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Research on Information Interaction and Computational Model Design in Multi-Terminal Grid Scheduling Optimization

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Abstract Multi-terminal grid system contains wind power, photovoltaic power generation, energy storage equipment and other distributed power sources, and its operating characteristics are complex and variable, so the traditional optimization method is difficult to effectively deal with the scheduling decision-making problem under multi-objective constraints. In this paper, an adaptive particle swarm optimization algorithm based on information interaction mechanism is proposed to address the problems of low information interaction efficiency and insufficient computational accuracy in multi-terminal grid scheduling optimization. The method constructs a multi-objective optimal scheduling model with the objectives of lowest operation cost, maximum environmental benefit and highest system security, adopts a chaotic initialization strategy to enhance the diversity of particle swarms, designs an information interaction mechanism to enhance the global search capability of the algorithm, and establishes an adaptive updating strategy to avoid local optimum. The performance of the algorithm is verified by the ZDT test function, and the results show that the SP value of the improved algorithm on the ZDT3 function is only 0.0096, which is 75% of that of the traditional PSO algorithm; the GD value is 1.9224e-04, which is better than that of the traditional algorithm, which is 2.0905e-04. In the actual multi-terminal grid scheduling experiments, the maximum load of the user is 2200kW, and the daily load rate is 44.5%. The total load fluctuation range of the grid is optimized from 400-900 MW to 560-760 MW after scheduling with the proposed method.This study provides effective technical support for the optimal scheduling of multi-terminal grids, and significantly improves the stability and economy of system operation.

Index Terms Multi-terminal grid, information interaction mechanism, adaptive particle swarm optimization algorithm, scheduling optimization, chaotic initialization, system security

I. Introduction

Electricity security has long been closely linked to social, political and national stability and development. With the continuous development of the social economy and the promotion of the "double carbon" goal, such as industrial production, information technology, health care, transportation, public safety and residential life put forward higher requirements for the security and stability of the power system, which promotes the development of the power system [1]-[3]. In addition, the electric power industry is a key area of energy transition. Traditional thermal power generation and nuclear power generation are gradually restricted, and the transition to clean energy has become an inevitable choice for the power industry [4], [5]. And nowadays, solar photovoltaic, wind, hydro and other renewable energy generation methods, become an important development direction of the power industry, the global installed capacity of renewable energy has long exceeded 4 billion kilowatts, leading to changes in the traditional grid scheduling [6], [7]. Due to the stochastic nature of the energy side of the traditional scheduling model of the misfit, making its uncertainty enhanced, at the same time, the terminal equipment is gradually diversified, and its scheduling problems have become the focus [8], [9].

In power systems, grid terminal equipment is the key infrastructure of the power system, which includes protection devices, condition estimation, monitoring and control and data acquisition systems, and phase measurement units, as well as communication equipment including the Internet and automation control systems [10]-[12]. These devices are responsible for the monitoring and management of a specific area or equipment and collect relevant grid data in real time. However, with the development and application of various types of modern grid terminal systems, problems such as temporal and spatial mismatch, protocol barriers, security, and efficiency of information interaction ensue, and the traditional computational model, with the increase of computational problems, has a lower response efficiency and poor adaptability in the face of specific renewable energy scenarios [13]-[16]. In order to ensure the safe and stable operation of the power system, rational scheduling of grid terminal equipment is crucial for the whole power system.

The transformation of energy structure and the intelligent development of power system have promoted the rapid progress of multi-terminal grid technology, and the large-scale access of distributed power supply has brought new challenges to the traditional grid scheduling. Multi-terminal grid system integrates wind power generation, photovoltaic power generation, energy storage equipment, micro-gas turbines and other heterogeneous power sources, and there are complex coupling relationships and uncertainty characteristics between the power sources, which makes the system scheduling decision face multi-dimensional constraints and multi-objective optimization problems. Existing scheduling methods have obvious deficiencies when dealing with information fusion, real-time decision-making and global optimization in a multi-terminal environment, especially in terms of algorithm convergence, computational efficiency and quality of the solution, which are difficult to meet the actual needs of engineering. Although the traditional particle swarm algorithm has the advantages of simple structure and easy implementation, it is easy to fall into the local optimum in multimodal complex optimization problems, with weak search ability in the later stage, and cannot effectively balance the relationship between exploration and development. The lack of information interaction mechanism leads to poor inter-particle collaboration, which affects the global optimization performance of the algorithm.

Based on the above problems, this study proposes an adaptive particle swarm optimization algorithm based on information interaction mechanism to solve the optimization problem of multi-terminal grid scheduling. Firstly, a multi-objective optimization model including operation cost, environmental benefit and system security is constructed, and a complete constraint system of power balance, output constraints and standby capacity is established. Secondly, a chaotic initialization strategy is adopted to achieve uniform distribution of particles, a neighborhood information interaction mechanism is designed to enhance the diversity of the population, and the performance of the algorithm is improved by the adaptive adjustment of the global-local search strategy. Finally, the effectiveness of the algorithm is verified by standard test functions, and scheduling optimization experiments are carried out in real multi-terminal grid systems to verify the engineering practicability of the proposed method.

