

Lithium ion Battery State of Charge Estimation, Management System for Hybrid Electric Vehicle

A. D. El-Ladan¹, O. Haas², A. Edicha³ & L. Bousselin⁴

^{1,2,4} *Control Theory and Applications Centre, Coventry University, UK*

³ *Petroleum Training Institute Warri, Nigeria*

Abstract

Hybrid electric vehicles (HEVs) have been considered as the most promising energy savings vehicle by many automobile industries, due to its environmental friendliness, low gas emission and less fuel consumption. But the major challenge for HEVs success performance is the energy storage system (battery pack) that can provide an acceptable life cycle for the vehicle as well as sustainable energy for the vehicle propulsion in full journey. Thus a battery management system (BMS) that can guarantee battery energy sustainability and efficiency is of major concern needs in electric vehicles (EVs) and HEVs success. The paper introduces state of charge (SOC) estimation with different estimation model structure from battery equivalent circuit; it also discusses the major issue concerning factors affecting battery for the attainment of an intelligent battery management for HEVs. Lithium ion battery is considered in this paper as the most promising battery technology for HEV. The paper presents comparisons of different types of estimation made.

Keywords: Battery management system (BMS), Electric vehicles (EVs), Hybrid electric vehicles (HEVs) and State of charge (SOC).

Background to the Study

Hybrid electric vehicles (HEVs) were identified with its uniqueness in its characteristics of multiple prime movers and energy sources. The main challenge in HEV design is to optimize the power flow to/from its multiple sources to obtain the best fuel economy or low emission at low cost. It can store the vehicle kinetic energy into battery while braking or at down sloping stage (deceleration) instead of losing the energy as heat at the braking drums (Shen, et al. 2011). The major challenge in its success is the electrical energy source, which is the battery pack (collection of single battery cells).

Lithium ion battery are widely accepted as the most proven energy storage device for HEVs and EVs applications due to its numerous advantage over other batteries; high energy and power density, stability, light weight and lower charge loss when unused (Reed, et al. 2011 ; Yeow, et al. 2012).

Xidong, et al. (2012) suggests that control for a vehicle propulsion system by the battery, an accurate knowledge of battery parameters is required e.g. state of charge (SOC) for the whole

pack, defined as the charge remaining in battery in percentage stored. This knowledge can be obtained by the use of a mathematical battery model that predicts not only SOC but also the battery current, voltage, and state of health (Daowd, et al. 2011). Battery parameter that is related to SOC is the electric equivalent open circuit voltage (the terminal voltage); moreover the battery is non-linear and timevariable due to its complex electrochemical processes (Zhu, et al. 2011).

Few methods from literature were examined whose focuses on the SOC and state of health SOH of battery, which are mainly based on coulomb counting. The major drawback of this method is that accurate initial SOC, which is always not known, is estimated on the basis of sensors measurements that also includes measurements error (Verbrugge, 2007).

The coulomb counting method is based on the continuous current measurements and computation of accumulated charge, on this basis the SOC is estimated. The precision of SOC estimation highly depends on the current sensors precision (Sun, et al. 2011).

SOC is a relative quantity in which battery voltage is described as the ratio of remaining capacity to the nominal battery capacity (Xu, et al. 2012). Given as

$$S(t) = S(0) - \int_0^t \frac{\beta \cdot I(t)}{C_n} dt \quad (1)$$

Where $S(t)$ is the SOC at instant time t [s], $S(0)$ is the initial SOC, C_n is the nominal capacitor, $I(t)$ is current at time t [s] and β is coulomb efficiency.

This method however suffers a lot of setback stated by Sun et al. (2012) & Junping, et al. (2009) that there is high accumulation of errors when battery is working under high or very low temperature due to current fluctuations.

