A Moving Window Least Mean Square Approach to State of Charge Estimation for Lithium Ion Batteries

Fereshteh Poloei
Department of Electrical and Computer Engineering,
Queen's University,
Kingston, Canada
fp13@queensu.ca

Amirhosein Akbari
Department of Electrical and Computer Engineering,
Queen's University,
Kingston, Canada
amirhosein.akbari@queensu.ca

Yan-Fei Liu
Department of Electrical and Computer Engineering,
Queen's University,
Kingston, Canada
yanfei.liu@queensu.ca

***Abstract*— A novel Lithium Ion (Li-Ion) battery model parameter identification technique based on a simple on-line adaptive approach is presented in this paper. The proposed technique is able to accurately estimate the State of Charge (SOC) in Li-Ion batteries by a very simple manner. A previously proposed Li-Ion battery model and its dynamical equations have been used to develop the proposed parameter estimation algorithm. Estimated model parameters are used to calculate the Open-Circuit Voltage (OCV) that is employed to determine the SOC with no advanced knowledge of the battery parameters. Furthermore, the paper introduces a moving window least mean square approach that adaptively updates estimated battery in a very fast manner. The SOC is recalculated at the end of each window cycle based on the newly estimated parameters. The proposed SOC estimation approach continuously tracks any changes in the battery/model parameters and is fast, accurate, and simple.**

Keywords*— *State of Charge (SOC), Li-Ion battery, Estimation, Least Mean Square.

I. INTRODUCTION

Li-Ion battery is used in almost all-electric vehicle, most of today's plug-in hybrid electric vehicles and also most portable consumer electronics such as laptops and cell phones due to its beneficial characteristics. A previous knowledge of the State of Charge (SOC) of the battery is unquestionably useful to improve battery's performance, safety, efficiency, life time, and reliability [1-6]. Therefore, precise SOC estimation is an important task in all applications that a Li-Ion battery is in service. The techniques developed and presented so far for SOC are categorized as: open circuit voltage method, coulomb counting method, intelligent method, and filter/ observer based method [7-12].

The open-circuit voltage (OCV) of the battery, if known, can directly be used to determine the SOC, and it is the simplest way to do so. However, when the battery is in service, the open circuit voltage cannot be measured. In fact the battery should be open circuited for at least two hours, open circuit voltage is measured, and SOC is calculated. This is not practical in most applications. Only for those applications in which the battery can rest for long time periods, direct measuring of OCV is functional. In all other applications, calculating of SOC based on the OCV is possible, if OCV can be estimated accurately by an appropriate modeling of the battery and by implementing an appropriate estimation scheme [13].

The dynamic equations of a Li-Ion battery are nonlinear and somehow complex. Battery parameters change with time, with the operating point conditions such as temperature, etc. This complexity and nonlinearity make battery modeling and the SOC estimation quite challenging. Variety advanced and intelligent methods including fuzzy logic, Artificial Neural Network (ANN), Radial Basis Function (RBF) network, Fuzzy Neural Networks (FNN) have been proposed to effectively handle such dynamic complexity. The mail issue with all these techniques is the need for a large amount of data to train the network, and update this training time to time. The advantages and disadvantages of each method have been summarized in the Table I.

TABLE I. PROS AND CONS OF SOC ESTIMATION METHODS

method	pros	cons
open circuit voltage	no need an algorithm to implement	battery needed to be in resting mode for long time
coulomb counting	easy to implement	dependent on the initial SOC, not suitable for PEV's with frequent charge or discharge profiles due to the need of accurate initial conditions
Intelligent algorithms	powerful ability to approximate nonlinear functions	need for a large amount of data to train the algorithm applicable for all operating conditions
Extended Kalman Filter	acceptable accuracy, dealing with white noise	need for an accurate enough battery model, large time and computational memory, complicated algorithm to implement
based -Observer (Luenberger)	acceptable accuracy	difficult for online application due to the complicated computational algorithm
based-Observer (Sliding mode)	acceptable ,accuracy robust against modeling uncertainties	complicated algorithm to implement, chattering problem

Kalman and advanced Kalman Filtering (KF) have alternatively used to estimate the SOC. Although applying KF for SOC estimation brings acceptable accuracy and deals with system noise, it suffers from a complicated algorithm, large computational memory, large computational time, and difficult calculation of feedback gain of Kalman filter [14,15].

