Analysis of a Li-ion battery state of charge by artificial neural network

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ABSTRACT

The state of charge (SOC) is a battery residual capacity crucial assessment metric. The need for a precise SOC estimate is very important to ensure the safe functioning of a Li-ion battery and to prevent overload and over-depletion. However, the renewable energy-based standalone application has become a key problem to determine the exact capacity of SOC of the Li-ion battery. To estimate the capacity over time, the battery management system calculates the SOC of a Li-ion battery. This allows for the implementation of intelligent control systems. This paper presents an enhanced radial basis function (RBF) of the SOC battery estimate following the limits and weaknesses of the back propagation (BP) neural network (NN) in estimating battery SOC, such as sluggish convergence speed, poor generalization and can increase the accuracy of the network but it takes time to iterate. Train the enhanced RBF with experimental data in real-time. The trained NN of SOC is compared to actual values and the MATLAB is used to simulate the method to evaluate its accuracy.

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1. INTRODUCTION

One of the most critical issues for battery systems is the estimate of the energy availability of the battery. Batteries are energy systems stored chemically which have no direct access to stored electricity. This problem predicts that the energy available is a tough challenge [1]. The factors which provide information on the energy available and aging of a battery is state of charge (SOC). In comparison with nominal capacity Qn [2], the SOC is often specified as a percentage of current capacity Q(t) by (1).

$$SOC(t) = Q(t)/Q_n \quad (1)$$

SOC can't be measured directly. Only a few testable parameters can be expected. The widely used SOC power battery prediction technique is used to monitor voltage level, amperage, impedance, warmth, and other parameters [3]. The SOC of a lead-acid battery and the open circuit voltage (OCV) are typically linear [4]. In contrast to a lead-acid battery, the link seen between OCV and SOC in a Li-ion battery is not linear [5]. The conventional SOC power battery prediction techniques include open-circuit voltage, discharge, and time integer and conduction method [6], [7]. This executive summary examines the estimate challenge for electrochemical batteries' SOC. Just use an electrical circuits design of the battery that has been published in the literature [8], it is demonstrated how, provided the battery current is sufficiently varied, the open-circuit voltage, which is directly related to the SOC, may be determined only from junction voltage or current observations. In this paper, common state of charge assessment techniques, together with their benefits and drawbacks, are presented [4]. The time integral technique offers high precision, easy computation, and can estimate online SOC, but the original value cannot be estimated and the cumulated error has been found in this method. The technique is better at evaluating the battery's residual power whether the battery is low or high, but it does not have linear properties and the change in battery size is quite big. Calman filtering, fuzzy logic, and neural network (NN) are the latest SOC prediction techniques for power battery products. The Calman technique of filtering can better represent the battery dynamics. The computation is, however, quite high and the precision are dependent on the correctness of the power battery equivalent circuit model [9]. The robust generalisation ability of the NN allows it to recognise the connection between the variables of complex input. Input and output nodes are not constrained and cannot depend on the non-linear characteristic and intrinsic process of the battery, hence the SOC predicting model does not account for accumulating errors caused by batteries [10], [11]. The NN model, which is more precise and complex in comparison to other approaches, requires a huge quantity of training data. The model's accuracy depends on the exactness of the training data. The network model is chosen for predicting the present SOC based on the vast number of data gathered from experiments. Four batteries of the same rating 2 Ah were utilized in this research. Advance NN method are used in recent area with more advantages in determine the battery aging [12], [13]. The ageing of Li-ion batteries often involves a deterioration that depends on consumption and usage. Both contribute to capacity loss and an increase in internal resistance. The end of life is characterized primarily as a 20% loss in capability or a 100% increase in resistance [14]. To investigate the impact of porous electrodes on fade behavior, numerical simulations are employed [15], [16]. The effectiveness of the suggested model is verified using data collected from four Li-ion phosphate battery packs as the target dataset, and its performance is evaluated in comparison to other NN models. The suggested model can at any time carry out rapid online capacity estimation [17]. In combination to volts, ampere, or temperatures as input data, the prediction model also takes into account the impact of the battery deterioration process, which includes charging and discharging durations as well as the most recent discharge charge [18]. An electrochemical-thermal-neural-network (ETNN) model is developed to predict the battery's condition of charge and state of heat under these circumstances [19]–[22]. Battery based water pumping system along with photovoltaic (PV) is discussed as battery application [23]. In this research, therefore, suggests a SOC model based on the NN back propagation (BP) and radial basis function (RBF). The superiority of the RBF approach is simultaneously proven, which can enhance battery efficiency and extend battery service lives. This article gives a brandnew idea for the PV standalone application design battery management system.

