World Academy of Science, Engineering and Technology
International Journal of Energy and Power Engineering
Vol:12, No:3, 2018

Presentation of a Mix Algorithm for Estimating the Battery State of Charge Using Kalman Filter and Neural Networks

Amin Sedighfar, M. R. Moniri

***Abstract*—**Determination of state of charge (SOC) in today's world becomes an increasingly important issue in all the applications that include a battery. In fact, estimation of the SOC 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 SOC estimation algorithm is expected to be precise and easy to implement. This paper presents an online method for the estimation of the SOC of Valve-Regulated Lead Acid (VRLA) batteries. The proposed method uses the well-known Kalman Filter (KF), and Neural Networks (NNs) and 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, VRLA battery.

I. Introduction

NOWADAYS, fluctuations in fuel prices and environmentalist 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 SOC 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. SOC Estimation Methods

Firstly, it is reasonable to deliberate conventional method 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. Reference [8] classified all kinds of them in detail. So, the mentioned methods are briefly listed afterwards.

Amin Sedighfar and M. R. Moniri are with the Department of Telecommunication Engineering, Islamic Azad University of Yadegar Emam Branch (e-mail: aminsedighfar@gmail.com, mr_moniri_h@yahoo.com).

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. SOC 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 occured. 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 NNs, fuzzy logic, Support Vector Machine (SVM), KF and so on [9]-[13].

KF, 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. KF approach is more accurate and robust than the CC 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 model 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].

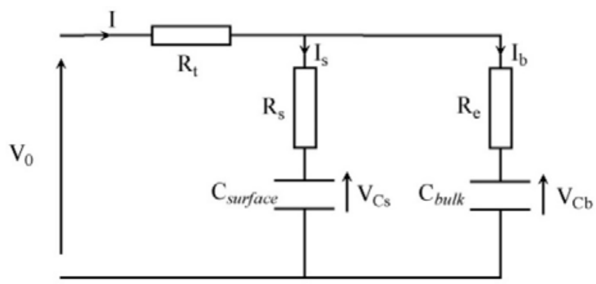


Fig. 1 RC battery model schematic

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. Proposed Method and Simulation

KF is used for estimating V_{cb}. KF equations are described in Table I.

TABLE I
KF EQUATIONS

System Dynamic

$$x_k = F_{k-1}x_{k-1} + G_{k-1}u_{k-1} + w_{k-1}$$
$$y_k = H_k x_k + v_k$$
$$E(W_K W_j^T) = Q_k \delta_{K-j}$$
$$E(V_K V_j^T) = R_k \delta_{K-j}$$
$$E(W_K V_j^T) = 0$$

Initialization

$$\hat{x}_0^+ = E(x_0)$$
$$P_0^+ = E[(x_0 - \hat{x}_0^+)(x_0 - \hat{x}_0^+)^T]$$

Kalman Equation Calculation

$$\hat{x}_k^- = F_{k-1}\hat{x}_{k-1}^+ + G_{k-1}u_{k-1}$$
$$P_K^- = F_{K-1}P_{K-1}^+ F_{K-1}^T + Q_{k-1}$$
$$K_K = P_K^- H_K^T (H_K P_K^- H_K^T + R_K)^{-1} = P_K^+ H_K^T R_K^{-1}$$
$$\hat{x}_K^+ = \hat{x}_K^- + K_K(y_K - H_K \hat{x}_K^-)$$
$$P_K^+ = (I - K_K H_K) P_K^- (I - K_K H_K)^T + K_K R_K K_K^T$$
$$= [(P_K^-)^{-1} + H_K^T R_K^{-1} H_K]^{-1} = (I - K_K H_K) P_K^-$$

Here, the noise process W_k and measurement noise V_k are white, zero-mean, uncorrelated, and gave known covariance matrices Q_k and R_k, respectively. δ_{k-j} is the Kronecker delta function; that is δ_{k-j}=1 if k=j, and δ_{k-j} =0 if k≠j and K_k defined as Kalman gain. Now estimation process begins.

