# PREDICTION OF SOC EFFECTS ON LEAD-ACID BATTERY CHARACTERISTICS USING NEURAL NETWORK PARAMETER MODIFIER

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#### 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<sup>[1]</sup>.

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<sup>[2]</sup>. 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. Willihnganz and Rohner, and De Bardelaben, 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.

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 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  $n \geq 2$  discrete frequencies, one can evaluate the component values of an equivalent circuit including 2n circuit elements 2n

In other hand, a new approach to modeling batteries is the Artificial Neural Network (ANN), a parallel, distributed information processing technique<sup>[7]</sup> and particularly suitable to solving obscure problems. The network consists of processing elements which are biologically inspired<sup>[8]</sup>. 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)<sup>[9]</sup>.

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 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<sup>[10]</sup>.

In this study, the equivalent circuit elements are evaluated by Champlin method in different SOCs and they are used to train ANN in parallel which inputs are SOCs and outputs are equivalent circuit parameters. The completed network responses are perfectly adjusted to the experimental parameters, such that a model is extracted in which one can approach an equivalent circuit model with specified parameters simply by entering the SOC.

### 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<sup>TM</sup> software.

The impedance spectroscopy sweeps are conducted from 65 kHz to 1 mHz at amplitude of 10 mV. All batteries are tested in 2<sup>nd</sup> cycle of charge-discharge. During second discharge cycle, the impedance spectroscopies are done under zero current in 18 different SOCs (5 to 100%). A 2 minute 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 3 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 2n electrical elements. By introducing 2n intermediate variables, the nonlinear equations are made linear and are systematically solved for the values of the model components<sup>[6]</sup>.

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

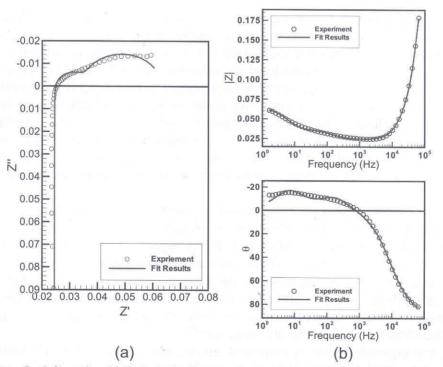


Figure 2: a) Complex, b) Bode impedance curves and their fit results for 95% SOC.

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 4 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. Figure 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.

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

SOC elements	95%		65%		35%		5%	
	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

## 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  $x_1, x_2, ..., x_n$  and the outputs are  $y_1, y_2, ..., y_m$ , which can be expressed as

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

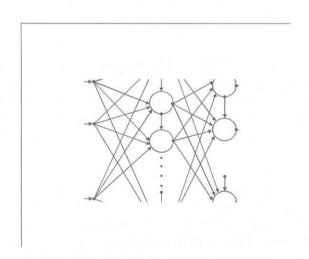


Figure 3: A two-layer network with n input elements and m output.

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 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*<sup>[11, 12]</sup>. The backpropagation method introduces a value function. While the value function gradient is zero, the weight of the layer remains constant. Thus the neural network can approximate the function. The weight in each step is defined as follow:

$$v_{ij}(k+1) = v_{ij}(k) - \eta \frac{\partial E(k)}{\partial v_{ij}(k)}$$

where, E is the value function,  $v_{ij}(k)$  is weight of layer I of neuron j in step k,  $v_{ij}(k+1)$  is weight of layer I of neuron j in step k+1 and  $\eta$  is the learning rate which is usually set between 0 to 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, impedances of SABA BATTERY 6SB6 in different SOCs are applied to obtain the equivalent circuit parameters, using Chapman method and Zview. A computational model based on the artificial neural network has been proposed to estimate these parameters by just knowing the SOC without any test requirement. The accuracy of this method has been verified by using the measured data and they have shown a high consistency to experiment.

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