II. Multi-terminal grid optimization scheduling model

This chapter takes the multi-terminal grid system as the research object, analyzes the operation mechanism of each distributed power source and constructs the corresponding mathematical model, then proposes the single-objective optimal scheduling which minimizes the operation cost and pollutant management cost, and the multi-objective joint optimal scheduling which optimizes the comprehensive benefit of the system, and finally clarifies the constraints that must be met by the operation of the multi-terminal grid system, which lays a foundation for the subsequent optimal scheduling of the energy source.

II. A. Objective function of the optimal dispatch model for multi-terminal grids

II. A. 1) Minimized total operating costs of the multi-terminal grid

Objective function 1: Minimize the total operating cost of the multi-terminal grid system. The operating cost includes the generation cost of each generation unit, the depreciation cost and the power exchange cost between the multi-terminal grid and the main grid.

$$C_1=\sum_{t=1}^{T}\left(\sum_{i=1}^{N}F_i(P_i(t))+C_{DE}(P_i(t))+kC_{grid}P_{grid}(t)\right) \tag{1}$$

When $k=0$, it means that the multi-terminal grid is in the state of isolated grid operation, and there is no electrical energy connection between the multi-terminal grid system and the main grid system; when $k=1$, it means that the multi-terminal grid is in the state of grid-connected operation, and there is an exchange of electrical energy between it and the main grid system:

$$F_i(P_i(t))=C_{Fi}(P_i(t))+C_{OMi}(P_i(t)) \tag{2}$$

$$C_{DE}(P_i(t))=\frac{C_{ADCCi}}{8760P_{fci}\times cf_i}\times P_i(t) \tag{3}$$

$$C_{grid}P_{grid}(t)=\begin{cases}C_{buy}P_{grid}(t), & P_{grid}(t)\geq 0\\ -C_{buy}P_{grid}(t), & P_{grid}(t)<0\end{cases} \tag{4}$$

$C_{OMi}(P_i(t))$ is the maintenance cost of operating the i th generation unit, where the maintenance cost is as follows.

$$C_{OMi}(P_i(t)) = K_{OMi} \times P_i(t) \tag{5}$$

C_{ADCCi} is the average annual cost of the installed cost of each generating unit in a multi-terminal grid, where,

$$C_{ADCCi} = C_i \times \frac{d(1+d)^L}{(1+d)-1} \tag{6}$$

II. A. 2) Maximum environmental benefits

The maximization of environmental benefits requires the minimization of emissions and the economization of pollution control behavior, which is where the social development trend lies and the focus of the environmental management system.

Objective function 2: Maximize environmental benefits, i.e., minimize the cost of treatment when discharging pollutants from multi-terminal power grids, the mathematical model is shown in Equation (7).

$$\min C_2 = \sum_{t=1}^{T}\left(\sum_{k=1}^{M} 10^{-3} C_k \left(\sum_{i=1}^{N} r_{ik} P_i(t) + ar_{gridk} CGP(t)\right)\right) \tag{7}$$

II. A. 3) Maximum security assessment of multi-terminal grid systems

Objective function 3: The security of the multi-terminal grid system is evaluated to be the highest, i.e., the multi-terminal grid system minimizes the operational risk in the operation process.

The power output of wind power generation varies greatly in a short period of time, therefore, in order to make the multi-terminal grid system safe and reliable in providing power to users, it is necessary to predict the wind power generation output in the multi-terminal grid to determine the upper and lower limits of the required standby capacity, in order to prevent the impact of fluctuations caused by the instability of the wind power generation unit on the system.

The mathematical model of the risk level of the multi-terminal grid system is formulated as follows:

$$C_3(t) = \begin{cases} 1 - \dfrac{R(t)}{risk \cdot P_{wp}}, & R(t) < risk \cdot P_{wp} \\ 0, & R(t) \geq risk \cdot P_{wp} \end{cases} \tag{8}$$

$$C_3 = \sum_{t=1}^{T} C_3(t) \tag{9}$$

$C_3(t)$ is the degree of risk in the operation of micro power sources in the multi-terminal grid system; risk is the weighting coefficient of the system to cope with the fluctuations generated by wind and PV power generation; $R(t)$ is the standby capacity that can be provided by the storage device at time period t; and P_{wp} is the sum of the rated capacity of wind turbines and PV batteries in the multi-terminal grid system.

II. A. 4) Maximizing the total benefits of multi-terminal grid operations

Maximizing the total benefit of multi-terminal grid operation means that the multi-terminal grid operation is the most economical, in order to operate the most economical, it is necessary to make a reasonable combination of the objective function 1, objective function 2, and objective function 3, so as to maximize the total benefit of multi-terminal grid operation. The weighted coefficient method is used to synthesize the three objective functions to calculate the total benefit, then the formula expression is as follows:

$$\min C_4 = w_1 C_1 + w_2 C_2 + w_3 C_3 \tag{10}$$

II. B. Multi-terminal grid operation constraints

Optimal scheduling belongs to the selection of multi-objective problems, mathematically they do not have a uniquely determined solution, it is often necessary to determine a mathematical model of the objective function, which needs to satisfy the corresponding requirements of the constraints to find the extreme values of the mathematical model. The usual mathematical description is:

Objective function:

$$\min f(x) \tag{11}$$

Constraints:

$$g(x)=0 \tag{12}$$

$$h(x)\le 0 \tag{13}$$

The constraints can not only optimize each power source output, but also make better economic operation of the multi-terminal grid operation system, the specific constraints of the tariff are as follows.

