ONLINE MODELLING AND STATE-OF-CHARGE ESTIMATION FOR LITHIUM-TITANATE BATTERY

LOW WEN YAO

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Specially dedicated to my beloved father, mother and friends for their encouragement and support

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ABSTRACT

Lithium-titanate (LTO) battery, which has features of fast charging and superior safety, is a promising energy storage element for electric vehicles. Its features can be fully utilised by using a fast charger and a high performance battery management system. Battery model is vital to a battery charger design for characterising the charging behaviours of a battery. Additionally, a robust state-of-charge (SoC) estimation should be realised for a reliable battery management. This thesis develops a battery model for charger design and a robust method for SoC estimation by using MATLAB. The thesis proposed a transfer function-based battery model which is applicable for small-signal analysis and large-signal simulation of battery charger design, in order to capture the charging profiles of LTO battery. Busse's adaptive rule, which has simple computations, is applied to improve the accuracy of Kalman filter-based SoC estimation. Busse's adaptive Kalman filters are also applied for SoC estimation with online battery modelling to eliminate the complicated process of battery modelling. This study was conducted by using 2.4 V, 15 Ah LTO batteries. The batteries were tested with continuous current test and pulsed current test at several ambient temperatures (-25 ºC, 0 ºC, 25 ºC and 50 ºC) and charge/discharge currents (0.5 C, 1 C, 2 C). Additionally, modified dynamic stress tests at several temperatures (-15 ºC, 0 ºC, 15 ºC, 25 ºC, 35 ºC and 50 ºC) were also performed to test the battery under real EV environment. Results of the battery modelling showed that the developed transfer function-based battery model is accurate where the root-mean-square modelling error is less than 30 mV. The results also revealed that the Busse's adaptive rule has effectively improved the Kalman filter-based SoC estimation for the case of offline battery model by giving a higher accuracy and shorter convergence time. Additionally, Busse's adaptive Extended Kalman Filter gave a better accuracy in SoC estimation with online battery modelling. The proposed transfer function-based battery model provides a helpful solution for the battery charger design while the proposed Busse's adaptive Kalman filter offers an accurate and robust SoC estimation for both offline and online battery models.

ABSTRAK

Bateri lithium titanat (LTO) yang mempunyai ciri-ciri pengecasan yang cepat dan keselamatan yang unggul merupakan elemen penyimpanan tenaga yang amat diyakini untuk kenderaan elektrik. Ciri-cirinya boleh digunakan sepenuhnya dengan merealisasikan pengecas bateri yang pantas dan sistem pengurusan bateri berprestasi tinggi. Model bateri adalah penting untuk merekabentuk pengecas bateri bagi menentukan tindakbalas bateri ketika dicas. Selain itu, kaedah anggaran keadaan cas (SoC) yang tepat perlu direalisasikan untuk sistem pengurusan bateri. Tesis ini membangunkan model bateri untuk kegunaan reka bentuk pengecas bateri dan juga kaedah anggaran keadaan caj bateri yang mantap menggunakan simulator MATLAB. Dalam tesis ini, model bateri yang berasaskan fungsi pemindahan serta sesuai untuk analisis isyarat kecil dan simulasi isyarat besar dalam merekabentuk pengecas bateri telah dibangunkan bagi mencirikan profil pengecasan bateri LTO. Peraturan penyesuaian Busse yang mempunyai pengiraan mudah telah digunakan untuk meningkatkan ketepatan penapis Kalman dalam anggaran keadaan caj bateri. Selain itu, penapis Kalman menggunakan peraturan penyesuaian Busse ini juga digunapakai untuk anggaran keadaan caj bateri dan model bateri secara talian untuk menghapuskan proses yang rumit dalam pemodelan bateri. Kajian ini telah dijalankan dengan menggunakan 2.4 V, 15 Ah bateri LTO. Bateri-bateri ini telah diuji dengan ujian arus berterusan dan ujian arus berdenyut pada beberapa suhu ambien (-25 º C, 0 ºC, 25 ºC dan 50 ºC) dan arus berlainan (0.5 C, 1 C, 2 C). Selain itu, ujian tekanan dinamik yang telah diubah suai juga dijalankan pada beberapa suhu persekitaran (-15 ºC, 0 ºC, 15 ºC, 25 ºC, 35 ºC dan 50 ºC) untuk mengujikan bateri dalam persekitaran EV yang sebenar. Keputusan pemodelan bateri menunjukkan bahawa model bateri berasaskan fungsi pemindahan yang telah dibangunkan adalah jitu, di mana ralat punca min kuasa dua untuk pemodelan adalah kurang daripada 30 mV. Selain itu, keputusan mendedahkan bahawa peraturan penyesuaian Busse telah meningkatkan prestasi penapis Kalman dalam anggaran keadaan caj bagi kes model bateri luar talian dengan memberikan ketepatan yang lebih tinggi dan masa penumpuan yang lebih singkat. Selain itu, penapis Kalman lanjutan yang menggunakan peraturan penyesuaian Busse ini juga memberi ketepatan yang baik dalam anggaran keadaan caj dan model bateri secara dalam talian. Model bateri yang berasaskan fungsi pemindahan telah menyediakan penyelesaian yang berguna untuk reka pengecas bateri manakala penapis Kalman yang menggunakan peraturan penyesuaian Busse telah menawarkan anggaran keadaan caj bateri yang jitu dan mantap bagi kedua-dua model bateri luar talian dan dalam talian.

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LIST OF ABBREVIATIONS

AC	-	Alternating current
ADVISOR	-	Advanced Vehicle Simulator
ANN	-	Artificial neural network
Ah	-	Ampere-hour
BMS	-	Battery management system
BV	-	Butler-Volmer
Busse-AEKF	-	Busse’s adaptive extended Kalman filter
Busse-AUKF	-	Busse’s adaptive unscented Kalman filter
CC-CV	-	Constant current constant voltage
CM-AEKF	-	Covariance-matching adaptive extended Kalman filter
CM-AUKF	-	Covariance-matching adaptive unscented Kalman filter
DST	-	Dynamic stress test
EIS	-	Electrochemical impedance spectroscopy
EKF	-	Extended Kalman filter
EV	-	Electric vehicle
FCEV	-	Fuel cell electric vehicle
GA	-	Genetic algorithm
HEV	-	Hybrid electric vehicle
HPPC	-	Hybrid pulse power characterization
ICEV	-	Internal combustion engine vehicle
IEA	-	International energy agency
I-V	-	Current-voltage
I/O	-	Input to output
KiBaM	-	Kinetic battery model
LCO	-	Lithium cobalt-oxide
LFP	-	Lithium ferro phosphate
LMO	-	Lithium manganese-oxide

LTO	-	Lithium-titanate
Li^+	-	The ion of lithium
Li-ion	-	Lithium-ion
MCU	-	Main control unit
MRE	-	Mean relative error
MW-RLS	-	Moving window recursive least square
NCA	-	Lithium nickel-cobalt-aluminium-oxide
NEDC	-	New European Driving Cycle
NMC	-	Lithium nickel-manganese-cobalt-oxide
NREL	-	National Renewable Energy Laboratory
NiMH	-	Nickel-metal hydride
OBD	-	On-board diagnosis
OCV	-	Open circuit voltage
PNGV	-	Partnership for a New Generation of Vehicle
RC	-	Resistance-capacitance
RLS	-	Recursive least square
RMSE	-	Root-mean-square error
SVM	-	Support vector machine
SZDC	-	Shenzhen driving cycle
SoC	-	State-of-charge
SoH	-	State-of-health
UKF	-	Unscented Kalman filter
UDDS	-	Urban Dynamometer Driving Schedule
USABC	-	United States Advanced Battery Consortium
UTM	-	Universiti Teknologi Malaysia
VTF	-	Vogel-Tammann-Fulcher

