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Short communication

A prediction model based on artificial neural network for surface temperature simulation of nickel–metal hydride battery during charging

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ABSTRACT

In this study, a prediction model based on artificial neural network is constructed for surface temperature simulation of nickel–metal hydride battery. The model is developed from a back-propagation network which is trained by Levenberg–Marquardt algorithm. Under each ambient temperature of 10 °C, 20 °C, 30 °C and 40 °C, an 8 Ah cylindrical Ni–MH battery is charged in the rate of 1 C, 3 C and 5 C to its SOC of 110% in order to provide data for the model training. Linear regression method is adopted to check the quality of the model training, as well as mean square error and absolute error. It is shown that the constructed model is of excellent training quality for the guarantee of prediction accuracy. The surface temperature of battery during charging is predicted under various ambient temperatures of 50 °C, 60 °C, 70 °C by the model. The results are validated in good agreement with experimental data. The value of battery surface temperature is calculated to exceed 90 °C under the ambient temperature of 60 °C if it is overcharged in 5 C, which might cause battery safety issues.

1. Introduction

Nowadays electric-driven vehicles are increasingly receiving concerns for the reasons of petroleum shortage and environment pollution. Power battery is extensively studied as a key device to prompt the utilization of new energy automobiles. Besides electrochemical performance, battery safety is of crucial significance to vehicles. For the close relationship with safety issue, battery thermal behavior is intensively focused in many studies. Shi et al. [1] studied heat generation in fast charge process of nickel–metal hydride battery through a two-dimensional mathematical model. Araki et al. [2] discussed the thermal behavior of small size Ni–MH battery in fast charge and discharge cycle. Kim et al. [3] investigated on thermal runaway of Lithium-ion battery via a three-dimensional thermal model. Zhang [4] analyzed three types of heat generation sources of cylindrical Li-ion battery using mathematic model calculation. Cai and White [5] proposed a thermal model of Li-ion battery based on multi-physics fields with the help of commercial soft ware (COMSOL Inc. Multi-physics). However, generally, the proposed models are involved with intricate internal physical–chemical reactions and complicated mathematical computing [6]. It will be greatly useful to construct a model for thermal behavior study of batteries with a simple and practicable method. For the reason, artificial neural network (ANN) which is usually used to deal with multiple-input and multiple-output cases irrespective of an internal mechanism [7] was employed for constructing a prediction model to simulate the surface temperature of Ni–MH battery in this work.

In the case of Ni–MH battery, its heat generation mainly appears in the process of charging, which may become more remarkable upon overcharging and fast charging [8]. In author's previous work, it was found that when the surface temperature of Ni–MH battery exceeded 90 °C, the electrolyte leakage might occur. If the temperature continued to rise, battery explosion would happen possibly. It will be effective to prevent the battery from thermal runaway if its surface temperature could be simulated accurately. As mentioned above, based on back-propagation (BP) network affiliating to ANN, a prediction model was constructed to focus on the changes of battery surface temperature during charging under various ambient temperatures, especially, under higher ambient temperatures (50 °C, 60 °C, 70 °C), battery safety was discussed as well.

2. Model descriptions

As a computational model mimicking human brain thinking, ANN has been applied extensively in a number of scientific and engineering domains. It is a massively parallel distributed processor that has a natural propensity for accommodating experiential regulation and making it available for use [9]. In practical applications, the most commonly proposed ANN structure is known as multi-layer perceptron which is a feed-forward neural network consisting of one input layer, one or more hidden layers and one

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output layer. Hidden Layer is composed of a number of processing units called neurons that can process the data from input layer, and the corresponding result will be given out by the output layer. In this process, the feed-forward neural network intends to catch the potential regulation of input data by taking advantage of its good learning ability. So, it is available to infer output results through the mastered regulation when new data are input to the model [11]. As a result, the processing of complex non-linear issues can be simplified with the ANN modeling [12].

