# STATE-OF-CHARGE ESTIMATION OF A LIFEPO$_4$ BATTERY USING AN ADAPTIVE OBSERVER

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Abstract: *Determining the state of charge (SoC) of a battery is a crucial factor for its proper functioning. Due to its strongly non-linear character, this is a real challenge for LiFePO4 (LFP) batteries. In this paper we present a technique for estimating the SoC, which is based on a third order RC network model and an adaptive observer. The observer gets, as input values, the voltage at the terminals of the battery and the discharge current, and provides the SoC of the battery as an output. Testing the performance of the adaptive observer is done by direct comparison of data from its output with the data obtained experimentally by discharging an LFP battery in keeping with the Urban Dynamometer Driving Schedule (UDDS) discharge cycle.*

## 1. INTRODUCTION

In the context of the global crisis related to the depletion of oil resources and the acute environmental issues, electric vehicles (EV) acquire an increasingly greater popularity [1]. They currently use Li-Ion batteries as the sole source of energy for both electric traction and the rest of the consumers. These batteries combine high current density, which ensures the discharge current needed, with high energy density, which provides the autonomy of the car. However, a number of operational safety issues, as well as their rather high cost, have triggered a search for still other energy storage solutions [2]. Among them, the LFP batteries promise to solve these problems. LFP batteries are part of the category of Li-Ion batteries, and they use a graphite anode and a cathode made of Li ferrophosphate. The olivine structure of the cathode gives these batteries a high structural and thermodynamic stability, making them the safest Li-based batteries [3]. Besides the advantages of safety and the fact that their structure does not contain rare metals (Ni, Co, Mn, etc.), LFP batteries also present a set of negative aspects as compared to the rest of Li-Ion batteries. The most important of them are the low energy density, the low electrical potential (3.2 - 3.3V compared to 3.6 - 3.7 V that is typical for Li-Ion batteries), the strongly non-linear character of the link between SoC and Open Circuit Voltage (OCV) [4], respectively internal resistance.

For the electric vehicles, the operation of batteries within the limits of safety is ensured by their management block (BMS). The role of that block is to monitor the operating parameters of the battery: the voltage at the terminals, the discharge current and the temperature, and, based on them, estimate its state parameters: SoC, State of Health (SoH), State of Energy (SoE) and State of Power (SoP) [1]. The main state parameter of the battery is SoC, which represents the ratio of battery capacity at a certain time and its rated capacity. There are several methods for determining the SoC, of which the most important are: OCV measurement method (OCV) [5], Coulomb-counting approach (Ah) [6], internal resistance method [7], impedance measurement [8] artificial neural networks [9], Kalman filter [10], [11], and so on.

Out of these, the Coulomb-counting method is the most straightforward [6]. It is based on the integration of the discharge current within a certain time interval, and thus it is easier to implement in the BMS. The main disadvantage of this method is that it suffers from the accumulated errors from current measurement drift [2] and difficulties in establishing the initial SOC. Besides, the precision of the method is affected by the fluctuations of the discharge current and environment temperature [12].

To overcome these problems, in recent years, a series of techniques have been developed for determining the SoC, which are based on the use of closed loop measurements. They use the battery model and various observers to accurately determine the SoC at a given time. The most important of these are: adaptive sliding mode observer (SMO) [2], nonlinear adaptive observer [13], dual-circuit observer states [1] and so on. SMO is used to reduce measurement errors, disturbances and modeling errors. In [2] a self-adjusting SMO is used to determine the SoC for a Li-Ion subjected to discharging and loading in keeping with a Hybrid pulse test, and a maximum relative error is obtained which ranges between 0.0089 and 0.0199 %. In [13] a non-linear adaptive observer is used to extract OCV from the voltage across the terminals of the battery. This value is then used to determine the SoC using a look-up table relationship between OCV and SoC. Through this method a maximum error of approx. 3% is reported in determining the SoC for a Li-Ion. Following a different approach, in [1] a dual circuit state observer is used, which is composed of a parameters-normalized PI based state observer and a practical approach to correct the current drifting. Based on it, an error less than 2.5% is obtained for an LFP battery subject to discharge in keeping with a dynamic cycle.

