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A dual extended Kalman filter for the state of charge estimation of lithium-ion batteries

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Highlights

- Estimating State of Charge (SoC) is crucial for battery management systems.
- Adaptive Dual Extended Kalman Filter (ADEKF) reduces estimation error and computational load.
- Performance verified through both simulations and practical tests, outperforming conventional EKF methods.
- ADEKF method successfully estimates battery charge level with improved accuracy.

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Abstract

There are always various functions and features in battery management systems. Among these functions, state of charge estimation is considered a basic and fundamental function. Because the performance of many other functions is related to knowing the estimated SoC. Estimation of battery charge level using an adaptive dual extended Kalman filter (ADEKF) is the main goal of this paper. Conventional extended Kalman filters always have a small estimation error due to the presence of linearization in their process. On the other hand, if the number of variables in the battery model state increases, the volume of calculations will also increase. In order to solve these problems, this paper uses an ADEKF, in which the estimation process is performed by two parallel processes, and in addition, its measurement covariance matrix is adaptively selected during a separate path. Therefore, the volume of calculations is reduced, and on the other hand, the accuracy of charge level estimation using the desired method increases. In order to check the performance of this method, a series of simulation tests as well as practical tests have been performed and the proposed method's performance has been compared with the conventional EKF methods. The results of practical tests and simulations confirm the good and successful performance of the desired method for estimating the battery charge level.

1. Introduction

A. Motivation and Incitement

Due to the environmental pollution caused by fossil fuels, the use of renewable energy has attracted the attention of engineers, industrialists and researchers in recent years. On the other hand, with the increase in the number of cars on the roads, the use of fossil fuels increases environmental pollution [1, 2]. For this reason, the use of electric cars is also a very suitable alternative to reduce environmental pollution. Therefore, in the applications of renewable energy and electric vehicles, rechargeable batteries are considered the main goal of researchers. Among rechargeable batteries, lead-acid batteries have been widely used. But due to the small volume, cheaper price and higher density of energy of LI batteries, lead-acid batteries have been replaced by lithium-ion batteries in recent years. But in lithium ion battery management systems, charging level estimation is a basic function [3]. Because the performance of many other functions in battery management systems depends on knowing the exact amount of battery charge level. The charge level of lithium batteries cannot be directly measured by any sensor and we should estimation methods. Many methods for the

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estimation of the level of charge for Li batteries have been proposed by researchers. Signal-based methods, electrochemical test-based methods, intelligent systems-based methods, and model-based methods. Among these methods, Ampere-hour counting methods, model-based methods are one of the most widely used charge level estimation methods, especially for high-current applications. The Ampere-hour counting method is structured on the following basis [4].

$$SoC(t) = SoC(t_0) + \int_{t_0}^{t} \frac{\eta I}{3600C_s} d\tau \tag{1}$$

- *.B. Literature Review and Research Gaps*

These methods are very simple to implement, but their main feature is their sensitivity to environmental conditions, and they are usually less accurate than model-based methods [5]. In estimating the level of charge using model-based methods, first a physical model is applied to the battery and then the dynamic equations of the state space are extracted for this model. Then, for this extracted state space model, an estimator is designed and tested in practical experiments. Until now, many model-based methods have been presented to estimate the charge level of lithium-ion batteries [6-8]. On the other hand, researchers have introduced various methods for modeling lithium-ion batteries. Among the modeling methods of lithium-ion batteries, electrical models [9] are the most widely used models for battery modeling. Because these models establish a compromise between accuracy and simplicity. Now we will examine the methods of estimating the charge level for lithium-ion batteries using electrical models.

One of the basic problems in estimating the battery charge level using textual methods on the model is the inaccuracy in identifying the model parameters and as a result the uncertainties created in the battery model. These model uncertainties cause estimation errors in the estimator [10]. Because there is always a difference between the extracted model and the real model of the battery, and it makes the accuracy of the answer taken in the simulations not taken in the practical test. To solve this problem, researchers proposed robust estimators. In these estimators, they use an uncertain band during the design of the estimator so that the estimation accuracy does not decrease in the presence of uncertainty in the model. The methods based on sliding [11-12] are among the most widely used methods for estimating the resistance level of charge. But the weakness of these methods is that they have chattering in their performance, which causes their accuracy to decrease. But the researchers have made the sliding estimators consistent by various methods and have eliminated the chat ring problem and the speed of convergence. In this regard, many researchers adapt or optimize the parameters and benefits of sliding estimators by additional methods such as fuzzy systems [13], neural networks [14] and optimization [15] algorithms in order to increase the accuracy of the estimator. and reduce the chattering problem. Among other robust methods for estimating the charger level, we can refer to H-infinity based methods [16-18]. These methods are also resistant to model uncertainties and provide good accuracy. But the complexity of calculations and the difficulty of implementing them on processors are considered as their weak points.

