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Enhanced Particle Swarm Optimization for Efficient and Sustainable Power System Dispatch

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Abstract: Electricity plays a vital role in socio-economic development, where effective economic dispatch in the power system is crucial for achieving sustainable development. Currently, there are issues with poor optimization performance and low accuracy in multi-objective economic dispatch methods. Therefore, an optimized particle swarm optimization for power system economic dispatch was built, and comparative analysis experiments were conducted. The accuracy and precision were 97.87% and 96.88%, surpassing those of the comparison algorithms. Subsequently, the algorithm was used for economic dispatch analysis. When the generation cost increased from \$5.04 to \$5.12, the carbon emissions decreased from 1.87×10^4d to 1.84×10^4d. During this process, both the generation cost and carbon emissions of the system were below those of the comparison algorithm. The designed algorithm can improve the optimization effect and accuracy, providing a theoretical basis for multi-objective economic dispatch.

Keywords: Economic dispatch, multi-objective, fast non-dominated sorting, power system.

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1. Introduction

With the development of the social economy, countries around the world face severe shortages of fossil fuels and environmental degradation (Wang et al., 2023). Improving power economic dispatch is particularly important for achieving energy conservation, emission reduction, and sustainable development. However, current multi-objective economic dispatch methods for power systems suffer from poor optimization performance and low accuracy. Many experts have conducted relevant research, but the results remain unsatisfactory. Ali et al. (2024) developed a Multi-Objective Optimization (MOO) based on bidirectional co-evolution to address the dual-objective nonlinear optimization problem of economic and environmental power dispatch, but the results were not satisfactory. Dashtdar et al. (2022) created an MOO that combined firefly and genetic algorithms for environmental and economic dispatch in thermal power plants, but the optimization effect was not ideal. Some research has also achieved results. For example, Sun et al. (2022) proposed a two-step solution method based on a chaotic sine map MOO algorithm and fuzzy set theory for multi-objective scheduling of microgrids with uncertainty in wind power prediction, which outperformed the comparison algorithm. Sahoo et al. (2022) suggested an optimization method using chaotic mapping to the butterfly optimization algorithm for economic and emission scheduling problems in thermal power plants, which was experimentally proven effective. Soni and Bhattacharjee (2024) introduced a balance optimizer technique to address the MOO dynamic economic emission scheduling of renewable energy sources. The technique showed significant improvements in accuracy, efficiency, and speed.

Adopting efficient scheduling methods for economic dispatch can greatly enhance resource utilization. Particle Swarm Optimization (PSO) is an optimization technique based on swarm intelligence. Known for its fast convergence and high efficiency, it is widely utilized in optimization problems (Gad, 2022). Wang et al. (2022) introduced a hybrid PSO to manage dispatch in wind power generation systems. After testing, the algorithm proved to be superior to existing methods. Zeng (2025) combined differential evolution algorithms with PSO for dispatch tasks and tested them on the F11 and F21 test sets, demonstrating strong practicality. Sayadi et al. (2023) developed an improved PSO to handle dispatch, with results confirming its effectiveness. Guo (2024) designed a multi-objective PSO based on competitive learning for dispatch in multi-regional systems, with tests showing its efficiency in different environments. Fu et al. (2024) implemented an optimized PSO to address coordination and scheduling issues in power grids, successfully reducing costs.

In summary, current methods for MOO dispatch in power systems face poor optimization performance and low accuracy.

As economic dispatch in power systems is an MOO problem, the research first developed an economic dispatch model as a planning problem, integrating PSO and a collaborative strategy to build a Multi-sub-population Coevolutionary algorithm based on PSO (MCPSO). To address challenges such as local optima, premature convergence, and difficulty in quickly finding the best solution in MOO problems, Fast Non-Dominated Sorting (FNS) and Crowding Distance (CD) are incorporated to enhance MCPSO. An improved PSO algorithm for power system economic dispatch (Multi-sub-population Coevolutionary Algorithm with Adaptive Cauchy-Polynomial Mutation (MCPSO-ACPM)) is created to improve utilization efficiency. The key innovation of this study lies in introducing collaborative strategies, information sharing methods, FNS, CD, and adaptive Cauchy mutation to improve PSO. This work aims to provide a theoretical basis for future research in this area.

Electricity is crucial to economic growth. However, efficiently generating and distributing electricity while reducing costs and minimizing environmental damage is a challenge. At present, the methods to achieve these goals are not yet optimized and precise enough, which makes it difficult to reduce electricity costs, cut carbon emissions and ensure a stable supply. This study aims to address these issues by developing more effective methods. The proposed algorithm can help energy companies and other relevant institutions make wiser decisions on power issues. It helps them strike a balance between cost and environmental issues and supports the Sustainable Development goals.

