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State of Charge Estimation of Ni-MH battery pack by using ANN

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1. Introduction

1.1 Background and significance of the research

Currently, the world's fuel vehicle is growing by the rate of 30 million per year. It is estimated that the total amount of the world's fuel vehicle for the whole year will reach one billion. The sharp increase demand in oil's resources, further aggravate the shortage of oil resources in the world [1-2]. Fuel vehicle exhaust emission is the main source of urban air pollution today, and the negative impact on the environment is enormous. Environment is closely related to the survival and development of human society. In the case of the energy shortage and environmental protection urgent need to improve, governments invest enormous human and material resources to seek new solutions. This is also bringing the development of electric vehicle [3-6].

As power source and energy storage of HEV, battery is the main factors of impacting on the driving range and driving performance of HEV [7-8]. At present, the most important question is the capacity and battery life issues with HEV application. Only estimate SOC as accurate as possible can we ensure the realization of fast charging and balanced strategy. The purpose of that is to prevent over charge or discharge from damaging battery, and improve battery life. This also has practical significance in increasing battery safety and reducing the battery cost [9].

How accurate tracking of the battery SOC, has been the nickel-hydrogen battery's researchers concerned about putting in a lot of energy to study. Currently, it is very popular to estimate the SOC with Ampere hours (Ah) algorithm as this method is easy to apply in HEV. The residual capacity is calculated by initial capacity minus capacity discharged. But Ah algorithm has two shortcomings. First, it is impossible to forecast the initial SOC. Second, the accumulated error cannot be ignored with the test time growing [10]. The researchers also used a new method that the battery working conditions will be divided into static, resume, three states of charge and discharge. Then estimate on the three state of SOC separately. It can disperse and eliminates the factors that affect the SOC value in the estimation process. Particularly in the charge-discharge state, they improve Ah algorithm by using the dynamic recovery value based on the coulomb efficiency factor. It solves the cause of the problem of accumulated error by Ah counting method, but this method cannot be displayed its accuracy in the complex conditions [11]. After analysis the large amounts of data under different charge or discharge test conditions, the researchers developed the battery model by cell theory and the external characteristics of the battery pack. Through a large number of experiments, the battery model is improved step by step. At last they completed the final model for measuring SOC in online and real-time. Through Digital model, the battery system's state equation and observation equation can be established. Kalman Filter is use to achieve the minimum mean square error (MMSE) of SOC estimation. The precision of the algorithm is analyses by a experiment in Different charge and discharge test conditions. Through continuous improvement, they can get the algorithm which does not demand exact conformity to initial SOC value. However, this method need researcher's high capacity and is too complicated to fit for the current application [12].

In addition, there have some other methods, such as open circuit voltage, resistance measurement, discharge experiment, the load voltage method and so on [13-15]. But they still cannot meet the requirements of the control requirement of HEV.

1.2 Main content

EV or hybrid electric vehicles (HEV) are mainly used secondary battery in power batteries. Than any other batteries, Ni-MH battery has many advantages: rapid charge or discharge high current, high resistance to charging and discharging capacity, low temperature performance, high mass-power ratio, environmentally friendly (no cadmium mercury or lead) and so on [16].Therefore, this paper studies how to fast and accurately track the SOC based on Ni-MH battery.

This paper designs an artificial neural network (ANN) for predicting Ni-MH batteries in EVs. For achieving the predictability of the network, the text use some basic characteristics of the ANN algorithm such as the ability of non-linear mapping, adapting to the self-learning, parallel processing method, and so on[16-17]. The influence between the current SOCt of Ni-MH battery and the previous SOCt-1 is not considered in most of published paper for the sake of tracking SOC by ANN when they select input variable. So the previous SOCt-1 is interpolated into input variable in this paper. That is to say, the input variable of this discourse are: battery discharging current I, battery terminal voltage U, and previous SOCt-1. Through training a lot of samples, ANN can study and adapt the unknown system's dynamic characteristics, and the characteristic will conserve inside the connected weight of ANN. Simulation results show that the proposed ANN algorithm can accurately predict Ni-MH hybrid vehicle battery SOC, and the average error of output results to reach about 5% in a short time.

