A hybrid artificial bee colony algorithm for transformer vibration fundamental frequency amplitude prediction

Jianping Wang*, and *Wanlin* Li

State Grid Xinzhou Power Supply Company, Shanxi, China

Abstract. The fundamental frequency amplitude of transformer surface vibration signal is an important basis for judging transformer status. It is very important to predict the amplitude of fundamental frequency quickly and accurately. In this paper, a method is proposed to optimize the prediction of the transformer vibration fundamental frequency amplitude by modifying the artificial bee colony algorithm. An opposition-based learning mechanism is introduced and the search formula of each bee species is improved at the initial stage of the artificial bee colony algorithm. The performance of the proposed method is evaluated by five standard test functions and transformer vibration fundamental frequency amplitude prediction. Experimental results show that the proposed method is much better than the original artificial bee colony algorithm in search accuracy, convergence speed, and robustness, and improve the prediction accuracy.

Keywords: Vibration signal, Fundamental frequency amplitude, Modified artificial bee colony algorithm.

1 Introduction

Online monitoring of transformers and the analysis of some characteristic indicators that can represent the health status of transformers in the monitoring data can be carried out in order to timely find the potential faults of transformers and carry out preventive maintenance [1, 2]. Vibration signal analysis can well reflect the potential faults of transformer internal parts and does not need to be involved in transformer operation. It also has many advantages, such as safe operation, strong anti-interference ability, and good economy, and has a broad application prospect [3]. In the normal operation of the transformer, its vibration energy will be concentrated in the fundamental frequency (2 times the power frequency) and its frequency multiplier; When the transformer is abnormal or in a fault state, its vibration spectrum amplitude and other characteristic values will show certain variation rules according to different fault types, which can effectively reflect the fault information inside the transformer box [4]. Studies have shown that the amplitude of fundamental frequency of transformer vibration is an important parameter to reflect its vibration characteristics. By comparing the predicted value of fundamental frequency

* Corresponding author: 273649634@qq.com

amplitude with the actual value, the current state of the transformer can be analyzed and judged. Therefore, accurate prediction is important, and this is affected by the parameters of the prediction model. In order to improve the performance of prediction models, in recent years, researchers have combined some intelligent algorithms with prediction models to strengthen the learning ability and generalization mapping ability of prediction models and made some progress [5].

Among many intelligent algorithms, the Artificial Bee Colony algorithm (ABC) has attracted wide attention due to its advantages such as high search accuracy, few control parameters, and strong robustness, and has been proved to have higher solving quality than commonly used intelligent algorithms such as genetic algorithm, particle swarm algorithm, and ant colony algorithm. However, it also has the defects of slow convergence speed and insufficient local search ability [6]. Many scholars at home and abroad have improved the ABC algorithm. Generally speaking, the main improvement methods can be classified into three types, namely, optimization of nectar source initialization strategy, improvement of bee species search mechanism, and combination with other intelligent algorithms, but the three often exist in the algorithm improvement process in the form of combination optimization or integration [7]. In order to improve the overall performance of ABC and reduce the implementation difficulty of the algorithm as much as possible, so as to better serve the follow-up fundamental frequency amplitude prediction, a hybrid artificial bee colony algorithm was proposed in this paper to improve the existing defects of the ABC algorithm.

2 Hybrid artificial bee colony algorithm

2.1 Opposition-based Learning

Opposition-Based Learning (OBL) mechanism is a search improvement strategy, the definition of OBL is as follows.

Suppose there exists a set of feasible solutions $x_i = (x_{i1}, x_{i3}, . . . , x_{iD})$, $x_{i,j} \in [a_j , b_j]$, $j \in [1,D]$; where D denotes the dimension of the feasible solution and the reverse solution $x'_i= (x'_{i1}, x'_{i2}, ... , x'_{iD})$ can be generated by equation (1) as follows.

$$x'_{ij} = a_j + b_j - x_{ij} \tag{1}$$

Extending (1) as shown in equation (2).

$$x'_{ij} = k\left(a_j + b_j\right) - x_{ij} \tag{2}$$

In Eq. (2), $x_{i,j} \in [a_j, b_j]$, $i \in [1,|popsize|]$, $j \in [1,D]$, pop size represents the initial population size of the algorithm, and $k \in [0,1]$. When k takes different values, it represents different types of opposition-based learning mechanisms.

