Analysis of Online Lyapunov-Based Adaptive State of Charge Observer for Lithium-Ion Batteries Under Low Excitation Level

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Abstract
The online estimation of the state-of-charge (SOC) of Li-ion battery using the adaptive Lyapunov-based observer is an attractive proposition due to the ensured stability, adaptability and reduced computing requirement. However, the observer requires the presence of the persistent excitation (PE) to guarantee the convergence of the battery model parameters to their correct values. The PE is satisfied using sufficiently rich (SR) signal that contains spectral components to excite the battery model. This paper revisits several important works that utilize such observer and highlights the absence of PE in their practical implementation. Since the previous works utilize dc excitation that lacks the SR characteristics, the validity of the published results is questionable. To rectify the problem, a scheme known as the forced excitation is proposed to estimate the battery parameters under dc or low excitation level. The SR signal is generated by chopping the battery current at a certain rate for specific interval. Moreover, the disruption of the load current (due to the chopping) is compensated using the supercapacitor. The concept is simulated by Matlab/Simulink and is realized experimentally using a Panasonic NCR18650B Li-ion battery. The forced excitation algorithm is implemented on the DS1104 dSPACE platform. The results show that the proposed method satisfies the PE condition and is able to correctly estimate the SOC even with low excitation signals.

Index Terms
Adaptive observer, lithium-ion battery, Lyapunov stability, persistent excitation (PE), state of charge estimation, sufficient richness (SR).

I. INTRODUCTION
Owing to the rapid growth of battery-based applications, particularly the electric vehicles (EV), smart grid storage system and mobile devices, the battery management system (BMS) plays indispensable role to ensure the safety, efficiency and the long life of the battery [1], [2]. In order to achieve these objectives, the BMS must be able to estimate the battery states with simplicity and accuracy. The battery states include the state of charge (SOC) [3], [4] (a measure to know the available charge in the battery), the state of health (SOH) [5], [6] (the battery aging level) and the state of power (SOP) [7] (the available power in the immediate future).

Technological-wise, the Li-ion is preferred due to its high energy density, lightweight, fast charging and low self-discharge. Furthermore, it can last longer as it exhibits a high number of charge-discharge cycles, compared to the lead-acid battery. However, Li-ion is relatively more expensive and is sensitive to over-charging and discharging conditions. Thus, additional care must be observed when designing its SOC algorithm.

In general, the SOC estimation methods can be classified into two broad categories: the non-model and model-based approaches. A simple technique for the non-model estimation is the coulomb counting. It is based on the principle of direct charge accumulation, where the charge is added to or subtracted (by integrating the battery current) from the initial value of SOC (i.e. SOC$_0$) [3]. One major problem with
coulomb counting is the lack of accuracy that results from the accumulation error of the current integration. Furthermore, it needs an accurate value of SOC₀ to begin with—which is not always available in a real system. Another popular non-model approach is the artificial intelligence method. The main advantage of this method is its ability to estimate the SOC independently, i.e. regardless of the battery’s nonlinearity [8]–[10]. Although it does not require the battery model, a huge number of data sets are needed to train the network. Moreover, it requires a powerful microprocessor due to the extensive computations involved in the algorithm.

On the other hand, the model-based SOC utilizes the battery’s current and voltage to estimate the parameters of an equivalent (electrical) circuit model. The most widely-use method is the Kalman filter (KF), and its variations such as extended Kalman filter (EKF) [11] and sigma-point Kalman filter (SPKF) [10], [12]. Since KF is basically designed as a state estimator, it requires an offline identification of the model’s parameters prior to the online estimation of the SOC. One possible solution is to utilize the simultaneous estimation for state and parameters using the dual (double) KF technique [13]. Alternatively, the online parameter estimation method, such as the recursive least square can be incorporated [14]. Furthermore, the noise statistics are required in order for the KF methods to obtain accurate SOC values. Thus, the improved versions, namely the adaptive EKF [13], [15], [16] and the adaptive SPKF [13], [17], [18] were developed for online adaptation of the noise covariance. However, their implementation mandates high computational power due to the need for complex online matrix inversion.

