Prediction of discharge capacity of lithium battery based on cloud neural network

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***Abstract*—The prediction of discharge capacity of lithium batteries was one of the main tasks of battery management system. The discharge capacity of lithium batteries was related with many parameters, including discharge current, voltage, temperature, and the past charge and discharge history. The prediction methods of existing lithium battery discharge capacity mostly have no learning capabilities and nonlinear prediction ability, in order to predict the discharge capacity of lithium battery more accurately, an algorithm based on cloud neural network (CNN) was presented. On the basis of the analysis of the actual data of NASA, determine the related influence factors of discharge capacity, set up a corresponding CNN prediction model using cloud model, and use the cloud model for adaptive adjustment of the learning speed. Comparing with the traditional NN method, the simulation result demonstrates that the CNN prediction model has smaller prediction error.**

Keywords- lithium battery; discharge capacity prediction; cloud model; neural network

I. INTRODUCTION

Because of its high working voltage, small volume, light quality, high energy density, no memory effect, low self-discharge, long life circulation and other advantages [1], lithium battery are widely used in portable computer, mobile power and other information industry. In recent years, along with increasingly mature technology of the lithium battery, its applications in aerospace get the favors of all countries increasely. Lithium battery installed in spaceborne, its performance change is directly related to whether the spacecraft can operate normally and complete the scheduled tasks. Through the forecast, the health management of lithium battery is easy to realize, so as to realize the safety of the aircraft flight, and reduces the cost of maintenance support.

The existing battery life intelligent predicting methods mainly include: grey model, neural network model based on the data driven and so on, but these models have some weak points such as the learning algorithms are easy to be trapped into local minimum, have limited generalization performance, and have difficulty in dealing with the uncertainty existed in the prediction of discharge capacity. Cloud is an alternative model of the uncertainty between qualitative concepts described by the language value and their quantitative representation; it completely combines the fuzziness and randomness, and constitutes a mutual mapping between qualitative and quantitative as the basis of knowledge representation [2]. Cloud model combined with neural network, not only has the learning ability of neural network, but also combines the ability of the cloud's theory to deal with the uncertainty of knowledge, which improves the accuracy of prediction [3].

Based on the characteristics of complexity and nonlinearity of the failure mechanism of lithium battery, taking into account several factors that influence the discharge capacity, the paper proposes a prediction method of neural network optimized by cloud model (cloud neural network for short), and makes estimation and prediction of the battery discharge capacity under different discharge modes.

II. ESTABLISHMENT OF PREDICTION MODEL OF CLOUD NEURAL NETWORK

A. Neural Network Model

Using BP algorithm for training multilayer perceptron is currently the most widely used neural network [4]. A three layer BP neural network is as shown in Figure 1.

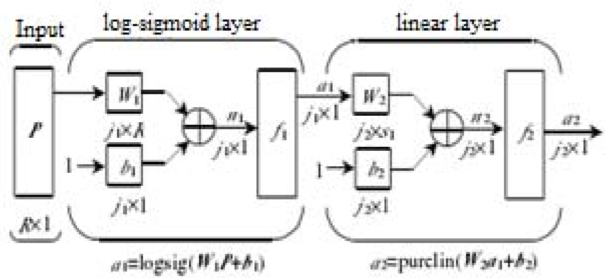

Figure 1 BP neural network

Order number of each matrix is shown in its lower part, the training functions f_1 f_2 of *1st* and *2nd* layer can choose *sigmoid*, *tansig*, *purelin* function, R is the dimension of the network input vectors, j_1 j_2 are the dimensions of the network output vectors of *1st* and *2nd* layer. Generally, the recursion relation of *M* layer BP network can be described as:

$$a_{m+1} = f_{m+1}(W_{m+1}a_m + b_{m+1}) \quad (m = 0,1,\cdots,M-1) \tag{1}$$

In which: $f_{m+1}, W_{m+1}, b_{m+1}, a_{m+1}$ respectively are the training function, weights, bias value and network output of the (m+1) layer. $n_{m+1} = W_{m+1}a_m + b_{m+1}$ is the net input of the m+1 layer network.

