Research Article

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Application of adaptive artificial bee colony algorithm in environmental and economic dispatching management

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Abstract: With the increasingly serious global environmental and energy issues, more countries are using environmental and economic dispatch (EED) models to optimize power systems. To better optimize the power system, an adaptive artificial bee colony (ABC) algorithm based on memory feedback mechanism was put forward to address the EED model, and the adaptive algorithm was used to adaptively adjust the population size. The study also used a benchmark function to set an appropriate population size. In addition, the study also considered both fuel cost and environmental factors in the model, and simultaneously considered four constraint conditions. To evidence the function of the adaptive algorithm, different algorithms were compared in the study. The outcomes denoted that the minimum values of the optimal solution under the Sphere function, Matyas function, and Dixon Price function were 1×10^{-273}, 1×10^{-162}, and 1×10^{-16}, respectively, and their corresponding population sizes were 7, 18, and 20. Under the Sphere function, the minimum average fitness values of the algorithm designed by the research, the ABC algorithm, and the current optimal ABC algorithm were 10^{-15}, 10^{-4}, and 10^{-11}, respectively. Moreover, the algorithm designed by the research tended to flatten out after nearly 30 iterations. The total cost of the adaptive algorithm, ABC algorithm, and the optimal algorithm was 102126.0573 yuan, 113001.0383 yuan, and 109594.9634 yuan, respectively. The pollutant emissions of the three algorithms were 1246.1048 yuan, 1250.5744 yuan, and 1344.3922 yuan, respectively. The adaptive algorithm based on memory feedback mechanism had obvious advantages in solving EED models. The adaptive algorithm proposed by the research achieved adaptive adjustment of population size, improved the operational efficiency of the algorithm, and had certain reference significance for solving other problems.

Keywords: adaptive, artificial bee colonies, environment economics, dispatch

1 Introduction

The power system's stability is conducive to that of the country, and the optimization of resource allocation in the power system is conducive to the sustainable development of the national economy. With the growth of China's economy, environmental and energy issues are gradually becoming prominent. Therefore, how to optimize the power system to alleviate environmental and energy issues is currently the focus of power grid optimization [1,2]. Economic dispatch is the foundation and core issue of optimizing the operation of power systems. However, traditional economic dispatch models only consider the cost of electricity and do not involve environmental pollution factors. In addition, traditional environmental and economic dispatch

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(EED) models are static without considering the actual operation of the power system [3]. At present, the EED model is widely used in power grid optimization, which considers both power cost and environmental pollution issues, and has only fewer constraints [4]. In response to the problem of limited constraints in the EED model, four constraint conditions are studied and designed, namely, unit output power constraint, unit output balance constraint, unit ramp rate constraint, and unit work dead zone constraint. For the solution of multi-objective environmental economic model, the current research mostly uses intelligent algorithm to replace the traditional mathematical programming method. The common solving algorithms currently include Pareto evolutionary algorithm, genetic algorithm based on non-dominated sorting, and swarm intelligence algorithm. Common swarm intelligence algorithms include particle swarm optimization (PSO), ant colony optimization, and artificial bee colony (ABC) algorithm [5]. Basak et al. designed a hybrid swarm intelligence optimization algorithm that combines traditional grey wolf optimizers, sine cosine algorithms, and crow search algorithms for demand side management in microgrid constrained economic dispatching, achieving further reduction in power generation costs [6]. Bai et al. designed an improved multi-objective differential evolution algorithm for the dynamic environmental economic dispatching problem containing wind power, achieving dynamic scheduling of wind power systems [7]. Although these algorithms have good results in solving the multi-objective environmental economic model, there are also some problems, such as the need to manually set the size of the group, the impact of subjective factors, susceptibility to local optima, premature convergence, etc. [8]. Among them, an important problem with swarm intelligence algorithms such as artificial bee colonies is the pre-setting of parameters, which leads to a significant impact of parameter values on experimental results. These algorithms are sensitive to parameter settings and require dynamic adjustment of parameters for optimization [9]. Therefore, the challenge and problem of research is to achieve dynamic adjustment of algorithm parameters and avoid the impact of manually setting parameters. To address the influence of subjective human factors in solving multi-objective environmental economic models and improve the performance of the algorithm, this study starts with the ABC algorithm and an innovative adaptive ABC algorithm is proposed, aiming to achieve automatic adjustment of population size and solve dynamic multi-objective EED models. The novelty of the research is to improve the ABC algorithm by introducing a memory feedback mechanism, so that the population size of the algorithm can be adaptively adjusted, thereby improving the performance of the algorithm. The aim of the research is to construct an environmental and economic model that considers both environmental pollution and electricity costs, alleviate the pressure on Earth's energy and environment, and respond to the call for national energy conservation and emission reduction. The contribution of the research is the design of an adaptive ABC algorithm, which achieves adaptive adjustment of population size, reduces the subjective factors caused by manually setting population size, and improves the performance of the algorithm and the efficiency of solving environmental economic models.

The study is divided into four parts. The first part is a literature review on EED, which involves different solving algorithms. The second part is the construction of an EED model and the design of corresponding solving algorithms. The third part is the validation of the algorithm's effectiveness and its performance in EED problems. The fourth part is the conclusion, shortcomings, and future prospects of the research.

2 Related works

With the highlighting of global environmental issues, EED has gradually become a hot topic in the power system, and many researchers have conducted research on it. To alleviate regional economic pressure, Gu et al. proposed to use opportunity constrained and robust optimization frameworks to describe stochastic emission aware economic scheduling. The laboratory outcomes demonstrated that the framework can well describe that with storage systems. However, this method will expand the optimization space of scheduling, increase the computational burden, and has inevitable conservatism [10]. Xz et al. used data from the State Grid of China to study the additional costs caused by fluctuations in the output of coal-fired units during the peak shaving of renewable energy priority scheduling. Research results proved that under current technological means, larger peak shaving would no longer produce a positive influence on economic costs. In addition, this study considered less other additional costs in energy scheduling, such as mechanical loss costs [11]. Gu et al. proposed a dual layer low-carbon economic optimization scheduling model for industrial parks that considered multiple energy price incentives to provide the best comprehensive energy price for comprehensive energy service institutions, and iteratively optimized this model. The laboratory findings denoted that this model can effectively improve the net income of comprehensive energy service institutions. However, this study tended to wander in the internal region when solving models, without accessing vertices, and did not have an advantage in solving small problems [12]. To avoid the impact of uncertainties in the heating system on user safety and comfort, Dong et al. conducted a comprehensive modeling of uncertainties. It is demonstrated that the model performed well in dealing with uncertain factors. The robust optimization in this method would expand the optimization space of scheduling, making it difficult to solve directly, and the calculation results would be limited by different uncertain sets, increasing the difficulty of solving [13]. Gurbuz and Akcay used a hydrogen fuel spark ignition engine operating in a lean mixture to discuss the impact of external turbochargers on environmental and economic indicators. The experimental results showed that under that condition, the environmental and social costs increased by 21%, while fuel costs decreased by 18%. This study lacked additional comparison in engine speed, with only one speed, making it difficult to analyze the situation at different speeds [14]. Akbari-Dibavar et al. proposed a multi-objective optimization framework to address renewable energy and economic emission scheduling to reduce the diffusion of carbon emissions. The research results demonstrated that this method could find the optimal solution to reduce carbon emission diffusion. However, the carbon capture and storage technology used in this study was difficult to successfully respond to climate change, and its cost was high, making it less advantageous compared to other technologies [15]. Zamani et al. used Landsat-8 images and weighted linear combination methods to determine the suitable planting area for saffron in Miyaneh. This study obtained climate and hydrological data from weather and climate stations over the past 30 years, and then used weighted linear combination methods to weight the importance of different regions. The results showed that the southeastern and northwestern regions of Miyaneh were more suitable for the cultivation of saffron. However, this study also has limitations in terms of large computational complexity. To reduce investment risks in the power sector, Ahmadi et al. adopted the concept of portfolio optimization to demonstrate the potential of using renewable energy and applied sensitivity analysis. The results showed that when the change in input cost factor was 10%, the percentage of renewable energy supply would only be partially affected. However, this method also faced the problem of data uncertainty [16]. Babaeinesami et al. designed an adaptive non-dominated sorting genetic algorithm to address supply chain configuration issues, and adjusted parameters using the Taguchi design method. The results showed that the algorithm could generate effective Pareto solutions. However, there were also issues with high computational complexity in this study [17].