Artificial intelligence [19] can be mentioned among other methods to estimate the battery charge level. In recent years, methods such as machine learning [20], deep learning [21], and reinforcement learning [22] have become the subject of many researchers to estimate the level of charge or even estimate the health level of lithium-ion batteries. In addition, neural networks [23] have also been used to estimate the battery charge level. The main advantage of these methods is that there is no need for battery modeling and only by using the data collected through laboratory tests, the charge level and health level of the batteries can be estimated. But the most important weakness of these methods is that there is a need for a reliable and sufficient training data series. In other words, in order to train these methods optimally, we need to consider a series of practical and reliable data to train these intelligent systems. In addition to learning-based methods, fuzzy systems also had many applications in estimating the battery charge level [24]. Sometimes fuzzy systems have been used independently and directly to estimate the level of battery charge, and sometimes fuzzy systems have been used as an auxiliary method for matching or increasing the accuracy of other methods. In some articles, neural networks are used to optimize fuzzy systems to increase the accuracy of fuzzy systems to estimate the charge level. The main weakness of fuzzy systems is that there is a need for a series of data and sufficient experience to set fuzzy rules and to set membership functions. And usually optimization methods and neural network should be used to increase the accuracy of fuzzy systems.

Kalman filters are among the optimal estimators for estimation operations. These filters are able to obtain a good estimate of the state variables in the presence of environmental noises as well as measurement noises. Therefore, in noisy environments or in the presence of cheap sensors, Kalman-based methods are a good option for estimating the charge level. The conventional type of Kalman filters is linear and if a linear model is extracted from the battery, they can be used to estimate the charge level. But due to a non-linear relationship between open circuit voltage and battery charge level, the state space model of lithium batteries is non-linear. For this reason, non-linear types of Kalman filters can be used to estimate the charge level. The first and most widely used type of non-linear Kalman filter is extended [25] as the employee filter used for the estimation of the battery charge level. These filters have good accuracy, but due to the linearization in their algorithm, they suffer from errors. For this reason, to solve this problem, researchers use unscented Kalman filters [26] to estimate the charge level. These filters do not have linearization in their algorithm and provide very good accuracy. But the volume of its calculations is more than the volume of calculations of extended Kalman filters [27]. The main advantage of Kalman filters is the ability to estimate in the presence of noise. But their main drawback is their need for a precise battery model. In other words, Kalman filters require an accurate model of the lithium battery to provide an accurate estimate of the charge level. But as you know, due to inaccuracy in identifying the model parameters, there are always model uncertainties for the battery. And these uncertainties of the model are the weak point of Kalman filters and cause the accuracy of their performance to decrease in practical tests. On the other hand, in the Kalman filters algorithm, the covariance matrices of the process noise and the measurement noise should be optimally determined in order to increase the estimation accuracy and convergence speed [28]. Usually, designers choose these two covariance matrices by trial and error. But in environments where there are colored noises, the accuracy of Kalman filters is greatly reduced. Because in their algorithm, white noise is considered [29].

- *C. Contributions*

Conventional extended Kalman filters always have a small estimation error due to the presence of linearization in their process. On the other hand, if the number of variables in the battery model state increases, the volume of calculations will also increase. In order to solve these problems, this paper uses an ADEKF, in which the estimation process is performed by two parallel processes, and in addition, its measurement covariance matrix is adaptively selected during a separate path. Therefore, the volume of calculations is reduced, and on the other hand, the accuracy of charge level estimation using the desired method increases.

- *D. Paper Organization*

The paper is divided into the following sections: Section 2 presents the battery model with unknown uncertainties. Section 3 provides information about the suggested ADEKF for the SoC estimation. The simulation and experimental tests for the battery SoC are conducted in section 4. This study is wrapped up in Section 5.

2. Battery modeling

Various methods for modeling lithium-ion batteries have been presented so far. For example electrochemical models, physical methods, electrical modeling methods, 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.

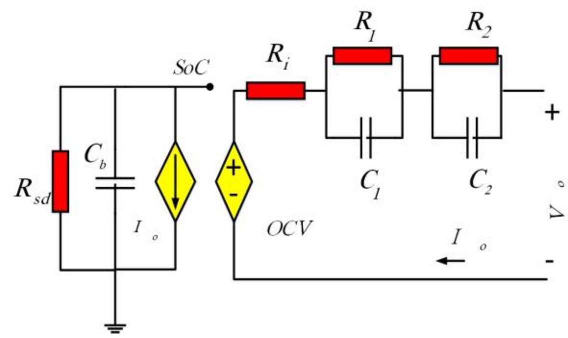

Fig. 1. Battery ECM model

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. Using the Kirchhoff laws, the voltage of the terminal can be formulated as:

$$V_o = V_{oc}(Soc) - V_1 - V_2 - I_o R_i \tag{2}$$

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

$$\dot{S}oC = -\frac{1}{R_T C_T} SoC - (\frac{I_o}{C_T}) \tag{3}$$

$$\dot{V}_1 = -\frac{V_1}{R_1C_1} + \frac{I_o}{C_1} \quad (4)$$

$$\dot{V}_2 = -\frac{V_2}{R_2C_2} + \frac{I_o}{C_2} \quad (5)$$

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:

$$V_{oc}(SoC) = L(SoC) \quad (6)$$

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

$$\dot{V}_o = \frac{\partial V_{oc}}{\partial SoC}\dot{S}oC - \dot{V}_1 - \dot{V}_2$$
$$\frac{\partial V_{oc}}{\partial SoC} = \dot{L}(SoC) \quad (7)$$

