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An augmented estimation of the state of charge and measurement fault for lithium-ion batteries for off-grid stationary applications

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Highlights

- Emphasis on the crucial role of sensor accuracy in estimating battery state of charge, particularly in high-scale applications.
- Recognition of the cost challenge associated with providing accurate sensors for a growing number of battery cells.
- Introduction of an augmented unscented Kalman filter to address measurement sensor faults, considering them as additive variables.
- Removal of the impact of faults on the estimation of other state variables in the battery model, ensuring accurate state of charge estimates.
- Performance validation through experiments with practical data, showcasing the proposed method's significant improvement (up to 3%) over the basic unscented Kalman filter in state of charge estimation.

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Abstract

In practical applications, especially in applications where the current scale is very high, the accuracy of measuring sensors is very important to estimate the battery state of charge. In addition, due to the increase in the number of battery cells in these applications, the cost of providing accurate sensors is very high. On the other hand, low-cost sensors have some error in the form of bias or fault on their output, which causes an estimation error in the battery state of charge. This paper addresses this problem and presents an augmented unscented Kalman filter in which the faults that occur on the measurement sensor are considered and estimated as an additive variable. On the other hand, the effect of these faults on the estimation of other state variables of the battery model, including the state of charge, is removed. In this way, an accurate estimate of the battery state of charge is obtained even in the presence of measurement sensor faults. In order to check the performance of the proposed method, a series of experiments have been conducted using practical data and the results have been compared with an unscented Kalman filter. The results show that the proposed method has a suitable and very good performance and can provide better accuracy than the basic method as much as 3% for estimating the state of charge.

Nomenclature

Variable	***Description***	***Variable***	***Description***
a_1	*Identification parameter*	*Ts*	*Sampling period*

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a_2	*Identification parameter*	Δf	*Unknown unction of nonlinearity and uncertainties*
b_1	*Identification parameter*	Γ	*Coefficient of the function*
b_2	*Identification parameter*	Φ	*Unknown variable*
$F(X,u)$	*Transient function of the battery model*	τ	*Process noise*
$H(SoC)$	*Non-linear relation between the SoC and Voc.*	ω	*Measurement noise*
Tpf	*Time constant of the RC loop*	X	*State vector*
Tps	*Time constant of the RC loop*		

1. Introduction

1.1. Motivation

In recent years, the use of rechargeable batteries has faced increasing growth. With the expansion of the use of renewable energy, the use of rechargeable batteries is inevitable. Among rechargeable batteries, until now, lead-acid batteries are among the most widely used batteries due to their reasonable price [1], [2]. But due to higher charge density, longer life, less weight, and output voltage stabilization, lithium-ion batteries are gradually replacing lead-acid batteries in recent years [3]. Estimating the parameters of lithium-ion batteries is one of the first and most basic functions in battery management systems. Because the performance of many other functions in these systems depends on having sufficient and accurate information about battery parameters, including charge level and health level [4]. In order to estimate the parameters, including the charge level, so far researchers have provided various methods. Among these methods are model-based methods. In this way, they first consider a model for the battery and then derive dynamic equations for the battery based on that. Then, an estimator based on dynamic equations is designed and implemented by hardware to estimate the level of battery charge [5]. There are various methods for battery modeling. Methods based on electrochemical principles, physical methods, electrical methods, and experimental methods. Among these methods, electrical methods are among the most popular routes for researchers and engineers to model lithium-ion batteries. Because these models can create a compromise between accuracy, speed, and simplicity [6].

1.2. Literature review

After the dynamic modeling of the battery using electrical methods, it is time to design the estimator. So far, researchers have provided various estimators to estimate the battery charge level using electrical models.

Kalman filters [7] are among the most widely used estimators for estimating the battery charge level. When the laboratory environment or measurement equipment is affected by noise, the best options for estimating the battery charge level are Kalman filters. Because these estimators are able to estimate the state variables of a system in the presence of noise, which here is the battery charge level. More advanced, researchers used different types of Kalman filters to estimate the charge level. Many researchers used the extended Kalman filter [8]–[11] for nonlinear battery dynamic models. Due to the presence of linearization in the extended Kalman filter algorithm, there will be some estimation errors. To solve this problem, the researchers used another type of non-linear Kalman filter called the unscented Kalman filter [12]–[15]. There is no linearization in the algorithm of these filters, but the volume of calculations is slightly heavier than other types of Kalman filters. In some other research, in order to increase the accuracy of the Kalman filters, the noise covariance matrix is adaptively calculated to increase the accuracy of the estimation, or in some articles, using fuzzy systems [16], the performance of the Kalman filter has been improved to reach a higher accuracy of the charge level. But the main disadvantage of these filters is that they need a precise battery model. In other words, if an error occurs during battery identification and modeling, there will always be a difference between the model extracted to design the Kalman filter and the actual battery model, and therefore the designed filter is not able to estimate the charge level of the actual battery model with high accuracy. For this reason, model uncertainties are among the most important weaknesses of these filters.