The paper seizes the opportunity of lithium-ion batteries equivalent circuit to estimate SOC using RLS, Kalman filter, ARX and Bilinear estimation methods and compare for best estimator thus to serve as vital information for an intelligent BMS; However factors affecting battery performance were also discussed in the paper. Coupled with dynamic parameter estimation..

$$x_{k+1} = f(x_k, u_k) + w_k \quad (2)$$

Extended Kalman Filter (EKF) or Kalman filter generally are mathematical algorithms that provide theoretical way and time-proven method of clean measurements of systems input and output that produce an intelligent estimation of dynamic system state. EKF however is not necessarily being an optimal way but it's obvious that it work very well to nonlinear systems as in equation 2 and 3 (Pleet, 2004).

$$y_k = g(x_k, u_k) + v_k \quad (3)$$

Where

w_k - is zero mean Gaussian white noise with covariance 'Q' and v_k is measurement noise with covariance R_k .

- represents nonlinear state function,
- represents nonlinear measurement function.

The adaptive approach is to estimate more battery parameters in real time for SOC estimation and other potential parameters with less look-up tables (Xidong, et al. 2012).

Battery Technology

Three major battery chemistry types have been used for HEVs and EVs power propulsion: Lead (Pb)-acid, Nickel-metal hydride (NiMH) and Lithium ion battery.

Li-ion is presently the most widely used battery technology for EV and HEV; this is because of its high energy density, power rating and its lightness in weight than the other batteries (Reed, et al. 2011). Lithium ion theoretically yields as much larger than 410Wh/kg specific energy, practically is highest at 150Wh/kg, against Ni-MH at 75Wh/kg and Pb-acid at 35Wh/Kg (Rahn & Wang, 2013).

A Battery management system (BMS) plays a pivotal role in EVs and HEVs performance, therefore the need for an intelligent BMS to capture the characteristic component of battery is of paramount importance.

The SOC in battery systems is an indicator of operating conditions system and is used to regulate charge /discharge decisions and however to ensure its safety and longevity. As such, accurate estimation of SOC is mostly an important task in BMS (Tang, et al. 2011 ;).

Electrical Equivalent Model.

The equivalent circuit model shown in Figure 1, can be used to represent Li-ion properties, the circuit include internal battery resistance and several resistance and capacitor (RC) pairs that characterizes the battery dynamics (Zhu, et al. 2011 & Xiong, et al. 2012).

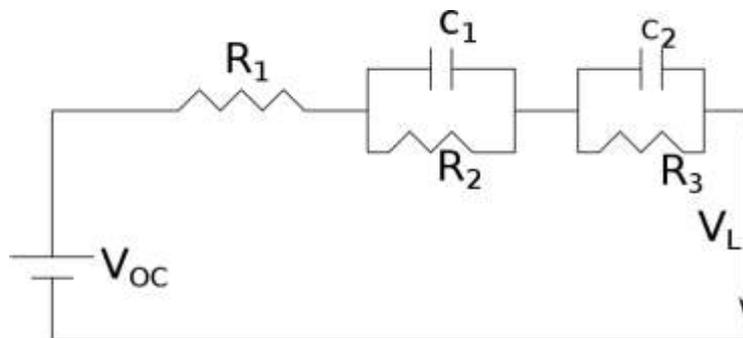


Figure 1. Equivalent circuit model for Li-ion battery.

The electric circuit model describes the relationship of major quantities in a circuit i.e. current and measured voltage at the terminal of the battery. Using the Kirchhoff's voltage circuit law the circuit load voltage V_L can be described as follows

$$V_L = V_{oc} - V_2 - V_3 - IR_1 \quad (4)$$

Where V_2 and V_3 are the measured voltage across R_2C_2 and R_3C_3 respectively, R_2 and R_3 are polarization resistance that characterises the activation and concentration polarization respectively similarly to C_2 and C_3 , however are used to characterise transient responses when power is transferred to and from the battery

