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Research on the SOC Prediction of Lithium Ion Battery Based on the Improved Elman Neural Network Model

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Lithium ion battery has the characteristics of good thermal stability, high energy ratio, long cycle life and so on. As an energy supply component, lithium ion battery is the key electronic equipment and a component of complex systems. Lithium ion battery (Li-ion battery) plays a crucial role in the overall system. In the current global advocacy of low carbon and emission reduction, these characteristics of the Li-ion battery make it a new driving power for electric vehicles. The prediction of SOC (State of Charge) of Li-ion battery is one of the key technologies of battery management. The research of the SOC prediction of Li-ion battery is of great importance to the development of electric vehicle industry. In this paper, we propose an improved Elman neural network model to predict the SOC of Li-ion battery. At the end of the paper, we found that the improved prediction model can provide better SOC prediction services for Li-ion battery and the prediction results are more accurately.

1. Introduction

With the decrease of non-renewable resources and the increasing pollution of the environment, the protection of the environment has aroused widespread concern of the public. The new energy technology has received extensive support from all sectors of society and these supports promote the development of new energy technologies. As an important symbol of new energy, electric vehicle attracts more and more countries' attention (Chellaswamy and Ramesh, 2017). Electric vehicle is the future development trend of automobile with the characteristics of low carbon emissions and clean energy (Liu et al., 2017).

As the power source of electric vehicles, the selection of batteries is very important. In general, battery for electric vehicles requires large battery capacity, light weight, small size, short charging time and so on. As a kind of green high energy rechargeable battery, Li-ion battery has made great progress in recent years. It has been widely used in the EV battery industry. Li-ion battery has been praised as a high-tech product of great significance to the national economy and people's life in twenty-first Century.

Li-ion battery is a new type of green rechargeable battery (Liu and Zheng, 2010). At present, the academic research on Li-ion battery mainly focuses on two aspects of energy density and safety improvement (Purkayastha and Meeking, 2013). The rapid development of Li-ion battery has put forward higher requirements for battery management. Therefore, it is very meaningful to predict the State of Charge of Li-ion battery (Lu et al., 2013). AS an important parameter in the operation of electric vehicles, accurate estimation of SOC is particularly important (Guo et al., 2017). At present, SOC prediction methods are mainly discharge experiment, ampere time integration, open circuit voltage, etc. (Ceraolo, 2000, Zhang and Lee, 2011).

We propose a modified Elman neural network model to better predict SOC for the Li-ion battery. In the Elman neural network model, we add error feedback and improve the inspirit function. These measures will increase prediction accuracy. The first part of this paper is the introduction, which mainly introduces the research background. The second part analyzes the Li-ion battery. The third part presents the Elman neural network model. In the fourth part, we propose a modified Elman neural network model. The fifth part is numerical experiment. In this part, we use the modified model to carry out the experimental analysis. The experimental results prove the high precision predicted by the modified method.

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2. Lithium ion battery analysis

The Li-ion battery can be divided into *LicoO*$_2$, *LiMn*$_2$*O*$_4$, *LiFePO*$_4$ and multi-element composite (Bittagopal et al., 2017). Li-ion battery is further developed on the basis of metal lithium batteries. The voltage of the single cell battery is higher than that of other batteries. At the same time, Li-ion battery has the advantages of small in size and light in weight, large specific energy, long service life and green environmental protection (Harting et al., 2017).

