Journal of Electrical Engineering and Automation (ISSN: 2582-3051)
www.irojournals.com/iroeea/

Robust Dissipative-based PI Observer Design for the State of Charge estimation of a Lithium-Ion Battery

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Abstract

As the battery is a non-linear system, a robust dissipative-based Proportional Integral (PI) observer is proposed in this work to estimate the SoC. As special cases based on energy-related concerns, the theory of the dissipative concept incorporates H∞, passivity, and L2 performances. In particular, developing Dissipative PI Observer for the SoC system with disturbances, uncertainty and non-linearity are the major novelties in this study. The suggested system's findings are compared to the results of the Equivalent circuit model method and Coulomb-Counting method. MATLAB/SIMULINK is used to simulate the proposed system. Moreover, using Lyapunov stability theory, a novel set of adequate necessities in terms of LMI is erected to secure the conservative outcome.

Keywords: State of Charge, Proportional Integral Observer, Extended Kalman Filter, Proportional Integral, Coulomb-Counting, Open Circuit Voltage, Linear Matrix Index, Lyapunov Krasovskii Function, Lithium-ion, Electric Vehicle, Kalman Filter

1. Introduction

1.1 Background and Motivation

Due to their longer lifespan and higher energy density as compared towards other battery technologies including Lithium polymer batteries or lead-acid batteries, lithium-ion batteries are widely employed in a variety of applications such as portable power devices and electric vehicles (EVs) [1, 2]. However, because lithium-ion batteries are unstable and can explode fast if not maintained, they require a complicated management system in real-world

DOI: https://doi.org/10.36548/jeea.2022.1.005
Received: 11.03.2022, received in revised form: 06.04.2022, accepted: 16.04.2022, published: 26.04.2022

applications. The SoC, one of the most critical battery metrics, must be monitored in order to control the battery system. The primary point to examine in this study is its estimate. Furthermore, it is an important parameter for improving the accuracy of EV range estimating methods and lowering range anxiety [3].

Since the batteries SoC cannot be measured directly, it must be approximated using data from the battery, such as voltage, current, and so on. Several attempts are made to measure the State of Charge of the batteries [4]. The error build-up caused by imprecise current measurement is a problem for the current integration approach. The OCV is also used to measure SoC, which is based on the relationship between the OCV and the SOC. However, because the OCV is measured by unplugging the battery from the circuit, this approach cannot be utilised for continuous battery operation [15].

Common algorithms for SoC estimation include the KF for nonlinear systems, the unscented KF and the EKF. These approaches outperform OCV and Coulomb counting, although they have significant downsides, such as state estimation divergence, especially when an incorrect feedback gain is used. In real-world applications, they also need accurate plant modelling and Gaussian noise distribution. Another filter that has shown resilience against model uncertainty is the so-called H∞ filter. [5] proposes a resilient H∞ filter that takes into account the battery's time-varying properties. Unlike the KFs, the H∞ filter does not require any assumptions regarding model and measurement uncertainties. The main disadvantage of H∞-based SoC estimation is that it necessitates a large amount of processing resources.

1.2 Common Factors affecting System Performance

In many industrial processes and real-time systems, several unpredictable factors affecting the characteristics of dynamics are indispensable. Bearing this in mind, the following factors that can influence control synthesis and the system analysis are considered in this work and their brief introduction is as follows:

Uncertainty - The accurate math model of the system is essential to obtain the desired system performance in the qualitative behaviour of dynamical systems. However, owing to variations or flaws between the mathematical model and the real physical systems, which are generally referred to as model uncertainties, precise modelling of physical systems is not always guaranteed in practise. Furthermore, the presence of uncertainties is classified by a number of characteristics, including modelling mistakes, physical parameter variation, operating point shifting, and overlooked nonlinearities.

Uncertainties are seen as unknown dynamics, which are typically a source of instability, due to poor knowledge of physical events. Designing the system with uncertainties is both essential and critical.. In the literature, there have been several fruitful publications on the stability and stabilisation analysis of uncertain dynamical control systems [6]-[8].

