Design of Power Economic Dispatch Method Integrating Differential Evolution and PSO

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Abstract: - As energy demand continues to grow and environmental problems become increasingly serious, optimizing the economic dispatch of the power system is crucial to ensuring the sustainability and economic benefits of energy supply. To ensure the safe operation of the power system, reduce power generation costs as much as possible, and develop a method that can adapt to the needs of different power systems, the experiment combines the differential evolution algorithm with the power economic dispatch problem and proposes a method based on improved differential evolution. Electric power economic dispatch method with particle swarm optimization algorithm. The experiment first introduces a moderate interference strategy to appropriately adjust the position of the particles; then combines the local mutation strategy to enhance the searchability of the differential evolution algorithm in the solution space and achieve good economic dispatch. The results show that when running on the F11 test set and F21 test set, when the system iterates to the 26th and 32nd times respectively, the loss function of the method constructed in the experiment begins to have a minimum value and remains stable thereafter. In addition, on the F11 test set, when the number of iterations is 150, this method has a minimum time of 0.153s. While running the loop for the first time on System 1, the total cost of this approach was only $\$1.01\times 10^{4}$. Through the actual operation of power generation equipment, under the operation of this method, the power system can ensure optimal operating power of each power generation equipment unit based on ensuring optimal cost. It can be seen from the above results that this method provides power system operators and decision-makers with a new tool to help them maximize cost-effectiveness while ensuring system stability and meeting power demand. In addition, the method's superior convergence and stability can effectively improve the solution's accuracy and speed and has strong practicality and promotion value.

Key-Words: - Differential evolution, PSO, Electric power, Economic dispatch, Constraint processing, Mutation strategy, Moderate interference.

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1 Introduction

In the operation of power systems, Economic Dispatch (ED) is a key optimization problem, whose goal is to minimize Power Generation Costs (PGCs) while satisfying load demands and system operation constraints. The complexity of this problem is increasing with the opening of the electricity market and the integration of renewable energy, [1], [2]. Traditional ED methods, such as linear programming, dynamic programming, etc., can no longer fully adapt to the requirements for optimization speed and quality under the new situation. Therefore, researchers have turned to heuristic algorithms to find more effective solutions. Differential Evolution (DE) algorithm and Particle Swarm Optimization (PSO) algorithm are two heuristic algorithms that are widely researched and applied, [3]. DE algorithm, with its simple logical structure, easy implementation, and powerful Global Search Capability (GSC), has demonstrated excellent performance in various complex optimization problems, [4]. The PSO algorithm is favored because of its fast convergence to the problem and less need for parameter adjustment. However, both algorithms have their limitations, [5]. For example, the DE algorithm may converge to the local optimal solution (OS) prematurely when dealing with multi-modal functions, while the PSO algorithm may fall into search stagnation in the late iteration, making it difficult to fine-tune the solution. To overcome these limitations, a new power ED method that integrates improved DE and PSO algorithms is proposed in the experiment. Through an in-depth analysis of the intrinsic mechanisms of DE and PSO algorithms, the study proposes a new fusion strategy, which aims to combine the advantages of both and improve the performance of the algorithm in solving power economic dispatch problems. This method can not only adapt to dynamic changes in power system operation but also achieve multi-objective optimization of economic dispatch while ensuring system reliability.

The article can be divided into four parts. The first part is a literature review, which mainly discusses and summarizes the current domestic and foreign DE algorithm and PSO algorithm as well as the development status of electric power ED. The second part is the research method, which proposes to combine the mutation strategy DE with the improved PSO and apply them together. In the ED of electric power. The third part analyzes the performance of the method proposed in the experiment is tested and its application effect is analyzed. The fourth part is the conclusion, which mainly summarizes the entire article.

2 Related Works

With the continuous development of the power market and the widespread access to renewable energy, traditional power ED methods are facing new challenges. In recent years, researchers have tried to integrate DE and PSO algorithms to combine the advantages of both to speed up the convergence of the algorithm. [6], proposed a multi-objective DE algorithm based on enhancement to solve the dynamic environmental ED problem in power system dispatch. This algorithm effectively combines total constraint violations with penalty functions to handle multiple constraints. The simulation showed the algorithm's effectiveness in dealing with wind power system problems. [7], designed an improved particle swarm optimization (PSOCS) to deal with the dynamic economic emission dispatch problem of the power system. The constraint processing method is used to repair infeasible solutions, and the CS mechanism is introduced to overcome the particle swarm falling into local optimization. Numerical experiments show that PSOCS can quickly find existing problems and propose feasible solutions. To solve nonlinear optimization problems in power systems, [8] proposed a power system detection method based on swarm intelligence and PSO algorithms. In the process, starting from the basic concepts, the actual performance of the improved particle swarm method is analyzed through actual cases. It was found that the performance of this method was significantly superior. To control the parameters of the power system and reduce the related costs of power generation and transmission, [9] proposed an adaptive DE algorithm (ESHADE) based on continuous history. Compared with other algorithms, the fuel cost and active power loss of the constructed algorithm are significantly superior. To find the optimal configuration and dispatch of renewable energy in the power distribution system, [10] proposed an algorithm built on improved PSO. It was greatly better than other algorithms and could quickly find the OS. To intelligently adjust the output power of electric power economic load dispatch, researchers such as [11] proposed a power system dispatching method based on an improved differential evolution method. Through experimental verification, it was found that this method has a faster convergence speed and its performance is significantly superior to other models.

