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RESEARCH ARTICLE

Optimization Effect Analysis of ACM-PSO Integrating Individual Adjustment and Cross Operation on Microgrid DG Technology

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ABSTRACT Microgrid, as a distributed power technology, has deep potential at present. This study deeply researches microgrid and electric vehicles. A grid-connectedmicrogrid power optimization management model is established, and an adaptive crossover multi particle swarm optimization (ACM-PSO) is proposed, which can adjust and operate individually. The proposed algorithm introduces individual adjustment operation and considers the start and stop state of the micro power supply. Besides, it does not need to decompose the unit commitment problem into two levels of optimization problems, which reduces the complexity of the optimization problem. A-PSO algorithm is prone to fall into local optimum. This problem can be avoided and its global search ability can be improved by introducing the crossover operation of ACM-PSO. According to the analysis of examples, the ACM-PSO algorithm has the best economic effect in different operation schemes among experimental methods. The running cost of the algorithm is $3111.17, $2932.62 and $2929.93, respectively, which is $0.3, $13.54 and $15.08 lower than that of A-PSO algorithm. The proposed method has better optimization performance and can effectively reduce the operation cost of microgrid (MG).

INDEX TERMS Priority ranking, individual adjustment, cross operation, microgrid, distributed technology.

I. INTRODUCTION

Wind power, photovoltaic and other uncontrollable power sources are intermittent and random.At present, a large number of distributed power sources are connected to the distribution network.It is necessary to fully explore the value and benefits that distributed power sources bring to the grid and users. The high permeability need of grid connection of distributed power sources is a problem for now. An effective and feasible solution is to adopt the system approach, which treats the power generation unit and its adjacent load as a subsystem, namely, the microgrid (MG). MG is a system composed of load and micro-power, which can provide electric energy and thermal energy at the same time. The power supply inside the MG is mainly converted and controlled by power electronic devices to ensure the safe and stable operation of the system and the necessary flexibility. The MG is a single control unit for the large grid, and can meet the user's requirements for power quality and power supply safety at the same time [1], [2], [3]. The research and demonstration of MG in China started latecompared with others. However, under the urgent need of effectively accepting a large number of distributed power sources and building smart grids, a series of measures have been introduced to support the development of MG. At present, the research and development of MG is not yet mature. It is found that there are still some key technical problems to be solved for MG in the pilot operation stage. For example, energy management of MG, small signal stability, power quality governance, coordination and control between MG groups, etc. [4], [5]. With the deepening of MG technology research, the technical difficulties have been constantly broken through, and the feasibility has been verified from many aspects. However, compared with the traditional power generation mode, the low operating efficiency of the MG is an

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important factor that hinders its development, mainly in terms of economic benefits. The efficiency of MG is the key to its promotion in the power system, so it is imperative to study the energy optimization management of it.The study proposes an optimization management method for microgrid power supply side based on multiple swarm particle optimization algorithms with individual adjustment and cross operation. This method introduces individual adjustment operations. It takes into account the startup and shutdown states of micro power sources, while avoidsthe need to decompose the unit commitment problem into two levels of optimization problems: startup and shutdown states and load distribution,thus reducing the complexity of the optimization problem. It introducescross operation of multiple swarm particle swarm optimization algorithms. This method aims to avoid the standard PSO algorithms'problem of easily falling into local optima and improve the global search ability. The research compares the method used in this article with other methods, and its content is shown in Table 1.

II. RELATED WORKS

With the development of information technology and the popularity of optimization algorithms, PSO and its optimization algorithms have been applied in many fields. To solve the problem that it is difficult to automatically identify new copolymers at present, Tsai and Fredrickson proposed a recognition algorithm combining PSO and self-consistent field theory, and made an empirical analysis of the algorithm. The recognition algorithm proposed by the research had high accuracy, and it provided the possibility to automatically identify the low free energy structure in the new block copolymer system [6]. Mao et al. proposed an extraction model based on two-group cooperative PSO to solve the problem that model parameters are difficult to extract accurately. The model could effectively identify noises and reduce the impact of them. The performance analysis of the model found that the online extraction of reliable model features of the model was highly feasible, and its maximum error was limited to 1% [7]. To optimize the controller parameters in the design of permanent magnet synchronous motor system, Fang's team proposed an improved hybrid PSO. The algorithm performed directional mutation operation on particles and enhanced the search ability in some remote areas. The empirical analysis of the algorithm showed that the optimization performance of the algorithm proposed in the study is acceptable [8]. Mai et al. proposed a hybrid algorithm based on fuzzy c-means clustering and PSO to solve the problem of unclear satellite images at present, and used this algorithm to process the boundaries and fuzzy areas of satellite images. The proposed algorithm's accuracy was 99.2%, which was superior to other comparison algorithms [9]. The automatic recognition system of atmospheric refractive index had low recognition rate. To solve the problem, Tang et al. proposed an estimation method of refractive index distribution based on the automatic recognition system and quantum behavior particle swarm optimization. The simulation analysis of this method showed that it could accurately retrieve the surface air duct and accurately estimate the atmospheric refractive index [10].

With the dramatic increase in power consumption and the emergence of various optimization technologies, more methods were applied to power system optimization. To meet the power load for daily usage, Hassan proposed a solar photovoltaic power generation system that integrated off-grid and grid-connected. The empirical analysis of the power generation system showed that the power generation system could not only meet the power load requirement, but also save a lot of costs compared with the traditional power grid [11]. To improve the power supply capacity of the power grid system in rural areas of Rwanda, Bedadi and Gebremichael proposed an electric power system based on the hybrid power model. Through empirical analysis of the power system proposed in the study, it was found that the power system not only had better power supply capacity than the traditional power system, but also had lower cost compared with the traditional power system [12]. Anh and Cao proposed an optimized energy management method based on intelligent optimization technology to solve the problem of poor isolation effect of mixed hot spots in MG. The simulation results showed that the optimized energy management method proposed in the study could be optimized in real time and the optimized power system had a better ability to meet the power demand of users [13]. Tan's team proposed a self-generation and load dispatching model based on mixed integer linear programming to solve the problem of high cost and insufficient power supply performance of current enterprise power system. The empirical analysis of the model showed that the proposed comprehensive model could not only reduce the total system cost but also improve the power supply performance of the grid. In addition, with the reduction of carbon emissions of the grid in the future, the proposed model will become more conducive to achieving economic and ecological benefits [14]. Qiu proposed a new two-level robust distributed optimal algorithm that can balance both individual and group interests. On this basis, a robust scheduling model based on two-level tracking strategy is proposed for each entity in the microgrid to minimize the single operation cost of the system. Based on the power surplus and load of each agent, multi-objective bargaining scheduling is implemented by the underlying coordination nodes.Collaborative optimization of connection line planning achieves energy complementarity between regions, and minimizes joint costs [15]. Islam et al. proposed a two-stage MG optimal energy management method that considers the BESS model and other scheduling resources. The recommended method is based on a schedule and a scheduling phase. Mixed integer linear programming is used to solve the two-phase energy management problem, and its performance is compared with that of particle swarm optimization. The results show that during the scheduling phase, the operating cost of BESS devices can be reduced by 7% to 6%. The results also indicate that losses have a significant impact on

TABLE 1. Method comparison table.

