Modeling Automotive Battery Diagnostics

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Automotive electrical systems are becoming increasingly complex as more and more electrical and electronic equipment is incorporated into new vehicles. With this trend, the growing demand for electrical power is placing greater demands on the automobile’s primary source of electrical energy storage — the lead-acid battery.

Whether the vehicle relies on an internal combustion engine, is a hybrid electric vehicle or is fully electric, the reliability of the battery must be ensured. To do so requires monitoring the car battery’s diagnostic parameters in the system while the vehicle is running.

Even when not in active use, a battery discharges and its health deteriorates. The task of identifying a faulty battery for replacement or a depleted battery in need of recharging is essential. If these actions are not performed in a timely manner, a system breakdown is likely.

Although there are devices and methods for monitoring a battery’s state of charge (SoC) and its state of health (SoH), they rarely operate in-system while the vehicle is running. Consequently, they do not provide timely warning for corrective action.

A new approach to measuring these diagnostic parameters overcomes this limitation by indicating the SoC in terms of the current-delivery capacity of the battery and the SoH in terms of the remaining percentage of battery life while the vehicle is operating with its various electrical loads. By modeling the SoC and SoH of a lead-acid battery using neuro-fuzzy and regression techniques, it’s possible to display the battery charge status and battery health in real time for the driver.

Indirect Measurement

In any automotive system, robustness is a necessity, and a graceful degradation in system performance is preferred over a sudden breakdown. Therefore, recording the battery status in-system is a value-added feature for the driver, because it helps avoid a sudden breakdown of the vehicle due to a battery malfunction.

Unfortunately, neither SoC nor SoH are directly measurable. Instead, these parameters need to be inferred from other measurements. The model for SoC described here uses a neuro-fuzzy approach coupled with in-system sensing of the charge status of the battery to provide a timely detection and warning of battery failure. SoC is determined from measurable battery parameters such as terminal voltage,
discharge/charge current, internal resistance, discharge/charge cycles, temperature as an input and specific gravity (SG) of a lead-acid battery as an output through a neural network model.

SoH can be expressed in terms of battery parameters using a regression equation. SoH is a function of the aging of the battery and its run-time consumption. Therefore, the regression equation for SoH is expressed as a function of those battery parameters that affect the aging and run-time consumption. The aging effect can be seen through various slopes of SG, terminal voltage and internal resistance (IR) with respect to discharge time. Run-time consumption can be observed through the battery’s ampere-hour (Ah) consumption. This work also has an important application in heavy mobile systems such as rocket launchers, missile launchers, submarines, satellites and trucks.

There are two major modes of battery operation in an automobile: slow discharge and engine cranking.\(^1\) When the alternator voltage is less than the battery voltage (when the engine is not running), the direction of the current flow is from the battery to the load. Otherwise, the current flows from the alternator to the load and to the battery (when the engine is running). This situation is known as the slow discharge of the battery through the car’s electrical load.

The electrical load of a car consists of many different vehicle subsystems such as sidelights, taillights, license-plate lights, headlamps (main and dip), dashboard lights, radio/cassette/CD, indicators, wipers, heater and other accessories. On average, the battery is required to supply the electrical load with 12 A of current when the engine is off.

At engine startup, when the alternator is not running, the engine requires an initial high torque of about 100 rev/min (engine cranking). This high torque, in turn, requires that the battery supply a pulse of high current.

Again, the ability to reach this high torque depends on several factors, among which battery characteristics play an important role along with the engine cranking resistance (torque required at the starting limit temperature) and the voltage drop between the battery and the starter. Thus, the battery should be able to supply a heavy current for a very short duration until the alternator can take over the function of supplying electrical power to the load.

Battery parameters affecting SoC are voltage, current, charge/discharge cycles (rate and method of charging), temperature, internal resistance, internal pressure, grid material (the grid refers to the frame of the battery’s electric...
more accurate results, it’s preferable to measure two additional parameters: the battery run-time and temperature.

A first step in designing the model was the selection of an actual battery from which data could be collected. The present study was made on an Exide model MF40sv/38 LM 20 car battery. For the purpose of the model design it was necessary to measure sufficient data on the battery under study.\[3\]

Data was collected while keeping the battery on a 12-A constant load corresponding to a slow discharge rate and drawing about 150 A of current for a few seconds to simulate real cranking. The latter action was simulated in the laboratory by 15 seconds of constant discharge at 150 A, followed by a rest of 15 seconds. Several data sets were taken for different environmental temperatures, battery ages and states of charge. Fig. 1 shows the activity chart for a single set of data collection.

As expected, the behavioral pattern observed was similar in the two cases of data collected on the MF40sv battery for slow discharge and real cranking as summarized below.\[3\]

Given a constant percentage of charge, the following occur as a result of increasing ambient temperature:

- The battery can run for a longer period of time
- The internal resistance of the battery decreases
- A very small variation occurs in battery terminal voltage
- The value of the SG decreases.