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

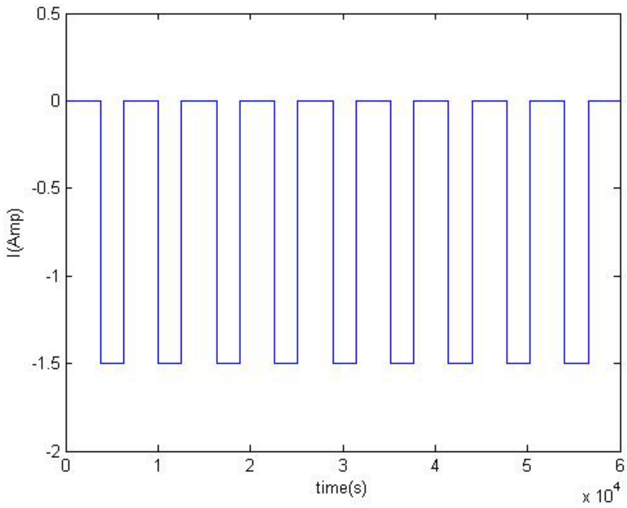
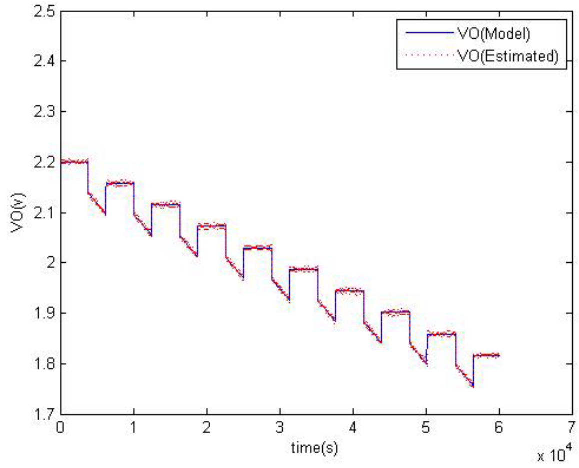


Fig. 2 Discharge pulse

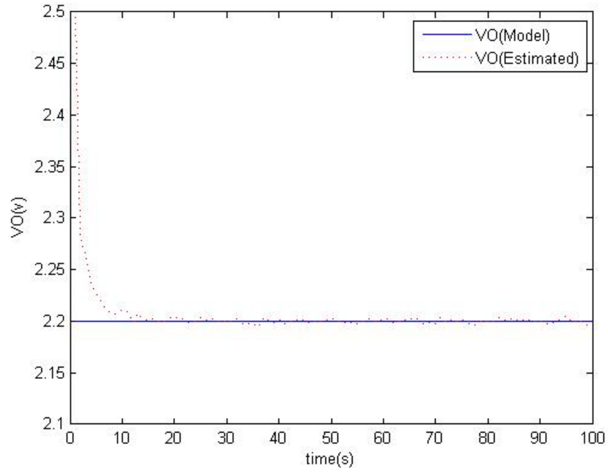
Secondly, output voltage with purposeful fault initialization is estimated and it is shown in Fig. 3. [13] mentioned that there is a linear relationship between SOC and V_{cb}. Hence, V_{cb} will be estimated with KF and SOC in continuation.

Thirdly, SOC with KF and conventional CC 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. 4.

Even though CC with 2% error is better than KF, accurate measurement needs costly sensors, other than this, Fig. 5 shows that CC, as mentioned previously, needs initial SOC. So, as in Fig. 5 it appears, if wrong initialization is used in calculation, final result is catastrophic while KF with recursive algorithm easily can solve this problem.