Steps of BP algorithm are as follows:

1) Input the learning samples to the input network and spread forward, and network accepts input P from the outside, that is

$$a_0 = P \tag{2}$$

2) Calculate the network output of the layers using formula (1).

3) Compare the actual output a of the network with the target output t, if the desired output is not achieved, the sensitivity s will be propagated back according to the formula for computing the sensitivity. Sensitivity is the sensitivity of mean square error between actual output and target output to the input changes, and the computation formula is as follows:

$$s_m = \dot{F}_m(n_m)W^T{}_{m+1}s_{m+1} \quad (m = M-1, M-2, \cdots, 1) \tag{3}$$

$$s_M = -2\dot{F}_M(n_M)(t-a) \tag{4}$$

In which, $\dot{F}_M(n_M)$ represents the first derivative standard matrix of the learning function to net input n_m in the m layer network.

4) Update the weights W and bias value b iteratively using the approximate steepest descent method, and their initial values are arbitrary small numbers for random.

$$W_m(k+1) = W_m(k) - \alpha s_m(a_{m-1})^T \tag{5}$$

$$b_m(k+1) = b_m(k) - \alpha s_m \tag{6}$$

In which, k is the iteration, α is the learning speed, output the result if the accuracy requirement is fulfilled after many iterations a_m, otherwise, return to step (2) and continue to iteration.

B. Cloud Neural Network Model

Suppose X is an ordinary collection, $X = \{x\}$ is known as the theory of domain. As to the fuzzy set $\tilde{A}$ in the theory of domain X, a random number $\mu_{\tilde{A}}(x)$ which has a stable tendency is existed for each element x, which is called the membership of x to $\tilde{A}$ .If the elements are simple and orderly in the theory of domain, then X can be regarded as a basic variable, and the membership in the distribution of X is called membership cloud; If the elements are not simple and orderly in the theory of domain, then X can be mapped to the other orderly theory of domain X' according to a rule f , one and only one x' corresponds to x in the X', then X' is the basic variable, and the membership in the distribution of X' is called membership cloud [5].

The three digital characteristics of the cloud are respectively the expectation Ex, entropy En and the super entropy He. The numerical characteristic diagrammatic sketch of the cloud is as shown in Figure 2. In which, the abscissa axis represents the range of the uncertainty metric of one concept, and the ordinate axis represents the membership degree.

The expectation Ex is the center of the theory of domain, and is the point which can represent the qualitative concept best, namely it belongs to the qualitative concept forever. Reflected in cloud is the "peak" of cloud, namely the point of 1 membership degree. Entropy En shows a range of a qualitative concept which is metrical, the larger the entropy, the more macroscopic the concept, namely range which is metrical is wider. Entropy reflects the margin of the fuzzy concept, namely the uncertainty of the qualitative concept, also known as the ambiguity. Reflected in the cloud is the "span" of cloud, namely the larger the entropy, the wider the cloud "span". Super entropy He is the entropy of entropy, and is used to represent the uncertainty of entropy, it represents randomness of the samples, namely the discrete degree of the cloud drops. Super entropy He associates fuzziness and randomness, and it represents the "thickness" of cloud, the larger super entropy, more "thick" the cloud [6].

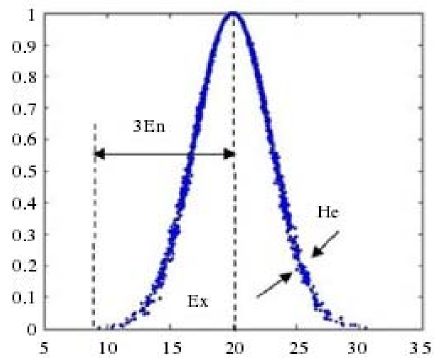

Figure 2 numerical characteristics of cloud

By means of the combination of cloud model and BP neural network, the cloud neural network model is established. Through the analysis of actual data, using cloud model to process the input data, and the processed data is taken as the network input to build prediction model.

Although the BP algorithm is the most commonly used algorithm in neural network learning algorithms [7], BP learning algorithm is slow and not easy to converge. Some improved methods are proposed in the literature, but there is a problem: all sorts of improved algorithms only solve one aspect of the problem, the advantage of each algorithm cannot be complementary, and so the problem of slow learning speed and local minimum cannot be effectively solved.

