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The Prediction of SOC of Lithium Batteries and Varied Pulse Charge

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***Abstract* - Improved RBF neural network arithmetic is mainly characterized by using TI's Impedance Track TM technology for reference which predict the status of charge (SOC) of lithium battery, and in accordance with the chemistry characteristics of lithium batteries, use varied pulse charge method for their rapid and efficient charging. The results show that the SOC which is predicted by improved RBF arithmetic can meet the performance target under the C++ compiler environment and adopting the varied pulse charge have shorten the charging time by 20%, this method is suitable for rapid charging system.**

Index Terms - Lithium batteries. Varied pulse charge. The prediction of SOC. Radial Basis Function Neural Network

I. INTRODUCTION

With the continuous development of the integration of function and the amalgamation of technology, laptops, smart phones and portable media players and other portable devices have become more sophisticated on the power requirements. As a major power which is rechargeable in such equipment, lithium-ion batteries it is difficult to keep up with the power needs of portable devices, the biggest difficulty is how to extend the battery running time in battery-powered system. In addition to looking for a higher energy density of the new power, the system designers are looking for the approach which can use battery power as efficiently as possible. Most of them focus on improving the DC / DC power conversion efficiency, thus it can extend battery run-time, and often overlooked with monitoring the battery power of the issue of accuracy which are equally important to the power conversion efficiency and battery capacity. If the error range of battery power monitoring is ± 10%, the system must only use 90% of battery power in order to prevent the loss of critical data. This is equivalent to a loss of 10% of battery capacity or battery run-time.

Wireless access account management, data processing and medical monitoring and many other mobile applications require higher demanding on the measurement accuracy of the remaining battery capacity, in order to avoid a sudden shutdown due to battery depletion. However, ensuring measurement accuracy is very difficult in the entire life cycle of the battery, over-temperature status or the remaining electricity load, The main reason is that the battery power available has functional relation with its discharge rate, temperature, aging and self-discharge characteristics. Developing a Arithmetic which can be precise definition of battery self-discharge characteristics and the aging degree to the impact of battery capacity can not be realized basically. Furthermore, the traditional monitoring of battery power require fully charging and fully discharging in order to update the battery capacity, which rarely happens in the real applications, thus it results in greater measurement error. Therefore, it is very difficult to accurately predict remaining battery capacity and working hours in the cell cycle run-time .

The (IT) technology of the tracking impedance is unique, and is also far more precise than the existing solution, the reason is that this technology has the study mechanism by itself which can solve the aged question caused by the battery impedance and chemistry entire capacity (Qmax) changing under the idling condition. The (IT) technology of the tracking impedance studies and tracks the battery characteristic using kinetic simulator algorithm, it means that under the actual processing, it surveys the impedance and the capacity value first then tracks its change. It should not need to carry on the adjustment regularly under the complete cyclical capacity using this algorithm.

Because the discharging depth has the nonlinear relationship with the current electricity, the current voltage and the current temperature. Under the normal temperature, we can ignore the factor of the temperature. We can determine a discharging curve under the constant current from the Sub-capacity cabinet which can be the norm curve. Then before the load we measure the OCV, when it access the load, we can measure the current voltage, through the current electricity, we can measure the averaged impedance. Assumed that the impedance is constant, we calculate the voltage in norm curve corresponding to the off-voltage 3V. Through the above nonlinear relationship, we can calculate the current remaining capacity.

We should accurately forecast the surplus battery capacity in order to exactly calculate the cruise duration of li-ion battery under current condition and be for more effective discharge of lithium batteries in the case of the same capacity. What's more, we carry out the charging control by the method of variable pulse charge, this charging method compared with the traditional charging method is possessed with the characteristics of fast charging and high efficiency. This can greatly extend the life of lithium batteries [1-4].

II. THE PREDICTION OF LITHIUM BATTERY SOC BY RBF

A. RBF network

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Radial basis function neural networks are on the base of using the knowledge of local regulation of biology and overlap to accept the regional for reference and a sampling of local receptive field to implement the mapping of function the artificial neural network. RBF neural network is a feed-forward back-propagation network, which has two network layer: the radial hidden layer and output linear layer, as shown in Fig.1. RBF network adopt the Gaussian function. Because of hidden layer response to the input signal only when the input signal is at the central location of Gaussian function. That is partial response, so the network has a good local approximation ability [7]. The RBF neural network is an algorithm which essentially switch the existing nonlinear relationship to the linear relationship in another space.

$$a(n) = e^{-n^2} \tag{1}$$

This control system is mainly that using RBF neural network implement approximation of lithium-ion battery discharge curve, because any function can be expressed as a set of the sum of weighted basis functions. In the radial basis network, we select the transfer function of hidden neurons to constitute a group-based function which approach discharge curves.

