The SOC Prediction of Lead-Acid Battery Based on MIV-OSELM Algorithm

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***Abstract*—In this work, an MIV-OSELM prediction model is constructed to predict the state of charge (SOC) of lead-acid battery, which combines the mean impact value (MIV) algorithm and the online sequence extreme learning machine (OSELM) algorithm. This model uses the MIV method to quantitatively calculate the impact value of the input variables on the output variables, and completes selection of the input variables of model; the OSELM method is used to carry out incremental learning of new samples generated during the use of battery, and track the potential impact of battery's state of health (SOH) on the SOC prediction of battery in a timely manner. Compared with the prediction results of other models, the MIV-OSELM method can improve the prediction accuracy of SOC during the charging and discharging processes of lead-acid batteries, which also has the adaptive ability to make dynamic adjustment of the model parameters according to the information of new samples.**

Keywords—lead-acid battery, state of charge (SOC), incremental learning, adaptive ability

I. INTRODUCTION

Lead-acid battery has the advantages of mature production technology, high reliability, low production cost, and strong environmental applicability, which is widely used in various fields such as power, energy storage, communication and emergency response as a secondary power source. During the charging and discharging processes of battery, the state of charge (SOC) can reflect the amount of energy stored in battery, and it is also the basis for further battery management and use. Therefore, it is of great significance to study prediction of the SOC of lead-acid battery for scientific management and safe use of battery.

At presents, in related researches both in China and other countries, the methods for SOC prediction of battery mainly include the following four categories: 1. Ampere-hour integral method [1]-[3]. In this method, the SOC of battery is obtained by integrating the battery current with time after high-frequency sampling of the battery current, which has an open-loop working model. In [3], YANG J Y et al. estimated the battery SOC based on the ampere-hour integration. This method is simple and easy to understand, but accumulative error may be caused by current integration during the calculation process, which leads to low precision of the final prediction results. 2. Characteristic parameter method [4]-[6]. The current SOC of battery is obtained by mapping the relationship between the open-circuit voltage or internal resistance of battery and the remaining capacity of battery. In [6], a new unsteady open-circuit voltage method is proposed, which can quickly and estimate the battery SOC in real time, realize parameter identification of the battery, and overcome the shortcoming of long measurement time for the steady-state open-circuit voltage of battery. 3. Data-driven method. Such method carries out modeling study on battery based on data, predicts and evaluates the SOC of battery using the established data model. The data-driven methods mainly include fuzzy logic method [7], artificial neural network [8]-[9], extreme learning machine [10] and support vector machine [11]-[13]. For example, the support vector machine algorithm is used in [13], and the battery SOC is completed predicted with voltage, current and temperature as the input variables of SVM. In [14],the input parameters of battery are selected, and a method combining genetic algorithm (GA) and BP neural network is proposed to improve the prediction accuracy. 4. Statistical filtering method. Such method is mainly used in model prediction of battery SOC, which mainly includes the two types of methods based on Kalman filter [15] and particle filter [16]-[18], respectively. In [19], based on the extended Kalman filter (EKF) method, a dual estimator applicable to the battery state and battery model is designed, which can achieve optimization and evaluation of the remaining capacity of battery, so as to complete SOC prediction.

Among the above methods, due to its strong nonlinear fitting ability, strong robustness and outstanding performances in modeling of various types of batteries, the data-driven method is applied in the SOC prediction of battery more frequently. Most of these methods predict and study the SOC of battery based on previous battery state by using related data as learning samples, while failing to effectively utilize the new usage states and data continuously generated during the use of battery, but such data often contains richer and more valuable battery information. Due to lack of corresponding incremental learning link, many prediction models cannot update and modify the model parameters in real time, which will affect the SOC prediction accuracy of battery. Moreover, the prediction accuracy will continuously decrease with the use of battery.

To address this problem, this paper constructs a prediction model by combining mean impact value (MIV) algorithm and online sequence extreme learning machine (OSELM) algorithm, which can be used to evaluate the state of charge (SOC) of lead-acid battery. This model calculates the impact of input variables on output variables using the MIV algorithm to completes the selection of model input variables. New samples generated by

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the system are learned and absorbed by using the OSELM method, and dynamic adjustment and update of related model parameters are carried out according to the new samples, so as to adapt to related change in the battery state of health (SOH). When learning new samples, the MIV-OSLEM model does not need to store or repeatedly learn old samples, but only needs to dynamically update and adjust the model parameters according to the system information contained in new samples, which can alleviate the storage pressure of system, reduce the computational complexity, and achieve the incremental learning.

