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State of Health (SOH) monitoring of Base Transceiver Stations (BTS) using Neural Network

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Smart Gujarat for New India Hackathon, SSIP, 2019

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1. Introduction

In the modern world, batteries are indispensable. They are among the foundations blocks for modern mobile computing technology, serve as backup for server farms that power the internet and are an important step in bridging the gap to complete renewable energy reliability. Moreover, with the electric vehicle (EV) revolution just around the corner, the market for batteries is going to grow by leaps and bounds. Lithium-ion batteries make up 70 percent of world's rechargeable battery market. Since then, EV-driven demand for lithium-ion batteries has risen, and will likely continue to rise as long as lithium-ion batteries are the primary power source for EVs. Bloomberg New Energy Finance Limited(BNEF) projects that global production capacity for lithium-ion batteries will increase from 103 gigawatt-hours (GWh) in the first quarter of 2017 to 273 GWh by 2021.13 [1].

Lithium-ion batteries are a preferred source for power back-up in BTS towers due to fast charging capacities, longer life cycle, enhanced safety, low maintenance costs and the ability to operate in a wide range of environmental conditions for long periods as compared to traditional batteries. To enable uniterrupted supply and to avoid sudden shutdowns, it becomes imperative to have accurate state of cha (SOC) and state of health (SOH) information. SOC is defined as the available capacity (in Ah) and expressed as a percentage of its rated capacity. The SOC parameter can be viewed as a thermodynamic quantity enabling one to assess the potential energy of a battery. It is also important to estimate the state of health (SOH) of a battery, which represents a measure of the batterys ability to store and deliver electrical energy, compared with a new battery.

2. Theory

2.1 State of Charge (SOC)

The releasable capacity ($C_{releasable}$), of an operating battery is the released capacity when it is completely discharged. Accordingly, the SOC is defined as the percentage of the releasable capacity relative to the battery rated capacity (C_{rated}), given by the manufacturer.

$$SOC = \frac{C_{releasable}}{C_{rated}} \times 100\% \tag{2.1}$$

When a battery is discharging, the depth of discharge (DOD) can be expressed as the percentage of the capacity that has been discharged relative to (C_{rated}),

$$SOC = \frac{C_{released}}{C_{rated}} \times 100\% \tag{2.2}$$

There are a number of methods to determine the SOC of a battery. Some of them are:

- Voltage Method
- Kalman Filter Method
- Neural Networks
- Enhanced Coulomb Counting

In the voltage method, the SOC of a battery, that is, its remaining capacity, can be determined using a discharge test under controlled conditions. The voltage method converts a reading of the battery voltage to the equivalent SOC value using the known discharge curve (voltage vs. SOC) of the battery. However, this approach is not as accurate as other ones, mainly because it is an open loop one and in addition the voltage is more significantly affected by battery current due to battery's electrochemical kinetics and temperature[2].

Kalman Filter provides a better estimate for SOC. The Kalman filter is an algorithm to estimate the inner states of any dynamic systemit can also be used to estimate the SOC of a battery. Kalman filters were introduced in 1960 to provide a recursive solution to optimal linear filtering for both state observation and prediction problems. Compared to other estimation approaches, the Kalman filter automatically provides dynamic error bounds on its own state estimates. By modeling the battery system to include the wanted unknown quantities (such as SOC) in its state description, the Kalman filter estimates their values and gives error bounds on the estimates. However, it needs a suitable model for the battery and a precise identification of its parameters. It also needs a large computing capacity and an accurate initialization.

In order to overcome the shortcomings of the coulomb counting method and to improve its estimation accuracy, an enhanced coulomb counting algorithm has been proposed for estimating the SOC and SOH parameters of Li-ion batteries. The initial SOC is obtained from the loaded voltages (charging and discharging) or the open circuit voltages. The losses are compensated by considering the charging and discharging efficiencies. With dynamic re-calibration on the maximum releasable capacity of an operating battery, the SOH of the battery is evaluated at the same time. This in turn leads to a more precise SOC estimation.[3]

2.2 State of Health (SOH)

A fully charged battery has the maximal releasable capacity C_{max}, which can be different from the rated capacity. In general, C_{max} is to some extent different from C_{rated} for a newly used battery and will decline with the used time. It can be used for evaluating the SOH of a battery.