In order to solve this problem of Kalman filters, other researchers have used robust methods [17] to estimate the battery charge level. In other words, in this research, a band of uncertainty is always considered for the model so that if there is a difference between the extracted model and the real model, the charge level estimation can be done with good accuracy. Among the resistant methods, sliding mode-based methods can be mentioned. Sliding estimators [18]–[20] have been widely used in estimating the charge level of lithium batteries. There is some chattering in the performance of these estimators, which makes many researchers design more advanced types of it. Many researchers use sliding estimators using different methods such as fuzzy systems [21], neural networks, or static methods in an adaptive way to solve several chattering problems. Some other researchers also solve this problem by choosing higher-order manifolds. The H∞ estimators [22], [23] are also another robust estimator for estimating the battery charge level, they are able to consider the uncertainties of the model during their design. But complex calculations and difficulty in implementation are among the weaknesses of observers.

In recent years, the use of smart methods and learning-based methods has also had a significant expansion in estimating the battery charge level. Methods such as machine learning [24], deep learning [25] and reinforcement learning [26] are among these methods to estimate the battery charge level and their health level. The main advantage of these methods is that they do not require battery modeling. But their main disadvantage is that they need a complete and reliable pack of learning data to get a good estimate of the charge level or battery health level. Usually, these data are extracted from various tests such as EIS [27]. In these tests, the batteries are placed in the discharge state with a very low discharge current and measure the voltage and current over a long period of time. Then, they pre-process this data and use smart methods to estimate the charge level or the health level of the battery. It should be noted that these methods are also used to identify the parameters of the battery model. In addition to these methods, other signal-based methods are also used to estimate the charge level. For example, some researchers have studied the same level of battery charge using ultrasonic sensors [28]. On the other hand, there are very simple and widely used methods to estimate the charge level, including the ampere-hour method. These methods are very simple and are used in many applications. But due to their high sensitivity to the laboratory environment, they are not very accurate. In practical applications, especially in applications where the current scale is very high, the accuracy of measuring sensors is very important to estimate the battery state of charge. In addition, due to the increase in the number of battery cells in these applications, the cost of providing accurate sensors is very high. On the other hand, low-cost sensors have some error in the form of bias or fault on their output, which causes an estimation error in the battery state of charge.

1.3.Contributions

This paper addresses this problem and presents an augmented unscented Kalman filter in which the faults that occur on the measurement sensor are considered and estimated as an additive variable. On the other hand, the effect of these faults on the estimation of other state variables of the battery model, including the state of charge, is removed. In this way, an accurate estimate of the battery state of charge is obtained even in the presence of measurement sensor faults. In order to check the performance of the proposed method, a series of experiments have been conducted using practical data and the results have been compared with an unscented Kalman filter. The results show that the proposed method has a suitable and very good performance and can provide better accuracy than the basic method as much as 3 % for estimating the state of charge.

1.4.Organization

This paper can be classified as follows. Section 2 shows the modeling of the battery. In part 3 the proposed observer is formulated and section 4 presents the results and their discussion. Finally, the conclusion of the paper is presented in section 5.

2. Battery modeling

Various methods for modeling lithium-ion batteries have been presented so far. Methods such as electrochemical models, physical models, electrical models, temperature models and experimental models. Among these methods, electric models have been highly regarded by engineers and designers. Because it creates an interplay between precision and simplicity for designers.

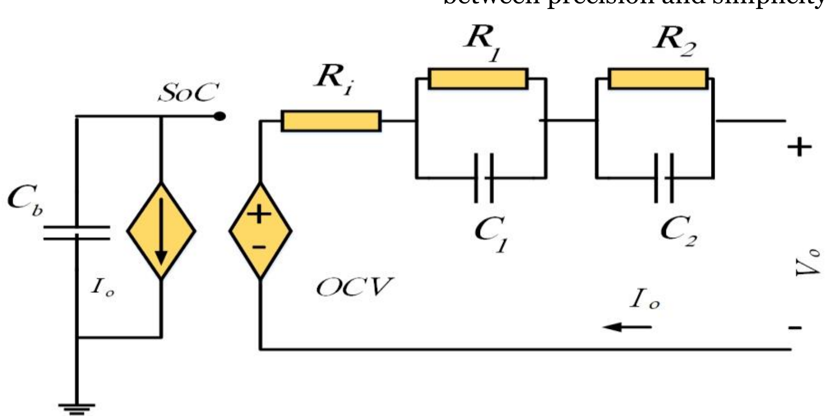

Fig. 1. Electrical battery model

As shown in Figure 1, in this paper, an electrical model is used to model the battery. This circuit model includes a resistor to show the internal resistance of the battery, two resistor/capacitor loops in order to simulate the transient behaviour of the battery (long-term and short-term), a dependent voltage source in order to introduce the OCV/SoC curve of the battery, a resistor for to show self-discharge and a capacitor is used to show the total capacity of the battery. Using the Kirchhoff laws, the voltage of the terminal can be formulated as:

$$V_o = V_{oc}(Soc) - V_1 - V_2 - I_o R_i \tag{1}$$

The dynamical equations of the SoC and V_1 and V_2 are:

$$\dot{S}oC = -\frac{1}{R_T C_T} SoC - \left(\frac{I_o}{C_T}\right) \tag{2}$$

$$\dot{V}_1 = -\frac{V_1}{R_1 C_1} + \frac{I_o}{C_1} \tag{3}$$

$$\dot{V}_2 = -\frac{V_2}{R_2 C_2} + \frac{I_o}{C_2} \tag{4}$$

In which V_1 and V_2 are the voltages over the (R_1C_1) and (R_2C_2), respectively. Generally, there is a non-linear relation between V_{oc} and SoC. So:

$$V_{oc}(SoC) = L(SoC) \tag{5}$$

In which, $L(SoC)$ defines the OCV-SoC relationship. Considering $dI_o/dt = 0$ and using Eqs. (2), (5) and (1), the dynamical equation of the terminal voltage Vo is formulated as:

$$\begin{aligned} \dot{V}_o &= \frac{\partial V_{oc}}{\partial SoC}\dot{S}oC - \dot{V}_1 - \dot{V}_2 \\ \frac{\partial V_{oc}}{\partial SoC} &= \dot{L}(SoC) \end{aligned} \tag{6}$$

The state vector is considered as $X = [SoC, V_1, V_2, V_o]^T$. I_o is the input and V_o is the output of the battery model. The state space-model of the battery by using equations (2), (3), (4) and (6), can be written as:

$$\begin{aligned} \dot{X} &= F(X,u) + \zeta \\ Y &= CX + \omega \\ C &= [0001] \end{aligned} \tag{7}$$

The noises related to process and measurement are represented by terms ζ, ω with zero mean. F can be written as:

$$F(X,u) = \begin{bmatrix} -\frac{1}{R_T C_T} SoC - \left(\frac{I_o}{C_T}\right) \\ -\frac{V_1}{R_1 C_1} + \frac{I_o}{C_1} \\ -\frac{V_2}{R_2 C_2} + \frac{I_o}{C_2} \\ \dot{L}(SoC)\dot{S}oC + \frac{V_1}{R_1 C_1} - \frac{I_o}{C_1} + \frac{V_2}{R_2 C_2} - \frac{I_o}{C_2} \end{bmatrix} \tag{8}$$

After extracting the dynamic equations of the battery model, through a series of experiments, the values of the parameters in the battery state space model are extracted. How to extract these parameters is presented in reference [14]. In this article, after extracting and identifying the values of the parameters of the battery model, the numerical model of the battery is simulated in the software environment and is given as the following relationship.

$$\begin{aligned} \dot{X}_i &= \begin{bmatrix} -(14e-7)SoC - (1.5e-3)I_o \\ -(11e-5)V_1 + 0.05 I_o \\ -0.01 V_2 + (7.5e-3)I_o \\ (-30e-6)SoC^3 + ((30e-7) - (3e-4)I_o)SoC^2 \\ +(31e-7)I_o.SoC - (I_o+1)(0.01)\,exp(-39SoC) \end{bmatrix} \\ Y_i &= (0001)X_i + \omega_i \end{aligned} \tag{9}$$

Always to validate the identified battery model, after simulating the battery model in the software environment, the terminal voltage is compared with the actual terminal voltage measured during practical tests. If the difference between the simulation voltage and the actual measured voltage is lower than a certain limit, the battery identification is successful and it is suitable to continue the round estimation design process [13].

3. Proposed observer formulation

As mentioned earlier, when measuring the voltage and discharge current of a lithium-ion battery, faults may occur on the measuring sensors due to various factors. For this reason, the goal of the observer design in this article is to be able to simultaneously estimate the sensor fault correctly and the state variables of the dynamic battery model, which includes the charge level, by removing the effect of the sensor fault.

