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Multi-Objective Optimal Dispatching of Microgrid With Large-Scale Electric Vehicles

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ABSTRACT Dispatching the output of distributed power sources is the main task in the microgrid operation phase. This task is more concerned with the optimal dispatch of large electric vehicles connected to the grid-connected microgrid today. Full consider the influence of storage battery and peak-valley electricity price, its objective is to minimize the operating cost of microgrid and the cost of environmental protection, and establishing economic dispatching model of microgrid. To solve this constrained optimization problem, an annealing mutation particle swarm optimization algorithm is proposed. Through simulation and comparison, the dispatching cost results of microgrid are obtained under two dispatching modes of electric vehicle disorder and order. It is concluded that the orderly charging and discharging mode guided by electricity prices can effectively reduce the operating cost and environmental protection cost of microgrid. Improving the economy and reliability of microgrid operation.

INDEX TERMS Microgrid, electric vehicle, particle swarm optimization, peak and valley price, optimal scheduling.

I. INTRODUCTION

WITH the improvement of social awareness of environmental protection and energy security, people gradually realize the inherent shortcomings of traditional power grid [1]. The smart microgrid technology provides innovation solutions for countries to build green, safe and sustainable power supply systems. Because the microgrid contains uncontrollable renewable energy, which has profound uncertainty [2], [3]. Therefore, the research on optimal dispatching of smart microgrid system plays a key supporting role in promoting the application and development of smart micro-grid projects.

Aiming at minimizing the operation and investment costs of the system throughout the life cycle of the microgrid, a multi-energy complementary low-carbon allocation optimization model is established and solved by genetic algorithm. The results prove the effectiveness of the proposed low-carbon configuration method for microgrid, but the impact of electricity price policy on microgrid system is not

considered [4]. Literature [5] studies the economic dispatch of microgrid system consisting of wind, light, storage, gas boilers and cogeneration under different electricity price policies. The simulation results show that different electricity price policies can reduce the operating cost of microgrid system, but the influence of electric vehicles on microgrid dispatching is not considered. Literature [6] proposes a microgrid scheduling model and strategy including electric vehicles for the energy storage characteristics of electric vehicles, but does not consider the economic impact of V2G(vehicle to grid) technology on electric vehicle users. Literature [7] considers that electric vehicles participate in grid-connected economic dispatch of microgrid through V2G(Vehicle to grid) technology under peak-valley electricity price. At the same time, the system model is set up to minimize the double objectives of microgrid operation cost and environment protection cost. The output power of distributed power supplies is optimized by improved particle swarm optimization algorithm. The results show that the dispatching of electric vehicles is effective for the economic operation of microgrid.

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However, only few electric vehicles are considered participating in dispatching process, and the economic impact of largescale electric vehicle interconnection on microgrid operation is not considered, which affects the safety and reliability of power grid operation.

In view of the deficiencies mentioned above[7], this paper comprehensively considers the influence of energy storage and V2G loss cost on microgrid dispatching operation, especially in large-scale electric vehicles situation. The optimal dispatching model of microgrid is re-established and the parameter adaptive particle swarm optimization algorithm [7] is applied simultaneously. The mutation characteristic of simulated annealing and the fine search characteristic of Gaussian mutation are used to improve it, then a particle swarm optimization algorithm based on annealing mutation is proposed for microgrid optimal scheduling.

II. PROBLEM DESCRIPTION

A. SCENE DESCRIPTION

The microgrid scenario in this section is shown in Fig.1 [8]. The scene mainly consists of five parts: Unidirectional Distributed Power Supply A, Fixed Energy Storage Equipment B, Mobile Energy Storage Equipment C, Public Power Grid D and Load E. Part A is mainly composed of WT (wind turbine), PV (photovoltaic generator), DE (diesel engine) and MT (micro turbine) which can only output but not input unidirectional distributed power. Part B is mainly composed of bi-directional BA (storage battery) energy storage equipment that can both output and input. Part C is composed of mobile lithium battery, which can be output and input. Part D consists of the main power grid dominated by traditional thermal power generation, which can be both output and input. Part E consists of various loads, including commercial loads, residential loads and industrial loads, etc. Signal transmission is carried out between each component by wired or wireless means.

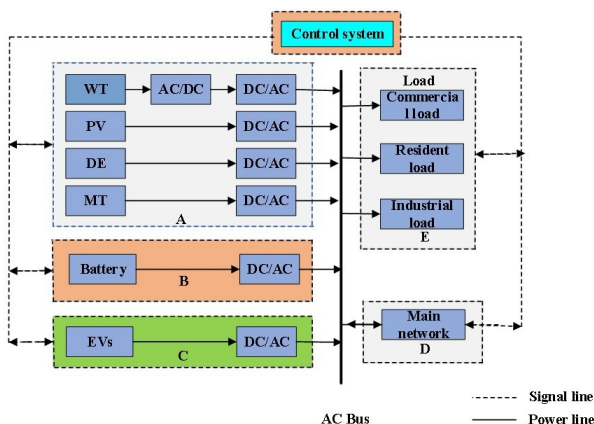


FIGURE 1. Micro grid system structure.

