A comparative study of ANN and Kalman Filtering-based observer for SOC estimation

H Ben Sassi¹, F Errahimi¹, N Es-Sbai¹ and C Alaoui².

¹Laboratory of Renewable Energies and Intelligent Systems (LERSI), Faculty of Sciences and Technology, Sidi Mohamed Ben Abdellah University Fez, Box 2202, Fez, Morocco
²University EUROMED, Fez, Morocco

E-mail: hicham.lbensassi@gmail.com

Abstract. Electrical Vehicle Batteries (EVB) study has gained a lot of interest in recent years, with the aim of better managing their use, due to the high changes in the electric vehicle dynamics and operational modes, which could cause severe damages to the battery if not properly managed. Recently lithium-ion (Li-ion) batteries have become the most suitable technology for electric vehicles, because of their interesting features such as a relatively long cycle life, lighter weight and high energy density. However, there is a lot of work that is still needed to be done in order to ensure safe operating lithium-ion batteries, starting with their internal status monitoring, cell balancing within a battery pack and thermal management. In this paper, a comparative study of two different methods for state of charge estimation techniques are presented: Kalman filtering observers and artificial neural network based observers. The respective results are compared in terms of accuracy, implementation requirement, and overall performances.

1. Introduction

Nowadays, electric mobility is starting to define society and is becoming more and more essential to daily activities. Safe and durable battery is of a great significance for this type of mobility, hence the increasing interest of research activity oriented to battery studies in order to ensure safe operating mode and to control the battery in case of any abnormal functioning conditions that could damage the battery, especially in the case of lithium-ion technology. Li-ion has presented itself as the most suitable existing technology for electrical storage, but still suffers from safety issues. An overcharge or overdischarge of the battery could lead to overheating and sometimes causes fire runway, which is why state of charge monitoring is a necessity. However, being seen that the state of charge is an unmeasurable variable, several approaches and algorithms have been proposed and implemented for lithium-ion batteries SOC estimation [1-5]. Out of these approaches, two have stood out due to their high performances, and are widely implemented especially in applications that require high precision. The first one is Artificial Neural Network (ANN) which is a data-oriented approach, it doesn’t require a detailed physical knowledge of Li-ion batteries (internal resistance, capacity…). This method is based on the black box battery models which describe the relationship between the SOC and the factors that influence its value. The implementation of this strategy was realized in [6] on a field-programmable gate away (FPGA) platform for speed estimation of the two-mass drive System. The second most popular method is Kalman filters which are online-based and sometimes considered as the optimal mean to predict and correct time-varying “state” of a dynamic system repeated as the
system operates [4]. A detailed extended kalman filter (EKF) hardware/software implementations on Altera FPGA is proposed in [7] for robot mapping applications. The EKF algorithm was coded in C and then implemented on Altera Nios II FPGA. In [8], a detailed design and implementation of a SOC observer based on EKF on FPGA platform was presented, comparing the performances of an FPGA implemented EKF and those of the same observer implemented on Matlab/Simulink environment. In [9], a combination of both methods was investigated for higher accuracy. In this paper, a comparative investigation of these two approaches is presented in terms of their performances.

The present paper is organized as follows: the second paragraph deals with the design of both strategies. Simulation results and discussion are presented in the third paragraph. This manuscript ends with a conclusion.

2. SOC estimation

2.1 Kalman filters

Kalman filters are online and sometimes considered as the optimal mean to predict and correct time-varying system in a way that minimizes the mean of the squared error. They are model based observers that require a prior knowledge of the battery’s model and accurate internal parameters identification. Hence in this paper the battery is modeled by using a shunt resistor \( R_0 \), an RC branch and open circuit voltage source \( U_{oc} \). The model is presented in figure 1. The internal parameters of the model, which were identified using Levenberg Marquardt nonlinear least square algorithm are given in Table 1. Equations (1) and (2) are the state space representation of the battery model. In equation (1) the state variables are the state of charge and the voltage across the RC branch: \( X=[SOC,V_{RC}]^T \). \( T \) is the sampling time, \( I_{b_k} \) represents the current across the battery terminals, while \( w_k \) and \( C_b \) are respectively the system noise covariance matrix and the nominal capacity of the battery. In equation (2) \( Y_k \) is the output voltage of the battery, whereas \( v_k \) represents the measurement noise covariance matrix.

