Design and Implementation of Neural Network Based Capacity Indicator for Lithium-Ion Battery

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Abstract

Usable remnant energy of a rechargeable battery is proportional to its state of charge, but the values of these two parameters are not exactly the same. A circuit based on neural network is developed for available capacity estimation of lithium-ion battery. To ensure the network consisting of optimal numbers of hidden layers and neurons, intensive experiments have been performed and various training algorithms have been evaluated. The experimental results reveal that the circuit is able to estimate the available capacity of a battery with arbitrary discharging profiles as well as continuous constant current discharging profiles. This paper presents the roadmap for the design and the practical constraints for hardware implementation of a neural network based lithium-ion battery capacity indicator.

Keywords

battery capacity indicator, neural network, lithium-ion battery, hardware implementation

1. INTRODUCTION

A number of papers have been published on theoretical modeling of a rechargeable battery, but few of them describe a practical way for real time estimation of the usable remnant capacity. Some of the proposed methods for remnant capacity estimation are too complicated to be implemented with a practical hardware circuit, or are only applicable to particular discharging profile. State of charge (SOC) defined in terms of ampere-hour is the amount of charge stored into a rechargeable battery. It can be measured by integrating the battery current with respect to time. However, SOC is not an accurate indication of residual capacity. Since the usable capacity that can be extracted from a battery depends on various factors including discharging current and profile. Usually, more ampere-hours can be obtained for a lower rate of discharge and discontinuous discharging profile. Moreover, trickle charging is not recommended for lithium-ion battery (Li-ion). The rate of self-discharge is difficult to measure and SOC is no longer a good approximation of the remnant capacity after a battery has been kept in standby mode for a certain period. Even though the self-discharging current is known, it is inappropriate to power up a monitoring circuit or a timer for measuring the length of standby period. In this paper, a practical circuit based on neural network for estimating the remnant capacity in terms of state of available capacity (SOAC) is presented. The inputs to the network involve battery voltage and discharging current only, and no historical information like previous SOC is required. The neural network is optimized to fit into a lower power consumption microcontroller with limited memory and throughput, and it can be completely powered off when the battery enters standby mode. Experimental results reveal that the circuit is applicable for different rate of discharge and arbitrary discharging profile. This paper focuses on the practical considerations for hardware implementation and the roadmap for design is presented in detail.

2. LI-ION BATTERY

More than 1500 millions Li-ion batteries of different sizes and geometries have been produced per year. For the past decade, the capacity of Li-ion battery was increased nearly 250% due to the improvement of design [Ritchie, 2004]. Three vehicle manufacturers successfully applied rechargeable Li-ion batteries to their electric vehicles [Pickert, 2001], [Bitsche et al., 2001], [Busch et al., 2001], [St-Pierre, 2001].

2.1 Battery characteristics

Unlike lead-acid battery and nickel-cadmium battery, Li-ion battery is susceptible to overcharge and over-discharge. The threshold voltages for termination of charging and discharging respectively are critical. Exceeding the limits can cause permanent damage. To maintain normal operation of a Li-ion battery, charging will be stopped whenever the voltage rises to 4.2V $\pm$ 0.05V whilst charging current is less than 0.1C. Discharging will be stopped whenever voltage drops below 3V. Safety circuit should isolate the battery from the charging and discharging circuit when the terminal voltage exceeding the upper and lower limit of 4.30V ± 0.05Vand 2.3V± 0.1V respectively [Panasonic, 2003].

2.2 Usable remnant capacity

Usable remnant capacity is defined as SOAC, which represents the residual ampere-hour capacity that can be extracted from a battery at a given rate of discharge. Although the SOC of a Li-ion battery can be determined, it cannot be estimated accurately without taking the discharging current into consideration. Even worst, self-discharge causes cumulative error when a battery is kept at standby mode for a certain period because trickle charge is not recommended to maintain the SOC at the fully charged state.

3. ARTIFICIAL NEURAL NETWORK

Theoretical proof has been published to show that multilayer neural network with sigmoid output function is able to approximate universally any function with finite number of discontinuities. The accuracy of the approximation depends on the number of layers and neurons in the network [Demuth et al., 2004], [Hagan, 1996], [Lapedes et al., 1988]. Thus, artificial neural network (ANN) with multiple layers is a good candidate to estimate the nonlinear SOAC of Li-ion battery.

