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Multi−dimensional firefly algorithm based on local search for solving unit commitment problem

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The Unit Commitment problem (UC) is a complex mixed-integer nonlinear programming problem, so the main challenge faced by many researchers is obtaining the optimal solution. Therefore, this dissertation proposes a new methodology combining the multi-dimensional firefly algorithm with local search called LS-MFA and utilizes it to solve the UC problem. In addition, adaptive adjustment, tolerance mechanism, and pit-jumping random strategy help to improve the optimal path and simplify the redundant solutions. The experimental work of unit commitment with the output of 10−100 machines in the 24-hour period is carried out in this paper. And it shows that compared with the previous UC artificial intelligence algorithms, the total cost obtained by LS-MFA is less and the results are excellent.

KEYWORDS

local search, multi-dimensional firefly algorithm, unit commitment, economic dispatch, artificial intelligence algorithm

1 Introduction

The electric power industry is becoming a key instrument in the economic and social development of a nation. It plays a vital role in the heavy industry and has long been the leading industry of a nation. With the continuous progress of human society and civilization, the power system has penetrated into all walks of life, so the effective, economic, secure, and stable operation of the power system has emerged as a powerful platform for the economic development of the nation. From national defence to daily life, the stability and reliability of the power system have been escorting social progress. There are some pieces of evidence to suggest that with the continuous expansion of the power system scale, it is challenging to achieve the balance of supply and demand and maximize economic benefits only by governing the output and commitment of the generators, which needs to adjust generators unit commitment and output scheduling in advance.

The unit commitment of a power system refers to reasonably adjusting the up-down state of units and active power distribution of units in a specified period (the example selected in this paper is a 24-hour period), so as to satisfy the balance between supply, demand, and spinning reserve requirement. And it can maximize the economic benefits of power system operation.

Among the traditional algorithms, literature (Su and Hsu, 1991) adopted fuzzy optimization theory to express load prediction, operation cost, and spinning reserve. They designed a fuzzy dynamic programming approach. One criticism of the literature was that it took a long time. A combination of the genetic algorithm and the quadratic programming approach was used in the literature (Mantawy, 1998) based on fuzzy optimization theory to obtain the unit commitment. Literature (Senjyu et al., 2003) based on heuristic methods provided a means of solving the problem of unit commitment, which improved the effectiveness of the algorithm. Dynamic programming was adopted in literature (Lee, 1991), and the average full-load consumption combined with the unit operation factor was selected for its reliability and validity. To better improve the accuracy of the solution, reference (Fan et al., 1996) undertook the sequential input method. Later, the exit commitment algorithm appeared. In literature (Xia et al., 2000), the use of reversing sorting according to the variation of unit operating cost after the unit shutdown was a well-established approach to finding the optimal solution. Besides, many researchers (Lowery, 1966; van den Bosch and Honderd, 1985; Snyder et al., 1987) have utilized the dynamic planning method to solve the problem of UC, but a major problem with the experimental method was the dimension disaster. So the procedures of this study were enhanced by the central improvement idea. That was to initialize the unit according to some economic characteristics indexes to generate the initial unit commitment, which greatly reduced the state variables. The Lagrangian Relaxation method (LR) was one of the most prominent procedures for determining commitment (Merlin and Sandrin, 1983; Zhuang and Galiana, 1988; Cohen et al., 1999) The benefit of this approach was that there was no dimension of disaster, and it performed well in solving large-scale optimization problems. However, there were certain drawbacks associated with the use of LR, for example, the convergence speed was not fast, and it appeared to oscillate. Literature (Carrión and Arroyo, 2006; Ostrowski et al., 2012) adopted a mixed integer programming method, but this method usually had no requirements on constraint conditions and a large amount of calculation, with slow calculation speed and convergence speed, so its practicability was not outstanding.

Recently, publications about UC more frequently adopted the artificial intelligence algorithm. Literature (Sasaki et al., 1992) depended on the Hopfield network model in Artificial Neural Networks (ANN) to solve the UC problem. Analysis of Hopfield involved in the traditional algorithm was first carried out. Various inequality constraints were taken into account in detail to determine the up-down state of each unit. But the model failed in convergence, and the results were not accurate. In 1996, Bai et al. published a paper in which they described the Tabu Algorithm (TB) to design a method that can be used for day-ahead scheduling plan adjustment or plan reorganization after the change of system running state (Bai and Shahidehpour, 1996). In an attempt to have good robustness and good calculation speed, the researcher (Maifeld and Sheble, 1996; Srinivasan and Tettamanzi, 1996) used the Genetic Algorithm (GA). Literature (Wong, 1998) used simulated annealing, which was a heuristic random algorithm based on Monte Carlo Iterative Solution Algorithm, but its convergence speed was behindhand, and some control parameters were difficult to determine.