\[
X_{k+1} = f(X_k, I_{b_k}) = \begin{bmatrix} 1 & 0 \\ 0 & e^{-\frac{T}{RC}} \end{bmatrix} X_k + \begin{bmatrix} \frac{-T}{C_b} \\ R(1-e^{-\frac{T}{RC}}) \end{bmatrix} I_{b_k} + w_k \tag{1}
\]

\[
Y_k = h(X_k, I_{b_k}) = U_{oc}(SOC) - X(2)_k - R_0 I_{b_k} + v_k \tag{2}
\]

![Figure 1: Lithium-ion battery model.](image)

Table 1. Battery internal parameters.

| Parameter | \( R_0 (\Omega) \) | \( C (F) \) | \( R (\Omega) \) |
|-----------|-----------------|----------|--------------|
| Value     | 0.0016          | 24000    | 0.0024       |

In literature there exists a variety of kalman filters, from classical linear Kalman filter to extended Kalman filter [4] and sigma point Kalman filters (SPKF) [10]. They all share the same principle and only differ in linearization process. In this paper, the performances of the unscented Kalman filter (UKF) are presented, since the state of charge estimation is a nonlinear problem and UKF is nonlinear Kalman filter which is based on the unscented transformation as linearization method. UKF algorithm is presented below, for more background theory refer to reference [11].

Step 1. Initialization
\[ Q_k = E(w_k w_k^T); \quad R_k = E(v_k v_k^T); \quad E(w_k v_k^T) = 0 \]  
\[ P_0 = E[(x_0 - \bar{x}_0)(x_0 - \bar{x}_0)^T] \]  
\[ \bar{x}_0 = E(x_0) \]  
\[ (3) \]  
\[ (4) \]  
\[ (5) \]

Where \( Q_k \) and \( R_k \) are diagonal matrices that represent respectively the process noise \( (w_k) \) covariance and the observation noise \( (v_k) \) covariance, \( P_0 \) is the state covariance matrix and \( \bar{x}_0 \) represents the mean of the state variable.

**Step 2. Compute sigma points**

A set of weighted sigma points are deterministically computed, as shown in the following equation:

\[ X_{k-1} = \left[ \bar{x}_{k-1}, \bar{x}_{k-1} + \left( \sqrt{(n + \lambda)\mathbf{P}_{x,k|k}^{-1}} \right), \bar{x}_{k|k-1} - \left( \sqrt{(n + \lambda)\mathbf{P}_{x,k|k}^{-1}} \right) \right] \]  
\[ (6) \]

Where \( \lambda \) is a scaling parameter that represents how far the sigma points are separated from the mean and \( n \) is the system dimension, in our case \( n=2 \). For more background theory refer to reference [8].

**Step 3. Prediction phase**

1) Propagating sigma points through the system/state function \( f(x, i_{bk}) \):

\[ X_{k|k-1}^{(i)} = f(X_{k-1}^{(i)}, i_{bk}) \]  
\[ (7) \]

2) Calculating the propagated mean and covariance:

\[ \bar{x}_{k|k-1} = \sum_{i=0}^{2n} W_m X_{k|k-1}^{(i)} \]  
\[ P_{x,k|k-1} = \sum_{i=0}^{2n} W_c[X_{k|k-1}^{(i)} - \bar{x}_{k|k-1}][X_{k|k-1}^{(i)} - \bar{x}_{k|k-1}]^T + Q_{k-1} \]  
\[ (8) \]  
\[ (9) \]

Where \( i \) stands for the number of sigma points, while \( W_m \) and \( W_c \) are respectively mean calculation and covariance calculation weights of sigma points.

3) Computing the new sigma points matrix using \( \bar{x}_{k|k-1} \) and \( P_{x,k|k-1}^- \):

\[ x_{k|k-1} = \left[ \bar{x}_{k|k-1}, \bar{x}_{k|k-1} + \left( \sqrt{(n + \lambda)\mathbf{P}_{x,k|k}^-} \right), \bar{x}_{k|k-1} - \left( \sqrt{(n + \lambda)\mathbf{P}_{x,k|k}^-} \right) \right] \]  
\[ (10) \]

4) Propagating the computed sigma points through the output/state function \( h(x, i_{bk}) \):

\[ Y_{k|k-1}^{(i)} = h(x_{k|k-1}^{(i)}, i_{bk}) \]  
\[ (11) \]

