ARTIFICIAL INTELLIGENCE APPROACH TO SoC ESTIMATION FOR SMART BMS

K.L. Man[1,2,3], C. Chen[5], T.O. Ting[1], T. Krilavičius[3,4], J. Chang[6] and S.H. Poon[7]
[1]Xi'an Jiaotong-Liverpool University, China; [2]Myongji University, South Korea; [3]Baltic Institute of Advanced Technology, Lithuania; [4]Vytautas Magnus University, Lithuania; [5]Global Institute of Software Technology, China; [6]Texas Instruments, Inc, USA; [7]National Tsing Hua University, Taiwan

***Abstract*:** One of the most important and indispensable parameters of a Battery Management Systems (BMS) is accurate estimates of the State of Charge (SoC) of the battery. It can prevent battery from damage or premature aging by avoiding over charge/discharge. Due to the limited capacity of a battery, advanced methods must be used to estimate precisely the SoC in order to keep battery safely being charged and discharged at a suitable level and to prolong its life cycle. In this paper, we review several effective approaches: Coulomb counting, Open Circuit Voltage (OCV) and Kalman Filter method for performing the SoC estimation; then we propose Artificial Intelligence (AI) approach that can be efficiently used to precisely determine the SoC estimation for the smart battery management system as presented in [1]. By using our proposed approach, a more accurate SoC measurement will be obtained for the smart battery management system.

***Keywords*:** Battery Management Systems (BMS), State of Charge (SoC), Artificial Intelligence (AI)

1. Introduction

In the modern society, environment and transportation problems are the main challenge for many countries. Due to the increasing awareness of global warming, the requirements for clean fuel are on the rise. Thus, there is a continuous shift towards the Electric Vehicles (EVs) and Hybrid Electric Vehicles (HEVs) [1]. Moreover, battery-powered electronic devices have become ubiquitous in modern society. Rapid expansion of the use of portable devices (e.g. laptops, tablet computers and cellular phones) creates a strong demand for a large deployment of battery technologies at an unprecedented rate. In addition, distinct requirements for batteries, such as high energy storage density, no-memory effect, low self-discharge and long cycling life, have drawn explicit attention recently. Due to the above-mentioned facts, Battery Management Systems (BMSs) become indispensable for modern battery-powered applications [11-13].

A BMS does not only monitor and protect the battery, but also provide the guidance on optimal usage of the battery. One of the most important and indispensable parameters of a BMS is to accurately estimate the State of Charge [5] of the battery. The SoC is defined as the present capacity of the battery expressed as a percentage of some reference. Due to the limited capacity of a battery, advanced methods must be used to estimate precisely the SoC of the battery in order to keep it safely being charged and discharged at a suitable level and to prolong the life cycle of the battery. However, the measurement of SoC is not a trivial task, because one should also consider the battery voltage, current, temperature, aging and so on. Accurate SoC estimation can prevent the battery from damage or rapidly aging due to unwanted overcharge and overdischarge on the battery.

The conventional SoC estimation method such as Coulomb counting [3] suffers from an error accumulation glitch which leads to inaccurate estimation [2]. In addition, the finite battery efficiency [2] and the chemical reaction taking place during charge and discharge cause temperature rise and badly influence the SoC estimation. Therefore, efficient algorithms are definitely needed for the accurate SoC estimation. Furthermore, neither Coulomb counting nor voltage measurement alone is sufficient for high accuracy SoC estimation, because the estimation of SoC is strongly influenced by many other factors such as charge/discharge rates, hysteresis, temperature, cell aging, etc.

A smart BMS for aged batteries and multi-cell batteries was presented in [1] which aims to meet the following requirements:

- Accurate estimation of SoC prevents battery damage or premature aging by avoiding unsuitable over charge and over discharge.
- SoC can be effectively used to deduce how well

the battery system is functioning relative to its nominal (rated) and end (failed) states.

- The battery aging process needs to be reduced by conditioning the battery in a suitable manner (e.g. through controlling its charging and discharging profile), under various load conditions and harsh environments.
- Hardware implementation of the BMS is flexible and adaptable in both Application-Specific Integrated Circuit (ASIC) and Field Programmable Gate Arrays (FPGA) technology.

