A Comparative Study on State of Charge Estimation using EKF and IEKF

Yassine Derouech[1*] and *Abdelouahed* Mesbahi[1]

[1] Laboratory Energy and Electrical Systems, National Higher School of Electricity and Mechanics, Hassan II University, Casablanca, Morocco

Abstract. The nature of the "Portable Intelligent Micro Device for Hemodialysis" system requires a mobile electrical energy source capable of providing the essential power for efficient system operation. A battery with a management system can ensure this operation, the first target is to model the battery with a simple model capable of combining the various internal and external parameters that can affect battery behavior, then we develop the equations required to compose the two filters "Extended Kalman Filter" and "Invariant Extended Kalman Filter" in order to guarantee the estimation of the state of charge, which is a key element for the desired operation, and finally a MATLAB/Simulink simulation to compare the two filters, which reveals the IEKF filter's performance in terms of stability and precision.

1 Introduction

A battery is needed to power the "Portable Intelligent Micro Device for Hemodialysis" system, to ensure its electrical independence. A battery model that describes its dynamic operation is essential for its use in many applications, to ensure normal functioning of the system. Several references feature different battery models, according to reference [1] and to better model battery dynamics, five methods have been developed and experimentally proven to deduce the best one, with the aim of sorting the battery cells and finding a relationship between the battery's dynamic parameters, the first method is based on battery capacity and internal resistance in AC "ACIR", where the cell capacity is found with different values of charging and discharging constant current, and the internal resistance is measured at a low alternating current with a constant frequency of 1 kHz in various states of charge, the second method is the best method for modelling battery dynamics by applying an alternating voltage with several frequencies to the battery terminals, then deducing the second-order circuit parameters using the Hough transform algorithm or impedance processing software, the third method is based on the voltage curve at the battery terminals during a charge cycle (Constant Current - Constant Voltage)/discharge cycle (Constant Current), and then deduces the parameters needed to characterize the battery's dynamics, the fourth method is presented with the PNGV model, deducing its parameters with Hybrid Pulse Power Characterization HPPC, the last method is based on the thermal behaviour of the battery, by calculating the surface temperature of the cells during multiple charge/discharge cycles with different current values.

---

[*] Corresponding author: yassine.derouech.doc20@ensem.ac.ma

Reference [2] presents a comparison between five models; “the Combined Model” is composed of an internal resistor, a polarization resistor and various constants to adjust the terminal voltage to the true voltage, “the Simple Model” is made up of a voltage that depends on the battery's state of charge and two different resistors, one for charging and the other for discharging, “the Zero-State Hysteresis Model” is presented by a voltage that depends on the state of charge, an internal resistance and a term that describe the hysteresis cycle, “the One-State Hysteresis” model is an improvement on the “the Zero-State Hysteresis Model”, where a hysteresis state variable is added to the state model, and finally “the Enhanced Self-Correcting” model, where by adding the capacitive effect seen in batteries during a charge/discharge current pulse, the cell voltage is delayed until it reaches its final value.

In order to estimate the battery's state of charge with a developed, easy-to-implement and efficient method, we need to choose a suitable model. The Enhanced Self-Correcting model presents remarkable results and minimizes error in state of charge estimation [3]. Many articles discuss various methods of estimating the state of charge, citing methods based on Coulomb counting [4-6] have the major disadvantage of accumulating error due to the initial state of charge, giving a divergent result. Other methods based on observers and Kalman Filters [7-11], the comparison in this study between EKF and IEKF shows that we can have a method for estimating the state of charge that is efficient and simple to implement compared with other methods, and finally methods that focuses on artificial intelligence [12-14] that require a large amount of data with good quality.