2. General layout of ANN

2.1 Basic principles of ANN

The ANN comprises by input layer, hidden layer and output layer. The hidden layer may be one or more layers. The topology of the network is illustrated as figure 1[18-20]:

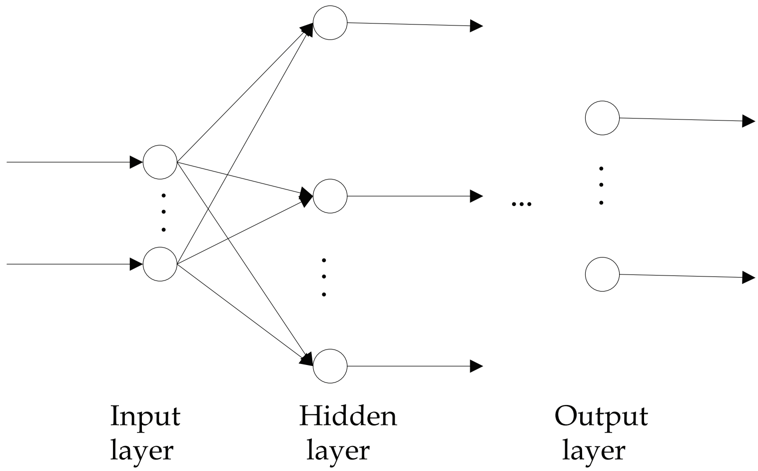

Fig. 1. The model of multilayer perceptron

The number of neurons in input layer is equal to the dimensions of the input signal, the number of hidden layers and hidden nodes depends on the special details, and the number of neurons in output layer is equal to the dimensions of the output signal. In addition to input and output layer, the multilayer perceptron includes one or more hidden units. The hidden units make the network be able to complete a more complex task by picking up more useful information from the input mode. Many synapses of the multilayer perceptron make the network more connective, the changes of the connection domain and connection weights will influence its connectivity. Multilayer perceptron has a unique learning method, which is the famous BP algorithm. Therefore the multilayer perceptron is frequently called the BP network.

It is supposed that the input units are n, the output units are m, and the effect of the network is the map from n-dimension space to m-dimension space. It can be proved that anyone of the nonlinear maps f can accomplish by a 3-layer network. That is to say, it will come true only by one hidden layer. The dimensions m, n of the vector have no any limiting condition. This makes many practical problems with the ANN method to solve possible. In theory, the BPNN can realize any link function map and its range of application is very wide.

2.2 Selection of sample

The performance of ANN is related to the choosing of samples. To successfully develop the useful ANN, the extraction of data samples is the key step. It contains initial data collection, data analysis, variable selection and data pretreatment. Only by these measures can ANN be for effective learning and training.

In this text, we collect once data every 10ms in many driving cycle which set up different initial condition (such as charge and discharge current). After receiving the real-time data of current, voltage and other basic parameters of hybrid car batteries, we can calculate the real-time SOC of the battery by Ampere hours (Ah) algorithm.

The collected data have a certain similarity, for example, directly extract training samples result in containing many redundant data. So they need preliminary sorting. It contain

abandon various kinds of irrational points that causing severe mutations of SOC, periodicity or consistently data also be selected only one group.
To a complex issues, how many data should be selected, which is also the key issues. System input-output relationship is contained in these data samples, so generally the more select data, the more learning and training result reflect the relationship between input-output data. But selecting too many data would increase the cost of the collecting data, the analysis data and network training; of course, selecting too few data could not receive the correct result. In fact, the number of the data depends on many factors, such as the size of the network, the need of the network test and the distribution of the input-output and so on. The size of the network is the most important, and ordinarily the larger network need the more training data [21].
Be inclusive of needing to pay attention to the attending training neural network data, also consider after the neural network finished, needing other test data to chow test the network, and the text data should be independent data assemble.

2.3 Establish the ANN model

The article focus on how to predict battery SOC in real-time according to the battery tested data (cell current 、voltage)based on neural network. Generally, its usual operation is that choose the simple network also meet the request. Design a new network type seems difficult. Currently, among the practical application of ANN, the most majority of neural network has adopted BP. Many studies have shown that BPNN with three layers could reach to factual function f( ), thus the article has introduced the triple layers most commonly used BP neural network. The battery current,voltage act as the measured parameter basis for the battery, it must compose the input parameter in neural network. Given the certain relationship between battery SOC changes and its previous SOC, therefore it has to elect the SOC_{t-1} as its input parameter among building the neural network.
Under current time t, determined that HEV Ni-MH battery SOC_t and the current I_t, voltage U_t as well as the raletionship with the preceding time SOC_{t-1}, this is a forecast to the function curve. We can also understand the SOC_t as a three circular function f which is constituted with I_t, U_t and SOC_{t-1}.This has determined the input and the output parameter of the neural network.
After having determined input and output variable, the node number of the network difference level and the output level also determined along with it. Regarding to the layer number of the hidden layer, we first only consider to how to choose a hidden layer, and the left question is how to choice the node point number of the hidden layer. In neural network's design, increases the number of the hidden layer's neurons can improve the precision which the network and the training set match, but the more of the hidden layer's neurons is not better. Too many number of the neuron will let the network remember all training data including noise. It will reduce pan-ability of the network. In the foundation of it can reflect correctly the relationships between input and output, selects the few hidden layer nodal point number. This makes the network to be as simple as possible [20]. After contrast simulation according to cut and try method the result discovered that neural network's hidden layer uses 10 neurons can describe curve relations about the input variable and the output variable quite accurately.
The ANN structure is used in this experiment shown in Fig. 2.

