IEEE Access
Multidisciplinary | Rapid Review | Open Access Journal

Received 7 May 2024, accepted 20 May 2024, date of publication 27 May 2024, date of current version 5 June 2024.

Digital Object Identifier 10.1109/ACCESS.2024.3406036

RESEARCH ARTICLE

Low Carbon Optimization Scheduling of Micro Grid Based on Improved Particle Swarm Optimization Algorithm

SANG YINGJUN[1], ZHANG WENZHI[1], MA JING[1], CHEN QUANYU[1], TAO JINGLEI[1], AND FAN YUANYUAN[2]

[1]Faculty of Automation, Huaiyin Institute of Technology, Huai'an 223003, China
[2]Faculty of Mathematics and Physics, Huaiyin Institute of Technology, Huai'an 223003, China

Corresponding author: Fan Yuanyuan (fyuanyuan123@163.com)

This work was supported in part by Jiangsu Provincial Department of Housing and Construction Project under Grant HGDJ202201; and in part by the Innovation and Entrepreneurship Project for Student under Grant 202311049015Z, Grant 202311049451YJ, Grant HGYK202209, and Grant HGYK202310.

ABSTRACT This article proposes a low-carbon operation analysis method for micro grids based on improved particle swarm optimization algorithm. Corresponding improvements have been made to the inertia weight, learning factor, and individual extreme of the algorithm, depicting the comprehensive low-carbon operation information of micro grids under the influence of carbon emission quotas and carbon trading mechanisms from the perspective of data visualization. The low-carbon scheduling of micro grids is carried out from three perspectives: environmental protection, economy, and comprehensiveness, which compensates for the limitations of focusing on traditional low-carbon operation and provides a powerful tool for analyzing low-carbon operation of micro grids. Firstly, establish the energy consumption cost and carbon emission cost functions of the micro grid system, add the two cost functions together and take the minimum sum to form the objective function of this article. Then, based on the characteristics of each unit, a low-carbon model is constructed to constrain the carbon emissions of each unit. Finally, simulation analysis was conducted on the micro grid system based on the improved particle swarm optimization algorithm, verifying the effectiveness and practicality of the proposed algorithm. The simulation results show that the improved particle swarm optimization algorithm can quickly and effectively reduce energy consumption and carbon emission costs, and improve the comprehensive efficiency of micro grid systems.

INDEX TERMS Micro grid, low carbon, particle swarm optimization algorithm, carbon emissions, carbon trading mechanism.

I. INTRODUCTION

With the large-scale integration of renewable energy sources such as wind and light into the grid, micro grids play an indispensable role in promoting the green and low-carbon transformation of energy structure [1], [2]. With the rapid development of China's economy, the demand for energy is also increasing, and the power industry is showing a good development trend. micro grids, as an important part of smart grids, play an indispensable role in sustainable economic development. Therefore, developing distributed energy is one of the important ways for China to achieve energy transformation and the "dual carbon goals". In 2022, the National Development and Reform Commission released the "14th Five Year Plan for Modern Energy System" [3], proposing to use the power grid as the basic platform to promote the development of distributed energy and reasonably configure distributed energy storage systems. As of the end of 2022, the installed capacity of distributed new energy in China has reached 250 million kilowatts, accounting for 10% of the total installed capacity in the country, including 145 million kilowatts of distributed photostatic [4]. Faced

The associate editor coordinating the review of this manuscript and approving it for publication was Akshay Kumar Saha.

with the dual pressures of energy and environment, finding new environmentally friendly energy sources has become a consensus. New renewable energy sources, represented by wind power and photostatic, have been widely applied. However, due to the significant environmental impact and randomness and volatility of new renewable energy sources such as wind power and photostatic, micro grids have emerged to address these issues. micro grids are also the key to solving energy and environmental problems.

Distributed energy sources such as wind power and photostatic have inherent characteristics such as volatility and intermittency. Their rapid grid connection development makes distribution network control more complex and uncertain, posing a huge challenge to the safe and economic operation of the power grid. On the other hand, micro grids with multiple elements of source, grid, load, and storage have high flexibility. Their operation modes and interaction strategies with the transmission network are rich, which can effectively utilize distributed new energy [5], achieve self-control, self-sufficiency, and autonomy of domestic power supply to a certain extent, improve power quality and safety, improve energy utilization efficiency, reduce carbon emission intensity [6], and meet the diverse needs of different users [7]. Therefore, micro grids are receiving widespread attention and research from scholars both domestically and internationally. Distributed power sources mainly include wind power, photostatic, diesel engines, gas turbines, etc. In recent years, guided by the strategy of "peaking carbon and achieving carbon neutrality", the development of clean energy generation has reached a new level. Therefore, optimizing the scheduling of micro grids requires comprehensive consideration of economic and environmental benefits.

The micro grid includes different types and control methods of energy, so for the optimization and scheduling of micro grids, it is a multi-objective table nonlinear optimization problem, which is also the core of micro grid optimization and scheduling. In order to purposefully optimize the scheduling of power sources, domestic and foreign scholars have conducted in-depth research and achieved remarkable results. Shen and Yang [8] optimized the scheduling of micro grids through an improved bat algorithm, but did not consider environmental costs, Li et al. [9] optimized the scheduling of micro grids through an improved particle swarm optimization algorithm, taking into account both economic and environmental costs, Huang [10]utilized the improved Grey Wolf algorithm to optimize the scheduling of micro grids, verifying the feasibility and superiority of the improved Grey Wolf algorithm, Li and Zhang [11]proposed an improved multi-objective harmony search algorithm based on dynamic probability parameters and virtual fitness to apply to the optimization scheduling model of micro grids, Zeng et al. [12] constructed a multi-objective optimization model with minimal operating costs and environmental pollution for micro grids, and used the bird swarm algorithm to solve the model, which has strong search ability, Chu [13] allocates the load under two operating modes: isolated

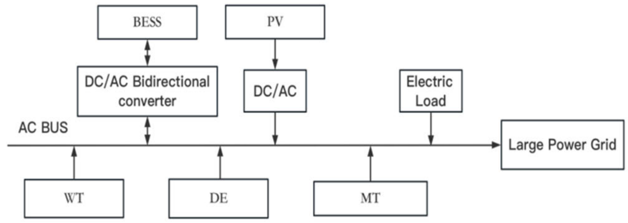

FIGURE 1. Structure diagram of micro grid system.

network operation and grid connected operation using genetic algorithm, Sarfi and Livani [14] proposed a multi-objective optimal scheduling model based on micro grid security constraints for the economic and reliable operation of micro grids, Feng and Hu [15]used simulated annealing genetic algorithm to solve the model.