(1) Power balance constraints

$$P_d^t + P_{loss}^t = \sum_{i=1}^{N} P_{Gi}^t + P_{grid}^t \tag{14}$$

P_d^t denotes the load power of the multi-terminal grid system within t time period; P_{loss}^t denotes the loss power in the multi-terminal grid system in the process of delivering electric energy within t time period; P_{Gi}^t denotes the power output from each power source of the multi-terminal grid within t time period; and N is the total number of generating units in the multi-terminal grid system; P_{grid}^t denotes the active power traded between the multi-terminal grid and the main grid during the t time period.

(2) Output constraints of power sources in the multi-terminal grid:

$$P_i^{\min} \le P_{Gi} \le P_i^{\max} \tag{15}$$

$P_i^{\min}$, $P_i^{\max}$ denote the values of minimum power and maximum power emitted by power source i in the multi-terminal grid at moment t, respectively.

(3) Constraints on power exchange between the multi-terminal grid and the main grid:

$$P_{grid}^{\min} \le P_{grid\_i} \le P_{grid}^{\max} \tag{16}$$

$P_{grid}^{\min}$ and $P_{grid}^{\max}$ denote the values of minimum and maximum power exchanged between the multi-terminal grid system and the main grid, respectively; if $P_{grid}^{\max} > 0$, it means that the main grid outputs power to the multi-terminal grid system, and $P_{grid}^{\min} < 0$, it means that the multi-terminal grid delivering power to the main grid system.

(4) Constraints on standby capacity

Standby capacity plays a role in smoothing fluctuations in the power generation process, which can solve the fluctuations generated by wind and solar power generation and other uncertainties that cause errors in load forecasting leading to system instability.

$$\sum_{n=1}^{N} P_n^{\max} \ge P_L(t) + P_s(t)\cdot L\% + p_{wp}(t)\cdot u_s\% \tag{17}$$

$L\%$ denotes the load demand factor for standby capacity in the multi-terminal grid system; $u_s\%$ denotes the demand factor for standby capacity of wind and photovoltaic generating units; and $p_{wp}(t)$ denotes the sum of the rated capacity of wind and photovoltaic generating units in the multi-terminal grid system at time t.

(5) CO_2, SO_2 and NO_x emission constraints:

$$\sum_{i=1}^{N} E_{CO_{2i}}(P_i) \le L_{CO_2} \tag{18}$$

$$\sum_{i=1}^{N} E_{SO_{2i}}(P_i) \le L_{SO_2} \tag{19}$$

$$\sum_{i=1}^{N} E_{NO_{xi}}(P_i) \le L_{NO_x} \tag{20}$$

In the above equations L_{CO_2}, L_{SO_2}, and L_{NO_x} denote the limits on the amount of CO_2, SO_2, and NO_x gases emitted at the time of micro-power outage in a multi-terminal grid system, respectively.

(6) Power constraints for batteries:

$$P_{bt}^{\min} \le P_{bt}^{i} \le P_{bt}^{\max} \tag{21}$$

$$\sum_{i=1}^{T} P_{bt}^{i}\delta = 0 \tag{22}$$

$P_{bt}^{\max}$, $P_{bt}^{\min}$ denote the maximum and minimum values of the charging and discharging power of the energy storage device.

II. C. Scheduling strategy

When running in different states, the scheduling strategies are different accordingly, as follows:

(1) When the multi-terminal grid operates in the grid-connected state, photovoltaic power generation and wind power generation should be required to be fully utilized, and at the same time, power should be sold and purchased from the main grid in accordance with the sale price of the main grid as appropriate, and the energy storage equipment of the multi-terminal grid should also be charged to generate power, so as to make the amount of its power reserve reach the constraints of the requirements.

(2) When the multi-terminal power grid operates in an isolated grid state, the same photovoltaic power generation and wind power generation should be required to be fully utilized, and the output power of other power generation units should be regulated through the relationship between the output power of the micro-power supply and the power consumption of the online users, and the output power of the other power generation units should be scheduled taking into account the comprehensive cost of their power generation to make them participate in the scheduling of the multi-terminal power grid in turn.

