Accurate Estimation on the State-of-Charge of Lithium-Ion Battery Packs

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Abstract. Lithium-ion batteries have been extensively used worldwide for energy storage and supply in electric vehicles and other devices. An accurate estimation of their state-of-charge (SoC) is essential to ensure their safety and protect them from the explosion caused by overcharge. Large amounts of training data are required for SoC estimation resulting in a great computational burden. Model-based observation method can effectively estimate battery SoC with a limited amount of data. This study applied a combined model, including a one-state hysteresis model and a resistor-capacitor (RC) model, to diminish the parameter estimation errors caused by the hysteresis phenomenon, increasing the estimation accuracy. The Luenberger observer was designed based on the hysteresis RC battery model and evaluated under dynamic stress test (DST) and federal urban driving schedule (FUDS). Our simulation results have shown that the hysteresis RC model has better performance in terms of SoC estimation accuracy using Luenberger observer. Additionally, after the investigation of communication technologies, 5G cellular network offers feasibility for real-time vehicle interaction.

Keywords: Luenberger observer · State-of-charge (SoC) estimation · Hysteresis resistor-capacitor model · Lithium-ion battery · Real-time vehicle interaction

1 Introduction

Lithium-ion (Li-ion) battery, as a promising technology with a long lifespan and high efficiency, has been generally employed as an energy storage device in electric vehicles (EV). Inside a battery pack, there are hundreds of Li-ion battery cells connected in series and parallel to deliver the desired output current and voltage [1]. However, Li-ion battery has potential safety hazard, such as explosion, when one or more of these battery cells overcharge. State-of-charge (SoC) is one of the most critical metrics in a battery management system (BMS) that indicates the current amount of energy stored in the battery. Compared with portable-electronic applications, EV applications require more accurate battery SoC estimation due to the high rate requirement and dynamic rate profiles, which incurs high data consumption and requires the trade-off between

W. Xiang et al. (Eds.): BROADNETS 2021, LNICST 413, pp. 251–262, 2022.
https://doi.org/10.1007/978-3-030-93479-8_17

estimation accuracy and response speed [2]. Nevertheless, most internal parameters of the battery, such as SoC, are hard to be observed after being manufactured. Battery SoC estimation is generally based on battery external characteristics, such as current, voltage, temperature, and etc.

The existing battery SoC estimation methods can be roughly classified into three categories, including the direct measurement methods, machine learning-based methods, and model-based methods. The direct measurement methods, such as the Coulomb counting method [3] and the open-circuit voltage method [4, 5], are used to quickly calculate the battery SoC. However, since these methods use open-loop control, the error will accumulate with time. Therefore, they are not accurate under dynamic working conditions. The machine learning approaches, for example, Artificial Neural network [6], fuzzy logic [7, 8], and support vector machine [9], regard a battery cell as a "black box" and establish the relationship between the inputs and outputs according to large amounts of training data [10]. Therefore, the quality and quantity of training data strongly influence the estimation accuracy. In addition, getting sufficient amount of data is time-consuming [10]. The model-based methods use a closed-loop observer to allow battery models to self-correct and tackle unexpected disturbance. Equivalent circuit models (ECMs) and electrochemical models (EMs) are commonly used to describe battery internal characteristics. The EMs are derived from the porous electrode and concentrated solution theories, describing the concentration and diffusion of Li-ions [11]. These models are more accurate but require large amount of computation. The ECMs use electrical circuit elements to describe the dynamic behaviours of a Li-ion battery. They are structurally simple and computationally efficient [12]. The hysteresis model usually combines with other types of model and depicts the battery hysteresis effects that are the discrepancy between the charge and discharge voltage under open-circuit conditions.

