Estimation of Equivalent Model Parameters for $LiFeO_4$ Batteries Based on Particle Swarm Optimization

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Abstract— State of charge (SOC) is an important parameter of battery management system (BMS) which reflects the reliability, safety, and lifetime of batteries. However, SOC cannot be measured directly and we have to estimate it via analyzing some other parameters such as voltage, current, and temperature. An accurate estimation strategy of SOC is necessary for the BMS and we propose a novel model based on particle swarm optimization (PSO) in this paper. The PSO is an optimization method which originated from artificial intelligence and evolutionary computation. It is a simple, effective, and universal theory which solves problems by seeking their individually best and globally best solutions. We apply this theory to optimally estimate the SOC parameters for $LiFeO_4$ Batteries and the simulated and experimental results have demonstrated its effectiveness.

1. INTRODUCTION

Power batteries are very important components in electric vehicles and they have a significant impact on the performance and security of a whole vehicle. To ensure the safe and reliable operation of batteries, designing an optimal battery management system (BMS) is very essential. The BMS manages the batteries based on their states and instructions from a vehicle management system (VMS). The voltage, current, and temperature of batteries can be measured directly by sensors while other parameters such as the state of charge (SOC) has to be estimated indirectly by certain algorithms which usually rely on the battery model and its parameters. The battery model and parameters are essential because they form the basis of loop simulations for hardware and SOC estimation, and also provide a reference for the control of BMS.

In this paper, we propose a unified form of equivalent circuit model for $LiFeO_4$ batteries based on the analysis of similarity between the internal mechanism and external characteristic of a chemical power source. A two-order equivalent circuit [1] of $LiFeO_4$ batteries is built and their resistance and capacity are estimated with a least square method (LSM) [2] and particle swarm optimization (PSO) [3]. By comparing the results from different estimation methods, we find that the relationship between the SOC and the electric motive force (EMF) or EMF-SOC can be significantly affected by the temperature. We also build a backward-propagation (BP) neural network [4] in which the EMF and temperature are taken as inputs while the SOC works as an output and the results are used to estimate the SOC. The simulated and experimental results show that the proposed estimation method can accurately estimate the SOC for $LiFeO_4$ batteries.

2. PARTICLE SWARM OPTIMIZATION (PSO)

The PSO was first proposed by Kennedy and Eberhart in 1995 [5]. It is an optimized computational method based on a swarm intelligence and simulates the internal action between individuals, group, and environment. Nowadays, the PSO is widely used in process optimization, parameter estimation, and system control. In the PSO theory, the position of a particle represents a solution of optimization problem. Each particle has a position and velocity that decide its direction and speed. The state of particles depends on adaptive values that are determined by objective function. Suppose in a D-dimension objective search space, a group is formed by m particles which are randomly initialized. Then the position and flying velocity of the ith particle can be represented by $X_i = (x_{i1}, x_{i2}, \dots, x_{iD})^T$ and $V_i = (v_{i1}, v_{i2}, \dots, v_{iD})^T$, respectively. Particles will track two extremum values in a solution space. On each iteration, the individual extremum $Pb_i = (pb_{i1}, pb_{i2}, \dots, pb_{iD})^T$ represents the best position of the particle while the global extremum $Gb = (gb_1, gb_2, \dots, gb_D)^T$ represents the best position of the group. The velocity and position are updated each time according to the following formulas:

$$v_{id}^{k+1} = v_{id}^k + c_1 r_1^k \left(p_{id}^k - x_{id}^k\right) + c_2 r_2^k \left(gb_d^k - x_{id}^k\right) \tag{1}$$

$$v_{id}^{k+1} = x_{id}^k + v_{id}^{k+1} \tag{2}$$

where v_{id}^k represents the velocity of the ith particle in the Dth dimension in the kth iteration and x_{id}^k represents its current position. Also, c_1 and c_2 are the acceleration factors or learning factors which adjust the maximum step size of the fight to the globally best particle and individually best particle. The adaptive values of c_1 and c_2 can accelerate the convergence and help the particles to avoid falling into a local optimum. In addition, r_1 and r_2 are the random numbers in the range $[0, 1]$, p_{id} represents the position or coordinate of the individual extremum point of the ith particle in the Dth dimension, and g_d represents the position of the global extremum point in the Dth dimension [6].