Besides KF, there are a number of techniques that utilize the circuit model of the battery. In [19], an accurate moving window least-squares (MWLS) method is employed for online estimation of the model parameters. Despite its effectiveness, a large computing power as well as memory are required. Authors in [20], proposed an adaptive sliding mode observer with reduced chattering, while in [21], another robust algorithm using H-infinity filter is developed to estimate the SOC under biased noise. Notwithstanding their excellent performance, the estimators mentioned in [20], [21] require initial knowledge of the battery parameters. Since the identification of the initial values has to be done offline, the ageing factor of the battery is not taken into account—unless the battery parameters are updated periodically throughout the life span of the battery.

Recently, another class of SOC estimator—based on online observer is published in several reputable journals [22], [23]. The main feature of this adaptive observer is the inherent stability, which is proven by Lyapunov approach. Another advantage is the simplicity of the observer’s structure. It does not require matrix inversion; thus, the computational burden is greatly reduced. Moreover, since the battery model parameters and the open circuit voltage (V₀) are estimated simultaneously, additional parameters estimation technique is not needed. In the subsequent works [24]–[26], a temperature post-compensation scheme was added to the basic observer, which allows parameter estimation for varying temperatures conditions.

To converge to the correct V₀ value (and thus to SOC), the observer must ensure that the input current and output voltage can characterize the dynamics of the battery. To make this possible, the persistence excitation (PE) is needed to excite the modes in the battery model during the observation interval. In practice, the PE condition is satisfied using sufficiently rich (SR) input current that contains a number of frequency components [27]. Despite this requirement, the online observers published in [23]–[26] did not provide any evidence on that; in its practical demonstration, the battery model was shown to be excited by dc current, which does not qualify as an SR signal. In principle, with the lack of frequency excitation, the observer will never converge to V₀. Since this critical issue was never taken into consideration, the validity of the published results is in serious doubt.

Based on these shortcomings, this paper revisits the observer in [23]–[26] to explicitly prove that the results—and by extension the conclusions therein, are indeed incorrect. To ensure that the SR signal is generated, a correction scheme known as the forced excitation is proposed. The purpose is to guarantee that the observer is able to operate properly under low excitation level, including dc. Thus, this method retains all the favourable features of observer, but at the same time fulfils the mandatory PE requirement. The forced excitation is achieved by interrupting (chopping) the battery current at a defined rate and for limited intervals—effectively creates an SR signal that sufficiently excites the battery model. To compensate for the interruptions of the battery current (due to the chopping), a rapid charging/discharging energy storage element is incorporated into the system. In this case, the supercapacitor is utilized.

The remaining of the paper is organized as follows: Section II presents the parameterization of the battery model and the derivation of the adaptive observer design, based on Lyapunov stability. Although the idea was originally presented in [23], the proof for Lyapunov given in that paper was inadequate; hence the need to improve its clarity. In Section III, simulation works using Matlab/Simulink are carried out to identify the problems when the observer lacks the PE excitation. Then, in Section IV the idea of forced excitation is simulated by Matlab/Simulink. The functionality of observer with the forced excitation is experimented using the DS1104 dSPACE controller and tested using a Panasonic NCR18650B Li-ion battery. This is described in Section V. It is important to note that the focus of the work is for system that has dc or low current excitation; one example is smart grid storage. For system that is sufficiently excited, for example EV (with certain driving profile), it can be assumed that the observer can operate properly.

II. THE ADAPTIVE OBSERVER DESIGN

A. GENERAL

In general, the Li-ion battery is modelled based on either its electrochemical or electrical characteristics. The latter is
preferred because it exhibits a good compromise between the accuracy and ease of computation [28]. The dynamic and static behaviors of the battery are represented by the combination of electrical components, namely voltage source, resistors, and capacitors. Moreover, the electrical model can be integrated directly into the modern circuit simulators such as PSpice and Matlab. This feature is very useful for system design. Figure 1 shows the popular single RC network electrical model for the Li-ion battery. It is the reduction of the double RC network proposed in [28]. The reduced model is considered as a good trade-off between robustness, complexity and computational speed and was adopted by numerous researchers, for example [29]–[32].

The design of the online observer comprises of three steps. First, the dynamic equations of the battery model are written. Second, the observer’s adaptive law is selected; in this work the Lyapunov stability criterion, is used. Third, the input signal to excite the model is selected. For the observer to work properly, it must fulfill the PE condition, i.e. the excitation signal must be of the SR type.

