ENHANCEMENTS OF ONLINE ADAPTIVE LYAPUNOV-BASED OBSERVER FOR STATE OF CHARGE ESTIMATION OF LITHIUM-ION BATTERIES

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ABSTRACT

Owing to the rapid growth of electric vehicles (EV), temporary energy storage and mobile applications, the battery management system (BMS) plays an indispensable role in ensuring the safety, efficiency, and longevity of the battery. To achieve these features, the state of charge (SOC) estimation algorithm must be enhanced. Since the BMS processor repeatedly executes the SOC for a massive number of cells, the algorithm must be computationally simple, efficient, and accurate. The online estimation of lithium-ion SOC using the recently published adaptive Lyapunov-based observer is an attractive proposition due to the stability, adaptability, and reduced computing requirements. However, the observer requires the presence of persistent excitation (PE) to guarantee the convergence of the battery model parameters to their correct values. Although several important works have utilized this observer, they only apply dc excitation—which implies that the PE condition was never met. Thus, one objective of this thesis is to modify the observer so that it can be used to estimate the SOC for the dc and low excitation signals. Furthermore, there is insufficient work in the literature that demonstrates the application of the observer to estimate the SOC for EV. The motivation is the possibility of capitalizing on the EV driving profiles' inherent sufficiently rich (SR) signals to satisfy the PE condition. The performance of the SOC algorithm based on the proposed online observer is simulated on MATLAB/Simulink. Furthermore, the experimental validations are done at room temperature for a 3 Ah single cell of type Lithium Nickel Manganese Cobalt oxide (NMC). The algorithm is tested using dynamic stress test (DST) and real EV driving profiles, namely the supplemental federal test procedure (US06) and the federal urban driving schedule (FUDS). The performance of the observer is compared to the extended Kalman filter-recursive least squares (EKF-RLS). The proposed scheme requires 2.5 times less computational effort while retaining similar degree of accuracy to the latter. In addition, to fulfil the PE condition at low current excitation, a method called forced excitation is proposed. The SR signals are generated by chopping the battery current at a certain rate for a specific interval. The simulation and experimental results showed that the forced excitation method enables the observer to estimate the SOC reliably under dc condition. In addition, a simple scheme using a supercapacitor to compensate for the interruption in battery current and deliver continuous current to the load is suggested. It is envisaged that the proposed observer can contribute to the design of a customized and high performance BMS for many applications.

