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Research on Load Optimal Dispatch for High-Temperature CHP Plants through Grey Wolf Optimization Algorithm with the Levy Flight

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Abstract: The combined heating and power (CHP) plants are considered one of the promising methods to support the goal of “Carbon Peak and Carbon Neutrality”. It is an important means to take heat and power load optimal dispatch (LOD) to further reduce the energy consumption of CHP plants. To achieve a better load dispatch scheme, this paper employs a potent algorithm by integrating the grey wolf optimization (GWO) algorithm and the Levy flight (i.e., Levy–GWO algorithm) to overcome premature convergence. Moreover, the constraint condition processing method is also proposed to handle the system constraints for ensuring the results within feasible zones. To confirm the effectiveness of this algorithm, it is tested on two widely used test systems (Test system I and Test system II). The accuracy of the used algorithm is proved by comparing the obtained results and reported data in other literature. Results show that the Levy–GWO algorithm can be used to obtain relatively lower power generation costs, with the values of 9231.41 \$/h (Test system I) and 10,111.79 \$/h (Test system II). The proposed constraint processing method effectively solves the problem that load optimal dispatch scheduling is difficult to solve due to the existence of multiple constraints. In addition, the comparison results indicate that the Levy–GWO algorithm owns a better robustness and convergence effect and has a promising application for solving LOD problems.

Keywords: CHP plants; grey wolf algorithm; Levy flight; load dispatch; economic operation



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1. Introduction

Recently, “carbon peak and carbon neutrality” has become one of the hot topics with the increasing concern about global warming [1]. Accordingly, the energy industry is affected greatly, owing to its biggest carbon emission [2,3]. To reduce carbon emissions, many efforts have been denoted to achieve it, such as low-grade heat recovery [4,5], utilization of clean energy [6,7], energy storage [8,9], and the development of advanced power cycles [10,11]. It is also a possible scheme to develop a combined heating and power plant, owing to its higher energy conversion efficiency [12,13]. According to the reported literature, the energy efficiency of CHP units can achieve 70% and above [14], and the costs will reduce by 20%~30% compared to those of conventional plants [15].

Moreover, to pursue a lower cost and reduce fuel consumption, the CHP plants have to deal with the load optimal dispatch (LOD) problem, providing an economic allocation of heating and power load instructions during the actual operation. A good load optimal dispatch (LOD) contributes to energy saving and consumption reduction well, which is reported to save 0.5% ~ 1.5% fuel in practical production [16,17]. The practical production load of the CHP system has real-time characteristics, which will significantly influence

the performance of the high-temperature thermodynamic system. Thus, reasonable load distribution is also of great significance to the safe and stable operation of the CHP plants.

Unlike the condensing power plants with obvious thermal characteristics, the CHP plants have more complex thermodynamic characteristics because of the strong coupling relationship of the heating and power loads. Accordingly, the LOD problem of CHP plants is more complex than that of condensing power plants. Generally, it is a non-convex and non-linear optimization problem with multiple constraints [18]. In the past, conventional mathematical algorithms have been used to address the LOD problems for CHP plants, which can preliminarily provide the LOD solutions [19,20]. However, due to the limitations of these algorithms, they cannot solve the nonlinear non-convexity optimization problem caused by the operation characteristics of CHP plants, resulting in a general optimization effect and a long solution time.

In this context, much attention is attracted by swarm intelligence optimization algorithms, which have the advantages of easy programming and parallel searchability. In other words, the swarm intelligence optimization algorithms can quickly find the optimal solution under multiple constraint conditions. Several classic intelligent optimization algorithms have been employed to solve the LOD problem. Song et al. [19] introduced the genetic algorithm (GA) to obtain the optimal LOD solutions. Their results demonstrated its effectiveness. Basu [21] compared the optimal costs obtained from the differential evolution (DE) algorithm, particle swarm optimization algorithm (PSO) and evolutionary programming (EP). According to his study, the DE-based method achieved the lowest cost. Then, the LOD solutions provided by bee colony optimization and artificial immune system were discussed in another similar research work by Basu [22,23]. However, if using a poor constraint processing approach, the location of the ideal results may be outside the practicable operation range of the involved CHP plant. Thus, the researchers also focus on the constraint processing approach to deal with complex constraints, especially the feasible operation region of the cogeneration unit. Narang et al. [24] proposed a hybrid algorithm that integrates civilized swarm optimization and Powell's pattern search. They reported that the obtained results were found to be satisfactory. Moradi-Dalvand et al. [25] presented a two-stage model to handle the nonconvex feasible operation regions. In their study, the linear approximation method was used to split nonconvex feasible operation regions into convex regions. Moreover, Chen et al. [26] introduced a novel constraint processing approach named the "repair technique" to guide the solutions toward feasible operation regions. Additionally, the external penalty parameters were proved as a good method for handling constraints [27].