As shown in fig. 1, Part A, C, D are the main application scenarios of document [7]. However, Part C only discusses the situation where three electric vehicles participate in microgrid

dispatching. A smart microgrid system is composed of WT, PV, DE, MT and a small amount of EV (Electric Vehicle). Multi-objective microgrid scheduling model including microgrid operating costs and environmental management costs is established. The model can satisfy a series of parameter indicators, such as the constraints of power balance, upper and lower limits of distributed power supply, minimum charge capacity for EV daily use, upper and lower limits of EV charging and discharging, etc. The output power of DE and MT, the sale and purchase power of microgrid, and the charging and discharging power of EV are six unknown variables solved by an improved variable parameter particle swarm optimization algorithm.

B. RESEARCH MOTIVATION

As Part C of document [7] only considers a small number of electric vehicles participating in grid connection, and does not consider the important influence of large-scale electric vehicles on grid dispatching. Therefore, in Part C of this section, the influence of a large number of electric vehicles participating in microgrid dispatching is considered, as well as the peak clipping and valley filling effect of energy storage system on microgrid. Based on the [7] scenario, Part B of fixed energy storage equipment is connected to further improve the microgrid scenario. By considering the electric energy cost lost by EV through V2G technology and the energy storage operation and maintenance cost, a double-objective microgrid optimal dispatching model is re-established. An improved variable parameter PSO algorithm with simulated annealing and Gaussian mutation is used to optimize the unidirectional output power of DE and MT and bidirectional charging and discharging power of BA and main network. The detailed work comparison of the two articles is shown in table.1.

TABLE 1. Work comparison.

Characteristic	Reference [7]	Work in this paper
EV Scheduling Quantity	A small number of EVs(3 vehicles)	Large-scale EVs (50 vehicles)
Distributed Power Generation Model	WT, PV, DE, MT	WT, PV, DE, MT, BA
Scene 1	WT, PV, DE, MT, Grid	WT, PV, DE, MT, BA, EV
Scene 2	WT, PV, DE, MT, A small amount of EV, Grid	Disordered Scheduling, Grid
Objective function	Only depreciation costs of EV batteries are considered	WT, PV, DE, MT, BA, EV
Algorithm	Variable parameter particle swarm optimization	Orderly Scheduling Grid
		The cost of power loss through V2G is considered
		Annealing mutation particle swarm optimization algorithm

III. SYSTEM MODEL

A. DISTRIBUTED GENERATION MODEL

The models of PV, WT, DE, and MT in Part A of this paper still use the model of reference [7]. The battery model of Part B and the electric vehicle model of Part C are added and reestablished and will be described in detail below.

1) BATTERY CHARGE AND DISCHARGE MODEL

When the storage battery participates in the power grid dispatching process, the state of charge in the charging and discharging process must be considered. Therefore, its charge-discharge model is as follows [9]:

$$SOC(t) = \begin{cases} (1-\eta) \cdot SOC(t-1) + \frac{P(t) \cdot \Delta t \cdot \beta_c}{E_{\beta\alpha}}, & P(t) > 0 \\ (1-\eta) \cdot SOC(t-1) + \frac{P(t) \cdot \Delta t}{E_{\beta\alpha} \cdot \beta_d}, & P(t) < 0 \end{cases} \quad (1)$$

In the formula, $SOC(t)$ and $SOC(t-1)$ respectively represent the time and the state of charge of the storage battery at the time. η is the self-discharge coefficient of the storage battery. β_c is the charging efficiency of the storage battery. β_d is the discharge efficiency of the storage battery. $E_{\beta\alpha}$ is the capacity of the battery. Δt is the duration of the battery, here 1 hour is the duration of the battery.

