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Back -Propagation Neural Network Estimator for State Of Charge (Soc) Of Lithium-Ion Battery

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ABSTRACT:
Since the state of charge (SOC) of the Li-ion battery is an important parameter representing the efficiency of the battery. Precision measurement of the SOC can not only conserve the battery but also keep the battery from being discharged or overcharged and increase the health and life of the battery. This paper suggests SOC prediction methods for a battery based on an artificial neural network and a three-layer backpropagation (BP) a lithium-ion battery of 18650 2800 m 37 v with a maximum load voltage of 42v and a cut-off discharge of 275.is measured by a battery testing system. We divided the work experiment into 3 parts, and three (3) training data from the 3 different experiments are established. The current is controlled by the ITECH IT8500, the Voltage is sampled by NI-USB-6210. To simulate and test the neural network model with data from the three (3) working conditions, Matlab / Simulink software is used.
KEYWORDS: *SOC estimation; backpropagation neural network; lithium-ion battery; training data; test data; Matlab/Simulink.*

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I. INTRODUCTION

The latest problems in oil and electricity have led the world to think about a potential supply of energy that is neither environmentally damaging nor threatens the ozone layer. This desire for renewable energy has motivated individuals from academia and business, government institutions, the automobile industry and academics from around the world to invest and build hybrid electric vehicles (EVs) and battery-powered EVs with efficient energy systems [1].

In addition to the production of various types of energy storage systems, EV technologies are growing, including lead-acid batteries, lithium-ion batteries, Ni-MH batteries, and Ni-Cd batteries [2]. Compared to other products, lithium-ion batteries have gained a lot of popularity for EV service due to their lucrative characteristics, including long lifetime, rapid charging, high energy density, high power efficiency, high environmental adaptability, high cell voltage, low memory, low emission, and lightweight [3].

To maintain overall device efficiency, the Battery Management System (BMS) is essentially needed to maintain that LiB packs run efficiently and safely with robust control and smart management algorithms that provide accurate state-of-charge (SOC), state of health (SOH), RUL [4,5,6,7]. SOC determination and control are increasingly important for EVs since the precise calculation of battery capacity can provide drivers with information about how much range can be powered and where and how long the battery can be charged. For this reason, SOC determination is a significant problem that researchers are studying [8,9,10].

However, precise and effective SOC calculation of the lithium-ion battery is a difficult challenge due to non-linear, time-varying properties, and dynamic electrochemical reactions. Besides, the lithium-ion battery is very susceptible to some internal and external factors [2,11].
Battery SOC of an EV is generally represented in terms of percentage as shown in eq. (1)

$$SOC = \frac{Qres}{Qmax} * 100\% \qquad (1)$$

Where $Qres$ represents the remaining capacity and $Qmax$ is the maximum capacity.

There are several SOC estimation algorithms and they are classified into different types, such as direct methods, bookkeeping methods, model-based methods, adaptive filtering methods, data-driven methods [12].

Lately, recent advances adaptive systems for SOC estimation have been developed with the advent of artificial intelligence. Kalman Filter, Back Propagation (BP) neural network, Fuzzy Logic Methods, Support Vector Machine, Radial Basis Function (RBF) Neural Network, and Fuzzy neural network, [13,14] are recently developed methods. Adaptive systems are self-designed systems that, in evolving systems, can be automatically adjusted [15].

In this article, for SOC accuracy the BPNN is used due to its good capacity for nonlinear modeling, self-learning, and self-organization. The relationship between input and target is non-linear and complex in the calculation of SOC, as the problem describes.

II. BACK PROPAGATION NEURAL NETWORK APPLICATION IN THE BATTERY SYSTEM

In engineering application, some complicated nonlinear systems are often encored and the state equation of these systems are complex and difficult to model accurately by a mathematical formula.
Artificial neural networks (ANN) or connectionist systems are computational
Structures are loosely influenced by the biological neural networks. ANN is a power and intelligent algorithm to map nonlinear input to a target output [16]. The network algorithm can be established to express these nonlinear systems and the unknown systems are regarded as a black box. ANN is training by inputting a large computational dataset, the unknown function is expressed then the output is predicted. It uses the initial inputs and output to predict future output values.
In Artificial Neural Networks, the BP Network, a supervised learning algorithm for Multilayer Perceptions (MLP) training, is the most common type. Each discontinuity function can well be calculated by ANN, provided appropriate neurons in the hidden layer.
The BP network architecture is shown in the figure below.