SOH is not an objectively defined quantity. It is defined differently by various manufacturers. It depends on various parameters such as:

- Internal impedance/conductance/impedance
- Capacity
- Self Discharge
- Number of charge discharge cycles
- Temperature of battery during previous uses

In our case, the SOH is defined as[4]:

$$SOH = \frac{Q_{now}}{Q_{rated}} \times 100\% \tag{2.3}$$

In a lot of cases, SOC and SOH are decoupled. This leads to inaccuracies in the measurement of SOH as well SOC in further iterations as SOC estimation might drift off as the battery degrades.

3. Our Approach

While the iterative estimation of SOH is not that inaccurate in enhanced coulomb counting, there are neural network based techniques that provide a better solution.

We plan to use enhanced coulomb counting for accurate determination of SOC[3]. For the calculation of SOH, we plan to use back propagating neural networks. This is to take into account factors such as humidity and temperature as well, which are not considered in enhanced coulomb counting. These factors taken into account because of the variability of the ambient conditions of the battery.

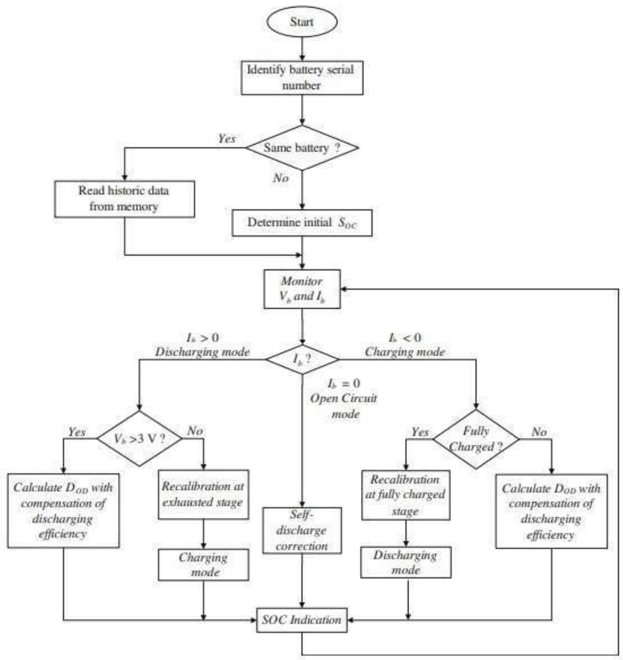

Figure 3.1: SOH determination using neural networks

The neural network based approach is advantageous as it takes multiple factors into account and is more robust than other approaches as change in the type or size of batteries can easily be accommodated by retraining the model.

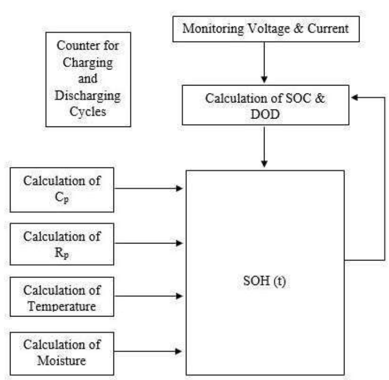

Figure 3.2: SOH determination using neural networks

The NN model is shown in Fig.1 (b), and it consists of three layers: input layer, hidden layer and output layer. In this model, the inputs are SOC, and the ECM parameters including ohmic resistance R_0, polarization resistance R_p and polarization capacity C_p. $\mathbf{iw}_{i,j}$ is the matrix of connecting weight from input layer to hidden layer. $\mathbf{lw}_{i,j}$ is the matrix of connecting weight from hidden layer to output layer. $\mathbf{b}_1$, $\mathbf{b}_2$ are the threshold matrix of hidden layer and output layer, respectively. In this paper, we choose back propagation neural network (BPNN) to train the input data. The output of this model is expressed in equation (2).

