# Exponential Moving Average Extended Kalman Filter for Robust Battery State-of-Charge Estimation

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# Exponential Moving Average Extended Kalman Filter for Robust Battery State-of-Charge Estimation

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***Abstract*—This paper proposes a exponential moving average extended Kalman filter (EMAF-EKF) for the purpose of battery state-of-charge (SOC) estimation. The proposed approach relies on a second-order RC circuit model of the Lithium-ion battery. In the proposed approach, first, exponential moving average filters are applied to the various input signals that are battery current, temperature and terminal voltage. Then, the filtered signals are feed to the conventional extended Kalman filter for the state-of-charge estimation. Unlike the convention extended Kalman filter, the proposed EMAF-EKF is very robust to measurement noises in the input signals. Moreover, compared to other noise robust extended Kalman filter, our solution is very simple and easy to implement. Experimental results with the Turnigy graphene 5000mAh 65C li-ion battery dataset are provided to show the performance improvement in SOC estimation by the proposed approach over the conventional counterpart.**

***Index Terms*—Lithium-ion battery; extended Kalman filter; state-of-charge; exponential moving average filter; robust estimation.**

## I. INTRODUCTION

Energy storage systems are very useful to facilitate large-scale deployment of renewable energy systems and electric vehicle [1]–[4]. Fast and accurate monitoring of energy storage system is very important in these applications. Monitoring plays and important role in the modern energy management systems. Out of various energy storage systems solution, lithium-ion battery became very popular for electric vehicle and grid-scale renewable energy powered energy storage systems.

Modern energy management systems typically require fast and accurate state of charge (SOC), battery terminal voltage, battery temperature etc. Out of these system parameters, terminal voltage and temperature can easily be measured using sensors. However, SOC can not be directly measured using sensors. So, model-based solutions are often preferred that can be used to measure the battery parameters with high-degree of noise immunity. In this work, we focus on two important battery parameters, which are SOC and terminal voltage.

In the case of terminal voltage, one can easily measure it with voltage sensor. However, due to various external and internal factors, the measured voltage can be very noisy. This kind of noisy measurement can indirectly result in inaccurate estimation of other parameters. In the case of SOC, the conventional solution is to use the Coulomb counting method [5] where the battery current is integrated over time and subtracted from the initial SOC value. This method often results in inaccurate estimation due to the measurement error and/or unreliable initial SOC value. Another simple method to estimate SOC is to obtain experimentally the SOC versus the battery open-circuit voltage (OCV). Although this method is relatively easy to implement, however, it is not very suitable for dynamic applications and/or cases where the SOC-OCV curve is very nonlinear. To overcome these issues, researchers have combined various techniques such as coulomb counting, SOC-OCV curve together with model-based approaches such as extended Kalman filter (EKF) [6]–[13]. In the case of EKF, mathematical model of the battery equivalent circuit is required.

The literature on Kalman filter-based battery parameter estimation is huge and it covers many types of batteries, test conditions, application scenarios etc. For a detailed review on this topic, interested readers can consult [14] and the references therein. In this work, we are focusing on improving the performance of extended Kalman filter in the noisy environment. Although extended Kalman filter can provide robust estimation, however, certain input parameters can significantly affect the performance of EKF. To overcome this issue, numerous modifications of the EKF structure are proposed in the literature [6]. However, these solutions often are very complicated, requires lot of real-time computationally expensive computation that can be prohibitive for low-cost energy management systems. Motivated by this fact, in this work, we propose the application of moving average filter [15]–[17] to the input signals. Out of various choices of moving average filter , in this work, exponential moving average is considered. The filtered signals are then feed to the conventional Kalman filter. The resulting structure is very simple to implement and can enhance the performance with prohibitive computational costs. Experimental results using real battery test data are provided to show the performance improvement by the proposed solution.

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The rest of this article is organized as follows: Sec. II presents the battery mathematical model, development of the Kalman filter and the proposed exponential moving average Kalman filter are given in Sec. III, results and discussions are given in Sec. IV, and finally, Sec. V concludes this article.