2) ELECTRIC VEHICLE MODEL

Private vehicles have great randomness. However, research shows that the usage habits of large-scale electric vehicles follow normal distribution[10]. x is the moment when the last trip of the electric car ends. In this paper, the car with on-board battery as ternary lithium battery is taken as the research object, and the battery capacity is about 30kWh. The charging and discharging behaviors of electric vehicles of users obey normal distribution, and the model is as follows [10]:

$$f_s(x) = \begin{cases} \frac{1}{\sqrt{2\pi} \cdot \sigma_s} \cdot \exp\left[-\frac{(x - \mu_s)^2}{2\sigma_s^2}\right], & \mu_s - 12 < x \leq 24 \\ \frac{1}{\sqrt{2\pi} \cdot \sigma_s} \cdot \exp\left[-\frac{(x + 24 - \mu_s)^2}{2\sigma_s^2}\right], & 0 < x \leq \mu_s - 12 \end{cases} \quad (2)$$

where: $\mu_s = 16.5$, $\sigma_s = 3.5$ The daily mileage model of the vehicle is as follows [11]:

$$f_d(x) = \frac{1}{\sqrt{2\pi} \cdot \sigma_d \cdot x} \cdot \exp\left[-\frac{(\ln x - \mu_d)^2}{2\sigma_d^2}\right] \quad (3)$$

where: $\mu_d = 3.1$, $\sigma_d = 0.87$. μ_d and σ_d are the expectations and variances of the respective distribution function.

B. OBJECTIVE FUNCTION

In this paper, the microgrid system is operated in a grid-connected mode. Considering its economic and environmental protection, a multi-objective economic dispatch model with minimum operation and maintenance costs and environmental compensation costs is established. This section improves the objective function [7] based on the objective function of literature, taking into consideration the cost of battery and electric vehicle losses.

1) OBJECTIVE FUNCTION f_1

f_1 is the operating cost of the microgrid. Including fuel cost of distributed power supplies, operation and maintenance cost,

sale and purchase cost of power exchange between microgrid and main network, and compensation cost of electric vehicles participating in grid dispatching. Therefore, it can be described as follows [8]:

$$f_1 = C_{fuel} + C_{OM} + C_{buy} - C_{sell} + C_{BAT} \quad (4)$$

Considering that diesel engines and micro turbines need fossil fuels for power generation, the fuel cost of the microgrid C_{fuel} can be described as follows:

$$C_{fuel} = C_{DE} + C_{MT} \quad (5)$$

During the operation of each distributed power supply, regular inspection and maintenance are required to ensure the stable and reliable operation of each distributed power generation equipment. Therefore, its operation and maintenance expenses C_{OM} are described as follows [12]:

$$C_{OM} = \sum_{t=1}^{24} K_{om,i} P_i(t) \quad (6)$$

where $K_{om,i}$ and $P_i(t)$ are the operation and maintenance coefficients (having the dimension \$/kWh) and the actual output power of the type i distributed power supply, respectively.

Following formula [13] is used to analysis the sensitivity of operation an maintenance costs.

$$S_{i_1, i_2, \dots, i_s} = \frac{D_{i_1, i_2, \dots, i_s}}{D} (1 \leq i_1 < \dots < i_s \leq k) \quad (7)$$

where S indicates sensitivity, D_{i_1, i_2, \dots, i_s} indicates S order eccentricity and D indicates model total variance.

Microgrid guides electricity consumption behavior of users by electricity price, which ensures that microgrid operates in a more economical way. The interactive costs can be divided into two parts: the purchase of electricity C_{buy} and the sale of electricity C_{sell} Detailed description is as follows [14]:

$$\begin{cases} C_{buy} = \sum_{t=1}^{24} P_{buy}(t) S(t) \\ C_{sell} = \sum_{t=1}^{24} P_{sell}(t) S(t) \end{cases} \quad (8)$$

In the formula, $P_{buy}(t)$ is the active power purchased by the microgrid from the main network at time t . $P_{sell}(t)$ is the active power of the microgrid sold to the main network at time t . $S(t)$ is the transaction price in the electricity market at time t . Peak and valley prices are used here.

Electric vehicles, as a portable energy storage device, can be charged and discharged when they participate in the operation of microgrid dispatching. However, when V2G technology interacts with the power grid, the battery life of EV will decrease gradually, and a small amount of power loss will be caused during charging and discharging. In the operation process of the smart microgrid system in this paper, it is necessary to consider the cost C_{BAT} generated by grid connection of electric vehicles, which mainly consists of

depreciation cost C_{bat} and electric energy loss cost C_{con} . Detailed description is as follows[15]:

$$C_{BAT} = C_{con} + C_{bat} \quad (9)$$

$$\begin{cases} C_{bat} = \sum_{t=1}^{24} \sum_{j=1}^n K_{EV} \cdot P_{EV,j}(t) \\ C_{con} = \sum_{t=1}^{24} \sum_{j=1}^n \frac{C_{sell}(t) \cdot (1 - \eta_{c,j} \cdot \eta_{d,j})}{\eta_{c,j} \cdot \eta_{c,j}} \cdot P_{EV,j}(t) \end{cases} \quad (10)$$

where C_{con} is the loss cost caused by the interaction between the V2G technology and the main network of the electric vehicle. C_{bat} is the depreciation cost of electric vehicle battery. $\eta_{c,j}$ and $\eta_{d,j}$ are the charging and discharging efficiencies of the No.j electric vehicle. $P_{EV,j}(t)$ is the discharge power of the second electric vehicle at t time. K_{EV} is the depreciation factor of the vehicle battery.