The state variables are 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:

$$\begin{aligned} \dot{X} &= F(X, u) + \zeta \\ Y &= CX + \omega \\ C &= [0\ 0\ 0\ 1] \end{aligned} \quad (8)$$

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

$$F(X,u) = \begin{bmatrix} -\frac{1}{R_TC_T}SoC - (\frac{I_o}{C_T}) \\ -\frac{V_1}{R_1C_1} + \frac{I_o}{C_1} \\ -\frac{V_2}{R_2C_2} + \frac{I_o}{C_2} \\ \dot{L}(SoC)\dot{S}oC + \frac{V_1}{R_1C_1} - \frac{I_o}{C_1} + \frac{V_2}{R_2C_2} - \frac{I_o}{C_2} \end{bmatrix} \quad (9)$$

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 [16]. 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.

$$\dot{X}_i = \begin{bmatrix} -(14e-7)SoC - (1.5e-3)I_o \\ -(11e-5)V_1 + 0.05I_o \\ -0.01V_2 + (7.5e-3)I_o \\ (-30e-6)SoC^3 + ((30e-7) - (3e-4)I_o)SoC^2 \\ +(31e-7)I_o.SoC - (I_o+1)(0.01)\,exp(-39SoC) \end{bmatrix} \quad (10)$$
$$Y_i = (0001)X_i + \omega_i$$

Always to validate the identified battery model, after simulating the model of the battery in the software environment, the voltage over the terminal 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 [16].

3. Proposed observer formulation

3.1. The dual extended Kalman filter

As mentioned earlier, in the estimator in question, first, a dual extended Kalman filter is used, in which the covariance matrix Q is selected adaptively. The reason for using the developed Kalman filter is that the dynamics of the extracted state space for the battery is non-linear. Therefore, we will first describe the relations of the dual extended Kalman filter and then describe the steps of its adaptation. The step-by-step procedure of the dual EK is described as follows.

A. *Initialization*

$$\hat{w}_0 = E[w], \qquad P_{w_0} = E[(w-\hat{w}_0)(w-\hat{w}_0)^T]$$
$$\hat{x}_0 = E[x] \qquad P_{x_0} = E[(x-\hat{x}_0)(x-\hat{x}_0)^T] \quad (11)$$

B. *Time-update equations for the weight filter*

$$\hat{w}_i^{\,-} = \hat{w}_{i-1}$$
$$P_{w_i}^{\,-} = P_{w_{i-1}} + R_{i-1} = \beta P_{w_{i-1}} \quad (12)$$

C. *State filter*

$$\hat{x}_i^{\,-} = F(\widehat{x_{i-1}}u_i, \hat{w}_{i-1})$$
$$P_{x_i}^{\,-} = A_{i-1}P_{i-1}A^T{}_{i-1} + Q \quad (13)$$

D. *The measurement-update equations for the state filter*

$$K_i^x = P_{x_i}^- C^T (CP_{x_i}^- C^T + R)^{-1}$$
$$\hat{x}_i = \hat{x}_i^{\,-} + K_i^x(y_i - C\hat{x}_i^{\,-}) \quad (14)$$
$$P_{x_i} = (I - K_i^xC)P_{x_i}^-$$

E. *those for the weight filter*

$$K_i^x = P_{x_i}^- C^T (CP_{x_i}^- C^T + R)^{-1}$$
$$\hat{x}_i = \hat{x}_i^{\,-} + K_i^x(y_i - C\hat{x}_i^{\,-})$$
$$P_{x_i} = (I - K_i^xC)P_{x_i}^-$$

$$A_{i-1} = \frac{\partial F(x,\hat{w}_i)}{\partial x}\Big|_{\hat{x}_{i-1}}, \qquad e_i = (y_i - C\hat{x}_i^{\,-}), \;\; C_i^w = -\frac{\partial e_i}{\partial w} = C\frac{\partial \hat{x}_i}{\partial w}$$

3.2. Adaptive Estimation of Q

Estimation of the dynamic noise covariance matrix Q is linked with measurement noise covariance matrix R since estimation of R requires the predicted state covariance $P_{\bar{k}}$ and hence Q. Based on covariance matching principles, R is estimated using innovation or residual. If R and $P_{\bar{k}}$ are known, Q can be selected by calculating a ratio between the estimation of the innovation covariance and the prediction of it [7].

$$\alpha = \frac{trace\left\{\hat{C}_i - R_i\right\}}{trace\left\{\hat{H}_i \hat{P}_{\bar{i}} H_i^T\right\}} \tag{15}$$

Q for epoch i is:

$$\hat{Q}_i = Q_{i-1}\sqrt{\alpha} \tag{16}$$

The factor α is greater or less than one. This causes the increase in the probability of tuning Q.