## II. State-Space Battery Model

SOC is a critical factor that determines how much capacity is left in the battery. This is very useful for battery users as it helps them to determine when to recharge the battery. A very simple way to estimate the SOC is by using the Coulomb counting method [5] which is given below:

$$\mathcal{S} = \mathcal{S}(0) - \xi \int_0^{\tau} i(t)dt, \tag{1}$$

where SOC is denoted by $\mathcal{S}$, initial SOC is given by $\mathcal{S}(0)$, the charging/discharging current is given by $i$, and the constant $\xi = 1/(3600C_{\text{bat}})$ with $C_{\text{bat}}$ being the battery capacity in Ampere-hours (Ah). Although eq. (1) is very simple to calculate the SOC but it has two limiting factors. Firstly, the initial SOC, i.e., $\mathcal{S}(0)$ may not be known. Secondly, accurate integration of the measured current may not be possible due to measurement noise and/or error. In a practical setting, measurement noise is often inevitable. Accumulation of the measurement noise through numerical integration by eq. (1) will produce inaccurate results. This motivated researchers to develop advanced SOC estimation methods where a large majority of them rely on model-based approach.

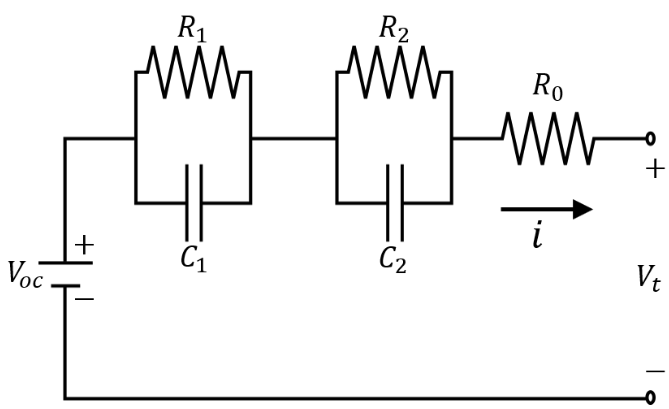



Fig. 1. Second-order equivalent battery model.

In model-based SOC estimation approach, mathematical model plays a very important role. Different types of models are already proposed in the literature. However, RC circuit-based models have gained serious traction in recent times. In this work, we are considering the second-order RC circuit-based equivalent model to study the battery. The considered model is given in Fig. 1 and this can also be found in [6], [18]. In this kind of modeling approach, open circuit voltage of the battery is denoted by $V_{oc}$ while the terminal voltage that is available to measure is denoted by $V_t$, internal resistance is denoted by $R_0$. Finally, the RC circuit parameters are denoted by $R_1, C_1$, and $R_2, C_2$. Let us denote the voltage drop across the first and second RC circuit as $V_1$ and $V_2$. Then, by applying Kirchhoff's circuit laws to Fig. 1, one can obtain that:

$$V_t = V_{oc} - V_1 - V_2 - iR_0, \tag{2}$$

$$i = \frac{V_1}{R_1} + C_1\frac{dV_1}{dt}, \tag{3}$$

$$= \frac{V_2}{R_2} + C_2\frac{dV_2}{dt}. \tag{4}$$

Let us consider $V_1$, $V_2$, and $\mathcal{S}$ as the state variables. Evolution of the state variables from eq. (1), (3), and (4) are then can be written as:

$$\frac{dV_1}{dt} = -\frac{1}{R_1C_1}V_1 + \frac{1}{C_1}i, \tag{5}$$

$$\frac{dV_2}{dt} = -\frac{1}{R_2C_2}V_2 + \frac{1}{C_2}i, \tag{6}$$

$$\frac{d\mathcal{S}}{dt} = -\xi i. \tag{7}$$

For notional simplicity, let us denote the time constants of individual RC circuits as $\tau_1 = 1/(R_1C_1)$ and $\tau_2 = 1/(R_2C_2)$. In state-space, eq. (5)-(7) can be written as:

$$\frac{d}{dt}\underbrace{\begin{bmatrix} V_1 \\ V_2 \\ \mathcal{S} \end{bmatrix}}_{\zeta} = \underbrace{\begin{bmatrix} -\tau_1 & 0 & 0 \\ 0 & -\tau_2 & 0 \\ 0 & 0 & 0 \end{bmatrix}}_{\mathcal{A}}\underbrace{\begin{bmatrix} V_1 \\ V_2 \\ \mathcal{S} \end{bmatrix}}_{\zeta} + \underbrace{\begin{bmatrix} \frac{1}{C_1} \\ \frac{1}{C_2} \\ -\xi \end{bmatrix}}_{\zeta}\underbrace{i}_{u}. \tag{8}$$