5) Calculating the mean of the output variable:

\[ \bar{y}_{k|k-1} = \sum_{i=0}^{2n} W_m Y_{k|k-1}^{(i)} \]  
\[ \text{for } i = 1 \ldots 2n \]  
\[ (12) \]

**Step 4. Measurement update**

1) Calculating the covariance of the measurement vector and the cross covariance respectively.

\[ P_{y,k} = \sum_{i=0}^{2n} W_c[Y_{k|k-1}^{(i)} - \bar{y}_{k|k-1}][Y_{k|k-1}^{(i)} - \bar{y}_{k|k-1}]^T \]  
\[ (13) \]  
\[ P_{xy,k} = \sum_{i=0}^{2n} W_c[x_{k|k-1}^{(i)} - \bar{x}_{k|k-1}][Y_{k|k-1}^{(i)} - \bar{y}_{k|k-1}]^T \]  
\[ (14) \]

2) Calculating the Kalman gain, in order to correct the estimations:

\[ K_k = P_{xy,k} P_{y,k}^{-1} \]  
\[ (15) \]

3) Update the estimated state with Kalman gain:

\[ \hat{x}_k = \hat{x}_{k|k-1} + K_k(y_k - \bar{y}_k) \]  
\[ (16) \]

4) Update the propagated state covariance using kalman gain:

\[ P_k = P_{x,k|k-1} - K_k P_{y,k} K_k^T \]  
\[ (17) \]

**2.2 Artificial neural network**

An ANN comprises a set of interconnected neurons that mimic the information processing of the human brain. It is very accurate and powerful tool that can model almost any nonlinear system if it is trained correctly. In literature there are several types of NN, and the choice of one over the other depends on the complexity of the system and the desired applications. In this paper, multilayer feed-
forward neural network (FFNN) is chosen due to its high performance in estimation problems. The FFNN is composed of three types of layers: an input layer with nodes to represent the input variables, hidden layers to model the nonlinearity between the system input and output, and an output layer to represent the system output variables. Based on an amperic choice after several tests and simulations, the chosen neural network is composed of 3 neurons in the first layer and 6 neurons in the hidden layers. The network has as input the voltage across the battery terminals, the discharge and the charge current, and temperature. The output of the ANN is the state of charge. Figure 2 show the structure of the chosen ANN.

The ANN is trained offline using data collected from charging and discharging process of 2Ah lithium-ion battery in Matlab/Simulink environment. The battery was charged with fixed current profile until it has reached 61%, and then switched to fixed voltage profile and the current decreases exponentially until the battery is fully charged. For the discharging process the battery was fully discharged with variable amplitude current profile. A sample of the current profile applied to the battery is presented in Fig. 3. Temperature variation was taking into consideration during all the charging/discharging process, because it affects the internal parameters of the battery such as the internal resistance and the SOC, as demonstrated in reference [11].

![Figure 2: Structure of the chosen multilayer feed-forward neural network.](image)

### 3. Simulation and results discussion

Following the design processes, both the UKF based observer and the ANN are simulated and tested under the same current profile presented in Figure 3. Figures 4 and 5 represent simulation results of the UKF, and Figures 6 and 7 are those of the ANN.

![Figure 3: Current profile applied to both observers.](image)

![Figure 4: UKF estimated SOC vs real SOC.](image)
From the above simulation results, it is clear that both strategies perform well in SOC estimation, although the ANN, which has maximal error value less than 1.8% and average error less than 0.5%, is slightly more accurate than the UKF, which has maximal error value less than 5% and average error less than 1%. This slight advantage of the ANN over UKF in terms of precision is due to modeling errors in the design process of the UKF and internal parameters uncertainty. On the other hand, the UKF has the advantage of being more accurate than the ANN for functioning condition outside the range covered by the training data. Once the battery is modeled and the internal parameters are accurately determined, Kalman filters produce more accurate estimations for any functioning condition.

From design point of view, both strategies require certain amount of data. In the case of the ANN, the data is required to train the network, while for Kalman filters, it is used to identify the battery’s internal parameters. Nevertheless, the amount of data required for ANN is much more important (350000 sample of each input data: current voltage and temperature, in addition to the state of charge, compared to 3000 in the case of UKF) in order to cover the real-life loading conditions as much as
possible in terms of SOC span, which is time consuming and extremely difficult to do. The design of the ANN observer is much easier than the UKF, which requires an accurate model and internal parameters identification, in addition to an accurate tuning of its covariance matrices [13–14].

