Towards a Hybrid Approach to SoC Estimation for a Smart Battery Management System (BMS) and Battery Supported Cyber-Physical Systems (CPS)

K.L. Man
Xi'an Jiaotong-Liverpool University, China
Myongji University, South Korea
Baltic Institute of Advanced Technology, Lithuania

T.O. Ting
Xi'an Jiaotong-Liverpool University, China

T. Krilavičius
Baltic Institute of Advanced Technology, Lithuania
Vytautas Magnus University, Lithuania

Kaiyu Wan
Xi'an Jiaotong-Liverpool University, China

C. Chen
Global Institute of Software Technology, China

J. Chang
Texas Instruments, Inc, USA

S.H. Poon
National Tsing Hua University, Taiwan

***Abstract*—One of the most important and indispensable parameters of a Battery Management System (BMS) is to accurately estimate the State of Charge (SoC) of battery. Precise estimation of SoC can prevent battery from damage or premature aging by avoiding over charge or 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. We review several existing effective approaches such as Coulomb counting, Open Circuit Voltage (OCV) and Kalman Filter method for performing the SoC estimation. Then we investigate both Artificial Intelligence (AI) approach and Formal Methods (FM) approach that can be efficiently used to precisely determine the SoC estimation for the smart battery management system as presented in [1]. By using presented approach, a more accurate SoC measurement can be obtained for the smart battery management system and battery supported Cyber-Physical Systems (CPS).**

Keywords- Battery Management Systems (BMS), State of Charge (SoC), Artificial Intelligence (AI), Formal Methods (FM), Cyber-Physical Systems (CPS)

I. INTRODUCTION

Batteries are the most common electrical energystorage approach for mobile devices. In the 21st century, battery technology is becoming the key bottleneck for many Cyber Physical Systems (CPS), which are critical to addressing the transportation, energy and environmental problems that face developing countries. Driven by an increasing awareness of global warming and CO_2 emissions, the demand for clean fuel and energy is on the rise. As a result there is a growing shift towards the green-energy transportation such as Electric Vehicles (EVs) and Hybrid Electric Vehicles (HEVs) [1] that require support from CPS. Moreover, battery-powered electronic devices have become ubiquitous in modern society due to a rapid expansion of the use of portable devices such as portable computers, tablet computers, smartphones, and cellular phones. This creates a strong demand for batteries with improved characteristics. There are distinct requirements for batteries, such as high energy storagedensity, no-memory effect, low self-discharge and long cycling life, so efficient Battery Management Systems (BMSs) become indispensable for modern battery-powered applications [2-4].

A BMS not only monitors and protects the battery, but also provides 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 (SoC) [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 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 suffers from an error accumulation glitch which leads to inaccurate estimation [6]. In addition, the finite battery efficiency and the chemical reaction taking place during charge and discharge cause temperature rise and badly influence the SoC estimation [2]. Therefore, efficient algorithms are definitely needed for the accurate SoC estimation. Furthermore, neither Coulomb counting nor voltage measurement alone is sufficient for high accuracy of 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 [7], 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 investigate a myriad of approaches in tackling SoC estimation for the smart battery management system and battery supported cyber-physical systems. The rest of the paper is organized as follows: Section 2 presents and discusses several techniques that have been widely applied for the battery SoC estimation. Artificial Intelligence (AI) approach for estimating the SoC of the smart battery management system is outlined in Section 3. Potential applications of Formal Methods (FM) for BMS are described in Section 4. Concluding remarks are given in Section 5 and directions for future work are pointed out at the same section.

II. 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.

A. *Current Based SoC Estimation*

Current based SoC estimation is also known as Coulomb Counting [8-10], 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 (see also Fig. 1 for details):

$$\mathrm{SoC_t} = \mathrm{SoC_0} + \frac{I*t}{C} \tag{1}$$

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 as no methodology is perfect. For instance, Coulomb Counting suffers from a drift over time. As mentioned in [6], 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.

