Online learning ANN model for SoC estimation of the Lithium-Ion battery in case of small amount of data for practical applications

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***Abstract*--A battery's state of charge (SoC) estimation with accuracy is presented in this paper. Its calculation time is accelerated using online model approach (during operation) with optimal generalization. This novel idea minimizes the initial error of the SoC with the help of artificial neural network (ANN). It is realized by an online learning with offline update parameter estimating model for a battery equivalent circuit. Although degradation of Lithium-Ion (Li-Ion) battery cell is inevitable, accurate estimation of the actual state is needed to extend its life of usage. It is, however, difficult to calculate the parameters by conventional methods, because the parameters are nonlinearly involved in the mathematical notation of the battery impedance and all other variables related with SoC estimation.**

Index Terms--Li-Ion battery, ANN model, online learning structure, fast estimation algorithm.

I. Introduction

Development of reliable and efficient energy storage system is one of aggressive challenges for the industrial applications particularly in smart grids and automobile applications as electric vehicles (EVs). Lithium-Ion Batteries (LIBs) are the most used type of batteries due to their high energy and power density, high efficiency, high open-circuit voltage (OCV), wide range of temperature operating and long-term usage [1].

A. *Conventional methods and approaches*

The conventional method of SoC estimation are based on 6 main groups which consists of current counting method, open circuit voltage (OCV) method, internal impedance method, electrochemical method, model-based method and pressure method. In this paper the definition of SoC will be based on the nominal capacity of the battery not from the actual capacity after every cycle.

1) *Current counting method*

Current counting is easy to use, low cost and low computational complexity to estimate the SoC of the battery [1].

$$SoC(k) = SoC(0) + \frac{1}{C_n}\int_0^k (\eta \cdot I(t) - S_d)dt \qquad (1)$$

where SoC(0) is the initial SoC, $I(t)$ is the current at time t, C_n is the nomial capacity of the battery, η is the coulombic efficiency, and S_d is the self-discharging rate. However, this method introduces few main drawbacks as the unknown initial SoC, self-discharge rate and current-sensor errors which serves as error sources for this method.

2) *OCV method*

OCV method uses the non-linear relationship between the battery electromotive force in the open circuit state and SoC to estimate the SoC [2]. Despite the fact that the relationship is stable, it is not the same for different batteries. It is closely related with capacity and chemical composition of the electrode material of the battery. Massive experiments should be conducted at different cycle of usage [3].

3) *Internal impedance method*

Internal impedance describes the electric characteristic of the battery and depends on current, SoC, SoH, temperature, etc. Although the impedance has been measured by a sinusoidal alternating current (AC) method, the method is difficult to apply to the online electrical impedance spectroscopy (EIS). The relation between the SoC and internal impedance is non-stable, and the measurement is accompanied with high cost. In addition, the value of internal impedance changes slowly which introduce difficulties to observe the SoC [6-8].

4) *Electrical circuit model (ECM) method*

It is important to define the correct and best ECM for each type of battery or problem that need to be resolved. Although the accuracy of the estimation will be improved by increasing the complexity of the circuit with parallel RC blocks, it comes with higher cost and time consuming as well. Even if the number of blocks is reasonably determined from a viewpoint of numerical calculation, the synthesized model cannot explain all the electrochemical processes of the battery. The trade-off relation between accuracy and computational complexity should be kept in mind.

5) *Electrochemical method*

Electrochemical method theoretically gives the most accurate SoC estimation. However, this method can be effectively used for off-line design and performance analysis for LIBs. The equations used for this method describe the physicochemical phenomena like diffusion, electrochemical kinetics occurring inside the battery etc. This model is typically and computationally challenging owing to a system with relation of time-varying partial differential equations.

6) Pressure method

This method can be applied to certain Ni-MH batteries. The internal pressure increases rapidly when the battery is charged. Usually it is employed in an extra protection system as a pressure switch indicating full-charging.

B. Aim of this research

Nowadays many different types of batteries based on lithium-ion are in production and commercial. It is of great importance to understand the differences between them, because each of these batteries is used for different applications based on their needs. The spider chart for LIBs with various anode and cathode materials is shown in Fig.1. One of the important variables to mention is the C-rate which explains the current value required for the battery to its rated capacity within the specified time. With the help of this chart it is possible to understand the advantages and drawbacks for each LIB type. The heat generation, charging/discharging ability, rated power and energy, thermal stability and deterioration level can be used for the further study of the real time SoC & SoH estimation of the battery cell/pack. As well these data can be used for a generalization of the problem.