Nonlinearity - Almost all practical systems exhibit nonlinear characteristics due to unexpected environmental changes, abrupt failures of the system components and unsystematic behaviour. Such nonlinearities may produce significant limitations in the study of stability and stabilization of dynamical systems. It is often difficult to design accurate control law to achieve the required performances of nonlinear control systems due to their complex dynamical behaviour.

But in practice, an appropriate control design for nonlinear systems is more essential to guarantee the desired system performance. Because of the potential applications of nonlinear control systems in engineering and research, numerous techniques to dealing with them have been proposed with the phenomenal rise of modern technology. Among them, linearisation techniques have gained a great deal of importance from both theoretical and application-based perspectives [9]-[14].

External Disturbances - In system dynamics, the occurrence of both matched and mismatched disturbance signals is critical. Notably, dynamical systems interact with their environment via inputs and outputs and the environmental inputs are usually act as disturbance signals. Unwanted changes, such as vibrations and machine faults, are unavoidable in this context.

In order to tackle these situations, abundance efforts are being made by the researchers in the development of disturbance rejection and attenuation strategies for control systems. In general, measuring the disturbances operating on a system is quite challenging. For this reason, various types of disturbance estimation techniques for distinct dynamical systems have been reported in the literature [16]-[20].

2. System Description and Preliminaries

2.1 Coulomb-Counting Method

The widely method for determining the State of Charge is the CC method. This approach uses current values of the battery that are mathematically integrated over time and then added to the original SoC value. Mathematically, it is given by,

$$SoC = SoC_0 + \frac{x}{C_c}\int_0^t idt$$

where, SoC0 = Initial SoC; Cc= Rated Capacity in Ampere-seconds; x = '+' for charging of battery and '-' for discharging of battery. Generally, the SoC OCV relationship is fairly accurate and reliable. The OCV is equal to the terminal voltage when the battery is not in use. Thus, before operating the battery the terminal voltage is measured which is actually the OCV and then from SoC-OCV mapping the initial SoC is estimated. The simplicity and stability of the Coulomb-Counting technique are its main advantages. However, because it is an open-loop technique, a tiny inaccuracy in measurement might have a large effect as a result of the merger process. Another constraint is that the battery's maximum usable capacity must be correctly recalibrated under varied operating situations and ageing levels. As a result, the initial estimation of SoC and the current sensor must be precise for the algorithm to operate efficiently. [35].

2.2 Model Based Estimation

The ECM (Equivalent Circuit Model) consists of multiple circuit parts stacked in series or parallel combination to simulate the battery's dynamics [36]. A series resistance, a voltage source, and one or more parallel RC pairs comprise the Thevenin equivalent circuit concept (s). The dynamical behaviour of the battery is captured by the RC pair(s). As the number of RC pairs rises, so does the accuracy in recording dynamical behaviour. In this study, the 2 RC battery model is utilized.

2.3 2RC Model of Lithium-Ion Battery

The 2 RC model of the battery is shown in Fig. 1. The circuit parameters are variable but unsystematic function of SoC. The OCV also depends with SoC and it's a non-linear relationship.

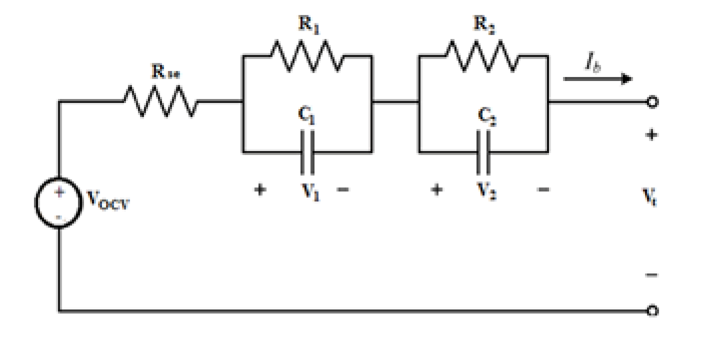

Figure 1. Equivalent circuit battery model

V_{OCV} =Open circuit voltage; R_{se}=Internal series resistance; V_t= Terminal voltage; R_2, C_2=Concentration polarization resistance and capacitance; R_1, C_1= Electrochemical polarization resistance and capacitance; I_b=Battery current. Applying KVL to the above circuit,