2. PRINCIPLE OF BACK PROPAGATION ALGORITHM

The BP algorithm includes backward and forward transmission. The sample is processed for forward transmitting from the input layer and the caching layers to the output layer when the output of every neuron layer affects just the states of the following layer. If the network output differs from the expected output Q_z, the algorithm enters the backward transmission. In backward transmission, the error signals are in opposition to the direction of the forward transmission and modify the neuron layer weight coefficient in the negative gradient direction of the error function, therefore reducing the predicted error function. The general architecture of a BP and RBF neural network (RBF-NN) is shown in Figure 1.

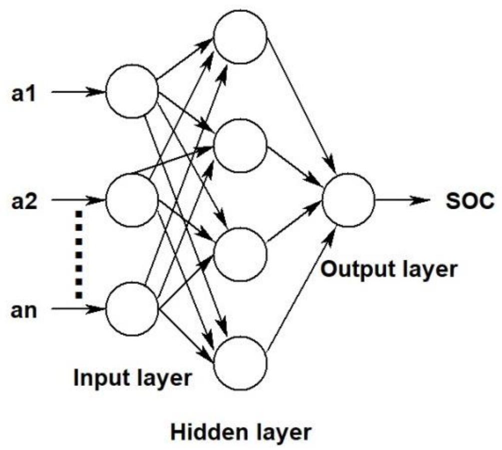

Figure 1. Architecture of NN

2.1. Back propagation algorithm training framework

The setting of the samples mode counters s and frequency counters p to 1. Introductory value for weight matrix z and y. Set zero to error and 0 to 1 for decimal acquisition efficiency and Qmin to positive decimal network training accuracy. Calculate each layer's output and input sample training. Assign ns and m_s to vector x and d as the current sample. Compute x and n components using (1) and (2).

$$xj = F\left(V_j^u X\right), j = 1,2, \ldots, n \tag{2}$$

$$nk = F\left(M_j^u, y\right), k = 1,2, \ldots\ldots, l \tag{3}$$

Network output error analysis: consider that the training sample is s-pairs. Error E_a varies from one sample to another. The root mean error square can be used either E_{max}, the highest value of the error or (4).

$$E_{rms}\sqrt{1/\sum_{s-1}^{s} E^s} \tag{4}$$

Compute each layer's error signal: δ_p^n and δ_w^y with a calculate (5) and (6).

$$\delta\_p\hat{}n = (d\_p - n\_p\ )\ n\_p, p = 1,2, \ldots., l \tag{5}$$

$$\delta\_w\hat{}y = (\sum\delta\_k\hat{}(n\ @n)\ g\_wk\ )(1 - y\_w\ )w, w = 1,2, \ldots\ldots, m \tag{6}$$

Updating each layer's weight: compute the Z, Y and components (7) and (8).

$$Z\_pw \leftarrow Z\_pw + \varepsilon\delta\_w\hat{}n\ x\_j \tag{7}$$

$$Y_{jw} \leftarrow Y_{jw} + \epsilon\delta_{w.}^{y} n_k \tag{8}$$

Check to confirm whether all samples in rotation are finished: if $s < S$, counter s, padd 1, return step (3) or step to (8). There are two techniques for adjusting weight in the present applications. This weight adjustment technique for rotating each sample is also known as the single sample training and the input samples should yield mistakes, as can be observed in the above steps.

$$E = 1\ /\ (2 \sum\_(s-1)\hat{}s\sum\_(p-1)\hat{}l(d\_p\hat{}s\ ) - N\_p\hat{}s)\hat{}2 \tag{9}$$

As one-piece practice is short on "selfish departmentalism," only the mistakes are adjusted for each sample it creates, so that the number of exercises is doubled and the convergence speed is too sluggish. The network errors after all sample inputs are also calculated. This batch form of cumulative errors can be referred to as batch training or epoch training, then calculating layer errors based on the total error and adjustment of weight (9). The training in batch has been carried out according to the 'collectivism' concept to reduce global error, ensuring a change in overall error in the direction of decrease. Batch training over convergence speed is quicker with large numbers of samples than single-sample training.