ABSTRAK

Berdasarkan pada perkembangan kereta elektrik, penyimpan tenaga sementara aplikasi mudah alih yang berasaskan bateri, sistem pengurusan bateri (BMS) memainkan peranan yang amat penting bagi memastikan keselamatan, kecekapan dan jangkahayat bateri. Untuk mencapai manafaat ini, algoritma anggaran keadaan cas (SOC) perlu di pertingkatkan. Oleh kerana pemproses BMS melaksanakan SOC secara berulang kali untuk sejumlah besar sel, algoritma mestilah bersifat ringkas, cekap dan tepat. Terbarun, anggaran dalam talian bagi Lithium-ion SOC dengan menggunakan pemerhati berasaskan Lyapunov merupakan cadangan yang menarik kerana kestabilan, kebolehsuaian dan pengurangan kepada keperluan pengkomputeran. Walau bagaimanapun, ia memerlukan kehadiran pengujaan berterusan (PE) untuk menjamin penumpuan parameter model bateri pada nilai yang betul. Walaupun beberapa kajian penting telah menggunakan pemerhati ini, mereka hanya menggunakan pengujaan arus terus (DC) - yang menunjukkan bahawa keadaan PE tidak dapat dicapai. Oleh itu, salah satu objektif kajian dalam tesis ini adalah untuk mengubah pemerhati sehingga dapat digunakan bagi menganggar SOC untuk dc dan isyarat rangsangan rendah. Tambahan pula, kajian yang tidak mencukupi dalam literatur yang menunjukkan penerapan pemerhati bagi menganggarkan SOC untuk kenderaan elektrik (EV). Motivasinya adalah kemungkinan bagi memanfaatkan isyarat yang cukup kaya (SR) dari profil pemanduan EV untuk memenuhi syarat PE. Prestasi algoritma SOC berdasarkan pemerhati dalam talian disimulasikan dalam MATLAB/Simulink. Kerja ujikaji dan pengesahan dilakukan pada suhu bilik untuk sel tunggal 3 Ah jenis Lithium Nickel Manganese Cobalt oxide (NMC). Algoritma diuji menggunakan ujian tekanan dinamik (DST) dan profil pemanduan EV sebenar, iaitu prosedur ujian persekutuan tambahan (US06) dan jadual pemanduan bandar persekutuan (FUDS). Prestasi pemerhati dibandingkan dengan penapis Kalman filter dipanjangkan-recursive least squares (EKF-RLS). Skim yang dicadangkan memerlukan 2.5 kali kurang usaha pengiraan sambil mengekalkan ketepatan yang serupa dengan yang terakhir. Tambahan lagi, untuk memenuhi syarat PE pada pengujaan arus rendah, kaedah yang dipanggil pengujaan paksa dicadangkan. Isyarat SR dijana dengan memotong arus bateri pada kadar tertentu untuk selang tertentu. Hasil simulasi dan ujikaji menunjukkan bahawa pengujaan paksa membolehkan pemerhati menganggar SOC dengan tepat di bawah keadaan dc. Sebagai tambahan, skema mudah bagi mengimbangi gangguan arus bateri dan untuk menyampaikan arus berterusan ke beban adalah disarankan dengan menggunakan supercapacitor. Adalah dinyatakan juga bahawa pemerhati yang dicadangkan ini dapat memberi sumbangan untuk merancang BMS yang sesuai dan berprestasi tinggi kepada banyak lagi aplikasi lain.

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LIST OF ABBREVIATIONS

AEKF	-	Adaptive Extended Kalman Filter
ASPKF	-	Adaptive Sigma Point Kalman Filter
BCU	-	Battery Charging Unit
BMS	-	Battery Management System
BP	-	Back Propagation
CALEC	-	Center for Advanced Life Cycle Engineering
CAN	-	Controller Area Network
CC	-	Coulomb Counting
CCCV	-	Constant Current Constant Voltage
CDKF	-	Central Difference Kalman Filter
D-EKF	-	Dual-Extended Kalman Filter
DST	-	Dynamic Stress Test
ECM	-	Equivalent Circuit Models
EIS	-	Electrochemical Impedance Spectroscopy
EV	-	Electric Vehicle
EKF	-	Extended Kalman Filter
FUDS	-	Federal Urban Driving Schedule
HEV	-	Hybrid Electric Vehicles
HPPC	-	Hybrid Pulse Power Characterization
ICE	-	Internal Combustion Engine
KF	-	Kalman Filter
LCO	-	Lithium Cobalt Oxide
LFP	-	Lithium Iron Phosphate
LMO	-	Lithium Manganese Oxide
LTO	-	Lithium-Titanate
MAE	-	Mean Absolute Error
ML	-	Machine Learning
MWLS	-	Moving Window Least-Squares
NaS	-	Sodium Sulphur
NCA	-	Nickel-Cobalt-Aluminium-oxide
NEDC	-	New European Driving Cycle