$$V_t = V_{OCV} - V_1 - V_2 - R_{se} \tag{1}$$

The OCV-SoC relation is non-linear and is written as,

$$V_{OCV} = bz \tag{2}$$

where, z=SoC; 'b'= SoC dependent parameter. The value of 'b' is obtained from lookup-table at different SoC levels. Derivating equation 2 w.r.t time,

$$\frac{dV_{OCV}}{dt} = b\frac{dz}{dt} + z\frac{db}{dt}$$

$$\frac{dV_{OCV}}{dt} = b\frac{dz}{dt} \tag{3}$$

since, z being in p.u., is small, and rate of change of 'b' is also small. From the equivalent circuit, the dynamical equations can be written as,

$$C_1\frac{dV_1}{dt} + \frac{V_1}{R_1} = i$$

$$\frac{dV_1}{dt} = -\frac{V_1}{C_1 R_1} = i \tag{4}$$

Similarly,

$$\frac{dV_2}{dt} = -\frac{V_2}{C_2 R_2} = i \tag{5}$$

The SoC as obtained from Coulomb Counting method is given by,

$$z = z_0 + \frac{x}{C_C}\int_0^t i dt$$

$$\frac{dz}{dt} = \frac{x}{C_c} i$$

$$\frac{V_{OCV}}{dt} = \frac{bx}{C_c} i \qquad (6)$$

Taking V_{OCV}, V_1 and V_2 as the states, V_t as output, and 'i' as the input to the system.

Therefore, $x_1 = V_{OCV}$, $x_2 = V_1$, $x_3 = V_2$, $Y = V_t$, $U = i$

Let,

$$a_1 = \frac{-1}{R_1 C_1} \quad a_2 = \frac{-1}{R_2 C_2} \quad a_3 = -R_{se}$$

$$b_1 = \frac{1}{C_1} \quad b_2 = \frac{1}{C_2} \quad b_3 = \frac{bx}{C_C}$$

The state equations are given as

$$\begin{cases} \dot{x}(t) = Ax(t) + Bu(t) + CF\big(x(t), u(t)\big) + Dd(t) \\ y(t) = Ex(t) \end{cases} \qquad (7)$$

Where

$$A = \begin{bmatrix} -a_2 & -a_1\alpha_1 + a_2\alpha_1 & 0 \\ a_3 & -a_1 - a_3\alpha_1 & a_3 \\ 0 & 0 & -a_2 \end{bmatrix}, \ B = \begin{bmatrix} -b_1\alpha_1 - b_2 - b_3 \\ 0 \\ b_2 \end{bmatrix}$$

$$C = \begin{bmatrix} a_2 \\ -a_3 \\ 0 \end{bmatrix}, F\big(x(t), u(t)\big) = \varphi(x_2)$$

The final term Dd(t) represents modelling flaws and time-varying components. It is assumed that the function d(t) is bounded $\| d(t) \| \leq d_0$. The uncertainty input matrix is represented by the parameter D.

Assumption 1:

The pair (***A, E***) is observable and (***A,*** [C D]) is stabilisable.

Assumption 2:

For a Lipschitz constant $L_P > 0$, the non-linearity $f\,(\boldsymbol{x}, u)$ satisfies the Lipschitz condition.

$$\|f(a,b) - f(\hat{a},b)\| \leq L_p \|a - \hat{a}\| \qquad (8)$$

The following condition is satisfied, as (7) is QSR dissipative,

$$\int_0^{T_f}(Z^T(t)QZ(t)+2Z^T(t)Sd(t)+d^T(t)Rd(t)ds \le \theta\int_0^{T_f} d^t(t)d(t)ds$$

where Q ≤ 0, R and S are real matrices with appropriate dimensions. In addition, the matrices R and Q are symmetric in nature.

