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SoC Estimation for Lithium-Ion Battery Using Recurrent NARX Neural Network and Genetic Algorithm

Guo Chuangxin[1], Yuan Gen[1,2], Zhu Chengzhi[3], Wang Xueping[2] and Cao Xiu[2]

[1]School of Electrical Engineering, Zhejiang University, Hangzhou 310027, Zhejiang Province, China,
[2]School of Computer Science, Fudan University, Yangpu District, Shanghai 200433, China,
[3]State Grid Zhejiang Electric Power Company, LTD., Hangzhou 310007, Zhejiang Province, China

E-mail address: 18210240242@fudan.edu.cn

Abstract. State of charge (SOC) is an important indicator for assessing the remaining capacity of the battery. An accurate SOC estimation is crucial for ensuring the safe operation of lithium batteries and preventing from over-charging or over-discharging in electric vehicle (EV) industry. However, to estimate an accurate capacity of SOC of the lithium batteries has become a major concern for the EV industry. In this paper, a recurrent nonlinear autoregressive external input neural network(NARXNN) model optimized by genetic algorithm(GA) is proposed to improve accuracy of SOC of lithium battery by finding the optimal value of input delays, feedback delays, and hidden layer neurons. The NARXNN based GA model is compared with the NARXNN in performance using statistical error values of mean absolute error and root mean square error are used to check the performance of the SOC estimation. The results show that the NARXNN based genetic algorithm outperforms NARXNN in estimating SOC with high accuracy.

1. Introduction

Global emissions have been a worrying issue in recent decades. Transportation accounts for 14% of global emissions, mainly caused by gasoline and diesel vehicles [1]. To meet the challenge, electric vehicles (EVs) are considered as one of the promising alternatives that use sustainable energy to reduce greenhouse gas emissions and effect of global warming. In recent years, the performance and efficiency of EVs have been improved due to the high storage capacity and long life of energy storage devices. However, developing electric vehicles with better quality and efficient energy storage management systems is still an important issue for researchers and car manufacturers [2]. There are different types of energy storage devices that being used in vehicle operation. Among them, lithium-ion battery is widely used in EV applications due to high efficiency, high energy density, long lifespan, no memory effect, low hysteresis and environmental friendliness [3].

The state of charge (SOC) is an important indicator of the amount of remaining charge left in a lithium-ion battery [4]. However, an accurate SOC estimation of battery is a big challenge due to complex electrochemical reactions of the lithium-ion battery. In addition, lithium-ion batteries are very sensitive to aging and temperature [5]. In order to achieve stable and reliable operation of the EV, high-precision SOC estimation must be performed. Accurate and robust SOC estimation technology can help to avoid over-charging, over-discharging and overheating of the lithium-ion battery which will increase the life of batteries [6]. The SOC is estimated based on current integration which is estimated using the available current capacity divided by the nominal capacity [7] as presented in (1).

$$SOC=SOC_0-\frac{1}{C_n}\int i\eta dt \tag{1}$$

where SOC_0 represents the initial value of SOC, i represents the battery current, C_n is the nominal capacity, t represents time, η represents coulomb efficiency.

There are many methods for estimating SOC in recent years, including Coulomb counting method, open circuit voltage method, Kalman filter method, particle filter method, fuzzy logic method and support vector machine. Coulomb counting is the simplest method implemented in battery management systems (BMS) with low power consumption [8]. However, this method fails to accurately determine the initial value of the SOC, which causes a large cumulative error. Open circuit voltage (OCV) is another commonly used method for estimating SOC with high precision [9]. However, OCV requires a long rest period to reach a steady state and it cannot be used to estimate SOC online. The Kalman filter method has been used widely for SOC estimation [10]. However, the results of the Kalman filter are not very satisfactory due to temperature variations, battery aging, inappropriate battery model and highly nonlinear characteristics of battery system. An intelligent method called fuzzy logic can estimate SOC with battery aging, temperature variation and noises [11]. However, the fuzzy method requires a large storage device to hold a large amount of training data.