Where:

$$\hat{R}_i = \hat{C}_i - \hat{H}_i \overline{P}_i H_i^T \tag{17}$$

$\hat{C}_i$ is the estimation of the variance/covariance V/C matrix related to the innovation and it is computed as follows.

$$\hat{C}_i = \frac{1}{m}\sum_{j=1}^{m} v_{i-j}\, v_{i-j}^T \tag{18}$$

4. Simulation and Experimental results

4.1.Simulation results

In order to check the performance of the proposed method, before conducting the practical tests, a series of simulations have been performed in the MATLAB software environment. According to Figure 2, a current in the form of a pulse has been applied as an input to the battery model. The result of estimating the battery charge level and also estimating the terminal voltage level are shown in Figures 3 and 4 along with their estimation error. As it can be seen from Figure 3, the proposed method has been able to estimate the battery charge level well and has an error close to zero. While in the Ah method, the battery SoC has an error of about 3%. Therefore, this figure shows the good performance of the desired method for estimating the battery charge level. For further ensure the estimator's accuracy, the battery terminal voltage has also been estimated using it. As it is clear from figure 4, the proposed method has been able to estimate the battery terminal voltage with high accuracy and an estimation error close to zero.

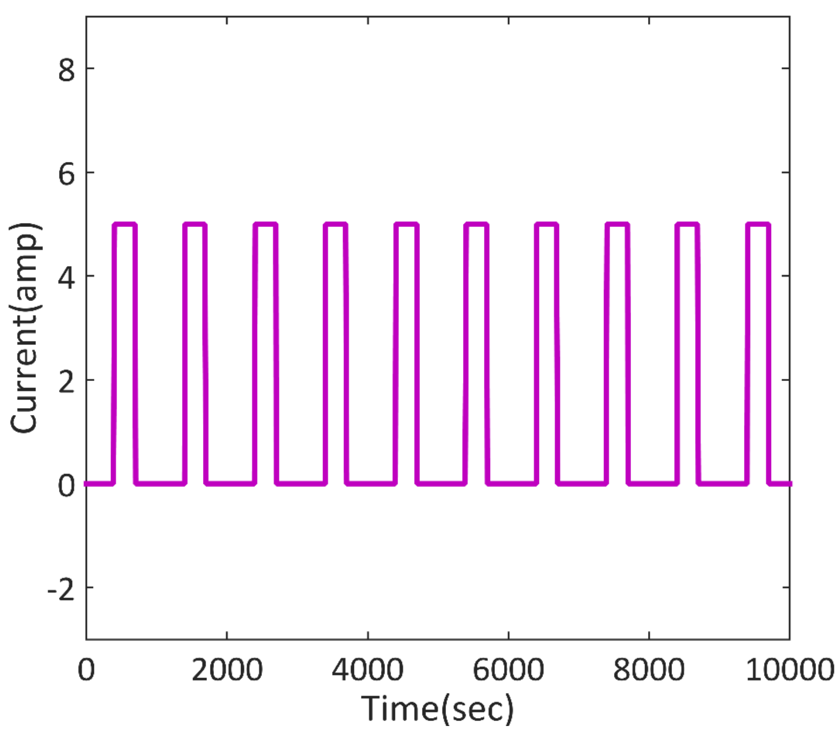

Fig. 2. Current profile

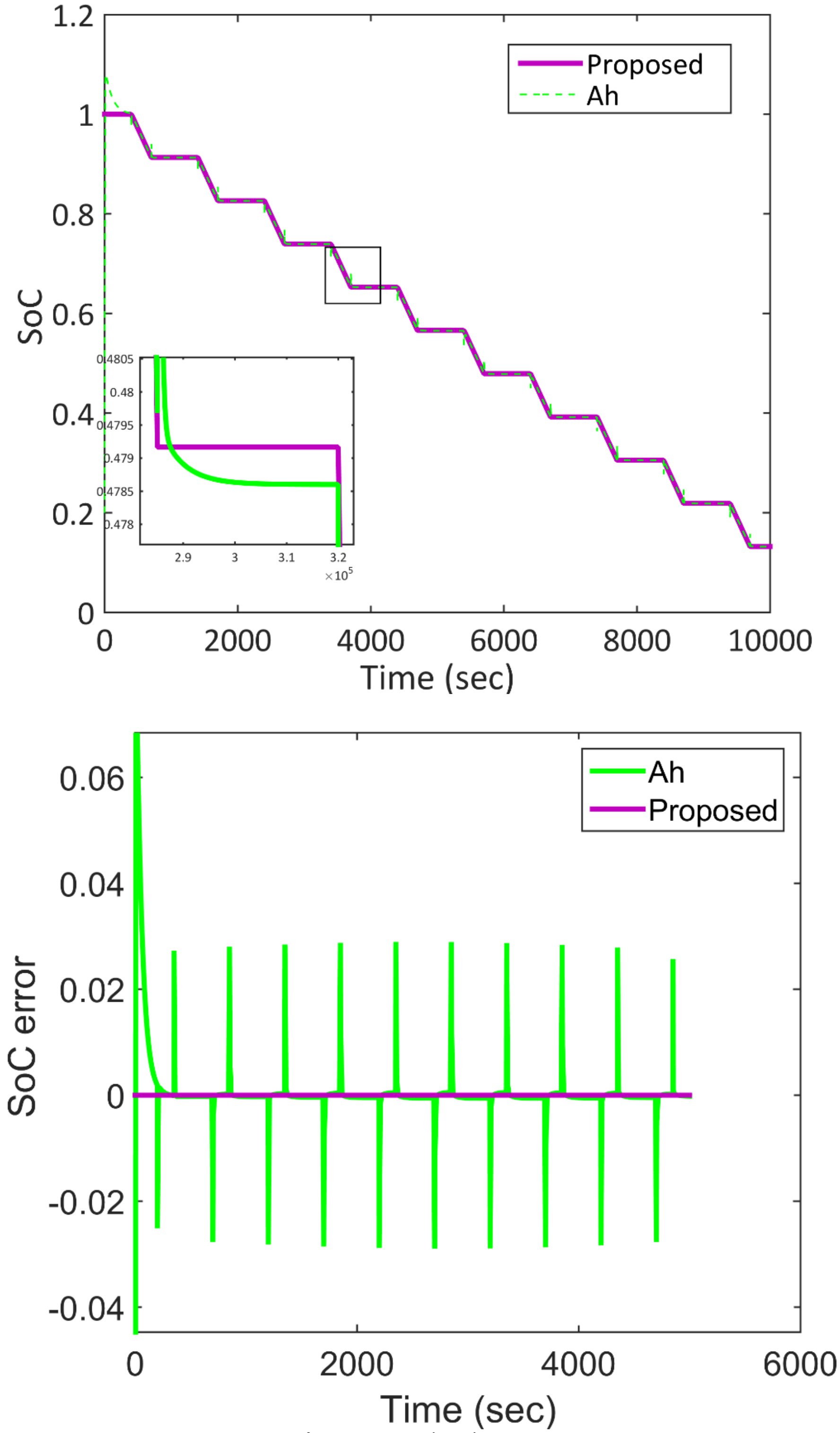

Fig. 3. SoC estimation

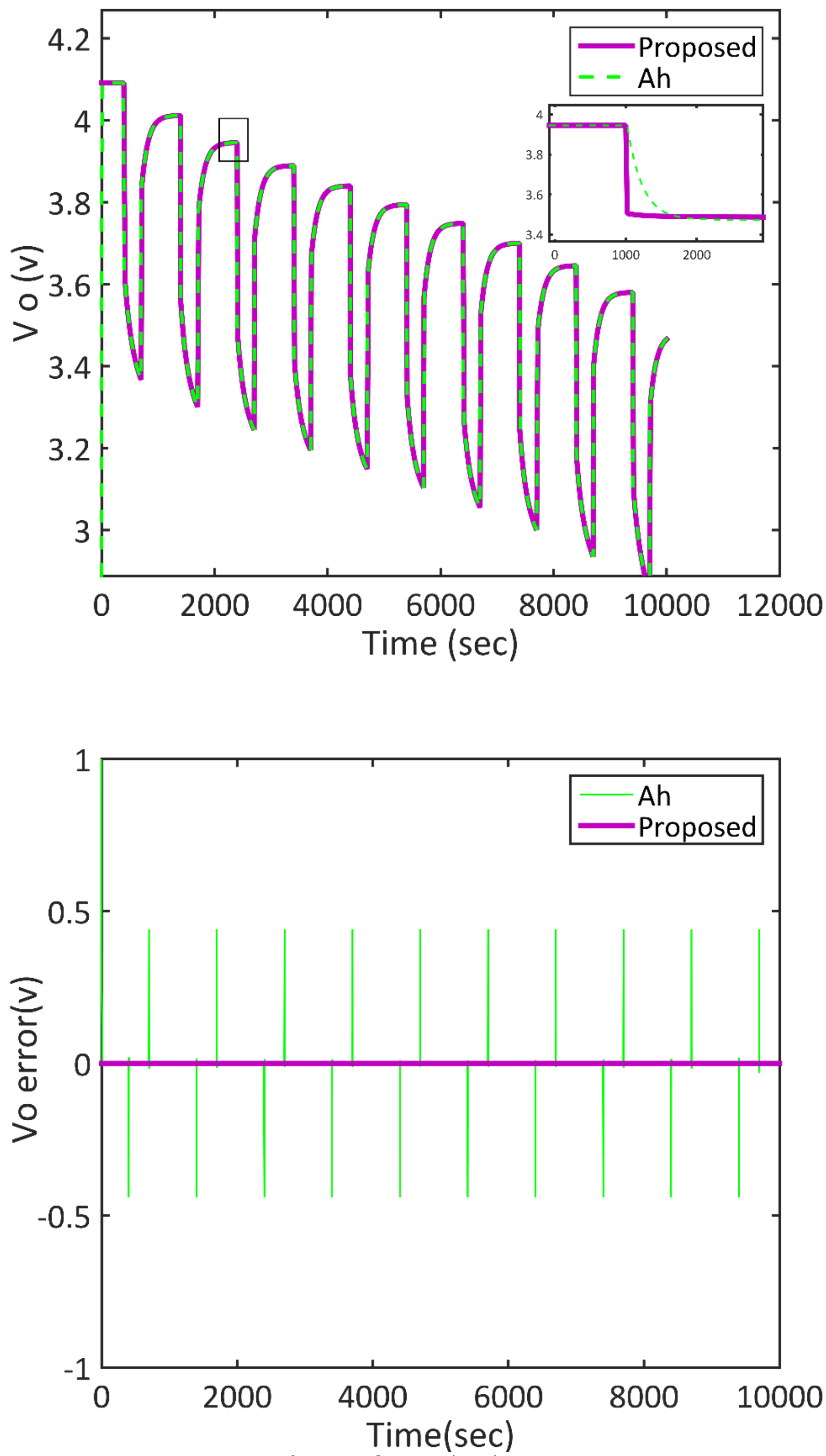

Fig. 4. Voltage estimation

4.2 Software-in-the -Loop results

After performing the necessary simulations, to check the effectiveness of the desired method in practical tests, the desired estimator has been measured using practical data. In order to perform these tests, a test table shown in Figure 5 was used. As it is clear from this figure, the practical test data is collected and measured by this table and then applied to the simulated model of the estimator. And finally, the result of estimation of battery terminal voltage charge level is checked using practical data.

Figure 6 compares the result of estimating the battery charge level using the proposed method and the conventional EKF method for practical data. As it is clear from this figure, the estimator in question has been able to estimate the battery charge level with higher accuracy. One of the reasons for the high accuracy of the estimator compared to other methods is that the covariance matrix of the measurement is selected adaptively in a separate path, which increases the accuracy of the estimator. Figure 7 also compares the result of battery terminal voltage estimation using the desired method and EKF method. As it can be seen from this figure, the desired estimator is also successful in estimating the terminal voltage and has been able to estimate the battery terminal voltage very accurately. In the second part of Figure 7, there is also the terminal voltage estimation error, which confirms the same issue. It should be noted that the normal estimator causes estimation errors due to the linearization in its process. But in the proposed method, this defect has been solved and in addition, by using an adaptive algorithm and adapting the measurement covariance matrix, the accuracy of the estimation has been increased.