2. Methods and Materials

2.1. Design of Economic Dispatch Model for Power Systems based on MCPSO

The power system is a crucial component of the national economy, and effective economic dispatch is beneficial for optimizing power generation costs, improving system stability, and promoting environmental sustainability. However, the current multi-objective economic dispatch methods for power systems suffer from poor optimization performance and low accuracy. Finding a more efficient, precise and environmentally friendly method for power production control is of great significance to the sustainable development of the environment. Therefore, the study first constructs a dynamic economic emission dispatch model. The optimization objective is determined through this model, that is, to minimize both power generation costs and pollution emissions simultaneously. This goal not only helps to reduce the operating costs of power companies but also minimizes the negative impact on the environment, thereby supporting the country's sustainable development. Subsequently, the PSO is introduced and improved, and the MCPSO-ACPM algorithm is established to solve the dispatch model. Through this algorithm, power companies can dispatch power resources more intelligently, ensure the stability of power supply, and optimize costs and environmental benefits simultaneously. Before solving this issue, it is necessary to construct a dynamic emission dispatch model. The construction process first calculates the total fuel cost consumed by the power system in producing electricity as the generation cost, as shown in Eq. (1).

$$f=\sum_{m=1}^{M}\sum_{i=1}^{N}a_i+b_iP_{im}+c_iP_{im}^2+\left|d_i sin(e_i(P_i^{min}-P_{im}))\right| \tag{1}$$

In Eq. (1), M signifies the total scheduling time periods; P_i^{min} signifies the minimum output of the i-th generator unit; a_i, b_i, c_i and e_i signify the cost coefficients of the i-th generator unit; f signifies the total fuel cost, which is the electricity generation cost; N signifies the total generator units; and P_{im} signifies the output of the i-th generator unit at time m. Then, the total amount of pollutants such as sulfur oxides and carbon oxides generated in the power system is determined as the pollution emissions, as shown in Eq. (2).

$$f_2=\sum_{m=1}^{M}\sum_{i=1}^{N}[\alpha_i+\beta_iP_{im}+\gamma_iP_{im}^2+\eta_i exp(\delta_iP_{im})] \tag{2}$$

In Eq. (2), f_2 signifies the total amount of pollution emissions and α_i, β_i, γ_i, η_i and δ_i signify emission factors of the i-th generator unit. Finally, the constraint is determined. The constraint scope includes load balancing, maximum and minimum values of generator output, and unit climbing rate. The load balancing limit can be represented by Eq. (3).

$$\sum_{i=1}^{N}P_{im}-P_{Dm}-P_{Lm}=0 \ m\in M \tag{3}$$

In Eq. (3), P_{Dm} and P_{Lm} represent the load demand and transmission loss at time m, respectively. P_{Lm} can be represented by Eq. (4).

$$P_{LM}=\sum_{i=1}^{N-1}\sum_{j=1}^{N-1}P_{im}B_{ij}P_{jm}+2P_{Nm}(\sum_{i=1}^{N-1}B_{Ni}P_{im})+B_{NN}p_{Nm}^2 \ m\in M \tag{4}$$

In Eq. (4), B signifies the matrix of transmission loss coefficients. P_{Nm} signifies the equivalent load at time m. j is the unit index. The maximum and minimum values of generator output can be represented by Eq. (5).

$$P_i^{min}<P_{im}<P_i^{max} \ i\in N,m\in M \tag{5}$$

In Eq. (5), P_i^{max} signifies the maximum output of the i-th generator unit. The climbing rate limit can be expressed in Eq. (6).

$$\begin{cases} P_{im} - P_{i(m-1)} \leq UR_i \\ P_{i(m-1)} - P_{im} \leq DR_i \end{cases} i \in N, m \in M \tag{6}$$

In Eq. (6), UR_i and DR_i are the maximum and minimum values of the climbing rate of the i. Thus, the dispatch model is constructed. According to the model, the objective of optimization is to ensure the minimum generation cost and pollution emission cost while meeting the constraints. Therefore, the study introduces PSO to solve it. PSO has advantages such as fast convergence speed and high efficiency, which is widely used in optimization problems and other fields. Fig. 1 displays the basic process of PSO.

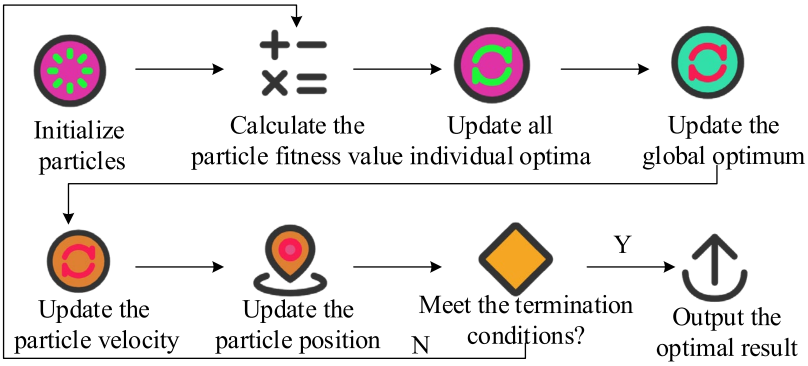


Fig. 1. Operation flow of PSO algorithm

From Fig. 1, the PSO process first initializes the particle swarm size and position. Secondly, the fitness of all particles in the particle swarm is obtained. After the calculation, the individual fitness is compared with that of the optimal position experienced in the past. In the comparison results, the individual with the best extremum is selected as the current best position. Then, the fitness values of all particles are compared with the historical global best fitness value, and the position corresponding to the optimal fitness value is the global best position. Finally, the velocity and position of the particles are updated. If the condition is satisfied, the result is output. On the contrary, the process returns to the second step to recalculate the fitness value until the conditions are met or the maximum iteration is reached. However, the economic dispatch belongs to an MOO problem. The PSO is suitable for single-objective optimization algorithms. When dealing with MOO problems, it is challenging to achieve optimal solutions for all objectives simultaneously. Therefore, the study introduces a cooperative co-evolution strategy to optimize the PSO and construct the MCPSO. The MCPSO structure is shown in Fig. 2.