Numbers, centers, widths of neurons in the hidden layer and weights of output layer are automatically determined at the process of creation and studying the RBF (first the nodes of hidden layer is one).

The basic principles of improved RBF neural network are as follows:

1) Simulate the network using all the samples input.

2) Find out the sample input that error is the most in the output of the network.

3) Add a radial basis neuron and use this sample input to be its center, the threshold b=0.5489/spread(Bigger the value of spread is, the more smooth the result of output is. but the value of spread is so big that it can lead to the difficult in numerical calculation).

4) Linear combination of the output of hidden layer network is as the input of linear layer and use the principle of least squares calculating the weights of output layer.

5) Whether the mean square error sums between the actual output value and the measured value meets the requirements of the error performance indicators, if not met, add a cluster center, repeat steps 1 ~ 3 until the number of neurons reaches the upper or mean square error meet the targets.

1) Principle of least square method

The basic principles of least squares method are: the best fitting straight line should make the sum distance of the

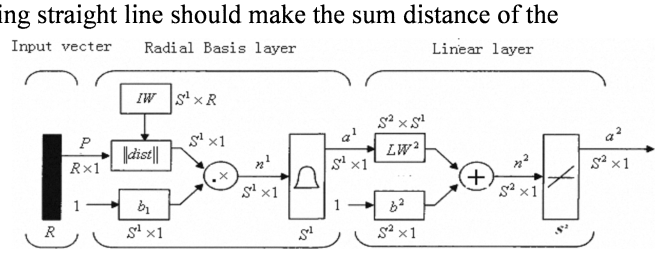

Fig.1 Model of radial basis function networks in matlab

to the straight-line the smallest, can also be expressed as making sum of square by distance smallest.

When provided by a large number of experimental data, we can not require the error which $\delta_i = \Phi(x_i) - y_i$ is strictly zero in the data point (x_i, y_i) from the fitting function $\Phi(x)$, but in order to reflect the trend of data points in approximate curve as far as possible, we should have a demand for the deviation. Usually it requires the least sum of the deviation square.

$$\sum_{i=1}^{m} | \delta_i^2 | = \sum_{i=1}^{m} (\Phi(x_i) - y_i)^2 . \tag{2}$$

Least square method is very convenient to be able to strike the weights of the output layer. Since to make the error sum of output of output layer the smallest (3), just met (4), you can solve linear equations. Using C language implement solution of linear equations, we can use Jacobi iteration method implementation (5).

$$\varepsilon = \sum_j (y_j - \sum_i w_i u_{ij})^2 . \tag{3}$$

$$\frac{\partial \varepsilon}{\partial w_i} = 0 . \tag{4}$$

$$\begin{cases} x^{(0)} = (x_1^{(0)}, \ldots, x_n^{(0)}) \\ x_i^{(k+1)} = \dfrac{1}{a_{ii}} (b_i - \sum\limits_{\substack{i=1 \\ i \neq j}} a_{ij} x_j^{(k)}) \end{cases} . \tag{5}$$

B. Discharge characteristics of lithium batteries

The cathode materials of Lithium battery typically compose with the active compounds of lithium, negative electrode compose with a special molecular structure of carbon. the major components of Common cathode materials is LiCoO2 (there are also other lithium salt used as cathode material), when charging, voltage adding on the electric polarization force compounds of the battery cathode release lithium-ion, embedded in carbon in which negative elements were arranged lamellar structure. When discharging, the lithium-ion separate out from the lamellar structure of the carbon, and re-combine with the compounds of the cathode. The movement of Lithium have had a current. With the discharging current increases, the electrochemical reaction expedite, partial pressure of internal impedance of the battery increases, caused electrode potential dropping in the same time, and as reflected depth increases, active material concentration of the electrode decreases, the same to the electrode potential. The process of the battery discharging is a exothermic process, the change of temperature caused the internal impedance of battery change. Thus, the electrode potential, temperature, current and reflected depth must exist the inner contact [5].

$$Q_D = f(U, I, T) \tag{6}$$

U, I, T for the current state of battery discharge voltage, discharge current and temperature. QD for the depth of discharging in the current status. To simplify the model, the temperature set to ambient temperature, the nonlinear function described by the above improved RBF neural network approximation.

