DETECTION OF STATE-OF-CHARGE IN LEAD ACID BATTERY USING RBF-NN

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Abstract: To realize a stable supply of electric power in an automobile, an accurate and reliable detection method of SOC (state-of-charge) in a lead acid battery is required. However the dynamics of the battery is very complicated. The characteristics of the battery greatly change due to its degradation. Moreover a automobile has many driving patterns, which are unknown beforehand. Thus it is not easy to detect the SOC analytically. In this paper, to overcome this problem, a new SOC detection method with a radial base function neural network is proposed. The detection accuracies for different sized batteries, various degradation states and driving patterns are investigated.

Keywords: Neural networks, Radial base function networks, Nonlinear models, Detection systems, Automobiles, SOC (state of charge), Lead acid battery

1. INTRODUCTION

In response to the demand for a safe and comfortable automobile that has a low environmental impact, the amount of the electrical equipment in automobiles has drastically increased in recent years. This has led to an increase in electrical load for the embedded battery in the automobile and a subsequent need for a battery power management system.

One of the main features in a power management system is the detection of state of charge (SOC) of the battery. The state of charge of a battery is its current capacity expressed as a percentage of its full capacity. The SOC of the battery gives information regarding how long the battery will continue to perform before it needs recharging.

Several methods of detecting the SOC of a battery have been investigated (M. Sauradip et al., 2001; P. Singh et al., 2001; A. Salkind, P. Singh et al., 2001; T. Torikai. et. al., 1992; C. C. Chan et al., 2000). One way to develop a detection system of SOC of a battery is based on the rigorous analytical model (White Box Model). However, this is typically time-consuming and simplifying assumptions are required to determine the parameters of such models. An alternative is to employ heuristic or time-series models (Black Box Models) of real systems. Many methods have been proposed to detect the SOC of a battery using non-analytical models but they have used linear time series models which are unwieldy and are usually only suitable for weak non-linearity. In such cases, a neural network is one of the alternative methods for modeling the nonlinearity of the characteristics of the battery.

A detection method of SOC using the Radial Basis Function (RBF) neural network has been proposed (M. Sauradip, S. K. Sinha, and K. Muthukumar, 2001). Although the effectiveness of the method has been shown under limited conditions, its effectiveness for practical uses has not been discussed.

In this paper, we propose the RBF neural network as a practical alternative to analytical and empirical methods for detecting the SOC of a lead acid battery. By employing this RBF neural network, the detection of the SOC under various conditions is obtained. The detection accuracies for the different sizes of batteries, degradation states and driving patterns are investigated using experimental data.

2. SOC DETECTION SYSTEM USING RBF NETWORK

In an actual battery in an automobile accurate detection of the SOC is required in various cases with various types of battery size, various modes and degrees of degradation, and various charge/discharge patterns. For this reason we have to use a lot of data obtained from many batteries in order to train neural networks and evaluate the detection accuracy. Therefore we have adopted the RBF neural network(RBF-NN). In the case of the RBF-NN, training is easy and takes a short time as compared with a FF neural network.

Moreover the RBF-NN is constructed using basis functions arranged in a limited input space. If the input space is known beforehand, the RBF type is an effective one. In general the range of the voltage and the current of a battery in an automobile can always be known beforehand. Therefore, in this study the RBF-NN is expected to be effective for the detection of the SOC.

The following steps show how the procedure was done.

- **Step 1**: Setting NN structure (input signal, teaching signal, $\cdots$.).
- **Step 2**: Measuring various kinds of data for NN training.
- **Step 3**: Training the NN using all measured data.
- **Step 4**: Evaluation of detection accuracy for each situation.

2.1 Battery modeling by RBF neural network

In the proposed detection system, the real-time value of the SOC in a lead acid battery will be detected by estimating the nonlinear characteristics using an RBF neural network. The nonlinear characteristics are the relation between the voltage/current and the SOC.