Based on the above studies, it could be concluded that, compared to conventional algorithms, the accuracy of optimization is strengthened by using intelligence optimization algorithms. It is also of great importance to combine a good constraint processing approach with the algorithms. Meanwhile, it is worth noting that no one intelligence optimization algorithm can efficiently solve all types of optimization problems with the best performance [28,29]. Therefore, it is still necessary to improve relevant algorithms and explore better intelligent optimization algorithms based on swarm intelligence algorithms to solve practical problems.

The grey wolf optimizer (GWO) algorithm is a powerful algorithm proposed by Mirjalili et al. in 2014 [30]. Their study suggests that the GWO algorithm performs well in the global optimization of complex functions. Accordingly, it is more adaptable to complex constraints and unknown space search in practical engineering optimization [31,32]. Theoretically, it is also suitable for obtaining an optimal LOD solution for the CHP plants. However, the GWO algorithm is easy to jump out of the local optimal when facing high-dimensional problems, such as LOD problems. Introducing the Levy flights to the GWO algorithm is a good choice to avoid these problems [33]. However, the performance of the potential combinations of the above two algorithms is not explored in solving LOD problems.

To fill this research gap, this paper improved the GWO algorithm by the combined Levy–GWO algorithm at first. What is more, both the optimization algorithms and constraint processing methods have obvious impacts on providing the LOD solutions based on the above discussions. Additionally, the constraint condition processing methods are also proposed according to the characteristics of the total power and heat loads. Then, the constraint condition processing methods are combined with the Levy–GWO algorithm to provide a better solution to the LOD problem. To test the performance of the algorithm, two test systems consisting of different units are selected to optimize the load distribution. Finally, a comprehensive comparative study is performed to study the performance of GWO and Levy–GWO algorithms.

The main contributions and novelty of this work can be summarized below:

- (1) To solve the LOD problems better, an improved Levy–GWO algorithm is proposed to boost the ability of global and local searches in solution space.
- (2) To deal with the complex constraints, a new constraint handling method is devised to achieve strictly feasible solutions.
- (3) The effectiveness of the proposed approach is proved by two test plants, from simple to complex.

2. Mathematical Model of LOD Problem

2.1. Description of the Objective Function

A CHP plant typically is composed of three different kinds of power or heating units, i.e., the pure condensed unit (producing power), the cogeneration unit (producing heating and power), and the pure heating unit (producing heating). Generally, solving a LOD problem requires achieving the lowest operating cost (f_{cost}) for the CHP plant under the total load requirements, and the objective function is expressed as [20]

$$\min f_{\text{cost}} = \sum_{i=1}^l C_i(P_i) + \sum_{j=1}^m C_j(P_j, H_j) + \sum_{k=1}^n C_k(H_k) \quad (1)$$

P and H stand for the production of power and heating, respectively, while C stands for the operating cost function, which can be written as follows [20]:

$$\begin{cases} C_i(P_i) = a_i + b_i P_i + c_i P_i^2 + |d_i \sin(e_i(P_i^{\min} - P_i))| \\ C_j(P_j, H_j) = a_j + b_j P_j + c_j P_j^2 + d_j H_j + e_j H_j^2 + f_j P_j H_j \\ C_k(H_k) = a_k + b_k H_k + c_k H_k^2 \end{cases} \quad (2)$$

The following constraints also should be adhered to:

$$\begin{cases} P_{i,\min} \leq P_i \leq P_{i,\max} \\ H_{i,\min} \leq H_i \leq H_{i,\max} \end{cases} \quad (3)$$

$$\begin{cases} \sum_{j=1}^m H_{\text{con},j} + \sum_{k=1}^n H_{h,k} = H_d \\ \sum_{i=1}^l P_{\text{con},i} + \sum_{j=1}^m Q_{\text{cog},j} = P_d \end{cases} \quad (4)$$

The unit of pure condensing, cogeneration and heating is represented by the subscripts *con*, *cog*, and *h*, respectively. The production limitations of each unit are indicated by the subscripts *min* and *max*, while the total load of heat and power are indicated by the subscripts H_d (MWth) and P_d (MW), respectively.

