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Abstract

Neural networking is a new approach to modeling batteries for electric vehicle applications. This modeling technique is much less complex than a first principles model but can consider more parameters than classic empirical modeling. Test data indicates that individual cell size and geometry and operating conditions affect a battery performance (energy density, power density and life). Given sufficient battery data, system parameters and operating conditions a neural network model could be used to interpolate and perhaps even extrapolate battery performance under wide variety of operating conditions. As a result the method could be a valuable design tool for electric vehicle battery design and application. This paper describes the on going modeling method at Texas A&M University and presents preliminary results of a tubular lead acid battery model. The ultimate goal of this modeling effort is to develop the values necessary to be able to predict performance for batteries as wide ranging as sodium sulfur to zinc bromine.

Introduction

Modeling a battery involves looking into the effect of a large number of parameters for which many relationships are unknown. Synthetic neural networks are particularly suitable to solving obscure problems. The model is not technology specific but can be used with any battery technology such as lead acid, sodium sulfur, and nickel metal hydride. Given the cell dimensions, mass, operating temperature range and rate of discharge, the network can estimate the performance of a battery in terms of energy density, power density and efficiency.

As an example the change in the geometry of cell can significantly effect power density with no change in energy density. The following table compares the performance of two different sodium sulfur cells, A04 from Brown Boveri/ABB in Germany and the PB cell from CSPL in England¹.

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Table 1 Comparison of Sodium Sulfur Cell Characteristics

Characteristics	ABB Cell A04	CSPL Cell PB
Diameter	35 mm	44 mm
Length	230 mm	45 mm
Weight	410 g	120 g
Specific Energy	176 Wh/kg	178 Wh/kg
Specific Power	390 W/kg	250 W/kg

Table 1 shows that the two sodium sulfur cell geometries are significantly different, their specific energies are essentially the same but the specific power is not. Given sufficient experimental data as a function of geometry and operating conditions a neural network model could be used to optimize the cell design for a desired performance characteristic.

The following sections discuss 1) the neural modeling technique 2) network training and 3) the modeling technique applied to a lead acid battery application.

Neural Networking - A Back Propagation Modeling Technique:

An artificial neural network is a parallel, distributed information processing technique. The network consists of processing elements which are biologically inspired². 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)³.

Figure 1. shows the neuron used as the fundamental building block for back propagation networks. A set of inputs is applied either from outside or a previous layer. Each of the inputs is multiplied by a weight and the products summed. The summation is termed 'NET' and must be calculated for each neuron in the network. After 'NET' is calculated, an activation function is applied to modify it producing the signal 'OUT'.

Figure 1. Process Element Schematic

The following formula shows the application of a typical activation function used with back propagation⁴.

$$\text{Out} = \frac{1}{(1 + e^{-N\alpha})}$$

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Neural Networking - Training Technique:

To train the network (initialize all values) back propagation based on experimental results is used. This training method is based on proposing an error function that penalizes misclassification and attempts to minimize this error using a gradient descent of values. The following Figure 2 shows a multilayer network with back propagation (the figure has been simplified for clarity). The first set of neurons serve distribution points, they perform no input summation. The input signal is passed through to the first layer of the network through the weighted links. The present figure consists of two layers a hidden layer and an output layer, the input layer is designated layer 0. It is possible to have a network with a greater number of hidden layers but most realizations are possible with just two.

Figure 2. Multilayer Network With Training

The weight of the links between elements decide the value of the output from the neurons, thus training the network develops the relationships that will be used to predict battery performance under different conditions. During training the experimental obtained input (current rate, temperature, geometry etc.) and output values (energy density, power density, efficiency) are referred to as training pairs. The more training pairs used and the more parameters in each training pair will result in a more comprehensive and accurate network, however this is at the expensive of computer time.

The weights of the links are to begin with initialized to small random numbers.

Training the network by back propagation requires the following steps^{5,6}:

1. Select the next training pair from the training set; apply the input vector to the input of the network.
2. Calculate output of the network.
3. Calculate the error between the network output and the experimental result (target vector from the training pair).
4. Adjust the weights of the network in a way that minimizes the error (the weight adjustment procedure is described below).
5. Repeat the steps for each vector in the training set until the error for the entire set is acceptably low.

Weight Adjustment Using the activation function described by equation 1 the link weight is adjusted as follows (equation nomenclature appears at the end of this section):

At the output layer a δ value is calculated at the compartor:

$$\delta = \text{Out}(1 - \text{Out})(\text{Target} - \text{Out}) \quad 2$$

A change in weight value is then calculated by:

$$\Delta W_{(pq,k)} = \eta \times \delta_{(q,k)} \times \text{Out}_{(pj)} \quad 3$$

$$W_{(pq,k)}(n+1) = W_{(pq,k)}(n) + \Delta W_{(pq,k)} \quad 4$$

For the hidden layer to adjust the weights we use the following:

$$\delta_{(p,j)} = \text{Out}_{(pj)}(1 - \text{Out}_{(pj)})(\sum(\delta_{(q,k)} W_{(pq,k)})) \quad 5$$

Using this value of $\delta_{(p,j)}$ and equations 3 and 4 the weights of all the other layers are adjusted.