Model (8) is in continuous-time while the measurements are available in discrete-time. As such, discretization of model (8) is required. For this purpose, let us consider that the discretization step or the sampling time is given by $T_s$. Exact-discretized version of model (8) is given below:

$$\underbrace{\begin{bmatrix} V_1 \\ V_2 \\ \mathcal{S} \end{bmatrix}}_{\zeta}(k+1) = \underbrace{\begin{bmatrix} e^{-\tau_1} & 0 & 0 \\ 0 & e^{-\tau_2} & 0 \\ 0 & 0 & 1 \end{bmatrix}}_{\mathcal{A}_d}\underbrace{\begin{bmatrix} V_1 \\ V_2 \\ \mathcal{S} \end{bmatrix}}_{\zeta}(k) + \underbrace{\begin{bmatrix} \frac{1}{C_1} \\ \frac{1}{C_2} \\ -\xi \end{bmatrix}}_{\zeta}\underbrace{i}_{u}(k), \tag{9}$$

where $k$ is the current sample time. From eq. (9), one can easily calculate the SOC if the initial value of the SOC is known and the current signal is sufficiently noise-free. If the initial SOC is unknown, then, this can be calculated through calculating the the open circuit voltage by using eq. (2) as given below:

$$V_{oc} = V_t - V_1 - V_2 - iR_0. \tag{10}$$

Note that here in addition to the current $i$, voltage drops across the RC circuits are also needed which are not available to measure. These signals can be estimated using appropriate filtering/estimation techniques and will be detailed in Sec. III. It is well known that $V_{oc}$ is a function of $\mathcal{S}$ and temperature (temp.):

$$V_{oc} = f\left(\mathcal{S}, \text{temp.}\right). \tag{11}$$

By *a priori* testing of the battery using the recommended charging/discharging profile, a look-up table or something similar can be made that will establish the relationship between the open-circuit voltage, temperature, and the SOC. From this table, $V_{oc}$ can be estimated as a function of $\mathcal{S}$.

Before developing the estimator, battery RC circuit parameters and the function (11) need to be estimated. In this work, we are considering the Turnigy graphene 5000mAh 65C li-ion battery dataset as given in [19]. Authors in [19] have reported the results of hybrid pulse power characterization (HPPC) for this particular battery. Results are conducted at different battery temperature values. Tested temperatures are: $-10°, 0°, 10°$,$25°$, and $40°$. Then, by using parameter optimization approach in Matlab [6], battery parameters are obtained at different SOC levels and temperatures. Then, using interpolation, temperature and SOC dependent RC circuit parameters are obtained and used for calculation of the system and input matrices.

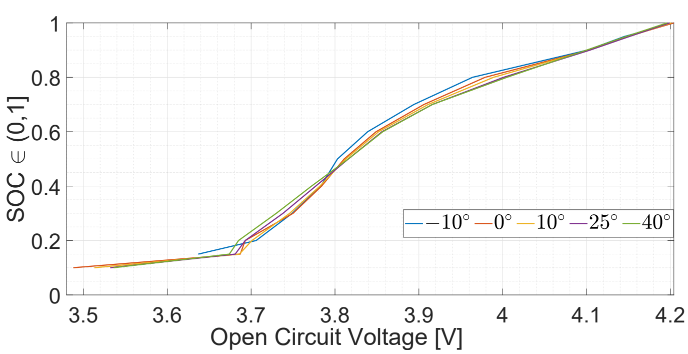



Fig. 2. Open-circuit voltage vs. SOC curve at different temperatures.