In order to solve the above problems, a method based on an improved artificial neural network (ANN) model is proposed. ANN is ideal for modelling nonlinear and complex systems, and it does not depend on battery models and mathematical relationships [12]. There are many studies on the SOC estimation methods for lithium-ion batteries using ANN, including back-propagation neural networks (BPNN) [13] and radial basis function neural networks (RBFNN) [14]. However, the existing ANN method has a problem of slow convergence, data over-fitting, and is easily trapped in a local minimum [15]. Nonlinear autoregressive with exogenous inputs neural network (NARXNN) performs better than BPNN and RBFNN in terms of learning ability, convergence speed, generalization performance and high accuracy. The general NARXNN architecture is indicated in Figure 1. At present, there are some SOC estimation studies based on NARXNN [16-18], but the performance of NARXNN model depends on input delay, feedback delay and hidden layer neurons, and it coats much time to select the value of parameters with experience and experiments. The results are not always satisfactory [16], and the existing lithium battery SOC estimation research hardly consider the impact of battery aging on SOC. This paper develops an improved NARXNN with an optimization algorithm to enhance the estimation intelligence and robustness of SOC estimation. Genetic algorithm is extensively utilized to solve problem. Using genetic algorithm to find input delay, feedback delay, and number of hidden layer neurons. The NARXNN-GA model takes into account the effects of current, voltage, temperature, and battery aging. By selecting appropriate training algorithms, activation functions, number of hidden layer neurons, and input delay and output delay to improve the performance of SOC estimation. The paper is structured as follows. Section two narrates the structure and implementation of the model, Section three narrates the results and analysis of experiment, and section four presents the conclusion.

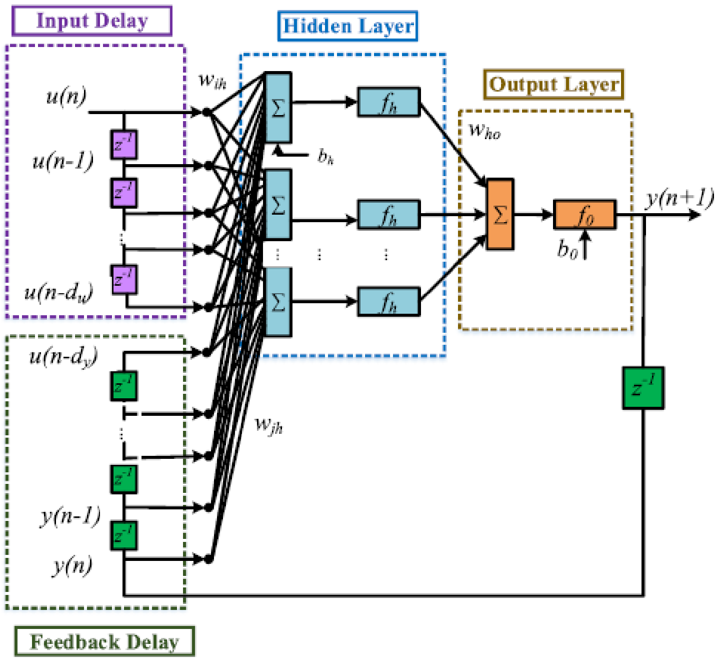

Figure 1. Recurrent NARXNN architecture.

2. Recurrent NARXNN based genetic algorithm

2.1. Recurrent NARX neural network

Recurrent Neural Network (RNN) is supervised machine learning algorithm with one or more feedback loops. In [19], RNN is designed based on control methods for the exact solution of algebraic equations with time-varying parameters. NARXNN is a subclass of RNN and is suitable for predicting nonlinear and time series problems. The NARXNN network uses limited feedback to form output layers instead of hidden layers. NARXNN performs better than traditional RNN in learning ability, convergence speed, generalization performance and high precision [20]. NARXNN can be used for time series applications with multiple inputs and multiple outputs. In this paper, current, voltage and temperature are taken as inputs and SOC is taken as output. A mathematical expression of NARXNN with three inputs and one output can be represented by (2).