2) OBJECTIVE FUNCTION f_2

f_2 is the environmental compensation cost of microgrid, including the environmental compensation cost of fossil energy combustion of diesel engine and gas turbine and the environmental compensation cost of fossil energy combustion in main network [16].

$$f_2 = \sum_{t=1}^{24} \sum_{h=1}^N ((C_{DE,h} u_{DE,h}) P_{DE}(t) + (C_{MT,h} u_{MT,h}) P_{MT}(t) + (C_{buy,h} u_{buy,h}) P_{buy}(t)) \quad (11)$$

Here, h is the type of pollutant, N is the total type of pollutants. There are three kinds of pollutant releases: CO_2 , SO_2 and NO_x , $C_{DE,h}$, h and $C_{MT,h}$, h are the compensation costs for the type h pollutants of diesel engines and micro turbines respectively. $u_{DE,h}$ and $u_{MT,h}$ are the emission coefficient of corresponding pollutants respectively. $C_{buy,h}$ is the compensation fee for pollutant h in the main network. $u_{buy,h}$ is the pollutant release coefficient corresponding to the main network. (3) The operation cost of smart microgrid and the environmental compensation cost of a smart microgrid are regarded as equally important objectives. Therefore, the economic dispatching objective of microgrid F can be determined as follows:

$$minF = f_1 + f_2 \quad (12)$$

C. CONSTRAINTS[18]

In order to ensure the stable and reliable operation of microgrid, microgrid should meet the following constraints. (1) Supply and demand balance constraints. The generation power in the microgrid at each time should be equal to the load demand in the microgrid.

$$\sum_{i=1}^N P_i(t) + P_{buy}(t) + P_{sell}(t) = P_{load}(t) + P_{EV}(t) \quad (13)$$

(2) Distributed generation power constraints. The output power of each distributed power supply should satisfy its

maximum and minimum power constraints so that it can operate normally.

$$P_{i,min} \leq P_i(t) \leq P_{i,max} \quad (14)$$

(3) Power exchange constraints in power grids. When the microgrid is connected to the grid, the power supply to the main network should satisfy the upper and lower limits of the tie-line, so that it can exchange power reasonably.

$$\begin{cases} 0 \leq P_{buy}(t) \leq P_{buy,max} \\ 0 \leq P_{sell}(t) \leq P_{sell,max} \end{cases} \quad (15)$$

(4) Electric vehicle charging and discharging power constraints. Electric vehicles can release and absorb electric energy when they participate in microgrid dispatching. When charging and discharging, the power should meet the upper and lower limits.

$$P_{EV,min} \leq P_{EV}(t) \leq P_{EV,max} \quad (16)$$

(5) Constraints on the state of charge. When battery and electric vehicle battery exchange power in microgrid, their charging state should be at a reasonable level to maximize their service life.

$$SOC_{ba,min} \leq SOC_{ba}(t) \leq SOC_{ba,max} \quad (17)$$

D. MICROGRID OPTIMAL DISPATCHING STRATEGY BASED ON ANNEALING MUTATION PARTICLE SWARM OPTIMIZATION

The model in this paper belongs to a typical multi-variable and multi-constraint optimization problem. In reference [7], a particle swarm optimization (PSO) algorithm with dynamically adjusting parameters is proposed, which dynamically adjusts the inertia weight and learning factor of the PSO algorithm to improve the global optimization ability of the algorithm. However, the optimization ability of the algorithm still needs to be improved. Therefore, this paper introduces simulated annealing mechanism and Gauss mutation operation on the basis of the algorithm to further improve the global search ability and local search ability of PSO algorithm, and help the algorithm to jump out of the local optimal solution. The algorithmic diagram is shown in fig. 2.

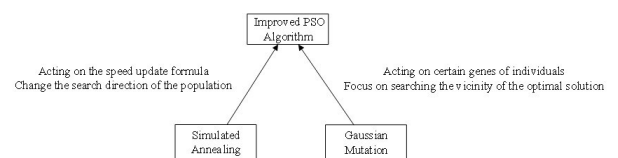


FIGURE 2. Algorithmic diagram.