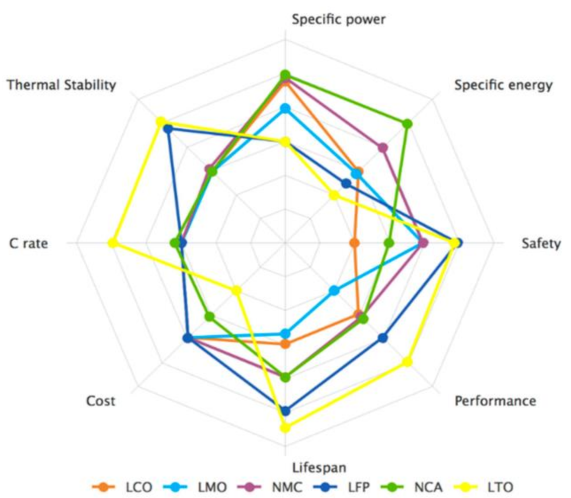

Fig. 1. Spider chart for LIBs with different chemistry materials [5].

For actual and future technologies of energy storage systems, the need for an online diagnosis (during operation) without the removal of the battery is very crucial in order to increase the efficiency and lifetime of the battery, to reduce the cost of conventional diagnosis system, and to reduce the non-operational time due to the maintenance schedule.

II. Battery State of Charge

A. Definition of the state of charge

The State of Charge can be defined by different methods and variables, but the most used definition is the ratio between the actual capacity and the reference capacity, which is the maximum actual value based on some specific conditions. These conditions refer to the constant current rate and ambient temperature, as well other conditions as cycles of usage (level of deterioration), chemical composition etc. Because battery is an energy storage device based on chemical composition, so many difficulties are introduced for a direct SoC measuring method.

B. Difficulties for estimating accurate SoC

Each method introduced in the previous chapter shows difficulties and drawbacks in the process of the estimation of SoC. The result obtained from a discharging test of the battery until the end of discharge process based on the criteria is mentioned in the datasheet of the manufacturer. Fig.2 shows a full charging and discharging process which concludes one cycle of test. The results are oabtained by Constant-Current-Constant-Voltage (CCCV) charging and CC discharging with 1C (2.25A) and with lower and upper voltages are 2.7V and 4.2V, respectively. This characterisitc can be obtained whithout the removal of the battery, and involves important information on SoH or SoC. Two variables, voltage and current will be used in this paper as the parts of the input data for the proposed artificial neural network (ANN) structure.

Fig.3 shows voltage deviations of a same battery but in different level of deterioration (a new battery with 0 cycle from a full deteriorated of 500 cycles). It is clear in Fig.3 that the effect of deterioration really affects the voltage level, terminal voltage, due to the degradation of the chemical composition which affect the internal impedance of the battery.

