International Journal of Power and Energy Systems, Vol. 45, No. 10, 2025
An Open Access Paper

CONSTRUCTION OF POWER SYSTEM LOAD ALLOCATION MODEL BASED ON IMPROVED ABC ALGORITHM

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Abstract

In response to the problem of redundant power grid data, this study proposes a sample processing model based on rough sets, which can process power grid data. Then, a power system load forecasting model based on an artificial bee colony (ABC) algorithm is designed, and the simulated annealing algorithm is introduced to perfect it. The experiment showed that the information retention rates of rough set model, fuzzy set theory model, grey system theory model, and probability graph model were 97.1%, 92.5%, 86.3%, and 84.1%, respectively. The accuracy of the research model was higher than that of other models. In the validation set, the accuracy of the four algorithm models was 0.94, 0.87, 0.85, and 0.83. This proves that the proposed improved ABC algorithm can effectively predict and schedule power loads, providing a solution for the scheduling problem of the power system.

Key Words

Power system, artificial bee colony (ABC) algorithm, rough set, power load forecasting (PLF), simulated annealing (SA) algorithm

1. Introduction

Power Load Forecasting (PLF) is the foundation of power system scheduling and operation optimisation. By accurately predicting the power load for a specific future period, the system can arrange the power generation and transmission resources to meet the power demand while ensuring the stability and reliability of the power system. In the load distribution of the power system (PSLD), medium- and short-term (St) PLF represents a significant area of focus and challenge for the power industry. PSLD involves the rational planning and allocation of power supply to meet the power demands of different users and regions while ensuring the stability and reliability of the system [1], [2]. Moreover, the rapid fluctuations in supply and demand can lead to situations where supply surpluses or shortages cause operational inefficiencies, economic losses, or even grid failures. For example, inaccurate forecasting can result in under- or over-generation, leading to wasted resources or, in extreme cases, blackouts [3], [4]. Despite the advancements in forecasting methods, current approaches often struggle with large datasets and nonlinear relationships. Traditional techniques fail to fully address issues, such as invalid data, missing values, and noise, which can severely degrade the quality of forecasts. These issues not only hinder the predictive accuracy but also lead to significant inefficiencies and increased operational costs. Therefore, how to improve the accuracy and efficiency of PLF has become a key issue that urgently needs to be addressed. Tang *et al.* proposed a prediction method based on variational mode decomposition and bidirectional long St memory network (Bi-LSTM) to accurately predict power loads and promote scheduling planning and environmental sustainability in power systems. This method effectively improved prediction accuracy and stability by decomposing the load sequence and optimising hyper-parameters, and could better track the trend of load changes [5]. Liu *et al.* established a prediction model combined with long-term (Lt) and St time series networks to accurately predict St power loads and improve power grid decision-making and user power management. This model captured the St and Lt characteristics of loads by analysing the correlation between variables and loads and combined them with convolutional neural networks (CNNs) and LSTM. This method model has shown good accuracy and stability in load forecasting [6]. Ciechulski *et al.* designed a predictive model based on recursive LSTM to develop an efficient St PLF method and applied it to 24-h load forecasting in the Polish power system. This model could effectively predict irregular trends, and the ensemble prediction method significantly improved prediction accuracy compared to a single predictor, reducing errors by more than 6% [7]. This study proposes a rough set-based sample processing (RSSP) method to handle the issue of complex power grid data, which can process power grid data and remove invalid data. Subsequently, a power system load forecasting

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Recommended by Hui Li
(DOI: 10.2316/J.2025.203-0598)