II. Method and Model

A. Mean Impact Value (MIV) Algorithm

In neural networks, the MIV algorithm is an important index used to evaluate influence of input variables on output variables. The process of MIV algorithm mainly includes: after training of model, each input variable of training sample is increased or decreased according to a certain adjustment rate, so that two sets of new training samples can be obtained as the input of model. The difference between the two output results is the impact value (IV) on the output variable. The IV is averaged by the number of observed cases to obtain the MIV of the input variable on the output variable. The MIV of each input variable is calculated, the input variables are sorted according to the absolute values of their MIVs, their impact on the output variables is determined, and thus, the selection of input variables is achieved.

B. Extreme Learning Machine (ELM)

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The ELM is a feedforward algorithm with single hidden layer, which randomly generates continuous weight between input layer and hidden layer and the threshold of neurons in hidden layer. There is no need for adjustment during the training process, and a unique optimal solution can be obtained by setting the number of neurons in the hidden layer, which has the advantages of learning speed and good generalization performance [20].

The structure of typical ELM model is as shown in Fig. 1. In this network, the input layer has n neurons, the hidden layer has l neurons, and the output layer has m neurons.

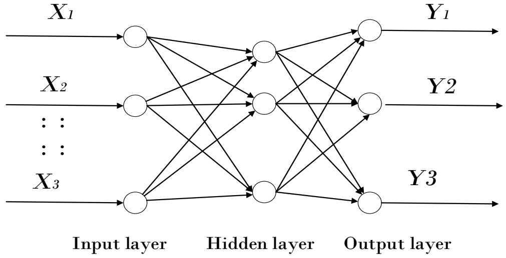


Fig. 1. Structure of ELM model.

Assume a training set containing Q samples, input matrix is X, and corresponding output matrix is T, where:

$$X = \begin{bmatrix} x_{11} & x_{12} & \dots & x_{1Q} \\ x_{21} & x_{22} & \dots & x_{2Q} \\ \vdots & \vdots & \vdots & \vdots \\ x_{n1} & x_{n2} & \dots & x_{nQ} \end{bmatrix}_{n \cdot Q} \quad T = \begin{bmatrix} t_{11} & t_{12} & \dots & t_{1Q} \\ t_{21} & t_{22} & \dots & t_{2Q} \\ \vdots & \vdots & \vdots & \vdots \\ t_{n1} & t_{n2} & \dots & t_{nQ} \end{bmatrix}_{n \cdot Q} \quad (1)$$

The sigmoid, sin or hardlim function is often chosen as the activation function $g(x)$ in the hidden layer, the output O of network is:

$$O = [o_1, o_2, \dots, o_Q] \quad (2)$$

$$o_j = \begin{bmatrix} o_{1j} \\ o_{2j} \\ \vdots \\ o_{mj} \end{bmatrix}_{m \cdot 1} = \begin{bmatrix} \sum_{i=1}^{l} \beta_{i1} g(w_i x_j + b_i) \\ \sum_{i=1}^{l} \beta_{i2} g(w_i x_j + b_i) \\ \vdots \\ \sum_{i=1}^{l} \beta_{im} g(w_i x_j + b_i) \end{bmatrix}_{m \cdot 1} \quad (j = 1,2,\dots,Q) \quad (3)$$

where, ω is the connection weight matrix between input layer and hidden layer, β is the connection weight matrix between hidden layer and output layer, b is the threshold of neurons in the hidden layer.

After transposing O, it can be represented as:

$$H\beta = O' \quad (4)$$

where, H is output matrix of hidden layer of model, and its specific form is as follows:

$$H(w_1, w_2, \dots, w_l, b_1, b_2, \dots, b_l, x_1, x_2, \dots, x_Q) = \begin{bmatrix} g(w_1 \cdot x_1 + b_1) & g(w_2 \cdot x_1 + b_2) & \dots & g(w_l \cdot x_1 + b_l) \\ g(w_1 \cdot x_2 + b_1) & g(w_2 \cdot x_2 + b_2) & \dots & g(w_l \cdot x_2 + b_l) \\ \vdots & \vdots & \vdots & \vdots \\ g(w_1 \cdot x_Q + b_1) & g(w_2 \cdot x_Q + b_2) & \dots & g(w_l \cdot x_Q + b_l) \end{bmatrix}_{Q \cdot l} \quad (5)$$