Considering the ABC algorithm in which the honey sources are randomly distributed in the solution space, and the distribution of honey sources largely affects the convergence speed and solution quality of the algorithm, the generalized opposition-based learning mechanism is introduced into the honey source initialization stage of the ABC algorithm.

2.2 Improve the search formula

In the ABC algorithm, since the nectar x_k is matched randomly, it is difficult to guarantee the quality of the nectar x_k from the probability point of view. This paper makes full use of the nectar source information available to the bee colony each time it searches to improve the search equation for hired and observed bees to equation (3), which enables it to approach the optimal nectar source at a faster rate and significantly improves the search efficiency of the bee colony.

$$v_{ij} = x_{best,j} + \varphi_{ij}\left(x_{best,j} - x_{ij}\right) + \varphi_{ij}\left(x_{ij} - x_{kj}\right) \tag{3}$$

In Eq. (3), x_{best} represents the best nectar source that can be searched for in the current colony; v_{ij} represents the new nectar source produced by competition with the original nectar source x_{ij}.

In addition, to improve the ability of the algorithm to jump out of the local optimum, on the basis of making full use of the optimal nectar source, this paper embeds the Cauchy mutation operator into the search process of the scout bee, which can strengthen the ability of the algorithm to jump out of the local optimum and reduce the randomness of the new nectar source generation, and improve the search formula as shown in equation (4).

$$x_{ij}^{new} = x_{best,j} + x_{best,j} \bullet cauchy(0,1) \tag{4}$$

In Eq. (4), $x_{best,j}$ is the current optimal honey source; *Cauchy*(0,1) is the standard Cauchy distribution function. Based on the above analysis, this paper embeds the opposition-based learning mechanism and the new search formula into the classical ABC algorithm, which constitutes the hybrid artificial bee colony algorithm (HABC). The algorithm optimizes the distribution of initial nectar sources and the working mode of each bee species, and its specific execution steps are as follows.

3 Experimental analysis

3.1 Test HABC by standard test function

3.1.1 The standard test function

To verify the effectiveness of the improved method in this paper, five representative standard test functions of Sphere, Step, Griewank, Rastrigin, and Ackley were used to test the HABC algorithm in 50-dimensional space and 100-dimensional space, respectively, and compared with the ABC algorithm.

3.1.2 Experiment

The improved HABC algorithm was set with the same initial parameters as the ABC algorithm, and the five standard test functions introduced in Section 3.1.1 were used as the fitness functions to test it. To show and compare the convergence process and the final solution accuracy of the two algorithms in different spaces more clearly, the convergence curves of the two algorithms on the five test functions are shown in Fig. 1 to Fig. 5.

In order to better compare and analyze the performance gap between the HABC algorithm and ABC algorithm, experiments are still carried out based on the above five standard test functions. The HABC algorithm and ABC algorithm are run 30 times each in 50 and 100 dimensional space, and the optimal value, worst value, average value, and standard deviation of the 30 running results are counted. Table 1 and Table 2 show the results of 30 statistical runs of the HABC algorithm and ABC algorithm in different Spaces.

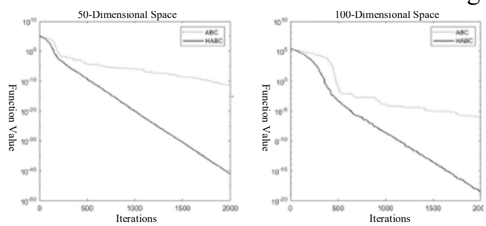

Fig. 1. The convergence curves of Sphere in 50-dimensional space and 100-dimensional space.

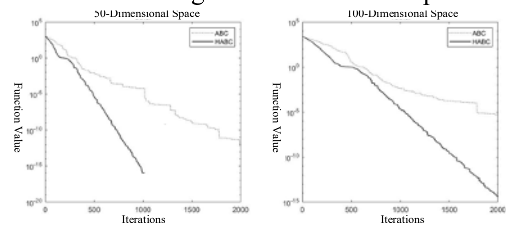

Fig. 2. The convergence curves of Step in 50-dimensional space and 100-dimensional space.