3. Robust Dissipative based PI Observer Design

With reference to the battery model (7), a dissipative-based PI observer is presented for robust estimate of states in the presence of modelling errors. The suggested PI observer is as follows,

$$\begin{cases}\dot{\hat{x}}(t)=A\hat{x}(t)+Bu(t)+CF\left(\hat{x}(t),u(t)\right)+K_p\left(\Psi(t)-\widehat{\Psi}(t)\right)+K_{I1}w(t)\\ \dot{w}(t)=K_{I2}\left(\Psi(t)-\widehat{\Psi}(t)\right)\\ \widehat{\Psi}(t)=E\hat{x}(t)\end{cases} \tag{9}$$

Where $\hat{x}(t)\in\mathcal{R}$ signify the estimated reconstructed states of *x(t)* and *Ψ(t); u(t)* is improved control input; $K_p\in\mathcal{R}^{n\times r}$and $K_{I1}\in\mathcal{R}^{r\times r}$ are the corresponding proportional and integral gains; $x_1(t)\in\mathcal{R}^r$ is a vector that represents the weighted output estimation integral.

Defining $e = x - \hat{x}$ as the state estimation error, its dynamic is determined as

$$\begin{cases}\dot{e}(t)=Ae(t)+C_g(x,\hat{x},u)+Dd(t)-K_pEe(t)-K_{I1}w(t)\\ \dot{w}(t)=K_{I2}Ee(t)\\ Z(t)=Ee(t)\end{cases} \tag{10}$$

Where z(t) represents output vector of the error system. Further the augmented structure of the feedback system is given as follows:

$$\dot{\epsilon}(t)=\bar{A}E(t)+\bar{C}g(x,\hat{x},u)+\bar{D}d(t) \tag{11}$$

Where

$$\epsilon(t)=\begin{bmatrix}e(t)\\ w(t)\end{bmatrix},\ \bar{A}=\begin{bmatrix}A+K_pE & K_{I1}\\ K_{I2}E & 0\end{bmatrix},\ \bar{C}=\begin{bmatrix}C\\ 0\end{bmatrix},\bar{D}=\begin{bmatrix}D\\ 0\end{bmatrix} \tag{12}$$

$$g(x,\hat{x},u)=F(x,u)-\hat{F}((\hat{x}),u) \tag{13}$$

The stability of the error dynamics is demonstrated by using quadratic Lyapunov function,

$$V(t) = \epsilon^T(t)P\epsilon(t) \tag{14}$$

Now, using the time derivative of the Lyapunov function v(t) and the augmented closed loop system trajectories,

$$\dot{V}(t) = \dot{\epsilon}^T(t)P\epsilon(t) + \epsilon^T(t)P\dot{\epsilon}(t) \tag{15}$$

By substituting (11) in above equation,

$$\dot{V}(t) = [\bar{A}\epsilon(t) + \bar{\epsilon}g(x,\hat{x},u) + \bar{D}d(t)]^T P\epsilon(t) + \epsilon^T(t)P[\bar{A}\epsilon(t) + \bar{C}g(x,\hat{x},u) + \bar{D}d(t)] \tag{16}$$

Now by considering,

$$J(t) = Z^T(t)Qz(t) + 2z(t)^T Sd\big(t + d^T(t)\big)(R - \theta I)d(t) \tag{17}$$

By combining (15), (16) and (17),

$$\dot{V}(t) + J(t) \le \varphi^T(t)\Gamma\varphi(t) \tag{18}$$

where,

$$\emptyset^T(t) = [E^T(t) \quad g^T(x,\hat{x},u) \quad d^T(t)]$$

$$\Gamma = \begin{bmatrix} P\bar{A} + \bar{A}^T P + \bar{E}^T Q\bar{E} + L_p I & P\bar{C}^T & P\bar{D}T \\ * & -I & 0 \\ * & * & -\gamma^2 I \end{bmatrix}$$

$$\Gamma = \begin{bmatrix} \bar{A}^T P_1 + P_1 A + P_1 K_p E + E^T E + L_p I & P_1 K_{KI} + E^T K_{I2}{}^T P_2 & P_1 C^T & P_1 D^T + 2E^T \\ * & -I & 0 & 0 \\ * & * & -I & 0 \\ * & * & * & -\gamma^2 I \end{bmatrix}$$