1) IMPROVED PSO ALGORITHM

Because the learning factor and inertia weight have important influence on the convergence speed and local optimization of particle swarm optimization. Therefore, a method of adaptive learning factor and inertia weight is proposed in reference [7],

which updates the position and velocity of particle swarm. Specific parameter adjustment strategies are as follows [7]:

$$\begin{cases} \omega = \omega_s + (\omega_e - \omega_s) \frac{it^2}{T^2} \\ c_1 = c_{1s} + (c_{1e} - c_{1s}) \frac{it^2}{T^2} \\ c_2 = c_{2s} + (c_{2e} - c_{2s}) \frac{it^2}{T^2} \end{cases} \quad (18)$$

where ω_s, ω_e are the starting and ending weights of inertia weight ω , respectively. it is the current iteration number. T is the total number of iterations. $c_{1s}, c_{1e}, c_{2s}, c_{2e}$ are the start and end factors of c_1 and c_2 parameters respectively.

2) IMMUNE SELECTION

Simulated annealing algorithm is mainly inspired by the law of energy change in the solid during heating and cooling to crystallization. Thus, it is introduced into the combinatorial optimization problem to solve some complex problems that other optimization algorithms can not solve[18]. The algorithm regards the objective function as the change of the internal energy of the object, and the optimal solution is the lowest state of energy. The initial solution is the initial state of the internal energy of the object. The temperature is a function related to the physical internal energy. With the decrease of the internal energy, the temperature decreases gradually [19]. In the simulated annealing mechanism, a random number is generated randomly in each iteration. When the probability of mutation of a particle is greater than this random number, the optimal solution of the particle so far is selected and replaced by the global optimal solution in the population velocity update formula, thus changing the direction of the population optimization, making the algorithm continue to search around the optimal solution randomly and reducing the calculation. The mutation probability formula is as follows [19]:

$$P_k = \frac{e^{-(f_{pk} - f_{pg})/T}}{\sum_{t=1}^N e^{-(f_{pk} - f_{pg})/T}} \quad (19)$$

where P_k is the mutation probability of particle k . N is the population size. f_{pk} is the current optimum fitness of particle. f_{pg} is the current global optimal fitness value of the population. T is the control parameter of temperature, i.e. mutation probability. The speed update formula of the original PSO algorithm is improved by simulated annealing algorithm as shown in formula [20]:

$$\vartheta_i^{it+1} = \omega \vartheta_i^{it} + c_1 \gamma_1 (p_i^{it} - X_i^{it}) + c_2 \gamma_2 (p_j^{it} - X_j^{it}) \quad (20)$$

where ω is the inertia weight, γ_1 and γ_2 are random numbers distributed between [0-1], the current number of iterations is tested, p_i^{it} is the optimal particle position of the individual, p_j^{it} is the global optimal particle position, and c_1 and c_2 are constants. ϑ_i^{it} is the particle velocity and X_j^{it} is the particle position.

E. GAUSS MUTATION OPERATION

Gauss mutation is to select individuals from the population with a certain probability of mutation, and then to randomly change a gene of the individual with a probability consistent with the Gauss distribution, that is to say, to focus on the random search of the region near the optimal solution. Therefore, it has a good search ability near the local small range [21]. In this paper, Gauss mutation operation is applied to the global search state of PSO algorithm, which guides individuals to search for the optimal solution of the population, speeds up the algorithm to find the optimal solution, and improves the convergence ability of PSO algorithm. The definition is as follows [22]:

$$X_m^{it} = X_i^{it} * (G(0, 1) + 1) \quad (21)$$

where, $G(0, 1)$ is a random variable obeying (0,1) normal distribution. X_i^{it} is the individual selected from the population by mutation probability P_m in the it th iteration. X_m^{it} is the individual generated by Gauss mutation in the it th iteration.

F. ALGORITHM FLOW

The implementation steps of the proposed algorithm are as follows and The flow chart is shown in fig. 3.

(1) Initialization of algorithm parameters. The population size, the initial value of two learning factors, the initial value of inertia weight, the total number of iterations, the mutation probability and the mutation factor are initialized.

(2) Calculate fitness. The fitness values of all particles in each iteration are calculated and recorded.

(3) Optimal selection. It is to select a local optimal solution as the global optimal solution of the objective function with a certain probability from multiple local optimal solutions generated in the process of algorithm optimization.

(4) Perform SA(Simulated Annealing) search. The mutation probability is used to modify the global optimal solution and change the global search direction of the population.

(5) Update inertia weight and learning factor. Two learning factors and inertia weights in the algorithm are updated by using the update formulas of inertia weights and learning factors proposed in reference [7].

(6) Update location and speed. The position and velocity updating formulas are used to update them.

(7) Gauss variation. The population varies with probability.

(8) Renewal population optimization. The fitness values of each mutation particle are calculated and compared with the historical individual optimum and the group optimum to update the group optimum.

(9) Judgment conditions. If the number of iterations reaches the maximum set of parameters, the power of each distributed power source will be output if it is satisfied; if it is not satisfied, it will jump to step 2 to continue the optimization.