In this paper, we propose an Artificial Intelligence (AI) approach [15] that can be efficiently used to precisely determine the SoC estimation for the smart battery management system.

This paper is organized as follows: Section 2 presents and discusses several techniques that have been widely applied for the battery SoC estimation. Our intended AI approach for estimating the SoC of the smart battery management system is outlined in Section 3. Concluding remarks are given in Section 4 and directions for future work are pointed out at the same section.

2. Battery SoC Estimation

Many techniques have been proposed previously to estimate the SoC of battery cells or battery packs, each of them has merits and demerits.

2.1. Current Based SoC Estimation

Current based SoC estimation is also known as Coulomb Counting [3-7], which takes integration of current and time into account to estimate SoC. Coulomb Counting requires an initial state namely SoC_0, and if the initial state of the battery is known, from then the SoC can be calculated though this method.

For example, the initial state is SoC_0, using *I* ampere current to charge the battery for *t* hours, that will add *I**t* Ah charge in the battery. Also, if the capacity of the battery is *C*, then the final SoC can be calculated as follows:

$$\mathrm{SoC_t} = \mathrm{SoC_0} + \frac{I*t}{C} \qquad (1)$$

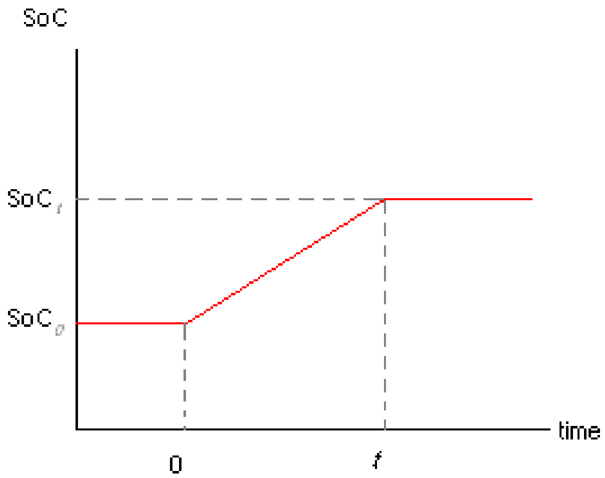

Fig. 1. Estimating SoC by using Coulomb Counting

According to theory, if a battery was charged for 3 hours at 2A, the same energy can be released when discharging. However, this is not the case in reality. No methodology is perfect. For instance, Coulomb Counting suffers from a drift over time. As mentioned in [3], battery aging causes a gradual small and constant error in the variable. The small and constant error causes a tiny error for measurement of current, which will be magnified during each charging and discharging cycle and will result in the SoC drift. Therefore, if there is a way to re-calibrate the SoC on a regular basis, such as reset the SoC to 100% when the battery is fully charged, Coulomb Counting can be used to accurate estimate SoC and often enough to overcome drift.

2.2. Voltage Based SOC Estimation

There are already many applications that measure the SoC based on voltage, such as the charge balance shown in cellular phones. The voltage is firstly measured and then converted to SoC. When the battery is discharging, the voltage drops more or less linearly [4]. In practice, there are two cases for the Lead Acid battery and the Li-ion battery [6]. For the Lead Acid battery, the voltage diminishes significantly when it is discharged as shown in Fig. 2 [4].

However, the voltage is significantly affected by the current, temperature, discharge rate and the age of cell. These factors need to be compensated, in order to achieve a higher accuracy of SoC.

For the Li-ion battery, there are very small changes for voltage between each charging and discharging cycle as shown in Fig.3. Due to the constant voltage of Li-ion battery, it is difficult to estimate the SoC by voltage based method. However, the voltage of the Li-ion battery changes significantly at both the ends of SoC range, which can be two important indicators of imminent discharge. For instance, for many applications an early warning is required before the battery is completely discharged or empty.