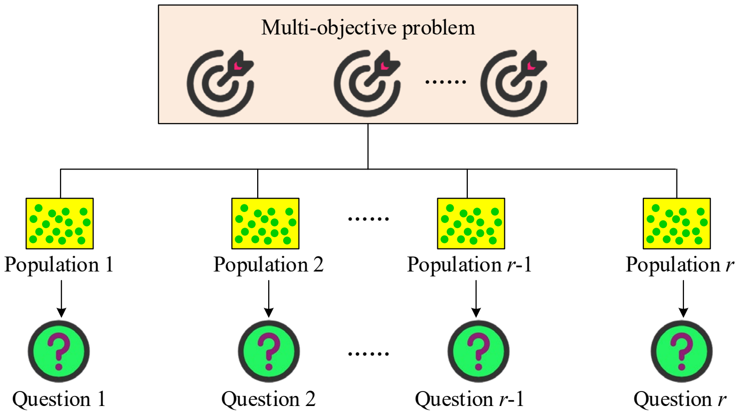


Fig. 2. Structure of the MCPSO algorithm

From Fig. 2, the algorithm decomposes an MOO problem into multiple sub-problems and optimizes them by generating PSO corresponding to the number of problems to approach the entire Pareto front. The Pareto front is the region of Pareto optimal solutions in the objective space, representing the optimal equilibrium point between different objectives and marking the boundary of the optimal solution set for decision-makers when weighing various objectives. Pareto optimality refers to the state in MOO problems where it is impossible to improve at least one objective by changing any relevant variables without deteriorating at least one other objective. If multiple problems need to be optimized, several different PSOs can be used to optimize each sub-problem, and all sub-groups are responsible for optimizing one problem each. The position corresponding to the particle with the smallest fitness in the r-th population is the global optimal position, which is the best position of each particle in its experience. The velocity update can be represented by Eq. (7).

$$V_{i,r}^{t+1} = wV_{i,r}^{t} + \lambda_1 s_1(pBest_{i,r} - X_{i,r}) + \lambda_2 s_2(gBest_{i,r} - X_{i,r}) \tag{7}$$

In Eq. (7), $V_{i,r}^{t+1}$ represents the updated speed; λ_1 and λ_2 signify learning factors; s_1 and s_2 signify random numbers and belong to the range of 0 to 1; $X_{i,r}$ is the current location; $pBest_{i,r}$ is the individual's optimal position; $gBest_{i,r}$ is the global optimal position; w signifies the inertia weight; and $V_{i,r}^{t}$ signifies the current speed. The position update of particles can be represented by Eq. (8).

$$X_{i,r}^{t+1} = X_{i,r}^{t} + V_{i,r}^{t+1} \tag{8}$$

In Eq. (8), $X_{i,r}^{t}$ and $X_{i,r}^{t+1}$ signify the current position and the updated position.

2.2. Design of MCPSO-ACPM for Economic Dispatch of Power Systems

Although the MCPSO can achieve an optimal scheduling of power systems, it still faces challenges such as easily falling into local optima, premature convergence, and the inability to find the optimal solution quickly. Therefore, the study first introduces information sharing strategies and FNS into the MCPSO. The FNS is an effective method for identifying non-dominated solutions in MOO problems, with advantages such as high efficiency and simplicity. It is widely used in multi-objective programming problems (Deng et al., 2022). The FNS flow is presented in Fig. 3 (Zheng et al., 2022).

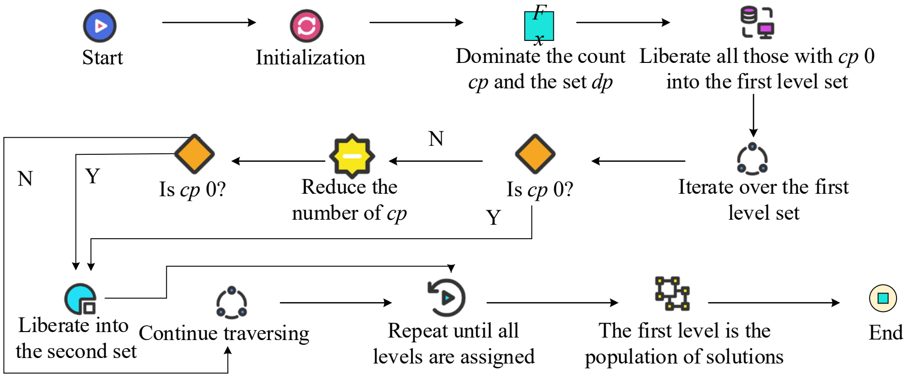


Fig. 3. Process of the FNS

From Fig. 3, the FNS initializes the solution set and calculates the quantity of the optimal solution (dominated count) cp for each solution and the set of dominated solutions dp. Then, the cp value is 0 and placed in the set of the first level. Next, the first level of the collection undergoes iterative operations to remove solutions that do not satisfy the requirements. According to the updated cp value, it will be released to the new hierarchical set, repeating this process until all solutions are assigned to all levels. Finally, the solutions in the first level set are the non-dominated solutions. Therefore, the FNS and information sharing strategy are introduced into the MCPSO algorithm. The algorithm structure after introduction is shown in Fig. 4.

