting Eq. (4.3) as follows:

\[ y_k = \theta_k^T \cdot \phi_k \]  

with the regressor vector \( \phi_k \) and the parameter vector \( \theta_k \) are defined in following equations:

\[ \theta_k = [b_{0,k}; \ b_{1,k}; \ a_{1,k}; \ OCV_k] \]  
\[ \phi_k = [I_k; \ I_{k-1}; \ (OCV_{k-1} - y_{k-1}); \ 1] \]

The variables of the parameter vector are calculated as follows where \( T_s \) is the sampling time:
\begin{equation}
    b_0 = R_0 \tag{4.7}
\end{equation}

\begin{equation}
    b_1 = -R_0 + \frac{T_s}{C_1} + \frac{T_s \cdot R_0}{C_1 \cdot R_1} \tag{4.8}
\end{equation}

\begin{equation}
    a_1 = \frac{T_s}{C_1 \cdot R_1} - 1 \tag{4.9}
\end{equation}

Therefore, \( R_1 \) and \( C_1 \) are obtained as follows:

\begin{equation}
    R_1 = \frac{b_1 - a_1 \cdot b_0}{1 + a_1} \tag{4.10}
\end{equation}

\begin{equation}
    C_1 = \frac{T_s}{b_1 - a_1 \cdot b_0} \tag{4.11}
\end{equation}

Eq. (4.4), Eq. (4.5), and Eq. (4.6) will be applied to both estimation algorithms, the conventional one and the proposed one while Eq. (4.7), Eq. (4.10), and Eq. (4.11) will be used to extract the battery model parameters after the estimation of the \( \theta_k \) is obtained.

### 4.3 Recursive Least-Squares (RLS) algorithm

The least squares estimation is a popular method to determine the approximate parameters value of a static system by minimizing the sum of the squared errors between the observed data and their estimated values. Continuous parameters monitoring and subsequent online estimation process require enormous computational effort for real-time application. To optimize the computation time, recursive techniques such as RLS estimation is preferable as the system model parameters are considered constant. Yet, in many applications, the model parameters
to be estimated are in fact time-varying. In case of abrupt but infrequent change in the parameters, the estimation can be covered by periodically resetting the computation scheme. While in case of slow-pace varying parameters, some mathematical method is required such as the RLS which employs a single fixed forgetting factor to reduce the influence of old data and keep the estimation always updated with new data [55, 94, 171].

### 4.3.1 Single Fixed Forgetting Factor RLS

Consider the dynamic system described in Eq. (4.4), the following equations present the RLS estimation procedure with employing a forgetting factor, $\lambda$, for the time-varying parameters vector, $\theta_k$:

$$\theta_k = \theta_{k-1} + L_k (y_k - \phi_k^T \cdot \theta_{k-1}) \tag{4.12}$$

$$L_k = \frac{P_{k-1} \cdot \phi_k}{\lambda + \phi_k^T \cdot P_{k-1} \cdot \phi_k} \tag{4.13}$$

$$P_k = \frac{1}{\lambda} (I - L_k \cdot \phi_k^T) P_{k-1} \tag{4.14}$$

where $L_k$ is the updated gain of the parameters vector $\theta_k$, $P_k$ is its covariance error, and $I$ is the identity matrix. The parameters vector $\theta_k$ which is expressed in Eq. (4.5) and Eq. (4.12) contains four components that represent the battery model parameters: OCV, $R_0$, $R_1$, and $C_1$. These parameters vary at different dynamic paces under the same working conditions, i.e., degradation, SOC, current magnitude, and temperature. This chapter address the impact of the SOC and dynamic current
magnitude. The temperature and degradation effects will be considered in the following chapters.

Among model parameters, OCV is supposed to vary gradually with SOC. As for $R_0$, it is considered to be constant with respect to current magnitude and SOC, however, it increases in a slow pace over several years due to the degradation of the battery [42]. On the contrary to $R_0$, $R_1$ varies based on all the aforementioned working conditions especially the current magnitude which is significantly subject to change due to the highly dynamic driving cycles. These different dynamic characteristics lead to the need of employing multiple forgetting factors (MFFs) in the estimation of the parameters vector. However, as can be seen in Eq. (4.13) and Eq. (4.14), the conventional single fixed forgetting factor (SFFF) RLS assumes that all the components to be estimated of the parameters vector $\theta_k$, in Eq. (4.5), vary with similar rates despite their discrepancies under the same working conditions of current and SOC of the battery. As a result, if there is a divergence in estimating one parameter, the same correction will be applied to all the parameters which then leads to estimation overshoot or undershoot. In addition, as discussed in Chapter 2, the forgetting factor $\lambda$ is fixed in this standard procedure which does not provide either good stability and fast convergence, or tracking ability [95]. To adapt to both abrupt and slow-pace changes in the system input, this paper will propose a combined approach, which will be explained in the next sub-section.
4.3.2 Multiple Adaptive Forgetting Factors RLS

Firstly, in order to overcome the impact of forgetting factor on the trade-off between the stability and convergence on one side and the tracking ability on the other side, some approaches utilizing variable forgetting factor have been proposed. One of the most well-known and widely used techniques is Fortescue's in [172] with its main idea is to employ a self-tuning regulator for variable forgetting factors as below:

\[ \lambda_k = 1 - \frac{1}{\sigma^2} \cdot \frac{\varepsilon_k^2}{1 + \phi_k^T \cdot P_{k-1} \cdot \phi_k} \] (4.15)

where \( \sigma^2 \) is the expected measurement variance [173]. This self-regulation works based on a combination of actual squared residual error \( \varepsilon_k^2 \) and leverage \( \phi_k^T \cdot P_{k-1} \cdot \phi_k \). As can be seen in Eq. (4.15), while a large residual leads to low \( \lambda \), a high leverage results in high \( \lambda \). However, in the current specific application of EV battery states estimation, whilst there is a big change in the operating current, i.e., the leverage is large, the forgetting factor should be small and vice versa to quickly adapt the estimation of the parameters to the change in the system input. Hence, the estimation algorithm in this thesis would rather adopt Fortescue's modified equation [173], which takes into account only the effect of the leverage, to overcome this problem as in following equation with \( \zeta \) is a constant factor that control the forgetting factor adaptation pace.

\[ \lambda_k = 1 - \frac{1}{1 + \frac{\zeta}{\phi_k^T \cdot P_{k-1} \cdot \phi_k}} \] (4.16)

Secondly, to cope with the different dynamics of parameters variation, a vector-type forgetting factor should be employed [174, 175]. This method is known as an
efficient approach to simultaneously keep different-dynamic-rate parameters on track [176, 177]. In [94], a simpler theory using MFFs was proposed and verified by experiments. Basically, the idea of MFFs and the vector-type forgetting factor is the same. Yet, the MFFs method has the advantage of transforming the majority of heavy matrix computations into simple scalar operations, with lower number of floating-point operations (FLOPs), which makes it more practical in the actual BMS applications where simplicity in computation procedure is essential. A method with optimized time-weighting factors was proposed in [178] to tackle with these issues yet the forgetting factors were not adaptive and the optimization of forgetting factors was done offline. In this thesis, the online adaptive algorithm, MAFF-RLS, used in [179, 180] is employed, which is a combined one of adaptive forgetting factor in [173] and MFFs in [94]. Fig. 4-2 shows a schematic of the MAFF-RLS algorithm with the following calculation procedure:

\[
\lambda_{i,k} = 1 - \frac{1}{1 + \frac{\phi_{i,k}^T \cdot P_{i,k-1} \cdot \phi_{i,k}}{\zeta_i}} \quad (4.17)
\]

\[
L_{i,k} = \frac{P_{i,k-1} \cdot \phi_{i,k}}{\lambda_{i,k} + \phi_{i,k}^T \cdot P_{i,k-1} \cdot \phi_{i,k}} \quad (4.18)
\]

\[
P_{i,k} = \frac{1}{\lambda_{i,k}} (1 - L_{i,k} \cdot \phi_{i,k}^T) P_{i,k-1} \quad (4.19)
\]

\[
\theta_k = \theta_{k-1} + L_k (y_k - \phi_k^T \cdot \theta_{k-1}) \quad (4.20)
\]

with

\[
L_k = \frac{1}{1 + \sum_{i=1}^{4} \frac{P_{i,k-1} \cdot \phi_{i,k}^2}{\lambda_{i,k}}} \begin{bmatrix}
P_{1,k-1} \cdot \phi_{1,k}^2 / \lambda_{1,k} \\
P_{2,k-1} \cdot \phi_{2,k}^2 / \lambda_{2,k} \\
P_{3,k-1} \cdot \phi_{3,k}^2 / \lambda_{3,k} \\
P_{4,k-1} \cdot \phi_{4,k}^2 / \lambda_{4,k}
\end{bmatrix} \quad (4.21)
\]
where $L_{i,k}$ is the updated gain for each single parameters vector component, $\theta_{i,k}$ and $L_k$ is the updated gain of the whole parameters vector, $\theta_k$. Similarly, $\lambda_{i,k}$ and $P_{i,k}$ are the forgetting factor and the covariance error of each component of $\theta_k$ while $\zeta_i$ is a constant whose values are defined by generic algorithms. Applying these general equations to the battery model gives:

\[
\lambda_{1,k} = 1 - \frac{1}{1 + \frac{\zeta_1}{L_k^2 \cdot P_{1,k-1}}} 
\]
\[
\lambda_{2,k} = 1 - \frac{1}{1 + \frac{\zeta_2}{L_{k-1}^2 \cdot P_{2,k-1}}} 
\]
\[
\lambda_{3,k} = 1 - \frac{1}{1 + \frac{\zeta_3}{(OCV_{k-1} - y_{k-1})^2 \cdot P_{3,k-1}}} 
\]
\[
\lambda_{4,k} = 1 - \frac{1}{1 + \frac{\zeta_4}{P_{4,k-1}}} 
\]

where the estimation of $R_0$ and OCV$_k$ is controlled by the forgetting factors $\lambda_{1,k}$ and $\lambda_{4,k}$ expressed in Eq. (4.22) and Eq. (4.25), respectively, while $\lambda_{2,k}$ and $\lambda_{3,k}$ in Eq. (4.23) and Eq. (4.24) are both responsible for controlling the estimation of $R_1$ and $C_1$, respectively. In comparison to the conventional algorithm when applied to the battery model system, this approach demands less computation effort due to number of FLOPs required. The conventional algorithm procedure, from Eq. (4.12) to Eq. (4.14), requires 132 FLOPs whilst the adaptive one, from Eq. (4.17) to Eq. (4.20), requires only 105 FLOPs. Consequently, this approach provides the ability to catch up with different dynamics of the battery model parameters by using four individual forgetting factors, yet maintains the simplicity in the computation.
4.4 Experimental Results

4.4.1 Experimental Configuration

To validate the proposed algorithm by experiment, the test bench has been configured as discussed in details in Chapter 3. LiFePO$_4$ batteries of 200 Ah with the specifications shown in Table 4-1 are deployed with the ambient temperature stabilized at 25°C. The data measurements from the experiments are sampled at 100 ms and stored in a host computer.