Battery testing processing go along with the Neware company's sub-capacity cabinet, and it automatically record all battery parameters (voltage, current, discharging capacity). Battery testing process include the following: first :all batteries discharge in the same discharge current 0.5C, after the completion and then by the same pulse charge method charging, and then discharge at different discharge rate.Including0.2C,0.3C,0.4C,0.5C,0.7C,1C,1.2C,2C. Record discharge voltage and discharge capacity by this method that interval 100mA choose a data point under each discharging current .

Battery SOC (flow in Figure 2) that can be expressed as:

$$SOC = (1 - \frac{Q_D}{Q_{\max}}) \times 100\% \,. \tag{7}$$

QD for battery discharge capacity under the current state, Qmax for the battery full charge capacity under the current status.

Capitalizing current status of SOC can be easily calculated (show as fig.2).

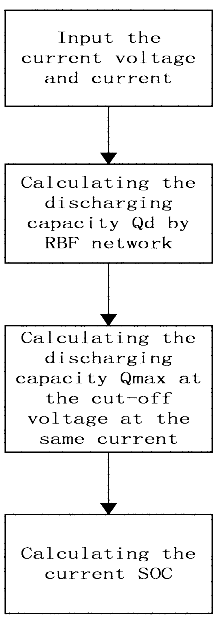

Fig.2 Battery SOC calculation of the current flow

C. Results of test

1) The approach to one discharging curve of li-ion (the value of current of discharging is 0.88mA show as Fig.4)

The number of the samples input is 21, the time of training is2.406sec,at last the error is 3.87,the number of radial basis nodes is 19, and protract the relation between the original curve and the approaching dots .

2) The approach to the discharging surface

Through the radial basis network approach to a number of discharging curve contemporarily (show as fig.6).the result is that when the number of input is 101,the final error is 25.642, the number of the centers of radial basis layer is 58.

In order to monitor the situation of the RBF network for the others input data, so I choose others input data from the discharging curve of 1.32A to be the input of the network (Fig.5). The result shows that when the voltage is under 3.5V, the error is relatively large. The method of solution is that I should choose more input training points under 3.5V, and then it can reduce the deviations .In the process of debugging, I found that the weights in second layer which we choose from the input sometimes could lead to diverge using the method of Gauss elimination or the method of iterative Jacobi.

The common method to handle this situation is normalizing, at first find out the maximum error and the minimum error in all the samples input, secondly deal with all

TABLE I

The current battery impedance	$R = \frac{V_{OC} - V_D}{I_D}$
Remaining capacity of battery	$RM = (SOC_{final} - SOC_{start}) * Q_{\max}$
Remaining time	$t = \frac{RM}{I_D}$
Battery full charge capacity of the current status	$Q_{\max} = \frac{Passedcharge}{\lvert SOC_1 - SOC_2 \rvert}$

Noting: Voc: the open circuit voltage of battery, VD, ID: the of voltage, current in the current status . SOCfinal: the SOC in the cut-off voltage under the current state, SOCstart: the SOC in The current status.

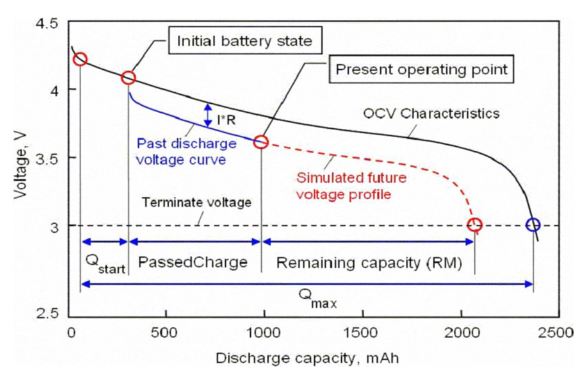

Fig .3 when loading , the battery discharge characteristics and the OCV curve [3]

