Battery State of Charge and State of Health Estimation for VRLA Batteries Using Kalman Filter and Neural Networks

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Abstract—**Determination of state of charge (SOC) and state of health (SOH) in today's world becomes an increasingly important issue in all the applications that include a battery. In fact, estimation of the SOC and SOH is a fundamental need for the battery, which is the most important energy storage in Hybrid Electric Vehicles (HEVs), smart grid systems, drones, UPS and so on. Regarding those applications, the estimation algorithms are expected to be precise and easy to implement. This paper presents an online method for the estimation of the SOC and SOH of Valve-Regulated Lead Acid (VRLA) batteries. The proposed method uses the well-known Kalman Filter (KF), and Neural Networks (NNs) and for SOH estimation uses Augmented Kalman Filter (AKF). All of the simulations have been done with MATLAB software. The NN is trained offline using the data collected from the battery discharging process. A generic cell model is used, and the underlying dynamic behavior of the model has used two capacitors (bulk and surface) and three resistors (terminal, surface, and end), where the SOC determined from the voltage represents the bulk capacitor. The aim of this work is to compare the performance of conventional integration-based SOC estimation methods with a mixed algorithm. Moreover, by containing the effect of temperature, the final result becomes more accurate.**

Keywords-Kalman filter; neural networks; state-of-charge; state-of-health; VRLA battery

I. INTRODUCTION

Nowadays fluctuations in fuel prices and environmentalists claim about pollution encouraged scientists toward energy storage systems. High efficiency and low contamination are the most important factors for energy storage systems, and the battery is one of them. Lead-acid batteries, Ni-cd batteries, Ni-MH batteries, and Li-ion batteries are the most common types of batteries in current industry [1]. Electrochemical batteries are distinguished as primary and secondary, depending on their ability of being electrically recharged. Therefore, the primary batteries are non-rechargeable, whereas the secondary ones can be recharged. The primaries often have higher energy than the secondary batteries, as a result of limitations on materials that are used in order to make the battery rechargeable. Between all kinds of the batteries for telecommunications applications, VRLA batteries are the most suitable selection. So many endeavors to modeling secondary batteries have been done and many papers published by knowledge seekers. The fundamental distinction among them is the method of presentation. To that extent, this can be categorized to three basic classes: electrochemical models, mathematical models and electrical models, and the third one is the most effective for circuit analysis [2]. In some papers, readers encounter many kinds of proposed equivalent circuit that used for estimation the battery parameters or SOC [2]-[5].

Sealed lead-acid batteries constitute an indispensable backup power supply for interruption-free telecommunication power supplies. In case of main AC failure, in urban or remote areas, they have to supply the telecommunication equipment with energy as long as the failure lasts. Therefore, a continuous, accurate, online indication of the battery state-of-charge and also estimation of their available capacity are considerably important for continuity of service [6]. This is specially in rural areas where power system is weak and because of the long distance, sometimes it is difficult to service them. In the past, human resources check acid density every month, whereas with a good estimation system better result will be achieved, and some financial matters will decrease too.

A battery is an electrochemical structure that can make and store energy. The energy capability of a battery depends on both constructional parameters such as material composition and geometry, and operating parameters such as discharge-charge rate, age, end voltage, temperature [7]. The capacity of battery is a parameter which is used to measure the amount of charge that can be stored in fully charge battery. During discharge of the battery, the amount of usable charge is decreasing. The parameter which describes the phenomenon is state of charge and it is defined by:

$$SOC = \frac{Q_{act}}{Q_{\max}} \times 100\% \tag{1}$$

where Q_{act} is the actual amount of stored charge at the moment, and Q_{max} is the charge of fully charged battery.

II. STATE OF CHARGE ESTIMATION METHODS

Firstly, it is reasonable to deliberate conventional methods and analyze pros and cons of them. Several types of

SOC estimation methods are used from the past till now that can be divided into several categories. [8] Classified all kinds of them in detail. So, the mentioned methods are briefly listed afterwards.