From implementation point of view both strategies have been implemented in several works [8, 15, 16, 17]. The UKF requires more computing power [8,15], due to the complexity of the equations, and less memory than the ANN, which requires a huge memory to store the training data [16, 6].

4. Conclusion

In this paper, a comparative study of Kalman filters and the artificial neural network was carried out, from design challenges to estimation accuracy and ending with resources required for implementation. From the obtained results, it can be concluded that both strategies are competitive in terms of precision, and the choice of one over the other depends on the available resources; if sufficient data to cover a wide operating range is available, together with a powerful platform for implementation, the ANN is powerful and recommended, otherwise, Kalman filters are preferable, due to their capability of operating with less data and under unpredicted scenarios.

5. References

[1] Hannan M A, Lipu M S H, Hussain A and Mohamed A 2017 A review of lithium-ion battery state of charge estimation and management system in electric vehicle applications: Challenges and recommendations Renewable and Sustainable Energy Reviews 78 834.
[2] Ng K S, Moo C S, Chen Y P and Hsieh Y C September 2009 Enhanced coulomb counting method for estimating state-of-charge and state-of-health of lithium-ion batteries Applied Energy 86 1506-11.
[3] Chen X, Shen W, Dai M, Cao Z, Jin J, and Kapoor A April 2016 Robust adaptive sliding mode observer using RBF neural network for Lithium-ion battery state of charge estimation in electric vehicles IEEE Transactions on Vehicular Technology 65 1936 – 47.
[4] Plett G L 2004 Extended Kalman filtering for battery management systems of LiPB-based HEV battery packs part 3. State and parameter estimation Journal of Power Sources 134 277–292.
[5] Burgos C, Sáez D, Orchard M E and Cárdenas R 2015 fuzzy modelling for the state-of-charge estimation of lead-acid Batteries” Journal of Power Sources 274 355-366.
[6] Orlowska K T, and Kaminski M August 2011 FPGA implementation of the Multilayer Neural Network for the speed estimation of the two-mass drive system” IEEE transactions on industrial informatics 7 436 – 445.
[7] Bonato V, Peron R, Wolf F D, De Holanda J A M, Marques E and Cardoso J M P 2007 An FPGA implementation for a Kalman Filter with application to mobile robotics International Symposium on Industrial Systems. SIES ’07 IEEE.
[8] Otero N, Eichi R H, Rodriguez Andina J J and Chow M Y July 3-5, 2014 FPGA implementation of an observer for state of charge estimation of lithium-Polymer Batteries International Conference on Mechatronics and Control ICMC Jinzhou China.
[9] He W, Williard N, Chen C and Pecht M 2014 State of charge estimation for Li-ion batteries using neural network modeling and unscented Kalman filter-based error cancellation Internationnal Journal of Electrical Power and Energy Systems IJEP 62 783–791.
[10] Plett G L 2006 Sigma-point Kalman filtering for battery management systems of LiPB-based HEV battery packs: Part 2: simultaneous state and parameter estimation Journal of Power Sources 161 1369–84.
[11] Gao L, Liu S, and Dougal R A september 2002 Dynamic Lithium-Ion Battery Model for System Simulation IEEE transactions on components and packaging technologies, 25 495 - 505.
[12] Julier S. et Uhlmann J, 1997 New extension of the Kalman filter to nonlinear systems, The 11th International Symposium on Aerospace/Defence Sensing, Simulation and Controls, Orlando, pp. 182-193.
[13] Leonardo A S and Da Cruz J J june 2016 Automatic tuning of the unscented Kalman filter and the blind tricyclist problem IEEE control systems magazine 36 70 – 85.
[14] Sun F, Hu X, Zou Y and Li S 2011 Adaptive unscented Kalman filtering for state of charge estimation of a lithium-ion battery for electric vehicles *Energy* **36** 3531-40.

[15] Dhaouadi R, Mohan N and Norum L July 1991 Design and Implementation of an Extended Kalman Filter for the State Estimation of a Permanent Magnet Synchronous Motor *IEEE transactions on power electronics* **6** 491 – 497.

[16] Botros N M and Abdul-Aziz M December 1994 Hardware implementation of an artificial neural network using field programmable gate arrays (FPGA’s) *IEEE transactions on industrial electronics* **41** 665 – 667.