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State of Charge Estimation of Lithium-Ion Batteries Using LSTM and NARX Neural Networks

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ABSTRACT Highly accurate state of charge (SOC) estimation of lithium-ion batteries is one of the key technologies of battery management systems in electric vehicles. The performance of SOC estimation directly influences the driving range and safety of these vehicles. Due to external disturbances, temperature variation and electromagnetic interference, accurate SOC estimation becomes difficult. To accurately estimate the SOC of lithium-ion batteries, this article presents a novel machine-learning method to address the risk of gradient explosion and gradient decent using the dynamic nonlinear auto-regressive models with exogenous input neural network (NARX) with long short-term memories (LSTM).The proposed hybrid NARX model embeds LSTM memory, which provides jump-ahead connections in the time-unfolded model. These jump-ahead connections provide a shorter path for the propagation of gradient information, therefore reducing long-term dependence on the recurrent neural network. Experimental results show that the estimation performance root mean square error (RMSE) of the proposed model is less than 1%, and this model has better multitime prediction performance. Finally, the hybrid NARX and LSTM model is compared with the standard back propagation neural network based on particle swarm optimization (BPNN-PSO), the least-squares support vector machine (LS-SVM) and LSTM existing models under urban dynamometer driving schedule (UDDS) and dynamic stress test (DST) conditions. The proposed hybrid NARX-LSTM model yield relative to other methods and can estimate the battery SOC with high accuracy. The RMSE of proposed model is improved by approximately 60% compared with the standard LSTM

INDEX TERMS Electric vehicles, state of charge, lithium-ion batteries, NARX, LSTM.

I. INTRODUCTION

Environmental protection and energy consumption reduction have gained widespread attention in the twenty-first century, and electric vehicles (EVs) have also developed rapidly [1]. Lithium-ion batteries are widely used in the field of EVs owing to their superior life cycle, high energy density and low self-discharge rate [2]. As one of the most important technologies of EVs, an increasing number of researchers have turned their focus to the battery management system (BMS) in recent decades [3]. The state of charge (SOC) of the battery is one important parameter in the BMS, as the accurate estimation of SOC greatly affects battery management technology [4], [5]. The accurate estimation of the SOC ensures the safety, stability and efficiency of EVs [6]. However, due to the influence of external disturbances, temperature variations and electromagnetic interference, SOC estimation for lithium-ion batteries is a typical, nonlinear instability problem.

Currently, methods for SOC estimation are divided into four categories: the characterization parameters method, the ampere hour integration method, the physical model method, and the data-driven method [7]–[10]. A method based on characterization parameters is represented by the open circuit voltage (OCV) method. The relatively stable OCV-SOC relationship is often used in the industry to calibrate the SOC of batteries, but the accurate measurement of the OCV takes a long time [11]. The ampere hour integration

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method uses the definition of SOC to estimate the SOC. However, an accurate value of the initial SOC is difficult to obtain, and the degradation of battery performance affects the accurate estimation of SOC [12]. Physical model methods include the Kalman filter [13], [14], sliding mode observer [15], [16], and particle filter [17], [18], among other methods. The Kalman filter is widely used, including, for example, the extended Kalman filter [19], unscented Kalman filter [20], and adaptive Kalman filter [21]. Although the Kalman filter method has better robustness and estimation accuracy, the accurate battery equivalent circuit model is difficult to build due to the changing internal resistance and changing capacitance [22]. At present, with the rapid development of artificial intelligence and machine learning methods, data-driven estimation methods have been used to estimate the SOC of lithium-ion batteries. The data-driven method can effectively solve the problems of nonlinearity and instability in battery data collection [23]. This method is based on a large amount of experimental offline data, and the characteristics of current, voltage and temperature are trained to establish a mapping model of the SOC, including neural network (NN) [24], [25], support vector machine (SVM) [26] and deep learning methods.

Neural networks are widely used in data-driven methods. According to whether the structure of the network has recurrent terms, neural networks are divided into the dynamic neural network (with recurrent terms) and static neural network (no recurrent terms). Static neural networks are represented by back propagation neural networks (BPNNs) and the radial basis function (RBF)[27]. Although these methods have good estimation performance, the estimation accuracy is low and time-consuming. The dynamic nonlinear auto-regressive models with exogenous input neural network (NARX) has a good memory function and can also be used to process time series [28], [29]. However, when the value of the gradient is greater than 1.0 during the process of training, the error increases exponentially with the step length of the reverse learning time, resulting in the phenomenon of an exploding gradient; when the gradient is less than 1.0, the error decreases exponentially with the increase of the backward learning time step, falling into the local optimal solution and causing the phenomenon of a vanishing gradient. With the increase in the reverse learning step time, the NARX neural network will lose long-term memory once the phenomenon of exploding gradients or vanishing gradients have occurred [30]. As a new machine learning technology, the long and short time series (LSTM) cell is used to replace the cell nucleus of the traditional recurrent neural network [31]. The important information is fed to the hidden layer by the LSTM cell, including forgetting gate, input gate, and output gate. To overcome the issues of exploding gradients or vanishing gradients, long and short time series (LSTM) is used in the NARX model for SOC prediction of lithium-ion batteries [32]–[34]. Therefore, a method combining LSTM and NARX neural networks for SOC estimation of lithium-ion batteries.