A. Voltage Based Methods

There is a significant coupling between the Open Circuit Voltage (OCV) of battery and SOC. Open-voltage of battery decreases with SOC, but the real value of SOC can be estimated only when the terminal voltage of battery takes approximately 3 hours [8]. Moreover, the voltage drop must be compensated during the discharge or charge of battery.

Methods based on battery voltage are simple and are widely used for example in cellphones, but for more sophisticated application the voltage restoration must be compensated to achieve high accuracy [8]. Also, the accuracy can be improved by adding parameters such as temperature, power rate, but the complexity and training data to describe the influence of those parameters rapidly grow. Furthermore, these parameters are changing by the effect of aging.

B. Book Keeping Methods

These methods are based on the fact that battery has final capacity of charge. State of charge can be achieved by counting the amount of charge during discharging or charging. The most common method is Coulomb Counting (CC). It is also the most common SOC method used in the world. It needs also initial value of SOC. Then, the actual value of SOC is described by formula [8]:

$$SOC_T = SOC_{t_0} \pm \int_{t_0}^{T} \frac{\eta I(\tau)}{Q} d\tau \tag{2}$$

where SOC_{t0} is the initial SOC (can be obtained via fully restored voltage of battery), SOC_T is the actualized SOC, η is the Coulomb efficiency, Q is the battery capacity. These methods have some major dark sides. First of all, there is a noticeable error which accumulates during operation. Second, they cannot estimate accurately when the charge and discharge is dynamically occurred. Last but not least, the methods essentially need precise measurement.

C. Impedance Methods

These methods are according to measurement of impedance of battery which is obtained by injection voltage or current pulses of variable frequency. One of these methods is impedance spectroscopy.

Impedance spectroscopy is often used in chemical process for determination of concentrations of chemical compounds. There have been many papers relating the low frequency AC impedance of cell with the cell's SOC. The main disadvantages of impedance spectroscopy for SOC estimation are that it is very temperature sensitive. Also, there is a strong influence of cell aging on the measurement of impedance could be strongly correlated. The difficulty of this correlation is to split out the effect of SOC from the effect of SOH [9].

D. Battery Model Based

Many tests have been performed on all types of battery ever since researchers started investigating the issue. What happens in a battery is an electrochemical phenomenon; thus, most models either are based on the electrochemistry of it or use equivalent circuits that describe the electrical behavior of a battery.

E. Adaptive Methods

More recently, adaptive methods of SOC estimation have been explored. So many methods exist, among these which have the ability to self-learn battery behavior belong to neural networks, fuzzy logic, Support Vector Machine (SVM), Kalman filter and so on [9]-[13].

Kalman filtering, aka Linear Quadratic Estimation (LQE), is an algorithm based on Markov chain that uses series of measurements observed over time. Although the mentioned filter faces inaccuracies in model and statistical noise, estimates unknown variables or states of system more accurate and precise than those based on a single measurement alone. The filter with a recursive algorithm estimates posteriori state from its priori.

The filter is named after Rudolf E. Kálmán, one of the primary developers of its theory and as it is seen. Kalman filtering approach is more accurate and robust than the coulomb counting method.

F. Hybrid Methods

In the last papers, hybrid methods become more common, because each method has its own bright sides and dark sides. Thus to achieve better performance of SOC estimation, combination of them by choosing merits of one method and replacing them instead of demerit of another often makes better desirable result.

III. BATTERY MODEL

A generic second order circuit model as can be seen in Fig. 1 consisting of a bulk capacitor to characterize the ability of the battery to store charge C_{bulk}, a capacitor to model surface capacitance and diffusion effect within the cell $C_{surface}$, a terminal resistance R_t, Surface resistance R_s and end resistance R_e is used. The voltage across the bulk and surface capacitors is denoted V_{cb} and V_{cs} respectively [14].