II. D. Particle Swarm Algorithm

The PSO algorithm [17] is inspired by the laws of bird activities in nature: (1) birds are group animals, and in the process of searching for food, they will follow the movement of the flock, thus gradually approaching the area where the food is located; (2) in the process of flying, the speed of the bird will be affected by its own initial speed as well as the migration speed of the whole flock, in addition to being related to the external environmental factors; (3) in the process of feeding and migration process, the birds will pass information to each other, through which they assist each other to reach the final destination. In PSO algorithm, the collection of particles is identified as a group, and each particle in the group represents the solution of the objective function, which move in different directions according to certain speeds and paths, and search for the optimal solution to satisfy the objective function in the process of movement, which is very similar to the movement law of the bird flocks, so the PSO algorithm is considered as a group optimization algorithm simulating the social behaviors of the bird flocks.

During the working process of the PSO algorithm, the individual optimal position of each particle needs to be recorded and stored, and the global optimal position found by the PSO algorithm in the whole population also needs to be maintained. The PSO algorithm consists of three main steps: (1) evaluating the fitness of each particle; (2) updating the global optimal position and individual optimal position of each particle; and (3) updating the velocity and position of each particle to further evaluate the fitness of the particle.

Each particle stores its best fitness value obtained during the operation of the algorithm, and the particle with the best fitness value compared to the other particles is also computed and updated during the iteration process, repeating the second and third steps until it reaches the maximum number of iterations or stops after satisfying certain criteria.

The optimization process of PSO algorithm is as follows:

(1) Initialize the parameters as well as the position and velocity of the particles.

(2) Calculate the fitness values of the particles to prepare for the iteration. The individual optimum is derived from the comparison of the historical positional fitness values of individual particles, and the population optimum is derived from the comparison of the individual optimums of all particles.

(3) The position and speed of the next search are updated according to Eq.

(4) When the number of iterations reaches the maximum or the expected optimal value is found, the group optimal is output, otherwise the cycle of the previous step continues.

(5) Algorithm optimization process ends.

II. E. Solution of adaptive particle swarm optimization algorithm based on information interaction

Particle swarm algorithms have now been successfully applied to many optimization problems due to their simple structure and easy implementation. However, the standard particle swarm algorithm tends to fall into local optimization and shows weak searchability in the later stage. In order to solve this problem, this chapter will propose an adaptive particle swarm optimization algorithm with an information interaction mechanism, which enriches the population diversity in terms of initialization method, optimality search mechanism and particle update strategy to improve the optimality search performance. In addition, the proposed algorithm is proved to be strictly convergent. Finally, the APSOIIM algorithm is practically applied to real engineering problems and optimal scheduling under multi-terminal grid systems [18].

II. E. 1) Chaos initialization

In order to achieve a uniform distribution of population particles as much as possible, a chaotic initialization strategy is introduced [19]. The initial particles are first randomly generated, and then the chaotic operation is executed by Eq. (24), and the obtained particles will be uniformly distributed in the solution space.

$$X_i = X_{\min} + (X_{\max} - X_{\min}) * r_1 \tag{23}$$

$$X_{i+1} = \mathrm{mod}\left(X_i + 0.2 - \frac{0.5}{2\pi} \times \sin(2\pi X_i), 1 \right) \tag{24}$$

where, X_i is the position of the i th particle; X_{i+1} is the position of the i th particle after the chaotic operation; $X_{\min}$ and $X_{\max}$ are the position limits; and r_1 is a random number between 0 and 1.

II. E. 2) Information interaction mechanisms

Aiming at the problem that standard particle swarm algorithms are generally prone to local optimization, an information interaction mechanism is investigated to enhance the diversity of the population. Based on the global model topology, the proposed mechanism evaluates the particle update from various perspectives, not only considering the individual optimality and global optimality, but also tracking the individual optimality of the neighboring particles, and guiding the particles towards the actual optimality from various aspects, as shown in Fig. 1.

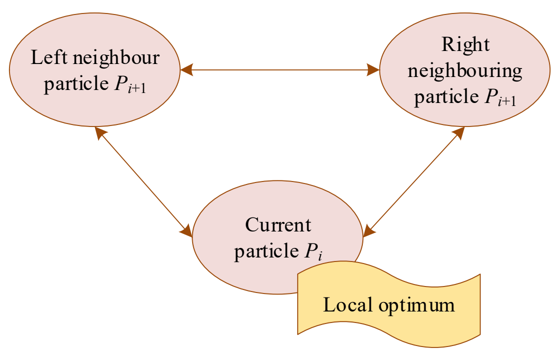

Figure 1: Schematic diagram of interactive information machine

Each upgrade iteration under the information interaction mechanism changes from single-particle to multi-particle (current particle, left-neighboring particle and right-neighboring particle). In this case, no matter any one of the three particles falls into the local optimum, the other two particles adjacent to it can still maintain the exact direction of optimization through information sharing, which reduces the probability of falling into the local optimum.

II. E. 3) Particle Update Strategy

The topology of PSO will be improved to address the problem of low accuracy and poor convergence at the late stage of PSO iterations. The common PSO topology is the global model, i.e., only the current individual optimum and the global optimum are considered in the iterative evolution of the algorithm, which is very easy to fall into the local optimum. In addition, there is the local model, which is really effective in avoiding falling into local optimum because it can only exchange information between neighboring particles, but its iteration time will be increased substantially and accompanied by slower iteration speed, so a new iteration form is developed, which optimizes the particle speed updating formula to not only interact with the information of neighboring particles, but also to take into account the global model. In this way, the particle update is not only affected by $pbest_{i,j}^t$ and $gbest_{i,j}^t$, but also by the local optimality of neighboring particles. This iterative approach, which integrates the particle evolution, enriches the diversity of the population while maintaining the iteration speed.

