LITHIUM FERRO PHOSPHATE ($LiFePO_4$) BATTERY STATE OF CHARGE ESTIMATION USING UNSCENTED KALMAN FILTER

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DEDICATION

This thesis is specially dedicated to my father, who taught me that the best kind of knowledge to have is that which is learned for its own sake. For my beloved mother, who always pray for my successfulness and happiness. For my wife and children that had sacrificed a lot during my study.

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ABSTRACT

Throughout the past year, the development of Electric Vehicles (EVs) has been rapidly increasing due to shortage of unsustainable energy source and global climate warming. Battery is one of the key technologies applied in EVs that also contributes to the restriction of EVs expansion. Lithium Ferro Phosphate ($LiFePO_4$) is one of the lithium-ion batteries that is widely used due to its high energy density, long lifespan, high efficiency, fast charging characteristic and low self-discharge. For battery management system (BMS), the state of charge (SOC) estimation of the battery is an indispensable parameter that need to be essentially considered. The accuracy of SOC estimation is very crucial to monitor the charging and discharging operation of the battery pack for optimizing the performance and prolong the lifespan of the battery. Since the battery stores the energy in the chemical state, and this chemical energy cannot be directly accessed, then the SOC estimation becomes very complex. This also includes many uncertainties and noises contribute a challenge in determining the accuracy of the SOC estimation. The objectives of this project focus on the development of the $LiFePO_4$ battery model using Equivalent Circuit Model (ECM) to predict the SOC by using Unscented Kalman Filter (UKF) algorithm. Several battery ECMs with up to three level of RC pairs have been studied to compare the accuracy of the model. The battery ECM parameters were estimated using MATLAB Parameter Estimation Tool by utilising the dynamic behaviours of the $LiFePO_4$ battery from the experimental data. The dynamic characteristics of the $LiFePO_4$ battery have been experimentally studied by using Constant Discharge Test (CDT), Pulse Discharge Test (PDT) and Random Charge and Discharge Test (RCDT). The SOC estimation by using UKF algorithm was implemented by using battery ECM from one RC pair until three RC pairs. Then, the accuracy of the battery ECMs were analysed by using error analysis such as Mean Absolute Error (MAE), Mean Square Error (MSE) and Root Mean Square Error (RMSE). From the result of error analysis, the most accurate battery ECM was selected to be implemented in the UKF algorithm to estimate the SOC of the $LiFePO_4$ battery The results from the simulation are then validated by comparing to the real SOC by using Coulomb Counting method Then, the performance of the UKF algorithm was compared to the Extended Kalman Filter (EKF) and Particle Filter (PF) by using error analysis of MAE, MSE and RMSE. From the result of the error analysis, the most accurate algorithm for estimating the SOC is determined.

ABSTRAK

Sejak beberapa tahun kebelakangan ini, pembangunan kenderaan elektrik sangat pesat dijalankan berikutan pemanasan iklim global dan kekurangan sumber tenaga asli. Bateri merupakan komponen yang sangat penting dalam kenderaan elektrik. *Lithium Ferro Phosphate* ($LiFePO_4$) merupakan salah satu daripada bateri *lithium-ion* yang digunakan secara meluas kerana ia mempunyai ketumpatan tenaga yang tinggi, kecekapan yang tinggi, jangka hayat yang lama, pengecasan pantas dan kadar nyahcas sendiri yang perlahan. Bagi sistem pengurusan bateri (BMS), anggaran keadaan cas (SOC) adalah parameter yang sangat penting untuk menentukan kadar operasi cas dan nyahcas bateri demi mengoptimumkan prestasi dan memanjangkan jangka hayat bateri. Memandangkan bateri menyimpan tenaga dalam keadaan kimia, dan tidak boleh diukur secara terus, maka proses anggaran SOC menjadi sangat kompleks. Ini juga disebabkan oleh banyak ketidakpastian dan gangguan dalam proses menganggar SOC secara tepat. Objektif projek ini adalah untuk membangunkan model bateri dengan menggunakan model elektrik setara (ECM) dan algoritma *Unscented Kalman Filter* (UKF) untuk menganggarkan SOC. Beberapa jenis ECM dengan satu hingga tiga pasangan RC telah dikaji dalam kecekapan menganggarkan SOC. Nilai bagi parameter RC dalam ECM ditentukan dengan menggunakan *MATLAB Parameter Estimation Tool* dan juga sifat dinamik bateri $LiFePO_4$ yang dikaji secara eksperimen. Tiga jenis pengujian bateri telah dijalankan iaitu pengujian nyahcas tetap (CDT), pengujian nyahcas denyut (PDT) dan pengujian cas dan nyahcas rawak (RCDT). Anggaran SOC telah dijalankan dengan mengunakan algoritma UKF dan ketiga-ketiga jenis ECM dan ketepatan anggaran SOC telah dianalisis dengan menggunakan kaedah analisis ralat seperti purata ralat mutlak (MAE), purata ralat kuasa dua (MSE) dan punca kuasa dua purata ralat kuasa dua (RMSE). Berdasarkan keputusan analisis ralat, model bateri yang mempunyai ketepatan yang paling tinggi telah ditentukan. Seterusnya, dengan menggunakan model bateri yang paling cekap, anggaran SOC telah dijalankan dengan menggunakan algoritma UKF. Kemudian keputusan simulasi ini telah divalidasi dengan membandingkan dengan SOC sebenar yang ditentukan melalui kaedah Pengiraan Coulomb. Seterusnya, prestasi algoritma UKF dinilai dengan menggunakan kaedah analisis ralat iaitu MAE, MSE dan RMSE. Prestasi algoritma UKF juga telah dibandingkan dengan algoritma *Extended Kalman Filter* (EKF) dan juga *Particle Filter* (PF) dalam ketepatan menganggarkan SOC. Berdasarkan keputusan analisis ralat, algoritma yang paling tepat dalam menganggarkan SOC telah ditentukan.