Among the model-based methods, the Kalman filter (KF) family and state observers are generally used algorithms for state estimation. The principle of an observer is to reconstruct system states from observations of its inputs and outputs [13]. The KF and the extended versions of KF, the extended Kalman filter (EKF) [14, 15] and unscented Kalman filter (UKF) [16, 17], are introduced to execute the battery SoC estimation. However, the EKF uses the linearization technique realized by applying Taylor series expansion with the assumption that the higher-order terms are negligible [18, 19]. This increases the estimation inaccuracy. Additionally, the Jacobian matrix used in this algorithm makes it difficult to compute [20]. The UKF applies a discrete-time filtering algorithm with Unscented Transform (UT) instead of the linearization technique [18, 19]. Thus, the accuracy and complexity of UKF is better than EKF as it can predicate states in a highly nonlinear system, and there is no need of a Jacobian matrix [19]. Nevertheless, this method suffers from poor robustness due to the uncertainty in modelling and disturbances in the system [19].

By adding a feedback term at the end of the state equation, the Luenberger observer is easily implemented. Since it is a close-loop observer, it is insensitive to parameter uncertainties, external disturbances and measurement noises. In [21, 22], Luenberger observers were designed to guarantee the nominal error convergence based on a reduced-order EM and a fractional-order model, respectively.

To the best of our knowledge, we are the first to investigate the performance of battery SoC estimation with and without considering the hysteresis phenomenon based on Luenberger observer. Firstly, taking the hysteresis into account, we established a hysteresis resistor-capacitor (RC) model that combines a hysteresis model [23] and an RC equivalent circuit model [1]. The Luenberger observer-based algorithm was used to evaluate the estimation performance of the hysteresis RC model. The system stability has been evaluated by using the Lyapunov method. Finally, we investigated the network capacity of the cellular network and Vehicular Ad hoc Networks (VANETs) applied in mobile vehicle environments, including the bandwidth, data rate, privacy and economy.

The rest of this paper was organized as follows: Sect. 2 introduced the principle of battery SoC and battery model. In Sect. 3, three Luenberger observers were applied to evaluate the hysteresis RC model. The experimental results were presented in Sect. 4. Finally, Sect. 5 analysed the network capacity for real-time vehicle interactions. Section 6 gave the conclusions.

2 Hysteresis Effect During Charging and Discharging of Rechargeable Batteries

Among model based battery SoC estimation methods, a precise battery model is essential to guarantee an accurate estimation. As previous discussion, equivalent circuit model has the advantage of simple structure and efficient computation. However, battery model establishment is still a big challenge due to the complex electrochemical reaction process. Adding the hysteresis will increase the modelling and battery SoC estimation accuracy. The zero-state hysteresis model and the one-state hysteresis are generally used in the literature. The zero-state hysteresis model simply assumes that the hysteresis voltage is a constant. However, this model is not adequate to simulate the behaviour of the battery under a dynamic environment because it cannot detect the slow transition of the hysteresis [24]. The one-state hysteresis model is designed to capture the change in the hysteresis value by adding a hysteresis state to the model [23]. Therefore, this research will utilize a combined model, including a hysteresis model and a RC equivalent circuit model.

2.1 State-of-Charge in Rechargeable Batteries

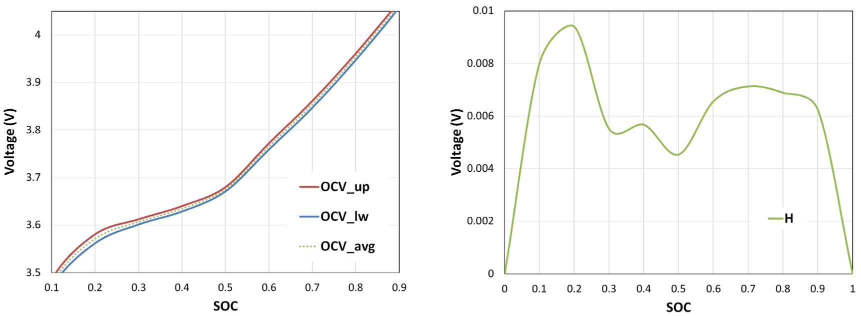
Battery state-of-charge (SoC) is one of the most important indicators that describes the residual capacity of a battery. SoC must be monitored for safety reason while charging the batteries. SoC denoted by Z can be defined as charges accumulated during the period from t_0 to t, which is formulated as follows:

$$Z(t) = Z(t_0) - \int_{t_0}^{t} I/C_n d\tau \tag{1}$$

$$\dot{Z}(t) = \frac{I}{C_n} \tag{2}$$

where I is input current; C_n is the capacity of the battery; $\dot{Z}$ is the changing rate of SoC.

An accurate estimation of SoC allows battery charging and discharging efficiently and could extend the battery life. However, it is also a challenge to find an effective method to measure battery SoC under dynamic operation conditions. Since the open-circuit voltage (OCV) is a known function of SoC, the battery SoC can be inferred from the OCV curve. Take INR 18650-20R battery [25] as an example, the relationship between OCV and SoC is shown in Fig. 1(a).



(a) **(b)**

Fig. 1. (a) OCV curve of INR 18650-20R battery [25]; (b) maximum deviation from the OCV_{avg} value.

2.2 Hysteresis Based Battery Model

Due to the hysteresis phenomenon in the physical systems, the OCV values in the state of charge and discharge are discrepant, as which are denoted as OCV_{up} and OCV_{lw}, respectively. The average value $OCV_{avg}(Z)$ can be expressed by:

$$OCV_{avg}(Z) = \left(OCV_{up} + OCV_{lw}\right)/2 \tag{3}$$

The one-state hysteresis model [23] can be described as below:

$$\dot{V}_h = \left|\frac{I\gamma}{C_n}\right|\left[H\left(Z, \dot{Z}\right) - V_h\right] \tag{4}$$

where V_h is the hysteresis voltage that can be defined as a variable related to the SoC and time; γ is a positive constant and affects the rate of decay; $H\left(Z, \dot{Z}\right)$ is a function that represents the maximum deviation from the OCV_{avg} value as a function of SoC and the rate of SoC, which can be demonstrated in Fig. 1(b) and Eq. (5):

$$H(Z, \dot{Z}) = (OCV_{up} - OCV_{lw})/2 \tag{5}$$

Therefore, the open-circuit voltage is given by:

$$V_{oc}(Z) = OCV_{avg}(Z) + sgn(I)V_h \tag{6}$$

where, $sgn(x)$ is a signum function allowing the equation to be stable for both charge and discharge [26]. By combining the hysteresis model [23] and a first-order resistor-capacitor (RC) ECM [1], the modified battery model becomes more accurate and can be described using several mathematical equations as follows, where V_t, V_{oc}, and V_p are three battery states representing the output terminal voltage, the open circuit voltage, and the polarization voltage respectively; $V_{oc}(Z)$ is known function of SoC and the relationship can be expressed by $\dot{Z} = k\dot{V}_{oc}$; k is the slop of V_{oc} function of SoC; R_t, R_p, C_p, and C_n are battery parameters indicating the Ohmic resistance, the diffusion resistance, the capacitor, and the capacity of the battery, which were identified using the Recursive Least Square (RLS) algorithm; I is the input current; and Δf is the model uncertainty.

$$\dot{V}_t = -a_1 V_t + a_1 V_{oc}(Z) + R_t \dot{I} + b_1 I \tag{7}$$

$$\dot{V}_{oc} = ka_2 V_t - ka_2 V_{oc}(Z) - ka_2 V_p \tag{8}$$

$$\dot{V}_p = -a_1 V_p + b_2 I + \Delta f \tag{9}$$

where $a_1 = 1/(R_p C_p)$; $a_2 = 1/(R_t C_n)$; $b_1 = k/C_n + 1/C_p + R_t/(R_p C_p)$; $b_2 = 1/C_p$.