Algorithm	Shortcoming	Advantage
WOA-BPNN	Slow convergence; Low accuracy	Operation plus; Easy to adjust parameters; Strong ability to jump out of local optima
GA-SVM	Poor performance in sample scaling; High difficulty in preprocessing data and parameter adjustment	When the number of data features is small, the processing of low-dimensional and high-dimensional data has better performance
ACM-PSO	Weak handling of discrete optimization problems	Fast search speed; High efficiency; Simple algorithm

MG management. Finally, the effectiveness of the optimization strategy was verified through optimization simulation results [16]. Based on the Stackelberg game theory, Wu et al. proposed an optimal strategy with multiple stakeholders and constructed an electricity trading model within a region. The model consists of a distribution network, a leader intermediary agent follower microgrid. The model is solved using a primary-secondary game method. In this model, the profits of each shareholder of MMG increased by 2.64%, 4.24%, and 1.38%, respectively. Empirical research shows that using the methods proposed in the study can effectively enhance the economic performance and energy autonomy of multiple entities in MMG [17].

In summary, it can be found that particle swarm optimization and its improved algorithms have been successfully applied in various fields and have achieved effective results. There are also various optimization algorithms used in the power system, and this research has been inspired by them. Therefore, applying multiple particle swarm optimization algorithms for individual adjustment and cross operation to microgrid distributed technology is a relatively novel attempt. The study aims to solve the problem of low efficiency in microgrid distribution technology through this method, with the aim of improving the profitability of microgrid distribution technology.

III. OPTIMIZATION OF ACM-PSO WITH INDIVIDUAL ADJUSTMENT AND CROSSOVER OPERATION

A. OPTIMIZATION OBJECTIVES OF MICROGRID DG TECHNOLOGY

The research focuses on the community microgrid as the research direction, and analyzes the orderly charging of AC slow charging of electric vehicles within the system. Micro power sources are generally divided into uncontrollable micro power sources and controllable micro power sources. The uncontrollable micro power includes wind powerand photovoltaic power. On the other hand, the controllable micro power includes micro gas turbine, diesel generator, fuel cell, etc. The schematic diagram of the microgrid structure is shown in Figure 1.

In general, the operation mode of microgrids is to operate it in parallel with the large power grid. A power side optimization management model for microgrid systems in grid connected operation was established, with the energy storage device located at the battery position. The goal of the study is to reduce the operating costs of the microgrid system, and to subdivide the total operating costs, as shown in Figure 2.

When considering the various costs of the micro power supply in Figure 2, the operation of the assembly is represented by formula (1).

$$\min C_{OPE} = \sum_{t=1}^{T}\left\{\sum_{n=1}^{N}[u_n(t)F_n(t)+M_n(t)+SS_n(t)]+PE(t)\right\} \tag{1}$$

In formula (1), T represents the optimized operating cycle; t represents the optimized time period; N represents the number of micro power sources; n represents the number of the micro power supply; $\min C_{OPE}$ represents the operating cost of the microgrid; $u_n(t)$ represents the start and stop status of the micro power supply; $F_n(t)$, $M_n(t)$, and $SS_n(t)$ respectively represent fuel costs, maintenance costs, and startup and shutdown costs; $PE(t)$ represents the interactive power cost between the main grid and the microgrid. Among them, the startup and stop status of the microgrid is represented by numbers 1 and 0, where 1 represents the startup status and 0 represents the stop status. The fuel cost in formula (1) can be expressed by the quadratic function of micro power output, as shown in formula (2).

$$F_n(t) = a_nP_n^2(t) + b_nP_n(t) + c_n \tag{2}$$

In formula (2), a_n, b_n, and c_n represent the quadratic, first-order, and constant coefficients of the fuel cost function; $P_n(t)$ represents the output power of the micro power supply. $M_n(t)$, $SS_n(t)$, and $PE_n(t)$ are shown in formula (3), respectively.

$$\begin{cases} M_n(t) = K_n^M P_n(t) \\ SS_n(t) = K_n^{SS}(1-u_n(t-1))u_n(t) \\ PE(t) = pe(t)P_{grid}(t)\Delta t \end{cases} \tag{3}$$

In formula (3), K_n^M represents the maintenance cost coefficient; K_n^{SS} represents the start stop cost; $P_{grid}(t)$ represents the interaction power between the main grid and the microgrid; $pe(t)$ represents the main grid electricity price; Δt represents the length of time for optimizing the runtime. When the value of $P_{grid}(t)$ is greater than 0, it indicates that the microgrid purchases electricity from the main grid; When the value of $P_{grid}(t)$ is less than 0, it indicates that the microgrid sells electricity to the main grid. Without considering related energy losses, microgrids need to meet power balance constraints, microgrid output range constraints, battery operating

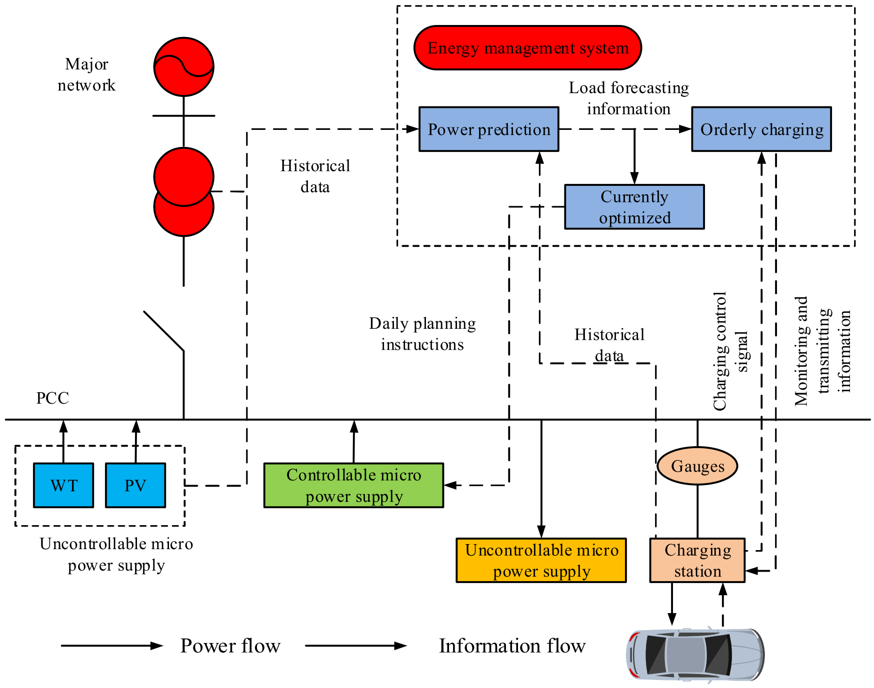

FIGURE 1. Schematic diagram of microgrid structure.