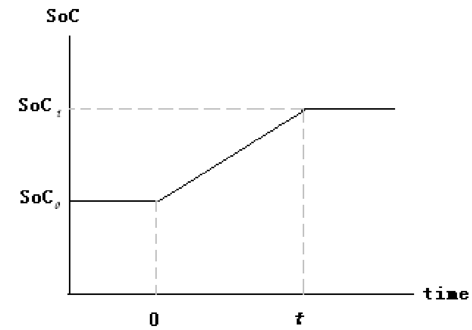

Figure 1. Estimating SoC by using Coulomb Counting

B. *Voltage Based SOC Estimation*

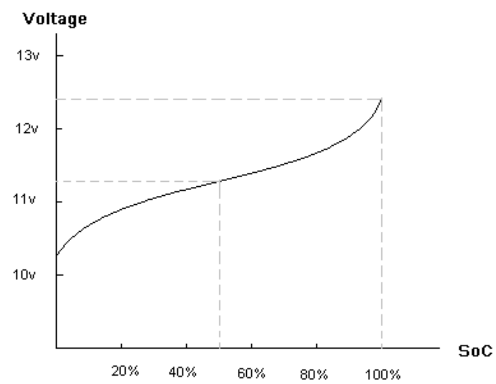

Figure 2. Relationship between Voltage and SoC of Lead Acid battery

There are 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 [8]. In practice, there are two cases, one for the Lead Acid battery and another for Li-ion battery [9]. For the Lead Acid battery, the voltage diminishes significantly when it is discharged as shown in Fig.2 [8]. 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 is a very small change 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 using voltage-based method. However, the voltage of the Li-ion battery changes significantly at the both ends of SoC range, which can be two important indicators of imminent discharge. As an example, for many applications an early warning is required before the battery is completely discharged or empty.

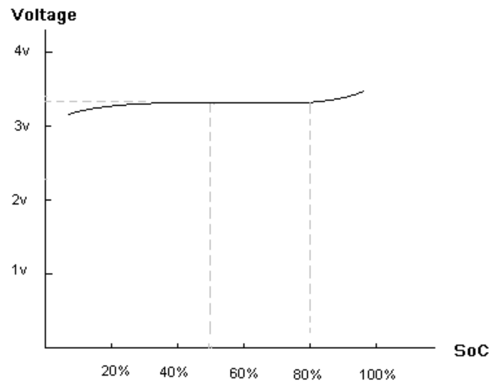

Figure 3. Relationship between Voltage and SoC in Li-ion battery

C. *Extended Kalman Filter*

In 1960s, Kalman Filter theory was proposed [11, 12] 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) [13] is used to estimate the SoC for such nonlinear battery systems. In addition, EKF linearization processes are used at each time step to approximate the nonlinear system with a linear time-varying system. EKF becomes an elegant and powerful solution to estimate the SoC.

III. Artificial Intelligence Systems for Battery SoC Estimation

In achieving the accurate estimation of SoC, Artificial Intelligence (AI) systems like Neural Networks [14] and Fuzzy Logic [15] systems have been regarded as universal approximators. Many techniques have been developed to approximate the nonlinear functions for practical applications [16-17]. The B-Spline Membership Function (BMF) is constructed in [16]. This BMF possesses the property of local control and has been successfully applied to Fuzzy-Neural control [18]. Also, the hybridization of Fuzzy Logic with Neural Network has been done 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 [18-22]. The adaptive Neural Fuzzy method was proposed in [23] 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 the Neural Network. A more practical approach, called merged-FNN is developed for SoC estimation [24]. In merged-FNN, the FNN strategy is combined with Reduced-form Genetic Algorithm (FNNRGA) and this performs effectively in a series-connected Li-ion battery string. The merged-FNN achieves a faster learning rate and lower estimation error than the traditional ANN with a back-propagation method.

The FNNRGA method is further applied to batteries connected in series [25] which modifies the Multiple-Input Multiple-Output (MIMO) system into Multiple-Input Single-Output (MISO). This reduces the number of free parameters and thereby reduces training of unnecessary parameters. From the discussions above, it is evident that the works involving SoC which circulate around the use of Neural Network techniques to accurately predict the SoC of any batteries. One of the reasons for the immense use of Neural Networks is due to their simplicity and a complex mathematical battery model [26] is not required to estimate SoC. However, one prominent drawback of Neural Network is the requirement of training process with many real data, usually more than a thousand (>1000). The more data given for the training, the more accurate is the Neural Network. Also, the input variable selection is very important to increase the accuracy of the estimation results. [23] adopts only one data set among several data sets (battery terminal voltage, discharge current and battery surface temperature). By decreasing the training data set, the training time of the Neural Network is greatly reduced. However, this reduces the similarity between the Neural Network model with the real SoC characteristics of battery.

IV. Application of Formal Methods to BMS

Formal Methods (FM) have been widely applied in different areas [27], e.g. mechatronics [28, 29], electronics [30, 31], medical systems [32, 33]. Battery power management systems are not exception, however, in most of the cases, Dynamic Power Management (DPM), i.e. minimization of power consumption by changing operation modes or by scaling their voltage or frequency is analyzed. In [34, 35] probabilistic model checking is used: system is modeled as a continuous- or discrete-time Markov chain, analyzed using Prism tool [34] and then constructed transition matrix is passed to Maple for optimization problem solving. In this case, model is more concerned in power consumption and is not battery-aware. Nevertheless, it allows choosing “an optimal” DPS and in such a way predicting power usage. Similar approach is taken in [36], where stochastic process algebra is used to model and analyze different control strategies. Again, it is battery-agnostic. A lot more interesting approach is described in [37], where battery-aware model using continuous-time Markov decision processes. Provided models with dual and single battery systems already provide a good insight on the applicability of such techniques to real-life BMS examples with many cells. Similar approach is discussed in [38].