To summarize the methods of traditional dispatching, dynamic dispatching, economic emission dispatching, and multi-regional economic dispatching problems, Lolla et al. evaluated the performance of centralized methods through data collection, and also reviewed the literature on consistency protocols related to decentralized and distributed methods. The research results showed that this method analyzed and explored traditional scheduling and other methods from different perspectives. Due to time constraints, the methods collected in this study are not very comprehensive, and the sources of literature are relatively single. Moreover, the screening methods for literature can be further improved [18]. Shilaja et al. proposed an improved multi-model optimization algorithm to reduce the unpredictability and intermittency of renewable energy on power grid planning, and introduced congestion calculation methods and new external storage processes into traditional kernel function methods. The research findings demonstrated that this method can effectively reduce the unpredictability of renewable energy and the impact of intermittency on power grid planning. This study did not consider a solution to reduce the time consumption of high-dimensional economic emission dispatching problems, and the modification of stored procedures was relatively cumbersome and had poor portability [19]. Dong and Wang proposed to transform the EED problem into a single objective problem through weighted summation to better solve the problem, and used Newton's method to iteratively solve the equation constraints. The research results showed that this method had good performance in solving EED problems. However, this study had issues such as local extremum or saddle point, inability to guarantee function value descent during the iteration process, and high computational complexity in solving the Hessian inverse matrix [20]. To solve the EED problem better, Mishra and Mishra proposed a new multi-objective differential evolution algorithm and verified it. The experimental results illustrated that the algorithm could provide good Pareto solutions and maintain the diversity of solutions. The parameter selection of differential evolution algorithm in this study depended on problem characteristics and experience, without unified theoretical guidance, which may affect the performance and stability of the algorithm. When facing large-scale, multi-constraint optimization problems, this method may have the disadvantage of slow convergence speed [21]. Rajeswari et al. proposed a temporary solution search strategy to avoid the lack of reinforcement and slow convergence speed in ABC algorithms, iterating the best solution through local best and neighbor best. The research results showed that this algorithm could improve the quality of solutions when solving numerical optimization problems, and was significantly superior to traditional ABC algorithms. However, this study could further improve the solving speed and optimize the computational burden [22]. Habib et al. used the judgment matrix method, PSO algorithm, and ABC algorithm to transform the multi-objective function into a comprehensive objective. The laboratory outcomes indicated that the ABC had significant advantages in cost minimization, and its effect was more significant in a large number of electric vehicles. The performance of the method in this study was easily affected by parameters, and it was also prone to getting stuck in local optima. Moreover, the convergence speed was slow, which can be further improved [23]. Esmaeili et al. designed a method that combines genetic algorithm and 3D convolutional neural network to select bands for hyperspectral images, and used embedded 3D convolutional neural network as the fitness function of genetic algorithm. In addition, the study also involved the parent checkbox. The results showed that the model designed by the research had a high accuracy, up to 99%. This study can be further optimized in terms of computational complexity, and the dependence on hyperparameters needs to be further improved. To optimize the dispatching of microgrids, Hou and Fujimura adopted PSO algorithm, combined with prediction technology, demand side management, and EED. The results showed that this method could solve low-cost and low emission power supply solutions. There is still room for improvement in the dynamic adjustment of parameters in this study [24]. In response to the shortcomings of multi-objective optimization methods in dynamic overlapping community detection, Jiang et al. designed a hybrid algorithm based on collaborative particle swarm multi-objective optimization, and initialized the particle swarm through community overlapping propagation algorithm. The results showed that the algorithm performed outstandingly in terms of hyper volume values and could approach the Pareto boundary. This study could further optimize the robustness of the algorithm [25].

To sum up, most of the research on solving the multi-objective EED model is realized by swarm intelligence algorithm. The advantages of these algorithms are their strong global search ability and parallelism, which can simultaneously consider multiple objective functions, thus finding a balance between multiple objectives. However, although these algorithms have certain effects, they also have certain problems, such as the need to manually set the group size, the large influence of subjective factors, susceptibility to local optima, and premature convergence. Therefore, to avoid the subjective impact of manually setting parameters, the research innovatively proposes an adaptive ABC algorithm based on memory feedback mechanism, which achieves automatic adjustment of population size through the adaptive ABC algorithm, and solves the dynamic multi-objective EED model.

3 Design of a dynamic multi-objective EED model based on adaptive ABC algorithm

3.1 Modeling of EED models

Electricity cost is generally considered in traditional economic dispatch problems, and the factors discussed are relatively single [26]. To improve the flexibility of unit operation, research has involved the design of dynamic economic dispatch models targeting power generation costs and EED models based on dynamic multi-objective. The dynamic economic dispatch model not only includes common unit output balance constraints and system upper and lower limit constraints but also incorporates constraints such as climbing speed and unit work dead zone. The combustion cost expression of the dynamic economic dispatch model is expressed in equation (1) [27].

$$\min(F) = \sum_{i=1}^{n} c_i P_i^2 + b_i P_i + a_i + |e_i \sin(f_i(P_{i\ \min} - P_i))|, \tag{1}$$