In particular, if the active network loss (P_L) is taken into account, then Equation (4) will be changed as follows [29]:

$$\begin{cases} \sum_{j=1}^m H_{con,j} + \sum_{k=1}^n H_{h,k} = H_d \\ \sum_{i=1}^l P_{con,i} + \sum_{j=1}^m Q_{cog,j} = P_d + P_L \\ P_L = \sum_{i=1}^{l+m} \sum_{j=1}^{l+m} P_i B_{i,j} P_j \end{cases} \quad (5)$$

P_L is the system active power loss, and B is the coefficient matrix.

2.2. Method for Processing Constraint

It can be found that there are many constraint conditions when dispatching the load distribution of a CHP plant. Therefore, to prevent the occurrence of the local optimal solution, the treatment of constraint conditions is also very important. In detail, these constraints can be divided into two types: one is the global constraints and the other the individual constraints. The following methods are used in this paper to handle those constraints.

(1) Cogeneration unit load constraints (individual constraints)

The typical load feasible region of cogeneration units is displayed in Figure 1, which is an irregular polygonal shape. The following measures are taken in this paper to satisfy the inequality constraints of cogeneration units: To satisfy the inequality constraints, during the optimization process, for the case where the individual location is out of the feasible range (regions 1–3), it is necessary to randomly generate a new value P_{new} on the boundary, then the H_{new} value is obtained by the boundary curve formula so as to obtain the new individual position. Conversely, the individual value does not need any adjustment when it is within the feasible range.

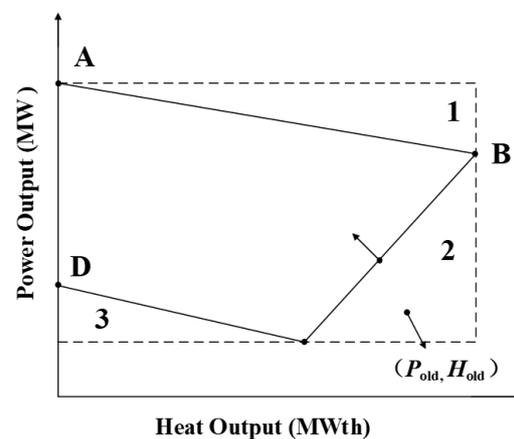


Figure 1. Typical feasible region of the cogeneration unit.

(2) Total load constraints of the heating and power networks (global constraints)

Intelligent algorithms usually encounter situations where some individuals do not satisfy the global constraints because intelligent algorithms have the characteristics of the random updates of individuals. In this paper, Equation (1) is transformed into a new

fitness function, which adds the global constraints of total demands (heating and power) as penalty terms, as follows:

$$F = f_{\text{cost}} + R_1 \left(\sum_{i=1}^l P_i + \sum_{j=1}^m P_j - P_D - P_L \right)^2 + R_2 \left(\sum_{j=1}^m H_j + \sum_{k=1}^n H_k - H_D \right)^2 \quad (6)$$

R_1 and R_2 are penalty factors. Therefore, the solution of the LOD problem is to meet the constraints (i.e., Equations (3) and (5)) while maintaining the minimal value of Equation (6). The heat and power provided by each unit are the independent variables.