To design the Augmented UKF the dynamical model of the lithium-ion battery can be formulated as:

$$\begin{aligned} \begin{bmatrix} X_{i+1} \\ \delta V_{i+1} \end{bmatrix} &= \begin{bmatrix} F(X_i) \\ 0 \end{bmatrix} + B^{aug} u_i + \begin{bmatrix} v_i \\ v_i^f \end{bmatrix} \\ Y_i &= H^{aug} X_i + \gamma_i \\ B^{aug} &= \begin{bmatrix} B \\ 0 \end{bmatrix}, H^{aug} = [H \;\; 0] \end{aligned} \tag{10}$$

In which, v_i^f is a white noise related to the measurement fault, and the new state vector including the fault is $X^{aug} = \begin{bmatrix} X \\ \delta V \end{bmatrix}$. So we:

$$\dot{X}^{aug} = F^{aug}(X^{aug}) + B^{aug}u + v^{aug} \tag{11}$$

The design and implementation steps of the estimator in this article can be described as follows:

A. Initialization

$$\hat{X}_{0|0}^{aug} = [\hat{X}_0 \;\; \widehat{\delta V}_0]^T \quad , \hat{P}_{0|0}^{aug} = \begin{bmatrix} \hat{P}_0^X & \hat{P}_0^{X,\delta V} \\ \hat{P}_0^{X,\delta V} & \hat{P}_0^{\delta V} \end{bmatrix} \tag{12}$$

In which, $\hat{P}^{aug}$ is the estimation cov-matrix, the auto-covariance of the state and fault estimation are $\hat{P}_0^X$, $\hat{P}_0^{\delta V}$, respectively and their cross-covariance are shown by $\hat{P}_0^{X,\delta V}$.

B: Sigma Points

At time i, the sigma points can be extracted to describe the state distribution as:

$$\zeta_{i,j}^{aug} = [X_{i|i,j}^{aug} \;\; X_{i|i,j}^{aug} - \left(\sqrt{(m^{aug} + \tau)\hat{P}_{i|i}^{aug}}\right)_j \;\; X_{i|i,j}^{aug} + (\sqrt{(m^{aug} + \tau)\hat{P}_{i|i}^{aug}})_{j-m^{aug}}]^T \tag{13}$$

The state vector including fault has a dimension of $m^{aug} = 5$. Parameter τ shows the scaling and is given as:

$$\tau = \alpha^2(m^{aug} + \kappa) - m^{aug} \tag{14}$$

In which, α has a small and positive value. κ denotes the secondary scaling coefficient and is selected as much as 0 or $3 - m^{aug}$.

C: Update

the states prediction and the cov-matrix of the prediction error are calculated as follow:

$$\zeta_{i+1|i,j}^{*aug} = F_i^{aug}(\zeta_{i,j}^{aug}) \tag{15}$$

$$X_{i+1|i}^{aug} = \sum_{j=0}^{2m^{aug}} \varphi_j^{(\mu)} \zeta_{i+1|i,j}^{*aug} \tag{16}$$

$$\hat{P}_{i+1|i}^{aug} = \sum_{j=0}^{2m^{aug}} \varphi_j^{(l)} [\zeta_{k=i+1|i,j}^{*aug} - X_{i+1|i}^{aug}][\zeta_{i+1|i,j}^{*aug} - X_{i+1|i}^{aug}]^T(17) + Q_{i+1}^{aug} \tag{17}$$

In which, $\varphi_j^{(\mu)}, \varphi_j^{(l)}$ represent the weights that are:

$$\varphi_0^{(\mu)} = \frac{\tau}{m^{aug} + \tau} \;\; , \varphi_0^{(l)} = \frac{\tau}{m^{aug} + \tau} + (1 - \alpha^2 + \Delta)$$
$$\varphi_j^{(\mu)} = \varphi_j^{(\mu)} = \frac{\tau}{2(m^{aug} + \tau)} \;\; , j = 1,2, \dots 2m^{aug} \tag{18}$$

In which, $\Delta = 2$ is a parameter for incorporation prior knowledge related to the mean value ‘s distribution.

$$\zeta_{i+1|i}^{aug} = [X_{i+1|i,}^{aug} \;\; X_{i+1|i}^{aug} - \left(\sqrt{(m^{aug} + \tau)\hat{P}_{i+1|i}^{aug}}\right)_j \;\; X_{i+1|i}^{aug} + (\sqrt{(m^{aug} + \tau)\hat{P}_{i+1|i}^{aug}})_{j-m^{aug}}]^T \tag{19}$$

$$Y_{i+1|i,j}^{aug} = H^{aug}\zeta_{i+1|i,j}^{aug} \tag{20}$$

$$Y_{i+1|i}^{aug} = \sum_{j=0}^{2m^{aug}} \varphi_j^{(\mu)} Y_{i+1|i,j}^{aug} \tag{21}$$

