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ARTICLE

CCHP-Type Micro-Grid Scheduling Optimization Based on Improved Multi-Objective Grey Wolf Optimizer

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ABSTRACT: With the development of renewable energy technologies such as photovoltaics and wind power, it has become a research hotspot to improve the consumption rate of new energy and reduce energy costs through algorithm improvement. To reduce the operational costs of micro-grid systems and the energy abandonment rate of renewable energy, while simultaneously enhancing user satisfaction on the demand side, this paper introduces an improved multi-objective Grey Wolf Optimizer based on Cauchy variation. The proposed approach incorporates a Cauchy variation strategy during the optimizer's search phase to expand its exploration range and minimize the likelihood of becoming trapped in local optima. At the same time, adopting multiple energy storage methods to improve the consumption rate of renewable energy. Subsequently, under different energy balance orders, the multi-objective particle swarm algorithm, multi-objective grey wolf optimizer, and Cauchy's variant of the improved multi-objective grey wolf optimizer are used for example simulation, solving the Pareto solution set of the model and comparing. The analysis of the results reveals that, compared to the original optimizer, the improved optimizer decreases the daily cost by approximately 100 yuan, and reduces the energy abandonment rate to zero. Meanwhile, it enhances user satisfaction and ensures the stable operation of the micro-grid.

KEYWORDS: Multi-objective; optimization algorithm; hybrid energy storage; micro-grid; CCHP

1 Introduction

With the continuous development of technology, renewable energy has played an important role in micro-grids, reducing the consumption of fossil fuels and carbon emissions, and enhancing the environmental friendliness of micro-grid systems [1]. At the eleventh meeting of the Central Finance and Economy Commission, China explicitly put forward the proposal of developing distributed smart grids [2]. Combined cooling heating and power (CCHP) micro-grids, in line with this proposal, are expected to become a major mode of end-of-pipe energy supply in the future. They can realize efficient utilization of primary energy, reduce pollutant emissions, and improve the reliability of energy supply through the complementary interactions between internal cooling, heating, and power [3]. To promote CCHP-type micro-grids, it is indispensable to solve the following optimization problems: reduce the operating costs and the rate of renewable energy abandonment, and provide sufficient energy supply to the users. The micro-grid system has many parameters and a complex structure, each independent variable has different constraints, the traditional derivation of function optimization is too difficult and ineffective, and even part of the function cannot be derived. So the search for a new function optimization method for micro-grid scheduling optimization is of great significance, such as the particle swarm optimizer [4] and the grey wolf optimizer [5].

These optimization problems for CCHP-type micro-grids have been studied at home and abroad. Yuan Quan reduced the operating cost of CCHP-type micro-grid systems by establishing a peer-to-peer transaction model for multiple micro-grids [6]. Zou Chao et al. optimized the economic and environmental costs of micro-grids under multiple constraints with an improved particle swarm optimizer [7]. Du Xiaoting used a genetic algorithm to optimize the load profile on the customer side, making the output of each micro-source relatively balanced [8]. However, all of the above literature used only a single energy storage method and did not describe the utilization rate of renewable energy. Literature [9] established a CCHP and electricity-to-gas model and reduces the modeled wind abandonment through a hybrid gravity algorithm and random forest regression while reducing the environmental cost and improving the economic efficiency, but it is not involved in the user-side satisfaction. Meng Xian et al. considered hybrid energy storage charging and discharging strategies to reduce costs and improve satisfaction, although it only considered wind power as a renewable energy source [10]. In [11], Zhao Na et al. adopted a hybrid energy storage system of batteries and hydrogen storage to reduce the cost and redundancy of micro-grids while improving the self-balancing rate of the system, but its load side is a single electrical load. In literature [12], Liu et al. introduced a distributed event-triggered surplus algorithm, rooted in surplus theory and finite time projection, the algorithm effectively rectifies network imbalances caused by directed graphs and addresses local inequality constraints. The algorithm greatly reduces the communication burden through the event-triggering mechanism. Nagarathinam et al. [13] proposed the design of an MPPT system for solar PV installations using the Differential Grey Wolf Optimizer (DGWO), which can efficiently track the Maximum Power Point (MPP). This research contributes to the development of advanced MPPT techniques for improving the efficiency and reliability of solar energy systems. In literature [14], an improved ant colony algorithm (ACO) dynamic programming (IACODP), incorporating attenuation parameter, and deflection angle factor, reduces the overall cost of power generation in micro-grid photovoltaic energy storage systems and enhances optimal operation reliability. However, literature [12–14] only considers photovoltaics as a single renewable energy source. In reference [15], Yan et al. presented a Modified version of the Chaos Grasshopper Algorithm (MCGA) as a solution to minimize the overall daily electricity price in an integrated clean energy micro-grid, incorporating fuel cell, battery storage, and photovoltaic systems. Notably, the MCGA approach exhibits high precision, flexibility, and adaptability to power prices and environmental constraints, leading to accurate and flexible solutions. In literature [16], Li et al. adopted a shared hydrogen storage strategy for solving the supply-demand imbalance within a micro-grid, which effectively reduces the total cost to the user and shows better economic advantages. Both references [15] and [16] have reduced the economic cost of micro-grids, but have not taken into account user satisfaction. In literature [17], Pang et al. proposed a nonlinear control parameter combination adjustment strategy for pure algorithmic improvement to speed up the convergence of the algorithm. But does not mention the problem that the grey wolf optimizer is prone to fall into local optimum. In literature [18], Özbay et al. proposed chaotic opposition-based learning ARO (COARO), an improved version of the ARO algorithm, the convergence speed of the algorithm increases and it explores the search space better. Summarize the literature as shown in Table 1.