$$y(n+1) = f_0\left[b_0 + \sum_{h=1}^{N} w_{h_0} f_h\left(b_h + \sum_{k=1}^{3}\sum_{ik=0}^{d_{uk}} w_{ikh}u_k(n-ik) + \sum_{j=0}^{d_y} w_{jh}y(n-j)\right)\right] \tag{2}$$

Where $y(.)$, $u(.)$ represent the output and input of step n at each discrete time respectively; j is the feedback delay, ik denote input delay of the first layer, the second layer and the third layer respectively. w_{ikh}, w_{h_0}, w_{jh} denote the weights from input layer to the hidden layer, hidden layer to output layer, output feedback layer to hidden layer respectively. b_0, b_h are the biases. $f_h(.)$, $f_0(.)$ are the functions of the hidden layer and the output layer respectively [21]. A tangent sigmoid transfer function(tansig) and a linear transfer function (purelin) are used for the perceptron at the hidden layer and the output layer respectively [22].

2.2. Experiment implementation

This experiment uses genetic algorithms to find the optimal value of the parameters. Genetic algorithm is a method of searching for optimal solutions by simulating natural evolutionary processes. The process is presented in Figure 2.

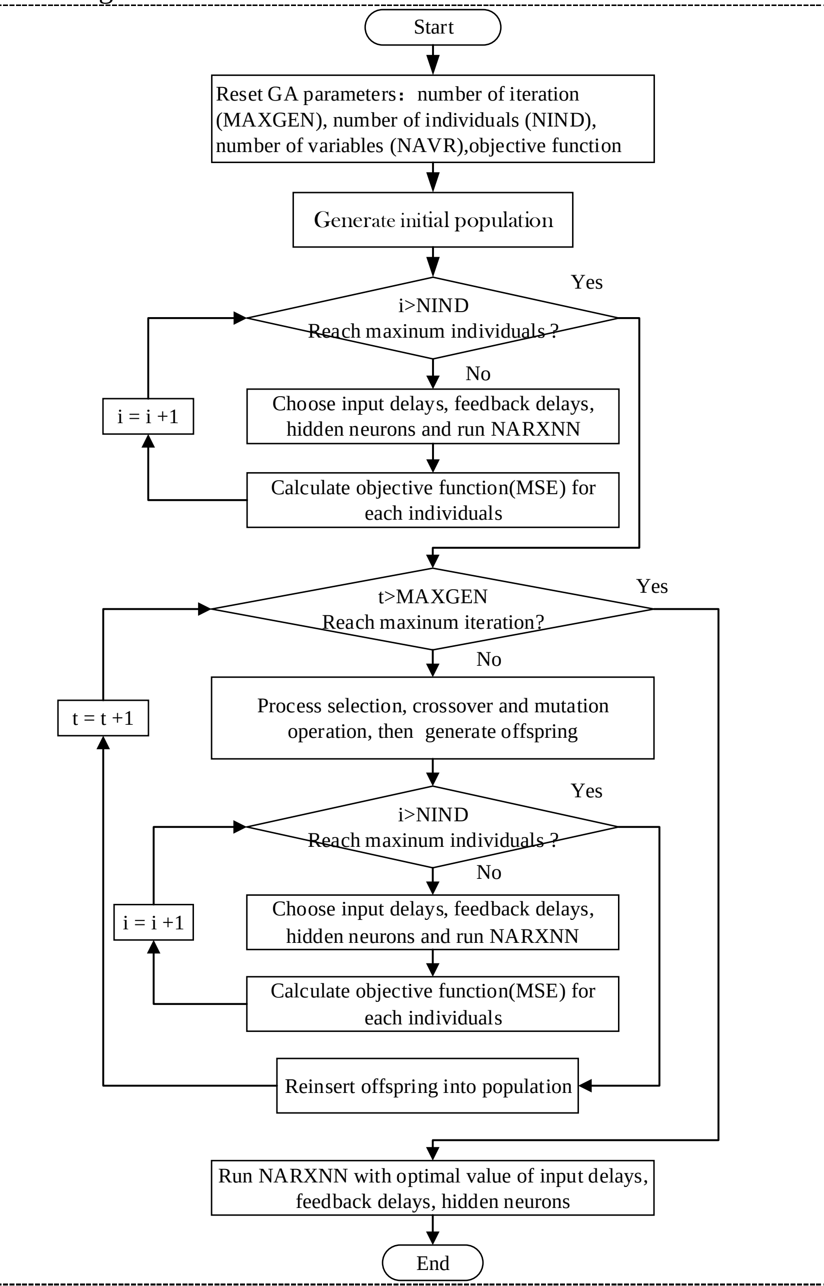

Figure 2. Flowchart of NARX-GA model

3. Experiment implementation

3.1. Data description

The experimental data set was obtained from NASA Ames PCoE's data repository [23], and data of the 6th battery was selected for experiments, including training and testing. As the charge and discharge cycle progresses, the battery capacity decreased significantly. In practical industrial applications, the number of decreased aging data samples may be much larger than this data set. The battery capacity of the B0006 battery is shown in Figure 3.

IOP Conf. Series: Materials Science and Engineering **486** (2019) 012076 doi:10.1088/1757-899X/486/1/012076