(a)



(b)

Fig. 3 (a) Real output voltage and estimated (b) The a part with zoom in time axis

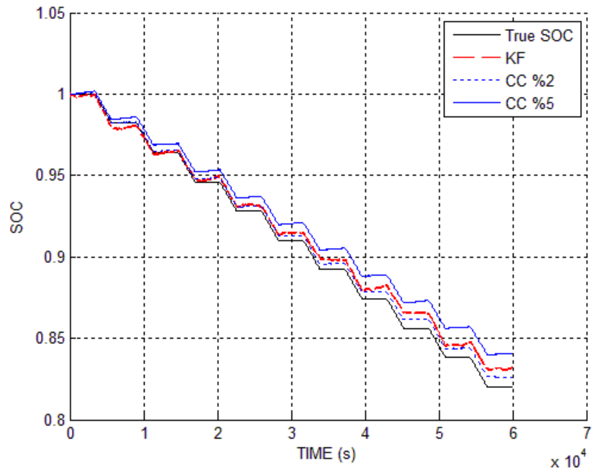


Fig. 4 Comparison between CC method and KF method with measurement error

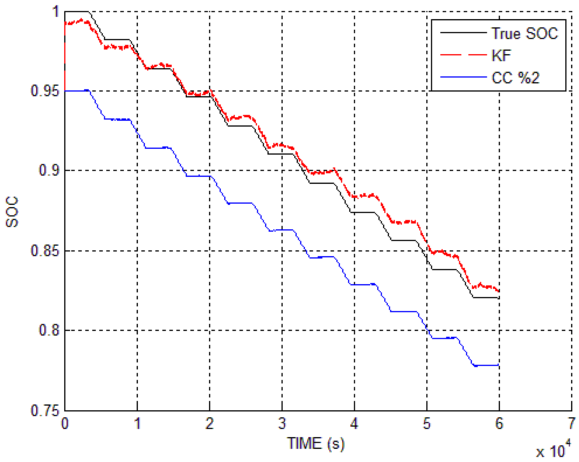


Fig. 5 Comparison between CC method and KF method with fault initialization

Now because Artificial Neural Networks (ANNs) are universal approximators and can approximate any nonlinear function with desired accuracies. Reference [15] again uses the estimation method with Multi-Layer Perceptron (MLP) NN. MLP is a class of feedforward ANNs. 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).

For training and of this research Levenberg-Marquardt method is used that is blend of Gradient Descend, Back Propagation and Adaptive Learning. A general structure of a MLP NN has been shown in Fig. 6.

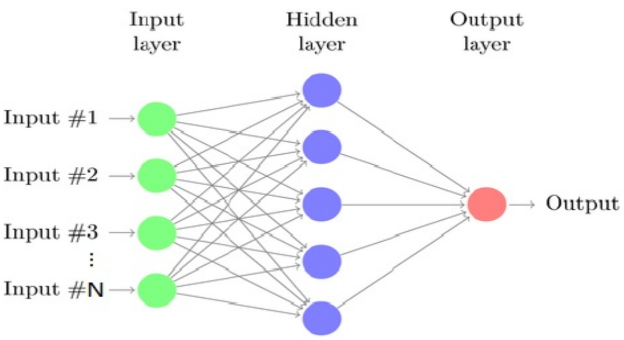


Fig. 6 General structure of an MLP NN

The result in Fig. 7 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 at the end to introduce the proposed method, combine MLP NN with KF. By using robustness and recursion of KF with MLP data, certainly better estimation will be achieved. Results are shown in Figs. 8 and 9.

