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The available capacity computation model based on artificial neural network for lead–acid batteries in electric vehicles

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Abstract

The available capacity computation model based on the artificial neural network (ANN) for lead–acid batteries in an electric vehicle (EV) is presented. Comparing with the methods based on the Peukert equation, which is often used for the calculation of the available capacity for lead–acid batteries in EVs, this model is more accurate. The results of the experiment have proven the accuracy of the proposed model; the computation values are in good agreement with experimental data, the associated error has been considered acceptable from an engineering point of view. © 2000 Elsevier Science S.A. All rights reserved.

Keywords: Artificial neural network; Battery model; Available capacity; Lead–acid batteries; Electric vehicles

1. Introduction

In response to the growing concern about energy conservation and environmental protection, the rekindling of interest in electronic vehicles (EVs) has been obvious. Due to its mature technology, lower cost and modest performance, lead–acid batteries are still widely used in the most commercially available EVs. Moreover, the present great improvement in lead–acid batteries has shown that, in the foreseeable future, it is almost impossible for other advanced batteries to replace lead–acid batteries completely in EVs.

However, the calculation of the available capacity of lead–acid batteries is always a tough task. Many empirical expressions have been presented, but only the Peukert equation [1], which describes the relationship between the available capacity (C_a) and discharge current (I_d), has found wide acceptance. It is expressed as:

$$C_a = K/I_d^{(n-1)} \tag{1}$$

where the constants n and K depend on the temperature, the concentration of the electrolyte, and the structure of lead–acid batteries. Originally the Peukert constants were obtained only using two reference points, which are usually the maximum and minimum, within the whole range of discharge currents (Method-I). Later, multilevel Peukert equation (Method-II) was presented by using three reference points to obtain two sets of Peukert constants [2], and still the least-square method (Method-III) was proposed to estimate the Peukert constants using several reference points [3]. These two methods improve the accuracy of Peukert equation to some extent. In this paper, the available capacity computation model based on the artificial neural network (ANN, Method-IV) for lead–acid batteries in EVs is presented. The results of experiments have proven the further improvement of accuracy with the proposed model. The computation values are in good agreement with experimental data.

2. Available capacity computation model based on the ANN

With the comparison of the above-mentioned methods based on Peukert equation, here only the discharge current (I_d) need be considered in the available capacity computation model based on the ANN. So the simple configuration of the ANN model is presented and shown in Fig. 1.

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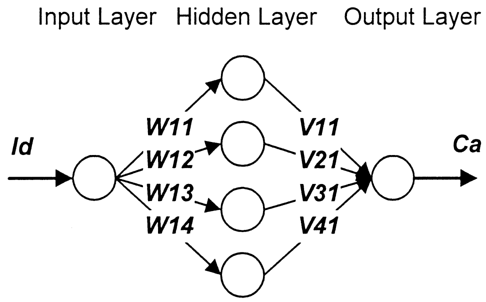

Fig. 1. Available capacity computation model based on the ANN.

In this configuration, the ANN has three layers, i.e., input, hidden, and output layers. The input layer has one node for the discharge current (I_d), the hidden layer has four nodes (this number was determined from studying the behavior of the available capacity computation model based on the ANN during the training process taking into consideration some factors such as convergence rate, mapping accuracy, etc.), and the output layer has one node for the available capacity (C_a). Again, the input of the node in the input layer is directly passed as the output, while each node in the hidden layer has the same activation function represented by the following expression:

$$f(x) = 2/(1+\exp(-2x)) - 1 \tag{2}$$

and its own bias denoted by $b_h(i)$ $(i=1,2,3,4)$, and the node in the output layer has its own bias denoted by b_o and its activation function expressed as follows:

$$g(x) = x \tag{3}$$

There are connection weights between each pair of layers. The weights between the input layer and hidden layer are represented by $W_{ij}(i=1;\ j=1,2,3,4)$ while the weights between the hidden layer and output layer are represented by $V_{ij}(i=1,2,3,4;\ j=1)$. The $f(x)$, the hyperbolic tangent (tanh), is a continuously differentiable nonlinear activation function, which is commonly used in the ANN. It is symmetric with respect to the origin and the amplitude of its output lies inside the range of $[-1,1]$. The linear function $g(x)$ is used to make the output be able to take the any value over the real numbers. This structure of the ANN can map the discharge current (I_d) to the available capacity (C_a) arbitrarily well if the sufficient nodes in the hidden layer are given [4].