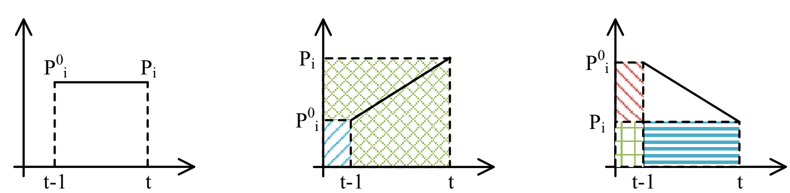
where n means the number of conventional units. P_i is the output power of the ith th unit. a_i, b_i, and c_i stand for the fuel combustion cost coefficients of unit i. $P_{i\ \min}$ indicates the lower limit of the output power of the ith unit. e_i represents the cost coefficient of unit i. There are four constraints for dynamic economic dispatch problems, among which the upper and lower values of unit output power are constrained as presented in equation (2) [28].

$$P_i^{\min} \le P_i \le P_i^{\max}, \tag{2}$$

where $P_i^{\max}$ is the max output of the ith unit. $P_i^{\max}$ means the mini output of the ith unit. The output balance constraint conditions of the unit are shown in equation (3) [29].

$$\sum_{i=1}^{n} P_i = P_{\mathrm{D}} + P_{\mathrm{L}}, \tag{3}$$

where P_{D} represents electricity demand. P_{L} represents load loss. The ramp rate changes of the unit are mainly divided into three situations: increase rate, unchanged rate, and reduction rate, as shown in Figure 1.



(a) (b) (c)

Figure 1: Three possible changes in power. (a) Unit power increase, (b) unit power remains unchanged, and (c) unit power reduction. Source: Created by the authors.

Figure 1(a) shows the situation when the unit power increases, which can be represented as $P_i - P_i^0 \le \mathrm{UR}_i$. Figure 1(b) represents the situation when the unit power remains unchanged, which can be expressed as $P_i = P_i^0$. Figure 1(c) shows the situation when the power of the unit decreases, which can be illustrated as $P_i^0 - P_i \le \mathrm{DR}_i$. Based on these three situations, the climbing rate constraint of the unit can be obtained, as shown in equation (4) [30].

$$\max(P_i^{\min}, P_i^0 - \mathrm{DR}_i) \le P_i \le \min(P_i^{\max}, P_i^0 + \mathrm{UR}_i), \tag{4}$$

where DR_i represents the lower limit of climbing speed. UR_i is the upper limit of climbing speed. P_i^0 represents the unit output value at $t - 1$ time. The working dead zone constraints of the unit are shown in equation (5) [31].

$$\begin{cases} P_i^{\min} \le P_i \le P_{i,1}^{l} \\ P_{i,j-1}^{u} \le P_i \le P_{i,j}^{l} j = 2, 3, 4\ldots\ n, \\ P_{i,n}^{u} \le P_i \le P_i^{\max} \end{cases} \tag{5}$$

where P_{ij}^{l} and P_{ij}^{u} are the upper and lower bounds of the jth working dead zone interval of the ith unit, respectively. The expression of the load loss matrix is shown in equation (6) [32].

$$P_{\mathrm{L}} = \sum_{i=1}^{n}\sum_{j=1}^{n} P_i B_{ij} P_j + \sum_{i=1}^{n} B_{0i} P_i + B_{00}, \tag{6}$$

where P_L represents the loss matrix, and B_{ij}, B_{0i}, and B_{00} represent the coefficients of the loss matrix. Unlike traditional economic dispatch that only considers one objective function, EED models take both electricity costs and environmental pollution as objective functions. The significance of doing so is to implement energy-saving and emission reduction strategies, solve environmental pollution and energy problems, and promote sustainable development of human society. In addition, EED simultaneously considers constraints such as valve point effect (VPE), climbing rate, and work dead zone, and equation (7) is its fuel cost function [33].

$$C_i(P_i) = \sum_{i=1}^{N}(a_i + b_iP_i + c_iP_i^2 + |e_i \sin(f_i(P_{i\ \min} - P_i))|), \tag{7}$$

where N is the number of units. $e_i \sin(f_i(P_{i\ \min} - P_i))$ means the VPE function. e_i and f_i represent the cost coefficients of the unit i. The total pollutant emission function of the power system is shown in equation (8) [34].

$$E_i(P_i) = \sum_{i=1}^{N}\alpha_i + \beta_iP_i + \eta_iP_i^2 + \varepsilon_i \exp(\lambda_iP_i), \tag{8}$$

where $\varepsilon_i \exp(\lambda_iP_i)$ represents the VPE function. α_i, β_i, η_i, ε_i, and λ_i represent the pollutant emission coefficients of the unit i. The overall objective function of the model is the combination of fuel cost function and total pollutant emission function, as shown in equation (9) [35].

$$F = \text{Min}\left[\sum_{i=1}^{N} C_i(P_i), E_i(P_i)\right], \tag{9}$$

where $C_i(P_i)$ is the fuel cost function. $E_i(P_i)$ is a function of total pollutant emissions. The constraints formulas of the EED model include upper and lower limits on output power, output balance constraints, ramp rate constraints, and work dead zone constraints. Through these constraints, the dispatching model can make more reasonable arrangements for the operation mode and load of the units, thereby meeting the electricity demand of end users. At the same time, actual operational constraints such as climbing speed and work dead zone can better assist the dispatching model in fundamentally optimizing the operational efficiency of the unit. The formula for the constraint conditions of the EED model is consistent with that of economic dispatch, so it will not be repeated here. The weight method is used to convert problems from multi into single objective, as shown in equation (10) [36].

$$\begin{cases} F = wC + (1 - w)\sigma E \\ \sigma = C(P_{\max})/E(P_{\max}) \end{cases}, \tag{10}$$

where w is used to balance the weights of the two optimization objectives. σ is used to balance the magnitude between two targets. E represents the total pollutant emissions. C represents fuel cost. F is the overall objective function.

3.2 Design of adaptive ABC algorithm

Based on the EED model, which involves two objective functions of environmental pollution and power cost, the adaptive ABC algorithm is used to handle the calculation of this model. The adaptive ABC algorithm has a wide range of applications in numerical function optimization and multi-objective optimization, and has good application effects. Compared with traditional optimization methods, the adaptive ABC algorithm differs in handling EED models in terms of high ranging accuracy, strong robustness, fast convergence speed, and fewer parameters that need to be set. Before designing the adaptive ABC algorithm, the study first introduced the traditional ABC algorithm, which is shown in Figure 2.

In the initialization phase of ABC, the algorithm will randomly generate SN feasible solutions, and obtain their fitness function value (FFV), as shown in equation (11) [37].