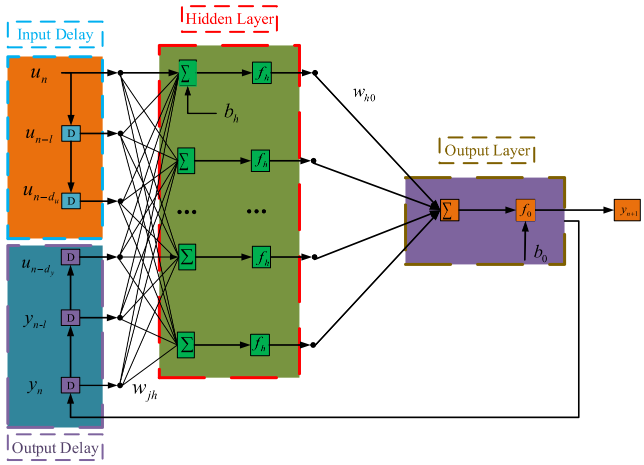

FIGURE 1. Structure of the NARX dynamic neural network.

In this article, the autoregressive model and machine learning methods for SOC estimation of lithium-ion batteries are combined. A fusion model of the NARX dynamic neural network and LSTM is proposed to solve the phenomenon of gradient disappearance and gradient explosion in NARX dynamic neural networks and improve estimation accuracy of SOC for the lithium-ion batteries. The estimation performance and multivariate time series for future forecasting of hybrid models are verified by experiments and analyzed under urban dynamometer driving schedule (UDDS) and dynamic stress test (DST) conditions. By comparison with back propagation neural network- particle swarm optimization (BPNN-PSO), least-square support vector machines (LSSVMs) and LSTM, the superiority of the proposed method is verified. The structure of this article is as follows: Section 2 introduces the NARX dynamic neural network and LSTM neural network. The model of the hybrid NARX and LSTM is proposed in Section 3. Section 4 includes the results and discussion and Section 5 includes the conclusion.

II. ESTIMATION MODELS FOR BATTERIES

A. TYPES OF NARX DYNAMIC NEURAL NETWORK

The nonlinear autoregressive model applies a dynamic neural network to time series forecasting, resulting in powerful forecasting performance. The NARX structure primarily includes an input layer, feedback layer, output layer, input delay and output delay [35]. The NARX model is defined by Equation 1, and the structure is shown in Fig. 1.

$$\begin{aligned} y(t) = f(&y(t-1), y(t-2)\ldots, y(t-n_y), \\ &u(t-1), u(t-2)\ldots, u(t-n_u)) \end{aligned} \tag{1}$$

where u_n is the input at time n and y_n is the output. n_u and n_y are input memory order and output memory order, respectively. Fig. 1 is a classic closed-loop NARX dynamic neural network, which feeds the output of the standard NARX neural network to the input.

The open-loop NARX neural network feeds back the real values to the input, and the structural expression is defined by

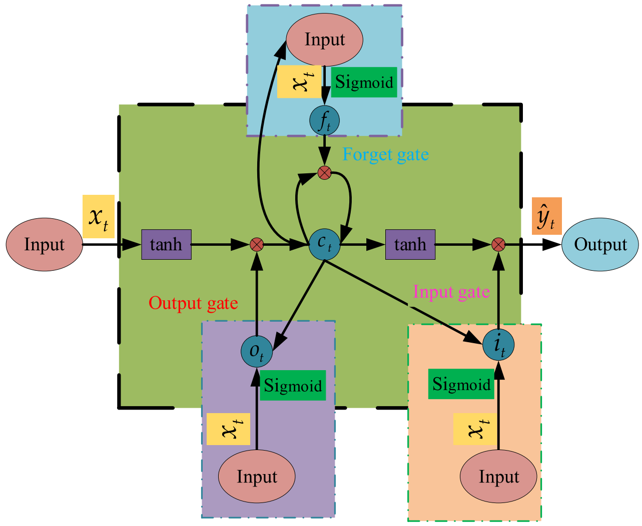

FIGURE 2. Structure of the LSTM recurrent neural network.

Equation 2.

$$\hat{y}(t) = \hat{f}(y_o(t-1); u(t-1)) = \hat{f}(y(t-1), y(t-2) \ldots, y(t-n_y), u(t-1), u(t-2) \ldots, u(t-n_u)) \quad (2)$$

The closed-loop NARX neural network feeds the estimated values to the input, and the structural expression is defined as Equation 3.

$$\hat{y}(t) = \hat{f}(y_o(t-1); u(t-1)) = \hat{f}(y(t-1), y(t-2) \ldots, y(t-n_y), u(t-1), u(t-2) \ldots, u(t-n_u)) \quad (3)$$

where, $\hat{y}$ is estimation SOC, y_n is the output, u_n is the input, n_u and n_y are input memory order and output memory, respectively.

To obtain a more accurate estimation of SOC, the open-loop NARX neural network is used [36]. However, the phenomenon of the exploding gradient and vanishing gradient has become an important factor restricting the NARX neural network, and therefore, the NARX dynamic neural network combined with LSTM is proposed to estimate the SOC of the battery.

B. LSTM NEURAL NETWORK

As a new machine learning technology, the LSTM neural network uses the traditional recurrent neural network to address the problem of the exploding gradient and vanishing gradient [37]. The LSTM cell nucleus is used to replace the cell nucleus of the traditional dynamic neural network; therefore, it has long-term memory capabilities. The information forgotten by the LSTM cell nucleus feeds important information to the hidden layer, including the forgetting gate, input gate, and output gate [38]. The memory cell of an LSTM recurrent neural network is shown in Fig. 2.