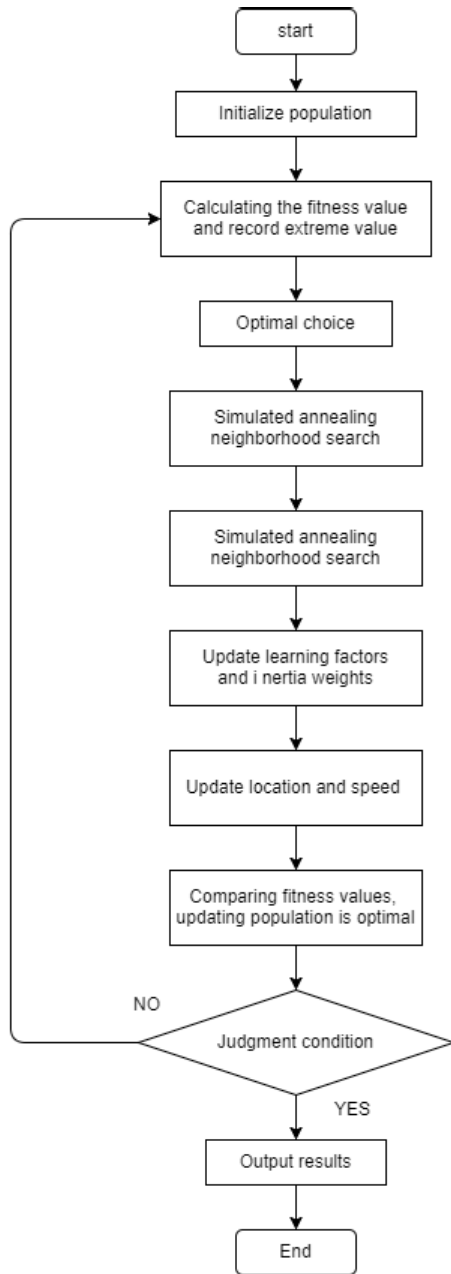


FIGURE 3. Algorithm flow chart.

IV. SIMULATION RESULTS AND ANALYSIS

A. EXPERIMENTAL SCENE AND RELATED DATA

The experimental data in this paper are obtained by Get-Data Graph Digitizer software from document [7]. Microgrid mainly uses wind power and photovoltaic power generation, and other distributed generators as auxiliary power supply. The solar output of wind power, photoelectricity and load in the microgrid is shown in fig. 4. As can be seen from Figure 4 the peak load period is from 8:00 a.m. to 23:00 p.m and the trough is from 24:00 p.m. to 7:00 a.m. Among them, the minimum load is 41.475 kW and the maximum load is 148.163 kW. In this paper, we consider the disorderly

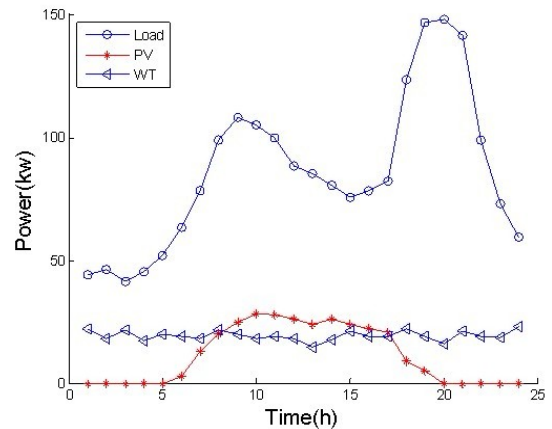


FIGURE 4. Load curve photovoltaic and wind power output curve.

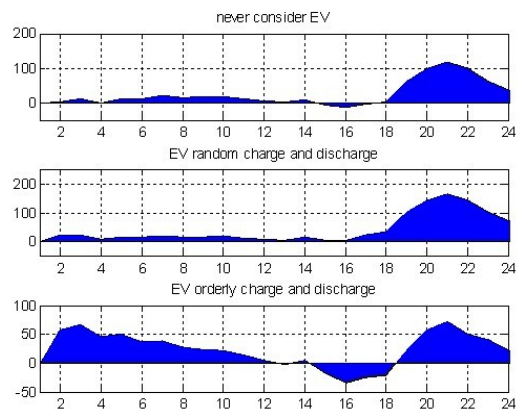


FIGURE 5. Balanced power.

charging (Scenario 1) and orderly charging and discharging (Scenario 2) of large-scale electric vehicles in the microgrid dispatching scenario. Therefore, the disordered and disordered charging and discharging power of large-scale electric vehicles can be simulated respectively according to the charging behavior and market price behavior of the user. Because wind power generation and photovoltaic power generation are the main components of microgrid. Therefore, when the microgrid without electric vehicle is dispatched, the balance power is the difference of load minus wind and light output. The two microgrid modes with orderly and disorderly charging and discharging behavior of electric vehicles are to superimpose the simulated power of electric vehicles on the balanced power required by the dispatching operation of microgrid. Therefore, the balanced power required for microgrid dispatching in three cases is shown in fig. 5. In this paper, the environmental compensation parameters of distributed power supply used in microgrid system are adopted in reference [4]. The operation constraints of each distributed power supply are shown in table. 2. The maintenance coefficients of each equipment are shown in table. 3. Peak and valley tariffs are used for policy guidance in microgrid. Specific tariff information is shown in table. 4.