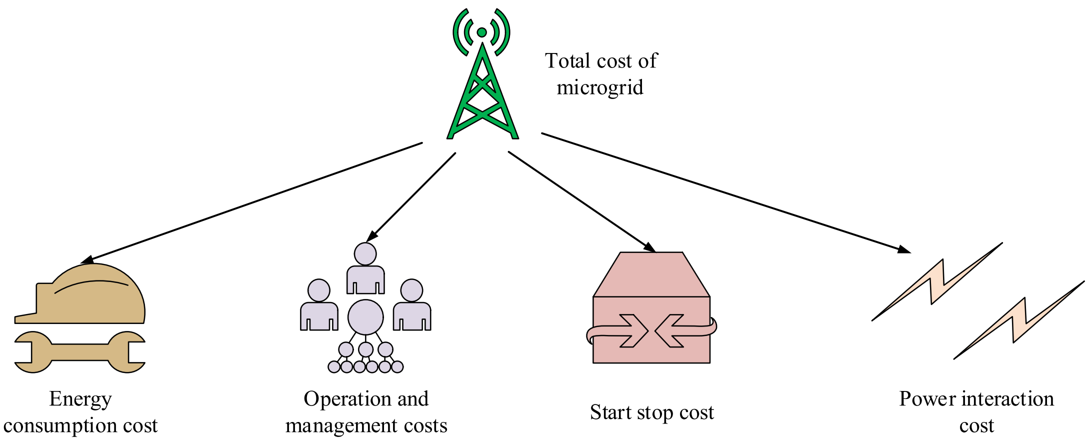

FIGURE 2. Schematic diagram of microgrid structure.

characteristics constraints, and tie line power constraints during operation. The power constraint conditions are shown in formula (4).

$$\sum_{n=1}^{N} P_n(t) + P_{bat}(t) + P_{grid}(t) - P_{load}(t) = 0 \tag{4}$$

In formula (4), $P_{bat}(t)$ represents the charging and discharging power of the battery; $P_{load}(t)$ represents the load capacity of the battery system. The output range constraint of the micro power supply is shown in formula (5).

$$\begin{cases} P_n^{\min} \leq P_n(t) \leq P_n^{\max} & u_n(t) = 1 \\ P_n(t) = 0 & u_n(t) = 0 \end{cases} \tag{5}$$

There are four main constraints on battery operation characteristics. Including charging power range constraints, charging and discharging equation constraints, and state of charge constraints. The expression is shown in formula (6).

$$\begin{cases} P_{bat}^{\min} \leq P_{bat}(t) \leq P_{bat}^{\max} \\ S(t-1) - P_{bat}(t)\Delta t / C_{bat} = S(t) \\ S_{\min} \leq S(t) \leq S_{\max} \\ S(0) = S(T) \end{cases} \tag{6}$$

In formula (6), $S(t)$ represents the battery state of charge; The upper and lower limits of SOC are represented by $S_{\max}$ and $S_{\min}$; The initial and final states of SOC are represented by S_0 and S_T; C_{bat} represents the battery capacity. Among them, a positive value of $P_{bat}(t)$ indicates that the battery is discharging; A negative value of 888 indicates that the battery is charging. The expression for the power constraint of the tie line is shown in formula (7).

$$P_{grid}^{\min} \leq P_{grid}(t) \leq P_{grid}^{\max} \tag{7}$$

In formula (7), the value of $P_{grid}^{\max}$ is a regular representation of the power flow of the interconnection line from the main grid to the microgrid; A negative value of $P_{grid}^{\min}$ indicates that the power of the interconnection line flows from the microgrid to the main grid [18], [19], [20].

B. OPTIMIZATION METHOD BASED ON PRIORITY RANKING

The research adopts the priority ranking method to solve the MG with a small number of micro-power sources or a clear output sequence of micro-power sources. And to avoid the problems caused by intelligent algorithms, the solution process is simplified. Secondly, with the continuous improvement of the penetration level of distributed generation in the MG, the optimization management needs to consider the optimization process involving a large number of distributed generation.The simple priority ranking method is difficult to solve this problem. Solving the large-scale unit commitment problem of traditional large power grid, ACM-PSO is proposed. This method can guarantee the feasibility of the optimization results by introducing individual adjustment and constraint conditions. At the same time, it can avoid decomposing the unit commitment problem into two-level optimization problems, and reduce the dimension of the optimization problem. This method introduces cross operation and adopts PSO of multiple groups to improve the global search ability of the algorithm, so as to avoid the algorithm falling into local optimal solution [7], [21], [22]. The two methods mentioned above have their advantages and disadvantages, and the comparison results are shown in Table 2.

The priority method proposed in the study is based on the objective function and optimization strategy concerned by researchers. On the basis of statistics and fitting of micro-power output data, the micro-power output sequence in themicrogrid system is sorted. When the load demand changes, the micro-power supply in the system shall be put into operation or shut down according to the established sequence, and the output of each micro-power supply shall be reasonably arranged. This method is simple and intuitive, convenient to use, and fast to calculate. It can be used in engineering practice. Firstly, the micro-power output-optimization target curve is established. The output data of each micro-power source in themicrogrid are statistically fitted, and the obtained curvecan optimize the operation cost, environmental benefit and comprehensive cost of themicrogrid. The main optimization objective of the research and test is the operation cost. Because the coupling of the model on the time section is not considered in the priority ranking method, the operation cost only includes fuel cost, maintenance cost and interactive power cost. For distributed power generation,

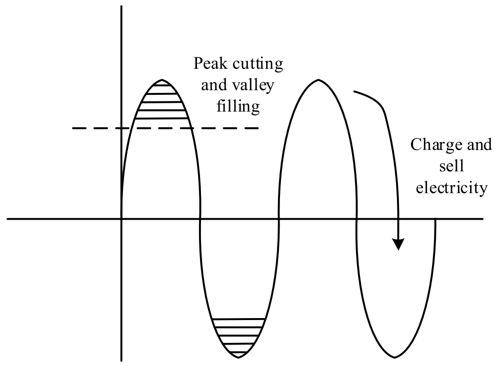

FIGURE 3. Function of energy storage system.

the fuel cost can be fitted by quadratic function. Maintenance cost is a function of maintenance coefficient. The cost of interaction success rate is a primary function related to the electricity price of the main network. Therefore, the priority of sequencing can be judged by the theory of linear programming. After the curve is established, according to different operation strategies, the linear programming theory is adopted on the basis of the curve to meet the priority ranking and ensure the requirements of different loads are satisfied. The net load calculation method of MG is shown in formula (8).

$$P_{nl}(t) = P_{load}(t) - P_{PV}(t) - P_{WT}(t) \tag{8}$$

$P_{nl}(t)$ represents the net load of the MG in formula (8). $P_{PV}(t)$ is the photovoltaic output. $P_{WT}(t)$ shows fan output. $P_{load}(t)$ is the total output of the MG. t represents time. After studying the net load curve, it is also necessary to optimize the operation of the energy storage system in the cycle. For grid-connected MG, the role of energy storage system is shown in Figure 3.

The energy storage system can cut the peak and fill the valley. The power fluctuation of the tie line has a good restraining effect in Figure 3. From the economic point of view, when the electricity consumption is in the low period and the electricity price is low, the system has priority to purchase electricity from the grid. In the peak period of electricity consumption, the electricity price is high. At this time, the energy storage system is discharged and can sell electricity to the power grid. On the one hand, the MG system gives priority to wind power and photovoltaic power. On the other hand, the operating state of energy storage is determined. Then the actual load demand at each time in the system is shown in formula (9).

$$P_{r\_nl}(t) = P_{load}(t) - P_{PV}(t) - P_{WT}(t) - P_{bat}(t) \tag{9}$$

$P_{r\_nl}(t)$ represents the actual load of the MG. $P_{bat}(t)$ is the discharge power of the energy storage system in formula (9). In actual operation, it is necessary to optimize the objectives and operation strategies adopted by operators. The research determines the output of micro-power at each time and at different load levels by setting the priority of micro-power output. Finally, generally speaking, the processing of the

TABLE 2. Comparison results of two optimization algorithms.