To obtain the function (11), battery SOC and $V_{oc}$ are obtained at different temperatures as shown in Fig. 2. Then, by using least-square method, an $11^{\text{th}}-$order polynomial is constructed to model the $V_{oc}$ as a function of $\mathcal{S}$ and is given below:

$$\begin{aligned} V_{oc} &= \alpha_1\mathcal{S}^{11} + \alpha_2\mathcal{S}^{10} + \alpha_3\mathcal{S}^9 + \alpha_4\mathcal{S}^8 + \alpha_5\mathcal{S}^7 + \alpha_6\mathcal{S}^6 \\ &\quad + \alpha_7\mathcal{S}^5 + \alpha_8\mathcal{S}^4 + \alpha_9\mathcal{S}^3 + \alpha_{10}\mathcal{S}^2 + \alpha_{11}S + \alpha_{12}, \end{aligned} \tag{12}$$

where $\alpha_1 - \alpha_{12}$ are the coefficients and given in Table I.

Model (8) or (9) provides the evolution of state variables of the battery equivalent circuit. However, the output or the value that is typically measured is the terminal voltage of the battery which is given by eq. (2). Then, with respect to the state-variables, the output can be written as:

$$V_t(k) = \underbrace{\begin{bmatrix} -1 & -1 & \frac{\partial V_{oc}}{\partial \mathcal{S}} \end{bmatrix}}_{\mathcal{C}} \underbrace{\begin{bmatrix} V_1 \\ V_2 \\ \mathcal{S} \end{bmatrix}}_{\zeta}(k) + \underbrace{\left[-R_0\right]}_{\mathcal{C}}\underbrace{i}_{u}. \tag{13}$$

Model (9) and (13) in familiar discrete-time state-space notation are given by:

$$\xi\left(k+1\right) = A_d\xi(k) + \mathcal{C}u\left(k\right), \tag{14}$$
$$V_t\left(k\right) = C\xi\left(k\right) + \mathcal{D}u\left(k\right). \tag{15}$$

This model will be used for the estimator in Sec. III

TABLE I
COEFFICIENT VALUES OF EQ. (12).

| Coeff. | Value | Coeff. | Value |
|---|---|---|---|
| $\alpha_1$ | 0.19 | $\alpha_2$ | $-1.1631$ |
| $\alpha_3$ | 3.1556 | $\alpha_4$ | $-4.9993$ |
| $\alpha_5$ | 5.13 | $\alpha_6$ | $-3.5732$ |
| $\alpha_7$ | 1.72 | $\alpha_8$ | $-0.5707$ |
| $\alpha_9$ | 0.1275 | $\alpha_{10}$ | $-0.0182$ |
| $\alpha_{11}$ | 0.0015 | $\alpha_{12}$ | $-1.6701$ |

## III. EXPONENTIAL MOVING AVERAGE EXTENDED KALMAN FILTER

As highlighted in the previous Section, measurement noise and unavailability of the initial SOC make it difficult to apply Coulomb counting method in practice. Extended Kalman filter (EKF) [6]–[9] is a popular choice in the literature to overcome these issues. EKF can easily be applied to the nonlinear system (14) and (15) and based on the estimated states, battery SOC and filtered version of the terminal voltage can be obtained. To develop EKF for the battery model, let us assume that the state equation (14) is corrupted with the process noise $w(k)$ while the output equation (15) is corrupted with the measurement noise $v(k)$ with the properties $w\left(k\right) \sim N\left(0, \mathcal{Q}(k)\right)$ and $v\left(k\right) \sim N\left(0, \mathcal{R}(k)\right)$. It is assumed that the noises are Gaussian and independent. Process and measurement noise covariance matrices are denoted by $\mathcal{Q}$ and $\mathcal{R}$. Then, for the second-order RC equivalent battery model, development of the EKF is given below where $\hat{}$ indicates estimated value, index $|k-1$ and $|k$ denote the *a priori* and *post priori* estimates [6]–[9]:

*Prediction Step:* In this EKF calculates the one-step ahead preiction value with respect to the available estimated state variables and the input

- One-step ahead prediction using the current value:

$$\hat{\xi}\left(k|k-1\right) = \mathcal{A}_d\xi\left(k-1|k-1\right) + \mathcal{B}u\left(k-1\right). \tag{16}$$