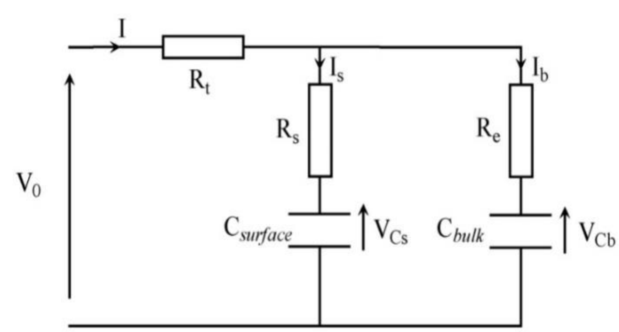


Figure 1. RC battery model schematic

Among many proposed battery models, the mentioned above is a complete equivalent circuit for estimating the VRLA battery SOC and SOH. Initial parameters of the cell are calculated before from experimental data. To check how it is done, formulation and state variables description of the battery model, please see [14].

IV. STATE OF CHARGE PROPOSED METHOD AND SIMULATION

Kalman filter is used for estimating V_{cb}. The Inputs of Kalman Filter are current and voltage with noise, and the outputs are V_o, $V_{cb,}$ and V_{cs}. Kalman filter equations are described in Table I.

TABLE I. KALMAN FILTER EQUATIONS

System Dynamic $x_k=F_{k-1}x_{k-1}+G_{k-1}u_{k-1}+w_{k-1}$ $y_k=H_kx_k+v_k$ $E(W_kW_j^T)=Q_k\delta_{k-i}$ $E(V_kV_j^T)=R_k\delta_{k-j}$ $E(W_kV_j^T)=0$
Initialization $\hat{a}_0^+=E(x_0)$ $P_0^+=E[(x_0-\hat{a}_0^+)(x_0-\hat{a}_0^+)^T]$
Kalman Equation Calculation $\hat{a}_0^-=F_{k-1}\hat{a}_{k-1}^++G_{k-1}u_{k-1}$ $P_k^-=F_{k-1}P^+_{k-1}F^T_{k-1}+Q_{k-1}$ $K_k=P^-_kH^T_k(H_kP^-_kH^T_k+R_k)^{-1}$ $=P^+_kH^T_kR^{-1}_k$ $\hat{a}_0^+=\hat{a}_0^-+K_k(y_k-H_k\hat{a}_k^-)$ $P_k^+=(I-K_kH_k)P_k^-(I-K_kH_k)^T+K_kR_kK^T_k$ $=[(P_k^-)^{-1}+H^T_kR_k^{-1}H_k]^{-1}$ $=(I-K_kH_k)P_k^-$

The general block diagram of system is drawn in Fig. 2:

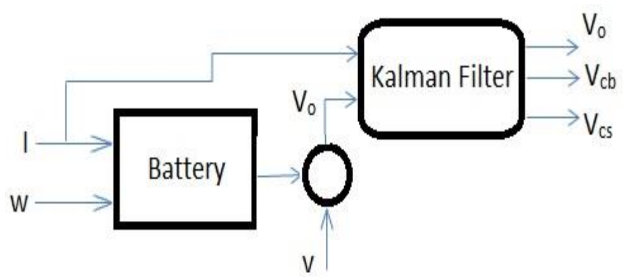


Figure 2. System block diagram

Firstly, the battery is fully charged (for experimental tests, a 2V 8Ah battery has been used). With pulse as shown in Fig. 3, the discharge process begins, and output voltage across the battery terminal can be seen.

