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APPLICATION OF RADIAL BASIS FUNCTION NEURAL NETWORK, TO ESTIMATE THE STATE OF HEALTH FOR LFP BATTERY

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ABSTRACT

This paper proposes a method that is based on the radial basis function (RBF) neural network, to estimate the state of health (SOH), for the LiFePO4 (LFP) batteries in discharging condition. The proposed method contains three hardware's, namely the battery voltage detection interface, discharge current detection interface, battery impedance measure interface. With a micro-processor integrated, the proposed SOH estimator is able to digital control which can improve the estimator reliability. The software of the proposed SOH estimator is the RBF neural network. The architectures of proposed RBF neural network, used in this paper contain three layers, an input layer, a hidden layer and an output layer. In order to demonstrate the accuracy of the proposed estimation method, the method has been tested using LFP batteries under several kinds discharging conditions. The accuracy of the proposed SOH estimation method is evaluated using two indices, namely the maximum absolute percentage error (MaxAPE) and the mean absolute percentage error (MAPE). The test results show that, the proposed RBF neural network based estimation method is accurate and effective.

KEYWORDS: *State of Health, LFP Batteries, RBF Neural Network, Micro-Processor*

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I. INTRODUCTION

The reducing crude oil and environmental pollution problems have led to the development of energy storage systems. The most important energy storage system is the battery, because of its low pollution and high efficiency. Batteries are used commonly for 3C devices, industrial applications, portable utilities and electric vehicles [1]. The LFP battery is one of the most attractive batteries, because the LFP battery has the advantages of low pollution, high working cell voltage, high power density low self-discharge rate, and no memory effect [2].

SOH estimating is one of the new challenges for LFP battery utilization. SOH of LFP battery is used to describe the health level of LFP battery. SOH is a very important index in LFP battery utility [3]. Since, the battery SOH is an important index, which reflects the battery performance, so the estimation accuracy of SOH can not only Indicates the residual life of battery, but also let the application of LFP battery more efficient and reliable [4].

Recently, several new methods have been employed, for the battery SOH estimation including: the Lyapunov-based adaptive state of health estimation method [1], the adaptive network-based fuzzy inference system method [4], the probabilistic neural network [5], the support vector regression algorithms [6], the second-order parabolic regression algorithm [7], the state of charge (SOC) method [8], and the fuzzy logic method [9].

The aim of this paper is proposing the RBF neural network based LFP battery SOH estimation method. The rest of the paper is organized as below: The principle of the RBF neural networks is presented in Section II. Section III discusses the training procedure of RBF neural network. The architectures of RBF neural network based SOH estimation method is described in Section IV. The test results with the proposed SOH estimating method are drawn in Section V. Finally, conclusion is discussed in Section VI.

II. PRINCIPLE OF RBF NEURAL NETWORK

The paper uses a RBF neural network to estimate the SOH for the LFP batteries. Figure 1 shows the typical architecture of RBF neural network. The nonlinear mapping from the input space Rm to the output space Rn is performed, on the RBF neural network [10]. The mapping relationship between input set and output set of RBF neural network can be described as the following function:

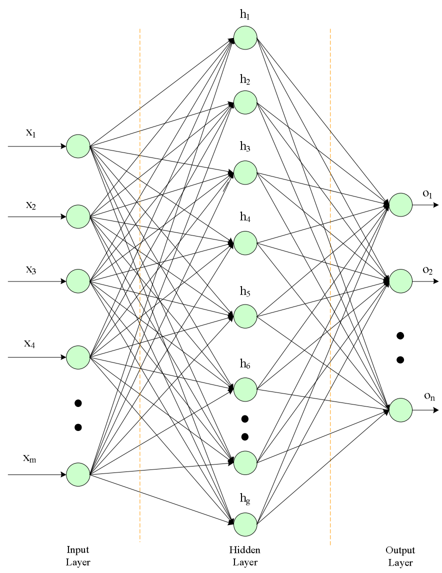

Figure 1: The Typical Architecture of RBF Neural Network

$$RBF \quad Neural \quad Network : \begin{cases} R^m \to R^n \\ \bar{x} \to \bar{o} \end{cases} \tag{1}$$

where the input set is $\bar{x}_i$={x_i, for i = 1,2,…,m}, the output set is $\bar{o}_j$= {o_j, for i = 0,1,2,…,n}.