The ELM model training aims to minimize the prediction error of the model, so the loss function of training samples can be defined as:

$$f = \|O' - T'\| = \|H\beta - T'\| \quad (6)$$

According to [21], the training error of the ELM algorithm can be approximated to an arbitrary $\varepsilon > 0$, $f = \|H\beta - T'\| < \varepsilon$. When the activation function $g(x)$ is infinitely differentiable, w and b can be randomly selected before training and remain unchanged during training. The connection weight β can be obtained by solving the least squares of the following equations:

$$min\|H\beta - T'\| \quad (7)$$

The solution is $\hat{\beta} = H^{+}T'$. In it, H^{+} is the Moore-Penrose generalized inverse of output matrix of hidden layer. In general, $H^T H$ is a non-singular matrix, so $H^{+} = (H^T H)^{-1} H^T$.

C. Online Sequence Extreme Learning Machine (OSELM)

The OSELM algorithm is based on the neural network of ELM. The model is trained offline using the existing training samples, and the output connection weights of the neural network are iterated and updated dynamically via incremental learning according to the newly acquired learning samples., which can minimize the computational burden, improve the update efficiency, and improve the prediction accuracy of network. The update principle of this method is as follows.

Combining the ELM algorithm, when N_1 new samples $\hat{N_1} = \{(x_i, t_i)\}_{i=N_0+1}^{N_1}$ are acquired for incremental learning, calculation of the new network output weight β_1 is equivalent to solving the minimum norm least squares of the new linear system, i.e.:

$$\left\| \begin{bmatrix} H_0 \\ H_1 \end{bmatrix} \hat{\beta} - \begin{bmatrix} T_0 \\ T_1 \end{bmatrix} \right\| = min_\beta \left\| \begin{bmatrix} H_0 \\ H_1 \end{bmatrix} \beta_1 - \begin{bmatrix} T_0 \\ T_1 \end{bmatrix} \right\| \tag{8}$$

where,

$$T_1 = \begin{bmatrix} t_{N_0+1}^T & t_{N_0+2}^T & \cdots & t_{N_0+N_1}^T \end{bmatrix}^T \tag{9}$$

We can obtain $\beta_1 = K_1^{-1} \begin{bmatrix} H_0 \\ H_1 \end{bmatrix}^T \begin{bmatrix} T_0 \\ T_1 \end{bmatrix}$, where:

$$K_1 = \begin{bmatrix} H_0 \\ H_1 \end{bmatrix}^T \begin{bmatrix} H_0 \\ H_1 \end{bmatrix} = \begin{bmatrix} H_0^T & H_1^T \end{bmatrix} \begin{bmatrix} H_0 \\ H_1 \end{bmatrix} = K_0 + H_1^T H_1 \tag{10}$$

$$\begin{bmatrix} H_0 \\ H_1 \end{bmatrix}^T \begin{bmatrix} T_0 \\ T_1 \end{bmatrix} = {H_0}^T T_0 + H_1^T T_1 = K_0 K_0^{-1} {H_0}^T T_0 + H_1^T T_1 =$$
$$(K_1 - H_1^T H_1)\beta_0 + H_1^T T_1 = K_1 \beta_0 - H_1^T H_1 \beta_0 + H_1^T T_1 \tag{11}$$

By using β_0 to represent β_1, we can obtain:

$$\beta_1 = K_1^{-1} \begin{bmatrix} H_0 \\ H_1 \end{bmatrix}^T \begin{bmatrix} T_0 \\ T_1 \end{bmatrix} = K_1^{-1}(K_1 \beta_0 - H_1^T H_1 \beta_0 + H_1^T T_1)$$
$$= \beta_0 + K_1^{-1} H_1^T (T_1 - H_1 \beta_0) \tag{12}$$

Similarly, when N_{k+1} training sample $\hat{N_{k+1}} = \{(x_i, t_i)\}_{i=(\sum_{j=0}^{k} N_j)+1}^{\sum_{j=0}^{k+1} N_j}$ are updated for the (k+1)-th time, the network output weight can be iteratively calculated as:

$$K_{k+1} = K_k + H_{k+1}^T H_{k+1};\ \beta_{k+1} = \beta_k + K_{k+1}^{-1} H_{k+1}^T (T_{k+1} - H_{k+1}\beta_k) \tag{13}$$