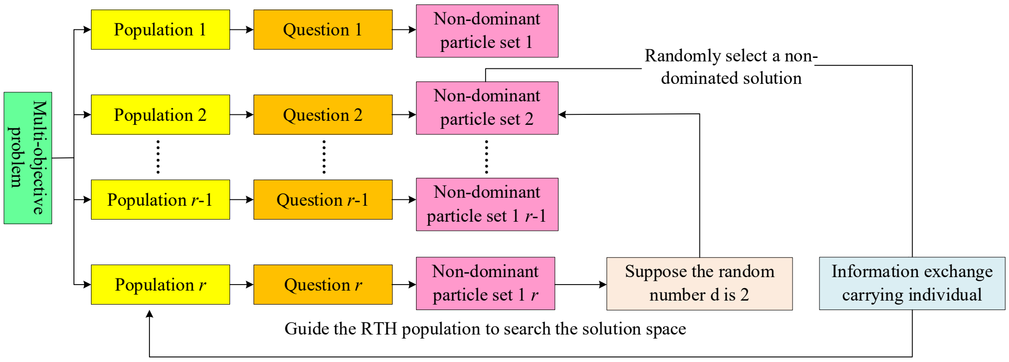


Fig. 4. The algorithm structure after introduction

In Fig. 4, the algorithm introduces an information-sharing strategy and FNS, allowing particles to evolve using their own and other population information, thereby avoiding getting stuck in local optima. The algorithm process first decomposes the problem into multiple sub-problems, with each problem corresponding to a population. Secondly, a fast non-dominated algorithm is used to sort each population, identify non-dominated individuals, and store them in a set. Next, the best location information $G_{r,d}$ is selected from other populations and stored in the set. The selection process of $G_{r,d}$

first sorts the remaining sub-groups in order of superiority and inferiority and selects the optimal solution as the non-dominated individual.

Meanwhile, a random method is used to choose a number of the remaining sub-groups, namely $[0, r-1]$. The number is rounded down to an integer d, where the value in d that is randomly selected is $G_{r,d}$. Then, the particle velocity and position are updated. Finally, the procedure is iterated, thereby resulting in the optimal solution. The new particle velocity update is shown in Eq. (9).

$$V_{i,r}^{t+1} = wV_{i,r}^{t} + \lambda_1 s_1 (pBest_{i,r} - X_{i,r}) + \lambda_2 s_2 (gBest_{i,r} - X_{i,r}) + \lambda_3 s_3 (G_{r,d} - X_{i,m}) \tag{9}$$

In Eq. (9), $\lambda_3 s_3 (G_{r,d} - X_{i,m})$ represents shared information from other populations, λ_3 and s_3 are learning factors and random numbers, respectively, and d is a random integer between 0 and r. However, when solving non-dominated problems, there are cases where two values are the same, and neither solution can dominate the other's problem. To solve this problem, the study introduces CD to calculate the CD of two solutions separately to select the solution with the largest CD as the optimal solution. CD is an indicator used in MOO algorithms to measure the distribution density of solutions. The calculation of CD is instrumental in averting premature convergence towards the local optimal solution. Fig. 5 displays the calculation process.

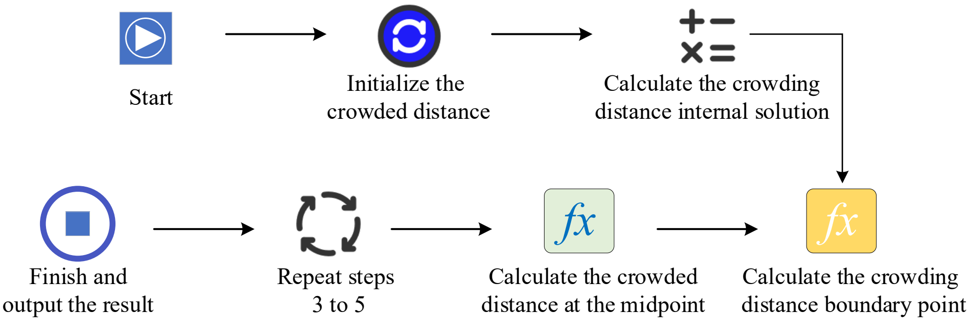


Fig. 5. Calculation process of crowding distance

As shown in Fig. 5, the process first initializes the CD of all solutions to 0. Then, for each objective function, the solutions in the non-dominated set are sorted based on their corresponding objective function values. The CD between the first and last solutions after sorting is set to infinity. The CD of the remaining solutions is calculated by accumulating the ratio of the difference in target values between adjacent solutions to the target value range. Finally, the CDs of each objective function are added to obtain the final CD. To address the issue of algorithms easily falling into local optima due to premature convergence, a method combining adaptive Cauchy mutation and polynomial mutation is proposed to enhance this aspect. This method first uses a convergence metric $C(p^{(g)})$ to determine whether the solution of the population has fallen into a local optimum. It can be represented by Eq. (10).

$$\begin{cases} o_i = \min\limits_{j=1} \sqrt{\sum_{q=1}^{Z} \left(\dfrac{f_q(i) - f_q(j)}{f_q^{max} - f_q^{min}} \right)} \\ C(p^{(g)}) = \dfrac{\sum_{i=1}^{Z} o_i}{Z} \end{cases} \tag{10}$$

In Eq. (10), $f_q(i)$ signifies the objective function value of the i-th individual; Z signifies the population size; f_q^{min} signifies the minimum value of the q-th problem to be optimized; $f_q(j)$ is the objective function value for the j-th individual; and f_q^{max} signifies the maximum value of the q-th problem to be optimized. If $C(p^{(g)})$ does not undergo significant changes after multiple iterations, $\left| C(p^{(g)}) - C(p^{(g-\sigma)}) \right| < \zeta$ is calculated, where ζ and σ are the threshold and evolutionary algebra, respectively, to determine whether the algorithm converges. Then, the diversity of solutions in the population is calculated across all dimensions. If the diversity of the j-th dimension is not greater than or equal to ζ, then mutation is performed. The mutation can be represented by Eq. (11).