As shown in Table 1, current research neither integrates wind and solar power generation nor explores multiple objectives. Additionally, the issue of the emerging Grey Wolf Optimizer falling into local optima remains unresolved. To address this research gap, this paper adopts a hybrid energy storage CCHP-type micro-grid as the model, expanding the scope of the investigation. Algorithmic improvements are implemented to reduce the likelihood of the Grey Wolf Optimizer becoming trapped in local optima.

Table 1: Advantages and limitations of the literature

Literature	Advantages	Limitations
[6]	Establishing a peer-to-peer transaction model for multiple micro-grids	Only a single energy storage method
[7]	Optimized the economic and environmental costs of micro-grids under multiple constraints with an improved particle swarm algorithm	
[8]	Used a genetic algorithm to optimize the load profile on the customer side, making the output of each micro-source relatively balanced	
[9]	Establishes a CCHP and electricity-to-gas model, and reduces the modeled wind abandonment through hybrid gravity algorithm and random forest regression, while reducing the environmental cost and improving the economic efficiency	Not involved in the user-side satisfaction
[15]	Presents a Modified version of the Chaos Grasshopper Algorithm (MCGA) as a solution	
[16]	Adopts a shared hydrogen storage strategy for solving the supply-demand imbalance within a micro-grid	
[11]	Adopted a hybrid energy storage system of batteries and hydrogen storage	Only electrical load
[10]	Considered hybrid energy storage charging and discharging strategies as a way to reduce costs and improve satisfaction	A single renewable energy source
[12]	Introduces a distributed event-triggered surplus algorithm, rooted in surplus theory and finite time projection	
[13]	Proposes the design of an MPPT system for solar PV installations using the Differential Grey Wolf Optimizer	
[14]	An improved ant colony algorithm (ACO) dynamic programming (IACODP), incorporating attenuation parameter	

Building upon the aforementioned research, this paper proposes a hybrid energy storage CCHP-type micro-grid model incorporating batteries, super-capacitors, and hydrogen storage. The renewable energy sources considered include photovoltaic and wind power. The objective functions are defined as minimizing the operating costs of the micro-grid, maximizing user-side satisfaction, and minimizing the abandonment rate of renewable energy. Enhancements to the multi-objective Grey Wolf Optimizer are introduced and implemented, accompanied by simulation comparisons and a comprehensive analysis of the results. Finally, under the aforementioned micro-grid model, two balanced sequences—Cold-Heat-Electricity and

Cold-Electricity-Heat—are considered scenarios. The multi-objective particle swarm optimizer, the multi-objective grey wolf optimizer, and the multi-objective grey wolf optimizer enhanced by Cauchy's variant are employed to obtain the results, thereby verifying the scientificalness and effectiveness of both the model and the improved algorithm.

2 Micro-Grid Structure and Mathematical Model

2.1 CCHP-Type Micro-Grid Modifications and Structure

Traditional hybrid energy storage systems typically rely on a single form of electric energy storage, such as batteries or super-capacitors, which cannot simultaneously meet the diverse demands of the power system. In contrast, the combination of electric energy storage and hydrogen energy storage offers complementary advantages, enhancing system performance and optimizing wind-solar power utilization [19]. Hydrogen storage has the advantages of long storage time, high energy density, no pollution, etc. [11], and environmental friendliness is very high, but also improves the rate of consumption of renewable energy, so this paper adds hydrogen storage as the third energy storage method.

The structure of the CCHP-type micro-grid established in this paper is shown in Fig. 1 below, which consists of a power generation part, an energy storage part, and an auxiliary part. The power generation part includes photovoltaic cells, wind turbines, and gas turbines. The energy storage part includes batteries, super-capacitors, hydrogen storage, and heat storage tanks. The auxiliary parts include electric heating, waste heat boilers, lithium bromide absorption chillers, and split air conditioners.

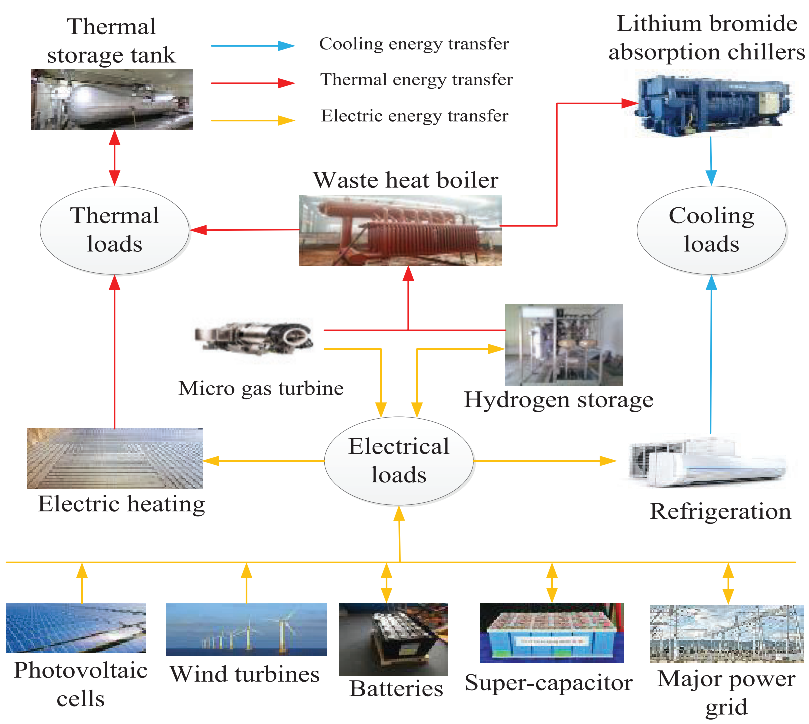


Figure 1: Structure of CCHP micro-grid

2.2 Mathematical Modeling of Energy Storage Micro-Sources

The mathematical model of the battery [10] is:

$$E_{\mathrm{b}} = N_{\mathrm{b}} C_{\mathrm{b}} U_{\mathrm{b}} / 10^3 \tag{1}$$

$$E_{\mathrm{bmin}} = N_{\mathrm{b}} C_{\mathrm{b}} U_{\mathrm{b}} \left(1 - \mathrm{D}_{\mathrm{depth}}\right) / 10^3 \tag{2}$$

$$P_{\mathrm{b}} = N_{\mathrm{b}} C_{\mathrm{b}} U_{\mathrm{b}} / 10^4 \tag{3}$$

In Eqs. (1)–(3), E_{b} is the rated capacity of the battery pack; N_b is the number of batteries; C_b is the rated capacity of the battery; U_{b} is the rated voltage of the battery; E_{bmin} is the minimum capacity of the battery pack; $\mathrm{D}_{\mathrm{depth}}$ is the maximum depth of discharge; and P_{b} is the rated value of the output power.

Mathematical modeling of super-capacitors [10] for:

$$E_{\mathrm{cmax}} = 0.5 N_{\mathrm{c}} C_{\mathrm{c}} U_{\mathrm{c\,max}}^2 / \left(3.6 \times 10^6\right) \tag{4}$$

$$E_{\mathrm{cmin}} = 0.5 N_{\mathrm{c}} C_{\mathrm{c}} U_{\mathrm{cmax}}^2 / \left(3.6 \times 10^6\right) \tag{5}$$

$$P_{\mathrm{cmax}} = N_{\mathrm{c}} U_{\mathrm{cmax}} I_{\mathrm{cmax}} / 10^3 \tag{6}$$

In Eqs. (4)–(6), E_{cmax}, E_{cmin}: maximum capacity and minimum capacity of super-capacitor, respectively; N_{c} is the number of super-capacitor; C_{c} is the electric capacity; U_{cmax}, U_{cmin}: the maximum and minimum voltage of super-capacitor, respectively; P_{cmax} is the maximum output power; I_{cmax} is the maximum operating current.

Mathematical Modeling of Hydrogen Energy Storage [11] for:

$$P_{\mathrm{q}} = P_{\mathrm{e-c}} \eta_{\mathrm{q}} \tag{7}$$

$$P_{\mathrm{r}} = P_{\mathrm{c-r}} \eta_{\mathrm{r}} \tag{8}$$

In Eqs. (7) and (8), P_{q} is the hydrogen power output from the electrolyzer; $P_{\text{e-c}}$ is the electric power input to the electrolyzer; η_{q} is the electrolyzer efficiency; P_{r} is the output power of the fuel cell; $P_{\text{c-r}}$ is the hydrogen power input to the fuel cell; η_{r} is the fuel cell efficiency.

2.3 Mathematical Modeling of the Objective Function

2.3.1 System Operating Costs

The cost of operating the micro-grid system in this paper consists of two parts: the system maintenance cost and the pollution control cost. The system maintenance cost includes the generation cost of the photovoltaic cells and the wind turbine, the maintenance cost of the micro-sources in the system, the gas purchase cost, and the power purchase cost of the power grid. Pollution control cost includes the pollutant control cost generated when the gas turbine is running and the pollutant control cost generated when interacting with the power grid. Calculate the cost per hour and summarize it as the cost required for system operation. The mathematical expression for the operating cost of the system is:

$$f_1 = \min\left(C_{\mathrm{wh}} + C_{\mathrm{wr}}\right) \tag{9}$$

$$C_{\mathrm{wh}} = \sum_{i=1}^{24} \left\{ P_{\mathrm{pv},i} * a_{\mathrm{pv}} + P_{\mathrm{W},i} * a_{\mathrm{W}} + \sum_{j=1}^{\mathrm{N}} \left|P_j\right| * a_j + \mathrm{C}_{\mathrm{gas}} * \frac{P_{\mathrm{MT},i}}{\eta_{\mathrm{MTE}}} \right\}_i \tag{10}$$

$$C_{\mathrm{wr}} = \sum_{i=1}^{24} \left\{ \sum_{k=1}^{\mathrm{n}} \left(W_{\mathrm{MT},k} * P_{\mathrm{MT},i} + W_{\mathrm{g},k} * P_{\mathrm{g},k} \right) * C_k \right\}_i \tag{11}$$

In Eqs. (9)–(11), C_{wh} is the 24-h maintenance cost of the system; C_{wr} is the 24-h pollution control cost of the system; i is time quantum; $P_{\mathrm{pv},\,i}$, $P_{\mathrm{W},\,i}$: the photovoltaic power and wind power in the i time period, respectively; a_{pv},a_{W}: the unit prices of photovoltaic power generation and wind power generation, respectively; P_j is the power of micro-source j; a_j is the maintenance unit cost of micro-source j; $\mathrm{C}_{\mathrm{gas}}$ is the price of natural gas; $P_{\mathrm{MT},i}$ is the power of gas turbine; η_{MTE} is the efficiency of the gas turbine; k is the type of pollutant gas emitted; $W_{\mathrm{MT},k}$ is the emission coefficient of the kth pollutant gas of the gas turbine; $W_{\mathrm{g},k}$ is the emission coefficient of the kth pollutant gas of the main grid; $P_{\mathrm{g},k}$ is the power to buy electricity from the main grid (0 when electricity is sold); and C_k is the unit cost of treatment of the pollutant gas.