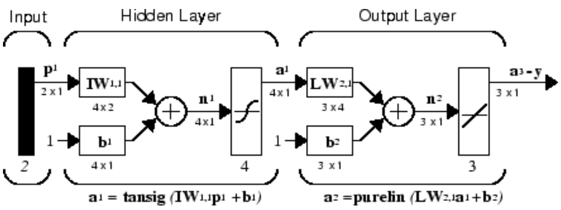

Fig.1 Structure of BP neural network

In general, the BP neural network consists of three major types of layers; an input layer that carries the initial data into the system for further processing; one or more hidden layers where the artificial neurons take the weighted inputs and generate the output via the activation function and the output layer which is the last layer of neurons that reflects the output vector of the system [17].

Inputs go from input layer to output layer from which output is produced; which is then compared to the target output which contains an error. To reduce the error, weight and biases are added in the hidden layer. During initialization, weights and bias are set to a random variable with a range and we can also define the maximum number of interactions. During each interaction, outputs of neurons are calculated in the hidden neuron and an output neuron. Information about the error in output and the hidden layer is a calculation using the Gradient descent technique or Delta rule. This process is repeated until we reach the maximum number of interactions or the value of the error becomes negligible [18].

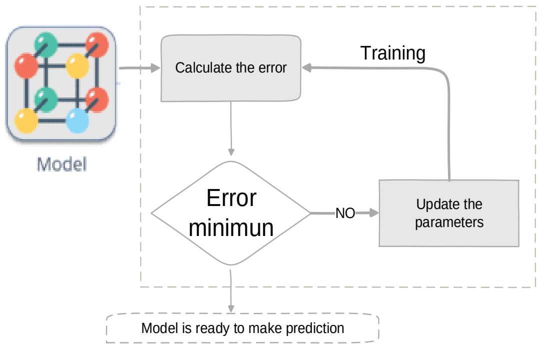

Fig.2 Error estimation model

The formula below is used to initialize a random weight

$$W_1 = randn(I, H)$$
$$W_2 = randn(1, O)$$

Where
W_1 is the weight between the neuron of the input layer and the neuron of the hidden layer, W_2 is the weight between the neuron of the hidden layer and the neuron of the output layer, I is the cumulative input of the

neuron of the input layer, H is the number of neurons of the hidden layer, and O is the neurons of the output layer.
We calculate the current error

$$error_t = pred_t - act_t$$

Where
Where $pred_t\ andact_t$ are the respective output values, $Error_t$ define the error between the target output value and the output value of the model.
$act_t$is given by the following formula

$$act_t = O(patnum, 1)$$

The following equation is used to calculate the $pred_t$:

$$pred_t = \tanh(I.W_1).W_2$$

The hyperbolic tangent function is the activation function applied to neurons in the hidden layer.
Then we adjust the weight value overall network error at end of each epoch

$$pred_t = W_2.\tanh(train\_inp.W_1)$$
$$error = pred_t - out_t$$

Where $train_inp_t$the actual input in the input layer neuron and out_t is the actual output in the output layer neuron
The total output mean square error (Err)

$$Err = \sqrt{\sum_{t=1}^{n}(Error_t)^2} = \sqrt{\sum_{t=1}^{n}(pred_t - out_t)^2}$$

III. Materials and Methods

III.1. Data training and Algorithm

A large amount of voltage and current measurement data is collected, according to the defined working conditions, the BP architecture shown in figure (3) is adopted to determine the data collected and the SOC through the learned algorithm interconnection, then we continuously updated the released relationship by reducing the error (tend to zero) through the weight updated.