In addition, it is worth noting that comparing the fitness value of the particle in the t th iteration with the optimal fitness value of the previous generation can determine the updating strategy of the next particle, as shown in Eq. (27).

$$v_{i,j}^{t+1} = \lambda \times \left[v_{i,j}^{t} + P \right] \tag{25}$$

$$x_{i,j}^{t+1} = x_{i,j}^{t} + v_{i,j}^{t+1} \tag{26}$$

$$P = \begin{cases} c_1 r_1 (pbest_{i-1,j}^{t} - x_{i,j}^{t}) + c_2 r_2 (pbest_{i,j}^{t} - x_{i,j}^{t}) & \text{if } fitness(particle_{i,j}^{t}) \\ + c_3 r_3 (pbest_{i+1,j}^{t} - x_{i,j}^{t}) & > fitness(gbest_{i,j}^{t-1}) \\ & \text{if } fitness(particle_{i,j}^{t}) \\ c_4 r_4 (gbest_{i,j}^{t} - x_{i,j}^{t}) & \leq fitness(gbest_{i,j}^{t-1}) \end{cases} \tag{27}$$

where, r_1, r_2, r_3 and r_4 are random numbers between 0 and 1; $v_{i,j}^{t}$ and $x_{i,j}^{t}$ denote the velocity and position components; $pbest_{i,j}^{t}$ is the individual optimum of the i th particle in the j th dimension under the t th iteration; $gbest_{i,j}^{t}$ is the global optimum of the i th particle in the j th dimension under the t th iteration; λ is the compression factor; and c_1, c_2, c_3 and c_4 are the acceleration factors.

Through Eq. (27), it can be seen that if the adaptation value of the t th iteration is better than that of the previous generation, the focus should be placed on local search and the parameters c_1, c_2 and c_3 should be set to 0, i.e., $c_1 = c_2 = c_3 = 0$. On the contrary, if no better fitness value is found, the global search should be maintained, i.e., $c_4 = 0$. The λ and c are updated using the following formula.

$$\lambda = \frac{2}{\left| \left(2 - c - \sqrt{c^2 - 4c} \right) \right|} \tag{28}$$

$$c = \sum_{i=1}^{4} c_i \tag{29}$$

$$c_i = \begin{cases} c_{iM} - (c_{iM} - c_{iN}) \times \dfrac{Iter}{Iter_{\max}}, & i = 1,2,3 \\ c_{iN} + (c_{iM} - c_{iN}) \times \dfrac{Iter}{Iter_{\max}}, & i = 4 \end{cases} \tag{30}$$

where, $Iter$ refers to the current iteration number; $Iter_{\max}$ denotes the iteration maximum; c_{iN} denotes the initial value and c_{iM} is the final value.

III. Multi-terminal grid optimization scheduling simulation experiment

III. A. Adaptive particle swarm algorithm performance test

In order to test the effectiveness of the improved APSOIIM algorithm in this paper, the improved APSOIIM algorithm is compared with the traditional PSO algorithm, and the improved APSOIIM algorithm is evaluated in terms of distributivity and convergence, respectively.

(1) Convergence index

Generation distance can represent the Euclidean distance between the solutions in the solution set to be evaluated and the true Pareto solution, but in this application, the dynamic change process of the population with non-dominated ordering of 1 needs to be measured, so the generation distance between the population in the current generation and the previous generation is taken, denoted as $GD*$, and the difference of $GD*$ between the solution sets of the 2 neighboring generations is denoted as Δ_{GD*}.

$$\Delta_{GD*}(t) = GD*(t) - GD*(t-1), t \geq 3 \tag{31}$$

where, $\Delta_{GD*}(t)$ is the difference between the generation distance of the t th-generation population and the $t-1$ th-generation population, which can characterize the convergence speed of the algorithm; When $\Delta_{GD*}(t) > 0$, the algorithm converges fast, and the variant size should be reduced to improve the efficiency of the algorithm; When

$\Delta_{GD*}(t) < 0$, the variant size has to be increased to improve the convergence and diversity of the algorithm. $GD*(t)$ is the generation distance of the population in generation t ; $GD*(t-1)$ is the generation distance of the population in generation $t-1$.

$$Q(t+1) = \begin{cases} \mathrm{int}\,eger(0.75Q(t)), & \Delta_{GD*}(t) > 0 \\ Q(t), & \Delta_{GD*}(t) = 0 \\ \mathrm{int}\,eger(1.25Q(t)), & \Delta_{GD*}(t) < 0 \end{cases} \tag{32}$$

where, $Q(t+1)$ is the variation scale of the $t+1$ th generation; $\mathrm{int}\,eger(\ )$ is the rounding function; $Q(t)$ is the variation scale of the t th generation, and $Q(t)$ is equal to the number of particles with the current nondominated ordering of 1 when $t = 1,2,3$.

