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Wind Power Prediction and Dynamic Economic Dispatch Strategy Optimization Based on BST-RGOA and NDO-WOA

Yuyang Hu*, Xiao Yang, Binbin Chen, Guangfeng Gu, Lianrong Pan
Electric Power Dispatching and Control Center Guangxi Power Grid Co., Ltd. Nanning, 530023, China
E-mail: huyy1514@163.com, 15277157589@163.com, chrithy@163.com, 18205193298@163.com, plr121@163.com
*Corresponding author

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In order to address the new challenges brought by large-scale wind power grid integration to the safe operation of the power system, a non-deterministic optimization whale swarm optimization algorithm is introduced to predict wind power. This method uses trend optimization function to optimize control coefficients and weight coefficients to ensure the algorithm randomness and avoid falling into local optima. On this basis, combined with the evolutionary strategy of bee species and the fast global search mechanism, a fast global optimization algorithm for bee species transition is proposed to achieve dynamic economic scheduling. The results showed that under clear weather conditions, the mean root mean square error of the prediction obtained by the non-deterministic optimization-whale optimization algorithm was only 2.68%, while the least squares support vector machine method was as high as 5.43%. Under cloudy conditions, the mean root mean square error of this algorithm was only 5.82%, which was 6.28% lower than the particle swarm optimization back propagation algorithm. Under rainy conditions, the mean root mean square error of the algorithm was only 6.75%. In addition, the average running time of the rapid global optimization algorithm for bee species transition on dynamic economic scheduling problems was only 28.9 seconds. The runtime of the artificial bee colony algorithm was as long as 198.6. Overall, the wind power prediction algorithm and dynamic economic dispatch algorithm have achieved significant advantages in prediction accuracy and solution effectiveness. This is conducive to achieving efficient optimization and scheduling of the power system, improving the stability and economy of the power system.

Povzetek: Razvita je nova metoda napovedovanja vetrne energije in dinamičnega ekonomskega razporejanja z uporabo naprednih optimizacijskih algoritmov, s čimer se povečuje stabilnost elektroenergetskega sistema.

1 Introduction

Wind energy is one of the most extensively used new energy sources, which is influenced by factors such as terrain, time, and climate, and has strong peak resistance characteristics [1-2]. Meanwhile, wind power has strong randomness, volatility, and uncertainty. Therefore, accurate power prediction and optimized scheduling are of great significance [3]. Among them, wind power prediction exerts a crucial function in subsequent power dispatch, as it can estimate the amount of wind power generation in a certain period of time in the future. Operators can arrange power generation plans reasonably based on the prediction results. At present, wind power prediction methods contain single algorithm and hybrid algorithm prediction models. However, single algorithms often have problems such as insufficient prediction accuracy, while hybrid algorithms can help improve the convergence speed and accuracy of prediction algorithms [4]. In addition, Dynamic Economic Dispatch (DED) is crucial in the operation and management of the power system. Considering the significant changes in the dynamic characteristics and load demand, DED is generally solved by dispersing the entire scheduling. DED mainly aims to minimize power generation costs and break physical and operational limitations. In traditional electricity economic dispatch, the cost function is essentially a quadratic function. Mathematically speaking, the DED is a non-convex, non-linear, and large-scale optimization problem with various complex constraints. Related scholars have adopted the Artificial Bee Colony (ABC) algorithm, but this method is prone to getting stuck in local optima. Therefore, it is necessary to introduce more advanced algorithms to solve the DED problem, in order to achieve more efficient power system scheduling and management [5].

Wind power prediction is meaningful in improving the wind power resource utilization and ensuring its safe and stable operation. Zhang et al. believed that different time series inputs had a significant impact on short-term wind power prediction. Therefore, a multi-source time attention network was proposed to predict its probability. The model weighted other similar products in both deterministic and probabilistic predictions [6]. Hossain et al. designed a prediction framework for 5-minute wind power generation, which combined Emperor Butterfly optimization, adaptive noise based complete ensemble empirical mode decomposition, and Long Short-Term Memory (LSTM). The prediction accuracy was effectively improved [7]. Abedinia et al. introduced a new empirical mode decomposition for intelligent wind power generation prediction to achieve wind measurement value decomposition. Meanwhile, the decomposed signal was input into the bagging neural network prediction model based on K-means clustering. The method achieved lower prediction error values [8]. Sun et al. found that traditional wind power prediction had significant prediction errors. Therefore, a new ultra short-term probability prediction method was built. This method combined principal component analysis, wavelet decomposition, and LSTM. Then, the prediction model achieved excellent prediction accuracy in the data prediction [9]. Wu et al. found that large-scale wind power grid integration had impacts on the stability of the power system. Accordingly, a ultra short term prediction strategy on the basis of convolutional neural network and LSTM was proposed. Compared with traditional prediction models, this strategy had better spatiotemporal feature extraction ability [10].

As one of the notable means to promote the upgrading and transformation of energy systems, DED has attracted widespread attention. Chen et al. proposed a coordinated robust DED model to address the uncertainty of renewable energy. Meanwhile, a distributed framework was designed to solve the DED model and risk model in a decentralized manner. The designed approach achieved significant achievements in the calculation of the 448 node T118D10 system [11]. In response to the scheduling difficulties caused by the integration of large-scale renewable energy, Song and Shi designed a DED model that considered several wind farms and various scheduling time scales. Simultaneously, an improved adaptive Cuckoo Search (CS) was

Table 1: Summary table of related work

Author	Publication year	Method	Key indicators
Zhang et al [6]	2021	Multi-source time attention network	The minimum root mean square error for prediction is 6.58%
Hossain et al [7]	2023	Complete Set Empirical Mode Decomposition and Long Short-Term Memory	The highest prediction accuracy is 92.69%
Abedinia et al [8]	2020	Improved Empirical Mode Decomposition and Bagging Neural Network Based on K-means Clustering	The highest prediction accuracy is 91.62%
Sun et al [9]	2020	Principal Component Analysis, Wavelet Decomposition Combined with Long Short-Term Memory Networks	The minimum root mean square error for prediction is 5.81%
Wu et al [10]	2021	Convolutional Neural Network - Long Short-Term Memory Ultra Short-Term Wind Power Prediction Model	The minimum predicted average absolute percentage error is 6.87%
Chen et al [11]	2021	Coordinated Robust DED Model and Distributed Framework	In the T118D10 system with 448 nodes, the operating cost has been reduced by 10%
Song and Shi [12]	2022	DED model considering multiple wind farms and different scheduling	Improved prediction accuracy to 95%