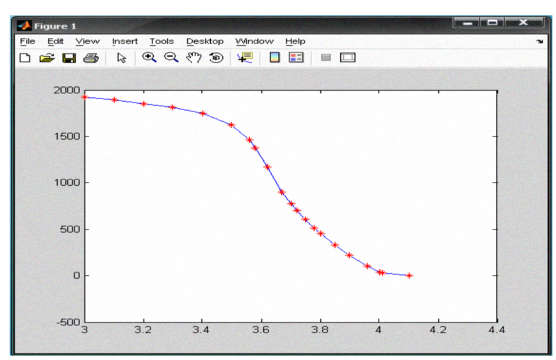

Fig.4 relation between the approach dots and real discharging curve those input data through formula 8 which method makes all the value of input between 0 and 1 .Thus can improve the convergence of the network. But now, I use another method to handle this situation which stores the value of error into one array from the maximum to the minimum after each training of network using Bubble act and the same time store the sequence into another array. If choose the value of input to be the center of radial basis node which lead to the maximum error in the last training in network, the result of output diverge. And than so do the second, third……until the result converge. Thus can avoid the inputs data dealing to do the normalizing and anti- normalizing . And can easy to real-time observe the situation of network training.

RBF neural network arithmetic are in the C + + compiler and debugging environment, index of error between the output of a set of training data input and the discharge capacity of test meet the error performance. So this method is feasible. Finally the weights and the threshold of the radial basis layer and the output layer by training of RBF network have stored in the array. there is no integration of the internal floating-point operations in ATmega8, and so adopt to the fixed-point instead of the floating-point. so the accuracy of the depth of discharge through the network to calculate are subject to certain limitations finally. After transplant into ATmega8, the radial basis network is equivalent to a block box that means that when input the current voltage and current, the network can output the depth of discharging. And than accord to the fig.2.what's more, it can calculate out the current remain capacity.

$$X_{nor} = \frac{X - X_{\min}}{X_{\max} - X_{\min}} \quad (8)$$

III VARIED PULSE CAHRGE

A. Varied pulse charger testing lab

The maximum discharge current have certain restrictions when Li-ion battery discharges. When the discharge current is greater than the maximum that will lead to shortened battery life or damage, it may also cause serious accidents such as explosions in a long high-current discharge.

Power tools normally used in DC motors, the current in state of starting the work is as XX times as the normal state, which is far beyond the endured value, what's more, the power tools often need frequent start and it make the battery in the state of high-current discharge chronically.

To find more effective ways of charging, it can carry on fast charging, improve the efficiency and save the energy and protect the environment at the same time .

There is a new variable pulse charge mode which make up of constant-current charge and variable pulse charge. The parameters of time and electric current of the constant high current charging and the parameters of variable width and variable cycle of variable pulse charging adapt to the chemical characteristics of the battery by itself in order to the best.

Following the pulse charge flow (fig.8), settings at the company Neware's sub-capacity cabinet are as follows:

Principle of pulse charging is similar to the traditional constant-voltage and constant-current charging method. Found in experiments, when the battery charge, the voltage of the terminal battery happens the virtual high (the greater the current, the higher virtual voltage), when shelved, the battery voltage would dropped, This is caused by partial voltage of the internal impedance of lithium batteries .So try to use constant-current charging to 4.2V, and then shelved at 5min, comparing the bias between the current battery voltage and 4.2V, if it is in the range of 0.5%, stop charging, or else reduce the current to recharge, and so the cycle until the voltage deviates at 0.5% reaching full request.

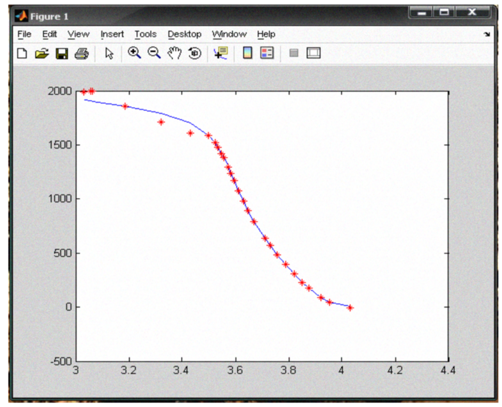

Fig.5 test the RBF network in effect map

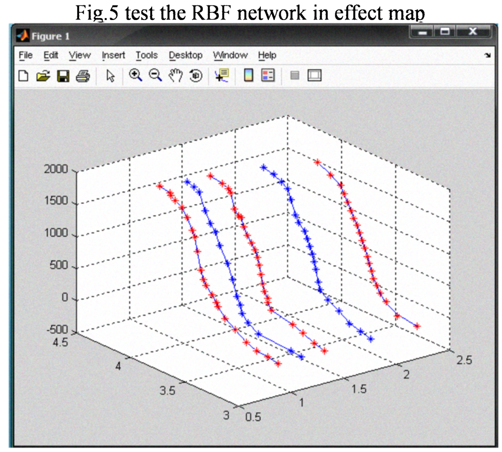

Fig.6 the approach to a number of discharging curve contemporarily

B. The results of testing

The capacity of charge is 2369mAh, the voltage of shelved after the completion of charging is 4.1989V,the total charge time is 207min. discharging capacity of 1C is 2367.7mAh.