In the present study the authors' own variant is presented of an adaptive observer devised to determine the SoC of an LFP battery. It uses a neural network to determine the initial battery SoC, and then it estimates the SoC by Coulomb-counting techniques and by determination of the variation of the battery terminals voltage, compared with the output voltage of the model. The rest of the paper is organized as follows: the presentation of the LFP battery model, in Section 2, the development of the adaptive observer in Section 3, the results obtained from the experimental measurements using the UDDS discharge cycle, in Section 4, and the last part contains the conclusions.

## 2. THE LFP BATTERY MODEL

To represent the behavior of the LFP battery subjected to discharge, a third order RC-network model was chosen because it is the optimal model for automotive applications which involve rapid discharge current variations, as in the UDDS cycle [14].

The battery model – Fig. 1 – consists of a current-controlled voltage source whose value – E0 is estimated by the OCV vs SoC curve, an internal resistance R0, which models the evolution of the internal resistance of the battery in accordance with SoC, and three parallel resistor-capacitor groups (R1-C1, R2-C2, R3-C3) that capture the effects of polarization occurring within the discharge

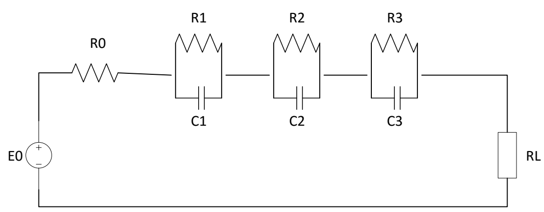


*Fig. 1.Third order RC network battery model*

### A) Determination of the parameters of the model

Model parameters determination was done following an extensive experimental study conducted in accordance with USABC manuals [15] and PNGV [16].

Following that study, the parameters – Table 1 – were determined for 16 different SoCs, focusing on the discharge interval between 80% - 20% SoC.

*Table 1 Third order RC network parameters estimation*

| **SoC** | **100%** | **90%** | **80%** | **75%** | **70%** |
|---|---|---|---|---|---|
| **$E_0$ [V]** | 3.425 | 3.333 | 3.333 | 3.323 | 3.313 |
| **$R_0$ [Ω]** | 0.169 | 0.135 | 0.150 | 0.160 | 0.131 |
| **$R_1$ [Ω]** | 0.014 | 0.019 | 0.014 | 0.004 | 0.038 |
| **$C_1$ [F]** | 686.8 | 515.1 | 686.8 | 2060 | 257.5 |
| **$R_2$ [Ω]** | 0.01 | 0.004 | 0.01 | 0.001 | 0.019 |
| **$C_2$ [F]** | 309.2 | 618.5 | 309.2 | 1545 | 154.5 |
| **$R_3$ [Ω]** | 0.004 | 0.029 | 0.004 | 0.002 | 0.019 |
| **$C_3$ [F]** | 1030 | 171.7 | 1030 | 1716 | 257.5 |
| **SoC** | **65%** | **60%** | **55%** | **50%** | **45%** |
| **$E_0$ [V]** | 3.303 | 3.292 | 3.292 | 3.292 | 3.292 |
| **$R_0$ [Ω]** | 0.150 | 0.140 | 0.155 | 0.155 | 0.160 |
| **$R_1$ [Ω]** | 0.019 | 0.01 | 0.024 | 0.008 | 0.033 |
| **$C_1$ [F]** | 515 | 1030 | 412 | 1145 | 294.3 |
| **$R_2$ [Ω]** | 0.011 | 0.007 | 0.003 | 0.002 | 0.009 |
| **$C_2$ [F]** | 257.5 | 390.3 | 772.6 | 1293 | 309 |
| **$R_3$ [Ω]** | 0.017 | 0.007 | 0.005 | 0.003 | 0.014 |
| **$C_3$ [F]** | 286.1 | 645.1 | 858.4 | 1432 | 343.3 |
| **40%** | **35%** | **30%** | **25%** | **20%** | **10%** |
| 3.292 | 3.282 | 3.272 | 3.262 | 3.241 | 3.201 |
| 0.145 | 0.145 | 0.145 | 0.155 | 0.135 | 0.155 |
| 0.014 | 0.024 | 0.024 | 0.014 | 0.033 | 0.033 |
| 686.8 | 412 | 412.2 | 686.8 | 294.3 | 294.3 |
| 0.01 | 0.003 | 0.015 | 0.013 | 0.007 | 0.005 |
| 09.2 | 772.6 | 193.2 | 220.7 | 386.5 | 515.4 |
| 0.014 | 0.005 | 0.023 | 0.020 | 0.011 | 0.008 |
| 343.6 | 858.5 | 214.6 | 245.2 | 429.5 | 572.7 |