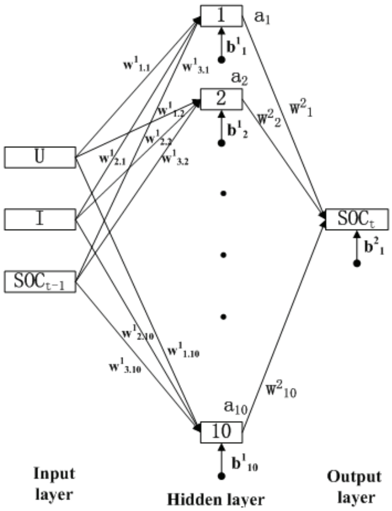

Fig. 2. Two layers of neural network structure

In the Fig. 2, w expresses the connection of weight between the two layers, b means every neuron's threshold, f expresses ANN's transfer function. Superscript on the $w^1{}_{1.1}$ expresses this value is the connection weights between input layer and hidden layer, while the weight of hidden layer and output layer expressed by number 2; the first number 1 of subscript means input is U_t, and the input I_t, SOC_{t-1} are expressed by number 2, 3; the second number 1 of subscript expresses the connection weights between the first neuron of the hidden layer and the input value. The superscript of $b^1{}_1$ means hidden layer neurons, and output layer neurons express with number 2. The subscript of $b^1{}_1$ means the first neuron of current layer. The a_1 expresses the first neuron's output in the hidden layer.
The output SOC of ANN's output layer defined as:

$$SOC = f[w^2 * f(w^1 * x + b^1)] + b^2 \tag{1}$$

x is the input value of ANN, and linear transfer function is $f(x)$ which equal to x in upper equation.

3. Training algorithm

In general, BP neural network is a kind of three or more than three multilayer neural network, it's about each neuron between the layers to achieve full connectivity, namely each layer in the left and right layers of neurons has a connection. BP network learning by a teacher's training. When a mode of learning provided to the network, its activation values of neurons will transmit from the input layer to the middle layer, land up output layer at last. Corresponds to the input mode, each neuron will export network response in the output layer. Then, follow the reduction of the desired output and actual output error principle, from the output layer through an intermediate layer, and finally back to the input layer connection weights layer by layer correction. This correction process is carried out from the output to the input layer. So it is called error back propagation algorithm. As this error back propagation constant training, the network input mode for the correct response rate is also rising.

It adopts the training and emulating alternate work model to avoid the net excess training. After the training samples achieve an net training, it keep the net weight value and threshold constant, validation samples data is used as the net input, running the net in forward direction and examining the average output error. During the simulation, the previous time simulation output is used for the next time simulation input, $SOC(i) = SOC'(i-1)$, $i > 1$ and is integral number. If continue training cannot decrease the average error, the net training is over. If we modify the parameter of NN such as learning rate slightly and keep the input and output constant, the average output error cannot decrease also, so we consider this net is the optimization result in the case of keeping the input and the Network Structure constant.
Commonly used BP algorithms exists a long time and slow convergence disadvantage etc. So this paper used the proportion conjugation gradient training algorithm. Conjugation gradient algorithm is required to search network linearly and then adjust its direction at each training cycle. This linear search at each search must be repeated for calculating all samples, this consumes a lot of time. While proportion conjugation gradient algorithm combines value trust region algorithm with the conjugation gradient algorithm, effectively reduce the search time mentioned above and improve the training speed of the network[22]. The BP neural network training process used in this article is shown in Fig. 3.

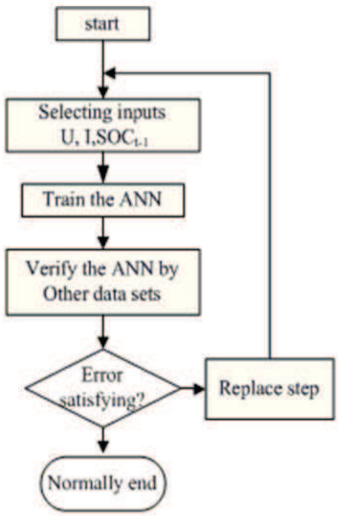

Fig. 3. The training flow chart of BPNN

Input training samples U and I are datum based on t moment in the Fig. 3. SOC is the data based on t-1 moment. ε represent a pre-set training ending goal. This goal is not the smaller the better, because over-training problem is existed in the network. Before we input the NN training sample, it must firstly assign the initial net parameter. ANN calculates the output of hidden neurons, and gets the Output of Output layer neuron. It also calculates every layer neuron output error. If the error is too big, we must modify the net weight value and threshold. After the sample are all trained, if the NN average error is smaller than the setting object for ending the training, the training is over, or else it keeps on new training after updating the total training steps.