In this paper, the above cloud neural network model is improved, and qualitative rules are created based on cloud model, adjusting the learning speed α , in order to meet the requirements of precision as soon as possible. For the adjustment of the learning speed, the general experience is when the error variable becomes smaller continuously, increase the learning speed to speed up the convergence speed; when the error variable becomes larger continuously, decrease the learning speed for smaller adjustment. If adding a certain stochastic process in the process of adjusting, then a compromise solution can be obtained from the choice of convergence speed and global optimal. In this paper, sensitivity s is taken as the indicator of error direction, and then the general rules used as adjustment are as follows:

1) *If s <0 and abs(s) is larger, then a larger learning speed α is adopted;*
2) *If s <0 and abs(s) is smaller, then a smaller learning speed α is adopted;*
3) *If s >0 and abs(s) is smaller, then a smaller learning speed α is adopted;*
4) *If s >0 and abs (s) is larger, then the minimum learning speed α is adopted.*

The sensitivity s taken as the indicator of the error direction is as the input parameters and based on this the *X*-conditional cloud generator is established, and the learning speed α reflecting the tendency of error adjustment is used to realize the *Y*-conditional cloud generator. Then this cloud generator organically unifies the stochastic process and the learning speed adaptive adjustment and gets an optimal solution. The stochastic process contained in the cloud model ensures that the neural network can obtain the best results in overall, namely, find the minimum, and the tendency of the rules in cloud model generator ensures the convergence rate in the implementation of the neural network.

III. SIMULATION AND ANALYSIS

A. Data Analysis

As to the lithium battery, because state parameters which are able to be detected are so limited and the collected data are often contaminated by noise. If these measurement data are used to predict the value directly, undoubtedly the accuracy of the prediction will be reduced. Therefore, first of all, preprocess the collected data sample and then select the state parameters which have strong correlation with the discharge capacity for the prediction of the discharge capacity of lithium-ion batteries.

Through the analysis of existing sample data, Figure 3, Figure 4, Figure 5 shows that the temperature T and discharge cut-off voltage U have a great influence on the discharge capacity C, that is, the temperature T and discharge cut-off voltage U have a necessary connection with the discharge capacity C. when the temperature T is about 20 ˚C, the discharge capacity C decreases slowest; when the temperature is too high or too low, the discharge capacity C decreases faster, and the effect of high temperature is more apparent than that of low temperature. The smaller the discharge cut-off voltage U is, the faster the decrease of discharge capacity.

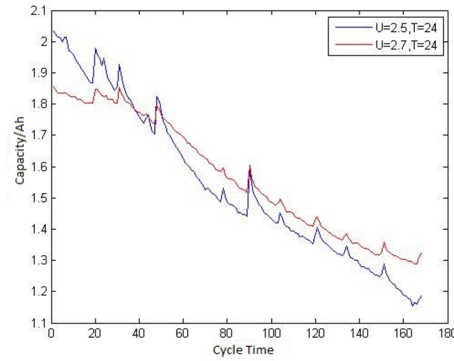

Figure 3 T is 24 ˚C, U changes

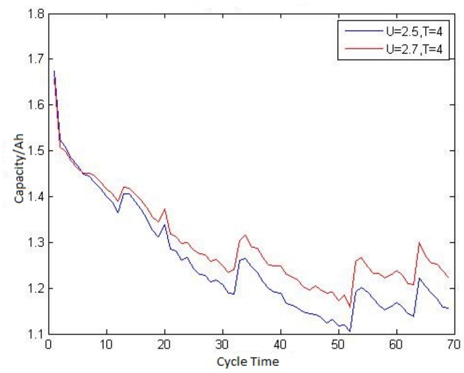

Figure 4 T is 4 ˚C, U changes

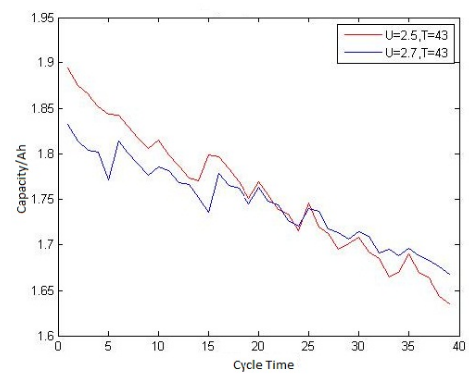

Figure 5 T is 43 ˚C, U changes

In conclusion, the battery discharge capacity C has a necessary connection with temperature T and discharge cut-off voltage U, and this connection is of fuzziness and randomness obviously.

