A State of Charge and Parameter Estimation of Li-Ion Polymer Battery: Current State

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Abstract: This paper presents an extensive study on issues related to the development of a recently researched Li-Ion Polymer (LiPO) battery. The vast area of research on LiPOsuch as state of charge (SoC) estimation, electrolyte, an equivalent circuit which includes electrical & thermal modelling, parameter identificationand validation cycles have extensively reviewed and discussed. Moreover, the parameter identification methods of the battery are also elaborated in detail. A novel attempt is made to prepare and compare the various SoC estimation techniques, stating its advantages and disadvantages. The error in the SoC estimation technique is greatly dependent on the battery model considered. Various electrical models are discussed that can replicate the battery's electrical performance. The complexity of the model increases as the number of performance parametersare included in the model. The estimation is incomplete if the technique is not validated and hence various validation cycles are discussed to validate the effectiveness of SoC estimation.

1 INTRODUCTION

Nowadays battery plays a very crucial role in several engineering applications due to numerous energy and environment concerns. The research on various aspects of battery picked up during the nineties after compulsion of environmental issues. Lithium based rechargeable batteries are very suitable power sources for several evolving applications.In Li-ion battery, Lithium-ion intercalated compound or either graphite or disordered form of carbon is used as electrodes. The battery reaction is as follows:

$Li^{+} + C_6 + e^{-} \Leftrightarrow C_6Li$: negative electrode reaction

$LiMO_2 \Leftrightarrow MO_2 + Li^{+} + e^{-}$: positive electrode reaction

Compared to its counterpart nickel metal hydride and nickel-cadmium batteries, Lithium batteries have high energy and power density,high voltage in a unit cell and high specific energy with long cycle life. Cutting edge competition between the two battery technology has led enormous development of Li-ion battery as compared to $NiMH_2$ batteries and is was well predicted that the two batteries had an almost equal number of sales during 2004 which was initially dominated by $NiMH_2$ battery (Blomgren, 2000). The secret of success lies within the progress of electrolytes which was very paramount after initial liquid electrolyte, progressed to solid electrolyte and thento polymer electrolyte. Table 1 shows the comparative analysis between solid, liquid and hybrid electrolyte. Sanyo, a manufacturer of Li-ion battery, showed that there was a 50% increase in the energy content of a Li-ion battery from 1994 to 1999. The challenge to the liquid electrolyte of Li-ion rechargeable batteries, as mentioned in Table 1, was eradicated by the use of the gel-based polymer. But they faced compatibility issue with lithium metal anode and had problems with leak proof packaging (Gozdz et al., 1995). The need to have thin batteries with flexible manufacturing and battery surface design forced to develop Li-Ion Polymer (LiPO) batteries that completely had solid electrolyte. The use of polymer PEO (Polyethene oxide) was common due tothe low conductivity of 10^{-6} to 10^{-7} S/cm due to crystallinity (Venkatasetty and Jeong, 2002). To achieve high conductivity lithium imide salts were developed. Numerous co-polymers have been created that can deal with the problem of crystallinity. The stability of these salts results ina maximum voltage of 4.5V. Salts such as $CF_3SO_2NLiSO_2C_2F_5$ and $CF_3SO_2NLiSO_2C_4F_9$ showed higher conductivity and optimized the blending condition with polymer

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electrolyte. To increase the conductivity of polymer, nano filters such as $BaTiO_3$ is added in the electrolyte, which also reduces the corrosion and growth of dendrites in electrode due to less reactive nature towards alkali metal.LiPO batteries though provided a solution but Solid Polymer Electrolyte (SPE) lacks the ionic conductivity due to low segmental mobility of polymer chain. Various development has been made in the types of polymer. Electrolytes such as 1-MLiPF$_6$-EC/PC has been developed with conductivity more than 10^{-3} S/m and strength upto 90-100°C. A polymer such as $BaTiO_3$less reactive to alkali metal and Formation of dendrites is less. Few environmental friendly polymers have been developed. This paper is an attempt to discuss various issues related to LiPO batteries such as SoC estimation, electrolyte, an equivalent circuit which includes electrical & thermal modelling, parameter identification and validation cycles. The contribution has been made to identify the advantages and disadvantages of various SoC estimation techniques. All the estimation techniques available for LiPO battery are briefly discussed. Further efforts were made towards the selection of battery model and techniques to identify the battery parameter.

Table 1: Comparison of various electrolytes in Li-based batteries

Electrolyte	Advantage	Disadvantage
Liquid	- High conductivity - Developed technology	- Leakage of electrolyte - costly separator - oxidation of electrolyte - no flexibility in design - Inefficient space utilization
Solid	- No leakage of electrolyte - simple polymer processing methods -Flexibility in design	- Low conductivity - Poor mechanical properties
Hybrid	- High conductivity - no leakage of electrolyte - easy polymer processing	-Electrochemical stability

Furthermore, the validation of SoC via various standard cycles have been identified. The state ofthe literature on the LiPO battery is shown in figure 1.

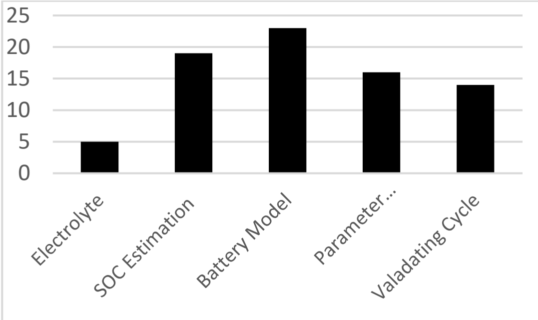

Figure 1: Number ofresearch paper under consideration for a particular topic.

2 LITERATURE REVIEW

2.1 Soc Estimation

With the development and wide application of Li based batteries, the estimation of battery's SoC is utmost important and hence the estimation of SoC has been extensively researched and different methods have been proposed. Battery system being highly non-linear it is very much important to have an accurate estimation of SoC as it can avoid the condition of overcharge or over-discharge thus increasing the life of the battery.

Various methods of SoC estimation proposed can be broadly classified into the direct method, Book Keeping method, artificial neural network and model based method with a filter algorithm, as shown in figure 2. The direct method to estimate SoC remains by monitoring voltage and electrochemical impedance. Though the method is simple and easy to implement. This method is difficult to implement in real-time as the driving cycle is very uncertain (Sathyanathan and Sugumaran, 2018). This requires to evaluate the charge retained by the battery before calculation. Moreover, it has a large measuring time Xiong et al., (2013), hence its practical application is very complex (Dowgialloal, 1976). Open circuit voltage estimation being another method for SoC estimation, but the time required by the battery to reach equilibrium is large and hence cannot be used for real-time application (Meng et al., 2016 and Lee et al., 2018).