4.4.2 OCV-SOC Correlation

The important correlation of OCV and SOC is firstly obtained through experiments. To do so, the capacity of the battery is verified by discharging a fully charged battery until the cut-off voltage (2.5 V for the battery under test) is reached at a constant current of 60 A. This procedure is repeated for 3 consecutive cycles for
assuring the precision of the battery capacity determination. Once the capacity is obtained, the battery is fully charged again by constant-current constant-voltage (CC–CV, 40A-3.8V) mode and then left to rest till the battery voltage reaches its equilibrium. Then, through a series of pulsed current tests, the time interval after which the voltage drop on the $R_0$ and the $RC_{\text{short}}$ network vanishes can be determined. For the batteries under test, this voltage drop disappears after 3 minutes and the terminal voltage of the battery reaches its equilibrium condition after 3 hours of relaxation time. Finally, the fully-charged battery is discharged until cut-off voltage by small current pulses to accurately characterize the OCV–SOC relationship, as depicted in Fig. 4-3. Fig. 4-4 shows the obtained OCV–SOC curves with different relaxation times at three minutes, and three hours which are used to build the look-up tables that will employed later to obtain the SOC from its corresponding estimated OCV.

Table 4-1. Battery specifications.

<table>
<thead>
<tr>
<th>LiFePO$_4$ battery</th>
<th>Specification at 25 °C</th>
</tr>
</thead>
<tbody>
<tr>
<td>Rated capacity</td>
<td>200 Ah</td>
</tr>
<tr>
<td>Operating voltage</td>
<td>2.5 V–4.0 V</td>
</tr>
<tr>
<td>Max discharge current</td>
<td>Impulse: 20 CA</td>
</tr>
<tr>
<td></td>
<td>Constant: 3 CA</td>
</tr>
<tr>
<td>Max charge current</td>
<td>3 CA</td>
</tr>
<tr>
<td>Ohmic resistance, $R_0$</td>
<td>2.6 mΩ</td>
</tr>
</tbody>
</table>
Chapter 4. SOC and Model Parameter Estimation under Dynamic Load Conditions

4.4.3 NEDC & UDDS Load Profiles

Two of the highly dynamic standard driving cycles, namely, the Urban Dynamometer Driving Schedule (UDDS) load profile Fig. 4-5(a) and the New European Driving Cycle (NEDC) load profile Fig. 4-6(a), are used. The calculation procedure of the load current is discussed in Chapter 3. For the UDDS load profile, the current cycles include very dynamic charge/discharge current that varies from 22
A charging current to 144 A discharging current. Similarly, the NEDC load current varies at a very dynamic pace from 30 A in the charging mode to 140 A in the discharging mode. Multiple consecutive cycles of UDDS and NEDC profiles are deployed for the experimental tests as shown in Fig. 4-5(b) and Fig. 4-6(b), respectively. As can be seen in Fig. 4-5(c) and Fig. 4-6(c), the corresponding terminal voltage for both UDDS and NEDC profiles responds dynamically to the changes in the current profiles which will likely cause difficulties in the state estimation. The data obtained from this experimental procedure will be employed to verify the effectiveness of the proposed technique compared to the conventional RLS technique which will be discussed in following sections.

Fig. 4-5. UDDS experiment profile: (a) Current profile for one cycle, (b) 32-cycle current profile and (c) 32-cycle voltage profile.
Chapter 4. SOC and Model Parameter Estimation under Dynamic Load Conditions

Fig. 4-6. NEDC experiment profile: (a) Current profile for one cycle, (b) 34-cycle current profile and (c) 34-cycle voltage profile.

4.4.4 Estimation Verification with Conventional SFFF-RLS

The conventional SFFF-RLS is investigated to analyze its performance for such dynamic tests. The verification process is implemented in MATLAB with the recorded current and voltage experimental data. The battery parameters are directly identified based on the estimation of the parameters vector, $\theta_k$, whilst the SOC is obtained from the estimated OCV via a look-up table built from the experimental OCV–SOC curves. Firstly, the impact of using a constant value of an SFFF is considered. The value of the forgetting factor is optimized by genetic algorithms (GAs) as in [55], [178] and [91]. By using GAs, the optimal value of forgetting factor of UDDS and NEDC experimental profiles is found to be 0.9990. However, to
fully investigate the performance of this approach, different values, 0.9980, 0.9995, and 0.9999 are also deployed along with the optimal value. As can be seen in the UDDS experiment in Fig. 4-7, any minor change in the forgetting factor value could lead to major errors in SOC estimation. The most accurate estimation of SOC with absolute errors less than 3% can be obtained by using optimal value, $\lambda = 0.9990$, which allows the estimated OCV to follow well the dynamics of the reference OCV. With $\lambda = 0.9980$ and $\lambda = 0.9995$, the method is still acceptable in terms of accuracy as the estimated OCV still follows the reference OCV with a slightly higher absolute error of 5% in SOC estimation. The estimation becomes worse when the algorithm loses its tracking ability in case of setting $\lambda = 0.9999$ as can be seen in Fig. 4-7.

**Fig. 4-7.** Conventional RLS estimation results in UDDS profile.
Similarly, when the same values of the forgetting factor are applied to NEDC profile, the estimation of SOC has absolute errors less than 4% for $\lambda = 0.9990$, and less than 7% and 10% with $\lambda = 0.9980$ and $\lambda = 0.9995$, respectively, as shown in Fig. 4-8. The estimation tracking ability becomes worse with $\lambda = 0.9999$ similar to what happens to the UDDS profile. The large estimation errors with $\lambda = 0.9999$ under both UDDS and NEDC profiles occurred because of following reasons. Firstly, with $\lambda$ close to 1, the mean squared error is significant [181] and the algorithm loses its tracking ability in the time-varying system [95]. Secondly, in the battery states estimation with RLS, the forgetting factor value has to be chosen near an optimal
value otherwise the estimation would have larger errors or even diverge [55] and [91]. This confirms the system sensitivity to selecting the forgetting factor value, which is a major concern of the conventional RLS technique.

As the OCV varies dynamically, the forgetting factor is required to be close to 0.9990 in order to get accurate SOC estimation. Under this circumstance, the estimation of the resistance $R_0$ is significantly dependent on the operating current magnitude as shown in Fig. 4-7 & Fig. 4-8 which clearly conflicts with the independence of $R_0$ on current magnitude at constant working temperature [42] and [133]. For this case, even though the estimation of SOC is precise, the estimation of $R_0$ is inaccurate. As $R_0$ is one of the most important and accurate indicators for SOH, it is crucial to have $R_0$ estimated precisely. This is a critical drawback of the conventional method employing only one SFFF, which needs to be improved.

### 4.4.5 Estimation Verification with the Proposed Adaptive Technique

This validation process of the proposed technique is done in the same manner as the conventional method. The estimation results for both UDDS and NEDC experiments are shown from Fig. 4-9 to Fig. 4-14. Fig. 4-9 and Fig. 4-11 show the adaptation of the four forgetting factors throughout the UDDS and NEDC cycles. Fig. 4-10 and Fig. 4-12 show the estimation results of $R_0$, $R_1$, $C_1$, and OCV. The significantly different dynamic rates of the four parameters and large discrepancies of the four forgetting factors' adaptation to the change of the battery working conditions are clearly seen through the experimental results shown in these figures.
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![Image]

**Fig. 4-9.** MAFF-RLS estimation results: Forgetting factors variation in UDDS profile.

![Image]

**Fig. 4-10.** MAFF-RLS estimation results: Model parameters in UDDS profile.
Chapter 4. SOC and Model Parameter Estimation under Dynamic Load Conditions

Fig. 4-11. MAFF-RLS estimation results: Forgetting factors variation in NEDC profile.

Fig. 4-12. MAFF-RLS estimation results: Model parameters in NEDC profile.
In Fig. 4-10(a) and Fig. 4-12(a), the estimation results of the ohmic resistance \( R_0 \) are almost constant at a value of 2.58 mΩ in UDDS profile and 2.61 mΩ in NEDC profile after convergence, which are very accurate compared to the reference value of the ohmic resistance mentioned in Table 4-1. The estimation of the charge-transfer resistance \( R_1 \) is dynamic corresponding to the change in the current amplitude and SOC as expected. It can be seen in Fig. 4-9 and Fig. 4-11 that \( \lambda_1 \) and \( \lambda_2 \) quickly converge as \( R_0 \) gets closer to its actual value. The variations of these forgetting factors are seen to be the same. This can be explained from Eq. (4.8) as \( b_1 \) is majorly controlled by \( R_0 \) because \( T_s/C_1 \) and \( T_s R_0/C_1 R_1 \) are relatively small compared to \( R_0 \). Thus, \( \lambda_{1,k} \) and \( \lambda_{2,k} \) are likely to have the same adaptation trend as they share the same main parameter. Differently, \( \lambda_3 \) varies significantly with the change of the current magnitude, which adapts the estimation of the charge transfer resistance \( R_1 \) to the dynamically changing working conditions. The forgetting factor \( \lambda_4 \) varies slowly from its initial value (i.e., the starting point of the cycles) to 1, which provides a smooth estimation result of the OCV that accurately follows the reference dynamic value shown in Fig. 4-10(d) and Fig. 4-12(d). These figures also show the reference value of the conventional OCV in black dashed line which is far from the estimated one proving that, when the conventional OCV is used with the one-RC model, the errors are critical as expected.

Fig. 4-13(a) and Fig. 4-14(a) show the good fitness of the estimated voltage by MAFF-RLS versus the measured one for one cycle of both UDDS and NEDC experiments. Most of the absolute errors lie within 5 mV which proves the high accuracy of the estimation by the proposed technique. The results of SOC estimation obtained by the proposed method compared to the conventional SFFF-RLS and the
reference SOC obtained from Coulomb counting with an accurate initial value in both profiles are shown in Fig. 4-13(b) and Fig. 4-14(b). As can be clearly seen in Fig. 4-13(c) and Fig. 4-14(c), compared to the conventional SFFF-RLS with optimal value of $\lambda = 0.9990$, the proposed MAFF-RLS approach has not only smaller error bounds but also smaller error peaks. The estimated SOC by MAFF-RLS tracks the reference value very well with absolute errors of less than 2.8% for both UDDS and NEDC experiments.

![Figure 4-13](image_url)

Fig. 4-13. Terminal voltage estimation and SOC estimation comparison in UDDS profile.
Fig. 4-14. Terminal voltage estimation and SOC estimation comparison in NEDC profile.

Based on experimental outcomes, it is evident that the proposed approach, with less number of FLOPs required, is not only able to solve the trade-offs and difficulties in selecting appropriate forgetting factor but also capable of dynamically capturing different dynamic paces of parameters under the same working conditions compared to the conventional algorithm. Moreover, the proposed technique has also provided a very consistent solution to the divergence problem, which may occur in the conventional RLS. Finally, the proposed technique yields the capability to precisely estimate an accurate indicator of the SOH of the battery, which is the ohmic resistance, $R_0$. 