3. PSO PARAMETER IDENTIFICATION BASED ON SECOND-ORDER RC EQUIVALENT

3.1. LSM

Mathematical model of a battery should reflect and take into account its self-discharge phenomenon, capacity, and resistance over potential and environmental temperature. In this paper, a second-order RC equivalent circuit model is used to simulate the battery. In this model, E represents the battery's voltage which is affected by the SOC and R_0 refers to its ohmic internal resistance. Also, R_1 and C_1 denote its electrochemical polarization resistance and capacitance, respectively, and they constitute a RC parallel circuit, while R_2 and C_2 indicate its consistent polarization resistance and capacitance, respectively, and they constitute another RC parallel circuit. The test data of a study on a 60AH-$LiFePO_4$ battery by means of a constant discharge is shown in Figure 2. The battery starts a discharge after 100 s, and stops the discharge when reaching the point B. The RC network is in a zero input response from the point A to point B and the voltage rebounds rapidly as soon as the circuit is broken. In the circuit, the loop current is zero and the ohmic internal resistance drop is also zero.

$$R_0 = \frac{U_D - U_B}{I} \tag{3}$$

At the same time, the RC network is in a zero input response. The voltage from the point B to point C is

$$U_B(t) = E_C(t) - I \times R_1 \times \mathrm{e}^{-\frac{t}{R_1 \times C_1}} - I \times R_2 \times \mathrm{e}^{-\frac{t}{R_2 \times C_2}} \tag{4}$$

where $E_{C(t)}$ refers to the voltage at the point C. We utilize the test data and LSM [7] to figure out the parameters including R_1, R_2, C_1, and C_2. The result is shown in Figure 3.

3.2. Battery's Parameter Identification Based on the PSO

We initialize 10 particles and each particle's position is $X_i = (R_{1i}, R_{2i}, \frac{1}{C_{1i}}, \frac{1}{C_{2i}})^T$ while its velocity is $V_i = (v_{i1}, v_{i2}, v_{i3}, v_{i4})^T$. All initial values are randomly chosen in the range of $[0, 1]$. On each iteration, the parameter

$$Y_1(t) = E_C(t) - I \times R_1 \times \mathrm{e}^{-\frac{t}{R_1 \times C_1}} - I \times R_2 \times \mathrm{e}^{-\frac{t}{R_2 \times C_2}} \tag{5}$$

is calculated while $Y_2(t)$ is its counterpart obtained by an experiment. The fitness function is

$$f = \sum_t \frac{|Y_2(t) - Y_1(t)|}{Y_2(t)} \tag{6}$$

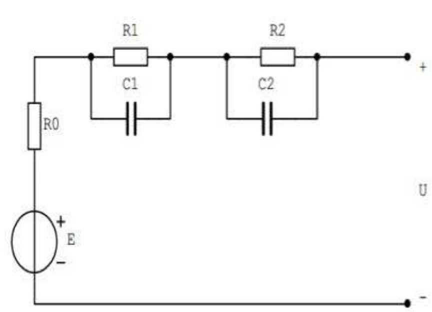

Figure 1: A model for an $FeLiPO_4$ battery.

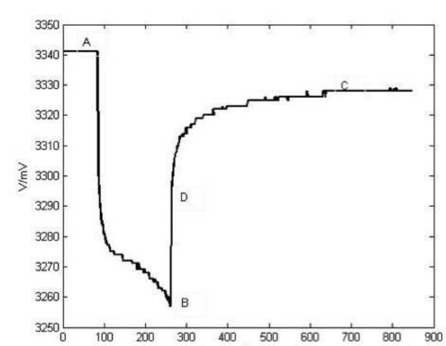

Figure 2: Discharge curve of an $FeLiPO_4$ battery.