		time scales	
Bai et al [13]	2021	Multi-objective differential evolution algorithm for joint dynamic scheduling and improvement of wind power and thermal power	Economic benefits have increased by over 15%
Wang et al [15]	2020	State Economy Scheduling Framework Based on Cloud and edge computing	The backup usage of the generator set has decreased by 18.62%

used to solve this problem. From the results, the proposed model achieved significant results [12]. Bai et al. conducted joint dynamic scheduling and thermal power to minimize economic costs and pollution emissions. Simultaneously, an improved multi-objective differential evolution strategy was applied to solve the joint dynamic scheduling model. The results indicated that the algorithm could effectively handle practical problems involving wind power [13]. Wang et al. designed a new DED scheme to address the variability and uncertainty in power systems. This plan balanced operating costs and reliability costs. The results indicated that the proposed scheme effectively reduced the reserve capacity of generator units and improved the safety and economy of power system operation [14]. Wang et al. designed an economic dispatching framework based on cloud and edge computing for micro-grid DED problems. This framework was mainly executed on remote cloud computing platforms and local digital signal processors. Compared with traditional methods, this method improved the economy and reliability of power dispatch [15]. The relevant work summary table is shown in Table 1.

In summary, domestic and foreign researchers have conducted extensive research on wind power prediction and DED in power systems, focusing on optimizing prediction algorithms and scheduling strategies to address the volatility and uncertainty of wind energy. Although these algorithms have improved accuracy, many methods suffer from local optima problems, are computationally complex, and lack interpretability. To this end, a series of intelligent algorithms have been introduced to improve wind power generation prediction and DED problem solutions. Among them, a Non-Deterministic Optimization-Whale Optimization Algorithm (NDO-WOA) is introduced for wind power prediction research. Meanwhile, the Bee Species Transition-Rapid Global Optimization Algorithm (BST-RGOA) is introduced to solve the DED problem. The research fills several key gaps between traditional wind power prediction and DED, including being trapped in local extremum trends, long computation times, and slow responses. The innovation of the research lies that the trend optimization function and weight coefficient are used to optimize the Whale Optimization Algorithm (WOA), which is prone to getting stuck in local extremes. Meanwhile, optimizing the original ABC algorithm using the bee species transition strategy function is beneficial for effectively solving the DED problem, thereby improving the stability and economy of the power system.

2 Methods and materials

With the rapid reduction of fossil fuels, reasonably utilizing wind energy is an important topic at present. In response to wind power prediction, the study introduces the NDO-WOA. The WOA is optimized by trend optimization functions and weight coefficients. On this basis, the BST-RGOA is introduced to solve the DED problem, in order to achieve effective power scheduling.

2.1 Wind power prediction based on NDO-WOA

Wind power generation can bring significant environmental benefits and has enormous development prospects in the new energy industry [16]. However, Wind Speed (WS) is often influenced by factors such as environment, weather, and terrain, resulting in strong randomness and volatility in wind power output. Therefore, predicting wind power is crucial [17-18]. The wind power output is primarily determined by the actual

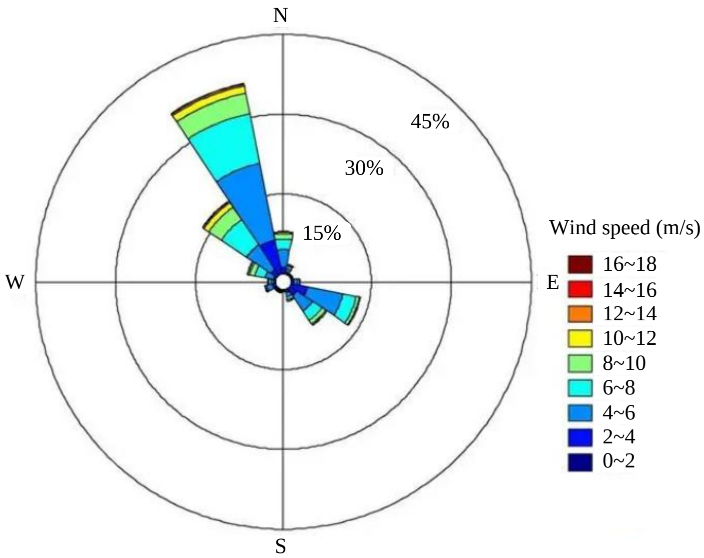


Figure 1: Schematic diagram of wind speed frequency rose diagram

WS and the generation parameters of the unit equipment. Accurately describing the WS variation pattern is crucial. Its distribution characteristics and direction in a certain area can usually be represented by a WS frequency rose chart, as shown in Figure 1.

In Figure 1, the maximum WS in this area reaches over 16m/s, and the range is roughly in the northwest. Although WS has strong volatility and randomness, historical research has found that WS fluctuations have a certain regularity. Probability distribution is applied to depict WS changes. The Weibull distribution is currently one of the most frequently used probability distribution models. This model can accurately fit the WS distribution, with a simple construction. Three basic parameters, namely shape parameters, scale parameters, and position parameters, need to be determined to simulate the actual changes in WS in a certain area. The model expression for Weibull distribution is displayed in equation (1).

$$f(v) = c^{-k} k v^{k-1} e^{-(\frac{v}{c})^k} \tag{1}$$

In equation (1), c represents the scale parameter of the Weibull distribution, and k signifies its shape parameter. v represents the WS. The size of parameter k is solved by the mean and standard deviation of the WS sequence, as shown in equation (2).

$$\frac{\sigma_v}{v_m} = \frac{\Gamma(1+2/k)}{\Gamma^2(1+1/k)} - 1 \tag{2}$$

In equation (2), v_m represents the WS sequence mean, and σ_v represents the standard deviation of the WS sequence. The scale parameter is shown in equation (3).

$$c = \frac{v_m}{\Gamma(1+1/k)} \tag{3}$$

In equation (3), Γ is the gamma function. The output power of wind turbines will vary with the fluctuation of WS. After describing the WS using the probability distribution of WS, the wind power output is calculated. The specific expression is shown in equation (4).

$$P = \frac{1}{2} C_P A \rho v^3 \tag{4}$$

In equation (4), P signifies the output power of the wind turbine at a certain moment. C_P signifies the utilization coefficient. C_P signifies the area swept by the fan blades of the generator set. ρ represents air density. A is shown in equation (5).