D: Update of measurement

The cov-matrix related to the cross-correlation error and also, the cov-matrix related to the error of measurement are:

$$\hat{P}_{XY}^{aug} = \sum_{j=0}^{2m^{aug}} \left\{\varphi_j^{(l)}[\zeta_{i+1|i,j}^{aug} - X_{i+1|i}^{aug}][Y_{i+1|i,j}^{aug} - Y_{i+1|i}^{aug}]^T\right\} \tag{22}$$

$$\hat{P}_{YY}^{aug} = \sum_{j=0}^{m^{aug}} \left\{\varphi_j^{(l)}[Y_{i+1|i,j}^{aug} - Y_{i+1|i}^{aug}][Y_{i+1|i,j}^{aug} - Y_{i+1|i}^{aug}]^T\right\} + R_{i+1} \tag{23}$$

The gain of augmented UKF is calculated as:

$$K_{i+1}^{aug} = \hat{P}_{XY}^{aug}(\hat{P}_{YY}^{aug})^{-1} \tag{24}$$

In the update step, the state estimation and the estimation error cov-matrix are updated as:

$$X_{i+1|i+1}^{aug} = X_{i+1|i}^{aug} + K_{i+1}^{aug}(Y_{i+1} - Y_{i+1|i}^{aug}) \tag{25}$$

$$P_{i+1|i+1}^{aug} = P_{i+1|i}^{aug} - K_{i+1}^{aug}\hat{P}_{YY}^{aug}(K_{i+1}^{aug})^T \tag{26}$$

As seen from the above algorithm, the desired estimator considers the faults created on the measurement sensors as an additional state variable and then estimates the state variables along with this fault. The point here is that the state variables are estimated by removing the fault effect. Therefore, the charge level of the lithium battery, which is one of the battery state variables, is estimated by removing the effect of the measurement error, and on the other hand, an accurate estimate of the measurement error is also obtained

4. Experiments and discussion

In order to check the performance of the desired method to estimate the charge level of lithium battery in the presence of measurement sensor fault, a series of experiments have been performed using practical data. On the other hand, the performance of the proposed method has been compared with the performance of a normal unscented Kalman filter, as the closest method to the proposed method of the article, so that the superiority of this method is clearly defined, especially in the case of measurement error. For this purpose, a 2.4 ampere-hour lithium-ion battery has been discharged by a programmable resistive load. The resistive load is programmed in such a way that the battery terminal current has pulse shape. Figure 2 shows the test table used for these practical tests. In order to check the best performance and method of the desired method, practical tests have been carried out in two categories, and in each of these categories, a resistive load is set in such a way that the current of the battery terminal becomes a pulse at a specific frequency.

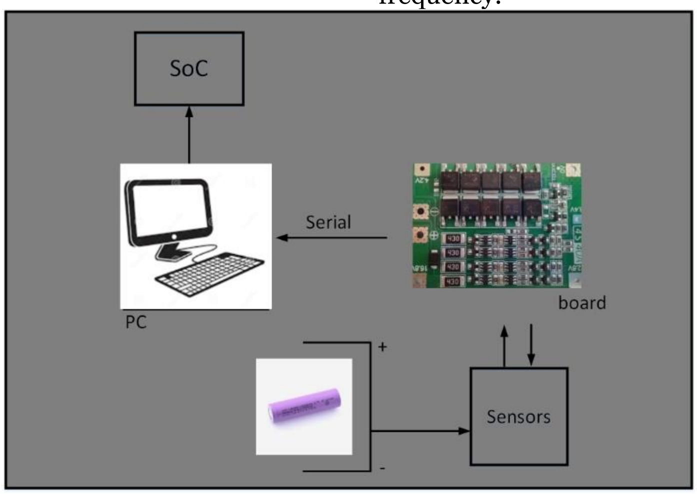

Fig. 2. Test table for practical evaluation

Figure 3 compares the estimation of the charge level of the lithium-ion battery using the proposed method and also using the conventional neutral Kalman filter. As it is known, the method in question has been able to estimate the charge level of the lithium battery very well and with high accuracy. While the traditional unscented Kalman method has an estimation error of 3 % percent. The reason for this is that in the measurement of these practical tests, which here is the terminal voltage, some fault has occurred on the voltage sensor. This fault has caused imprecise information to reach the unscented Kalman filter, and as a result, it has caused an estimation error in this filter. In other words, the measurement of the conventional unscented Kalman filter has an error, which causes the estimation error. In contrast, the method presented in this paper has provided good accuracy. Because by using this method, the fault that occurred first is considered as an additional state variable, and in addition to the fact that the amount of the fault is accurately estimated, its effect is removed during the estimation of the charge level to accurately estimate the level. Battery charge will be given. Figure 4 also compares the estimation of lithium battery terminal voltage using the two mentioned methods. This figure also confirms all the things mentioned above. In other words, the desired method has been able to estimate the terminal voltage with high accuracy and by removing the effect of the fault that happened on it. While the unscented Kalman filter has not been able to provide good accuracy in estimating the terminal voltage. Figure 5 also shows the amount of bias created on the measurement sensor. Here, the bias is considered as a fault.