The LSTM recurrent neural network is an architecture that maps the output series (SOC) through the input series (voltage, current, temperature, etc.). The input gate is used as an evaluation index for updating current information. Before generating new memories, the gate network needs to determine whether the current information is important and decide whether to remember. The forgetting gate only evaluates the information of the past memory cell and evaluates whether to forget information from the past. The self-recurrent connection generates new memories after merging the past and current memory information. The purpose of the output gate is to separate the final memory. The mathematical expression is as follows:

$$i_t = \sigma(w_{xi}x_t + w_{hi}x_{t-1} + b_i) \quad (4)$$

$$f_t = \sigma(w_{xf}x_t + w_{hf}x_{t-1} + b_f) \quad (5)$$

$$o_t = \sigma(w_{xo}x_t + w_{ho}x_{t-1} + b_o) \quad (6)$$

$$c_t = f_t c_{t-1} + \tanh(w_{xc}x_t + w_{hc}h_{t-1} + b_c) \quad (7)$$

$$h_t = o_t \tanh c_t \quad (8)$$

Among them i_t, f_t, o_t and c_t represent the input, forget, output, and cell state at time t, respectively. σ and tanh are the sigmoid activation function and the hyperbolic tangent activation function, respectively.

III. HYBRID NARX AND LSTM MODEL

The model combining NARX and LSTM is proposed to integrate the advantages of each model and obtain stronger estimation performance. The most important feature of the hybrid NARX dynamic neural network is the embedding of LSTM memories, which provide jump ahead connections in the time-unfolding network. These jump ahead connections provide a shorter path for the propagation of gradient information, reducing the long-term dependence on the recurrent neural network. Due to address the nonlinear system identification and latching problem, NARX dynamic neural network is chosen for estimation SOC. The proposed model not only improves the estimation accuracy but also prevents the overfitting caused by long-term dependence in the structure of the recurrent neural network. In addition, our embedded LSTM memory is not sophisticated embedded memory cells and simply consists of tapped delayed information to other neurons. The hybrid NARX and LSTM model is shown in Fig. 3.

The hybrid NARX and LSTM model is mainly divided into two sections. First, the SOC of the battery is preliminarily predicted by the NARX recurrent neural network using the input current and voltage. Second, the initial predicted SOC and measured current and voltage are transferred to the LSTM recurrent neural network to predict the SOC.

$$\tilde{y} = f(\sum_{i=1}^{n} \alpha_i) \quad (9)$$

$$Y(t) = g(\tilde{y}, \sum_{i=1}^{n} \alpha_i \quad (10)$$

$$(11)$$

where $\tilde{y}$ is the SOC estimated by the NARX dynamic neural network, Y is the final SOC estimated by the

