Available online at www.sciencedirect.com
ScienceDirect
Journal of Power Sources 158 (2006) 932–935
JOURNAL OF POWER SOURCES
www.elsevier.com/locate/jpowsour

Short communication

Prediction of state-of-charge effects on lead-acid battery characteristics using neural network parameter modifier

N. Abolhassani Monfared [a,*], N. Gharib [a], H. Moqtaderi [a], M. Hejabi [b], M. Amiri [a], F. Torabi [a], A. Mosahebi [a]

[a] *Vehicle, Fuel and Environment Research Institute, University of Tehran, Iran*
[b] *Niru Battery Manufacturing Co., Tehran, Iran*

Available online 20 December 2005

Abstract

In this study, impedances of SABA BATTERY 6SB6 in different SOCs are applied to obtain the equivalent circuit parameters using Champlin method in different SOCs. Champlin method answers are used as Zview initial values to get fit results and the Artificial Neural Network (ANN) is trained by these final results. The presented ANN inputs are SOCs and outputs are equivalent circuit parameters. The completed network responses are perfectly adjusted to the experimental parameters. Accuracy of this method has been verified by using the measured data and they have shown a high consistency to experiment. So that a model is extracted in which one can approach an equivalent circuit model with specified parameters simply by entering the SOC.

Keywords: Lead-acid battery; Equivalent circuit; State-of-charge; Neural network

1. Introduction

The dynamical behavior modeling of electrochemical power sources is a noticeable issue in simulation of automotive power systems, photovoltaic systems, electric and hybrid vehicles. Furthermore, battery monitoring and battery management systems require dynamic battery models, which are continuously adapted to the battery behavior [1].

For an accurate model of any electrochemical device, one might employ a rigorous theory taking all the factors into consideration, but in practice that becomes too complicated. Therefore, equivalent circuits may be used to simulate the dynamical behavior of a battery [2]. An equivalent circuit model is an interconnection of electrical elements introduced to represent terminal characteristics of the battery. The small-signal behavior of an equivalent circuit model bears a correspondence with the terminal properties of the battery over a band of frequencies. Thus, arriving at a good model from the Electrochemical Impedance Spectroscopy (EIS) data continues to be a challenge. Such models have been described by a number of researchers including Hampson et al. [3], Willihnganz and Rohner [4], and De Bardelaben [5]. However, none of the above references has presented means for determining an equivalent circuit model parameters from a small number of measurements obtained at a few selected "spot" frequencies [6].

The traditional approach in extracting these equivalent circuit values is to collect as much EIS data as possible and subject it to complex nonlinear least squares algorithm. Champlin [6] identified the importance of sparse observations and proposed a technique in which by measurement of real and imaginary parts of impedance of a cell at n (≥ 2) discrete frequencies, one can evaluate the component values of an equivalent circuit including $2n$ circuit elements [2].

In other hand, a new approach to modeling batteries is the Artificial Neural Network (ANN), a parallel, distributed information processing technique [7] and particularly suitable to solving obscure problems. The network consists of processing elements which are biologically inspired [8]. As in a biological system each element or neuron has a limited processing capability, every neural network model is characterized by its interconnection of the processing element (neuron) [9].

Neural network is an inductive, or data based model for simulation of input/output mapping. ANNs require training data to learn patterns of input/output behavior, and once trained, can be used to simulate system behavior within that training region. This can be done by interpolating specified inputs among the

* Corresponding author.
E-mail address: n_a_monfared@alum.sharif.edu (N. Abolhassani Monfared).

0378-7753/$ – see front matter © 2005 Elsevier B.V. All rights reserved.
doi:10.1016/j.jpowsour.2005.11.023

training inputs to yield outputs that are the interpolations of training outputs. The reason for using ANNs to simulate system behavior is that they provide accurate approximations of system behavior and are typically much more computationally efficient than phenomenological models. This efficiency is very important in situations where multiple responses or prediction computations are required [10].

2. Experimental

The batteries upon which measurements are made are SABA BATTERY 6SB6 Sealed Lead-Acid Maintenance free batteries. The charge, discharge and impedance data are obtained with SOLARTON 1470, a multi-channel Potentio/Galvanostate battery test system, controlled by solarton cell test™ software.

The impedance spectroscopy sweeps are conducted from 65 kHz to 1 mHz at amplitude of 10 mV. All batteries are tested in 2nd cycle of charge–discharge. During second discharge cycle, the impedance spectroscopies are done under 0 current in 18 different SOCs (5–100%). A 2 min rest is allowed in each step.

3. Modeling/analysis of impedance data

The equivalent circuit model used to fit the impedance data is shown in Fig. 1. The bulk resistance of battery is modeled by the series resistance R_1 and the two electrodes are modeled by parallel resistor–capacitor networks. The series inductor is used to model the high frequency part of the impedance characteristics.

Choosing different three member groups of frequencies, in each SOC, the circuit parameters are calculated by applying Chapman method. In this method, by using the real and imaginary parts of complex impedance of a cell or battery at *n* discrete frequencies, where *n* is an integer number equal to or greater than 2, one can evaluate components of an equivalent circuit model comprising 2*n* electrical elements. By introducing 2*n* intermediate variables, the nonlinear equations are made linear and are systematically solved for the values of the model components [6].