LIST OF SYMBOLS

α	-	Coefficient of scale calculation of UKF
β	-	Coefficient of weight calculation in UKF
ρ	-	Sigma points for the estimated output in UKF
μ	-	Temperature factor for temperature-based normalised charging voltage
θ	-	Vector of parameter for RLS algorithm
ε	-	Coefficient of adaptive forgetting factor equation
ε_Q	-	The window size in Busse's adaptive rule that controls the update change of process noise covariance
ε_R	-	The window size in Busse's adaptive rule that controls the update change of measurement noise covariance
λ	-	Scale of UKF
σ	-	Sigma points of states in UKF
σ_c	-	Capacity coefficient
τ_1	-	Time constant for the first RC parallel network in Thevenin model
τ_2	-	Time constant for the second RC parallel network in Thevenin model
Π	-	State vector for model parameters
$\emptyset$	-	The ambient temperature
χ	-	Augmented state vector
ΔV	-	DC voltage offset
Δx	-	The change of estimated state at measurement update of Kalman filter
Δy	-	The change of estimated output at measurement update of Kalman filter
A	-	Jacobian matrix of extended Kalman filter that represents the partial derivative of state equation with respect to states
B	-	Jacobian matrix of extended Kalman filter that represents the partial derivative of state equation with respect to input

C	-	Jacobian matrix of extended Kalman filter. It represents the partial derivative of output equation with respect to states
C_i	-	Capacitor for the i-th RC parallel network in Thevenin model
C_1	-	Capacitor for the first RC parallel network in Thevenin model
C_2	-	Capacitor for the second RC parallel network in Thevenin model
C_S	-	Storage capacitor in resistor-capacitor equivalent circuit model
C_U	-	Usable capacity of battery at certain current rate and ambient temperature
C_b	-	Storage capacitor in RC model
C_{sur}	-	Surface capacitor in RC model
D	-	Jacobian matrix of extended Kalman filter. It represents the partial derivative of output equation with respect to input
E	-	Statistical expectation operator
F	-	Forgetting factor
G	-	Covariance matrix for RLS
G_1	-	Laplace transform for the time derivative of f_1
G_2	-	Laplace transform for the time derivative of f_2
H	-	Average of the square of output residuals
H_0	-	Transfer function of battery with removal of DC resistance
H_b	-	Overall transfer function for battery
I	-	Identity matrix
I_L	-	Load current of battery
K	-	Algorithm gain
K_S	-	Time scaling coefficient
M	-	The number of samples of output residuals in covariance matching adaptive rule
N	-	Dimension of state vector
OCV	-	Open circuit voltage of battery
P	-	Error covariance matrix
P^+	-	Posterior error covariance matrix
P^-	-	Priori error covariance matrix
P_0	-	Initial error covariance of Kalman filter
P_{xy}	-	Cross-correlated covariance
P_y	-	Measurement covariance
Q	-	Covariance matrix for process noise

Q^*	-	Measure of process noise
R	-	Covariance matrix for measurement noise
R^*	-	Measure of measurement noise
R_i	-	Resistor for the i-th RC parallel network in Thevenin model
R_1	-	Resistor for the first RC parallel network in Thevenin model
R_2	-	Resistor for the second RC parallel network in Thevenin model
R_S	-	Series resistor in equivalent circuit model
R_{dc}	-	DC resistance corresponding to dc offset in curve normalisation
SoC	-	State-of-charge
T	-	Normalised charging time
Tr	-	The trace of the matrix
V_{cb}	-	Voltage across storage capacitor in RC model
V_{csur}	-	Voltage across surface capacitor in RC model
V_i	-	Voltage across the i-th RC parallel network in Thevenin model
V_1	-	Voltage across the first RC parallel network in Thevenin model
V_2	-	Voltage across the second RC parallel network in Thevenin model
V_N	-	Temperature-based normalised charging voltage
V_R	-	Reference of normalised charging voltage
$V_{c,d}$	-	CC charging voltage at c charging rates and d temperatures
V_t	-	Terminal voltage of battery
$V_{t,EXP}$	-	Experimental terminal voltage of battery
$V_{t,SIM}$	-	Simulated terminal voltage of battery
$W_i^{\ c}$	-	Weight of the error covariance for i-th sigma points in UKF
$W_i^{\ m}$	-	Weight of the i-th sigma points in UKF
X	-	The true value of state
Y	-	The measured value of system output
a_1 to a_{10}	-	Coefficient of 9^{th} order polynomial equation
b	-	The index weighted coefficient of Sage-Husa adaptive rule
b_1 to b_7	-	Coefficients of equation (4.14)
c_1 to c_5	-	Coefficients of equation (4.15)
cc_1 to cc_9	-	Coefficient of second-order Thevenin model at charge condition
d_1 to d_5	-	Coefficient of exponential curve fitting equation in equation (2.5)
dd_1 to dd_9	-	Coefficient of second-order Thevenin model at discharge condition

dt	-	Sampling time
e	-	Output residuals
err	-	Estimation error
f_1	-	The fixed component in normalised charging voltage
f_2	-	The temperature-based component in normalised charging voltage
h	-	Regressor of RLS algorithm
i	-	Column of a matrix
j	-	Row of a matrix
k	-	Discrete-time index
l	-	Coefficient of adaptive forgetting factor equation
n	-	Number of sample for error analysis
p_0 to p_3	-	Coefficient of normalised charging curve
r	-	Process noise for the model parameters
r'	-	Adjustable coefficient in the judgement condition of Sage-Husa adaptive rule
t	-	Time
t_E	-	Ending time of rest
t_S	-	Starting time of charge/discharge process
t_R	-	Starting time of rest
u	-	System input
v	-	Measurement noise of system
v_R	-	DC offset due to the DC resistance
w	-	Process noise of system
x	-	State vector of system
x_0	-	Initial state
x^+	-	Posterior estimated state
x^-	-	Priori estimated state
y	-	System output
z	-	Discretisation operator in bi-linear transformation
z'	-	The output residual of Sage-Husa adaptive rule

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CHAPTER 1

INTRODUCTION

1.1 Background

Fossil fuels, such as oil, coal and natural gas, are the main resources for the world's energy supply. However, the usage of fossil fuels leads to the emission of greenhouse gas that contributes to global climate change. One of the efforts to reduce greenhouse gas emissions is the transformation of energy technology in the transportation sector. According to International Energy Agency (IEA), this transformation can be realized by implementing electric vehicles (EVs) and hybrid electric vehicles (HEVs) [1]. Through vehicle electrification, vehicles are powered by a rechargeable energy storage system and enabled by an electric motor, thus providing the means for a clean and efficient roadside transportation system. Electric vehicles are expected to aggressively penetrate the market of roadside transportation in the near future, where the sales for both EVs and HEVs are expected to reach 50 million by 2050 [1].