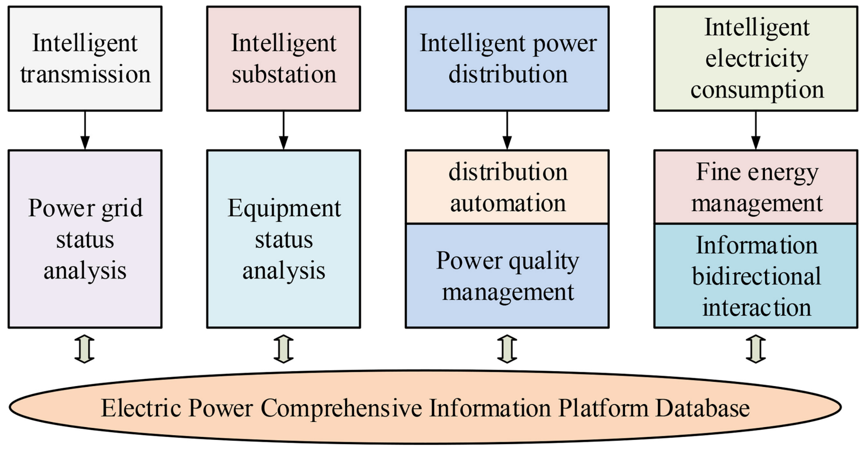

Figure 1. Power grid system structure.

(PSLF) model is constructed using the artificial bee colony (ABC) algorithm. To address the issue of the model converging on local optima, the simulated annealing (SA) algorithm is introduced. It aims to provide a scientifically reliable solution for PSLD. The contribution of this study lies in proposing a rough set theory (RST) for attribute reduction of complex and error-prone power grid data to identify the most important attributes in the data.

1.1 Construction of PSLD Model Based on Improved ABC Algorithm

1.2 RSSP Method

The power grid system refers to a complex network composed of power generation, transmission, distribution, and users, used to transport electricity from power stations to end-users. Its structure is shown in Fig. 1.

In Fig. 1, the system is mainly composed of the power generation end, the electricity consumption end, and the dispatch end. In the power grid system, power grid data are affected by various factors, such as network failures, hardware equipment failures, and adverse weather conditions, resulting in significant errors or missing data in the collected data. This study adopts a parallel approach of horizontal and vertical processing to process erroneous data. Under normal circumstances, the power load is a continuous and stable sequence. When there is an unstable situation, it is necessary to process the data horizontally. Its expression is given by (1).

$$Y(d,t) = \frac{Y(d,t-1) + Y(d,t+1)}{2}. \tag{1}$$

In (1), t represents the sampling point. d is the quantity of days. $Y(d,t)$ means the power load value at sampling point t on day d. The load data also have obvious regularity, that is, the load values at the same time every day are basically the same or similar. If the difference exceeds the design threshold, vertical processing method needs to be used to process the data, as shown in (2).

$$Y(d,t) = \begin{cases} m(t) + r(t), Y(d,t) > m(t) \\ m(t) - r(t), Y(d,t) < m(t) \end{cases}. \tag{2}$$

In (2), $r(t)$ represents the threshold, and $m(t)$ represents the predicted average value of the same sampling point in recent days. To input the normal data of the same type that is observed both before and after the missing data into the fitting curve, it is necessary to apply the principle of least squares, as expressed in (3).

$$\sum_{k=1}^{m} a_k^2 = \Delta_{\min}. \tag{3}$$

In (3), a_k^2 represents the input data. $\Delta_{\min}$ represents the sum of squared differences. The units of data in PLF have significant differences, so to reduce the abnormal results caused by unit differences, it is needed to process the data so that all influencing factors are within the same numerical range, as shown in (4).

$$x_n = \frac{x - x_{\min}}{x_{\max} - x_{\min}}. \tag{4}$$

In (4), x represents the data that needs to be normalised. x_n represents the data output after normalisation processing. $x_{\max}$ and $x_{\min}$ represent the maximum and minimum values of x. Due to the complexity of power data and the interdependence of various factors, relying solely on experience cannot accurately determine which is an important attribute. Therefore, attribute reduction using rough sets is used to identify important attributes. RST is a mathematical tool used to process incomplete information, mainly used in fields, such as data mining, pattern recognition, and decision support [8]. This approach guarantees that the computational complexity and real-time performance of the model will be maintained while retaining the capacity to process uncertain data, as illustrated in (5).