$$\begin{cases} v_{i,j} = v_{i,j} + \phi * \chi(0,1),\ diversity(j) < \varepsilon \ and \ rand < 0.5 \\ v_{i,j} = v_{i,j} + (2 * rand)^{1/\varphi+1},\ diversity(j) \geq \varepsilon \ and \ rand < 0.5 \\ v_{i,j} = v_{i,j} + (1/(2*(1-rand)))^{1/\varphi+1},\ diversity(j) \geq \varepsilon \ and \ rand < 0.5 \end{cases} \tag{11}$$

In Eq. (11), φ is the polynomial mutation coefficient. $v_{i,j}$ signifies the value the i-th solution of the j-th dimension; ε signifies the preset threshold; $\chi(0,1)$ is a Gaussian distribution; ϕ is the Cauchy coefficient of variation; and $diversity$ represents diversity. $diversity$ can be represented by Eq. (12).

$$diversity(j)=\sqrt{\frac{1}{Z}*\sum_{i=1}^{Z}\left(\frac{v_{i,j}-\overline{v}_{i,j}}{\varpi_j-\vartheta_j}\right)^2} \tag{12}$$

In Eq. (12), ϖ_j signifies the maximum value of the j-th dimension; $\overline{v}_{i,j}$ signifies the average value of the individual's j-th dimension; and ϑ_j signifies the minimum of the j-th dimension. Finally, based on the above content, the MCPSO-ACPM algorithm for economic dispatch is built, as presented in Fig. 6.

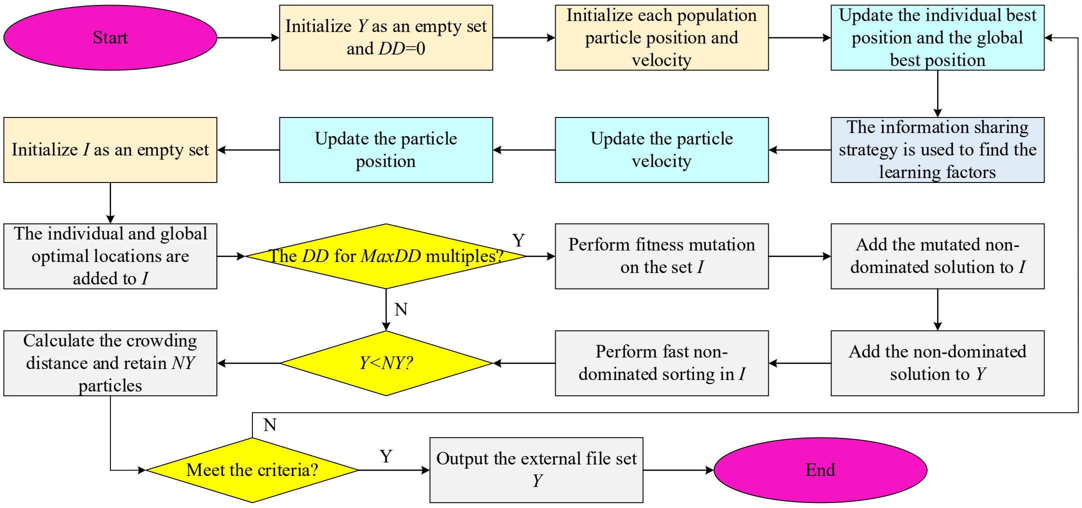


Fig. 6. The process of the MCPSO-ACPM algorithm

Fig. 6 I represents the external archive set; NY is the size of the external archive set; DD signifies the current iteration count; Y is a temporary set; and $MaxDD$ signifies the maximum iteration. In Fig. 6, the MCPSO-ACPM process begins by initializing I to store non-dominated solutions and setting DD to 0. Secondly, the velocity and position are initialized. Next, $pBest_{i,r}$ and $gBest_{i,r}$ are updated using Eq. (9) and (8). Subsequently, λ_1, λ_2 and λ_3 are used to update the velocity and position. Next, the temporary set Y signifies initialized, and the obtained individual best and global best particles are placed in Y. If DD is a multiple of $MaxDD$, the particles in Y are subjected to a Cauchy mutation, and the mutated particles are added to Y. Then, FNS is performed in Y, and the obtained non-dominated solutions are added to I. Whether the size of I is smaller than NY is judged, where the process will continue to execute if it is. Otherwise, the CD is calculated and NY particles are retained. Finally, whether the conditions are satisfied is determined. If not, the procedure returns to iteration to continue execution. Otherwise, the I-bit final non-dominated solution set is output, ending the algorithm.