Now by considering $P_1K_P=Y_1$, $P_1K_{I1}=Y_2$, $P2K_{I2}=Y_3$. As a consequence, the liner matrix inequality in the following form is obtained.

$$\Gamma = \begin{bmatrix} A^T P_1 + P_1 A + Y_1 E + E^T E + L_p I & Y_2 + E^T Y_3{}^T & P_1 C^T & P_1 D^T \\ * & -I & 0 & 0 \\ * & * & -I & 0 \\ * & * & * & R - \theta I \end{bmatrix}$$

Then by proving Γ<0, and by the definition of Lyapunov stability theory, which ensures the error system's stability with a satisfying disturbance attenuation index γ.

4. Simulation Verification

4.1 Battery Model

A 2RC equivalent circuit model of a Lithium-Ion battery is considered in this work. The parameters of the circuit are obtained from [37]. The circuit parameters are taken for 1C current discharge rate. The parameter values at discrete SoC levels are listed in Table 1. The 2RC equivalent circuit is built in MATLAB Simulink. Lookup-table is used to acquire the parameter values at discrete SoC levels.

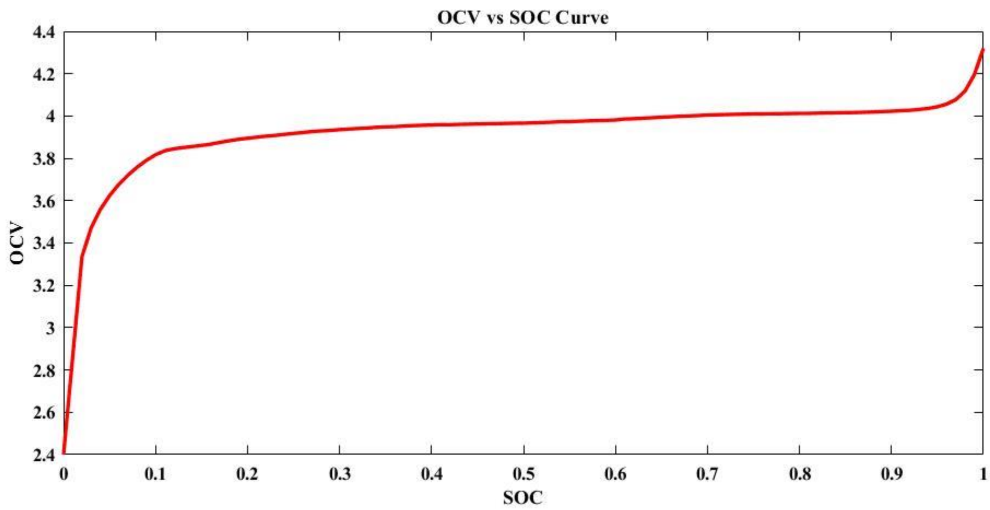

Figure 2. OCV-SoC Curve

Table 1. Battery parameters at various SoC levels

SoC (%)	b	R_{se} (ohm)	R_1 (ohm)	C1 (Farad)	R2 (ohm)	C2 (Farad)
5	42.26	0.0023	0.005308	411.0358	0.001692	956.2855
10	21.31	0.001923	0.003385	600.2254	0.000923	1597.527
20	10.785	0.001846	0.001846	999.6919	0.000615	2256.787