$$k = |\mathrm{POS}_p(Q)| \, / \, |U| \,. \tag{5}$$

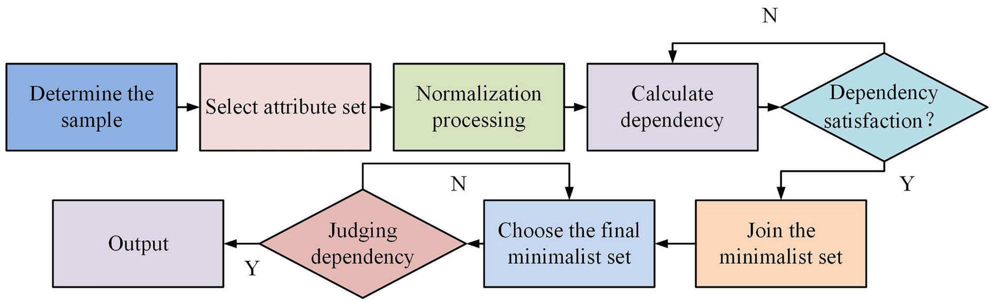

Figure 2. Attribute reduction process diagram.

In (5), k represents the degree of dependency and Q is the set of attributes. p represents the attribute space and U is the set of all objects. Based on this premise, the importance of attributes can be further determined, as shown in (6).

$$\begin{aligned}\sigma_{\mathrm{CD}}(c_1) &= \gamma_C(D) - \gamma_{C-c_1}(D) \\ &= \frac{|\mathrm{POS}_C(D)| - |\mathrm{POS}_{C-c_1}(D)|}{|U|}.\end{aligned} \tag{6}$$

In (6), D represents the decision attribute. Therefore, the reduction algorithm based on attribute dependency is shown in Fig. 2.

In Fig. 2, the first step is to determine the sample, followed by selecting the set of conditional and decision attributes, and then normalising to generate the decision table. The reduction set is initially defined as an empty set, and the dependency relationships of each attribute are subsequently calculated to ascertain whether the dependency relationships satisfy the requisite conditions. If the conditions are not met, this step will continue to execute [9]. If it is satisfied, a reduction set is added and the combination with the highest dependency is selected as the final reduction set to determine whether the decision attribute has the same dependency on the conditional attribute and the reduction attribute. If the results are the same, the results are output to obtain data.

1.3 PSLD Model Based on Improved ABC Algorithm

After extracting the attributes of various factors that affect PLF, the preprocessing of the predicted data has been completed. This study uses the ABC algorithm to predict and schedule power loads [10]. The ABC algorithm process is shown in Fig. 3.

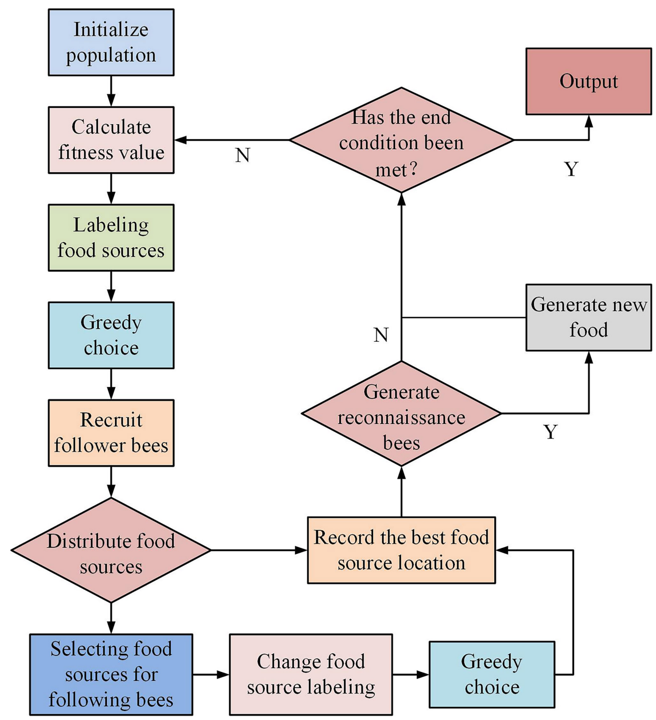

Figure 3. ABC algorithm process.