3. Solution Methods

3.1. Classic Grey Wolf Algorithm

The hierarchy and foraging behavior of the grey wolves—a classed social hierarchy made up of α , β , δ , and ω —are the roots of the traditional GWO algorithm. As shown in Figure 2, the α wolves are regarded as the leader of the wolf groups, which means that the group follows their instructions. The β and δ wolves help the alphas make choices, while the ω is the lowest ranked grey wolf. Generally, the wolves α , β and δ own the greatest information on the prey, while the other wolves (ω) are updated using their current locations. In addition, the GWO approach consists of three basic steps: encircling, hunting, and attacking the prey [30]. When solving optimization problems, the best fitness solution is regarded as the α wolves, and the followed solutions are β , δ , and ω , respectively. Then, here are more details about the three steps.

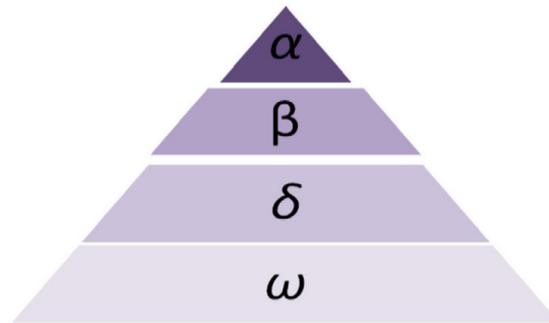


Figure 2. Social hierarchy of a pack of grey wolves [30].

(1) Encircling prey.

In the process of predation, the behavior of grey wolves encircling prey is calculated by using the following equations [30]:

$$\vec{D} = \left| \vec{C} \cdot \vec{X}_p(t) - \vec{X}(t) \right| \quad (7)$$

$$\vec{X}(t+1) = \vec{X}_p(t) - \vec{A} \cdot \vec{D} \quad (8)$$

\vec{D} , \vec{X} and \vec{X}_p represent the direction, position vector for grey wolf, and the position vector of prey, while \vec{C} and \vec{A} are the oscillation and convergence factors, which are calculated by [30]

$$\vec{C} = 2\vec{r}_1 \quad (9)$$

$$\vec{A} = 2a\vec{r}_2 - \vec{a} \quad (10)$$

a reduces from 2 to 0 during the iterations. \vec{r}_1 and \vec{r}_2 are the random vectors which are from 0 to 1.

(2) Hunting.

When the grey wolf finds its prey, the α wolf leads the β and δ packs to progressively encircle the prey. Assuming the α , β and δ wolves have all the prey information, the information they have is used to update the location of ω wolves. According to the decreasing order of fitness of the three optimal solutions, the distance between any wolf \vec{X} and the three optimal wolves is as follows [30]:

$$\begin{cases} \vec{D}_\alpha = \left| \vec{C}_1 \cdot \vec{X}_\alpha(t) - \vec{X}(t) \right| \\ \vec{D}_\beta = \left| \vec{C}_2 \cdot \vec{X}_\beta(t) - \vec{X}(t) \right| \\ \vec{D}_\delta = \left| \vec{C}_3 \cdot \vec{X}_\delta(t) - \vec{X}(t) \right| \end{cases} \quad (11)$$

Utilizing the subsequent formulae, one can utilize these distances to determine the wolf's new location. Thus, by repeatedly using the two operators of encircling and hunting, the prey or the optimal solution is located [30].

$$\begin{cases} \vec{X}_1 = \vec{X}_\alpha - \vec{A}_1 \cdot \vec{D}_\alpha \\ \vec{X}_2 = \vec{X}_\beta - \vec{A}_2 \cdot \vec{D}_\beta \\ \vec{X}_3 = \vec{X}_\delta - \vec{A}_3 \cdot \vec{D}_\delta \end{cases} \quad (12)$$

$$\vec{X}(t+1) = \frac{\vec{X}_1 + \vec{X}_2 + \vec{X}_3}{3} \quad (13)$$

3.2. Levy-GWO Algorithm

As said before, based on the improvement of swarm intelligence algorithms and exploring better intelligent optimization algorithms, practical problems can be better solved. In contrast, the traditional location update method weakens the global searchability, while the traditional GWO algorithm has limited local optimization capabilities. Thus, to deal with that issue, the following steps are used in this study.

- (1) Nonlinear convergence of control factor a .

