State of Charge Estimation based on Port AGV Dynamic sPSO-DBN-ELM

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Abstract

The state of charge (SOC) of the battery is a crucial aspect in ensuring the safe charging of Automated Guided Vehicles (AGVs). However, with battery aging, it becomes challenging for the Battery Management System (BMS) to maintain the accuracy of SOC data, leading to overcharging during the charging process. To address this issue, a SOC estimation method based on DBN-ELM for AGVs is proposed, along with the use of an improved dynamic simplified particle swarm optimization to overcome the issue of manually setting parameters in traditional DBN. Furthermore, for addressing missing data during the charging process, bidirectional LSSVM is utilized for data completion. Experimental results demonstrate that this method effectively enhances the SOC prediction accuracy of AGVs and holds practical significance.

Keywords

SOC Estimation; DBN; ELM; Dynamic Simplified Particle Swarm; LSSVM.

1. Introduction

In recent years, with the rapid development of transportation industry, the automation level of ports has been increasing. As a major transportation equipment in automated ports, AGVs have been rapidly developed and applied, and their charging safety, control, scheduling, obstacle avoidance, etc. have become the research hotspots [1]. The battery state of charge (SOC) is closely related to the charging safety of AGVs. However, with battery aging, the data in the Battery Management System (BMS) becomes inaccurate. Accurate prediction and estimation of SOC can effectively prevent safety issues such as overcharging of AGVs [2].

Traditional methods for studying SOC mostly focus on individual batteries or battery packs. Commonly used methods include ampere-hour integration, open circuit voltage, Kalman filtering, and neural networks [3]. Reference [4] proposes an SOC observer that predicts battery SOC using a differential algebraic model. Reference [5] combines ampere-hour integration and EKF for estimating battery SOC and uses recursive least squares to determine the model parameters. Reference [6] predicts SOC using particle swarm optimized BP neural networks, while reference [7] combines support vector machines with Bayesian optimization for predicting battery SOC. In summary, current SOC methods mostly rely on establishing battery models for prediction.

However, AGV batteries consist of multiple battery packs, and the internal data of the batteries are confidential information for the battery manufacturers. In practical charging processes, the charging station cannot obtain detailed internal data of the batteries, making it difficult to establish an ideal mathematical model [8]. Therefore, traditional modeling methods struggle to accurately estimate the SOC of AGVs during charging. This paper proposes a data-driven SOC estimation method for multi-machine learning port AGVs. By using real charging vehicle data and comparing real-time BMS data with predicted data, this method can effectively monitor SOC, provide important scientific basis for

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optimizing the BMS system, and prevent battery overcharging. The advantages of this method are as follows:

(1) To address the issue of algorithm accuracy affected by missing data, a bidirectional least squares support vector machine (LSSVM) method is used to complete the missing data. This method accurately completes the missing data and improves the quality of the data.

(2) To handle complex charging data, a deep belief network (DBN) is used to extract and process charging data features, and an extreme learning machine (ELM) is used to predict SOC, thereby improving the algorithm's generalization performance and prediction accuracy.

(3) To overcome the problem of manually setting parameters for traditional DBNs, a dynamic simplified particle swarm optimization (sPSO) is employed to optimize the hidden layer parameters of the DBN, adaptingively selecting the optimal parameters.

The arrangement of this article is as follows: The first chapter introduces the research background and significance of this article; Chapter 2 introduces the two-way interpolation method of the drop data; the third chapter introduces the SOC estimation method based on dynamic SPSO-DBN-Artm; Analysis of the results; Chapter 5 summarizes the method of this article.

2. Data Pre -processing

2.1 Data Replacement

During the charging process, part of the data may be lost due to network or equipment failure, and the use of missing data directly as training and prediction samples will increase the difficulty and error of the algorithm. Literature [9] proposes to repair the lack of data and abnormal data based on GAN -based methods; the literature [10] is distributed according to the data of the data, and combined with Bayesian to make up for the missing data. At present, most studies are based on unidirectional data. Complete and repair the loss of missing values and abnormal values. LSSVM is an algorithm that solves nonlinear problems that can map non -linear problems to high-dimensional [11]. This article uses a two-way LSSVM method to predict the value of the missing point. Compared with one -way data model, this method can simultaneously use all data before and after the missing point, and the two -way fusion of the missing point can be used. The specific operation steps are as follows:

(1)Extract historical charging data in the database, find missing data features as the output of the LSSVM model, and other complete data features as the input of the LSSVM model;

(2)To reverse the order of all positive data Xp ,sorted by time, we obtain the reversed data Xr;

(3) Setting the parameters of LSSVM;

(4) Input the positive and reverse data into the LSSVM model to obtain the data values Yp and Yr for the missing points. The regression function of LSSVM is as follows[11] :

$$y = \omega^T \varphi(x) + b \tag{1}$$

In which, ω is the weight vector, φ is the mapping function,and b is the bias term. Based on the principle of risk minimization, it is necessary to solve the inequality problem[11]:

$$min\frac{1}{2}\ \|\omega\|^2 + \frac{1}{2}C\sum_{i=1}^{n} e_i \tag{2}$$

$$s.t\ \ \omega^T \varphi(x_i) + b + e_i = y_i, i = 1, 2..., m \tag{3}$$

where C is the regularization parameter and e is the slack variable.

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The radial basis kernel function is used in this paper for LSSVM, and its expression is:

$$K(x,x_i) = \exp\{-\frac{\|x-x_i\|^2}{2\sigma^2}\} \tag{4}$$

where x is the m-dimensional input vector of LSSVM, x_i is the center of the i-th radial basis function in m dimensions, and σ is the width of the kernel function.

2.2 Data Normalization

The input data for LSSVM and DBN-ELM used in this study is the feature data of real port AGVs, and the dimensions of different features are inconsistent. Therefore, it is necessary to normalize the data.

$$\bar{x} = \frac{x - x_{\min}}{x_{\max} - x_{\min}} \tag{5}$$

Whereas $\bar{x}$ represents the normalized data and x represents the data before normalization.

3. Dynamic sPSO-DBN-ELM Prediction Model

3.1 DBN Feature Extraction

DBN consists of multiple layers of Restricted Boltzmann Machines (RBM) and one layer of neural network. N The training process of DBN is conducted layer by layer. By inputting data into the first RBM layer of DBN for training, the output obtained is used as the input for the second RBM layer, and this process is recursively conducted until the output of the last RBM layer is used as the input for the BP neural network. Finally, the weights are adjusted using backpropagation[13]. The basic structure of DBN is shown in Figure 1[13]:

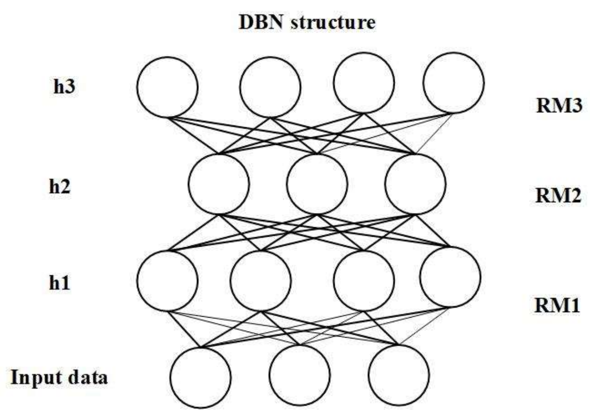

Figure 1. Traditional DBN Structure Diagram

3.2 ELM Model

ELM (Extreme Learning Machine) is a feedforward neural network that consists of three layers: input layer, hidden layer, and output layer. It is suitable for both supervised and unsupervised learning problems[14]. During the training process of ELM, the connection weights between the input layer and the hidden layer, as well as the thresholds of the hidden layer neurons, are randomly generated and do not require iterative operations. ELM has been widely applied to various nonlinear problems in fault diagnosis and prediction[15]. In this study, ELM is used as the prediction model.

The mathematical model of ELM is as follows[16]:

$$\sum_{i=1}^{L}\beta_i g(W_i \cdot X_j + b_i) = o_j, j = 1,\dots,N \tag{6}$$

Where $g(x)$ is the activation function, β_i is the weight vector between the i-th hidden layer and the output layer, L is the number of nodes in the hidden layer, W is the input weight, b is the bias value of the hidden unit, and X is the input sample.
The training objective of ELM is to minimize the output error, which can be expressed as[16]:

$$\sum_{i=1}^{L}\left\| o_i - t_i \right\| = 0 \tag{7}$$

where t_i is the desired output, β_i and W_i , and b_i are such that,Obtain[17]:

$$\sum_{i=1}^{L}\beta_i g(W_i \cdot X_j + b_i) = \mathrm{t}_j \tag{8}$$

Formula (8) can be represented using matrices as follows[17]:

$$H\beta = T \tag{9}$$

Where H represents the output of the hidden layer nodes, β represents the output weights, and T represents the desired output. The final output weights can be obtained as follows[16]:

$$\hat{\beta}=H^{+}T = (H^T H)^{-1} H^T T \tag{10}$$

Where H^+ is the output matrix and H is the Moore-Penrose pseudoinverse of H .

