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An Intelligence-Based State of Charge Prediction for VRLA Batteries

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***Abstract*—** A battery management system (BMS) has three main functions, voltage monitoring, current discharge monitoring and remaining life monitoring. This paper primarily focuses on remaining life monitoring through the estimation of battery's state of charge (SOC). An Experimental set-up was prepared to measure the Valve-Regulated Lead-Acid (VRLA) battery's SOC under different operating conditions. Backpropagation (BP) neural network to estimate the battery's SOC using the experimental data. The results showed a satisfactory estimation of battery's SOC with a small (4.25%) root mean square perdition error (RMS).

Keywords- SOC, state of charge, SOC estimation, Neural Network

I. INTRODUCTION

VRLA batteries are widely used in many systems and devices because of its energy density, rechargeability, and low cost. Due to the multitude of applications for VRLA batteries, they need to be managed properly [1-3]. A huge part of the management system is in predicting the battery's SOC and adapting accordingly. An accurate prediction of a battery's SOC is still a concerning issue within in a BMS. The definition of a battery's SOC is the ratio of available capacity within the battery to the maximum capacity [4].

$$SOC\ \% = \frac{C_{available}}{C_{max}} * 100 \qquad (1)$$

Without a proper estimation of the battery's SOC the battery can fall into harmful and irreversible situations that will ultimately diminish its performance and life expectancy [5]. Situations that include overcharging which could lead to explosions and over-discharging that will over exhaust the battery. Conventional techniques such as coulometric counting and open circuit voltages are used to estimate the battery's SOC, however, these techniques cause great inaccuracy. Common models for VRLA batteries include electric circuit models, electrochemical models, and neural networks [5]. The method presented in [6] suggested that in order to accurately estimate battery data, such as SOC, a model to understand the internal workings of the battery would be essential. However, the internal resistance is not an intrinsic value; the internal resistance model requires a lot of experimental data. Such as the maximum capacity of the battery at different temperatures, the output voltage of the battery at different current magnification, the internal resistance of the battery at different temperatures. In addition, it is difficult to find a suitable function to describe the battery model due to the very complex chemical reactions inside the battery. Therefore, the authors in [4], proposed the use of neural network with a radial basis function as the data training method to estimate SOC. A simple structure was used for the neural network with three layers, and with limited number of inputs such as voltage, current , and temperature [4]. This paper proposed a method of neural networking with backpropagation and increased inputs. Regarding previous work, this method of this paper eliminates the need for battery modeling by collecting enough parameters as inputs to represent the battery's state. It also disregards the action of data reduction presented in [7]. This neural network encompasses a set of increased inputs in the form of time and battery age in addition to common data such as voltage, current, and temperature. The work in this paper is based on a long term research in the back up battery system for communication systems. The different characteristics of our research provides a prediction model with wide varieties. Compared to the work done in [4] and [5], the application in our research has the relatively stable conditions and regularisation for the charging and discharging periods.

The rest of this paper is organized as follows, Section II will explain experimental setup and the data collected to perform the training of the neural network explained in Section III. Finally, Section IV will provide a discussion for the neural network results and SOC values based on the method's effectiveness through error analysis and comparison.

II. DATA COLLECTION AND ANALYSIS

This section describes the experiment that was conducted to collect the data for SOC prediction. This paper focuses on

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the mature and widely accepted data from VRLA batteries to verify the model's accuracy and the practicality in industry. In addition, the model in this paper can be extended to study different types of batteries such as the lithium battery. A batch with flexible packaging for the VRLA was ordered from a domestic manufacturer ENERSYS-CYCLON with nominal voltage 12V and nominal capacity 8Ah, as shown figure 1. Test equipment for the multi-channel battery charge and discharge tester (model PCBA 5010-4 battery analyzer).