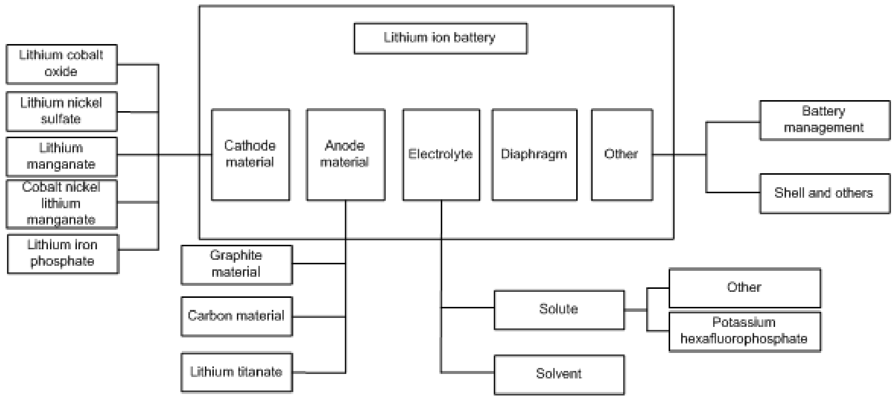

Figure 1: Assumption diagram of lithium ion battery

In China, lithium iron phosphate is always used as the cathode material of Li-ion battery because of the characteristic of good cycle performance and safety.
When the battery is in charge state, Li^+ is removed from the anode and embedded in the negative electrode. Discharged is in reverse.
Charge

$$LiFePO_4 \rightarrow Li_{(1-x)}FeO_4 + xLi^+ + xe^- \quad (1)$$

Discharge

$$Li_{(1-x)}FeO_4 + xLi^+ + xe^- \rightarrow LiFePO_4 \quad (2)$$

LiFePO$_4$ is the positive electrode of the battery. *LiFePO*$_4$ is connected by aluminum foil to the positive electrode of the battery. In the middle of the battery is the diaphragm of the polymer, separating the anode from the negative.
Lithium ions Li^+ can pass through the septum and electrons e^- cannot pass through it. The other half is a battery anode made of carbon. When the *LiFePO*$_4$ battery is charged, the lithium ions Li^+ in the positive electrode move through the polymer diaphragm to the negative electrode. During the discharge, the lithium ions in the negative electrode migrate through the septum to the positive electrode (Chen et al., 2017).
Lithium batteries have the following characteristics
(1) Higher energy. The size of the Li-ion battery is 30% smaller than that of the Ni MH battery and the quality is 50% lighter than that of nickel hydrogen batteries. Li-ion battery of the same volume and weight can provide higher energy.
(2) High operating voltage. The nominal voltage of the Li-ion battery is 3.6V, 3 times of nickel chromium and nickel hydrogen battery, and 1.8 times of lead-acid battery.
(3) Charge and discharge more frequently. The charge and discharge times of Li-ion battery can reach 2000. Most other batteries are usually 300-500 times. This shows that the Li-ion battery has a long cycle life.
(4) Self discharge rate is low. The self discharge rate of Li-ion battery is low. Li-ion battery maintains a very long charge time in the same environment.
(5) No memory effect. Memoryless effect of Li-ion battery. Both Ni Cr batteries and Ni MH batteries have memory effects.
(6) Wide temperature range. The working temperature of the Li-ion battery is between -20 and 60 degrees. Especially in extreme -20 cases, it is still capable of releasing 90% of the capacity.
(7) Green environmental protection. Regardless of production, use and scrap, Li-ion battery does not contain or produce any Toxic heavy metal elements and substances.

3. Elman neural network model

Elman neural network has the characteristics of fast convergence and good prediction accuracy (Hsu, 2014). Elman neural network is a feed-forward neural network with local memory capability and local feedback link (Liu et al., 2015). Undertake layer is mainly used for the internal feedback connections among the hidden layers (Li et al., 2014).

