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An Accurate and Precise Grey Box Model of a Low Power Lithium-Ion Battery and Capacitor/Super-Capacitor for Accurately Estimation of State of Charge

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Abstract

The fluctuating nature of power produced by renewable energy sources results in a substantial supply and demand mismatch. In an attempt to curb the imbalance, energy storage systems comprising batteries and super capacitors are widely employed. However, due to variety of operational conditions, the performance prediction of the energy storage systems entails a substantial complexity that leads to capacity utilization issues. The current article attempts to precisely predict the performance of lithium-ion battery and capacitor/super-capacitor under dynamic conditions to utilize storage capacity to fuller extent. Grey box modelling approach that involves the chemical and electrical energy transfers/interactions governed by ordinary differential equations is developed in MATLAB. The model parameters are extracted from experimental data employing regression technique. The state of charge (SoC) of the battery is predicted by employing extended Kalman estimator, unscented Kalman estimator. The model is eventually validated through the loading profile tests. Relaying on the performances, extended Kalman estimator indicates much competitiveness to the developed model (in tracking the internal states e.g. SoC) which have non-linarites of first order.

Keywords: Lithium ion battery; State of charge; State of health; Gray box modelling; Extended Kalman estimator; Unscented Kalman estimator

Introduction

Energy Storage is a key component of renewable energy systems to ensure reliable and sustained energy supply. The energy storage comprises mainly of chemical, electrochemical and electrical systems. Chemical energy storage involves conversion of electrical energy in electrochemical for intermediate storage classified as batteries, fuel cells and electrochemical capacitors [1]. Electrochemical energy storage consisting of batteries and capacitor/super capacitors are classified as primary (non-rechargeable), secondary (rechargeable), thin film batteries and super capacitors. The lithium ion (Li-ion) are secondary batteries that dominated market penetration and have attracted substantial research interest into their performance prediction in the last decade [2,3]. The thin film Li-ion batteries are miniaturized version of conventional Li-ion being integrated extensively in modern, smarter and compacter electronic devices.

Due to delicate nature of miniaturized smart low power electrochemical components, precise estimation of battery attributes like state of charge (SoC) and state of health (SoH), internal resistance and temperature dependency are crucial for effective power management [4,5]. SoC is considered to be the most crucial parameter governing power flow, however is not measurable and requires estimation practiced through several methodologies.

Doyle, Fuller and Newman [6] introduced white box or electrochemical model for parameter estimation characterized by higher accuracy yet extreme impracticable complexity. On the contrary the black-box technique affords pragmatics simplification and thus is widely adopted. These models are extremely simplified, involve fewer parameters and afford ease of handling [7-9]. The model however possesses certain drawback of limited ability to predict capacity, power fading, degradation and temperature effect [10]. The technique employs fuzzy logic and empirical functions such as Peukert law [11,12] given by the eqn. (1).

$$C_p = I^k t \qquad (1)$$

where C_p is battery Capacity, I is discharge current, k is Peukert coefficient and t is time for discharging the cell. Additionally, Shepherd, Unnewehr and Nernst introduced method of estimating terminal voltage with respect to charge and discharge conditions [13]. Artificial intelligence-based models are being employed to predict internal cell dynamics effectively. The limitation lies in lengthier training process, exhaustive data requirements and inability to embrace physical aging of the cell [14].

Grey box modelling technique emerged as a middle ground between white and black box models such as equivalent circuit model ECM [15,16]. Grey box model combines the prior physical knowledge with the experimental data for physical interpretation to assign numerical values to model parameters. Modelling the complex system such as ECM, the model has some unknown parameters. For instance, modeling the Li-Ion battery, internal impedance is greatly affected by temperature and SoC, but their accurate relationship is not well defined. These parametric values are estimated by using the statistical relationship (system identification) from the experimental data as shown in the Figure 1 [17].

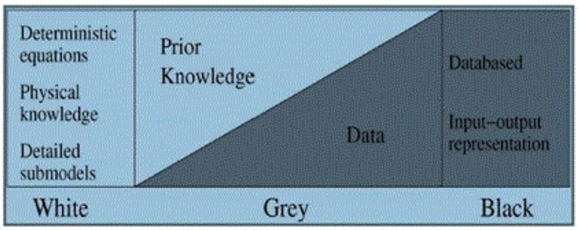

Figure 1: Grey box modelling.