In Fig. 3, the first step is to initialise the population and then calculate fitness values. Scout bees ensure the initial labelled food source (FS) and explore new FS. The second step is to calculate the fitness value and perform greedy selection. According to the roulette wheel method, scout bees recruit follower bees and determine whether to allocate FSs to them. If not, an FS for the follower bees is selected. Follower bees search for FSs, change FS labels, calculate fitness values, make greedy choices, and record the best FS location [11]. If allocated, the point is directly recorded as the best FS location. The third step is to determine whether a reconnaissance bee has been generated. If so, a new FS is generated to replace the labelled FS and mark the new FS to determine whether the end condition has been met. If it does not occur, it is necessary to determine whether the end condition has been met. If the end condition is met, the result is output. If it is not met, the above processes will be continued. The load forecasting chart based on the ABC model is shown in Fig. 4.

In Fig. 4, the historical data in the sample is first preprocessed, and then the preprocessed data are normalised. RST is used to extract data features. The extracted results are used as input variables to determine the various relevant parameters of the model, thereby obtaining the optimal parameter values, and finally conducting load forecasting. Although the ABC algorithm has certain advantages in solving optimisation problems, it relies on the search behaviour of bees, resulting in the algorithm falling into local optima and being unable to find global optima. Therefore, the SA algorithm is adopted to improve the model. SA simulates the behaviour of solid materials during annealing, gradually lowering the

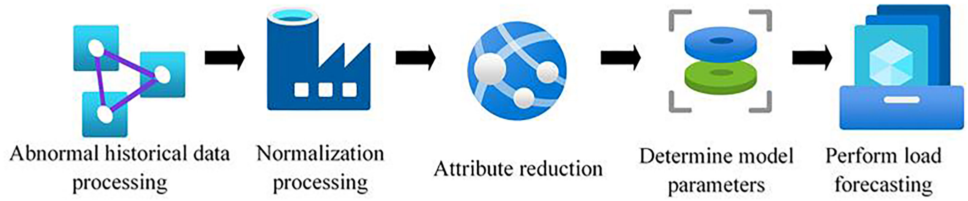

Figure 4. Load forecasting process based on ABC model.

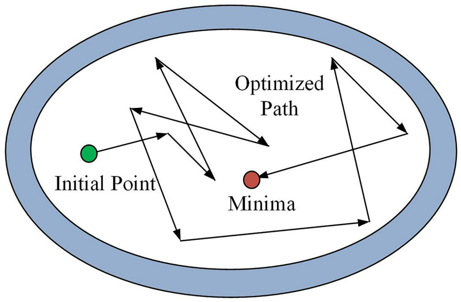

Figure 5. Optimisation diagram of ABC-SA algorithm.

temperature to approach the global optimal solution by randomly searching in the solution space. The judgement basis is given by (7).

$$r = \exp\left(-\frac{E_j - E_i}{t}\right). \tag{7}$$

In (7), r represents the probability of being marked as important, and t is the temperature. i represents the original state of the solid, and E_i is the energy in that state. j represents the new state of the solid after being disturbed. E_j is the energy in that state. The ABC-SA algorithm integrates the local search capability of the ABC algorithm with the global optimisation advantage of SA, thereby markedly enhancing its performance. ABC-SA has stronger adaptability and can dynamically adjust search strategies to handle complex optimisation problems and constraints. The optimisation diagram of the ABC-SA algorithm is shown in Fig. 5.

In Fig. 5, the first step is to initialise the algorithm parameters. The initial solution expression of the parameter dimension is given by (8).

$$\tau = N_i \times N_h + N_h + N_h \times N_o + N_o. \tag{8}$$

In (8), N_i, N_h, and N_o are the amount of neurons in the input, hidden, and output layers. Then, a complete set search is performed to generate a solution. In the bee picking stage, one honey source corresponds to one bee picking, and the expression for the new honey source is given by (9).

$$V_i^b = X_i^b + r\ and\ (0,1)(X_i^b - X_q^b). \tag{9}$$

In (9), V represents the new honey source and X represents the solution. Then, the difference in fitness between the new and old honey sources is calculated, as shown in (10).