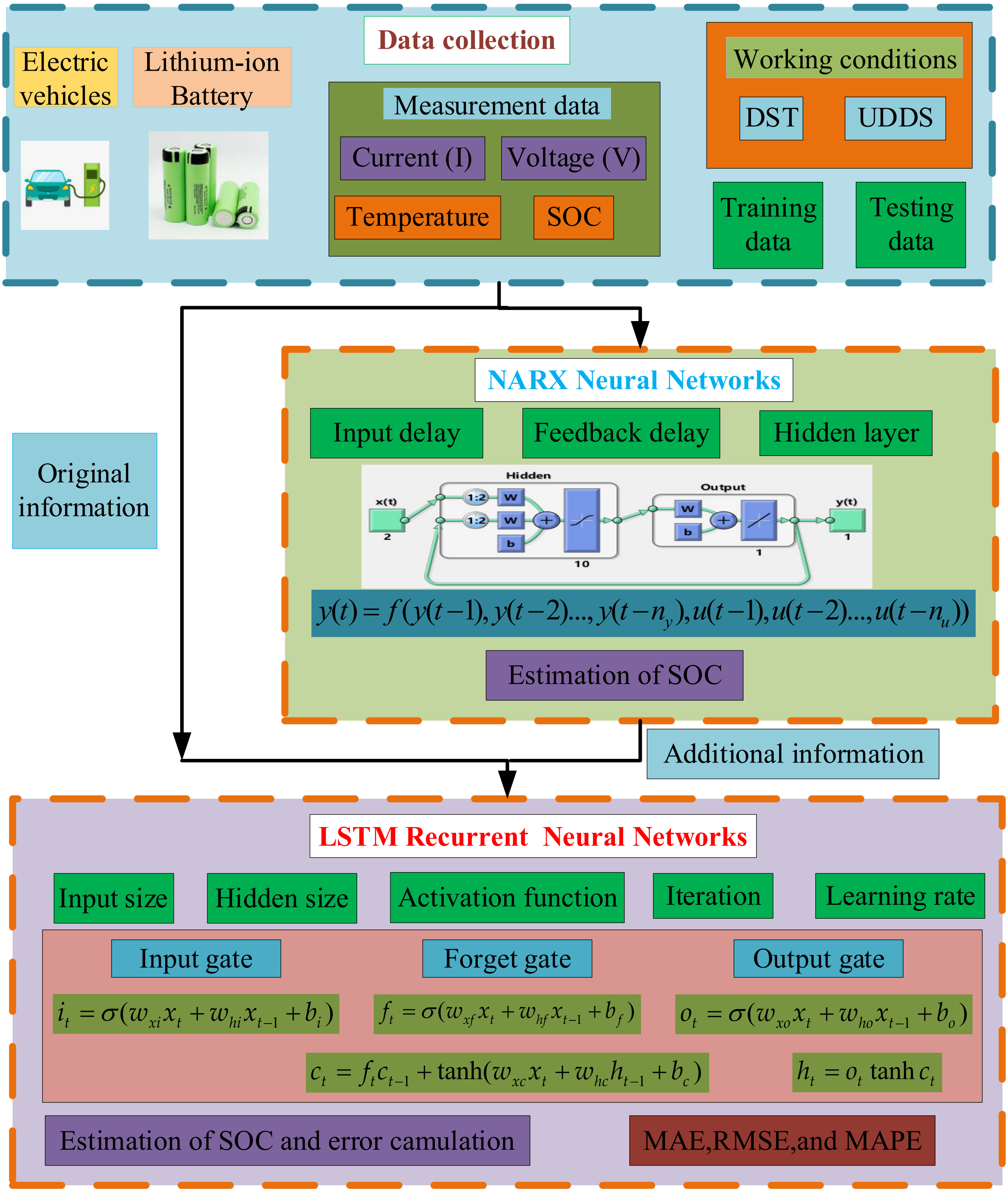

FIGURE 3. Schematic diagram of the hybrid NARX and LSTM model for SOC estimation.

hybrid NARX and LSTM, and α_i is the input data. To explain the proposed method clearly, the algorithm of hybrid NARX and LSTM model is presented, as shown in table 1.

IV. RESULTS AND DISCUSSION

In this study, the data are collected on the lithium-ion phosphate battery under UDDS conditions and the 18650 lithium-ion battery under DST conditions. The

TABLE 1. The algorithm of hybrid NARX and LSTM.

Algorithm: The algorithm of hybrid NARX and LSTM model
Step1. Input data (Current, Voltage, and Temperature)
Step2. Input Delay, Feedback Delay, Hidden layer, and Train function (Trainlm)
Step3. Training date (70%), Validation data (15%), and Testing data (15%)
Step4. Train the model of the NARX dynamic neural network $y(t) = f(y(t-1), y(t-2)..., y(t-n_y), u(t-1), u(t-2)..., u(t-n_u))$
Step5. Estimate the SOC with the NARX dynamic neural network $\tilde{y} = f(\sum_{i=1}^{n} \alpha_i)$
Step6. Add the SOC from the NARX dynamic neural network to the database
Step7. Train the LSTM neural network
Input gate: $i_t = \sigma(w_{xi}x_t + w_{hi}x_{t-1} + b_i)$
Forget gate: $f_t = \sigma(w_{xf}x_t + w_{hf}x_{t-1} + b_f)$ $c_t = f_t c_{t-1} + \tanh(w_{xc}x_t + w_{hc}h_{t-1} + b_c)$
Output gate: $o_t = \sigma(w_{xo}x_t + w_{ho}x_{t-1} + b_o)$ $h_t = o_t \tanh c_t$
Step8. Output the final estimation SOC $Y(t) = g(\tilde{y}, \sum_{i=1}^{n} \alpha_i)$

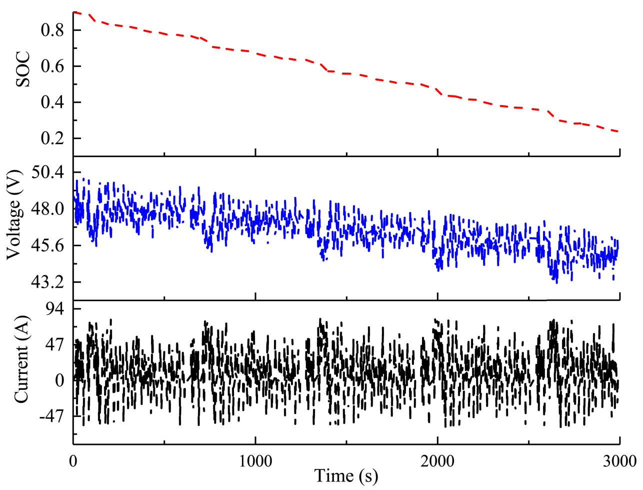

FIGURE 4. Current, Voltage, and SOC under UDDS conditions.

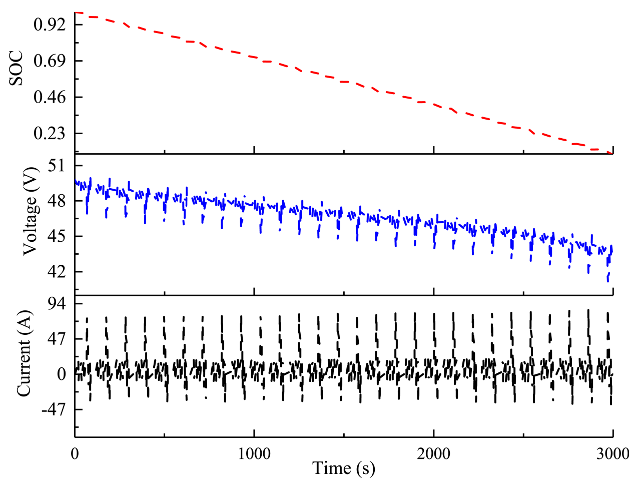

FIGURE 5. Current, Voltage, and SOC under DST conditions.