In this work, rather than using the a , which converges linearly from 2 to 0, the nonlinear convergence approach is applied.

$$a = 2 \cdot \left(1 - \frac{e^{\frac{i}{\max_iter}} - 1}{e - 1} \right) \quad (14)$$

- (2) Individual position update strategy

As mentioned before, the GWO algorithm is vulnerable to settling into a local optimum. Thus, the method of position update is improved by adopting the Levy flight here [33], which can be expressed as

$$X_i(t+1) = X_i(t) + \gamma \oplus L(\lambda), 1 < i \leq n \quad (15)$$

λ is the step control variable. \oplus is a point-to-point product. $L(\lambda)$ is a column-dimensional distribution function.

Based on the above discussion, Figure 3 illustrates the computation procedure to solve a LOD problem.

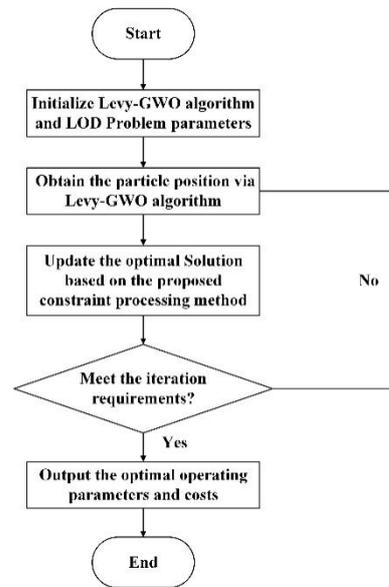


Figure 3. Flow chart of solving the LOD problem through the Levy-GWO algorithm.

4. Results and Discussions

Two different test systems with differing levels of computing difficulty are solved to evaluate the viability and efficacy of the involved algorithm. The simulation is built in MATLAB software and implemented on the same PC. The best outcome is used as the final result after each system has been performed independently 50 times.

4.1. Test System I

Test system I consist of four units, namely two cogeneration units (unit 2 and 3) and one power-only (unit 1), and one heat-only unit (unit 4), which was proposed by Guo et al. in 1996 [20]. For the sake of simplicity, test system I neglects the valve-point effects and transmission loss. Table 1 lists the relevant parameters for various unit operating cost functions, and Figure 4 displays the feasible operation region of cogeneration units 2 and 3.

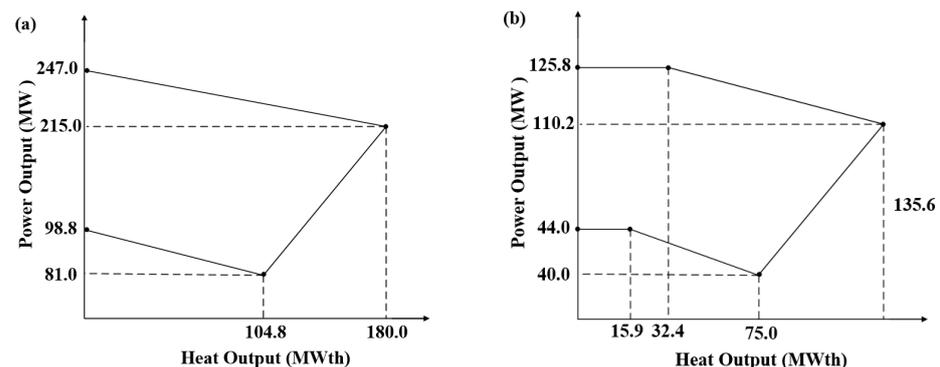


Figure 4. Feasible operation region of two cogeneration plants. (a) cogeneration unit 2 and (b) cogeneration unit 3.

Table 2 summarizes the optimal results obtained from the proposed algorithm. It is noted that the P_D and H_D are 200 MW and 115 MWth, respectively, which are kept the same as in the literature [19]. The optimization algorithm used in this paper is the reliability of the comparison with the results of the literature [19]. The results from Table 2 show that the generation costs obtained from the Levy-GWO algorithm are close to the reported data. Moreover, the optimization results of the GWO algorithm and the Levy-GWO algorithm are better than those of the GA and PSO algorithms. In general, the Levy-GWO algorithm can be used to obtain the minimum cost, owning 9231.41 \$/h. What is more, the penalty

factor does strengthen the constraint of the equation because the GWO and Levy–GWO algorithms can better satisfy the constraint of the equation.