3.3 Data Replacement

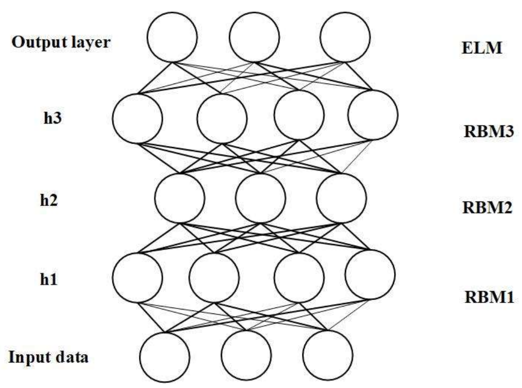

Figure 2. Structure Diagram of DBN-ELM

Due to the complexity of charging data, directly using it as input for ELM will affect the prediction accuracy of the algorithm. Therefore, this paper proposes an optimized prediction model called DBN-

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ELM. DBN consists of multiple RBMs and can process data to obtain the most representative data features [18]. Thus, this paper uses the output of the last layer of DBN as input for ELM. This method not only has the superior ability of DBN to automatically extract data features but also has the fast learning and generalization abilities of ELM. The structure diagram is shown in Figure 2.

Usually, the number of nodes in each hidden layer of DBN needs to be manually tuned, which often makes it difficult to select the optimal parameters. PSO is a classical parameter optimization algorithm that has been widely used in combination with various algorithms due to its simplicity and efficiency [21]. In literature [19], a method of dynamic inertia weight and learning factor was proposed to improve the traditional particle swarm optimization. Literature [20] presented a simplified particle swarm algorithm and proved its velocity term and final convergence results. However, this algorithm still has many limitations, such as premature convergence of particles. Based on this, this paper proposes a dynamic simplified particle swarm optimization method to improve the parameters of ELM. The dynamic sPSO update formula is as follows:

$$x_i^{k+1} = \omega x_i^k + c_1 r_1 (p_{\mathrm{i}} - x_i^k) + c_2 r_2 (p_g - x_i^k) \tag{11}$$

$$\omega = \begin{cases} \omega_{\min} - \dfrac{(\omega_{\max} - \omega_{\min}) \times (f - f_{\min})}{f_{avg} - f_{\min}}, f \le f_{avg} \\ \omega_{\max}, f > f_{avg} \end{cases} \tag{12}$$

Where x_i^{k+1} represents the current position of the i-th particle at time $k+1$, p_{i} and p_g represent individual best and swarm best, respectively. c_1 and c_2 are learning factors, r_1 and r_2 are random numbers between 0 and 1. ω is the dynamic inertia weight, f represents the fitness value of the current particle, and f_{avg} is the average fitness value of the population.

The flowchart of the dynamic sPSO-DBN-ELM algorithm is shown in Figure 3, and the specific steps are as follows:

Step 1: Firstly, select charging data from the database. In order to improve the accuracy of prediction, this study chooses charging data with SOC changes exceeding 60%, as this provides a wider range of SOC data variations.

Step 2: Initialize parameters for sPSO, DBN, and ELM. This includes learning factors for particle swarm optimization, maximum iteration times, inertia weight, number of hidden nodes in DBN, learning rate, etc.

Step 3: Calculate the Mean Absolute Error (MAE) as the fitness value for each particle, and update the adaptive inertia weight and particle positions based on their fitness values. The particle positions represent the parameters of the hidden layers in DBN.

Step 4: Update the fitness values of particles and determine the individual best and global best based on the new fitness values.

Step 5: Check if the maximum iteration times have been reached. If not, continue iterating; if the maximum iteration times have been reached, output the optimal ELM parameter values. Use these optimal values as the parameters for the ELM prediction model.