TABLE 2. Distributed power supply parameters.

Type	P_{\min} (kW)	P_{\max} (kW)
DE	0	40
MT	0	50
BA	-30	30
Grid	-80	80

TABLE 3. Operational maintenance coefficient.

Type	PV	WT	DE	MT	BA
Operational Maintenance Co-efficient(Yuan/kW)	0.01	0.13	0.04	0.08	0.05

TABLE 4. Operational maintenance coefficient.

Type	Valley time (0:00-6:00)	Peacetime segment (Other)	Peak period (9:00-13:00, 18:00-22:00)
Selling electricity	0.30	0.50	0.78
Power purchase	0.41	0.69	1.08

B. COMPARATIVE ANALYSIS OF ALGORITHMS

In order to verify the performance of the algorithm proposed in this section, the objective functions of scenario 2 are optimized by using traditional PSO, IPSO in reference [4] and SAGAPSO in this section. In this section, the algorithm parameters are set as follows: Other parameters such as inertia weight and learning factor are consistent with those in reference [4]. The comparison results of the three algorithms are shown in fig. 6.

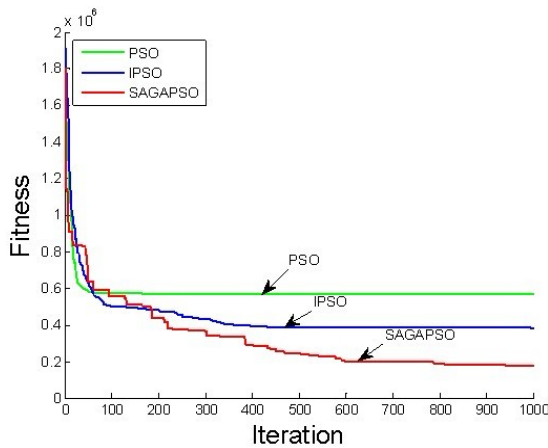


FIGURE 6. Algorithmic comparison.

As can be seen from fig. 6, it can be seen that the basic PSO algorithm falls into the local optimal solution about 70 times, and the optimal value is constant. The IPSO algorithm in reference [4] is better than the basic PSO algorithm, and keeps searching for the optimal solution until the 500 iterations, when the algorithm falls into the local optimal solution, the optimal value is constant. Before 620 times, the algorithm proposed in this paper constantly explores and jumps out of local optimum, and finally find the optimal solution

in 620 times, and the optimal solution is smaller than that found by IPSO and basic PSO.

From reference[23], it is difficult to obtain a theoretical solution for the optimization problem of strong oscillation multimodal function by PSO algorithm and GA algorithm, but SAGAPSO can obtain the theoretical solution. It can be seen that his adaptability is better than PSO and GA algorithm. The result is shown in table. 5.

C. ANALYSIS OF SCENE OUTPUT

As can be seen from fig. 4, the microgrid scenario with random charging behavior of electric vehicles enlarges the difference between peak and valley power, and increases the load that the microgrid needs to balance. In the microgrid scenario with orderly charging and discharging of electric vehicles, because electric vehicles can charge and discharging, the difference of balanced power required by the microgrid can be reduced by adding them to the original load, and the surplus (negative power) power can be sold to the grid at a low price to reduce the dispatching cost of the smart microgrid. The dispatch of each micro-source in the smart microgrid model including the random charging behavior of electric vehicles is shown in fig. 7.

TABLE 5. Function solution comparison.

Optimal Solution	GA	PSO	SAGAPSO
0	0.30	0.50	0.78

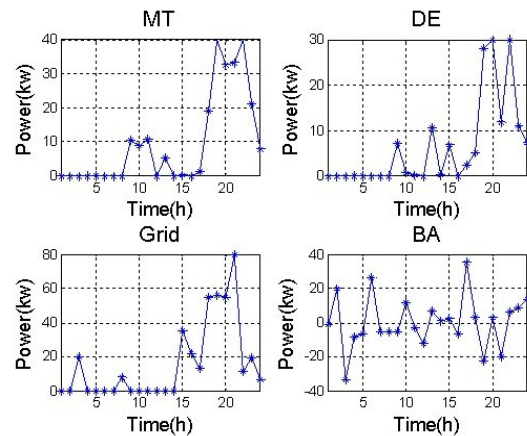


FIGURE 7. Output power of EV disorderly charging devices in microgrid.