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4.5 Conclusion

In this chapter, a multiple adaptive forgetting factors recursive least-squares technique has been proposed for the online estimation of the dynamic model parameters and the SOC of the LiFePO$_4$ battery in EVs. The proposed technique required lower computation power than the conventional SFFF-RLS in addition to its adaptability to the highly dynamic operating conditions, which is a challenging task in EV applications. The validity of the proposed technique has been confirmed by accurate SOC and model parameters estimation results with maximum error of 2.8% in two standard driving cycles, namely the UDDS and the NEDC. Moreover, as this novel technique takes into consideration the different dynamic paces at which battery model parameters change, it provides an accurate indicator for the battery's SOH, which will be considered later in this research. Finally, the feasibility of this method has been proven by the simplicity of the model and the light scalar computations in algorithm.
Chapter 5

SOC Estimation under Dynamic Load and Variable Temperature Conditions

5.1. Introduction

Dynamic loads and variable temperature are inevitable during the operation of LiFePO₄ batteries in electric vehicles under working conditions. These dynamics have a significant impact on different aspects of the battery, which is a major obstacle to maintaining an accurate SOC estimation for the battery. In this chapter, a simple approach to addressing these dynamic working conditions with a focus on the temperature effect on the battery is proposed. This approach is a development of the previously proposed SOC estimation technique in Chapter 4, with an additional simple model of the OCV to the SOC over a wide range of temperature, which has been empirically devised from experimental investigations. The modeling and
estimation in this chapter are based on a new term for the SOC, which is defined based on experimental findings to take into account the battery recovery capacity due to temperature variations. The developed approach is validated through Urban Dynamometer Driving Schedule (UDDS) experiments including harsh temperature conditions, which have been mostly overlooked in previous research. The obtained results show that this approach maintains an accurate state of charge estimation under such conditions. The accuracy and the simplicity of the proposed algorithm under such conditions are crucial for a feasible battery management system to be used in electric vehicles.

5.2. Estimation Approach

As the to-be-developed approach is the development of the previously proposed SOC estimation in Chapter 4. Therefore, the multiple adaptive forgetting factors recursive least-squares (MAFF-RLS) estimation algorithm, the battery model shown in Fig. 5-1 and its derivations remained the same. In this chapter, only a summary of the estimation approach is shown.

![Fig. 5-1. The electrical equivalent circuit battery model.](image-url)
The system equation of the battery model is written below:

\[ y_k = \theta_k^T \cdot \phi_k \]  \hspace{1cm} (5.1)

with the regressor vector \( \phi_k \) and the parameter vector \( \theta_k \) are defined in following equations:

\[ \theta_k = [b_{0,k}; b_{1,k}; a_{1,k}; OCV_k] \]  \hspace{1cm} (5.2)

\[ \phi_k = [I_k; I_{k-1}; (OCV_{k-1} - y_{k-1}); 1] \]  \hspace{1cm} (5.3)

The battery model parameters \( R_0, R_1, \) and \( C_1 \) are calculated as follows:

\[ R_0 = b_0 \]  \hspace{1cm} (5.4)

\[ R_1 = \frac{b_1 - a_1 \cdot b_0}{1 + a_1} \]  \hspace{1cm} (5.5)

\[ C_1 = \frac{T_s}{b_1 - a_1 \cdot b_0} \]  \hspace{1cm} (5.6)

The algorithm estimates the parameter vector \( \theta_k \) through measurements of the battery voltage and current. While the OCV, as one of the vector components, is obtained directly, the other battery model parameters are calculated by the last three equations and three intermediate variables, namely, \( b_0, b_1, \) and \( a_1 \). As previously mentioned, the temperature has an impact on the battery parameters, but thanks to the adaptation capability of the MAFF-RLS, the estimated OCV, and the other parameters can be adapted to changes in the working conditions. Hence, the main goals are to thoroughly study the impact of temperature on the OCV-SOC relationship and then propose a simple approach to model it. This will be discussed in the following section.
Table 5-1. Summary of the MAFF-RLS algorithm.

| State space equation: $y_k = \theta_k^T \cdot \phi_k$ |

Computation procedure:

Forgetting factor time update:

$$\lambda_{i,k} = 1 - \left[ 1 + \zeta_i \left( \phi_{i,k}^T \cdot P_{i,k-1} \cdot \phi_{i,k} \right)^{-1} \right]^{-1}$$

Gain time update:

$$L_{i,k} = P_{i,k-1} \cdot \phi_{i,k} \left[ \lambda_{i,k} + \phi_{i,k}^T \cdot P_{i,k-1} \cdot \phi_{i,k} \right]^{-1}$$

Error covariance time update:

$$P_{i,k} = \lambda_{i,k}^{-1} \left( 1 - L_{i,k} \cdot \phi_{i,k}^T \right) P_{i,k-1}$$

Vector gain time update:

$$L_k = \left[ \begin{array}{c} \lambda_{1,k}^{-1} \cdot P_{1,k-1} \cdot \phi_{1,k} \\ \vdots \\ \lambda_{4,k}^{-1} \cdot P_{4,k-1} \cdot \phi_{4,k} \end{array} \right] \left[ 1 + \sum_{i=1}^{4} \lambda_{i,k}^{-1} \cdot P_{i,k-1} \cdot \phi_{i,k}^2 \right]^{-1}$$

State estimation measurement update:

$$\theta_k = \theta_{k-1} + L_k (y_k - \phi_k^T \cdot \theta_{k-1})$$

5.3. Temperature Impact on the OCV-SOC Relationship

As the SOC is calculated based on the battery capacity at certain given conditions, therefore, the OCV-SOC relationship is dependent on the capacity. In this section, the impact of temperature on the capacity and the OCV are firstly studied, then a model for the OCV, SOC, and temperature is proposed. To do so, a test bench was configured as discussed in Chapter 3. This test bench employed 90 Ah LiFePO$_4$ batteries, a programmable temperature chamber, a programmable charging machine, and a host computer. A number of experiments have been conducted, which include capacity, recovery capacity, OCV-SOC characteristic, and the UDDS load profile.
The experimental sequence is repeatedly applied at different temperature values (°C): -10, 0, 10, 20, 30, 40, and 50. More details of the test bench configurations and experimental load profiles can be found in Chapter 3.

5.3.1. Temperature Effect on Capacity

To determine the effect of temperature on the battery capacity, the fully charged battery is discharged in 45A constant current (CC) mode and a specific temperature until it reaches the cut-off voltage, 2.5V for the batteries under test. Then, the battery is fully charged again in constant current constant voltage (CC-CV, 45A-3.8V) mode. During these experiments, it was noticed that, whilst the battery’s delivered capacity remained relatively unchanged at 30°C and above, it decreased exponentially as the temperature went below 30°C. The efficiency, which is defined as the ratio of the discharge capacity to the charge capacity, however, remained virtually 1 at all temperatures. This leads to the conclusion that the battery was not fully discharged when its voltage reached the cut-off value after the discharge at a temperature below 30°C. Therefore, further experiments were carried out at lower temperatures than 30°C to study and explain this effect.

Table 5-2. Battery specifications.

<table>
<thead>
<tr>
<th>LiFePO₄ battery</th>
<th>Specification</th>
</tr>
</thead>
<tbody>
<tr>
<td>Rated capacity</td>
<td>90 Ah</td>
</tr>
<tr>
<td>Operating voltage</td>
<td>2.5 V–3.8 V</td>
</tr>
<tr>
<td>Max discharge current</td>
<td>Impulse: 20 CA</td>
</tr>
<tr>
<td></td>
<td>Constant: 3 CA</td>
</tr>
<tr>
<td>Max charge current</td>
<td>3 CA</td>
</tr>
</tbody>
</table>
In these experiments, the fully charged battery was discharged to 2.5 V at a certain temperature, and the battery was left to rest for a suitable period of time after the ambient temperature returned to 30°C (considered as the reference working temperature). It was then discharged to 2.5 V again at 30°C. The results obtained from this experiment, which are illustrated in Fig. 5-2, are quite interesting. The solid lines with symbols represent the battery voltage in the first discharging cycle at the initial temperature, while those without symbols after the dashed-line segments represent the battery voltage in the second discharging cycle after relaxation. It is evident that after returning to the reference temperature, the battery is capable of delivering extra Ah (recovery capacity), which makes its total discharge capacity approximately equals to the discharge capacity at 30°C and above. Therefore, this total discharge capacity at 30°C is considered as its full potential capacity (reference capacity).

Fig. 5-2. Discharging experiment at different constant temperatures.
5.3.2. Temperature Effect on OCV

To determine accurately the impact of temperature on the OCV-SOC relationship, the fully charged battery was discharged by 45A-3Ah constant current pulses (CCP) until its voltage reached the cut-off value. This procedure was repeated for the proposed temperature range taking into account that a suitable relaxation time was applied between the pulses. Based on the measured data, the voltage drop on both the internal resistance (ohmic resistance) $R_0$ and the $RC$ network representing the short-term voltage recovery vanishes after 3 minutes, and the battery voltage was relatively unchanged after 1 hour of relaxation. The experimental results also showed that at any temperature below 30°C, the total discharge capacity was smaller than that of the CC discharge experiment. This can be explained by the battery temperature differences in these experiments. At low ambient temperature, whilst the battery temperature inevitably increases in CC experiments, it remains relatively stable in CCP experiments thanks to the relaxation periods. As a result, the capacity acquired from the CCP testing is deemed more reliable. From this point, the capacity of the battery acquired from the CCP experiment at 30°C is denoted as $C_{\text{Full}}$ and that at any other temperature, $T$, is denoted as $C_{\text{Temp}}$. Then, a new term for the SOC, namely, $\text{SOC}_{\text{F}}$, is proposed, which is calculated based on $C_{\text{Full}}$ as opposed to the conventional SOC, i.e., $\text{SOC}_{\text{T}}$, which is based on $C_{\text{Temp}}$. Fig. 5-3 illustrates the ratio of $C_{\text{Temp}}$ to $C_{\text{Full}}$, $\rho(T)$, for different temperature values. It can be seen from the figure that at 30°C or higher temperatures, the factor is virtually 1. At low temperature, however, this temperature-capacity factor is exponentially decreasing with respect to the decrease in temperature. This relationship can be modelled by piecewise linearization method for the sake of simplicity.
5.3.3. Proposed OCV-SOC-Temperature Model

The experimental OCV-SOC curves for both SOC\(_T\) and SOC\(_F\) are presented in Fig. 5-4. Fig. 5-4(a&b) presents the conventional OCV-SOC\(_T\) curves with respect to \(C_{\text{Temp}}\) which considers that the battery is fully discharged when it first reaches its cut-off value. It can be seen from Fig. 5-4(a) that with the same SOC\(_T\), which is above 22% approximately, the higher the temperature is, the greater the voltage is. This provides the possibility of modeling these 3-min OCV curves vs. temperature, e.g., linear interpolation or LUT. For the remaining range of the SOC\(_T\), the OCV curves are steep and mostly overlapping, except for the curve at -10\(^\circ\)C. The curve at -10\(^\circ\)C is higher than those at higher temperatures at the same SOC\(_T\), which is different from the case where the SOC\(_T\) is above 22%. This requires a more complicated modeling approach. In the case of 1-hour OCV, Fig. 5-4(b) shows a

![Temperature-capacity factor vs. temperature](image-url)
similar situation, where the temperature is below 30°C and the SOC\textsubscript{T} is less than 34%, especially for the -10°C curve at SOC\textsubscript{T} from 54% to 70%. It is evident that it would be a tremendous challenge to address the changes in both OCVs over wide ranges of the SOC\textsubscript{T} and temperature. Moreover, as mentioned above, the battery is not necessarily fully discharged when SOC\textsubscript{T} is 0% at a low temperature because when the battery temperature is returned to a higher value, it is possible to deliver more capacity. Thus, there is a necessity to have an alternative term that represents the SOC of the battery based on the full potential capacity, which is the SOC\textsubscript{F}.