A popular SOC estimation technique that has been addressed in many review articles is Filter/Observer-based method. This method applies the measured input and the present/past state signals to the battery model to calculate the

978-1-5386-8086-5/19/$31.00 ©2019 IEEE

model output, then the error signal which is the difference between the calculated and measured output is feedback to update the model states estimation [16-20].

Luenberger observer, Sliding mode observer, Proportional - Integral observer (PI) are some examples of the Feedback / Observer-based method and hold some advantages and disadvantages summarized in the Table I.

Conclusively, it appears that the methods for SOC estimation applied so far neither accurate nor simple enough and the necessity of a method with the characteristics of simplicity, being easy to implement, and accuracy; together is noticeable.

II. Discret Time Model For Battery

Based on our proposed discrete linear four parameters model in Fig. 1, Voc is estimated. Since there is a relationship between SOC and Voc defined by a Voc-SOC curve, SOC can be calculated from the estimated Voc.

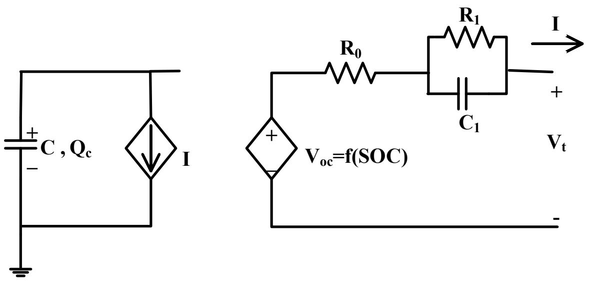

Fig. 1. Ion battery model-Li.

During battery charging/discharging for the model we have Eqs. (1) and (2) as:

$$V_t(t) = V_{OC}(t) - V_{C_1}(t) - R_0 I(t) \quad (1)$$

$$\frac{dV_{C_1}}{dt} = \frac{I(t)}{C_1} - \frac{V_{C_1}(t)}{C_1 R_1} \quad (2)$$

Where $V_t(t)$ and $I(t)$ represent the charging/discharging terminal voltage and current of the battery, respectively. Considering $I(t)$ within in a small time interval, Δt , if we discretize Eq. (2) we will have

$$\frac{V_{C_1}(t+\Delta t) - V_{C_1}(t)}{\Delta t} = \frac{1}{C_1} I(t) - \frac{1}{C_1 R_1} V_{C_1}(t) \quad (3)$$

During Δt due to the large ratio between the battery's capacitor, C , and the transient capacitor, C_1, we have

$$V_{OC}(t+\Delta t) - V_{OC}(t) \to 0 \quad (4)$$

And we can have:

$$e(t) = -\frac{\Delta t}{C_1} I(t) + \frac{\Delta t}{C_1 R_1} V_{C_1}(t) - R_0 I(t+\Delta t) + R_0 I(t) \quad (5)$$

Where $e(t)$ is defined as

$$\begin{aligned} & e(t) = V_t(t+\Delta t) - V_t(t) \\ & t_k = t_{k-1} + \Delta t \quad ; \quad k = 2, \ldots, n \end{aligned} \quad (6)$$

By replacing V_{C_1}, we have Eq. (7) as

$$\begin{aligned} e(t) = {} & R_0 I(t+\Delta t) + I(t)\left[\frac{\Delta t}{C_1} + \frac{\Delta t}{C_1 R_1} R_0 - R_0\right] + \\ & \frac{\Delta t}{C_1 R_1} V_t(t) - \frac{\Delta t}{C_1 R_1} V_{OC}(t) \end{aligned} \quad (7)$$

We can have Eq. (8) as

$$e(t) = \alpha_1 I(t+\Delta t) + \alpha_2 I(t) + \alpha_3 V_t(t) + \alpha_4 \quad (8)$$