2.3.2 Renewable Energy Abandonment Rate

When the supply of energy exceeds the demand for the current time period, the excess is treated as abandoned energy, and the abandoned energy is considered as part of the renewable energy sources. The energy abandonment rate is calculated as the ratio of the total abandoned energy to the sum of the renewable energy sources. The energy abandonment rate can show the degree of utilization of renewable energy and is an important indicator in the process of micro-grid operation. The mathematical expression for the energy abandonment rate is:

$$f_2 = \min\left(\frac{\sum_{i=1}^{24} \left| P_{\mathrm{qi},i} \right|}{\sum_{i=1}^{24} \left(P_{\mathrm{pv},i} + P_{\mathrm{w},i} \right)} \right) \tag{12}$$

In Eq. (12), $P_{\mathrm{qi},i}$ is the discarded energy for the i time period, which is negative.

2.3.3 User Satisfaction

User satisfaction is related to the sum of energy shortages per time period, and user satisfaction decreases when the micro-grid is short of energy, in other words, when the energy supply is insufficient to meet the load. The mathematical expression for user satisfaction is:

$$f_3 = \max\left(1 - \frac{\sum_{i=1}^{24} P_{\mathrm{que},i}}{\sum_{i=1}^{24} \left(P_{\mathrm{P},i} + P_{\mathrm{T},i} + P_{\mathrm{C},i} \right)} \right) \tag{13}$$

In Eq. (13), $P_{\mathrm{que},i}$ is the energy deficit in the i time period; $P_{\mathrm{P},i}$, $P_{\mathrm{T},i}$, $P_{\mathrm{C},i}$: the electric load, heat load and cooling load in the i time period, respectively.

2.4 Constraints

To satisfy users' demands for heating, cooling, and electricity, enhance user satisfaction, and ensure the stable operation of the micro-grid, it is must that the system consistently adhere to the constraints of electrical load, thermal load, cooling load, and the upper and lower power limits of each micro-source.

The electrical load constraint means that the generation of renewable energy, the charging and discharging of each energy storage, the power consumption of each micro-source, the power interacting with the larger grid, and the possible lack or abandonment of power have to be equal to the electrical load in total. The electrical load constraint of the system during the time period is:

$$P_{\mathrm{pv},i} + P_{\mathrm{W},i} + P_{\mathrm{MT},i} - P_{\mathrm{xu},i} - P_{\mathrm{dr},i} - P_{\mathrm{qin},i} + P_{\mathrm{g},i} + Q_{\mathrm{ec},i} + Q_{\mathrm{eh},i} + P_{\mathrm{qi\_E},i} + P_{\mathrm{que\_E},i} = P_{\mathrm{P},i} \tag{14}$$

In Eq. (14), $P_{\mathrm{xu},i}$, $P_{\mathrm{dr},i}$, $P_{\mathrm{qin},i}$: the output power of battery, super-capacitor and hydrogen storage during the i time period, where charging of battery, super-capacitor and hydrogen storage is positive and discharging is negative; $P_{\mathrm{g},i}$ is the power of the interaction power with the power grid during the i time period, where purchasing power is positive and selling power is negative; $Q_{\mathrm{ec},i}$, $Q_{\mathrm{eh},i}$: the power output to split air conditioning and electric heating during the i time period, respectively; $P_{\mathrm{qi\_E},i}$, $P_{\mathrm{que\_E},i}$: the power shortage and power abandonment of the system during the i time period, respectively.

The heat load constraint means that the power of the waste heat boiler, the charging and discharging power of the heat storage tank, and the possible lack of heat or heat abandonment in total should be equal to the heat load. The heat load constraint of the system during the i time period is:

$$P_{\mathrm{bl},i} + Q_{\mathrm{eh},i} + E_{EST,i} + P_{\mathrm{qi\_T},i} + P_{\mathrm{que\_T},i} = P_{\mathrm{T},i} \tag{15}$$

In Eq. (15), $P_{\mathrm{bl},i}$, $E_{\mathrm{EST},i}$: the power of the waste heat boiler as well as the heat storage tank during the i time period, where the heat storage tank is negative for heat storage and positive for heat release; $P_{\mathrm{qi\_T},i}$, $P_{\mathrm{que\_T},i}$: the power of the system's lack of heat and abandoned heat during the i time period, respectively.

Cold load constraint means that the combined power of the lithium bromide absorption chiller and the possible lack of or abandoned cooling power should be equal to the cold load. The cold load constraint of the system during the i time period is:

$$Q_{\mathrm{ec},i} + P_{\mathrm{ac},i} + P_{\mathrm{que\_C},i} + P_{\mathrm{qi\_C},i} = P_{\mathrm{C},i} \tag{16}$$

In Eq. (16), $P_{\mathrm{ac},i}$ is the power of the lithium bromide absorption chiller in the i time period; $P_{\mathrm{que\_C},i}$, $P_{\mathrm{qi\_C},i}$: the power of the system's cooling shortage and cooling abandonment in the i time period, respectively.