This article analyzes the output of each unit in the micro grid, with the objective function of minimizing the sum of energy consumption cost and carbon emission cost. It studies the low-carbon optimization scheduling method of the micro grid, and combines the characteristics of each unit to construct a low-carbon model to constrain the carbon emissions of each unit. Finally, an improved particle swarm optimization algorithm is used to simulate and analyze the micro grid system on MATLAB. From the perspectives of environmental protection, economy, and comprehensiveness, low-carbon scheduling of micro grids is carried out. Simulation results show that the improved particle swarm optimization algorithm can quickly and effectively reduce energy consumption and carbon emission costs, and improve the comprehensive efficiency of micro grid systems.

The micro grid studied in this article mainly includes wind turbines, photovoltaic generators, micro gas turbines, diesel engines, energy storage equipment, main grid interaction, and electrical loads [16]. The structure is shown in Figure 1.

The terminology list of symbols and meanings involved in this article is as follows.

Category	Symbol	Significance
Wind turbines	$P_{WT,t}$	The actual output power of wind turbines
	V	Actual wind speed of wind turbines
	V_i	Cutting in wind speed of wind turbines
	V_e	Rated wind speed of wind turbines
	V_0	The cut-off wind speed of wind turbines
	P_e	Rated power of wind turbines

	$K_{WT,1}$、$K_{WT,2}$	Power characteristic parameters of wind turbines
Photovoltaic unit	$P_{PV,t}$	The actual output power of photovoltaic generators
	P_{STC}	Maximum output power in standard environment
	G_{STC}	Light intensity under standard environment
	T_{STC}	Environmental temperature under standard environment
	G_C	Actual light intensity
	T_C	Actual ambient temperature
	μ	temperature coefficient
Storage battery	SOC_t	the stored energy of the battery at time t
	SOC_{t-1}	the stored energy at time t-1
	η_c	Charging coefficient of battery
	η_f	Discharge coefficient of battery
	λ	the self charging and discharging rate of the battery
	$P_{bess,t}$	the charging and discharging power of the battery at time t
Diesel engine	F_{DE}	the operating cost of the diesel engine
	$P_{DE,t}$	the power generated by the diesel engine at time t
	α、β、γ	the operating cost coefficient of the diesel engine
gas turbine	F_{MT}	the operating cost of the micro gas turbine
	K_{MT}	the cost coefficient of the micro gas turbine
	η_{MT}	the operational efficiency of micro gas turbines
	LHV	the Low calorific value of natural gas
	$P_{MT,t}$	the power generated by the gas turbine at time t

Main network interaction	F_{grid}	the total cost of the interaction between the micro grid and the main grid
	$C_{buy,t}$	the purchase prices of the micro grid and the main grid at time t
	$C_{sell,t}$	the sale prices of the micro grid and the main grid at time t
	$P_{grid,t}$	the purchasing and selling power of the micro grid and the main grid at time t
Objective function	ω_1	the weighted coefficient of energy consumption cost
	ω_2	the weighted coefficient of carbon emission cost
	F_N	the energy consumption cost of the microgrid system
	F_C	the cost of carbon emissions for micro grid systems
	F_{WT}	the operating cost of the wind turbine
	F_{PV}	the operating cost of photovoltaic generators
	F_{best}	the Cost of energy storage
	λ_{WT}	the operating cost coefficient of wind turbines
	λ_{PV}	the operating cost coefficient of photovoltaic generators
	λ_{bess}	the cost coefficient of energy storage
	a、b、c	the carbon emission factors per unit power of the battery, diesel engine, and gas turbine at time t
	K_C	the penalty coefficient for the excess unit carbon emission power
	S_t	the carbon emission quota power of the current unit at time t
	ε	the unit power emission quota coefficient,δ is the carbon emission cost coefficient
	δ	the carbon emission cost coefficient
	D_t	the actual carbon emission power generated by the current unit at time t
	ΔE_t	the Power for excess carbon emissions
	$P_{grid,t}$	the generation power of the main network interaction at time t

Constraint	$P_{L,t}$	the total power of the microgrid system at time t
	$P_{max,WT}$,$P_{min,WT}$	the upper and lower limits of wind farm output
	$P_{max,PV}$, $P_{min,PV}$	the upper and lower limits of the output of the photovoltaic power station
	$P_{max,bess}$,$P_{min,bess}$	the upper and lower limits of the output of the energy storage device
	SOC_{max},SOC_{min}	the upper and lower limits of energy storage capacity
	$P_{max,DE}$, $P_{min,DE}$	the upper and lower limits of diesel engine output
	$P_{max,MT}$, $P_{min,MT}$	the upper and lower limits of the output of the micro gas turbine
	$P_{max,grid}$, $P_{min,grid}$	the upper and lower limits of the transmission power of the interconnection line
PSO	d	the current number of iterations
	K	the total number of iterations
	ρ	the adjustment coefficient
	ω_{start},ω_{end}	the initial and ending values of the inertia weight factor
	$c_{1,start}$,$c_{1,end}$	the initial and ending values of c_1
	$c_{2,start}$,$c_{2,end}$	the initial and ending values of c_2
	$p_{best,new}$	updated individual extremum

