Prediction of Secondary Battery Output at Cold Cranking Behavior for Automobile Application

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Abstract

A wide range of research works on secondary battery models are carried out with varying degrees of complexity. They capture battery behavior for specific purposes using battery design, battery available parameters ranging from performance estimation to circuit simulation. This work explains the computation model of a secondary battery based on the artificial neural network (ANN), which focuses on the prediction of discharge behavior at high rates and cold cranking behavior at low temperature for automobile application. The novelty in this communication is that we have predicted with the function of less discharge time, less working hour and saved energy. The accuracy of this method has been verified by using experimentally measured data. The computation values are in good agreement with experimental data and the related error has been considered acceptable. The final conclusion of this work will demonstrate how battery operators can have better control over their quality and the performance of the batteries of different applications. This method can be utilized as a quality assurance tool in automotive industry.

Keywords: *cold cranking behavior, lead-acid battery models, artificial neural network.*

1. Introduction

With the tremendous increase in the computing power of hardware and the relatively slow growth in the energy densities of the battery technologies, design of the lifetime and performance behavior of battery for a given size and weight is difficult .Generally testing for a cell/battery is carried out to determine whether a cell or battery is fit for the purpose for which it is intended before it is approved for use as product [1]. It also includes testing finished battery packs before the product is approved for release to the customer. To predict the discharge behavior of a battery at high rate and low rate is not relatively simple, if there is either very good empirical link or models, such as curve fitting technique. However these empirical models are inflexible due to variation in battery operating conditions. Interpolation and extrapolation from test results and field data can be used to predict life time by means of parameter fitting but discharge behavior is not possible. For performance study, common modeling approach is to develop an electrical circuit that is designed to be functionally equivalent to the battery. The accuracy of these models depends upon the number of characterization tests performed to identify the values of the circuit elements. In some cases, compensation factors are required to eliminate the influence of temperature. These limitations make equivalent electrical circuit models impractical for system level battery behavioral simulation [2-5]. In this paper, we have developed a technique which uses short term information to predict long term information with the measured data. For this, artificial neural network with specifically feed-forward back propagation algorithm is developed. ANN overcomes the limitations of the conventional approaches by extracting the desired information directly from the experimental data. However, this method is typically time-consuming and simplifying assumptions of real - time systems. Hence, a neural network is one of the alternative methods for modeling the nonlinearity of the characteristics of the battery. The complex set of interacting physical and chemical processes within battery systems have made the development of analytical models to be a significant challenge. Hence, Advanced simulation tools are needed to become more accurately model battery systems which will reduce the time and cost required for product realization. So, development of cell/battery performance modeling using non-phenomenological models for lead acid battery systems based on neural network which uses Matlab 7.6.0(R2008 b) is proposed. A Neural network based learning system method has been proposed for estimation of discharge behavior at high rates and cold cranking behavior at low temperature for automobile application of lead-acid battery. To train this network, back propagation algorithm based on experimental result is used. Based on our knowledge, there is only one report about modeling of cold cranking test [6-7]. In the present work, the use of ANNs for the inductive modeling of input/output relations in lead-acid batteries for knowing about the behavior of cold cranking Amps (CCA) at sub zero temperature has been explained. The proposed models were used for inexpert operators in industries of lead-acid batteries in order to prediction of cold cranking behavior at high discharge currents and in order to determine of acceptable amount of CCA based on experimental low discharge currents data for a lead-acid battery as a non-destructive test.

2. Materials and methods

ANN is a powerful data modeling tool that can be used to capture complex input/output relationships. There are many kinds of ANN models that have been developed for various applications. Artificial neural networks (ANNs) are biologically inspired computer programs designed to simulate the way in which the human brain processes information. ANNs gather their knowledge by detecting the patterns and relationships in data and learn through experience. An ANN is formed from thousands of single units, artificial neurons or processing elements are connected with coefficients called as weights, which constitute the neural structure and are organized in layers. The power of neural computations comes from connecting neurons in a network. Each Processing elements has weighted inputs, transfer function and output. The behavior of a neural network is determined by the transfer functions of its neurons, by the learning rule, and by the architecture itself. The weights are the adjustable parameters so a neural network is called as a parameterized system. The weighed sum of the inputs constitutes the activation of the neuron. The activation signal is passed through transfer function to produce a single output of the neuron. Transfer function introduces non-linearity to the network hence during training, unit connected neurons are optimized until the error in predictions is minimized and the network reaches the specified level of accuracy. Once the network is trained and tested it can be given new input information to predict the output [8-9]. The architecture of the neural network used in this study is the multilayered feed-forward network architecture with 3 input nodes, 5 hidden nodes, and 1 output nodes.