In order to compete with the existing transportation market, attention should be given to the energy storage element of EVs. Generally, energy density (Wh/L) and specific energy (Wh/kg) are the prime considerations for choosing the energy storage element for EVs. High value of energy density and specific energy reduces the size and mass of the energy storage element and thus extends the travel range of EVs. In addition, power density (W/L) and specific power (W/kg) are also important in determining the available power for EVs under various load demands and driving states. Besides, safety also needs to be addressed for selecting an energy storage element so that the extreme emission of gaseous substances or heat will not take place under normal operation [2]. Other criteria for selecting energy storage elements are efficiency, maintenance requirement, cost, and environmental friendliness [3].

Rechargeable batteries, fuel cells and super-capacitors, are the three potential candidates for the energy storage element of EVs. The comparison of their power density and energy density is shown in Figure 1.1. The diagram reveals that fuel cells have the highest value of energy density among the energy storage elements. Therefore, fuel cells provide a longer travel mileage to the vehicle. Today, several fuel cell electric vehicles (FCEVs) are available in the transportation market, such as Hyundai ix35, Honda FCX Clarity and Toyota Mirai. Theoretically, the electrical energy of a fuel cell is generated by using oxygen from the air and compressed hydrogen through a direct electrochemical reaction without undergoing combustion. The electrochemical process of fuel cells only produces heat and water, thus gives zero greenhouse gases emission [4]. Similar to the conventional internal combustion engine vehicles (ICEVs), FCEVs can be refilled with hydrogen within a very short period. However, due to the low density of hydrogen gas, the on-board hydrogen storage has become a challenging task [5]-[6]. With the same volume, gasoline can give 10 times more of energy than hydrogen gas [5]. Due to this reason, it is costly transporting hydrogen gas from the production site to the refill station. Likewise, a large hydrogen tank is required in each FCEV for energy storage purpose [7]. In addition, a potential risk exists in the storage of hydrogen gas because it is highly flammable. Presently, further development of an efficient hydrogen storage system is required to realise the application of FCEV [6].

Super-capacitor is also potentially applied as the energy storage element for EVs due to its advantages in term of power capability, cycle life performance and charge-discharge efficiency [8]. However, it is also not suitable for application as the primary energy source for EVs due to its extremely low energy density (less than 10Wh/kg) and its high self-discharge rate (i.e. 5% per day [9]). Today, super-capacitors are applied together with batteries or fuel cells to form a hybrid energy storage system [10]–[19], where the advantages of the high power capability of super-capacitors and the high energy density of the batteries are combined to fulfil the power and energy demands of EVs. In this context, the batteries are operating in nearly steady state conditions whereas the super-capacitors are applied to supply transient power demands and peak loads of EVs [20].

Compared to fuel cells and super-capacitors, rechargeable batteries are considered as the most appropriate choice as the primary energy storage element for EVs. The technology of rechargeable batteries has been improved from lead acid batteries to nickel-metal hydride (NiMH) batteries, and then from NiMH batteries to lithium-ion (Li-ion) batteries. However, the battery technology is often criticized due to its slow progression, and cannot keep up pace with the demands of current technology [21]. Currently, Li-ion battery is considered as the most promising energy storage element for EVs since it owns the highest specific energy (150Whkg^{-1}) and the highest specific power (up to 5kWkg^{-1}) compared to other batteries [22]-[23]. Besides, Li-ion battery has no memory effect, long cycle life, and excellent discharge characteristics [24]. Today, Li-ion battery has been applied in several EVs, such as BYD E6, Tesla Motor, Nissan Leaf and Chevrolet Volt [25].

Despite the impressive advantages of Li-ion batteries, several issues are vital to be considered for the application of Li-ion batteries. Firstly, the power density and energy density of Li-ion battery is much lower compared with the fuel of ICEVs. As a result, a huge size of battery pack, which is formed by series and parallel connection of Li-ion cells, is applied to fulfil the energy and power demands of EVs. Besides, the recharge time of Li-ion battery pack is relatively longer compared to the fuel refill time of ICEV. Thirdly, Li-ion battery is chemically reactive and it is sensitive to its operating temperature and voltage. Due to these reasons, the huge size of battery pack, the limited drive range, the lengthy battery recharge time and safety issue have become the main challenges for EV development. The improvement of battery technology and the development of an efficient battery management system (BMS) are the two important aspects to realise a reliable EV.

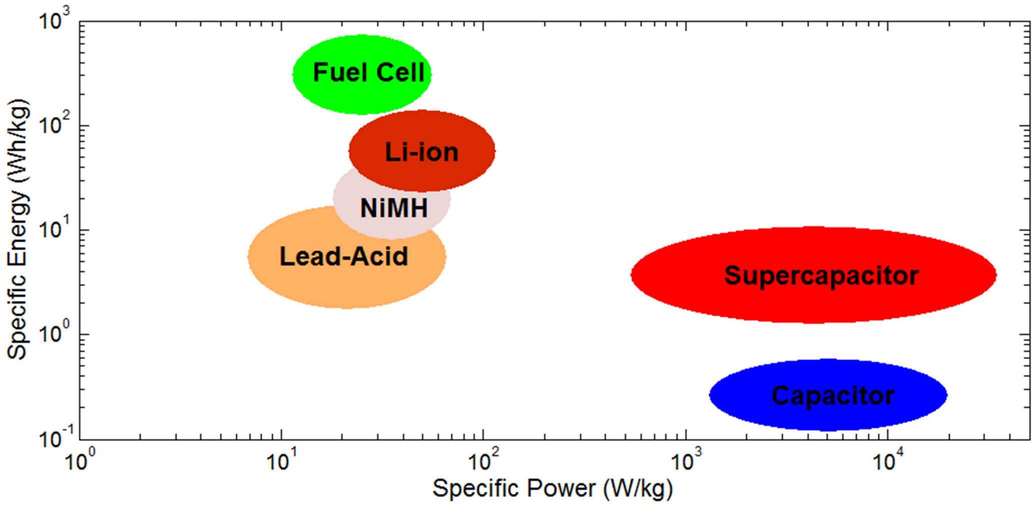

Figure 1.1 Comparison between various energy storage elements in terms of power and energy density [26]

1.1.1 Lithium-ion Battery Technology

Over the years, scientists have been committed towards improving the technology of rechargeable batteries. The rechargeable batteries have been improved from lead acid batteries to nickel-based batteries, and then from nickel-based batteries to Li-ion batteries. Currently, Li-ion battery is considered as the most promising type of rechargeable battery and it has penetrated the market of portable electronic devices.

Theoretically, lithium is the lightest and most electropositive metal, thus owning remarkable characteristics for the design of energy storage element with high energy density and high specific energy. However, lithium metal is highly reactive, and it is flammable when it reacts with water. Therefore, the early developed Li-ion batteries, which used lithium metal as its cathode, suffered from its safety issues [24]. Generally, an external protection case is required for the earlier developed Li-ion battery in order to ensure its safety during usage. This additional packaging not only increases the cost and weight of the battery, but also reduces the flexibility in design.

Today, the safety problems of Li-ion battery have been drastically reduced through the development of advanced materials for its construction. Currently, instead of using lithium metal, lithium liberating compound is applied as cathode material and graphite is applied as anode. Therefore, the operation of modern Li-ion battery is based on the intercalation of lithium ions (Li^+). In this aspect, Li^+ is intercalated into the cathode in the discharge process and into the anode in the charge process through the electrolyte. Furthermore, the construction of Li-ion battery has been improved with the invention of solid-state cell. Instead of using liquid electrolyte, solid-state cell uses the solid electrolyte in its cell construction. Without the existence of liquid electrolyte, the solid-state cell is free from harmful chemical leakage, thus offering better safety without using heavy protective case. Besides, solid-state cell is flexible enough to be shaped into several shapes according to its usage [27], such as cylindrical, coin, prismatic and flat shapes as shown in Figure 1.2 [21] .