$$\Delta f = f_{x'} - f_x. \tag{10}$$

In (10), Δf represents the difference in fitness. $f_{x'}$ and f_x represent the fitness of new and old honey sources. After all the bees complete searching, they will share their honey source information and fitness with the observation bees. Reconnaissance bee determines the probability of each bee being followed by selecting probabilities, as shown in (11).

$$p_i = fit_i / \sum_{i=1}^{N} \mathrm{fit}_i. \tag{11}$$

In (11), p_i represents the selection probability. fit_i represents the calculated fitness function value. Through the roulette wheel strategy, follower bees are selected to switch between bees, engage in search behaviour, and determine the reserved honey source based on the SA mechanism. The next step is to determine if the honey source has been exhausted. When the number of iterations is greater than or equal to the iteration limit, the corresponding scout bees will transform into reconnaissance bees. Finally, the reconnaissance bee randomly generates new honey sources in the search space and outputs the results. When using ABC-SA for PLF, the performance of the model is affected by multiple key parameters, such as population size, cooling rate, and maximum iteration times. The population size determines the diversity of the search space, and larger populations can increase the coverage of the solution space, but also increase computational costs. Through experimental tuning, select a population size between 50 and 100 to balance efficiency and accuracy. The cooling rate controls the rate at which the temperature decreases during SA. Faster cooling may cause the algorithm to fall into local optima early on, while slower cooling rates can lead to longer computation times. The cooling rate is set to 0.95 to optimise search efficiency. The maximum number of iterations and stopping conditions are key parameters for controlling computational complexity and convergence speed, and appropriate adjustments can avoid computational waste. To evaluate the impact of these parameters, a sensitivity analysis was conducted. The results indicate that population size has a significant impact on prediction accuracy, with larger populations improving accuracy but also increasing computation time. The adjustment of cooling rate directly affects the global search ability of the algorithm, and too fast cooling will reduce accuracy.

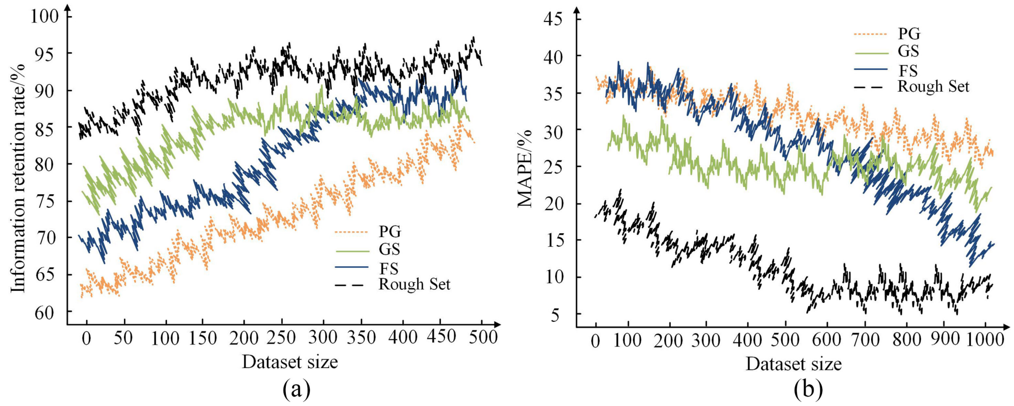

Figure 6. Performance analysis of various algorithm models: (a) Comparison of information retention rates of different algorithm models and (b) Comparison of RAPE for different algorithm models.

2. Performance Analysis of PSLD Model Based on Improved ABC Algorithm

2.1 Performance Analysis of RSSP Model

The central processor is Intel Core i5-8750H, and the graphics processor is NVIDIA Geforce GTX2080Ti. The graphics memory is 8 GB, the memory is 16 GB, and the operating system is Windows 10. This study uses the publicly available Global Energy Forecasting Competition (GEFCom) dataset. This dataset contains electricity load data from different regions and periods. Fuzzy Set Theory (FS), Grey System (GS) Theory, and Probability Graphical (PG) models are introduced and compared with the proposed Rough Set (RS) model. Figure 6 shows the results.