$$A = \pi R^2 \tag{5}$$

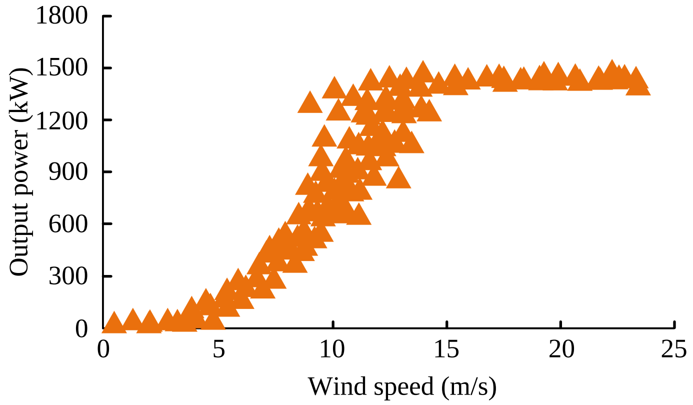


Figure 2: Actual power output of electric field units

In equation (5), R represents the blade radius of the unit. Taking a wind farm unit as an example, due to various uncertain factors such as the environment, the actual power output of the wind farm units is shown in Figure 2.

$$f(t)=\begin{cases} 2\cos(\frac{2\pi}{3}\cdot\frac{t}{T\max}), & 0<t\le\frac{T\max}{2} \\ 4(\frac{t-T\max}{T\max})^2, & \frac{T\max}{2}<t\le T\max \end{cases} \quad (7)$$

In equation (7), when $0<t\le\frac{T\max}{2}$ is reached, the control coefficient gradually decreases, improving the efficiency and sufficiency of individual search without objectives. When $\frac{T\max}{2}<t\le T\max$ is satisfied, the decay rate of the control coefficient also decreases with time, allowing the whale population to explore and discriminate near the approximate optimal solution in local search, thereby improving the accuracy of local search.

Introducing trend optimization functions can ensure that the algorithm maintains a dynamic balance between global and local searches at any time. In addition, the WOA lacks mutation ability when reaching the threshold limit, resulting in low local search accuracy. To this end, weight coefficients are introduced in the study to ensure the randomness of the algorithm, which is beneficial for escaping local optima and avoiding falling into local optima. The wind power prediction process on the basis of NDO-WOA is displayed in Figure 3. In Figure 3, firstly, the WOA running parameters are initialized, including the number of whale individuals, iteration times, and search space. Then, an initial solution is randomly generated in the search space, which is the position of individual whales. Each individual represents a potential solution. Subsequently, the trend optimization function is used to dynamically adjust the control coefficients and adjust the sensitivity of the prediction model.

The weight coefficients are updated based on the optimization results to balance multiple influencing factors of the model. Next, the updated parameters and weights are used to construct a wind power prediction model. The minimum prediction error is saved again to evaluate the performance of the model. A single coordinate is updated and a new

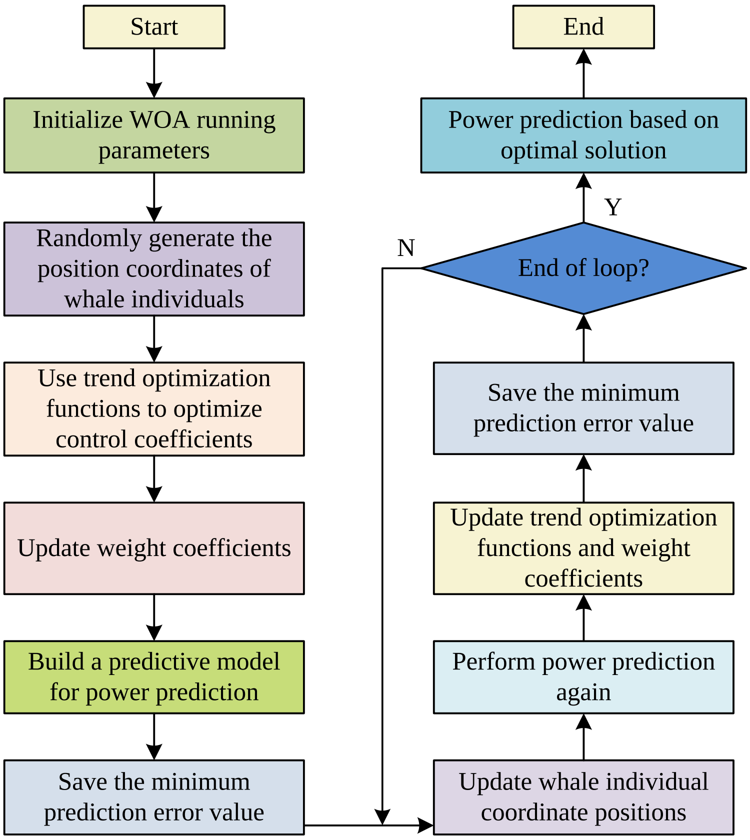


Figure 3: Wind and solar power prediction process based on NDO-WOA

prediction loop is executed to further optimize parameters and compare errors until the termination condition is met. Finally, based on the obtained optimal solution, wind power prediction is carried out to ensure that the model has good adaptability and predictive ability in dynamic environments.

In order to analyze the relationship between the convergence time and population size of the WOA, the study sets the population size to N_1. The dimension size is W, and the number of iterations is E. The time complexity of both WOA and NDOWOA is $O(E \cdot N_1 \cdot W)$. As the population size N_1 increases, the time complexity also increases, which affects the execution efficiency of the algorithm.

In the WOA, each individual performs 1 addition, 3 subtractions, and 4 multiplications per iteration. In the NDO-WOA, each individual undergoes 1 addition, 4 subtractions, 5 multiplications, and 1 division. Compared with the WOA, the NDO-WOA can locate the optimal solution faster, thereby shortening the convergence time.

2.2 Dynamic economic scheduling based on BST-RGOA

The study achieves wind power prediction through NDO-WOA. Then, it is applied to DED. The power demand of DED varies over time, and its objective function is the total production cost of several generator units at a certain interval, which is a quadratic function from the active power output of the generator units [19-20]. The expression for total production cost is shown in equation (8).

$$F_{it}(P_{it}) = a_i P_{it}^2 + b_i P_{it} + c_i + \left| e_i \sin(f_i(P_{it}^{\min} - P_{it})) \right| \quad (8)$$

In equation (8), P_{it} signifies the actual output power of the i -th engine at time t . a_i , b_i and c_i represent cost coefficients. e_i and f_i are consumption coefficients. $P_{it}^{\min}$ signifies the minimum output power of the i -th generator set. In the DED model, unconstrained scheduling can result in generator units operating within unsafe ranges, leading to equipment failures or power outages.