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LIST OF ABBREVIATIONS

BMS	-	Battery Management System
DAQ	-	Data Acquisition
EKF	-	Extended Kalman Filter
EV	-	Electric Vehicle
HEV	-	Hybrid Electric Vehicle
KF	-	Kalman Filter
$LiFePO_4$	-	Lithium Ferro Phosphate
MAE	-	Mean Absolute Error
MSE	-	Mean Square Error
OCV	-	Open Circuit Voltage
PDT	-	Pulse Discharge Test
PF	-	Particle Filter
RC	-	Resistor-Capacitor
RMSE	-	Root Mean Square Error
SOC	-	State of Charge
SOH	-	State of Health
UKF	-	Unscented Kalman Filter
UTM	-	Universiti Teknologi Malaysia

LIST OF SYMBOLS

α	-	Battery capacity
α_U	-	Usable capacity
C_1	-	Capacitance in first RC parallel network
C_2	-	Capacitance in second RC parallel network
C_3	-	Capacitance in third RC parallel network
R_S	-	Series resistance
R_1	-	Resistance in first RC parallel network
R_2	-	Resistance in second RC parallel network
R_3	-	Resistance in third RC parallel network
t	-	Battery runtime
t_E	-	Ending time of relaxation
t_R	-	Ending time of loaded condition
t_S	-	Starting time of loaded condition
V_{k1}	-	Voltage across first RC parallel network
V_{k2}	-	Voltage across second RC parallel network
V_{k3}	-	Voltage across third RC parallel network
V_t	-	Battery voltage
γ	-	State of charge
γ_0	-	Initial SOC of battery
v_k	-	The sensor noise
w_k	-	Process noise or disturbance to the system
x_k	-	System state vector at time index k
y_k	-	Defined as output equation

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CHAPTER 1

INTRODUCTION

1.1 Project Background

The world's energy supply is heavily reliant on non-renewable energy resources like oil, coal, and natural gas, which produce greenhouse gases including carbon monoxide, CO, and carbon dioxide, CO_2. According to International Energy Agency (IEA), by 2018, the world total energy supply is mostly generated by using oil which is 31.6%. The CO_2 emission by 2018 contributed by the consumption of oil and fuel combustion is almost 34.1%. For electricity generation, 38.2% of the total electricity energy is generated by using coal. The coal combustions has produced about 44.0% of CO_2 emission [1]

According to statistics provided by [1], the highest sector that consume oil as the energy source is from transportation sector that includes aviation and rail, which contributes about 58.4%. Due to the price of oil and coal is keep increasing caused by the depletion of the resources and the GHGs effect, hence the transformation in this sector may greatly reduce the dependency on the natural resources and will reduce the GHGs effect.

By referring to [1], the electricity generation by using non-hydro renewable resources that includes solar energy harvesting, contributes about 9.8%. Hence, to reduce more the GHGs effect, the electricity generation must go greener by using more renewable resources. Since the transportation sector have also contributed a severe GHGs effect as describes earlier, thus Electric Vehicle (EV) has got the attention and interest of scientists due to its advantages of zero GHGs emissions and higher efficiency.