This paper focuses on an artificial intelligence algorithm—Firefly Algorithm (FA) which eradicates the old and fosters the new. The FA was designed by Yang of Cambridge University in 2009 (Yang, 2009). It simulates the unique social behavior of fireflies in nature—luminous. And it generates a random optimization algorithm. Firefly Algorithm not only has a simple procedure, but also less relevant data, even can better overcome the common problem of local fast convergence of artificial intelligence algorithms. Therefore, this algorithm is beloved when it solves complex optimization problems with multiple constraints. The Firefly Algorithm is a random optimization algorithm generated according to the characteristics of the firefly's flashing behavior in nature. Without considering the biological significance of the firefly's luminescence, the firefly only uses its luminescence characteristics to search for companions in its search area and advances toward individuals with a higher brightness than itself to complete the update of the position. Firefly Algorithm was first carried out in 2005 at the IEEE conference on Swarm Intelligence. There has been an amount of application since it was proposed, such as the use of robots in the group, looking for multiple source localization, harmful gas emissions, contamination inspection, and multimodal optimization problems (Krishnanand and Ghose, 2005, 2006; Krishnanand K. and Ghose, D. 2009; Krishnanand K. N. and Ghose, D. 2009), which show the FA has a good performance, causing the favor of the researchers around the world, gradually becomes new popular research in the intelligent computing field.

This dissertation employs the Multidimensional Firefly Algorithm combined with Local Search (Balas and Vazacopoulos, 1998) named LS-MFA to solve the UC problem, considering discrete and continuous variables, and the output of generators, the unit minimum up-down time constraints, the load constraints. Meanwhile, the ramp rate constraints are also involved, which has the system is no longer a single independent section of optimization during the run time. Instead, it is sequent, setting out to obtain the unit commitment and the unit output distribution as well as having a significant price advantage compared with the previous literature. Meanwhile, the Firefly Algorithm itself is improved, one of which is to replace the fixed movement factors of FA with a new dynamic parameter adjustment method. Otherwise, different from the modern heuristic algorithms which use a penalty function to deal with equality constraints, this article does not add an additional objective function. It engages with the tolerance mechanism and amends the infeasible solution to the feasible region, which avoids being difficult to find a feasible solution due to multifarious equality constraints in the dynamic economic dispatch (DED). Beyond that, the random strategy is adopted aiming to increase the diversity of the population and prevent local premature convergence. It is worth mentioning that this paper proposes a new methodology for dealing with discrete variables. It joins the thought of Local Search (LS) including the "jumping pit strategy". And according to minimum up-down time limits, it sets up mandatory units that must run, mandatory units that must be turned off, and the free unit, which greatly reduces the amount of calculation of the unit commitment. Faster and more efficient optimization is achieved by adjusting free units. Furthermore, the injection of the "self-comparison" strategy ensures the rapid convergence of the search range. Frequently, compared with previous literature, the results show that LS-MFA facilitates the economy.

This paper is composed of six themed chapters. And it has begun with the above overview and introduction to UC. It will then go on to specifically introduce the proposed new methodology LS-MFA. The second part deals with the models and formulas of UC. Chapter Three begins by laying out the improvement both in the random movement factor α and the attractiveness, as well as the theoretical dimensions of LS-MFA, and looks at how it deals with the UC, which is the novelty of this study. The fourth chapter is concerned with the methodology used for this study. Chapter Five analyses the results of simulations and discussions. The sixth part is the summary of this paper and the vision for future work.