Method	Sort based on priority	Improved particle swarm optimization
Advantage	Convenient calculation and fast speed	Strong adaptability and accurate calculation results
Shortcoming	It is difficult to consider the coupling of the optimization model on the time section; There can be errors in the calculation result	The calculation is complex, and the calculation speed is slow
Scope of application	The number of micro-power sources in themicrogridis small, or the output sequence of micro-power sources is clear	The MG contains a large number of micro-power sources, which is difficult to solve with priority ranking method

micro-power supply does not meet the constraints. The minor adjustments are needed for the micro-power supply.

C. OPTIMIZATION BASED ON IMPROVED PSO

The ACM-PSO algorithm proposed by the research is mainly divided into four steps. The first step is to determine the charging and discharging period of the battery. The second step is population initialization. The third is to find the optimal solution for multiple groups, and to carry out cross operations between groups. The last step is to merge the population and iterate in the later stage to make the model converge. During the operation of the model, the individualposition update needs to be adjusted by the individual to resolve the constraint, so as to ensure that the individual meets all constraints [23], [24], [25]. Figure 4 shows the specific flow chart of ACM-PSO algorithm.

it in the condition option represents the iteration of the algorithm in Figure 4. $T_{\max 1}$ and $T_{\max 2}$ are the maximum iteration of the algorithm in the first iteration process and the second iteration process. *num* is the number of intersections of each iteration. $Num_{\max}$ represents the maximum number of crossings. Individual P_i can be expressed in the form of real number matrix, as shown in formula (10) [26], [27], [28].

$$\begin{aligned} P &= [C_1, C_2, \cdots, C_t, \cdots, C_T] \\ &= [R_1, R_2, \cdots, R_k, \cdots, R_{V+2}] \\ &= \begin{bmatrix} P_{bat,1} & P_{bat,2} & \cdots & P_{bat,t} & \cdots & P_{bat,T} \\ P_{1,1} & P_{1,2} & \cdots & P_{1,t} & \cdots & P_{1,T} \\ \cdots & \cdots & \cdots & \cdots & \cdots & \cdots \\ P_{n,1} & P_{n,2} & \cdots & P_{n,t} & \cdots & P_{n,T} \\ \cdots & \cdots & \cdots & \cdots & \cdots & \cdots \\ P_{N,1} & P_{N,2} & \cdots & P_{N,t} & \cdots & P_{N,T} \\ P_{grid,1} & P_{grid,2} & \cdots & P_{grid,t} & \cdots & P_{grid,T} \end{bmatrix} \begin{matrix} (battery) \\ (DG_1) \\ \cdots \\ (DG_n) \\ \cdots \\ (DG_N) \\ (grid) \end{matrix} \end{aligned} \tag{10}$$

C_t represents the load distribution in formula (10). R_k is the generation plan of a certain generation unit within the cycle. The start and stop state $u_n(t)$ of the micro power supply is shown in formula (11).

$$u_n(t) = \begin{cases} 0 \\ 1 \end{cases} \tag{11}$$

The start and stop status of $u_n(t)$ is determined by the output of the micro power supply. The initialization of individual speed is to calculate the fitness value of the individual, and initialize the optimal individual, as shown in expression (12).

$$P_{best} = (pb_1, pb_2, \cdots, pb_p) \tag{12}$$

The optimal value corresponding to formula (12) is expressed by formula (13).

$$Pb_{value} = (pv_1, pv_2, \cdots, pv_p) \tag{13}$$

All individuals are divided into a certain number of subpopulations on average. Formula (14) is the number of individuals owned by each subpopulation.

$$A = \frac{p}{M} \tag{14}$$

In formula (14), M represents subpopulation. p represents the number of individuals in the population. Formula (15) is the optimal population expression in the initial subpopulation.

$$G_{best} = (gb_1, gb_2, \cdots, gb_M) \tag{15}$$

The optimal value corresponding to the subpopulation in formula (15) is shown as follows.

$$Gb_{value} = (gv_1, gv_2, \cdots, gv_M) \tag{16}$$

In the individual adjustment of the system, the micro power supply needs to be adjusted to meet the constraints of thepower generation upper and lower limits. The constraints are as shown in formula (17).

$$P_{n,t\_adjust} = \begin{cases} p_n^{\max} & p_{n,t} > p_n^{\max} \\ p_{n,t} & p_n^{\max} \geq p_{n,t} \geq p_n^{\min} \\ p_n^{\min} & p_n^{\min} > p_{n,t} \geq \alpha p_n^{\min} \\ 0 & p_{n,t} < \alpha p_n^{\min} \end{cases} \tag{17}$$

The power output of the battery also needs to be adjusted to meet the upper and lower limit constraints of power generation. The constraints are shown in formula (18).

$$P_{bat,t\_adjust} = \begin{cases} P_{bat}^{\max} & P_{bat,t} > P_{bat}^{\max} \\ P_{bat,t} & P_{bat}^{\min} < P_{bat,t} < P_{bat}^{\max} \\ P_{bat}^{\min} & P_{bat,t} < P_{bat}^{\min} \end{cases} \tag{18}$$

In addition to the power output of the micro power supply and the battery, the power output of the tie line should also be adjusted to the power generation constraints. The expression is shown in formula (19).

$$P_{g,t\_adjust} = \begin{cases} P_{grid}^{\max} & P_{grid,t} > P_{grid}^{\max} \\ P_{grid,t} & P_{grid}^{\min} < P_{grid,t} < P_{grid}^{\max} \\ P_{grid}^{\min} & P_{grid,t} < P_{grid}^{\min} \end{cases} \tag{19}$$