Table 1. Characteristic parameters of test system I.

Unit	Cost Function Coefficient						Load Limitation (Unit)
	a	b	c	d	e	f	
1	/	50	/	/	/	/	[0, 150] (MW)
2	2650	14.5	0.0345	4.2	0.030	0.0311	Shown as Figure 4a
3	1250	36.0	0.0435	0.6	0.027	0.011	Shown as Figure 4b
4	/	23.4	/	/	/	/	[0, 2695.2] (MWt/h)

Table 2. Calculation results of different optimization algorithms for test system I.

Items	PSO [19]	GA [19]	GWO	Levy–GWO
P ₁ (MW)	0.05	0	0.05	0
P ₂ (MW)	195.43	159.23	159.97	159.74
P ₃ (MW)	40.57	40.77	40	40.25
H ₂ (MWt/h)	39.97	39.94	40.00	40.00
H ₃ (MWt/h)	75.03	75.06	75.00	75.00
H ₄ (MWt/h)	0	0	0	0
P _{total} (MW)	200.05	200	200.02	199.99
H _{total} (MWt/h)	115	115.83	115.00	115.00
Cost (\$/h)	9265.1	9267.21	9250.92	9231.41

4.2. Test System II

Moreover, this paper chooses another system consisting of seven units as test system II, which includes two cogeneration units (units 5 and 6) and four power-only (units 1–4), and one heat-only unit (unit 7). However, in test system II, the valve-point effects and transmission losses are considered. Accordingly, Table 3 lists the relevant parameters for various unit operating cost functions. Figure 4 also displays the feasible operation region of the two cogeneration.

Table 3. Characteristic parameters of test system II [21].

Unit	Cost Function Coefficient						Load Limitation (Unit)	Active Power Loss Coefficient Matrix
	a	b	c	d	e	f		
1	25	2.0	0.008	100	0.042	/	[0, 75] (MW)	$B = \begin{Bmatrix} 49, 14, 15, 15, 20, 25 \\ 14, 45, 16, 20, 18, 19 \\ 15, 16, 39, 10, 12, 15 \\ 15, 20, 10, 40, 14, 11 \\ 20, 18, 12, 14, 35, 17 \\ 25, 19, 15, 11, 17, 39 \end{Bmatrix} \times 10^{-6}$
2	60	1.8	0.003	140	0.040	/	[20, 150] (MW)	
3	100	2.1	0.0012	160	0.038	/	[30, 175] (MW)	
4	120	2.0	0.001	180	0.037	/	[40, 250] (MW)	
5	2650	14.5	0.0345	4.2	0.030	0.0311	Shown Figure 4a	
6	1250	36.0	0.0435	0.6	0.027	0.011	Shown Figure 4b	
7	950	2.0109	0.038	/	/	/	[0,2695.2] (MWth)	

According to Ref. [21], test system II has a power load (P_D) of 600 MW and a heat load (H_D) of 150 MWth. The lowest cost (\$ 10,117.79) may be obtained with the Levy–GWO method, as shown in Table 4. When compared to the lowest figure of \$ 10,317 in the literature, which provided data [21], there is a reduction of \$ 205.21. The P_{total} and H_{total} values of the Levy–GWO algorithm are found to be quite near the provided power and heating demand when compared to the outcomes produced by other algorithms. In other words, it further supports the penalty factor method’s significant impact on meeting the equation’s restriction.

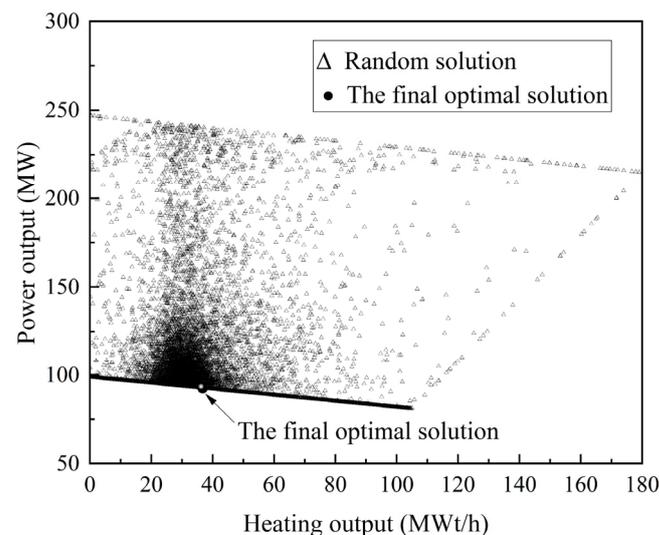
Table 4. Calculation results of different optimization algorithms for test system II.