During micro-grid operation, the power of each micro-source should be between the maximum and minimum values of the micro-sources [19]:

$$P_{j,\min} \le P_{j,i} \le P_{j,\max} \tag{17}$$

In Eq. (17), $P_{j,\min}$ is the minimum operating power of the micro-source j. $P_{j,i}$ is the actual operating power of the micro-source j; $P_{j,\max}$ is the maximum operating power of the micro-source j.

3 Multi-Objective Algorithm and Improvements

3.1 Multi-Objective Algorithms

The Multiple Objective Particle Swarm Optimization (MOPSO) algorithm is commonly used to solve optimization problems. It has the following characteristics: does not depend on the problem information and uses real numbers for the solution; the algorithm is highly general; the principle is simple and few parameters need to be adjusted. Its updated formula is:

$$V_{\mathrm{id}}^{k+1} = \omega V_{\mathrm{id}}^{k} + c_1 r_1 \left(P_{\mathrm{id}}^{k} - X_{\mathrm{id}}^{k}\right) + c_2 r_2 \left(P_{\mathrm{gd}}^{k} - X_{\mathrm{id}}^{k}\right) \tag{18}$$

$$X_{\mathrm{id}}^{k+1} = X_{\mathrm{id}}^{k} + V_{\mathrm{id}}^{k+1} \tag{19}$$

In Eqs. (18) and (19), ω is the inertia weight; r_1, r_2: random numbers in the interval $[0, 1]$; k is the current iteration number; ${P_{\mathrm{id}}}^k$ is the individual optimal particle position; ${P_{\mathrm{gd}}}^k$ is the group optimal particle position; c_1, c_2: the weights of local optimization and global optimization, respectively; V is the particle velocity; X is the particle position.

Multi-objective Grey Wolf Optimization (MOGWO) is a multi-objective optimization method based on the Grey Wolf Optimization Algorithm. MOGWO is a new group intelligence optimization algorithm inspired by the cooperative feeding process of wolf packs in literature [20]. Multi-objective Grey Wolf Optimization algorithm was proposed on this basis in 2015. Its updated formula is:

$$D_i^k = \left|C * X_p^k - X_i^k\right| \tag{20}$$

$$X_i^{k+1} = X_p^k - A * D_i^k \tag{21}$$

In Eqs. (20) and (21), X_p is the current location of the prey; X_i is the location of the grey wolf particles; C, A are the impact factors and the calculation formulas are shown below:

$$A = 2aR_1 - a \tag{22}$$

$$C = 2R_2 \tag{23}$$

$$a = 2 - 2 \times \frac{k}{k_{max}} \tag{24}$$

In Eqs. (22)–(24), R_1, R_2 are random numbers in the interval $[0, 1]$; k is the current iteration number.

However, in the face of complex optimization problems, the above commonly used multi-objective algorithms have a common disadvantage: due to the strong randomness of the particles and the limitations of the search range, the search accuracy is not high, so the algorithm is easy to fall into the local optimal solution in the optimization process.

3.2 Cauchy Variant Improved Multi-Objective Grey Wolf Optimizer

In order to expand the search scope and reduce the possibility of the algorithm falling into a local optimum, Cauchy variation is applied to the multi-objective grey wolf optimizer. Cauchy mutation is a common mutation strategy used in improved swarm algorithms, which uses the Cauchy distribution to generate random numbers with long-tailed properties. It aims to enhance the algorithm's global search capability and be more helpful in exploring the search space.

The object of Cauchy mutation is the screened first echelon wolf (α wolf β wolf γ wolf), which is subjected to Cauchy mutation when the preset number of iterations is not reached. Through the Cauchy mutation increased update formula, expand the search range of the first echelon of wolves, so as to avoid falling into the local optimum. Cauchy mutation after the improvement of the increase of the update formula is:

$$x_{new} = x_{old} + x_{old} * Cauchy\left(0, 1\right) \tag{25}$$

In Eq. (25), x_{new} is the position of grey wolf after Cauchy's mutation; x_{old} is the position of grey wolf before the mutation; $Cauchy(0, 1)$ indicates the formula of Cauchy's distribution when the position parameter is 0 and the scale parameter is 1, and the specific formula is shown below:

$$Cauchy\left(0, 1\right) = \frac{1}{\pi\left[1 + r^2\right]} \tag{26}$$

In Eq. (26), r is a random number within $[0, 1]$. The flowchart of the multi-objective grey wolf optimizer improved by one of the Cauchy variants is shown below in Fig. 2.