NiCd	-	Nickel Cadmium
NiMH	-	Nickel Metal-Hydride
NMC	-	Lithium Nickel Manganese Cobalt oxide
NN	-	Neural Network
OCV	-	Open Circuit Voltage
PIO	-	Proportional Integral Observer
PDEs	-	Partial Differential Equations
PDF	-	Probability Density Function
PE	-	Persistence Excitation
PNGV	-	Partnership for a New Generation of Vehicles
PSO	-	Particle Swarm Optimization
P2D	-	Pseudo-Two-Dimensional Model
RE	-	Renewable Energy
Redox	-	Oxidation-Reduction
RLS	-	Recursive Least Square
RMES	-	Root Mean Square Error
RNN	-	Recurrent Neural Network
ROM	-	Reduced-Order Model
RPF	-	Radial Basis Function
SZDC	-	Shenzhen Driving Cycle
SMO	-	Sliding Mode Observer
SOC	-	State of Charge
SOE	-	State of Energy
SOH	-	State of Health
SOP	-	State of Power
SP	-	Single Particle Model
SPMe	-	Single Particle Model with Electrolyte Dynamics
SPKF	-	Sigma Point Kalman Filter
SR	-	Sufficiently Rich
SVR	-	Support-Vector Regression
UAV	-	Unmanned Aerial Vehicles
UDDS	-	Urban Dynamometer Driving Schedule
UKF	-	Unscented Kalman Filter
UPS	-	Uninterruptible Power Supply
US06	-	Supplemental Federal Test Procedure

ZEBRA	-	Zeolite Battery Research Africa Project

LIST OF SYMBOLS

C	-	Dynamic Capacitor in EMC Model
C_B	-	main capacitor for storing charge
C_b	-	Series capacitor in PNGV model
E_0	-	DC gain in mathematical model
e	-	Terminal voltage estimation error
$G^n_{best,i}$	-	Best position for all numbers of iterations
I_n	-	Identity matrix
I_b	-	Battery Current in general
I_{meas}	-	Battery measured current
I_{actu}	-	Battery actual current
I_{noise}	-	Current measurement noises
I_{offset}	-	Offset of the current sensor
$I_{A/D}$	-	Error of A/D convergence in current measurement
$I_{self\ disch}$	-	self discharge current
I_{leak}	-	leakage current
i_k	-	Cell current in mathematical model
K_d	-	Strictly Positive Observer Gain
K_1, K_2, K_3	-	Curve fitting constants. in mathematical model
$M\ (\omega)$	-	Magnitude gain of battery's impedance
$P^n_{best,i}$	-	Best position for the particle in one iteration
Q	-	Total Capacity of Battery
Q1C	-	1C-Rate Discharge Capacity of Battery
Qnom	-	Nominal capacity of Battery
R	-	Dynamic Resistance in EMC Model
R_b	-	Internal Resistance in EMC Model
R_k	-	Cell internal resistance in mathematical model
ra_1, ra_2	-	Two random numbers in the range [0,1].
SOC_0	-	Initial value of SOC
V_{max}	-	Maximum Allowed Voltage by Battery's Manufacturer
V_{min}	-	Minimum Allowed Voltage by Battery's Manufacturer
V_{oc}	-	Open Circuit Voltage
V_p	-	Voltage over the RC Network in EMC Model

V_k	-	Battery voltage in mathematical model
$v_i^n(k)$	-	Velocity of the particle in PSO
$w(k)$	-	Inertia weight
W	-	Vector of actual parameters of battery model
$\widehat{W}$	-	Vector of estimated parameters of battery model
$x_i^n(k)$	-	Position of the particle in PSO
$Z(\omega)$	-	battery's impedance as function of frequency
α_0, α_1	-	Positive constant
β	-	Observation period
$\emptyset\ (\omega)$	-	Phase shift of battery's impedance
Φ	-	Regressor vector contains the inputs of adaptive observer
Γ	-	Positive Adaptive Gain
η	-	Columbic Efficiency
Λ_1	-	Cognitive learning factors
Λ_2	-	Social learning factors

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APPENDIX	TITLE	PAGE

CHAPTER 1

INTRODUCTION

1.1 Background

Battery-powered devices such as mobile phones, laptops, home appliances, portable tools, electric bikes, and electric vehicles (EVs) have become an indispensable part of modern daily life. The batteries, which are the workhorses of these devices, are in great demand, particularly in the areas of renewable energy (RE) and electric vehicle (EV). In the RE system, batteries are utilized to stabilize the grid and provide assistance during the absence of renewable sources [1]. Since the sources are intermittent, it is vital to store the energy during excess generation and re-deliver it when the demand is high. For EV, many countries have set new policies that aim to replace internal combustion engine (ICE) vehicles to reduce air pollution and prepare for the expected depletion of fossil fuels.