The SoC estimation is crucial for the power management and control in battery systems. Numerous factors can influence the precise measurements of SoC such as hysteresis phenomena among charge and discharge cycles, white noise, characteristic of open circuit voltage and current. Inaccurate SoC estimation can lead to the shorter calendar life and poor performance due to overcharge and over discharge of the battery. The techniques available to estimate the SoC of battery are are classified as direct discharge method, coulomb counting, impedance based and model based coupled with estimating algorithms [18-21] that are governed by parameters that varies with SoC thus creating and implicit relation. The current paper attempts to resolve the issues of overly complicated as well as overly simplified battery modelling through reasonably accurate yet simplified grey box modelling approach. The Li-ion battery and super-capacitor are modelled by employing extend Kalman, and unscented Kalman estimators for parameter identification for to estimate SoC of Li-ion battery and capacitor/super-capacitor [22].

Modelling Methodology

Experimental setup

A test bed consisting of a battery and super capacitor, Agilent-SMU, a host PC and control temperature cabin is established indoors as depicted in Figure 2 [23]. The setup is capable of measuring current and voltage in the order of μV and pA and can operate in continuous and pulse, constant current and constant voltage modes simultaneously. An rechargeable solid state lithium thin film battery having $LiCoO_2$ cathode, LiPON ceramic electrolyte and a lithium anode with capacity of 0.7 mAh (EFL700A39 and a DMF series high performance double layer capacitors are used for the test.

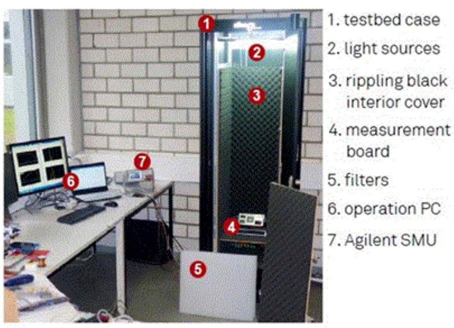

Figure 2: Test bed for experiment.

An accurate mathematical relationship between the model input and output is establish categorized as input/output structure. In conformance with the input/output structure, the experimental data is processed for parameter estimation, identification and distinction.

The model identification process involves a current signal being fed into the battery/capacitor and respective output voltage is generated, where discharge current is positive as per standard test condition as demonstrate in the Figure 3.

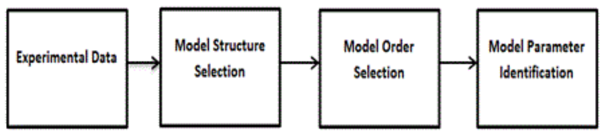

Figure 3: Identification of grey box model.

Data set

Several experiments including capacity test, pulse test, open circuit voltage(voltage under no load conditions generally depends upon battery design and operating temperature) and state of the charge test (OCV-SoC) test and loading profile test are conducted at variant temperatures from 5°C to 25°C with 5°C interval. The capacity test reveals information about current capacity to the nominal capacity of different Li-ion batteries ($LiMn_2O_4$ LiB cell (C/LMO) which uses carbon as its negative electrode and lithium magnesium oxide for the positive electrode and the other one is lithium iron phosphate (C/LFP)). The capacity differed from the maximum capacity due to aging process as presented in Table 1.

Li-ion battery	C/LMO	C/LFP
Nominal Capacity (Ah)	35	1.35
Maximum Available Capacity (Ah)	34.5	1.23
Nominal Voltage(V)	3.7	3.2
Upper Cut-off Voltage(V)	4.2	3.65
Lower Cut-off Voltage	3.0	2.5

Table 1: Comparison of Li-Ion battery specification.

Charge-discharge efficiency test is used to determine the coulomb efficiency of the cells and later on for the compensation of the developed model and accuracy of SoC estimation, pulse test estimate about the model internal parameters. Results for OCV-SoC test are depicted in Figure 4. Figure 4a represent recharging of the battery under constant current constant voltage conditions (CCCV) and Figure 4c shows that as the voltage approaches to its upper cut-off level current decreases to minimum. Figure 4b and 4d indicates the terminal voltage of the battery in charging and discharging modes.