2.2. Principle of radial basis function algorithm

The RBF-NN is a successful and globally approximated future network model [24]. A RBF-NN has nodes termed RBF units in its buried layer. The length and center of each RBF unit are governed by two fundamental variables [25]. For unreliable information systems, the RBF-NN is a useful tool. The relationships among one pattern and further analogous sequences in a given collection can be investigated [26]. The creation of a RBF-NN is demonstrated in Figure 1. Without using linear mapping, this approach efficiently transfers the input vector from Rq to the output space, Rw. The following function serves as the foundation for the mapping relationship between the input and the output vector of the RBF-NN:

$$RBF - NN\colon \{R^q \to R^w, \vec{m} \to \vec{z} \tag{10}$$

where the $\vec{m} = \{m_j, for\ j = 1, 2, b\}$ and $\vec{z} = \{z_j, for\ j = 1,2, \ldots, n\}$ (10). A Gaussian function is calculated using the i[th] hidden neuron of the RBF neural system:

$$d_i\ (\vec{m}) = exp(-(\vec{m}) + \mu_i)\hat{}2 \mid 2\sigma_i^2), for\ i = 1, 2, \ldots. r \tag{11}$$

where the centre and duration of the ith neuron's hidden state of the feasible Gaussian function are μi and σi respectively (11). The l[th] receiver node of the RBF-NN computes a linear function using the presented in Figure 1:

$$z\_l = \sum\_(i-1)\hat{}r.v\_li\,.d\_i\,(\vec{m}) \quad (12)$$

where z_l is an output in the output layer of the l[th] node, v_{li} is the output between the i[th] node in the hidden layer and the output layer in the i[th] node and $d_i(\vec{m})$ is ai[th] node output from the hidden layer (12).

Number of times neurons in the hidden layer cover the input vector space is a difficult question to answer. The optimal number of nodes for the hidden layer is calculated using several methods, although this problem has not yet been resolved. The classic RBF-NN training procedure modifies a number of weights, centres, and widths using the stochastic gradient technique. The main drawback of the stochastic gradient is that the learning algorithm is at least partially constrained. The Levenberg-Marquardt approach is used in this article's RBF-NN training stage to attain the following three parameters: weight should be adjusted so that the error function can be promptly reduced.

3. RESEARCH PREDICTION

3.1. Data

The experimental data of the NN provided in this paper obtained from *c3.nasa.gov*. Three distinct operating profiles (charge, discharge and impedance) were used for four Li-ion batteries at room temperature. In continuous current (CC) mode charging was performed at 1.5 A up to 4.2 V battery voltage and then the current of charge fell to 20 mA in constant voltage (CV) mode. The battery voltage was depleted at a constant existing level (CC) of 2 A until it reached 2.7 V, 2.5 V, 2.2 V, and 2.5 V (5, 6, 7, and 18 batteries) respectively. To measure impedances, a spectroscopy of electrochemical impedance was employed. Between 0.1 Hz and 5 kHz, the frequency sweep electrical impedance spectroscopy (EIS), is located. Impedance tests can shed light on the intrinsic battery properties that vary as batteries age, whereas repeated charging and discharging cycles cause batteries to age quickly. The trials came to a conclusion when the final (end-of-life) criteria were satisfied, with a 30% drop in rating capacity (from 2 hr to 1 hr 40 min). Table 1 shows properties of a Li-ion battery. The overall flow chart for the SOC estimation technique based on the NN is given in Figure 2. In the following phases the proposed technique of estimation is briefly described:

- Stage 1: create the dataset for battery discharge, which should include information on terminal volts, discharge amperage, temperature, and SOC.
- Stage 2: to standardise all battery discharge data.
- Stage 3: create the training data for the RBF-NN.
- Stage 4: the RBF-NN hidden layer's optimum number of neurons is chosen.
- Stage 5: utilize L-M training to create the RBF SOC estimate NN.
- Stage 6: put an end to the training process to safeguard the Gaussian function center, widths, and link weights between the output and hidden layers of the created RBF-NN.