According to the Woodbury principle, K_{k+1}^{-1} can be rewritten as:

$$K_{k+1}^{-1} = (K_k + H_{k+1}^T H_{k+1})^{-1} =$$
$$K_k^{-1} - K_k^{-1} H_{k+1}^T (I + H_{k+1} K_k^{-1} H_{k+1}^T)^{-1} \cdot H_{k+1} K_k^{-1} \tag{14}$$

Let $P_{k+1} = K_{k+1}^{-1}$, then the above equation can be rewritten as:

$$P_{k+1} = P_k + P_k H_{k+1}^T (I + H_{k+1} P_k H_{k+1}^T)^{-1} \cdot H_{k+1} P_k \ \beta_{k+1} = \beta_k + P_{k+1} H_{k+1}^T (T_{k+1} - H_{k+1}\beta_k) \tag{15}$$

Therefore, as more new samples are collected, online iteration and update of the connection weights of the OSELM neural network can be completed using the above equation.

III. Model Prediction Process

The prediction process of the SOC of lead-acid battery using the MIV-OSELM model is as follows:

1. Obtain the data collected during the charging and discharging test, and construct the data samples of model.

2. Perform data preprocessing such as data supplementation, elimination, and normalization on the data samples, and divide the data into the training set and test set.

3. The impact values of various input variables are calculated using MIV method, and input variables of model are selected.

4. Initialize related parameters of the model, such as the number of nodes in hidden layer of OSLEM, and the number of new samples for batch learning.

5. After determining the input variables, the ELM method is employed to learn the training samples offline.

6. The model predicts the test samples in chronological order, and the test samples are accumulated as newly acquired learning samples during the prediction process.

7. Calculate whether the number of newly acquired learning samples reaches the number of new samples required for batch learning set by the model. If so, dynamically update the model parameters using the new samples, go to the step of online learning, and complete the incremental learning process of model. If not, go to Step 6.

8. Clear the number of newly acquired samples and go to Step 6, until the prediction and incremental learning of all test samples are completed.

The prediction process of lead-acid battery SOC based on the MIV-OSELM model is presented in Fig. 2:

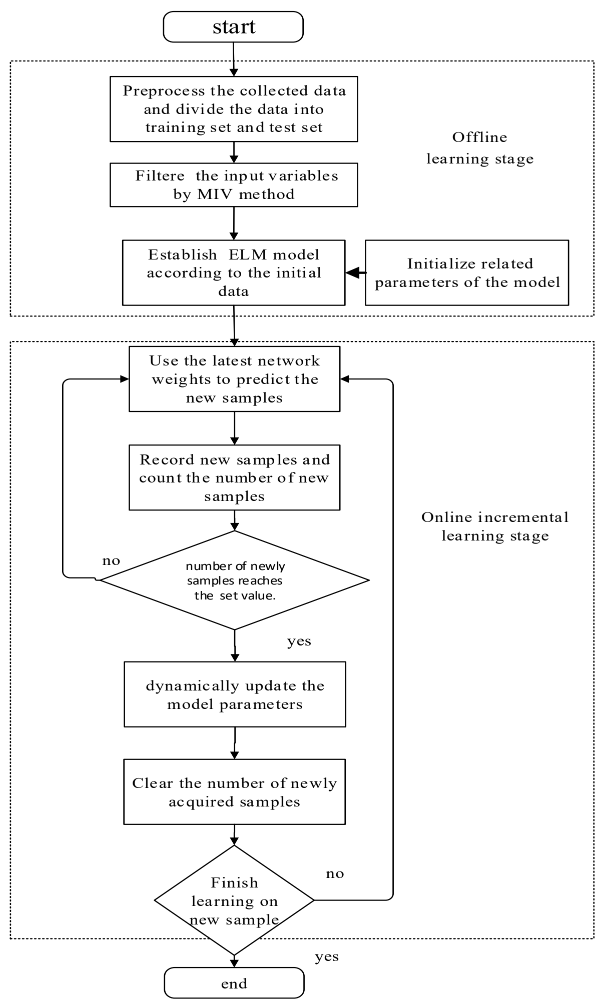


Fig. 2. Predict process of MIV-OSELM Neural network.