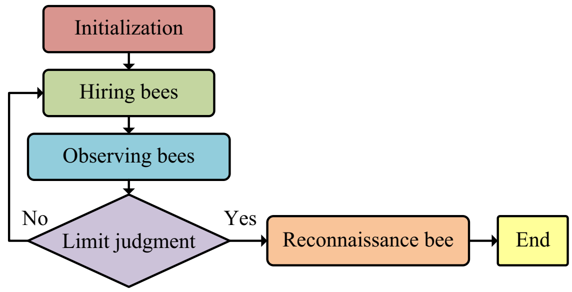


Figure 2: Flowchart of ABC algorithm. Source: Created by the authors.

$$X_{i,j} = X_{\min,\ j} + \text{rand}(0,1)(X_{\max,\ j} - X_{\min,\ j}), \tag{11}$$

where the value range of i in C is $i = 1, 2, ..., \text{SN}$. SN represents the D dimensional vector. D is the number of optimization parameters, $j \in \{1, 2, ..., D\}$. The ABC algorithm will update the solution during the hiring phase, as shown in equation (12) [38].

$$V_{i,j} = X_{x,j} + \phi_{i,j}(X_{i,j} - X_{k,j}), \tag{12}$$

where $k \in \{1, 2, ..., \text{SN}\}$, k represents the number of digits of a random number. $\phi_{i,j}$ represents a random number between −1 and 1, and $k \neq i$, $\phi_{i,j} \neq i$. In the bee observation phase, ABC algorithm will select and update the solution according to the FFV. The selection is shown in equation (13) [39].

$$P_i = \frac{f_i(X_i)}{\sum_1^{\text{SN}} f_i(X_i)}, \tag{13}$$

where $f_i(X_i)$ represents the FFV of the ith solution, and the corresponding fitness calculation is shown in equation (14) [40].

$$f_i = \begin{cases} 1/(1 + f_i), f_i > 0 \\ 1 + \text{abs}(f_i), \text{otherwise} \end{cases}. \tag{14}$$

During the reconnaissance bee phase, the ABC algorithm will set a limit parameter value for each solution. This parameter value will record the number of times each solution has not been changed. When it reaches the specified value, the corresponding solution will be deleted, the corresponding hired bee will change into a reconnaissance bee, and a new solution will be randomly generated. The group size parameters of swarm intelligence algorithms such as ABC have a more obvious impact on the experimental results, and the common adjustment strategy is to manually set the maximum and minimum group size intervals, without allowing the algorithm itself to converge to a better group size. The adaptive ABC algorithm can allow the algorithm to converge to an optimal population size, but an appropriate population size needs to be set first. Therefore, the study uses four types of benchmark functions from CEC-2014, as shown in Figure 3.

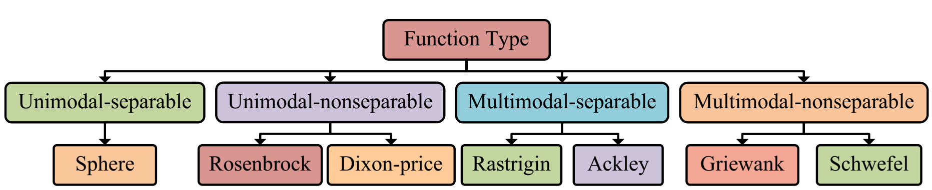


Figure 3: Four types of benchmark functions. Source: Created by the authors.

Benchmark functions are mainly divided into four categories, including single-peak separation, single-peak non-separation, multi-peak separation, and multi-peak non-separation functions. Among them, single-peak separation mainly involves the Sphere function, while single-peak non-separation function mainly includes the Rosenbrock and Dixon-price functions [41]. The multi-peak separation mainly involves Rastrigin and Ackley functions, while the multi-peak non-separation function mainly involves Griewank and Schwefel functions. The adaptive ABC algorithm achieves dynamic population size adjustment by deleting poor individuals and adding good ones. The specific methods used are memory feedback mechanism and memory matrix [42]. At the same time, to achieve the convergence of population size towards the optimal value, the study recorded the speed of evolution during the algorithm operation, namely, the "evolution rate," to achieve the locking of the optimal population size. The size of the population has a significant impact on the performance of swarm intelligence algorithms. The role of memory feedback mechanism in adaptive ABC algorithm is to dynamically adjust the size of the population, maintain the diversity of individuals in the population, improve the global optimization effect of the algorithm, avoid falling into local optima, and thus improve the performance of the algorithm. The implementation of memory feedback mechanism is mainly achieved through memory matrix. Through the memory matrix, the adaptive ABC can record the times each individual ranks best and worst during its own operation, and use these times as a basis to determine the potential of each individual. For individuals with poor potential, the algorithm will delete them. The mechanism generates new solutions based on solutions with high potential and removes solutions with minimal potential, which is the first step in implementing the memory feedback mechanism. Therefore, the study used two memory matrices to record the number of times an individual ranked best and worst. Matrix best_memory[][] and matrix worst_memory[][] record the number of times an individual ranked best and worst, respectively. For the implementation of optimal population size convergence, the adaptive ABC algorithm mainly locks in the optimal population size through evolution rate. The algorithm first uses a one-dimensional array memory_rate[] to characterize the speed of individual evolution, and then records the population size and average evolution speed of the entire population using average_rate[]. Then, memory_foodchange[][] is used to record the changes in the evolution rate of each individual. The expressions of memory_rate[] and average_rate[] are shown in equation (15) [43].

$$\begin{cases} \text{Memory\_rate}[i] = \dfrac{f[i][\text{pre\_iter}] - f[i][\text{current\_iter}]}{f[i][\text{pre\_iter}]} \\ \text{Average\_rate} = \text{Average}(\text{memory\_rate}) \end{cases}, \tag{15}$$

where $f[i][\text{current\_iter}]$ and $f[i][\text{pre\_iter}]$ represent the FFV of the current generation and the previous generation, respectively. There are generally two strategies for changing the population size of adaptive ABC, one is to raise the number of groups, while the other is to decrease that. Each of them includes two situations, namely, the change in population size when average(memory_rate) increases and average(memory_rate) decreases. The basic framework of adaptive ABC is shown in Figure 4.

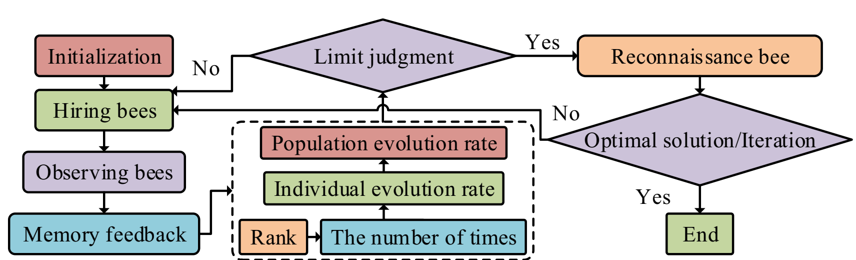


Figure 4: The basic framework of adaptive ABC algorithm. Source: Created by the authors.