Table 1. Properties of a Li-ion battery

CC mode (charging)	CV mode	Discharging mode CC mode	Frequency sweep
1.5 A to 4.2 V	20 mA	2.2 V to 2.5 V	0.1 Hz to 5 kHz

3.2. Neural network training

Due to variation in voltage, current, and SOC. To achieve an equal weight of the sample components and in the same critical network training role. Signals should be standardized for input (13).

$$\propto = (\propto_k - \propto_{min})/(\propto_{max} - \propto_{min}) \quad (13)$$

The BP and RBF network modeling software MATLAB is utilized. Implement the training programed for the network.

4. RESULTS AND DISCUSSION

Figure 1 shows, set of maximal training goal for SOC estimation. Figure 2 show the training procedure. After 2 epochs, the network satisfies the criterion for accuracy training steps and the tracking curve error converges to 0.0027 as shown in Figure 3. The battery voltages were discharged at a CC level of 2 A up to 2.6 V, 2.5 V, 2.2 V and 2.5 V correspondingly for batteries 1-4 as shown in Figures 4(a)-(d).

The NN training error may be viewed in real time with the performance Figure 5. Error reaches 7.32e-30, which is less than the limit error value, following 15 epochs Figure 5 illustrates the performance. Figure 6 shows regression plot, with high linear correlation and regression constant over 0.2 seen in the training information, validation data and test data predicted response and simulation output. It is more accurate for RBF than for BP. To calculate data, BP takes more time. Table 2 shows results simulation results.

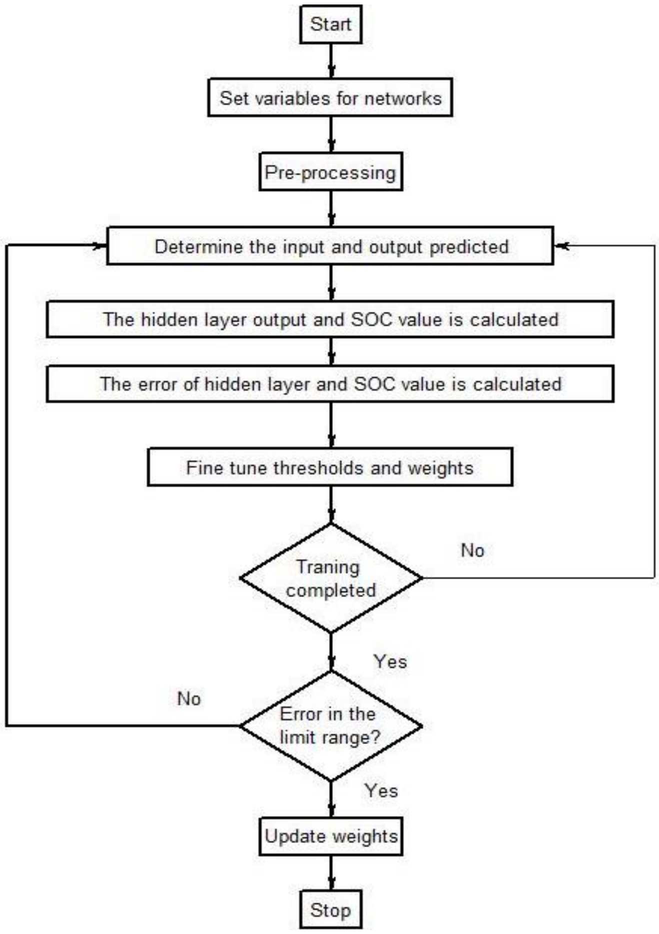

Figure 2. Flow chart for SOC estimation technique

Table 2. Simulation results

Parameter	BP	RBF
Mean squared error (MSE)	0.0027	7.32e-30
Number of iterations	2	15
Amount of hidden neuron	10	10