30	7.26	0.001769	0.001462	1217.596	0.000462	2887.164
40	5.502	0.001692	0.001231	1408.094	0.000462	2887.164
50	4.452	0.001615	0.001077	1576.78	0.000462	2887.164
60	3.768	0.001538	0.001077	1576.78	0.000462	2887.164
70	3.3014	0.001538	0.001	1679.105	0.000462	2887.164
80	2.9725	0.001462	0.001077	1576.78	0.000462	2887.164
90	2.73	0.001462	0.001	1679.105	0.000462	2887.164
95	2.645	0.001385	0.001154	1487.209	0.000462	2887.164

The OCV-SoC curve is shown in the figure 2. The relationship is non-linear and the OCV value is given by,

$$V_{OCV} = bz$$

4.2 SoC Estimation by Coulomb-Counting Method

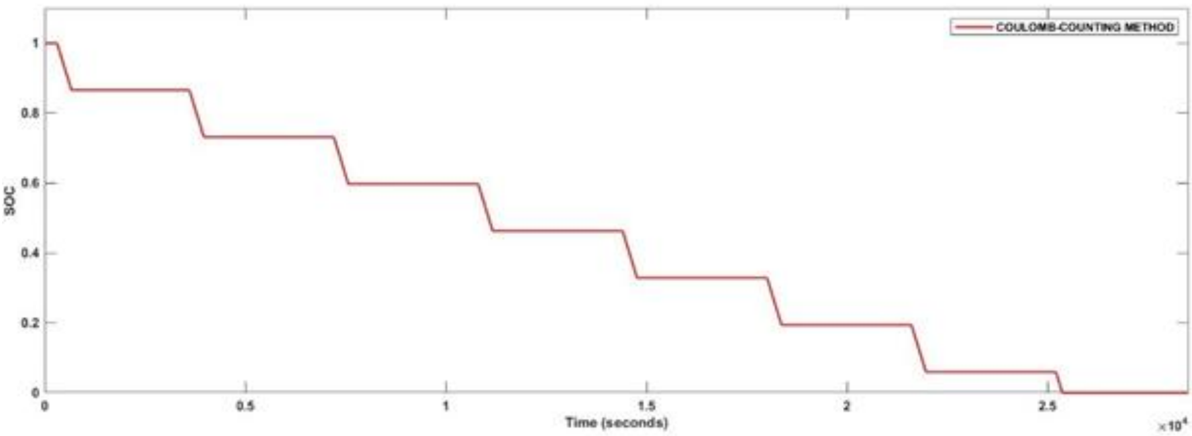

Figure 3. SoC estimated by CC method

As mentioned in section 3.2, the SoC is assessed using the Coulomb-Counting approach. Figure 3 depicts the simulation outcome. Initially when the current is high, the SoC decreases faster and then the change in SoC is very small.

4.3 Model based SoC Estimation

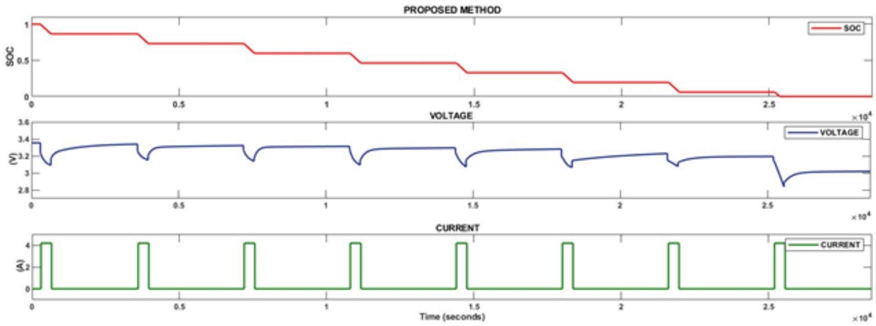

Figure 4. SoC, Voltage and Current waveforms of the model

The battery's 2 RC model is utilised because it reflects both the long-term and short-term transient reactions caused by the battery's relaxation effect.

4.4 Proposed Method

The most often used approaches for estimating SOC are those based on battery models. The basic concept is to apply the measured input signals to the model and calculate the output using the model's current and/or previous states and parameters. The disparities between estimated and measured values, or so-called errors, are sent into an algorithm, which intelligently updates the model state estimates. The Kalman filter [27]-[30], the sliding mode observer [32][33], and the Luenberger observer [22]-[24] are examples of model-based SOC estimation approaches.