### B) The model implementation

Approximation of the evolution of the parameters in concordance with the SoC, as part of the model, is done using a Feed-Forward Neural Network (FFNN). This type of network was chosen because it best approximates the evolution of the parameters of the LFP battery for the UDDS discharge cycle [17]. The architecture of the proposed FF network consists of one neuron in the input layer for SoC, nine neurons in the hidden layer, and five neurons in the output layer for the model parameters. The nine neurons of the hidden layer were obtained through trial-and-error so that the neural network would not be overfitted or underfitted.

The model thus developed was implemented in Matlab/Simulink and is shown in Fig. 2.

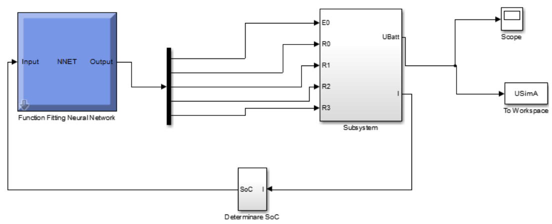


*Fig. 2. Model implementation*

## 3. THE DEVELOPMENT OF THE ADAPTIVE OBSERVER

The main contributions of this paper lie in developing an adaptive observer which is meant to determine the SoC of the LFP battery subjected to discharge. The observer gets, as input values, the discharge current, the voltage across the terminals of the battery, and the output voltage of the model provides the SoC of the battery.

The structure of the observer – Fig. 3 – comprises a block for determining the initial SOC of the battery and a block for correcting it when the voltage across the terminals very much differs from the output voltage of the model.

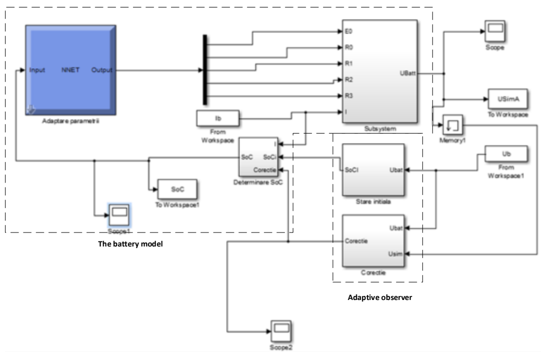


*Fig. 3. Adaptive observer structure*

When the discharge process starts, the block for determining the initial SoC of the battery reads the voltage at the battery terminals and approximates its SoC, which it then conveys to the model. The latter determines the value of the parameters and provides an output voltage that should be close to the value of the voltage across the terminals of the battery. If between the two voltage values the difference is greater than 40 mV, then the correction block intervenes and adjusts the SoC value so that the output voltage of the model be close to the voltage at the battery terminals. During the discharge, determining the battery SoC is done by means of Coulomb-counting techniques, with the correction block intervening to keep the output voltage of the model close to the voltage at the terminals of the battery, thereby eliminating the accumulation of measurement errors.

The block for determining the initial SoC – Fig. 4 – is composed of a FFNN that has a similar structure to that used in the model. In the initial layer there is one neuron for the voltage at the battery terminals, nine neurons in the hidden layer, and one neuron in the output layer for the SoC. The network is trained with the data in Table 1, using the Levenberg-Marquardt algorithm.

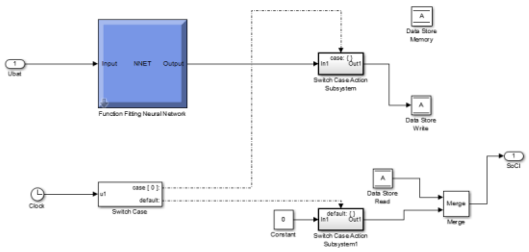

*Fig. 4. Initial SoC estimating block*

The error correction block – Fig. 5 – follows the evolution of the voltage values at the terminals of the battery and at the output of the model. If the differences between these values are greater than ± 40 mV (greater than the measurement error introduced by the sensor), the observer intervenes and adjusts the SoC that is part of the model by ±0.025%. Through these discrete steps, the output voltage of the model is reset to the values of the voltage at the battery terminals, and the model SoC is considered to be the SoC of the battery.