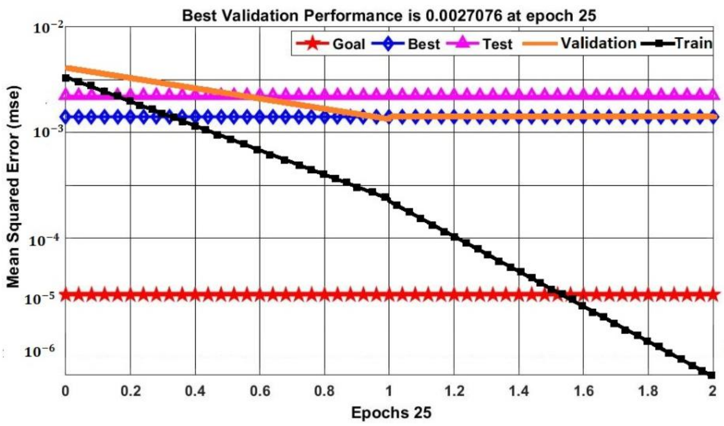

Figure 3. Performance curve for BP

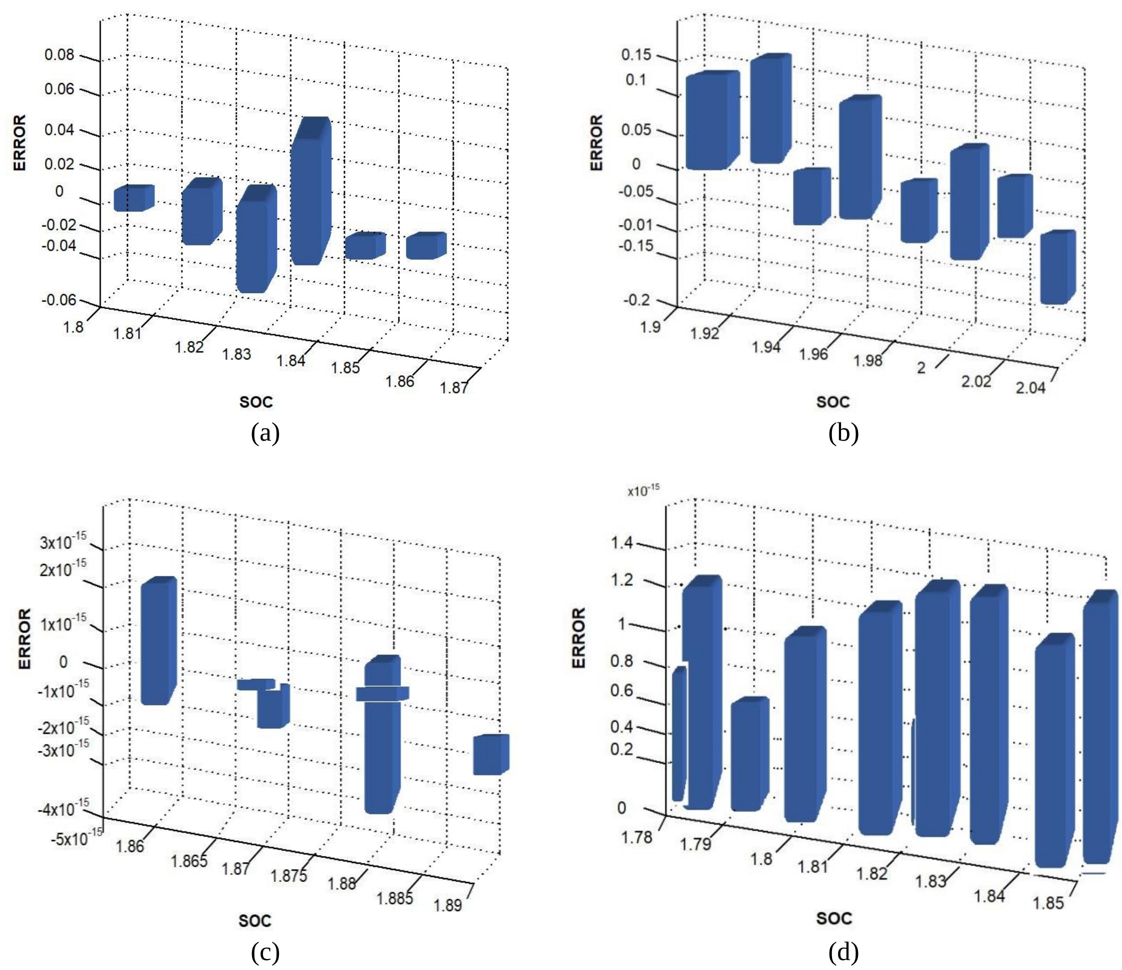

Figure 4. Error vs. SOC (a) first battery, (b) second battery, (c) third battery, and (d) fourth battery