The Generation Distance (GD) evaluation method is used, and the smaller the value of GD, the closer the solution set obtained by the algorithm is to the real Pareto optimal frontier.

$$GD = \frac{1}{n}\sqrt{\sum_{i=1}^{n} d_i^2} \tag{33}$$

d_i denotes the distance between the Pareto front derived by the algorithm and the true Pareto.

(2) Distributability index

The spatial evaluation method (SP) is used, and the smaller the value of SP, the more uniformly the Pareto solution set is distributed.

$$SP = \sqrt{\frac{1}{n-1}\sum_{i=1}^{n}(d' - d_i)^2} \tag{34}$$

$$d_i = \min\left(\left|f_1^i(x) - f_1^j(x)\right| + \left|f_2^i(x) - f_2^j(x)\right|\right), i, j = 1, \cdots, n \tag{35}$$

d' denotes the average of all d_i ; n denotes the size of the known Pareto boundary.

ZDT1:

$$\begin{aligned} &\min f_1(x) = x_1 \\ &\min f_2(x) = g(x)\left[1 - \sqrt{f_1(x)/g(x)}\right] \quad 0 \le x_i \le 1 \\ &g(x) = 1 + \frac{9\left(\sum_{i=2}^{n} x_i\right)}{(n-1)} \quad 1 \le i \le 30 \end{aligned} \tag{36}$$

ZDT2:

$$\begin{aligned} &\min f_1(x) = x_1 \\ &\min f_2(x) = g(x)\left[1 - \left(\frac{f_1(x)}{g(x)}\right)^2\right] \quad 0 \le x_i \le 1 \\ &g(x) = 1 + \frac{9\left(\sum_{i=2}^{n} x_i\right)}{(n-1)} \quad 1 \le i \le 30 \end{aligned} \tag{37}$$

ZDT3:

$$\begin{aligned} &\min f_1(x) = x_1 \\ &\min f_2(x) = g(x)\left[1 - \sqrt{x_1/g(x)} - \frac{x_1}{g(x)}\sin(10\pi x_1)\right] \quad 0 \le x_i \le 1 \\ &g(x) = 1 + \frac{9\left(\sum_{i=2}^{n} x_i\right)}{(n-1)} \quad 1 \le i \le 30 \end{aligned} \tag{38}$$

Simulation experiments are conducted using the APSOIIM algorithm before and after improvement for ZDT1, ZDT2 and ZDT3 test functions, respectively. The parameters are set as follows: the maximum value of inertia weight is 0.8 and the minimum value is 0.3; the learning factor is $c_1 = c_2 = 2$; for the ZDT test function, the initialized population size is 200 and the external archive size is 150; and the maximum number of iterations is 600.Fig. 2~Fig. 7 represent the algorithms of the traditional PSO algorithm and the improved APSOIIM algorithm for the test functions ZDT1, ZDT2, and ZDT3 respectively Simulation results.

Comparing Fig. 2~Fig. 7, it can be seen that the Pareto front of the improved APSOIIM algorithm overlaps with the real Pareto front more.