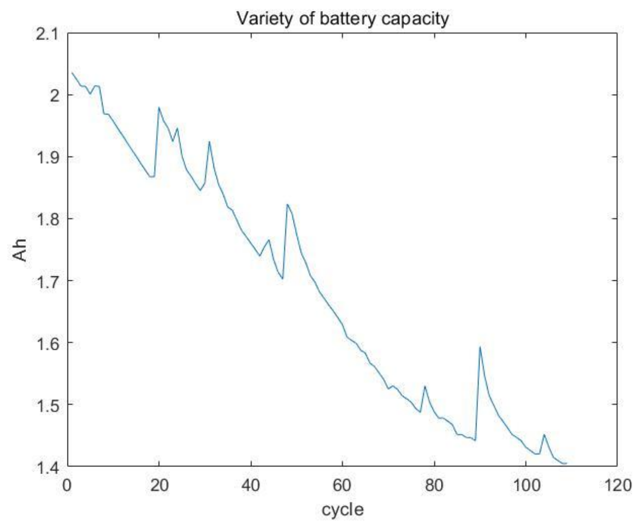

Figure 3. Variety of B0006 battery capacity.

The data used in this experiment consists of 109 discharge cycles with a battery capacity range from 1.4 Ah to 2.0 Ah. The training set, test set, and verification set are divided into 70%, 15%, and 15%. The parameters of genetic algorithm are the number of iterations (MAXGEN)=100, the number of individual populations (NIND)=40, the number of variables (NAVR)=3, the length of coding (PRECI)=20, the generation difference (GGAP)=0.9, the probability of mutation (pm) = 0.001, crossover probability (px) = 0.97, and mean square error (MSE) is chosen as the fitness function.

3.2. Model evaluation

The NARXNN with optimal value of input delay, feedback delay and hidden layer neurons is trained and validated by training set data and test set data, and the model is compared with the NARXNN without genetic algorithm optimization. Two network models were used to estimate the SOC and compare their forecast results with reference values. The performance of the proposed model is checked based on mean square error (MSE) and mean absolute error (MAE). The mathematical expression is as follows:

$$MSE = \sqrt{\frac{1}{N}\sum_{i=1}^{N}\left(y_1 - y_0\right)^2} \tag{3}$$

$$MAE = \frac{1}{N}\sum_{i=1}^{N}\left|y_1 - y_0\right| \tag{4}$$

Where y_1, y_0 are the estimated output and reference value of the SOC, respectively.

The training network model is presented in Figure 4. Network is trained in open loop fashion. When using network model to predict SOC, you need to remove a time step, as presented in Figure 5.

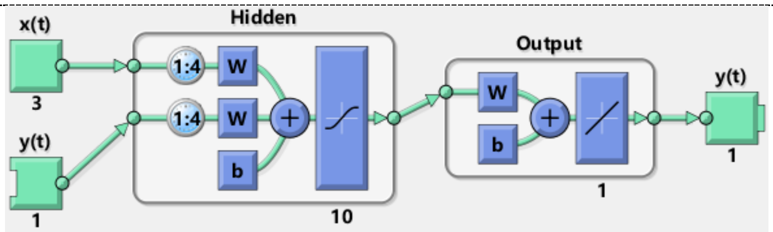

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Figure 4. Open loop NARXNN.