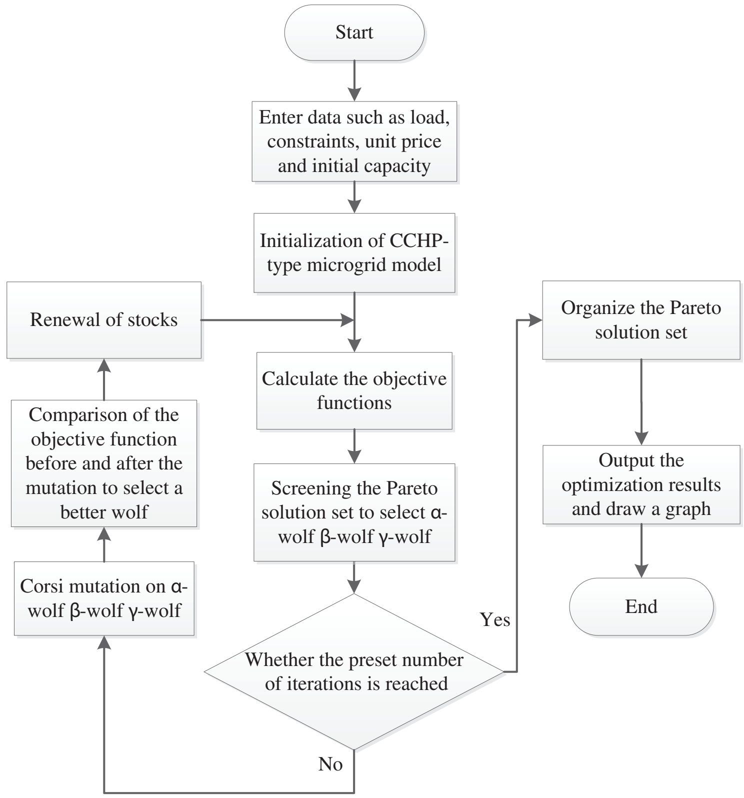


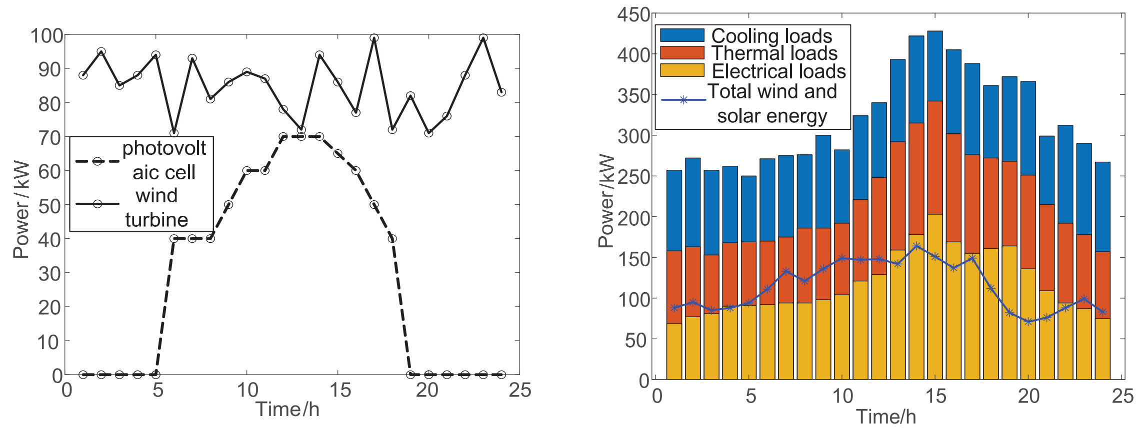
Figure 2: Flowchart of Cauchy mutation improved MOGWO

4 Example Analysis

4.1 Basic Data

The basic data required for the initialization of the CCHP micro-grid model include: wind power as well as photovoltaic power generation prediction (Fig. 3a); cooling, thermal and electrical loads prediction (Fig. 3b); parameters of each micro-source of the micro-grid (Table 2) [21]; the price of electricity trading with the big grid, the unit price of the treatment of the polluted gases (Table 3), and the unit price of natural gas. The capacity of the storage battery and super-capacitor is preset to be capped at 80 kW/h, the capacity of the hydrogen storage is capped at 100 kW-h, and the initial capacity is 40 kW/h; the price of trading with the big grid is fixed at 0.5 yuan kW/h; the price of the natural gas is 0.175 yuan/kW/h; the maximum rate of climb of the gas turbine is set to 40 kW/h, and the initial power is 80 kW/h. Among the three multi-objective algorithms, the number of particles is set to 100, the number of iterations is set to 400, and the final Pareto solution set size is set to 150. The MOPSO inertia weight is set to 0.5, and the overall optimal weight and local optimal weight are set to 0.7.

The data used in the paper are cited from the literature [19], and the software used for the simulation experiments is MATLAB R2022a. After setting up the basic data, the multi-objective particle swarm algorithm, multi-objective grey wolf optimizer, and improved multi-objective are used to optimize the operation process of the micro-grid to obtain the optimization results, respectively.



(a) Forecast of renewable energy generation (b) Cooling, thermal and electrical loads

Figure 3: Renewable energy and load forecasting

Table 2: Relevant data of CCHP micro-source

Micro-source	Equipment operating power limit/kW	Lower limit of equipment operating power/kW	Maintenance prices/(yuan/kW/h)
Micro gas turbine	200	0	0.04
Accumulators	40	−40	0.045
Super-capacitor	30	−30	0.045
Electrolyzer	30	−30	0.02
Photovoltaic cell	80	0	0.01
Ventilator	100	0	0.045
Major power grid	150	−150	0.012
Absorption chillers	100	0	0.01
Heat storage tank	200	−200	0.02
Electric heating	80	0	0.02
Split type air conditioner	80	0	0.03
Waste heat boiler	200	0	0.025

Table 3: Unit price and emission coefficient of pollution gas treatment

Pollutant gas type		**CO_2**	**SO_2**	**NO_X**
Unit price of treatment (yuan/kg)		0.21	14.824	62.964
Contaminated gas emission factor (g/kW/h)	Micro gas turbine	724	0.0036	0.2
	Major power grid	922	2.295	3.583

4.2 Optimization Results under Two Equilibrium Orders

Two equilibrium orders were selected as scenarios to be optimized separately [22].

In Scenario 1, the order of load balance is cold balance-heat balance-electricity balance, and the electricity balance is used as the final energy balance. At first, the power to be supplied by the waste heat boiler is deduced by the cooling and heating loads, and then the energy to be consumed is apportioned by the gas turbine and the hydrogen storage according to a certain ratio. Through the above power balancing process, the electric power generated by gas turbine and hydrogen storage is derived. Finally performing the electric power balancing, and the electric power is stored or sold in case of surplus or purchased through the power grid in case of shortage. In this scenario, the internal power change of each energy storage micro-source and the output of the gas turbine after optimization by the improved multi-objective Grey Wolf Optimizer are shown in Fig. 4.