For Ni–MH battery, heats generated in the process of charging include reaction heat, combination heat, polarization heat and ohm heat [13]. Reaction heat is exothermic during regular charging (as seen in Eq. (1)) [14], while hydrogen and oxygen reacts releasing plenty of combination heat during overcharge (as seen in Eq. (2)) [13]. Polarization and ohm heats are generated along with the whole charging process. Thus, it is inevitable to raise the surface temperature of battery with these several aspects of heats generated. It is speculated that, the more heat generated, the higher battery surface temperature becomes under the same charging conditions.

$$\mathrm{Ni(OH)_2 + M \rightarrow NiOOH + MH} \quad -14.65\,\mathrm{kJ\,mol^{-1}} \tag{1}$$

$$\mathrm{2H + 1/2O_2 \rightarrow H_2O} \quad -285.9\,\mathrm{kJ\,mol^{-1}} \tag{2}$$

In experiments, it is found that the surface temperature (T_s) of battery is influenced by charging current (I), ambient temperature (T_{amt}) and charging time (t) if the heat dissipating to environment is unconsidered. However, the specific calculation mode is unknown among these variables. But, T_s might be expressed in using of Eq. (3),

$$T_s = f(I, T_{amt}, t) \tag{3}$$

In order to obtain T_s from the function which does not give out the detailed expression of the variable relationship, it is helpful to introduce an ANN model in the work based on above statements. The model's schematic diagram is shown in Fig. 1. It is expected that T_s could be calculated out through the model and the purpose of predicting T_s during charging under different ambient temperatures could be achieved.

The learning ability of ANN is realized by means of model training. The most popular training algorithms recommended are back-propagation (BP) algorithm and its variants [15]. Back-propagation means that the network error will be propagated back if it does not reach an expected value in the model training process, meanwhile the network weights and biases values are adjusted constantly to obtain the minimum error [16]. The feed-forward neural network trained by BP algorithm is often called BP network which is an ideal choice to the model construction of this work. Based on BP network, the prediction model is designed and its structure with three layers is illustrated in Fig. 2, where parameters adopted in the model are determined by trial and error. p represents the data input to the model in the chart, u means the model output result that is the T_s, w and b are of weights and biases values, respectively. There are two nodes in the input layer, because when current I is set up, T_s will change with T_{amt} and t. According to Kolmogorov Theorem ($j = 2i + 1$) [10], the number of neurons used in hidden layer can be determined as 5. That one neuron is set up in the output layer is ascribed to T_s as an only output of the model. The transfer functions selected for the model construction are tangent-sigmoid and log-sigmoid in last two layers, respectively, written in Eqs. (4) and (5) [17].

$$\text{Tan-sigmoid function,} \quad f(n) = \frac{e^n - e^{-n}}{e^n + e^{-n}} \tag{4}$$

$$\text{Log-sigmoid function,} \quad f(n) = \frac{1}{1 + e^{-n}} \tag{5}$$

The output value (y_j) of each neuron (j) in the hidden layer is calculated by Eq. (6) [18],

$$y_j = f\left(\sum_{i=1}^{2} p_i w_{ij} + b_j\right), \quad i = 1, 2, \quad j = 1, \ldots, 5 \tag{6}$$

here p_i is input vector, w_{ij} is weight value connecting the ith input vector and the jth neuron, b_j is biases values, $f(\,)$ represents tan-sigmoid transfer function. On the basis of the results of Eq. (6), the model final output u can be calculated from Eq. (7) [18],

$$u_\nu = f\left(\sum_{j=1}^{5} y_j w_{j\nu} + b_\nu\right), \quad \nu = 1 \tag{7}$$

here ν is the number of neurons in the output layer, $f(\,)$ represents log-sigmoid transfer function. Thereafter, the prediction values of T_s are attained finally through above modeling.