And V_{oc} is the open circuit battery voltage which comprises of equilibrium potential V_e and hysteresis potential V_h as

$$V_{oc} = V_e + V_h \quad (5)$$

However

$$\dot{V}_3 = -\frac{V_3}{R_3C_3} + \frac{1}{C_3}I \quad (6)$$

And

$$\dot{V}_2 = -\frac{V_2}{R_2C_2} + \frac{1}{C_2}I \quad (7)$$

Laplace

$$E(s) = V_L - V_{oc} = -I(s) \left(R_1 + \frac{R_2}{(1 + R_2C_2s)} + \frac{R_3}{(1 + R_3C_3s)} \right)$$

Therefore

$$G(s) = \frac{E(s)}{I(s)} = - \left(R_1 + \frac{R_2}{(1 + R_2C_2s)} + \frac{R_3}{(1 + R_3C_3s)} \right) \quad (8)$$

The equivalent circuit describes the relationship between current and voltages across the terminal.

Factors affecting Battery power and life time

Review Stage

The real life operational concept of battery energy required in EVs and HEVs is for battery ability to regain power when it is lost (utilized) i.e. charging and discharging phenomena. Battery pack requires a precise real-time estimation of key parameters that affects the power availability to meet the acceleration and climbing power requirements (Sun, et al. 2011).

Battery power profile has an impact in determining the effects of driving behaviours of HEV and battery pack performance (Xing, et al. 2011).

Battery management however requires adequate supervision of battery pack cells, most importantly temperature measurement (Texas Instrument, 2012).

The following are identified as factors affecting battery power and life cycle

- a. Temperature
- b. Voltage Cell balancing
- c. Charging/discharging Current
- d. Chemical properties
- e. Resistance effect
- f. Self-discharge (Tang, et al. 2011).

Battery SOC estimation Methodology

Kalman filter

Kalman filtering is a well-known method of system parameter estimation of input and output to produce dynamic system state estimation, for non-linear system an extended Kalman filter is used to produce similar estimation (Tang, et al. 2011; Qui, et al. 2011). The inputs this study is current and with a constant internal resistance and output is obviously is the voltage. However Kalman filter are designed to minimize the mean of square error to help in obtaining accurate information on systems (Sun, et al. 2011). The estimation is done in the manner that the mean square error is minimized. The general structure illustrated in figure 2.

Transforming equation 6, 7 and 5 into discrete-time form

$$V_2(k) = -\frac{1}{R_2 C_2} V_2(k-1) + \frac{1}{C_2} I(k-1) \quad (9)$$

$$V_3(k) = -\frac{1}{R_3 C_3} V_3(k-1) + \frac{1}{C_3} I(k-1)$$

$$V_L(k) = V_{oc} + \frac{1}{R_2 C_2} V_2(k) - \frac{1}{C_2} I(k) + \frac{1}{R_3 C_3} V_3(k) - \frac{1}{C_3} I(k) - R_1 I(k) \quad (10)$$

Let

$$a_1 = -\frac{1}{R_2 C_2}, \quad b_1 = \frac{1}{C_2}, \quad a_2 = -\frac{1}{R_3 C_3} \text{ and} \\ b_2 = 1/C_3.$$

Rearranging equation (10), therefore

Substituting these equation into equation 5 and 6 in to 4 we have

$$V_L(k) = V_{oc} + a_1 V_2(k) + a_2 V_3(k) - (b_1 + b_2 + R_1) I(k) \quad (11)$$

$$V_L(k) - V_{oc} = a_1 V_2(k) + a_2 V_3(k) - (b_1 + b_2 + R_1) I(k) \quad (12)$$

Equation 9 and 10 can be transforming into state space form.

$$V_2(k); V_3(k) = A[V_2(k-1); V_3(k-1)] + BI(k) \quad (13)$$

$$V_L(k) - V_{oc} = C[V_2(k); V_3(k)] + DI(k) \quad (14)$$

Where $A = \text{diag}(a_1, a_2)$, $B = [b_1 \ b_2]^T$, $C = [1 \ 1]$, and $D = R_1$