The state equations correspond to Fig. 2, in which the hysteresis component consisting of hysteresis voltage and the average OCV is circled by a rectangle.

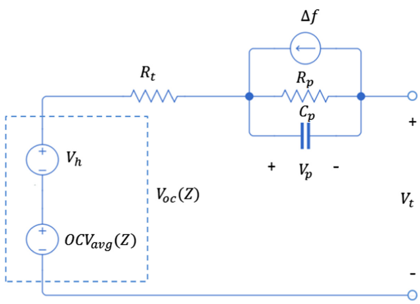


Fig. 2. Schematic diagram of the hysteresis RC equivalent circuit battery model.

3 Robust Battery SoC Estimation Using Luenberger Observer

After the battery model is established, the battery SoC can be estimated using observer-based methods. Among available methods, the Luenberger observer is insensitive to internal parameter uncertainties, external disturbances and measurement noises.

Based on the hysteresis RC model, three Luenberger observers can be designed for three battery states, including output voltage, open circuit voltage, and polarization voltage. In the battery case, the internal states are open circuit voltage and polarization voltage, while the external measurements are the input current and output voltage. Internal states can be estimated subsequently by calculating the observation error of output voltage:

$$\dot{\hat{V}}_t = -a_1\hat{V}_t + a_1\hat{V}_{oc}(Z) + R_t\dot{I} + b_1 I + L_t\left(V_t - \hat{V}_t\right) \tag{10}$$

$$\dot{\hat{V}}_{oc} = ka_2\hat{V}_t - ka_2\hat{V}_{oc}(Z) - ka_2\hat{V}_p + L_{oc}\left(V_{oc} - \hat{V}_{oc}\right) \tag{11}$$

$$\dot{\hat{V}}_p = -a_1\hat{V}_p + b_2 I + L_p\left(V_p - \hat{V}_p\right) \tag{12}$$

$$\hat{V}_{oc}(Z) = \widehat{OCV}_{avg}(Z) + sgn(I)\hat{V}_h \tag{13}$$

where L_t, L_{oc}, and L_p are constant feedback gains; and the estimated values are denoted by a "hat". Three observation errors can be defined as $e_t = V_t - \hat{V}_t$; $e_{oc} = V_{oc} - \hat{V}_{oc}$; and $e_p = V_p - \hat{V}_p$. Then, Eq. (10)–(13) can be rewritten as follows:

$$\dot{e}_t = -a_1 e_t + a_1 e_{oc} - L_t e_t \tag{14}$$

$$\dot{e}_{oc} = ka_2 e_t - ka_2 e_{oc} - ka_2 e_p - L_{oc} e_{oc} \tag{15}$$

$$\dot{e}_p = -a_1 e_p + \Delta f - L_p e_p \tag{16}$$

The Lyapunov candidate function can be chosen as $V_1 = 1/2 \cdot e^2$ to analyse the stability of the system, where V_{t1}, V_{oc1}, V_{p1} are Lyapunov candidate functions for three battery states:

$$\begin{aligned} \dot{V}_{t1} &= e_t\dot{e}_t = -a_1 e_t^2 + a_1 e_{oc} e_t - L_t e_t^2 \\ &\le a_1|e_{oc}||e_t| - (a_1 + L_t)e_t^2 \end{aligned} \tag{17}$$

When selecting $L_t > a_1(|e_{oc}/e_t| - 1)$, the sign of e and $\dot{e}$ is opposite. Thus, $\dot{V}_{t1} = e_t\dot{e}_t < 0$. The first observer forces the estimated terminal voltage towards the system output. Then the open circuit voltage error can be estimated as $e_{oc} \approx L_t e_t / a_1$.

$$\begin{aligned} \dot{V}_{oc1} &= e_{oc}\dot{e}_{oc} = ka_2 e_t e_{oc} - ka_2 e_{oc}^2 - ka_2 e_p e_{oc} - L_{oc} e_{oc}^2 \\ &\le ka_2\left(|e_t| - \left|e_p\right|\right)|e_{oc}| - (ka_2 + L_{oc})e_{oc}^2 \end{aligned} \tag{18}$$