- One-step ahead prediction of the error covariance matrix $\mathcal{P}$:

$$\mathcal{P}\left(k|k-1\right) = \mathcal{A}\mathcal{P}\left(k-1|k-1\right)\mathcal{A}^T + \mathcal{Q}. \tag{17}$$

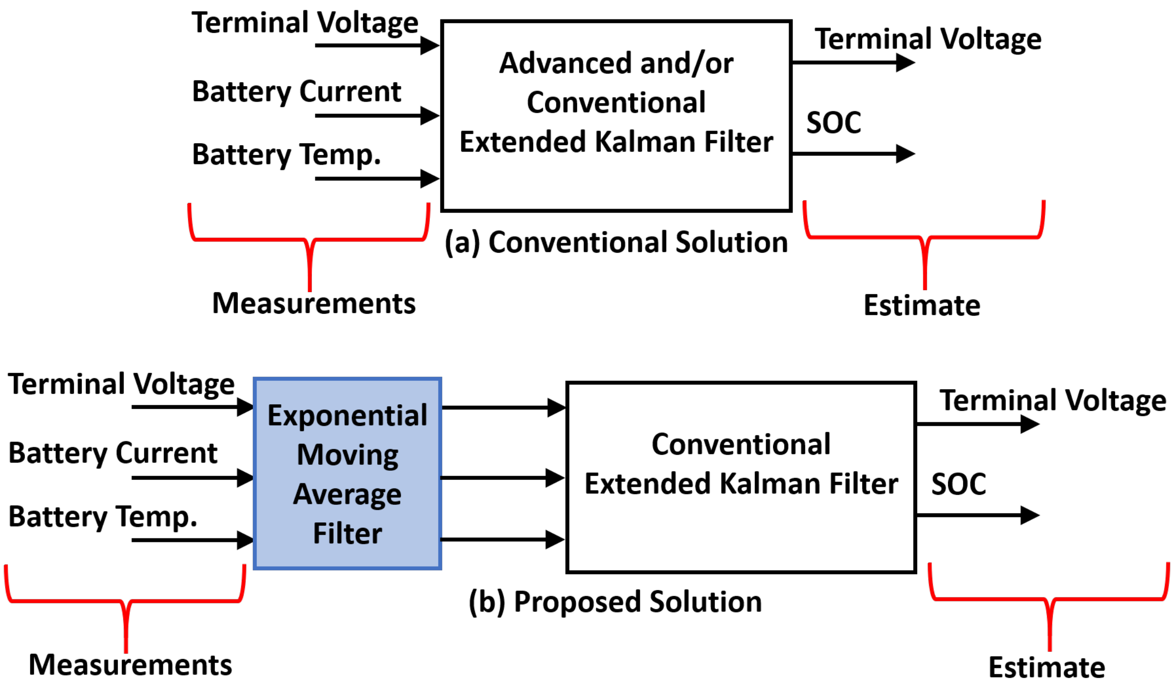



Fig. 3. Proposed solution vs. the literature.

*Correction Step:* In predicting the one-step ahead values, no information of the available output is used. In the step, this output will be used to refine/correct the prediction.

- Kalman innovating gain calculation which is necessary to refine/correct the prediction:

$$\mathcal{K}(k) = \mathcal{P}(k|k-1)\,\mathcal{C}^T\left(\mathcal{C}\mathcal{P}(k|k-1)\,\mathcal{C}^T + \mathcal{R}\right)^{-1}. \quad (18)$$

- Correction of the state variables prediction using the Kalman innovation gain and the available measurement:

$$\hat{\xi}(k|k) = \hat{\xi}(k|k-1) + \mathcal{K}(k)\left(v_t(k) - \mathcal{C}\hat{\xi}(k|k-1) - i(k)\,R_0\right). \quad (19)$$

- Update the process covariance matrix using the Kalman innovation gain:

$$\mathcal{P}(k|k) = (I - \mathcal{K}(k)\,\mathcal{C})\,\mathcal{P}(k|k-1). \quad (20)$$

EKF as described above works with linearized state and output matrices. In our case, $\mathcal{A}$,$\mathcal{B}$, and $\mathcal{D}$ are already linear. Matrix $\mathcal{C}$in eq. (13) is nonlinear and needs to be evaluated with respect to the current estimate of the $\mathcal{S}$ to obtain the linear value. In developing the EKF, it was assumed that the noise covariance matrices $\mathcal{Q}$ and $\mathcal{R}$ are constant.