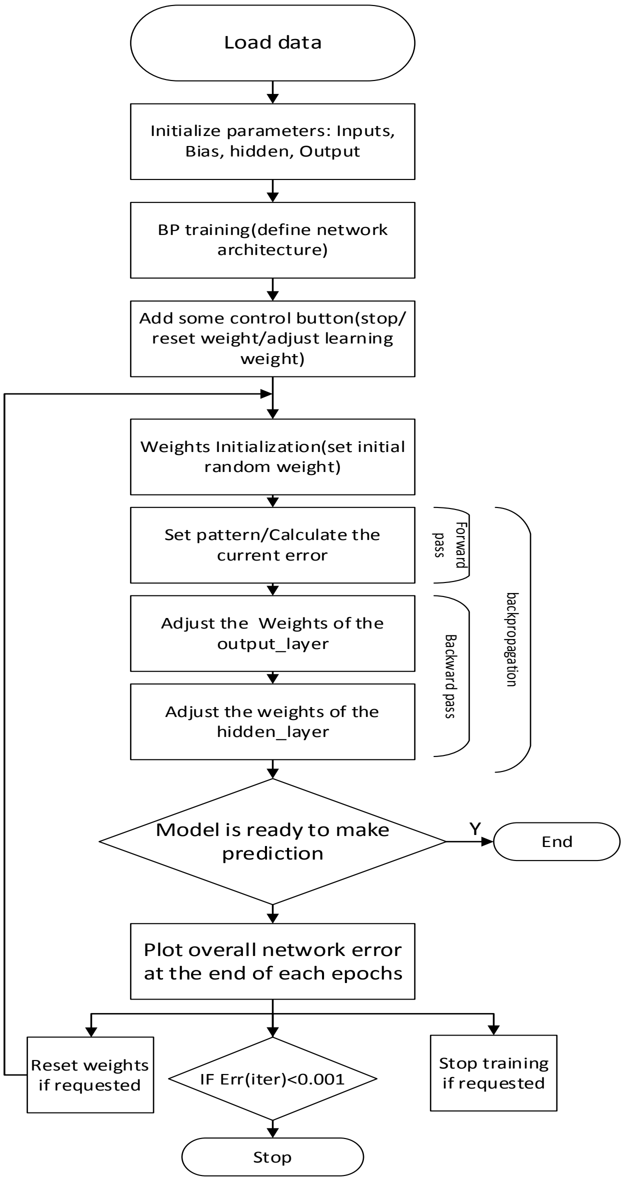

Fig.3 BPNN flowchart algorithm

LI-ion NCR 18650 BD, widely used for electric vehicle systems, smart grids, and mobile computing, is studied in this article. The NCR 18650 BD has a rechargeable lithium-ion battery type, a current of 2800mA, a power focus of 3.7V, a voltage of 4.2V, a discharge of 2.75V, and a short-circuit temperature of 212ºf. First, we used 75% of the data for training and 25% for the testing network with a constant temperature rate, a variable current, and voltage as input, and SOC as output. Then in the second and third, we used the experiment data for only testing the network performance with different current and voltage intervals.

In the first case, with a constant temperature of throughout the experiment, the voltage is varied decreasingly starting from a value close to the threshold voltage 4.2 v to 3 v. The current first decrease constantly from 1.5A to 0A during a short time interval then exponentially from 0A to 3.3A with a learning rate interval of 0.1A and a constant time interval rate of 0.02s.

In the second case, the temperature always remains constant, the voltage also always decreases. During this experiment phase, the current varies periodically (0 or 1.5) with different time intervals [10, 90, 710, 90] at 0.5C. The 90s represents that the value of the current is 0A and [10, 710] indicates that the current is equal to 1.5A.

In the third case, similar to the two cases, the temperature remains constant. The voltage also varies in different pulse. The current also varies periodically at a capacity rate of 1C. The current pulse discharge 3A also changes in different time intervals [10, 900, 350, 1800] with a constant time variation of 0.1S over time. The SOC always belongs between 0 and 1.