Each node in the hidden layer computes the Gaussian function as shown in the Equation (2):

$$h_k(\bar{x}) = \exp[\frac{-(\bar{x}^T - \bar{\mu}_k)^2}{2\sigma_k^2}], for \quad k = 1,2,......., g \tag{2}$$

Where μ_k and σ_k are the center and the width of the Gaussian function of the kth node, in the hidden layer of RBF neural network respectively

Each neuron in the output layer of the RBF neural network calculated the output value by using the linear function as shown below:

$$o_j = \sum_{j=1}^{g} w_{jk} h_k(\bar{x}) + \theta_k , for \quad j = 1,2,\ldots\ldots,n \tag{3}$$

Where, w_{kj} is the weight between kth neuron in the hidden layer and jth neuron in the output layer, θ_j is the bias of the jth neuron in the output layer, $h_k(\bar{x})$ is the output from the kth neuron in the hidden layer, and o_j is the output of the jth neuron in the output layer.

III. THE TRAINING PROCEDURE OF RBF NEURAL NETWORK

The training procedure of RBF neural network can be decomposed into two stages: first is evaluating the center and the width of the Gaussian function μ_k, σ_k and second is estimating the weights between the hidden neuron and output neuron w_{kj} [11]. The first stage of training procedure is the μ_k and σ_k evaluation can be described briefly as the following steps:

Step1: Randomly set the initial value of μ_k and its associated width σ_k (initially $\sigma_k = 0$);

Step2: Find out the nearest point μ_l of the same class by using the Euclidean distance;

Step3: Calculate the mean of μ_k and μ_l to obtain a new point with its associated width by using the Equation (4):

$$\sigma = (\|\mu_k , \mu_l\|)/2 + \sigma_k \tag{4}$$

Step4: Calculate the distance D between the new point and the nearest point of all other classes;

Step5: If the distance $D < 2\sigma$, then accept the combination of μ_k and μ_l, go to the *Step 2* start again; if $D \geq 2\sigma$, then reject the combination of μ_k and μ_l, go to the *Step 1*;

Step6: Repeat Steps 1-5 until all the clusters of each class have been choose.

After the Gaussian function centers μ_k, and widths σ_k have been calculated at first stage, the connection weights w_{kj} between the hidden neuron and output neuron can be computed, by using the pseudo-inverse matrix algorithm [11].

IV. RBF NEURAL NETWORK BASED SOH ESTIMATION METHOD

The proposed RBF neural network based SOH estimation method has been successfully implemented, by using a RBF neural network based control core. The system block diagram of the proposed SOH estimating method is shown in Figure 2. In this system, the battery voltage detection interface detects the terminal voltage of the battery; the discharge current detection interface detects the discharge current of battery; and the battery impedance measure interface measures the internal impedance of the battery. The micro-processor is the control core of the SOH estimation system. There two programs installed in micro-processor. First is a back propagation neural network based SOC estimation program, in which the SOC of battery is estimating. Second is a RBF neural network based SOH estimation program, in which the SOH of battery is estimating. The value of SOH is shown in the LCM Display.

The architecture of the SOH estimating RBF neural network of the proposed estimation system is shown in Figure 3. The RBF neural network model was developed for SOH estimating by using C++ language. There are three layers contained in the RBF neural network used in this study. The first layer of the RBF neural network is input layer, which contains 4 neurons: the terminal voltage of battery, the discharge current of battery, the internal impedance of battery, and the state of charge value of battery. The second layer of the RBF neural network is hidden layer. In this study the number of neuron in hidden layer has been selected as 9, through the experimental results.

The third layer of the RBF neural network is output layer, which contains only one neuron for the SOH estimating value.