At the same time, many scholars have analyzed the ED of power systems. To analyze and control the electrical and mechanical parameters of the permanent magnet synchronous motor (PMSM) controller, [12] proposed a PMSM control method that combines the quasi-oppositional learning algorithm and the PSO. This algorithm can find the OS value and has good performance and certain feasibility. To analyze the time, resources, and costs that affect the progress of construction projects, [13] proposed a non-dominated sorting DE algorithm based on reference points. The most appropriate schedule is developed through this algorithm. This algorithm was applied to actual construction projects and it was found that the algorithm has very superior applicability. To achieve the optimal combination of hybrid thermal and power isolation microgrids, two scholars, [14] proposed an optimal energy management method based on intelligent optimization technology. When this method was applied to actual microgrid operation, it was found that the optimal multi-objective solution obtained was significantly superior. To solve the virtual scheduling issue in dynamic cloud environments, [15] proposed a group-based metaheuristic algorithm. The DE strategy is utilized to replace the randomly generated solution of WOA. The completion time is shorter than other algorithms, and the cost trade-off is excellent. To keep the load demand of the standard microgrid system consistent with the actual demand, the teams of [16] proposed a hybrid CSAJAYA algorithm. The electricity price is calculated based on the user's electricity consumption time, and the total cost of electricity consumption is comprehensively calculated. By utilizing this algorithm, the total PGC of the system is significantly reduced by 30% to 40%. To reduce the amount of pollutants and costs generated when thermal power plants produce electricity, scholars such as [17] proposed a power economic dispatch method based on the Crow search algorithm and differential evolution. This method was applied to different power systems for experiments, and it was found that the economic cost of this method is low, and the CPU time is also significantly superior.

In summary, it can be seen that power economic dispatch, as one of the core issues of power system optimization management, has always received widespread attention from scholars and engineers. With the continuous opening of the power market and the increasing complexity of the energy structure, traditional power economic dispatch methods are facing new challenges. Various intelligent algorithms, such as PSO algorithm, GA algorithm, and DE algorithm, are widely cited in various fields and the field of power economic dispatch. However, a single optimization algorithm is often difficult to simultaneously meet the multi-objective, nonlinear, and dynamic characteristics of economic dispatch problems in actual power systems; and it still faces challenges in improving the quality of solutions and maintaining the diversity of the search process. Given this, the experiment proposes a power economic dispatch method that combines improved differential evolution and particle de-optimization algorithms. This method includes a new algorithm framework that can not only deal with economic and reliability issues in the power system, but also It is able to adapt to changes in electricity markets and the volatility of renewable energy. It is expected that this method will maintain the stable operation of the power system while reducing the power generation cost of the power system.

3 Power Economic Dispatch Method Integrating Differential Evolution and Improved PSO

For ED problems in power systems, traditional optimization methods often face challenges such as high computational complexity and slow convergence speed. To solve these problems, the experiment proposes a hybrid optimization method that combines DE with mutation strategy and an improved PSO algorithm. This method, it aims to improve the efficiency and performance of the ED of the power system while ensuring the robustness and practicality of the algorithm.

3.1 Electric Power Load Economic Dispatch Method based on Moderate Interference- PSO Algorithm

In the operation management of modern power systems, the economic load dispatch (ELD) problem is crucial, [18]. The goal of ELD is to adjust the output power of the generator set to minimize the operating cost of the entire system while satisfying system stability and operating constraints. The power market and the gradual integration of renewable energy are developing, causing ELD problems have become increasingly complex and changeable, and traditional optimization methods have been unable to meet the high-efficiency and high-precision dispatch requirements. Therefore, researching and developing new optimization algorithms to improve the solution quality of ELD problems has become an important direction in power system research. The PSO algorithm has been widely utilized because of its simple principle and excellent parallel performance. The running process of the PSO algorithm is Figure 1 (Appendix).

However, when dealing with the ELD problem of power systems, the traditional PSO algorithm may face premature convergence and insufficient exploration capabilities, which limits its application effect in complex power dispatch tasks. To overcome these limitations, the experiment proposed a particle swarm algorithm (Moderate Disturbance Particle Swarm Optimization, MDPSO) based on the moderate interference mechanism. This algorithm introduces a novel interference strategy based on traditional PSO, which moderately disturbs the position of particles to prevent the algorithm from prematurely converging on the local OS and enhance the GSC of the algorithm, [19]. Through this moderate interference, particles can fall into the local optimum and explore a broader solution space, thereby finding more economical and reliable solutions to the power load ED problem. First, to ensure that the system can always provide a large power to the particles during operation and support the particle swarm to maintain the probability of jumping out of the current local search area, the experiment proposes a moderate interference factor, which is defined in Equation (1).

$$\gamma = abs\left(normrnd\left(0,\alpha 1\right)/rand\right) \tag{1}$$

In $normrnd$ Equation (1), represents the random sequence of the composite Gaussian distribution; $\alpha 1$ represents the standard deviation of the Gaussian distribution; $rand$ represents the random function. Considering $rand$ the characteristics of the function, the experiment also proposes a moderate random search function γ . The resulting particle swarm iterative calculation is shown in Equation (2).

$$x_{id}(t+1) = Q_d + \alpha * \gamma\left(mbest_{id} - x_{id}(t)\right) \tag{2}$$

In Equation (2), the first parameter Q_d provides a very effective direction for particle evolution; the second parameter $\alpha * \gamma\left(mbest_{id} - x_{id}(t)\right)$ ensures the searchability of the entire particle. Which α represents the only control parameter in the MDPSO algorithm. The function of this parameter is similar to the inertia factor. The value has a direct impact on the individual's searchability. Based on the above, the experiment assumes that the power system grid connection framework is shown in Figure 2 (Appendix).

The ED problem of the power system aims to reasonably allocate the active power output of different generating units to minimize the total PGC of the system under the premise of meeting specific technical and safety constraints. This problem is usually expressed through a mathematical model, and its goal is to minimize the PGC. The specific objective function is Equation (3).

$$\min F = \sum_{i=1}^{n_g} F_i(p_i) = \sum_{i=1}^{n_g} a_i p_i^2 + b_i p_i + c_i \tag{3}$$

In Equation (3), n_g represents the total number of generating units in the system; F represents the total PGC; p_i is the output active power of the unit i ; $F_i(p_i)$ is the power consumption characteristic curve of a_i, b_i, c_i the generating unit; i all are i the cost coefficients of the unit. In the actual operation of power systems, the impact of the valve point effect must be taken into consideration. Therefore, for the unit that takes the valve point effect into account i , the corresponding consumption characteristic function is calculated as shown in Equation (4).

$$\begin{cases} F_i(p) = a_i p_i^2 + b_i p_i + c_i + V_i \\ V_i = \left| e_i * \sin(f_i * (P_{i\min} - P_i)) \right| \end{cases} \tag{4}$$

Equation (4), V_i represents the change in consumption characteristics caused by the valve point effect; e_i, f_i represents the parameter; $P_{i\min}$ represents i the lower limit of the active power output of the first generating unit. When dispatching the power system, constraints such as unit operation limitations and power balance need to be taken into consideration. The power balance constraint needs to ensure that the total active power of the generator is equal to the total load of the system plus the network loss, where the network loss is generally calculated based on the generator power, transmission line parameters, and network structure. The overall conditional constraint processing operation is shown in Figure 3 (Appendix).