As can be seen from fig. 7, 1:00-8:00 DE and MT have no power output. During this period, the microgrid mainly receives power supply from the large grid and storage. Because, at this time, renewable energy can not meet the demand of load and electric vehicle charging, while the price of the main network is at a low level, which is lower than the generation cost of controllable power supply. At about 9:00-13:00, it is mainly powered by batteries, and hardly interacts with large power grids. Because grid prices are at their peak at the moment, From 14:00 to 23:00, diesel

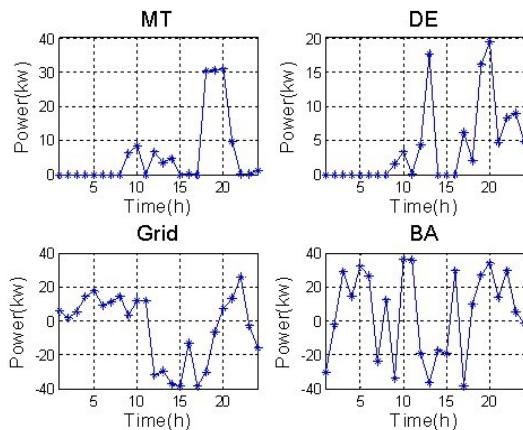


FIGURE 8. Output power of EV disorderly charging devices in microgrid.

engines and gas turbines began to work with the increasing demand for load and electric vehicles. But it can not meet the power demand of the load. Then the high price purchases electricity from the main network, and the total load decreases around 24:00, and the output power of the controllable power supply decreases. As can be seen from fig. 8, the load in the microgrid is mainly supplied by the large grid at 1:00-8:00. And the power supply decreases gradually with the decrease of net load, while DE and MT do not work. Because the cost of purchasing electricity from the main network is less than the cost of generating electricity from DE and MT. Because the cost of purchasing electricity from the main network is less than the cost of generating electricity from DE and MT. From 9:00 to 12:00, there is little energy interaction between the microgrid and the large grid, and the power supply is provided by DE, MT and energy storage. Because at this time, with the photovoltaic work, the net load in the microgrid gradually decreases, and the grid price is higher at this time. From 13:00 to 18:00, DE and MT do not work and electricity is sold to the main network for profit. This is because, under the guidance of electricity prices, electric vehicles discharge, and photovoltaic power generation, wind power release more electricity than load demand. So at the moment, there is enough electricity in the microgrid, some of which are stored in batteries, and some of which are sold to the large grid for profit. From 18:00 to 24:00, with the decline of photovoltaic output, load demand is once again greater than that of electric vehicles, wind and light. Therefore, at this time, DE and MT start to work again, output power, and buy part of the power from the main network at a high price. The dispatching cost of microgrid in two scenarios is 844.42 yuan (scenario 1) and 776.63 yuan (scenario 2), respectively. Comparing the two scenarios, the orderly charging and discharging mode of electric vehicle guided by electricity price in microgrid makes the operation cost of microgrid more economical. Because the electric vehicle can release electricity when the electricity price is high and reduce the load, thus saving the dispatching cost. Scene 2 saves 67.79 yuan compared with Scene 1.

V. CONCLUSION

This paper presents our microgrid scenario and compares it with the work of reference [4]. Then, according to the micro-grid scenario, under the mechanism of peakvalley tariff, the objective is to minimize the operation cost and environmental protection cost of microgrid. Under the constraint of satisfying the balance between supply and demand of microgrid, we establish our economic dispatching model of microgrid. This model not only takes into account the energy loss cost of electric vehicles participating in the microgrid dispatching process through V2G technology, which increasing the energy storage capacity. In order to optimize the dispatching results of microgrid, an annealing mutation particle swarm optimization algorithm is proposed. Finally, through simulation and comparison, the dispatching cost results of microgrid under two dispatching modes of electric vehicle: disorderly and orderly. By comparing the dispatching results of two modes of electric vehicle, the orderly charging and discharging mode guided by electricity price can effectively reduce the operation cost and environmental protection cost of microgrid, and improve the economic and reliability of microgrid operation.

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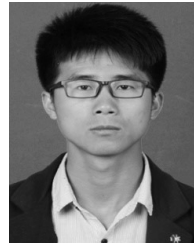
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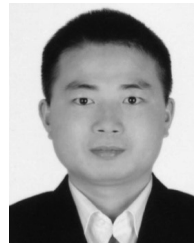
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