Fig. 5-4. OCV-SOC characteristic curves.
Fig. 5-4(c&d) shows the OCV-SOC\textsubscript{F} correlation with respect to the full potential capacity, $C\text{Full}$, which takes into consideration the recovery capacity. As can be seen, unlike the traditional OCV-SOC\textsubscript{T} curves, both the 3-min and the 1-hour OCV-SOC\textsubscript{F} curves have a unified relationship with temperature. It is obvious that, as the temperature decreases, OCV value tends to be smaller for the same SOC\textsubscript{F}. Thus, modeling the changes in the OCV-SOC\textsubscript{F} curves vs. temperature is more feasible.

In terms of the SOC estimation, using SOC\textsubscript{F} is more practical and accurate when the battery is under dynamic temperature working conditions. In terms of vehicle control, however, the conventional SOC\textsubscript{T} is necessary to predict the remaining driving range of the battery. The following equations are employed to obtain both SOC\textsubscript{T} and SOC\textsubscript{F} using the proposed temperature-capacity factor $\rho(T)$ as follows:

$$\text{SOC}\textsubscript{T} = 1 - \frac{C_{\text{disch}}}{C_{\text{Temp}}}$$  \hspace{1cm} (5.7)

$$\text{SOC}\textsubscript{F} = 1 - \frac{C_{\text{disch}}}{C_{\text{Full}}}$$  \hspace{1cm} (5.8)

with $C_{\text{disch}}$ is the discharged capacity. Substituting $C_{\text{Temp}} = \rho(T) \cdot C_{\text{Full}}$ into Eq. (5.7) yields:

$$\text{SOC}\textsubscript{T} = 1 - \rho(T)^{-1} \frac{C_{\text{disch}}}{C_{\text{Full}}}$$  \hspace{1cm} (5.9)

Substituting Eq. (5.8) into Eq. (5.9), we have:

$$\text{SOC}\textsubscript{T} = 1 - \rho(T)^{-1} (1 - \text{SOC}\textsubscript{F})$$  \hspace{1cm} (5.10)

The final equation of the relationship is written as follows:

$$\text{SOC}\textsubscript{T} = \rho(T)^{-1} \text{SOC}\textsubscript{F} + 1 - \rho(T)^{-1}$$  \hspace{1cm} (5.11)
The following modeling procedure is shown for the 3-min OCV-SOC_F curves, but it can be adopted similarly for the 1-hour ones. To establish the model for the 3-min OCV-SOC_F curves with respect to temperature, firstly, the deviation of the OCV value, OCV_{dev}, at any arbitrary temperature, $T$, from its corresponding value at 30°C at the same SOC_F is calculated from the following equation:

$$OCV_{dev}(SOC_F, T) = OCV(SOC_F, T) - OCV(SOC_F, 30) \quad (5.12)$$

To further emphasize the dependence of OCV and OCV_{dev} on the SOC_F and $T$, they are formulated as functions of both SOC_F and $T$ in Eq. (5.12). The calculated deviations at different SOC_F values are shown in Fig. 5-5. It is noticeable from the figure that the deviations change exponentially with respect to temperature. Thus, to initially model the OCV_{dev} from its corresponding value at 30°C with high accuracy, an asymptotic regression model (Model 1) is used:

$$OCV_{dev}(SOC_F, T) = m(SOC_F) - n(SOC_F) \cdot p(SOC_F)^T \quad (5.13)$$

The fitting accuracy (adjusted R-squared) of the model and fitting values of the parameters $m$, $n$, and $p$ are shown in Table 5-3. The results show that the model is highly precise. All the three parameters, namely, $m$, $n$, and $p$, vary nonlinearly with respect to the SOC_F. It is clear that $m$ only represents an offset factor, which can be eliminated in the final OCV-SOC_F model. In addition, from the fitting values of $p$, it can be noted that there is a possibility of further simplifying the model by fixing the value of $p$ at 0.96. Then, the simplified model (Model 2) can be written as follows:

$$OCV_{dev}(SOC_F, T) = m(SOC_F) - n(SOC_F)0.96^T \quad (5.14)$$
The fitting adjusted R-squared value, $m$, and $n$ for this simplified model, are also shown in Table 4-1. It can be seen that, there are insignificant differences in the adjusted R-squared values if the SOC$_F$ is higher than 29.8%, although larger differences occur in the remaining range. The fitting results for some OCV deviation curves in the two models are presented in Fig. 5-5. As expected, the OCV deviations are well fitted by both models in Fig. 5-5(a-d). Meanwhile, in Fig. 5-5(e&f), Model 1 has better fitting results compared to Model 2. Although the results show that Model 2 has a slightly larger fitting error than Model 1, the former offers better computational efficiency, which is highly desirable in real-time EV application.

In terms of accuracy, Model 2 still retains a high fitting accuracy, especially in the important working range of the SOC$_F$. Based on the fitting accuracy, $OCV_{dev}(SOC_F, 30) \approx 0$, thus $m(SOC_F) = n(SOC_F)0.96^{30}$. Substituting this into Eq. (5.14) yields:

$$OCV_{dev}(SOC_F, T) = -n(SOC_F)(0.96^T - 0.96^3)$$

Finally, to obtain the value of the OCV at any given temperature $T$, the following equation is used:

$$OCV(SOC_F, T) = OCV(SOC_F, 30) - n(SOC_F)(0.96^T - 0.96^3)$$

In Eq. (5.16), OCV(SOC$_F$, 30) and $n(SOC_F)$ are obtained from the temperature-independent LUTs, which were constructed based on the experimental data and the model fitting. From these values, the LUT for the OCV-SOC$_F$ correlation at temperature $T$ is constructed. Fig. 5-6 shows a comparison between the modeled and the measured OCV-SOC$_F$ curves at different temperatures. It is noteworthy that, at
low SOC\textsubscript{F}, the modeling error of the OCV\textsubscript{dev} shown in Fig. 5-5 will be unlikely to result in significant estimation errors in the SOC\textsubscript{F} thanks to the steep slope of the OCV-SOC\textsubscript{F} curves. As a whole, the proposed OCV modeling method is simple yet fairly accurate, taking into account the significant discrepancies between OCV curves at different temperatures. Moreover, it requires neither a large amount of dedicated memory nor heavy computational resources while performing the estimation, which is a noticeable advantage in real-time applications.

**Fig. 5-5. OCV difference and its fittings with the two models.**
Table 5-3. $OCV_{dev}$ fitting parameters and accuracy of Model 1 and Model 2.

<table>
<thead>
<tr>
<th>$SOC_F$ (%)</th>
<th>Model 1</th>
<th></th>
<th>Model 2</th>
<th></th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>$m$</td>
<td>$n$</td>
<td>$p$</td>
<td>Adjusted R-Squared</td>
<td>$m$</td>
</tr>
<tr>
<td>97.2</td>
<td>0.012</td>
<td>0.037</td>
<td>0.965</td>
<td>0.996</td>
<td>0.009</td>
</tr>
<tr>
<td>88.8</td>
<td>0.012</td>
<td>0.041</td>
<td>0.964</td>
<td>0.991</td>
<td>0.009</td>
</tr>
<tr>
<td>80.4</td>
<td>0.023</td>
<td>0.057</td>
<td>0.973</td>
<td>0.990</td>
<td>0.011</td>
</tr>
<tr>
<td>71.9</td>
<td>0.017</td>
<td>0.046</td>
<td>0.971</td>
<td>0.993</td>
<td>0.009</td>
</tr>
<tr>
<td>63.5</td>
<td>0.017</td>
<td>0.044</td>
<td>0.970</td>
<td>0.998</td>
<td>0.010</td>
</tr>
<tr>
<td>55.1</td>
<td>0.018</td>
<td>0.046</td>
<td>0.968</td>
<td>0.996</td>
<td>0.012</td>
</tr>
<tr>
<td>46.7</td>
<td>0.020</td>
<td>0.054</td>
<td>0.968</td>
<td>0.996</td>
<td>0.014</td>
</tr>
<tr>
<td>38.3</td>
<td>0.010</td>
<td>0.047</td>
<td>0.948</td>
<td>0.991</td>
<td>0.017</td>
</tr>
<tr>
<td>29.8</td>
<td>0.004</td>
<td>0.038</td>
<td>0.929</td>
<td>1.000</td>
<td>0.011</td>
</tr>
<tr>
<td>21.4</td>
<td>0.004</td>
<td>0.052</td>
<td>0.923</td>
<td>0.999</td>
<td>0.015</td>
</tr>
<tr>
<td>13.0</td>
<td>0.005</td>
<td>0.102</td>
<td>0.898</td>
<td>0.999</td>
<td>0.032</td>
</tr>
</tbody>
</table>

Fig. 5-6. Measured and modeled OCV at different constant temperatures.
This novel model is applied to the estimation approach discussed in Section 5.2. Fig. 5-7 shows the block diagram of the whole estimation approach. The MAFF-RLS algorithm estimates the OCV from the voltage and current measurements at any given temperature. Then, the estimated OCV is converted to its corresponding SOC\textsubscript{F} through the OCV-SOC-Temperature model. The SOC\textsubscript{T} can be calculated from the temperature-capacity factor $\rho(T)$ and the estimated SOC\textsubscript{F}.

5.4. Experimental Verification

To validate the developed estimation approach, a number of experiments have been carried out. Fig. 5-8(a) shows the UDDS load profile which is used as the current sequence (one UDDS cycle). As can be seen, the load current is highly dynamic and continuously varying from charge to discharge with different magnitudes. The whole experimental current load profile, which consists of 20 UDDS cycles, is shown in Fig. 5-8(b). This load profile has been applied to the battery for experiments at different temperatures. Based on the experimental voltage, current, and temperature, the verification process has been implemented. The MAFF-RLS algorithm estimates the OCV from the voltage and current measurements at any given temperature. Then the estimated OCV is translated into SOC\textsubscript{F} through the LUT of the OCV-SOC\textsubscript{F} relationship, which is constructed based on the OCV model and the measured temperature.
5.4.1. Experimental Verification at Constant Temperatures

The validation of the proposed approach was firstly performed with the UDDS experiments at different constant temperatures from -10°C to 50°C. The SOC\textsubscript{F} estimation errors of these experiments, represented by the peak error (PE), root-
mean-square error (RMSE), and mean absolute error (MAE), are shown in Table 5-4. Fig. 5-9 to Fig. 5-12 show the measured values of the voltage and temperature, and the estimation results for the OCV and the SOC\textsubscript{F} compared to their reference values at four temperatures, namely, -10\textdegree C, 10\textdegree C, 30\textdegree C, and 50\textdegree C. The experimental results at -10\textdegree C are shown in Fig. 5-9.