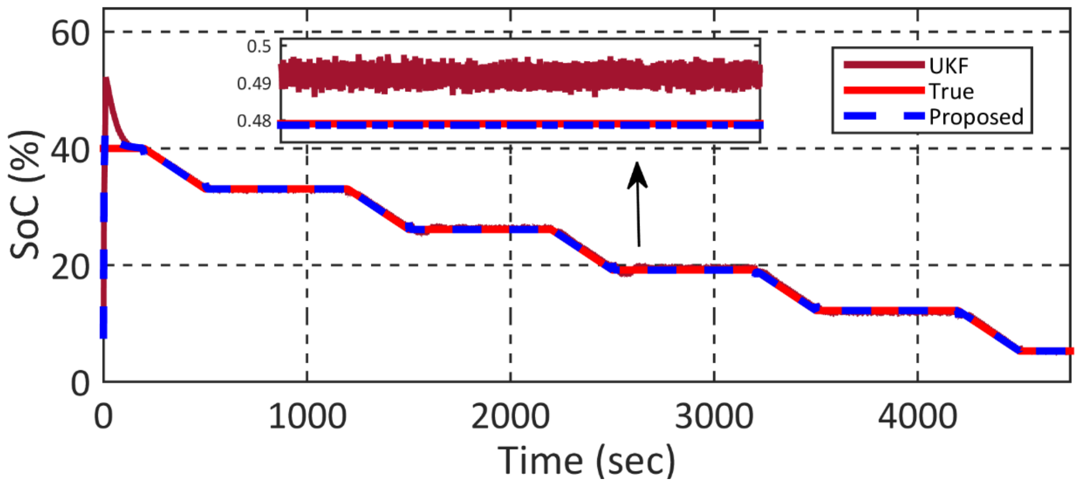

Fig. 3. SoC (first scenario)

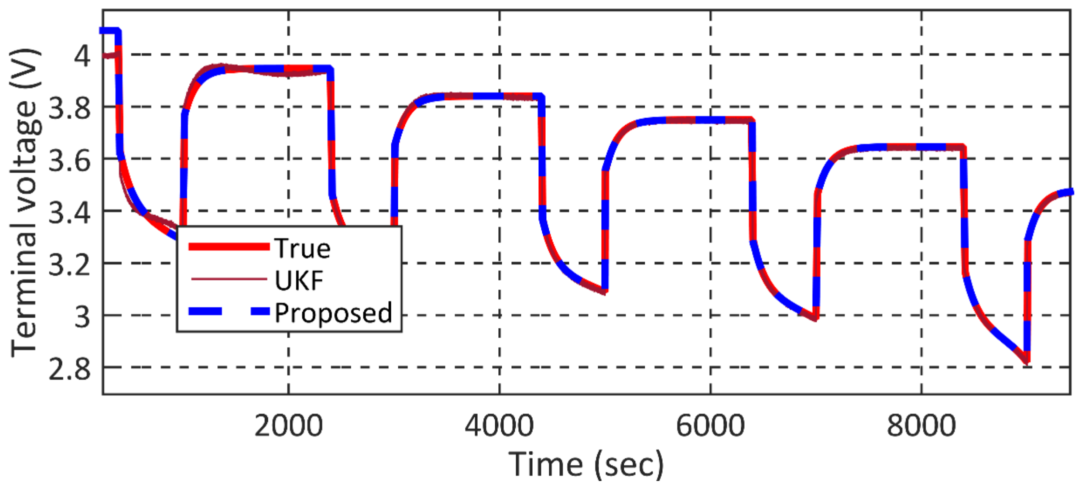

Fig. 4. Voltage (first scenario)