From the above it shows that are functions of resistance and capacitance for in comparison with the RC pairs in the equivalent circuit. The second order battery model could be establish by using electrical parameters as in the equation (4) in form of discrete time differential as
 Where is the parameter of six vectors for the second order battery model and
 Is the vector signals and constants

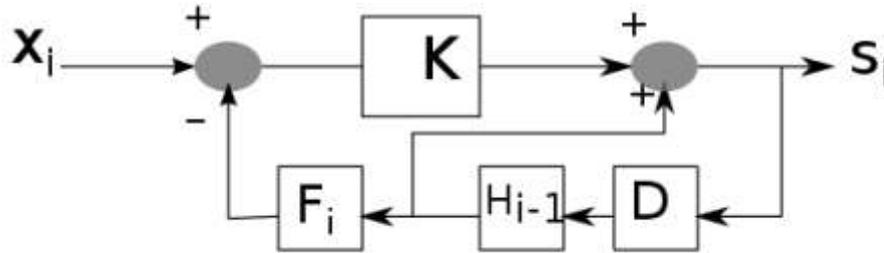


Fig 2. Kalman filter block structure

Implementation

The state input, plus initialization state of $V_2(0)$, $V_3(0)$, and setting Covariance matrix with a defined forgetting factor. However in the presentation of this paper temperature input variation is not considered thus is to be presented in the next series on battery degradation in lumped model.

After initializing, new values of are recorded.

$$\theta(k) = \theta(k-1) + K * e(k) \quad (8)$$

Then calculating the vector signal after obtaining the data the previous states

Transformation for the computation of the estimation error as

$$e(k) = V(k) - \theta^T(k-1) * \delta(k) \quad (9)$$

Then updating the parameter to reduce the error of the estimate

$$I(k), V(k-1), I(k-1) \dots V(k-2), I(k-2) \quad (10)$$

Finally calculating battery electric parameter from

ARX Estimation

A time varying systems has parameters that are dependent on time, battery systems is such a dynamic time varying type, for estimation of such parameter an adaptive control approach was utilized in this paper using Auto-Regressive models with an exogenous variable (ARX) it is describes as

$$y_k = \varphi_k^T \theta + e_k \quad (20)$$

Or alternatively in transfer function as

$$y_k = \frac{B(q^{-1})}{A(q^{-1})} u_k + \frac{1}{A(q^{-1})} e_k \quad (21)$$

Exogenous means the input signal enters into the system from outside and represents manipulated varying over time process variable. In the implementation of this model a noise is generated into mathematical algorithm in mat lab. The ARX structural system is as shown in figure 3 however the model is expected to provide an appropriate battery cells dynamics process as in Yuan (Rahimi & Chow 2013).

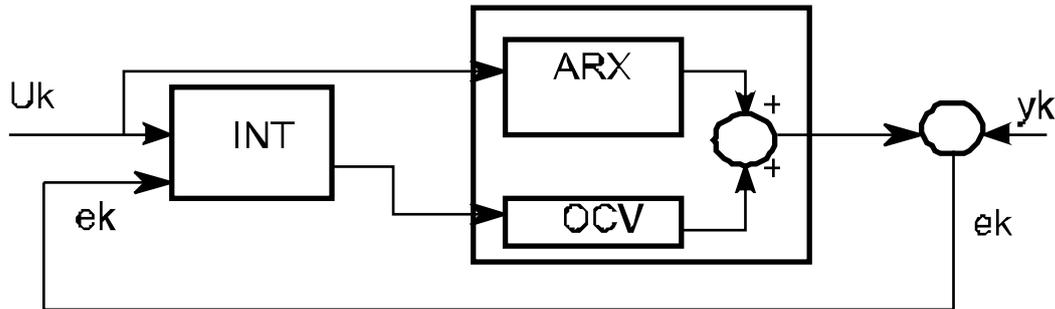


Fig.3 ARX model estimation, INT-means integration, OCV is open circuit voltage

Bilinear Estimation model

Bilinear model has same structure with linear model in that the model is linear with respect to model parameters. The model can be classified into three types; state-space, polynomial type and parametric type (Yao & Choo, 2006). The polynomial and parametric are usually used in adaptive control method as in this case based on the identification algorithms, thus in the case of present study parametric bilinear model structure were employed. The Bilinear transformation represented as