Book Keeping method is based on battery current integration also called as Ampere-hour counting or Coulomb counting method Johnson, (2002) is so versatile that it is still the basis of SoC estimation in Battery Management System (BMS) provided the accuracy in measuring the current and initial SoC of battery is maintained (Xiong et al., 2013; Lee et al., 2018; Xu et al., 2014 and Chen et al., 2016). This method is simple and easy to implement (Xu et al., 2014). Since this method is an open-loop system, so neither of errors in the system can be detected nor fixed thus accumulating errors (Xu et al., 2014). Further, SoC estimation does not take into account battery age, health, temperature (Sathyanathan and Sugumaran, 2018 and Hansen et al., 2005). Artificial neural networks and fuzzy logic system were developed for SoC estimation but it required high and very complex computational so it cannot be applied on the online system (Lee et al., 2018; Xu et al., 2014 and Chen et al., 2016). The various model based method with filter algorithms such as Support Vector Machine (SVM) method, Sliding Mode Observer, Kalman filter was developed to estimate SoC.Every method has its own pros and cons. Support Vector machine requires low memory but accurate training data and proper kernel function are required (Lee et al., 2018 and Hansen et al., 2005).Kalman Filter is a powerful tool as SoC estimation does not depend on initial SoC value and it can detect and model cell ageing Hansen et al., (2005) but to accomplish this advantage an accurate battery model and appropriate knowledge of system noise are required (Sathyanathan and Sugumaran, 2018; Xiong et al., 2013; Xu et al., 2014; Xiong et al., 2005 and Junet et al., 2014). Sliding Mode Observer leads in simple control and robust performance under uncertain environments (Xu et al., 2014 and Junet et al., 2014) but the chattering phenomenon cannot be ignored (Xu et al., 2014). Some advancements in these basic techniques, such as Robust Sliding mode observer, Extended Kalman filter, Adaptive unscented Kalman filter were employed to escape from those drawbacks, to have fast convergence, error below 3%, less computational burden and many more. A detailed comparison of various techniques has been described in table 2.

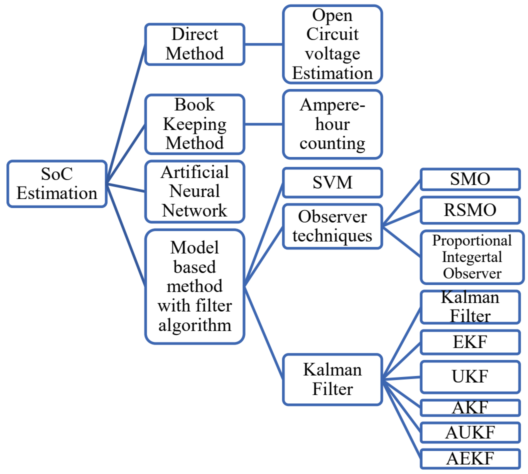

Figure 2: Classification of SoC estimation techniques

2.2 Battery Model

To estimate the exact performance of battery such as SoC and State of Health (SoH), it is important to have an accurate battery model. Further, this will help to improve the charging and discharging pattern of the battery (He et al., 2011). Modelling of the battery for any application can be achieved via electrochemical model, statistical model, probabilistic model, neural network model, equivalent circuit model and analytical battery models. A detailed comparison of these models has been shown in table 3. Numerous electrical equivalent circuit models were developed to simulate the battery performance. Further, development has been made to model and compensate for the temperature error (Moshirvaziri et al., 2015) and fault diagnosing (CemKaypmaz et al., 2011).

Table 2: Comparison of various SoC estimation techniques.

S.No.	SoC Estimation Techniques	Advantage	Disadvantage
1	Direct Method	Simple and easy to implement	-Uncertainty in driving cycle leads to difficulty in measurement of SoC and parameter characterization in real time**(Sathyanathan and Sugumaran, 2018)** -Before new calculation, BMS requiresto determine the charge remaining in battery**(Xiong et al., 2013)** - Large measuring time. **(Xiong et al., 2013)**
	Open circuit voltage estimation	Simple and easy to implement	-Time required by battery to reach equilibrium is large and hence cannot be used for real time application **(Meng et al., 2016) (Lee et al., 2018)**.
2	Ampere-hour counting or Coulomb counting	-Simple and easy to implement **(Xu et al., 2014)** -Consider both current	-Accuracy of estimation depends on accurateness in measurements of the current and initial SoC of battery **(Xiong et al., 2013; Lee et al., 2018; Xu et**

	or current integrationmethod	measurement and integration - Basis of SoC estimation in BMS	**al., 2014 and Chen et al., 2016)** -The coulomb counter cannot detect and fix the starting error -SoC estimation does not take into account battery ageing**(Meng et al., 2016 and Hansen et al., 2005)** - Since the system is open loop, it is prone to accumulation error**(Xu et al., 2014)**.
3	Artificial Neural Networks or Fuzzy Logic	A powerful tool for non-linear system **(Xu et al., 2014)**	-Learning process requires high computational and is very complex and cannot be applied on online system **(Lee et al., 2018; Xu et al., 2014 and Chen et al., 2016)** -High burden on BMS **(Chen et al., 2016)** -Large memory is required.
Model based method with a filter algorithm			
	Luenberger observer		-The result depends highly on the accuracy of the model **(Xu et al., 2014)** - Computational complexity is high enough for online application **(Xu et al., 2014)**
	Sliding mode observer (SMO)	-Easy control and robust performance in uncertain environments **(Xu et al., 2014 and Junet et al., 2014)**. -Good convergence **(Junet et al., 2014)**. -Compensate for the effect of nonlinearity and uncertainty	-The chattering phenomenon causes an error **(Xu et al., 2014 and He et al., 2011)** -Inappropriate switching gain can cause slow estimation of SoC.**(He et al., 2011)**
	Robust Sliding mode observer (RSMO)	-Strong robustness for time-varying and non-linear battery system **(Chen et al., 2016)** - Fast convergences and accurate results when compared to SMO	- The chattering phenomenon causes an error.
	Proportional Integral observer	-More robust performance under uncertain environments	-The chattering phenomenon causes an error **(Xu et al., 2014 and He et al., 2011)**
4	Kalman filter	- SoC estimation does not depend on initial SoC value - It can detect and model cell ageing **(Hansen et al., 2005)** - It is an optimization method of the Luenberger observer **(Xu et al., 2014)**	- The result depends highly on the accuracy of the model. - Inappropriate knowledge of noise in the system will lead to remarkable error and divergence **(Sathyanathan and Sugumaran, 2018); Xiong et al., 2013; Xu et al., 2014; Xiong et al., 2005 and Junet et al., 2014)** - Computational complexity is high enough for online application **(Xu et al., 2014)** - It linearizes the non-linear system **(Meng et al., 2016 and Chen et al., 2016)**
	Extended Kalman Filter (EKF)	- SoC estimation does not depend on the initial SoC value **(Lee et al., 2018)**. - Detect and model cell ageing and other lifetime effects on battery, the accuracy of ±5% can be achieved **(Hansen et al., 2005)**. - Linearizes the non-linear system **(Meng et al., 2016; Chen et al., 2016 and Wu al., 2018)**	- SoC depends on a particular type of system. - High computational complexity, computational time and implementation cost **(Hansen et al., 2005)**. - Since higher order terms are ignored, linearization error is expected **(Meng et al., 2016 and Chen et al., 2016).** - Accuracy is reached for first order only **(Wu al., 2018)**
	Unscented Kalman Filter (UKF)	- More accurate and easier to implement when compared to EKF **(Meng et al., 2016)**	- Noise still remains a major issue. - The high computational burden **(Meng et al., 2016)**.

		-Unscented transformation to approximate the probability density function **(Chen et al., 2016)**.	
	Adaptive unscented Kalman filter (AUKF)	-Adaptively adjusts process noise covariance **(Meng et al., 2016)**	- Result depends highly on the accuracy of model. -High computational burden **(Meng et al., 2016)**.
	Adaptive Extended Kalman filter (AEKF)	- System adaptively updating the process and measurement noise covariance.	- High computational burden
	Support Vector Machine (SVM)	-Memory requirement is less. - Successful for the highly non-linear system. -After training, SVM does not require to call intensive math function, as in case of EKF -An optimized SVM can offer an accuracy comparable to EKF at the cost of simple coulomb counter **(Hansen et al., 2005)**	Accurate training data and proper kernel function are required. **(Lee et al., 2018)**

Table 3: Comparison of various battery models.