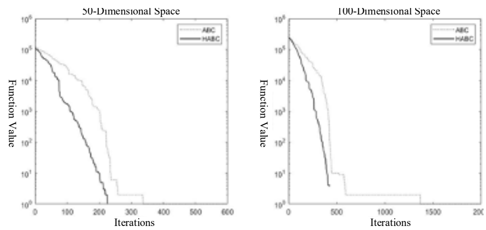

Fig. 3. The convergence curves of Griewank in 50-dimensional space and 100-dimensional space.

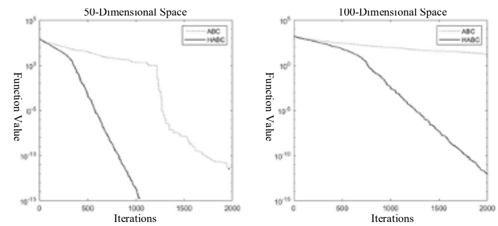

Fig. 4. The convergence curves of Rastrigin in 50-dimensional space and 100-dimensional space.

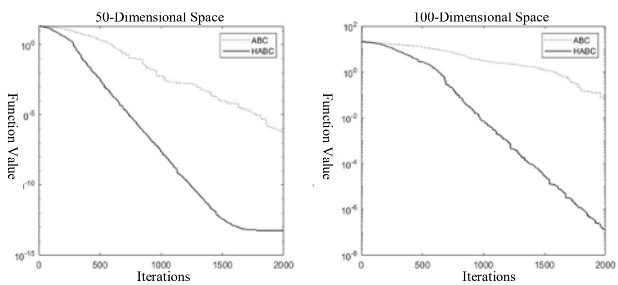

Fig. 5. The convergence curves of Ackley in 50-dimensional space and 100-dimensional space.

Overall, HABC at the end of the iteration algorithm to search the objective function value is far less than the ABC algorithm, at the same time, in some cases HABC algorithm is stable to search to the global optimal value of 0. Combined with the statistical results in Table 1, the four indexes of the HABC algorithm are all lower than the ABC algorithm, which proves that the HABC algorithm is far superior to the ABC algorithm in terms of optimization accuracy, convergence speed, and calculation stability, and verifies the effectiveness of the improved method in this paper.

3.2 Application in fundamental frequency amplitude prediction

In this section, the transformer vibration fundamental frequency amplitude is predicted by ELM, and HABC is used to optimize the input layer weights and hidden layer biases of ELM. The HABC-ELM prediction model is established. The operating voltage, load current and oil temperature are taken as the inputs of the model to predict the fundamental frequency amplitude.

Table 1. HABC algorithm and ABC algorithm run 30 times in 50- dimensional space and 100-dimensional space.

Test Function		The Optimal Value		The Worst Value		The Average Value		The Standard Deviation	
Dimensional space		50	100	50	100	50	100	50	100
Sphere	ABC	2.85E-13	8.23E-08	6.15E-12	1.26E-06	2.46E-12	5.95E-07	2.00E-12	4.31E-07
	HABC	7.87E-44	5.69E-20	9.82E-42	5.08E-19	2.70E-42	1.89E-19	3.07E-42	1.34E-19
Step	ABC	0	0	0	2.01E+00	0	5.33E-01	0	5.71E-01
	HABC	0	0	0	0	0	0	0	0
Griewank	ABC	6.17E-14	1.10E-06	3.17E-10	1.22E-02	2.82E-11	1.38E-03	6.86E-11	3.39E-03
	HABC	0	2.22E-15	0	3.88E-12	0	1.43E-13	0	7.05E-13
Rastrigin	ABC	1.67E-12	9.41E+00	5.02E-10	2.37E+01	6.94E-11	1.74E+01	1.16E-10	3.73E+00
	HABC	0	6.25E-13	0	4.95E-12	0	2.00E-12	0	1.19E-12
Ackley	ABC	1.56E-07	1.02E-2	1.40E-06	1.11E-1	4.56E-07	4.65E-2	2.26E-07	2.43E-2
	HABC	4.00E-14	8.31E-08	6.84E-14	1.57E-07	5.70E-14	1.17E-07	6.42E-15	1.91E-08

3.2.1 The data set

On a transformer of SFZ9-5000/110 in normal operation, data collection of surface vibration and working conditions is completed. The layout of vibration sensors is shown in Fig. 6.