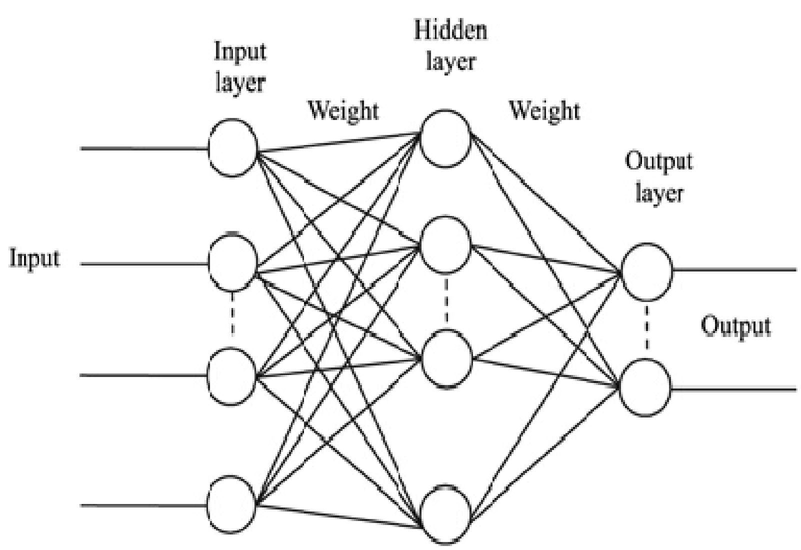


Fig.1: Schematic diagram of general Artificial Neural Network structure

The number of input nodes is determined by the group of data collected for analyzing; the number of hidden nodes is determined through trial and error method and the number of output nodes is represented as a range of classification. The most widely used neural-network learning method is the Back Propagation algorithm. Learning in a neural network involves modifying the weights and biases of the network in order to minimize a cost function. Additionally, it may include a complexity term that react a prior distribution over the values that the parameters can take. The activation function considered for each node in the network is the binary sigmoid function. This is a common function used in many Back Propagation network. This function limits the output of all nodes in the network to be between 0 and 1. Note all neural networks are basically trained until the error for each training iteration stopped decreasing. The complete set of final data is presented to the generic network. Training a neural network is the process of setting the best weights on the inputs of each of the units. The goal is to use the training set to produce weights where the output of the network is as close to the desired output as possible for as many of the examples in the training set as possible. Also it has been proved that Genetic Algorithm and Back-Propagation neural network hybrids in selecting the input features for the neural network reveals the performance of ANN can be improved by selecting good combination of input variables. The training set is a part of the input dataset used for neural network training. The validation set is a part of the data is used to tune network topology or network parameters other than weights. To choose the best network we can by change the number of units in the hidden layer and finally the validation set is used. The test set is a part of the input data set used to test how well the neural network will perform on new data. The test set is used after the network is ready or trained, comparing with this test set only errors will occur during future network application. This set is not used during training and thus can be considered as consisting of new data entered by the user for the neural network application. Following table shows the network structure used for our prediction.

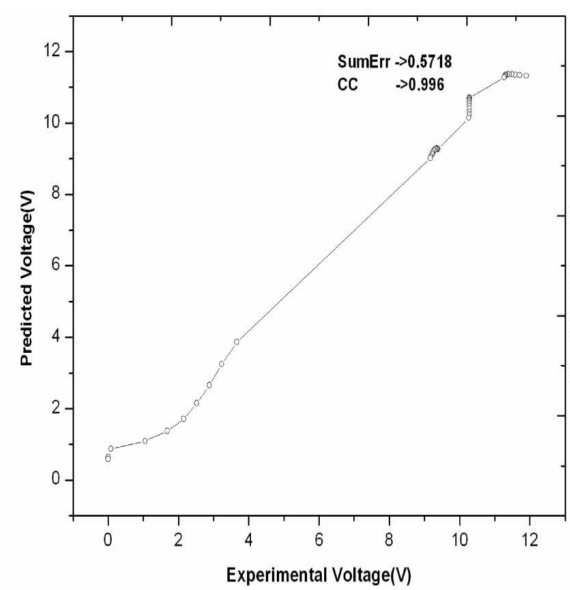
No	*Model Parameters*	*No.of parameters used*
1	*No. of nodes in input layer*	*3*
2	*No. of nodes in Hidden layer*	*5*
3	*No. of nodes in output layer*	*1*
4	*Learning Rate*	*0 .9*
5	*Momentum*	*0.6*
6	*Number of epochs*	*10000*
7	*Transfer function*	*Log-sigmoid*