4. Experiment results and analysis

4.1 Experiment and result

4.1.1 Training

In accordance with the above training methods, we first use the training sample to get a neural network and recorded it as network 1. In this topic research, we don't use the traditional authentication method, as lead the validation data into the model, and analyze difference value between the model prediction value and real value. The specific flow chart is shown in Figure 4. In the actual application, it only supplies the initial value or even the wrong initial value when we use battery management system to estimate electrokinetic cell SOC. In the research of this topic, we completely use the prediction technique. In the first time of prediction, we can get the input current, voltage and battery SOC, which the primary neural network model is needed. In the second prediction, we only input the collected current and voltage. The battery SOC is as the predication results as last time. In such a way, it can reflect the model's ability of self-adapting and tracing whole. When we have traced many times and amended the parameters such as network learning rate and so on, the output average error of the network still can't diminish. We will consider this network as the best result at present during the network input parameters are not changed. This paper will replace the network with the network 1 finally.

In the similar way, we can continue to add training samples b into the network 1, and obtain the network 2 by training. By parity of reasoning, when we have added the training sample of c, d and e, we can get network of 3, 4 and 5 respectively. The average error of each network at different time is shown in chart 1. As can be seen from chart 1, the average error of the output from the neural network 1 to neural networks 4 is gradually reduced, but it begin to increase from the network 5. It shows in the same case of input samples and training algorithm, network 4 is the best results we can get. This paper uses the network 4 as the neural network model, which will be tested finally. In which the training samples used as input of neural network's output comparison chart is shown in Fig.5. It uses the validation sample as input of neural network's output comparison chart is shown in Fig.6.