Where the parameters are defined as

$$V_{OC} = -\frac{\alpha_4}{\alpha_3} \quad (9)$$

$$R_0 = \alpha_1 \quad (10)$$

$$R_1 = \frac{\alpha_2 - \alpha_3 \alpha_1 + \alpha_1}{\alpha_3} \quad (11)$$

$$C_1 = \frac{\Delta t}{\alpha_2 - \alpha_3 \alpha_1 + \alpha_1} \quad (12)$$

III. Proposed Algorithem Fof Parameters Estimation

By rewriting Eq. (8) in a discrete form, we have:

$$E = A\alpha \quad (13)$$

In which each of the matrix A, α, E are defined as Eq. (9) and n is the n[th] discrete-time data sample with a time interval Δt:

$$E = \begin{bmatrix} e(n) \\ e(n+1) \\ e(n+2) \\ . \\ . \\ . \\ e(n+N) \end{bmatrix} \quad (14)$$

$$A = \begin{bmatrix} I(n+1) & I(n) & V_t(n) & 1 \\ . & . & . & . \\ . & . & . & . \\ . & . & . & . \\ I(N+n+1) & I(n+N) & V_t(n+N) & 1 \end{bmatrix} \quad (15)$$

$$\alpha = \begin{bmatrix} \alpha_1 \\ \alpha_2 \\ \alpha_3 \\ \alpha_4 \end{bmatrix} \quad (16)$$

And lets supposed we have N+1 data samples in one-time interval, Δt. Now we should find the best fit for elements of vector α to have a minimum Euclidean norm, also called norm 2th of the error vector or min of the $\| E - A\alpha \|_2$ which the solution is [22]:

$$\alpha = (A^T A)^{-1} A^T E \quad (17)$$

Now our goal is to estimate V_{oc} with no knowledge of parameters and just by means of current and terminal voltage and we propose our method as following. It is supposed that V_{oc} is constant during all N samples. The number of samples is a trade-off between the accuracy of the estimation scheme, the validity of assuming a constant V_{oc}, and the computation efforts.

In the proposed algorithm, an array of N+2 elements of the battery's terminal voltage and current is formed. It is assumed that V_{oc} is constant during $\Delta t \times (N+2)$, which as mentioned before, is a valid argument.

The algorithm can be explained as following.

1. At the first step, N+2 samples of terminal voltage and current are obtained and fill in the array.
2. The algorithm runs and reports the estimated values.
3. The N+2 moves one step ahead that means the first sampled data is thrown away, and a new voltage and current sample is added to the array. In other words, the window moves one step ahead, such that it does not include the oldest data sample, but includes the newest one. The step 2 repeats as shown in Fig. 2.
4. The algorithm runs till an accurate parameters set is achieved.

The proposed algorithm always applies the last N+2 data samples of terminal voltage and current of the battery to run the estimation process.

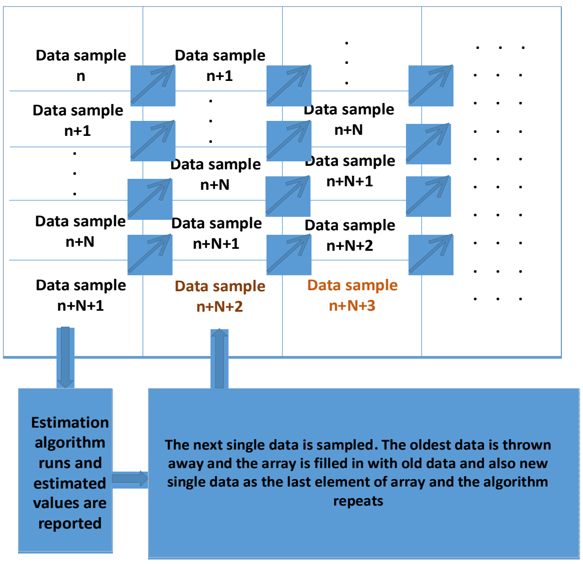

Fig. 2. Schematic diagram of proposed algorithm.