**B. OBSERVER DESIGN BASED ON LYAPUNOV STABILITY**

The dynamics of the battery can be represented by the state space representation of the model, i.e.

\[ \dot{V}_p = -\frac{1}{RC} V_p + \frac{1}{C} I_b \]  
\[ V_b = V_{oc} - V_p - R_b I_b \]

where \( I_b \) is the discharging current, \( V_b \) is the terminal voltage at the output, \( V_p \) is the state variable voltage across the \( RC \) network and \( V_{oc} \) represents the open circuit voltage. In addition, \( R_b \) denotes the internal resistance of the battery, while the transit response is represented by \( RC \). In Figure 1, the only known values are \( V_b \) and \( I_b \). However, \( V_p \) is not measurable and the model parameters (\( R_b, R \) and \( C \)) are unknown prior to the estimation. Moreover, these parameters are time varying due to the changes in operating conditions, i.e. current and temperature. The values are also influenced by the aging of the battery. The observer aim is to estimate the value of \( V_{oc} \); once this parameter is known, the SOC can be readily calculated using the relationship provided by the SOC versus \( V_{oc} \) curve of the specific battery [33].

The input/output relationship of the battery model is written by substituting \( V_b \) from (2) into (1) and assuming \( V_{oc} \approx 0 \). The assumption is valid since the dynamics of the battery is known to vary slowly with respect to SOC and \( V_{oc} \) [22], [23]. The estimated parameters are considered to converge to their actual value when the error between \( \hat{V}_b \) and \( V_b \) becomes zero [34]. Thus,

\[ V_b = -R C \dot{V}_b - R_b R C \dot{I}_b - (R + R_b) I_b + V_{oc} = \Phi^T W \]  

In (3), \( W \in R^4 \) is the vector that represents the actual parameters of the battery, i.e.

\[ W^T = [W_1 W_2 W_3 W_4] = [R C R_b C (R + R_b) V_{oc}] \]

Also, \( \Phi \in R^4 \) is the regressor vector, given by

\[ \Phi^T = [-\dot{V}_b - I_b - I_b 1] \]

Thus, the reference model of the system can be written as

\[ \dot{\hat{V}}_b = \hat{\Phi}^T \hat{W} + K_d e \]

where \( \hat{W} \in R^4 \) is defined as the vector of estimated parameters of the battery, i.e.

\[ \hat{W}^T = [\hat{W}_1 \hat{W}_2 \hat{W}_3 \hat{W}_4] = [R \hat{C} \hat{R}_b \hat{R} \hat{C} (\hat{R}_b + \hat{R}) \hat{V}_{oc}] \]

And \( \hat{\Phi} \in R^4 \)

\[ \hat{\Phi}^T = [-\dot{\hat{V}}_b - \dot{I}_b - I_b 1] \]

The constant \( K_d \) is defined as a strictly positive observer gain, while \( e \) is defined as the terminal voltage estimation error, i.e.

\[ e = V_b - \hat{V}_b \]

To achieve an asymptotic stable system, i.e. for \( e \) to converge to zero, the following adaptation law is proposed:

\[ \dot{\hat{W}} = \Gamma.\hat{\Phi}.e \]

where \( \Gamma = [\gamma_1, \gamma_2, \gamma_3, \gamma_4] \) are positive adaptive gains. Furthermore, to prove the system stability, the following Lyapunov function is chosen:

\[ V = \frac{1}{2}[RCe^2 + \hat{W}^T \Gamma^{-1} \hat{W}] \]

where \( \hat{W} = W - \hat{W} \) is the error for the estimated parameter. Taking the derivation of \( V \) yields

\[ \dot{V} = RC\dot{e}e - \hat{W}^T \Gamma^{-1} \hat{W} \]

Since parameters in vector \( W \) are considered to be constant or slowly time-varying [22], [23], the following is assumed to be true:

\[ \dot{\hat{W}} = -\hat{W} \]

Substitute (6) in (7) yields

\[ \dot{\hat{V}} = RC\dot{e}e - \hat{W}^T.\hat{\Phi}.e \]