$$SOH(t) = \mathrm{purelin}(\mathbf{lw} \cdot (\mathrm{logsig}(\mathbf{iw} \cdot \mathbf{p} + \mathbf{b}_1)) + \mathbf{b}_2) \tag{2}$$

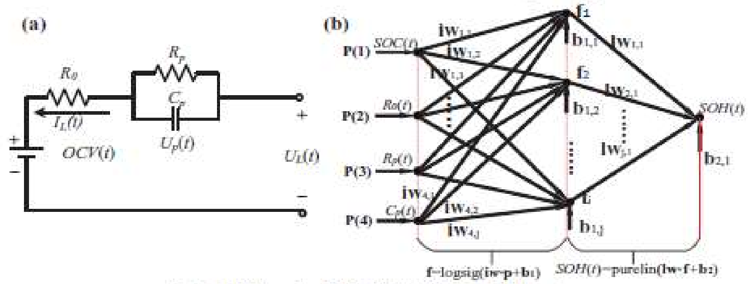

Fig.1.(a) First-order ECM. (b) The NN model structure.

3. Parameter Identification

The HPPC test is usually used for model parameter identification and model accuracy verification. The part graph of HPPC profile in a circle is shown in Fig.3. U_0 in Fig.2 (b) is the voltage of R_0. The ohmic resistance R_0 can similarly be seen as the ratio of dropout voltage and dropout current when the current is changed suddenly, which is expressed as equation (3). R_p and C_p can be reflected by the continuous voltage change after the voltage leaps and they can be estimated by least squares fit. The formula that needs to fit is shown as equation (4) [14], which only has R_p and C_p two variables:

$$R_0 = \frac{\Delta U_0}{\Delta I_L} \tag{3}$$

$$U_p(k+1) = \exp(\frac{-\Delta t}{R_p C_p}) \cdot U_p(k) + R_p I_L(k) \cdot (1 - \exp(\frac{-\Delta t}{R_p C_p})) \tag{4}$$

where Δt means sampling time. $U_p(k+1)$, $U_p(k)$ and $I_L(k)$ are the initial data processed by discretization.

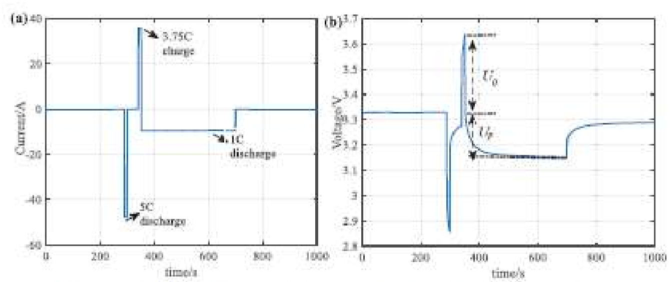

Fig.2. Part graph of HPPC profile. (a) Current profile. (b) Voltage profile.

Conclusion

A simple method estimating battery's SOH based on BP neural network is proposed in this paper. In this method, with several parameters of the first-order ECM, we can estimate the value of SOH using a three-layer BP neural network. The proposed method has 3 characteristics: (1) low computation cost (the computation time of training the NN is 21ms). (2) Low memory requirement. (3) Easy to understand. The accuracy of result is dependent on the accuracy of identification algorithm, the quantity of training data, the precision of ECM model which is chosen, the test profiles and etc. The training rate depends on the learning algorithm, the numbers of layers and neurons, etc. The error during the work is inevitable because of the error initial sampling data, algorithm error and the inaccuracy of the NN model. So the outputs shall be filtered before being used to computing the final SOH value of a battery.

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