IV. Example Analysis

A. Experimental Data

The battery charging and discharging experimental device includes a large-capacity flooded lead-acid battery pack, battery auxiliary system, data collection system and discharge resistance. During the battery charging process, a multi-stage constant-current charging method is adopted, and different current rate is used according to the number of battery cycle during the discharging process. various parameters are collected regularly, including the terminal voltage, charging and discharging current, charging and discharging time, battery life cycle, electrolyte density, electrolyte temperature and ambient temperature of the battery.

The SOC of battery refers to the ratio of the current carrying capacity of battery to the battery capacity. For the large-capacity flooded lead-acid battery, its voltage and current tend to fluctuate greatly during use, and it is difficult to calculate the current carrying capacity of battery. The battery density can reflect its current carrying capacity to a certain extent, which will not fluctuate with the load, so the battery density is used as the reference of the battery SOC, and the prediction of battery SOC is the prediction of the battery density during the charging and discharging process. A total of 3400 groups of data samples were collected in the experiments.

B. Selection of Battery Input Variables by MIV Method

The MIV algorithm is used to select input variables of the ELM model which is set with 60 hidden layer nodes, and the selection adjustment rates are 10%, 20% and 30%, respectively. The MIVs corresponding to various input characteristic parameters of the battery are calculated, as shown in Table I:

TABLE I. MIV OF DIFFERENT CHARACTERISTIC PARAMETERS

characteristic parameters	rate of MIV (%)			sort
	10	20	30	
Current(I)	-0.3156	-0.2836	-0.2265	1
Initial density(ρ 0)	0.1432	0.2456	0.3251	2
Time(t)	-0.0903	-0.1123	-0.1635	3
Initial voltage(V)	-0.0227	-0.0245	-0.0307	4
Cycle(K)	-0.0042	-0.0053	-0.0123	5
Electrolyte temperature (T0)	0.0016	0.0018	0.0021	6
ambient temperature(T)	0.0006	0.0008	0.0006	7

According to the calculation results, the impacts of the input variables on the output variables are in following importance order: current, initial density of electrolyte, time, initial voltage, cycle, temperature of electrolyte, and ambient temperature. Because the internal electrodes of lead-acid battery are charged or discharged by an external current and have chemical reactions to store or release electrical energy, the chemical reaction process is mainly related to the density of electrolyte. Therefore, from the perspective of chemical reaction, the main influencing factors on battery SOC include the current, the time and initial density of electrolyte, while changes in features such as battery terminal voltage, service cycle and temperature will also generate certain secondary impacts on the charging and discharging process of battery. Therefore, the importance order of the input variables of prediction model obtained using the MIV algorithm is in line with the actual charging of battery.

The first 80% of the data is used as the training data, and the last 20% is used as the test data. The prediction accuracy of various models are evaluated according to the mean absolute error (MAE), mean absolute percentage error (MAPE) and mean square error (MSE).

The prediction results of input variables under the four schemes are shown in Table II. According to the results, it can be seen that when the input variable scheme 2 is adopted, the corresponding prediction results of neural network model are the most accurate, that is, the selected input variables of neural network are: the charging current, initial electrolyte density, charging time, terminal voltage, cycle and electrolyte temperature.

TABLE II. PREDICTION ERROR OF THE PREDICTION MODEL UNDER DIFFERENT INPUT VARIABLE SCHEME

Model	Input variable	mse	mae	$mape$
Scheme 1	I, ρ 0, t, V, K, T0, T	0.0045	0.0432	0.0376
Scheme 2	I, ρ 0, t, V, K, T0	0.0021	0.0253	0.0213
Scheme 3	I, ρ 0, t, V, K	0.0148	0.0510	0.0474
Scheme 4	I, ρ 0, t, V	0.0201	0.0701	0.0592

C. Effectiveness Verification of the OSELM Model

The variables of battery terminal voltage, current, time, battery use cycle, starting terminal voltage, and battery electrolyte temperature recorded in the experiments are used as the input variables of prediction model, and the battery density is used as the prediction variable.