The developments in electro-chemistry research and manufacturing processes have paved the way for various battery technologies with different capabilities and features. Among them, the lithium-ion battery is the most popular due to its intrinsic advantages, such as low self-discharge, high energy density, and high efficiency. It also has an extensive lifespan and offers more deep-discharge cycles [2]. However, lithium-ion batteries are sensitive to over-charging and over-discharging problems. Therefore, a battery management system (BMS) has become a necessity to monitor, control, and maximize the battery's lifetime. The BMS needs to acquire, measure, condition, and process the voltage, current, and temperature signals, perform cell balancing, and protect the battery pack from over-charging and over-discharging. For EV applications, it also acts as an interface with other electronic devices inside the vehicle [3, 4].

Many battery-related accidents have been reported in recent years, mainly in mobile phones (particularly Samsung phones), e-cigarettes, and EVs. For example, critical accidents were repeated three times in the lithium-ion battery pack of the Boeing 787 aeroplanes. These accidents happened at Boston Airport (2013), Takamatsu Airport, Japan (2013), and Narita International Airport (2014) [5]. Figure 1.1 shows the new and damaged lithium-ion battery pack in one of the said aeroplanes. A malfunctioning BMS is believed to be the main reason for the damage, in which the thermal runaway initiates the problem in a cell of the pack.

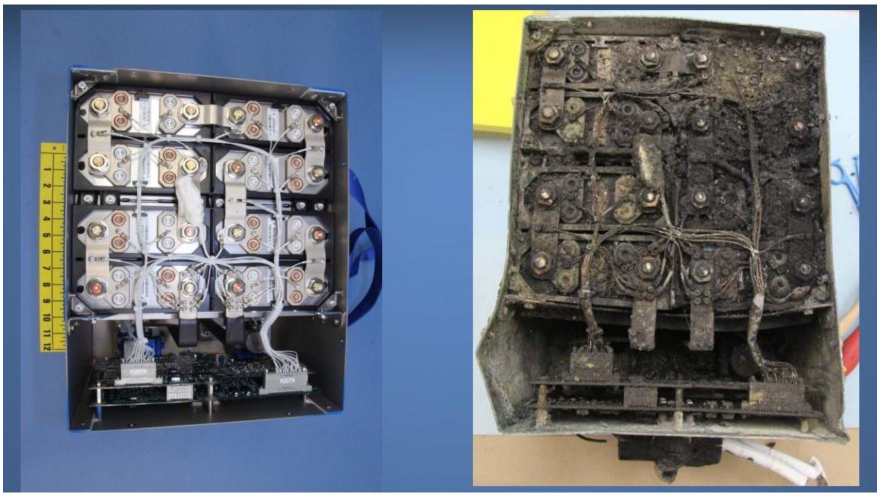

Figure 1.1 A new and damaged lithium-ion battery pack in a Boeing 787 [6]

1.2 State of Charge Estimation

The main function of the BMS is to estimate the battery states accurately. Three important indices are the state of charge (SOC) [7], the state of health (SOH) [8] and the state of power (SOP) [9]. The SOC is a measure to know the available charge in the battery; the SOH provides the battery ageing level information; and the SOP indicates the available power in the immediate future.

By far, the SOC is the most important function for BMS. Therefore, any work related to BMS should directly improve the accuracy and efficiency of the SOC algorithm. The SOC estimation approaches vary widely: one can opt for the simple but inaccurate coulomb counting (CC) method [7]. There are options to utilize advanced algorithms based on machine learning and artificial intelligence [10, 11]. High accuracy can be achieved, but at the expense of complexity and high computing requirements.