The terminal voltage and current curves of various working conditions during the discharge phase are shown in Fig (4).

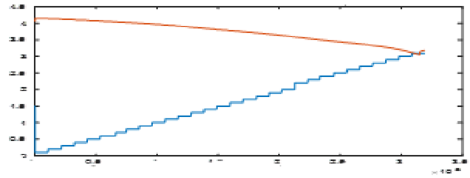

Fig.3a first case

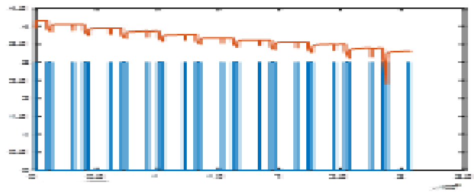

Fig.3b second case

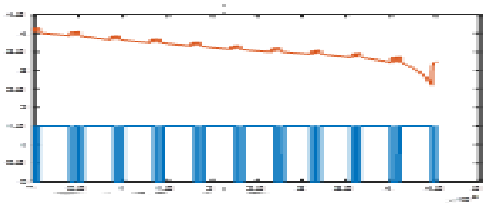

Fig.3c third case

Fig.4 discharging voltage and current curves

III.2. Framework

The precision of the battery SOC is estimated by the BP neural network. In Figure (5), the external BP model adopted is shown and contains an input layer, a hidden layer, and an output layer. Three types of layers are used in the BPNN: an input layer with nodes representing the input variables, hidden layers modeling the nonlinearity between the output and input systems, and an output layer representing the output system. After multiple experiments and simulations, the selected neural network consists of two (2) neurons as inputs, battery terminal voltage and current over time, one (1) hidden layer with ten (10) neurons with TANGSIG transfer function, and the output layer has 1 neuron represented the battery SOC

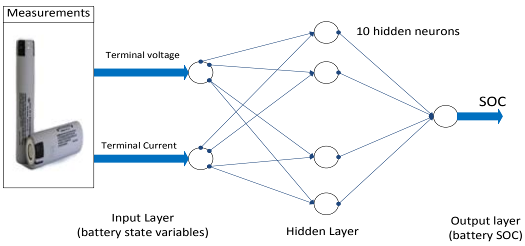

Fig.5 SOC estimation model of BP network

III.3. Soc Estimation under changeable discharge conditions

To verify the proposed SOC estimation, a thermostat is used to adjust the temperature of the heating device. We set the preferred temperature to (25ºc) and the thermostat holds the environment at the optimal. The voltage is sampled by NI-USB-6210 and the current is controlled by IT8500 DC and the SOC is determined by the nonlinear function relationship between inputs and output as shown in fig (6). The battery model is tested at various time intervals during the entire process by discharging 100% to 0% SOC. In Matlab / Simulink program the ANN is trained offline in simulation using data obtained from the lithium-ion charging and discharging process. During the process, the battery was discharged completely with a variable amplitude current profile.

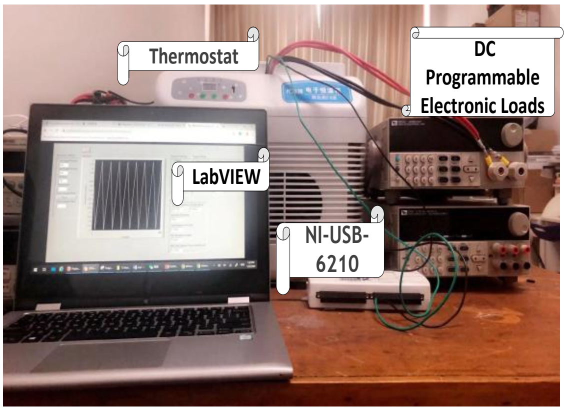

Fig.6 Battery system diagram

IV. TRAINING RESULT

After 1000 epochs of interaction, the learning activation function used is Trainlm, the best validation performance function Mean Square Error (MSE), and the performance gradient are shown in fig (7) and (8).