IV. Simulation And Experimental Results

In order to prove the validity of the proposed algorithm in estimating the model parameters and, its competitive features, and its performance behavior, comprehensive computer simulations have been carried out. The simulation results show that our proposed algorithm can converge to real values. Even by sudden, big, and fast changes in the parameters. For this simulation, battery's terminal voltage and current are sampled with a sampling frequency of 500Hz for period of 2 seconds to have N+2 data samples for the first step of the proposed algorithm. Sample simulation results are shown in Fig. 3, 4, 5, 6, 7, 8 and show the algorithm's power to follow the changes and update the model parameters and converges very quickly.

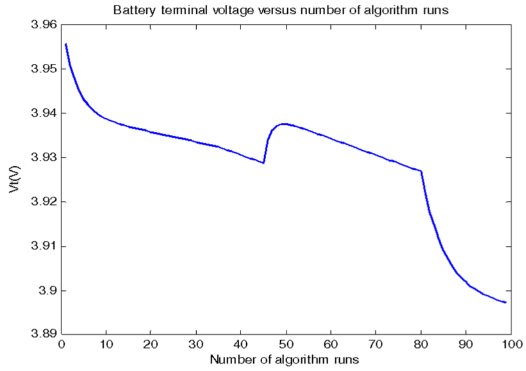

Fig. 3. Terminal voltage vs. number of algorithm runs for C and R_1 changes.

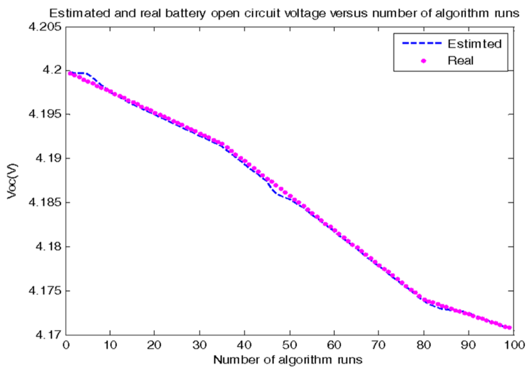

Fig. 4. V_{oc} vs. number of algorithm runs for C and R_1 changes.

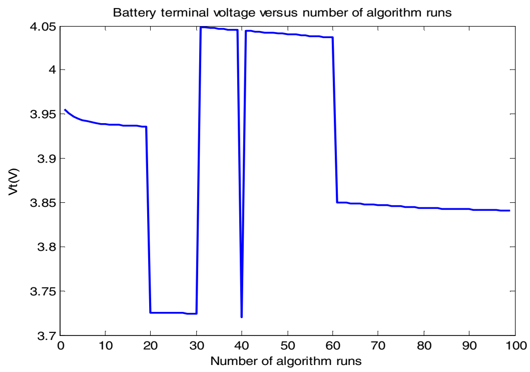

Fig. 5. Terminal voltage vs. number of algorithm runs for C and R_0 changes.

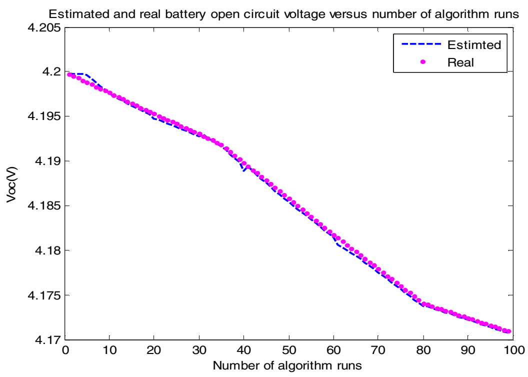

Fig. 6. V_{oc} vs. number of algorithm runs for C and R_0 changes.

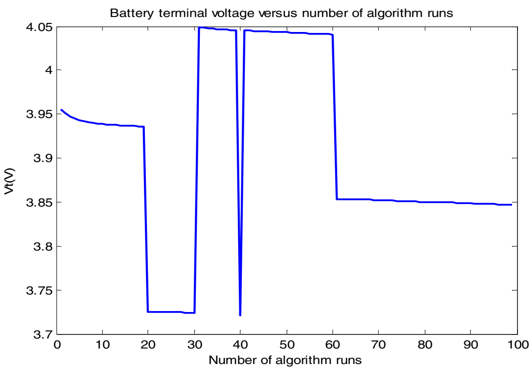

Fig. 7. Terminal voltage vs. number of algorithm runs for C_1 and R_0 changes.