Analyzing Figure 3 (Appendix), the constraints of power balance are defined in Equation (5).

$$\sum_{i=1}^{n_g} p_i = P_D + P_L \tag{5}$$

In Equation (5), P_L is the total network loss of the system; P_D represents the total load of the system. The upper and lower limit constraints of the unit output are shown in Equation (6).

$$p_{i\min} \le p_i \le p_{i\max} \tag{6}$$

Then the constraints of the unit's operating restricted area are obtained, as shown in Equation (7).

$$p_i \in \begin{cases} p_{i\min} \le p_i \le p_{i,1}^l \\ p_{i,j}^u \le p_i \le p_{i,j}^l \quad j = 2,3,\cdots,m_i; i = 1,2,\cdots,n_g \\ p_{i,m_i}^u \le p_i \le p_i^{\max} \end{cases} \tag{7}$$

In Equation (7), $p_{i\min}$ and $p_{i\max}$ are the minimum and maximum technical output of the i unit. $p_{i,j}^l$ and $p_{i,j}^u$ are the lower and upper limit of the j and i unit's working restricted area. m_i represents the quantity of the i unit's working restricted area. B matrix is the loss coefficient.

3.2 Electric Power Load Economic Dispatch Method based on Mutation Strategy-DE algorithm

In the power system, since most power points and load centers are located in different regions and cannot be stored in large quantities, their production, transmission, distribution and consumption are all completed at the same time and organically form a whole in the same region. In the process of power system operation and production, multiple extreme values will be generated. For functions with multiple local extreme points, it is easy to fall into local extreme values when using the PSO algorithm to solve them, and we get Not getting the correct result. Therefore, the experiment then introduced the DE to solve it. Different from the PSO, the DE mainly contains three steps of operations, namely mutation, crossover and selection. The position update of particles does not rely on speed, but implements learning and position update by performing differential operations on three randomly selected particles. This mechanism allows particles to learn from each other and move toward convergence together. In essence, DE is a search algorithm that adopts a greedy strategy and follows the principle of optimization and retention, [20]. The DE algorithm has strong GSC and is easy to understand and implement. Therefore, the algorithm has been widely used in many fields. The running steps of the DE algorithm are shown in Figure 4 (Appendix).

During the DE operation, a set of original populations is first randomly produced. Assume that the particle size is NP and the corresponding dimension is D . The obtained initialization calculation is Equation (8).

$$X_i^t = \left(x_{i1}, x_{i2}, , x_{id}\right)^T \in \Omega \tag{8}$$

In Equation (8), Ω represents D the feasible region of the optimization problem in dimensions; i represents the th i individual particle; t represents the current iteration as the th t generation; i the size and dimension of the population remain unchanged during the optimization process of particles. Then the particles enter the mutation process.

For each mutated particle X_i^t , three different particles are randomly selected through the DE calculation process a,b,c . The mutation vector is Equation (9).

$$V_{id}^t = X_{ad}^t + F * \left(X_{bd}^t - X_{cd}^t\right) \tag{9}$$

In Equation (9), d means the current number of dimensions. F is the crossover factor, which controls the amplification of the deviation vector between particles. In addition, to positively improve the diversity of particles, a crossover probability is introduced in the experiment CR . A new test vector is generated through Equation (10), and the calculation is Equation (10).

$$U_{id}^t = \begin{cases} V_{id}^t & rand \le CR \quad or \quad j = randr \\ x_{id}^t & rand \ge CR \quad or \quad j \ne randr \quad j = 1, 2, \cdots, D \end{cases} \tag{10}$$

In Equation (10), $rand$ is a random number with a value range between [0,1]; CR the value range of is also [0,1]. $randr$ It represents a certain number of dimensions randomly selected between [1, D]. This parameter can ensure that the test vector V_i gets at least one dimension from it. Otherwise, there will be no crossover, that is, no new vector will be generated. Then the DE algorithm begins to enter the selection operation. If and only if the generated test vector U_i^t is better than the original vector, it will be saved in the next generation of particles, otherwise the particles will not be updated. Finally, in the DE process, when a certain dimension of the generated vector is not within the feasible region, it is determined that the vector exceeds the boundary range, and the dimension needs to be reinitialized. The optimal individual information copying mechanism in the DE is Figure 5 (Appendix).

In Figure 5 (Appendix), the execution process of the DE algorithm can be divided into two basic stages: the generation of the initial population and the iterative update of the population. In the initial stage, the algorithm constructs an initial population by randomly generating a series of initial solutions. Subsequently, in the iterative evolutionary update stage, the population is promoted to develop in a direction that satisfies the termination conditions. In the application and research of DE algorithms, how to properly balance the GSC and local search capabilities has always been a research hotspot.

Improving the diversity of individuals in the population is crucial to enhancing the algorithm's optimization capabilities in the solution space and improving GSC performance and reliability. At the same time, ensuring that the population can search efficiently near the current OS is the key to enhancing local search capability., is also an effective means to improve search efficiency. However, how to find a balance between the two is a problem, [21], [22].