The architecture of the RBF-NN consists of one input layer, one hidden layer and one output layer as shown in Fig. 1. In Fig. 1, the output of hidden neurons $h_j(x)$ is determined by a set

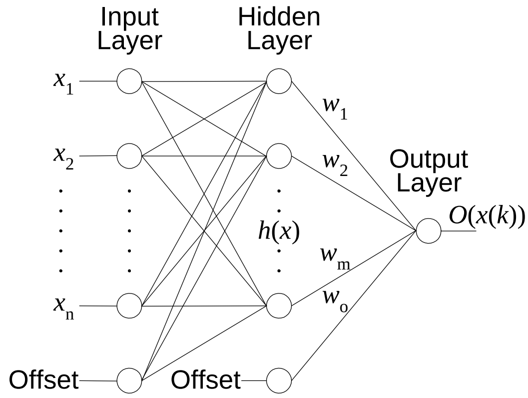

Fig. 1. Structure of RBF neural network

of input signals x_i, $i = 1, 2, \cdots, n$, where n is the number of input neurons. The output of the RBF-NN $O(x(k))$ is the linearly combined signal of the outputs of the hidden layer $h_j(x(k))$ with the synaptic weights w_j as follows:

$$O(x(k)) = \sum_{j=1}^{m} w_j h_j(x(k)), \tag{1}$$

where m is the number of hidden neurons, and $h_j(x(k))$ is the radial basis function described by

$$h_j(x(k)) = \exp\Big(\sum_{i=1}^{n}\big(-\frac{|x_i(k) - c_{ij}|^2}{r_{ij}^2}\big)\Big), \tag{2}$$

where c_{ij} and r_{ij} are the center and the radius of the *j-th* neuron for the *i-th* input. The value of a radial basis function decreases monotonically with distance from its center.

2.1.1. Additional Inputs Since the battery has the property of hysteresis, it is difficult to detect the SOC from the relationship between the voltage and the current at this time. For this reason we consider past values of the voltage and the current as additional inputs to the neural network. The input $x(k)$ for the neural network consists of a combination of past values of the voltage $v(k)$ and current $i(k)$ of the battery as follows:

$$x(k) = [v(k-4), \cdots, v(k), i(k-4), \cdots, i(k)]^T . \tag{3}$$

Moreover it is known that the internal resistance and the open circuit voltage are related to the degree of degradation of the battery. For this reason these two physical values are added as inputs in order to increase the detection accuracy for various degradations. The internal resistance $r(k)$ and the open circuit voltage $V_O(k)$ are calculated using the method of least squares with the present voltage and current values and their past values for a specified period of time. Thus, the input $x(k)$ for the neural network is rewritten as follows:

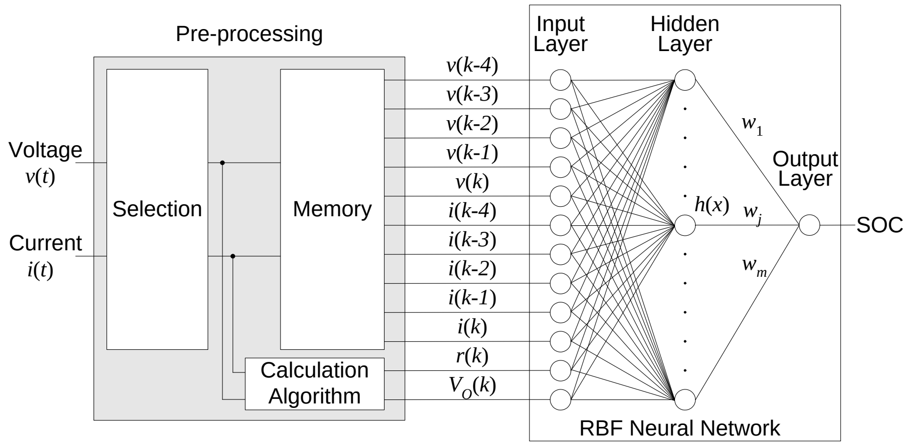

Fig. 2. Construction diagram of the RBF-NN

$$x(k) = [v(k-4), \cdots, v(k), i(k-4), \cdots, i(k) \\ r(k), V_O(k)]^T. \quad (4)$$

The construction diagram of the RBF-NN is shown in Fig. 2.