Adding and subtracting \( e^2 \)

\[ \dot{\hat{V}} = e^2 + RC\dot{e}e - e^2 - \hat{W}^T.\hat{\Phi}.e \]

\[ \dot{\hat{V}} = e[e + RC\dot{e} - e] - \hat{W}^T.\hat{\Phi}.e \]
The Lyapunov theory guarantees the stability of the observer. This information is preserved in the regressor vector \( \Phi \). It is defined in [34] that the \( \Phi \) is said to satisfy the PE condition if
\[
\alpha_0 I_n \leq \frac{1}{\beta} \int_{t}^{t+\beta} \Phi \Phi^T dt \leq \alpha_1 I_n \quad \forall t > 0 \tag{11}
\]
where \( \alpha_0 \) and \( \alpha_1 \) are all positive values. Variable \( \beta \) is the observation period, while \( I_n \) is an identity matrix. This criteria guarantees that, whatever the past changes that have taken place in the battery, the information will be carried by \( \Phi \) over the next \( \beta \) time interval. In other words, \( \Phi \) is said to retain the dynamics of the battery. Consequently, the observer can converge to the actual values when \( \Phi \) is fed to it [35]. However, since PE examines the condition of \( \Phi \), it is extremely difficult to decide which type of the input signal (i.e. \( I_b \)) that can meet condition imposed by Eqn. (11). Therefore, in practical, the PE is translated to a condition for the input signal only, called sufficient richness (SR). A signal is considered as an SR if it contains as many spectral lines as the parameters of the battery model [27]. Hence, the examination of \( \Phi \) which fulfills (11) can be replaced by examining the content of \( I_b \) only.

### III. THE ABSENCE OF PE IN PREVIOUS WORKS

Recently, an online observer with favorable features for SOC estimation was described in [23]–[26]. It was demonstrated that by using pulsating \( I_b \) as the source of excitation, the observer appears to be working properly in Matlab/Simulink. This is expected as the pulse waveform contains odd frequency components and thus, fulfills the PE requirement perfectly. However, in the experimental verification, only dc excitation is used. Nevertheless, the observer is shown to obtain similar results to simulation. In principle, this is not possible because dc current does not qualify as an SR signal, which implies that the PE is absent.

To demonstrate this inadequacy, the same observer (which is also shown in Figure 2) is simulated for the pulse and dc excitation. The configuration is similar to the set-up proposed by [23]. The actual parameters of the battery are as follows: \( R_b = 0.05 \Omega, R = 0.05 \Omega, C = 2 \text{ F} \). The initial values of the estimated parameters are set to \( \tilde{V}_b = [0.0005 3] \). The observer gain \( K_d \) is set to 300, while the adaptive gains \( \Gamma = [\gamma_1, \gamma_2, \gamma_3, \gamma_4] = [800 30 20 200] \). These values are selected based on trial and error where the small values result in slow convergence time and the large ones increase the effect of noise. To represent the measurement noise (of the battery current and voltage), a white noise is added. The noise for the current has zero mean value and a variance of \( \sigma_i^2 \) (i.e. \( 4 \text{ mA}^2 \) (standard deviation \( \approx 63 \text{ mA} \)). This variance is selected to mimic the noise produced from the current sensor in experimental results. The noise in voltage signal has variance \( \sigma_v^2 \) (\( \approx 0.01 \text{ mV}^2 \)). The observer’s responses in discharge mode are examined.

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**FIGURE 2.** The block diagram of the adaptive Lyapunov-based observer for Li-ion SOC estimation.
A. PULSE EXCITATION

Initially, the battery is placed in the relaxation mode for 300 s. Then a 5 A pulse discharge current \(I_b\) with 50% duty cycle and period of 5 s is applied, as shown in Figure 3(a). The actual terminal voltage of the battery \(V_b\) and the estimated one, i.e. \(\hat{V}_b\) are shown in Figure 3(b), while the error between the two is depicted in Figure 3(c). The very small value of error confirms that the Lyapunov adaptive law is able to drive the observer to stability. The estimated battery model parameters, i.e. \(\hat{W}_1, \hat{W}_2, \hat{W}_3\) and \(\hat{W}_4\) are shown in Figures 4(a) through (d), respectively. Recall that these variables are directly related to \(R, R_b, RC\) and \((R + R_b)\), respectively. The fourth parameter, namely \(\hat{W}_4\) is used to estimate the SOC; its value equals the estimated open circuit voltage \(V_{oc}\). As can be seen in the figure 4(d), the adaptive mechanism of the observer updates \(\hat{W}_4\) at each iteration until it converges exponentially to its actual value. From these results, it is clear that using pulse excitation, the observer is capable of estimating all the parameters correctly. This is to be expected because the pulse qualifies as the SR signal; it contains odd harmonics with sufficient magnitudes to excite the modes inside the battery. It is important to note that the added white noise which originates from the sensors does not contribute to the excitation.