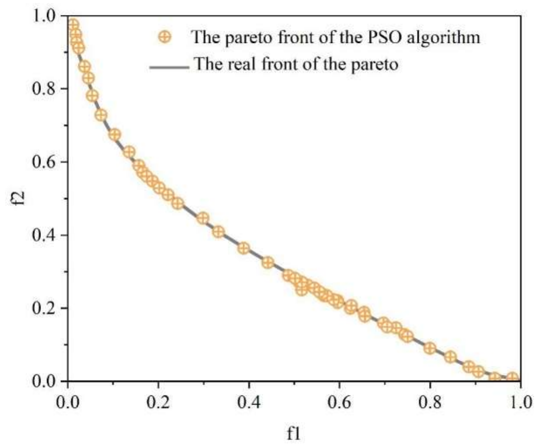

Figure 2: Optimization results of the PSO algorithm ZDT1

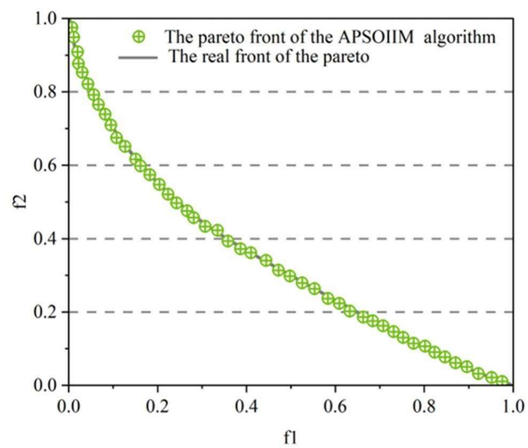

Figure 3: Optimization results of the APSOIIM algorithm ZDT1

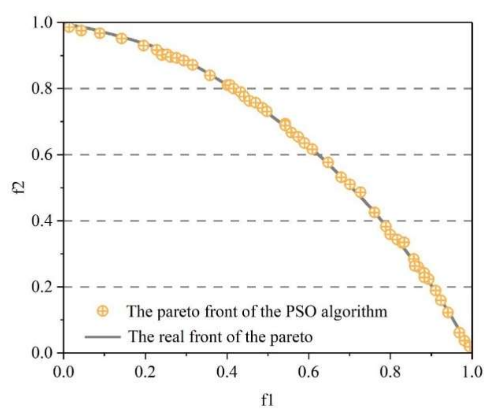

Figure 4: Optimization results of the PSO algorithm ZDT2

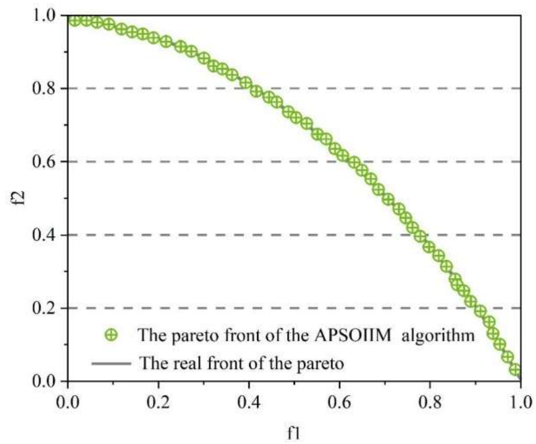

Figure 5: Optimization results of the APSOIIM algorithm ZDT2

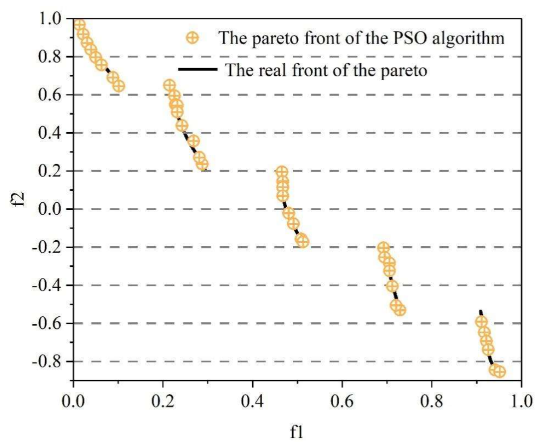

Figure 6: Optimization results of the PSO algorithm ZDT3

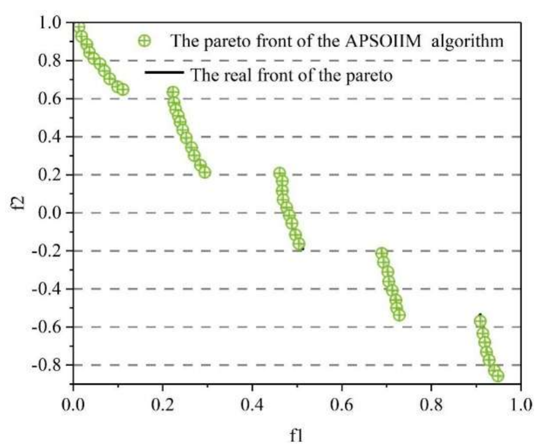

Figure 7: Optimization results of the APSOIIM algorithm ZDT3

The two algorithms are used to run 30 times for ZDT1~ZDT3 respectively, and the convergence metrics and distribution metrics of the algorithms before and after the improvement are obtained based on the solution results. Tables 1 and 2 show the average values of the results of the two algorithms GD and SP run 30 times, respectively.

Comparing Table 1 and Table 2, it can be seen that the mean values of GD and SP of the improved APSOIIM algorithm are smaller than the indicators of the traditional PSO algorithm, which verifies that the convergence and distribution of the improved algorithm are better than that of the pre-improvement algorithm.The SP of the APSOIIM algorithm on the ZDT3 function is only 0.0096, which is 75% of the SP of the PSO algorithm.

Table 1: GD evaluation of test functions

Contrast algorithm	ZDT1	ZDT2	ZDT3
PSO	1.8744e-04	1.5655e-04	2.0905e-04
APSOIIM	1.2126e-04	6.7321e-05	1.9224e-04

Table 2: SP evaluation of test functions

Contrast algorithm	ZDT1	ZDT2	ZDT3
PSO	0.0105	0.0109	0.0128
APSOIIM	0.0079	0.0084	0.0096