In ANN modeling, it is important to choose a suitable algorithm to train the constructed model. For BP network, the basic principle of BP training complies with gradient descent method which can reduce the network error by altering the weights and bias values along the direction of the negative gradient. In this work, a variant of the gradient descent method called Levenberg–Marquardt (LM) algorithm is employed to train the constructed model [9]. LM algorithm is expressed in Eq. (8) [9],

$$x_{k+1} = x_k - [J^T J + zD]^{-1} J^T c \tag{8}$$

here x_k represents a vector of weights or biases, J is Jacobian matrix including first derivatives of network errors with respect to weights and biases [19], D is unit matrix, c is network error, z is test scalar. LM algorithm integrates together gradient descent method and Newton method. Gradient descent method makes a good convergence, and when it is used for ANN training, the initial iterations descend down quickly. However, with closing to optimal value, the target function becomes to descend down very slowly. Newton method can produce an ideal search direction nearby the optimal value although it is inferior to gradient descent method in convergence effect. Thus, the iteration can continue to proceed quickly. Under the convergence guarantee circumstance, LM algorithm is expected to convert to Newton method with the aim of ensuring model training speed and accuracy [19]. The training quality of the constructed model needs to be evaluated for its effective use.

3. Experiments

A 8 Ah cylindrical Ni–MH battery was charged to its SOC of 110% in the rate of 1 C, 3 C and 5 C under each ambient temperature of 10 °C, 20 °C, 30 °C and 40 °C to obtain the training data for the ANN prediction model. The data recording was carried out by an infrared thermal imager (VarioCAM hr from German Infra Tec Company). The model was constructed in MATLAB software platform to predict the surface temperature of battery charged under ambient temperatures of 50 °C, 60 °C and 70 °C.

The learning rate was set as 0.05 during model training, and the training epochs were 5000.

4. Results and discussion

4.1. Training results

The model's training results are shown in Figs. 3–5. Fig. 3 is the convergence curve of model's mean square error (MSE). It is shown that the MSE has almost converged at the 500th epoch where the value is 4.98621e−006. Obviously, the model trained by LM

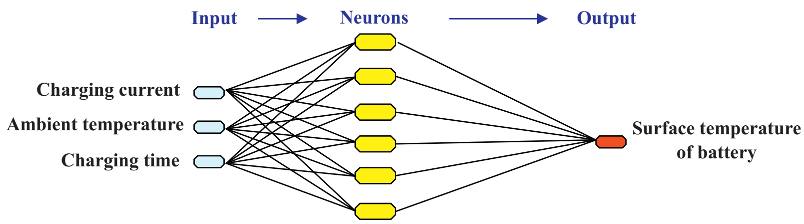

Fig. 1. ANN model to predict the surface temperature of battery.

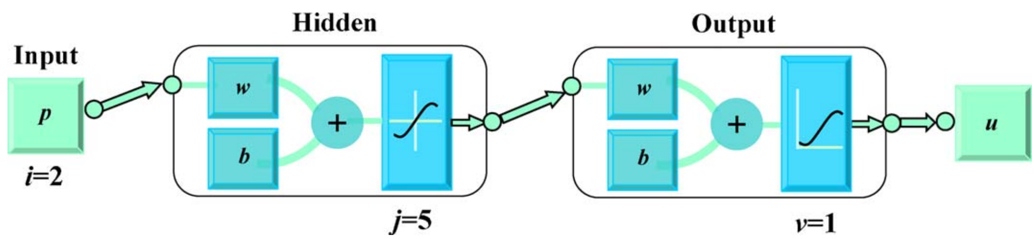

Fig. 2. BP network structure.