2.1.2. Selection of detecting opportunity In actual automobile batteries there are charge and discharge phases. The characteristics of the batteries are different in the charge/discharge phases. So in order to increase the detection accuracy, we construct a neural network for each phase. In this paper we detect the SOC only during the discharge phase. In the case of the charge phase we expect to obtain similar results with the proposed method.

The polarization of the battery is the biggest problem when attempting to detect the SOC. In this study we eliminate the polarization phase from the detecting period. For this purpose we do not detect the SOC obtained in the first few seconds after shifting from the charge phase to the discharge phase.

It was found from some simulations that it is difficult to detect the SOC when the current does not change much. For this reason we detect the SOC in the period when the amount of scatter of the current is large. The amount of scatter of the current is calculated using the standard deviation of the current for a specified period of time.

2.1.3. Output The output of the neural network $O(x(k))$ corresponding to the SOC is calculated by summing the current entering and leaving the battery as follows:

$$SOC(k) = SOC(0) + \sum_{l=1}^{k} i(l) \times \eta / Q_0, \quad (5)$$

where $SOC(0)$ is the initial value of the SOC, η is the coefficient depending on the capacity of the battery, and Q_0 denotes the full charge capacity of the battery. The full charge capacity is related to the degree of degradation of the battery at this time. One should note that all these values are unknown, which makes it difficult to estimate the SOC.

3. EXPERIMENTAL DATA

To construct the NN and to evaluate the proposed detection method based on the NN, input data consisting of the transient voltage and the transient current of the battery are prepared by some experiments as follows:

(1) Eight batteries are prepared as shown in Table 1.
(2) Two kinds of desired current patterns are prepared.
(3) By using the electrical load equipment and connecting it to each battery, the actual current is controlled so as to become the desired current pattern.
(4) By measuring the current and the voltage under the different conditions (eight batteries and two desired current patterns) the input data is obtained.
(5) The SOC is calculated using the measured current.

Actually there are many degradation causes in a used battery, for example sulfation, corrosion, stratification, softening of the battery grid and so on. The degree of the degradation varies from case to case. Moreover, degradation may occur due to a combination of the various degradation causes. Therefore, it is necessary to evaluate the detection error of the proposed method for various types of degradation. For this purpose, we prepare eight batteries: a new battery, degraded batteries with

Table 1. Batteries used to measure training data.

No.	Battery	Size	Full charge capacity [Ah] 10.15 / LA4
1	New	34B	21.8 / 19.9
2	Grid corrosion	34B	25.8 / 23.7
3	Softening	34B	24.8 / 22.6
4	Sulfation	34B	16.5 / 16.6
5	Used #1	34B	24.4 / 25.0
6	Used #2	34B	27.6 / 27.8
7	Used #3	45D	42.6 / 41.0
8	Used #4	34B	25.6 / 18.4

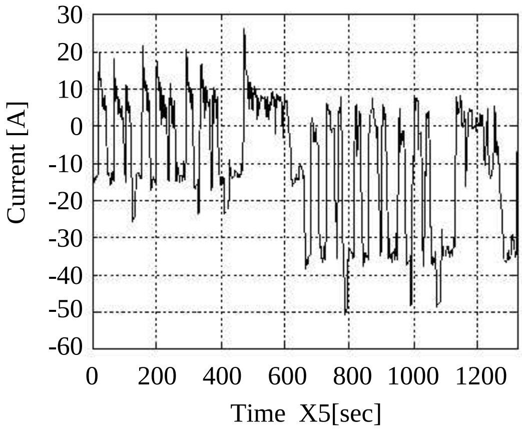

Fig. 3. Current signal (10.15 mode)