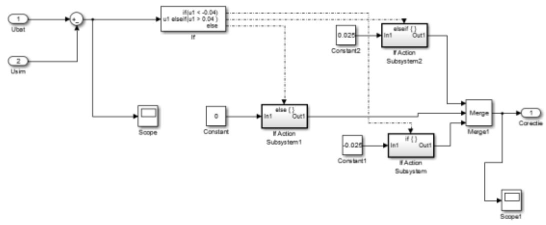

*Fig. 5. SoC correction block*

## 4. RESULTS AND DISCUSSION

Determining the performance of the adaptive observer was done by direct comparison of the results it provides against the data obtained from the discharge of an LFP battery in concordance with the UDDS discharge cycle.

Comparison of the results was made both for the entire UDDS cycle, and for the two discharge profiles extracted from it, which start from SoC = 76%, respectively 41%. The results obtained are shown in Fig. 6, 7 and 8.

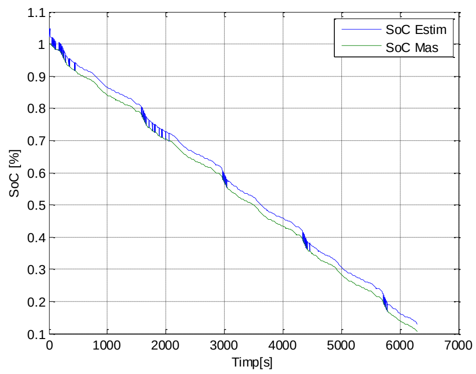


*Fig. 6. SoC estimation for an UDDS full cycle*

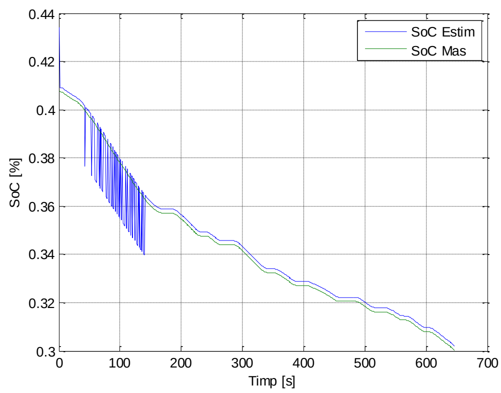


*Fig. 7. SoC estimation for an UDDS cycle that starts at SoC = 41%*

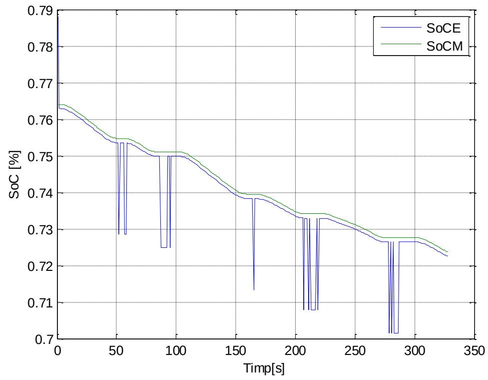


*Fig. 8. SoC estimation for an UDDS cycle that starts at SoC = 76%*

After the analysis of the results, it is observed that, in all three cases, the maximum errors are reached within moments of the start of the discharge process, when the observer is trying to estimate the initial SoC. At that stage the values of those errors are 10.26% for the full UDDS cycle, respectively 3.60% and 6.54% for the other profiles. Those errors, although big enough, do not significantly influence the performances of the observer because they act over a short period of time, and after the intervention of the correction block the values are significantly reduced reaching values of 5.83% for the full UDDS cycle, respectively 0.43% and 0.93% for the other profiles.

## 5. CONCLUSIONS

This paper presents a technique for determining the SoC of a battery involving the use of an LFP battery model and an adaptive observer. The structure of the observer comprises a unit devised to determine the initial SoC of the battery and a correction block. The block for determining the initial SoC is composed of an FFNN which gets the input voltage from the battery terminals and supplies its SoC at the output. The correction block compares the voltage across the battery terminals with the voltage at the model output, and if the differences exceed ± 40 mV, it intervenes on the current SoC value. The observer we developed was tested for an LFP battery subjected to discharging in keeping with the UDDS cycle, and we obtained an error of about 5%.