Therefore, it is necessary to set reasonable constraints to maintain the stability and security of the system. The research mainly considers load and loss, output power of generator units, and the rise and fall speed of each unit. In practical applications, the setting of constraints is not just a theoretical consideration, but based on a large amount of empirical data and standards. The research mainly analyzes the performance of generator sets under different loads and environmental conditions to identify their safe operating range. In addition, by analyzing historical data and combining industry standards with engineers' practical experience, corresponding constraints have been set. The expression for the load and loss constraints of the system is shown in equation (9).

$$\sum_{i=1}^{N_G} P_{it} = P_D + P_L \quad (9)$$

In equation (9), P_D signifies the total system load. P_L signifies the loss. N_G signifies the total online generator units to be scheduled. The output power of each generator set has an upper and lower limit, as shown in equation (10).

$$P_{it}^{\min} \le P_{it} \le P_{it}^{\max} \quad (10)$$

In equation (10), $P_{it}^{\max}$ signifies the maximum output power of the i -th generator set. If the power generation increases, the constraint conditions for the rising and falling speeds of each unit are shown in equation (11).

$$P_{it} - P_{it}^{t-1} \le UR_i \quad (11)$$

In equation (11), UR_i signifies the upper slope. P_{it}^{t-1} represents the power generation of generator set i in the previous hour. If the power generation decreases, the constraint condition is shown in equation (12).

$$P_{it} - P_{it}^{t-1} \le DR_i \quad (12)$$

In equation (12), DR_i represents the lower slope. The voltage constraint is shown in equation (13).

$$U_{\min} \le U_i \le U_{\max} \quad (13)$$

In equation (13), $U_{\min}$ and $U_{\max}$ represent extreme voltage values.

The ABC is introduced to solve the DED in the power system. In the ABC algorithm, different roles of the bee colony are responsible for different tasks. Following bees mainly conduct local searches, while reconnaissance bees and lead bees are responsible for exploring the entire solution space. In the traditional ABC algorithm, the number of leading bees and following bees accounts for 50% of the total bees, which limits the global search ability and results in low efficiency. In the stage of searching for food sources, the ABC algorithm uses specific formulas to determine whether to extract food sources. When the threshold limit is reached, the algorithm lacks mutation ability and is prone to falling into local optima. In addition, during the stage of following bees to search for food sources, the ABC algorithm determines whether to develop food sources through roulette wheel, which leads to low local search accuracy of the algorithm. In response to these problems, the BST-RGOA is proposed by combining bee species transition and fast global search mechanism. In the bee species transition strategy, the bee species transition strategy function is mainly introduced in the early stage of the ABC. This function is an optimization method based on natural selection and group cooperation

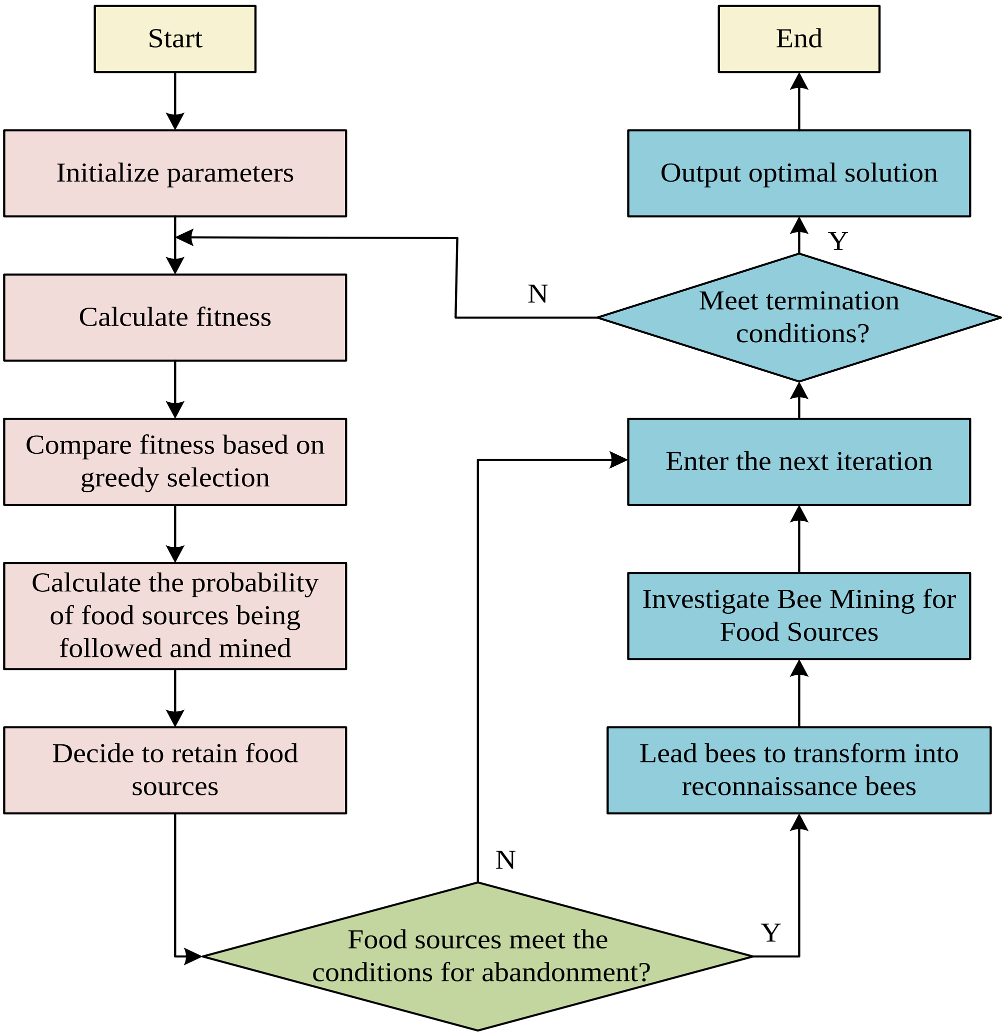


Figure 4: Dynamic economic scheduling flowchart based on BST-RGOA

mechanisms, inspired by the foraging behavior and species evolution of bees. The design objective is to improve the global search capability and local search accuracy of the ABC, in order to achieve better solutions in complex optimization problems. Leading bees optimize based on this function, thereby improving its global search ability. The calculation of this function is shown in equation (14).