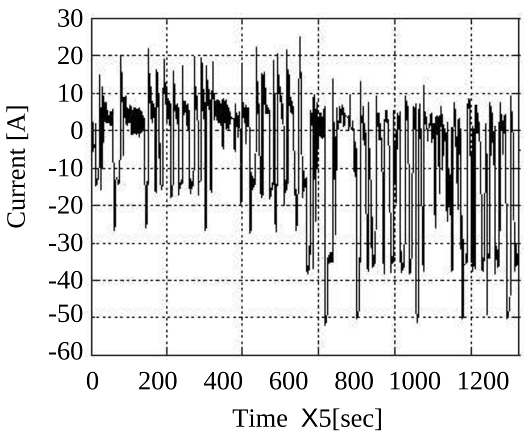

Fig. 4. Current signal (LA4 mode)

grid corrosion, softening and sulfation, and used batteries. A list of the prepared batteries is shown in Table 1. No.7 is different from the others in terms of battery size. The full charge capacities, which are measured before the experiment for each pattern, are also shown in Table 1

The current (charge/discharge) pattern of the battery depends mainly on the driving pattern of an automobile. In general two driving patterns, 10.15 mode and LA4 mode, are used as typical examples to evaluate the fuel efficiency of an engine. For this reason, we use these two driving patterns to get the current patterns. First of all, the current

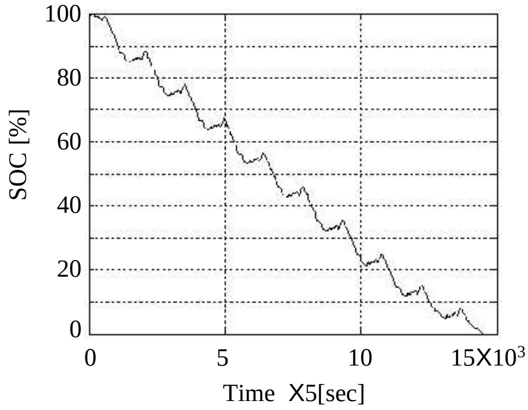

Fig. 5. SOC (10.15 mode)

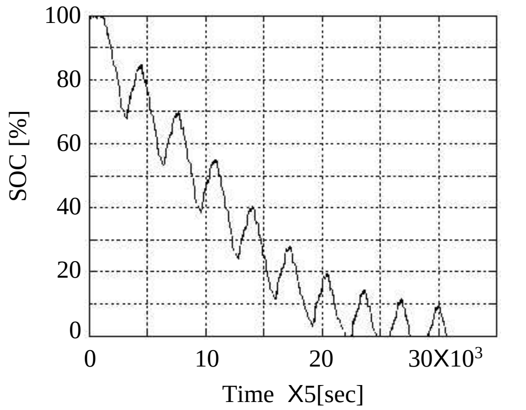

Fig. 6. SOC (LA4 mode)

patterns are calculated on the basis of these two driving patterns. To give the current patterns a discharging tendency, a constant electrical load is added. This means that the SOC will have a decreasing tendency. As the resulting current patterns are shown in Figs.3 and 4. By calculating the SOC using Eq.(5) and the current patterns, time histories of the SOC are obtained as shown in Figs.5 and 6.

The voltage and the current are measured with a sampling time of 0.1[sec]. To reduce the noise of the measured data, a downsampling method is used. The downsampling time is 5[sec].

4. EXPERIMENTAL RESULTS AND EVALUATION

In this section, we evaluate the proposed detection method by using the sixteen kinds of measured data prepared in the previous section. The evaluation procedure is as follows:

(1) The NN is trained using all data.
(2) One kind of data is applied to the trained NN.
(3) The detection accuracy is evaluated using the root mean square (RMS) of detection error:

Table 2. Detection error.

No.	Battery	Detection error [%]	
		10.15 mode	LA4 mode
1	New	10.6	6.8
2	Grid corrosion	7.4	7.6
3	Softening	11.0	8.3
4	Sulfation	5.3	6.7
5	Used #1	17.4	9.5
6	Used #2	9.3	8.6
7	Used #3	9.3	7.5
8	Used #4	8.6	7.2

$$RMS = \frac{\sqrt{\sum_{k=1}^{N}\left(SOC(k) - \overline{SOC(k)}\right)^2}}{N}, \quad (6)$$

where $\overline{SOC(k)}$ is the training data and N is the number of measurements. A detected value of more than 100% or less than 0% $SOC(k)$ is regarded as 100% or 0%, respectively.