2 Mathematical model of UC

2.1 Objective function

The UC problem is to determine the best commitment of the unit state and generate the corresponding active power output in order to minimize the sum of power generation cost and start-up cost in the cycle. Its mathematical model is expressed as follows:

$$\boldsymbol{min\,.F} = \sum_{t=1}^{T}\sum_{i=1}^{N}\left[U_{it}C_{it} + U_{it}\left(1 - U_{i,t-1}\right)S_i\right] \tag{1}$$

In the formula, F is the total unit cost, N represents the number of units; T represents the operation period; U_{it} represents the state of the generator N in time period t. It can be described as follows:

$$U_{it} = \begin{cases} 1, \textit{when the machine is turned on} \\ 0, \textit{when the machine is turned off} \end{cases} \tag{2}$$

Where, C_{it} presents the generation cost of the unit i in time period t, and its function can be expressed as:

$$C_{it} = a_i P_{i,t}^2 + b_i P_{it} + c_i \tag{3}$$

In the formula,$a_i\,(/MW^2), b_i\,(/^{MW),c_i}()$ are the fuel cost coefficients of conventional generator set i.P_{it} is the active power output of the generator set during the period. S_i is the start-up cost of generator set i, which can be expressed as:

$$S_i = \begin{cases} S_{hi}, T_{off} \le X_{off} \le T_{off} + H_{csi} \\ S_{ci}, X_{off} > T_{off} + H_{csi} \end{cases} \tag{4}$$

Where, $S_{hi,}$ is the hot start-up cost of unit i, S_{ci} is the cold start-up cost of unit i, T_{off} is the minimum downtime of unit i;X_{off}, is the continuous downtime period from unit i to t, and H_{csi} is the cold start-up time of unit i.

2.2 Unit input also needs to meet the following constraints

2.2.1 Supply and demand balance constraints

The equality constraint in unit commitment optimization is the active power balance constraint. The total generating capacity of the generator needs to be equal to the load in real-time.

$$\sum_{i=1}^{N} U_{it}P_{it} = D_t\,(t = 1, 2, \cdots T) \tag{5}$$

Where, D_t is the load of the system at the time t

2.2.2 Constraints on spinning reserve requirement

In order to ensure the reliability of the system, sufficient spare capacity should be left in the power system, which can be expressed as:

$$\sum_{i=1}^{N} U_{it}P_{i,t}^{max} \ge D_t + R_t\,(t = 1, 2, \cdots T) \tag{6}$$

Where, $P_{i,t}{}^{max}$ is the maximum active power output of unit i in time period t; $R_t$is the spinning reserve requirement of the power system at time period$t$, which is generally set as the percentage of the total load of the system at that time, and is set as 10% in this paper (Kazarlis et al., 1996).

2.2.3 Constraints on unit operation output

$$U_{it}P_{i,t}^{min} \le P_{i,t} \le U_{it}P_{i,t}^{max} \tag{7}$$

Where, $P_{i,t}{}^{min}$ is the minimum active power output of unit i in time period t.

2.2.4 Constraints on start and stop time

When the unit changes its state, it needs to meet a certain time, otherwise, it will threaten the normal operation of the unit, which can be expressed in the following formula:

$$\begin{cases} X_{on} \geq T_{on} \\ X_{off} \geq T_{off} \end{cases} \tag{8}$$

Where, X_{on} is the continuous uptime until t, and T_{on} is the minimum uptime of unit i;X_{off} is the continuous downtime of unit i until t, and T_{off} is the minimum downtime of unit i.

2.2.5 Climbing and descending constraints

$$max\left(P_{i,t}^{min}, P_{i,t-1} - DR_i\right) \leq P_{i,t} \leq min\left(P_{i,t}^{max}, P_{i,t-1} + UR_i\right) \tag{9}$$

The formula, UR_irepresents the ramp-up rate of unit i, DR_i represents the ramp-down rate of unit i.

3 Proposed improved LS-MFA model

3.1 Firefly algorithm

Light intensity and attractiveness are the crucial roles of FA. For mathematical expression, the position of fireflies in the space coordinates determines the brightness of the firefly, which can be described as different positions matching different brightness. Meanwhile, its relative brightness decides the attraction between the individual and the probability of attraction, for this reason, it affects the distance and the direction of the individual movement. Therefore, each individual will change its light intensity in the process of moving. Finally, all kinds of updates are completed and at the same time, the optimization of the target is completed. The mathematical expressions in this process are as follows:

3.1.1 Relative attractiveness of fireflies

$$\beta^k = \beta_0 e^{-\gamma\left(r_{mn,t}^k\right)^2} \tag{10}$$

Where, β_0 is the brightness of the individual's initial position, and its intensity decreases with the increase of distance; γ is the light absorption coefficient. In the original FA, both β_0 and γ are constant constants, usually 1. $r_{mn,t}^k$ represents the Cartesian distance between two individuals.