To train this model, a learning process will be carried out, which is achieved by adapting the connection weights in response to a number of training pairs of discharge current (I_d) and available capacity (C_a). The aim is to arrive at a unique set of weights that are capable of correctly associating all the discharge currents with their desired available capacities. The back-propagation ANN model for this research was developed using the ANN toolbox in the *Mat*rix *Lab*oratory (MATLAB).

3. Experiment results and comparison

The selection of training pairs is essential to make the ANN achieve better performance. For the training of the proposed ANN model, discharge currents should cover the wide range of currents (e.g., from 0.2 C_5 to 1.0 C_5, here C_5 refers to the rated capacity of battery on a 5-h discharge rate) which are typically discharged in EVs. Fig. 2 shows the relationship between the available capacity and the discharge current of the CS-E105A traction battery installed in the tested EV.

From this figure, two sets of data are obtained, which are shown in Tables 1 and 2, respectively. Data-I will be used in training while Data-II will be used in verifying.

Using Data-I in Table 1 as training set, the weights between neighboring two layers and corresponding biases are determined. The results are shown as follows.

The weights between the input layer and the hidden layer are $W_{11}=0.0114$, $W_{12}=0.3216$, $W_{13}=1.6628$, $W_{14}=1.1714$; The biases in hidden layer are $b_h(1)=0.2392$, $b_h(2)=10.1633$, $b_h(3)=-49.3865$, $b_h(4)=16.7807$; The weights between the hidden layer and the output layer are $V_{11}=-69.2601$, $V_{12}=22.0759$, $V_{13}=-2.6964$, $V_{14}=26.6636$; The bias in output layer is $b_o=86.7334$.

For verifying the accuracy of the proposed ANN model, the discharge current of Data-II is used to estimate the available capacity with the trained ANN model. Moreover, these estimation values are compared with the measured available capacities. The results are shown in Table 3 and Fig. 3, respectively.

It can be seen that almost consistent accuracy level is kept within less than 1% except only one point.

For the comparison study, Method-I, Method-II and Method-III have been obtained for Data-I in Table 1. Through the analysis, the following three models which

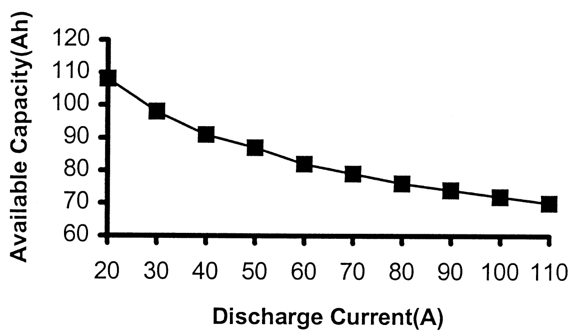

Fig. 2. Relationship between available capacity and discharge current.

Table 1
Data set (Data-I) for training available capacity computation model based on ANN

I_d (A)	20.0	30.0	40.0	50.0	60.0	70.0	80.0	90.0	100.0	110.0
C_a (A h)	108.0	98.0	91.0	87.0	82.0	79.0	76.0	74.0	72.0	70.0

Table 2
Data set (Data-II) for verifying available capacity computation model based on ANN

I_d (A)	25.0	35.0	45.0	55.0	65.0	75.0	85.0	95.0	105.0	110.0
C_a (A h)	102.0	94.0	89.0	85.0	80.0	77.0	75.0	73.0	71.0	70.0

are corresponding to the above three methods are derived for the estimation of the available capacity:
Method-I:

$$C_{a1} = K_1 / I_d^{(n1-1)} = 231.4015 / I_d^{0.2544} \qquad I_d \subseteq [20,110] \qquad (4)$$

Method-II:

$$C_{a21} = K_{21} / I_d^{(n2-1)} = 228.8653 / I_d^{0.2507} \qquad I_d \subseteq [20,60] \qquad (5)$$

$$C_{a22} = K_{22} / I_d^{(n3-1)} = 238.7688 / I_d^{0.261} \qquad I_d \subseteq [60,110] \qquad (6)$$