$$q(s) = \sqrt{1-\lambda \cdot (\frac{s}{S})^2} \quad (14)$$

In equation (14), S is the maximum number of iterations. s represents the current iteration count. λ represents a random number in [0,1]. The number of leading bees is represented by equation (15).

$$Y = q(s) \cdot M \quad (15)$$

In equation (15), M represents the total bee colonies. Y signifies the total leading bees. As the iteration progresses, the strategy function gradually decreases, resulting in a decrease in the number of leading bees and an increase in the proportion of following bees, thereby enhancing the local exploration ability. The descent rate of the evolutionary strategy function accelerates in later the stage. The update of food sources tends to be stable and gradually approaches the optimal solution. The number of leading bees is relatively reduced, and the proportion of following bees is increased. On this basis, the study further introduces a fast global search mechanism. In the ABC algorithm, reconnaissance bees are mainly responsible for finding better food sources. In order to improve local exploration

Table 2: Summary table of experimental parameters

Parameter Name	PSO-BP	WOA	NDO-WOA	LS-SVM
Learning rate	0.01	/	/	0.1
Maximum number of iterations	100	50	100	200
Number of particles	30	/	/	/
Convergence criteria/	Mean Squared Error (MSE) < 0.01	MSE < 0.05	MSE < 0.01	MSE < 0.05

Table 3: RMSE values for different control coefficients and weight coefficients

Number	Control coefficient	Weight coefficient	RMSE (%)
1	0.1	1	12.62
2	0.5	1	9.35
3	1.5	1	6.28
4	2.0	1	7.69
5	0.1	2	14.68
6	0.5	2	9.54
7	1.5	2	4.67
8	2.0	2	7.54

ability, when the upper threshold is reached, the BST-RGOA introduces better food sources from the previous iteration through a fast global search mechanism, thereby optimizing the food source search mechanism in the next iteration. The dynamic economic scheduling flowchart based on the BST-RGOA is shown in Figure 4.

3 Results

The study first validates the prediction ability of the wind power prediction model based on the NDO-WOA under different time scales and meteorological conditions. Subsequently, the dynamic economic scheduling effect based on BST-RGOA is verified under different population sizes, including convergence effect and running time.

3.1 Analysis of wind power prediction results based on NDO-WOA

To present the prediction ability of the NDO-WOA under different time scales and meteorological conditions, the wind power output data of a wind farm in a certain region at different time points are used for power prediction analysis. The test dataset for the 4-hour prediction scale is the data from 20:00 to 23:45 on January 8, 2022. The test dataset for 24-hour prediction scale is from 8:00 on January 9th to 7:45 on January 10th. Meanwhile, the comparative algorithms selected for the study include WOA, Least Squares Support Vector Machine (LS-SVM), and Particle Swarm Optimization Back Propagation (PSO-BP) algorithm. The summary table of experimental parameters is shown in Table 2. The parameters in the table can be used for repeated experiments in other studies.

In order to conduct parameter sensitivity analysis of control coefficients and weight coefficients in the NDO-WOA, corresponding experiments are designed to compare the performance of the algorithm under different parameter settings on the Rosenbrock function. This function is often used as a benchmark test for optimizing algorithms, which can be used to evaluate algorithm performance. The study uses RMSE as a performance evaluation

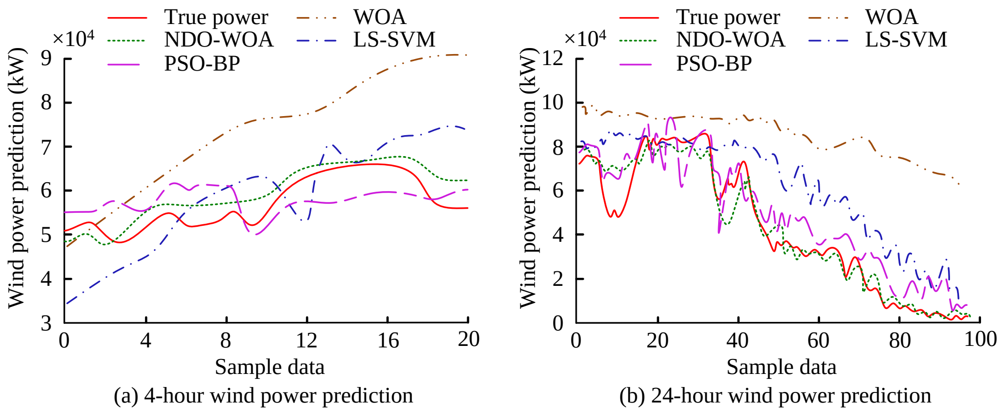


Figure 5: Wind power prediction results at different time scales

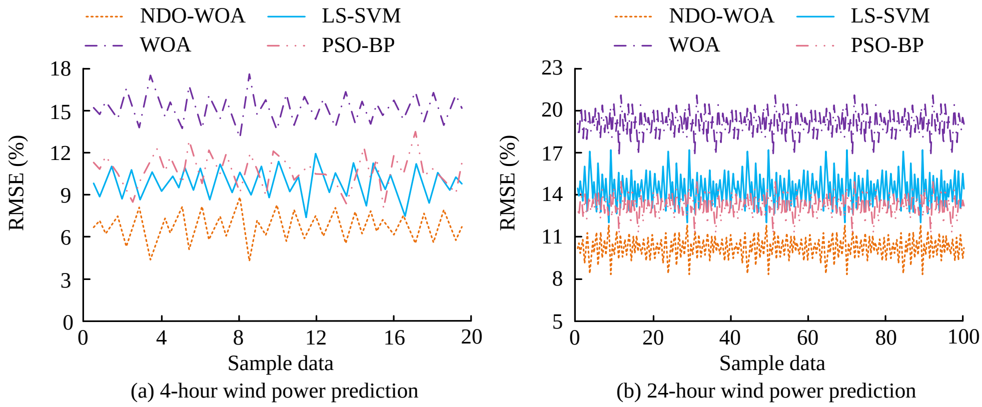


Figure 6: RMSE values for power prediction of various models at different time scales

metric. The RMSE values for different control coefficients and weight coefficients are shown in Table 3. According to Table 3, when the control coefficient is 1.5 and the weight coefficient is 2, the NDO-WOA has the best performance and can be applied to subsequent wind power prediction analysis.