II. A LOW-CARBON OPTIMIZATION SCHEDULING MODEL FOR MICROGRIDS

A. WIND TURBINE MODEL

The principle of wind power generation is to use wind power to drive the blades of a windmill to rotate, and then increase the speed of rotation through a booster engine to drive the generator to generate electricity. The working state of a wind turbine is related to its actual wind speed, cut-in wind speed, and cut-out wind speed. When the actual wind speed is less than the cut-in wind speed or greater than the cut-out wind speed, the operating requirements are not met, and the output power is zero, When the actual wind speed is between the cut-in wind speed and the rated wind speed, the power generation is shown in the formula, When the actual wind speed is between the rated wind speed and the cut out wind speed, it is the most ideal state for operation, and the unit operates at rated power [17].

$$P_{WT,t} = \begin{cases} 0 & 0 \leq V \leq V_i \\ K_{WT,1}V^3 + K_{WT,2}V_i^3 & V_i \leq V \leq V_e \\ P_e & V_e \leq V \leq V_0 \\ 0 & V \geq V_0 \end{cases} \tag{1}$$

$$\begin{cases} K_{WT,1} = \dfrac{P_e}{V_e^3 - V_i^3} \\ K_{WT,2} = -K_{WT,1} \end{cases} \tag{2}$$

In Eq. (1-2), $P_{WT,t}$ is the actual output power of the wind turbine, V, V_i, V_e and V_o are the actual wind speed, cut-in wind speed, rated wind speed, and cut-out wind speed of the wind turbine, P_e is the rated power of the wind turbine, $K_{WT,1}$ and $K_{WT,2}$ are the power characteristic parameters of wind turbines.

B. PHOTOVOLTAIC GENERATOR MODEL

Photovoltaic power generation is based on the principle of photovoltaic effect, using solar cells to directly convert solar energy into electrical energy. The working state of photovoltaic generators is related to light intensity and environmental temperature, and the specific photovoltaic output power formula is as follows [18].

$$P_{PV,t} = P_{STC} \times \frac{G_C}{G_{STC}} [1 + \mu(T_C - T_{STC})] \tag{3}$$

In Eq. (3), $P_{PV,t}$ is the actual output power of the photovoltaic generator. P_{STC}, G_{STC} and T_{STC} are the maximum output power, light intensity, and ambient temperature in the standard environment. G_C and T_C Respectively refer to the actual light intensity and actual environmental temperature,μ is the temperature coefficient.

C. BATTERY MODEL

The position of energy storage devices in the optimization and control of micro grids is very important. Energy storage can achieve peak shaving and valley filling, ensure the stability of the power system, and improve the quality of energy consumption.

$$SOC_t = \begin{cases} (1-\lambda) \times SOC_{t-1} + \dfrac{1}{\eta_f} \times P_{bess,t} & P_{bess,t} \leq 0 \\ (1-\lambda) \times SOC_{t-1} + \eta_c \times P_{bess,t} & P_{bess,t} > 0 \end{cases} \tag{4}$$

In Eq. (4), SOC_t and SOC_{t-1} are respectively the stored energy of the battery at time t and the stored energy at time t-1.η_c and η_f respectively refer to the charging and discharging coefficients of the battery, λ is the self charging and discharging rate of the battery,which is ignored due to its very small self discharging ratio, $P_{bess,t}$ is the charging and discharging power of the battery at time t.

D. DIESEL ENGINE MODEL

The fundamental principle of a diesel generator is to convert the chemical energy of the engine fuel into rotational mechanical energy, which is then converted into electrical energy by the generator, The speed control system adjusts the engine speed, i.e. the frequency of electricity, by adjusting the fuel supply, and adjusts the output active power at a fixed frequency.

$$F_{DE} = \sum_{t=1}^{T} \alpha P_{DE,t}^2 + \beta P_{DE,t} + \gamma \tag{5}$$

In Eq. (5), F_{DE} is the operating cost of the diesel engine, $P_{DE,t}$ is the power generated by the diesel engine at time t, α, β, γ are the operating cost coefficient of the diesel engine.

E. MICRO GAS TURBINE MODEL

Compared with traditional power sources [19], micro gas turbines have significant advantages such as long service life, simple maintenance, and so on.

$$F_{MT} = \sum_{t=1}^{T} K_{MT,t} \times \frac{P_{MT,t}}{LHV \times \eta_{MT}} \tag{6}$$

In Eq. (6), F_{MT} is the operating cost of the micro gas turbine, K_{MT} is the cost coefficient of the micro gas turbine, η_{MT} is the operational efficiency of micro gas turbines, LHV is the Low calorific value of natural gas, $P_{MT,t}$ is the power generated by the gas turbine at time t.

F. MAIN NETWORK INTERACTION

$$F_{grid} = \sum_{t=1}^{T} (C_{buy,t} - C_{sell,t}) \times P_{grid,t} \tag{7}$$

In Eq. (7),F_{grid} is the total cost of the interaction between the micro grid and the main grid. $C_{buy,t}$ and $C_{sell,t}$ are the purchase and sale prices of the micro grid and the main grid at time t, $P_{grid,t}$ is the purchasing and selling power of the micro grid and the main grid at time t.