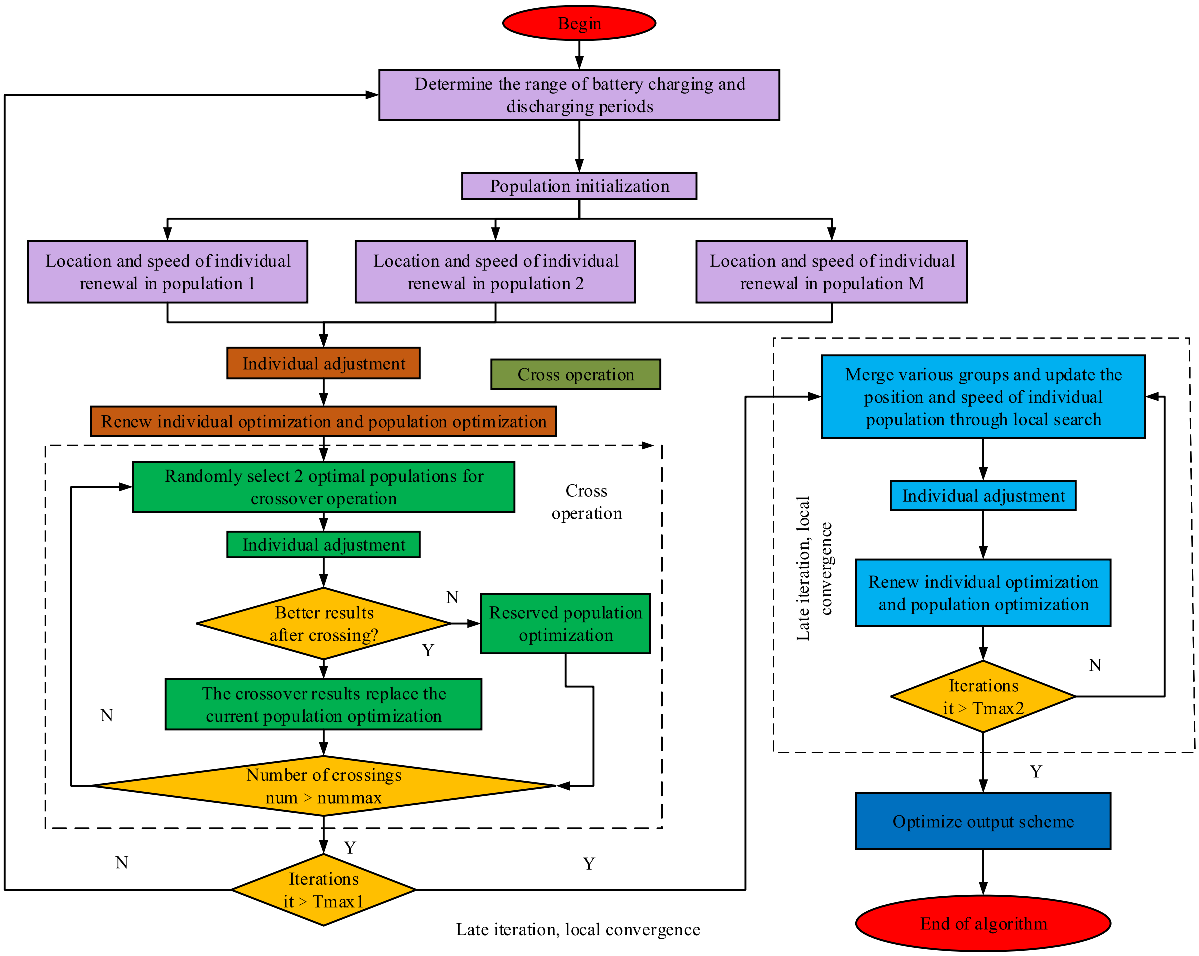

FIGURE 4. Specific flow chart of ACM-PSO algorithm.

P_{n,t_adjust} represents the adjusted output of the micro power supply in formulas (17) - (19). P_{bat,t_adjust} is the adjusted output of the battery. P_{grid,t_adjust} stands for the adjusted output of the interactive power. α represents the adjustment coefficient, which is usually in the range of 0 to 1. The battery charging and discharging plan was adjusted to meet the SOC related constraints. In the charging stage, if the SOC exceeds $S_{\max}$ at the end of a certain period, it means that the battery is overcharged, and the overcharged part is randomly deducted from each charging power period. During the discharge period, if the SOC at the end of a period is lower than $S_{\min}$, it means that the battery is over-discharged. Similarly, the excessive discharge part is randomly deducted from each discharge power period, and the total discharge power cannot exceed the electric energy reserve at the charging stage. After the adjustment of the above two steps, the total output of the power generation unit in the T period may not be equal to the system load, and load redistribution is required. The specific adjustment method is as follows.When the total output is less than the load, the balance constraint can be satisfied by increasing the output of micro power supply and the power of tie line. When the total output is greater than the load, the micro-power output and tie line power will be reduced [29], [30], [31].

For better global search ability, the crossover operation in genetic algorithm is introduced. It can cross the population optimization of each subpopulation to avoid premature population and local optimization. Before crossing, two subpopulations are randomly selected from the population as crossing objects [32]. The optimal values of these two subpopulations are $gb_{select1}$ and $gb_{select2}$. The time period when the output of each power generation unit in the two subpopulations is different is counted. That is, if the output difference of any generating unit is greater than a certain decimal point, it is considered that there is a difference in this period. The individuals generated by the crossover operation are adjusted individually, and finally their fitness is calculated. If the adjusted fitness is better than the original one, the individuals obtained after the crossover will replace the original optimal population. The evolution mode of particle swarm is shown in formula (20).

$$v_i(it+1) = wv_i(it) + c_1r_1[pb_i - x_i(it)] + c_2r_2[gx_i - x_i(it)]$$
$$x_1(it+1) = x_i(it) + v_i(it+1) \quad (20)$$

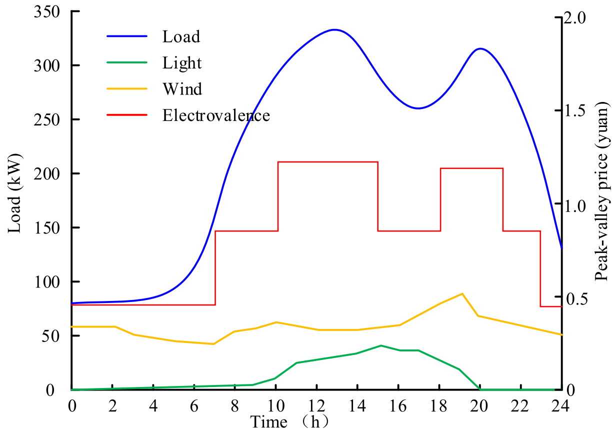

FIGURE 5. Results of various predicted values of the system.

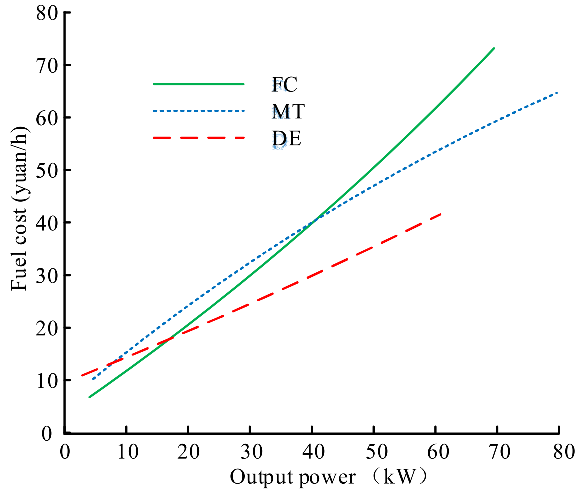

FIGURE 6. Fuel cost change results.

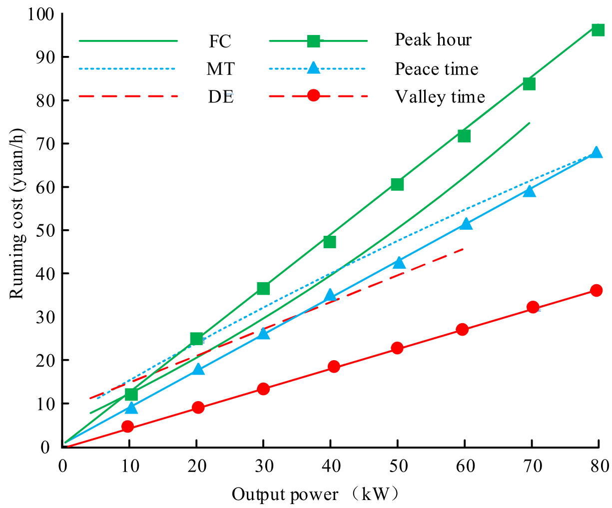

FIGURE 7. Changes in operating costs.

w is the inertia weight in formula (20). c_1 and c_2 are acceleration constants. r_1 and r_2 represent uniformly distributed random numbers. v_i stands for the speed of the individual. x_i refers to the position of the individual. gx_i represents the best particle position in the learning range. When multi-populations seek optimization and communicate through cross operation, gx_i takes the best of their subpopulations. When the population merges for local search, gx_i takes the optimal total population of each combination.