Battery model type	Advantages	Disadvantages
Electrochemical model	-Fully describe the characteristics of battery (He et al., 2011 and Ceylan et al., 2014) - Most accurate and can be used as a reference for comparison with other models	-Very complicated and difficult to configure. (He et al., 2011; Ceylan et al., 2014) - Difficulty in simulating the dynamic performance (He et al., 2011) - Long computation time (Ceylan et al., 2014)
Statistical models	-Extract data from samples of data. (Ceylan et al., 2014 and Krintz et al., 2004) -Compact and fast (Ceylan et al., 2014 and Krintz et al., 2004)	-Not as accurate as physical models (Ceylan et al., 2014 and Krintz et al., 2004)
Probabilistic model	-Extract data from sample data. (Ceylan et al., 2014 and Rao et al., 2005) - Better results as compared to Statistical models	- Complex method - Require advanced simulation techniques (Ceylan et al., 2014 and Rao et al., 2005)
Neural network model	High accuracy under certain conditions (He et al., 2011)	- Accuracy and calculation burden of the model was influenced by the choices and quantity of input variables of theneural network. (He et al., 2011) - Neural network trained by data can only be used within the original scope of that data (He et al., 2011)
Equivalent circuit model	- High dynamic simulation with high accuracy (He et al., 2011) - Temperature dependent model of the battery is available	- Not as accurate as Electrochemical model.
Analytical Battery Models	- Electrochemical and statistical methods are combined (Ceylan et al., 2014) - High accuracy, robust, compact and fast (Ceylan et al., 2014 and Jongerden et al., 2009)	

2.3 Parameter Identification

Once the battery model is known then it is required to identify the parameters of the model so as to incorporate the dynamic performance of the battery. Many such techniques that identify and optimize the battery parameters are Recursive Least Square (RLS), Genetic Algorithm, Generalized Pattern Search (GPS) Hooke Jeeves optimizationalgorithm, extended Kalman filter, least square support vector machines. Temperature and ageing parameters of the battery were also modelled by many authors to investigate the battery depth of discharge, efficiency and much other performance parameters (Dogger et al., 2011). The importance of temperature in the battery was felt and authors in Lee et al., (2012) installed temperature sensor in battery and authors in Pruteanu et al., (2012) proposed a method to predict the thermal behaviour of LiPO battery.

2.4 Charging of Batteries

A proper charging cycle would increase the life of the battery. The basic charging pattern is Constant Current/Constant Voltage (CC/CV) charging which is not sufficient for fast charging. Authors in (Choe et al., 2013) have developed a charging algorithm that determines the magnitude of charging current and duration of charging current on the basis of SoC of the battery and the Li concentration at the surface of the electrode. Authors Kim et al., (2016) proposed a strategy to reduce the charging losses inLiPO battery while in Amanor et al., (2018) authors discussed the strategies to have faster and efficient battery charging techniques by determining the pulse width and frequency of the charging pulse.

3 SOC ESTIMATION TECHNIQUES

SoC estimationof a battery is very much vital for battery based devices such as Mobile phones, Laptop, Electric Vehicles (EV) Solar charger and much more applications.

SoC is defined as the measurement of the charge contained in the electrode calculated in terms of the lithium concentration. SoC can also be understood as an indicator or energy available within the battery (Watrin et al., 2012). So estimating the SoC is of the utmost important parameter in a battery. Definition of SoC is not very easy and consistent as it can be expressed by other parameters (Dogger et al., 2011; Charkhgard and Farrokhi, 2010). In general, the SoC has described the relationship between the current capacity (q(t)) and rated capacityof the battery as given in equation 1 (Dogger et al., 2011; Charkhgard and Farrokhi, 2010).

$$SoC\ (t) = \frac{Remaining\ Capacity}{Rated\ Capacity} = \frac{q(t)}{q_n} \quad (1)$$

Equation 2 gives the expression of SoC in continuous form and discrete form with Δt as the sampling interval.

$$\begin{cases} SoC\ =\ SoC_o - \frac{\int_0^t \eta.Idt}{q_n} \\ SoC_k = SoC_{k-1} - \eta.I\frac{\Delta t}{q_n} \end{cases} \quad (2)$$

Where η is charge or discharge efficiency, I refer to current flowing through the battery $q_n$is the rated capacity of the battery. SoC_K is the SoC at the k^{th} instant.

In the Direct method, SoC is estimatedfrom the open circuit voltage (OCV)and SoC curve of the batteryof a Li-ion Polymer. There is no linear relationship between SoC and OCV of Li-ion PO battery (Shown in figure 3) and the relationship is different for different batteries.

In Open circuit voltage estimation method employs the fact that internal impedance causes voltage to drop as the battery discharges. In other words, one can say that EMF of battery is related to SoC.This method comes with serious drawback that as the battery is near to get discharged, the error in SoC estimation is large (Chang et al., 2013).

In Ampere-hour counting or Coulomb counting or current integrationmethod, the discharging current I(t) is integrated to calculate the charge remaining in the battery and thus estimating the State of Charge (SOC(t)) of the battery as mentioned in equation 3.

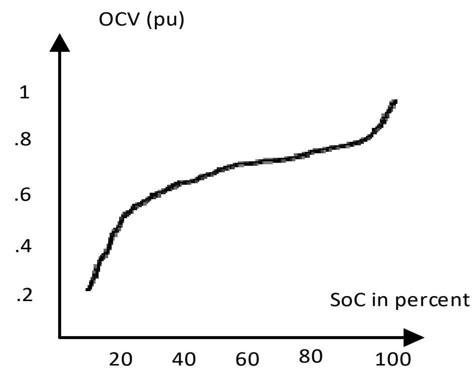

Figure 3.

$$SOC\ (t) = SOC\ (t-1) + \frac{I\ (t)}{Q_n}\Delta t \qquad (3)$$

Where SoC (t-1) is previously estimated SOC value. Accuracy in SoC estimation depends on various factors such as discharging current pattern, battery SoH, temperature and life cycle.

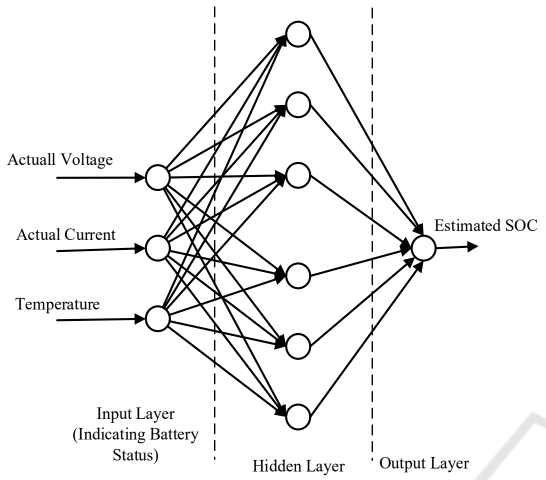

Figure 4: SOC estimation using backpropagation techniques

In Back propagation neural network method, SoC is predicted on the basis of recent data of current, voltage and battery temperature Linda et al., (2009), a typical block diagram for back propagation technique is shown in figure 4. The architecture contained actual voltage, actual current and actual temperature as inputneurons. Output layer, containing one layer, is used to estimate the SoC.Architecture is shown in figure 4. Equation 4 governs the input of neurons inthe hidden layer.

$$neti_j = \sum_{i=1}^{3} x_i v_{ij} + b_j \qquad (4)$$

Where $neti_j$ is referred to input to j^{th} hidden layer neuron; x_i is referred to input to hidden layer neuron j; v_{ij} is referred to weighted function between i and j and finallyb_j is referred to bias function of the hidden layer neuron j. The governing equation of output layer neuron is similar to that of equation 4.
The activation function applied to hidden layer neuron and output layer neuron is the hyperbolic tangent function and sigmoid function, respectively. The advantage of this technique is that it has the ability to self-learn, self-organize and efficient mapping of non-linear system.