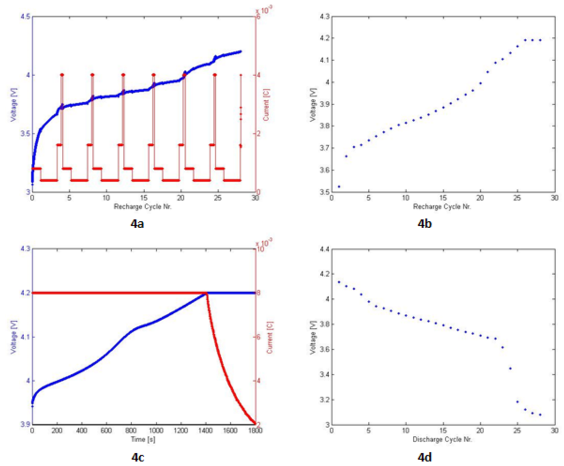

Figure 4: Recharging of the lithium ion battery and charging and discharging voltages under no load conditions.

Model development and state space representation

The general representation of grey box model is represented as [24]

$$dX \;\; = f(x_t, u_t, t, \theta) + e_k \qquad (2)$$

$$y_k \;\; = h(x_k, u_k, t, \theta) + e_k \qquad (3)$$

where t is time dependent variable, xt represent the system state vector, ut is the input variable and ek is the noises present in the system, ɵ is the vector of unknown parameters. The first term of eqns. (2) and (3) is categorized as drift and the second one as diffusion subsequently.

The order of the model is determined by employing the statistical methods (i.e. System identification) through curve fitting process. The final model involving the ECM and electrochemical model is discretized and represented by the set of differential equations as given below:

Li-Ion battery model

$$V_{k+1} \;\; = \exp\left(-\frac{T}{T_1}\right)V_k + I_{l,k}\left(-\frac{T}{T_1}\right) \qquad (4)$$

$$V_{t,k} \;\; = V_{ocv}\text{-}I_{l,k}R_o\text{-}I_{l,k} \qquad (5)$$

Super capacitor model

$$V_{c,k} \;\; = \left(\frac{T}{C}\right) i_{k-1} \qquad (6)$$

$$V_{Rc,k} \;\; = \exp\left(\frac{T}{T_1}\right)V_{k-1} + i_{k-1}\left(\exp\left(-\frac{T}{T_1}\right)\right) \qquad (7)$$

$$V_{t,k} \;\; = V_{R,k} + V_{c,k} + V_{Rc,k} \qquad (8)$$

For estimating the state of charge (SoC), basic definition of coulomb counting method is adopted [18].

$$\mathrm{Z_k} = \mathrm{Z_k} - \frac{\eta I_1 T}{Cn} \qquad (9)$$

C_n and T represent battery capacity in as and sampling time respectively. Eqns. (4), (5) and (9) representing states and output of the battery model can be given as:

$$\mathrm{X_k} = \left[V_{k+1}\mathrm{Z_k}\right]^{\mathrm{t}} \qquad (10)$$

$$y_{\mathrm{k}} = [\mathrm{V_{t,k}}] \qquad (11)$$

$$u_{\mathrm{k}} = [\mathrm{I_{I,k}}] \qquad (12)$$

where $x_{(k)}$, $y_{(k)}$ and u_k are the battery state, output and input matrix respectively. It can also be represented in the matrix form as:

$$A = \begin{pmatrix} exp\left(-\frac{T}{T_1}\right) & 0 \\ 0 & 1 \end{pmatrix} \quad B = \left(R\left(1 - \exp\left(-\frac{R}{R_1}\right)\right)\right)$$

$$C = \left(-1d/dzV_{ocv}\right) \qquad D = \left(R_0\right)$$

Model output and states for super capacitor in matrix form is given as:

$$A = \begin{pmatrix} 1 & 0 \\ 0 & \exp(-T/T_1) \end{pmatrix} \quad B = \begin{pmatrix} (T/C) \\ R\left(1 - \exp\left(-\frac{R}{R_1}\right)\right) \end{pmatrix}$$

$$C = (11) \qquad D = (Rs)$$

Model validation

The developed model is validated through loading profile test in which a load is attached to the battery and super capacitor, current is applied under various C-rates and outputs measured. The same current is applied to the model and its output behavior is estimated. Two techniques namely unscented and extended Kalman estimator are applied for the output and state of charge (SoC) estimation [25,26]. Input is applied to the model and terminal voltage is estimated. The measured and estimated terminal voltages are compared and the error is minimized between the two outputs by adjusting the Kalman gain. The new gain value is subsequently applied for the trade-off of the state estimation error. The parameters of the battery are updated by using new values of the states and terminal voltage is estimated at new sampling interval. The measured and estimated output for battery and super capacitor is depicted in Figure 5a and 5b respectively. It can be seen that overall, the estimated output voltage tracks the measured voltage accurately despite some localized errors caused by adjusting the Kalman gain value.