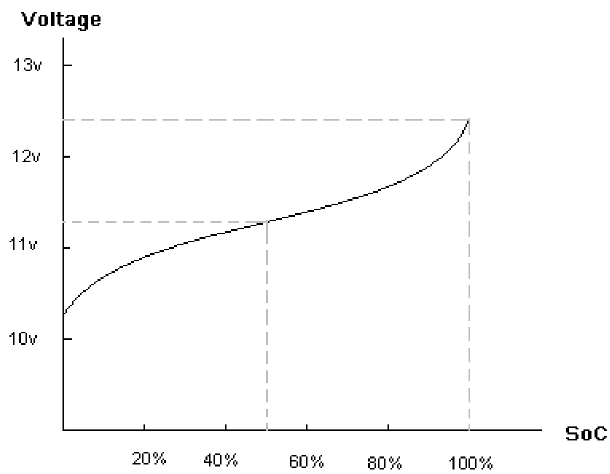

Fig. 2. The relationship between Voltage and SoC in Lead Acid battery

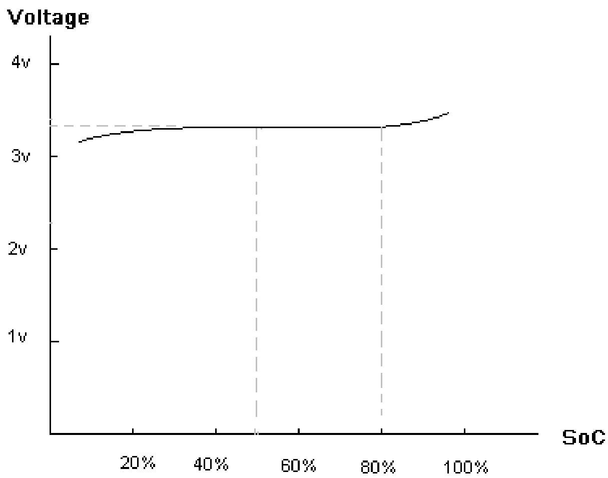

Fig. 3. The relationship between Voltage and SoC in Li-ion battery

2.3. Extended Kalman Filter

In 1960s, Kalman Filter theory was proposed [9] to accurately estimate the state for the linear systems, especially for systems with multiple inputs, by removing unwanted noise from a set of data. However, for the systems with specific requirements, such as non-normality and non-linearity, the application of the Kalman Filter method is not feasible.

Due to the time-variance, nonlinear model of the battery, noise assumption and the measurement error of the BMS, extended Kalman Filter (EKF) [14] is used to estimate the SoC for these nonlinear battery systems. With EKF method linearization process are used at each time step to approximate the nonlinear system with a linear time-varying system [10]. EKF becomes an elegant and powerful solution to estimate the SoC.

3. Artificial Intelligence Approach to Estimate SoC

The battery pack charge and discharge processes are so complex that it is essential to consider many factors such as cell voltage, current, internal impedance and temperature gradients [16]-[18]. The battery pack connected in series presents a more complex problem. Careful monitoring and control is necessary to avoid any single cell within a Li-ion battery pack from undergoing over-voltage or under-voltage. In a Li-ion battery module-management system, the individual battery SoC must be monitored because of overcharge and over-discharge issues. Therefore, it is essential to have methods capable of estimating the battery SoC.

As mentioned above, Kalman Filter (KF) is a powerful tool for the state estimation of systems. Some research have used this filter to estimate the open-circuit voltage or other parameters of batteries that have a direct relationship with the SoC [19]. In [20, 21] the KF is employed to estimate some physical quantities, which have direct effects on the SoC.

To achieve the accurate estimation of SoC, Artificial Neural Networks [22] (ANN) and Fuzzy Logic [23] systems have been treated as the universal approximators. Many techniques have been developed to approximate the nonlinear functions for practical applications [24, 25]. The BMF constructed in [24] possesses the property of local control and has been successfully applied to Fuzzy Neural Control [26]. Also, the hybridization of fuzzy logic with ANN has been used to improve the efficiency of function estimation. For instance, Fuzzy Neural Networks (FNN) have been used in many applications, especially in identification of unknown systems. The FNN can effectively model the nonlinear system by calculating the optimized coefficients of the learning mechanism [26-30].