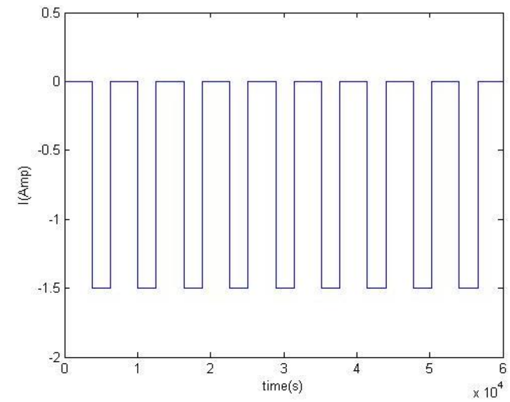
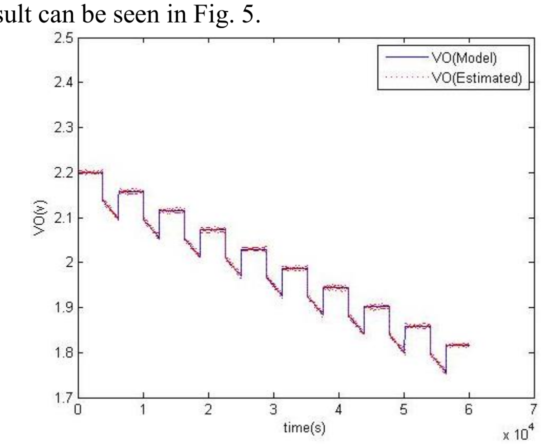


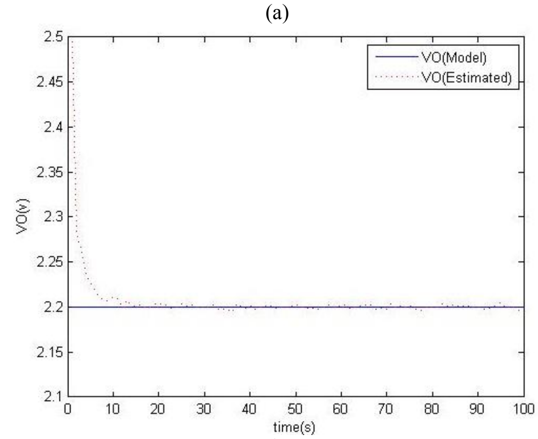
Figure 3. Discharge pulse

Secondly, output voltage with purposeful fault initialization is estimated and it is shown in Fig. 4. [13] mentioned that there is a linear relationship between SOC and V_{cb}. Hence, V_{cb} will be estimated with Kalman filter and SOC in continuation.

Thirdly, SOC with Kalman filter and conventional Coulomb counting was estimated. The CC method used two times, one with 2% error and another with 5%. It is obvious that, this 3% error can cause a big fault during cycles. And also this shows CC sensitivity to accurate measurement. Result can be seen in Fig. 5.



(a)



(b)

Figure 4. (a) Real output voltage and estimated (b) The a part with zoom in time axis

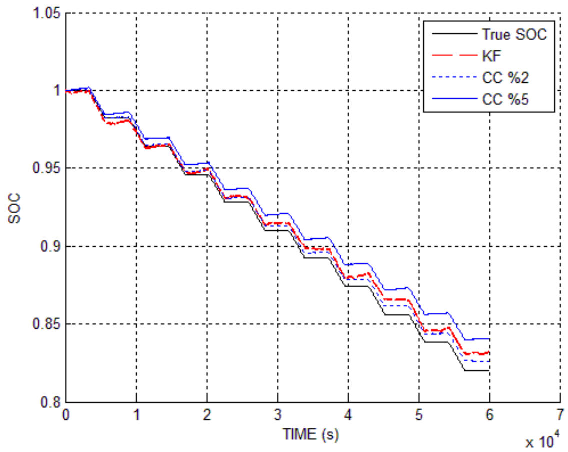


Figure 5. Comparison between CC method and KF method with measurement error

Even though CC with 2% error is better than Kalman Filter, accurate measurement needs costly sensors, other than this, Fig. 6 shows that CC, as mentioned previously, needs initial SOC. So, if wrong initialization is used in calculation, final result is catastrophic. While Kalman filter with recursive algorithm easily can solve this problem.