Conversely, when the ambient temperature was held constant and the battery’s SoC was varied, it was seen that:

- A battery with a high SoC runs longer
- The battery’s internal resistance increases with a decrease in charged state
- The SG of the battery decreases along with a decrease in charged state
- The initial voltage decreases with a decrease in charged state.

**SoC Model**

Artificial neural networks (ANNs) are well known for simulating nonlinear physical processes, and ANNs coupled with fuzzy logic provide a powerful mechanism to linguistically translate the behavior of a complex physical process. The nonlinear adaptive-learning capability of ANNs is used here to simulate the discharging process of a battery, which is translated linguistically using fuzzy logic to represent the charged state of the battery for maneuvering battery operations. The term linguistically refers to the fact that the battery’s SoC is expressed in relative terms such as fully charged, half charged or fully discharged.

A schematic of the model\[4\] is shown in Fig. 2. In this schematic, 1 through 5 represent the in-system inputs to be given to the ANN to generate the output in terms of

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**Fig. 2.** A schematic diagram of the SoC model illustrates how the artificial neural network simulates the discharge process of a battery, and how that result is then translated using fuzzy logic into terms representing the various states of charge for the battery.

**Fig. 3.** In this ANN model diagram, LW{(i,j)} and b{(i)} refer to weights and biases of synapse of layer (i) and neuron (j), respectively. Each node outcome is given by a summation as \( \Sigma \) LW{(i,j)} x{(k)} + b{(i)}, where x{(k)} is the input to the neuron followed by the activation function. This box defines a nonlinear sigmoidal activation function to limit the neuron output.

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1. Artifical neural networks
2. Fuzzifier
3. State of charge
4. Specific gravity
5. Artificial neural networks

- Fully charged
- >Half charged
- Half charged
- <Half charged
- Fully discharged

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A schematic of the model\[4\] is shown in Fig. 2. In this schematic, 1 through 5 represent the in-system inputs to be given to the ANN to generate the output in terms of
SoC. These inputs are directly measurable in-system battery parameters. These parameters include terminal voltage, current drawn, internal resistance, internal battery temperature and time of battery consumption.

The ANN output is the SG, which along with temperature is the input to a "fuzzifier" outputting the SoC of the battery in linguistic form such as very high, high, half, low and very low. The ANN architecture and weights have to be obtained with the battery out of the system using a prior training of the ANN on the specific battery under study.

ANN Modeling

The design of an ANN and its training are done using the Neural Network Toolbox of MATLAB version 6.0. The back propagation learning algorithm in a fully connected multi-layer architecture of neurons was employed for supervised learning in ANN.[5] With standard steepest descent, the learning rate was held constant throughout the training.

The performance of the algorithm is very sensitive to the proper setting of the learning rate. If the learning rate is too high, the algorithm will oscillate and become unstable, while if too low, the algorithm takes longer to converge.[6] The activation functions used are log sigmoid in the hidden layer and purelin at the output layer. A block diagram of the ANN model employed in the present study is shown in Fig. 3.

This work aimed to obtain a generalized ANN model of battery behavior. Therefore, simulation was first performed on training the ANN with separate sets of data for slow discharge and real cranking functions of a car battery of different ages.[3] (This data appears in a figure in the online version of this article.) Then the same ANN was trained with the combined data of slow discharge and real cranking at all ages at different environmental temperatures.

The loss in accuracy due to generalization was found to be not more than 0.4%. Here we have seen that there is no loss of accuracy when training is done with mixed data of various charged states, but it does take a longer time to learn to converge. The loss of accuracy further increases if training is performed with data on batteries of various ages as shown in Table 1.

After training the ANN with an input-output dataset, it needs to be tested with given data. Fig. 4 shows the results of both training and testing when the data of batteries of different ages, different SoCs and different operating temperatures is employed.

Fuzzy logic was employed for the purpose of transforming the ANN output SG to the target output (i.e., battery SoC).[7] The complete process is shown in Fig. 5.

In this module all three parameters — input parameters SG and temperature, and output parameter percentage of SoC — are taken to be fuzzy. While the fuzzy membership for the temperature and percentage of SoC parameters are defined with five linguistic variables, the SG parameter is represented by seven fuzzy states. The fuzzy states for each of the three fuzzy variables are given here:

- Temperature (input variable) — very low, low, medium, high and very high
- SG (input variable) — very very low, very low, low, medium, high, very high and very very high

Table 1. Results of training the ANN with mixed data of RC and SD on mixed SoC and with mixed temperatures.

<table>
<thead>
<tr>
<th>Age of battery</th>
<th>Epochs</th>
<th>Surface error</th>
<th>Accuracy at 1.240 SG</th>
</tr>
</thead>
<tbody>
<tr>
<td>One year old</td>
<td>4645</td>
<td>0.000499</td>
<td>99.96%</td>
</tr>
<tr>
<td>New + one year old + two year old (mixed)</td>
<td>1481</td>
<td>0.005337</td>
<td>99.597%</td>
</tr>
</tbody>
</table>
BATTERY DIAGNOSTICS

Fig. 5. The "fuzzifier module" transforms the specific gravity data generated by the ANN into a state of charge for the battery.