The prediction results at different time scales are displayed in Figure 5. Figure 5 (a) displays the results at a 4-hour prediction scale. The results NDO-WOA were similar to the actual power values, with the best fitting effects. The results of the WOA were the worst. Figure 5 (b) illustrates the results at the 24-hour prediction scale. The prediction results of the NDO-WOA were still similar to the actual power. The wind power prediction model based on NDO-WOA has excellent predictive performance at different time scales.

This study continues to analyze the prediction accuracy of various algorithms at various time scales, with Root Mean Square Error (RMSE) as an evaluation indicator. The power prediction RMSE of each model is displayed in Figure 6. As shown in Figure 6 (a), at the 4-hour prediction scale, the average predicted RMSE of the NDO-WOA was only 7.36%. Compared with WOA and LS-SVM, NDO-WOA reduced by 8.49% and 2.94%, respectively. The average RMSE value of PSO-BP algorithm was as high as 11.02%, which was 3.66% higher than that of NDO-WOA. In Figure 6 (b), at the 24-hour prediction scale, the average predicted RMSE of the NDO-WOA was only 10.01%. The average RMSE predicted by WOA was as high as 19.34%, LS-SVM algorithm was as high as 14.61%, and PSO-BP algorithm was as high as

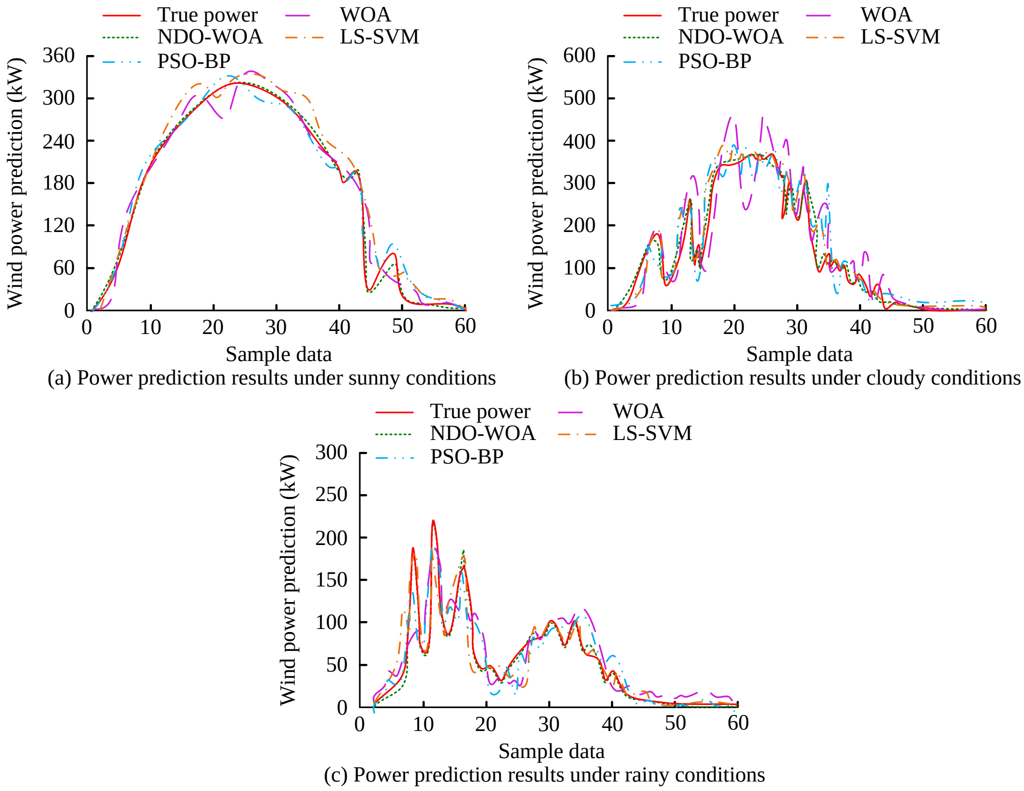


Figure 7: Power prediction results of various algorithms under different meteorological conditions

13.68%. The designed NDO-WOA has high prediction accuracy.

Then, the study verifies the prediction ability of various algorithms under different meteorological conditions, selecting three typical weather data of sunny, cloudy, and rainy days for power prediction analysis. The sample data for sunny days is from 7:00 to 17:50 on January 8, 2022. The sample data for cloudy days is from 8:00 to 18:50 on January 11. The sample data for rainy days is from 9:00 to 19:50 on January 6, 2022. The power prediction results of each algorithm under different meteorological conditions are shown in Figure 7. From Figure 7 (a), under sunny conditions, there was not much difference between each algorithm and the actual power, but the wind power prediction curve based on the NDO-WOA had the best fitting effect with the actual power curve. According to Figure 7 (b), under cloudy conditions, the results from the NDO-WOA were closest to the actual power, while the WOA had the largest deviation from the actual power. In Figure 7 (c), under rainy conditions, the wind power prediction results of NDO-WOA were still better than other algorithms, with a maximum deviation of only 35kW from the actual power. The NDO-WOA wind power prediction has more significant effects.

The study continues to validate the predicted RMSE values of various algorithms under different meteorological conditions, as shown in Figure 8. In Figure 8 (a), under sunny conditions, the average predicted RMSE of the NDO-WOA was only 2.68%. The average RMSE of LS-SVM was 5.43%, significantly higher than that of NDO-WOA. The RMSE value of PSO-BP algorithm was 6.49%, significantly higher than that of NDO-WOA. In Figure 8 (b), under cloudy conditions, the average predicted RMSE of the