Figure 6(a) shows the changes in information retention rates of various algorithm models as the size of the training set increases. The X-axis represents the size of the dataset, and the Y-axis represents the information retention rate, measured in percentages. The higher the information retention rate, the more valuable information the model can retain, indicating that the algorithm is more efficient in processing data. Figure 6(b) shows the average relative error variation of different algorithm models as the training set increases. The X-axis also represents the size of the dataset, while the Y-axis represents the average relative error, measured in percentages. A lower error value indicates a higher accuracy of the model in prediction. As shown in Fig. 6(a), with the increase of the training set, the information retention rate of each algorithm model also increases continuously. When the dataset size is around 300, the performance of the rough set algorithm model tends to stabilise and shows convergence. When the dataset size is 500, the information retention rates of the rough set algorithm model, FS algorithm model, GS algorithm model, and PG algorithm model are 97.1%, 92.5%, 86.3%, and 84.1%, respectively. As shown in Fig. 6(b), as the training set increases, the average relative error of each algorithm model decreases continuously. When the dataset size is around 500, the performance of the rough set algorithm model tends to stabilise and shows convergence. When the dataset size is 1000, the average relative errors of the rough set algorithm model, FS algorithm model, GS algorithm model, and PG algorithm model are 8.2%, 14.7%, 22.3%, and 26.4%, respectively. The results of comparing the processing time of various method models are shown in Fig. 7.

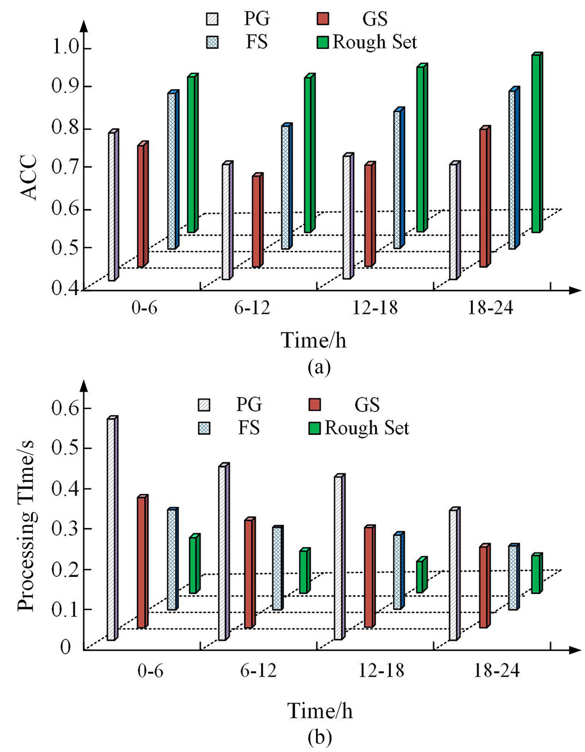

Figure 7. Comparison of processing times for various algorithms: (a) ACC under different time and (b) Model processing time under different time.

Figure 7(a) and 7(b) shows the accuracy and processing time of each model after processing data from different periods. In Fig. 7(a), the accuracy of RS for each period is 0.92, 0.90, 0.95, and 0.97, respectively. The performance of RS is the most outstanding among the four models. In Fig. 7(b), at each period, the data processing time of RS is 0.25 s, 0.21 s, 0.20 s, and 0.23 s, respectively. Among the four algorithm models, the shortest time is used.