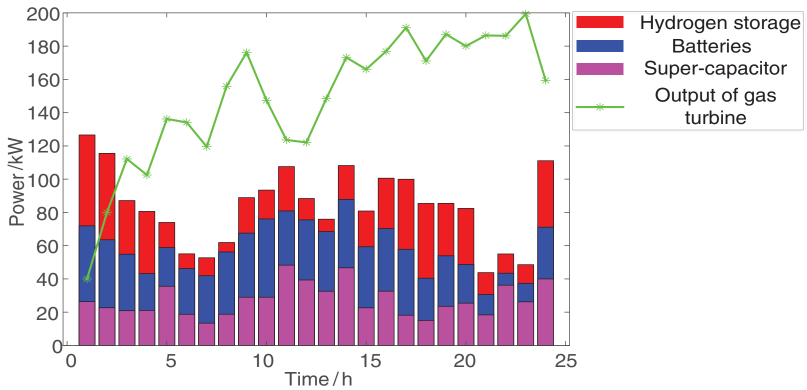
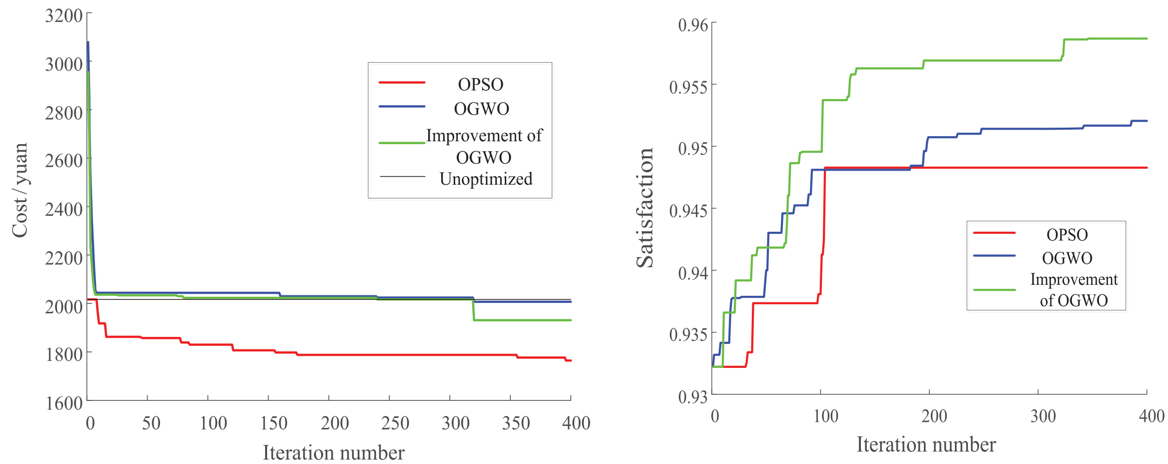


Figure 4: Scenario 1: power changes of each energy storage micro sources and gas turbine output after optimization by the improved GWO

Analyzing Fig. 4 shows that the gas turbine output power rises overall from 1:00 to 9:00, while it decreases from 9:00 to 11:00, and then rises again and maintains high power output. This shows that the trend of the gas turbine's output curve is roughly similar to the trend of the load forecast, i.e., the gas turbine is able to adjust accordingly with the load change and track the load curve better. The energy storage micro-sources have relatively uniform power output in each time period, which is conducive to the stable operation of the micro-grid system.

The optimization results for this scenario are shown in Fig. 5. The data visualization is not performed because all renewable energy abandonment rates are reduced to zero. The cost of OPSO optimization results in the best, reduced to below 1800 yuan. The final optimization result of improving OGWO is 1891.7 yuan, which is lower than the final optimization result of OGWO, 2043.2 yuan. It can be seen that the optimization result of improving OGWO through Cauchy's variation is significantly better than that of OGWO; user-side satisfaction, improves the OGWO optimization results by close to 96%, and the enhancement is higher than the OGWO and OPSO. The direction of the optimization curves shows that the effects of the three optimization algorithms have obvious differences: MOPSO has an advantage in optimizing the operating cost; the optimization result of the improved OGWO algorithm is better than the unimproved one.

In Scenario 2, the load balancing sequence is cold balancing-electric balancing-heat balancing, with heat balancing as the final energy balance: cold power balancing is the same as in the previous scenario, but in this scenario, the electric power required for electric loads as well as electric heating and air conditioning is calculated firstly. The power needed for gas turbine and hydrogen storage is determined after balancing the micro-sources of storage and renewable energy sources, and the power needed for gas turbine and hydrogen storage is filled in by purchasing power from the power grid if it exceeds its upper limit. Otherwise, the waste heat boiler power is calculated for thermal power balancing. In this scenario, the internal power change of each energy storage micro-source and the output power of the gas turbine after optimization by the improved multi-objective Grey Wolf Optimizer are shown in Fig. 6 below.