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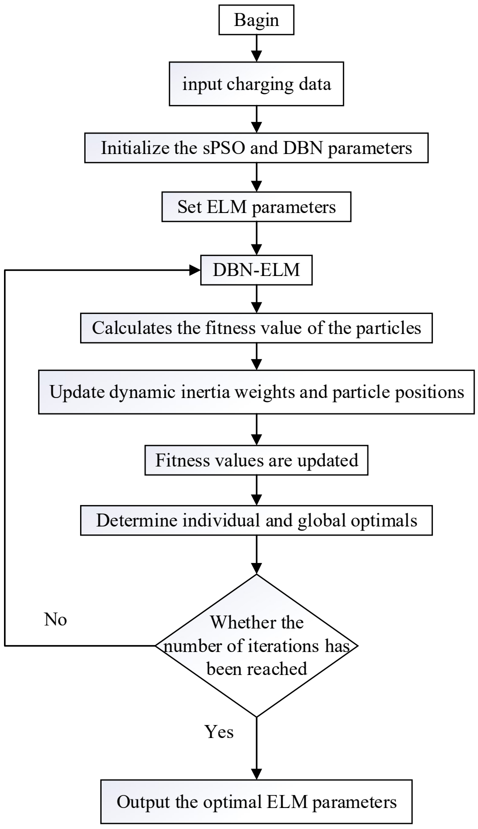

Figure 3. Flowchart of Dynamic sPSO-DBN-ELM

4. Experimental Analysis

The data used in this study was obtained from a charging operation department in a port in Shanghai. The algorithms were implemented in Matlab 2019b. A total of 5089 data points were used, with 5069 for training and 30 for prediction. To validate the proposed algorithm, various models were compared in this study. The following parameter settings were used: population size of the particle swarm optimization (PSO) was set to 20, c1=c2=2, inertia weight ranged from 0.6 to 0.95, ELM had 40 hidden neurons, and the restricted Boltzmann machines (RBMs) in the deep belief network (DBN) were iterated 100 times. The evaluation metrics used in this study included mean absolute percentage error （MAPE）, root mean square error （RMSE）, and correlation coefficient （R）.

$$MAPE = \frac{1}{n}\sum_{i=1}^{n}\frac{|\hat{y}_i - y_i|}{y_i}\times 100\% \tag{13}$$

$$RMSE = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(\hat{y}_i - y_i)^2} \tag{14}$$

$$r = \frac{\mathrm{cov}(y_i, \hat{y}_i)}{\sigma(y_i)\sigma(\hat{y}_i)} \tag{15}$$

In the equation, σ represents the standard deviation, cov represents the covariance, and n represents the number of data points.

To highlight the feasibility of the proposed algorithm, multiple algorithms were compared and the results are shown in Figure 4:

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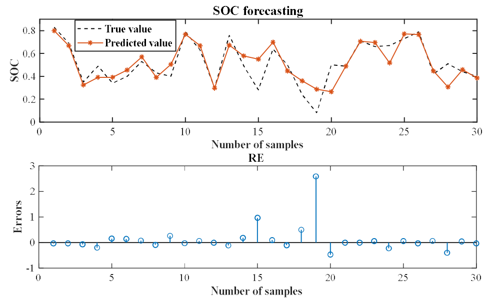
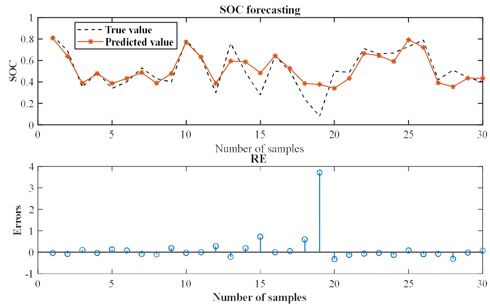
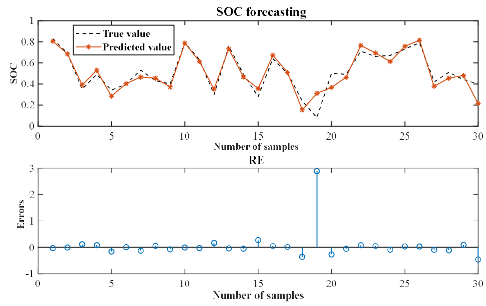


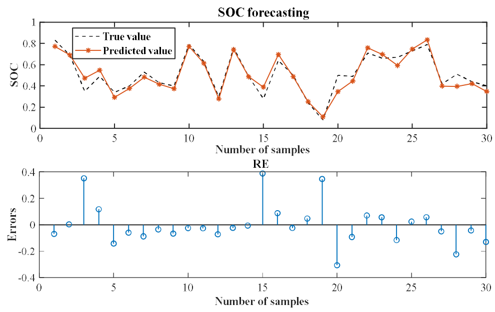
(a) Port AGV SOC prediction chart based on ELM.