(4) Steps (2) and (3) are repeated for all cases.

In constructing the RBF-NN, the centers and radii of a set of RBFs are determined using the method (Mark J. L. Orr, 1999). This method uses regression trees to create a set of candidate RBFs but differs in the way in which a subset is selected for the network. In this method, we have to determine the minimum number of cases allowed in each regression tree node. The minimum number is 10. The maximum of the radii is 5. The resulting number of neurons is about 300.

The detection errors are shown in Table 2. The required detection accuracy is 15%. The detection errors, which do not depend on the states of the degradation states, the charge/discharge patterns, and the battery size, are less than 15%. The time histories of the detection values are shown in Figs.7–14. The solid line denotes the teaching data (theoretical value). The dotted lines denote the 85% and 115% lines of the theoretical values. The dots denote the detected values. The accuracy of the detected values is almost in the region of 85% to 115% of the theoretical values.

Scattering is found in the detected values. However, by using a sample and hold technique, the scattering can be reduced. This is very useful and practical result.

In the case of battery No.5 with 10.15 mode, the RMS of the detection error is large as shown in Table 2, and the detection errors are large around the 100% SOC as shown in Fig. 11. This is because the discharge property, that is the relationship between the voltage and the SOC, is different from the other cases.

5. CONCLUSIONS

By employing an RBF neural network to model a lead acid battery, we could present the possibility

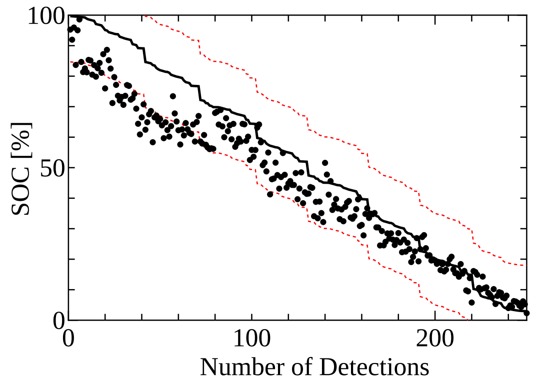

Fig. 7. Detection result of No.1 with 10.15 mode

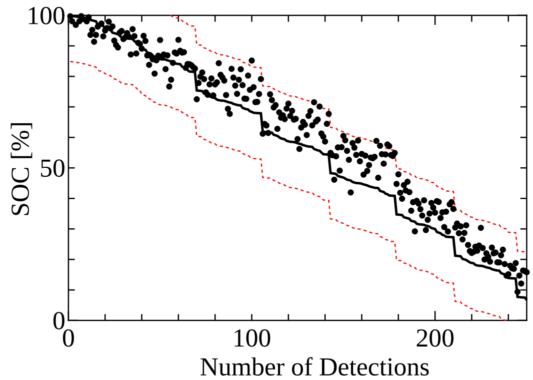

Fig. 8. Detection result of No.1 with LA4 mode

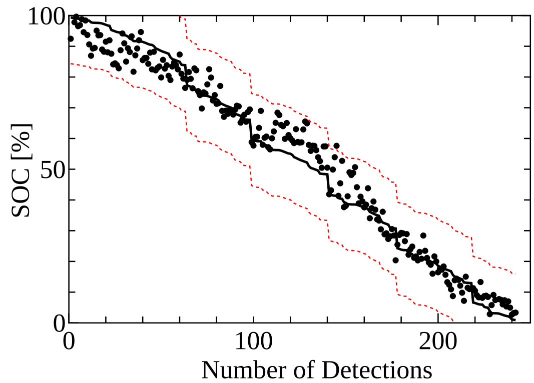

Fig. 9. Detection result of No.4 with 10.15 mode

of detecting the SOC in the battery with reliable precision. The training and detection of the SOC was conducted using a new battery, aged batteries and batteries with several types of defects. Once the RBF network is trained off-line, then it just needs a simple calculation to detect the SOC in the battery on-line.