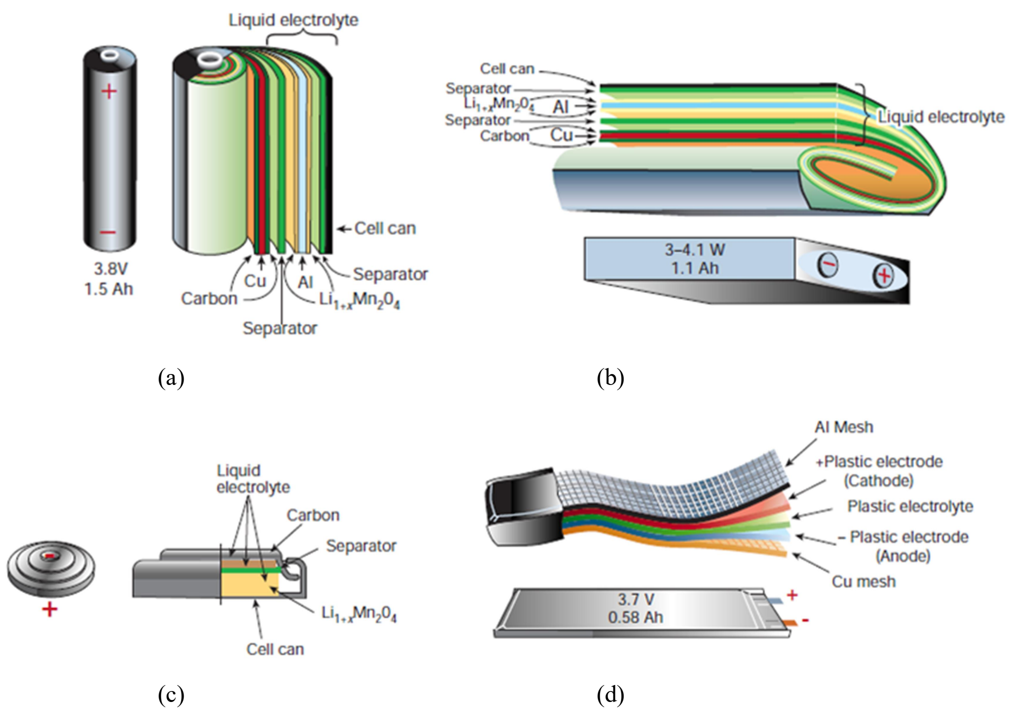

Figure 1.2 Configurations of solid state cell: (a) cylindrical, (b) prismatic, (c) coin, and (d) thin and flat [21]

Several types of Li-ion battery have been developed by using different cathode or anode materials. The Li-ion battery is named based on the main active material that gives its character. Presently, there are six common types of Li-ion in the market, they are lithium cobalt-oxide ($LiCoO_2$ or LCO), lithium manganese-oxide ($LiMn_2O_4$ or LMO), lithium nickel-manganese-cobalt-oxide ($LiNiMnCoO_2$ or NMC), lithium ferro phosphate ($LiFePO_4$ or LFP), lithium nickel-cobalt-aluminium-oxide ($LiNiCoAlO_2$ or NCA), and lithium-titanate ($Li_4Ti_5O_{12}$ or LTO) batteries.

LCO and LMO battery are the most popular Li-ion batteries in the market. They have been widely applied in several digital devices, such as cell phones, laptops and cameras. LCO battery consists of cobalt-oxide cathode which offers a high specific energy [28]. However, its performance is limited by its poor thermal stability. Moreover, the usage of cobalt brings toxic hazards to the environment [24] [29]. Compared to the LCO battery, LMO battery uses lithium manganese-oxide as its cathode, which has spinel structure and provides lower internal resistance, higher current handling capability and higher thermal stability. Additionally, manganese is cheaper and more environmentally friendly compared to cobalt [24]. However, the performance of LMO battery is limited by its short cycle life. Besides, its energy density is 20% lower compared to LCO battery [29].

The advantages of LCO and LMO battery have been combined in the NMC battery. NMC battery consists of cathode material that is formed by the combination of nickel, manganese and cobalt. The ratio of nickel-manganese-cobalt is typically set as 1:1:1 [29]. However, this ratio can be adjusted by NMC battery manufacturers in order to get the highest performance [24]. NMC not only improves the safety of LCO battery, but it is also less expensive than LCO battery. Today, it is a preferred candidate for certain EV manufacturers and it has been applied in Nissan Leaf, Chevy Volt, and BMW i3.

NCA battery, which uses the combination of nickel, cobalt and aluminium as its cathode, shares certain similarities with NMC battery. Currently, NCA battery has been applied in Tesla Motor S-model due to its high specific energy, high specific power and long life span [29]. However, the stability of NCA battery is poorer than NMC battery and LMO battery. In this aspect, NCA battery has a lower onset temperature (150 ºC) for cathode decomposition, and thus it is less resistant to thermal abuse [2]. Due to this reason, the thermal management of NCA battery is vital. For instance, Tesla has assembled the NCA batteries into a liquid-cooled battery pack with strong metal enclosure.

LFP battery is a modern Li-ion battery which uses phosphate as its cathode. It offers superior thermal and chemical stabilities, thus providing a better safety feature than other aforementioned batteries [24][29]. In this aspect, LFP battery has a greater capability to withstand over-voltage and short-circuit conditions. Besides, it also provides several advantages in term of low internal resistance, high current rating and long cycle life [29]. As a trade-off of using phosphate cathode, it has a lower cell voltage and specific energy compared to LCO, LMO, NMC and NCA battery. However, due to its excellent safety features, it has been applied in BYD E6.

Apart from the development of cathode material, Li-ion has also improved in terms of anode material. Instead of using graphite anode, LTO battery uses lithium titanium oxide ($Li_4Ti_5O_{12}$) as its anode. Fast charging is considered the most attractive feature of LTO battery. The nano-particles of LTO increases the electrode-electrolyte contact area and reduces the diffusion distance for ions and electrons, thus reducing the polarisation resistance and allowing for fast charging [30]-[31]. Moreover, it has superior safety, long cycle life, excellent low-temperature performance, low toxicity and good thermal stability. As a trade-off, LTO has a lower cell voltage, and thus has a lower specific energy compared to other Li-ion batteries. Currently, it has a higher cost due to the limited production. However, due to its fast charging capability, it has been applied in several EVs, such as Mitsubishi i-MiEV, Honda Fit EV. The characteristics of these batteries are summarised in Table 1.1 [29][32].