Items	PSO [21]	EP [21]	DE [21]	GWO	Levy-GWO
P_1 (kW)	18.46	61.36	44.21	55.82	51.78
P_2 (kW)	124.26	95.12	98.54	97.42	98.73
P_3 (kW)	112.78	99.94	112.69	122.04	113.05
P_4 (kW)	209.82	208.73	209.77	209.67	210.05
P_5 (kW)	98.81	98.8	98.82	92.56	93.50
P_6 (kW)	44.01	44.00	44.00	40.12	40.00
H_5 (MWt/h)	57.92	18.07	12.54	36.75	31.39
H_6 (MWt/h)	32.76	77.55	78.35	73.15	74.99
H_7 (MWt/h)	59.32	54.37	59.11	40.95	43.63
P_{total} (MWt/h)	600.00	600.01	599.99	600.08	599.99
H_{total} (MWt/h)	150.00	150.00	149.99	149.95	150.01
P_L (MWt/h)	8.14	7.96	8.04	7.55	7.54
Cost (\$/h)	10,613	10,390	10,317	10,174.49	10,111.79

4.3. Performance Comparison between GWO Algorithm and Levy-GWO Algorithm

The results of the above two test systems confirm that the Levy-GWO algorithm has a reliable performance in solving the LOD problem. In other words, the necessity of improving the intelligent algorithm is confirmed as well. Therefore, based on the results of test system II, this section carried out a further comparison of the performance of GWO and Levy-GWO algorithms.

Figures 5 and 6 display the trace of the individual optimization of cogeneration unit 5 with GWO and Levy-GWO algorithms, respectively. For the GWO algorithm, the entire feasible region is almost filled with individual particles, but for the Levy-GWO algorithm, the feasible region is only covered by a few individual particles. This phenomenon indicates, owing to the Levy flight, the approximate range in which the optimal individual can be found by the Levy-GWO algorithm. Then the Levy-GWO algorithm starts fine-tuning in this range. In addition, it is clear from the two figures that no single particle exceeds the unit's power or thermal load limits, demonstrating that the constraint processing approach suggested has a very positive impact on the way inequality constraints are handled.

**Figure 5.** The individual optimization trace of cogeneration unit 5 with GWO algorithm.

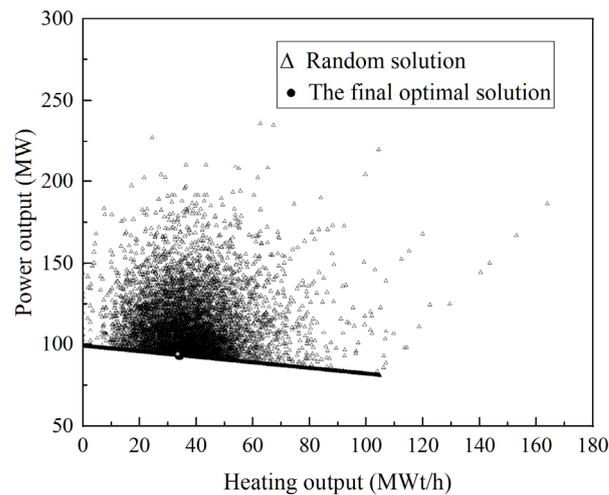


Figure 6. The individual optimization trace of cogeneration unit 5 with Levy-GWO algorithm.

Figure 7 shows the results of the repeatability of the two algorithms. The figure shows that the Levy-GWO algorithm can achieve greater economic benefits because its minimum value is lower than the GWO algorithm. Moreover, the Levy-GWO algorithm has better robustness because the distribution interval of the optimization results is narrower.