The adaptive Neural Fuzzy method was proposed in [31] to estimate battery residual capacity. Although the estimation of battery residual is accurate, the algorithm utilizes the least-square method to identify the optimal values and hence, learning rate is computationally expensive; much time is wasted in training an ANN. A more practical approach, called merged-FNN for SoC estimation is proposed in [32]. In merged-FNN, the FNN strategy is combined with Reduced-form Genetic Algorithm (RGA) [33] which performs effectively on SoC estimation in a series-connected Li-ion battery string. The merged-FNN achieved a faster learning rate and lower estimation error than the traditional ANN with a back-propagation method.

Due to the above-mentioned facts, it is not hard to see that AI is a promising approach for fast, precise and reliable SoC estimation.

4. Conclusions

An overview of current techniques for battery State of Charge SoC (SoC) estimation has been given. An intended Artificial Intelligence (AI) approach that can be efficiently used to precisely determine the SoC estimation for a smart battery management system has been presented. Our future will focus on the implementation of a new AI technique to accurately estimate the SoC of various types of batteries.

5. Acknowledgment

The research work presented in this paper is partially sponsored by SOLARI (HK) CO (www.solari-hk.com) and KATRI (www.katri.co.jp and www.katri.com.hk).

6. References

1. Chen C., Man K.L., Ting T.O., Chi-Un Lei, Krilavičius T., Jeong T.T., Seon J.K., Sheng-Uei Guan and Prudence W.H. Wong, Design and Realization of Smart Battery Management System, Iin proceedings of the IAENG International MultiConference of Engineers and Computer Scientists - IMECS'12, Hong Kong, 2012, p. 1173-1176.
2. Cheng K.W.E., Divakar B.P., Hongjie Wu, Kai Ding, Ho Fai Ho. Battery-Management System (BMS) and SOC Development for Electrical Vehicles. Vehicular Technology, IEEE Transactions on,vol.60, no.1, 2011, p. 76 – 88
3. Battery Management Systems (BMS). http://www.mpoweruk.com.