EVT500-500 equipment test system, host computer, Fluke data recorder, and related devices are used for data collection at 20°C to obtain training data and test data. The collected data of the two working conditions are shown in Fig. (4, 5)

To evaluate the performance of the proposed algorithm, mean absolute error (MAE), root mean square error (RMSE) and mean absolute percentage error (MAPE) are used. The mathematical formulas of MAE, RMSE, and MAPE are as follows:

$$\mathrm{MAE} = \frac{\sum_1^n |Y_e - Y_i|}{n} \tag{12}$$

$$\mathrm{RMSE} = \sqrt{\frac{\sum_1^n (Y_e - Y_i)^2}{n}} \tag{13}$$

$$\mathrm{MAPE} = \frac{1}{n}\sum_1^n \frac{|Y_e - Y_i|}{|Y_i|} \tag{14}$$

A. THE HYPER-PARAMETERS OF HYBRID NARX AND LSTM

Although the standard NARX neural network can effectively address the nonlinear problem with time series, as time passes, some problems such as gradient explosion and gradient disappearance can occur. To address this problem, the hybrid NARX and LSTM model is proposed. However, the number of hidden layers is an important hyper-parameter of the hybrid NARX and LSTM model. Fig. (6, 7) show the estimation results of the proposed model with the number of hidden layers at 50, 60, 70, and 80 under UDDS and DST conditions. According to the results, although the estimated SOC of lithium-ion batteries can be better obtained using different hidden layer numbers, the best performance is estimated when the number of neurons is 70. Therefore, 70 is selected as the number of hidden layers for the hyper-parameters of the hybrid NARX and LSTM.

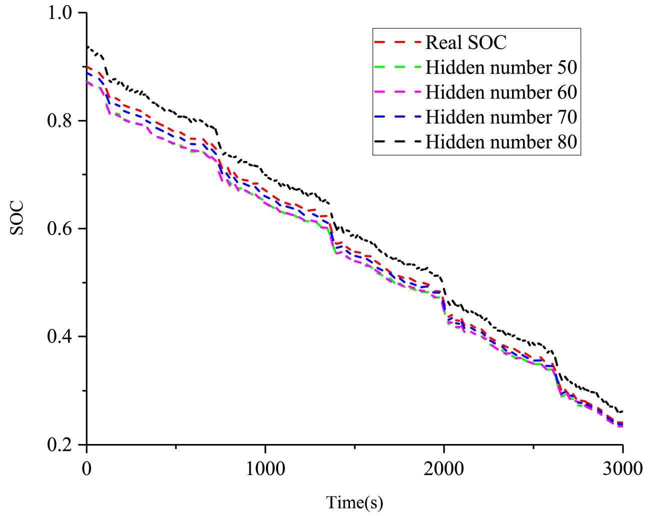

FIGURE 6. Results of SOC estimation using different hidden layer numbers (UDDS).

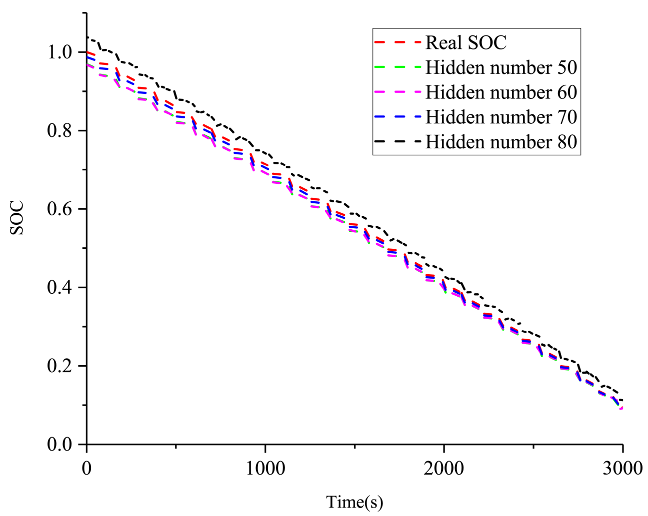

FIGURE 7. Results of SOC estimation using different hidden layer numbers (DST).

B. SOC ESTIMATION RESULTS

Real-time data for lithium-ion batteries (current, voltage, and SOC) are used as training data and testing data for the hybrid NARX and LSTM models under UDDS and DST conditions. The training data includes current and voltage, which is divided into three parts (70% training data, 15% verification data, and 15% test data). Input delay, feedback delay, and hidden layers are set to 1:2, 1:2, and 20, respectively. The training function is 'trainlm'. The primary estimation of SOC for lithium-ion batteries is obtained through the NARX dynamic neural network, and then 3000 samples including primary SOC estimations as well as initial current and voltage are input into the LSTM model as training data. The LSTM number is 70, the number of iterations is 100, and the learning rate is 0.01. After training, the trained hybrid NARX and LSTM model is used and the test samples are input for the final SOC estimation. At the same time, in order to verify that the proposed model has higher accuracy, it is compared and