It is obvious from Fig. 5-9(a) that the estimated OCV tracks its reference well, which results in an accurate estimation of the SOC\textsubscript{F}, as shown in Fig. 5-9(c). The accuracy of the SOC\textsubscript{F} estimation is also obvious from Table 5-4, where the PE is less than 4.6\%, the RMSE is 2.0\%, and the MAE is 1.7\%. Similar accurate estimation results for \(T = 10\textdegree C\) can be seen in Fig. 5-10 and Table 5-4. For experiments conducted at 30\textdegree C and 50\textdegree C, slightly larger errors occur compared to those at lower temperatures, as shown in Fig. 5-11, Fig. 5-12, and Table 5-4. Nevertheless, the RMSE and the MAE are still less than 1.7\% and 2.2\%, respectively. The accuracy of the estimation is also retained at other temperatures, namely, 0\textdegree C, 20\textdegree C, and 40\textdegree C, as presented in Table 5-4. Figures for these experimental results can be found in Appendix B.

The slight increase in the SOC\textsubscript{F} estimation error at higher temperatures can be explained by the decrease in the OCV slope as the temperature tends to increase. When comparing the experimental results obtained at these four temperatures, it is clear that under the same current load, the battery voltage is significantly dependent on temperature. Thanks to the adaptation capability of the MAFF-RLS algorithm, the estimated OCV is still accurate which results in a good estimation of the SOC\textsubscript{F} at any given temperature.
Chapter 5. SOC Estimation under Dynamic Load and Variable Temperature Conditions

**Fig. 5-9.** Experimental results of the UDDS load profile at -10°C.

**Fig. 5-10.** Experimental results of the UDDS load profile at 10°C.

**Fig. 5-11.** Experimental results of the UDDS load profile at 30°C.

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5.4.2. Experimental Verification at Variable Temperatures

To further investigate the performance of the proposed estimation method, two UDDS experiments with different patterns of temperature changes were conducted. While in the first experiment, the temperature was increased from 10°C to 40°C by a ramp-shaped profile, in the second experiment, the temperature changed as a step function from 10°C to 40°C. The results of both experiments are shown in Fig. 5-13 and Fig. 5-14. As seen in the figure, the temperature has a profound impact on the battery voltage under the same current profile. In the second experiment, the voltage response shown in Fig. 5-14 is more dynamic, with three visible steps of changes. For the first experiment, these changes are less obvious due to the gradual increase in the temperature shown in Fig. 5-13. Yet, these voltage profiles are significantly different from those in any of the constant temperature experiments. Despite the high dynamics of the voltage and temperature, the estimated OCV still precisely tracks the reference one. Consequently, the SOC estimation error is less than 5.2%, while
the RMSE is 2.3% and the MAE is 1.8% in both experiments with variable temperature. These errors are slightly higher than that for the constant-temperature experiments, as expected, because the temperature profiles are more dynamic. It should be noted from all the experimental results (constant and variable temperatures) that the OCV generally decreases when the SOC$_F$ gets lower. Yet, it is clearly seen in Fig. 5-14(b-3) that the reference OCV increases while the SOC$_F$ decreases with time when the temperature changes from 20$^\circ$C to 38$^\circ$C. The accurate tracking of the estimated OCV with respect to the reference OCV strengthens the validation of not only the OCV modeling method, but also the adaptability of the estimation algorithm.

It is also noteworthy that the SOC$_F$ estimation error always experiences its peak in the range of the SOC$_F$ from 95% to 80% and from 65% to 40%. This can be explained by the characteristic OCV-SOC$_F$ curves of the lithium iron phosphate battery. In these two ranges, the OCV-SOC$_F$ curves are relatively flat, which means that even the smallest error in the estimated OCV would cause a large error in the SOC$_F$ estimation. To address this issue, a technique such as a state observer might be required. This state observer uses the difference between the estimated OCV and the modeled OCV to correct the estimation. The modeled OCV is obtained from the SOC$_F$, which is calculated from the Coulomb counting method. This approach might help to further enhance the estimation accuracy, however, it will require more computational resources.
Fig. 5-13. Experimental results of the UDDS load profile at ramp-shape variable temperature.

Fig. 5-14. Experimental results of the UDDS load profile at step-shape variable temperature.

Table 5-4. $SOC_F$ estimation errors under different temperature conditions.

<table>
<thead>
<tr>
<th>Temperature experiments</th>
<th>PE (%)</th>
<th>RMSE (%)</th>
<th>MAE (%)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Constant</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>-10°C</td>
<td>4.6</td>
<td>2.0</td>
<td>1.7</td>
</tr>
<tr>
<td>0°C</td>
<td>4.5</td>
<td>1.7</td>
<td>1.4</td>
</tr>
<tr>
<td>10°C</td>
<td>4.6</td>
<td>1.8</td>
<td>1.5</td>
</tr>
<tr>
<td>20°C</td>
<td>5.1</td>
<td>1.6</td>
<td>1.4</td>
</tr>
<tr>
<td>30°C</td>
<td>5.2</td>
<td>2.0</td>
<td>1.7</td>
</tr>
<tr>
<td>40°C</td>
<td>5.2</td>
<td>2.2</td>
<td>1.7</td>
</tr>
<tr>
<td>50°C</td>
<td>5.2</td>
<td>2.1</td>
<td>1.7</td>
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<tr>
<td>Variable</td>
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<td></td>
<td></td>
</tr>
<tr>
<td>Ramp</td>
<td>5.1</td>
<td>2.3</td>
<td>1.8</td>
</tr>
<tr>
<td>Step</td>
<td>5.1</td>
<td>2.2</td>
<td>1.8</td>
</tr>
</tbody>
</table>
Through the experimental verification, the herein-developed approach has proven its accuracy, which is demonstrated by the accurate OCV modeling and the adaptability of the estimation algorithm, MAFF-RLS, especially under load conditions with both current and temperature are dynamically varying. These experimental conditions are more dynamic than those considered in the previous researches discussed in the literature review in Chapter 2. This is one of the advantages that makes the proposed approach applicable to various geographical areas with different temperature conditions. In addition, the estimation approach is advantageous due to its simplicity, which arises from the combination of the light-computation MAFF-RLS algorithm and the simplified OCV modeling. The accuracy and the simplicity are two of the critical requirements for a feasible estimation technique to be implemented in the BMS. As a whole, the estimation developed in this chapter has overcome the drawbacks of the previous researches that take into account the temperature effect.

5.5. Conclusion

In this chapter, numerous experiments have been conducted, and an original model-based approach has been presented to address the impact of dynamic working conditions, especially temperature variations, on SOC estimation of the LiFePO$_4$ battery in EVs. On the one hand, based on the experimental investigation, a new SOC term based on the full potential battery capacity, $\text{SOC}_F$, has been introduced to feasibly develop a simple method that accurately models the OCV in the full range of SOC over a broad temperature range from -10°C to 50°C. The proposed model is simple, yet fairly accurate, taking into account the critical dependence of OCV-SOC.
Chapter 5. SOC Estimation under Dynamic Load and Variable Temperature Conditions

curves on temperature. On the other hand, thanks to the MAFF-RLS algorithm, the OCV can be accurately estimated with the significant adaptability, even under harsh working conditions. Eventually, through the proposed OCV model, the $\text{SOC}_F$ is precisely obtained from the estimated OCV.

The estimation approach has been validated by many experiments under the standard dynamic load profile, UDDS, at different constant or time-varying temperatures. Even so, this approach still achieves an accurate estimation of the $\text{SOC}_F$ with an error of less than 5.2%, and the RMSE and the MAE are smaller than 2.3% and 1.8%, respectively. This advance in dealing with the temperature effect is vital, not only for retaining simplicity, but also for improving the accuracy and reliability of the battery’s SOC estimation under dynamic working conditions. In the next chapter, the estimation approach developed in this chapter will be further improved and validated on different states of battery aging. In addition, an approach for the state of health estimation is to be developed in order to have a comprehensive estimation approach for battery states.
Chapter 6

SOH and SOC Estimation for the Degraded Battery

6.1 Introduction

Battery degradation is inevitable due to Li-ion battery characteristics. The SOH estimation is crucial, and consequently, an investigation of the SOC estimation for the degraded battery is also needed. In this chapter, the SOH estimation method is proposed. This method involves only the changes of the ohmic resistance due to aging, which is estimated by the MAFF-RLS estimation approach. The SOC estimation method, which developed in Chapter 5, is further improved to address the impact of degradation on the estimation accuracy. This is done by taking into account the impact of the degradation on the OCV-SOC relationship. Finally, the comprehensive estimation method, for both the SOC and the SOH, is introduced. The proposed estimation algorithms have been verified with the battery at its different stages of aging.
6.2 Experimental Setup

To investigate the influence of battery conditions on its characteristics and performance, a test bench was configured as mentioned in detail in Chapter 3. For aging-related experiments, a battery of the same type is used as 90 Ah LiFePO$_4$ batteries that were used in the temperature experiments. Since the battery lasts for thousands of cycles before reaching its end of life (EOL) under normal working conditions, an accelerated degradation process is employed. There are various approaches that have been proposed to accelerate the aging mechanism of the LIB \[141, 182\], and in this research, the cycling method based on high temperature is used. The battery is put under charge/discharge cycling at current density of 90 A and temperature of 55°C. After each cycling sequence, the battery was subjected a list of experiments including: capacity, OCV-SOC characteristic curve, and the Urban Dynamometer Driving Schedule (UDDS) load profile.

Fig. 6-1 shows the degradation of the battery, which was measured at five different stages of aging at 20°C. At the first stage, namely, beginning of life (BOL), the battery is fresh and the SOH is 100%. At the next three degraded stages, which are defined as middle of life stages 1, 2, and 3 (MOL1, 2, 3), the SOH reduced approximately to 95%, 91%, and 87%, respectively. In this research, the battery is assumed to be at its EOL when the SOH reduced to 77%. The full charging voltages of the battery after a complete discharge are shown in Fig. 6-2. It can be seen that, under the same CC-CV (45A-3.8V) charging configuration, the voltage reaches the CV mode more rapidly over time. The changes in the charging current profile are presented in Fig. 6-3. The Coulombic efficiency calculated from these experiments is virtually maintained at 100% throughout its lifetime.
Fig. 6-1. Discharge voltage vs. discharge capacity at different stages.

Fig. 6-2. Charging voltages at different stages.