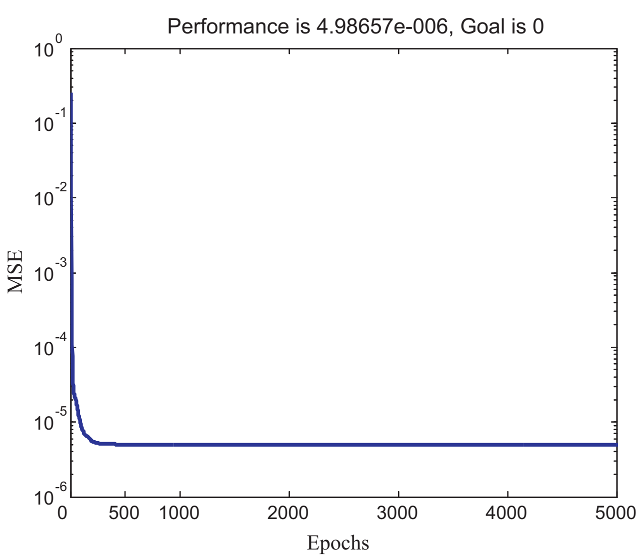

Fig. 3. Mean square error (MSE) of the model.

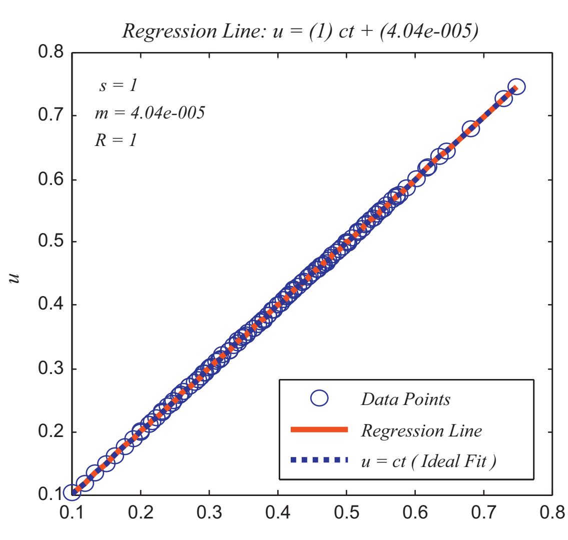

Fig. 4. Linear regression relationship between model outputs and targets.

algorithm is of fast convergence and high accuracy. At the 5000th training epoch, the value of MSE is 4.98657e−006, it changes little compared with the value at the 500th epoch. In this case, the model can be qualified as a well-trained one [20] that can be come into use though the MSE does not achieve the ideal value of 0. Reasonably, 5000 epochs designed for training is enough for meeting the demands of the model application.

Fig. 4 presents a linear regression relationship between each element of the model output (u) and the corresponding target (ct) to check the quality of the model training further, here u is the modeling result and ct is practical data. S and m correspond to the slope and the y-intercept of the regression line (red solid line) which is given out by the trained model. The ideal fit is shown as a dashed line ($s = 1$ and $m = 0$) when outputs are exactly equal to targets [21]. For the regression line, 1 and 4.04e−005 are obtained for s and m, respectively, and the value of m is very close to 0. So, the regression line and the ideal fit line almost overlap in the figure, it is indicated that the model outputs fit the targets very well. R represents the correlation coefficient between outputs and targets. If the value of R reaches 1 or approaches to 1, the correlation will become much better [22], then the ANN modeling will perform more effectively. In the case of the trained model, R's value of 1 means a perfect correlation leading all output data (as marked in hollow cycle) distribute

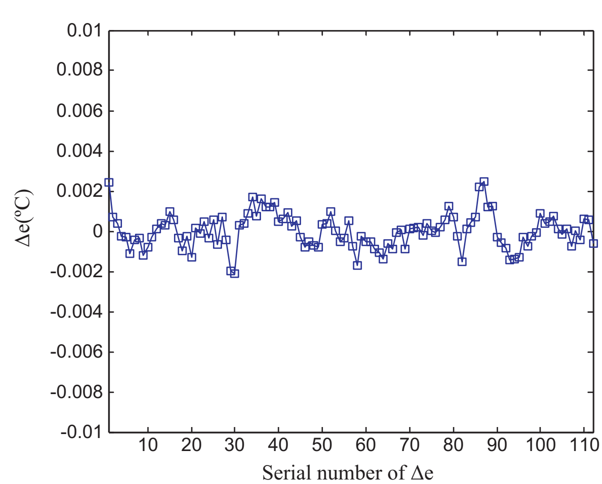

Fig. 5. Absolute errors (Δe) between model outputs and targets.