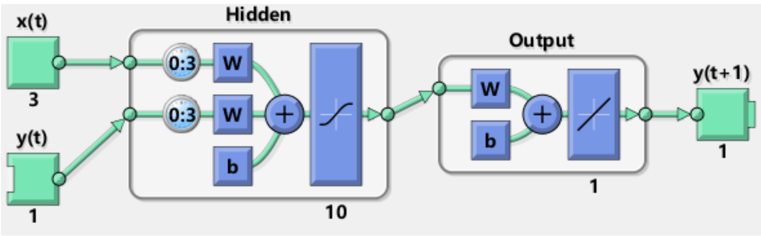

Figure 5. Early prediction NARXNN.

4. Analysis of results

4.1. Training performance of model

The optimal values of input delay, feedback delay, and number of hidden layer neurons are 2, 10, and 6, respectively. The input delay, feedback delay, and number of hidden layer neurons used in [24] are 4, 4, and 10, respectively. The training performance of the two models on the dataset in this paper is presented in Figure 6 and Figure 7.

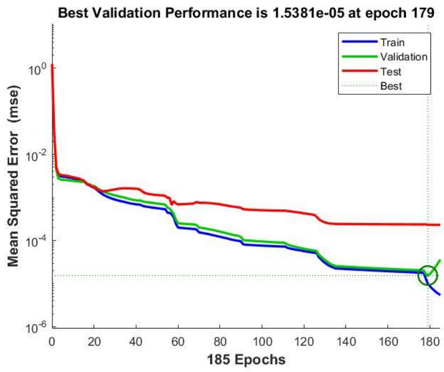

Figure 6. The train performance of NARXNN-GA model.

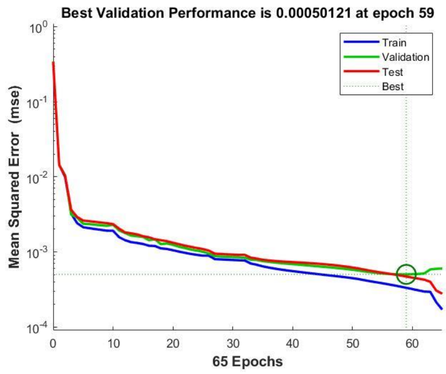

Figure 7. The train performance of NARXNN model.

As shown in the figure, the NARXNN-GA model obtained best validation performance of 1.5381×10^{-5} at 179 Epoch. The MSE of the NARXNN-GA model is 2.0995×10^{-5}, the MAE is 0.0033, and the model training duration is about 2s. The NARXNN model obtained best validation performance of 0.0005012 at 65 Epoch. The MSE of the NARXNN model is 3.7808×10^{-4}, the MAE is 0.0036, and the model training duration is about 1s. The training time of NARXNN-GA has increased slightly but the accuracy has been greatly improved.

4.2. SOC estimation

The 10th, 33rd, and 79th discharge cycles were selected from data set, and the trained network model was used for SOC estimation. The results as follows:

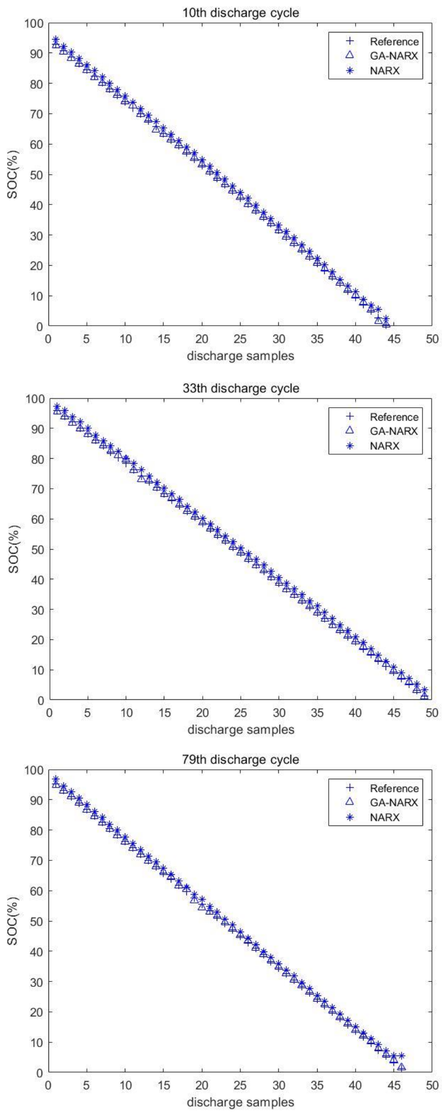

Figure 8. SOC estimation results of 10th, 33rd, 79th discharge cycle.

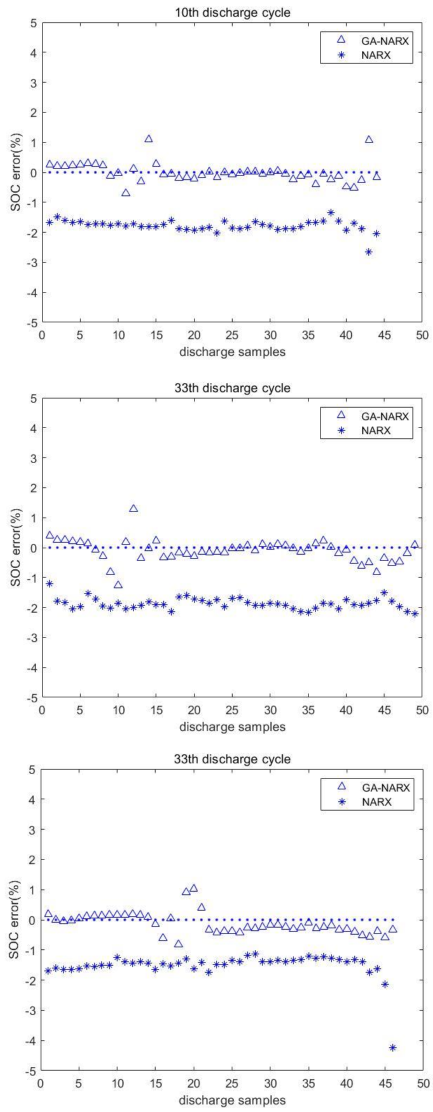

Figure 9. SOC estimation error of 10th, 33rd, 79th discharge cycle.

The capacities of the three discharge cycles are 1.9572 Ah (10th), 1.8553Ah (33rd), and 1.5041Ah (79th) respectively. The prediction results of SOC estimation for the 10th, 33rd, and 79th discharge cycles using NARXNN-GA and NARXNN respectively are shown in the Figure 8. The MSE of the prediction results of the NARXNN-GA model is 1.384×10^{-5} , 1.608×10^{-5} , 2.545×10^{-5} respectively. And the MSE of the NARXNN model is 6.312×10^{-4} , 9.310×10^{-5} , 1.610×10^{-4} respectively. Figure 9 shows the MAE of the two methods. The MAE of NARXNN-GA model is 0.0026, 0.0026, 0.0020, the error bound is found at [-0.0119~0.0173], [-0.0163~0.0209], [-0.0525~0.0150], respectively. And the MAE of NARXNN is 0.0043, 0.0039, 0.0032, the error bound is found at [-0.3318~0.0497], [-0.1723~0.0310], [-0.0346~0.0440], respectively. The error of SOC estimation of the optimized NARXNN model is significantly reduced.

5. Conclusion

This paper proposed a NARXNN-GA model for improvement performance of SOC estimation. This study chose a lithium-ion battery because of high capacity and long life. Input delay, feedback delay, hidden layer neurons are the most important parameters, they are usually randomly assigned or empirically distributed and do not provide a satisfactory solution. Therefore, genetic algorithm is used to improve the capabilities of the NARXNN model. The contribution of this study is to propose a robust and accurate SOC estimation method under the uncertainty of considering the battery aging leading to capacity change. The proposed model can be implemented in a modular design for real-time EV applications.

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