BP neural network or optimized BP neural network is used as the prediction model in the SOC prediction research of battery in many papers. For contrast, the model based on the BP neural network, the model based on the BP neural network optimized with genetic algorithm (GA-BP), the ELM model and the OSELM model were used to predict the battery density during the charging and discharging process, respectively. For various prediction models, the main parameters under high prediction accuracies are selected, and their settings are as follows:

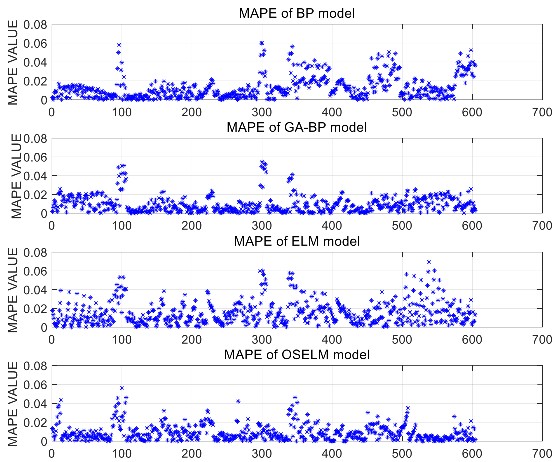
1. The BP neural network has 3 hidden layers, 9 hidden nodes of each layer, and 1 output node. The Levenberg-Marquardt algorithm is used as the training algorithm, and the training transfer function is a $tan\,s\,ig$ function.

2. The GA-BP model has the same parameters as the BP model. In the genetic algorithm part, the initial population number is 10, the maximum evolutionary generation is 50, and the probabilities of crossover and mutation in the genetic algorithm are 0.4 and 0.3, respectively.

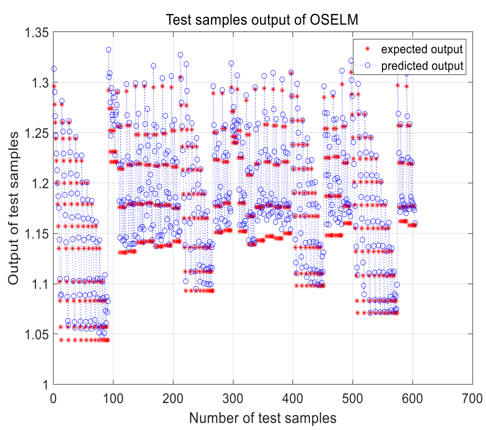
3. The ELM model is set with 60 hidden layer nodes, and the sig function is chosen as the output activation function.

4. The OSELM model has 60 hidden layer nodes. When the number of newly acquired samples reaches 30, the model output weights are updated once. The sig function is chosen as the activation function.

The first 80% of the data is used as the training data, and the last 20% is used as the test data, and this scheme is used for model training in the first learning case; the first 50% of the data is used as the training data, and the last 50% is used as the test data, and this scheme is used for model training under the second learning case. In both cases, various neural networks are trained, the SOC prediction results of the charging and discharging process using of various network models are presented in Fig. 3 and Fig. 4.

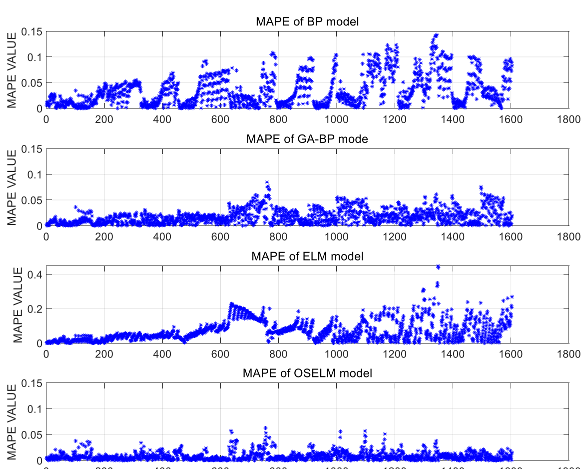


(a) The test samples MAPE of each model



(b) Comparison of predicted output with expected output in OSELM

Fig. 3.Predicted outputs of different neural networks in the first case.



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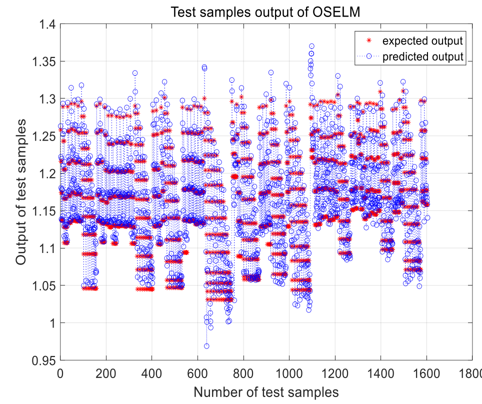

(b) Comparison of predicted output with expected output in OSELM

Fig. 4. Predicted outputs of different neural networks in the second case.