Solar energy harvesting and electric vehicle need energy storage to efficiently operate. According to [2], lead acid battery is most widely used in solar photovoltaic (PV) system. However, recent study has shown that lithium-ion battery has an accumulated advantage to replace the lead acid battery in terms of a better energy efficiency and cost effective. For EV application, lithium-ion battery has also been widely utilised due to its long cycle lifespan, high energy efficient and density and considerably environmental safe [3]. Since the lithium-ion battery has been widely implemented in EV and solar PV system, thus the battery management system (BMS) plays an important role to ensure the safe battery operation by monitoring the charge and discharge process based on the state of charge (SOC), state of health (SOH), state of power (SOP) and state of energy [3].

1.2 Battery Management System

The main purpose of BMS implementation is to continuously monitor and manage various states of the lithium-ion battery throughout its operation period [4]. The BMS must has an ability to observe and estimate the battery parameters such as an operating voltage and current, SOC, SOH, ambient temperature, battery aging and internal impedance [4]. A general BMS can be illustrated as shown Figure 1.1.

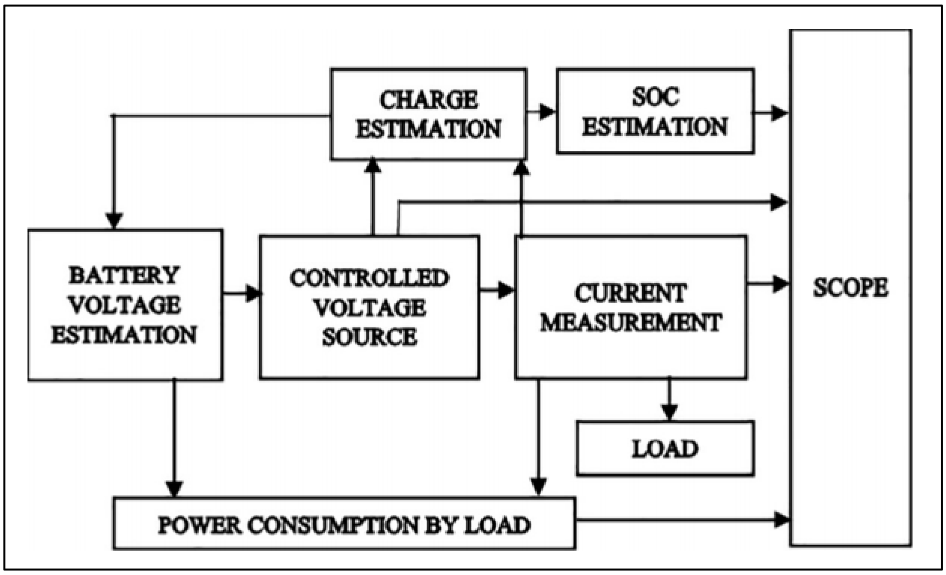

Figure 1.1 Block Diagram of General BMS [4]

1.2.1 Battery Modelling

Battery model is implemented in the BMS to indirectly represents the physical battery. Various sensors are implemented to sense the surface temperature, terminal current and voltage of the battery. Then all the measurements will be applied to the battery model to estimate the battery states such as SOC, SOH and SOP. The battery model parameters must be pre-determined in order for the battery model to perform accurately [5].

There are various battery models that had been studied. They are mainly categorised into three categories which are equivalent circuit model, empirical model and electrochemical model. Electrochemical model is considered as the most accurate model since the model is developed based on physical and chemical reaction in the battery. However, it is not the most suitable model to be implemented in the BMS due to the complexity of the model. Empirical model also known as mathematical model is the simplified model version of electrochemical model. The complexity is reduced but this affects the battery model accuracy by almost 20%. Equivalent circuit model (ECM) consists of series resistor and resistor-capacitor (RC) pair to model the battery characteristics. It has a considerably good accuracy and less complex to be applied in the BMS [5].