B. DC EXCITATION

The experiments in [23]–[26] showed that, under dc excitation, the observer successfully estimates the battery resistance and \(V_{oc}\). However, this finding is questionable because, unlike pulse, dc signal does not qualify as an SR signal. To prove this fact, a similar experiment as described in [23]–[26] is repeated. The battery is discharged by 5 A dc, as shown in Figure 5(a). The estimated \(V_b\) is plotted in Figure 5(b). Again, since the observer fulfils the Lyapunov stability criteria, the \(V_b\) is tracked. This is proven by the small error depicted in Figure 5(c). However, the observer could not estimate \(\hat{W}_1, \hat{W}_2, \hat{W}_3, \hat{W}_4\) correctly; they diverge from the actual values significantly, as can be observed in Figures 6(a)-(d). The reason for the divergence is the lack of frequency excitation, i.e. \(\Phi\) could not retain the dynamic information on the battery. This observation is related to the battery model, shown in Figure 1. The capacitor \(C\) is an open circuit at dc; consequently, the current and voltage signals of the battery—which are the inputs to the observer in Figure 2, do not contain any information on the dynamics of \(C\). This is in contrast to the pulse excitation, where the frequency content in the SR signal is able to excite the capacitor.
IV. THE PROPOSED FORCED EXCITATION

A. CONCEPT

The above analysis confirms that the battery current must qualify as an SR signal in order for the observer to guarantee parameter convergence. Unfortunately, this requirement is not easily implementable (especially in the discharging mode), as the current changes uncontrollably, according to the battery consumption. A typical solution in parameter estimation problem is to add a perturbation that characterize the SR signal and to remove it once the convergence is achieved [36], [37]. However, adding an external signal means an additional current need to be drawn from the battery. This is unacceptable as it disrupts the main function of the battery by hastening its discharge. On top of that, a physical circuit is needed to generate the signal within the battery system. Therefore, a method has to be devised so that the SOC can be estimated without severely impacting the discharging current profile to the load. This work suggests a scheme, known as the forced excitation to resolve the PE requirement for the observer with dc or slow varying current. This is achieved by chopping the battery current (dc) at a certain rate at periodic intervals. Thus, the desired excitation only takes place within a portion of the current. Consequently, the observer is able to estimate the actual parameters, with minimum interruption on the power flow to the load.

To investigate the workability of the forced excitation, the same dc current profile of Figure 5(a) is used. However, the dc is chopped at every 2000 s, as shown in Figure 7(a). This pulse is maintained for 100 s. Within this period, the current is chopped further at 0.2 Hz to generate a pulse train that characterizes an SR signal. Figure 7(b) shows the actual and estimated battery voltage $V_b$, while the error between the two is shown in Figure 7(c). As can be seen, the error is acceptably small, except at the points of excitations. However, these spikes vanish rapidly. The small error manifests the stability of the observer as guaranteed by Lyapunov. Figures 8(a)-(d) show the estimated values of the model parameters, i.e. $\hat{W}_1$, $\hat{W}_2$, $\hat{W}_3$ and $\hat{W}_4$. The results show marked improvement compared to the case of (pure) dc excitation. It is clear that the forced excitation allows the estimated parameters to converge to actual values only during the excitation intervals. Once the pulse train is removed, the estimated values begin to diverge away. This sequence is unavoidable since the SR signal, which is provided by the pulse, is no longer available. Then a new forced excitation (after 2000 s) is needed to pull back the parameters to their actual values. In essence, the forced excitation can be considered as a compromised solution to enable the observer to work under dc condition. Otherwise, the observer is not able to carry out the estimation at all.
B. STABILIZING THE LOAD CURRENT

During forced excitation, the battery current (that feeds the load) is interrupted. This interruption results in a discontinued load current, as shown in Figure 7(a). However, this problem can be minimized by adding an auxiliary energy storage that provides rapid charging/discharging of large amount of charge, such as supercapacitor. One application where this can be suitably implemented is the hybrid energy storage system for micro grid system [38].

A method to stabilize the load current using supercapacitor is shown in Figure 9. The circuit comprises of two switches, which work in complement to each other. The first switch (which is normally opened) is connected between supercapacitor and load. The second switch is connected between battery and load; it is normally closed. The objective of this connection is to provide a continuous current to the load by alternating the source of current between the battery and supercapacitor. For the first half of the forced excitation interval, the load is connected to the battery; thus, it is disconnected from supercapacitor. For the second half, the connection is reversed. The battery and supercapacitor current profiles are depicted in Figures 10(a) and (b), respectively. Since the load current is the summation of battery and supercapacitor currents, it is stabilized (i.e. without the presence of pulses). This is shown in Figure 10(c).