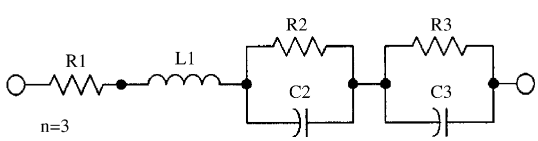

Fig. 1. The equivalent circuit model used to fit the impedance data.

In each SOC, the equivalent circuit parameters extracted from this method are applied as initial values of the equivalent circuit modeling of Zview software to obtain fit results and error percentages. Table 1 depicts the circuit element values and their error percentages in one of the samples and in four different SOCs. Fig. 2 also illustrates the impedance curve and its fitting curve by using equivalent circuit model of the same sample in 95% SOC as an example. Fig. 2 and Table 1 show that this method could achieve acceptable results. The modified results of Zview are used as neural network training inputs. For each SOC the experiments are repeated at least for 10 batteries and the neural network is trained by these results.

4. Neural network and training

A mathematical model of a two layer neural network is depicted in Fig. 3 which shows the weight matrices *V*, *W* the firing thresholds v_{i0}, w_{j0} (also called bias), the summation of weighted incoming signals, and nonlinear function $\sigma(.)$. The inputs are the *n* signals $x_1, x_2, \ldots, x_n$ and the outputs are $y_1, y_2, \ldots, y_m$, which can be expressed as:

$$y_i = \sigma\left(\sum_{l=1}^{L} w_{il}\sigma\left(\sum_{j=1}^{n} v_{lj}x_j + v_{l0}\right) + w_{i0}\right) \quad i = 1, 2, \ldots, m$$

Once the network weight and biases have been initialized, the network is ready for training. The network can be trained for function approximation. The training process requires a set of examples of proper network behavior (network input (*x*) and target (*y*)). During the training the weight and biases of the network are interactively adjusted to minimize the mean square error.

In this paper, a double-layer neural network has applied in which the hidden layer is its first layer and the second layer is the

Table 1
Equivalent circuit elements of different SOCs in a sample battery

Elements \ SOC	95%		65%		35%		5%	
	Value	Error (%)	Value	Error (%)	Value	Error (%)	Value	Error (%)
R1	0.038408	0.7346	0.042075	0.8434	0.05073	0.87707	0.09674	2.0013
R2	0.018574	6.4757	0.035201	6.7578	0.03291	5.3427	0.10053	5.4799
R3	0.014971	4.1214	0.022403	4.0087	0.02107	4.69	0.064689	4.8387
L	4.58E-07	1.2793	4.54E-07	1.5744	4.46E-07	1.6237	3.93E-07	3.7812
C2	15.33	11.01	12.62	9.164	4.41	10.015	0.31627	11.58
C3	0.34581	8.2999	0.36551	7.5713	0.13984	9.1969	0.002636	11.371

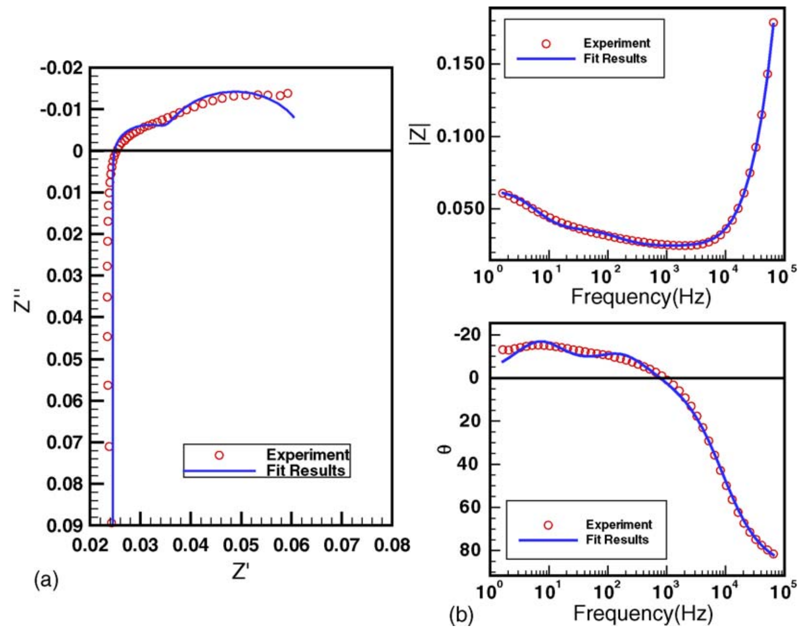

Fig. 2. (a) Complex and (b) bode impedance curves and their fit results for 95% SOC.