3.1.2 Cartesian distance

The distance between individuals can be called Euclidean or Cartesian distance, and it can be expressed as follows:

$$r_{pq} = \left\|x_p - x_q\right\| = \sqrt{\sum_{i=1}^{d}\left(x_{p,s} - x_{q,s}\right)^2} \tag{11}$$

Where, $x_p$and $x_q$are the positions of two individuals$p$ and q; $x_{p,s}$and $x_{q,s}$are the s-dimensional space coordinates of the$p$ and$q$ individuals; d is the total number of dimensions;$q \in \{1, 2, \cdots, F_n\}$ was chosen at random; F_n is the total number of individuals.

3.1.3 Location update basis

The formula that individual i is attracted and updates to the position of j, which is brighter than itself:

$$x_p^{'} = x_p + \beta(r) \times \left(x_p - x_q\right) + \alpha(rand - 0.5) \tag{12}$$

In the formula, $\beta(r) \times (x_p - x_q)$ changes according to the attractiveness; $\alpha', rand$ represents a function that selects random numbers between 0 and 1. It is a disturbance term set to avoid the population falling into the local optimal solution, and it is based on these random terms that the algorithm is improved later.

3.1.4 Flow chart of basic firefly algorithm

How the FA gets down evolutionary operation can be demonstrated as Figure 1

3.2 Improved firefly algorithm

3.2.1 In modifying and improving the random movement factor α

In Firefly Algorithm, the random movement factor α plays an important role. If the random movement factor α is always large, the speed of optimization can be improved, but the accuracy of the solution will be reduced. If the random movement factor is always small, although the accuracy of understanding is improved, the optimization speed of the algorithm is greatly slowed down. Therefore, in the initial stage of the algorithm, α is relatively large, which can accelerate the speed of optimization. At the later stage, a relatively small step factor is needed, because, at this time, the population in the space has been mostly concentrated near the optimal solution, and a small step factor can improve the accuracy of the solution. Therefore, we need to adopt dynamic α to adjust the optimization.

In literature (Zhang et al., 2017), Zhang constructed a Firefly Algorithm with adaptive step size. The paper pointed out that under ideal conditions, all individuals in the population would gradually converge to the same point and eventually converge during the optimization process. That is, for two individuals X_i and X_j in space, we can get:

$$\lim_{t \to \infty} X_i(t) = \lim_{t \to \infty} X_j(t), \forall i \neq j \tag{13}$$

$$\lim_{t \to \infty} X_i(t+1) = \lim_{t \to \infty} X_i \tag{14}$$

Where,$i, j = 1, 2, \cdots, N$) Eq. 13 means that all individuals (solutions) converge to a point, and Eq. 14 means that the convergent solution does not change. According to Eqs 10, 13, 14 it can be obtained:

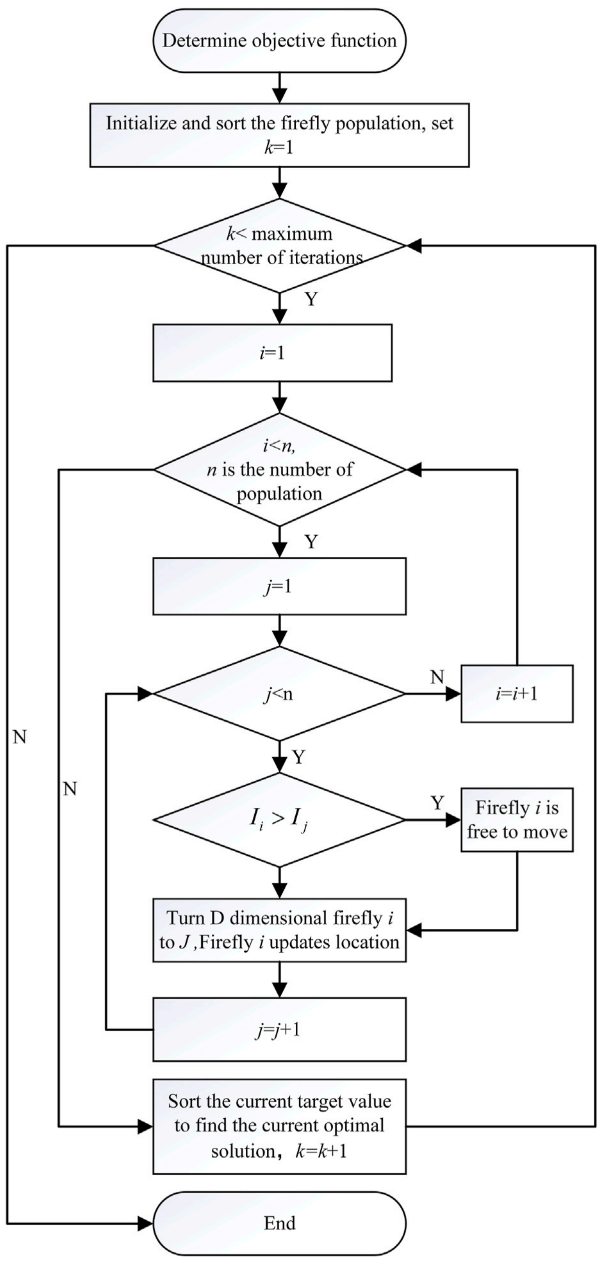

FIGURE 1
Firefly algorithm flow chart.

$$
\begin{aligned}
&\left(\lim_{t\to\infty} X_i(t+1) - X_i(t) = 0\right.\\
&\Longrightarrow \beta_0 \cdot \lim_{t\to\infty} e^{-\gamma r_{ij}^2} \cdot \lim_{t\to\infty}\left(X_j(t) - X_i(t)\right) + \varepsilon \cdot \lim_{t\to\infty} \alpha = 0\\
&\Longrightarrow 0 + \varepsilon \cdot \lim_{t\to\infty} \alpha = 0\\
&\Longrightarrow \lim_{t\to\infty} \alpha = 0
\end{aligned}
\tag{15}
$$

Where, Eq. 15 shows that when the firefly algorithm converges, the random movement factor α will approach 0.

Therefore, this paper adopts Eq. 16 to dynamically update the random movement factor α:

$$
\mathit{Method}\ 1\text{: } \alpha(k) = \left(1 - \left(1 - \left(10^{-4} \div 9\right)^{\frac{1}{K_{max}}}\right)\right) \times \alpha(k-1) \tag{16}
$$

From Figure 2, we can see that its value gradually decreases and tends to zero with the number of iterations, which is in line with the inference of the above formula. Meanwhile, the following calculation examples show that the improved method can help us find the optimal solution.

At the same time, another four different α adaptive adjustment methods are used for comparison, respectively.

$$
\mathit{Method}\ 2\text{: } \alpha(t+1) = \left(1 - \frac{t}{T_{max}}\right) \cdot \alpha(t) \tag{17}
$$

$$
\text{Method 3: } \alpha(t+1) = \left(\frac{1}{9000}\right)^{\frac{1}{t}} \cdot \alpha(t) \tag{18}
$$

$$
\mathit{Method}\ 4\text{: } \alpha(t+1) = 0.99 \cdot \alpha(t) \tag{19}
$$

$$
\mathit{Method}\ 5\text{: } \alpha(t+1) = \alpha(t) \cdot \exp\left(-\mathit{rand}(1) \cdot \frac{t}{T_{max}}\right) \tag{20}
$$

It can be seen from Figure 2 that **M2** converges too fast, resulting in too short step factor and local premature maturation. The initial stage of **M3** is too small and the optimization range is too small, which is not conducive to population diversity. **M4** converges too slowly, so that the step size factor in the final stage is too large, resulting in slow convergence. From the local enlarged image, **M5** has a random term, which makes the float and unstable changes. Therefore, **M1** is the correct choice in this paper, which ensures better convergence and relatively stable.

3.2.2 In terms of improving the attractiveness

According to previous studies, it is found that the optimization result of the algorithm is not so satisfactory when the algorithm is based on Eq. 10. To deal with this phenomenon, many change strategies have been proposed by researchers, among which the most well-known is the change mechanism proposed by Fister et al. (Fister et al., 2012). The improvement in this example is shown in Figure 3, and the formula can be expressed as follows:

$$
\beta^k = \beta_{min} + \left(\beta_{max} - \beta_{min}\right) e^{-\gamma\left(r_{mn,t}^k\right)^2} \tag{21}
$$

As can be seen from Figure 3, in the optimization of the whole stage, the values of attractiveness remain at around 0.2, but there are a few times that the attractiveness reaches 1, ensuring the diversity of the population, avoiding excessive prematurity, meanwhile, as progress through the iteration is smooth, this is because most of the fireflies are already clustered around the brightest individuals in the space. Most of the attraction converges at about 0.2, which