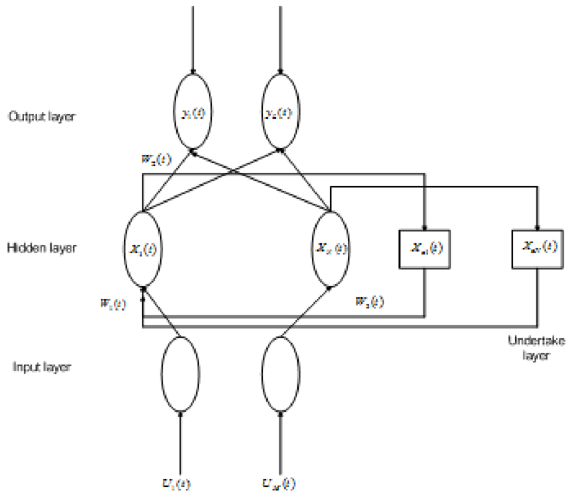

Figure 2: Elman neural network model structure diagram

According to the figure 2, we learn that the output value of the network structure at *k* time is

$$x_{c,l}(k) = a \cdot x_{c,l}(k-1) + x_l(k-1), l = 1, 2, \cdots, m \tag{3}$$

$x_{c,l}$ and x_l is the output of the l hidden layer element, a is the feedback gain factor of self-connection.
When a=0, the neural network is the standard Elman network (Achanta and Gangashetty, 2017).
u is the r dimensional output vector. x is the n dimensional intermediate layer node element vector. x_c is the n dimensional feedback state vector. y is m dimensional output node vector. w_1 is the connection weight from the undertake the layer to the middle layer, while w_2 is the one from the input layer to the middle layer and w_3 is the one from the middle layer to the output layer. f(*) is the neuron activation function of the hidden layer. g(*) is the output neuron activation function. The nonlinear state expression of the Elman neural network is as follows.

$$y(k) = g(w_3 x(k)) \tag{4}$$

$$x(k) = f(w_1 x_c(k) + w_2 u(k-1)) \tag{5}$$

$$x_c(k) = x(k-1) + a x_c(k-1) \tag{6}$$

4. Improved Elman neural network

For improving the prediction accuracy, the structure of the neural network is improved. We first add the error feedback between the input layer and the output layer. Error refers to the relative error between the predicted and the true values. When we predict, we use the *nth* predicted value to correct the (*n*-1)*th* predicted value. We feed the results back to the input layer and retrain the network and the prediction accuracy of the network will be greatly improved. Then, we use the *nth*, (*n*+1)*th*,…, (*n*+*m*-1)*th* predicted value to predict the (*n*+*m*)*th* predicted value. The prediction accuracy will be greatly improved.
The improved error is *E'*. The input is *u*'(*k*-1). The hidden layer unit output is *x*'(*k*). *y*'(*k*) is the output of the output layer unit. The expected value is *d*(*k*).
We support

$$u'(k-1) = u(k-1) - m\nabla E \tag{7}$$

So

$$x'(k) = f(w_1 x(k-1) + w_2 u(k-1) - w_2 mE) \quad (8)$$

Support

$$\omega = w_1 x(k-1) + w_2 u(k-1) \quad (9)$$

$$\omega' = w_1 x(k-1) + w_2 u(k-1) - w_2 mE \quad (10)$$

$$m' = w_2 mE \quad (11)$$

Namely

$$x'(k) = f(\omega'), x(k) = f(\omega) \quad (12)$$

If

$$E > 0 \quad (13)$$

Then

$$m' > 0, \omega > \omega' \quad (14)$$

So

$$x'(k) < x(k) \quad (15)$$

$$y'(k) < y(k), E < E \quad (16)$$

When

$$E < 0 \quad (17)$$

And

$$E' > E \quad (18)$$

We can get

$$|E'| < E \quad (19)$$

sigmoid function is used as an incentive function $f(x)=1/(1+e^{-x})$,Linear function is used as output layer function. But the sigmoid function often slows the convergence rate and makes it easy to get the network into local minimum, so it is improved.
The improved excitation function is

$$f(x) = m + 1 \big/ (1 + e^{-h(x+n)}) \quad (20)$$

Derivative function is

$$f'(x) = -\frac{h}{(f-(m+\frac{1}{2}))^2} + \frac{h}{4} \quad (21)$$

Among them, m and n are constant. h is slope. By setting the values of m and n, the function moves along the vertical and horizontal directions. parameters of m, n and h are corrected. In addition, the learning rate is related to the derivative function $f'(x)$ of the excitation function. The greater the value of the derivative function $f'(x)$, the faster the speed of learning. By adjusting the parameters of m, n and h, this model can reach the optimum convergence speed and prediction accuracy.