$$s = \frac{z-1}{T_s} \frac{1+z^{-1}}{1+z^{-1}} \quad (22)$$

This transformation was adopted in the battery model in equation 8.

Simulation studies

Models comparison

The results shown in Figure 4, shows the measured and estimated terminal voltage of the battery. Figure 5 illustrate measured SOC and estimated SOC. However the estimated terminal voltage and SOC estimation shows a clear fitness to the measured data this indicates that the battery model with RT= 99.98% and mean square error (MSE) =7.797x10⁻⁰⁶, can effectively simulate battery dynamics, thus this is a different case to coulomb counting that is with error in the initial SOC and difficulty in estimating columbic efficiency.

In this study the paper introduces Bilinear and ARX parameter estimation method of the battery iteratively as illustrated in Figure 6 and 7 respectively.

The paper introduces an SOC estimation comparison approach on various estimation methods using measured data with ARX, Bilinear and Kalman filter shown in figure 8. The effort made was to investigate the best estimator in this case. It indicates Kalman filter fits the measured data showing high degree of error elimination; however it shows high level accuracy compared with other estimation methods used.

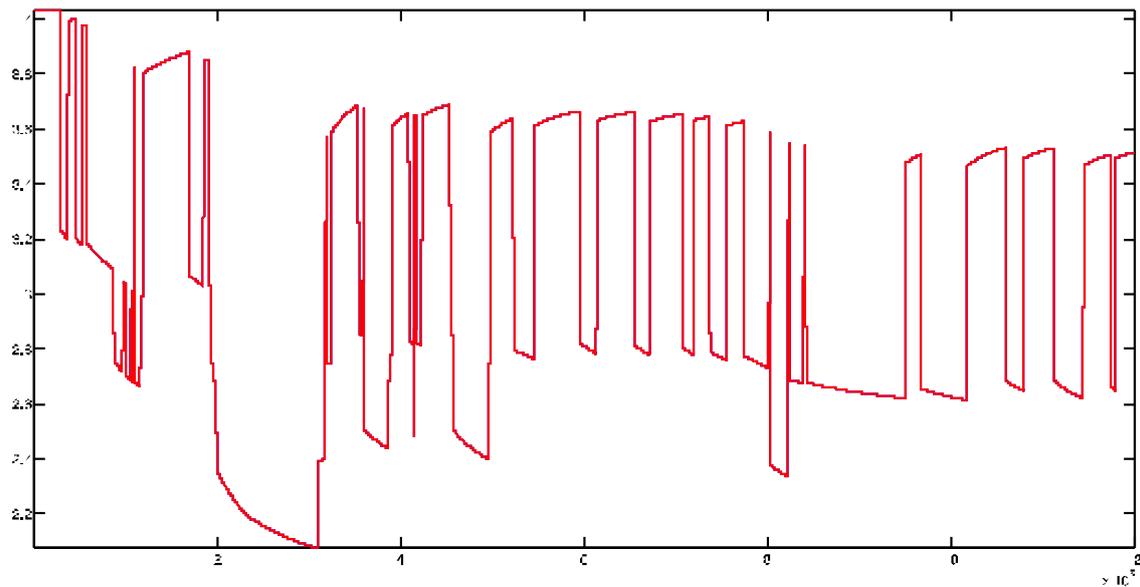


Figure 4. Output Voltage profile estimation result.