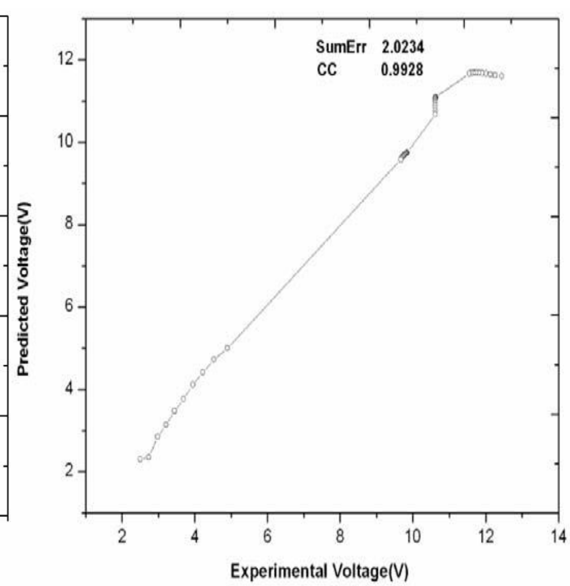
Table.1: The designed artificial neural network structure

The first step in neural network modeling is the development of a database. The database is necessary to train the network and to estimate its ability to generalize. Even if a neural network is a purely empirical model, the understanding of the physical mechanisms involved on a battery is necessary. The inputs to the network need to contain sufficient information relating to the target output, so that there exist a mathematical function relating correct outputs to inputs with the desired degree of accuracy. From the experimental cases, the training cases were built: a training case is the measured efficiency associated with the input parameters. The training time and the number of hidden nodes were optimized using the 4 x 5 cross-correlation, the data were randomly divided 30 times into training sets which is composed of 60% of the data and test sets composed of 40% of the data. The neural network was trained on the 20 different training sets and tested on the 20 corresponding test sets. The weights were optimized using the back-propagation algorithm. The performance of the neural networks on training and test sets was evaluated by the absolute average error. For every combination hidden nodes, the absolute average error on the train set and test set is reported. As explained above, the criterion for choosing the best neural network is its ability to generalize, to make predictions for new data which were not used during the learning phase. Consequently, for a one hidden layer straightforward neural network, the best generalization will be obtained with a 10 hidden nodes network trained with 10000 epochs. The real test of neural networks occurs when the trained network is able to produce good results for new data. The key aspect of building successful neural networks knows when to stop training. If the network is trained too little, the net will not learn the patterns and if the network is trained too much, the net will learn the noise or memorize the training patterns and not generalize well with new patterns. In the present study, overtraining was prevented using so-called net-perfect algorithm. This algorithm optimizes the network by applying the current network to an independent test set during training. The algorithm ends the optimum network for the data in the test set (which means that the network is able to generalize well and give good results on new data). It does this by computing the mean-squared error between actual and predicted for all outputs over all patterns. Then it computes the squared error for each output in a pattern totals them and then computes the mean of that number over all patterns in the test set.

3. Results and discussion

In this work studies on cold cranking behavior on VRLA battery at low temperature for automobile application is analyzed. The charge and discharge sequence were run using an LCN programmable tester, manufactured by Bitrode Corporation which is designed to test as per the standards such as BCI, SAE, DIN, JIS, IEC, BS. Cold Cranking Ampere (CCA) is defined as the ability of the lead - acid battery to start an engine in cold temperature. Discharge duration of lead - acid batteries are significantly reduced at sub-zero centigrade temperature. As the discharge proceeds the concentration of the acid decreases, with a consequent increase in the freezing temperature. In this study we have used ANN technique to predict the behavior of 12V/40Ah VRLA battery for different cold current cranking at sub-zero temperature. We have used the following cranking conditions namely the time - voltage behavior of the battery during every 10s discharge time and time to reach final discharge voltage of 6V.Experimental data are collected for temperatures namely -20ºC,-15ºC,-10ºC,-5ºC for the currents 1C, 3C, and 5C.These data are fed into the training set of ANN to predict for the currents 7C, 9C 11C, 13C, and 15C and validation for 17C.Fig .5 a-d. Shows the validation of predicted vs. experimental voltages for 17 C discharge current at -20 ºC,-15 ºC,-10 ºC,-5 ºC respectively .Table .3. gives the sum - square error and R^2 behavior of battery. Except at -5ºC ,correlation coefficient is better than reported at -18ºC .It is clear that the prediction made by using ANN technique is better.