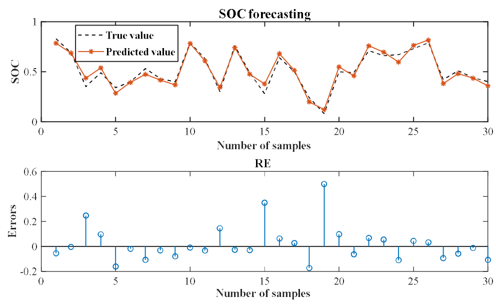
(b) Port AGV SOC prediction chart based on DBN



(C) Port AGV SOC prediction chart based on DBN-ELM.



(d) Port AGV SOC prediction chart based on PSO-DBN-ELM.



(e) Port AGV SOC prediction chart based on sPSO-DBN-ELM.

Figure 4. Comparison of prediction of each model

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Table 1. Three Scheme comparing

algorithm	RMSE	MAPE(%)	r	T(s)
ElM	0.15	0.15	0.55	0.17
DBN	0.10	23.67	0.83	6.21
DBN-ELM	0.07	19.61	0.92	0.39
PSO-DBN-ELM	0.06	10.50	0.95	109.36
sPSO-DBN-ELM	0.04	9.66	0.97	106.33

The predicted results of each model are shown in Figure 4. Figure 4(a) represents the SOC prediction based on ELM, Figure 4(b) shows the SOC prediction based on DBN, Figure 4(c) displays the SOC prediction based on DBN-ELM, Figure 4(d) illustrates the SOC prediction based on PSO-DBN-ELM, and Figure 4(e) demonstrates the SOC prediction based on sPSO-DBN-ELM. It can be observed that ELM, DBN, and DBN-ELM all exhibit data points with significantly large AE errors. After particle swarm optimization (PSO), the DBN-ELM model effectively reduces the AE error. The error comparison and time consumption analysis for each model are presented in Table 1. ELM has the shortest processing time but with relatively large errors, reaching a MAPE error of 41.75%. Traditional DBN requires more time compared to ELM but offers improved accuracy. The enhanced DBN-ELM algorithm not only enhances prediction accuracy but also inherits the advantages of ELM in terms of speed and reduced processing time. Among all methods, the proposed approach demonstrates the highest accuracy, reducing the MAPE error by 31.79% and 13.71% compared to traditional ELM and DBN methods, respectively. The sPSO-DBN-ELM method reduces the MAPE error by 0.54% and RMSE by 0.02 compared to the traditional PSO-DBN-ELM method, while also reducing the processing time by 3.03 seconds. As PSO is an optimization algorithm, it increases the training time of the algorithm, primarily reflected in offline data training, while it does not affect the prediction time for online data, which remains consistent with DBN-ELM. In summary, the proposed improved algorithm not only exhibits very high prediction accuracy for online SOC estimation of new AGVs, but also ensures efficient algorithm operation speed.

5. Conclusion

A dynamic sPSO-DBN-ELM method for estimating the State of Charge (SOC) of AGVs in ports affected by battery aging is proposed in this study. This method combines the Deep Belief Network (DBN) with the Extreme Learning Machine (ELM), offering both a high learning rate and a high prediction accuracy. Additionally, a dynamic version of the Particle Swarm Optimization (sPSO) is employed to automatically optimize the parameters of the DBN's hidden layers, thereby avoiding the accuracy degradation caused by manual parameter setting. In contrast to traditional experimental simulations for SOC estimation, this paper adopts a data-driven approach that provides more realistic reference and engineering significance.

References

[1] Zhai Gaoshuai. Research on Multi-Resource Collaborative Scheduling in Automated Port Considering the Influence of AGV Charging [D]. Jilin University, 2023. DOI: 10.27162/d.cnki.gjlin.2023.001143.

[2] LING S,NGUYEN K,ROUX-LANGLOIS A,et al.A lattice-based group signature scheme with verifier-local revocation [J].Theoretical Computer Science,2018,730(19):1-20.