IV. ACM-PSO ANALYSIS AND COMPARISON OF FUSION INDIVIDUAL ADJUSTMENT AND CROSSOVER OPERATION

A. ANALYSIS OF OPTIMIZATION ALGORITHM BASED ON PRIORITY RANKING

In the experiment, simulation experiments were used to study and analyze the microgrid system. The simulation experiments included two calculation examples, and the data was sourced from the charging station data of electric vehicles. The distribution of microgrids is distributed power sources including wind turbines (WT), photovoltaics (PV), diesel engines (DE), fuel cells (FC), and micro gas turbines (MT). Figure 5 shows the output power value results of short-term PV and wind forecasting, load demand forecasting, and peak and valley electricity prices of the system on a certain day.

In Figure 5, the maximum power load demand of the MG system is at 13:00, and the load reaches about 330KW. The maximum PV output power value is from 14:00 to 17:00, and its output load value is about 40KW. The maximum output power of the fan is at 19:00, and the output load value is about 80KW. The peak and valley electricity price is \$1.2 at the highest and\$0.48 at the lowest.

Figure 6 shows the relationship between output power and fuel cost. When the output power is less than 10KW, the DE fuel cost is the highest. In the range of 10KW to 20KW, MT fuel cost is the highest, reaching\$20 per hour. When the output power is 40KW, the fuel cost of FC is the highest, reaching \$40 per hour. The fuel cost of the three power output modes is in direct proportion to the output power. When the output power is high, the main output modes are FC and MT.

The experiment uses the optimization algorithm of priority ranking to obtain the micro-power output - operation cost curve. The operation cost includes fuel cost and maintenance cost, and the change of operation cost is shown in Figure 7. Under the same power, the operating cost of the peak-hour main network is higher than that of the normal main network and the peak-hour main network. When the output power is 80KW, the operating cost of the peak-hour main network is 97 \$/h. In the case of high output power, the operating cost of FC is also higher. When the output power reaches 70KW, the operating cost of FC is 75 \$/h.

To control the operation cost, the experiment adopts three different optimization schemes. Scheme A is that the main network does not participate in the optimization and the interactive power is single when the micro-power supply is not divided into output sequence. Scheme B is that the main network participates in the optimization and the interactive power is single when the micro power supply is not divided

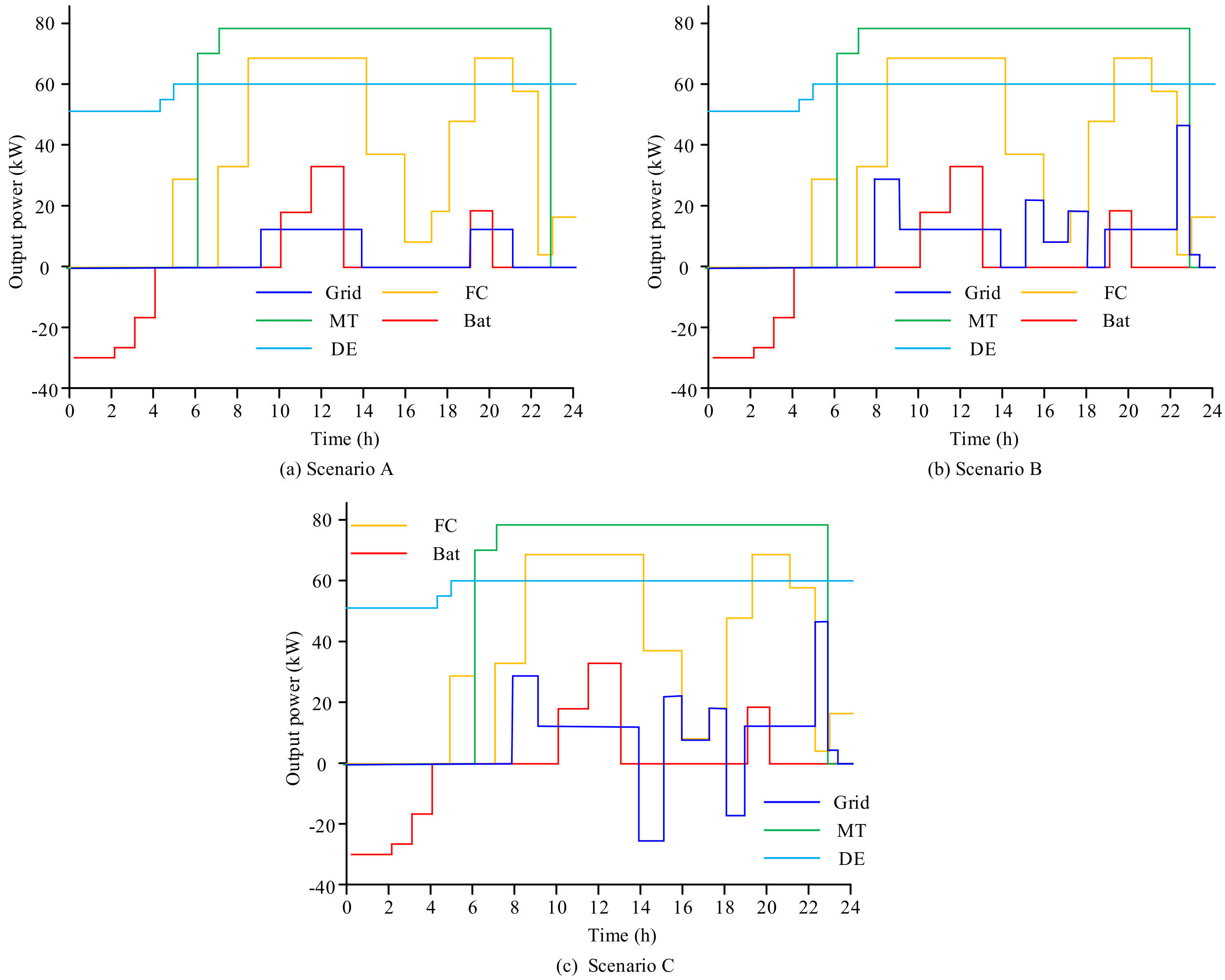

FIGURE 8. Output power results under different micro-power optimization strategies.

into output sequence. Scheme C is that the main network participates in the optimization and the interactive power is bidirectional when power supply dose not divide the order of force 2. In Figure 8 (a), when the power demand of the micro power supply is small, the power is output through Grid and FC first, and then transmitted by other micro power supplies. When the output power does not meet the demand, the group finally transmits power from the main grid to the MG. In Figure 8 (b), the micro-power supply and the main network participate in the optimization at the same time. In the case of high power demand, the power output is allocated. In Figure 8 (c), under the condition that the load meets the demand, the micro-power will have a negative output power, indicating that the micro-power will sell electricity to the main network during the peak period of the electricity price to gain benefits or reduce costs. It shows that the operating costs of Scheme A, B and C are thus reduced. The specific results are shown in Table 3.

Table 3 shows the operation cost optimization of the three schemes for the MG. The optimized operation cost of Scheme C is the lowest, with an operation cost of$3035.65. Compared with the PSO optimization algorithm, the error is not higher than 0.1%. It shows that the priority ranking method has high prediction accuracy and can effectively reduce the operation cost, and has application value in engineering practice.

B. ANALYSIS OF OPTIMIZATION ALGORITHM BASED ON ACM-PSO

The experiment is optimized based on the net load and peak-valley electricity price in Figure 9. Solve the model with MATLAB programming, and set the following parameters. Acceleration constant $c1 = c2 = 1.2$. The weight decreases linearly from 0.9 to 0.4 as the number of iterations increases. The initial population size of the model is set to 500. The subpopulation is set to 10, the first iteration number is set to 300, and the second iteration number is set to 500. The optimized operation plan includes the battery discharge plan, micro-power output and tie-line power plan.