3. Results

3.1. Performance Analysis of the MCPSO-ACPM Algorithm

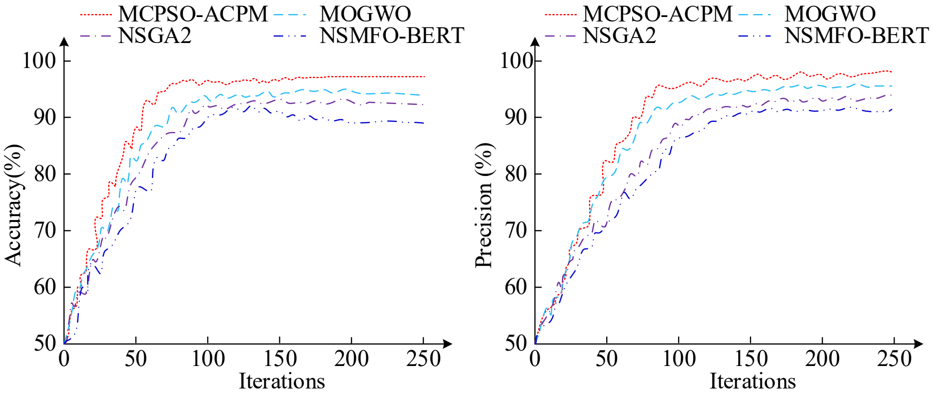
After constructing the MCPSO-ACPM algorithm, the study conducts performance comparison and analysis experiments with other algorithms. The experiment uses MATLAB software for data analysis and simulation. The inertia weight is 0.6, the population size and iteration times are 100 and 300, the external archive size and learning factor are 100 and 1.33, and the thresholds ε and ζ are 0.4 and 0.05, respectively, and $\phi=0.5-0.4*DD/MaxDD$. The dataset comes from the PGECI dataset, with a total of 18,903 entries, of which 70% are the training set, 20% are the testing set, and 10% are the validation set. Data preprocessing involves removing missing values and using median padding. Secondly, outliers are detected and removed. Then, the minimum maximum normalization algorithm is used for normalization processing. Finally, principal component analysis is taken to reduce the data dimensionality. The experimental comparison algorithms include MOGWO algorithm, NSGA2 algorithm, and NSMFO-BERT algorithm. The experimental comparison indicators include accuracy, F1 value, precision, etc. The experimental environment for each algorithm is shown in Table 1.

According to Fig. 7(a), the accuracy of MCPSO-ACPM, MOGWO, NAGA2, and NSMFO-BERT algorithms was 97.87%, 93.24%, 91.13%, and 89.97%, respectively. The MCPSO-ACPM had the highest accuracy. From Fig. 7(b), the precision of the MCPSO-ACPM algorithm was 96.88%, which was higher than that of MOGWO (94.58%), NAGA2 (93.61%), and NSMFO-BERT (90.26%). The higher the precision and accuracy, the better the optimization effect. Compared with comparison algorithms, the MCPSO-ACPM algorithm has the most superior performance. The F1 values and recall results of each algorithm are presented in Fig. 8.

Table 1. Experimental configuration

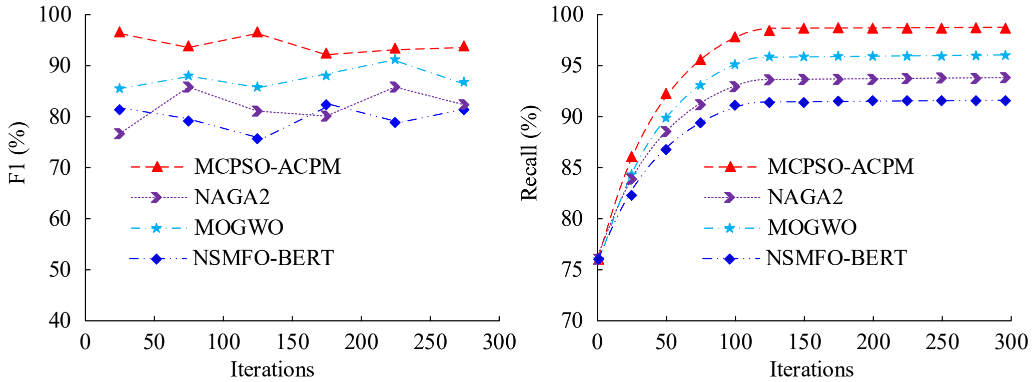
Parameter names	Parameter
Processor	Intel Core I9 13900KF
Main frequency	5.8GHz
Internal memory	32GB
Hard disk capacity	500GB
Operating system	Windows 10 64
MATLAB version	MATLAB 2022a

In the above environment, the study first conducts comparative experiments on the accuracy and precision, as presented in Fig. 7.



(a) Accuracy comparison result (b) Precision comparison result

Fig. 7. Comparison results of accuracy and precision

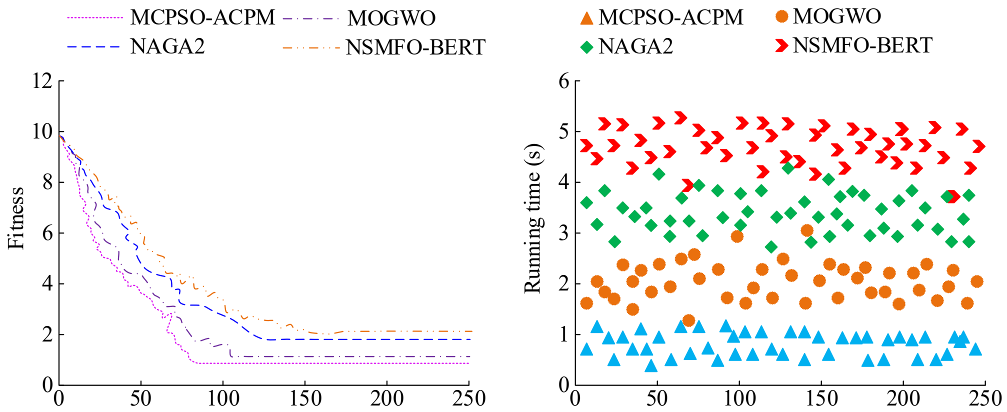


(a) Comparison results of F1 values (b) The Recall comparison results

Fig. 8. F1 values and recall results

From Fig. 8(a), the MCPSO-ACPM had the highest average F1 value, which was 97.49%. MOGWO was 88.76%, NAGA2 was 82.45%, and NSMFO-BERT was 80.14%. According to Fig. 8(b), the recall rates of MCPSO-ACPM, MOGWO, NAGA2, and NSMFO-BERT algorithms were 98.12%, 94.88%, 93.37%, and 92.17%, respectively, with the MCPSO-ACPM algorithm having the highest recall. The high F1 value and recall of the algorithm indicate its excellent performance in accurately discovering the optimal value. The MCPSO-ACPM performs better on F1 value and recall compared with other algorithms. The fitness and running time of each algorithm are presented in Fig. 9.