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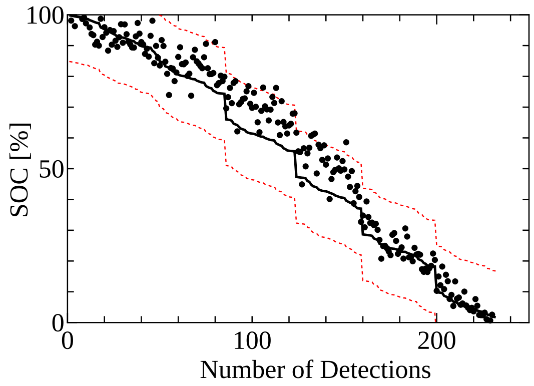

Fig. 10. Detection result of No.4 with LA4 mode

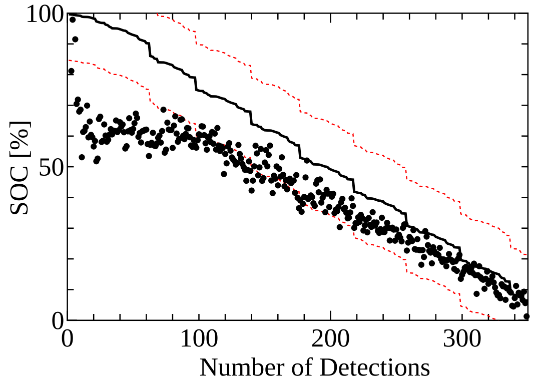

Fig. 11. Detection result of No.5 with 10.15 mode

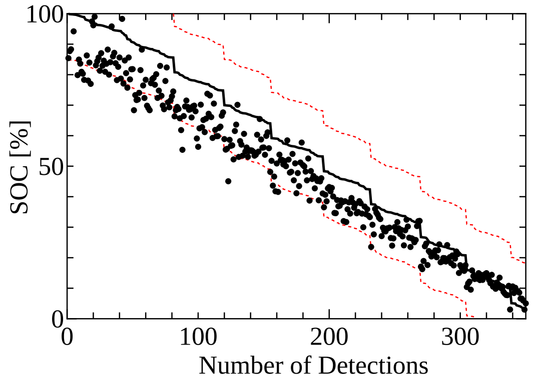

Fig. 12. Detection result of No.5 with LA4 mode

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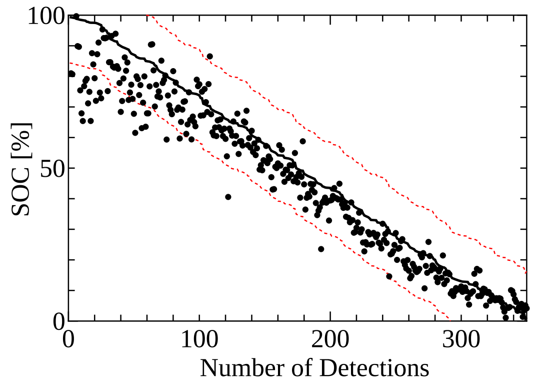

Fig. 13. Detection result of No.8 with 10.15 mode

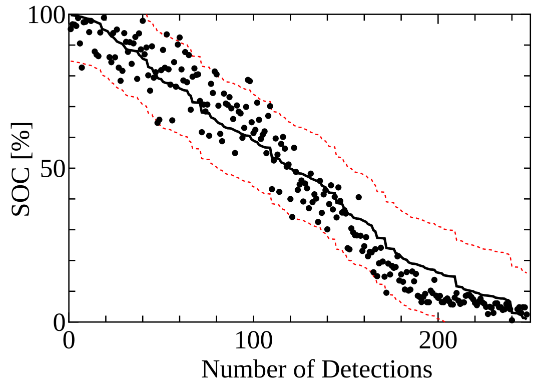

Fig. 14. Detection result of No.8 with LA4 mode

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