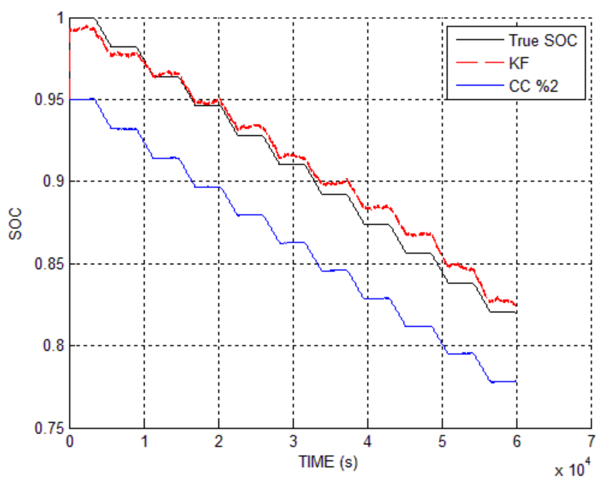


Figure 6. Comparison between CC method and KF method with fault initialization

V. Temperature Consideration

Batteries show different behavior in different temperature (e.g. deep discharge), the primary tests has been performed in a chamber room. Therefore in order to contain temperature in calculations, another thing is needed. Because Artificial Neural Networks (ANNs) are universal approximators and can approximate any nonlinear function with desired accuracies. Many papers use the estimation method with neural networks. Multi-Layer Perceptron (MLP) is a class of feedforward artificial neural networks. An MLP consists of at least three layers of nodes: input layer, hidden layer, output layer. Input layer is inputs of systems, hidden layer uses neurons, and output layer is linear output of the network. MLP utilizes a supervised learning technique called Back Propagation (BP)[15].

For training and of this research Levenberg-Marquardt method is used that, it's a blend of Gradient Descend, Back Propagation and Adaptive Learning. A general structure of a MLP neural network has been shown in Fig. 7.

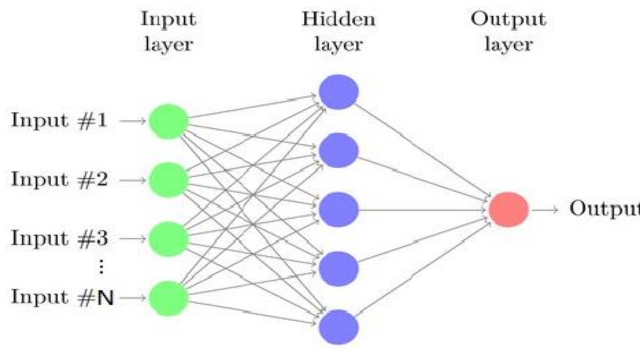


Figure 7. General structure of an MLP NN

The result in Fig. 8 shows inaccurate estimation, and in order to overcome it, NN must retrain and needs more time and data.

In this paper, first KF and CC tests separately and now the proposed hybrid method (combination of MLP NN with KF) is going to introduce. By using robustness and recursion of KF with MLP data, certainly better estimation will be achieved. Results are shown in Figs. 9 and 10.