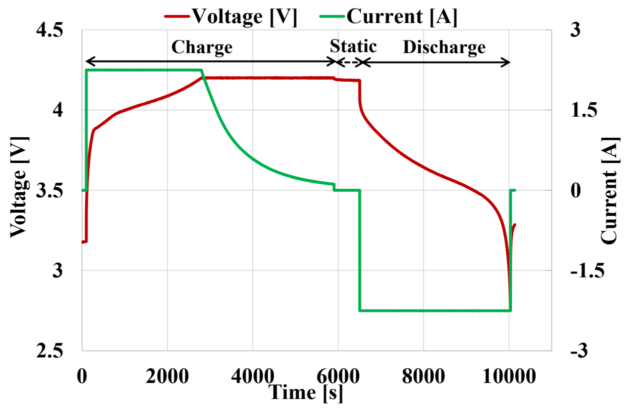

Fig. 2. Charge and Discharge waveform

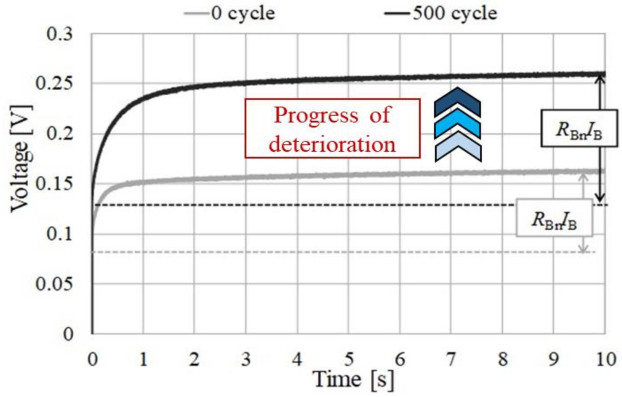

Fig. 3. Voltage difference during the deterioration.

III. PROPOSED MODEL

In this paper, an adaptive online learning algorithm based on an ANN is used. This ANN employs the feed forward backpropagation model with a reduced data scenario. The ANN has self-learning skills and adaptability to demonstrate a complex non-linear model as explained in [11]. It accurately estimates the SoC without knowing the internal structure of the battery and the initial SoC. There are different types of approaches when it comes to the Machine Learning (ML) paradigm method, mostly they are divided into three groups:

1) Reinforcement learning (RL)
2) Supervised learning (SL)
3) Unsupervised learning (UL)

The RL method is different from the supervised or unsupervised approach. The RL is based on an agent which learns how to behave in an environment by performing actions and seeing the results, and for each action it received a reward. The RL learning requires clever exploration tools. Randomly selecting actions without reference to an estimated probability distribution shows poor performance. Many RL algorithms utilize dynamic programming techniques as explained in [12-14].

The SL focuses on the task of learning function that correlate an input to an output based on example input-output pairs [15]. It infers a function from labeled training data based on a groups of training examples.

The UL is a term used for Hebbian learning, which is one of learning methods without teachers, and also is known as self-organization [16]. The main application of unsupervised learning is in the field of density estimation in statistics.

A. *Proposed SoC estimation model*

Usually, the ANN method uses the LIB terminal voltage, discharge or charge current, and ambient temperature as the input and SoC as the output. The novel in this paper is the modified input time-delayed neural network model that takes into accounts both deterioration and temperature effects. This study investigates further on the reduction of input data for low power computational hardware in order to reduce the cost from a viewpoint of industrial applications. An online training and offline update weights, which enables offline decision-making for the SoC estimation, is introduced to reduce the needs not only for high computing power but also for large memory storage of the whole system. Fig.4 shows Cole-Cole plots of a battery during charging until the SoC reaches to 100%. These characteristics involve very important information which shows the increase of the internal impedance during charging, this clearly explain the physical meaning of the electrochemical process.

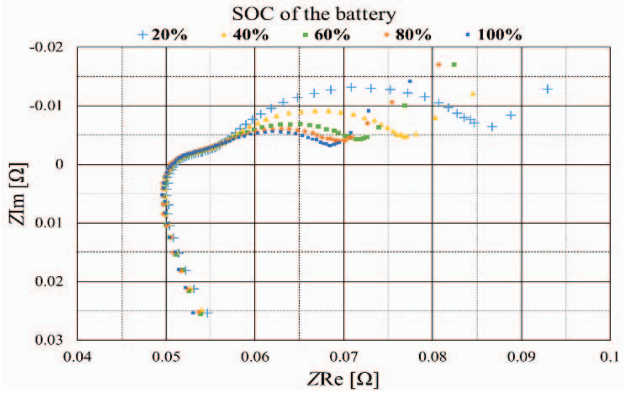

Fig. 4. Cole-Cole plot related with SoC%

Figs. 5 and 6 show the characteristics of voltage and current during charging and discharging in CCCV mode. These data are genuine and all obtained through real experiments. The authors would like to emphasize the effect of ratio in the SoC process. These data are used in the database of the proposed ANN during the training process. Some experiments are initiated even from different level of upper voltage, not only from 4.2V but also from 4V or 3.8V, in order to imitate a real scenario of usage of the battery during moment when the battery is not full charged/discharged. This helps to increase the quality of the estimation and improve the generalization of the ANN.