Figure 9 (a) shows the optimization of the MG system when Scheme A is adopted. The load is preferentially powered by the micro-power unit in the MG. When the output of all micro-power sources reaches the power limit and still

TABLE 3. Operation cost.

/	Sort based on priority($)	Based on particle swarm	Error(%)
Option A	3105.00	3105.00	0
Option B	3038.25	3038.02	<0.1
Option C	3035.65	3035.42	<0.1

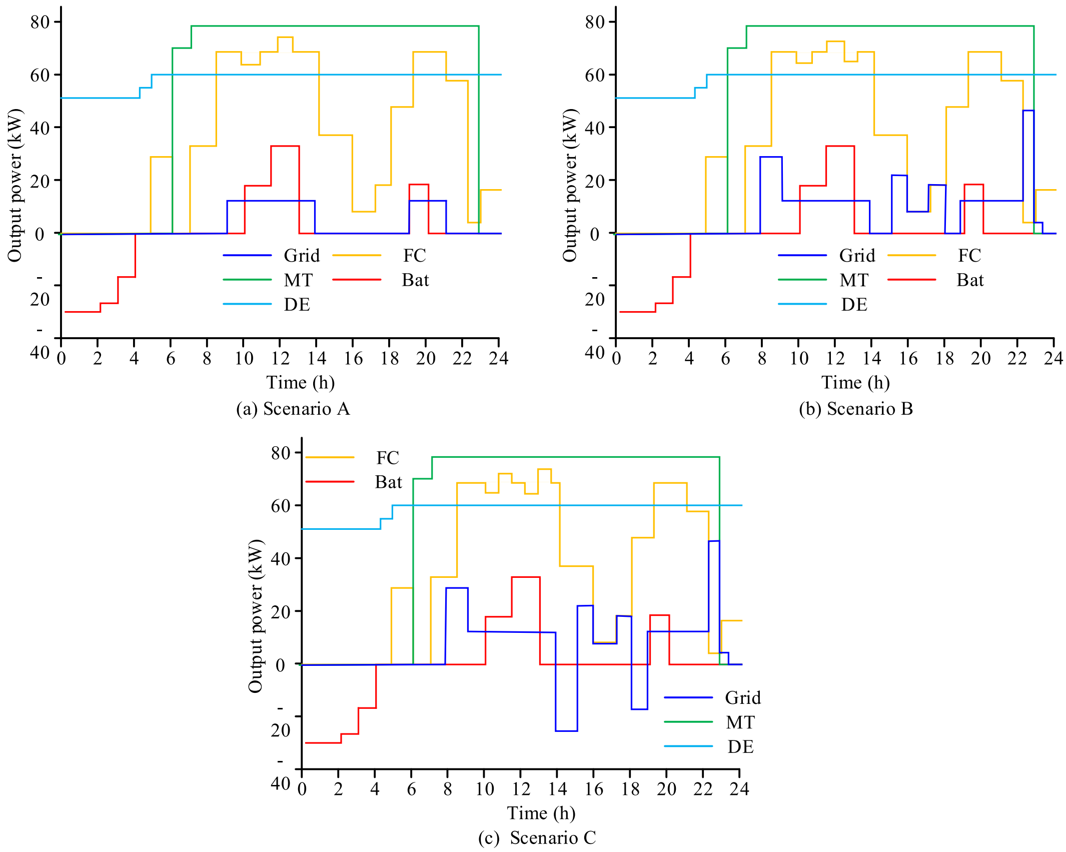

FIGURE 9. Output power results of ACM-PSO model with different micro-power optimization strategies.

cannot meet the load requirements, such as 9:00 to 10:00 and 11:00 to 13:00, the main grid provides power to the MG. During the low power consumption period, from 0 to 4 o'clock, DE will send the remaining electricity to charge the battery. Figure 9 (b) shows the power consumption when Scheme B is adopted. During the low power consumption period, such as 23:00 to 7:00, when the power grid price is lower than the power generation cost of micro-power, the power grid power shall be preferentially used to meet the load and charge the battery. During the peak period of power consumption, such as 10:00 to 15:00 and 18:00 to 21:00, the cost of micro-power generation is lower than the power grid price, except that the cost of power generation when the FC output is larger than the power grid price. Therefore, the micro-power output is used to meet the load, and the insufficient part is met by the power grid. Figure 9 (c) shows the power consumption when Scheme C is adopted. In the peak period of power consumption, such as 14:00 to 15:00 and 18:00 to 19:00, when the load is met, the micro-power still has reserve capacity, and the power generation cost of the micro-power is far lower than that of the grid. Therefore, Scheme C will transmit low-cost power from the MG to the grid to achieve better economic benefits.

In Table 4, the experiment compares the economic benefits of A-PSO algorithm and ACM-PSO algorithm in three schemes. The best economic benefit of A-PSO in Scheme A is $3111.47, and the average benefit is$3125.82. The best economic benefit of ACM-PSO in Scheme A is $311.17, and the average benefit is $311.19. The best economic benefit of A-PSO in Scheme B is $2946.16, and the average benefit is $2966.44. The best economic benefit of ACM-PSO in Scheme B is$2932.62, and the average benefit is$2932.65. The best economic benefit of A-PSO in Scheme C is $2945.01, and the average benefit is$2946.79. The best economic benefit of ACM-PSO in Scheme C is$2929.93, and the average benefit is$2929.51. The results show that the

TABLE 4. Comparison of optimization results with standard PSO.

Scheme	Method	Best benefit ($)	Worst benefit ($)	Average ($)
A	A-PSO	3111.47	3140.17	3125.82
	ACM-PSO	3111.17	3111.20	3111.19
B	A-PSO	2946.16	2986.72	2966.44
	ACM-PSO	2932.62	2932.67	2932.65
C	A-PSO	2945.01	2984.56	2964.79
	ACM-PSO	2929.93	2929.09	2929.51

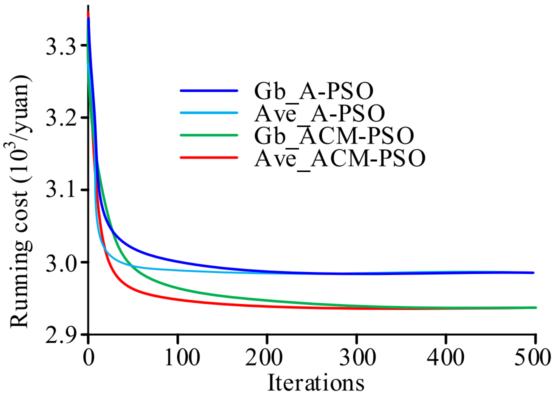

FIGURE 10. Convergence curve of ACM-PSO algorithm in scheme B.

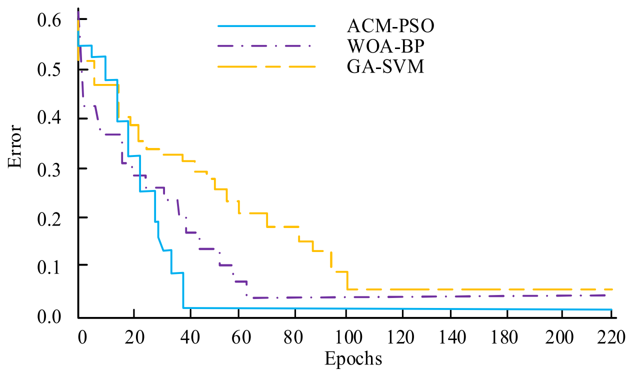

FIGURE 11. Convergence of three models.