[3] KUANG L D DENG Q Y, Li Z T. A new method for estimating SOC of lithium battery [J]. Computer engineering and applications, 2013, 49(06):249-252.

[4] Antonucci, Giovanni Artale, Giovanni Bruna-ccini, Giuseppe Caravello et a1. Li-ionModeling and State of Charge Estimation Method Including the Hysteresis Effect[J]. Electronics, 2019,8(11):453-459.

ISSN: 2414-1895 DOI: 10.6919/ICJE.202404_10(4).0005

[5] Fan B, Luan X, Zhang R, et al. Research on SOC Estimation Algorithm for Lithium Battery Based on EKF Algorithm and Ampere-hour Integration Method[C]//Science and Engineering Research Center. Proceedings of 2017 2nd International Conference on Electrical, Control and Automation Engineering (ECAE 2017). Science and Engineering Research Center: Science and Engineering Research Center. 2017: 110-114.

[6] ZHAO G, ZHU F X, DOU R Z. Estimation of Lithium-ion Battery SOC for Electric Vehicle Based on PSO-BP [J]. Chinese Journal of Power Sources, 2018,42(09):1318-1320.

[7] BAO W, GE J J. Based on sparse sampling data of electric buses battery SOC prediction method research [J]. Journal of automobile engineering, 2020,42(03):367-374.

[8] Frendo O, Graf J, Gärtner N, et al. Data-driven smart charging for heterogeneous electric vehicle fleets[J]. Energy and AI, 2020, 1: 100007.

[9] ZHAO H X, SHEN X D, LU L, LAN P, LIU J Y, LIU D Y. Load Data Restoration based on GAN and its Application in EV Short-term Load Forecasting [J]. Automation of Electric Power Systems, 2021,45(16): 143-151.

[10] Mu Shoukuan, Zhou Wei. An Expectation-Maximization Algorithm and Markov Monte Carlo Method for Missing Data Processing [J]. Advances in Psychological Science, 2011, 19(07):1083-1090.

[11] Guo L, Zhang Y. Application of SPCA-LSSVM model in soft measurement of Gasoline dry point[C]// 2020 13th International Symposium on Computational Intelligence and Design (ISCID). IEEE, 2020: 200-204.

[12] LEI B Y, WANG Z C, SU Y Q, SUN W Z, YANG L Y. Research on Short-term Load Forecasting Method Based on EEMD-CS-LSSVM [J]. Proceedings of the CSU-EPSA, 2021,33(09):117-122.

[13] DENG Y, JIANG T, LAI Z Y. Research on Pipeline Gas Pressure Detection Method Based on DBN and LSSVM [J]. Journal of Electronic Measurement and Instrumentation, 2021,35(06): 198-204.

[14] TAN E M, WANG C. Analog Circuit Fault Diagnosis Based on Representation Learning [J]. Computer Engineering and Science, 2022, 44 (01):27-35.

[15] YAO F L, XIE C K, LV S N, YANG H, MENG Z. Research on Rolling Bearing Fault Diagnosis Based on Wavelet Packet Transform and ELM [J]. Journal of Safety and Environment, 2021,21(06):2466-2472.

[16] SONG F, XIA K W, YANG W B. Multi-strategy Bird Swarm Algorithm and ELM Model Optimization for Reservoir Identification [J/OL]. Computer Engineering and Applicat-ions :1-10[2022-02-11].

[17] YUAN F, WANG X S, LIANG Y J. Research on power load Forecasting method based on DBN-ELM [J]. Scientific and Technological Innovation,2020(33):1-5.

[18] N Roux, Y Bengio. Deep Belief Networks are Compact Universal Approximators [J].Neural Computation, 2010, 22 (8):2192-2207.

[19] ZHANG K, TIAN Y B, CONG J C, LIU Y H, YAN N, LU T. Low Energy Consumption Machining Method for Grinding Based on Dynamic Inertia Weighted Particle Swarm Optimization [J].Diamond & Abrasives Engineering, 2021,41(01):71-75.

[20] HU W, LI Z S. A Simplified and Efficient Particle Swarm Optimization Algorithm [J]. Journal of Software,2007(04):861-868.

[21] HU X J, CHEN X J, ZHAO N, XUE W. PSO_BFA Optimized word bag model and Protein subcellular Localization prediction [J]. Computer Engineering and Applications,2020, v. 56; No.944(01):165-171.