2 System modelling

The circuit used to model the battery is one of the best models describing battery operation, the Enhanced Self-Correcting model, shown in the following figure:

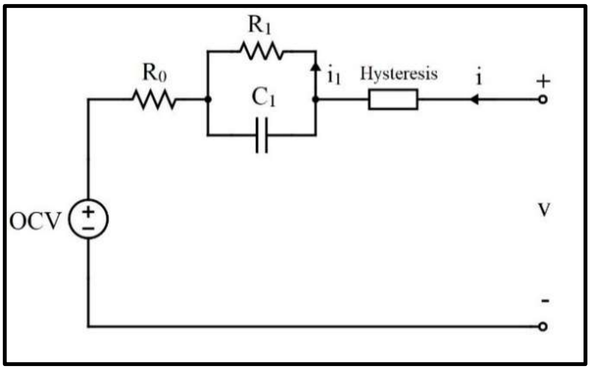

Fig. 1. Equivalent circuit of ESC model.

The voltage measured in discrete time at instant $k \in Z$ is expressed by the following relationship:

$$v_k=OCV(SOC_k)+R_0 i_k+R_1 i_{1_k}+Hysteresis_k \qquad (1)$$

With i_k is the line current, i_{1_k} the current in resistor R_1, C_1 is the condenser capacitance, $OCV(SOC_k)$ is the open-circuit voltage at the battery terminals, $Hysteresis_k$ presents the hysteresis cycle in the battery. R_0, R_1 and $OCV(SOC_k)$ are internal parameters and can be expressed as a function of the state of charge, external cell temperature, battery life and many other parameters that affect battery operation more or less, the hysteresis cycle is expressed by the following equation [2]:

$$\begin{cases} Hysteresis_k = c_0 h_k + c_1 m_k \\ h_k = \begin{cases} sign(i_k), |i_k| > 0 \\ h_{k-1}, \ otherwise \end{cases} \end{cases} \tag{2}$$

Where c_0 and c_1 are constants, h_k represents battery charge/discharge and m_k denotes slow cycle variation.

Later on, we'll need the state representation of the system, the state vector is composed by $\mathbf{x_k}=[SOC_k, i_{1_k}, m_k]^T \in \mathrm{R}^3$, the input vector is $\mathbf{e_k}=[i_k, sign(i_k)]^T \in \mathrm{R}^2$ and the output $s_k=v_k \in \mathrm{R}$. The discrete state representation of the system is presented by the following equation [3]:

$$\begin{cases} \mathbf{x_k} = \begin{bmatrix} SOC_k \\ i_{1_k} \\ m_k \end{bmatrix} = \mathrm{g}(\mathbf{x_{k-1}}, \mathbf{e_k}) = \begin{bmatrix} SOC_{k-1} + \delta \frac{\Delta t}{C} i_k \\ e^{\frac{-\Delta t}{R_1 C_1}} i_{1_{k-1}} + \left(1 - e^{\frac{-\Delta t}{R_1 C_1}}\right) i_k \\ e^{-\left|\frac{\Delta t \delta \varepsilon i_k}{C}\right|} m_{k-1} + \left(e^{-\left|\frac{\Delta t \delta \varepsilon i_k}{C}\right|} - 1\right) sign(i_k) \end{bmatrix} \\ s_k = \mathrm{f}(\mathbf{x_k}, \mathbf{e_k}) = OCV(SOC_k) + R_1 i_{1_k} + c_1 m_k + R_0 i_k + c_0 sign(i_k) \end{cases} \tag{3}$$

Where δ and ε are parameters characterizing the battery and C represents the battery capacity.

3 State of charge estimation

The major presence of batteries in recent years has meant that battery management systems have become increasingly important, precisely in terms of estimating the state of charge, this study compares two methods for estimating the state of charge with Kalman filters; Extended Kalman Filter and Invariant Extended Kalman Filter. To apply these two methods, we need to reformulate the system state representation and the filter gains to find the estimated values, the state representation becomes:

$$\begin{cases} \mathbf{x_k} = \mathrm{g}(\mathbf{x_{k-1}}, \mathbf{e_k}, \omega_k) = \mathrm{F}_{k-1} \mathbf{x_{k-1}} + \mathrm{G}_{k-1} \mathbf{e_k} + \omega_k \\ s_k = \mathrm{f}(\mathbf{x_k}, \mathbf{e_k}, \nu_k) = \mathrm{H}_k \mathbf{x_k} + \mathrm{N}_k \mathbf{u_k} + \nu_k \end{cases} \tag{4}$$