The framework of adaptive ABC algorithm mainly involves the initialization stage, hiring bee stage, memory feedback stage, and reconnaissance bee stage of the algorithm. In the memory feedback phase, the adaptive ABC algorithm needs to sort all solutions according to the FFV, and record the best and worst times of each solution's ranking. Then, the algorithm needs to record the evolution rate of each solution and the evolution rate of the entire population. After recording the data, the algorithm needs to adjust the population size. When the number of times an individual ranks the worst and the best reaches the limit, the algorithm will reduce and increase the population size, respectively. In addition, when the population size decreases and the individual's evolution rate is less than the population's evolution rate, the algorithm will increase the population size, otherwise the algorithm will reduce the population size. When the evolution rate of an individual is smaller than that of a population after the population size increases, the algorithm will reduce the population size, otherwise it will increase the population size. When an individual does not update within the limit number of times, the algorithm enters the reconnaissance bee stage. The algorithm will not stop operation until it reaches the optimal solution and the greatest number of iterations.

4 Analysis of the results of the EED model based on adaptive ABC algorithm

4.1 Effectiveness analysis of adaptive ABC algorithm

To clarify the impact of population size on algorithm performance, the study selected four different styles of benchmark functions for experiments. There were a total of seven benchmark functions, namely, Sphere, Ackley, Dixon-Price, Rosenbrock, Rastrigin, Schaffer, and Griewank. Except for the Schaffer function, which has a dimension of 2, all other functions had a dimension of 30, and the allowable errors for all functions were 1.0×10^{-10}. The final group size chosen for the experiment was 10, with a maximum iteration of 33,600. The performance of the algorithm could be effectively evaluated through the optimization effect on the function and the average fitness (AF) evolution curve. The operating system used in the experiment was Windows 11 (64 bit), with an Intel Core i5 12600K processor. The processor had a main frequency of 3.7 GHz, a maximum core frequency of 4.9 GHz, and a maximum supported memory of 128GB. The sensitivity of benchmark functions for different categories to group size varied, and the specific sensitivity results are shown in Figure 5.

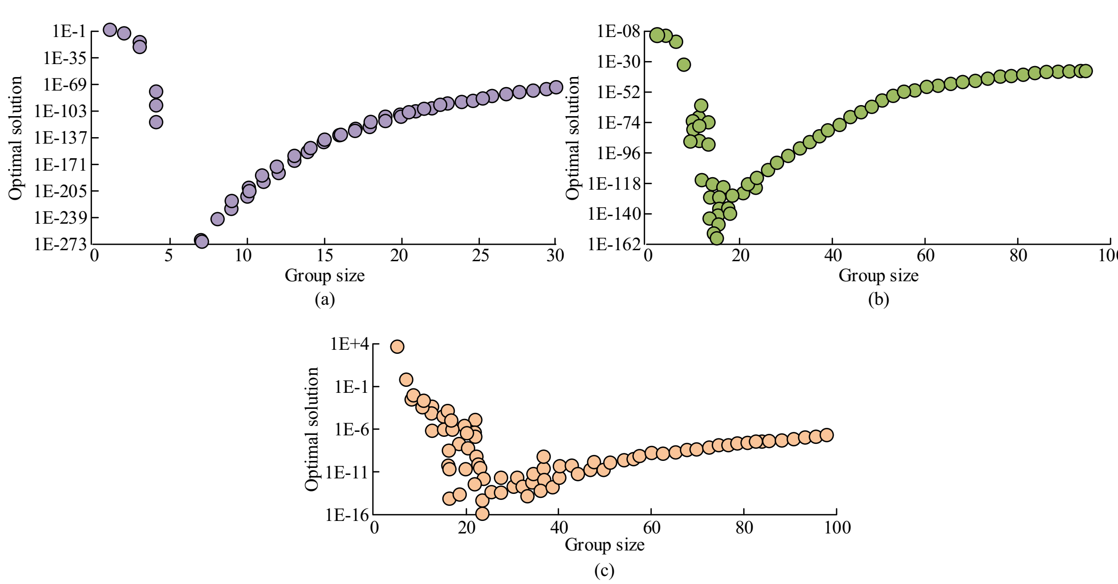


Figure 5: The sensitivity of different classes of functions to population size. The optimal solution corresponding to different population sizes of (a) Sphere, (b) Matyas, and (c) Dixon-price. Source: Created by the authors.

From Figure 5(a), the max and the mini value of the optimal solution under the Sphere function were 0.1 and 1×10^{-273}, and the corresponding population size were 1 and 7. When the population size was from 0 to 4, the trend of the optimal solution was gradually decreasing. When the population size was 4–5, the optimal solution basically changed in a vertical downward trend, but the overall change amplitude was relatively small. When the population size was greater than 5, the optimal solution first did not exist. When the population size was 7, the optimal solution reappeared and gradually increased as the population size increased. In Figure 5(b), the max and the mini value of the optimal solution under the Matyas function were 1×10^{-08} and 1×10^{-162}, and the population size approached 0 and 18 at this time. When the population size was 0–10, the trend of the optimal solution was gradually decreasing. When the population size was 10–20, the optimal solution showed a nearly vertical downward trend, but the overall decline interval was small and the range of optimal solution values was relatively close. When the population size was greater than 20, the trend of the optimal solution gradually increases with the increase in the population size and presented a relatively smooth arc. From Figure 5(c), the maxi and the mini value of the optimal solution under the Dixon-Price function were around 1×10^4 and 1×10^{-16}, and the corresponding population size was around 1 and 20. When the population size was from 0 to 20, the overall trend of the optimal solution was gradually decreasing, but the overall decreasing range was relatively small and the value range was relatively close. As population size exceeded 20, the trend of the optimal solution gradually increased. The comparison results between adaptive ABC algorithm and ABC algorithm and their variants are displayed in Table 1.

Table 1: Comparative results of adaptive ABC algorithm and ABC algorithm and their variants

Function	Algorithm	Mean value	Variant
Sphere	ABC	1.38×10^{-178}	1.38×10^{-178}
	Best-so-far ABC	1.28×10^{-15}	4.59×10^{-15}
	Adaptive ABC	$1.965038 \times 10^{-316}$	0
Ackley	ABC	5.32×10^{-120}	1.60×10^{-119}
	Best-so-far ABC	1.60×10^{-138}	8.78×10^{-138}
	Adaptive ABC	1.97×10^{-152}	4.88×10^{-106}
Dixon-price	ABC	5.92×10^{-11}	3.22×10^{-10}
	Best-so-far ABC	0.256973428	0.68809989
	Adaptive ABC	1.02×10^{-14}	2.78×10^{-14}
Rosenbrock	ABC	0.6014	1.2149
	Best-so-far ABC	10.0959	9.5955
	Adaptive ABC	0.0912	0.1509
Rastrigin	ABC	0	0
	Best-so-far ABC	1.37436×10^{-09}	7.52393×10^{-09}
	Adaptive ABC	0	0
Schaffer	ABC	0	0
	Best-so-far ABC	0	0
	Adaptive ABC	0	0
Griewank	ABC	2.1464×10^{-16}	4.0540×10^{-17}
	Best-so-far ABC	2.3685×10^{-16}	5.6335×10^{-17}
	Adaptive ABC	2.1094×10^{-16}	3.3876×10^{-17}

In Table 1, the adaptive ABC under the benchmark function performed better than the ABC and its variants. Under the Rastrigin and Schaffer functions, the mean and variant of the adaptive ABC algorithm were the same as those of the ABC algorithm, indicating that the adaptive ABC algorithm did not have an advantage at this time. When not in the Rastrigin and Schaffer functions, the mean and variant of the adaptive ABC were smaller than those of the ABC and its variants, indicating that in most cases, the adaptive ABC algorithm had more advantages. In summary, the adaptive ABC algorithm has more advantages than the ABC algorithm and its variants. In Table 1, the AF evolution curves of three algorithms under three benchmark functions are generated as shown in Figure 6.

