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Development of a Neural Network Model for SoH of $LiFePO_4$ Batteries under different Aging Conditions

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Abstract. $LiFePO_4$ batteries have a variety of superior properties, such as higher power densities, higher capacities, longer lifetimes and better safety. For these reasons, $LiFePO_4$ batteries are used extensively in electric vehicles and energy storage devices. However, there is an issue with the battery capacity in that it begins to rapidly fade after a certain number of charge and discharge cycles under compound influence of temperature and discharging current, which may lead to safety concerns. Therefore, it is very important to investigate the characteristics (voltage, current and capacity) of $LiFePO_4$ batteries in relationship to the number of cycles and environmental temperature. In this paper, for the sake of high efficiency and safe operation of $LiFePO_4$ batteries, we propose a Back Propagation neural network (BPNN) model which estimates the state of health (SoH) of the battery, so that the accumulated error of the capacities under different operating environments can be corrected. The accuracy of the model was verified in an electric vehicle with an average error of only 1.56%. The results show that the proposed model is satisfactory.

1. Introduction

$LiFePO_4$ is structurally one of the minerals under olivine, with characteristics of not including precious elements like cobalt, low raw material price as well as phosphorous and iron being abundant in the Earth's resources. The working voltage of the battery ranges generally between 3.4V and 3.2V. It has a large capacity (170 mAh/g) and a high discharge rate, as well as can be rapidly charged and also having a long cycle life. In recent years the $LiFePO_4$ battery has become one of those receiving much attention from academia and industry. It has become a very important research topic with developmental potentials. It can satisfy usage in electric and hybrid vehicles[1].

Although the $LiFePO_4$ battery has many merits, its aging would directly influence battery performance, being still an important issue needing to be understood. Battery aging is influenced by various external factors, e.g., temperature of the operating environment, depth of discharge, charging and discharging rates as well as no. of cycles. Currently there are already many researches investigating in depth the mechanisms of battery aging [2]. However, it is still a big challenge to quantify these factors' influence on battery performance.

2. Related work

Researching the attenuation mechanism in lithium ion battery is very important for designing battery management systems. Since the attenuation is influenced by multiple factors, the potential mechanisms are very complex, leading to considerable difficulties in estimating battery capacity and power [3]. Understanding the reasons for battery performance downgrading will help the improvement of design and safety in battery management systems. Attenuation in lithium ion battery is a complex mutual interactional process. High charging/discharging rate, high or low temperature and deep discharge can all accelerate battery degradation. Mechanisms of lithium ion battery deterioration vary under different conditions of aging, causing errors in models estimating battery capacity. For the $LiFePO_4$ battery, the loss of active lithium ions is considered one of the main causes within the aging mechanism [4]. It is commonly understood that electrolyte breakdown is strongly influenced by environmental temperature, thickening the solid electrolyte interface (SEI) and consuming active lithium ions, thus leading to worsening of cathode performance [5]. On the other hand, a high temperature environment can lead to iron ions dissolving and their structural degeneration, causing mismatch between the cathode and anode strengths, greatly influencing the attenuation of the battery's capacity [6].

The factors above all strongly influence battery performance and life. Battery management is used for calculating the battery's remaining strength and state of health (SoH) as well as to prevent over charging or discharging, so as to lengthen the battery's working life. Thus, to realize safe and efficient operation of the battery, these factors must all be considered. Since batteries are connected serially or in parallel into battery pack, after many charging and discharging cycles, there will be slight differences between the batteries, e.g., difference in capacity or internal impedance. As the number of cycles increase, that kind of difference will become more and more apparent. For a battery pack of serial connection, the total capacity is limited by the battery unit with the least capacity. If there are no methods to balance out, under the same working conditions the battery with the least capacity will sustain greater tension compared to others, worsening the problem of imbalance. Thus, battery SoH is one of the most significant components in a battery management system, especially for a battery pack. There SoH can be employed as the indicator for battery replacement.

In order to resolve the above issues, this research proposes Back Propagation neural network (BPNN) to estimate SoH. It can be executed under various dynamic loads and different temperatures, with the advantage that it is not necessary to consider the relevant details of electro-chemical reactions, as well as able to handle any non-linear and complex systems, possessing universality and suitable for estimating SoH under various operational environments. However, a lot of sample data are needed for the training. The sample data and the training method can greatly influence the estimation error [7].