Table 1
Configuration

ABC	Parameter Name	Colony Size	Food Source Size	Max Iteration	Limit	Exploration Factor
	Reasonable Value	100	50	300	150	Randomly Initialised
ABC-SA	Parameter Name	Initial Temperature	Cooling Rate	Termination Temperature	/	/
	Reasonable Value	500	0.95	0.001	/	/
ABC-PSO	Parameter Name	Inertia Weight	Individual Learning Factor (C1)	Social Learning Factor (C2)	Particle Velocity	/
	Reasonable Value	0.7	1.7	1.7	20	/
ABC-GA	Parameter Name	Crossover Probability	Mutation Probability	Population Size	/	/
	Reasonable Value	0.8	0.05	100	/	/

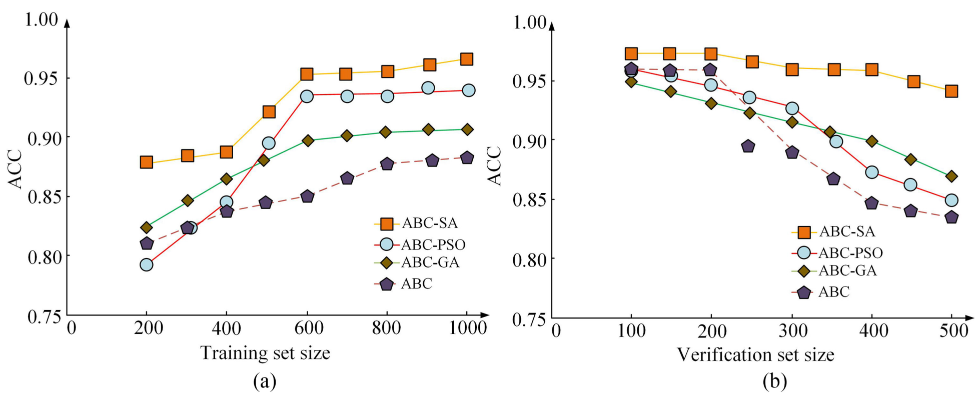

Figure 8. (a) The accuracy of four algorithm models under different training sets and (b) The accuracy of four algorithm models under different validation sets.

2.2 Performance Analysis of Load Allocation Model Built on Evolutionary ABC

This study uses the GEFCom dataset, which is separated into a training and a validation set in a 4:1 ratio. The experiment uses the ABC model, the ABC-Genetic Algorithm (ABC-GA) model, and the ABC-PSO model to compare. The parameter configuration is shown in Table 1.

According to Table 1, for the ABC algorithm, the main parameters include population size, FS size, maximum iteration times, and constraints on abandoning poor FSs. Figure 8 shows the performance of each model.

Figure 8(a) shows the accuracy performance of each algorithm model in the training set. The X-axis represents the size of the training set, and the Y-axis represents accuracy, used to compare the learning performance of different algorithms on training data. Figure 8(b) shows the accuracy of each algorithm model in the validation set. The X-axis represents the size of the validation set, and the Y-axis represents the accuracy of the validation set. As shown in Fig. 8(a), with the increase of the training set, the performance of each algorithm model gradually improves. When the training set size is around 600, each algorithm model is basically trained and its performance tends to stabilise. When the training set size is around 1000, the accuracy of ABC-SA algorithm model, ABC-PSO algorithm model, ABC-GA algorithm model, and ABC algorithm model are 0.97, 0.94, 0.90, and 0.88, respectively. As shown in Fig. 8(b), with the increase of the validation set, the performance of each algorithm model shows a clear downward trend, among which the ABC-SA algorithm model has the smallest downward trend. When the validation set size is 500, the accuracy of the ABC-SA algorithm model, ABC-PSO algorithm model, ABC-GA algorithm model, and ABC algorithm model are 0.94, 0.87, 0.85, and 0.83, respectively. The experimental results show that the ABC-SA algorithm model has the highest accuracy on the training set, reaching 0.97. Figure 9 shows the predicted scheduling time of the four method models.