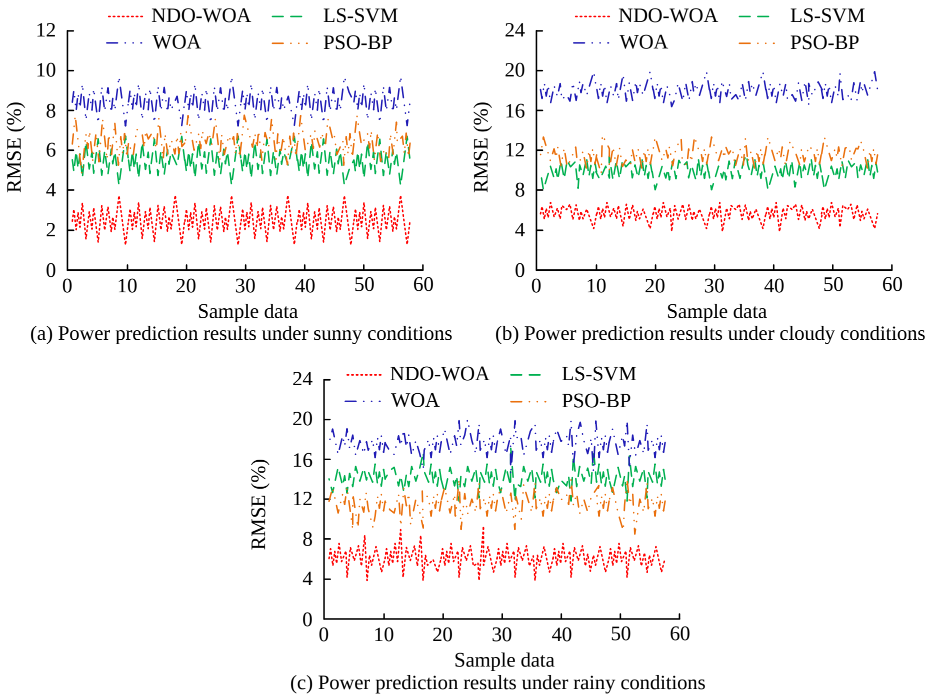


Figure 8: Predicted RMSE and MAE values under different meteorological conditions

Table 4: MAPE values of various algorithms

Wind direction	MAPE(%)			
	PSO-BP	LS-SVM	WOA	NDO-WOA
0°	5.21	6.35	7.14	4.86
45°	5.89	6.03	7.51	4.68
90°	4.95	6.54	7.24	4.37
135°	5.51	6.28	7.07	4.71

NDO-WOA was only 5.82%, which was a decrease of 12.04% compared with the WOA. Compared with the PSO-BP algorithm, it reduced by 6.28%. As shown in Figure 8 (c), under rainy conditions, the average predicted RMSE of NDO-WOA was only 6.75%, significantly lower than other algorithms. This once again confirms the effectiveness of wind power prediction based on NDO-WOA.

Further research is conducted to verify the accuracy of wind power prediction for various algorithms in geographical locations with different wind directions. A total of 1563 pieces of wind speed and power data are collected under different wind directions and divided into training and testing sets. Each algorithm is trained and predicts on the test set. Meanwhile, the study uses Mean Absolute Percentage Error (MAPE) as the evaluation metric, and the MAPE values of each algorithm are shown in Table 4. According to Table 4, the MAPE value of NDO-WOA was significantly lower than other algorithms in different wind directions, with only 4.37% in the case of a wind direction of 90°. The MAPE values of PSO-BP, LS-SVM, and WOA reached 4.95%, 6.54%, and 7.24%, respectively when the wind direction was 90°. The NDO-WOA achieves significant advantages in predicting wind power in different wind directions, which is suitable for different wind farms with different meteorological conditions.

Table 5: Simulation environment

Project	Parameter settings
Processor	Inter(R)Core (TM)i5-4590S3.00G Hz
Operating system	Windows 7 Ultimate 64-bit
Memory	8GB
Programming software	MATLABR2014a

Table 6: Parameter settings for wind turbines

Coefficient	Unit 1	Unit 2	Unit 3	Unit 4	Unit 5
a_i	0.0080	0.0012	0.0030	0.0015	0.0012
b_i	3.0	2.0	1.8	1.8	2.1
c_i	25	120	60	40	100
e_i	100	180	140	200	160
$P^{\min}$	10	40	20	50	30
$P^{\max}$	75	250	125	300	175
UR_i	30	50	30	50	40
DR_i	30	50	30	50	40

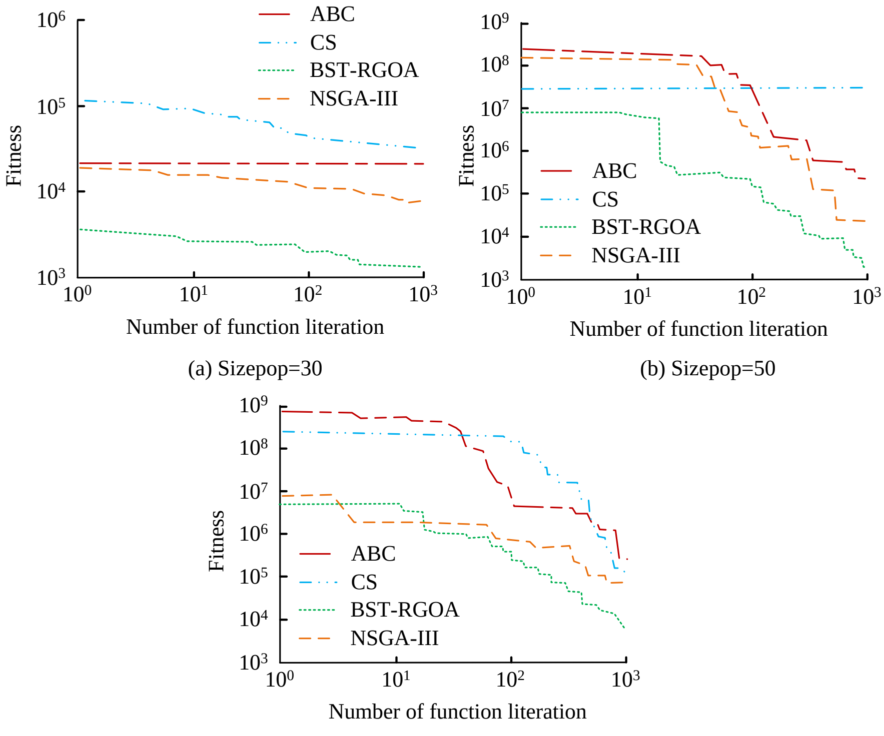
3.2 Analysis of dynamic economic scheduling results based on BST-RGOA

To verify the dynamic economic scheduling effect based on the BST-RGOA, the study selects ABC, Non-dominated Sorting Genetic Algorithm-III (NSGA-III), and CS for comparison. The study uniformly runs each algorithm independently 50 times under the condition of 50 dimensions and 1000 iterations, while conducting simulation analysis under population sizes of 30, 50, and 100. Table 5 displays the simulation environment.

In the simulation study, the parameter environment of five wind turbines in the wind farm are shown in Table 6.

The convergence curves of each algorithm under different population sizes are displayed in Figure 9. The horizontal axis signifies the iteration, and the vertical axis stands for the fitness value. From Figure 9 (a), when the population size was 30, the initial position of the convergence curve of BST-RGOA was smaller than that of ABC, with higher search performance. It can find the optimal solution within a limited number of iterations, which can achieve lower power generation costs when solving the DED problem. As shown in Figure 9 (b), when the population size was 50, as the iteration increased, the convergence curve of the BST-RGOA gradually showed more twists and turns, indicating that the algorithm repeatedly jumped out of local optima. As shown in Figure 9 (c), when the population size was 100, the convergence curve slope of the BST-RGOA was significantly higher than that of other algorithms. BST-RGOA can effectively select the number of units in the DED problem, which in turn helps to reduce cost.