To this end, many scholars have proposed various improvement strategies. Based on the above background, and due to the slow convergence speed of the DE when solving complex functions, the experiment combined the characteristics of the existing improved DE and designed a new DE algorithm based on Local Mutation Differential Evolution Algorithm (LMDE). This algorithm aims to lift the algorithm's searchability in the solution space by introducing a local mutation strategy. In the LMDE algorithm, function optimization adopts the definition of state generator (see equation (11)).

$$x' = x + \eta * v \tag{11}$$

Equation (11), η represents the disturbance amplitude parameter; ν represents random disturbance. Random perturbations in DE generally obey Gaussian, Cauchy distribution and different uniform distributions. The function value generated by the Cauchy mutation function is more accurate. Applying this function to the evolutionary algorithm can ensure that the group has more opportunities to search the local space. Therefore, the Cauchy function was selected as the variation factor of the particle swarm in the experiment. The Equation of the Cauchy function is equation (12).

$$\begin{cases} f(x) = \dfrac{1}{\sqrt{2\pi}\sigma}\exp\left(-\dfrac{x^2}{2\sigma^2}\right), -\infty < x < \infty \\ f(x) = \dfrac{1}{\pi} * \dfrac{t}{t^2 + x^2}, -\infty < x < \infty \end{cases} \tag{12}$$

Equation (12), σ and t represent the variance of Gaussian and Cauchy distributions. In the Cauchy function distribution, the Cauchy function can produce smaller function values under the same conditions, which means that the Cauchy function has a greater probability of jumping out of the local search point. Based on the above equations, the flow of the improved LMDE algorithm can be obtained, as shown in Figure 6 (Appendix).

As can be seen from Figure 6 (Appendix), the method constructed in the experiment first initializes the parameters and the population, then calculates the fitness values of the individuals in the population, and ascends, descends and sorts the individuals according to their fitness values to obtain the optimal fitness value. Then implement the optimal individual information copy mechanism to find the position of the optimal individual, and integrate the mutation operation of Cauchy perturbation to reduce the probability perturbation rate, thereby utilizing the intersection between the obtained central solution and the optimal solution improvement step operate. Then, based on the selection operation of the greedy strategy, the control parameters are adaptively adjusted to obtain the maximum number of evolution iterations. If the maximum number of iterations is not met, it is judged whether G is equal to G+1, and then the fitness value of the individual is calculated, and the cycle is repeated until the maximum number of iterations is met, and the optimal solution is finally output, and then the process ends.

The data were analyzed and processed through SPSS 22.0 software. For quantitative data that meet the conditions of normal distribution, the independent sample t test method is used. Statistical significance is judged by P value less than 0.05. If P<0.05, it means that the difference between the data is statistically significant.

4 Performance Testing and Application Analysis of Improved Power Economic Dispatch Methods

4.1 Performance Test

To verify the superior performance of the method constructed in the experiment, a power system ED hybrid method that integrates gain sharing knowledge algorithm and differential evolution (GSK-DE), a wind power comprehensive ED system based on artificial bee colony algorithm and differential evolution (ABC- DE), industrial energy scheduling method based on reinforcement learning and differential evolution (RL-DE) are compared with the constructed method, [23], [24], [25]. The experiment was conducted in a professional laboratory in China. The study described the experimental data and results in detail, and ensured that all data were accurate and repeatable. Before conducting experiments, it is necessary to ensure that the simulation environment and parameters of all algorithms are consistent to ensure that the obtained data are not affected by accidental errors. See Table 1 for relevant parameter settings.

Table 1. Settings of related parameters

Project	Parameter
Network architecture	Pytorch v1.2.0
Experimental environment	COREi7
O perating system	Windows 10
Memory	8GB
f	3.41GHz
Main frequency	3.40GHz
simulation software	Matlab R2018b

The experiment uses two benchmark test functions in CEC2017 to conduct simulation experiments on the four algorithms. The selected benchmark functions are F11 and F21 respectively. Among them, F11 is a hybrid function and F21 is a combination function. First, the loss function values of the four algorithms on two different functions are compared. The specific results are shown in Figure 7 (Appendix).

Figure 7(a) (Appendix) shows the changes in the loss function values of the four algorithms on the F11 test set. It can be found that as the number of system iterations increases, the loss function values of all algorithms begin to decrease. When the system iteratively runs for the 26th time, the loss function of the IDE-PSO begins to have a minimum value, and the value becomes stable in subsequent runs. When the GSK-DE, ABC-DE, and RL-DE algorithms become stable, the system iterates to 31, 40, and 48 times respectively. Figure 7(b) (Appendix) shows the changes in loss function values of different algorithms on the F21 test set. It can be observed that when the loss function value of the IDE-PSO tends to the target value of 0.00, the iteration coefficient of the system corresponds to 32 times. In addition, when the number of iterations of the system is 40, 50, and 61 times respectively, the GSK-DE, ABC-DE and RL-DE algorithms begin to move toward the minimum loss function value. There is a certain gap between the loss function value of IDE-PSO algorithm and the loss function value of other algorithms (P>0.05). It can be run on different test sets and has superior robustness.

To reduce the accidental error of the experimental results, the experiment began to compare the average time-consuming of the four algorithms running on different test sets. The specific results are shown in Figure 8 (Appendix).

Figure 8(a) (Appendix) shows the running time on the F11 test set. As the number of iterations increases, the average running time of the four algorithms begins to change with different amplitudes. However, the run time of the IDE-PSO shows a significant reduction trend. When the iteration is 150, the mean time consumption of the IDE-PSO begins to tend to a stable value and has a minimum time of 0.153s. The average time taken by the GSK-DE, ABC-DE and RL-DE algorithms is significantly greater than that of the IDE-PSO, and during the entire iteration process, the average time taken has been increasing and is unstable. Figure 8(b) (Appendix) shows the running time of the algorithm on the F21 test set. During the entire iteration process, when the system iterated 35 times, the average time consumption of the IDE-PSO was 0.254s; it has been on a decreasing trend since then; when the number of iterations was 210, the IDE-PSO had the minimum running cost. time, it is only 0.117s. The other three methods are always more time-consuming than the IDE-PSO. In summary, the average running time of the IDE-PSO is significantly less than that of other algorithms, and it can reach a stable state in a very short time and respond quickly to power ED problems. Then four different algorithms were applied to two different power systems of a power company for testing. System 1 consists of 4 pure electric units, 2 cogeneration units, and 1 pure thermal unit. The electrical load and thermal load of the system are 600MW and 150MW respectively. This system only considers valve point effects and transmission losses. The population size is 100 and the maximum iteration is 500. System 2 consists of 13 pure electric units, 6 combined heat and power units, and 5 pure thermal units. The electrical load and thermal load of the system are 2350MW and 1250MW respectively. This system only considers the valve point effect and does not consider transmission losses, with a population size of 100 and maximum iterations of 5000. The two systems were run 5 times in cycles, and the changes in total costs are shown in Figure 9 (Appendix).