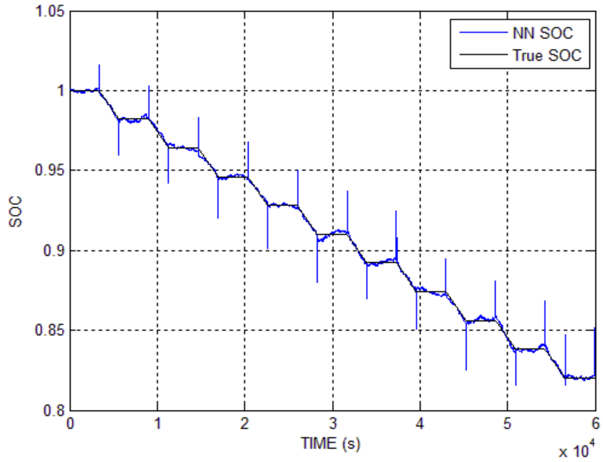


Fig. 7 SOC estimation with MLP NN

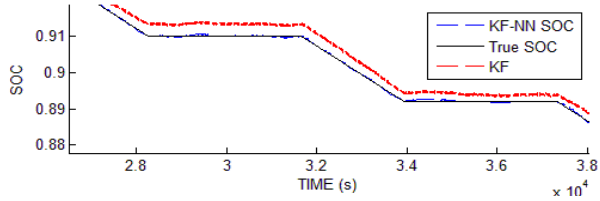


Fig. 8 Comparison between KF and mixture of NN and KF

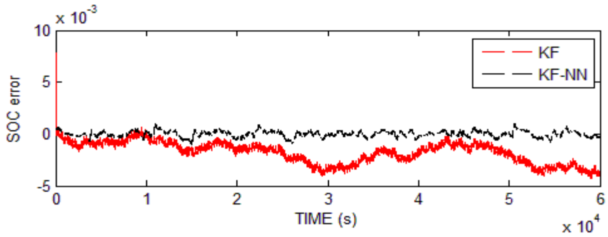


Fig. 9 Error plot

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.10 and 11.

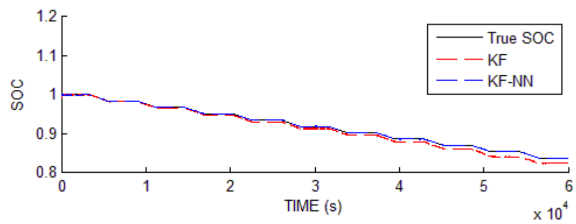


Fig. 10 Comparison between KF and mixture of NN and KF in 45 degree Celsius

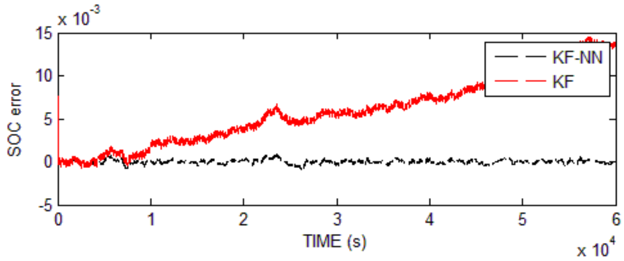


Fig. 11 Error plot

V. Conclusion

This paper presents a blend estimation approach for estimating the better SOC by application of KF and MLP NN. When using narrow training data or incorrect initialization, results become unreliable. The proposed estimator in comparison with [14] that only used KF showed better accuracy and also fast convergence to the actual state variables, independent of charging conditions of initialization of the KF.

VI. Future Works

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

Acknowledgment

This work has been supported by National Iranian Gas Company-Dist3. And the authors wish to thank to the claimed company.

References

[1] Wen-Yean Chang "The State of Charge Estimating Methods for Battery: A Review" *Hindawi Publishing Corporation*, Article ID 953792, 7 pages, Volume 2013.

[2] Goran Kujundzicm Mario Vasak, Jadranko Matusko "Estimation of VRLA Battery States and Parameters Using Sigma-Point Kalman Filter" *International Conference on Electrical Drivers and Power Electronics*, pp. 204-211, 21-23Sep 2015.

[3] Guo Xiangwei, Kang Longyun, Huang Zhizhen "On-Line State of Charge Estimation of Lithium-Ion Power Battery Pack Using Optimized Unscented Kalman Filtering" *ITEC Asia-Pacific*, 2014.