With $\mathrm{Q}_k = \mathrm{Cov}(\omega_k \in \mathrm{R}^3) = \mathrm{E}[\omega_k \omega_k^T] \in \mathrm{R}^{3\times3}$ and $\mathrm{R}_k = \mathrm{Cov}(\nu_k \in \mathrm{R}) = \mathrm{E}[\nu_k \nu_k^T] \in \mathrm{R}^{1\times1}$ are the covariance matrices, ω_k and ν_k are the unknown random Gaussian noises, in order to make the prediction and correction of the estimated state, the state representation becomes :

$$\begin{cases} \mathbf{x_k} = \begin{bmatrix} 1 & 0 & 0 \\ 0 & e^{\frac{-\Delta t}{R_1 C_1}} & 0 \\ 0 & 0 & e^{-\left|\frac{\Delta t \delta \varepsilon i_k}{C}\right|} \end{bmatrix} \mathbf{x_{k-1}} + \begin{bmatrix} \delta \frac{\Delta t}{C} & 0 \\ 1 - e^{\frac{-\Delta t}{R_1 C_1}} & 0 \\ 0 & e^{-\left|\frac{\Delta t \delta \varepsilon i_k}{C}\right|} - 1 \end{bmatrix} \mathbf{e_k} + \omega_k \\ s_k = [dOCV(SOC_k) \quad R_1 \quad c_1] \mathbf{x_k} + [R_0 \quad c_0] \mathbf{e_k} + v_k \end{cases} \tag{5}$$

The main advantage of the Kalman Filter is the correction of the estimated or predicted value of the state vector, the first step is the propagation and is done by calculating the estimated vector and the covariance of the estimation error with the following equations in the case of the two filter types EKF and IEKF, where $\bar{\bar{E}}_{k-1}$ is the corrected covariance at time 'k-1':

$$\bar{\mathbf{x}}_{\mathbf{k}}=F_{k-1}\bar{\bar{\mathbf{x}}}_{\mathbf{k-1}}+G_{k-1}\mathbf{e}_{\mathbf{k-1}} \qquad (6)$$

$$\bar{E}_k=F_{k-1}\bar{\bar{E}}_{k-1}F_{k-1}^T+G_{k-1}Q_{k-1}G_{k-1}^T \qquad (7)$$

And for correction of the estimated state vector and covariance, we use the following equations for EKF:

$$M_k=\bar{E}_kH_k^T\left(H_k\bar{E}_kH_k^T+N_kR_kN_k^T\right)^{-1} \qquad (8)$$

$$\bar{\bar{\mathbf{x}}}_{\mathbf{k}}=\bar{\mathbf{x}}_{\mathbf{k}}+M_k[s_k-h(\bar{x}_k)] \qquad (9)$$

$$\bar{\bar{E}}_k=(I_n-M_kH_k)\bar{E}_k \qquad (10)$$

The only difference between EKF and IEKF in the correction is the equation of the corrected state vector:

$$\bar{\bar{\mathbf{x}}}_{\mathbf{k}}=\exp\left(\mathrm{diag}[\mathrm{sign}(\bar{\mathbf{x}}_{\mathbf{k}})]\mathrm{diag}\{G_k[s_k-h(\bar{x}_k)]\}\right)\bar{\mathbf{x}}_{\mathbf{k}} \qquad (11)$$

4 The simulation and results:

By using MATLAB/Simulink/Simscape, we choose a battery based on a lookup table to implement the simulation, using the previous equations we make a model with Simulink blocks to create the two types of Kalman filter, the following figure shows the block diagram of the filters:

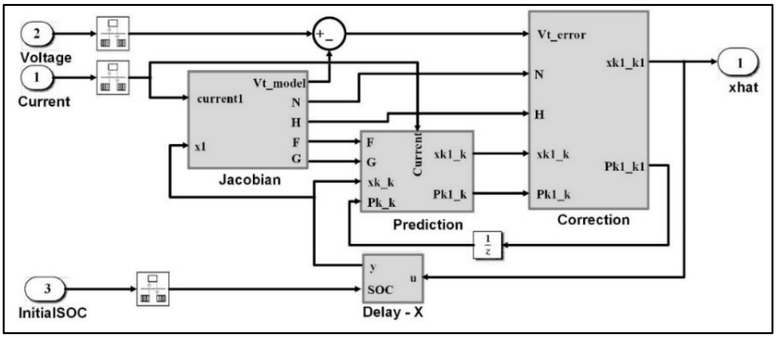

Fig. 2. The block diagram of EKF and IEKF under MATLAB/Simulink.

The state of charge is estimated using the two filters EKF and IEKF, with constant charge and random discharge, and depth of charge/discharge equal to 60%, where we start charging the battery when the state of charge reaches 20% and begin the discharge cycle when 80% is reached. The following figure shows the state of charge estimated by EKF and the error found:

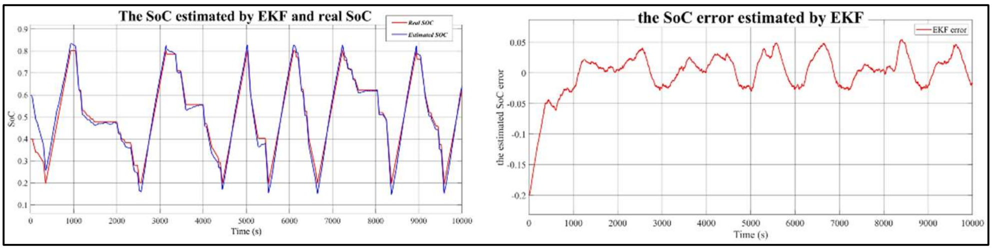

Fig. 3. The state of charge estimated by EKF and the error.

Even with an incorrect initial value, the estimated state of charge tends towards the true value, and after several charges/discharges of the battery the error varies between 5.492% and -3.039%. The following figure shows the estimated state of charge and the error found by IEKF:

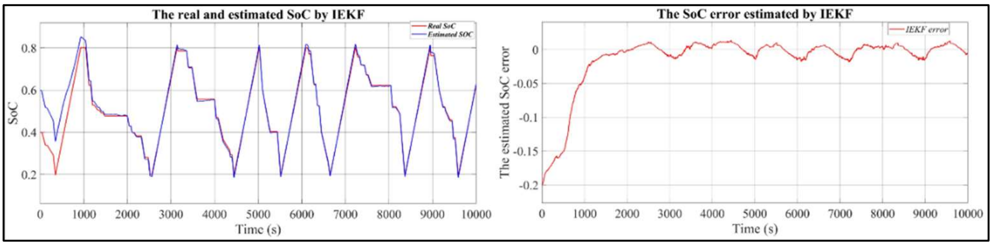

Fig. 4. The state of charge estimated by IEKF and the error.

The state of charge estimated by IEKF tends towards the real value, and after a few charges/discharges of the battery the error found varies between 1.39% and -1.84%. We can see that IEKF performs better than EKF, and is more stable but more or less slow, which is beneficial in terms of results, IEKF is more stable even to random changes in discharge current, and has a limited error that is due to the model chosen as well as the charge estimation method.

5 Conclusion:

In conclusion, the proposed model gives good results for both the EKF and IEKF Kalman filters, as both are efficient in non-linear systems which is the case here, a simple and efficient model. The comparison between these two principles of state of charge estimation proves that IEKF is more accurate and stable, and with a simple change in the calculation algorithm we can get much better results, which is advantageous, in terms of either calculation complexity or the results obtained.

The performance of the chosen model and filters needs to be approved by experience, since the MATLAB/Simulink/Simscape model chosen does not take into account many phenomena, such as the variation of battery parameters (OCV, battery resistances, hysteresis cycle, etc.) as a function of temperature and state of charge, it may generate more ideas to improve the efficiency of the proposed algorithms for estimating the state of charge and achieving the main objective which is the high performance function of the hemodialysis system.