Figure 9(a) (Appendix) shows the cost changes of different algorithms on System 1. When the system loop runs for the first time, the total cost of the IDE-PSO begins to approach the minimum value, which is only 1.01×10^{4} US dollars; the cost value has tended to be stable since then. Figure 9(b) (Appendix) shows the total cost changes of different algorithms on system 2. When the IDE-PSO has the minimum total cost, the total cost at this time is 5.80×10^{4} US dollars, and the corresponding system loop runs for the second time. When the GSK-DE, ABC-DE, and RL-DE algorithms are run in the two systems, the cost is significantly greater than the IDE-PSO.

4.2 Application Effect Analysis

Combining the above analysis, the IDE-PSO has the superior optimization accuracy and convergence speed among the two systems. Then the pollutant emissions of the four algorithms after different iterations are compared. The specific results are shown in Figure 10 (Appendix).

Figure 10(a) (Appendix) shows the changes in pollutant emissions when the four algorithms are iterated for 100 times. At the beginning of the iteration, the IDE-PSO was not significantly better than other algorithms; but at 25 iterations, the amount of pollutant emissions under the IDE-PSO was 33.8T/hour. This shows that the IDE-PSO is significantly better than other algorithms in reducing pollutant emissions. Figure 10(b) (Appendix) shows the change in pollutant emissions when iterating 200 times. When the system iteratively runs for the 50th time, the amount of pollutant emissions under the IDE-PSO is 34.2T/hour. In the future, pollutant emissions will always be smaller than other algorithms. In summary, using the IDE-PSO can effectively reduce electricity costs and reduce the amount of pollutant emissions. Finally, the operating power of each power generation equipment unit under optimal cost is analyzed. The specific results are shown in Figure 11 (Appendix).

It can be found in Figure 11 (Appendix) that as time goes by, wind power generation power shows a trend of first increasing and then decreasing. Among them, the photovoltaic power generation increases rapidly between 8:00 and 19:00, has the maximum power generation between 13:00 and 14:00 at noon time, and then begins to show a decreasing trend. The load power has been fluctuating throughout the process; the battery begins to store electrical energy when power consumption is low, and sells power during peak power consumption, making full use of the peak-valley difference to reduce the operating cost of the system. Under the operation of the IDE-PSO, the power system can ensure optimal operating power of each power generation equipment unit based on ensuring optimal cost.

5 Discussion and Conclusion

5.1 Discussion

The study proposes an innovative power economic dispatch method by integrating the differential evolution algorithm (DE) and the particle swarm optimization algorithm (PSO). This method not only improves the efficiency of power dispatching and reduces operating costs, but also improves the stability and reliability of the power system through optimization algorithms. The specific contributions can be divided into two points: First, the fusion of two optimization algorithms was successfully realized, making full use of the advantages of DE in global search and the characteristics of PSO in local search efficiency. Second, to solve the problem of slow convergence speed of the differential algorithm, it is proposed to introduce gbest into the mutation strategy of DE, so that particles can learn from other particles while also learning from the current global optimal. This strategy effectively improves the convergence speed and has good testing results on the data set.

Although the research has achieved certain results, there are still some limitations. For example, the performance of the algorithm may be affected by parameter settings, and further research is needed to determine the optimal parameter configuration. In addition, the study was tested on different data sets, but may require further adjustment and optimization under specific grid structures or specific electricity market environments. In response to the above limitations, future research work can further study the automatic adjustment mechanism of algorithm parameters to reduce the demand for computing resources and improve the adaptability and robustness of the algorithm; at the same time, consider incorporating more goals (such as environmental impact , integration of renewable energy, etc.) into the optimization framework of power economic dispatch, and the proposed method is tested in a wider range of actual grid environments to verify its applicability and stability under different conditions.

5.2 Conclusion

As the scale of power systems expands and the operating environment becomes more complex, traditional ED methods face challenges when solving high-dimensional, nonlinear, and multi-peak optimization problems, especially the contradiction between GSC and convergence speed. To address the above problems, a hybrid algorithm grounded on DE and PSO was proposed in the experiment to lift the efficiency and accuracy of power ED. The proposed hybrid algorithm cleverly integrated the powerful GSC of DE and the fast convergence characteristics of PSO to form a new iterative update strategy. The data shows that on the F11 test set and F21 test set, when the iterations are 150 and 35 times, the mean run time of the IDE-PSO is 0.153s and 0.254s respectively; while the average time-consuming of other algorithms is significantly is greater than 0.300s. When the total cost of the IDE-PSO on system 2 has a minimum value of 5.80×10^{4} US dollars, the corresponding system cycle runs to the second time. When the power generation equipment is running, under the operation of the IDE-PSO, the power system always maintains stable operation and the equipment has optimal operating power. In summary, the IDE-PSO not only improves the performance of the ED of the power system but also has strong practicability and promotion potential. However, the dynamics and uncertainty of power systems require dispatch methods to be more adaptable and robust, which is also a focus of future research. Future work can focus on optimizing the performance of the hybrid algorithm and exploring its application in more complex power system scenarios.

Declaration of Generative AI and AI-assisted Technologies in the Writing Process

The author wrote, reviewed and edited the content as needed and he has not utilised artificial intelligence (AI) tools. The author takes full responsibility for the content of the publication.

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Contribution of Individual Authors to the Creation of a Scientific Article (Ghostwriting Policy)

The author contributed in the present research, at all stages from the formulation of the problem to the final findings and solution.