Fig. 6-3. Charging currents at different stages.
6.3 Capacity-Resistance-Temperature Model for SOH Estimation

Among the SOH estimation approaches discussed in the literature review in Chapter 2, the resistance-based SOH estimation has been one of the most popular and reliable on-board methods. This method basically estimates the SOH by the resistance estimation majorly thanks to adaptive algorithms. The total resistance of the battery is a combination of the internal resistance (ohmic resistance), the charge-transfer resistance, and the diffusion resistance. This total resistance is dependent on several factors, namely, the current magnitude, the SOC, and the temperature. Therefore, in order to have accurate information on the resistance changes, the measurements should be carried out under the same conditions as for these factors. The ohmic resistance, however, is virtually invariant to the SOC and current magnitude. The increase in the ohmic resistance with respect to aging is a well-known phenomenon in EIS measurements. An example of EIS profiles at different SOHs of the battery is shown in Fig. 6-4. It is clear that, when the battery is degraded, the EIS impedance, under the same measurement conditions, shifts to the right in the Nyquist plot [183, 184] as the ohmic resistance increases. The ohmic resistance in the EIS impedance is measured within a range of 200 Hz to 10 Hz. This ohmic resistance is equivalent to the time-dependent ohmic resistance $R_0$ in the Thevenin-based model at the corresponding sampling frequency. As can be seen, the changes within the range are not significant, and therefore, if the resistance is measured at the same frequency within the range, the correlation between the aging and the resistance can be obtained. The sampling frequency can be as high as 1 kHz, depending on the microprocessor capability; in the following experiments, however, 10 Hz is used, as it is suitable for low-cost hardware.
In this research, the SOH is determined from the estimated capacity, which is computed from the estimated $R_0$ and the $R_0$-capacity relationship. A simple model of capacity vs. resistance is constructed through experiments. The current capacity of the battery can be estimated under any given battery conditions, thanks to the accurate estimation of the $R_0$ from the estimation approach, MAFF-RLS, which had been developed in Chapter 4. In the following subsections, the relationship between the SOH, capacity, $R_0$, and temperature is investigated.

### 6.3.1 Temperature-dependent Ohmic Resistance Modeling

Firstly, the resistance dependence on temperature is studied. In order to have an accurate investigation of the battery throughout its lifetime, fresh 90 Ah LFP batteries are employed. The temperature effect on the ohmic resistance is simply obtained by averaging multiple instantaneous voltage drops in the CCP experiments.

Fig. 6-4. An example of Nyquist plots at different degradation levels [185].
at a sampling time of 100 ms, which is the same as the sampling time of the estimation algorithm. Fig. 6-5 shows the ratio of the ohmic resistance at an arbitrary temperature to the value at 50°C. This ratio, $r(T)$, can be modeled by the Arrhenius equation to represent the dependence of the resistance on temperature [186, 187]. In this research, however, a modified Arrhenius equation, written as follows, is used for better fitting accuracy:

$$r(T) = r_0 + r_1 \cdot \exp(r_2 \cdot T)$$  \hspace{1cm} (6.1)

By fitting the function with the experimental curve in Fig. 6-5, the values of the function are found. In this research, the impact of temperature on the battery was considered to be unchanged when the battery was degraded. Consequently, the fitting parameters, namely, $r_0$, $r_1$, and $r_2$, are assumed independent of aging.

![Temperature-resistance ratio at BOL of the battery.](image)

Fig. 6-5. Temperature-resistance ratio at BOL of the battery.
6.3.2 Resistance-Temperature-Capacity Model

As the battery is at its full potential capacity at 30°C for any SOH, the correlation between the capacity and the ohmic resistance was established at 30°C thanks to the temperature-capacity factor, \( \rho(T) \), and the temperature-resistance ratio, \( r(T) \). Fig. 6-6 shows the correlation with the resistance obtained at each stage of aging. For the sake of simplicity, a simple linear function was constructed for this relationship as follows:

\[
C_{\text{Full}} = c_0 + c_1 \cdot R_0(30) \quad (6.2)
\]

It is possible to obtain the capacity directly from the resistance at an arbitrary temperature by employing the correlation with the resistance at 30°C to other temperatures. The correlation is derived based on the temperature-resistance ratio as follows:

\[
\frac{r(30)}{r(T)} = \frac{R_0(30)}{R_0(50)} \cdot \frac{R_0(50)}{R_0(T)} \quad (6.3)
\]

Rearranging Eq. (6.3) yields:

\[
R_0(30) = R_0(T) \cdot \frac{r(30)}{r(T)} \quad (6.4)
\]

Based on Eq. (6.4), the \( R_0 \) at 30°C can be calculated from its estimation value at any arbitrary temperature. This value will be used for comparison in the estimation validation. Substituting the \( R_0 \) (30) from Eq. (6.4) into Eq. (6.2) yields the capacity-resistance-temperature model of the ohmic resistance, temperature, and capacity as follows:

\[
C_{\text{Full}} = f_{\text{SOH}}(R_0(T)) = c_0 + c_1 \cdot R_0(T) \cdot \frac{r(30)}{r(T)} \quad (6.5)
\]
6.4 OCV-SOC-Temperature-SOH Model for SOC Estimation

6.4.1 Aging Effect on Open Circuit Voltage

When the battery is degraded, the capacity is diminished, which consequently has an impact on the OCV-SOC relationship. Therefore, there is a necessity to investigate the changes in the OCV-SOC with respect to the SOH. To determine accurately the impact of aging on the OCV-SOC relationship, the fully charged battery was discharged by 45A-3Ah CCP mode until its voltage reached the cut-off value, 2.5 V. This procedure was repeated for different SOHs at 20°C, taking into account that a suitable relaxation time was applied between the pulses. Based on the measured data, the battery voltage was relatively unchanged after 1 hour of relaxation. In terms of the voltage drop on the ohmic resistance $R_0$ and the $RC$ network representing the short-term voltage recovery, the vanishing times vary, but they are assumed to be 3 minutes for the sake of simplicity.
Fig. 6-7. OCV-SOC characteristic curves.

Fig. 6-7(a&b) presents the conventional 3-min and the 1-hour OCV-SOC\(_T\) curves with respect to the current capacity. It can be seen that, although the OCV virtually is equal higher as the battery degraded, the changes of the OCVs, however, are nonlinear and distinct in different ranges of the SOC. Therefore, it is evident that it would be a tremendous challenge to address the changes in both OCVs over the battery life. Fig. 6-7(c&d) shows the OCV-SOC\(_{BOL}\) correlation with respect to the original full potential capacity at the BOL. As can be seen in the figure, unlike the OCV-SOC\(_T\) curves, both the 3-min and the 1-hour OCV-SOC\(_{BOL}\) curves are
considerably overlapped during aging. The only obvious differences are observed for the OCV at the EOL with the SOC\textsubscript{BOL} from 67% to 73%, and at the OCV at the BOL with the SOC\textsubscript{BOL} less than 9%. To avoid the complexity in the OCV modeling, these differences are neglected in this research. The OCV-SOC\textsubscript{BOL} relationship can be used for the SOC\textsubscript{BOL} estimation without the need of any additional factor or model. Once the SOC\textsubscript{BOL} is estimated, the SOC\textsubscript{F} and SOC\textsubscript{T} can be obtained through their correlation.

6.4.2 Proposed OCV-SOC-Temperature-SOH Model

As been discussed above, the OCV- SOC\textsubscript{BOL}\textsuperscript{F} curves are overlap significantly during degradation, and therefore, the following model equation of the OCV&SOC\textsubscript{BOL}\textsuperscript{F} with respect to temperature for all SOHs is the same as for the OCV-SOC-Temperature relationship developed in Chapter 5.

\[
OCV(SOC_F^{BOL}, T) = OCV(SOC_F^{BOL}, 30) - n(SOC_F^{BOL})(0.96^T - 0.96^3) \tag{6.6}
\]

Next, the correlation of the SOC\textsubscript{F} to the SOC\textsubscript{BOL}\textsuperscript{F} is investigated by the following equations, where \(C_{\text{remained}}\) is the remaining charge in the battery.

\[
SOC_F^{BOL} = \frac{C_{\text{remained}}}{C_{\text{Full}}} \tag{6.7}
\]

\[
SOC_F = \frac{C_{\text{remained}}}{C_{\text{Full}}} \tag{6.8}
\]

\[
\therefore SOC_F = \frac{C_{\text{remained}}}{C_{\text{Full}}} \cdot \frac{C_{BOL}}{C_{\text{Full}}} \tag{6.9}
\]

Substituting the SOH into Eq. (6.9) yields the following:

\[
SOC_F = \frac{SOC_F^{BOL}}{SOH} \tag{6.10}
\]
Chapter 6. SOH and SOC Estimation for the Degraded Battery

The following equation is used to describe the correlation between the SOC_T and the SOC_F, which was developed in Chapter 5.

\[
SOC_T = \frac{SOC_F}{\rho(T)} + 1 - \frac{1}{\rho(T)} \tag{6.11}
\]

Substituting SOC_F from Eq. (6.10) into Eq. (6.11) yields the correlation between the SOC_T and SOC^BOL_F as follows:

\[
SOC_T = \frac{SOC^BOL_F}{\rho(T) \cdot SOH} + 1 - \frac{1}{\rho(T)} \tag{6.12}
\]

From Eq. (6.10) and Eq. (6.12), the SOC_F and SOC_T can be calculated from the estimation of the SOC^BOL_F and the SOH.

6.5 Comprehensive SOC and SOH Estimation Approach

In this section, the comprehensive estimation approach for both SOC and SOH under various conditions is presented, with its block diagram shown in Fig. 6-8. This is a development of what was previously proposed in Chapter 4 and Chapter 5. The estimation algorithm, MAFF-RLS, has been discussed in detail in Chapter 3. The MAFF-RLS estimates OCV^{RLS}_k and R^{RLS}_0,k from the battery’s voltage and current at arbitrary temperature. Then, these estimated values and the measured temperature are used in the SOC observer and the SOH observer. The SOC observer requires updated information on the SOH and the battery capacity from the SOH observer. These observers are employed to enhance the robustness and accuracy of the estimation. A program flowchart of this comprehensive estimation approach can be found in the Appendix C.
6.5.1 SOH Observer

The SOH observer is constructed based on the estimation of the ohmic resistance. In order to increase the robustness of the estimation, the resistance is estimated by the following equation, with $R_{0,k}^{RLS}(T)$ is the resistance estimated at temperature $T$ by the estimation algorithm, MAFF-RLS, and $k_{R0}$ is the feedback gain.

$$R_{0,k}(T) = R_{0,k-1}(T) - k_{R0} \cdot \left( R_{0,k-1}(T) - R_{0,k}^{RLS}(T) \right)$$  \hspace{1cm} (6.13)

The capacity-based SOH calculation is defined in the following equations:

$$\text{SOH} = \frac{C_{\text{Full}}}{C_{\text{BOL}}}$$  \hspace{1cm} (6.14)
Substituting the estimated $R_{0,k}(T)$ and the model function $C_{\text{Full}}$ into $R_{0,k}(T)$ from Eq. (6.5) to Eq. (6.15) yields

$$\text{SOH}_k = \frac{f_{\text{SOH}}(R_{0,k}(T))}{C_{\text{BOL}}}$$

(6.15)