The study analyzes the convergence speed of various algorithms in the DED problem, with economic cost as the optimization objective. The convergence speed comparison results of various algorithms in the DED problem are shown in Figure 10. BST-RGOA already found the lowest economic cost after 36 iterations. The ABC only converges after 45 iterations, which was 9 times higher than the BST-RGOA. Meanwhile, the NSGA-III algorithm tended to converge with up to 46 iterations. The CS algorithm converged after



(a) Sizepop=30 (b) Sizepop=50

(c) Sizepop=100

Figure 9: Convergence curves of various algorithms under different population sizes

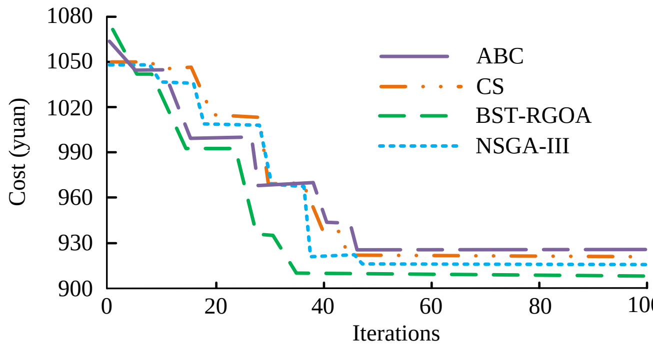


Figure 10: Comparison of convergence rates of various algorithms in DED problems

45 iterations, and its minimum cost was as high as 924 yuan, which was significantly higher than the BST-RGOA. Specifically, the main operations in each iteration of the BST-RGOA include evaluating fitness, updating solutions, and performing mutations. If the problem size is set to N_2, the time complexity of each iteration is $O(N_2 \cdot H)$, where H represents the number of operations. The overall time complexity is $O(B \cdot N_2 \cdot M)$, where B is the number of iterations. Due to its fast convergence speed and smaller B value, BST-RGOA has lower overall time complexity compared with other algorithms. The spatial complexity of the BST-RGOA is mainly composed of the space required to store the current solution and temporary variables. As the iteration progresses, multiple solutions will be stored. Its spatial complexity is represented as $O(N_2 + K)$, where K is the number of stored solutions, which is relatively small.

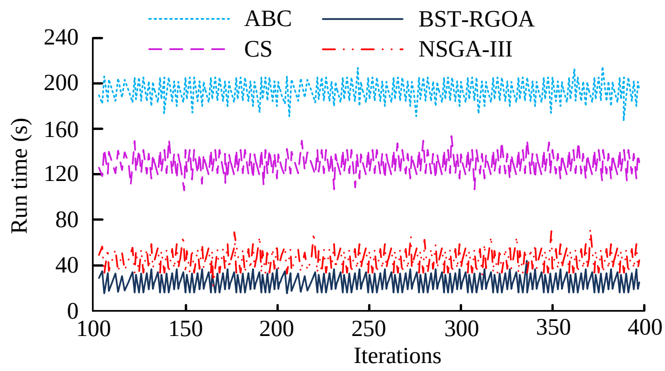


Figure 11: The running time of each algorithm under different iterations

Therefore, the spatial complexity of this algorithm is low. The BST-RGOA has a faster convergence speed and achieves better convergence results.

This study further explores the running time of various algorithms in solving the DED problem. The running time of each algorithm in different iterations is shown in Figure 11. From Figure 11, the average running time of the BST-RGOA on the DED problem was only 28.9s. The ABC was as high as 198.6s. Meanwhile, the running time of the NSGA-III was 53.6, which was 24.7s longer than the BST-RGOA. The running time of the CS algorithm was as long as 135.8s, which was significantly inferior to the BST-RGOA. This indicates that the designed BST-RGOA has high search efficiency in DED problems.

4 Discussion and conclusion

The large-scale integration of wind power into the grid poses new difficulties to the safe operation of the power system. Therefore, the study introduced the NDO-WOA and BST-RGOA to achieve wind power prediction and solve the DED. The results indicated that in wind power prediction experiments, at the 4-hour and 24-hour prediction scales, the wind power prediction results of the NDO-WOA were similar to the actual power values, and the fitting effect was the best. Meanwhile, under different meteorological conditions, the wind power prediction results of the NDO-WOA were also closest to the actual power. The WOA had the greatest deviation from the actual power. Zhang H used a multi-source time attention network for wind power prediction. The algorithm achieved an average RMSE of 6.58% in good weather conditions and exceeded 10% in severe weather conditions [6]. The NDO-WOA predicted an average RMSE of only 2.68% under clear weather conditions. The predicted mean RMSE under rainy conditions was only 6.75%. NDO-WOA can accurately capture the instantaneous changes in wind power generation, while multi-source time attention networks perform poorly in dealing with uncertainty and extreme weather conditions. In the simulation analysis of the BST-RGOA, when the population size was 30, the initial position of the convergence curve of BST-RGOA was smaller than that of ABC, and it had higher search ability. When the population size was 50, as the iteration increased, the convergence curve of the BST-RGOA gradually showed more twists and turns. It could jump out of local optima multiple times. When the population size was 100, the convergence curve slope of the BST-RGOA was significantly higher than that of other algorithms, which could effectively reduce costs in solving DED problems. In addition, the BST-RGOA achieved the lowest economic cost of only 913 yuan after only 36 iterations. The ABC algorithm only converged after 45 iterations, which was 9 times higher than the BST-RGOA. The CS algorithm converged after 45 iterations, and its minimum cost was as high as 924 yuan. Bai et al. adopted an improved multi-objective differential evolution algorithm, which utilized the advantages of feasible solutions and non-dominated sorting selection strategies to improve optimization performance. The results indicate that the algorithm can provide the best reasonable compromise solution that balances both environmental and economic aspects [13]. The BST-RGOA mainly focuses on improving economy, without considering environmental factors, and needs further improvement. Overall, The NDO-WOA and BST-RGOA can achieve efficient optimization scheduling of power systems. However, when conducting power optimization scheduling, the research only considers minimizing economic costs. Further consideration can be given to minimize pollution emissions and voltage deviations.

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