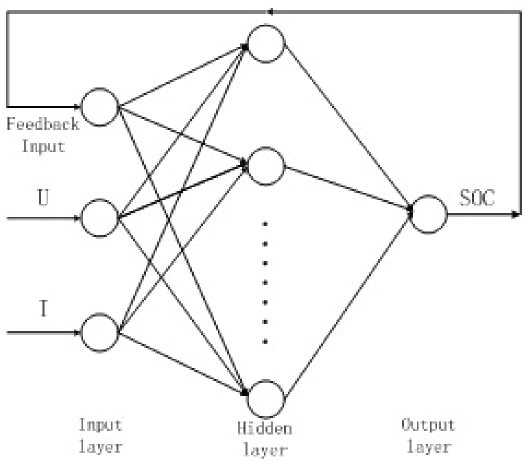

Fig. 4. The flow chart of checking model

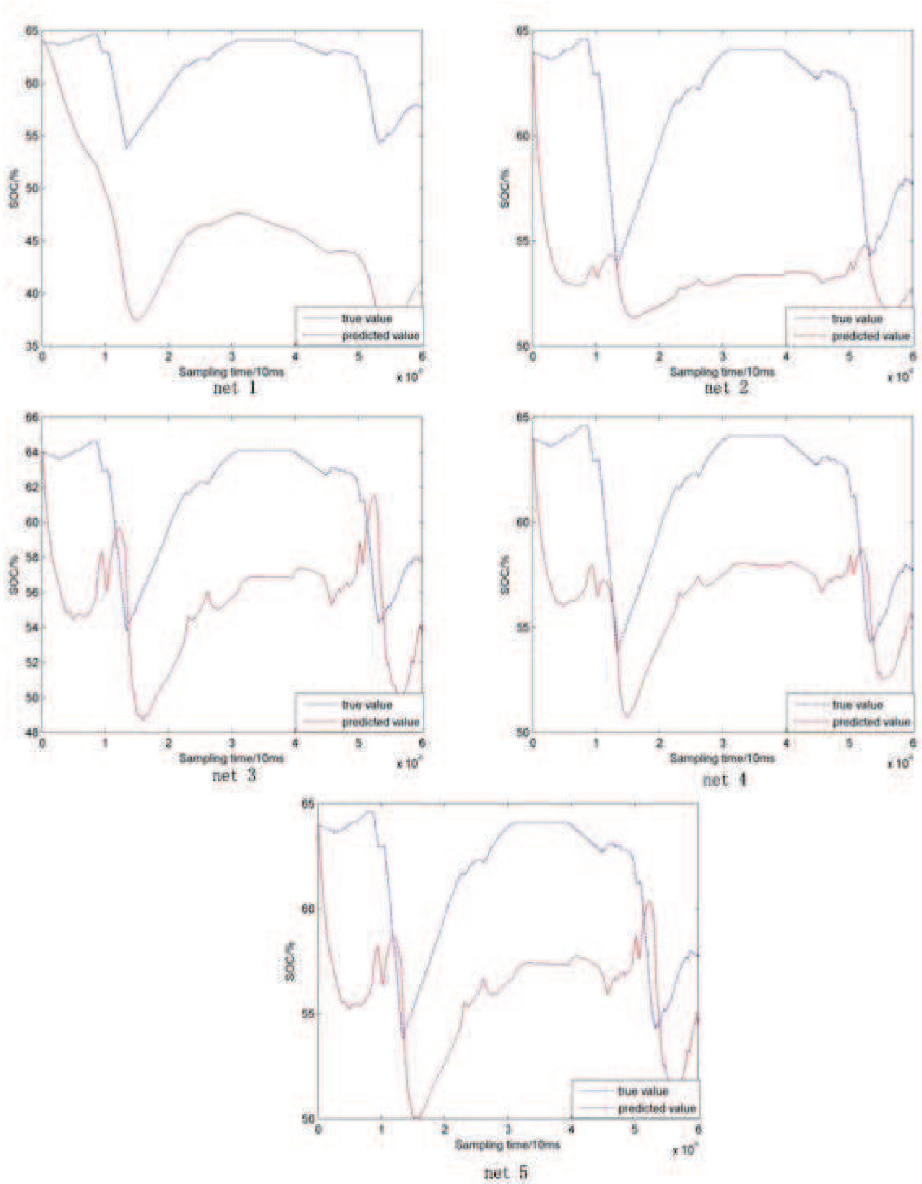

Fig. 5. The output result waveform of the training sample

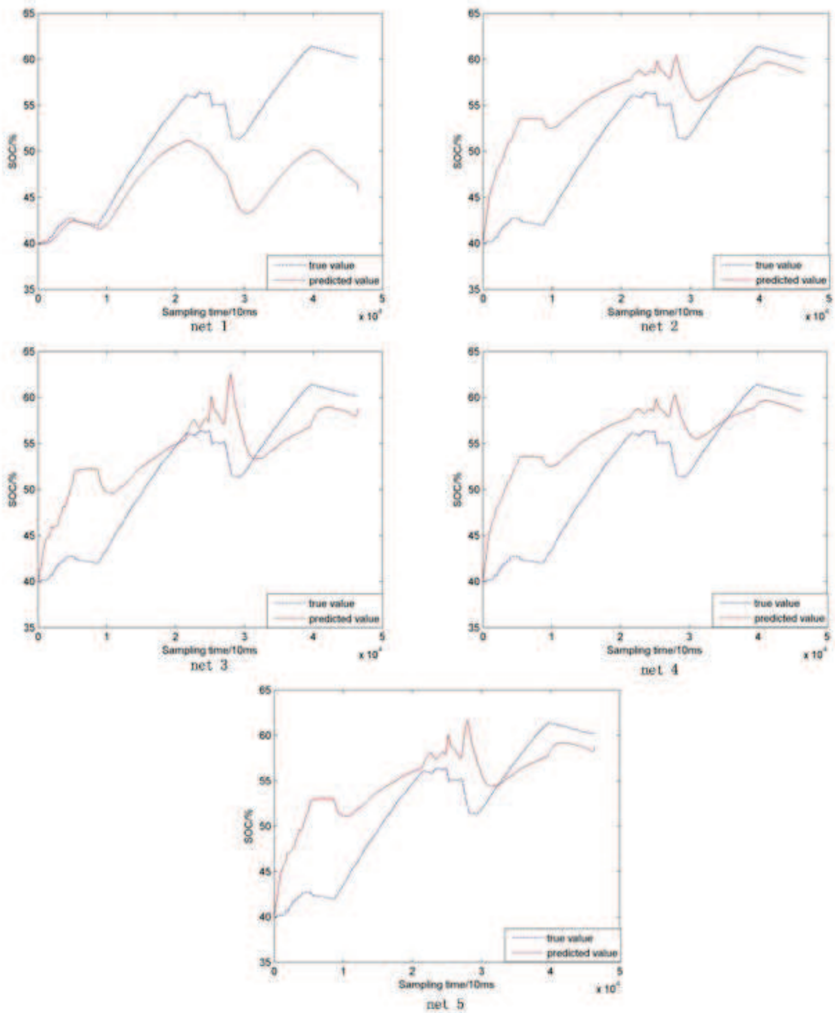

Fig. 6. The output result waveform of the checking sample is input.