III. OBJECTIVE FUNCTION

For the low-carbon optimization model of micro grids, taking into account two types of optimization objectives: energy consumption cost and carbon emission cost, a weighted coefficient method is used to establish an objective function. The objective function is as follows [21].

$$F_Z = \min(\omega_1 \times F_N + \omega_2 \times F_C) \tag{8}$$

$$\omega_1 + \omega_2 = 1 \tag{9}$$

In Eq. (8-9), ω_1 is the weighted coefficient of energy consumption cost and ω_2 is the weighted coefficient of carbon emission cost, F_N is the energy consumption cost of the micro grid system, F_C is the cost of carbon emissions for micro grid systems. The energy cost objective function is as follows.

$$F_N = F_{WT} + F_{PV} + F_{bess} + F_{DE} + F_{MT} + F_{grid} \tag{10}$$

In Eq. (10), F_{WT} is the operating cost of the wind turbine, F_{PV} is the operating cost of photovoltaic generators, F_{best} is the Cost of energy storage. The functions of F_{WT}, F_{PV}, and F_{best} are as shown in Eq. (11-13).

$$F_{WT} = \sum_{t=1}^{T} \lambda_{WT} \times P_{WT,t} \tag{11}$$

$$F_{PV} = \sum_{t=1}^{T} \lambda_{PV} \times P_{PV,t} \tag{12}$$

$$F_{bess} = \sum_{t=1}^{T} \lambda_{bess} \times SOC_t \tag{13}$$

In Eq. (11-13), $\lambda_{WT,}$ $\lambda_{PV,}$ λ_{bess} are the operating cost coefficient of wind turbines, the operating cost coefficient of photovoltaic generators, and the cost coefficient of energy storage.

Compare the actual carbon emissions of the system with the carbon emission quota allocated by the system under the carbon trading mechanism, introduce different carbon emission factors for the relevant units, and introduce penalty coefficients. If the actual carbon emissions exceed the carbon emission quota, the micro grid system will choose a scheduling model with a penalty mechanism, which can effectively regulate the carbon emission standards of the micro grid system and achieve the "redistribution" of the output of each unit, Reduce carbon emissions and minimize the overall cost of micro grid systems.

The carbon emission cost objective function of the micro grid system is as follows.

$$F_C = \begin{cases} \sum_{t=1}^{T} \delta(aP_{bess,t} + bP_{DE,t} + cP_{MT,t}) & \Delta E_t \le 0 \\ \sum_{t=1}^{T} \delta(aP_{bess,t} + bP_{DE,t} + cP_{MT,t}) + K_C \Delta E_t & \Delta E_t > 0 \end{cases} \tag{14}$$

$$\begin{cases} S_t = \varepsilon(P_{bess,t} + P_{DE,t} + P_{MT,t}) \\ D_t = aP_{bess,t} + bP_{DE,t} + cP_{MT,t} \\ \Delta E_t = D_t - S_t \end{cases} \tag{15}$$

In Eq. (14-15), a, b, and c are the carbon emission factors per unit power of the battery, diesel engine, and gas turbine at time t, K_C is the penalty coefficient for the excess unit carbon emission power, S_t is the carbon emission quota power of the current unit at time t, ε is the unit power emission quota coefficient,δ is the carbon emission cost coefficient, D_t is the actual carbon emission power generated by the current unit at time t, ΔE_t is the Power for excess carbon emissions.

A. CONSTRAINT CONDITION

The constraints of the micro grid system described in this article include: system power balance constraints, diesel engine output constraints, gas turbine output constraints, tie line transmission power constraints, energy storage device constraints, photovoltaic capacity upper and lower limits constraints, and wind power capacity upper and lower limits constraints.

Among them, the system power balance constraint is represented as:

$$P_{PV,t} + P_{WT,t} + P_{bess,t} + P_{grid,t} + P_{DE,t} + P_{MT,t} = P_{L,t} \tag{16}$$

In Eq. (16), $P_{PV,t}$ is the power generated by the photovoltaic power station at time t, $P_{WT,t}$ is the power generated by the wind farm at time t, $P_{bess,t}$ is the Charge and discharge power of the battery at time t, $P_{grid,t}$ is the generation power of the main network interaction at time t, $P_{DE,t}$ is the power generated by the diesel engine at time t, $P_{MT,t}$ is the power generated by the micro gas turbine at time t, $P_{L,t}$ is the total power of the micro grid system at time t.

The upper and lower limits of wind power capacity constraints are expressed as:

$$P_{min,WT} \le P_{WT,t} \le P_{max,WT} \tag{17}$$

In Eq. (17), $P_{max,WT,}P_{min,WT}$ represents the upper and lower limits of wind farm output, $P_{WT,t}$ is the output of the wind farm at time t.

The upper and lower limits of photovoltaic capacity constraints are expressed as:

$$P_{min,PV} \le P_{PV,t} \le P_{max,PV} \tag{18}$$

In Eq. (18), $P_{max,PV,}$ $P_{min,PV}$ represents the upper and lower limits of the output of the photovoltaic power station, $P_{PV,t}$ is the output of the photovoltaic power plant at time t,

The constraint of the energy storage device is expressed as:

$$\begin{cases} P_{min,bess} \le P_{bess,t} \le P_{max,bess} \\ SOC_{min} \le SOC_t \le SOC_{max} \end{cases} \tag{19}$$

In Eq. (19), $P_{max,bess,}$ $P_{min,bess}$ represents the upper and lower limits of the output of the energy storage device, $SOC_{max,}$ SOC_{min} represents the upper and lower limits of energy storage capacity.

The diesel engine output constraint is expressed as:

$$P_{min,DE} \le P_{DE,t} \le P_{max,DE} \tag{20}$$

In Eq. (20), $P_{max,DE,}P_{min,DE}$represents the upper and lower limits of diesel engine output, and $P_{DE,t}$ represents the generating power of the diesel engine at time t,

The output constraint of the gas turbine is expressed as:

$$P_{min,MT} \le P_{MT,t} \le P_{max,MT} \tag{21}$$

In Eq. (21), $P_{max,MT,}$ $P_{min,MT}$ represents the upper and lower limits of the output of the micro gas turbine,$P_{MT,t}$ represents the power generated by the micro gas turbine at time t,

The transmission power constraint of the interconnection line is expressed as:

$$P_{min,grid} \le P_{grid,t} \le P_{max,grid} \tag{22}$$

In Eq. (22), $P_{max,grid,}$ $P_{min,grid}$ represents the upper and lower limits of the transmission power of the interconnection line,$P_{grid,t}$ represents the generation power of the main network interaction at time t.