3.1 Support Vector Machine (SVM)

The SVM Hansen et al., (2005) uses a non-linear estimator that gives robustness to this technique. SoC estimation starts with the training of SVM. The training data should be different from the testing data and it should cover the entire range of operation of SVM. Next, the optimum SVM parameter is calculated. Now the processing of the test data to obtain the SoC is done in the same way as that of training data. The root mean square error was approx. 5% with a positive maximum as +16% and a negative maximum of9%.

An optimum SVM can condense thousands of training points to a manageable number of support vectors. Unlike EKF, matrix inversion and complex math function are not required to be called in SVM.

3.2 Sliding Mode Observer (SMO) Technique

The key to the success of SMO Junet et al., (2014) technique is a simple control structure with unmatchable performanceunder uncertain environments. The modified Thevenin model of battery or Dual Polarization model has been used so as not to compromise with accuracy in estimation of SoC.

The technique starts with developing piece-wise relationship between SoC and OCV. Then battery system that includes various parameters such as R_{t1}, R_{t2}, C_{t1} and C_{t2}, (as mentioned in table 5) is developed in state space form, as shown in equation 5. The battery system needs two additional terms namely sliding feedback gain and Luenberger-type gain. Luenberger gain ensures stability to the observer. An additional function $sgn_{eq}(y)$, defined in equation 6, is added to the state-space equation to remove the chattering levels produced by this technique.

$$\begin{bmatrix} \dot{V_{t1}} \\ \dot{V_{t2}} \\ SoC \end{bmatrix} = \begin{bmatrix} {}^{-1}/_{R_{t1}C_{t1}} & 0 & 0 \\ 0 & {}^{-1}/_{R_{t2}C_{t2}} & 0 \\ 0 & 0 & 0 \end{bmatrix} \begin{bmatrix} V_{t1} \\ V_{t2} \\ SoC \end{bmatrix} + \begin{bmatrix} {}^{1}/_{C_{t1}} \\ {}^{1}/_{C_{t2}} \\ {}^{-\eta}/_{C_N} \end{bmatrix} I \qquad (5)$$

$$sng_{eq}(e_y) = \frac{e_y}{|e_y| + \mu} \qquad (6)$$

The results from the SMO techniques show that steady state error is asymptotically stable which make its performance better for an unpredictable environment.

3.3 Robust Sliding Mode Observer (RSMO)

RSMO Chen et al., (2016) technique comes with switching adaptive gain that helps to predict the SoC in an unpredictable environment. This is achieved by designing feedback gain matrix and observer input function in such a way that robustness and convergence of error aredefinite. The technique proceeds with modelling the battery system in discrete form. Error dynamics is calculated by obtaining the difference between estimated states and true states. With the adaption of Radial Basis Function Neural Network in the RSMO, prediction techniques can gain robust tracking capability of parameter against system uncertainty. It can further significantly restrain the chattering magnitudes in the SoC estimation

3.4 Extended Kalmanfilter (EKF)

The main focus was to develop the temperature compensated model of LiPO battery via EKF Lee et al., (2018), to estimation SoC. The temperature ranges from 37°C to 40°C. Estimation of SoC is based on reducing the error between the measured value and estimated value by adjusting the Kalman gain. Prediction begins with developing the battery model in a state-space form that includes Gaussian Process noise and Gaussian measurements noise. State-space model of Thevenin battery model is represented in equation 7.

$$\begin{bmatrix} SoC_k \\ V_{t1,k} \end{bmatrix} = \begin{bmatrix} 1 & 0 \\ 0 & \frac{-1}{R_{t1,k-1}(T)C_{t1,k-1}(T)} \end{bmatrix} \begin{bmatrix} SOC_{k-1} \\ V_{t1,k-1} \end{bmatrix} \pm \begin{bmatrix} 1/q_{n,k-1}(T) \\ 1/C_{t1,k-1}(T) \end{bmatrix} I_{k-1} \tag{7}$$

Once the battery terminal voltage and state of charge are calculated then the battery internal voltage is observed using equation 8 as,

$$[V_{t,k}] = [a_k(T) \quad 1] \begin{bmatrix} SOC_k \\ V_{1t,k} \end{bmatrix} + I_k R_{1,k}(T) + b_k(T) \tag{8}$$

Where $R_{1t,k-1}(T)$ refers to the battery resistance at a particular temperature.

The temperature and voltage are measured and the initial SoC is determined. Temperature compensated model is identified and the SoC is estimated using the EKF algorithm as shown in figure 5.

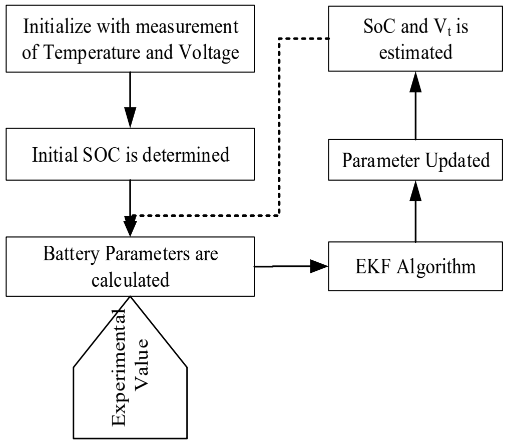

Figure 5: SoC Estimation block diagram for EKF technique.

3.5 Unscented Kalman Filter (UKF)

UKF Wu et al., (2018) proceeds with the discretization of non-linear system dynamics in the state space equation. SoC is defined on the basis of equation 2. For SoC estimation in discrete form, the sampling time of Δt =1 sec is considered. State-space model of battery is given in equation 9

$$V_{t1,k} = V_{t1,k-1} e^{-\Delta t / C_{t1} R_{t1}} + I_{k-1} . R_{t1} \left(1 - e^{-\Delta t / C_{t1} R_{t1}}\right) \tag{9}$$

State variable X_k, comprises of two variable, namely SoC_k, $V_{t,k}$. The observation equation is shown in equation 10

$V_{t,k} = V_{in}(SOC_k, T) - I_k R_1(SoC_k,T) - V_{t,k}$

(10)

SoC is estimated by flow chart as given in figure 6.

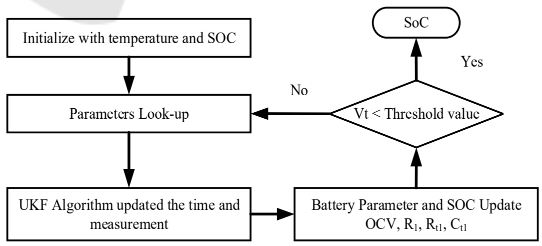

Figure 6: Flow chart to estimate SoC using UKF.

3.6 Adaptive Unscented Kalman Filter (AUKF)

AUKF **Meng et al., (2016)** method gives successful result in the estimation of SoC because of the fact that sampling of a non-linear battery system. AKUF based SoC estimation starts with the basic SoC equation as shown in equation 2.To incorporate the system noise, the parameter q_k has been added in equation2.The accurate model of the system is developed via LSSVM where another parameter $r_k$has introduced that account for measurement noise.