In Fig. 9, training sets 1–4 are arranged in ascending order for datasets of different sizes, and the validation set

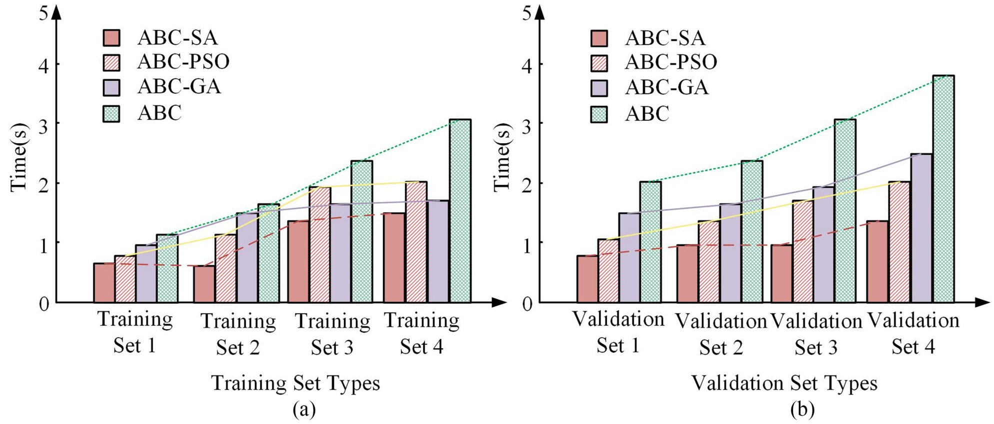

Figure 9. Comparison of training and processing times for various models: (a) Training time for different models and (b) Response time for different models.

Table 2
Performance Analysis of ABC-SA Model in Different Datasets

Dataset	ACC (Training)	ACC (Validation)	F1 (Training)	F1 (Validation)	RMSE (Training)	REMS (Validation)	Time (s)
GEFCom	0.97	0.94	97.10%	94.00%	8.20%	8.50%	0.25
UCI	0.95	0.92	95.30%	92.80%	10.50%	11.20%	0.31
PJM	0.93	0.89	94.00%	90.50%	94.00%	13.10%	0.35
REDD	0.96	0.93	96.20%	93.50%	9.80%	10.00%	0.21

is the same. Figure 9(a) and 9(b) represents the training time and processing time of each model in the training set and validation set. In Fig. 9(a), the ABC-SA model has a lower training time, with training times of 0.7 s, 0.7 s, 1.2 s, and 1.3 s in different training sets, respectively. In Fig.(b), ABC-SA is able to handle validation sets of various sizes and has high efficiency for larger datasets. The processing time of ABC-SA in different validation sets is 0.8 s, 0.9 s, 0.9 s, and 1.2 s, respectively. Therefore, the ABC-SA model has high computational efficiency. To verify the universality of the model, three different power datasets were selected for the study, and the results are shown in Table 2.

According to Table 2, the accuracy showed high values on both the training and validation sets, indicating that the model has strong classification ability on these datasets. The ACC of the UCI dataset on the training and validation sets were 0.95 and 0.92, respectively, demonstrating the model's good generalisation ability. The RMSE of the PJM dataset on the training and validation sets are 94.00% and 13.10%, respectively, which are relatively small and demonstrate its predictive accuracy. Finally, the required time column shows the time consumed to train these models. The training time of the REDD dataset is 0.21 s, which is the shortest among the four datasets, indicating its high efficiency in model training. The experimental results show that the proposed method has excellent generalisation ability.

3. Conclusion

In response to the problem of redundant power grid data and difficulty in predicting electricity, this study proposed an RSSP model that could process power network data. Then, a PSLF model based on the ABC model was proposed, and the SA was introduced to improve it to address the condition of the model dropping into the local optima. The results showed that when the validation set size was 500, the accuracy of ABC-SA, ABC-PSO, ABC-GA, and ABC models were 0.94, 0.87, 0.85, and 0.83, respectively. This study indicates that the proposed algorithm model has excellent performance. To address these issues, future research may consider the following potential solutions. Due to the extensive computation and iteration required by the ABC-SA algorithm, especially when dealing with large-scale datasets, parallel computing techniques can significantly accelerate the algorithm's computation process. By assigning tasks to multiple processing units, computation time can be effectively reduced and algorithm efficiency can be improved. To further improve the adaptability and stability of the algorithm, an adaptive parameter adjustment mechanism can be introduced. This mechanism can dynamically adjust algorithm parameters, such as temperature, learning factor, and population size based on the progress of the optimisation process, thereby avoiding premature convergence or overly random search behaviour.

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