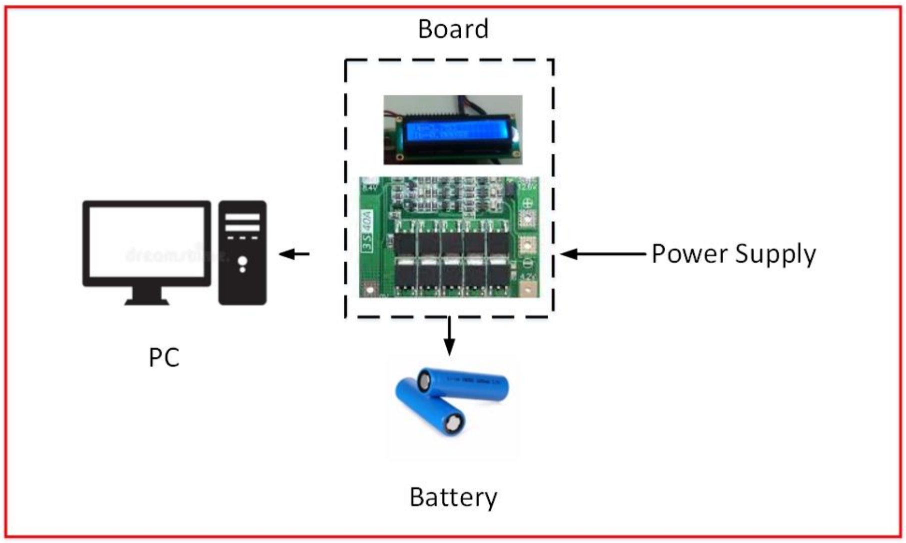

Fig. 5. Test bench

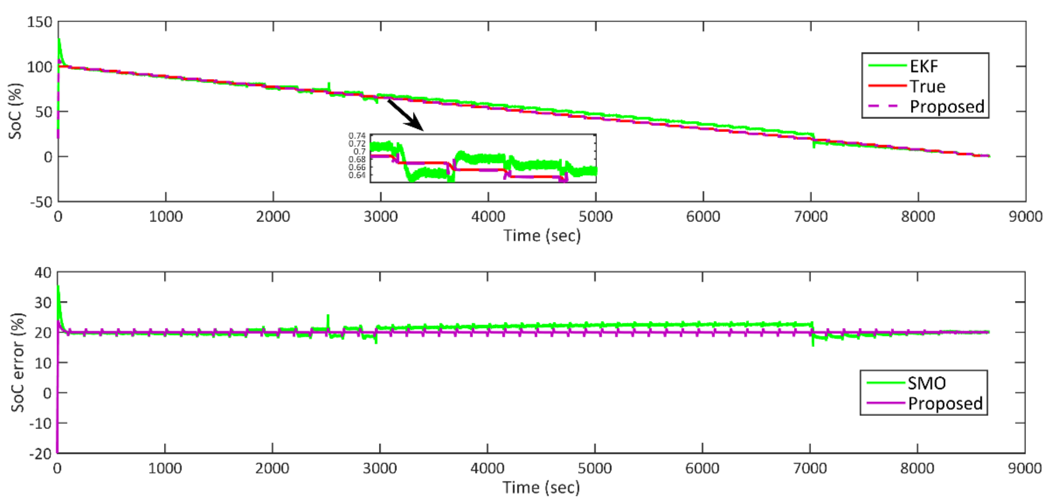

Fig. 6. SoC estimation (experiment)

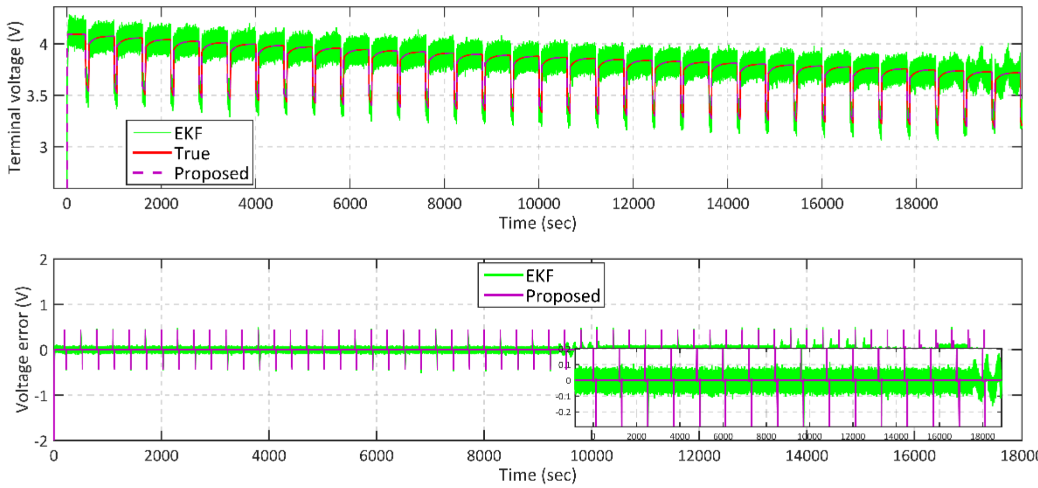

Fig. 7. Voltage estimation (experiment)

5. Conclusion

The linearization error is a major factor in reducing the estimation accuracy in EKF estimators. In order to solve this problem, this paper uses a special EKF estimator, in which the estimation operation is performed by two parallel processes. On the other hand, the covariance matrix of the estimator measurement is selected adaptively by a separate path to increase its accuracy. The reason for this is that the selection and adaptation of the measurement noise covariance matrices and the process is a main and determining factor in the accuracy of the Kalman family estimators. The results of simulations and practical tests to estimate the level of charge and terminal voltage of the lithium ion battery using the estimator show that this estimator can estimate the level of charge and terminal voltage with high accuracy compared to conventional EKF estimators. According to the results, the proposed method can estimate charge and voltage levels above 3% and 3V, respectively, more accurately than conventional EKF estimators.