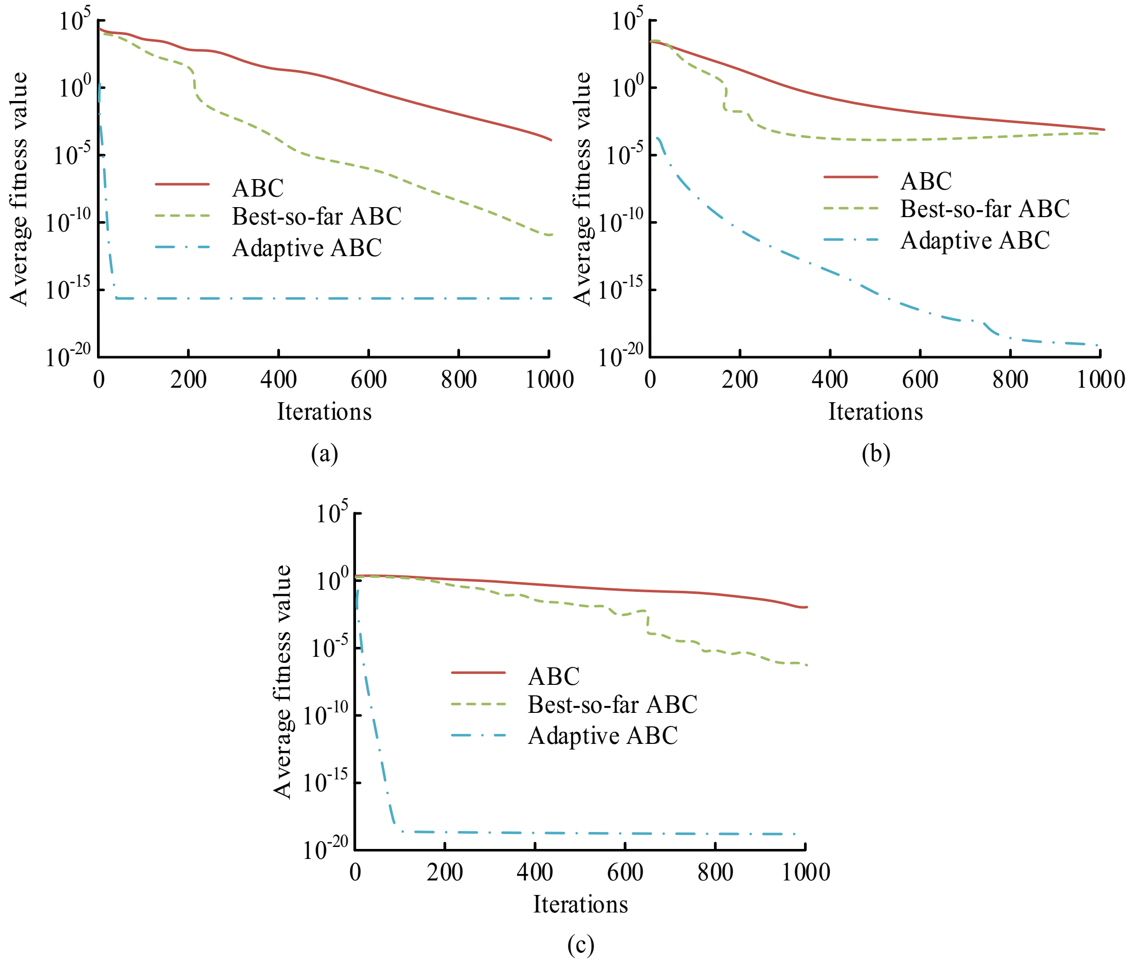


Figure 6: AF evolution curve of different algorithms under different functions. (a) Sphere function evolution curve, (b) Rosenbrock function evolution curve, and (c) Ackley function evolution curve. Source: Created by the authors.

In Figure 6(a), the maximum and the minimum values of the AF of the adaptive ABC algorithm were 1 and 10–15, respectively. The trend of the adaptive ABC algorithm was to quickly decrease to the minimum as the number of iterations increased. When the number of iterations of the adaptive ABC was around 30, its trend was a straight line. The maximum AF value of ABC algorithm and the current best-so-far ABC (Best-so-far ABC) was 105, and the minimum value was 10–4 and 10–11, respectively. The change trend of the two algorithms was gradually declining on the whole. As shown in Figure 6(b), the adaptive ABC algorithm had a minimum value of 10–15 after 1,000 iterations. The trend of the adaptive ABC algorithm was gradually decreasing. The maximum value of AF of ABC and Best-so-far ABC algorithm was 108, and the minimum value was 103 and 102, respectively. The trend of change in the ABC was gradually and slowly decreasing, while the trend of change in the Best-so-far ABC algorithm was relatively fast before 250 iterations and a relatively straight line after 250 iterations. In Figure 6(c), the AF value of the adaptive ABC algorithm reached the minimum value of 10–15 after 100 iterations, while the change trend of the adaptive ABC algorithm dropped rapidly before 100 iterations, and it was a straight line after 100 iterations. The maximum value of AF of ABC and Best-so-far ABC was 1,010, and the minimum value was 10–1 and 10–4, respectively. The change trend of both algorithms was gradually declining. In summary, the adaptive ABC has faster convergence speed, accuracy, and high stability.

4.2 Analysis of the results of an EED model based on adaptive ABC algorithm

The experimental results of the dynamic economic dispatching model based on adaptive ABC algorithm were mainly expanded from two aspects, namely, the optimal solution and convergence effect. The operating system used in the experiment was also Windows 11 (64 bit), and the processor and memory settings were consistent with Section 4.1, so they will not be repeated here. The dataset used in the experiment was the IEEE six-unit system, which includes parameter data of the loss matrix, corresponding parameter data for each unit, and power demand data. The comparison of the optimal solutions between adaptive ABC, ABC, and Best-so-far ABC is shown in Figure 7.