- Percentage of SoC (output variable) — flat, less than half, half, greater than half and full.

For temperature and SG, the membership function is chosen to be Gaussian with extreme states open. For percentage of SoC, the fuzzy membership function is taken to be bell shaped.

If-then rules are defined to specify the relationship between the input and the output. For each input, some rules are fired. For each rule being fired, the degree of membership of the percentage of SoC is implied. Then the membership value of all the outputs is aggregated to produce the final output.

The fuzzy rule base[8] employed for the case under study is given in Table 2. Implementation of fuzzy logic is done using MATLAB’s Fuzzy Logic Toolbox. The inputs and outputs are designated in the Fuzzy Inference System (FIS) editor window in the Fuzzy Logic Toolbox.

The fuzzy rules defined in Table 2 are verified with the observed data. For different sets of data on SG and temperatures, the percentage of SoC is thus computed. A typical result of fuzzy inference is demonstrated in Fig. 6, where temperature equals 45°C (very high), SG equals 1.178 (medium) and the corresponding percentage of SoC is 50% (half charged).

SoH Modeling
The SoH of a battery is defined as the remaining life of the battery given a specific load. The cause of battery health deterioration is the effect of aging on the grid, electrodes, contacts, corrosion and charging/discharging cycles.

The SoH of a battery is modeled using multivariate linear regression[9] on the aging effect and the on-time consumption of the battery. The values of various slopes for the Exide car battery under study are given in tabular form with different SoC conditions at different temperatures for ages of batteries in the face of real cranking and slow discharge, respectively. (This data is available in a table in the online version of this article.)

It is seen that the slopes of parameters like SG, terminal voltage and internal resistance indicate the effect of aged on battery performance. SG and terminal voltage decrease with discharge duration, and internal resistance increases with the discharge of the battery. The negative slope of SG and terminal voltage has a sharper decrease with age, and the positive slope of internal resistance also shows an incremental rise with age.

From the online table it can also be observed that smaller values of slopes of SG and terminal voltage were not as significant as values of the IR slope. This fact is verified later with the results that internal resistance affects the SoH more than SG and terminal voltage.

Initially, the regression technique had been applied to only two factors on which the SoH depends: SG and open circuit voltage (OCV). The various slopes of the SG and OCV have been used to obtain a formula. The results obtained were not very satisfactory, so we realized that internal resistance is also an important factor on which SoH depends. Therefore, internal resistance should be included in the formula developed to model SoH.

The formula obtained after applying the multiple regression technique is:

\[
\text{SoH} = 1.0043 + 0.0088(\text{TT} \times \text{C}) + 3.8925 \text{m}(\text{SG}) + 0.2444\text{m}'(\text{OCV}) - 0.0863\text{m}''(\text{IR}),
\]

where TT is the run-time of the battery and C is the discharge rate and IR is the internal resistance. TT × C gives the ampere-hour consumption of the battery and m(SG), m'(OCV), m''(IR) are slopes.

The regression results, from the data collected from the car battery, show that the current consumption affects 60% (for real cranking of a car for 15 sec), the IR slope affects 30% and the remaining two parameters — the SG slope and the terminal voltage slope—affect only 10% of the battery’s SoH. The SG in-system measurement is difficult and its slope values also are not significant, so it can be ignored.

This work concentrates on an intelligent modeling of the nonlinear behavior of a battery, not through mathematical/algorithmic approach like prior work in this field, but through a simulation of the entire process based on real data, using battery parameters measured in-system. A nonlinear be-

<table>
<thead>
<tr>
<th>Temperature</th>
<th>Specific gravity</th>
</tr>
</thead>
<tbody>
<tr>
<td>Very very low</td>
<td>Very low</td>
</tr>
<tr>
<td>Flat</td>
<td>Flat</td>
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<td>Flat</td>
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<td>Flat</td>
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<tr>
<td>Flat</td>
<td>&lt;Half</td>
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Table 2. The fuzzy rule base for percentage of SoC output.
Behavior mapping of the battery has been conducted using an ANN and the regression technique. This has been found to provide a more-reliable and accurate estimation of SoC and SoH than previous methods. A relative indication of SoC is implemented through the use of fuzzy logic and SoH is expressed as a remaining percentage of battery life.

The objective of the study was also to achieve a desired accuracy with an optimized hardware model (i.e., highly accurate and low cost). The process model has the potential to be implemented in product form as a panel display in automobiles. While preferred model parameters have been given and described, various modifications may be made without departing from the spirit and scope of the process. The hardware used to implement these models can be a low-cost, easy-to-build module consisting of a DSP or microcontroller and signal-conditioning circuits.

Acknowledgement

We gratefully acknowledge the assistance provided by Exide, R&D Lab, Kolkata, Exide Industries Ltd. India in terms of financing the project and facilitating the experimentation in their laboratory without which this research work could not have been accomplished.

References