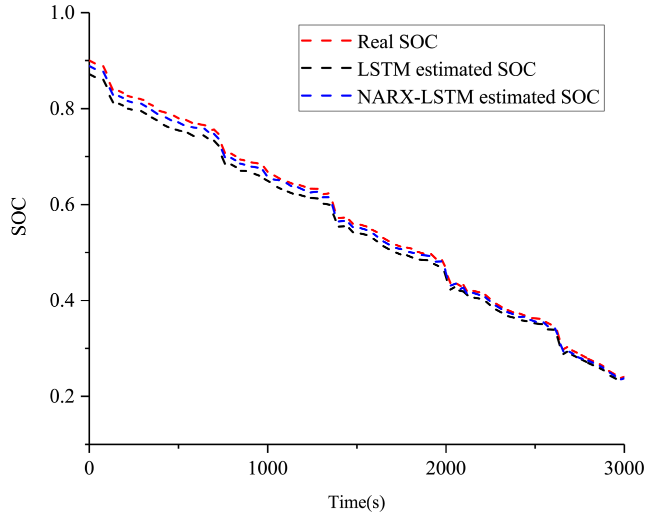

FIGURE 8. Results of SOC estimation under UDDS conditions.

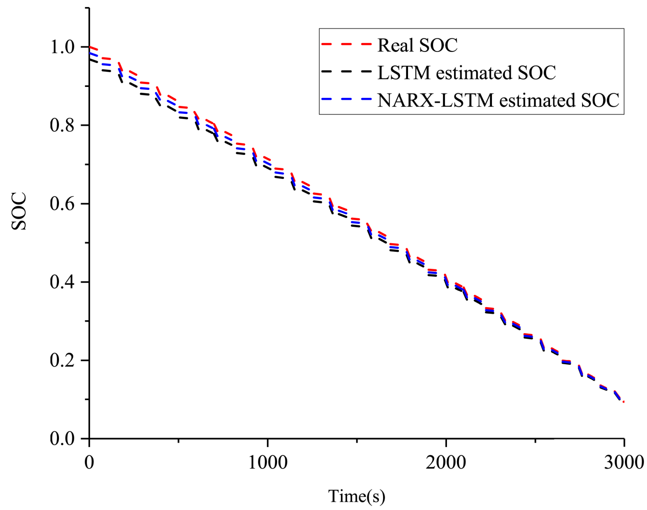

FIGURE 9. Results of SOC estimation under DST conditions.

analyzed with the standard LSTM model under UDDS and DST conditions. The estimation results of the hybrid NARX and LSTM model and the classic LSTM model are shown in Fig. (8, 9)

From Fig. (8, 9), we can discern that the proposed hybrid model and the standard LSTM model can estimate the SOC of lithium-ion batteries with higher accuracy. According to the enlarged image in the figures, it can be concluded that the estimation accuracy of the hybrid NARX and LSTM model is higher than the standard LSTM. The accuracy improves because the proposed model has two stage feature preprocessing and combines the estimation results of the standard NARX dynamic neural network with the original input data as the input data for the secondary training, which has high estimation accuracy.

C. PERFORMANCE OF MULTIVARIATE TIMES SERIES FORECASTING

Based on the real-time data of lithium-ion batteries collected in experiments, a multivariable time series forecasting model

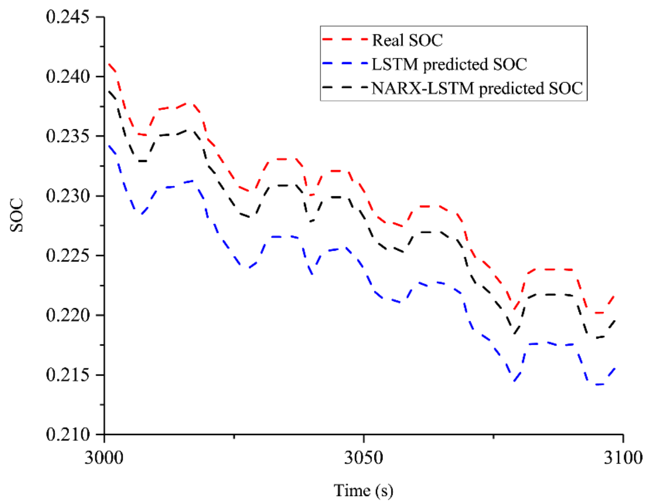

FIGURE 10. Results of SOC estimation under UDDS conditions.

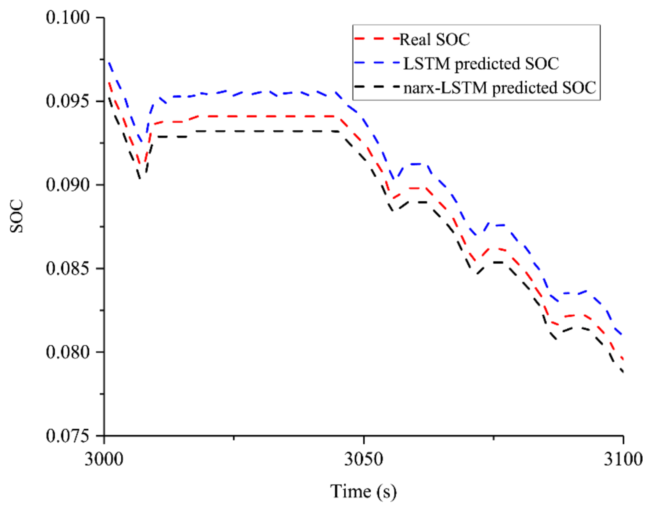

FIGURE 11. Results of SOC estimation under UDDS conditions.