From Fig. 9(a), the fitness curve of the MCPSO-ACPM algorithm proposed in the study converged around 73 iterations, ahead of other algorithms. The fitness curve of MOGWO began to converge around 108 iterations, NAGA2 converged around 128 iterations, and NSMFO-BERT converged around 153 iterations. According to Fig. 9(b), the average computation time of MCPSO-ACPM, MOGWO, NAGA2, and NSMFO-BERT algorithms was 0.89s, 2.78s, 3.59s, and 4.89s, respectively. The MCPSO-ACPM had the shortest average computation time. The faster the running time, the higher the execution efficiency, which meant that tasks could be completed in a shorter time. The fast convergence speed indicates that the algorithm can find suitable solutions faster during the calculation process. For running time and fitness curve, the proposed algorithm performs better.



(a) Fitness comparison results (b) Comparison results of running time

Fig. 9. Comparison of fitness and running time

From Fig. 9(a), the fitness curve of the MCPSO-ACPM algorithm proposed in the study converged around 73 iterations, ahead of other algorithms. The fitness curve of MOGWO began to converge around 108 iterations, NAGA2 converged around 128 iterations, and NSMFO-BERT converged around 153 iterations. According to Fig. 9(b), the average computation time of MCPSO-ACPM, MOGWO, NAGA2, and NSMFO-BERT algorithms was 0.89s, 2.78s, 3.59s, and 4.89s, respectively. The MCPSO-ACPM had the shortest average computation time. The faster the running time, the higher the execution efficiency, which meant that tasks could be completed in a shorter time. The fast convergence speed indicates that the algorithm can find suitable solutions faster during the calculation process. For running time and fitness curve, the proposed algorithm performs better.

3.2. Analysis of Economic Dispatch Effectiveness

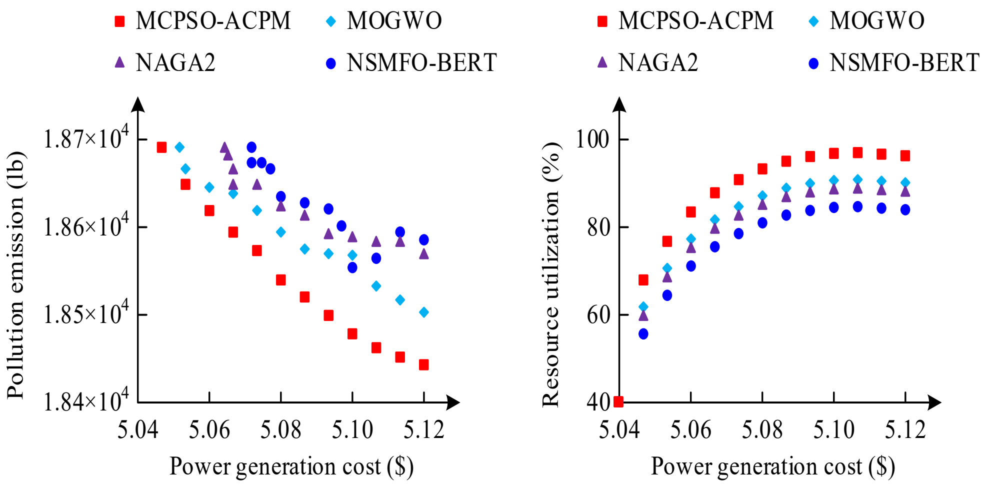
After comparing the MCPSO-ACPM, the economic dispatch model established is analyzed for its effectiveness in economic dispatch. One day is divided into 24 scheduling periods, and 5 thermal power generation units are selected for experimentation. Table 2 displays the parameters of power system units.

Table 2. Partial parameters of power system units

Unit number	Max Output (MW)	Lower output limit (MW)	Cost factor a ($/h)	Cost factor b ($/MWh)	Cost factor c ($/MW^{2}h)	Cost factor d ($/h)	Cost factor e (rad/MW)
1	74	15	0.042	25	1.9	100	0.008
2	290	60	0.035	480	1.7	200	0.002
3	115	10	0.039	60	1.7	130	0.003
4	240	30	0.038	110	1.9	170	0.001
5	160	400	0.036	90	2.0	180	0.001

In the above parameter settings of the power system, economic dispatch experiments are conducted using MCPSO-ACPM, MOGWO, NAGA2, and NSMFO-BERT algorithms. The experimental indicators are the Pareto optimal frontier and the resource utilization rate, as displayed in Fig. 10.