1.2.2 State of Charge Estimation

State of charge (SOC) of the battery cannot be directly measured since it represents the electrical energy stored in the chemical state. Hence, SOC needs to be estimated in the BMS by utilising the battery model and the measured battery parameters such as surface temperature, terminal current and voltage of the battery. The performance of the SOC must be accurate, reliable and robust. There are many methods of SOC estimation that had been studied. They generally can be categorised as conventional method, adaptive method and learning algorithm. Conventional method includes open circuit voltage (OCV) method that has high accuracy but cannot be implemented in online BMS application. Adaptive filter includes various filters such as Kalman Filter and Particle Filter (PF) [6]

1.3 Problem Statement

Lithium Ferro Phosphate ($LiFePO_4$) battery is widely implemented in EV that acts as an energy storage element since it could supply a higher energy capacity throughout the longer period and environmentally safe. Hence, a BMS that includes a battery model is critical as a guide for a system designer to forecast the dynamic behaviours of the battery. By utilising an accurate battery ECM along with an accurate state estimation algorithm, the BMS can accurately estimate the SOC of the battery and therefore optimise the battery's performance by managing the charge and discharge process of the battery.

However, to accurately design the SOC estimation of the battery is very challenging due to many uncertainties and noises. The effect of ambient temperature, battery temperature, stability of the sensor's measurement, fluctuation in terminal voltage and current would deteriorate the accuracy and precision of the SOC prediction. Therefore, further study on the battery SOC estimation is very crucial in order to compensate all the noises and uncertainties for a more accurate prediction of the battery SOC.

1.4 Objectives

The objectives of the research are:

a. to develop a battery model by using Equivalent Circuit Model (ECM) and estimate the battery model's parameters based on experimental data of $LiFePO_4$ battery characteristics.

b. to apply the battery ECM for SOC estimation by using Unscented Kalman Filter (UKF) algorithm, then determine the best model of battery ECM.

c. to analyse the performance of UKF SOC estimation by comparing the simulation result with real SOC by Coulomb Counting of $LiFePO_4$ battery and with Extended Kalman Filter (EKF) and Particle Filter (PF) algorithm that had been conducted from the previous research.

1.5 Scope of work

In order to achieve the above-mentioned objectives, this research will focus on the scopes as below:

a. LiFePO4 battery is chosen due to fast charging performance and environmentally friendly.
b. battery ECM is considered as a cell level only, so that the common multiple cells problem such as cell imbalance and individual cell voltage monitoring can be neglected.
c. up to three level of RC pairs will be studied for the battery ECM.
d. UKF algorithm is chosen to perform SOC estimation due to its accuracy and robustness.
e. the performance of UKF will be analysed by comparing to the real SOC by Coulomb Counting method, EKF and PF method.

1.6 Report Outline

To further proceed for this report, some literatures and previous works are reviewed and studied in chapter 2. Two main parts of the literature review is to study the battery modelling and state of charge (SOC) estimation methods. Several battery models are reviewed and compared to determine the best battery model to be implemented. Then, various SOC estimation methods are studied to compare the performance and complexity of each SOC estimation method. Consequently, the SOC estimation method with considerably high accuracy and less complex is chosen.

In chapter 3, the methodology to achieve the research objectives are being proposed. The method starts with the experimental works for the $LiFePO_4$. The dynamic characteristic of the battery is studied by conducting the Constant Discharge Test (CDT), Pulse Discharge Test (PDT) and Random Charge Discharge Test (RCDT), thus the battery model parameters can be determined by using MATLAB Parameter Estimation Tool. Since the SOC of the $LiFePO_4$ battery cannot be assessed directly, then the Coulomb Counting method based on measured current is performed to determine the SOC. This SOC is considered as the real SOC of the $LiFePO_4$ battery. Then, the SOC estimation by using Unscented Kalman Filter (UKF) has been performed. The performance of the UKF has been evaluated by analysing the error analysis as compared to the real SOC, EKF and PF method. Thus, the best SOC estimation method can be suggested.

In chapter 4, the results have been discussed. The CDT, PDT and RCDT are presented. Thus, the dynamic characteristics of the $LiFePO_4$ battery can be observed. Then, the real SOC $LiFePO_4$ battery has been determined by using Coulomb Counting method. The results from the previous researcher that includes the EKF and PF method for SOC estimation also have been presented in this chapter. The results of battery ECM RC parameters estimation by using MATLAB Parameter Estimation Tool are also presented. Then, the performance of all battery ECMs in estimating the SOC by using UKF algorithm are analysed and presented. For the last result, the performance of UKF algorithm is discussed by comparing to the performance of EKF and PF algorithm

Chapter 5 discuss about the future works that could possibly be conducted in the future. This includes the implementation of new estimation algorithm such as Dual EKF (DUKF) and Dual UKF (DUKF) since these improved algorithms are known to have a better accuracy in state estimation.

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