EKF as described above can provide good estimate of the state variables and the output. However, there are several issues that can effect the performance of the EKF. Firstly, constant $\mathcal{Q}$ and $\mathcal{R}$ can be restrictive in practice as these matrices may change as the battery ages. Moreover, various measured values such as temperature, terminal voltage, and current can be very noisy due to various external factors. To overcome these issues, various advanced EKF are proposed in the literature. One such solution as reported in [6] involves real-time adaptation of the process covariance matrix $\mathcal{Q}$ through using the Kalman innovation gain $\mathcal{K}$. However, those solutions are very computationally expensive and require real-time adaptation, matrix inverse etc. To overcome these issues, in this work, we propose the application of exponential moving average filter to the various measured signals. These filtered measured signals are then applied to the EKF given in eq. (16)-(20). This is a practical solution to enhance the performance of EKF in a noisy environment. An overview of our solution over the literature is given in Fig. 3.

To provide details of the exponential moving average filter (EMAF), let us first consider the moving average filter. Simple moving average (SMA) filter is given as:

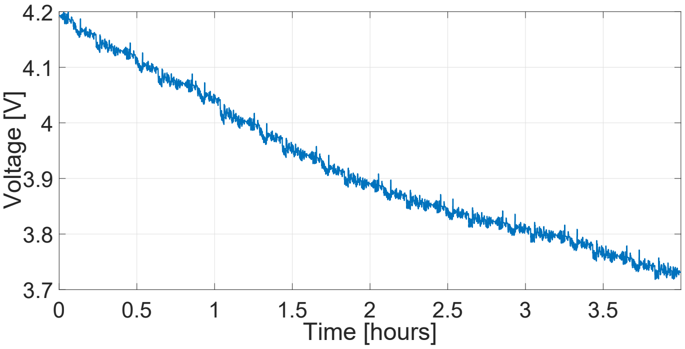
$$\bar{x}(k) = \frac{1}{N}\sum_{n=0}^{N-1} x(k-n), \quad (21)$$

where $N$ is the window length, $\bar{x}$ is the filtered signal and $x$ is the input signal. SMA filter gives equal weight to the all the data points in the averaging window. This do not take into account the system dynamics. In practice, giving more weights to recent data points while less to older data points may be beneficial. One such solution is known as exponential moving average filter (EMAF). EMAF filter is given by:

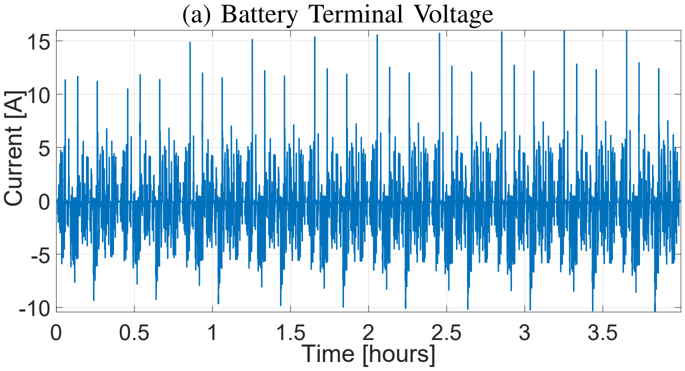
$$\bar{x}(k) = \alpha x(k) + (1-\alpha)\,\bar{x}(k), \quad (22)$$

where $\alpha \in (0, 1)$ is the weighting factor. Higher value of $\alpha$ means more weight to the recent data and vice-versa. For dynamically changing data such as battery signals, EMAF can be a very suitable to enhance the performance of EKF in noisy environment