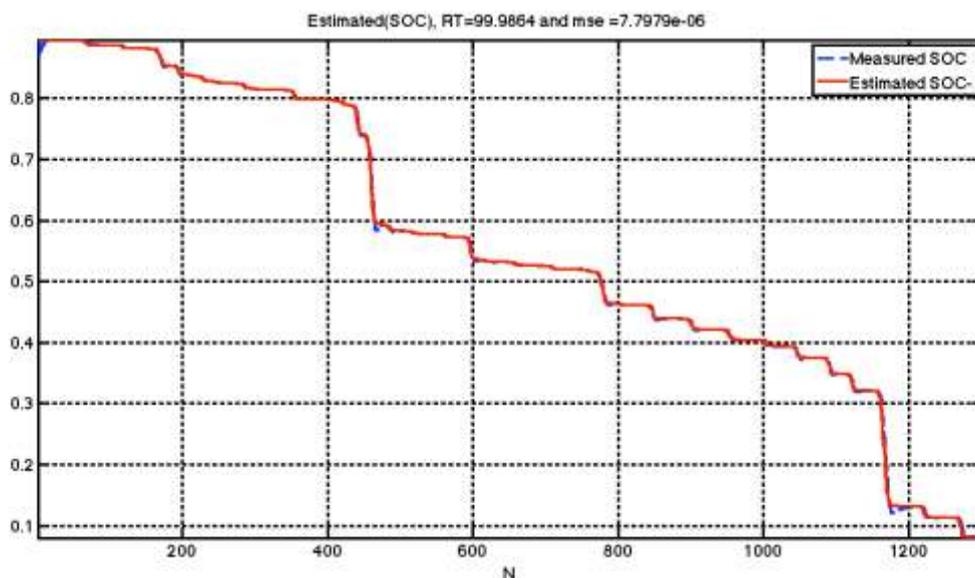


Figure 5. Estimation results.

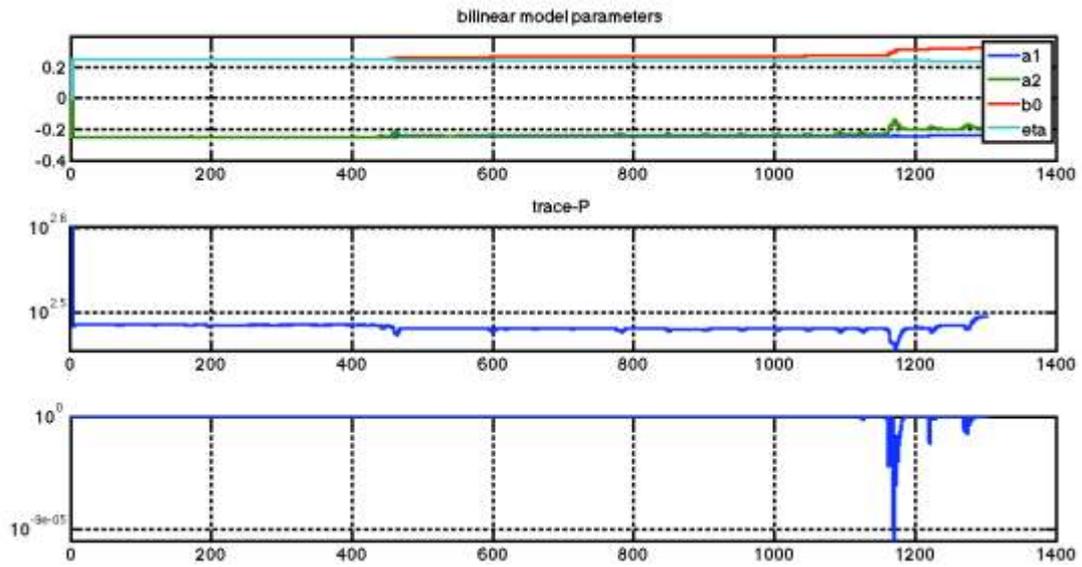


Figure. 6. Parameter estimation result profile.