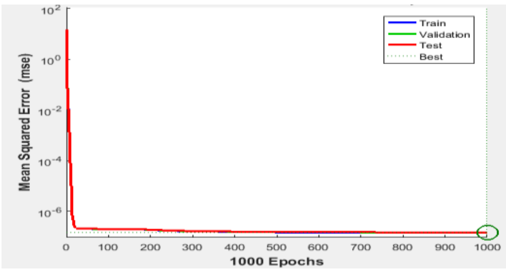

Fig.7 Performance function MS

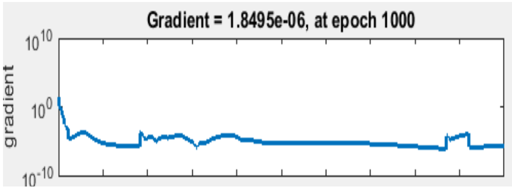

Fig.8 Training gradient diagram

Our working conditions data verify the SOC model estimate. By comparing the real SOC from the equipment to the predicted SOC from the model, the input data in the model verifies the SOC estimation algorithm of BPNN.

In the presence of different cases, the measurement errors generated by the input currents are different. Figures (9), Fig (10), and Fig (11) show the results obtained from various experimental research profiles at 25ºC. During the whole discharge phase, we can see a correlation between the actual and the expected SOC, the error becomes gradually smaller, and the approximate errors vary around one. In the first case, the estimation algorithm generated a mean square error of 1% at 25ºC, 0.8% in the second case, and 0.95% in the third case during the complete study.

However, the maximum error is based on the number of neurons in the hidden layer shown in table (1). We can notice that the best performance is obtained by a model with 10 hidden neurons with minimal error test profiles at 25ºC. For example, even if the mean square error does not reach (1%) one percent, the use of twenty (20) neurons in the hidden layer raises the maximum error instead of ten (10) neurons. This shows the over-fitting problem.

The predictive accuracy of the model may meet the industry's error requirement of less than 5%, which has some guiding value.