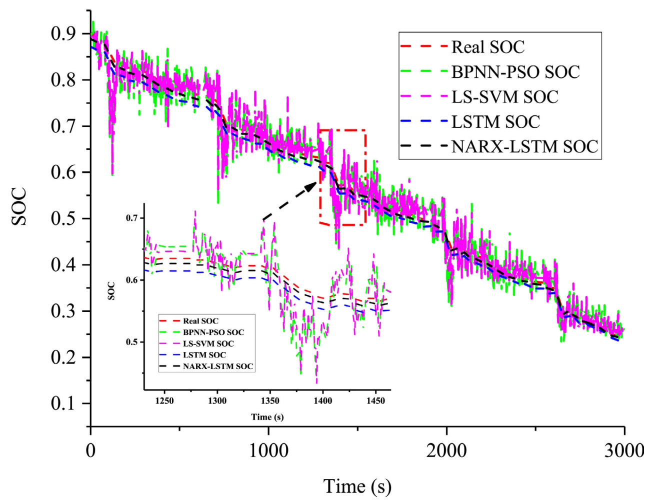

FIGURE 12. The result of SOC estimation under UDDS conditions.

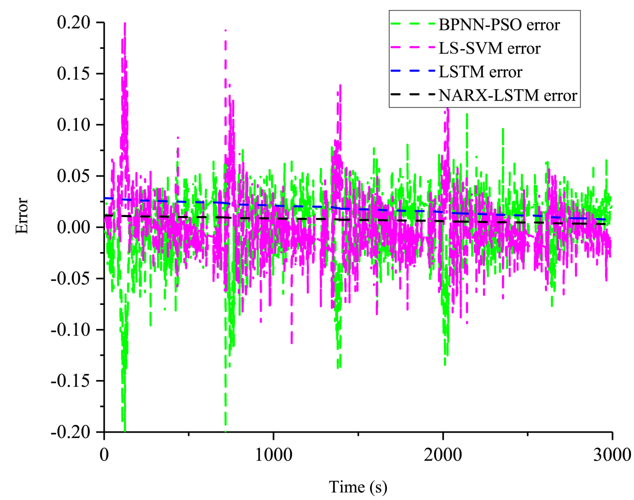

FIGURE 13. Error of SOC estimation under UDDS conditions.

of hybrid NARX and LSTM is established to extract the dynamic trend characteristics of the SOC of lithium-ion batteries and combine the real-time data of lithium-ion batteries for future estimation. It is primarily divided into two steps. The time series data from the first 2000 lithium-ion batteries is used to establish a multivariable time prediction model of NARX and LSTM for offline training. Online prediction uses the trained prediction model to forecast the real-time operating status of lithium-ion batteries. To verify that hybrid NARX and LSTM have better performance than multivariate time series forecasting, the performance of multivariate time series forecasting is compared with standard NARX. The prediction results of the hybrid NARX and LSTM model and the classic NARX model are shown in Fig. (10, 11)

The results of multivariate time series forecasting are shown in Fig. (10, 11) under UDDS and DST conditions.

It can be seen from the figures that when the hidden layer number is set to 70, the prediction accuracy of the proposed model is higher than that of the traditional LSTM model. The RMSE of the prediction accuracy of LSTM is 0.64% and 0.27% under UDDS and DST conditions, respectively. The RMSE of the prediction accuracy of LSTM is 0.27% under UDDS conditions; the RMSE of prediction accuracy is 0.13% under DST conditions. These results demonstrate that the proposed model has better performance than multivariate time series forecasting.

D. VERIFICATION WITH EXISTING METHODS

To further verify the effectiveness of the hybrid NARX and LSTM model, the proposed model is compared with the standard BPNN-PSO, LL-SVM, and LSTM models. The estimation results and error are shown in Fig. (12-15). Due to external interference and temperature variation, the real rate of SOC presents a nonlinear and unstable trend. Although the classic BPNN-PSO and LL-SVM can better estimate SOC for the lithium-ion battery, the estimation error is large for the slope of the SOC curve, and the lithium-ion battery SOC estimation fluctuates greatly during the entire estimation process. It can be noticed that the proposed model is outperforming the existing methods from the points between the real SOC

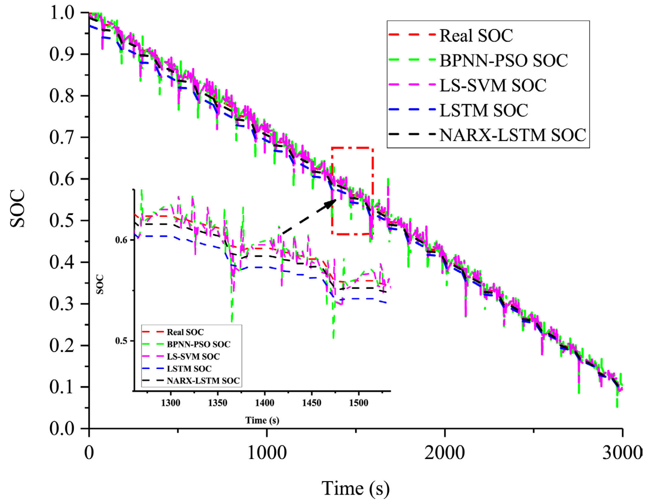

FIGURE 14. Result of SOC estimation under DST conditions.