### 6.5.2 SOC Observer

In this observer, the SOC based on the full potential capacity of the battery at the BOL, $\text{SOC}_F^{\text{BOL}}$, is first estimated. This $\text{SOC}_F^{\text{BOL}}$ is the key intermediate parameter for the $\text{SOC}_F$ and $\text{SOC}_T$ estimation in the current condition of the battery. To enhance the estimation error observed in the experimental results in Chapter 5, a simple close-looped observer is constructed. This method employs the error of the estimated OCV with respect to the modeled OCV to update the priori of the $\text{SOC}_F^{\text{BOL},k|k-1}$, which is computed based on the Coulomb-counting method with respect to the full potential capacity at the BOL, $C_{\text{Full}}$, as written in Eq. (6.16).

$$\text{SOC}_F^{\text{BOL},k|k-1} = \text{SOC}_F^{\text{BOL},k|k-1} + \frac{I_k \cdot \Delta \tau}{C_{\text{BOL}}}$$

(6.16)

During long-term usage, the hysteresis effect exists in the battery; therefore, following model, which is based on the well-known piecewise linearization model of the hysteresis voltage with respect to the charge throughput is employed [168]:

$$V_h = V_{h,\text{max}} \cdot \left[ \sum_{i=1}^{n} h_i \cdot \alpha_i \right]$$

(6.17)
Chapter 6. SOH and SOC Estimation for the Degraded Battery

\( V_{h,\text{max}} \) is the maximum hysteresis voltage, \( h_i \) represents the normalization factors with \( \sum h_i = 0 \), and the hysteresis saturated integrator \( \alpha_i \) values are calculated as follows:

\[
\alpha_i = \int \frac{m_i \cdot I \cdot d\tau}{e_{\text{Full}}^{\text{BOL}}} \quad (6.18)
\]

with \( m_i \) is the width factor, which determines the charge throughput for the transition from \( \alpha_i = 0 \) to 1. The impact of the temperature and aging on the hysteresis voltage is not studied in this thesis. Finally, the correction equation based on the feedback gain, \( k_{\text{OCV}} \), and the OCV error of the estimated and the reference OCVs is written as follows:

\[
\text{SOC}_{F,k}^{\text{BOL}} = \text{SOC}_{F,k|k-1}^{\text{BOL}} - k_{\text{OCV}} \cdot [\text{OCV}(\text{SOC}_{F,k|k-1}^{\text{BOL}}, T) - (\text{OCV}_{k}^{\text{RLS}} - V_{h,k})] \quad (6.19)
\]

Once the \( \text{SOC}_{F}^{\text{BOL}} \) is estimated, the \( \text{SOC}_F \) and \( \text{SOC}_T \) are obtainable from the SOH, the temperature-capacity factor, Eq. (6.10), and Eq. (6.12). The cooperation of the SOC observer and the SOH observer helps to maintain the accuracy of the SOC estimation.

### 6.6 Experimental States Estimation with Degraded Battery

To validate the proposed approach, a number of experiments have been carried out. Firstly, the SOC estimation and the SOH estimation are verified separately. In this validation, the SOC is estimated based on its incorrect initial value and a known current capacity. Secondly, the two battery states are validated simultaneously, in
other words, the estimation is conducted for its unknown current conditions. In both experimental verifications, the temperature is allowed to keep freely changing.

### 6.6.1 Separate State Estimations with Known Capacity

In the following experiments, the UDDS load profile, shown in Fig. 6-9, has been applied to the fully charged battery for experiments that have different states of degradation, namely, BOL, MOL2, and EOL. The results of these experiments are shown in Fig. 6-10, Fig. 6-11, and Fig. 6-12, respectively. In each figure, the battery voltage, the temperature, the estimation, and the reference values of the resistance, the OCV, the \( \text{SOC}_{F}^{\text{BOL}} \), the \( \text{SOC}_{F} \), and the SOH are included. In the experiment conducted with a fresh battery, the initial \( R_0 \) at 30\(^\circ\)C is set at 2.5 m\( \Omega \), which is equivalent to an initial SOH of 86\%, approximately. The estimation of the resistance converges closely to the reference value, as shown in Fig. 6-10(c) after a period of time, which results in an accurate estimation of the SOH with an error of less than 3.2\%, as shown in Fig. 6-10(f). Fig. 6-10(a) shows the battery voltage with the estimated OCV and the reference OCV. As can be seen, the estimated OCV closely tracks the reference OCV after the initial correction. As a result, the \( \text{SOC}_{F}^{\text{BOL}} \) estimation error is accurate, with error less than 3.7\%, despite its inaccurate initial value as in Fig. 6-10(e). It should be noted that the \( \text{SOC}_{F}^{\text{BOL}} \) estimation correction takes place quickly, thanks to the known current capacity. In this experiment, the \( \text{SOC}_{F}^{\text{BOL}} \) and \( \text{SOC}_{F} \) are identical, as the SOH is 100\%. 

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Fig. 6-9. UDDS current profiles.

Fig. 6-10. UDDS experiment at the BOL.
Fig. 6-11. UDDS experiment at the MOL2.

Fig. 6-12. UDDS experiment at the EOL.
Similar accurate results can be seen in these remaining experiments. In the second experiment, the battery is at the MOL2. The estimations of the resistance and the SOH are precise, as shown in Fig. 6-11(c&f) thanks to MAFFF-RLS. The error of the SOH estimation in this experiment is 2.7% as. In terms of the SOC, the estimated SOC\textsubscript{F} follows its reference closely in Fig. 6-11(d), which results in its small estimation error of 3.1% presented in Fig. 6-11(e). This accurate estimation result is also seen in the SOC\textsubscript{F} in the same figures. The SOC\textsubscript{F} starts from 100% compared to SOC\textsubscript{F}\textsubscript{BOL}, which is from 91%. The SOC\textsubscript{F} estimation error is higher than that of the SOC\textsubscript{F}\textsubscript{BOL} due to the scaling down of the capacity, yet its maximum is still less than 3.4%.

In the EOL experiment, the UDDS profile almost completely discharges the battery, as seen in Fig. 6-12(a). As can be seen in Fig. 6-12(b), the temperature changes in this experiment are slightly higher than in the experiments at the BOL and the MOL2. The estimation of the resistance is accurate, which tracks the reference value closely at 2.34 mΩ from the initial value of 2.5 mΩ. The SOH estimation error remains less than 1.9%. The estimation error of the SOC\textsubscript{F}\textsubscript{BOL} and SOC\textsubscript{F} are less than 3.2% and 4.1%, respectively. Throughout its life, the SOH estimation and the SOC estimation with known current capacity are highly accurate.

### 6.6.2 Comprehensive State Estimations with Unknown Capacity

In this experiment, the SOC and the SOH are estimated with an unknown condition of the battery. A load profile, which consists of 6 consecutive cycles of 8 UDDS sequences followed by a CC charging, is applied to the battery, which is at the MOL3.
The battery voltage is shown in Fig. 6-13(a). As can be seen in Fig. 6-13(b), most changes in the temperature take place when the battery is in the CC charging mode. The initial value of the ohmic resistance is set to 2.25 mΩ which is equivalent to an initial SOH of 97.2%, whereas the true SOH is 87%. This initial value of the SOH is applied for both the SOC and the SOH estimation. As can be seen in Fig. 6-13(c), the estimated resistance converges accurately to its reference value at 2.42 mΩ. As a result, the SOH estimation is highly accurate, with an error of less than 1.5%, as seen in Fig. 6-13(f). In terms of the SOC estimation, as the battery is fully charged before undergoing this experiment, the reference SOC\(_F\) is 100% and the SOC\(_F^{BOL}\) is 87%. In the first UDDS sequence shown in Fig. 6-13(d&e), the SOC estimation error is large, which can be explained by the incorrect initial values of both the SOC and the SOH. In this first cycle, the SOH estimation error is still high. After the SOH estimation becomes more accurate, higher accuracy of the SOC estimation is achieved. The
estimation error of the $\text{SOC}_{F}^{\text{BOL}}$ and $\text{SOC}_{F}$ are less than 3.5% and 4.1%, respectively. The results in this experiment have proven the proposed comprehensive estimation approach for both the SOC and the SOH.

### 6.7 Conclusion

In this chapter, a comprehensive estimation approach for SOC and SOH estimation has been proposed and validated through a number of experiments. The approach can achieve an accurate estimation result for the SOH from the estimated ohmic resistance from the estimation algorithm, the MAFF-RLS, and the measured battery’s voltage, current, and temperature. The SOC estimation with any SOH is possible thanks to the newly proposed OCV-SOC$_{F}^{\text{BOL}}$-Temperature-SOH model. The $\text{SOC}_{F}$ with respect to the current full potential capacity is calculated from the estimation of the $\text{SOC}_{F}^{\text{BOL}}$. The estimation results for both the SOC and the SOH are accurate, even if the condition of the battery is unknown. The accuracy, simplicity, and robustness of the developed approach make it feasible for EV application.
Chapter 7

Conclusions and Future Work

7.1 Conclusions

A comprehensive online estimation approach to determining the state of charge (SOC) and the state of health (SOH) of LiFePO₄ batteries in electric vehicles has been developed. This approach provides a simple yet effective solution for the state estimations, which only come from the measured battery’s voltage, current, and temperature. The estimation approach has been developed and constructed based on three steps, in which each step addresses one of three major impacts on the battery characteristics, namely, the dynamic load, variable temperature, and degradation.

In the first step, to address the effects of dynamic loads, the multiple adaptive forgetting factors recursive least-squares (MAFF-RLS) estimation approach has been proposed, which accurately estimates the battery model parameters simultaneously and also takes into account the different dynamic paces of these parameters. This has provided the capability for accurate battery modelling under various conditions.
In the second step, the impact of temperature on the estimation has been investigated. Through various temperature-related experiments, new findings on battery capacity recovery have been discovered; in other words, the total potential capacity is temperature-independent. Based on this capacity, a new term for the state of charge (SOC), $\text{SOC}_F$, has been defined. This $\text{SOC}_F$ is a crucial term for feasible modelling development of the open circuit voltage (OCV), SOC, and temperature relationship. In these first two steps, the SOC has been simply obtained from the estimated OCV by MAFF-RLS and lookup tables at the measured temperature.

In the final step, the influence of the battery depletion has been taken into account. Based on the experimental results, a novel model of the OCV, SOC, temperature, and state of health (SOH) has been proposed. This model has been based on the $\text{SOC}_F^{\text{BOL}}$, which is calculated from the full potential capacity at the fresh stage of the battery. On the other hand, the relationship between the battery capacity and the ohmic resistance has been determined at different stages of aging. This has provided a simple technique for the SOH estimation from the estimated resistance. In terms of the SOC estimation, the $\text{SOC}_F^{\text{BOL}}$ has been firstly estimated through an observer. Then, the conventional $\text{SOC}_T$ and the full potential $\text{SOC}_F$ are calculated from the estimated $\text{SOC}_F^{\text{BOL}}$ and its developed correlations.