4. White Paper - Estimating the State Of Charge of Li-Ion batteries. http://liionbms.com/php/wp_soc_estimate.php
5. State of Charge. http://en.wikipedia.org/wiki/State_of_charge
6. How to Measure State-of-charge. http://batteryuniversity.com/learn/article/how_to_measure_state_of_charge
7. Zhiwei He, MingyuGao, JieXu. EKF-Ah Based State of Charge Online Estimation for Lithium-ion Power Battery. Computational Intelligence and Security, 2009. CIS '09, 2009 p. 142 – 145
8. Christianson C.C., Bourke R.F. Battery state of charge gauge. US Patent 3,946,299, filed 11 Feb.1975
9. Kalman R. A new approach to linear filtering and prediction problems, Transactions of the ASME—Journal of Basic Engineering, vol. 82, 1960, p. 35–45.
10. Bucy R., Kalman R., Selin I. Comment on the Kalman filter and nonlinear estimates of multivariate normal process. IEEE Transactions on Automatic Control. Vol. 10, p. 118-119.
11. Duryea S., Islam S., Lawrance W. A battery management system for stand-alone photovoltaic energy systems. IEEE Ind. Appl. Mag., vol. 7, no. 3, 2001, p. 67–72.
12. Hauck B. BATTMAN—A Battery Management System, Milan, Italy, 1992.
13. Affanni A., Bellini A., Franceschini G., Guglielmi P., Tassoni C. Battery choice and management for new-generation electric vehicles. IEEE Trans. Ind. Electron., vol. 52, no. 5, 2005, p. 1343–1349.
14. Extended Kalman Filters. Wikipedia. http://en.wikipedia.org/wiki/Extended_Kalman_filter
15. Cai C.H., Du D., Liu Z.Y. Battery state-of-charge (SOC) estimation using adaptive neuro-fuzzy inference system (ANFIS). in Fuzzy Systems, 2003. FUZZ '03. The 12th IEEE International Conference, vol.2, 2003, p. 1068-1073.
16. Caumont P., Moigne Le, Rombaut C., Muneret X. Energy gauge for lead-acid batteries in electric vehicles. IEEE Trans. Energy. Convers., vol. 15, no. 3, 2000, p. 354-360.
17. Garche, J., Jossen A. Battery management systems (BMS) for increasing battery life time. In proc. of the 3rd Int. Conf. Telecommunications Energy Special, Dresden, Germany, 2000, p. 81-88.
18. Nagasubramanian G., Jungst R. G.. Energy and power characteristics of tithium-ion cells. J. Power Sources, vol. 72, 1998, p. 189-193.
19. Barbarisi O., Vasca F., Glielmo L. State of charge Kalman filter estimator for automotive batteries. Control Eng. Pract., vol. 14, no. 3, 2006, p. 267-275.
20. Lee J., Nam O., Cho B.H. Li-ion battery SoC estimation method based on the reduced order extended Kalman filtering. J. Power Sources, vol. 174, no. 1, 2007, p. 9-15.
21. Santhanagopalan S., White R.E. Online estimation of the state of charge of a lithium ion cell. J. Power Sources, vol. 161, no. 2, 2006, p. 1346-1355.
22. Hornik K., Stinchcombe M., White H. Multilayer feedforward networks are universal approximators. Neural Netw., vol. 2, 1989, p. 359-366.
23. Wang L.X., Mendel J. M. Fuzzy basis functions, universal approximation, and orthogonal least squares learning. IEEE Trans. Neural Netw., vol. 3, no. 5, 1992, p. 807-814.
24. Wang C. H., Wang W.Y., Lee T.T., Tseng P.S. Fuzzy B-spline membership function (BMF) and its applications in fuzzy-neural control. IEEE Trans. Syst., Man, Cybern. B, vol. 25, no. 5, 1995, p. 841-851.
25. Wang, L. X. Adaptive Fuzzy Systems and Control. Englewood Cliffs, NJ: Prentice-Hall, 1994.
26. Wang W.Y., Lee T.T., Liu C.L. Function approximation using fuzzy neural networks with robust learning algorithm. IEEE Trans. Syst., Man, Cybern. B, vol. 27, no. 4, 1997, p. 740-747.
27. Karam M., Fadali M.S., White K. A Fourier / Hopfield neural network for identification of nonlinear periodic systems. In Proc. 35th Southeast. Symp. Syst. Theory, Morgantown, NY, 2003, p. 53-57.
28. Chang Q.Z., Sami Fadali, M. Nonlinear system identification using a Gabor / Hopfield network, IEEE Trans. Syst., Man, Cybern. B, vol. 26, no. 1, 1996, p. 124-134.
29. Park S.K.. Bearing estimation using Hopfield neural network. in Proc. 22nd Southeast. Symp. Syst. Theory, Cookville, Tn, Mar. 1990, p. 440-443.
30. Kamiura N., Isokawa T., Matsui N. Learning based on fault injection and weight restriction for fault-tolerant Hopfield neural networks. Proc. IEEE Int. Symp. Defect Fault Tolerance in VLSI Syst., Cannes, France, Oct. 2004, p. 339-346.
31. Shen W.X., Chan C.C., Lo E.W.C., Chau K.T. Adaptive neuro-fuzzy modeling of battery residual for electric vehicles. IEEE Trans. Ind. Electron., vol 49, 2002, p. 677-684.
32. I-Hsum Li, Wei-Yen Wang, Shun-Feng Su, Yuang-Shung Lee. A merged fuzzy neural network and its applications in battery state-of-charge estimation. IEEE Trans Energy Conv., vol. 22, 2007, p. 689-708.
33. Wang W.Y., Li I.H. Evolutionary learning of BMF fuzzy-neural networks using a reduced-form genetic algorithm. IEEE Trans. Syst., Man, Cybern. B, Cybern., vol. 33. no. 6, 2003, p. 966-976.