3. Experimental set up and procedures

Under various temperatures in the temperature controlled chamber, the $LiFePO_4$ batteries are discharged under 0.5C-Rate, 1C-Rate, 2C-Rate and 3C-Rate by an automatic charging and discharging machine. Information such as capacity attenuation and no. of cycles of the batteries are computer recorded. The equipment is shown in Figure 1 and the technical specifications are listed in Table 1.

SoH reflects the capacity attenuation of $LiFePO_4$ batteries. Its standard definition is the ratio between the battery's fully charged capacity and the nominal capacity given by its manufacturer. Equation (1) states the standard SoH definition [8]. Conditions of the $LiFePO_4$ battery under various aging conditions are described in Table 2.

$$\mathrm{SoH} = \frac{Q_m}{Q_n} \times 100\% \tag{1}$$

where Q_m is capacity of $LiFePO_4$ batteries fully charged, and the nominal capacity Q_n of the $LiFePO_4$ batteries is 10Ah, as provided by the manufacturer.

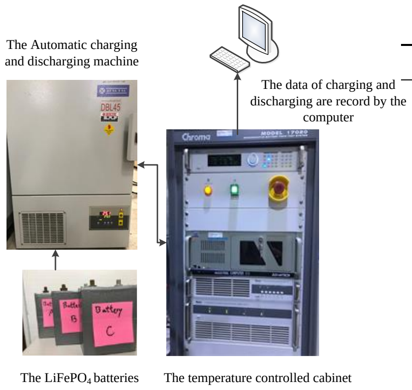

Figure 1 The experimental equipment.

Table 1 Specification for testing $LiFePO_4$ batteries.

Specification	Value
No. of batteries	60 (Training data (28 batteries) is produced by Chroma 17020 Automatic machine; Testing data (32 batteries) is produced by EV)
Nominal capacity	10 Ah
Nominal operating voltage	3.4 V
Charge cut-off voltage	3.6 V
Discharge cut-off voltage	2 V
Charging method	CC-CV method
Capacity Rate	0.5 C, 1 C, 2 C, 3 C
Operating temperature	-10 °C, 0 °C, 10 °C, 20 °C, 30 °C, 40°C, 50°C

Table 2 SoH of $LiFePO_4$ batteries discharged at different C-Rate and temperatures (First cycle)

Temperature	Discharging Current Rate			
	0.5 C-Rate	1 C-Rate	2 C-Rate	3 C-Rate
-10°C	89.63%	88.94%	89.50%	91.08%
0°C	95.31%	95.33%	93.89%	92.42%
10°C	100.06%	101.5%	101.2%	96.67%
20°C	108.11%	109.00%	106.94%	108.33%
30°C	108.29%	107.69%	104.28%	101.58%
40°C	107.03%	107.17%	108.94%	109.67%
50°C	114.50%	108.94%	108.22%	105.08%

3.1. Analysis of SoH under different temperatures

Figures 2, 3 and 4 illustrate the $LiFePO_4$ battery discharging under -10°C, 0°C and 10°C respectively, showing the results after 400 cycles of different discharge rates. Figures 5 and 6 illustrate the SoH of the $LiFePO_4$ battery discharging at 20°C and 30°C through 400 cycles under different discharging rates. Figures 7 and 8 illustrate the SoH of the $LiFePO_4$ battery discharging at 40°C and 50°C through 400 cycles under different discharging rates.

3.2. Analysis and comparison of parameters

Accurately describing and predicting the degeneration process of lithium ion batteries has become an important issue in battery management. SoH is an important indicator within, reflecting the remaining capacity of the battery before falling to the preset threshold. Owing to compound effects of environmental temperature and discharge rate, big variation of the remaining capacity will be engendered, indicating the state of the battery is not as expected. If the $LiFePO_4$ battery continues to be used, there could be some safety concerns. In order to resolve this issue, the common method is to propose a model to represent relationships of the battery SoH and operating conditions (e.g., no. of cycles, internal impedance, temperature, etc). Then predictions can be made on models of deterioration such as simplified electrochemical models or semi-experiential models based on SoH. SoH indicates the state of aging of the battery. When the capacity has fallen to 80% of the nominal, the battery is considered not suitable for vehicular usage and should be replaced [9].