The comparisons of prediction indicators are shown in Table III and Table IV:

TABLE III. COMPARISON OF PREDICTION INDEXES OF DIFFERENT NEURAL NETWORKS IN THE FIRST CASE

Model	BP	GA-BP	ELM	OSELM
MAE	0.0151	0.0113	0.0253	0.0126
MAPE	0.0128	0.0096	0.0213	0.0114
MSE	8.38*e-4	4.57*e-4	0.0021	6.07*e-4
Time(s)	0.64	93	0.025	0.033

TABLE IV. THE PREDICTION INDEXES OF DIFFERENT NEURAL NETWORKS IN THE SECOND CASE

Model	BP	GA-BP	ELM	OSELM
MAE	0.0393	0.0285	0.0818	0.0108
MAPE	0.0338	0.0249	0.0709	0.0093
MSE	0.0027	0.0016	0.0114	3.48*e-4
Time(s)	0.59	75.12	0.011	0.062

According to the prediction results, in the first learning case, there are more training samples and less test samples, which means there are less samples for incremental learning. In this case, the prediction accuracies of different models all fail to satisfy the requirement for industrial application. Among these methods, the ELM method has the highest computational efficiency and the shortest computation time; the OSELM and GA-BP model have the higher prediction accuracy. The GA-BP model can improve the prediction accuracy of the BP model. The OSELM model has the best overall prediction effect when the computational efficiency and accuracy are considered comprehensively.

In the second learning case, the number of training samples is reduced, while the number of test samples is increased, that is, there are more samples for incremental learning. In this case, the OSELM model has the highest prediction accuracy, which is significantly higher than the prediction accuracies of the other three models and has higher computational efficiency. Although GA-BP has optimized the prediction performance of BP model to a certain extent, this model does not have the incremental learning ability, and only carries out optimization on the basis of original data. It is difficult for GA-BP to learn and absorb the information of new samples, so the optimization effects are not obvious. During the use of battery, the prediction errors of GA-

BP neural network, BP neural network and ELM model are becoming bigger with time. This is mainly because the state of health of battery will change during its use, thus affecting the prediction accuracy of SOC. The OSELM model can improve the prediction accuracy of battery in full time domain. In particular, with the use of battery, the prediction accuracy of OSELM model does not decrease, and its prediction results are significantly better than those of other models. The main reason is that as the OSELM model carries out incremental learning of newly generated samples, it tracks the change process of battery's state of health in time, and obtains valuable information from the new samples. Based on this, related parameters of the model are dynamically updated and adaptively adjusted to improve the prediction accuracy.

For the large-capacity lead-acid battery, new data samples are continuously generated during its use, and new samples often contain more valuable information. In particular, the accumulated number of new samples will increase with the time of use, and the incremental learning ability of new samples is particularly important for the model to accurately predict the battery SOC. The OSELM model has the best overall prediction effect when the computational efficiency and accuracy are considered comprehensively, and can accurately predict the SOC of lead-

V. Conclusions

In this paper, combining MIV algorithm and OSELM method, the MIV-OSELM prediction model is constructed to predict the SOC of large-capacity flooded lead-acid battery. By comparing the prediction results of our model with other network models, we can draw the following conclusions:

1. The MIV method can quantitatively analyze the IV of the input variable of the model on the output variable. Based on analysis and comparison of the impact values, the input variables can be selected, and the prediction accuracy of model can be improved.

2. The OSELM method can iterate and update the output weights of model based on the newly acquired samples without repeatedly training the old samples, which only generates a small computational burden. This method can achieve incremental learning of the model, with high learning efficiency and strong adaptive ability.

3. The MIV-OSELM prediction model has the incremental learning ability. Compared with the battery SOC prediction results obtained with the model based on BP neural network, GA-BP neural network and the ELM model, we can see that with its incremental learning ability, the MIV-OSELM model can absorb more valuable information from new samples, and it shows excellent results in calculation and accuracy, which can provide accurate prediction of the SOC of large-capacity lead-acid batteries.

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