Sources of Funding for Research Presented in a Scientific Article or Scientific Article Itself

No funding was received for conducting this study.

Conflict of Interest

The author has no conflicts of interest to declare.

APPENDIX

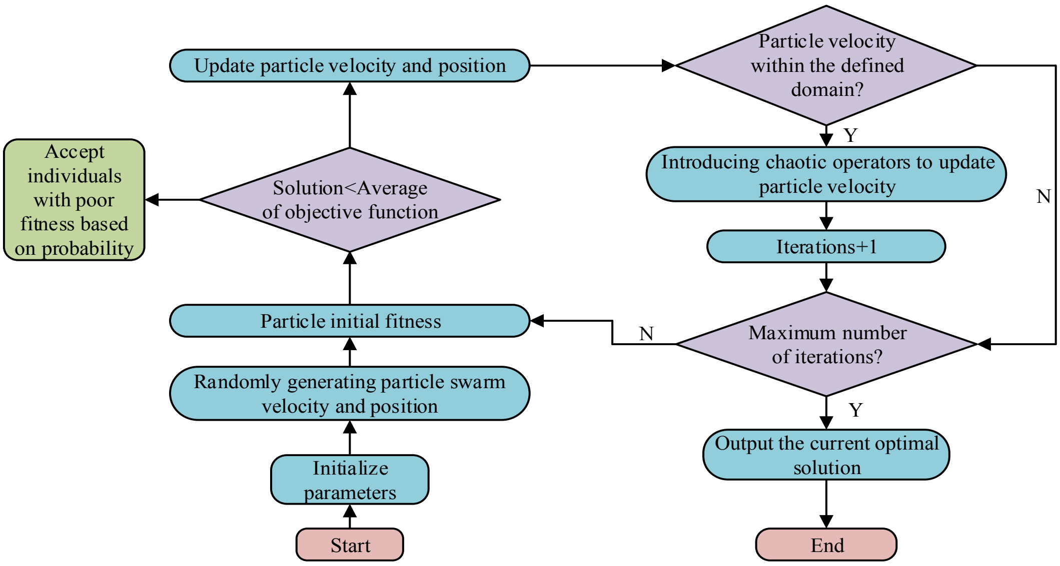


Fig. 1: The running process of PSO

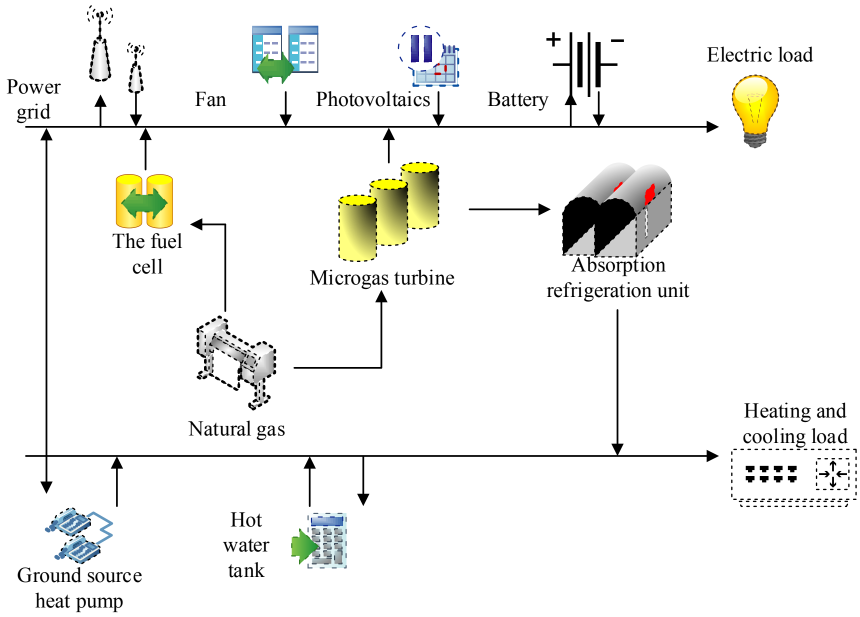


Fig. 2: Framework of power ED system