		Net 1	Net 2	Net 3	Net 4	Net 5
start time error	training sample	29.9%	13.9%	8.9%	7.3%	8.1%
	checking sample	17.3%	9.7%	7.5%	9.5%	8.4%
3minutes 20seconds after error	training sample	29.8%	13.3%	8.2%	6.7%	7.5%
	checking sample	23.7%	7.1%	4.7%	4.2%	4.3%

Table 1. Different network's average error

4.1.2 Test and result

When you are sure the neural network which you have got is the best, use the validation sample and training sample to test the tracking of network respectively. That is in the any case of initial value setting of SOC, how long the neural network required to reduce output error to an acceptable extent. All samples' sampling time is 10ms. The initial value of SOC is obtained by Ah algorithm or is set arbitrarily (0, 30, 50, 70, 100 separately). Since the emulated waveform contains a number of fluctuations which are caused by current's mutation and voltage's mutation, this experiment uses a weighted filtering to process results. It consider the first few moments of factors in the current results (their own value instead of the output value at the start time). Through testing, the weighted parameters of all time choose the best one. Chart 2 shows the average error of some samples for the artificial neural network 4's forecast of results, which is in the condition of different initial value of SOC.

	Sample time t/s	average prediction error		Sample time t/s	average prediction error
Checking sample	87	6.9%	Training sample	64	7.2%
	150	4.8%		150	6.9%
	200	4.2%		200	6.7%

Table 2. The average error of ANN output

4.2 Result analysis

4.2.1 Training result

As can be seen from Table 1, we calculate the average error of the output from the initial moment. The inaccuracy of five networks which respectively use the training sample as the input are reduce at first, then its increase, and the NO.4 network's inaccuracy is the smallest. The inaccuracy of five networks changes to be quite disorderly which use the confirmation sample as the input. But apart from the network 1, the other four networks errors are about 8% and the differences are not large. As we calculate the average error of output from 3 minutes and 20 seconds, the inaccuracy of five networks are reduce at first which respectively use the training sample as the input, then its increase. The NO.4 network is the smallest. Regarding other abilities of ANN, generally we pay more attention to its generalization ability and tracking ability of the network running. From experimental results in Table 1, we know this paper focuses on change of the output's average error, which ANN uses the validation sample as input and start from 3 minutes and 20 seconds. At last the auto-adapted ability of Network 4 is the best, and the forecasting result is most accurate. From the comparison ware-form of output result in Fig.5, Fig.6 and Fig.7, we know, the output wave-form of network 4 is more close to the real value than other networks.

As Shown in Fig.7, it's the comparison chart of five network output value which ANN uses the validation sample as input value. Compares with other network's output result, the output result profile of network 4 and the network 5 are obviously closer the changes

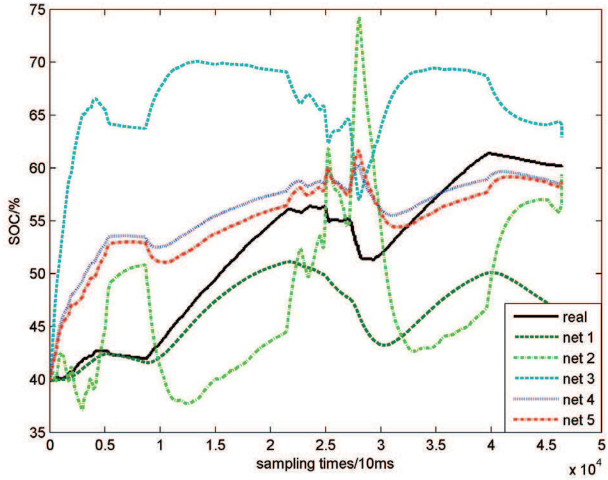

Fig. 7. Test Chart of five sample test network

waveform of real value in Fig.7. But from the Table 1 we know, the output average error of network 4 which calculated after a period of time after is smaller than the value of the network 5. Therefore, the network 4 is the networks which this laboratory needs.

Through the above analysis of training results, we use the network 4 as Neural Network which predicts the car battery SOC. Network structure of the network 4 as shown in Fig.8. And the weight of concealment level to output level is middle line of data in Fig.8. The weight of input level to conceals between the level as shown in Table 3.