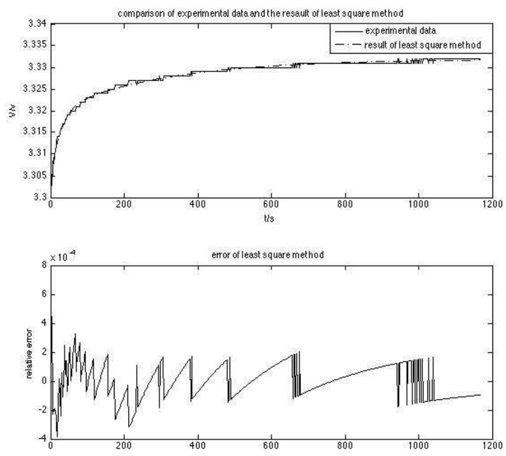

Figure 3: Parameters figured out by a LSM.

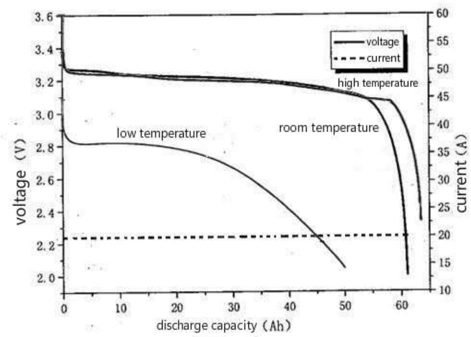

Figure 4: EMF-SOC relationship in different temperatures.

and the iteration is performed by the following steps:

Step 1: When $g = 1$, the position X_i^1 and velocity V_i^1 of the searched points are initialized with the random numbers in the range of $[0, 1]$, and $P_i^1 = X_i^1$. Then we calculate the individual extremum values and the global extremum value is the best one among the individual extremum points. Record the index of the best particle and set G as the position of that particle.

Step 2: Update the new position X_i^2 and velocity V_i^2 for each particle by Equations (1) and (2) and calculate the particle's new fitness value. If the new value is better than the previous value, then let $P_i = X_i^2$. If there is an individual value that is better than the current global value, the position of that particle will be set as G and the index of that particle will be recorded. The global extremum value is then updated correspondingly.

Step 3: If the number of iterations reaches the maximum value that is set in advance, then the iteration will stop and the best solution will be output. Otherwise, go back to Step 2.

3.3. EMF-SOC Model of $LiFePO_4$ Battery Based on BP Neural Network

The initial capacitance should have been known before an ampere-hour method is used to calculate the residual capacitance of a battery. Currently, the relation of $SOC = f(SOC)$ is mostly used to get the initial SOC. If the battery has rested for a long time, its terminal voltage can be regarded as the EMF. For different temperatures, the same EMF corresponds to different SOCs as shown in Figure 4. The BP network is a one-way-communication and multilayer-feed-forward neural network and the BP means the backward propagation of errors whose main idea is the gradient descent. Using the gradient search techniques can make the actual output value of network have an expected error of square minimum value. The initial capacitance is affected by terminal voltage and temperature. The EMF-SOC BP neural network can be obtained by setting the EMF and temperature of the battery as an input while setting the SOC as an output.

3.4. Construction of State Space for Battery

We can get the state space for a battery according to the following equations

$$\begin{bmatrix} SOC_k \\ U_k^0 \\ U_k^1 \\ U_k^2 \end{bmatrix} = \begin{bmatrix} 1 & & & \\ & 0 & & \\ & & e^{-\frac{\Delta t}{R_1 \times C_1}} & \\ & & & e^{-\frac{\Delta t}{R_1 \times C_1}} \end{bmatrix} \times \begin{bmatrix} SOC_{k-1} \\ U_{k-1}^0 \\ U_{k-1}^1 \\ U_{k-1}^2 \end{bmatrix} + \begin{bmatrix} -\frac{\eta \Delta t}{Q} \\ R_0 \\ R_1\left(1 - e^{-\frac{\Delta t}{R_1 \times C_1}}\right) \\ R_2\left(1 - e^{-\frac{\Delta t}{R_2 \times C_2}}\right) \end{bmatrix} \times i_{k-1} + w_{k-1} \quad (7)$$