When selecting $L_{oc} > ka_2\left[\left(|e_t| - |e_p|\right)/|e_{oc}| - 1\right]$, $\dot{V}_{oc1} = e_{oc}\dot{e}_{oc} < 0$. The second observer pushes the open circuit voltage error towards zero. Then the polarization voltage error can be estimated as $e_p \approx -L_{oc}e_{oc}/ka_2$.

$$\begin{aligned}\dot{V}_{p1} = e_p\dot{e}_p &= -a_1e_p^2 + \Delta f e_p - L_p e_p^2 \\ &\leq |\Delta f||e_p| - (a_1 + L_p)e_p^2\end{aligned} \tag{19}$$

When selecting $L_p > |\Delta f/e_p| - a_1$, $\dot{V}_{p1} = e_p\dot{e}_p < 0$. The third observer can force the polarization voltage error towards zero. After three estimated states converge to the real battery states, the battery SoC can be inferred from the OCV curve.

4 Results and Discussion

The Luenberger observer-based battery SoC estimation method discussed in this paper was evaluated using the experimental data provided by the Center for Advanced Life Cycle Engineering (CALCE) at the University of Maryland. Parameters of the battery sample under room temperature are given in Table 1.

Table 1. Parameters of the battery sample (INR 18650-20R) [25].

Characteristics/parameters	Name/values
Model type	LNMC/Graphite
Nominal capacity	2000 mAh
Nominal voltage	3.6 V
Charging cut-off voltage	4.2 V
Discharging cut-off voltage	2.5 V
Maximum current	22 A

4.1 Hysteresis Based Battery Model

The performance of battery SoC estimation has been tested by the dynamic street test (DST) and the federal urban driving schedule (FUDS) test. The DST simulates a dynamic discharge regime of an EV, which is a simplification of the real-life loading conditions of batteries [25]. The FUDS is more complex representing the power demands of an industry standard automobile [25]. Accurate battery SoC estimation is essential due to the high rate requirement and dynamic rate profiles [2]. Figure 3 gives the measured current and voltage of the sample battery under DST and FUDS, which will be used as input and output for real-time battery SoC estimation. It can be seen from Fig. 3 that the current variation range (the input) and the voltage variation trend (the output) of using DST and FUDS are the same. However, the FUDS presents high frequency and complex current and voltage profiles.

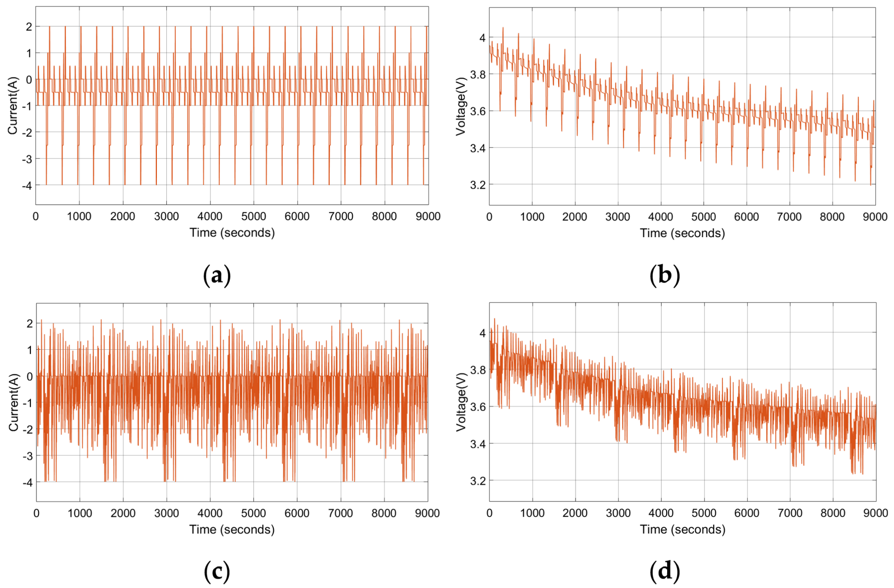


Fig. 3. Measured current and voltage of the battery sample: (a) measured current under DST; (b) measured voltage under DST; (c) measured current under FUDS; (d) measured voltage under FUDS.