IV. PARTICLE SWARM OPTIMIZATION

A. TRADITIONAL PARTICLE SWARM OPTIMIZATION ALGORITHM

If the dimension of the target search space is D, and the population is composed of N particles,then the position and velocity of any particle are $x_i^t = (x_i^1, x_i^2, x_i^3 \cdots x_i^D)$ and $v_i^t = (v_i^1, v_i^2, v_i^3 \cdots v_i^D)$,So far, the optimal individual value found by any particle i is $pbest_i^t = (p_i^1, p_i^2, p_i^3 \cdots p_i^D)$,The optimal value of the searched population is $gbest_i^t = (g_i^1, g_i^2, g_i^3 \cdots g_i^D)$. After finding these two optimal values, the velocity and position of particles can be updated using the following formula:

$$v_i^{t+1} = w(t) \cdot v_i^t + c_1 r_1 (pbest_i^t - x_i^t) + c_2 r_2 (gbest_i^t - x_i^t) \tag{23}$$

$$x_i^{t+1} = x_i^t + v_i^{t+1} \tag{24}$$

In Eq. (22-23), v_i^{t+1} and x_i^{t+1} represent the velocity and position of the i-th particle at the t-th iteration, respectively. $pbest_i^t$ and $gbest_i^t$ are the optimal positions for the i-th particle and the population, respectively. w(t) is the inertia weight, with a range of [0.2,1],c_1 and c_2 are self cognitive learning factors and social cognitive learning factors, with a range of (0,2],r_1 and r_2 are a random number on the interval [0,1], The standard particle swarm optimization algorithm has fewer adjustment parameters, fast solving speed, and good optimization effect. However, in the early stage of the algorithm, it is susceptible to the influence of initial particles, causing the population to deviate from the optimal solution direction, and in the later stage, it faces the situation of falling into a local optimal solution [20].

B. IMPROVED PARTICLE SWARM OPTIMIZATION ALGORITHM

In order to avoid the algorithm falling into local optima, this article will improve from two aspects: inertia weight, learning factor, and individual extreme. To improve inertia weight, a nonlinear inertia weight improvement formula is proposed to balance the algorithm's global and local search capabilities, A dynamic adaptive adjustment formula for learning factors is proposed to improve the learning factors, so that the trend of learning factor changes meets the needs of iterative development of particle swarm optimization, A dynamic adaptive adjustment formula based on geometric averaging method is proposed to improve the individual extreme, which enhances the stability and accuracy of population approximation to the Pareto optimal frontier and enables particles to better approach the global extreme.

1) IMPROVEMENT OF INERTIA WEIGHT

The dynamic adjustment of inertia weights can improve the performance of the algorithm to a certain extent, but it is difficult to adapt to complex multi-modal problems. Research has shown that compared to linear decreasing inertia weight adjustment strategies, nonlinear decreasing strategies have better optimization effects. Therefore, this article proposes a segmented inertia weight adaptive improvement formula:

$$\omega_{new} = \begin{cases} \omega_{start} + 0.1 \times rand & d \le \frac{K}{3} \\ \frac{\omega_{start} + \omega_{end}}{2} + \frac{(\omega_{start} - \omega_{end})}{2} X^{\frac{1}{1+\rho \frac{d}{K}}} & \frac{K}{3} < d < \frac{2K}{3} \\ \omega_{end} - 0.1 \times rand & d \ge \frac{2K}{3} \end{cases} \tag{25}$$

In Eq. (24), d is the current number of iterations, K is the total number of iterations, ρ is the adjustment coefficient ω_{start} and ω_{end} are the initial and ending values of the inertia weight factor.

2) IMPROVEMENT OF LEARNING FACTORS

At present, the improvement of learning factors mainly focuses on adaptive adjustment formulas. The main principle is to make the learning factor c_1 linearly increase with the number of iterations, and the learning factor c_2 linearly decrease with the number of iterations. This can make the algorithm converge faster in the early iteration stage, and quickly converge to the global optimal in the later stage. Meanwhile, the learning factor c1 is greater than c_2 in the early stage and less than c_2 in the later stage. Therefore, this article proposes an improved learning factor adaptive formula:

$$\begin{cases} c_{1,new} = c_{1,end} + (c_{1,start} - c_{1,end}) \cos(\pi^{\frac{1}{2}} \frac{d^2}{K^2}) \\ c_{2,new} = c_{2,end} + (c_{2,start} - c_{2,end}) \cos(\pi^{\frac{1}{2}} \frac{d^2}{K^2}) \end{cases} \tag{26}$$

In the Eq. (25), $c_{1,\mathrm{start}}$ and $c_{1,\mathrm{end}}$ represent the initial and ending values of c_1, $c_{2,\mathrm{start}}$ and $c_{2,\mathrm{end}}$ represent the initial and ending values of c_2,

3) MPROVEMENT OF INDIVIDUAL EXTREMUM

The role of individual extreme is mainly reflected in two aspects: velocity update and position update of particles. As particles approach the individual extreme position, their speed gradually decreases, thereby slowing down the speed of particle evolution and preventing the occurrence of "over-fitting" phenomenon. At the same time, as particles approach the individual extreme position, their accuracy also increases, effectively avoiding particles falling into local optima and improving search performance. This article proposes an improved individual extreme value adaptive formula:

$$pbest_{new} = (pbest_1 \times pbest_2 \times \cdots \times pbest_n)^{\frac{1}{n}} \tag{27}$$

C. ALGORITHM FLOW

This article adopts an improved particle swarm optimization algorithm to establish a corresponding low-carbon optimization scheduling model. The specific steps are:

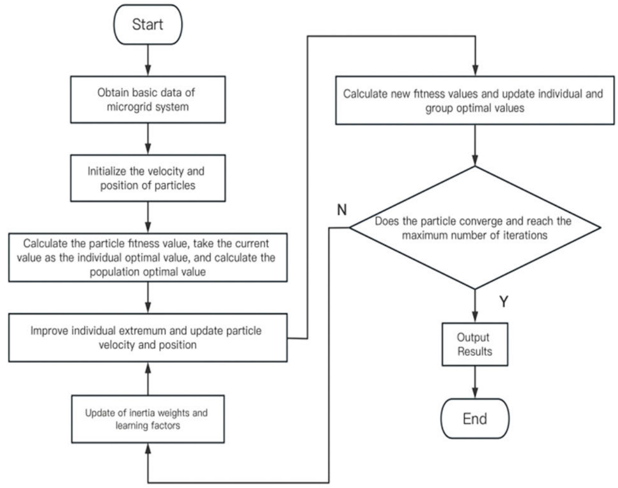

FIGURE 2. Algorithm flow chart.