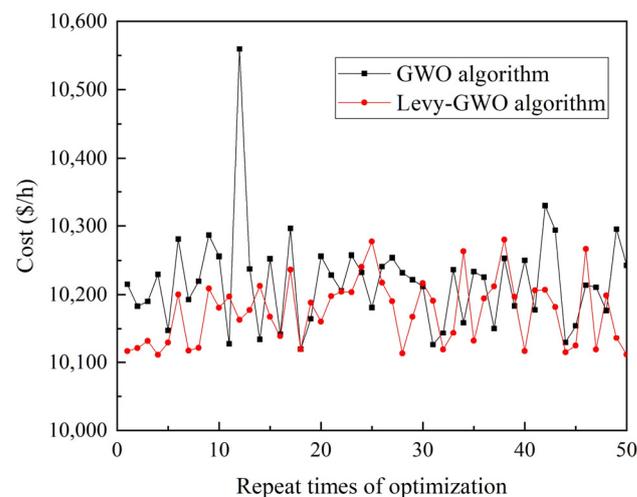


Figure 7. The distribution of calculated results of GWO and Levy-GWO algorithms.

In addition, it is also necessary to compare the convergence of the GWO and Levy-GWO algorithms. Figure 8 indicates the convergence curves of involved optimization algorithms. The figure shows that in the initial stage of the optimization, the GWO algorithm converges faster than the Levy-GWO algorithm. However, due to the Levy flight location updates method, the Levy-GWO algorithm converges stronger and shows the randomness of the individuals. In the later optimization process, the convergence speed of the Levy-GWO algorithm began to accelerate because the optimal region was clearly defined and finally achieved a better convergence effect with a lower optimal value. Moreover, the results indicate that the next necessary step is to achieve a better convergence speed of the algorithm.

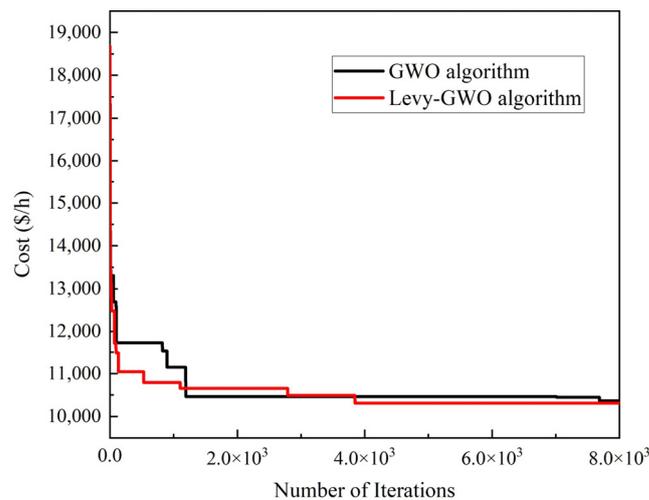


Figure 8. Convergence curve of GWO and Levy–GWO algorithms.

5. Conclusions

Aiming at solving the LOD problems of CHP plants to lower energy consumption, this paper used a new hybrid intelligence algorithm called the Levy–GWO algorithm. The Levy–GWO algorithm as well as the constraint processing approach based on the actual load optimal distribution were utilized to obtain an optimal dispatch of the load for CHP plants. The algorithm performance was tested and compared based on two different test plants with 3 and 7 units. Finally, the GWO algorithm and Levy–GWO algorithm were used to optimize and compare the performances of the CHP plants. The main conclusions are as follows.

- (1) The optimization results of Test systems 1 and 2 show that the two GWO algorithms used in this article can be used to solve the power plant LOD problem. It is proved that the improved strategy of the algorithm strengthens the ability of the search performance.
- (2) By comparing with the literature results, the optimized operating cost of the Levy–GWO algorithm is lower, showing better performance than the GWO algorithm. The proposed Levy–GWO algorithm can effectively reduce the cost from \$ 9265.1 to CNY 9231.41 in the 3-unit CHP plants, and the cost of the 7-unit plants decreases from \$ 10,317 to \$ 10,111.79 with respect to the reported data.
- (3) The tested results also show that the constraint processing method also brings advantages to solving the LOD problem, ensuring that the obtained solution is within the practicable operation range.

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