B. Establishment of Prediction Model of Discharge Capacity

On basis of the above analysis, selecting temperature T, discharge cut-off voltage U as the input parameters of the cloud neural network, and the battery discharge capacity C is chosen as the output of the cloud neural network. First of all, use cloud model for the fuzzification of the temperature T, discharge cut-off voltage U, and establish the corresponding membership cloud, as is shown in Figure 6 and Figure 7.

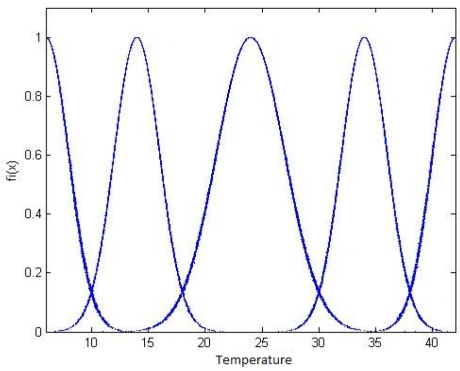

Figure 6 temperature membership cloud

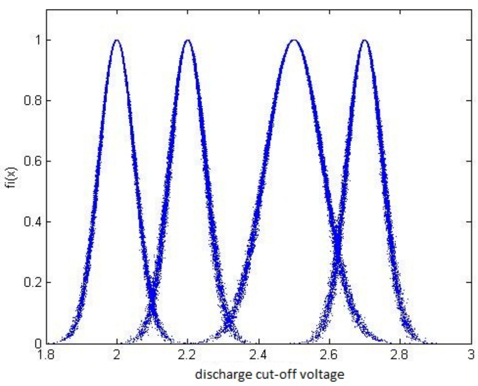

Figure 7 discharge cut-off voltage membership cloud

Normalization processing of discharge capacity C according to the following formula:

$$C_n = \frac{C - C_{\min}}{C_{\max} - C_{\min}} \quad (7)$$

In which, $C_{\max}$ represents the maximum discharge capacity, $C_{\min}$ represents the maximum discharge capacity, C represents actual discharge capacity C_n represents the normalized discharge capacity. By means of formula (7), the discharge capacity can be normalized in (0, 1), and thus effectively preventing saturation phenomenon occurring in a network training.

BP network is chosen as the training network, the input node is nine, node 1 ~ 5 represents 5 membership degrees of temperature T, node 6 ~ 9 represents 4 membership grades of discharge cut-off voltage U. Output node is 1, which is on behalf of normalized discharge capacity C_n . According to the experiment situation, the number of hidden layer is determined to be 1, the nodes of the hidden layer is 12, tansig function is adopted as the excitation function of the input layer to hidden layer, purelin function is adopted as the excitation function of the hidden layer to output layer, and trainlm function is adopted as the training function.

The overall prediction process is shown in Figure 8.