The estimation results of the SOC and the SOH are accurate and robust throughout the battery’s lifetime under dynamic conditions. This proves that the estimation approach does not need to be excessively complicated and advanced. This research provides a new simple pathway for the SOC and the SOH estimations, which does not require extensive laboratory experiments. Moreover, the estimation
approach demands only light computational resources because of the simplicity of the battery model, the OCV model, and the light scalar computations. The estimation approach is applicable for the battery management system (BMS) thanks to its accuracy, and simplicity.

### 7.2 Future Work

It is certain that this work can be further improved by investigating the impact of temperature on the battery under different aging conditions. Due to the time allowance, the impact has been assumed to be unchanged throughout the battery’s life. Similarly, an investigation of the impact of the temperature and aging on the hysteresis phenomenon could be conducted to increase the robustness of the estimation. Therefore, it is recommended for future work to conduct experimental investigations of these assumptions. In addition, whilst the LiFePO$_4$ has a unique OCV-SOC characteristic curve which is almost flat at ranges; the developed approach still achieved accurate estimation results. It is believed that the outcome of this thesis is applicable to other types of rechargeable batteries, nevertheless, validations are recommended in future work.

The estimation approach developed in this thesis is for a single cell, although it is economically possible to have a management board for each cell thanks to its high capacity rate. One worthwhile direction of future work would be to verify whether the estimation approach is able to monitor a number of cells. This could potentially help to reduce the cost of the hardware required for a complete system.
Appendix A

Publications & Presentations

Publications:


Presentations:

Appendix B

Additional Experimental Results

Fig. B-1. Charge and discharge voltage under humidity conditions at 25°C.

Fig. B-2. Experimental results of the UDDS load profile at 0°C.
Appendix B. Additional experimental results

Fig. B-3. Experimental results of the UDDS load profile at 20°C.

Fig. B-4. Experimental results of the UDDS load profile at 40°C.

Fig. B-5. Cycling voltage during aging acceleration process.
Appendix C

Program Flowchart

Fig. C-6. A program flowchart of the developed estimation approach.
Appendix D
Acronyms

List of symbols:

$A_f$  
front area

$b_0, b_1, a_1$  
variables of the regressor vector

$C$  
battery capacity

$c_0, c_1$  
fitting parameters of battery capacity $C$

$C_1$  
parallel capacitance in the battery model

$C_{\text{bulk}}$  
bulk layer capacitance

$C_{\text{disch}}$  
discharged capacity of the battery

$C_D$  
aerodynamic drag coefficient

$C_{\text{Full}}$  
full potential capacity of the battery

$C_{\text{remained}}$  
remaining charge of the battery

$C_{\text{surface}}$  
surface capacitance

$C_{\text{Temp}}$  
battery capacity at any given temperature

$E_{\text{eq}}$  
equilibrium voltage

$f_r$  
rolling resistance coefficient

$G$  
transfer function of the battery impedance

$g$  
gravity acceleration

$h_i$  
normalization factor

$I$  
battery current

$i$  
grade of road (chapter 3)

$I_b$  
bulk layer current

$I_s$  
surface current

$k_{\text{OCV}}$  
feedback gain of state of charge estimation
<table>
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<tr>
<th>Acronym</th>
<th>Definition</th>
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<tr>
<td>$k_{R0}$</td>
<td>feedback gain of resistance estimation</td>
</tr>
<tr>
<td>$L$</td>
<td>vector gain for the parameter vector</td>
</tr>
<tr>
<td>$L_i$</td>
<td>gain for each variable of the parameter vector</td>
</tr>
<tr>
<td>$M$</td>
<td>vehicle mass with passengers</td>
</tr>
<tr>
<td>$m, n, p$</td>
<td>parameters of the asymptotic regression model</td>
</tr>
<tr>
<td>$m_i$</td>
<td>width factor</td>
</tr>
<tr>
<td>$N$</td>
<td>number of batteries</td>
</tr>
<tr>
<td>$P_i$</td>
<td>covariance error for each variable of the parameter vector</td>
</tr>
<tr>
<td>$r$</td>
<td>temperature-resistance ratio</td>
</tr>
<tr>
<td>$R_0$</td>
<td>internal resistance (ohmic resistance) in the battery model</td>
</tr>
<tr>
<td>$r_0, r_1, r_2$</td>
<td>fitting parameters of temperature-resistance factor $r$</td>
</tr>
<tr>
<td>$R_{0 \text{RLS}}$</td>
<td>$R_0$ estimated by MAFF-RLS</td>
</tr>
<tr>
<td>$R_1$</td>
<td>parallel resistance in the battery model</td>
</tr>
<tr>
<td>$R_{\text{BOL}}$</td>
<td>resistance of the battery at the beginning of life</td>
</tr>
<tr>
<td>$R_{\text{EOL}}$</td>
<td>resistance of the battery at the end of line</td>
</tr>
<tr>
<td>$R_e$</td>
<td>bulk layer resistance</td>
</tr>
<tr>
<td>$R_s$</td>
<td>surface resistance</td>
</tr>
<tr>
<td>$R_t$</td>
<td>terminal resistance</td>
</tr>
<tr>
<td>$RC$</td>
<td>resistance-capacitance parallel circuit</td>
</tr>
<tr>
<td>$RC_{\text{short}}$</td>
<td>$RC$ network representing the charge-transfer phenomenon</td>
</tr>
<tr>
<td>$RC_{\text{long}}$</td>
<td>$RC$ network representing the diffusion phenomenon</td>
</tr>
<tr>
<td>$s$</td>
<td>complex variable in Laplace transform</td>
</tr>
<tr>
<td>$T$</td>
<td>battery temperature</td>
</tr>
<tr>
<td>$t$</td>
<td>time</td>
</tr>
<tr>
<td>$t_h$</td>
<td>long relaxation time</td>
</tr>
<tr>
<td>$t_m$</td>
<td>short relaxation time</td>
</tr>
<tr>
<td>$T_s$</td>
<td>sampling time</td>
</tr>
</tbody>
</table>
Appendix D. Acronyms

UFRC voltage drop on the impedance
VB battery working voltage
Vh,max maximum hysteresis voltage
Vh hysteresis voltage
y battery voltage in the system equation

List of abbreviations:
MAE mean absolute error
PE peak error
RMSE root-mean-square error
AEKF adaptive extended Kalman filter
ANN artificial neural network
ARX autoregressive exogenous model
AUKF adaptive unscented Kalman filter
BMS battery management system
BOL begin of life
CC constant current
CCP constant current pulse
CPE constant phase element
CV constant voltage
DEKF dual extended Kalman filter
ECM electrochemical model
EECM electrical equivalent circuit model
EIS electrochemical impedance spectroscopy
EKF extended Kalman filter
EOL end of life
EV electric vehicle
FLOP floating-point operation
<table>
<thead>
<tr>
<th>Acronym</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td>GA</td>
<td>genetic algorithm</td>
</tr>
<tr>
<td>IC</td>
<td>incremental capacity</td>
</tr>
<tr>
<td>JEKF</td>
<td>joint extended Kalman filter</td>
</tr>
<tr>
<td>KF</td>
<td>Kalman filter</td>
</tr>
<tr>
<td>LCO</td>
<td>lithium cobalt oxide</td>
</tr>
<tr>
<td>LFP</td>
<td>lithium iron phosphate</td>
</tr>
<tr>
<td>LIB</td>
<td>lithium-ion battery</td>
</tr>
<tr>
<td>LMO</td>
<td>lithium manganese oxide</td>
</tr>
<tr>
<td>LUT</td>
<td>lookup table</td>
</tr>
<tr>
<td>MAFF</td>
<td>multiple adaptive forgetting factor</td>
</tr>
<tr>
<td>MFF</td>
<td>multiple forgetting factor</td>
</tr>
<tr>
<td>MOL</td>
<td>middle of life</td>
</tr>
<tr>
<td>NEDC</td>
<td>New European Driving Cycle</td>
</tr>
<tr>
<td>NMC</td>
<td>lithium nickel-manganese-cobalt</td>
</tr>
<tr>
<td>NN</td>
<td>neural network</td>
</tr>
<tr>
<td>OCV</td>
<td>open circuit voltage</td>
</tr>
<tr>
<td>OCV_{RLS}</td>
<td>OCV estimated by MAFF-RLS</td>
</tr>
<tr>
<td>OCV_{dev}</td>
<td>OCV deviation between different temperatures</td>
</tr>
<tr>
<td>P2D</td>
<td>pseudo-two-dimensional</td>
</tr>
<tr>
<td>PDE</td>
<td>partial differential equations</td>
</tr>
<tr>
<td>PF</td>
<td>particle filter</td>
</tr>
<tr>
<td>RBFNN</td>
<td>radial basis function neural network</td>
</tr>
<tr>
<td>RLS</td>
<td>recursive least-squares</td>
</tr>
<tr>
<td>SFFF</td>
<td>single fixed forgetting factor</td>
</tr>
<tr>
<td>SMO</td>
<td>sliding mode observer</td>
</tr>
<tr>
<td>SOC</td>
<td>state of charge</td>
</tr>
<tr>
<td>SOC^{BOL}_{F}</td>
<td>state of charge based on $C_{\text{Full}}$ at BOL</td>
</tr>
</tbody>
</table>
Appendix D. Acronyms

<table>
<thead>
<tr>
<th>Acronym</th>
<th>Definition</th>
</tr>
</thead>
<tbody>
<tr>
<td>SOC_F</td>
<td>state of charge based on $C_{\text{Full}}$</td>
</tr>
<tr>
<td>SOC_T</td>
<td>state of charge based on $C_{\text{Temp}}$</td>
</tr>
<tr>
<td>SOH</td>
<td>state of health</td>
</tr>
<tr>
<td>SPM</td>
<td>single particle model</td>
</tr>
<tr>
<td>SVM</td>
<td>support vector machine</td>
</tr>
<tr>
<td>SVR</td>
<td>support vector regression</td>
</tr>
<tr>
<td>UDDS</td>
<td>Urban Dynamometer Driving Schedule</td>
</tr>
<tr>
<td>UKF</td>
<td>unscented Kalman filter</td>
</tr>
</tbody>
</table>

List of Greek symbols:

- $\alpha$: scaling factor
- $\alpha_i$: hysteresis saturated integrator
- $\delta$: rotational inertia factor
- $\varepsilon$: residual error
- $\eta$: Coulombic efficiency
- $\eta_r$: efficiency from wheel to battery
- $\eta_w$: efficiency from battery to wheel
- $\lambda_i$: forgetting factor for each variable of the parameter vector
- $\phi$: regressor vector in the ARX model
- $\rho$: temperature-capacity factor
- $\rho_a$: air density
- $\theta_i$: parameter vector in the ARX model
- $\zeta_i$: constant factor for forgetting factor

List of main subscripts:

- $i$: vector parameter index
- $k$: time step index
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