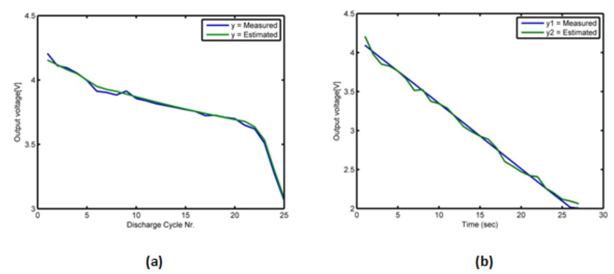

Figure 5: Measured and estimated output terminal voltage.

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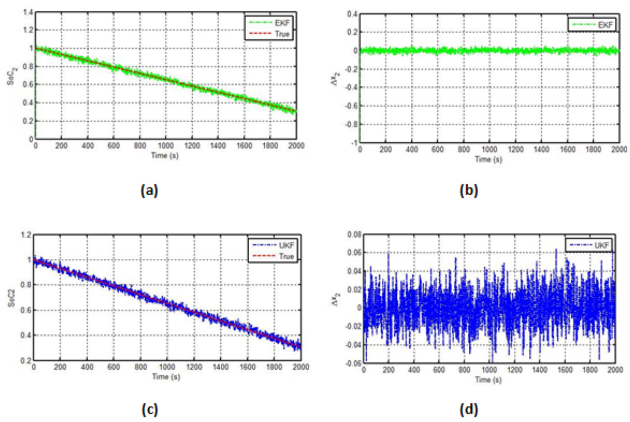

Figure 6: Estimation of SoC and error in estimation.

The performance of the two estimators for estimating the SoC for battery is represented in Figure 6. Figure 6a and 6b depicted the SoC estimation and error in estimation by employing the extend Kalman estimator while 6c and 6d represent the estimation and its corresponding error by using unscented Kalman estimator. As the given model is of first order, the performance of extend Kalman estimator is much better than the unscented Kalman estimator. SoC estimation error in the case of the EK estimator is under 1% while it approaches 6% for the UK estimator. Based upon these findings, for the first order nonlinear models, the EK estimator shows noticeable better performance for the SoC estimation compared to the UK estimator.

For establishing the robustness of the estimation methods, a wrong initial SoC is set and performance of the estimation techniques for super capacitor can be seen in Figure 7. Figure 7a and 7c depicted the SoC estimation with wrong initial values while 7b and 7d represent error in estimation. At the start the error value between measured and estimated SoC is higher wherein the estimators compensate the error by setting the larger gain value and then adjust the estimation in an effective close loop manner. As a result, estimators converge to the original true value even with the wrong initial guess.

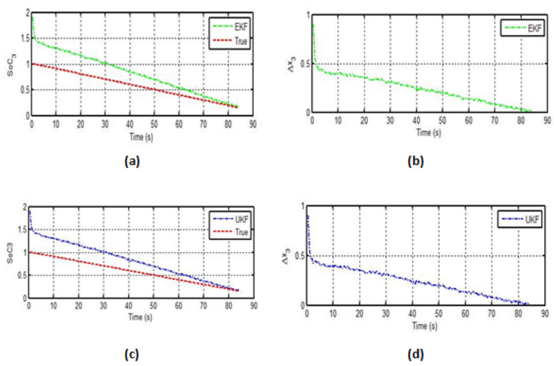

Figure 7: Estimation of SoC and error in estimation.

Conclusions

A model is implemented and validated in this research paper for lithium ion battery and super capacitor. Grey box technique is selected for modeling purpose which includes the partial information of white and black box.

The relationship between the open circuit voltage and state of the charge is established through the Nernst model. Regression (least square estimation) technique is selected for its simplicity and ease in calculation for parameter identification.

The identified model is represented by set of differential equations and validated through loading profile tests.. Model tracks the output effectively which established the model accuracy under real conditions.

Extended and unscented Kalman estimators are employed for estimating the internal states such as state of charge. It is concluded that extended Kalman estimator is well suited to the models which have non-linarites of first order in their dynamic behavior. The robustness of techniques is described by setting the wrong initial guess about the SoC. Results indicates that even having the wrong initial guess the model tracks the true value of SoC.

The limitation of the model is that, it did not model the state of health of the battery and super capacitor. Further study can be conducted that can investigate the aging effect of miniature size Li-ion battery and super capacitor.

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