4.2 Performance Evaluation Between Different Battery Models

The battery SoC has been estimated using Luenberger observers based on the hysteresis RC model (red dotted line) and the model without hysteresis terms (blue solid line) under the DST and FUDS test. The estimation results using Luenberger observers are illustrated in Fig. 4.

Figure 4(a) and Fig. 4(b) are the comparative results between estimated SoC and measured SoC, which has been zoomed from 3000 s to 5000 s. The simulation results were evaluated by the root mean square error (RMSE), which shows how close a fitted line consisting of estimates is to the measured data points [25]. The SoC estimation error is illustrated in Fig. 4(c) and Fig. 4(d).

It can be seen that the modified model (red line indicating) when considering the hysteresis effect is more close to the measured SoC (green solid line). Additionally, the FUDS results in a faster variation of battery SoC. Thus it has a high requirement in terms of response speed and system stability. The RMSEs based on the hysteresis RC model are 1.94% for DST and 1.95% for FUDS, while the RMSEs based on the model without hysteresis terms are 2.12% for DST and 2.07% for FUDS, respectively. It can be seen from Fig. 4 (a) and (b) that the estimated SoC can converge to the true values at about 1000 s.

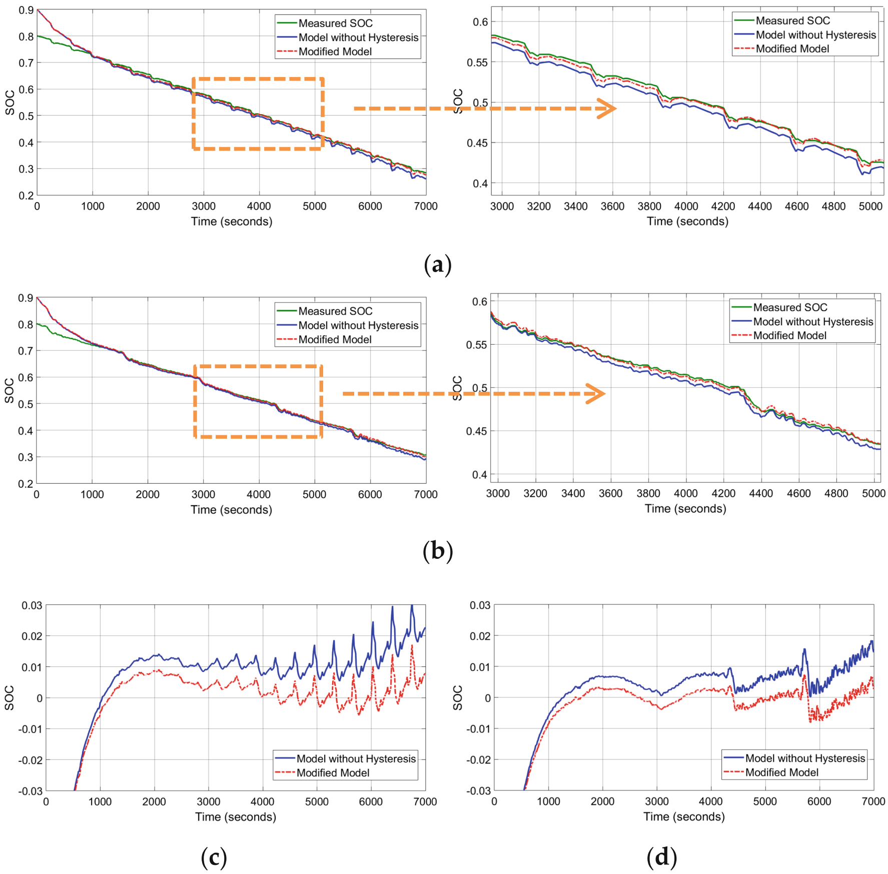


Fig. 4. Battery SoC estimation results using Luenberger observers: (a) SoC estimation results under DST; (b) SoC estimation results under FUDS; (c) SoC estimation error under DST; (d) SoC estimation error under FUDS.