V. Conclusions

An overview of current techniques for battery SoC estimation has been given. We have the intuition that there will be space for research related to the core aspect of battery SoC estimation using both AI and FM approaches. Also, a combined approach of AI and FM will complement the current research in the area of battery SoC estimation. Any progress in the research in this direction will significantly impact the design and implementation of the smart BMS and battery supported cyber-physical systems. Our future will focus on the development of new hybrid techniques to accurately estimate the SoC of various types of batteries.

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REFERENCES

[1] K.W.E. Cheng, B.P. Divakar, 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, pp.76 – 88

[2] S. Duryea, S. Islam, W. Lawrance, "A battery management system for stand-alone photovoltaic energy systems," IEEE Ind. Appl. Mag., vol. 7, no. 3, 2001, pp.67–72.

[3] B. Hauck, BATTMAN—A Battery Management System, Milan, Italy, 1992.

[4] A. Affanni, A. Bellini, G. Franceschini, P. Guglielmi, C. Tassoni, "Battery choice and management for new-generation electric vehicles," IEEE Trans. Ind. Electron., vol. 52, no. 5, 2005, pp.1343–1349.

[5] State of Charge. http://en.wikipedia.org/wiki/State_of_charge

[6] Battery Management Systems (BMS). http://www.mpoweruk.com.

[7] C. Chen, K.L. Man, T.O. Ting, Chi-Un Lei, T. Krilavičius, T.T. Jeong, J.K. Seon, Sheng-Uei Guan and W.H. Prudence Wong, "Design and Realization of Smart Battery Management System," in proceedings of the IAENG International MultiConference of Engineers and Computer Scientists - IMECS'12, Hong Kong, 2012, pp.1173-1176.

[8] White Paper - Estimating the State Of Charge of Li-Ion batteries. http://liionbms.com/php/wp_soc_estimate.php

[9] I. Buchmann, "How to Measure State-of-charge," Battery univerity, 2012, http://batteryuniversity.com /learn/article/how_to_measure_state_of_charge

[10] Zhiwei He, MingyuGao, Jie Xu, "EKF-Ah Based State of Charge Online Estimation for Lithium-ion Power Battery," Computational Intelligence and Security, 2009. CIS '09, 2009, pp.142 – 145

[11] R. Kalman, "A new approach to linear filtering and prediction problems," Transactions of the ASME—Journal of Basic Engineering, vol. 82, 1960, pp.35–45.

[12] R. Bucy, R. Kalman, and I. Selin, "Comment on the Kalman filter and nonlinear estimates of multivariate normal process," IEEE Transactions on Automatic Control. Vol. 10, pp.118-119.

[13] Extended Kalman Filters, Wikipedia, http://en.wikipedia.org/wiki/Extended_Kalman_filter

[14] K. Hornik, M. Stinchcombe, and H. White, "Multilayer feedforward networks are universal approximators," Neural Netw., vol. 2, pp. 359-366, 1989.

[15] L.X. Wang and J. M. Mendel, "Fuzzy basis functions, universal approximation, and orthogonal least squares learning," IEEE Trans. Neural Netw., vol. 3, no. 5, pp. 807-814, Sep. 1992.

[16] C. H. Wang, W. Y. Wang, T. T. Lee, and P. S. Tseng, "Fuzzy B-spline membership function (BMF) and its applications in fuzzy-neural control," IEEE Trans. Syst., Man, Cybern. B, vol. 25, no. 5, pp. 841-851, May 1995.

[17] L. X. Wang, Adaptive Fuzzy Systems and Control. Englewood Cliffs, NJ: Prentice-Hall, 1994.

[18] W. Y. Wang, T. T. Lee, and C. L. Liu, "Function approximation using fuzzy neural networks with robust learning algorithm," IEEE Trans. Syst., Man, Cybern. B, vol. 27, no. 4, pp.740-747, Aug. 1997.

[19] M. Karam, M.S. Fadali, and K. White, "A Fourier / Hopfield neural network for identification of nonlinear periodic systems," in Proc. 35th Southeast. Symp. Syst. Theory, Morgantown, NY, pp. 53-57, Mar. 2003.