$$U_{k-1} = OCV(SOC_{k-1}) - i_{k-1} \times R_0 - U_{k-1}^1 - U_{k-1}^2 + V_{k-1}. \quad (8)$$

In the equations, SOC_k is the value of the SOC at the kth moment, U_k^0 is the terminal voltage of ohmic internal resistance, U_k^1 and U_k^2 are the terminal voltages of polarization resistance, Δt is the sampling time, η is the coulomb coefficient, Q is the nominal capacitance of the battery, i is the current, and U_{k-1} is the voltage of the battery. The random signal w_{k-1} and $v_{k-1)}$ refer to an incentive noise and observation noise, respectively. We assume that they are white noises which are independent of each other and follow a normal distribution.

4. SIMULATION RESULTS

We present the simulation results for the battery parameter identification based on the PSO method. Assuming that $c_1 = c_2 = 2$ and r_1 and r_2 are the random numbers in the range of $[0, 1]$. The dimensional speed v_d is clamped between $[v_{d\min}, v_{d\max}]$ to prevent particles from moving away from the search space. The number of iterations is selected as 10 and the identification results with corresponding errors are shown in Figure 5. On the other hand, if the number of hidden layers of the neural is selected as 5, the output of hidden layers of the neuron is selected as a "tansig" function, the transfer function of the output is a "purelin"function, and the training function is a "trainlm" function, then the EMF-SOC BP neural network can be established by setting the EMF and temperature of the battery as an input while setting the SOC as an output. The result is shown in Figure 6.

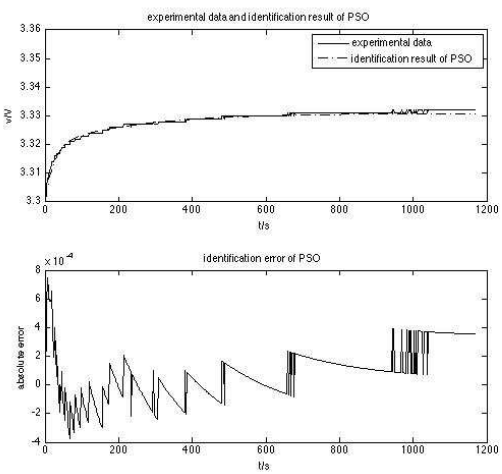

Figure 5: Result of the PSO.

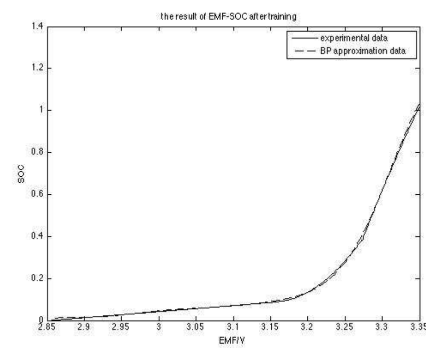

Figure 6: Result of the EMF-SOC based on the BP network.

5. CONCLUSION

We use the LSM to identify the parameters of battery model. We also establish a second-order RC network model for the $LiFePO_4$ battery and figure out the values of some parameters such as capacitances and resistances by the LSM and the PSO. Comparing these two algorithms, we find that the PSO can reach the same accuracy as the LSM. The structure of EMF-SOC neural network based on the BP neural network can be obtained via setting the EMF and temperature as an input and the SOC as an output. The accuracy of calculating the SOC can be enhanced by considering the influence of temperature. We present some simulated and experimental data to demonstrate the estimation method and good results have been observed.

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