3.1 SOAC estimation

The feedforward ANN consists of one or more hidden layers could be employed. The block diagram of the ANN for SOAC estimation is shown in Figure 1. The activation functions of the hidden layer and output layer are sigmoid and linear function respectively. Since sigmoid function produces compressed output, experimental results reveal that linear function is more appropriate for the output layer in order to obtain a full range of SOAC. If sigmoid function is employed, error will be increased dramatically when SOAC approaches to either 100% or 0%.

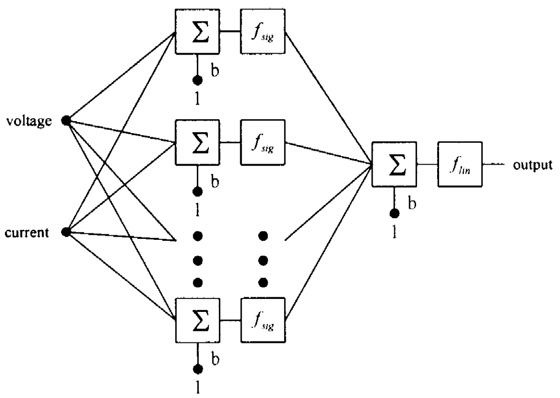


Fig. 1 Neural network for SOAC estimation

Mathematically, the output of the kth neuron at the hidden layer can be described as:

$$y_k = sig\left(\sum_{i=1}^{n}(\omega_i x_i + b_i)\right) \qquad (1)$$

where xis are battery voltage and discharging current respectively, and bs are the biases.

The SOAC can be expressed as:

$$SOAC = lin\left(\sum_{k=1}^{m}(\omega_k y_k + b_k)\right) \qquad (2)$$

4. ROADMAP FOR DESIGN

CGR18650 cells are chosen for the experiment. Data for training the neural network is taken from the discharging profiles as shown in Figure 2. The cells are subjected to different rates of discharge, which includes 1C, 0.9C, 0.8C and 0.7C respectively. The terminal voltage of the batteries declines faster with higher discharging current. Both battery voltage and current should be taken into consideration in finding the SOAC. The influence of operation temperature is not significant, and a rise of 25℃ can only cause a voltage change less than 0.1V. Thus, the impact of temperature is ignored because the error will be overridden by other factors like measurement tolerances and circuit noise. The discharging profiles are obtained with ambient temperature of 25℃.

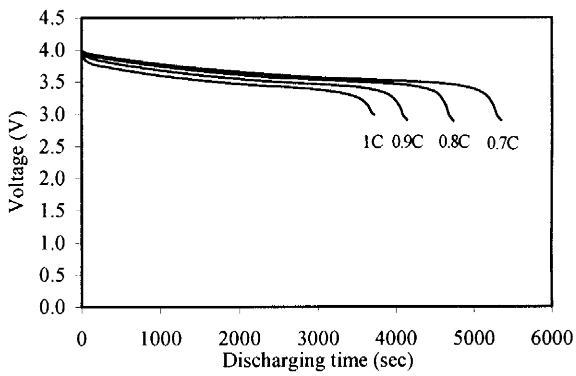


Fig. 2 Discharging profiles with various rate of discharge

4.1 Optimal number of layers

In 1957, the Soviet mathematician, A. N. Kolmogorov put forward the Kolmogorov Existence Theorem, which is a useful guide for determining an optimal number of layers. The theorem states that non-linear monotonic increasing function with single variable and linear summations can be taken to approximate any continuous function of k variables. It also states that a three layer perception with k(2k+1) nodes can be used to compute any continuous function of k variables. Thus, a neural network with multiple layers can be used to emulate any continuous function. Both the number of hidden layers and number of neurons per layer contribute to the accuracy of the output. More layers imply that smaller number of neurons can be taken to obtain an output with desired error. However, the accuracy of the output can also be controlled by the number of neurons per layer with fixed number of layers. A number of studies reveal that it is not necessary to employ a neural network with more than three layers. Previous researches show that a three-layer neural network can be trained to approximate any relationship between inputs and outputs [Picton, 2000].