Adding the hysteresis will increase the modelling and battery SoC estimation accuracy but also increase the computational complexity. By considering this, advanced technology such as 5G network may show a better future due to higher bandwidth consumption and higher date rate requirement.

5 Network Capacity for Real-Time Vehicle Interactions

Taking the advantage of bidirectional chargers, some EVs can supply or harvest energy to or from the grid. However, high penetration of EVs into the grid can bring challenges such as voltage instability, peak demand imbalance and power loss. [27] Vehicle-to-vehicle (V2V) charge sharing is considered as one of the most effective strategies to reduce the dependence on the power grid [28] and address the immediate charge needs of vehicles especially in the absence of nearby charging stations [29]. The accurate battery SoC estimation ensures the safety exchange of energy, while the V2V network allows the real-time vehicle communication and interactions. Recent studies mostly focus on Vehicular Ad hoc Networks (VANETs) and Cellular Network based communication frameworks. Those studies aim to minimize the charging cost and develop efficient and secure energy supply and demand matching strategies.

Vehicular Ad hoc Networks (VANETs) based communication frameworks were designed in [27, 28, 30] for communication among mobile vehicles, which demonstrates excellent communication performance and enhanced security [31] by means of road-side units (RSUs) and on-board units (OBUs) and provides a cost-effective solution with the Dedicated Short Range Communication (DSRC) technology or IEEE 802.11p standard. VANETs-based technologies have advantageous characteristics of privacy and economy. However, DSRC cannot support high data rates (1 Gbps) of V2V applications due to limited bandwidth (typically 10 MHz in 5.9 GHz spectrum band) [32]|. Additionally, VANETs may suffer from intermittent disconnections due to the short-range V2V communications [28].

Due to the large coverage area of base stations, cellular networks (such as LTE, 4G and 5G) provide a direct communication between nearby vehicles and enable location based application and services [31]. Through the broadcasting, EV owners can find nearby charging stations and V2V chargers based on their requirement for charging. However, the existing 4G-LTE cellular systems are not dedicated for vehicular data collection. Better communication incurs ever high cost and may lead to network congestion for other cellular services [27, 28]. Millimeter-wave (mmWave) technology is one of the key radio technologies in 5G cellular network, which can support high-date-rate V2V applications with its large bandwidths (possibly hundreds of megahertz) [33]. Therefore, 5G network offers greater capacity, higher data rate, lower latency, massive device connectivity, reduced cost and better Quality of Experience, which gives rise to better V2V real-time communication [34].

6 Conclusions

This paper aims to improve the state-of-charge (SoC) estimation accuracy by adding a hysteresis term into an RC equivalent circuit model that diminishes the parameter estimation errors caused by the hysteresis phenomenon. The validation test was carried out based on the hysteresis RC model and the model without the hysteresis terms under DST and FUDS, using Luenberger observers. Simulation results have shown that the Luenberger observer-based SoC estimation with the hysteresis RC model had better performance in terms of estimation accuracy comparing with the model without hysteresis terms. Additionally, 5G cellular network offers feasibility for real-time vehicle interaction. This paper is valuable for engineers in developing V2V energy and information sharing. Since EV applications requires both accurate SoC estimation and high convergence speed, future works will focus on methods that able to achieve both faster response speed and higher estimation accuracy. Moreover, reliable communication technologies will be investigated to allow V2V real-time communication.

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