ACM-PSO model has better economic benefits and lower operating costs in any scheme. Moreover, the best cost produced by ACM-PSO model is similar to the average cost, which indicates that the model has strong stability.

Figure 10 shows the convergence curve of ACM-PSO algorithm in Scheme B. The A-PSO algorithm converges after 50 iterations, and the running cost converges to $3111.47, while the ACM-PSO algorithm converges after 75 iterations, and the running cost converges to $2929.93. The results show that A-PSO algorithm falls into local optimum prematurely, and ACM-PSO algorithm has better global search ability.

Table 5 compares the two algorithms and two cost operations. The operation cost of ACM-PSO algorithm is lower in the three schemes. The optimal operation cost of ACM-PSO algorithm is very close to the worst operation cost, which shows that the operation method has strong performance and stability.

C. COMPARISON OF OPTIMIZATION ALGORITHM PERFORMANCE

In addition to the models proposed in research, the most advanced power data optimization algorithms currently available are the Support Vector Machine Model (GA-SVM) optimized by genetic algorithm and the BPNN improved by Whale Optimization Algorithm (WOA-BPNN).The convergence of the above three models is tested using the training set, as shown in Figure 6. In Figure 6, it can be seen that when the minimum error of the model is reached, the ACM-PSO model requires 39 iterations, which is 25 and 64 fewer than the WOA-BPNN model and GA-SVM model, respectively. In addition, the minimum error of the ACM-PSO model is also lower than that of the WOA-BPNN model and GA-SVM model. The above results indicate that the ACM-PSO model has better convergence and can achieve smaller errors faster.

Using a test set, the distributed optimization performance of the ACM-PSO model is compared with WOA-BPNN model, and GA-SVM model for microgrids. The accuracy and F1 value are selected as performance indicators for model evaluation. The evaluation performance of the ACM-PSO model, WOA-BPNN model, and GA-SVM model is shown in Figure 7. In Figure 7 (a), the accuracy of the ACM-PSO model reaches 99.05%, which is 0.63% and 1.06% higher than the WOA-BPNN model and GA-SVM model, respectively. In Figure 7 (b), the F1 value of the ACM-PSO model is 96.43%, which is 0.42% and 1.36% higher than the WOA-BPNN model and GA-SVM model, respectively. The above results indicate that the ACM-PSO model performs better in the optimization evaluation of microgrids.

V. DISCUSS

The research explores the optimization and management of the power side of grid connected microgrids. A power side energy optimization management model has been established for microgrids containing multiple types of micro power sources in grid connected operation mode, with the optimization goal of minimizing operating costs. The constraints include power balance, micro power constraints, battery constraints, and tie line power constraints. Next, three common grid connected microgrid operation strategies were analyzed based on the output sequence of micropower sources.

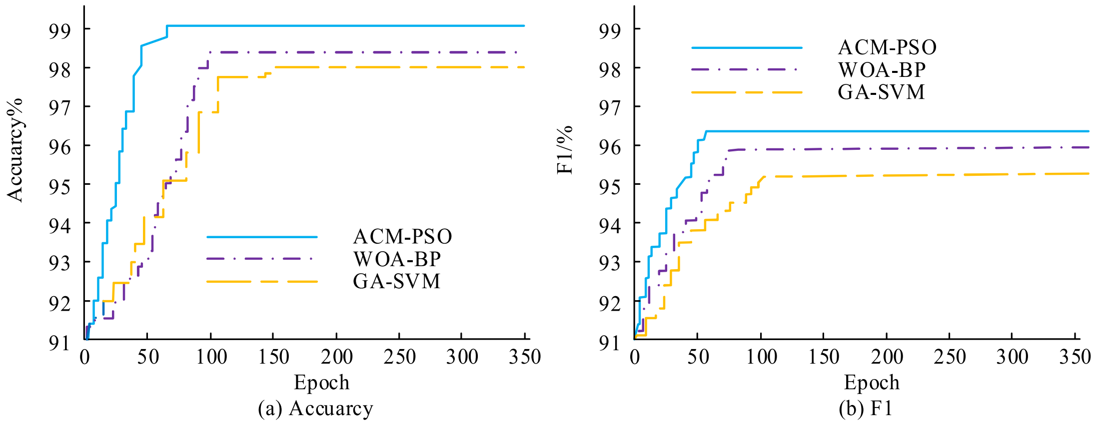

FIGURE 12. Accuracy and F1 value of three models.

TABLE 5. Comparative effects of two optimization algorithms.

Scheme	Method	Best benefit ($)	Worst benefit ($)	Average ($)
A	Sort based on priority	3105.00	3140.17	3122.59
	ACM-PSO	3111.17	3111.20	3111.19
B	Sort based on priority	3038.25	3086.72	3062.49
	ACM-PSO	2932.62	2932.67	2932.65
C	Sort based on priority	3035.65	3054.56	3045.11
	ACM-PSO	2929.93	2929.09	2929.51

Whether the main grid participates in optimized operation, and the power exchange method between the microgrid and the main grid are studied. Then, under different application conditions and accuracy requirements, two optimization methods are proposed, namely, an optimization method based on priority ranking and an optimization method based on multi swarm particle swarm optimization algorithm with individual adjustment and cross operation. The optimization method based on priority ranking is suitable for microgrids with fewer micro power sources or clear output order. Through calculation and analysis of numerical examples, and comparison of the solution results of intelligent algorithms, it is shown that the use of priority ranking method can ensure operational accuracy while greatly reducing computational time. It avoids problems such as local minima and being difficult to solve due to excessive dimensionality. Its application in engineering practice appears simple and effective. Although this method is simple and effective in application, its application scope has certain limitations and there is room for further improvement in accuracy. Therefore, this study proposes an optimization method for microgrid power side optimization management based on multiple swarm particle swarm optimization algorithms with individual adjustment and cross operation. This method has been verified to be practical and effective, with good adaptability and global search ability by calculating examples, analyzingoptimization schemes, and comparing the optimization results with the standard PSO method.

VI. CONCLUSION

This paper studies the optimal management of distributed power sources in MG, and proposes the ACM-PSO optimization algorithm. The research uses this algorithm to establish a management model that includes multiple power side energy optimization. With the purpose of reducing the operation cost of the MG distribution, the power balance, micropower, battery and tie line power are constrained, and three MG operation schemes are used for analysis. Two examples are used for experiments. The operation cost of the priority-based method in the three operation schemes is $3105.00, $3038.25 and $3035.65 respectively. Compared with the running cost of A-PSO algorithm, the error of the priority-based method is less than 0.1%. The operation cost of the three operation schemes based on ACM-PSO algorithm is $3111.17, $2932.62 and $2929.93 respectively. The proposed ACM-PSO algorithm has good performance, can minimize the running cost, and has strong stability. The main contribution of the research is to analyze the guiding mechanism and benefit allocation of electric vehicle charging management in microgrids, making micropower distribution technology more economically beneficial.However, the research still has the possibility of further exploration. With the continuous construction of MG, the off-grid MG formed has high research value. The distribution of MG can be applied to more fields, and the actual application can be further analyzed.

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