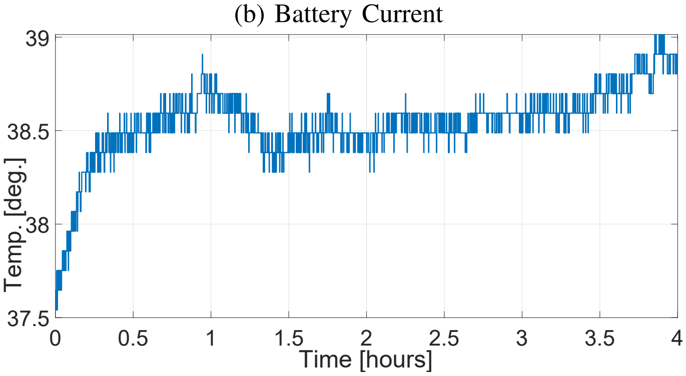
## IV. Results and Discussion



(a) Battery Terminal Voltage



(b) Battery Current

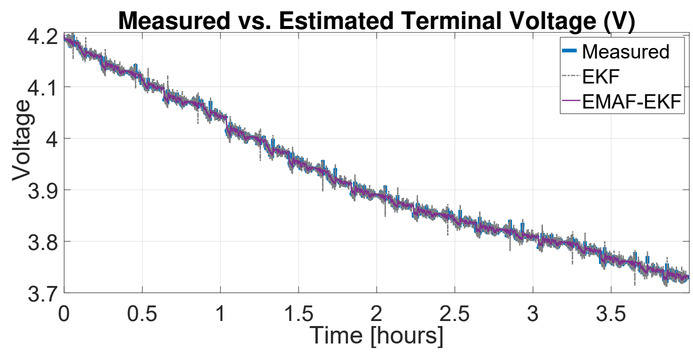


(c) Battery Temperature

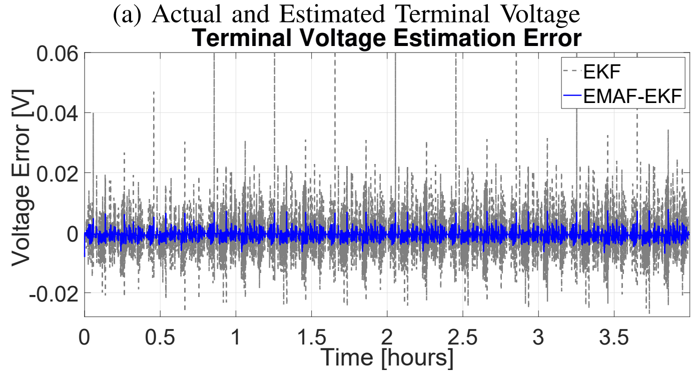
Fig. 4. Battery inputs signals.

In this Section, the proposed method will be validated using experimental data set given in [19]. As comparison method, we have considered the conventional EKF as given in [6]. Matrices $Q$ and $\mathcal{R}$ are selected as: $\mathcal{Q} = \mathrm{diag}\left(10^{-5}, 10^{-5}, 10^{-6}\right)$and $\mathcal{R}$ $=2\times10^{-5}$. Process covariance matrix $\mathcal{P}$ is initialized as: $\mathcal{P} = \mathrm{diag}\left(0.01, 0.01, 0.025\right)$. EMAF parameter is selected as $\alpha = 9\times10^{-1}$. Input signals are given in Fig. 4. Input signals show that the measured voltage, current, and temperature signals are very noisy. This makes the estimation challenging

Estimation results and the estimation error for terminal voltage and SOC are given in Fig. 5 and 6. Both results show that the proposed EMAF-EKF outperformed the conventional EKF in both cases. To further verify the results, two further tests are performed by considering $\pm0.1$A offset in the measured current. Root mean square error (RMSE) in all three cases are given in Fig. 7. Results in Fig. 7 show that the proposed solution outperformed the conventional technique in all three cases in terms of root mean square estimation error. In all cases, the performance has been improved by at least $10\%$ or higher. for the terminal voltage estimation. In case of SOC estimation, the performance improvement is at least $15\%$ or higher. These numbers demonstrate the effectiveness of the proposed approach over the conventional EKF.