III. B. Analysis of optimized scheduling simulation experiment results

In order to verify the overall effectiveness of the research method of local outage load scheduling for new energy multi-terminal grid based on particle swarm algorithm, a new energy multi-terminal grid is taken as an example to conduct the relevant tests. MATLAB software was chosen as the experimental platform and its operating system is CentOS7 with 8GB of RAM and 400GB of hard disk. Data sampling of a new energy multi-terminal grid, in which the load sampling is mainly from the daily electricity consumption, the maximum user load is 2200kW, and the daily load rate is 44.5%. The adaptive particle swarm algorithm is used to solve the constructed new energy multi-terminal grid local outage load scheduling model, the learning factor in the adaptive particle swarm algorithm is set to 12, the use of weights W is set to 0.6, the number of particles takes the value of 40, the number of dimensions is two-dimensional, the number of iterations is formulated to be 100, the maximum flying speed will not exceed 10% of the maximum speed, and the minimum allowable error for the algorithm termination is 0.5% In the two-dimensional space, the optimal solution of 40 particles is searched, the velocity variable and position variable of the particles are updated in the search space, the control factor is introduced to adjust the inertia weight that exists in the basic particle swarm algorithm, to avoid the problem of the local extreme point field; the variation processing of the particles is realized according to the probability of variation, and the variation factor is introduced to avoid the algorithm from appearing as a local optimum, and the strategy of random disturbance is used to complete the variation of the particles.

The total load variation curve before optimization of new energy microgrid is shown in Figure 8. The total load variation interval is within 380-900W.

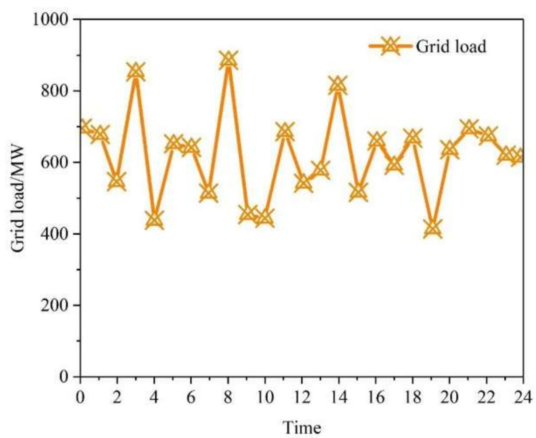

Figure 8: The total load of the grid before optimization

The proposed method, PSO method and MOPSO method are used to dispatch the above new energy microgrids, and the scheduling results are shown in Fig. 9.

After scheduling the new energy microgrid with PSO method and MOPSO method, the total load of the grid still has a large fluctuation, and its fluctuation range is 400-900 MW; while after scheduling the new energy microgrid with the proposed method, the total load of the grid tends to be stable, and its fluctuation range is 560-760 MW. This result shows that the proposed method is better than the other two methods, and the reasons for it are. The proposed method constructs a power consumption information acquisition system to obtain the basic situation of new energy microgrid operation, and then builds a scheduling model on this basis to implement scheduling, which improves the scheduling effect.

This paper proposes a method of multi-terminal grid scheduling optimization under power consumption information acquisition, which obtains the operation of multi-terminal grids based on the collected information and realizes load scheduling on this basis. The total load of the grid tends to be stabilized after scheduling the multi-terminal grid using the method proposed in this paper. The optimization of the proposed method can make the net load of the grid more stable and the load scheduling effect is obvious. The method solves the problems in the current method and lays the foundation for the development of the multi-terminal power grid.

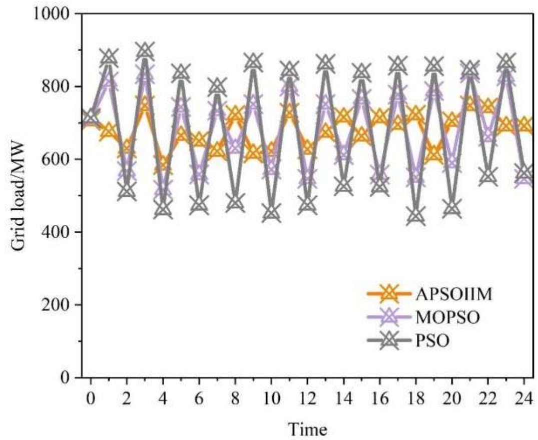

Figure 9: Scheduling results contrast

IV. Conclusion

The adaptive particle swarm optimization algorithm based on the information interaction mechanism effectively solves the key technical problems in multi-terminal grid scheduling optimization. The algorithm performance test results show that the GD value of the improved algorithm reaches 1.2126e-04 on the ZDT1 function, which is significantly improved compared with the 1.8744e-04 of the traditional PSO algorithm; on the ZDT2 function test, the SP value is 0.0084, which is significantly better than that of the traditional algorithm of 0.0109.

The actual multi-terminal grid scheduling experiments verify the engineering applicability of the method, and the total system load fluctuation range is controlled from 380-900W before optimization to 560-760MW, with significant load regulation effect.

The chaotic initialization strategy ensures the uniform distribution of particles in the solution space, the information interaction mechanism effectively avoids the local optimal trap through the collaboration of neighboring particles, and the adaptive updating strategy enhances the global search capability of the algorithm while maintaining the convergence speed.

The multi-objective optimization model comprehensively considers the economic cost, environmental benefit and system security, and provides comprehensive decision support for multi-terminal grid operation. The method proposed in this paper shows good convergence and distributivity when dealing with multi-objective optimization problems under complex constraints, providing an effective technical means for the optimal scheduling of new energy multi-terminal grids, which is of great significance in promoting the efficient use of clean energy and the sustainable development of power systems.

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