Algorithm of AKUF estimation, as shown in figure 7 starts with an initial value of SoC and then measurement error and noise in the system is determined. Then, calculating sigma point and weighting coefficients. Now, prediction and correction are done based on set equations. Finally, adjustment of noise covariance.

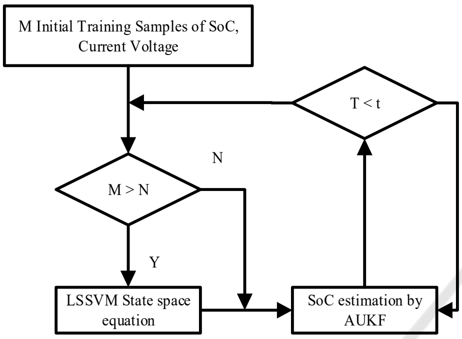

Figure 7: Flowchart of AUKF algorithm for SoC estimation.

In order to reduce the computational burden and size of the data set, the data collection is done by moving window method. SoC estimation of the battery is done on the basis of parameters in equivalent circuit model that is consistently updated on the basis of age, operating time. Further for computation of SoC, the initial training sample required for computation is less.

3.7 Adaptive Extended Kalman Filter (AEKF)

SoC and peak power capability for a 3.7V/35Ah $LiMn_2O_4$ Li-ion battery is robustly determined by AEKF(Sathyanathan and Sugumaran, 2018); Xiong et al., 2005 and Sun et al., 2014). This method is also used to calculate State of Power (SoP) (Sun et al., 2014).

SoC is defined and estimated on the basis of equation 2. The voltage is updated equation is similar to equation 9 and reproduced here for ready reference. SoC estimation requires discretization of the battery system as given in equation 11.

$$\begin{cases} V_{t1\prime k} = V_{t1,k-1} e^{-\Delta t / C_{t1} R_{t1}} + I_{k-1}.R_{t1}(1 - e^{-\Delta t / C_{t1} R_{t1}}) \\ V_{t\prime k} = V_{in,k-1} + I_{k-1}.R_1(1 - e^{-\Delta t / C_{t1} R_{t1}}) \end{cases} \tag{11}$$

Additional terms such as ω_k representing unmeasured process noise and υ_k representing the measured noise are required to be added in equation 11 (Sun et al., 2014).

Before initialization the AEKF algorithm, it is required to develop the measurement model and state transition model that can relate SoC to OCV The block diagram of AEKF is shown in figure 8. The algorithm requires the Development of non-linear model of the battery and then real time current profile is measured and loaded to the model. This helps in parameter identification by Recursive least square. Identified parameters are used to update the SoC which further helps in updating the OCV.Now the parameter data and voltage error are transmitted to AEKF based SoC estimation technique. With the estimated SoC, OCV is updated and after computation terminal voltage error converges to set value. Then SoC reflects the reference voltage thus estimating correct SoC.

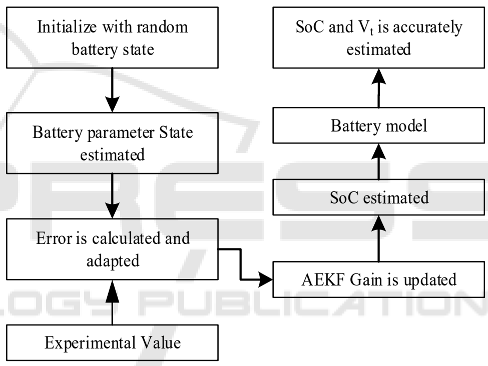

Figure 8: Block diagram of SoC estimation via AEKF technique.

3.8 Proportional-integral Observer

SoC is defined similarly to equation 1 and 2. Battery model could be fully regarded as a linear system if there is no modelling error or non-linearity are considered.Non linearity of the system has been considered as an added to the battery system by adding a parameter $E\upsilon(t)$, as shown in equation 13.

$$\begin{cases} \dot{x} = Ax + Bu + E\upsilon(t) \\ y = Cx + Du \end{cases} \tag{13}$$

E refers to as non-linearity and $\upsilon(t)$ refers to as disturbances. There are various parameters that cause a disturbance in the system such as sensor noise, temperature and so on. The parameter $d\upsilon(t)/dt \approx 0$ since temperature variation is slow, drift in the current sensor is also slow. So simple case of $d\upsilon(t)/dt \approx 0$ is considered. The Proportional Integral observer Xu et al., (2014)model is developed according to the Li-ion battery system as per the definition. The parametersK_p, K_{i1} and $K_{i2}$of the observer technique are identified using Linear Quadratic method.

Finally, to provide a clear view of SoC estimation, table 4 represents the comparative analysis of various SoC estimating techniques and the error associated with it.

Table 4: Comparison of error in various SOC estimation techniques using a different model and validating cycles.

S.No	SOC Estimation technique	Error	Validating cycle	Model considered	Remark
1	T-UKF	3	NEDC	Thevenin Model	Temperature compensation
2	RSMO	2.23	UDDS	DP Model	
3	SMO	5.81	UDDS	DP Model	
4	REKF	1.56	FUDS	DP model	
5	AEKF	2	-	Thevenin model	
6	T-EKF	3	PCC	Thevenin model	
7		1.5	FTP72	Thevenin model	
8	EKF	5.31	-	Thevenin model	
9	SMO	1.31	-	Thevenin model	
10	UKF	3	PCC		SOC ≥ 20%
11	AUKF	1.2	PCC		SOC ≥ 20%
12	PI observer	2	UDDS	Thevenin model	
13	AEKF	1.5	FUDS	Thevenin model	
14	SVM	5.76			
15	AEKF	1	UDDS	Thevenin model	
16	AEKF	3	FUDS	DP model	
17	EKF	3	-	Neural Network model	
18	AEKF	1.06	FUDS	DP model	

4 ELECTROLYTE

Electrolyte plays an important role in the safety of the battery and hence solid electrolyte is preferred over liquid electrolyte. But this advantage comes with the cost of reduced conductivity and many more issues as mentioned in table 1. Many types of research are conducted to overcome their disadvantages.

$BaTiO_3$nanocomposite polymer is shaped with the electrolyte of LiPO battery in order to achieve better Li-ion concentration at the electrode surface which was found to be around 3.5 × 10^4 mol/m^3(Sathyanathan and Sugumaran, 2018).This has an added advantage of increased conductivity about 2.4 × 10^{-3} S/cm at 343K. The voltage dip from 4.02V to 3.92V in just 5 Sec but remained saturated at that point.A low cost commercially available polymer is developed for polymeric binder for LiM_xO_y cathodes, coke or graphite based anode. Random copolymers of vinylidene fluoride with hexafluoropropylene can be solvent cast in the presence of at least 50-60 volume%of liquid electrolyte solutions, such as 1-M $LiPF_6$-EC/PC, to give strong, homogeneous filmswhich exhibit good mechanical properties even when temperature raise to 90°C - 100°C(Gozdz, Tarascon, Schmutz, Warren, Gebizlioglu and Shokoohi, 1995).Research has been carried out in lithium salts and copolymer to have electrochemical stability and conductivity up to 3×10^{-5} S/cm (Venkatasetty and Jeong, 2002). A low cost environmental friendly polymer electrolyte membrane (Adding $LiClO_4$, to polyvinyl alcohol (PVA) and polyethene oxide (PEO)) polymer for LiPO battery has been developed by casting of polymer solution(Rochliadi et al., 2015). The optimum ionic conductivity with mechanical strength of the polymer electrolyte membrane was observed when PVA and PEO were mixed in the ratio of 7:3. When the ratio of PVA and PEO changed to 8: the conductivity increases with the cost of low mechanical strength. PVA-PEO-$LiClO_4$ has the potential to qualify as biodegradable electrolyte membrane for Li-ion battery. The nanocomposite polymer electrolyte for Li-ion polymer battery was developed by mixing 50 percent by weight of polyhedral oligomericsilsesquioxane-functionalized with polyethene glycol (POSS-PEG) nanoparticle and polyethylene oxide (PEO)with lithium bisoxalate borate (LiBOB) which increased the conductivity to 3.98 × 10^{-6} S/cm(Reddy et al., 2018).