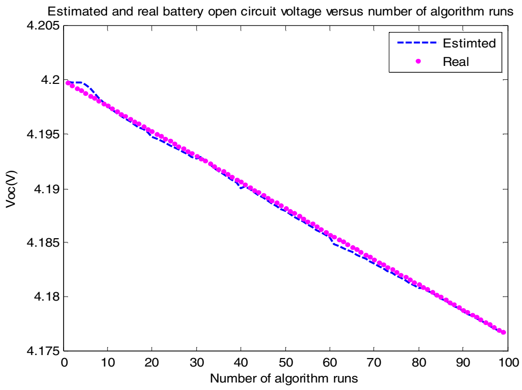

Fig. 8. V_{oc} vs. number of algorithm runs for C_1 and R_0 changes.

Fig. 9 and Fig. 10 show the experimental setup and the PCB of the experimental setup which have been used to test and verify the proposed algorithm for SOC estimation in the Li-Ion cell battery. In the hardware implementation, there are two capabilities. The setup is able to act autonomously and file the terminal voltage and current of the battery. We can apply arbitrary current profile to test the battery cell. These result in evaluating the algorithm in presence of sudden changes applied to the battery and showing the power of proposed algorithm to follow the changes and still adaptively working.

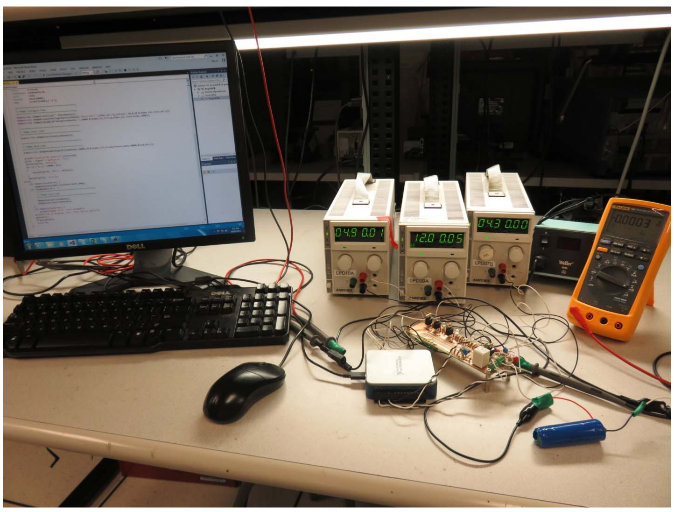

Fig. 9. Picture of the experimental setup.

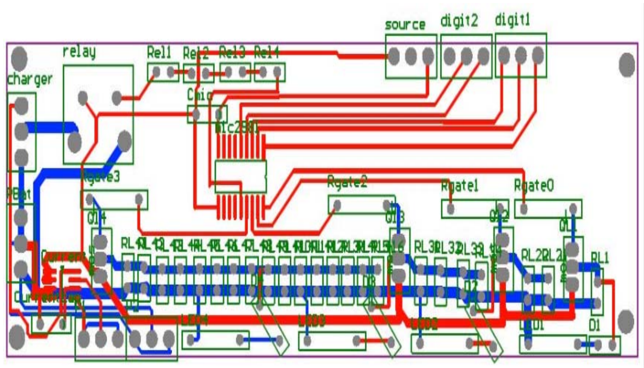

Fig. 10. PCB of the experimental setup.

A Li-Ion battery cell (CGR18650CG) with characteristics of 2200mAh nominal capacity, 4.2V maximum voltage is used for the experimental results. We use some resistances connected in parallel and series, hardware switches controlled by a National Instruments USB-6001 data acquisition(DAQ) device (NI USB-6001), two analog inputs with the resolution of 14-bit applied for terminal voltage and current acquisition. The data sampled from terminal voltage and current by NI USB-6001 are saved and applied for SOC estimation as shown in Fig. 9. The experimental setup configuration is shown in Fig. 11.