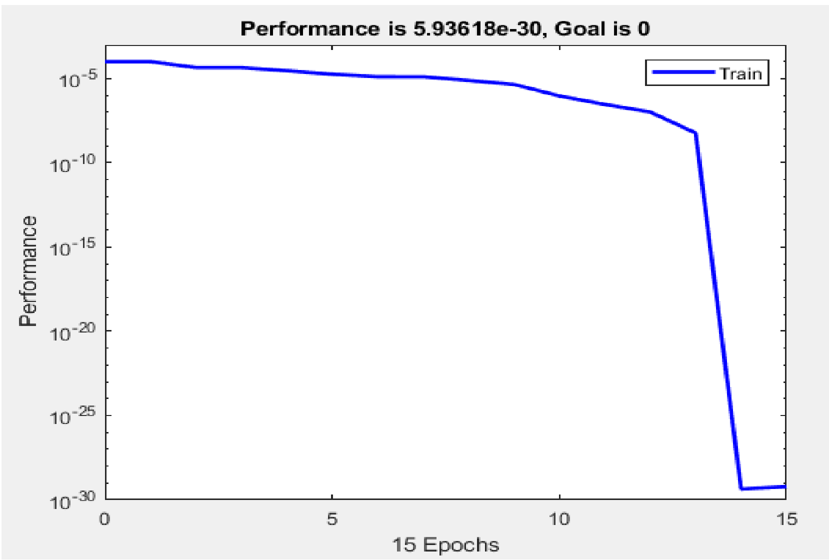

Figure 5. Performance curve for RBF

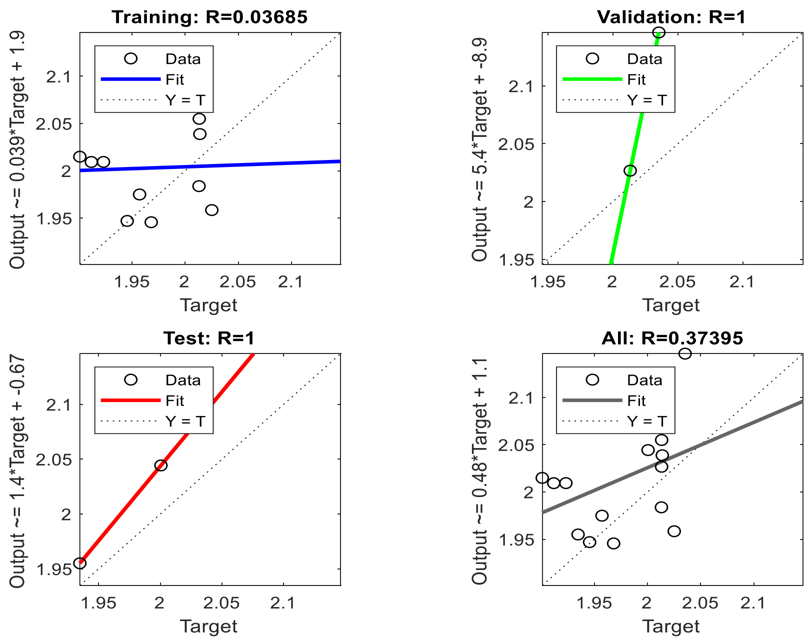

Figure 6. Regression plot

5. CONCLUSION

Temperature should be kept low to reduce calendar ageing in the case of Li-ion battery storage periods. In cycling, a greater temperature should be established, especially while charging the battery, as the result of the lithium plating reduces the ageing. In lower temperatures, current rates should be modest when charging a battery for a long time, in order to decrease lithium plate. The SOC level also significantly impacts ageing in addition to the temperature. High amounts of SOC have been harmful to calendar and cyclic life.

A high SOC should thus be avoided as much as possible in order to reduce battery ageing. In addition, the major driver of lithium placing was found as long-lasting charge durations. This reduces battery ageing by decreasing the discharge depth while cycling. This research explained the 2 Ah Li-ion battery estimate SOC with artificial intelligence technique BP and RBF approach for identifying the battery's SOC are proposed. The prior SOC information helps to plan solar energy for domestic application and stand-alone application. From results it is noted that with MSE=7.32e-30, RBF requires 15 epochs require to obtain more SOC estimate accuracy than BP.

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