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ANN can handle a large amount of data in complex and non-linear systems. It can accurately predict SoH under various operating conditions. However, the cost of high calculation load is one of the defects for applying ANN algorithms. In addition, the training data is another limitation in achieving accurate results. To stimulate neural functions for emulating electrochemical characteristics of batteries, a lot of dissimilar data must be processed. Reference [10] employed ANN methods and model discernment to monitor battery SoH, indicating ANN has shown fair results in achieving high precision. Through adding more training data, like discharge rate and temperature, ANN's performance can be raised further. Hence, this research employs three-layered back propagation neural network (BPNN) as the estimation model of capacity attenuation. Various practices in ensuring accuracy and lowering calculation costs are also proposed.

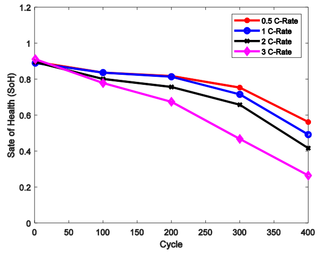

Figure 2 SoH of $LiFePO_4$ batteries at -10°C under different C-Rates with 400 cycles.

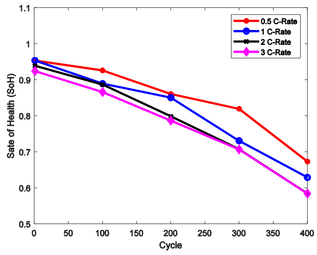

Figure 3 SoH of $LiFePO_4$ batteries at 0°C under different C-Rates with 400 cycles.

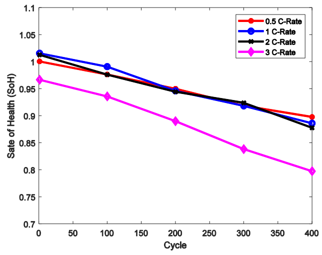

Figure 4 SoH of LiFePO4 batteries at 10°C under different C-Rates with 400 cycles.

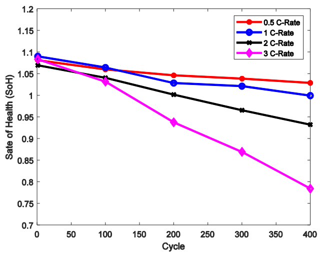

Figure 5 SoH of LiFePO4 batteries at 20°C under different C-Rates with 400 cycles.

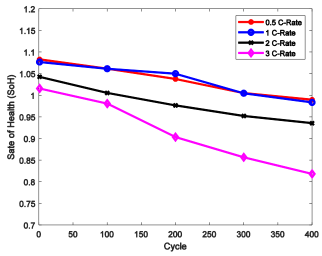

Figure 6 SoH of LiFePO4 batteries at 30°C under different C-Rates with 400 cycles.

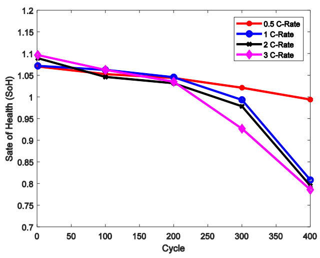

Figure 7 SoH of LiFePO4 batteries at 40°C under different C-Rates with 400 cycles.

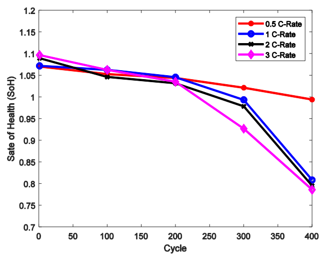

Figure 8 SoH of $LiFePO_4$ batteries at 50°C under different C-Rates with 400 cycles.

4. Modeling and algorithm

This research makes use of three-layered BPNN to study the model for estimating capacity attenuation. The detailed operation flow of the BPNN is described below.

BPNN is a multi-layer feedforward network that can learn and store a lot of input and output modes. It is also one of the commonly used neural network models. Its rule of learning makes use of gradient descent. Through back propagation weights and thresholds of the whole network are continually adjusted, minimizing the network's error square summation (cost). The topographic structure of BPNN includes (1) input layer: input variables, incl. environmental temperature *(T)*, output current *(i)* and cumulated discharge time *(cdt)*; (2) one or more hidden layers; (3) output layer. This model is indicated in Figure 9.