The battery test system consists of two parts: cycle test and standard capacity test. The specific steps of the cycle test are (for example, 40% DOD cycle):

1. With C/10 magnification current on the battery discharge to 0% SOC (10.5V), standing 15min;
2. Charge the battery to 100% SOC (14.7V) with C/10 magnification current, then discharge the battery to 70% SOC with C/10 magnification current for 30s;
3. With C/10 rate of current on the battery discharge to 30% SOC, standing 15min;
4. With C/10 magnification current on the battery charge to 70% SOC, put it aside for 15min;
5. Repeat steps 3), 4) 100 times, and discharge the battery to 0% SOC (10.5V) with C/10 magnification current.

Standard capacity test specific steps:

1. With C/10 magnification current on the battery discharge to 0% SOC (10.5V), standing 15min;
2. Charge the battery to 100% SOC (14.7V) with C/10 magnification current for 15 min;
3. With C/10 rate of current on the battery discharge to 0% SOC (10.5V), standing 15min;
4. Repeat steps 2), 3) 3 times, with the last discharge capacity as the actual capacity of the battery.

During the cycle test, the battery is stored in the upper and lower limits of the corresponding SOC, and the battery input energy and output energy of each cycle are recorded. The battery is calibrated every 100 cycles. Tables I and II show the input and output data used in training the neural network. The cycle (age), average open circuit voltage, discharge current, terminal voltage, average temperature, elapsed time, start day, start month, and start year are all used as affecting data to the battery's SOC. Fig. 1 shows the experimental setup used for the purpose of this paper.

TABLE I
PARTIAL LIST OF NEURAL NETWORK INPUT DATA

Inputs				
Cycle Number	**Avg. Voltage**	**Discharge Current**	**End Voltage**	**Avg. Temp**
1	12.03	0.8	11.10	24
2	12.11	0.8	11.10	23
3	12.11	0.8	11.10	22
4	12.10	0.8	11.10	22
5	12.11	0.8	11.10	22
6	12.01	0.8	10.20	23
7	12.01	0.8	10.20	20
8	12.02	0.8	10.20	22
9	12.02	0.8	10.20	22
10	12.02	0.8	10.20	24
11	12.02	0.8	10.20	23
12	12.02	0.8	10.20	23
13	12.04	0.8	10.20	22
14	12.02	0.8	10.20	22

TABLE II
PARTIAL LIST OF NEURAL NETWORK INPUT AND OUTPUT DATA

Inputs					Output
Cycle Number	**Elapsed Time H:M**	**Start Day**	**Start Month**	**Start Year**	**SOC (%)**
1	8.33	3	2	2015	85.5
2	9.11	5	2	2015	91.9
3	9.14	9	2	2015	92.3
4	9.27	11	2	2015	94.5
5	9.29	13	2	2015	94.9
6	10.01	18	2	2015	100
7	10	20	2	2015	100
8	10.02	23	2	2015	100
9	10.03	25	2	2015	100
10	10.03	27	2	2015	100
11	9.55	2	3	2015	99.2
12	9.56	5	3	2015	99.5
13	9.52	6	3	2015	98.7
14	9.49	10	3	2015	98.1

Fig. 1. Experimental Setup

III. Neural Network Model

This section describes the neural network model used for the purpose of predicting SOC. The problem with SOC estimation is the complex nonlinear relationship between its affecting data and its prediction. The backpropagation learning algorithm is chosen because of its ability to provide suitable non-linear mapping and self-learning. Fig. 2 shows the general structure for neural network with back propagation learning, in which numbers of neurons are arrayed to form a layer. Input layer is where the input from external world is connected, hidden layer is not connected to the external world and the output layer gives output to the external world [8].