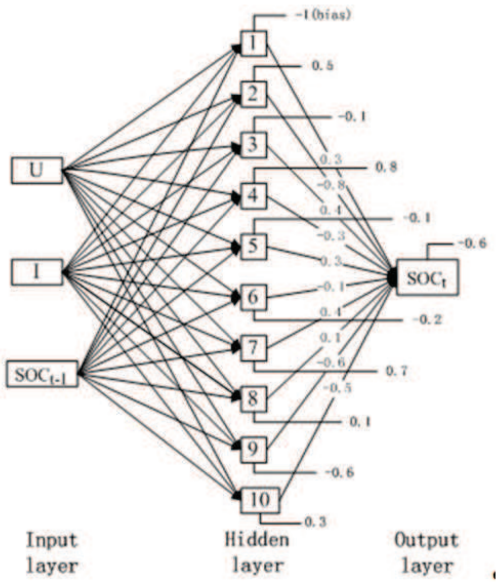

Fig. 8. Actual structure of neural network.

Hidden layer neuron	1	2	3	4	5
U/v	0.7	-0.3	0.1	0.02	0.6
I/A	0.3	0.5	0.9	0.7	-0.6
SOC/%	-0.8	-0.4	0.6	-1	-0.7
Hidden layer neuron	6	7	8	9	10
U/v	0.5	-0.2	-0.9	0.7	0.03
I/A	-0.2	0.9	0.8	-0.2	0.7
SOC/%	-0.6	-0.5	0.2	-0.5	-0.6

Table 3. The weight between input level and concealment level

4.2.2 Analysis of test results

In this paper, we illustrate the tracking performance of the neural network though the training sample and validation sample results. The SOC initial value of simulation respectively supposes 0, 30, 50, 70, 100 and the sample real value. The simulation result of training samples and confirmation sample of network 4 are shown in Fig.9.

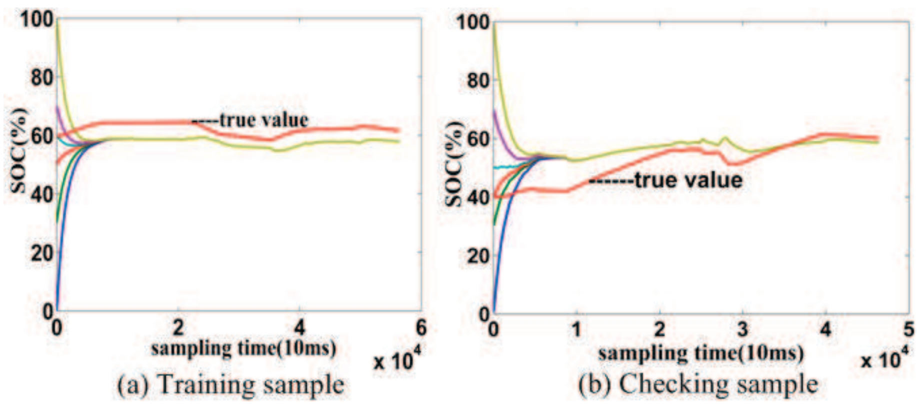

Fig. 9. The forecasting result of ANN as set the different SOC initial value

From Table 2, Table 3 and Fig. 9, we can draw that neural network can basically overcome prediction effect of the initial value of sample SOC set arbitrarily after training samples pass 64 seconds and checking samples pass 87 seconds. For checking samples, error comes to 6.9% after 87 seconds when the initial value is arbitrarily set 0, which is smaller than average error of 9.5% when the initial value is set true value. For training samples, error comes to 7.2% after 64 seconds when the initial value is arbitrarily set 0, which is smaller than average error of 7.3% when the initial value is set true value. As the time passes by, whatever the

initial value of experiment it is, the prediction average error of neural network is smaller and smaller, and the average error values are less than 10%. Through the above analysis, we can see that the neural network after training can be close to the target value of training network at a very short time and it has strong self-adaptive ability.
The waveform of the sample input variant U, I is shown in Fig. 10 and the sampling time is 10s.