Here we first define the symbols and meanings of the artificial neural networks in this research, referring to Figure 10[11]. Operational steps under the BPNN structure are described as show in Figure 11.Calculating following the steps above with Matlab, the setup is shown in Figure 12. Mean-square error (MSE) is used to find the square summation of distances between the predicted value and the actual values. It was found to be only 0.00212, meaning the BPNN has resulted in convergence. The result is satisfactory.

5. Model verification

There are 32 modules in the battery pack. Batteries in each module are connected in parallel. The connection between modules is serial. In order to speed up the experiment, we reduced the no. of batteries in each module to one. They are installed into an electric vehicle, as shown in Figure 13.

Table 4 shows the errors with the model for discharging under different current loads. The method of testing is taking 30 readings for each type of current load, in the order of 0.5 C-Rate, 1 C-Rate, 2 C-Rate, 3 C-Rate and pulse current. Thus we observed the errors with model estimation during actual discharging. The various manners of discharging are captured as below and calculated with mean absolute percentage error (MAPE). Table 3 shows the errors with the model for discharging under different current loads. The method of testing is taking 30 readings for each type of current load, in the order of 0.5 C-Rate, 1 C-Rate, 2 C-Rate, 3 C-Rate and pulse current. Thus we observed the errors with model estimation during actual discharging.

6. Conclusion

SoH is the indicator for estimating battery life. To ensure safe operation and prevent over discharge, an accurate SoH estimation is very important for lithium ion batteries. That has already become the main focus of electric vehicle development.

This research makes use of lithium iron phosphate batteries with 10Ah capacity and 3.4V rated voltage for testing under various environmental temperatures and discharge rates. Under testing conditions of 400 discharge cycles the discharge voltage and current of the batteries during the discharge process are recorded. We analyzed batteries with different degrees of aging and gathered their corresponding characteristics. The ANN model can respond to temperature and current changes to precisely estimate the SoH of $LiFePO_4$ battery and can be actually applied for testing in electric vehicles. Results obtained indicate that the average error of the ANN model for predicting information of the electric vehicle under different current load and environmental temperatures to be only 1.56%. The degree of accuracy is satisfactory.

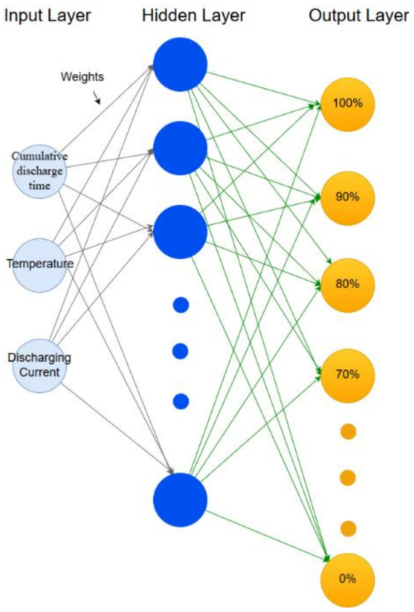

Figure 9 Architecture of a neural network model.

(1) Input vector layer: $\mathrm{net}_{(k)} = (a_1^k, a_2^k, \dots, a_n^k), k = 1, 2, \dots m$;
(2) Target vector layer: $\mathrm{T}_{(k)} = (y_1, y_2, \dots, y_q)$;
(3) Hidden layer nodal input vector $S_{(k)} = (s_1, s_2, \dots, s_p)$ and output vector $B_{(k)} = (b_1, b_2, \dots, b_p)$;
(4) Output layer nodal input vector $L_{(k)} = (l_1, l_2, \dots, l_p)$ and output vector $C_{(k)} = (c_1, c_2, \dots, c_p)$;
(5) Connection weight from input layer to hidden layer $w_{(i,j)}, \mathrm{i} = 1, 2, \dots, \mathrm{n}, \mathrm{j} = 1, 2, \dots, \mathrm{p}$;
(6) Connection weight from hidden layer to output layer $v_{(j,t)}, \mathrm{j} = 1, 2, \dots, \mathrm{p}, \mathrm{t} = 1, 2, \dots, \mathrm{p}$;
(7) Output thresholds of nodes in hidden layer θ_j, $\mathrm{j} = 1, 2, \dots, \mathrm{p}$;
(8) Output thresholds of nodes in output layer γ_j, $\mathrm{j} = 1, 2, \dots, \mathrm{p}$.

Figure 10 Symbols of the neural network model.