(a) Cost optimization curve (b) Satisfaction optimization curve

Figure 5: Scenario 1: optimization curve

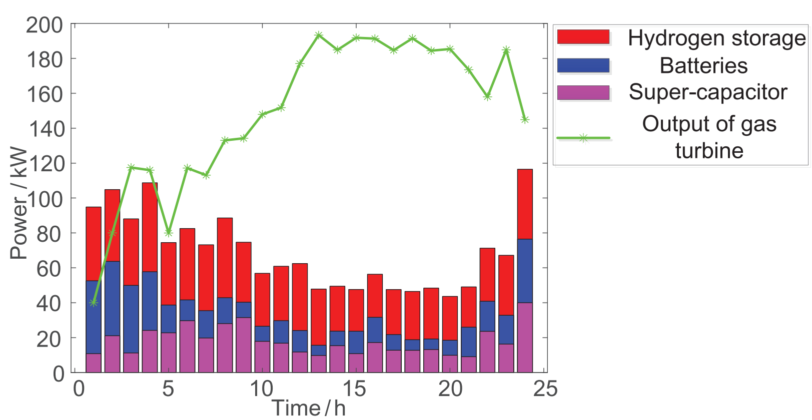
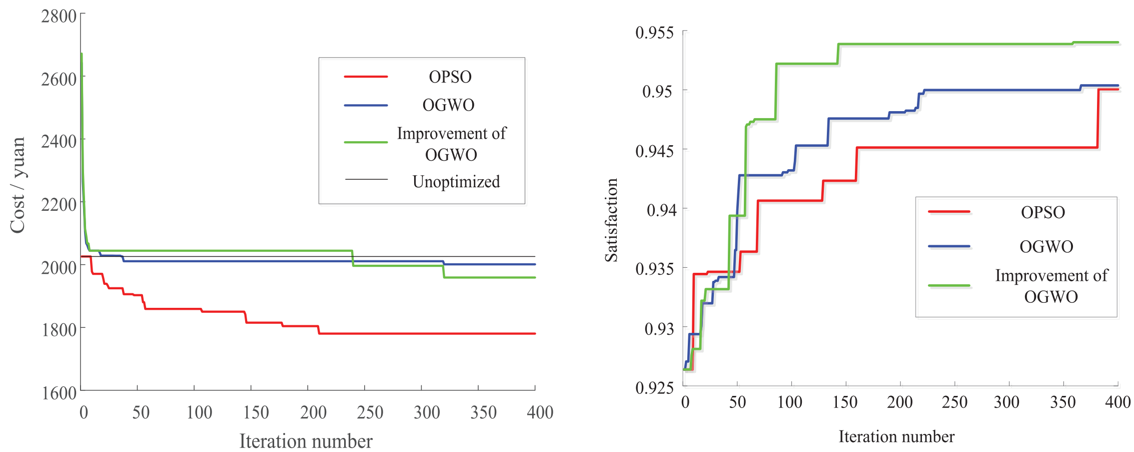


Figure 6: Scenario 2: power changes of each energy storage micro sources and gas turbine output after optimization by the improved GWO

It can be seen that in this scenario the gas turbine does not have a decreasing trend from 9:00 to 11:00, but rather the power continues to rise, then starts to reduce the power from 19:00 to 22:00. The internal power of each energy storage micro-source of the micro-grid also decreases compared to Scenario 1, but does not fluctuate significantly.

The optimization results for this scenario are shown in Fig. 7. The energy abandonment rate is the same as that of Scenario 1, and the optimization result is reduced to zero. The cost is still the optimal result obtained by OPSO optimization, which is between 1700 yuan and 1800 yuan, and the optimization result of improved OGWO is better than that of OGWO; the satisfaction is similar to that of scenario one. From the optimization results, it can be seen that the optimization results of the three algorithms in this scenario are not significantly different from the previous scenario.



(a) Cost optimization curve (b) Satisfaction optimization curve

Figure 7: Scenario 2: optimization curve

5 Conclusion and Outlook

5.1 Conclusion

In this paper, by building a CCHP-type micro-grid model with added hydrogen storage, taking the lowest system operating cost, the highest user satisfaction, and the lowest renewable energy abandonment rate as the objective function, and then utilizing MOPSO, MOGWO, and the improved MOGWO algorithms to conduct simulation and analysis, which verified the model as well as the algorithms' scientificity and validity, and obtained the following conclusions:

(1) Successfully reduces the operating cost of the micro-grid system as well as the renewable energy abandonment rate compared to the pre-optimization period, while increasing the satisfaction of the user side;

(2) The three objectives to be optimized have a certain conflict between them, and can not reach their respective optimum at the same time, in the optimization of the objectives of the same weight, only to find the relative optimum point;

(3) The multi-objective grey wolf optimizer improved by Cauchy's variation outperforms the multi-objective grey wolf optimizer in terms of optimization.

By adopting the improved Grey Wolf Optimizer, the trade-offs between multiple objectives of the CCHP-type micro-grid can be effectively balanced so as to obtain the relative optimal point, which provides a reference for the further development of the micro-grid as well as the algorithm research; at the same time, the reduction of the abandonment rate of renewable energy sources also improves the energy supply efficiency of the micro-grid.

5.2 Future Work

(1) The optimization of CCHP-type micro-grid with hybrid energy storage does not only include two parts: modeling and algorithm optimization, but also the charging and discharging strategy selection of the hybrid energy storage. The next step will continue to explore the charging and discharging strategy of the hybrid energy storage in-depth, to obtain better optimization results.

(2) Uncertainty about photovoltaic and wind energy will affect the micro-grid system, and how to cope with the uncertainty as well as the error will also be our research topic in future research.

(3) In order to realize the transition from theoretical modeling to practical applications, some factors such as communication delays, control system limitations, and dynamic load variations need to be considered and solved.

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Ethics Approval: Not applicable.

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