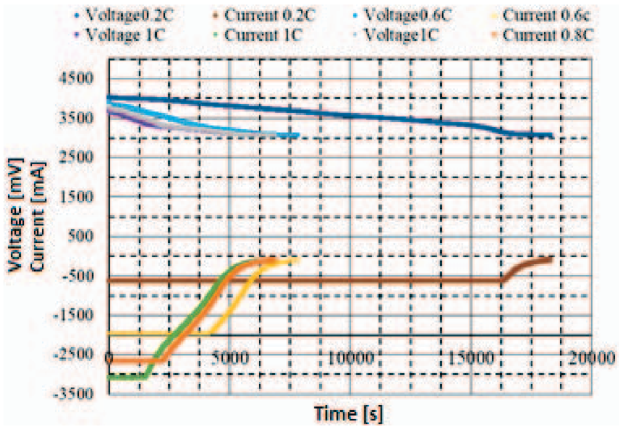

Fig. 5. Comparison of discharging characteristics between different current ratio during CCCV mode

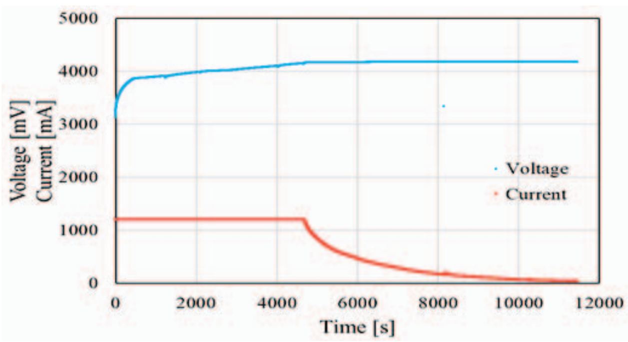

Fig. 6. Characteristics of Li-ion during CCCV charging

B. *ANN model & estimated results*

As already explained in the previous chapter regarding the ML based on the supervised/unsupervised method, ANN is one of them, which electronically imitates the neural structure of brain. This approach consists of three processes, learning, validation and test. The proposed NN is processed in MATLAB R2018a. In the training process, the selection of the most appropriate NN configuration is crucial. The typical structure of the ANN is composed of an input layer, a hidden layer and an output layer. In the proposed structure, the number of input types is 4, voltage, current, cycles and temperature. Regarding the voltage and current, it is very easy to obtain these data during operation with actual sensors without the stoppage of the operation. Most of actual low-cost devices give this information without any extra cost, and this helps for the online diagnosis system.

Regarding the cycles, the authors have used two types of the counting cycle data, one structure during every 50 cycle of deterioration, and the other is 100. The former means that only 11 data cells are required for from 0 cycle battery to a full deteriorated battery of 500-cycle. The later structure (every 100-cycle) needs only 6 data cells. Even if the number of data is reduced to almost half, the increase of the error is only 2.3% in the worst case. This cycle counting is very easy, and is realized in low cost. This method is applicable to any industrial systems without difficulties.

The dynamic temperature, i.e., battery surface temperature can be entered as the fourth and final input. The signal can be used as a precaution to protect the system. However, a temperature sensor has to be installed on the battery cell. Ambient temperature can be used as the fourth data because the sensitivity against the data is low. In this paper, 25 and 35 degree Celsius are used for the ANN. To reduce the cost further, the fourth data can be optional. However, the estimation error slightly increases. Fig.7 shows the temperature information of the ambient, cell body and transistor controlling the charging/discharging.

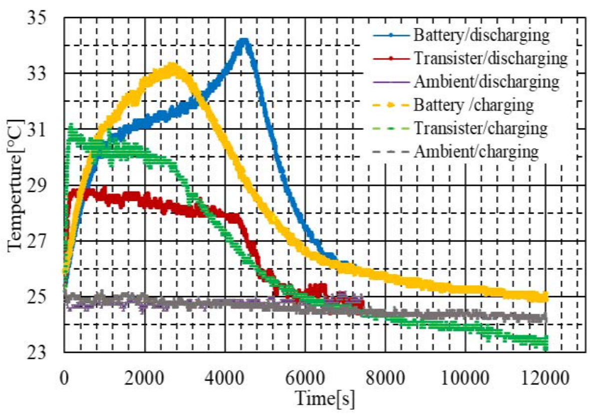

Fig. 7. Temperature characteristics during charging and discharging with 3A

Both experiments during charging and discharging are introduces in order to include the dynamic behaviour during different operations. Regarding the transistor temperature this information it is not used as the input for the proposed ANN structure, but is just introduces as a possible extra information for the industrial applications. Regarding the transistor temperature will discussed more in detail in the appendix.