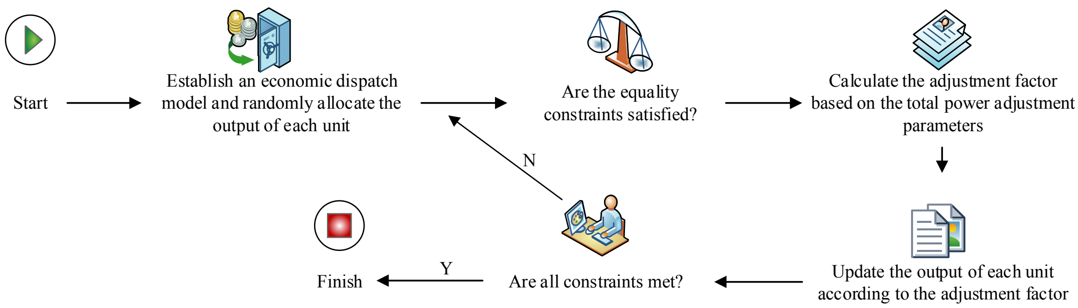


Fig. 3: Conditional constraint processing flow

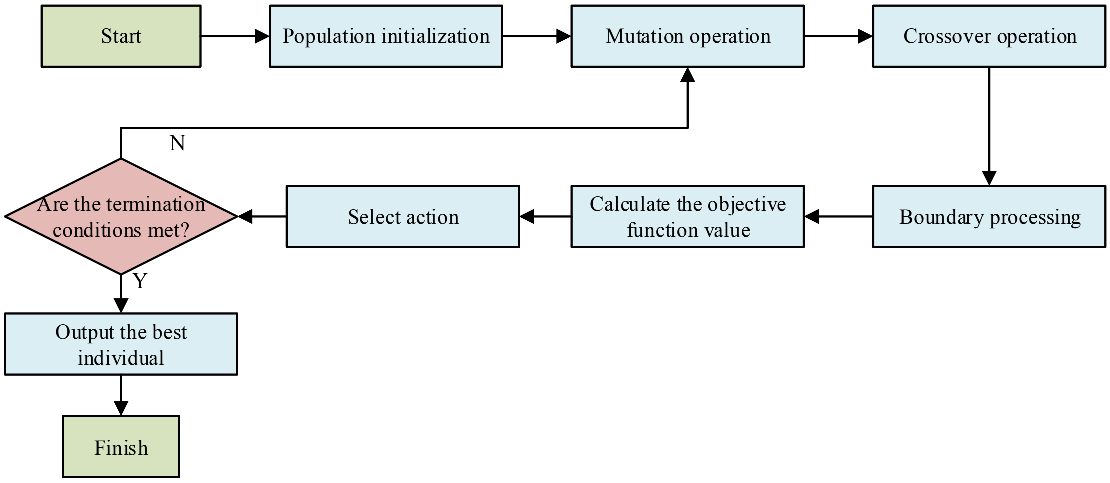


Fig. 4: Running steps of DE algorithm

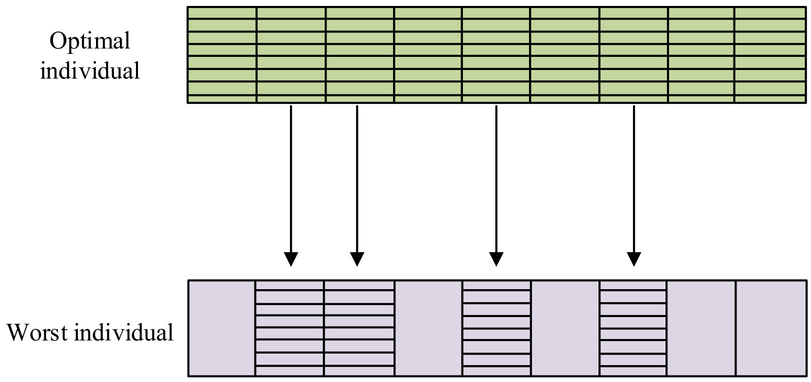


Fig. 5: Optimal individual information replication mechanism

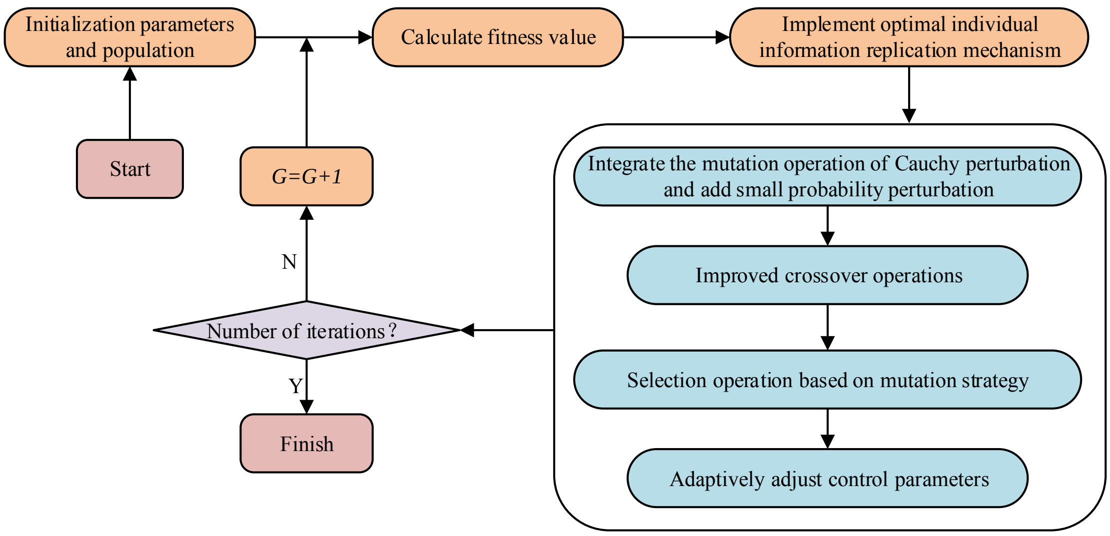
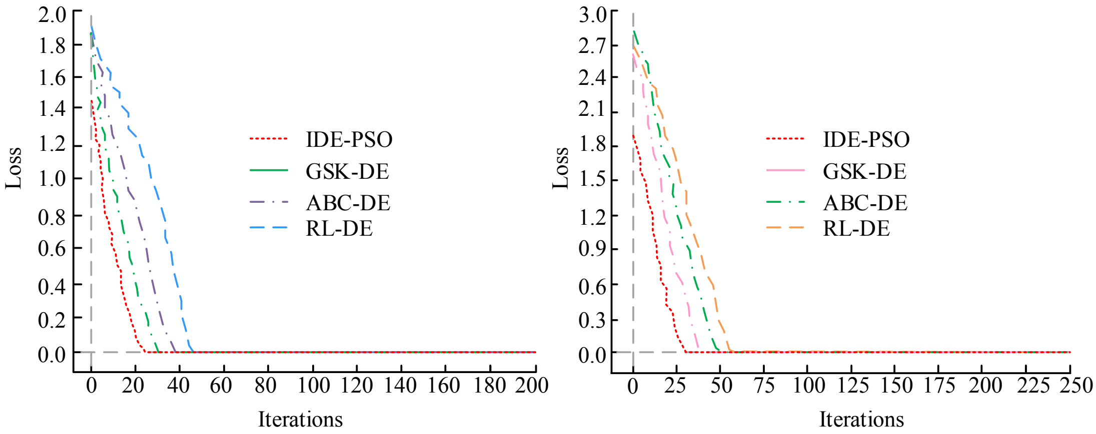
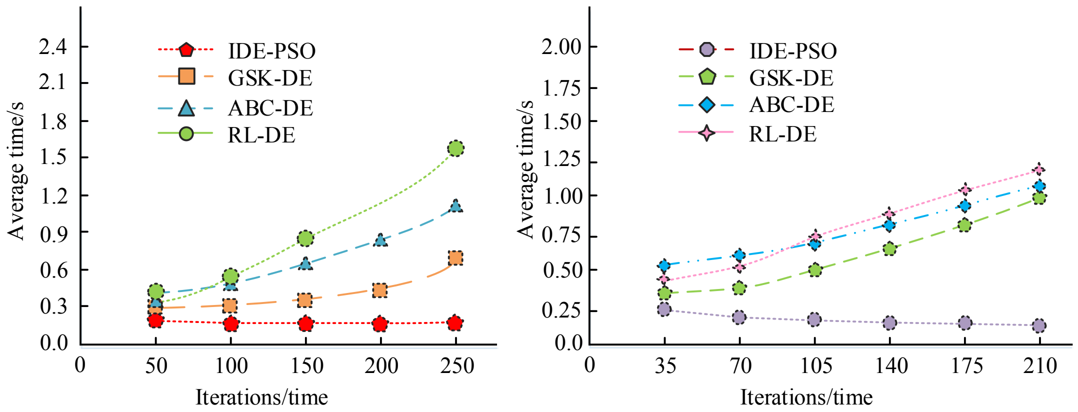