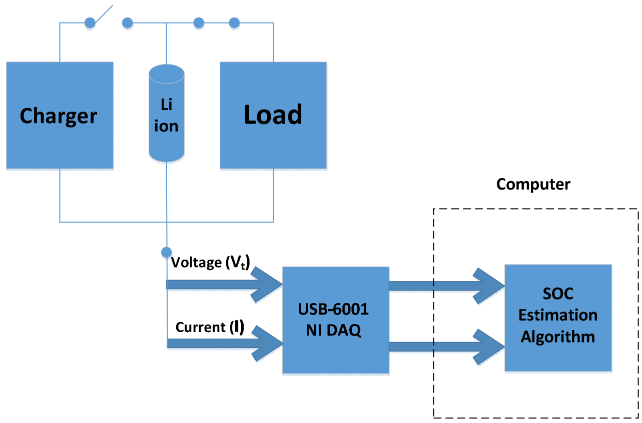

Fig. 11. Experimental setup configuration.

By means of the proposed algorithm and the SOC-VOC curve we gained in [21], the experimental result is shown in Fig. 12.

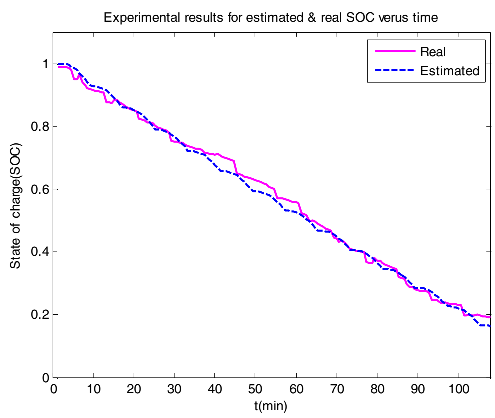

Fig. 12. Experimental results for estimated and real SOC vs. time.

V. Conclusion

A simple, accurate, fast, easy to implement, and almost ideal SOC estimation is presented has been presented in this paper. The proposed online adaptive estimation algorithm based on an extended moving window least mean square preserves all the simplicity, quickness, and accuracy factors together and needs just the battery terminal voltage and current. The proposed powerful method can follow all changes in the battery parameters due to various factors. All other SOC estimation schemes proposed to far, sacrifice either the simplicity or the accuracy for the sake of other factors.

VI. Reference

[1] H.Rahimi-Eichi, U. Ojha, F. Baronti, and M. Chow, "Battery management system: An overview of its application in the smart grid and electric vehicles," in *IEEE Industrial Electronics magazine*, vol. 7, pp. 4-16, 2013.

[2] R. Salas-Puente, S. Marzal, R. Gonzalez-Medina, E. Figueres, G. Garcera, "Practical Analysis and Design of a battery Management system for a grid-connected DC microgrid for the reduction of thr Tarrif cost and battery life maximization", in *Journal of energies*,vol. 7, July 2018.

[3] Ch. Zhang, K. Li, S. Mcloone, Zh. Yang, "Battery Modelling Methods for Electric Vehicles - A Review," *European Control Conference (ECC)*, pp. 2673-2678, June 2014.

[4] I. Baccouche, S. Jemmali, A. Mlayah, B. Manai, N. Essoukri, B. Amara, "Implementation of an improved Coulomb-Counting Algorithm based on a piecewise SOC-OCV relationship for SOC estimation of Li-Ion battery," in *International Journal of Renewable Energy Research,* Vol. 8, No. 1, March 2018.

[5] L. Buccolini, A. Ricci,Cris, C. Scavongelli, G. DeMaso-Gentile, S. Orcioni, M. Conti, "Battery Management System(BMS) simulation environment for electric vehicles," *IEEE 16th International Conference on Environment and Electric Engineering (EEEIC)* Florence, Italy, 7-10 June, 2016.

[6] Z. Pei, X. Zhao, H. Yuan, Z. Peng, L. Wu, "An Equivalent Circuit Model for Lithium Battery of Electric Vehicle considering Self-Healing Characteristics," in *Journal of Control Science and Engineering*,Vol. 2018, June 2018.