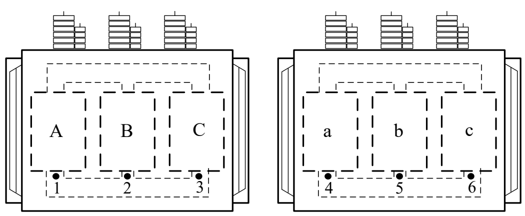

Fig. 6. Diagram of measuring point location of transformer.

Vibration data of the measuring points at low voltage phase a and operating condition data is selected as the original data, and the fundamental frequency amplitude of the measuring points, operating voltage, load current, and top oil temperature at the same time are analyzed and processed to form the experimental sample set. The data numbered odd numbers are taken as the training set, the data numbered even numbers as the test set.

3.2.2 Experiment

The parameters (input layer weight and hidden layer threshold) corresponding to the optimal nectar source searched by HABC algorithm and ABC algorithm are used to establish the HABC-ELM model and ABC-ELM model respectively, and the same training set and test set are used for training and verification. The same method is used to build another ELM model for comparison, the number of hidden layer neurons in the ELM model is also set as 15.

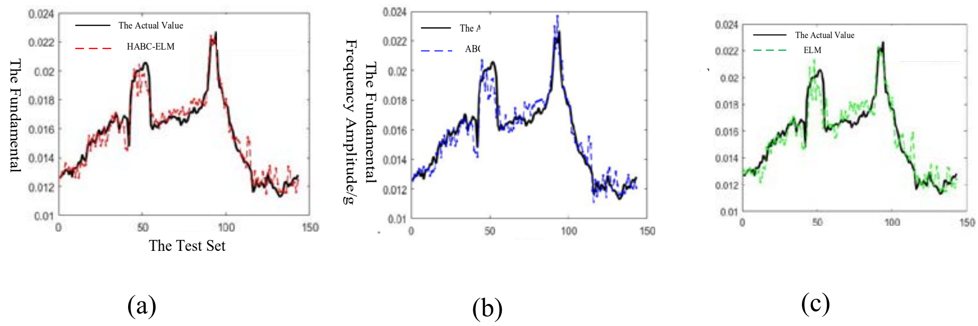

Fig.7. Comparison of prediction results of each models (low voltage phase a).

According to Fig.7, the three models, HABC-ELM, ABC-ELM, ELM, can better learn and memorize the nonlinear relationship between working condition data and fundamental frequency amplitude in terms of vibration fundamental frequency amplitude of measuring points of low voltage phase a. The prediction effect of HABC-ELM and ABC-ELM is better than that of ELM, and the predicted value of the HABC-ELM model is closer to the actual value.

To objectively analyze and evaluate the performance of the three models, the maximum absolute percentage error (MAXAPE), mean absolute percentage error (MAPE), mean absolute error (MAE), and coefficient of determination (R^2) are used to analyze the prediction results. The calculation indexes of the predicted results of each model are recorded in Table 3.

Table 3. Comparison of evaluation indexes of each model (low voltage phase a).

Model Name	MAXAPE (%)	MAPE (%)	MAE (g/10-4)	R^2
ELM	18.612	4.427	7.115	0.875
ABC-ELM	14.491	3.792	6.019	0.901
HABC-ELM	13.685	3.560	5.598	0.919

It can be seen from Table 3, HABC-ELM is lower than the other two models in MAXAPE, MAPE, and MAE, and is closest to 1 in R^2, indicating that HABC-ELM has the best comprehensive performance and the highest reliability, and is suitable for the prediction of amplitude of fundamental frequency of transformer vibration.

4 Conclusion

Aiming at the problem of slow convergence and weak local exploitation ability of the ABC algorithm, a HABC algorithm is proposed in this paper. By introducing an opposition-based learning mechanism and improving the search formula, the proposed method has obvious advantages in searching precision, convergence speed, and calculation stability compared with the classic ABC algorithm.

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