The only variation between the three ways is the feedback method, and the structure of the three systems is essentially identical. The input signal is the voltage response of the real battery, and the output signal is the voltage response of the battery model. As a result, the feedback technique might be thought of as a controller. The PI controller, also known as the PI observer in the structure, takes the role of the feedback technique. The dissipative-based PI observer is presented for Li-ion battery SOC estimation.

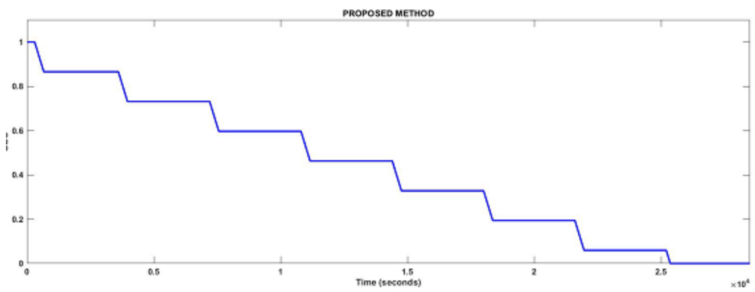

Figure 5. SoC estimation by the proposed method

It has been claimed that adding an integrator to a PI observer increases the observer's resilience in the face of modelling uncertainty [34]. Because there are always modelling uncertainties for a battery model, the PI observer enhances the accuracy and speed of Li-ion battery SoC estimate. A battery SoC estimation algorithm based on a PI observer has been proposed for Li-ion battery. In addition to that SoC is also calculated via model based method and CC method. The results of all the methods are given in fig. 6. The majority of the faults in the PI-based SOC estimating approach are less than 1.5 percent.

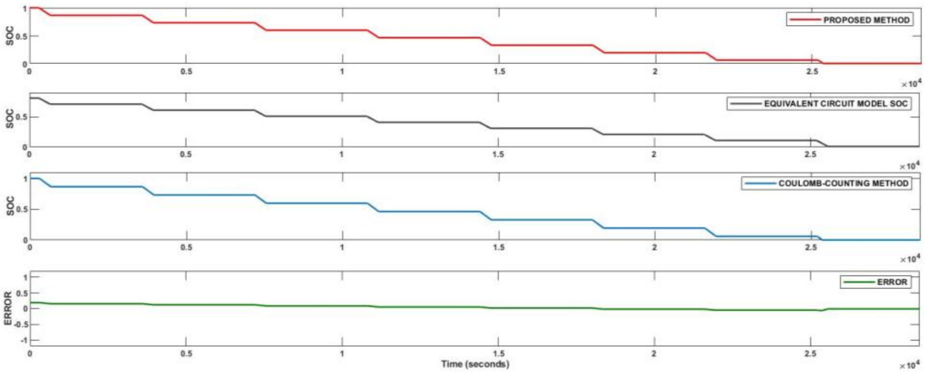

Figure 6. SoC estimation result

It is worthy to mention that the presences of unpredictable factors induce more technical challenges in stability analysis and control synthesis, and many unsolved problems still exist. However only few research efforts have been made in this study. In particular, developing Dissipative PI Observer for the SoC system with disturbances, uncertainty and non-linearity is one of the major novelty in this study.

5. Conclusion

A robust dissipative-based PI observer is suggested and compared with Coulomb-Counting and model-based methods to properly estimate the SoC of a lithium-ion battery. This exact SoC estimation helps to enhance battery performance and reliability but not only limited to effective battery management, as well as increasing the accuracy of range estimating techniques, resulting in less range anxiety. The suggested method's significant characteristic is its resilient performance in the face of modelling mistakes and uncertainties. Under uncertain conditions, this feature helps the observer to adjust for estimation mistake. Furthermore, the suggested scheme's design approach is straightforward. The stability of the observer is also confirmed using the Lyapunov criterion.

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