Table 1.1 : Characteristics of lithium-ion batteries [32][29]

	LCO	**LMO**	**NMC**	**NCA**	**LFP**	**LTO**
Cathode	$LiCoO_2$	$LiMn_2O_2$	$LiNiMnCoO_2$	$LiNiCoAlO_2$	$LiFePO_4$	Graphite
Anode	Graphite	Graphite	Graphite	Graphite	Graphite	$Li_4Ti_5O_{12}$
Nominal voltage (V)	3.6	3.7	3.6	3.6	3.2	2.4
Operating voltage (V)	2.5 – 4.2	2.5 – 4.2	2.5 – 4.2	3.0 – 4.2	2.5 – 3.65	1.5 – 2.75
Operating Temperature (ºC)	Charge: 0 − 55 Discharge: -20 − 55	Charge: 0 − 55 Discharge: -20 − 55	Charge: 0 − 55 Discharge: -20 − 55	Charge: 0 − 55 Discharge: -20 − 55	Charge: 0 − 55 Discharge: -20 − 55	Charge: -30 − 55 Discharge: -30 − 55
Specific Energy(Wh/kg)	150 – 200	100 – 150	150 – 220	200 – 260	90 – 120	70 – 80
Typical Charge rate (C)	0.7 – 1.0	0.7 – 1.0	≤ 1.0	≤ 0.7	≤ 1.0	≤ 5.0
Maximum Charge rate (C)	1.0	3.0	1.0	0.7	3.0	5.0
Typical Discharge rate (C)	≤ 1.0	≤ 1.0	≤ 1.0	≤ 1.0	≤ 1.0	≤ 10
Maximum Discharge rate (C)	1.0	30 (pulse)	2.0	1.0	5.0	10
Cycle life	500-1000	1000	2000-3000	2000-3000	> 3000	> 5000
Safety	Average	Good	Good	Average	Very good	Very good
Cost	Low	Low	Low	High	Low	Very high
Application in EV	-	-	Nissan Leaf, BMW i3	Tesla Motor	BYD E6	Mitsubishi i-MiEV

1.1.2 Battery Management System

Safety concerns are crucial for the application of Li-ion battery because it is sensitive to its operating condition. In order to ensure its safety, the battery must operates within its safety operating window, which is restricted by voltage and temperature [25]. The battery could burn or even explode if used beyond its maximum operating voltage (over-voltage). Besides, under-voltage or over-discharge of batteries could lead to irrecoverable capacity degradation [33]. On the other hand, the high operating temperature would cause battery destruction and the emission of flammable gases. At extreme high temperatures, the thermal runaway would occur. Besides, low operating temperatures will reduce the cycle life of the battery due to the deposition of metallic lithium on the surface of negative electrode. At the extreme low temperatures, the cathode of the battery will break down and cause internal short circuit of the battery [25]. The concepts of safety operating window is illustrated in Figure 1.3 [34].

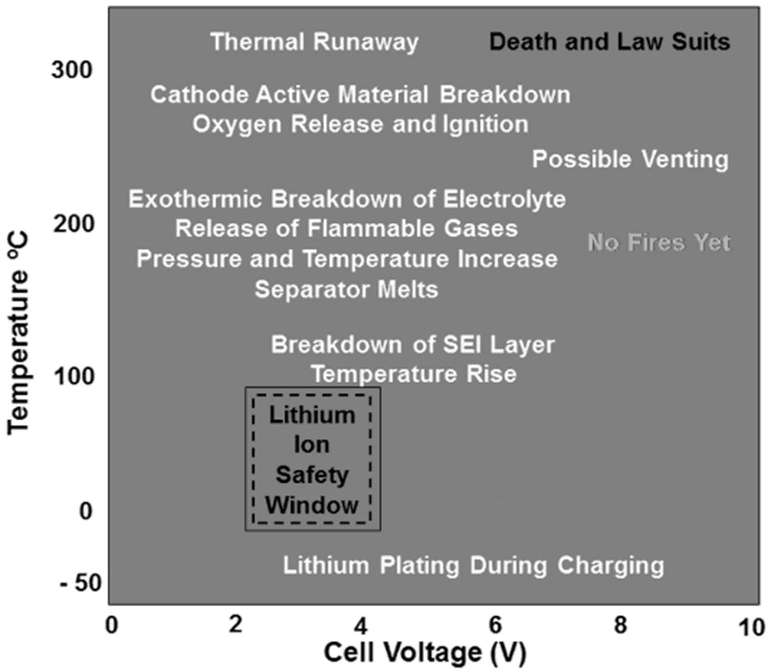

Figure 1.3 Operating window for Li-ion battery [34]

A battery management system (BMS) is vital to realize a safe and reliable EV. The main function of the BMS is to ensure the proper usage of battery packs while it provides the sufficient electrical power for the operation of EVs. Apart from preventing the battery from over-voltage, under-voltage and thermal abuse, the sub-functions of BMS also include data acquisition, battery states estimation, safety management, cell balancing, charge control, and thermal management [25], [35]–[37]. The schematic structure of a typical BMS is shown in Figure 1.4.

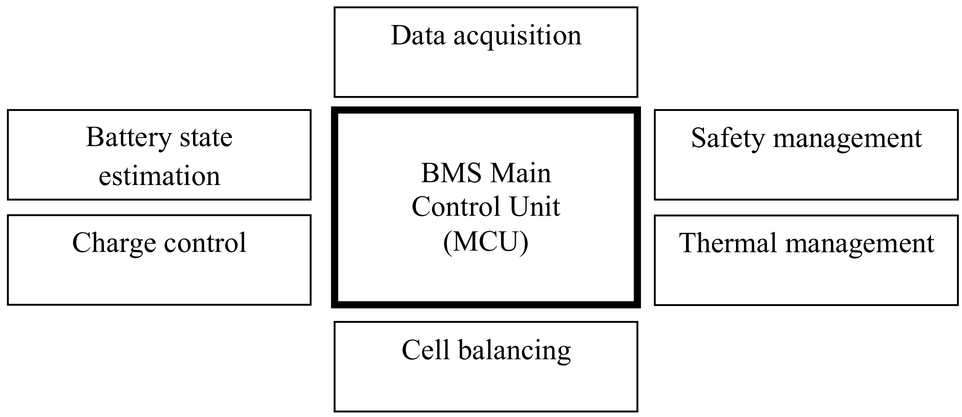

Figure 1.4 Schematic structures of BMS

Data acquisition acts as the input for BMS. Generally, it measures the battery terminal voltage, battery current, battery temperature and ambient temperature. Since the battery pack of EV is built up by multiple battery cells, the measurement on each individual cell is necessary to ensure that each cell operates within its safety window. Advanced data acquisition system also includes smoke detection, collision detection insulation detection and impedance detection for the detection of battery faults.

Safety management is the primary task of BMS to prevent batteries from critical operating conditions, such as over-voltage, under-voltage, ultra high temperature, over-current, short-circuit, and loose connections. For advanced versions of BMS, on-board diagnosis (OBD) system is also included for the maintenance of battery packs. In this aspect, OBD stores the historical data of the battery and discovers the failure and abnormal status of the battery. When an abnormal status is found, the warning devices will be activated to send an alert to the EV drivers.

Thermal management is also an important function of BMS in order to manage the operating temperature of battery. In this aspect, the temperature among the cells is equalised so that the operation of the battery cells is uniform. Thermal management system detects the temperature distribution in the battery packs, and control the cooling power or heating power for batteries. Generally, due to cost and space limitation, an air-cooling system is applied. Apart from air-cooling, liquid cooling and phase-change materials are also applied in thermal management system [38][39].