Varied pulse charging method and constant-current and constant-voltage charging method is contrast to the relationship as follows (table II):

The table II data indicates that pulse charging method is more effective than the traditional constant-current constant-voltage method.

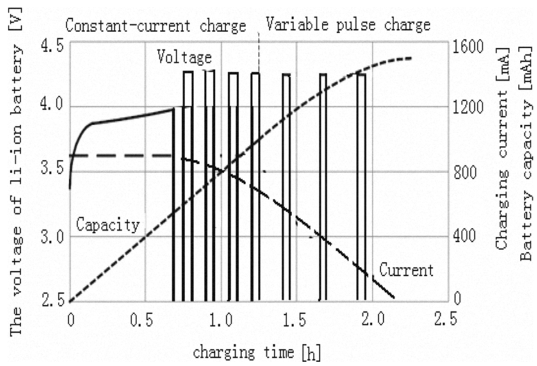

Fig.7 the variable pulse charging curve of li-ion battery

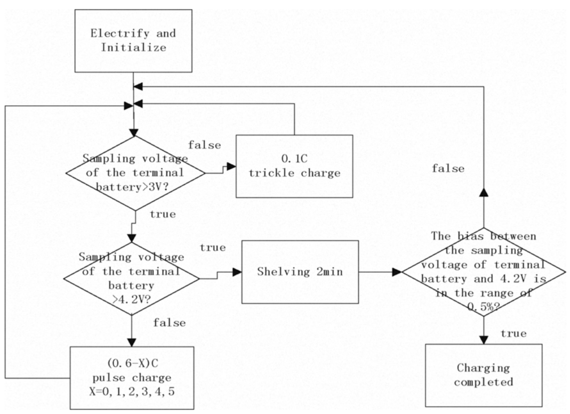

Fig.8 Variable pulse charging flow chart

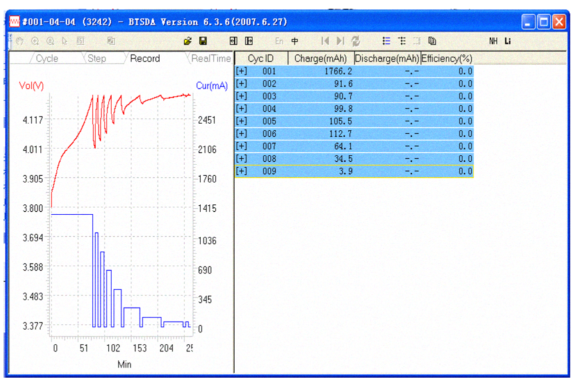

Fig.9 Varied pulse charging data chart

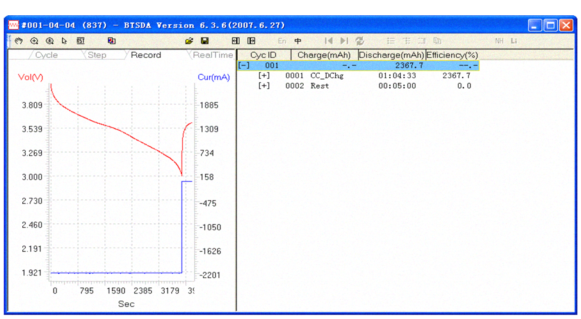

Fig. 10 1C Varied pulse discharging data chart

TABLE II

	The charging time	Cut-off voltage	Discharging time
The method of variable pulse charging	207min	4.1989V	2367.7mAh
The method of constant-current and constant-voltage	260min	4.192V	2328mAh

IV SUMMARY

Through the improved RBF neural network arithmetic predict the residual current battery capacity, results show that the accuracy of the model meets the requirements. But there is still some limitations ,through the battery SOC can predict the remaining battery capacity in the current state, the next step should using the current integrator to integral the inflow / outflow of current sampling value, and regularly keep required discharge voltage, current and depth of discharge database maintenance. If you can meet the three conditions above, we can accurately detect the dynamic remaining battery capacity. Coupled with the rapid and efficient battery charging, the full utilization of the battery characteristics, those can greatly improve the battery life and efficiency.

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