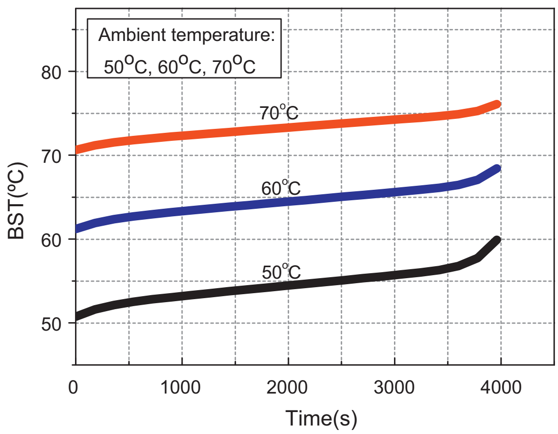

Fig. 6. Change curves of battery surface temperatures (BST, predicted data) with time, charged in 1 C rate under various ambient temperatures.

on the regression line [23]. In conclusion, it is shown that the model is of excellent training quality.

The absolute error between each element of the model output and the corresponding target is described in Fig. 5. The maximum error is 2.51×10^{-3} °C and the minimum value is 8.88×10^{-6} °C. Actually, even considering the value of the maximum error, it is so tiny compared to the practical surface temperature of battery in experiments that it can be neglected. Also, it is elucidated that the model is trained with a high quality.

4.2. Prediction results and validation

The curves of predicted T_s when the battery is charged in different rates under various ambient temperatures are shown in Figs. 6–8. It is seen that the beginning values of these curves are equal to the values of corresponding ambient temperatures. T_s will get increase as the charging process going. The highest temperature of battery surface appears at the end of charging. Besides, T_s will become large as the ambient temperature rises when the battery is charged in the same rate. Under the same ambient temperature, the rise rate of T_s could be determined from the curve slope. It will increase with the rising of charging rate. So, the T_s rise rate is the highest in 5 C charging, while the value is the lowest in 1 C charging. The results may be attributed to different polarization effect generated when the battery is charged in different rates.

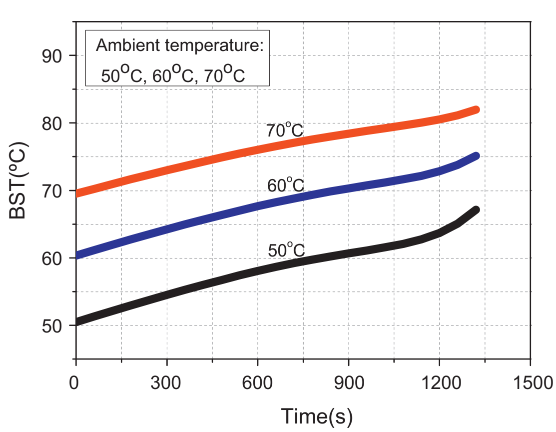

Fig. 7. Change curves of battery surface temperatures (BST, predicted data) with time, charged in 3 C rate under various ambient temperatures.

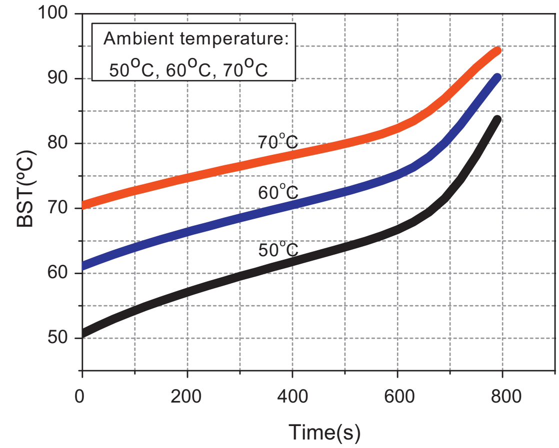

Fig. 8. Change curves of battery surface temperatures (BST, predicted data) with time, charged in 5 C rate under various ambient temperatures.