V. EXPERIMENTAL VERIFICATION

A. TEST-RIG SETUP

An experimental test-rig is built to validate the performance of the observer under two modes: 1) high excited current and 2) low excited current but supported by the forced excitation algorithm. The Panasonic Li-ion battery (NCR18650B) with the capacity of 3040 mAh \((V_b = 3.6 \text{ V})\) is used. The battery has a cut-off and full charge voltages at 2.5 and 4.2 V, respectively. Figure 11(a) illustrates the schematic diagram of the experimental set-up, while Figure 11(b) shows the photograph of the entire test bench. The current is measured using the LA25-NP sensor. For the voltage, its value is less than 5 V; thus, it is measured directly (without a sensor). An electronic load is used to enable constant discharging current and high excited current. The DS1104 dSPACE controller is used to implement the forced excitation algorithm. The control signal opens and closes the solid-state relay, which in turn...
chops the battery current at predetermined intervals. The dSPACE controller is also used for data acquisition where the acquired voltage and current signals are digitized and filtered. After that, the digitized data is sent to Matlab for algorithm implementation. In addition, Matlab is also used for analysis and post-processing of the results. All measurements are performed at room temperature. The sampling time is set to 0.01 s.

**B. THE SOC-V_{OC} CURVE**

The estimated value of $V_{oc}$ ($\hat{V}_{oc}$) is used to determine the SOC. This is done by utilizing the SOC versus $V_{oc}$ conversion curve. Figure 12 shows the experimental curve of the NCR18650B battery; it is obtained using the incremental measurement method, as suggested by [33]. The fully charged battery (4.2 V) is discharged regularly at 0.5 C (1.52 A) for six minutes; this is equivalent to 5% decrease in the SOC per discharge interval. For each interval, the voltage is measured after being cooled down for 54 minutes; the idea is to allow the battery to relax. Since $I_b = 0$ in (3), it follows that $V_{oc} = V_b$. This procedure is repeated until the battery is fully discharged (0% SOC). The SOC values are plotted; thus, any value of $\hat{V}_{oc}$ can be converted to its equivalent SOC. It is important to note that the temperature and hysteresis effects are not considered, as the focus of this work is on resolving the PE issue.

**C. RESULTS**

The fully charged battery is discharged according to the profile shown in Figure 13(a). The profile has two main sections: the high excited and the low excited current (such as dc). For the latter, the forced excitation is applied. In between the two modes, the battery is allowed to rest. Initially, the battery is in the relaxation mode. Then at $t = 5$ min, the highly excited current is imposed for 43 minutes. The magnified current waveform is shown as the first inset in Figure 13(a). Here, the battery current is varied rapidly using six dc current steps (0, 1.5, 0.6, 2.5, 1, 2 A), with 5 s width for each step. The motivation is to show that the observer works perfectly when sufficient excitation is available. An example of the application of such profile is EV. The 43 minutes discharging time under this mode causes the battery SOC to decline from 100 to 70%.

After that the battery is left to rest for 20 min (rest period), it is subjected to the third mode, i.e. discharging under low excited current. The objective is to expose the shortcoming of the observer at the same time, to demonstrate the effectiveness of the forced excitation method. The pulses are generated by chopping the current using the relay at 0.2 Hz, while the duty cycle is maintained at 50%. This is shown by the second inset in Figure 13(a). Initially, the battery is discharged using 2 A dc current; the SOC drops from 70% to 60%. Then, the first forced excitation is applied; the dc current is chopped for 2 minutes, producing an SR signal.
The tracking of the battery voltage ($V_b$) is shown in Figure 13(b) whereas the error between the actual voltage and the estimated voltage is shown in Figure 13(c). As can be seen, the observer requires minimal time to converge with good tracking performance. The estimation errors vary between ±0.01 V. This result confirms the stability of the Lyapunov method proposed.