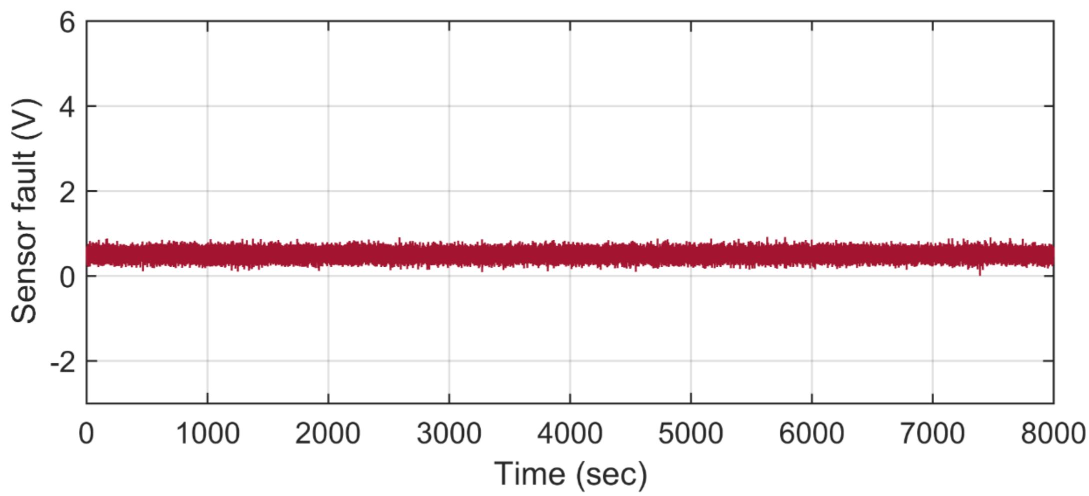

Fig. 5. Fault (first scenario)

As mentioned, the performance of the proposed method is also checked at another frequency of the terminal current to measure its performance in terms of convergence speed. As in the previous experiments, the performance of the proposed method is compared with the performance of the unscented Kalman filter. Figures 6 and 7 also show the estimation of the charge level of the lithium battery and its terminal voltage using the method of the article. As it is clear from these figures, the desired method in these frequencies has been able to provide good accuracy of the charge level and terminal voltage. In other words, at this current frequency, the filter presented in this article has very high convergence and accuracy. While, the unscented Kalman filter still has estimation errors when estimating the charge level and terminal voltage. In other words, the proposed method has a higher accuracy than the unscented Kalman filter for estimating the charge level and voltage by 3.2% and 0.6V, respectively. The noteworthy point is that since the fault is considered as an additional state variable, the desired filter at any frequency can immediately estimate this fault and remove its effect from the estimation of other state variables, including the charge level. slow Figure 88 also shows the amount of sensor fault estimation. As it is known, the desired filter has been able to estimate well the bias created on the measurement sensor.

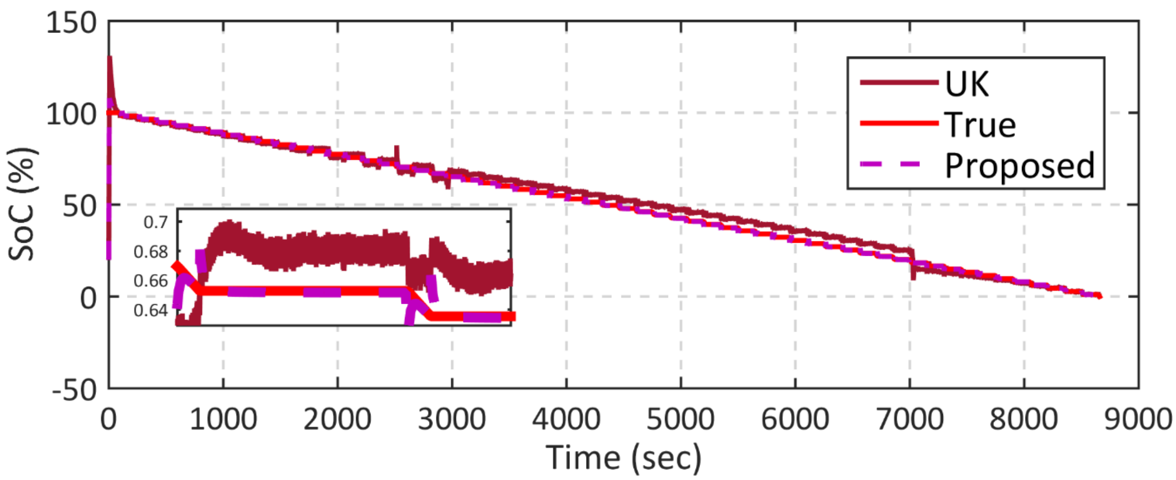

Fig. 6. SoC (Second scenario)