Cell balancing is also an important feature of BMS so as to establish the uniformity of each cell in battery packs. This is due to the fact that all cells are not alike although they are same type, same specifications, and manufactured at the same conditions. The differences between each battery cells are unavoidable in term of capacity, internal resistance or self-discharge rate. The difference could be caused by poor production and packaging process of the battery manufacturer. Without this feature, the uniformity of battery cells will be degraded with the increase of operating time, which leads to over-voltage and under-voltage problems in battery pack. Passive balancing and active balancing are the two typical approaches for cell balancing [40]. Passive balancing technique compares the cell voltage to detect the difference between highest voltage cell and lowest voltage cell. Then, the high voltage cell will be discharged by using a discharge resistor. On the other hand, active cell balancing technique transfers charge from high voltage cells to low voltage cells, thus owning higher energy efficiency than passive balancing technique. However, passive balancing technique is still preferred by EV industries because its cost is much lower compared to active balancing technique.

Charger control is an important feature of BMS used in order to control the recharge process of the battery. Generally, constant current constant voltage (CC-CV) charging scheme is applied to charge Li-ion battery. With assistance from cell balancing system and safety management system, a safe and uniform charging process is expected. Then, a charger control system is applied so that the battery pack is charged under appropriate charging voltage and charging rate. The settings for the charger are unique according to the capacity and voltage of the battery pack.

Battery state estimation is also an important function for BMS. State-of-charge (SoC) and state-of-health (SoH) are the two important states to be estimated. In this context, SoC gives information of the remaining capacity of the battery while SoH presents the performance degradation of battery. These battery states are vital for the EV driver to estimate the real-time status of battery pack. It is considered as the most challenging task for a BMS because the states cannot be measured directly. Moreover, the estimation must be done without affecting the operations of the EV.

1.1.3 State-of-charge Estimation

In general, SoC is defined as the remaining storage energy of a battery. For EV application, SoC estimation acts as the "fuel gauge", which is crucial for the prediction of driving range. An accurate SoC estimation is required to prevent EVs from running out of charge on the road [41]. Moreover, SoC is important to increase the efficiency of battery by optimally controlling the charge and discharge processes [42], especially in hybrid energy storage systems. However, the estimation of SoC is a complicated process which is dependent on several factors, such as temperature, usable capacity and internal resistance [43]-[44]. Several techniques have been proposed for SoC estimation as shown in Figure 1.5, which can be categorized into three groups [45]–[47]:

(i) direct measurement methods,
(ii) black-box model-based methods, and
(iii) state-space model-based methods.

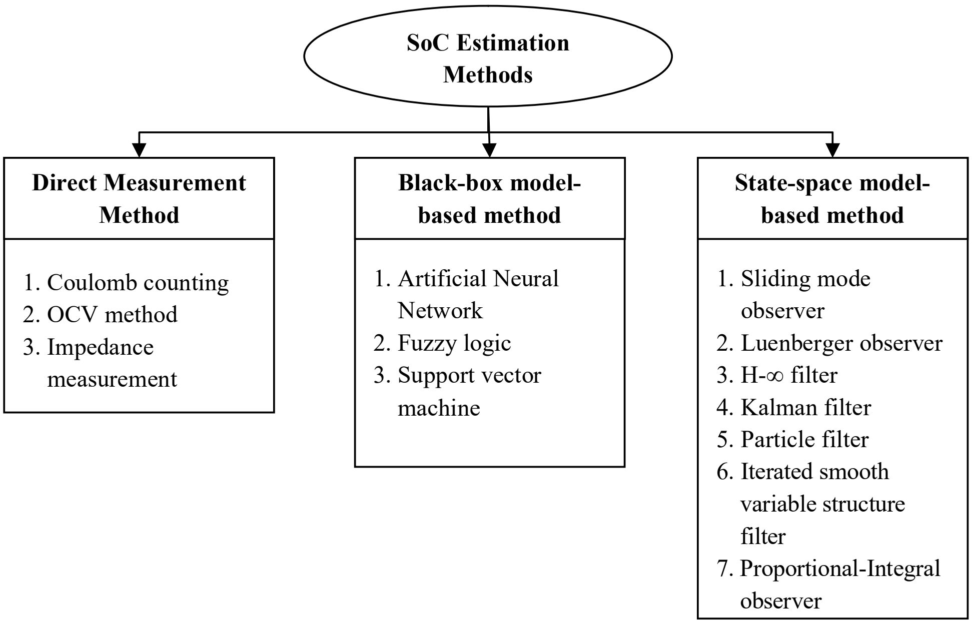

Figure 1.5 SoC estimation methods

Direct measurement methods, such as coulomb counting method [48]–[49], open circuit voltage (OCV) method [50] and impedance measurement method [51]–[52], are the open-loop approaches for SoC estimation. These methods indicate SoC by measuring a particular SoC-related parameter. Coulomb counting method, which uses real-time current integration, is widely applied in EVs' BMS because it is easier to implement with low computation. However, its accuracy is unavoidably affected by the accumulative error caused by uncertain disturbances and sensor noises. Moreover, the method relies on prior knowledge of the initial SoC, which is rarely available in practical applications [46].

OCV method is also applied to indicate SoC by knowing for a fact that the battery terminal voltage at chemical equilibrium state is dependent on SoC. However, an accurate SoC is difficult to be estimated from OCV because the OCV-SoC relationship is nearly flat. It was reported that the variation of OCV is less than 0.2 V for the SoC range between 10 % and 90 % SoC, especially for LFP battery [53]. Therefore, it requires high precision voltage sensors for practical application. Typically, OCV method is applied together with coulomb counting method to postulate the value of initial SoC. However, a long relaxation time is required for battery to reach its OCV, which is considered impractical for EV applications [54].

Impedance measurement is also a straight-forward method for SoC measurement. In this method, by using electrochemical impedance spectroscopy (EIS), a small alternating current (AC) signal with various frequencies is injected into the battery for impedance measurement. However, the results obtained from EIS is difficult to interpret because the impedance is varied with SoC and temperature [55]. Moreover, the impedance measurement should be done on a battery which is disconnected from a charger or load [56]. Therefore, it is considered not suitable for EV application because the SoC estimation should be done without affecting the EVs' operation.

Black-box battery models, which were established by computational intelligence approaches, are also applied for SoC estimation. In this aspect, a nonlinear relationship between SoC and its influencing parameters are modelled by using artificial neural network (ANN) [57]–[59], fuzzy logic [60]–[62], or support vector machine (SVM) [63][64]. Generally, black-box model-based methods give a good accuracy in SoC estimation due to the powerful capability of the computational intelligence. Unlike coulomb counting method, initial SoC is not required for these methods. Moreover, black-box model can be establishing solely based on the existing input-output training data sets without understanding the chemical reaction of battery. However, their performance is greatly affected by the reliability and the amount of the training data set [65]. Limited amounts of training data set would result in poor robustness [46]. Therefore, a large amount of battery tests are needed to obtain a good model which can be very time-consuming. In addition, the offline learning processes for the black-box model requires iteratively tuning, which leads to heavy computational [47].

State-space model-based methods seem to be the best approach for SoC estimation due to their closed loop nature, real-time estimation, and good reliability. Currently, more attention have been given on the methods and several algorithms, such as sliding-mode observer [66]–[70], Luenberger observer [71], proportional-integral observer [72], particle filter [73]–[74], iterated smooth variable structure filter [75]–[76], H-∞ filter [43][77], and Kalman filter [78] have been applied in state-space model-based SoC estimation method. The methods measure current and voltage signals while considering the estimation error range, and thus form a close loop and online SoC estimation method [47][79]. The methods do not rely on an accurate initial SOC, and thus avoids the problem of accumulative error. An accurate state-space model is necessary to establish an accurate SoC estimation. In general practice, state-space model derived from equivalent circuit battery model is applied. Although state-space model can also be derived from electrochemical model [80], a heavier computational burden is required to solve the complicated equations of the electrochemical model.