Equation Nomenclature:

$W_{(pq,k)}(n)$	=	the weight of the link from neuron p in the hidden layer to a neuron q in the output layer at step n(before adjustment); note the subscript k indicates that weight is associated with its destination layer.
$W_{(pq,k)}(n+1)$	=	value of the weight at step n+1 (after adjustment).
$\delta_{(q,k)}$	=	the value of δ .(from 2.) for a neuron q in the output layer k.
$\text{OUT}_{(pj)}$	=	the value of OUT for neuron p in the hidden layer j.
η	=	learning rate (typically 0.01 to 1.0)

Neural Network Modeling of Lead Acid Batteries:

The primary use of the modeling technique is to design batteries for different applications depending upon the relative importance of the design parameters. A two layer neural network containing a hidden layer and an output layer along with the input layer was simulated by a software program written in FORTRAN. It is possible to make a hardwired circuit for this purpose but since speed of execution of the program is of no major concern we used the software approach.

A Chloride EV Systems lead acid battery (model ET-205) was used to generate the data required for the study. The ET-205 is a three cell module with a mass 32.8 kg. and is used in the EPRI/Conceptor G-Van vehicle. The cells use a tubular positive electrodes and a conventional negative electrode.

The battery data for the neural network model was collected at Texas A&M University by a computer controlled battery cycler. The battery was charged by a three step constant current charge sequence (36/24/12 A) followed by a constant voltage of 7.9 volts. The three charge rates were applied until module voltages of 7.2, 7.5 and 7.9 volts were reached. The final charge rate was held at 7.9 volts and terminated when the amperage fell to 6. The battery discharge profile was varied to get the performance at different operating conditions. Since the data obtained experimentally was of sets having different orders of magnitude, i.e., temperature was of the order of 20 to 40 degrees Celsius while efficiencies were of the order of 0.7 to 0.9 the data had to be conditioned for training the network. In the present case the temperature was divided by 100 to ensure the magnitude of the temperature was comparable to the magnitude of the efficiency.

The neural network model had the input vector elements as measures of the following battery module data:

- Lowest temperature seen during the charge/discharge cycle.
- Highest temperature seen during the charge/discharge cycle.
- Rate of discharge used.
- Mass of the battery (32.8 kg)

The output vector elements as measures of

- Energy density.
- Voltaic efficiency
- Coulombic efficiency.

Selected data from the experimental set up and modeling is provided in the following Tables. Table 2. presents the experimental data used to train the network. The inputs include specific current over the discharge, and the beginning and ending temperature. The listed target values are the experimental results in Wh/kg. The

Current rate has a primary influence on the target values while the temperature is secondary. End of discharge for the module was based on a voltage of 5.25. The input values were chosen to represent a large change in current and change in temperature at a specific current. Increasing current resulted in lower values of energy density, increasing temperature increased energy density.

After training the network the same inputs were used and the network predicted values compared to the experimental values. The difference is presented in the error column.

Table 2 Neural Network Training Data and Predicted Values

Input Current in Amps	Input Temp. Start	Input Temp. End	Target Value Measure- Wh/kg	Predicted Value Wh/kg	Error Wh/kg
20	30	37	34.8	32.5	2.3
60	33	40	27.3	25.2	2.1
90	31.5	49	22.3	24.3	-2.0
90	40	48.5	23.9	21.8	2.1
90	39	56	24.4	26.1	-1.7

Notes - Learning rate 0.1, Iterations = 300,000, Error at Convergence = 0.015

The fact that there is an error in the predicted values when the same inputs were used for network training is the result of incomplete convergence and the fact a limited number of parameters have been provided (incomplete model). Note that in the case of the temperature variation at 90 amps the error is both positive and negative.

Given the now trained network, a new set of experimental input data for which the experimental performance results were known were submitted to the network. The input values, measured result, and predicted result are presented in Table 3 and Figure 3. The input data was selected to be an interpolation of the training data.

Table 3 Neural Network Predicted Values

Input Current in Amps	Input Temp. Low	Input Temp. High	Measure Value Wh/kg	Predicted Value Wh/kg	Error Wh/kg
30	34	37	32.0	29.4	2.6
40	34	38	29.8	27.9	1.9
50	34	40	28.2	26.9	1.3
70	34	44.5	25.7	25.3	0.4
80	35	46	24.8	23.8	1.0

Notes - Learning rate 0.1, Iterations = 300,000, Error at Convergence = 0.015

Figure 3. Comparison of Experimental and Neural Network Predicted Energy Density

The above figure indicates that the trained neural network accurately modeled the battery energy density. The predicted results are lower than the actual results. The accuracy of the prediction could probably be improved if the final error value during training had been very low or more parameters had been used e.g. a mid discharge temperature.

It is conceivable that as the model versatility is increased by training with more parameters in more detail it will become a general design tool for a specific battery couple. This effort is now on going at Texas A&M university to develop comprehensive neural network models for lead acid, zinc bromine and sodium sulfur batteries.

Conclusion

The rechargeable battery is very complex electrochemical system. The large number of battery couples, performance parameters, and operating conditions make it extremely difficult for a designer to analysis or even specify a battery for an electric vehicle application.

A neural network is a general modeling technique that given sufficient experimental can interpolate and perhaps even extrapolate battery performance under a wide variety of conditions. The technique is not limited in the number of parameters that can be modeled. The development of neural network models for specific electric vehicle batteries is now on going at Texas A&M University. This paper presented the modeling technique, the model training and an actual comparison of experimental and predicted results. The method

shows promise in that given development it could become a general purpose design tool for electric vehicle batteries as finite element programs have for stress analysis. It is conceivable, that in its developed form the neural network could predict in vehicle performance, and even life cycle cost give a battery type, geometry and application conditions.

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