Step 1: Obtain basic data of the micro grid system and perform parameter initialization.
Step 2: Initialize the particle population, with each particle in the population corresponding to a scheduling scheme.
Step 3: Calculate the fitness function and input a mathematical model with the minimum comprehensive operating cost as the objective function.
Step 4: Take the current value as the individual optimal value and calculate the group optimal value.
Step 5: Start iteration.
Step 6: Improving individual extreme values.
Step 7: Update the velocity and position of particles using the improved velocity update formula, calculate the updated fitness value, and update the individual and group optimal values of particles.
Step 8: Determine whether the particles converge, and if not, continue the iteration, On the contrary, the optimal solution is output, Provide optimization scheduling methods.

The process flow of the improved particle swarm optimization algorithm is shown in Figure 2:

V. SIMULATION STUDY

A. INTRODUCTION TO THE EXAMPLE

In this example, the dispatching time of the micro grid system is divided into 24 dispatching periods in units of one hour, and the objective function of the micro grid is solved by the improved particle swarm optimization algorithm. For the operation simulation of the micro grid system, the parameters provided on a typical day are used as the basis for simulation, and the optimal output of each distributed power source in the micro grid is determined, so that the comprehensive operation cost of the entire optimization dispatching cycle is minimized, and the low-carbon optimal operation of the micro grid system is realized. For the conventional particle swarm algorithm parameters fixed as constants, the present invention sets the inertia weight and learning factor as a one-dimensional vector, then Equation 24 and Equation 25 are

TABLE 1. Parameters of each unit.

Parameter name	Diesel engine	Gas turbine	Contact line	Wind generator	Photovoltaic generators
Maximum power/kW	53	63	32	20	10
Minimum power/kW	6	9	-32	0	0

TABLE 2. Peak-to-valley electricity prices for purchase and sale.

Transaction method	Price/[RMB/kW.h		
	Peak hours	Weekdays	Valley hours
Purchase electricity	1.55	0.82	0.55
Selling electricity	0.9	0.5	0.38

TABLE 3. Battery energy storage parameters.

Type	Parameter name	Numeric value
Accumulator	Maximum capacity/(kW.h)	163
	Minimum capacity/(kW.h)	10
	Initial energy storage capacity/(kW.h)	50
	Maximum input power/kW	32
	Maximum output/kW	32
	Charge rate	0.9

the updated iterative formulas of the inertia weight and the learning factor, respectively. Where: ω_{start} is 0.9, ω_{end} is 0.4, $c_{1,\text{start}}$ and $c_{2,\text{start}}$ is set to 2.5 and 0.5, $c_{1,\text{end}}$ and $c_{2,\text{end}}$ is set to 0.5 and 2.5, respectively. The number of populations is set to 100, and the maximum number of iterations is 200.

Table 1 shows the parameter data of each unit, setting the maximum power and minimum power, including five units: diesel engine, gas turbine, tie line, wind turbine and photovoltaic generator.

Table 2 shows the specific data of peak and valley electricity prices for electricity purchase and sale.

Table 3 is the battery energy storage parameter data, which specifies the maximum capacity, minimum capacity, initial energy storage capacity, maximum input power, minimum input power and charge and discharge rate of the battery.

B. SIMULATION RESULTS

According to the low-carbon optimal dispatching model and improved particle swarm algorithm of micro grid established in this paper, Matlab is used to program to achieve the purpose of load optimization, and the parameters provided on a typical day are used as the basis for simulation, and the output of each unit of the micro grid in the dispatching time is simulated, as shown in Figure 3.

Referring to the illustration of Figure 3, in order to better compare and analyze, the total load after optimization is compared with the total load before optimization, as shown in Figure 4

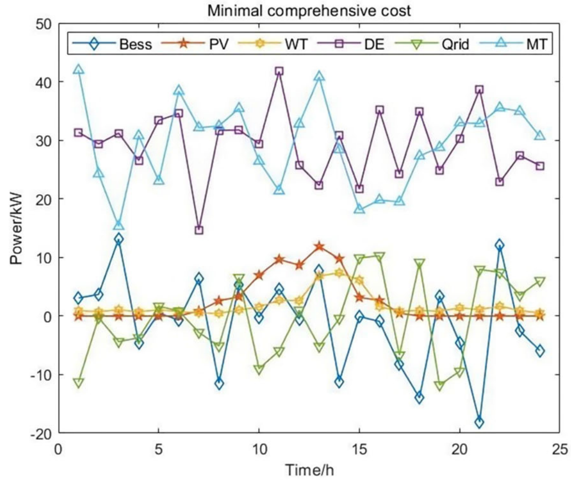

FIGURE 3. The output diagram of each unit after improvement.

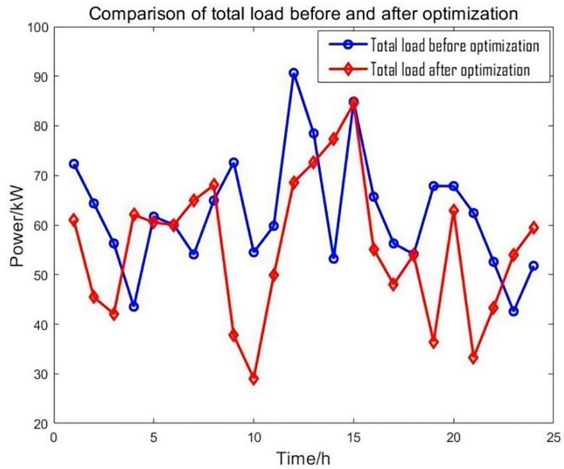

FIGURE 4. Comparison of total load before and after optimization.