The Kalman filter (KF)-based methods are the most widely used SOC. They estimate the battery state very accurately, even in the presence of noise. It has several variations, for example, the extended Kalman filter (EKF) [12] and the sigma point Kalman filter (SPKF) [13, 14]. One of the main drawbacks of the KF-based methods is the need for extensive computing power to perform a large number of matrix multiplications. As a result, it consumes a large portion of BMS's computing resources [15]. Moreover, the EKF requires prior knowledge of the battery model's parameters before the estimation can be made. To obtain these parameters, additional procedures have to be incorporated into the original EKF algorithm. Two popular methods, namely the dual EKF (D-EKF) [16] or EKF with recursive least square (EKF-RLS) [17], are used. By using this improved approach, the algorithm is able to estimate the state and the parameters simultaneously. Although the estimation performance is improved, the D-EKF and EKF-RLS require even more processing time to satisfy these additional functions.

Recently, another SOC method based on an online adaptive observer has been published in several reputable journals [18-23]. Its main feature is inherent stability, which is proven by the Lyapunov approach. Another advantage is the simplicity of the observer's structure. It contains a few simple recursion equations without matrix inversion; thus, the computational burden is significantly reduced. In addition, it is claimed that the observer achieves simultaneous estimation of SOC and the battery's model parameters. Therefore, additional parameter estimation technique is not needed. This is in contrast with the methods (for example, EKF), which require all battery parameters to be known prior to the estimation. It also avoids the need for an additional online parameter estimation technique (for example, D-EKF and EKF-RLS).

Despite these favourable advantages, the above-mentioned adaptive observer requires the persistence excitation (PE) condition to be fulfilled. In order to estimate the battery parameters, PE entails that the current and voltage signals of the battery must contain sufficient information about its dynamics. In practice, the PE condition is satisfied using a sufficiently rich (SR) input current that includes a number of frequency components [24]. For EV applications, PE can be achieved by the driving profiles, which have a fluctuating nature. However, in the literature, the observer has not been extensively studied in this context. Therefore, it is important to test the observer's performance under different driving profiles of EVs. On the other hand, for the application that exhibits low current excitation, or dc, the PE can never be met, and thus, the observer does not work under this condition.

It has to be noted that the PE requirement is not easily implementable, especially in the discharging mode. This is because the current changes uncontrollably according to battery consumption. A typical solution in parameter estimation to fulfil PE is to add a perturbation that is considered an SR signal and remove it once the convergence is achieved [25, 26]. However, adding an external signal means additional current needs to be drawn from the battery. This process is unacceptable as it disrupts the primary function of the battery by hastened discharge. On top of that, a physical circuit is needed to generate the signal within the battery system. Therefore, a method needs to be devised so that the SOC can be estimated without severely impacting the discharging current profile on the load.

1.3 Problem Statement

Based on the overview mentioned above, it is concluded that the online adaptive Lyapunov-based observer is a noteworthy concept and worth investigating. It has several distinct advantages that make it superior to other SOC methods. However, this particular observer has one significant restriction: it needs to excite the battery with an SR signal, which can be achieved by fulfilling the PE conditions. Since the typical charging and discharging profiles of the battery are not able to create such a condition, the observer is not practically viable [18-23].

Although the application of this observer is reported in [19-22], they did not provide any evidence for the fulfilment of PE. For its practical demonstration, the battery model is shown to be excited by direct current, which does not qualify as an SR signal. With the lack of frequency excitation, the observer will never converge toward the battery parameters, and thus, the validity of the published results is in serious doubt. Based on these premises, the following research statements are written:

1. There is a need for a comprehensive proof of this observer stability criterion, based on the Lyapunov theory, under the PE condition.

2. There is a potential for this observer to be applied as the SOC scheme of an EV application. This is due to the inherent availability of SR signals in the EV driving profiles. Moreover, it is important to evaluate its performance when compared to other more established SOC methods. Since there is insufficient research on these aspects, the observer's implementation for EV applications needs to be investigated.

3. Furthermore, it is essential to find a scheme that will allow the observer to be used under dc and slow time-varying signals. Thus, the observer can still be used in applications such as storage for RE systems. An analysis and solution for the observer under a low excitation level needs to be sought.

1.4 Research Objectives

The research statements on the application of the adaptive Lyapunov-based observer for SOC estimation have led to the following objectives:

1. To improve the design of an adaptive Lyapunov-based observer for simultaneous estimation of battery parameters and SOC.