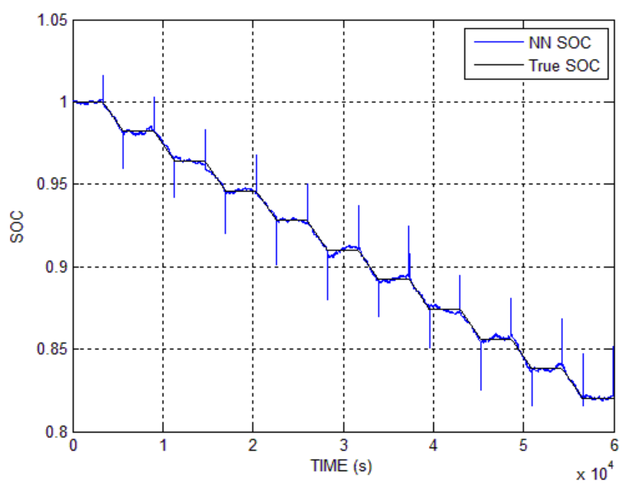


Figure 8. SOC estimation with MLP NN

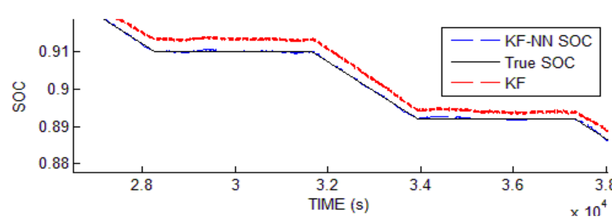


Figure 9. Comparison between KF and mixture of NN and KF

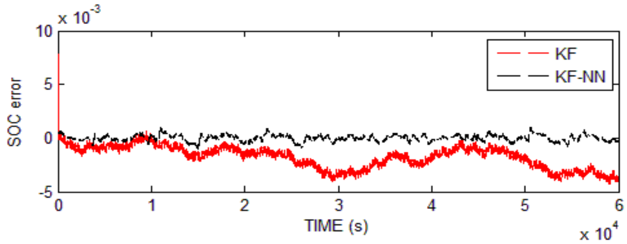


Figure 10. Error plot

But, do not forget that temperature is a vital factor and never should omit. With changing the temperature, output error is going to increase. Therefore, with a complete lookup-table for different temperature, the MLP algorithm chooses amounts smartly and tries to fit them to the most accurate estimation. So, in order to check this, we again use simulation in 45 degree Celsius temperature, and the result can be seen in the following in Figs. 11 and 12.

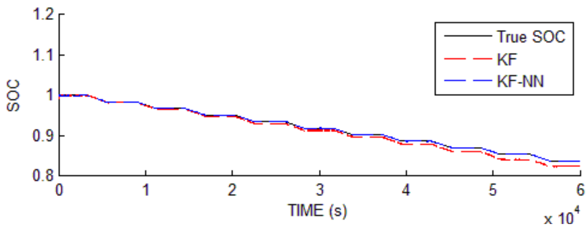


Figure 11. Comparison between KF and mixture of NN and KF in 45 degree Celsius

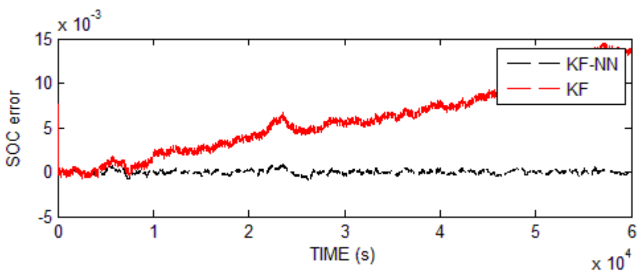


Figure 12. Error plot

VI. State of Health Estimation

SOH is the ability of a battery to store energy. It means SOH shows how long a cell can be used. It is crystal clear as a fact that, the efficiency of a battery gradually decreases during the time [16]. The SOH can be calculated as follow:

$$SOH = \frac{C_{b(aged)}}{C_{b(new)}} \times 100\% \qquad (3)$$

Where $C_{b(aged)}$ is the amount of C_b of the aged battery, and $C_{b(new)}$ is the amount of C_b of the battery when it is new.

For this part, again the proposed equivalent circuit with some considerations is going to use. The parameter that has direct impact on SOC and SOH is C_b. For estimating SOC, V_{cb} must estimate and for SOH, the amount of C_b. By assuming that, there is no offset, SOC will be obtained by dividing the V_{cb} at the moment by the fully charged V_{cb}. With the same assumption, SOH will be obtained by dividing the aged C_b by the C_b when the battery is new. It is needless to say that some battery parameters will change during the time and by considering C_b as a variable parameter, makes state equations non-linear. Therefore by augmented kalman filtering method it can estimate.

Two common methods for non-linear kalman filtering exist. First one is Extended Kalman Filter (EKF) which is used Tailor series expansion and also for approximations needs Jacobian matrix calculations. Most of the times, this matrix decreases estimation accuracy. Second one is Unscented Kalman Filter (UKF) that based on Unscented Transform (UT). This transformation is a method for random variable statistics calculation in non-linear cases. By choosing a set of deterministic vectors call sigma points [17].