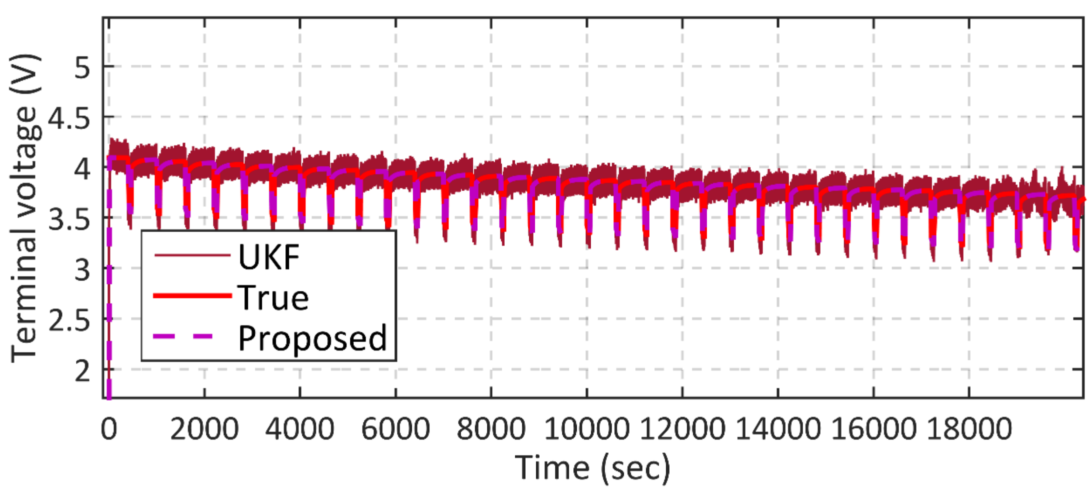

Fig. 7. Voltage (Second scenario)

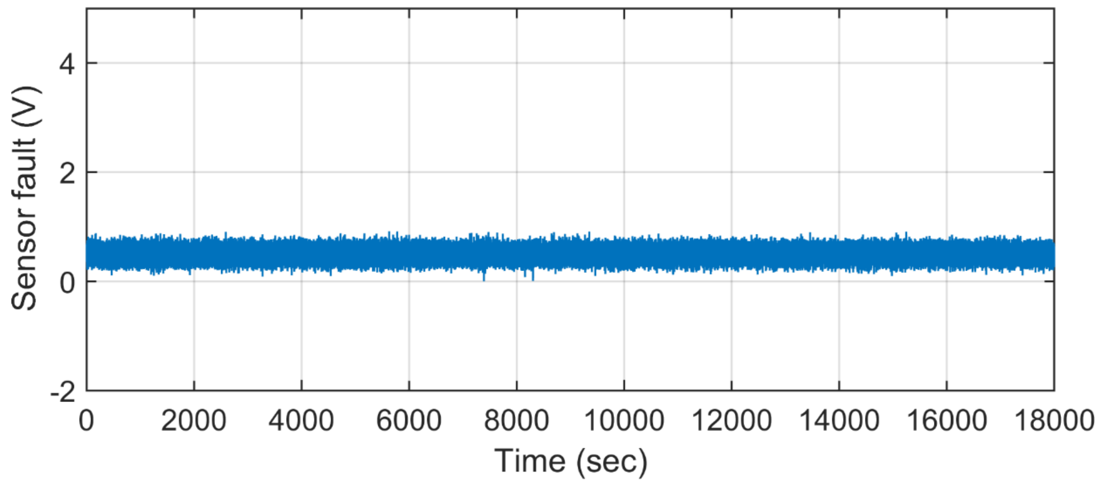

Fig. 8. Fault (Second scenario)

5. Conclusion

In this article, the estimation of the charge level of the lithium battery in the presence of the measurement sensor fault was investigated. Always in practical tests, errors may occur on measurement sensors. These errors may be in the form of bias, noise or something else. This error can be considered as a fault on the sensor. The occurrence of a fault on the measurement sensors causes inaccurate information to reach the estimator, and as a result, the estimation of the battery charge level is incorrect. This may occur in many large-scale current applications. In order to solve this problem, this paper presented an augmented method based on Kalman filters, which was able to estimate the fault that occurred on the sensor as an additive state variable, and on the other hand, other state variables such as the battery charge level can be estimated with eliminating the effect of fault. With this method, information on the amount of sensor fault is obtained and the estimation of the battery charge level is done with high accuracy. To show the effectiveness of this method, a series of experiments were conducted using practical data and the results were compared with an unscented Kalman filter. As it was clear from the results, the proposed method was able to estimate the level of charge with better accuracy in the presence of the fault and as much as 3 %. Also, It was able to estimate the terminal voltage with a better accuracy as much as 0.6 V compared to the other method. As a suggestion for future research, designing an estimator that can withstand the uncertainties of the battery model in addition to considering the sensors' faults seems to be an attractive topic.

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