Method-III:

$$C_{a3} = K_3 / I_d^{(n4-1)} = 229.63016 / I_d^{0.25159} \qquad I_d \subseteq [20,110] \qquad (7)$$

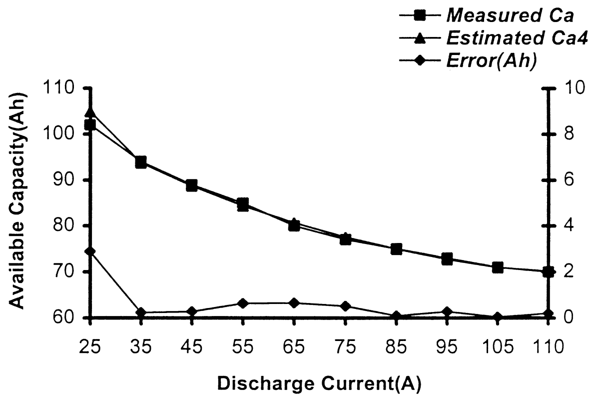

Fig. 3. Comparison with measured C_a and estimated C_{a4}.

By using the ANN model and the three methods above, the available capacities have been estimated by the discharge currents whose range is from 20 to 110 A. The results are shown in Table 4. When utilizing the ANN model, the error level is low compared with those obtained by using the methods based on the Peukert equation.

In order to compare with the methods based on Peukert equation, the current available capacity computation model based on ANN does not take the influence of battery temperature and battery history into account. In considering the battery temperature, the new input (battery temperature) will be introduced in the input layer of the ANN based model, whereas in considering the battery history the adaptive ANN based model will be presented. These two factors of influence on the available capacity computation model based on the ANN will be discussed in detail in another paper.

Table 3
Estimation accuracy of available capacity computation model based on ANN
Note: Error^1 = |Measured C_a − Estimated C_{a4}|; Error^2 = |Measured C_a − Estimated C_{a4}|/Measured C_a.

I_d	25.0	35.0	45.0	55.0	65.0	75.0	85.0	95.0	105.0	110.0
Measured C_a	102.0	94.0	89.0	85.0	80.0	77.0	75.0	73.0	71.0	70.0
Estimated C_{a4}	104.88	93.77	88.73	84.37	80.65	77.52	74.90	72.73	70.96	70.20
Error^1 (A h)	2.88	0.23	0.27	0.63	0.65	0.52	0.10	0.27	0.04	0.20
Error^2 (%)	2.76	0.24	0.30	0.74	0.81	0.67	0.13	0.37	0.06	0.28

Table 4
Comparison of measured available capacity and estimated available capacity based on Peukert equation and ANN model

I_d	Measured C_a	Method-I (4)		Method-II (5), (6)		Method-III (7)		Method-IV (ANN)	
		C_{a1}	Error (%)	C_{a2}	Error (%)	C_{a3}	Error (%)	C_{a4}	Error (%)
20.0	108.0	108.0	0.0	108.0	0.0	108.1	0.056	108.0	0.0
30.0	98.0	97.4	0.612	97.6	0.408	97.6	0.612	98.0	0.0
40.0	91.0	90.5	0.549	90.8	0.220	90.8	0.220	91.2	0.220
50.0	87.0	85.5	1.724	85.8	1.379	85.8	1.379	86.5	0.575
60.0	82.0	81.7	0.366	82.0	0.0	82.0	0.0	82.4	0.488
70.0	79.0	78.5	0.633	78.8	0.253	78.9	0.127	79.0	0.0
80.0	76.0	75.9	0.131	76.1	0.132	76.2	0.263	76.1	0.132
90.0	74.0	73.7	0.405	73.8	0.270	74.0	0.0	73.8	0.270
100.0	72.0	71.7	0.417	71.8	0.278	72.0	0.0	71.8	0.278
110.0	70.0	70.0	0.0	70.0	0.0	70.4	0.571	70.2	0.286

4. Conclusion

The accurate estimation of the available capacity of battery is very important for EVs when EVs are on the road. An available capacity computation model based on the artificial neural network (ANN) has been proposed. The accuracy of this method has been verified by using the measured data. Comparing with the methods based on Peukert equation, the method based on the ANN gives the highly accurate estimation of the available capacity.

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