1.2 Problem Statement

The implementation of a new battery technology and development of an efficient BMS is the key to improving the performance of EVs. Currently, LTO battery, which has the features of fast charging and superior safety, is considered as a promising candidate for EV's energy storage system. The fast charging features of a LTO battery can be fully utilised if a reliable battery charger control is realised. For this purpose, an accurate battery model that simulates the charging characteristic of LTO battery is vital.

In addition, an accurate SoC estimation should be realised in order to monitor the operation of the battery. Extended Kalman filter (EKF) and unscented Kalman filter (UKF) are presently considered as the most promising methods for SoC estimation due to their excellent state estimation and noise immunity. However, the accuracy of Kalman filter-based SoC estimation is highly dependent on the prior setting of error covariance. Although the covariance matching adaptive rule is a convenient way to improve the accuracy of Kalman filters, it requires large memory space to operate. An improvement of Kalman filter-based SoC estimation should be further explored and a new adaptive in order to overcome this shortage must be established.

Meanwhile, the accuracy of the battery model gives a large impact on the Kalman filter-based SoC estimation. Generally, a huge amount of laboratorial experiments are carried out to establish an accurate battery model, which is costly and time consuming. Moreover, the parameters of the battery model are typically varied with several factors, such as SoC, ambient temperature and current. Therefore, the formulated battery model might only be suitable for the specified operating condition. A better approach should be configured to solve these problems.

1.3 Thesis Objectives and Contributions

The objectives of this study are:

(i) to investigate the dynamic behaviours of LTO battery through several battery tests.

(ii) to develop a battery model for battery charger design which is suitable for small signal analysis and large signal simulation.

(iii) to develop a robust SoC estimation method using Kalman filter with genetic algorithm (GA) offline battery modelling.

(iv) to develop a robust SoC estimation method with online battery modelling using Kalman filter.

While performing this study, the thesis makes the following contributions:

(i) A new transfer function-based battery model is developed to simulate the charging behaviour of LTO batteries under several charging rates and ambient temperatures. The proposed battery model provides a good solution to the small-signal analysis and large-signal simulation of battery charger designs.

(ii) Busse's adaptive rule is applied to improve the accuracy of Kalman filter-based SoC estimation. The main motivation is to reduce the complexity of the existing adaptive rules which require large memory space. Application of Busse’s adaptive rule does not need large memory capacity to store the historical data of estimation, and thus is suitable for real-time implementation.

(iii) Busse’s adaptive rule is applied in joint Kalman filter for SoC estimation and online battery modelling. In this aspect, the SoC and model parameters are estimated simultaneously by using Kalman filter. The parameters of the battery model are estimated in real-time without requiring precise measurement tools, experienced researchers and large amount of battery tests, thus reducing the overall complexity of BMS development.

1.4 Methodology

In this thesis, the research methodology is divided into 4 different sessions:

(i) Experimental test on LTO battery,

(ii) Formulation of transfer function-based battery model,

(iii) SoC estimation using Kalman filter, and

(iv) SoC estimation and online battery modelling using joint Kalman filter.

MATLAB and MATLAB/Simulink are used as the simulator throughout the thesis.

1.4.1 Experimental Test on LTO Battery

First of all, the dynamic voltage-current behaviours of LTO batteries are investigated by using battery tests. In the experimental study, continuous current charge, continuous current discharge, pulsed current charge, and pulsed current discharge tests are combined to form a single profile. This profile is called as continuous current test (CCT) and pulsed current test (PCT). The tests are conducted by using 3 current rates (i.e. 0.5 C, 1 C, and 2 C) under 4 ambient temperatures (i.e. -25 ºC, 0 ºC, 25 ºC, and 50 ºC). Since the PCT is unable to perform at 2 C / -25 ºC due to the limitation of battery, only 11 tests are applied for CCT and PCT tests. On the other hand, modified DST is also applied to test the LTO battery under dynamic load conditions. The test is made by modifying the conventional DST so that it suits to our lab capability. The test are conducted under 6 ambient temperature, i.e. -15 ºC , 0 ºC, 15 ºC, 25 ºC, 35 ºC and 50 ºC. Throughout the test, the battery voltage is monitored so that its operating temperature is within 1.6 V − 2.75 V to avoid over-voltage and under-voltage of the battery. The details of the experimental test are further explained in Chapter 3.

1.4.2 Formulation of Transfer function-based Battery Model

In this study, a transfer function-based battery model is formulated to simulate the charging profiles of LTO battery. Figure 1.6 illustrates the methodology for the formulation of transfer function-based battery model.

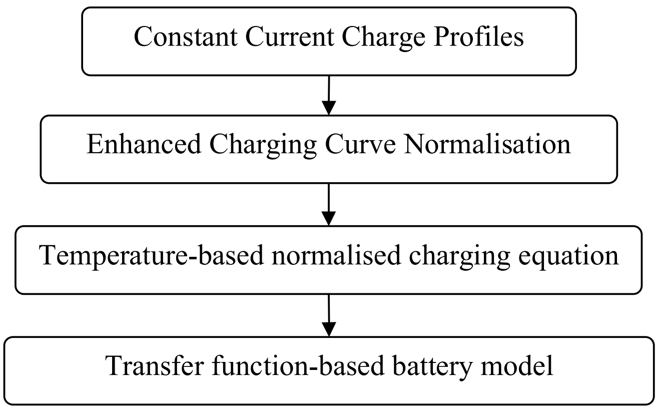

Figure 1.6 Formulation of transfer function-based battery model

The charging behaviours of LTO battery are obtained from the experimental results of continuous current charge. Enhanced charging curve normalisation is applied to find out the common characteristics of the battery charging profiles. Then, temperature-based normalised charging equation is developed to simulate the battery charging behaviours at several charge rates and ambient temperatures. Lastly, a transfer function is formulated based on the developed normalised charging equation. The accuracy of the battery model is evaluated by comparing the simulated and experimental charging profiles. Then, the error of the battery modelling is analysed by using root-mean-square error (RMSE) and mean relative error (MRE). The details are further explained in Chapter 4.

1.4.3 SoC Estimation using Kalman Filter

Figure 1.7 illustrates the methodology of SoC estimation using Kalman filter; both with adaptive rule and without adaptive rule.