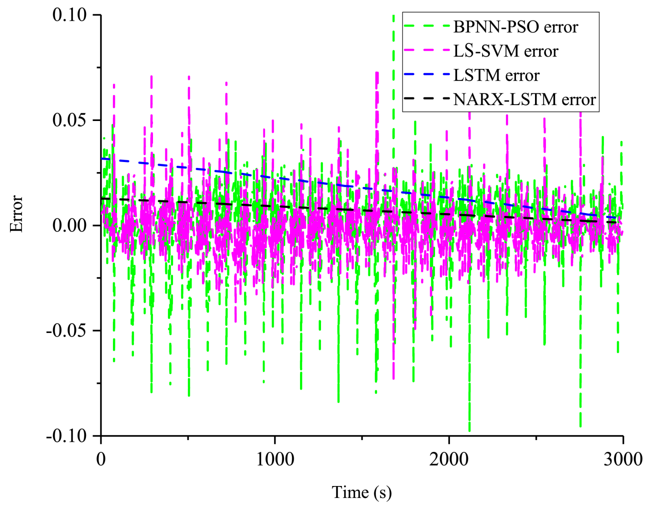

FIGURE 15. Error of SOC estimation under DST conditions.

and estimated SOC. The proposed hybrid NARX and LSTM presents a high correlation as well as this model smoothly follows the real data. Due to embed the LSTM memory and time series, the error of proposed model exhibits a downward trend with the increasing time. The standard LSTM and hybrid NARX and LSTM models can accurately estimate the SOC of the battery when compared with BPNN-PSO and LS-SVM. Due to embed LSTM memories, long-term dependence on the recurrent neural network is reduced. The hybrid NARX-LSTM model not only effectively solves the gradient descent and gradient disappearance of the NARX dynamic neural network but also improves the estimation accuracy relative to the standard LSTM model. Furthermore, the embedded LSTM cells is not sophisticated embedded memory and simply consists of tapped delayed information to other neurons.

To further verify the effectiveness of the proposed model, BPNN-PSO, LS-SVM, LSTM, and hybrid NARX-LSTM are compared and analyzed under UDDS and DST conditions, respectively. Table 2 describes the proposed model and existing methods of prediction performance. According to Table 2, under UDDS conditions, the RMSE, MAPE, and MAE of the classic BPNN-PSO are 3.19%, 4.38%, and 2.29%, respectively. Under DST conditions, the RMSE, MAPE, and MAE are 1.45%, 2.23%, and 0.97%, respectively. Among the four methods, the standard BPNN-PSO method has the lowest estimation accuracy. The RMSE of LS-SVM under UDDS and DST conditions is 1.71% and 1.17%, MAPE is 3.49% and 1.79%, and MAE is 1.84% and 0.81%.

TABLE 2. Prediction performance of tested methods.

Methods	Conditions	RMSE(%)	MAPE (%)	MAE(%)
BPNN-PSO	UDDS	3.19	4.38	2.29
	DST	1.45	2.23	0.97
LS-SVM	UDDS	2.71	3.49	1.84
	DST	1.17	1.79	0.81
LSTM	UDDS	1.87	3.14	1.72
	DST	1.95	3.17	1.77
NARX-LSTM	UDDS	0.76	1.28	0.72
	DST	0.78	1.24	0.69

Although the estimation performance of LS-SVM is better than that of BPNN-PSO, the error fluctuates greatly. In the standard LSTM model, RMSE, MAPE, and MAE are 1.87%, 3.14%, and 1.72%, respectively, under UDDS conditions. Under DST conditions, RMSE, MAPE, and MAE are 1.95%, 3.17%, and 1.77%, respectively. The classic LSTM has better estimation performance. In the hybrid NARX and LSTM model, the RMSE is 0.76% and 0.78% under UDDS and DST conditions, respectively; MAPE is 1.28% and 1.24%, respectively, and MAE is 0.72% and 0.69%, respectively. The estimation accuracy of the proposed model is the highest among the four methods, and the three evaluation indicators basically fluctuate around 1%. Compared with LSTM, RMSE is increased by 59% under UDDS conditions and 60% under DST conditions.

V. CONCLUSION

To address the phenomenon of gradient explosion and disappearance intrinsic to the traditional NARX recurrent neural network, a model combining NARX and LSTM is proposed to improve the estimation accuracy. The proposed model combines the advantages of the NARX model and the LSTM model. This model not only breaks the constraints of the traditional physical model but also has LSTM memory cells with external input nonlinearity, which can prevent gradient explosion and gradient disappearance. The preliminary prediction of the NARX model combines the original collected voltage and current as the training data of the LSTM model. The appropriate number of hidden layers is selected, and the estimation performance and multitime prediction performance are verified under UDDS and DST conditions. Under UDDS and DST conditions, the RMSE of the estimation performance of this hybrid NARX and LSTM model is

0.76% and 0.78%, respectively, and the performance of multivariate time series forecasting is 0.27% and 0.13%, respectively. Experimental results show that the proposed model has strong estimation performance and multitime prediction performance. Finally, the proposed method is compared with BPNN-PSO, LS-SVM and LSTM, which verifies that the estimation accuracy of the proposed model is significantly higher than existing methods, and the RMSE estimation performance of the proposed model is improved by approximately 60% compared with the classic LSTM estimation model. This study presents the combination of autoregressive model and machine learning methods for SOC estimation of lithium-ion batteries. The proposed model obtains higher estimation and prediction characteristics. In this respect, the combination of autoregressive model and machine learning methods in time series estimation presented by the proposed model in this study opens the door for an accurate long term estimation.

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