[7] F. Mostofi, H. Shayeghi, "Feasibility and Optimal Reliable Design of Renewable Hybrid Energy System for Rural Electrification in Iran," in *International Journal of Renewable Energy Research,* Vol. 2, No. 4, 2012.

[8] E. Hossain,M. Zawad, Kh. R. Islam, M. Q. Akash, " Design a Novel Controller for Stability Analysis of Microgrid by managing Controllable Load using Load Shaving and Load Shifting Techniques; and Optimizing Cost Analysis for Energy Storage System," in *International Journal of Renewable Energy Research,* Vol. 6, No. 3, 2016.

[9] J. Hossain, N. Sakib,E. Hossain, R. Bayindir, "Modelling and Simulation of Solar Plant and Storage System: A Step to Microgrid Technology," in *International Journal of Renewable Energy Research,* Vol. 7, No. 2, 2017.

[10] Q. Yu, R. Xiong, Ch. Lin, "Online Estimation of State-Of-Charge based on the H infinity and Unscented Kalman Filters for Lithium Ion Batteries," in *Journal of Energy Procedia*, Vol. 105, pp. 2791-2796, May 2017.

[11] K-M. Jin, E-H. Kim, "Evaluating the impact of BESSs in the Jeju island power system", *International Conference on Renewable Energy Research and Applications (ICRERA),* 11- 14 Nov. 2012.

[12] B. Balasingam, G. V. Avvari, B. Pattipati," Robust battery fuel gauge algorithm development part 3:state of charge tracking", *International Conference on Renewable Energy Research and Applications (ICRERA),*. Milwaukee, WI, USA,19-22 Oct. 2014.

[13] A. Hajizadeh, A. H. Shahirinia, S. Arabameri, D. C Yu Ch ,"Control of solar system's battery voltage based on state of charge estimation (SOC*)*," *International Conference on Renewable Energy Research and Applications (ICRERA),*. Milwaukee, WI, USA,19-22 Oct. 2014.

[14] B. Pattipati, B. Balasingam, G. V. Avvari, K. Pattipati and Y. Bar-Shalom , "Robust battery fuel gauge algorithm development , part 0: Normalized OCV modeling approach," *International Conference on Renewable Energy Research and Applications (ICRERA),* Milwaukee, WI, USA,19- 22 Oct. 2014..

[15] Z. Chen, Y. Fu and C. C. Mi, "State of Charge Estimation of Lithium-Ion Batteries in Electric Drive Vehicles Using Extended Kalman Filtering,*" in IEEE Transactions on Vehicular Technology,* vol. 62, no. 3, pp. 1020-1030, March 2013.

[16] B. Xia, H. Wang, M. Wang, W. Sun, Zh. Xu, Y. Lai , " A new method for state of charge estimation of Lithium-Ion battery based on strong tracking Cubature Kalman filter, " in *Journal of Energies*, November 2015.

[17] F. Zhang,G. Liu,"Estimation of battery state of charge with H_∞ observer: Applied to a robot for inspecting power transmission lines," *in IEEE Transaction on Industrial Electronics*, vol. 59, No. 2, 2012.

[18] Ch. Zhang, K. Li, S. Mcloone, Zh. Yang, "Battery Modelling Methods for Electric Vehicles - A Review," *European Control Conference (ECC)*, pp.2673-2678, June 2014.

[19] T. Weigert, Q. Tianb, and K.Lianb,"State of State-of-charge prediction of batteries and battery- supercapacitor hybrids using artificial neural networks," *Journal of Power Sources*, vol. 196, no. 8, pp. 4061-4066, 2011.

[20] M. Charkhgard and M. Farrokhi, "State-of-Charge Estimation for Lithium-Ion Batteries Using Neural Networks and EKF," in *IEEE Transactions on Industrial Electronics*, vol. 57, no. 12, pp. 4178- 4187, 2011.

[21] F. Poloei, A. Bakhshai and Y. Liu, "A novel online adaptive fast simple state of charge estimation for Lithium Ion batteries," *IEEE 6th International Conference on Renewable Energy Research and Applications (ICRERA)*, San Diego, CA, pp. 914-918, 2017.

[22] O. Nelles, Nonlinear System Identification, Springer, 2001.