REFERENCES

[1] Sobhani, Behrooz, H. Kazemi Kargar, and Adel Akbarimajd. "A mixed active-passive algorithm for islanding detection of wind turbine DG units." International Review of Electrical Engineering 6.2 (2011).
[2] Cao, Wenxuan, Xiao Pan, and Behrouz Sobhani. "Integrated demand response based on household and photovoltaic load and oscillations effects." International Journal of Hydrogen Energy 46.79 (2021): 39523-39535.
[3] Abedinia, Oveis, Mohamed Lotfi, Mehdi Bagheri, Behrouz Sobhani, Miadreza Shafie-Khah, and João PS Catalão. "Improved EMD-based complex prediction model for wind power forecasting." IEEE Transactions on Sustainable Energy 11, no. 4 (2020): 2790-2802.
[4] Abedinia, Oveis, Ali Ghasemi-Marzbali, Venera Nurmanova, and Mehdi Bagheri. "Optimal Strategy for Bidding in Deregulated-Structure of Electricity Market: A Competitive Model." In 2021 IEEE International Conference on Environment and Electrical Engineering and 2021 IEEE Industrial and Commercial Power Systems Europe (EEEIC/I&CPS Europe), pp. 1-5. IEEE, 2021.
[5] Jia, Qiangang, et al. "Deviation insurance for Risk-Averse wind power producers in the Nordic power market." International Journal of Electrical Power & Energy Systems 134 (2022): 107431.
[6] Shayanfar, H. A., et al. "Optimal sizing and placement of distribution generation using imperialist competitive algorithm." Proceedings on the International Conference on Artificial Intelligence (ICAI). The Steering Committee of The World Congress in Computer Science, Computer Engineering and Applied Computing (WorldComp), 2012.
[7] Hamidan, Mohammad-Ali, and Farzaneh Borousan. "Optimal planning of distributed generation and battery energy storage systems simultaneously in distribution networks for loss reduction and reliability improvement." Journal of Energy Storage 46 (2022): 103844.
[8] Ali, Mohammed Hamouda, et al. "An improved wild horse optimization algorithm for reliability based optimal DG planning of radial distribution networks." Energy Reports 8 (2022): 582-604.
[9] Avar, Ali, and Mohammad Kazem Sheikh-El-Eslami. "Optimal DG placement in power markets from DG Owners' perspective considering the impact of transmission costs." Electric Power Systems Research 196 (2021): 107218.
[10] Qu, Yinpeng, et al. "A global optimum flow pattern for feeder reconfiguration to minimize power losses of unbalanced distribution systems." International Journal of Electrical Power & Energy Systems 131 (2021): 107071.
[11] Shaik, Muqthiar Ali, Padma Lalitha Mareddy, and N. Visali. "Enhancement of Voltage Profile in the Distribution

system by Reconfiguring with DG placement using Equilibrium Optimizer." Alexandria Engineering Journal (2021).
[12] Hung, Duong Quoc, Nadarajah Mithulananthan, and Kwang Y. Lee. "Optimal placement of dispatchable and nondispatchable renewable DG units in distribution networks for minimizing energy loss." International Journal of Electrical Power & Energy Systems 55 (2014): 179-186.
[13] Azad-Farsani, Ehsan. "Loss minimization in distribution systems based on LMP calculation using honey bee mating optimization and point estimate method." Energy 140 (2017): 1-9.
[14] García-Muñoz, Fernando, Francisco Díaz-González, and Cristina Corchero. "A novel algorithm based on the combination of AC-OPF and GA for the optimal sizing and location of DERs into distribution networks." Sustainable Energy, Grids and Networks 27 (2021): 100497.
[15] Avar, Ali, and Mohammad Kazem Sheikh-El-Eslami. "Optimal DG placement in power markets from DG Owners' perspective considering the impact of transmission costs." Electric Power Systems Research 196 (2021): 107218.
[16] Das, Bikash, V. Mukherjee, and Debapriya Das. "Optimum DG placement for known power injection from utility/substation by a novel zero bus load flow approach." Energy 175 (2019): 228-249.
[17] Suresh, M. C. V., and J. Belwin Edward. "A hybrid algorithm based optimal placement of DG units for loss reduction in the distribution system." Applied Soft Computing 91 (2020): 106191.
[18] Murty, Vallem VSN, and Ashwani Kumar. "Optimal placement of DG in radial distribution systems based on new voltage stability index under load growth." International Journal of Electrical Power & Energy Systems 69 (2015): 246-256.
[19] Doagou-Mojarrad, Hasan, et al. "Optimal placement and sizing of DG (distributed generation) units in distribution networks by novel hybrid evolutionary algorithm." Energy 54 (2013): 129-138.
[20] Jaghargh, Mohammad Javad Poursalimi, and Habib Rajabi Mashhadi. "An analytical approach to estimate structural and behavioral impact of renewable energy power plants on LMP." Renewable Energy 163 (2021): 1012-1022.
[21] Roushenas, Ramin, Ehsan Zarei, and M. Torabi. "A novel trigeneration system based on solid oxide fuel cell-gas turbine integrated with compressed air and thermal energy storage concepts: Energy, exergy, and life cycle approaches." Sustainable Cities and Society 66 (2021): 102667.