4.2 Optimal number of neurons

Once the number of layers has been defined, the number of neurons of the hidden layer should be determined through experiments. First of all, a fully charged Li-ion battery undergoes discharging tests with various current levels to obtain sets of training data. The data sets are subjected to neural networks with different number of neurons in the hidden layer. Backpropagation algorithm is adopted for training. The criteria for terminating the training are number of epochs and change of mean square errors (MSE). The target change of MSE and maximum number of epochs are 0.1 and 500 respectively.
The MSE and number of epochs are recorded for comparison. The results are shown as Figure 3. MSE is a monotonic decreasing function with the number of neurons. Hidden layer with too few neurons leads to convergence problem, and more epochs of training cannot reduce the error significantly. However, the maximum number of neurons should be limited due to various constraints. The first constraint is the physical memory size of the SOAC estimation circuit. The weight associated with a neuron is represented by a floating-point value that takes up 4 bytes of memory. Usually, a microcontroller possesses less than 512 bytes of internal random access memory (RAM) and more than 1 kilobytes of read only memory (ROM). If the weights are stored in ROM, then onboard training becomes impossible and the neural network is not adaptive. Besides, if more than enough neurons are included to the network, it will have a greater tendency to overfit the data. It is desirable to have a hidden layer with the number of neurons that is much less than the number of training data. Based on the trend of MSE shown in Figure 3 and hardware constraints, a single hidden layer ANN with 20 to 30 neurons is applicable.

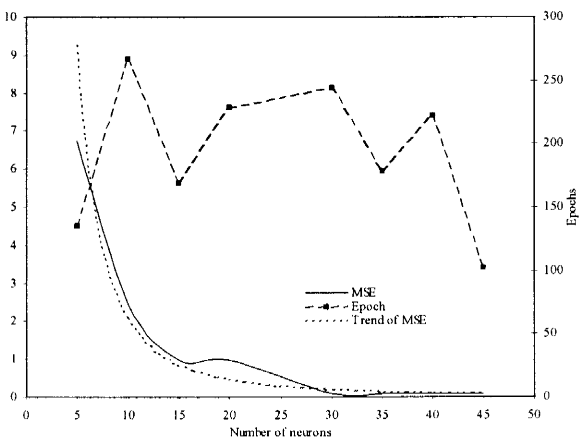
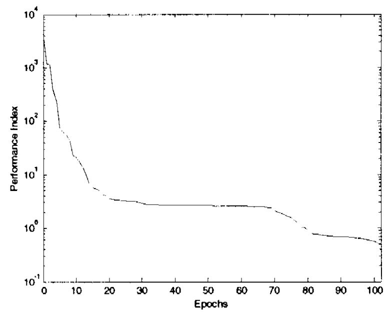
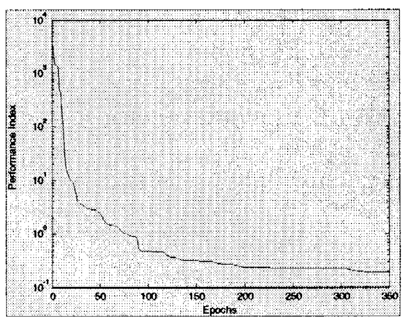


Fig. 3 MSE and epochs vs. number of neurons

Intensive experiments have been preformed for the network with 20 and 30 neurons respectively. The performance indexes in terms of MSE are shown in Figure 4 (a) and (b) respectively. The goal of the training is to obtain a MSE less than 0.1. The output of the network with 20 neurons converges and is almost steady after 100 epochs. However, the MSE is much greater than the target value. The output of the network with 30 neurons converges significantly within 30 epochs and keeps on decreasing after 300 epochs. Thus, a network of 30 neurons is chosen for SOAC estimation.



(a)



(b)

Fig. 4 Performance index vs. epochs for (a) 20 neurons and (b) 30 neurons

4.3 Training algorithms

Training vectors consist of too many data could cause overfitting and validation is important. A set of data is separated into two groups that are known as training set and validation set respectively [Masters, 1993]. Backpropagation training algorithm has been chosen for the previous experiment to find out the optimal number of neurons in the hidden layer, but it takes a long time to obtain the predefined MSE. Faster training algorithms are available, which fall into two main categories. They are based on heuristic technique and standard numerical optimization technique respectively. It is impossible to know which algorithm will be the fastest for a particular problem. The number of epochs for training depends on various factors like the desired error, size of training vector, and complexity of problem [Demuth, 2004].