The estimated open circuit voltage $\hat{V}_{oc}$ is shown in Figure 13(d). Since the battery was initially in relaxation state, $V_{oc} = V_b$. The observer updates $\hat{V}_{oc}$ until it equals the actual value $V_{oc}$. When the highly excited current is applied, $I_b \neq 0$, which implies that $V_{oc} \neq V_b$. Therefore, $\hat{V}_{oc}$ drops away immediately, as shown by the inset of Figure 13(d). However, the presence of the pulse current helps $\hat{V}_{oc}$ converges back to $V_{oc}$. Thus, by having a pulse train, the PE is maintained and the observer is able to achieve good estimations results. After the rest period, the observer is triggered by the dc current; thus, the high excitation (from the pulse) is no longer available. As expected, $\hat{V}_{oc}$ begins to diverge from $V_{oc}$, which is consistent with the findings in [23]. If the dc current is not interrupted, $\hat{V}_{oc}$ will diverge further away from the actual ($V_{oc}$) locus. This is where the PE is needed. By applying the forced excitation, the $\hat{V}_{oc}$ is pushed to converge to $V_{oc}$.

The next step is to determine the actual SOC (i.e. the reference SOC) based on the principle of coulomb counting in order to validate the estimated SOC. In this method, three quantities must be known: 1) the actual capacity of the battery, 2) the initial SOC and 3) the measured battery current. The capacity is known (3040 mAh), while the initial SOC is deliberately set to 100%. For the current measurement, special care must be taken to ensure the noise is not present when the reading is taken. For this purpose, the high precision laboratory electronic load is used. It has the following characteristics: resolution 10 mA; accuracy ±0.05% of reading + 0.05% of full scale. This current was also calibrated using a high accuracy ammeter (DC amps: resolution 1 mA, accuracy ±1.0% of reading +3 counts). By adopting these settings, the exact SOC value can be calculated. This value is used to validate the estimated SOC by the observer [39].

The estimated SOC is determined from $\hat{V}_{oc}$ by utilizing the SOC-$V_{OC}$ curve, shown in Figure 12. The SOC estimation and SOC error are shown in Figures 13(e) and (f), respectively. The forced excitation is applied seven times. Every excitation runs for 2 minutes interval. The first minute is considered as the convergence period, while the estimation error is recorded at the second minute. Clearly, the observer achieves good results when the current is highly excited. However, for the low excitation mode, the estimated SOC drifts away from the actual value (the error reaches to 8%). Upon the application of the forced excitation, the estimated SOC is brought back near to the actual value (within 1% error), as shown by the inset in Figure 13(e). The mean absolute error (MAE) and root mean square error (RMS) are used to quantify the SOC estimation accuracy under different modes. The results are recorded in Table 1, where the error is firstly calculated for the high excited current then for the low excited current. Finally, the average error for the seven
times of forced excitation is calculated. The results show the remarkable improvement in the SOC when the dc current is accompanied by the forced excitation.

D. RECOMMENDED APPLICATIONS FOR THE FORCED EXCITATION

The experiment concluded that the observer works best with high excited current due the presence of the SR signals. This condition can be associated to EV, where its driving profiles comprise of rapid changes in the current due to the power demand in EV. Under this circumstance, the need for forced excitation may not be very great.

On the other hand, if the current has a slow time varying nature, the observer is exposed to diverge due to the lack of SR signal. One example is the smart grid storage system, where the battery is discharged in an almost constant manner. In this case, the implementation of the forced excitation is highly recommended to ensure the workability of the observer.

VI. CONCLUSION

This paper highlights the need for the persistence excitation (PE) condition in adaptive observer to guarantee SOC estimation for the Li-ion battery, particularly for applications that have low current excitation. Despite this mandatory requirement, the analysis of the previous works revealed the PE is not considered in the experimental—thus raising doubt on the validity of the published results. An improved method, called forced excitation is proposed to fulfill the PE condition. This is done by chopping the battery current at a certain rate for specific interval. This action creates sufficient richness (SR) signal in the battery current which allows the observer to converge to the correct SOC. The simulation and experimental results showed the improvement in the SOC estimation compared to its predecessors. In addition, a simple scheme to compensate the interrupting in battery current and to deliver continuous current to the load is suggested using a supercapacitor.

Finally, as suggestions for the future works, it is important to determine the width of forced excitation interval and the space between each two intervals. It is also important to know the effect of chopping frequency on the speed of convergence, where the higher the frequency the faster the convergence. In addition, the current amplitude has similar effect where higher amplitude results in faster convergence. All these effects can be studied for a certain application, where the prior knowledge of the expected current profile is helpful to optimize all these criteria in order to get the best SOC estimation.

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