5. Numerical experiment

Improved Elman neural network model is used to predict the SOC of Li-ion battery. SOC prediction is a very important part of the battery management system. This index reflects the state of the battery. The accurate prediction of the battery charge state (SOC) is the primary task of the battery management system.
In general, the SOC of the Li-ion battery is defined as

$$SOC = (Cr/Co) \cdot 100\% \tag{22}$$

Cr is the battery residual capacity. Because of the future discharge will be affected by *Cr* and *Co*, it is usually used SOC_a to indicate the state of charge:
Cr can be defined as

$$Cr = Ca - Cu \tag{23}$$

Cu is the current battery status that has been consumed

$$Cu = \int_0^t k \cdot i\,dt \tag{24}$$

k is the weighting factor for power consumption at different discharge rates.
We first use different prediction methods to predict the SOC and compare the different predicted values with the actual values. The result of the experiment is shown below.

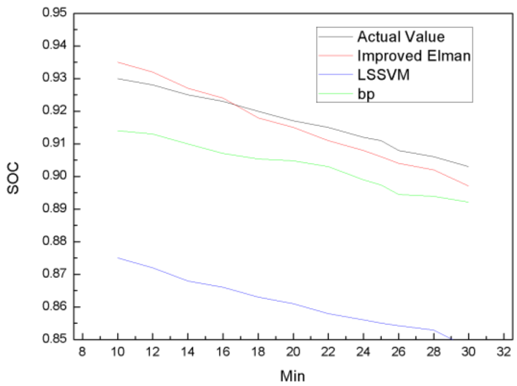

Figure 3: Comparison chart of SOC of different methods

We can see that the modified Elman neural network model is the closest to the actual value compared with other methods, which demonstrates that the prediction method has higher prediction accuracy than the compared methods.

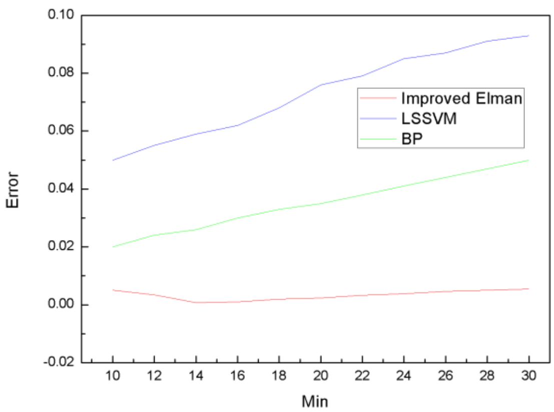

Figure 4: Comparison chart of error of different methods

The error of the improved Elman model proposed in this paper is minimum and the error of other methods is larger. Figure 3 and figure 4 illustrate that the improved Elman neural network model has achieved good results in SOC prediction of Li-ion battery.

6. Conclusion

The whole society is paying more and more attention to environmental protection. At the same time, the non renewable energy is decreasing. These two factors contribute to the development of the pollution-free energy and renewable energy. Automobile exhaust is an important pollution source of air pollution. The use of new power instead of gasoline can reduce pollution. Li-ion battery is characterized by small size, high voltage and high specific energy. The development of Lithium ion battery technology as an electric vehicle power is the current trend of development. In this paper, we research the SOC prediction of Li-ion battery to realize better management. We use the improved Elman neural network model to predict the SOC of Li-ion battery.
The main work of this paper includes (1) introducing the background of this paper (2) analyzing the Li-ion battery (3) introducing the Elman neural network (4) putting forward the improved Elman neural network and predicting the SOC of Li-ion battery. The experimental results show that the improved Elman neural network can predict the capacity of Li-ion battery more accurately.

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