Fig. 3 shows the structure for neural network with back

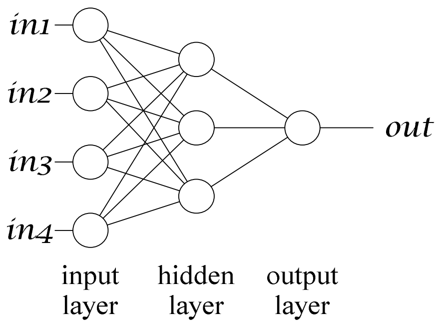

Fig. 2. Basic Multi-layer Feed Forward Network with Back Propagation Learning.

propagation learning using for SOC prediction and implemented on NeuralWare software, in which the neural network has 9 inputs, 2 hidden layers, and 1 output. The first hidden layer has 8 neurons, and the second one has 4 neurons. The number of neurons in the hidden layer was found by trial and error to provide the minimum RMS error for training and testing stages. The activation function used is Delta-Rule-Sigmoid. NeuralWare software has been used to compute the ANN. NeuralWare is developing and deploying empirical modeling solutions based on neural networks [9]. It is mainly used for prediction, classification, or pattern recognition. The ANN computes system parameters while learning the input variables, which is called training.

IV. Results And Discussion

This section discusses the results of inputting the experimental data presented in Section II into the SOC neural network model described briefly in Section III. The RMS error was used to evaluate the effectiveness of the proposed method. The results showed that:

- Training RMS error = 0.0088.
- Testing RMS error = 0.0425.

In which 70 % of the (76 cycles) data presented in Section II was used for training, and 30 % was used for testing.

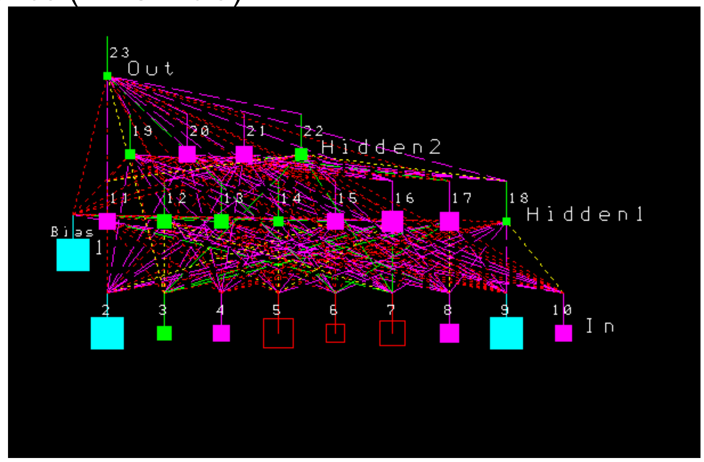

Fig. 4 shows the actual and predicted SOC for the tested data. The inaccuracy is from all the parts of the modeling procedure, including battery measurement (data collection), modeling design (data analysis). It can be concluded that the predicted SOC adequately followed actual SOC. It is expected that performance of the neural network will improve as the size of data set for training and testing

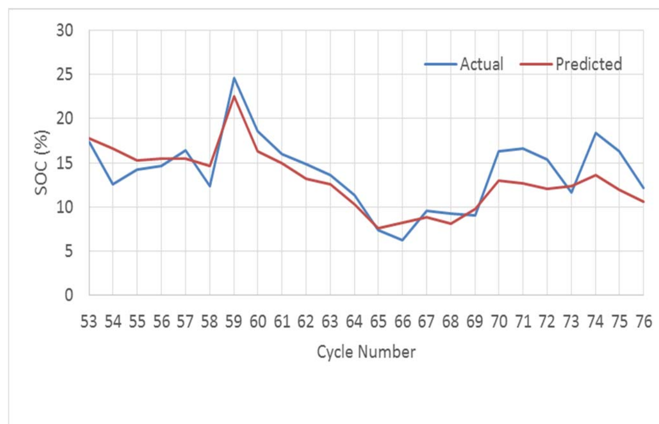

Fig. 4. Actual versus predicted SOC for the tested cycles

increases.

V. Conclusion

In this paper, the neural network was designed to avoid the needs for battery modeling and data regression. In avoiding these methods, the work load of the battery management system (BMS) is reduced while still providing accurate predictions within 4.25% of the actual outcome. Future work will focus on increasing the accuracy of neural network prediction by providing a larger set of experimental data with different battery models. In addition, the cyber security aspect of BMS will be considered and its effect on the SOC prediction.

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