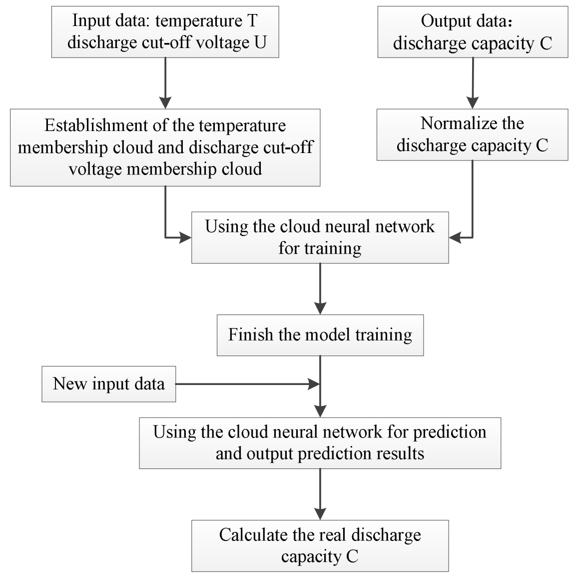

Figure 8 prediction process

C. *Predicted Results*

The lithium battery of 2 Ah rated capacity is selected as the testing battery in this paper. The discharge mode is that the lithium battery discharges at a constant current of 2A until the battery voltage falls to discharge cut-off voltage U under a certain temperature T. In charge mode, the lithium battery charges with a constant current of 1.5A until the battery voltage is 4.2 V and then charges with constant voltage until the charging current dropped to 0.02A. Using the temperature T, discharge cut-off voltage U to predict discharge capacity C, and the results are as shown in Figure 9, Figure 10, Figure 11.

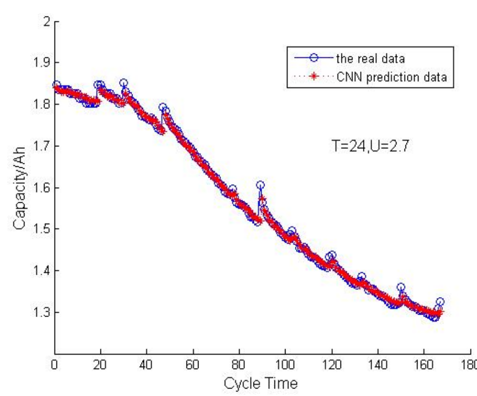

Figure 9 Prediction results

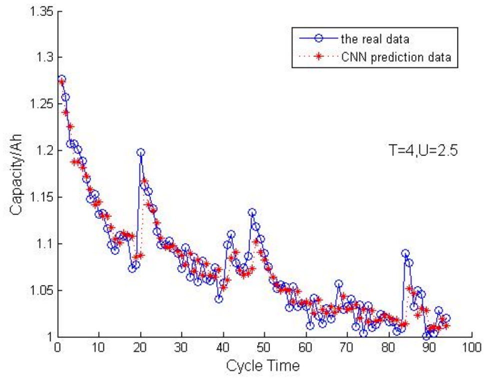

Figure 10 Prediction results

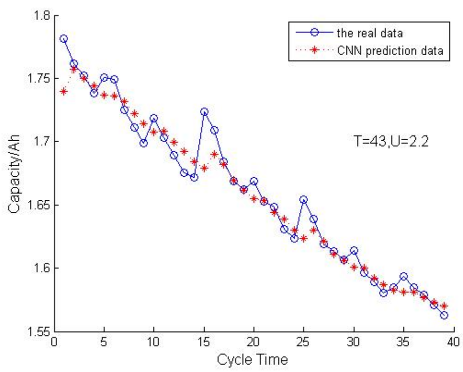

Figure 11 Prediction results

Two kinds of performance index are selected to compare the prediction results of traditional neural network and cloud neural network, respectively, mean absolute percentage error e_{MAPE} and root mean square error e_{RMSE}. The calculation formulas are as follows:

$$e_{MAPE} = \frac{1}{n}\sum_{i=1}^{n}\left|\frac{y_i - \hat{y}_i}{y_i}\right| \quad y_i \neq 0$$
$$e_{MASE} = \sqrt{\frac{1}{n}\sum_{i=1}^{n}e^2{}_i} = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(y_i - \hat{y}_i)^2} \tag{8}$$

The comparison of the prediction error e_{RMSE} is as follows:

Figure number	CNN	NN
9	0.00043068	0.0042758
10	0.00574335	0.0128265
11	0.00394782	0.0082653

It can be seen that the overall prediction performance of cloud neural network is better than that of the traditional neural network method.

IV. CONCLUSION

Simulation results show that the proposed cloud neural network predicting method can effectively predict the discharge capacity of lithium batteries, and the comparison with the traditional neural network method proves that the proposed method has a better prediction precision. But this method also has disadvantages, due to the discharge current of lithium battery is considered to be constant-current in the paper, when the discharge current changes, prediction accuracy of cloud neural network will be relatively reduced, how to realize the interaction of predicted data and training data considering the premise of uncertainties and establish a dynamic prediction model is the direction of further research.

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