From Figure 4, it is clear that the total load has been significantly improved during the peak hours of electricity consumption from 9:00 am to 12:00 pm and from 17:00 pm to 21:00 pm, and the total load of the optimized system is lower and more stable than that of the system before optimization.

The low-carbon optimal dispatch model of micro grid established in this paper not only considers the cost of energy consumption, but also takes into account the cost of carbon emissions, to ensure that the comprehensive benefits of the micro grid system are maximized, in order to optimize the dispatch more comprehensively and stably, this paper considers the optimization results under different schemes, as shown in Figure 5 and Figure 6.

Referring to the illustration of Figure 3 ∼ Figure 6, in order to better compare and analyze, it is divided into three schemes for optimal scheduling analysis, and the specific data is shown in Table 4

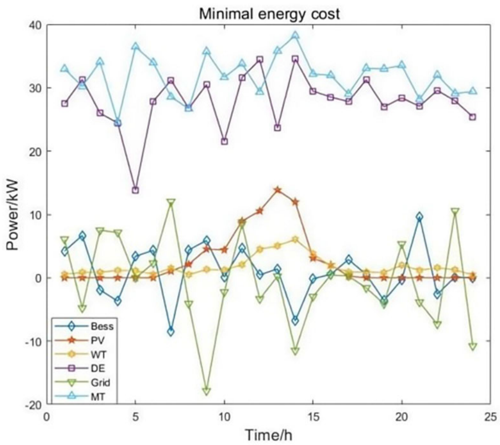

FIGURE 5. Energy consumption cost minimum power.

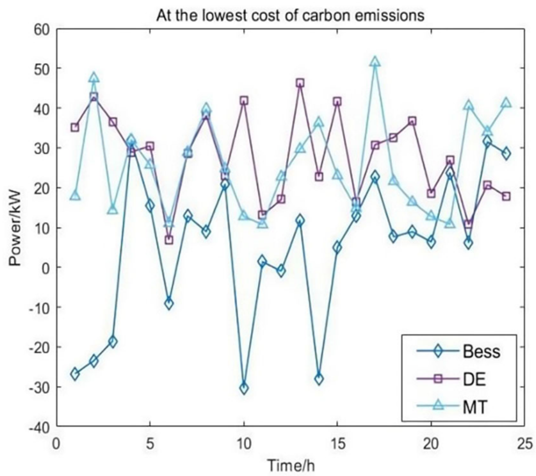

FIGURE 6. Carbon emission cost minimum power.

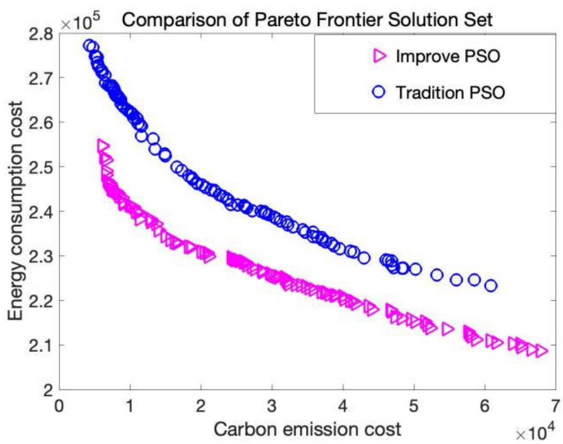

FIGURE 7. Comparison of Pareto front-edge solution before and after optimization.

Table 4 shows that when the energy cost of the system is prioritized, the total cost is reduced by 6.6%, when the carbon cost is prioritized, the total cost is reduced by 6.5%, and the total cost is reduced by 6.8% when the total cost is considered. It can be seen that under comprehensive consideration, the low-carbon carbon optimization dispatch effect of the micro grid system is the best. The simulated Pareto leading edge solution is shown in Figure 7.

TABLE 4. Results before and after optimization under different scenarios.

Scheme	System comprehensive cost/element under traditional particle swarm algorithm	Improved system synthesis cost/element under particle swarm algorithm
Prioritize energy costs	268506	250892
Prioritize carbon costs	266006	248668
Comprehensively considered	267525	249350

VI. CONCLUSION

In order to reduce the daily operating costs of micro grids, this article comprehensively considers the energy consumption and carbon emission costs of micro grid systems, reducing both the operating costs of micro grids and carbon emissions. This article utilizes an improved particle swarm optimization algorithm for iterative optimization. The algorithm deceptively improves the formula by introducing segmented inertia weights, Introducing an improved learning factor adaptive formula, Introducing an improved formula for individual extreme is beneficial for the algorithm to quickly jump out of local optima and improve convergence speed, thereby improving global convergence ability. After optimized scheduling, the comprehensive cost of the micro grid system decreased by 6.8% compared to before optimization. The simulation results of the example show that the improved model and algorithm have fast convergence speed, more accurate results, and can effectively allocate the output of each unit in the micro grid system. They can reasonably and effectively allocate the output of each unit in the micro grid system, providing an economic and environmentally friendly optimization scheduling method.

REFERENCES

[1] J. Xu and Y. Yi, "Multi-microgrid low-carbon economy operation strategy considering both source and load uncertainty: A Nash bargaining approach," *Energy*, vol. 263, Jan. 2023, Art. no. 125712.

[2] Z. Li, L. Wu, and Y. Xu, "Risk-averse coordinated operation of a multi-energy microgrid considering Voltage/Var control and thermal flow: An adaptive stochastic approach," *IEEE Trans. Smart Grid*, vol. 12, no. 5, pp. 3914–3927, Sep. 2021.

[3] *14th Five Year Plan for Modern Energy*, Nat. Develop. Reform Commission, Beijing, China, 2022.