Fig. 8 shows the proposed ANN structure. During the training process, the data are obtained using 10 new batteries, and deteriorated from 0 cycle to 500 cycles. For the voltage and current input, 350 data are used for each of them. For the cycle input (3rd input), 6 or 11 data cells are used based on the selected mode also for the temperature around 400 data cells were used in the training process in case of a variable temperature system, except the case of static temperature.

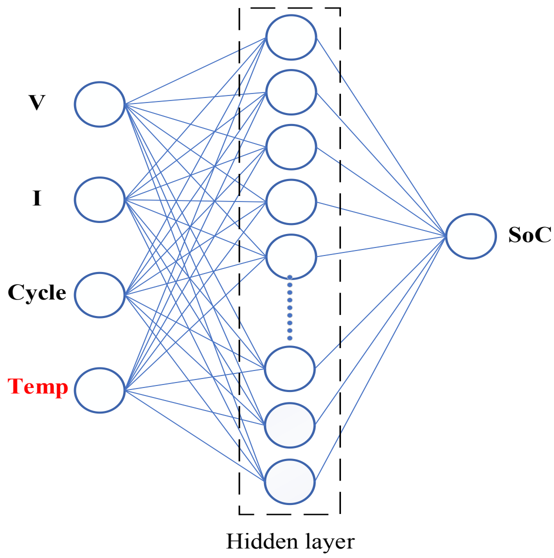

Fig. 8. ANN structure for the proposed model

The ANN with double or single hidden layers are tested in this paper. The best structure is 22 neurons with single hidden layer, or 31 neurons with two hidden layers. The initial learning rate was set to 0.11 and in the end after the optimization the learning rate was set to 0.021. The best estimation model was achieved with maximum error of 3.1% in the worst case. Fig. 9 shows the measured and estimated OCV-SoC characteristics.

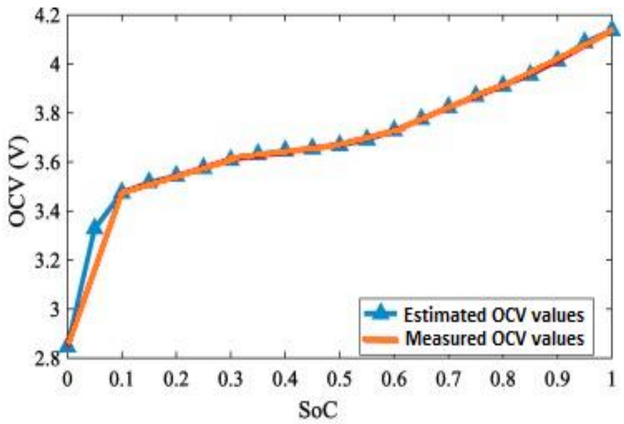

Fig. 9. Comparison between the estimated and measured OCV

IV. CONCLUSIONS

An SoC estimation method with accuracy and quick calculation is proposed in this paper. It is important for BMS in any application field. In this paper a proposed method is introduced based on adaptive ANN model which asymptotically achieves optimal error rates for realizing stochastic rules. The data used for this study are all genuine experimental data which introduce a correct physical meaning and relation with all the variables. Li-Ion batteries with different level of deterioration are used in order to obtain and understand the differences from the obtained data. After the final optimization of the proposed structure, the accuracy of the model was obtained with the maximum error of 2.9% in the worst case. The estimation can be concluded in the range from 23.9 to 32.4 seconds.

This model is mostly focus on the online learning model in order to make an optimized generalization for further application in different fields as portable devices or even static one for the renewable energy applications.

APPENDIX

In Fig.7 the temperatures of battery cell, ambient and transistor are obtained through the sensors. The surface temperature of the battery is the most important information regarding the temperature comparing to the ambient which is more stable characteristics as shown in Fig.7. The transistor temperature is the related with the power transistor of the PCB which control the charging/discharging ratio. This info is important to shows the range of current operation for normal operation within the nominal values. As well it is used as an evaluation system regarding the safety and reliability of the application.

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