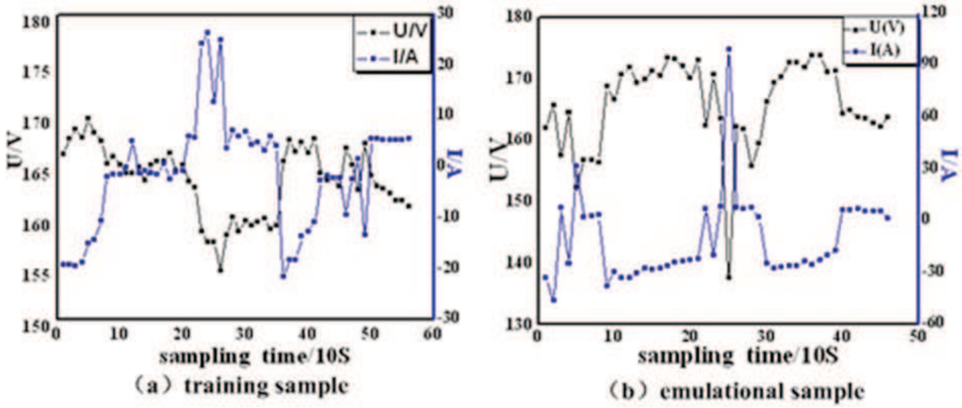

Fig. 10. Experimental data of current and voltage

The waveform of sample input variant U, I is shown in Fig.10 and the sampling time is 10s. Compared prediction waveform in Fig. 9 with the trend of sample current, voltage in Fig. 10, we can also see that the prediction ability of BP neural network algorithm can better reflect the trend of battery current and voltage. That is, when the current is negative, prediction result of SOC turns to decrease respectively. Output average error within 10% and the correspondence between input variable U, I demonstrate that it is very accurate to predicting the SOC of automotive power battery with BP neural network algorithm.

5. Conclusion

In order to predict the SOC of nickel hydrogen battery in real-time when the car is running, and at the same time guarantee the accuracy of prediction and good self-adaptive capacity, this paper designs a artificial neural network with three inputs and ten neurons and one output that can be used to predict the SOC of nickel hydrogen power battery. The neural network puts previous state of charge that is SOC_{t-1} to the prediction of the neural network, thus the effect of SOC_{t-1} toward predicting SOC_t is considered, so the self-adaptive ability of neural network is improved. Proportion conjugation gradient algorithm is used in the neural network training process, the connection weight value of the network is constantly changed via alternative training simulation and finally form fixed memory model for the prediction of the SOC. In the training network, but still pay attention to the selection of data, it has a great influence that different data sample finally forecast accuracy of network. Each training the neural network, it will gain a better simulation results, and then again add the data to back training network. At the same time, according to the comparison of the different neural networks, we can avoid over-training network. Simulation of the samples indicate that artificial neural network built by experiment can accurately predict the SOC of the nickel hydrogen power battery of hybrid automobile and the self-adaptive is good. These features make the algorithm has a very high application value.

6. Future work

In recent years, the new energy industry and electric cars were pushed to unprecedented level, which will generate a new round of development opportunities. The battery is essential to new energy, automotive and other industries as the energy storage device. In response to industrial restructuring, the healthy development of the emerging industry requirements, the battery capacity technology have higher requirements, the development of remaining battery capacity of prediction is very urgent. In this environment, this article from the battery capacity forecasting technology's current present situation and the trend of development, combined with the actual situation of nickel-metal hydride batteries, and established a BP neural network model. The algorithm in predicting SOC values more consider the weight factors which can be measured, and other unpredictable factors do not consider. To further improve the algorithm accuracy and reliability in harsh environments, much work will need to be done:

1. In order to effectively improve the accuracy of the algorithm, so that parallel operation, it also need to increase the inclusiveness of the data and add another algorithm in the neural network.
2. To take further the reliability of the quantitative analysis, this method only changes in charge and discharge current mode of qualitative analysis and evaluation, and no failure mode of the system reliability parameters, such as the quantitative calculation of system failure.
3. In addition to the above-mentioned factors, there are other factors to consider in the battery of the work environment, such as battery temperature of their environment, the consumption of battery life and other factors. Future research needs to take these factors into account, so it makes BP neural network is more complete and has better predictability.

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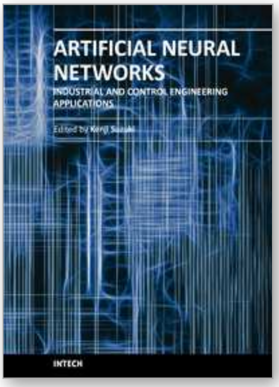

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Artificial neural networks may probably be the single most successful technology in the last two decades which has been widely used in a large variety of applications. The purpose of this book is to provide recent advances of artificial neural networks in industrial and control engineering applications. The book begins with a review of applications of artificial neural networks in textile industries. Particular applications in textile industries follow. Parts continue with applications in materials science and industry such as material identification, and estimation of material property and state, food industry such as meat, electric and power industry such as batteries and power systems, mechanical engineering such as engines and machines, and control and robotic engineering such as system control and identification, fault diagnosis systems, and robot manipulation. Thus, this book will be a fundamental source of recent advances and applications of artificial neural networks in industrial and control engineering areas. The target audience includes professors and students in engineering schools, and researchers and engineers in industries.