## 6. REFERENCES

[1]. X. Tang, Y. Wang, Z. Chen, "*A method for state-of-charge estimation of LiFePO4 batteries based on a dual-circuit state observer*", Journal of Power Sources, 296, (2015), pp. 23-29.

[2]. F. Zhong, H. Li, S. Zhong, Q. Zhong, C. Yin, „*An SOC estimation approach based on adaptive sliding mode observer and fractional order equivalent circuit model for lithium-ion batteries*", Commun Nonlinear Sci Numer Simulat, 24, (2015), pp. 127–144.

[3]. G. Pistoia, „*Lithium-Ion Batteries Advances and Applications*", Ch. 4 – N. Hudak, „*Nanostructured Electrode Materials for Lithium-Ion Batteries*," Ed. Elsevier, 2014, pp. 57-82.

[4]. M.-A. Roscher, D.-U. Sauer, „*Dynamic electric behavior and open-circuit-voltage modeling of LiFePO4-based lithium ion secondary batteries*," Journal of Power Sources, 196, (2011), pp. 331–336.

[5]. S. Lee, J. Kim, J. Lee, B.H. Cho, "*State-of-charge and capacity estimation of lithium-ion battery using a new open-circuit voltage versus state-of-charge*", Journal of Power Sources, 185, (2008), pp. 1367–1373.

[6]. K.S. Ng, C.-S. Mooa, Y.-P. Chen, Y.-C. Hsieh, "*Enhanced coulomb counting method for estimating state-of-charge and state-of-health of lithium-ion batteries*", Applied Energy, 86, (2009), pp. 1506–1511.

[7]. Y.-H. Chiang, W.-Y. Sean, J.-C. Ke, "*Online estimation of internal resistance and open-circuit voltage of lithium-ion batteries in electric vehicles*", Journal of Power Sources, 196, (2011), pp. 3921–3932.

[8]. J. Illig, J.P. Schmidt, M. Weiss, A. Weber, E. Ivers-Tiffée, "*Understanding the impedance spectrum of 18650 LiFePO4-cells*", Journal of Power Sources, 239, (2013), pp. 670-679.

[9]. E. Jensi Miriam, S. Sekar, S. Ambalavanan, "*Artificial Neural Network Technique for Predicting the Lifetime and Performance of Lead - Acid Battery*", IRACST – Engineering Science and Technology: An International Journal (ESTIJ), ISSN: 2250-3498, Vol.3, No.2, April 2013, pp. 393-401.

[10]. Y. Tian, B. Xia, W. Sun, Z. Xu, W. Zheng, "*A modified model based state of charge estimation of power lithium-ion batteries using unscented Kalman filter*", Journal of Power Sources, 270, (2014), pp. 619-626.

[11]. R. Xiong, X. Gong, C.C. Mi, F. Sun, "*A robust state-of-charge estimator for multiple types of lithium-ion batteries using adaptive*

*extended Kalman filter*", Journal of Power Sources, 243, (2013), pp. 805-816.

[12]. N. Yang, X. Zhang, G. Li, „*State of charge estimation for pulse discharge of a LiFePO4 battery by a revised Ah counting*", Electrochimica Acta 151, (2015), pp. 63–71.

[13]. Y. Li, R.D. Anderson, J. Song, A.M. Phillips, X. Wang, "*A Nonlinear Adaptive Observer Approach for State of Charge Estimation of Lithium-Ion Batteries*", in Proc. AACC, San Francisco, CA, USA June 29 - July 01, 2011, pp. 370 - 375.

[14]. B.-A. Enache, M.E. Alexandru, L.M. Constantinescu, "*A LiFePO4 Battery Discharge Simulator for EV applications– Part 1: Determining the Optimal Circuit Based Battery Model*", Proc. the 9th International Symposium on ADVANCED TOPICS IN ELECTRICAL ENGINEERING, ATEE – 2015, pp. 877-882.

[15]. ***, "*USABC Electric Vehicle Battery Test Procedures Manual*", 1996.

[16]. ***, "*PNGV Battery Test Manual*", Revision 3, 2001.

[17]. B.-A. Enache, M.E. Alexandru, L.M. Constantinescu, "*A LiFePO4 Battery Discharge Simulator for EV applications– Part 2: Developing the battery simulator*", Proc. the 9th International Symposium on ADVANCED TOPICS IN ELECTRICAL ENGINEERING, ATEE – 2015, pp. 883-888.