5 ELECTRICAL MODEL

A well-defined battery model will lead to an accurate estimation of SoC, SoH, OCV. A detailed comparison of various modelshas been presented in table 3.Based on the dynamic characteristics and working principles of the battery, the electrical equivalentcircuit model such as Rint Model, RC model, Thevenin equivalent circuit model, PNGV Model, Dual polarization model, Randels equivalent circuit was developed by using resistors, capacitors and voltage sources to form a circuit network (He et al., 2011). Electrical equivalent model of battery contains various parameters of battery that are modelled as resistance, capacitance and ideal voltage source.

Table 5: Various Parameter of commonly used battery model.

Common	q(t)	Remaining battery capacity
	q_n	Rated capacity of battery
	V_t	Terminal voltage of battery
	V_{in}	Open circuit voltage
	I	Load current
Rint Model	R_l	Electrolytic resistance
Thevenin Model	R_{t1}	Polarization resistance
	C_{t1}	Polarization capacitance
	R_l	Electrolytic resistance
PNGV Model	C_{acc}	voltage due to accumulation of load current.
	R_{t1}	Polarization resistance
	C_{t1}	Polarization capacitance
	R_l	Electrolytic resistance
Dual Polarization Model	R_{t1}	Polarization resistance
	C_{t1}	Polarization capacitance
	R_l	Electrolytic resistance
	R_{t2}	Electrochemical Polarization Resistance
	C_{t2}	Electrochemical Polarization capacitance

The Rint model comprises of resistance and an ideal voltage source, both being a function of SoC, SoH and temperature. Positive and negative load current denotes for discharging and charging current, respectively. The open circuit voltageis given by $V_t = V_{in} - IR_1$.The equivalent circuit is shown in figure 10. Resistance was evaluated via the following equation $R_1(SoC) = R_{1_0} + k_{R_1}^{SoC} \times SoC$ Einhorn et al., (2013) where k_{R1}^{SoC} iscoefficient for change in R_l with SoC.In RC model two capacitors C_c, C_b represents the battery state. C_c represents the capacitance due to surface effect of battery and has a small value. The Capacitor C_b, with large capacitance, represents the chemical energy stored in the battery and is responsible for the SoC of battery. The resistances are R_t (Terminal resistance), R_e (end resistance) and R_c (Capacitor Resistance) and the two capacitance C_c, C_b describes the electrical behaviour of battery. The equivalent circuit is shown in figure 10.

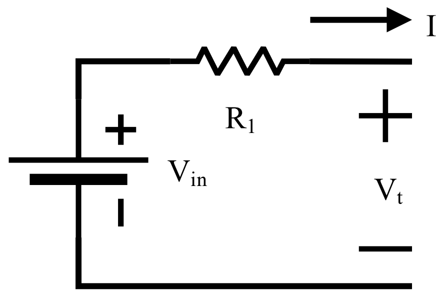

Figure 9: Rint model of a battery

In order to include the transient performance of the battery in Rint model, a parallel RC network is connected in series, thus giving Thevenin equivalent circuit model as shown in figure 11. The resistance R_{t1} denotes polarization resistance and capacitance C_{t1} describes the transient response of battery during charging and discharging. The governing equation of the model is $V_{in} = IR_1 + V_{t1}$ (Sathyanathan and Sugumaran, 2018; Meng et al., 2016; Lee et al., 2018; Xu et al., 2014; Chen et al., 2016; Xiong et al., 2005; He et al., 2011 and Einhorn et al., 2013)

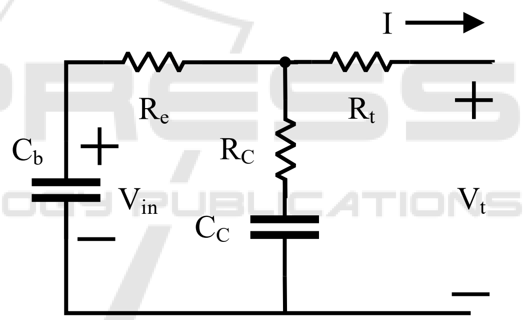

Figure 10: RC model of a battery

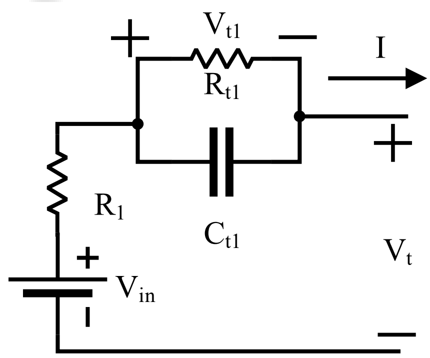

Figure 11: Thevenin equivalent model of a battery

The parameter of the equivalent circuit model dependent on SoC and Temperature.In (Ceylan et al., 2014),the model was used with a new mathematical function: $V_{in} = V_t + (R_1 + R_{t1})I - R_{t1}Ie^{-t/R_{t1}C}$ whereas in (Sun et al., 2014) open circuit voltage is given by $V_{in} = K_o + K_1 \times SoC + K_2/SoC + K_3 \times \ln SoC + K_4 \times \ln(1-SoC)$.

PNGV model takes into account of change in open circuit voltage in the time accumulation of load current. This change is incorporated in the Thevenin model thus giving the PNGV model of battery. The governing equation of the battery is $V_{in} = V_t + V_{t1} + {}^1/_{C_{acc}} \int Idt + IR_1$ and the equivalent circuit diagram is shown in figure 12.

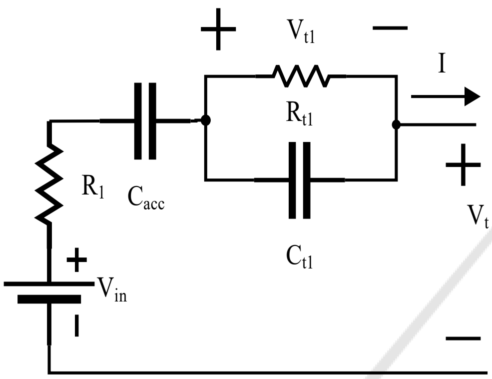

Figure 12: PNGV equivalent model of a battery.

Thevenin model to some extent can easily model the polarization characteristics of the battery. The complete polarization is considered in dual polarization (DP) model. the This model takes into consideration of polarization that is caused due to concentration polarization and electrochemical polarization (Chen et al., 2016; Junet et al., 2014; He et al., 2011; Choe et al., 2013; Kim et al., 2016 and Einhorn et al., 2013). The governing equation is $V_{in} = V_{t1} + V_{t2} + IR_1$ and the equivalent circuit is shown in figure 13.