Fig. 6: Electric power ED method based on IDE-PSO algorithm



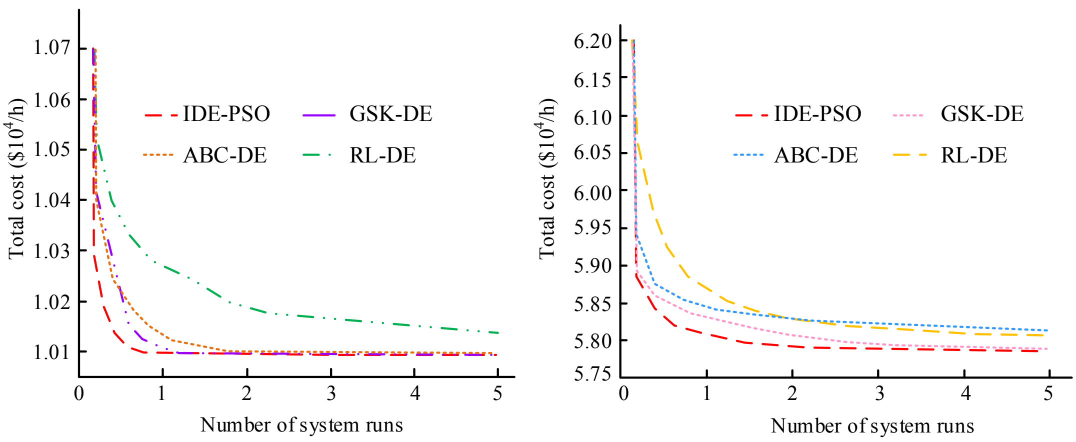
(a) F11 test set (b) F21 test set

Fig. 7: Comparison of loss function values of different algorithms on two test functions



(a) F11 test set （b） F21 test set

Fig. 8: Changes in average running time



(a) System 1 cost (b) System 2 cost

Fig. 9: Changes in the total cost of operating the two systems

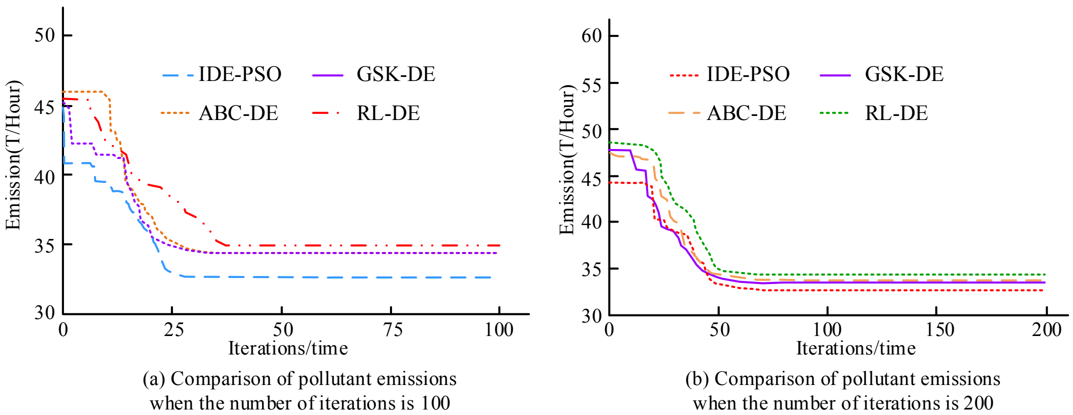


Fig. 10: Comparison of pollutant emissions from different algorithms

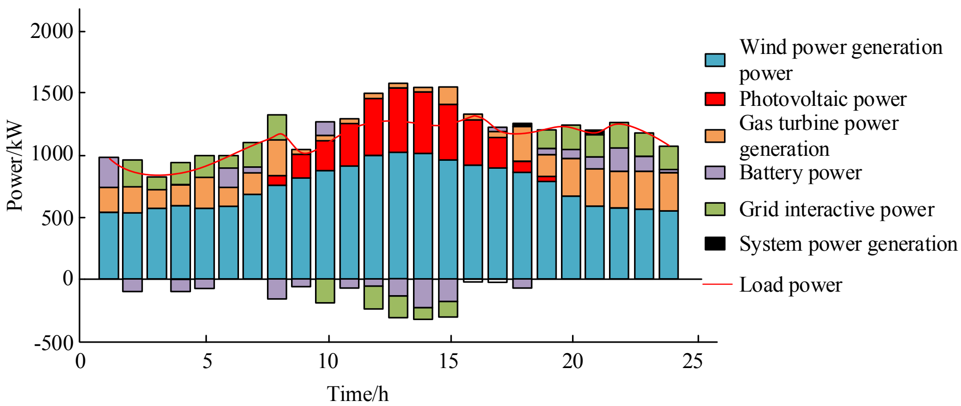


Fig. 11: Operating curve of power generation equipment