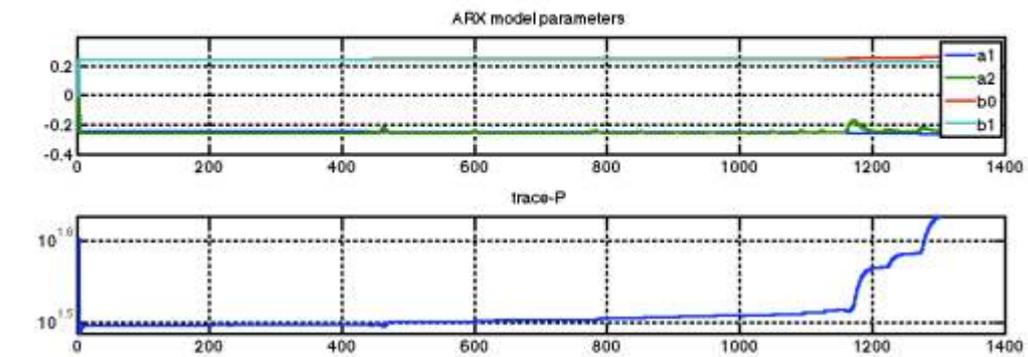


Figure 7ARX parameterestimation

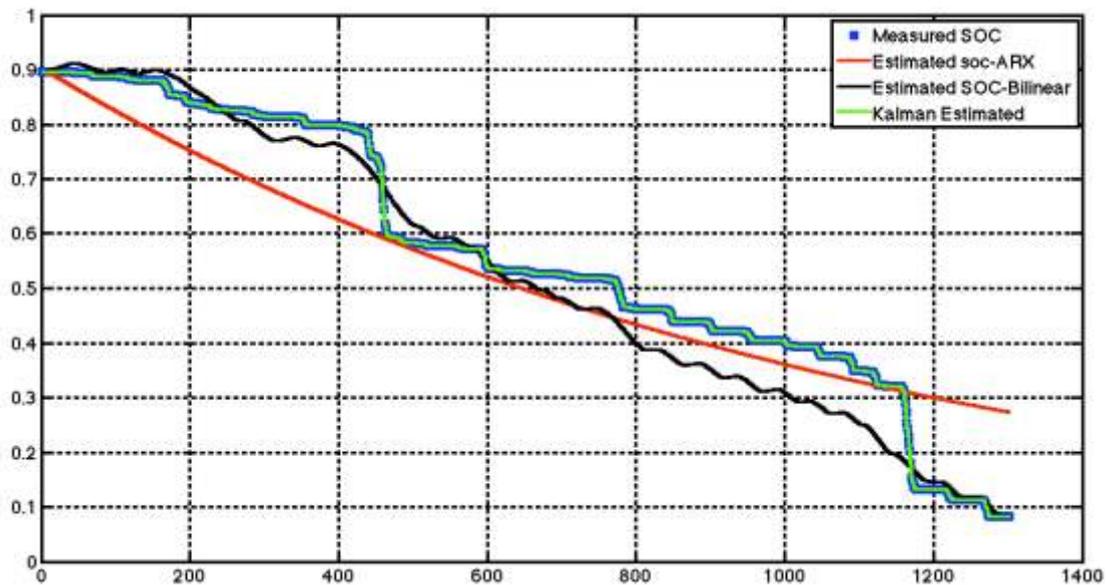


Figure 8. Comparison of SOC estimations

Conclusion

The paper presented the RC battery equivalent circuit characteristics; it also identified the major obstacles of battery performance. The model input discharging current was driven from EPA Urban Dynamometer Driving Schedule (UDDS) drive cycle. SOC estimation was presented with different estimation method with comparison approach. However the model shows flexibility for accommodating different drive cycle e.g. European and American drive cycle.

The approach uses parameter estimation options in estimating the battery characteristic properties and its potentials to provide the means of further work for the development of degradation of battery models and control.

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