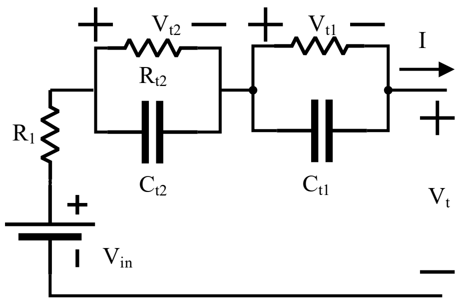

Figure 13: Dual polarization model of battery.

6 THERMAL MODEL

The temperature has a serious effect on the battery and hence it is vital to have thermal modelling. The battery parameters such as resistance, OCV, Capacitance are observed as the temperature is changed from 0°C to 40°C with the interval of 10°C and then parameters are selected on the basis of temperature (Wu al., 2018). Conductivity increases as the temperature was increased from 273K and reach its maximum value at 343K and then falls off (Sathyanathan and Sugumaran, 2018).

Change in battery capacity was increased from 0.6116 Ah to 0.6218 Ah as the temperature is increased from 37^0C to 40^0C.With the help of experimental data and then employing least square curve fitting method to get the relation OCV(T,SoC) = a(T) × SoC +b(T)(Lee et al., 2018).

Temperature effect on internal resistance and capacitance is determined by the direct current internal resistancemethod.

Another relation between the Equivalent series resistance and temperature provided the ageing effect is neglected. $R = R_0e^{A/T}$(Dogger et al., 2011).

7 IDENTIFICATION OF BATTERY PARAMETER

Once the electrical model of the battery is developed, the next foremost important thing is to determine the value of the parameter in the equivalent circuit. The most basic method is to experimentally observe the variation in the parameter with the SoC level at adifferent interval and then develop the relationship between various parameters and with SoC or temperature or with age. The parameter can be identified via conducting experiments that make battery undergo standard technique such as pulse current discharge (PCD), pulse current charge (PCC), Hybrid Power Pulse Characterization (HPPC), battery test bench with dedicated software or using estimating techniques that include least square method with advancements, support vector machine, extended Kalman filter.Parameter identification is not limited to the above methods and can be estimated by combining the experimental and estimation techniques. Figure 14 presents various battery parameter extraction techniques.

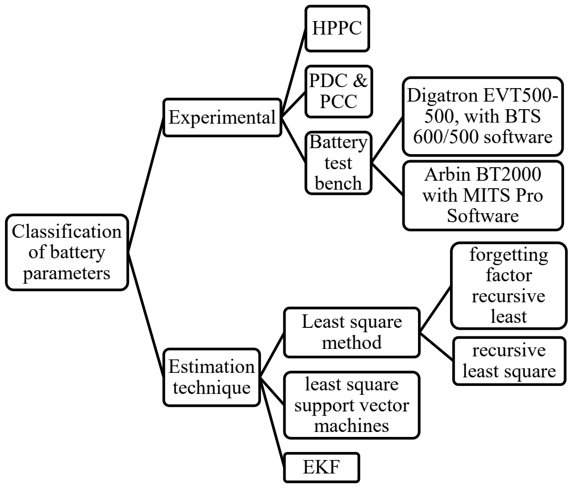

Figure 14: Various method of battery parameter identification techniques.

A combined version of PCD and PCC test was conducted to obtain to give the offline battery parameters that were identified via the least square method. In real-time or online battery parameter is identified via forgetting factor recursive least square (Chen et al., 2016).

One such technique is the HPPC test.The experiment was conducted with the help of Digatron EVT500-500 hardware and BTS 500 software at constant 20ºC and data from the test were used for parameter extraction (He et al., 2011). The battery parameter of improved Thevenin model was identified with battery test bench that includesDigatron EVT500-500, with BTS 600 software (He et al., 2011). Various experiments were conducted on ArbinBT2000 battery test system hardware and MITS Pro Software within a thermal chamber with different charge and discharge rates to determine the parameter (Sathyanathan and Sugumaran, 2018). Another approach is to collect data from the experiments andthenemploy Recursive Least Square (RLS) method with forgetting factor to determine the electrical parameter of the battery model (Wu al., 2018).The format given by HPPC to extract the model parameter, cannot be used by BMS, so prediction based on particle swarm optimization can be employed to optimize the parameters(Sun et al., 2014).

Experiments are conducted and controlled by LabVIEW in a closed environment and computation of data is done by MATLAB. The experiments were conducted from 37ºC to 40ºC at an interval of 1ºC. The least square method is used to find the battery modelparameter (Lee et al., 2018).The circuit parameter has been calculated with the 10A discharge curve drawn between OCV and SOC. The circuit impedance is measured at a various frequency ranging from 0.07 Hz to 7 kHz with temperature ranging from 5ºC to 20ºC, thus helping to extract the model parameters. The model parameters are updated itself, based on temperature(Moshirvaziri et al., 2015).

Battery parameters were mathematically modelled and were identified with the help of experimental data, governing equation and a build-in real-time data acquisition system that was loaded with the Discharge curve of the battery(Ceylan et al., 2014).

The least square method is used to estimate the battery parameter with some advanced technologies such as recursive least square with optimal forgetting algorithm used in Xiong et al., (2005) where battery model parametershave been identified by multiple linear regression method.

Parameter identification and optimization were based on cross validation method for least square support vector machines(Meng et al., 2016).

The battery parametersare identified by the EKF algorithm(Junet et al., 2014).

Another interesting technique was used in(Einhorn et al., 2013) where the value of capacitor C is extracted from the datasheet provided by the manufacturer and the parameter is linearized. Linear parameterization requires significantly less time with a setback of loss of accuracy. The parameter has been optimized by using GPS Hooke Jeeves optimizationalgorithm in GenOpt software.

8 VALIDATION CYCLE

Validating cycle simulates the real life condition to test the battery,thus making it cost effective.Validating the battery parameter gives the accurateness in the battery model. Validating would also increase battery life with optimized battery performance (Brandt, 1992).A various method such as Dynamic Stress Test (DST),Federal Urban Driving Schedule (FUDS),Urban Dynamometer Driving Schedule (UDDS) or Federal Test Procedure -72 (FTP-72),New European Driving Cycle(NEDC), HPPCTest were used for validating the battery parameters.

DST is performed with the intentions to simulate the dynamics of battery discharging exclusively for automotive application. To perform this test a battery test bench, a temperature controlled chamber and temperature sensors are required. Test is performed with the battery fully charged at the controlled environment and the battery is loaded with the set current profile (shown in figure 15) that include charging and discharging of battery and it lasts for 360 seconds. Test is continued till the end of discharge point is reached which is specified by either by rated battery capacity in ampere-hour or 80% of rated capacity in ampere-hourUnited States Council For Automotive Research, (2016).

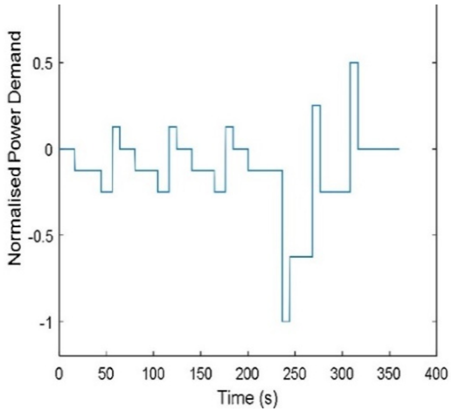

Figure 15: Standard Power profile of DST set by USABC United States Council For Automotive Research, (2016).