(a) Actual and Estimated Terminal Voltage

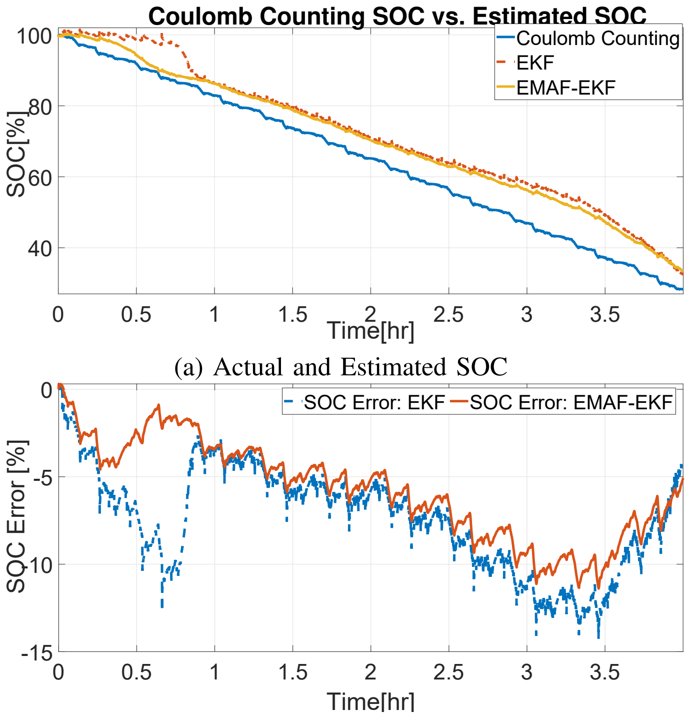


(b) Terminal Voltage Estimation Error

Fig. 5. Terminal voltage estimation results. (a) Actual and estimated terminal voltages and (b) estimation error.

## V. Conclusion

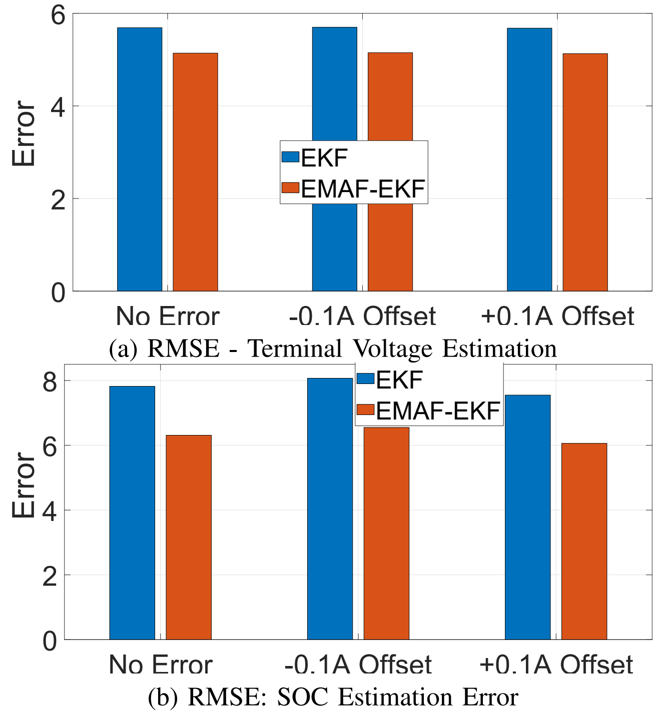
Battery state-of-charge estimation in a noisy environment is a challenging problem. In this paper, this problem has been solved by applying exponential moving average filter as a pre-filter to various input signals. The pre-filtered signals are then fed to the conventional extended Kalman filter. The resulting structure is very robust to measurement noise and can provide better estimate of various battery parameters compared to the conventional counterpart. Experimental validations highlighted the performance improvement by our method. The proposed method showed lower root mean square estimation errors compared to conventional extended Kalman filter. Further research into various pre-filtering methods will be considered in a future work.




(a) Actual and Estimated SOC

(b) SOC Estimation Error

Fig. 6. SOC estimation results. (a) Actual and estimated SOCs and (b) estimation error.




(a) RMSE - Terminal Voltage Estimation

(b) RMSE: SOC Estimation Error

Fig. 7. RMSE for different test cases.

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