[4] John Chiasson, Baskar Vairamohan "Estimating the State of Charge of a battery" *IEEE Control System Society*, April 2005.

[5] H. Rahimi-Eichi, F. Barnoti, M.Y. Chow "Modeling and Online Parameters Identification of Li-Polymer Battery Cells for SOC Estimation" *Industrial Electronics (ISIE), IEEE International Symposium*, 2012.

[6] Koray Kutluay, Yigit Cadirei, Yakup S. Ozkazanc "A New Online State-of-Charge Estimation and Monitoring System for Sealed Lead-Acid Batteries in Telecommunication Power Supplies" *IEEE Transactions on Industrial Electronics*, Volume 52, No 5, pp. 1315-1327, Oct 2005.

[7] D. Linden, T. B Reddy, *Handbook of Batteries*, Third Edition, McGraw Hill, 2001.

[8] M. Galad, P. Spanik, M. Cacciato, G. Nobile "Comparison of Common and Combined State of Charge Estimation Methods for VRLA Batteries" *Published in Elektro*, pp. 220-225, 2016.

[9] Micheal Wahlstorm, *Design of a Battery State Estimator Using a Dual Extended Kalman Filter*, a MS Thesis Presented to University of Waterloo, pp. 45-47, 2010.

[10] Juan Carlos Alvarez Anton, Paulino Jose Garcia Nieto, Celcilio Blanco Viejo, Jose Antonio Vilan Vilan "Support Vector Machines Used to Estimate the Battery State of Charge" *IEEE Transaction on Power Electronics*, Volume 28, No 12, pp. 5919-5926, Dec 2013.

[11] T. Hansen, C. J Wang, "Support Vector Based Battery State of Charge Estimator" *Journal of Power Sources*, Vol. 141, No.2, pp. 351-358, 2005.

[12] Renjian Feng, Shuai Zhao, Xiaodong Lu "On-Line Estimation of Dynamic State-of-Charge for Lead Acid Battery Based on Fuzzy Logic" *2nd International Conference on Measurement Information and Control*, China, pp. 447-451, Aug 2013.

[13] Mohammad Charkhgard, Mohammad Farrokhi "State of Charge Estimation for Lithium-Ion Batteries Using Neural Networks and EKF" *IEEE Transaction on Industrial Electronics*, Volume 57, No 12, pp. 4178-4187, Dec 2010.

[14] B. S Bhangu, P. Bentley, D. A. Stone, C. M. Bingham "Nonlinear Observers for Predicting State-of-Charge and State-of-Health of Lead-Acid Batteries for Hybrid-Electric Vehicles" *IEEE Transaction on Vehicular Technology*, Volume 54. No 3, pp. 783-794, May 2005.

[15] S. Haykin, *Neural Networks: A Comprehensive Foundation*, 2nd edition, Englewood Cliffs, Prentice-Hall, 1999.

Amin Sedighfar obtained his BS degree on telecommunication engineering in 2011 from Islamic Azad university of Yadegar Emam branch and now undergraduate MS in telecommunication engineering from Islamic Azad University of Yadegar Emam branch. His interests are telecommunication systems and estimation theory. Now he is a telecommunication engineer with over 7 years of experience in dealing with telecommunication equipment repairs as well as SCADA system maintenance. His job experiences are maintaining telemetry systems, acquaintance with Remote Terminal Unit (RTU) protocols, acquaintance some gas elements measuring equipment, working on Cisco routers and some kind of wireless transmitters and receivers. Become a Member of **World Academy of Science, Engineering and Technology** in 2018.

M. R. Moniri obtained his PhD on Telecommunication engineering. Currently he holds a position of associate professor in telecommunication engineering in Islamic Azad University of Yadegar Emam branch. His researches focus on Electro Magnetic Compatibility (EMC), Signal Processing and Radar systems.