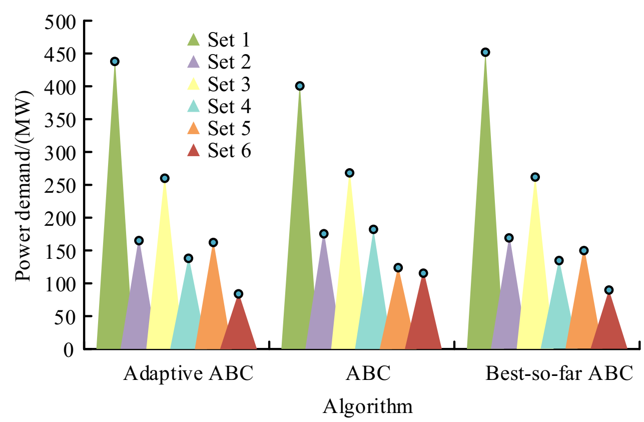


Figure 7: Comparison of optimal solutions of three algorithms. Source: Created by the authors.

From Figure 7, the max and the mini power demands of the unit under the adaptive ABC were 446.13 and 86.30 MW, respectively. Those under the ABC were 406 and 121.26 MW, respectively. Those under the Best-so-far ABC were 456 and 89.75 MW, respectively. The total output of the adaptive ABC was 1275.02 MW, with a total loss of 11.98 MW and a total cost of 15,442 yuan. The total output of the ABC algorithm was 1274.78 MW, with a total loss of 11.71 MW and a total cost of 15,443 yuan. The total output of the Best-so-far ABC was 1276.8 MW, with a total loss of 13.76 MW and a total cost of 15,447 yuan. The adaptive ABC has the lowest total power cost and minimal total loss. The comparison of convergence performance between adaptive ABC, ABC, and Best-so-far ABC is shown in Figure 8.

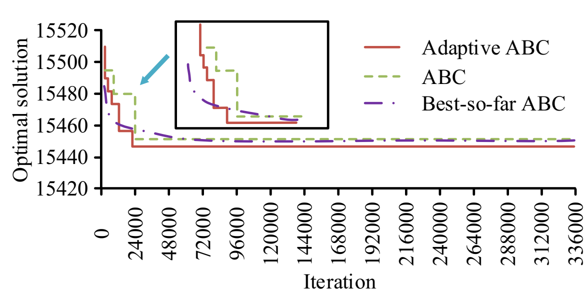


Figure 8: Comparison of convergence effects of three algorithms. Source: Created by the authors.

As shown in Figure 8, the adaptive ABC algorithm, ABC algorithm, and Best-so-far ABC algorithm obtained the optimal solution 15,448 after 23,000 iterations, 15,450 after 24,000 iterations, and 15,452 after 27,000 iterations, respectively. The adaptive ABC algorithm had a faster convergence speed, with the optimal solution corresponding to 1,000 and 4,000 iterations faster than the ABC algorithm and Best-so-far ABC algorithm, respectively. The adaptive ABC algorithm had better convergence performance, with two and four fewer optimal solutions than the ABC algorithm and Best-so-far ABC algorithm, respectively. The adaptive ABC algorithm was superior to the other two algorithms in terms of optimal solution and convergence performance. The solution results of the EED model based on the adaptive ABC algorithm are shown in Figure 9.

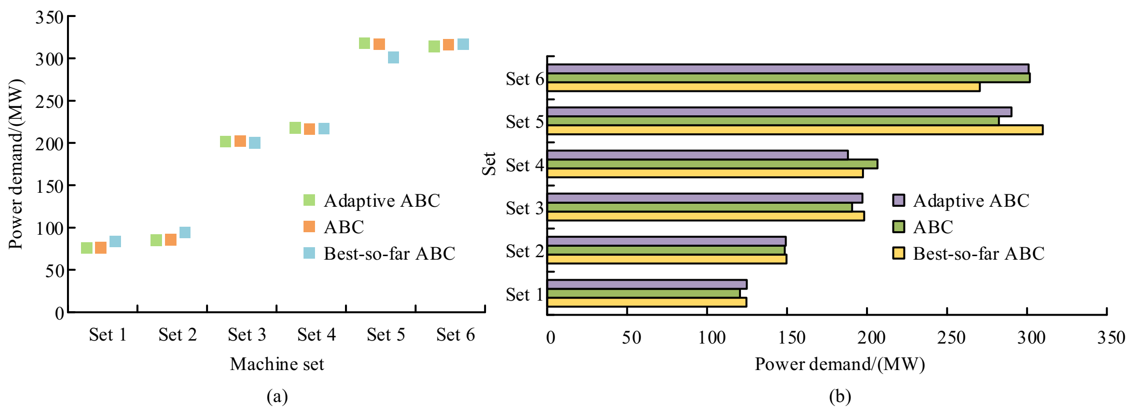


Figure 9: Comparison of optimization effects of different methods. (a) Optimization results of targeting cost as the objective, and (b) Optimization results of pollutant emissions as the objective. Source: Created by the authors.

From Figure 9(a), the maximum and the minimum values of unit power demand under the adaptive ABC algorithm were 324.7741 and 82.7018 MW, respectively. Those under ABC algorithm were 323.3140 and 83.0506 MW, respectively. Those under the Best-so-far ABC algorithm were 323.2239 and 90.3950 MW, respectively. The fuel cost of the above three algorithms were 64050.456, 64053.5869, and 64285.1297 yuan, respectively. From Figure 9(b), the maximum and minimum values of unit power demand under the adaptive ABC algorithm were 309.8755 and 124.5736 MW, respectively. Those under ABC algorithm were 301.8332 and 120.5106 MW, respectively. Those under the Best-so-far ABC algorithm were 301.0797 and 124.8142 MW, respectively. The pollutant discharge of the above three algorithms were 1240.000, 1250.000, and 1243.3853 yuan, respectively. In summary, the adaptive ABC algorithm achieved optimal solutions in model optimization targeting power costs and pollutant emissions, respectively. The comparison results of solving multi-objective environmental economic model under different models that simultaneously target power costs and pollutant emissions are shown in Figure 10.

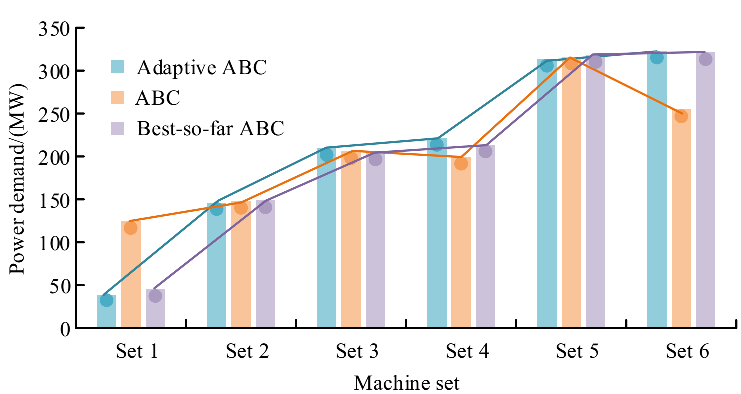


Figure 10: Comparison effect of multi-objective environmental economic model under different models aiming at power cost and pollutant emissions. Source: Created by the authors.