[4] Smart Research Consulting. (2023). *2023 China Distributed Energy Industry Overview*. Accessed: Jul. 4, 2023. [Online]. Available: https://www.sohu.com/a/694218882_120961824

[5] K. Chongqing, D. Ershun, G. Hongye, L. Yaowang, F. Yuchen, Z. Ning, and Z. Haiwang, "Analysis of six elements of new power systems," *Grid Technol.*, vol. 47, no. 5, pp. 1741–1750, 2023.

[6] K. Gao, T. Wang, C. Han, J. Xie, Y. Ma, and R. Peng, "A review of optimization of microgrid operation," *Energies*, vol. 14, no. 10, p. 2842, 2021.

[7] Z. Haibo, H. Yukang, L. Zhengrong, and W. Guorong, "Optimization of energy storage configuration considering the risk of insufficient flexibility in high density load areas," *Grid Technol.*, vol. 47, no. 12, pp. 4926–4936, 2023.
[8] Y. Shen and B. Yang, "Demand responsive micro grid optimization scheduling and improved bat algorithm," *J. Huazhong Univ. Sci. Technol., Natural Sci. Ed.*, vol. 48, no. 2, pp. 120–125, 2020.
[9] L. Xingshen, Z. Jing, H. Yu, Z. Ying, L. Yu, and Y. Kaifeng, "Multi-objective optimization scheduling of micro grids based on improved particle swarm optimization algorithm," *Power Sci. Eng.*, vol. 37, no. 3, pp. 1–7, 2021.
[10] H. Sen, "Research on daily operation optimization of AC/DC hybrid microgrid based on improved grey wolf algorithm," Xi'an Univ. Sci. Technol., 2022, doi: 10.27397/d.cnki.gxaku.2021.000772.
[11] X. Li and K. Zhang, "Research on micro grid optimal dispatch based on improved harmony search algorithm," *J. Northeast Electric Power Univ.*, vol. 42, no. 5, pp. 83–89, 2022.
[12] Z. Ceng, P. Chunhua, W. Kui, Z. Yanwei, and Z. Minghan, "Multi objective operation optimization of micro grids based on bird swarm algorithm," *Power Syst. Protection Control*, vol. 44, no. 13, pp. 117–122, 2016.
[13] H. Chu, "Optimization scheduling of micro grids based on genetic algorithms," *Ind. Control Comput.*, vol. 32, no. 2, pp. 151–153, 2019.
[14] V. Sarfi and H. Livani, "An economic-reliability security-constrained optimal dispatch for microgrids," *IEEE Trans. Power Syst.*, vol. 33, no. 6, pp. 6777–6786, Nov. 2018.
[15] Y. Feng and D. Hu, "Research on optimal dispatching of grid connected micro grids based on simulated annealing genetic algorithm," *Electr. Mater.*, vol. 183, no. 6, pp. 75–80, 2022.
[16] G. Yu, H. Sen, C. Liuxin, and H. Junhu, "Economic optimization dispatching of grid connected AC micro grid based on improved grey wolf algorithm," *Sci. Technol. Eng.*, vol. 20, no. 28, pp. 11605–11611, 2020.
[17] L. Keming, "Optimization scheduling of microgrids based on improved genetic algorithm," Xi'an Univ. Technol., 2018.
[18] X. Yan, W. Jiekang, W. Qiang, and M. Xiaoming, "Optimization and coordination model and solution method for combined cooling," *Chin. J. Electr. Eng.*, vol. 35, no. 14, pp. 3616–3625, 2015.
[19] L. Wang, "Research on optimal dispatching of island micro grids based on particle swarm optimization," *Electr. Technol.*, no. 4, pp. 55–57, 2020.
[20] A. Tharwat, M. Elhoseny, A. E. Hassanien, T. Gabel, and A. Kumar, "Intelligent Bézier curve-based path planning model using Chaotic Particle Swarm Optimization algorithm," *Cluster Comput.*, vol. 22, no. 4, pp. 1–22, 2019.
[21] C. Xiaohua, W. Jiekang, and C. Shengyu, "Optimization method for micro grid economic operation based on improved particle swarm optimization algorithm," *Heilongjiang Electr. Power*, vol. 45, no. 1, pp. 23–29, 2023.

SANG YINGJUN was born in Laizhou, Shandong, in February 1980. He received the Ph.D. degree in electrical engineering from Southeast University. From December 2016 to August 2017, he was a Visiting Scholar and an Assistant Fellow with The University of Hong Kong. He is currently an Associate Professor and a Supervisor with Huaiyin Institute of Technology. His main research interests include new energy conversion and control technology, and signal and image processing.

ZHANG WENZHI is currently pursuing the master's degree in electrical engineering and automation with the Faculty of Automation, Huaiyin Institute of Technology, China. His main research interest includes wind/solar/storage multi-source collaborative control in smart microgrids.

MA JING is currently pursuing the bachelor's degree in electrical engineering and automation with the Faculty of Automation, Huaiyin Institute of Technology, China. Her main research interests include economic scheduling, artificial intelligence, smart microgrids, and demand-side management and control of power systems.

CHEN QUANYU is currently pursuing the bachelor's degree in electrical engineering and automation with the Faculty of Automation, Huaiyin Institute of Technology, China. His main research interests include economic scheduling, artificial intelligence, smart microgrids, and neural networks.

TAO JINGLEI is currently pursuing the bachelor's degree in electrical engineering and automation with the Faculty of Automation, Huaiyin Institute of Technology, China. Her main research interests include demand-side management and control of power systems, artificial intelligence, smart microgrids, circuits, and electronic technology.

FAN YUANYUAN was born in November 1979. From December 2019 to November 2020, she was a Visiting Scholar and an Assistant Fellow with The University of Hong Kong. She is currently a Professor and a Supervisor with Huaiyin Institute of Technology. Her research interests include intelligent transportation, new energy and its control technology, demand side management and control of power systems, and signal and image processing.