Table 1
Predicted values of battery surface temperature (BST) at the end of charging, under various ambient temperatures (T_{amt}).

T_{amt} (°C)	BST (°C)		
	1 C	3 C	5 C
50	59.91	67.13	83.74
60	68.44	75.11	90.20
70	76.09	81.96	94.33

The predicted values of T_s at the end of charging under various ambient temperatures are listed in Table 1. Taking charging under 60 °C for example, it is found that the terminal temperature of battery surface is 68.44 °C when the charging rate is 1 C, it is 8.44 °C higher than the ambient temperature, while the difference is 15.11 °C in the case of 3 C. However, if the charging rate changes to 5 C, the surface temperature even reaches over 90 °C, and the difference value becomes much larger. Certainly, the battery thermal behavior is influenced as the charging rate increases. Moreover the high surface temperature over 90 °C might cause battery safety issues if no cooling measures are taken.

Fig. 9 is a comparison of the simulating results and the experimental data. For the sake of safety, experiments were only carried out under the ambient temperature of 50 °C to validate the model. Results show that the simulated curves fit well with the measured

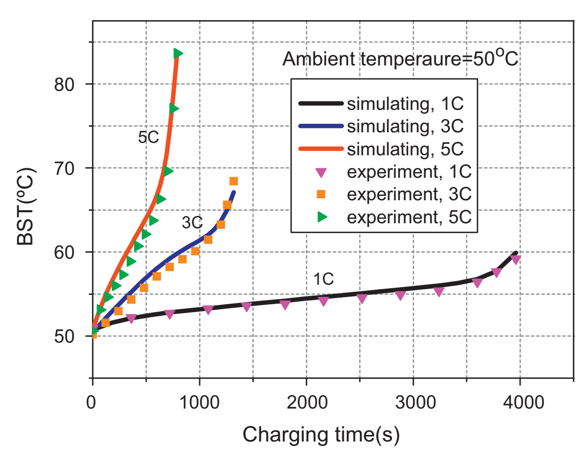

Fig. 9. The comparison between simulating results and experimental data, ambient temperature of 50 °C.

data in three cases of 1 C, 3 C and 5 C with a maximum temperature difference of 1.30 °C. It is acceptable to make the prediction with such a small error in contrast to the practical battery surface temperature of above 50 °C. Clearly, the predicted values are in good agreement with the experimental data, which also confirms that the model is effective in working.

In this study, the number of parameters involved in the ANN modeling is relatively less in reference to empirical models [1,2] performing similar simulations. The model construction, training and prediction can be finished in a little time. Furthermore, it is supposed that the prediction model could be extended to Li-ion batteries to study their thermal behavior and serve for thermal management system of battery pack.

5. Conclusions

An ANN model was constructed for the surface temperature (T_s) prediction of Ni–MH battery. The model was developed from BP network containing three layers. There are two nodes in the input layer, five neurons in the hidden layer and one neuron in the output layer. The model was trained by LM algorithm and its training quality is examined by linear regression method as well as model MSE and absolute error. It is shown that the model is of excellent training quality for the guarantee of prediction accuracy. Then, T_s values are computed by the well-trained ANN model under various ambient temperatures and charging rates. It is validated that T_s accord well with the experimental data, which manifests that the model is effective in simulation. The prediction results indicate that the surface temperature would even exceed 90 °C when the battery was overcharged in the rate of 5 C under the ambient temperatures of 60 °C and 70 °C. In this case, the battery might suffer safety problem more readily if no effective measures were taken to cool down it. Also, it is suggested that the prediction method could be used in Li-ion batteries and thermal management system of battery pack.

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