Estimating the state of charge accurately and specifically for this device ensures efficient system operation, since the micro device's main power supply is the battery, thus increasing battery life while avoiding abnormal battery operation (overcharging/undercharging).

References

1. X. Li, T. Wang, L. Pei, C. Zhu, and B. Xu, "A comparative study of sorting methods for lithium-ion batteries," in *2014 IEEE Conference and Expo Transportation Electrification Asia-Pacific (ITEC Asia-Pacific)*, (2014): IEEE, pp. 1-6.
2. G. L. Plett, "Extended Kalman filtering for battery management systems of LiPB-based HEV battery packs: Part 2. Modeling and identification," *Journal of Power Sources,* vol. 134, no. 2, pp. 262-276, 2004/08/12/ (2004), doi: https://doi.org/10.1016/j.jpowsour.2004.02.032.
3. A. Wadi, M. Abdel-Hafez, H. A. Hashim, and A. A. Hussein, "An invariant method for electric vehicle battery state-of-charge estimation under dynamic drive cycles," *IEEE Access,* vol. 11, pp. 8663-8673, (2023).
4. M. Murnane and A. Ghazel, "A closer look at state of charge (SOC) and state of health (SOH) estimation techniques for batteries," *Analog devices,* vol. 2, pp. 426-436, (2017).
5. K. S. Ng, C.-S. Moo, Y.-P. Chen, and Y.-C. Hsieh, "Enhanced coulomb counting method for estimating state-of-charge and state-of-health of lithium-ion batteries," *Applied energy,* vol. 86, no. 9, pp. 1506-1511, (2009).
6. M. Verbrugge and E. Tate, "Adaptive state of charge algorithm for nickel metal hydride batteries including hysteresis phenomena," *Journal of Power Sources,* vol. 126, no. 1-2, pp. 236-249, (2004).
7. D. Di Domenico, A. Stefanopoulou, and G. Fiengo, "Lithium-ion battery state of charge and critical surface charge estimation using an electrochemical model-based extended Kalman filter," (2010).
8. C. Jiang, A. Taylor, C. Duan, and K. Bai, "Extended Kalman Filter based battery state of charge (SOC) estimation for electric vehicles," in *2013 IEEE Transportation Electrification Conference and Expo (ITEC)*, (2013): IEEE, pp. 1-5.
9. J. Meng, G. Luo, and F. Gao, "Lithium polymer battery state-of-charge estimation based on adaptive unscented Kalman filter and support vector machine," *IEEE Transactions on Power Electronics,* vol. 31, no. 3, pp. 2226-2238, (2015).
10. A. Wadi, M. F. Abdel-Hafez, and A. A. Hussein, "Mitigating the effect of noise uncertainty on the online state-of-charge estimation of Li-ion battery cells," *IEEE Transactions on Vehicular Technology,* vol. 68, no. 9, pp. 8593-8600, (2019).
11. E. A. Wan and R. Van Der Merwe, "The unscented Kalman filter for nonlinear estimation," in *Proceedings of the IEEE 2000 adaptive systems for signal processing, communications, and control symposium (Cat. No. 00EX373)*, (2000): Ieee, pp. 153-158.
12. W.-Y. Chang, "Estimation of the state of charge for a LFP battery using a hybrid method that combines a RBF neural network, an OLS algorithm and AGA," *International Journal of Electrical Power & Energy Systems,* vol. 53, pp. 603-611, (2013).
13. L. Kang, X. Zhao, and J. Ma, "A new neural network model for the state-of-charge estimation in the battery degradation process," *Applied Energy,* vol. 121, pp. 20-27, (2014).
14. H. Sheng and J. Xiao, "Electric vehicle state of charge estimation: Nonlinear correlation and fuzzy support vector machine," *Journal of Power sources,* vol. 281, pp. 131-137, (2015).