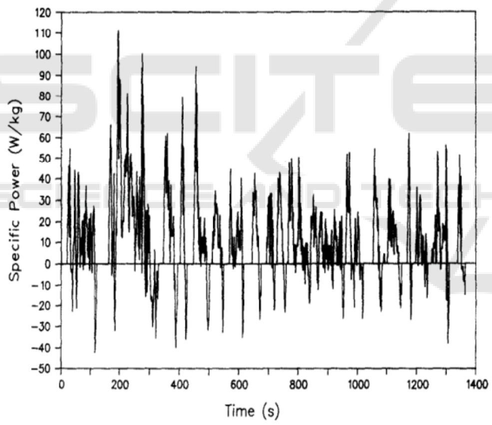

Figure 16: Federal Urban Driving Schedule charging and discharging profile United States Council For Automotive Research, (2016).

FDDS test is conducted for 1372 sec with different power levels shown in figure 16. Such test requires costly test hardware that includes large storage.

NEDC, as shown in figure 17, the cycle lasts for 1190 seconds and lasts for 10.93KM. The average speed is 43.10 Km/hr reaching a maximum speed of 120 Km/hr.

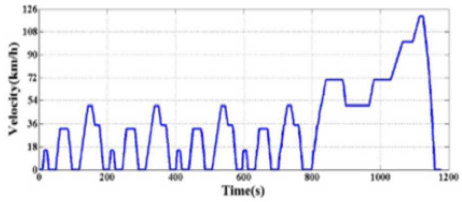

Figure 17: New European Driving Cycletesting profile (Jeong et al., 2016).

The HPPC test conducted with the aim to determine the dynamic performance of the device with 10 sec discharge pulse with 10 sec charging pulse through regenerative action. This action is repeated after every 10% discharge with 1-hour rest period as mentioned in figure 18.

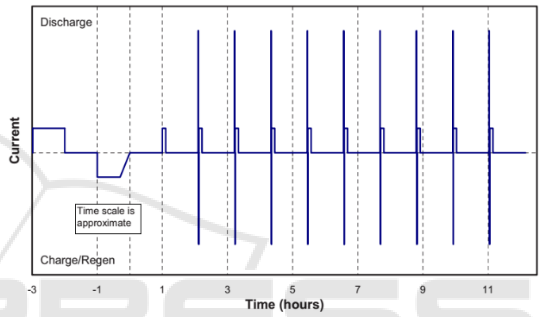

Figure 18: HPPC compete test sequence United States Council For Automotive Research, (2016).

The standard test cycle discussed above has been put into the test for different SoC estimation techniques and the error obtained is mentioned in the upcoming paragraph.

In Wu al., (2018), to verify the accurateness of the Thevenin model of battery with temperature compensation. The test was performed at 5 different temperatures. The error in battery parameter was less than 1 percent and the average absolute error was 0.2551 percent.

The parameter is verified via various current profile such as PCD, PCC and urban dynamometer driving schedule. The error in voltage was bounded within -0.04V to +0.04V(Chen et al., 2016).

Battery parameters were verified via six succeeding Dynamic Stress Test cycle. It was observed that Rint model had a maximum error. Thevenin model and DP model gave error less than 1 percent(He et al., 2011).

EightUDDS tests were used to verify the parameters(Sathyanathan and Sugumaran, 2018).The battery model is validated through loading FTP72 or UDDS current profile in battery model and practical battery in sealed environment at 20°C. The error was below 0.5 percent. The error would have gone to lower value if currentmagnitude is made large(Einhorn et al., 2013).

The model is validated with MATLAB Simulink environment and experiment with Kokam SLPB (Superior Lithium Polymer Battery) battery. On average, the discrepancy in data from modelling is less than 0.422 percent with the maximum value less than 3 percent at the end stage of discharging(Ceylan et al., 2014).

To validate the battery parameter, the calculated parameter has been compared with experimental data obtained from Arbin battery test system BT2000 with MITS Pro software and the average error was under 0.8806 percent(Junet et al., 2014).

Accuracy of least square support vector machines based model is done by testing it in a Simulink model with discharging current profile that rapidly changes between 0A to 6A. Experiment was conducted on Li-ion PO battery manufactured by KOKAM Company. The average absolute error was less than 2%(Meng et al., 2016).

Simulated results and experimental result showed 3% error in thermal model and 3.5% of SOC error (Moshirvaziri et al., 2015).

The UDDS profile was loaded to Arbin BT2000 battery system with sealed environment, to verify and evaluate the effectiveness of battery model parameters.To verify and evaluate the battery parameters, an experimental setup that contains Arbin BT 2000 battery test system which was maintained at 25°C was tested for Federal urban driving cycle schedule and Dynamic stress test current profile. The maximum error was 1%(Sun et al., 2014).

The battery model is verified by Arbin BT 2000 battery test system. Battery was loaded to Federal urban driving schedule and the error was confined to 2%(Xiong et al., 2005).

Federal urban driving cycle schedule current profile was loaded to system to verify the battery parameters and the error in parameter was under 3%(Xiong et al., 2013).

Evaluation of various battery models (RC model, Thevenin equivalent circuit model, PNGV Model, Dual polarization model,) in United States Council For Automotive Research, (2016) were realized through various tests such as HPPC, DST and FUDS. Since different cycle gave a different error on the available models. So the author concluded that DP model and Thevenin model gave the least error in SoC estimation.

9 CONCLUSION AND FURTHER WORK

In this paper, an attempt has been made to discuss issues related to the development of Li-Ion polymer battery namely state of charge (SOC) estimation, electrolyte used, modelling which includes electrical & thermal modelling and validation cycles.

Following are the major concluding remarks for this study:

- Among various SOC estimation techniques, model based method with filter algorithmgave resultswith the error of less than 3 % with low burden on battery management system. The common limitation to these techniques is non linearity of battery system that is resolved by adopting advanced methods in Kalman filter such as Robust Sliding mode observer, unscented Kalman filter, Adaptive unscented Kalman filter Adaptive extended Kalman filter.
- The success of SOC estimation techniques depends on the selection of battery's electrical model. Among various battery model,dual polarization model gave better results, followed by Thevenin equivalent circuit model. But dual polarization model would create high computation burden on the system. So, the selection should be in such a way that it does not increase the computation burden on the system and still maintain the accuracy in SOC estimation. Hence, Thevenin equivalent circuit model is more useful.
- Parameters of Battery model need to be determined so as to imitate the battery performance. Various experimental/analyticalestimation techniquescan be used to extract the battery parameters. Experimental data were collected from battery test benches such as Digatron EVT500-500 and Arbin BT2000 with dedicated software to determine the battery parameter.
- The estimated parameters need to be validated in order to have practical applicability. Various standard test cycles have been developed to verify the battery model. Error on battery model depends on the choice of test cycle. All the model discussed gave the maximum error of 3.0 % and minimum error of 0.26%.
- It has been clear from table 4that error by estimation technique depends on the considered model and validating cycle.

The paper focuses on the development of Li-ion battery with polymer as electrolyte. This gave flexibility in the design of battery. Polymers $CF_3SO_2NLiSO_2C_2F_5$ and $CF_3SO_2NLiSO_2C_4F_9$gave high conductivity. Further electrolytes were developed that resist the formation of dendrites in battery. Eco-friendly electrolytes were also developed.

- Finally, it will provide a comprehensive text on Li-ion polymer battery, which will help the engineers, researchers and technical persons in this area.

Thefuture directions related to this workare summarized as.

- Very few works of literature were found which discuss temperature effect on SoC
- Few papers discussed reducing the computation burden onthe battery management system.
- Ageing model of the battery needs to be developed for accurate estimation.
- More research is required to develop anaccurate relationship between battery SoC and battery SoHfor better estimation.

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