2. To apply the adaptive Lyapunov-based observer for SOC estimation in an EV application and to evaluate its superiority in terms of computational cost compared to EKF-RLS.

3. To propose the forced excitation approach, which allows the observer to work with low excitation levels.

1.5 Research Scope

This research has the following limitations:

1. The algorithm is developed to estimate the SOC for a single lithium-ion cell. In general, most of the SOC algorithms in the literature are evaluated on a signal cell only, while the SOC calculation for the whole pack is related to another research scope. In the battery pack, if the cells are connected in series, they will have the same current but different voltages. On the other hand, if they are connected in parallel, they will have the same voltage but different currents. Since the SOC algorithm requires the voltage and current for each individual cell, the SOC estimation for the whole battery pack is performed first by the SOC estimation of each individual battery. Then, the average results can be taken.

2. The experimental work and algorithm validation are done at room temperature. The validation for different temperatures can be done in the future if a temperature chamber is available. The relationship between open circuit voltage (OCV) and the SOC of the battery can be acquired at different temperatures. Then, a temperature post-compensation scheme can be added to the observer [20-22], allowing parameter estimation for varying temperature conditions.

3. The algorithm is tested for the Lithium Nickel Manganese Cobalt oxide (NMC) battery type. However, it is also applicable to other kinds of lithium-ion and different types of batteries. It is important to note that the

implementation for the Lithium Iron Phosphate (LFP) chemistry is expected to result in less accuracy due to the flat OCV-SOC relation compared with other batteries.

1.6 Thesis Organization

The thesis is organized into six chapters. The outlines of the contents are as follows:

1. Chapter 2 presents the battery's working principle and the characteristics of the most common battery types. Then the main functions of the BMS are explained. After that, the benefits of SOC and definitions related to it are introduced. A large part of this chapter is dedicated to a comprehensive literature review of SOC methods, showing advantages and disadvantages for each of them.

2. In chapter 3, the adaptive observer design is presented, which contains four main steps: At the beginning, the first-order battery model is written as one input/output equation. Second, the adaptive laws of the observer are proposed, and its stability is proved based on the Lyapunov theory. Third, simulation analysis of the observer performance is discussed to show the appropriate input signals that achieve the PE condition. Finally, the continuous-time equations of the observer are discretized. Thus, the observer can be directly implemented on a digital controller.

3. In Chapter 4, the experimental verification of the proposed method is shown. In the beginning, the initial tests on the lithium-ion battery are conducted, which include a capacity test, a SOC-OCV curve, and the identification of the battery model parameters using Particle Swarm Optimization (PSO). These tests are essential as reference values to validate the observer’s performance and battery model. After that, the observer algorithm validation under real driving profiles of EV is presented and compared with EKF-RLS. Finally, the

proposed observer code's computational cost evaluation shows a massive improvement compared to the EKF-RLS code.

4. In Chapter 5, the observer is evaluated when the input current has low level excitation, which does not meet the PE condition. Simulation work is carried out using MATLAB and Simulink to demonstrate the flaws in previous works that claim the observer's workability under DC excitation. Then, the idea of forced excitation is simulated by MATLAB/Simulink. The functionality of the observer with forced excitation has been experimented on the tested battery. Finally, the recommended applications that require the implementation of forced excitation are described.

5. In Chapter 6, the conclusion of the thesis is presented. An overview of the recommended and expected work to improve the observer in the future is suggested.

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LIST OF PUBLICATION

Journal with Impact Factor

1. **Othman BM**, Salam Z, Husain AR. A computationally efficient adaptive online state-of-charge observer for lithium-ion battery for electric vehicle. *Journal of Energy Storage.* 2022 May. 1;49:104141. **(Q1, IF:6.583)**

2. **Othman BM**, Salam Z, Husain AR. Analysis of online Lyapunov-based adaptive state of charge observer for lithium-ion batteries under low excitation level. *IEEE Access.* 2020 Sep. 28;8:178805-15. **(Q2, IF:3.367)**