[20] Q. Z. Chang and M. Sami Fadali, "Nonlinear system identification using a Gabor / Hopfield network," IEEE Trans. Syst., Man, Cybern. B, vol. 26, no. 1, pp. 124-134, Feb. 1996.

[21] S. K. Park, "Bearing estimation using Hopfield neural network," in Proc. 22nd Southeast. Symp. Syst. Theory, Cookville, Tn, Mar. 1990, pp.440-443.

[22] N. Kamiura, T. Isokawa, and N. Matsui, "Learning based on fault injection and weight restriction for fault-tolerant Hopfield neural networks," in Proc. IEEE Int. Symp. Defect Fault Tolerance in VLSI Syst., France, Oct. 2004, pp.339-346.

[23] W. X. Shen, C. C. Chan, E. W. C. Lo, and K. T. Chau, "Adaptive neuro-fuzzy modeling of battery residual for electric vehicles," IEEE Trans. Ind. Electron., vol 49, pp.677-684, Jun. 2002.

[24] I-Hsum Li, Wei-Yen Wang, Shun-Feng Su, and Yuang-Shung Lee, "A merged fuzzy neural network and its applications in battery state-of-charge estimation," IEEE Trans Energy Conv., vol. 22, pp.689-708, Sep 2007.

[25] Y. Lee, W. Wang, T. Kuo, "Soft computing for battery state of charge (BSOC) estimation in battery string systems," IEEE Trans. Ind. Eletron., vol 55, pp.229-239, Jan. 2008.

[26] Z.M. Salameh, M. A. Casacca and W.A. Lynch, "A mathematical model for lead-acid batteries," IEEE Trans. Energy Convers., vol 26, no. 2, 2011.

[27] K.L. Man, T. Krilavičius and Kaiyu Wan, "Recent advanced languages and tools for hybrid systems," IAENG Int. Jour. of Comp. Sc., vol. 37, issue 3, 2010. pp. 224-233.

[28] T. Krilavičius, "Simulation of mechatronic systems using behavioural hybrid process calculus," Electronics and Electrical Engineering, No. 1(81), 2008. 5 pp.

[29] T. Krilavičius, V. Miliukas, "Functional modelling and analysis of a distributed truck lifting system," Proc. Of the 5th International Conference on Electrical and Control Technologies (ECT 2010), Kaunas, Lithuania, June 2010.

[30] K.L. Man, A. Asthana, H.K. Kapoor, T. Krilavičius, J. Chang, "Process algebraic specification of DI circuits." Proc. of the 7th IEEE Int. SoC Design Conference (ISOCC), pp. 396-399, 2010. Korea.

[31] K.L. Man, T. Krilavičius, C. Chen and H.L Leung, "Application of bhave toolset for systems control and mixed-signal design," Int. MultiConf. of Engineers and Computer Scientists (IMECS), Hong Kong, 17-19 March, 2010.

[32] T. Krilavičius, D. Vitkutė-Adžgauskienė and K. Šidlauskas, "Simulation of the Radiation Therapy System for Respiratory Movement Compensation," Journal of Vibroengineering, 14:1, 2012. p. 99-104.

[33] K.L. Man, T. Krilavičius, Kaiyu Wan, D. Hughes and K. Lee, "Modeling and analysis of radiation therapy system with respiratory compensation using Uppaal," Proc. of the 9th IEEE Int. Symp. on Parallel and Distributed Processing with Application (ISPA 2011), Korea, May, 2011.

[34] R.K. Gupta, S. Irani, and S.K. Shukla, "Formal methods for dynamic power management", in Proc. ICCAD, 2003, pp.874-882.

[35] G. Norman, D. Parker, M. Kwiatkowska, S. Shukla and R. Gupta, "Using probabilistic model checking for dynamic power management," Formal Aspects of Computing, 17(2), 2005, pp. 160-176,.

[36] A. Acquaviva, A. Aldini, M. Bernardo, A. Bogliolo, E. Bontà and E. Lattanzi, "A methodology based on formal methods for predicting the impact of dynamic power management", in proc. SFM, 2005, pp.155-189.

[37] P. Rong, and M. Pedram, "Battery-aware power management based on Markovian decision processes," Proc. of the 2002 IEEE/ACM international conference on Computer-aided design (ICCAD '02). ACM, New York, NY, USA, 2002, pp.707-713.

[38] L. Benini, G. Castelli, A. Macii, E. Macii, M. Poncino, and R. Scarsi, "Extending lifetime of portable systems by battery scheduling," Proc. of Design Automation Test Europe DATE Conf (IEEE Comput. Soc), 2001, pp. 197-201.