(1) Initialization. $w_{(i,j)}$ and $v_{(j,t)}$ are given to each weight; θ_j and γ_j are assigned to thresholds. Random variables are set.
(2) Randomly select a group of input vectors $net_{(k)} = (a_1^k, a_2^k, \dots, a_n^k)$ and output vector $(s_1^k, s_2^k, \dots, s_q^k)$.

Input the data $net_{(k)}$,connection weight $w_{(i,j)}$ and threshold θ_j to calculate the input of the nodes of the hidden layer $S_{(j)}$, then through log-sigmoid the output $b_{(j)}$ of the nodes of the hidden layer are calculated, as indicated in equation (2). $S_j\left(\sum_{i=1}^{n} w_{j,i}\, a_i + \theta_{j,i}\right), j = 1, 2, \dots, p$

$$b_j = sigmoid(S_j), j = 1, 2, \dots, p$$

$$sigmoid(x) = \frac{1}{1+e^{(-x)}}$$

(3) Through output b_j of the hidden layer, connection weight $v_{(j,t)}$ and threshold γ_j calculate the output $L_{(t)}$ of the nodes of the hidden layer. Through log-sigmoid the response $C_{(t)}$ of the units of the output layer are calculated.

$$L_t\left(\sum_{j=1}^{p} v_{j,t}\, b_i + \gamma_t\right), t = 1, 2, \dots, q$$

$$C_t = sigmoid(L_t), t = 1, 2, \dots, q$$

(4) Making use of target vector $\mathrm{T}_{(k)} = (y_1^k, y_2^k, \dots, y_q^k)$ and the actual BPNN output C_t, error d_t^k of the nodes of the output layer are calculated, as indicated in equation (4). $d_t^k = C_t(1 - C_t)(y_t^k - C_t)$ (4)
(5) Making use of the connection weight $v_{(j,t)}$, error d_t^k of the nodes of the output layer and output b_j of nodes of the hidden layer, error e_j^k of the nodes of the hidden layer are calculated, as indicated in equation (5). $e_j^k = \left[\sum_{t=1}^{q} d_t \cdot v_{j,t}\right] b_j (1 - b_j)$ (5)
(6) Making use of error d_t^k of the nodes of the output layer and the output b_j of the nodes of the hidden layer to adjust the weight $v_{(j,t)}$ and threshold γ_j, as indicated in equation (6).

$$v_{(j,t)}(N+1) = v_{(j,t)}(N) + \alpha \cdot d_t^k \cdot b_j$$

$$\gamma_t(N+1) = \gamma_t(N) + \alpha \cdot d_t^k$$

where $t = 1, 2, \dots, q, \mathrm{j} = 1, 2, \dots, \mathrm{p}, 0 < \alpha < 1$

(7) Making use of error e_j^k of the nodes of the hidden layer and the input $\mathrm{net}_{(k)}$ of the nodes of the input layer to adjust the $w_{(i,j)}$ and threshold θ_j, as indicated in equation (7).

$$w_{(i,j)}(N+1) = w_{(i,j)}(N) + \beta \cdot e_t^k \cdot a_t^k$$

$$\theta_j(N+1) = \theta_j(N) + \beta \cdot e_t^k$$

where $i = 1, 2, \dots, n, \mathrm{j} = 1, 2, \dots, \mathrm{p}, 0 < \beta < 1$

(8) Randomly select the next learning sample vector for the model and return to step 3, until the training of *m* samples is finished.
(9) From the *m* samples randomly select a set of input and target samples, return to step 3, until the error of the model *e* is lower than the preset value, which would indicate network convergence. If the no. of times of learning is greater than *e*, it would indicate unable to converge.
(10) Learning completes.

Figure 11. BPNN Algorithm

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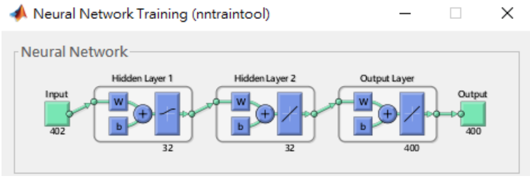

Figure 12 BPNN Architecture.

Figure 13 The tested EV.

Table 3 MAPE between ANN Model and Data from EV

C-Rate	0.5	1	2	3	Pulse	Avg.
Temp. (°C)	16	20	18	17	22	
MAPE (%)	1.18	1.59	1.16	1.28	2.58	1.56

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