This stochastic network can play a good role in quality control laboratory. The technique employed does not require the use of expensive instruments. One of the key factors limiting the use of neural networks is the source of errors arises from the input data which differs significantly from the data used to train the network.

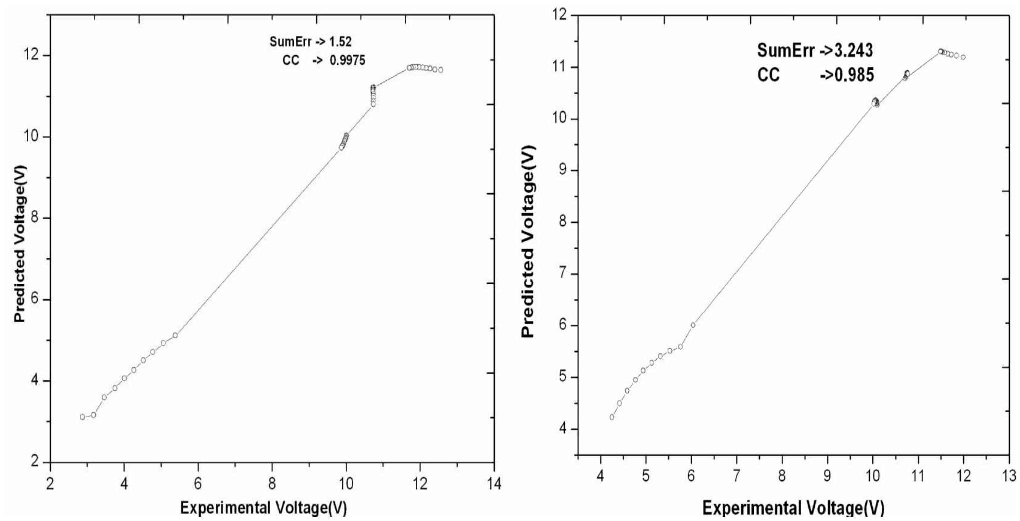


Fig.2: Validation of Experimental and predicted data for 17C at a) – 20 º C. b) – 15 º C. c) – 10 º C .d) – 5 º C.

S.no	Temperatureº C	Sum-Square Error	R^2
1	-18	5.59	.9829
2 (Exptl)	-20	.5718	.996
	-15	2.0234	.992
	-10	1.52	.997
	-5	3.243	.985

Table 2 .ANN Prediction of Cold Cranking behavior of battery at low Temperature

During rapid discharge the electro chemical reactions take place mostly on the surface of the plate. This is due to the limited time available for the diffusion of the electrolyte into the pores of the active material. The cold cranking current (A) decreases as the temperature decreases. Table .4 .shows that for a particular cut off voltage of 6V, the final cold cranking current at sub zero centigrade temperature and time to attain the same .Due to the combined effect of electrode and concentration polarization the battery cut of voltage is reached earlier.

Time	TEMPERATURE	Cold Cranking Amps
43	-20°C	360A
61	-15°C	440A
70	-10°C	520A
75	-5°C	600A

Table.3: Cranking current to reach final voltage 6V at sub-Zero degree centigrade temperature the time taken.

4. Conclusions

This stochastic network can play a good role in design of the battery .One of the key factors limiting the use of neural network is the source of errors arises from the input data which differs significantly from the data used to train the network. The final and most important step in this work of neural networks is to test the programs designed. The programs were tested using different input and output values that were not given for training previously. The test results were compared with the output values that were experimentally obtained and kept for testing. The testing results were compared with the experimental values. Based on these results it is concluded that the performance of the algorithm is excellent. The predicted results compare reasonably well with experimental data, especially at medium to low rates. The present model predicts battery life over a wide range of discharges and can be used as an effective tool for designing batteries, including those for EV and HEV applications. The results show that the developed technique has good performance.

Acknowledgments

The authors are thankful to the council of scientific and industrial research for the support to carry out this work.

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