Figure 13 and 14 are examples of reduction in V_O when the battery is new and aged (with 10% decrease in capacity). Usually in battery manufacture's datasheet, recommend the battery for 4 or 5 years, but this recommendation is not general and depends on number of charge and discharge.

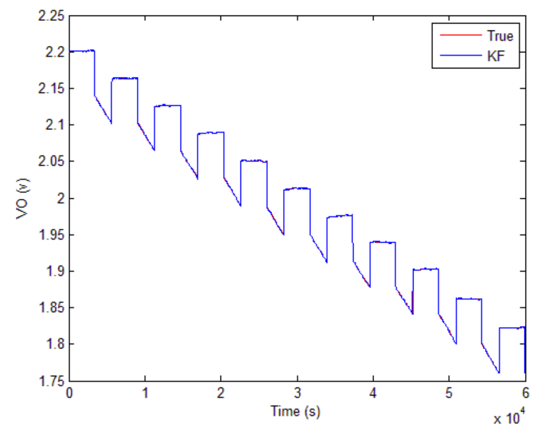


Figure 13. V_O estimation when battery in new

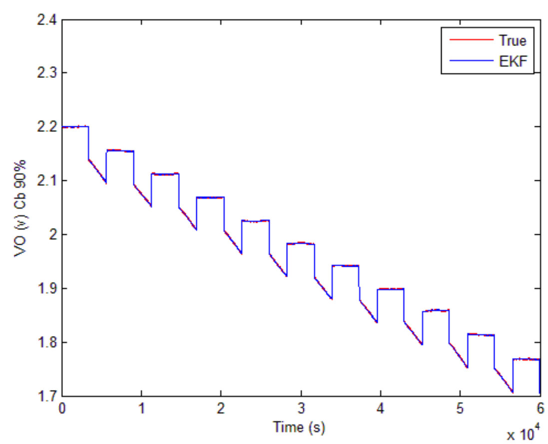


Figure 14. V_O estimation when battery capacity decrease 10%

The given snapshots visually present the amount of V_O in same duration, and more descent can be seen in Fig. 14.

Simulations have been performed with EKF and UKF in order to compare and contrast. Fig 15 is an attempt to graphically illustrate the difference of these two methods.

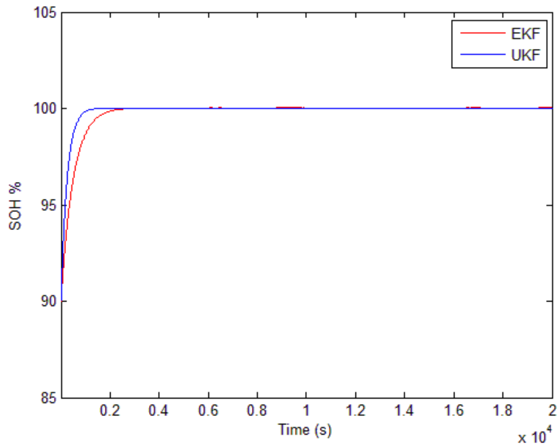


Figure 15. UKF and EKF SOH estimation comparison

A thorough glance at Fig. 15 highlights that UKF is more accurate and has fast convergence in comparison with EKF. Hence, augmented kalman filtering by using UKF algorithm, will result accurate SOH estimation.

VII. CONCLUSION

This paper presents a blend estimation approach for estimating the better state of charge by application of Kalman Filter and MLP neural network. When using narrow training data or incorrect initialization, results become unreliable. The proposed estimator in comparison with [14] that only used Kalman filter showed better accuracy and also fast convergence to the actual state variables, independent of charging conditions of initialization of the Kalman filter. For second part by assuming V_{cb} as a variable parameter and using augmented Kalman filtering, accurate SOH is estimated

VIII. FUTURE WORKS

Use the proposed method with another kinds of NNs such as Radial Basis Function (RBF) or SVM and also use particle filter or H_∞ filter instead of KF.

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