In order to minimize the training time and power consumption of a microcontroller used for SOAC estimation, it is necessary to find out an effective training algorithm for this case. Different training algorithms are performed on a PC with the same set of data. The target MSE is 0.1 and the maximum number of epochs is limited to 5000. The benchmark with the numbers of epochs in ascending order is listed in Table 1. BFGS Quasi-Newton, Scaled Conjugate Gradient, Fletcher-Powell Conjugate Gradient, and Conjugate Gradient with Powell/Beale can achieve the performance index with less than a thousand epochs. However, if the network is subjected to certain training algorithms like Gradient Descent Backpropagation and Variable Learning Rate Backpropagation, the outputs are fail to converge after five thousand epochs.

Table 1 Performance and convergence of different training algorithms

Training Algorithm	Performance Index	Epochs
BFGS Quasi-Newton (BFG)	0.099	439
Scaled Conjugate Gradient (SCG)	0.100	469
Fletcher-Powell Conjugate Gradient (CGF)	0.100	574
Conjugate Gradient with Powell/Beale (CGB)	0.100	865
One-step Secant (OSS)	0.100	1421
Polak-Ribiere Conjugate Gradient (CGP)	0.100	2350
Resilient Backpropagation (RP)	0.110	5000
Levenberg-Marquardt (LM)	0.384	5000
Variable Learning Rate Backpropagation (GDX)	0.340	5000
Gradient Descent Backpropagation (GD)	0.499	5000

Based on the experiments, initial values of the weights of the network can also affect the rate of convergence. As an extreme case, MSE bounces around a particular value that is much greater than predefined limit after thousands epochs of training. However, MSE decreases readily with the same training algorithm but with different initial values of weights. It is advisable to reinitialize the network weights and biases and start the training again if the output fail to converge. Quasi-Newton training is chosen for the SOAC neural network.

5. RESULTS

After the network has been trained with the discharging profiles ranged from 1C to 0.7C, the result is verified with separate validation data sets. The applicability will be appraised with different types of discharging profiles.

5.1 Uniform discharging profile

Validation is preformed with another set of data with the same rates of discharge as the training data. The MSEs and maximum errors are tabulated in Table 2. As shown in Figure 5, the estimated SOAC is close to the actual values. Maximum error occurs when SOAC is less than 5% or greater than 98%.

Table 2 Validation result

Discharge Current	Mean Square Error	Maximum Error
1C	0.253%	2.965%
0.9C	0.203%	2.407%
0.8C	0.129%	2.413%
0.7C	0.268%	1.910%

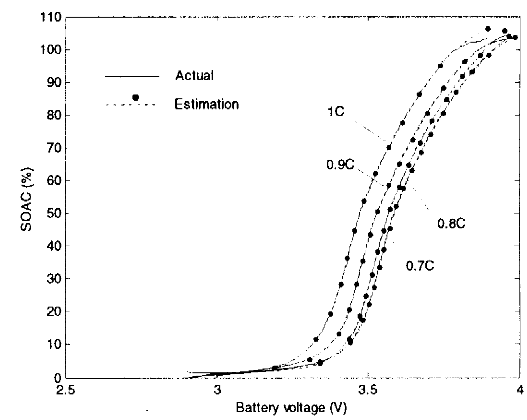


Fig. 5 Actual SOAC and estimated SOAC

5.2 Arbitrary discharging profile

Apart from the continuous constant current discharging profile, the network is applied to estimate the SOAC of an arbitrary discharging profile as shown in Figure 6. Battery voltage bounces to a higher value whenever discharging ceases. The experiment reflects the influence of voltage fluctuation on the network due to discontinu-