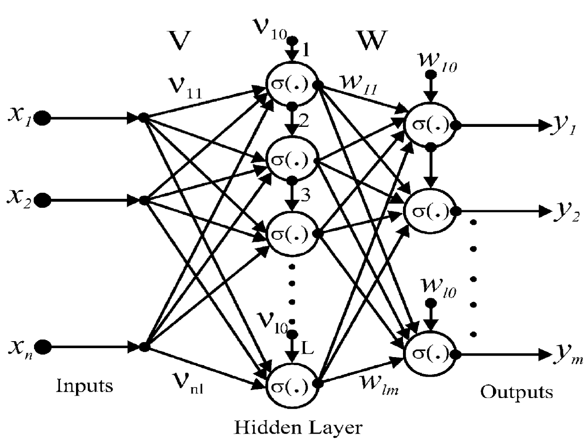

Fig. 3. A two-layer network with n input elements and m output.

output layer. The input of this network is SOC of the battery and its outputs are the battery equivalent circuit parameters including three resistances, two capacitances and an inductance.

The neural network has trained using 10 similar batteries in their second cycle of discharge and in 20 different SOCs. For scaling network inputs and targets, the mean and standard deviation of the training set are normalized so that they will have zero mean and unity standard deviation.

In the present study, the neural network has trained using Backpropagation method [11,12]. The backpropagation method introduces a value function. While the value function gradient is 0, the weight of the layer remains constant. Thus the neural network can approximate the function. The weight in each step is defined as follow:

$$\nu_{lj}(k+1) = \nu_{lj}(k) - \eta \frac{\partial E(k)}{\partial \nu_{lj}(k)}$$

where E is the value function, $\nu_{lj}(k)$ is weight of layer l of neuron j in step k, $\nu_{lj}(k+1)$ is weight of layer l of neuron j in step $k+1$ and η is the learning rate which is usually set between 0 and 1. Error in each step is defined as:

$$e_l(k) = Y(l) - y_l(k)$$

where $Y(l)$ is target, $y_l(k)$ is neural network output in each step and $e_l(k)$ is error in each step. In addition the value function is defined as:

$$E(k) = \frac{1}{2}\sum_{l=1}^{L} e_l^2(k) = \frac{1}{2}\sum_{l=1}^{L}(Y(l) - y_l(k))^2$$

To compare the results of neural network with a real battery, a battery is tested in SOCs in which the neural network had not been trained. For example, Table 2 depicts a comparison between the parameters in 45% SOC achieved from experiment and neural network. As it shows the neural network approximations have an acceptable accuracy to predict the equivalent circuit parameters in each SOC.

Table 2
A comparison between artificial neural network and experiment in 45% SOC

	R1	R2	R3	L	C2	C3
Neural network approximation	0.034702	0.029609	0.015898	4.13E−7	4.843655	0.165896
Experimental	0.0347268	0.029989	0.016086	4.11E−7	4.5396	0.151401
Error (%)	0.070	1.27	1.69	0.459	6.7	9.573

5. Conclusions

In this paper, a computational model based on the artificial neural network has been proposed to estimate a battery equivalent circuit parameters of the same group of those batteries which were used to train ANN by just knowing the SOC, and without any test requirement. This computational model works fast and the accuracy of this method verified by using the experiment. The presented method can be extended for other different equivalent circuit models, and also can be modified to simulate the battery characteristics by entering other battery parameters.

Acknowledgements

This work was supported financially by Niru Battery Manufactory Company. The use of company facilities is gratefully acknowledged.

References

[1] E. Karden, S. Buller, R.W. De Doncker, A frequency-domain approach to dynamical modeling of electrochemical power sources, Electrochim. Acta 47 (2002) 2347–2356.
[2] S.R. Nelatury, P. Singh, Equivalent circuit parameters of nickel/metal hydride batteries from sparse impedance measurements, J. Power Sources 132 (2004) 309–314.
[3] N.A. Hampson, The impedance of electrical storage cells, J. Appl. Electrochem. 10 (1980) 3–11.
[4] E. Willihnganz, P. Rohner, Battery impedance, Electr. Eng. 78–79 (1959) 922–925.
[5] S. De Bardelaben, Determining the End of Battery Life, INTELLEC 86, IEEE Publication, 1986, pp. 365–386.
[6] K.S. Champlin, Method and apparatus for determining battery properties from complex impedance/admittance, US Patent 6,037,777 (2000).
[7] D.H. Swan, M.P. Arikara, A.D. Patton, Battery modeling for electric vehicle applications using neural networks, Texas Engineering Experiment Station, Texas A&M University System.
[8] P.D. Wasserman, Neural Computing: Theory and Practice, Van Nostrant Reinhold, New York, 1989.
[9] R. Beale, T. Jackson, Neural Computing: An Introduction, Adam Hilger, Bristol, Philadelphia and New York, 1990.
[10] C.C. O'Gorman, D. Ingersoll, R.G. Jungstand, T.L. Paez, Artificial neural network simulation of battery performance, Sandia National Labratories, 1997.
[11] F.L. Lewis, Neural Network Control of Robot Manipulators and Nonlinear Systems, Taylor & Francis, 1998.
[12] Mathwork, Neural Network Tools Box User's Guide, Mathwork Inc., 2002.