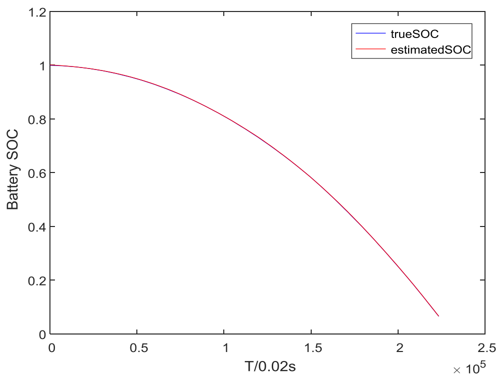

Fig.9a Comparison simulation and measurement of training sets

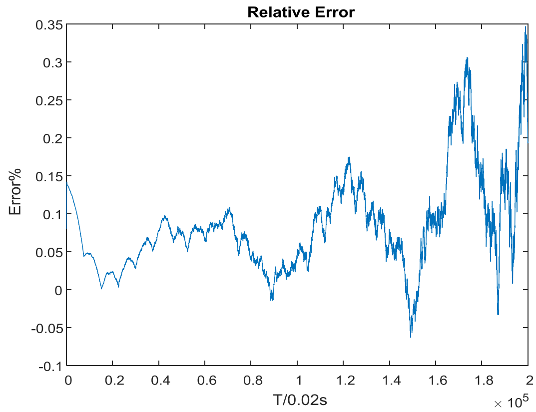

Fig.9b Relative Error

Fig.9 measurement of training sets and Comparison simulation

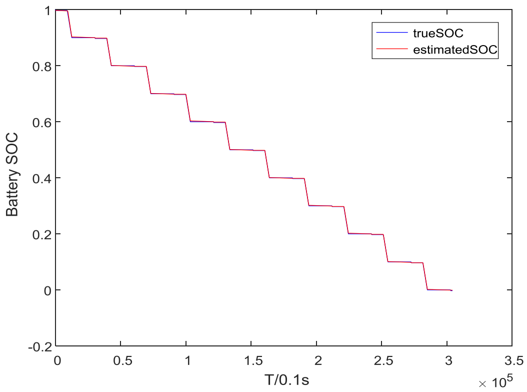

Fig.10.a Simulation results from test data

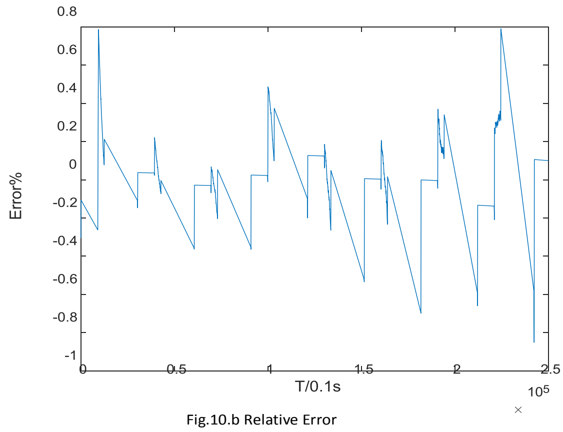

Fig.10.b Relative Error

Fig.10.a Results of simulation from test data

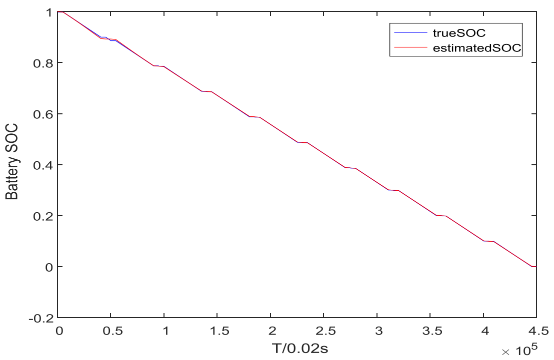

Fig.11.a Simulation results from test data

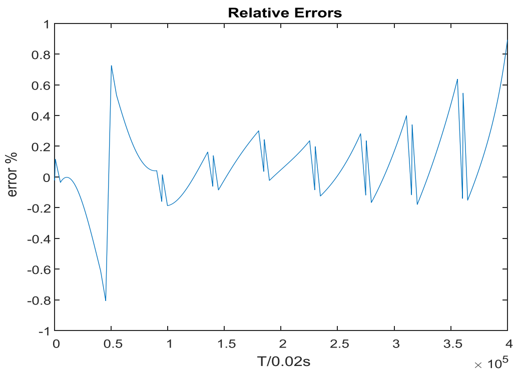

Fig.11.b Relative Error

Fig.11. Test data simulation results

Table.1: Error analysis

Cases	number of hidden neurons	maximum error	mean square error
	10	1.81%	0.37%
Case 1	15	2.237%	0.185%
	20	1.565%	0.167%
	10	2.74%	0.943%
Case 2	15	2.76%	1.015%
	20	3.48%	1.28%
	10	5.05%	0.859%
Case 3	15	4.89%	0.886%
	20	4.5%	0.801%

V. CONCLUSION

In this article, the BP neural network was developed based on the benefit and disadvantage of the SOC estimation algorithm and the problem of SOC estimation of the power battery. A training algorithm using the Matlab script is then adapted to evaluate the effective structure of interconnection, a sufficient number of hidden layers of neurons that find the best data match.

The simulation results showed the BP has a good ability of nonlinear mapping, compared to other models, it does not need modeling a complex equivalent circuit battery model and can meet nonlinear prediction requirements for HEV. The key contribution of this work is, therefore, a proposition of BPNN with 10 hidden neurons involved in the estimation of lithium-ion battery SOC through the use of significant sampling to accurately choose both current and voltage for the neural network input model of BP.

Machine learning algorithms have challenges but their effectiveness, accuracy, and ability to take in the characteristics of the battery as inputs cannot be overlooked. This work can be extended to other chemistries of the batteries combined with other methods of SOC estimation. In this research only two inputs are used, more characteristics of the battery can be integrated as inputs for better SOC estimation.

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