In Fig. 10(a), during economic dispatch, the MCPSO-ACPM algorithm had a pollution emission of 1.87×10^4d when the power generation cost was 5.04 $, and a pollution emission of 1.84×10^4d when the cost increased to 5.12 $. During this process, both the cost and pollution emissions were lower than those of MOGWO, NAGA2, and NSMFO-BERT algorithms. From Fig. 10(b), when the power generation cost reached $5.12, the resource utilization rates of MCPSO-ACPM, MOGWO, NAGA2, and NSMFO-BERT algorithms were 98.99%, 93.67%, 91.54%, and 84.62%, respectively. The MCPSO-ACPM had the highest resource utilization rate and can achieve lower pollution emissions and higher resource utilization at lower power generation costs. Its performance is superior to other algorithms, indicating that it has significant advantages in economic dispatch. To verify the effectiveness, accuracy and environmental friendliness of the proposed algorithm in power production control, it was placed in the small-scale power system of a certain company for practical application. The reduction in power generation costs, reduction in pollution emissions, improved resource utilization, and environmental friendliness score are compared with the results of the original system, as shown in Table 3.



(a) Pareto optimal frontier results (b) Resource utilization results

Fig. 10. Experimental results

As can be seen from Table 3, the power generation cost of the algorithm proposed in the research is reduced by 14.27%, which is significantly higher than that of the MOGWO algorithm at 7.58%, the NAGA2 algorithm at 5.49%, and the NSMFO-BERT algorithm at 53.76%. In addition, the reduction in pollution emissions and improved resource utilization were 15.89% and 6.79% respectively, which were significantly higher than those of the comparison algorithm. Moreover, its environmental friendliness score is high, which is superior to the comparison algorithm. MCPSO-ACPM can reduce costs and enhance market competitiveness and profitability of power enterprises and achieve environmentally friendly production by reducing pollution emissions. The above results indicate that the MCPSO-ACPM algorithm has significant advantages in practical applications, especially in scenarios where a balance between economic benefits and environmental responsibilities is required.

4. Discussion

The research analyzed the performance of MCPSO-ACPM and its effectiveness in power systems. The MCPSO-ACPM algorithm had obvious advantages in multiple indicators. The accuracy of MCPSO-ACPM, MOGWO, NAGA2, and NSMFO-BERT was 97.87%, 93.24%, 91.13%, and 89.97%, respectively. The MCPSO-ACPM had the highest accuracy, indicating that the introduced information-sharing strategy and FNS have improved accuracy. This result is inconsistent with the research findings obtained by Zheng Y et al. (2022) on improving the PSO algorithm. In the precision comparison experiment, the precision of MCPSO-ACPM, MOGWO, NAGA2, and NSMFO-BERT algorithms was 96.88%, 94.58%, 93.61%, and 90.26%, respectively. The MCPSO-ACPM algorithm proposed in the study had the highest precision, signifying that the introduced sharing strategy, FNS, and CD improve the optimization performance. This result aligns with the research findings presented by Li Q et al. (2023). During operation, the computation time of MCPSO-ACPM, MOGWO, NAGA2, and NSMFO-BERT algorithms was 0.89s, 2.78s, 3.59s, and 4.89s, respectively. The MCPSO-ACPM had the shortest average computation time, denoting that the introduced information sharing strategy, FNS, crowded distance, and adaptive Cauchy mutation improves the convergence speed and computational efficiency. This result is consistent with the research findings drawn by Zaaraoui et al. (2022). In addition, the MCPSO algorithm proposed in the study had an average F1 value of 97.49%, a fitness convergence iteration number of about 73, and a recall rate of 98.12%, surpassing those of the comparison algorithms. This result further validates superiority. Subsequently, MCPSO-ACPM, MOGWO, NAGA2, and NSMFO-BERT algorithms reduced carbon emissions from 1.87×10^4ld to 1.84×10^4ld when the generation cost increased from \$5.04 to \$5.12. In this process, both cost and pollution emissions were lower than MOGWO, NAGA2, and NSMFO-BERT algorithms, which indicates that the introduced information sharing strategy, FNS, crowded distance, and adaptive Cauchy mutation improves the optimization performance. This result is matched with the conclusion obtained by Yafei and Liang (2023). The above results show that electricity is essential for economic growth but producing and delivering it in a way that is affordable, reliable, and environmentally friendly remains a major challenge. Traditional scheduling methods often struggle to balance these goals, as they can be slow, inaccurate, or too simplistic to identify the cheapest and cleanest ways to generate power. The MCPSO-ACPM algorithm was developed to address this issue by providing power companies with a faster and more accurate way to determine the best combination of generators to use at any given time. This helps reduce fuel costs, lower carbon emissions, and maintain grid stability, ultimately supporting smarter, more sustainable energy decisions without compromising on cost, reliability, or environmental responsibility.

5. Conclusion

Due to the poor optimization effect and low accuracy of multi-objective economic dispatch methods, the study first constructed a power system dispatch model and developed the MCPSO-ACPM, upon which comparative analysis experiments were conducted. The algorithm demonstrated good performance in terms of F1 value, precision, running time, and fitness, all of which were superior to those of the comparison algorithms. Subsequently, in the economic dispatch experiment, the MCPSO-ACPM outperformed the comparison algorithms in both the Pareto optimal frontier and resource utilization rate. The MCPSO-ACPM also has good performance and has sound application effects in economic dispatch of power systems, offering significant practical benefits for power system operators. It can control power production more efficiently and accurately, thereby reducing fuel consumption and operating costs. By optimizing dispatch decisions, the approach supports cleaner and more environmentally sustainable energy management, which is essential for meeting emission reduction targets and environmental standards. The limitation of this study is that it does not take into account the economic dispatch of new energy sources like wind and solar energy integration. Further research should focus on the economic dispatch of new energy integration.

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Institutional Review Board Statement

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Declaration of Artificial Intelligence (AI) Tools

The author confirms that no AI tools were used in the preparation of this manuscript.

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