From Figure 10, the maximum and the minimum power demands of the unit under the adaptive ABC algorithm were 323.2475 and 38.3868 MW, respectively. Those under the ABC algorithm were 316.2580 and 125.0000 MW, respectively. Those under the Best-so-far ABC algorithm were 321.2730 and 45.3862 MW, respectively. The fuel cost of the three algorithms were 65931.9177, 65994.1247, and 64872.6673 yuan, respectively. The pollutant emissions of the three algorithms were 1246.1048, 1250.5744, and 1344.3922 yuan, respectively. The total cost of the three algorithms were 102126.0573, 113001.0383, and 109594.9634 yuan, respectively. In terms of total cost, the value of adaptive ABC algorithm was significantly lower than ABC algorithm and Best-so-far ABC algorithm, and was 10874.981 and 7468.9061 yuan lower, respectively. In terms of pollutant emissions, the value of adaptive ABC algorithm was 4.4696 and 98.2874 yuan lower than that of ABC algorithm and Best-so-far ABC algorithm, respectively. The adaptive ABC algorithm has significant differences in total cost and pollutant emissions compared to the ABC algorithm and Best-so-far ABC algorithm. In summary, the adaptive ABC algorithm has the lowest total cost and more obvious advantages in solving EED problems. The convergence effect comparison effect of multi-objective environmental economic model under different algorithms that simultaneously target power cost and pollutant emissions is shown in Figure 11.

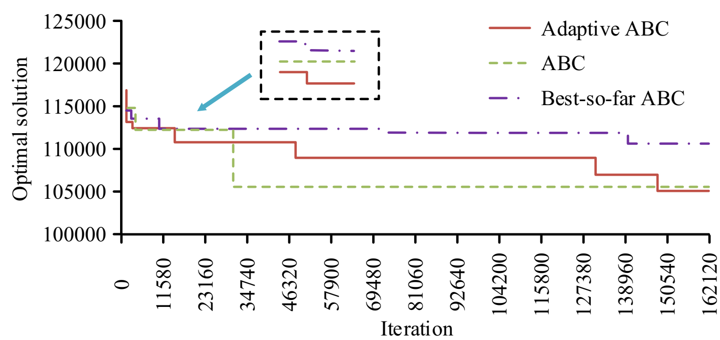


Figure 11: Comparison of convergence effects of different algorithms in multi-objective environmental economic model. Source: Created by the authors.

From Figure 11, the adaptive ABC algorithm had a maximum and a minimum optimal solution of 117,000 and 106,000, respectively. The maximum and minimum optimal solutions of ABC algorithm were 115,050 and 106,050, respectively. The Best-so-far ABC algorithm had a maximum and a minimum optimal solution of 115,000 and 113,000, respectively. In summary, the adaptive ABC algorithm has better optimal solution and convergence performance than the other two algorithms. To better demonstrate the advantages of adaptive ABC algorithm, the study would demonstrate the scalability of the algorithm from its computational time and demonstrate its robustness from its accuracy in dealing with missing data. The study continued to use data from the IEEE six-unit system dataset and processes it through random removal to generate missing data. The comparison of time consumption and accuracy of different algorithms is shown in Table 2.

Table 2: Comparison of time consumption and accuracy of different algorithms

Algorithm	Time consumption				Accuracy			
	Number of experiments (ms)				Number of experiments (%)			
	1	2	3	4	1	2	3	4
ABC	87	84	92	95	72.35	73.68	74.59	76.82
Best-so-far ABC	57	59	53	51	83.41	82.55	86.43	88.57
Adaptive ABC	34	27	21	26	90.72	93.56	94.77	96.84

From Table 2, in terms of computational time, the maximum value of adaptive ABC algorithm was 34 ms, which is significantly lower than the comparison algorithm. When facing missing data, the maximum accuracy of adaptive ABC algorithm was 96.84%, which is 24.49 and 14.29% higher than the maximum values of ABC algorithm and Best-so-far ABC algorithm, respectively. From this, it can be seen that the adaptive ABC algorithm has good scalability and robustness, with obvious advantages. The implication of the research was that the adaptive ABC algorithm can effectively solve environmental and economic scheduling problems, thereby improving the environmental and economic benefits of the power system, and alleviating environmental pollution and energy problems.

5 Conclusion

To better optimize power system, an adaptive ABC algorithm based on memory feedback mechanism was proposed to solve the EED model and adaptively adjust the population size. The lab outcomes showed that in the solution of the multi-objective environmental economic model that simultaneously targeted the cost of electricity and pollutant emissions. The pollutant emissions of the adaptive ABC, ABC, and Best-so-far ABC were 1246.1048, 1250.5744, and 1344.3922 yuan, respectively. The total cost of the adaptive ABC, ABC, and the Best-so-far ABC was 102126.0573, 113001.0383, and 109594.9634 yuan, respectively. The adaptive ABC had the lowest total cost and a more obvious advantage in solving EED problems. In the comparison of convergence effects of dynamic multi-objective environmental economic model of different algorithms, the maximum and minimum optimal solutions of adaptive ABC were 117,000 and 106,000, respectively. The maximum and minimum optimal solutions of ABC were 115,050 and 106,050, respectively. The Best-so-far ABC had a maximum and minimum optimal solutions of 115,000 and 113,000, respectively. In addition, considering VPE in the EED model could make the EED model more in line with the actual operating state of the power system and achieve more accurate solution results. For VPE, the study overlaid its consumption portion onto the electricity cost function, and then extended the cost function to the entire time interval to form the final fuel cost. In summary, in optimal solution and convergence performance, the adaptive ABC is superior to the other two algorithms. The advantage of the adaptive ABC algorithm is that it can improve the solving speed of environmental and economic scheduling problems, while also finding scheduling solutions with lower total costs, providing advanced technical support for solving EED problems, reducing pollutant emissions, and reducing total costs. In addition to the EED model, the adaptive ABC algorithm also has value and space for application in other similar multi-objective optimization problems. To better apply the adaptive ABC algorithm, it is necessary to combine practical situations similar to multi-objective optimization problems, such as the completeness of the dataset. In addition, for algorithms that require adjusting population size, the memory feedback mechanism and evolution rate used in adaptive ABC algorithm can be used to dynamically adjust parameters, but it is also necessary to determine whether to use them based on specific situations. The innovation of the research is reflected in the adaptive adjustment of the ABC algorithm, allowing the algorithm to converge to a better population size, and introducing a memory feedback mechanism and evolution rate to improve the running speed of the ABC algorithm. The research on the solution of environmental economic model is mainly based on the weight method, while other methods and ideas have not been further explored. For example, the study did not draw on the experience of non-dominated sorting genetic algorithm and multi-objective genetic algorithm in solving multi-objective problems. Future research can improve this problem and explore the potential of ABC algorithm in multi-objective optimization problems in depth. The consideration of energy structure in constructing dispatching models is relatively single and does not involve new energy. Future research can consider constructing environmental and economic models based on multiple energy structures. In addition, research has given less consideration to the volatility of new energy and the arrangement and selection of multiple energy sources. Future research can conduct in-depth research in this direction.

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