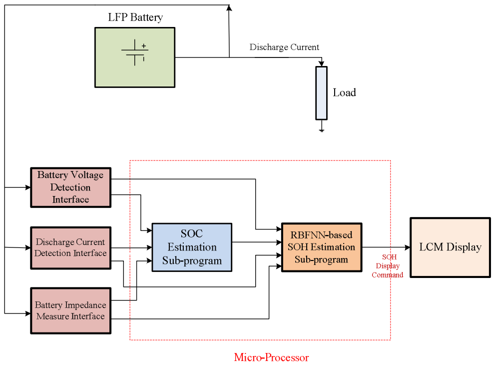

Figure 2: The System Block Diagram of the Proposed SOH Estimating Method

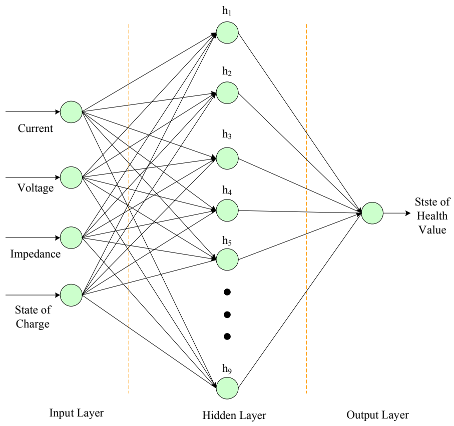

Figure 3: The Architecture of the SOH Estimating RBF Neural Network of the Proposed System

V. TEST RESULTS

To verify the proposed SOH estimation method, the method has been applied for SOH estimating for the practical LFP batteries. The experiments were conducted in the laboratory. A prototypical RBF neural network based SOH estimator was set up in the laboratory. The specification of the tested LFP batteries is 3.2V, 10 Ah.

After the training process described in Section III, the RBF neural network is constructed. The training dataset is composed of the input vectors and the desired output vectors. After experiments, the input set with 4 elements and the output set with one element were constructed. The four input data include the terminal voltage, discharge current, internal impedance combined with the state of charge constitute the input vectors. The output vector is the estimated SOH value.

For the discharge test, the battery was full charged by fixed 1A current. In the experiments, 4 kinds of different discharging current of tested LFP batteries are used to verify the accuracy of the proposed SOH estimation method, which are: (1) discharging current is fixed at 3A, (12) discharging current is fixed at 7A, (3) discharging current is fixed at 10A, (4) varied discharging current with 30 min. at 3A, 20 min. at 10A, 47 min. at 7A.

The estimation errors of the proposed SOH estimation method in the fixed current discharged tests are shown in Table 1. The estimation errors of the proposed method in the varied current discharged test are shown in Table 2. Table 1 and Table 2 show both the maximum absolute percentage error (MaxAPE) and the mean absolute percentage error (MAPE) of the RBF neural network based estimation method.

As shown in Table 1 and Table 2, the good accuracy of the proposed RBF neural network based SOH estimation method was ascertained. The accuracy of the proposed SOH estimation method has been validated in the experimental tests. The test results show that the RBF neural network based SOH estimation method can estimate the SOH of LFP battery easily and accurately.

Table 1: The Estimation Errors of Proposed Method in the Fixed Current Discharged Tests

Discharge Current	Error Type	RBF Neural Network Method
3A	MAPE	3.67%
3A	MaxAPE	5.98%
7A	MAPE	3.45%
7A	MaxAPE	6.79%
10A	MAPE	3.67%
10A	MaxAPE	7.35%

Table 2: The Estimation Errors of Proposed Method in the Varied Current Discharged Tests

Error type	RBF neural network method
MAPE	4.56%
MaxAPE	8.12%

VI. CONCLUSIONS

This paper has proposed a RBF neural networks based method using for LFP battery SOH estimating. The performance test of the proposed method to SOH estimating is accurate. The accurate evaluation of the estimating methods is performed, using the estimation value of SOH of the practical LFP batteries. The test results demonstrate the accuracy of the proposed estimating method and this method provided improved accuracy for the SOH estimating of LFP battery.

VII. ACKNOWLEDGMENTS

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