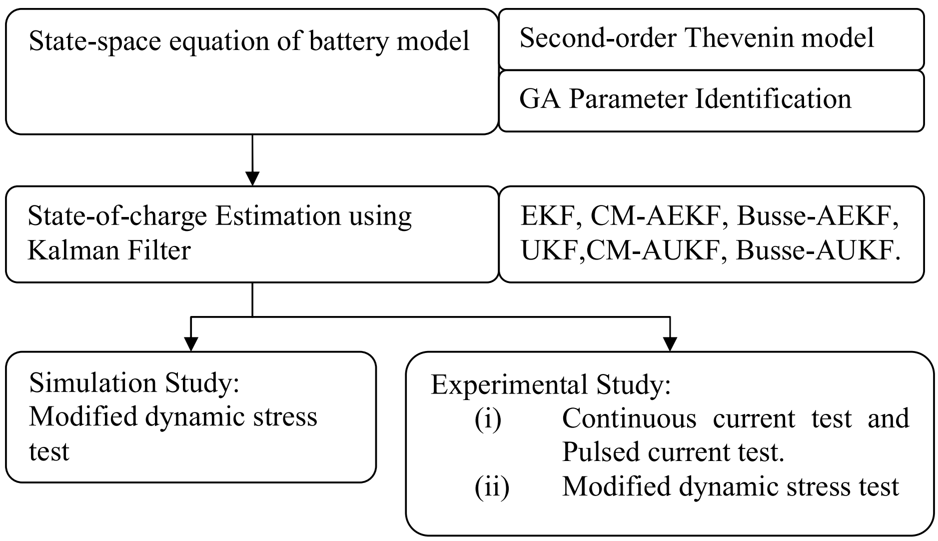

Figure 1.7 SoC estimation using Kalman filter

In SoC estimation, second-order Thevenin model is used to simulate the electrical behaviours of the battery. Genetic algorithm (GA) is applied to identify the parameters of the battery model. In order to implement Kalman filter-based SoC estimation, the second-order Thevenin model is first transformed into a state-space model. Based on the state-space model, the SoC estimation is performed by using Extended Kalman filer (EKF), Unscented Kalman filter (UKF), Covariance-matching adaptive EKF, Covariance-matching adaptive UKF, Busse's adaptive EKF, and Busse's adaptive UKF. The accuracy of the SoC estimation is analysed by using simulation and experimental study. Then, the error of SoC estimation is analysed by using root-mean-square error (RMSE) and mean relative error (MRE). The details are further explained in Chapter 5.

1.4.4 SoC Estimation and Online Battery Modelling using Joint Kalman filter

Figure 1.8 illustrates the methodology of SoC estimation and online battery modelling using joint Kalman filter.

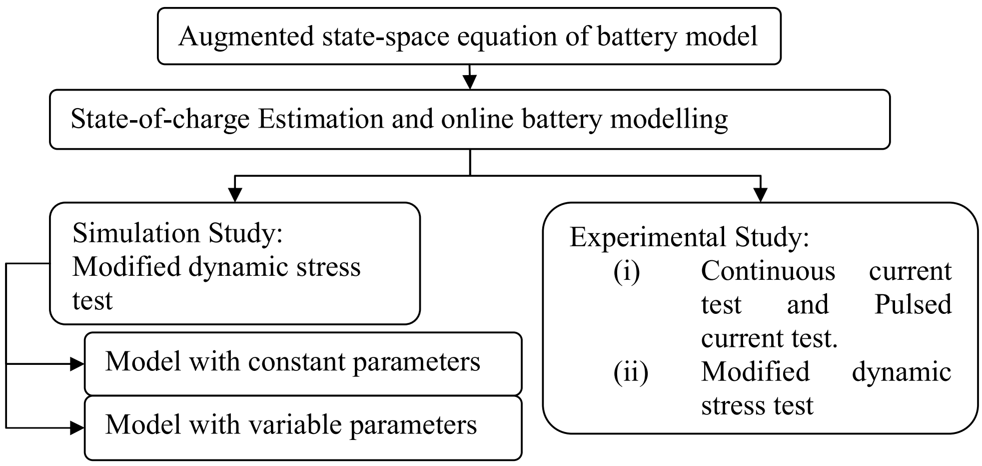

Figure 1.8 SoC estimation and online battery modelling using Joint Kalman filter

In order to implement joint Kalman filter, an augmented state-space model is formed based on the structure of second-order Thevenin model, where the state equation includes both battery state and battery parameters. By using the augmented state-space model, the SoC estimation and online battery modelling are performed simultaneously by using Extended Kalman filer (EKF), Unscented Kalman filter

(UKF), Covariance-matching adaptive EKF, Covariance-matching adaptive UKF, Busse's adaptive EKF, and Busse's adaptive UKF. The accuracy of the SoC estimation is analysed by using simulation and experimental study. In simulation study, battery model with constant parameters, and battery model with variable parameters are applied to investigate the accuracy of SoC estimation and online battery modelling performed by the algorithms. Moreover, the error of SoC estimation and battery modelling are analysed by using root-mean-square error (RMSE) and mean relative error (MRE). The details are further explained in Chapter 6.

1.5 Scope of Research

Battery modelling and SoC estimation are wide-ranging research topics. In this thesis, LTO battery is chosen since it is considered as the latest technology for Li-ion battery. Transfer function-based model and equivalent circuit model are studied in detail in this thesis. The transfer function-based model is developed based on the charging behaviours of LTO cells, however, it is also believed that the methodology of the formulation of transfer function-based model could be applied for another types of battery. The transfer function-based model is developed for the purpose of charger design and it represents battery behaviours as an empirical equation. It is important to clarify that it is not representing the exact electrochemical processes within the battery.

For equivalent circuit model, second-order Thevenin model is applied in this research. The battery model is formulated based on the electrical characteristics of the LTO battery without considering OCV hysteresis effect, self-discharge effect, capacity fading losses and calendar losses. The thermal modelling of the battery is also not included in the battery modelling. Most importantly, only cell level modelling is presented in this thesis, which is not similar to the multiple cells as applied in EV battery pack. This approach is made in order to avoid the multiple cells issues, such as cell imbalance and cell voltage monitoring.

Kalman filter-based SoC estimation technique is chosen for this thesis due to its robustness as proven by the previous literatures. Extended Kalman filter and Unscented Kalman filter are applied in the study. Moreover, covariance matching rule and Busse's adaptive rule are chosen as the adaptive rules for Kalman filter. For the purpose of verification, a benchmark for the SoC estimation is created, where the laboratorial Ah-counting method is applied to find out the true SoC value throughout the battery tests.

1.6 Thesis Organisation

The rest of the thesis is organised as follows:

Chapter 2 provides a literature review on the dynamic behaviours of a battery, battery models, battery tests and parameter identification techniques. The applications of Kalman filters for online battery modelling and SoC estimation are also reviewed. The algorithm of EKF, UKF and the existing adaptive rules are also explained in detail.

Chapter 3 describes the experimental set-up used in the thesis. The procedures of battery tests, which are used to identify the parameters of the battery model are presented and described.

Chapter 4 proposes a transfer function-based battery model to simulate the charging behaviours of LTO battery. A new approach of capturing nonlinear charging behaviours is also presented in detail. Simulation and the experimental study on the proposed battery model are also presented. The performance of the proposed battery model is discussed.

Chapter 5 proposes the application of Busse's adaptive rule in Kalman filter-based SoC estimation. In this case, the Busse's adaptive rule is applied on both EKF and UKF. The performance of Busse’s adaptive EKF and Busse’s adaptive UKF is compared with the conventional EKF and UKF, as well as the covariance-matching adaptive EKF and covariance-matching adaptive UKF. Simulation and experimental studies have been done to verify the proposed method.

Chapter 6 applies Kalman filter for SoC estimation with online battery modelling. In this case, SoC and model parameters are estimated simultaneously by using joint Kalman filters. Similar to Chapter 5, Busse’s adaptive rule is proposed to increase the accuracy of the SoC estimation with online battery modelling. The simulation and experimental studies have been done to verify the proposed method.

Chapter 7 gives the conclusion of the thesis and possible directions of further research on this work.

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