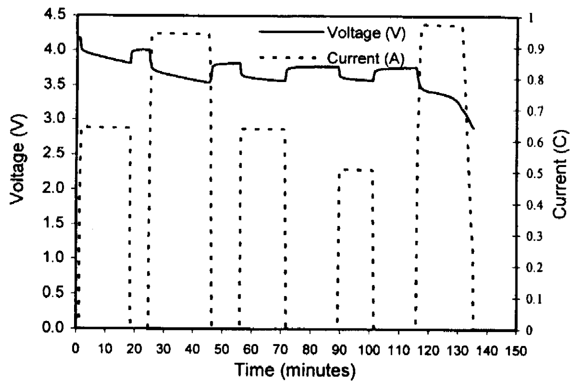


Fig. 6 Arbitrary discharging profile

ous discharging profile as well as variable discharging current. First of all, the battery is fully charged. Before applying the network for SOAC estimation, the battery is discharged based on the discontinuous profile with different discharging currents. Thus, the network does not receive any information about the previous SOC and discharging profiles. The result is shown in Figure 7. Although the error of estimation is greater than 10% at the beginning, it has significant improvement after 3 minutes. The error is around 5% after 4 minutes and continues to reduce to minimum after 10 minutes of discharging.

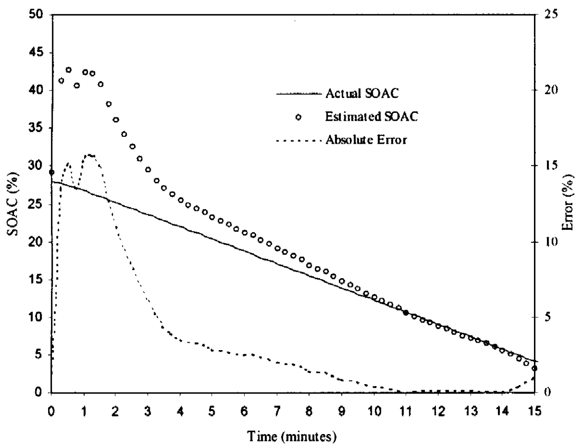


Fig. 7 Actual SOAC and estimated SOAC against discharging time

6. DESIGN CONSIDERATIONS

The network is a generalised SOAC indicator and involves no complicated circuit. It is suitable for medium to long discharging duration. As a practical application, mixed mode of SOAC estimation can be employed. Conventional SOAC estimation by counting the ampere-hour can be applied for the first 5 minutes of discharging. Then a more accurate estimation can be obtained by subjecting the battery voltage and current to the network. Optimal number of neurons is important for the estimation. Too fewer neurons at the hidden layer provide inaccurate SOAC. In contrast, too many neurons and epochs of training may cause overfit. It means the network output is accurate for the training data, but it makes the network applicable only for particular discharging profiles that are the same as those profiles for training. Training algorithm is another factor affected the result of estimation. Appropriate training algorithm not only speeds up the training, but also has influence on the convergence of the output. Some of the algorithms may not be applicable for this project because the error is higher than the goal after several thousands epochs. The block diagram of the circuit is shown as Figure 8. Any microcontroller with following features is applicable:

- 2 channels of 10-bit or 12-bit AD converter
- Not less than 256 bytes internal RAM
- Not less than 125 bytes EEPROM for storing the values of weights and biases

Results reveal that the network is applicable for SOAC estimation for the discharging current in range of 0.7C to 1C. The discharging profile, previous SOC and self-discharge have little influence on the estimation. The network is extendable for other rates of discharging. Similar training procedures can be applied to the network for estimation of SOAC with discharging current less than 0.7C.

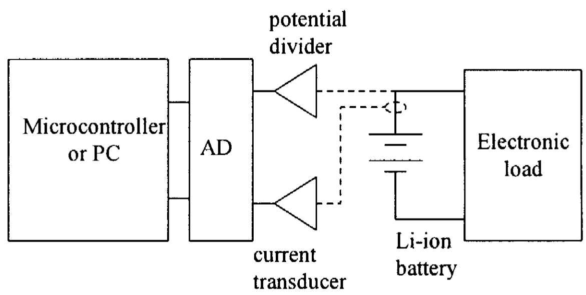


Fig. 8 Circuit for SOAC Estimation

7. CONCLUSION

A SOAC indicator for Li-ion battery has been developed. Intensive experiments are performed to find out the optimal configuration of the neural network with the concerns of accuracy, training efficiency, and hardware constraints. This paper presents the roadmap of design and the practical considerations. The experimental results show that the circuit is applicable for continuous discharging profiles with various rates of discharging and arbitrary discontinuous profiles such as electric vehicle operation.

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