SOC Estimation Based on Time Series Neural Network and Its Performance Evaluation

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Abstract. Aimed at the disadvantage of state of charge (SOC) estimation by using traditional feed forward neural network, a new method proposed to solve the problem. The time series neural network is introduced to estimate the SOC. The experiments results show that the time series neural can estimate the SOC more accurate. In addition, the different structures and the key parameter are discussed to achieve the best performance.

1. Introduction

Many researchers focused the field of state of charge (SOC) estimation. They tried to estimate the SOC more accurate and developed many methods such as ampere hours [1], open circuit voltage [2, 3], Kalman filter [4, 5] and neural network [6, 7]. Since neural network has good nonlinear data processing ability, it has been widely studied. However, when drastic discharging data was used, the prediction error increases significantly. This paper proposed to use the time series neural network (TSNNT) to estimate the SOC, which can overcome the disadvantage of the traditional neural network. The paper is organized as follows: The experiment data are introduced in the second section; the third section gives the details about the TSNNT. The fourth section gives the experiment data from the proposed method and discusses the results. In addition, this section evaluates the performance of the TSNNT with different structures and parameters. The fifth section is the conclusion and the future works.

2. The time series neural network and experiment data

The time series neural network has three types: nonlinear input–output time series neural network (NIO), the nonlinear autoregression time series neural network (NA), and the nonlinear autoregressive time series neural network with exogenous inputs (NARX). The NIO can predict the SOC by series values of voltage and current, as the shown in Eq (1). The c and v mean current and voltage, respectively. The d in the equation is the important parameter in the TSNNT, namely time delay.
\[ SOC(t) = f(\{c(t)\ldots c(t-d), v(t)\ldots v(t-d)\}) \]  \hspace{1cm} (1)

The NA uses the series outputs to predict the next output, as shown in Eq (2). The NARX adds current and voltage data on the basis structure of NA, as shown in Eq (3).

\[ SOC(t) = f(SOC(t-1)\ldots SOC(t-d)) \]  \hspace{1cm} (2)

\[ SOC(t) = f(\{c(t)\ldots c(t-d), v(t)\ldots v(t-d), SOC(t-1)\ldots SOC(t-d)\}) \]  \hspace{1cm} (3)

In order to test the performance of the TSNNT, two discharging data sets were used: the Urban Dynamometer Driving Schedule (UDDS) and the Dynamic Stress Test (DST) \[8\]. The terminal current and the terminal voltage of two discharging data sets are shown in Fig. 1.

\[ Error(\%) = \left| \frac{SOC_{\text{real}} - SOC_{\text{sim}}}{SOC_{\text{real}}} \right| \times 100 \]  \hspace{1cm} (4)

\[ MSE = \left( \sum_{i=1}^{n} E_{SOC}^2 \right) / n \]  \hspace{1cm} (5)

3. Experiment result and analysis

3.1. Analysis of three TSNNTs

The prediction result of NA is shown in Fig.2. The results indicated that the NA neural network can’t be used to estimate SOC. The reason is that the NA predicts the next output by the previous outputs. If the output changes irregularly, the NA neural network will lose its ability to predict the desired SOC.
The feed forward, the NIO and the NARX neural network were trained by the same training dataset. After that, the validation datasets were used to predict. The results are shown in Fig.3 and Fig.4, and the prediction errors are shown in Fig.5 and Fig.6.
Tables 1 gives the maximum errors and the minimum MSE of the validation dataset when using the DST and UDDS discharge data to predict. From the Table 1 and the Fig. 3- Fig.6, it could be found that the time series neural network is more superior than the feed forward. The NARX takes advantage in the Error Maximum and the MSE of the NIO is better when the UDDS discharging data is used. However, when the DST discharging data is used, the error of NARX increased significantly. Since the DST discharging data changes more drastically than the UDDS discharging data. Thus, the NARX is not fit to estimate SOC in drastic discharging data.

Table 1. Minimum MSE and maximum error from two discharging validation dataset.

|       | UDDS | DST |
|-------|------|-----|
| Feed forward | Minimum MSE | Maximum Error | Minimum MSE | Maximum Error |
|       | 1.66 | 7.06% | 2.17 | 8.07% |
| NIO   | 0.70 | 6.09% | 0.60 | 6.82% |
| NARX  | 2.66 | 4.84% | 15.52 | 12.65% |

3.2. Analysis of time delay
The TSNNT has an important parameter, the time delay, which means how many previous data will be used in the training and prediction. It will affect the accuracy of the neural network. The prediction results with different time delays and NIO by using the DST discharging data are shown in Fig.7 and Fig.8.
The min MSE and error maximum are shown as Table 2. It shows that the accuracy increases when the time delay is set as a large value by using the training dataset to predict. However, when the validation dataset is used, with the increasing of the time delay, the accuracy of neural network is decreases. The reason is that with the increase of time delay, the TSNNT is more suitable for the time characteristics of training data. When other data is used, the pre-trained TSNNT cannot adapt to the time characteristics of new data, so the error is large. Therefore, when we choose the time delay value, we need to consider the data characteristics comprehensively.

Table 2. Minimum MSE and maximum error in DST with different time delays.

| d   | Training Set | Validation Set | |
|-----|--------------|----------------|---|
|     | Min MSE      | Max Error      | Min MSE | Max Error |
| 2   | 0.96         | 8.80%          | 1.94%   | 25.96     |
| 4   | 0.70         | 6.07%          | 3.70%   | 40.09     |
| 6   | 0.54         | 5.62%          | 6.15%   | 39.34     |
| 6   | 0.30         | 4.33%          | 5.13%   | 46.96     |

4. Conclusion

In this paper, the time series neural network is introduced to estimate the SOC of battery. It can overcome the disadvantage of the traditional SOC estimation method based on feed forward neural network. Three different time series neural network principles are introduced, namely the nonlinear input–output time series neural network (NIO), the nonlinear autoregression time series neural network (NA), and the nonlinear autoregressive time series neural network with exogenous inputs (NARX). SOC estimates under complex discharge conditions are obtained by applying these three models. The results indicate that the second model is not applicable to battery SOC estimation, whereas the first and third models produce more accurate predictions than the feedforward network. Moreover, the time delay is also a crucial parameter in a time series neural network. If it is set to a small value, the prediction accuracy will decrease. On the other hand, if the parameter is set to a very large value, overfitting will occur, and the prediction accuracy will again decrease. To address these issues, the time delay should be determined carefully.

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