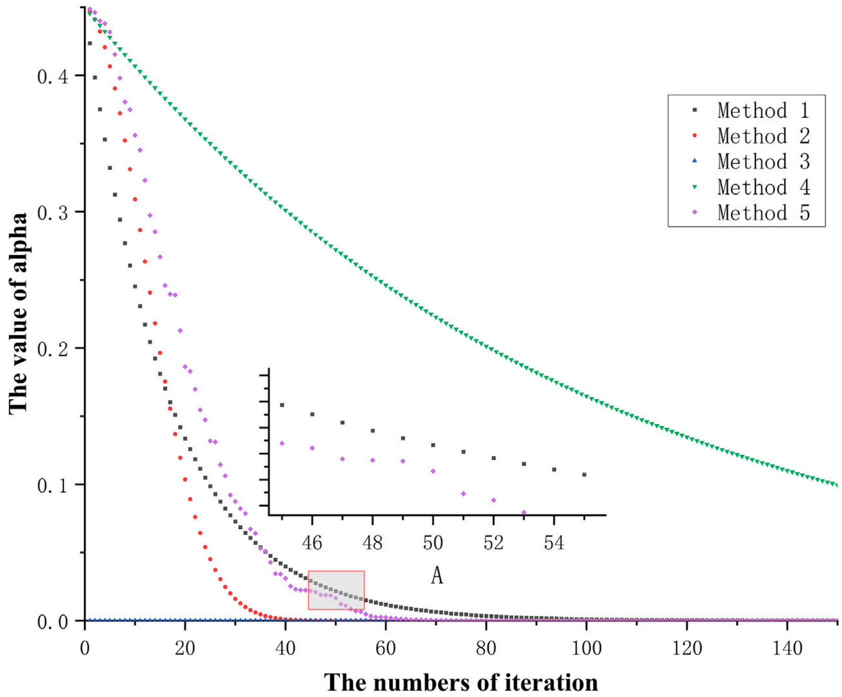

FIGURE 2
The iterated graph of alpha.

is conducive to improving the convergence rate of the population.

3.3 Combine local search

Local Search is a simple, efficient, and fast local search algorithm. A local search is constructed for the unit commitment problem, and a local adjustment method is created to ensure that the final result obtained by the algorithm can satisfy all the constraints and to ensure the feasibility of the optimization results.

In this essay, the Local Search method is used to solve the discrete variable problem of unit commitment. Firstly, according to Eq. 8, mandatory units that must be turned on, mandatory units that must be turned off, and the free units are determined. If C_{on} represents a mandatory unit that must be turned on, C_{off} represents a mandatory unit that must be turned off, and C_{free} represents free unit that can be started or stopped, the three shall meet the following requirements:

$$\begin{cases} C_{on} \Longrightarrow X_{on} < T_{on} \\ C_{off} \Longrightarrow X_{off} < T_{off} \\ C_{free} \Longrightarrow X_{on} > T_{on} \ \& X_{on} < T_{off} \end{cases} \tag{22}$$

There are many indexes to measure the unit input sequence, and different parameter indexes can be selected according to the characteristics of different units and loads. In this paper, based on the minimum specific consumption, Eq. 23 is used as the ranking index of units that are free:

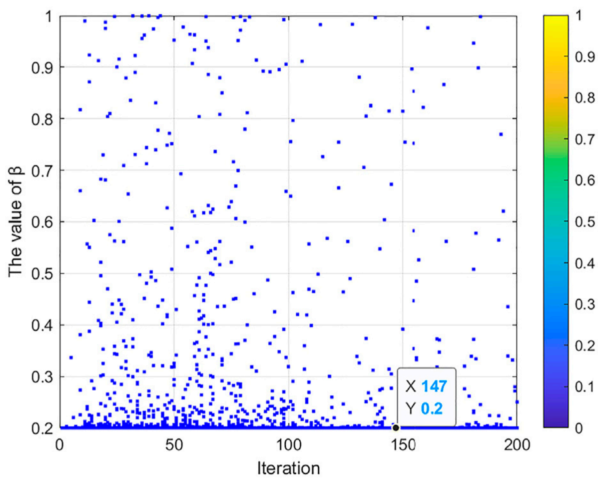

FIGURE 3
The iterated graph of β.

$$k = \frac{\textit{Minimum specific consumption}}{\textit{Maximum output of the unit}} \tag{23}$$

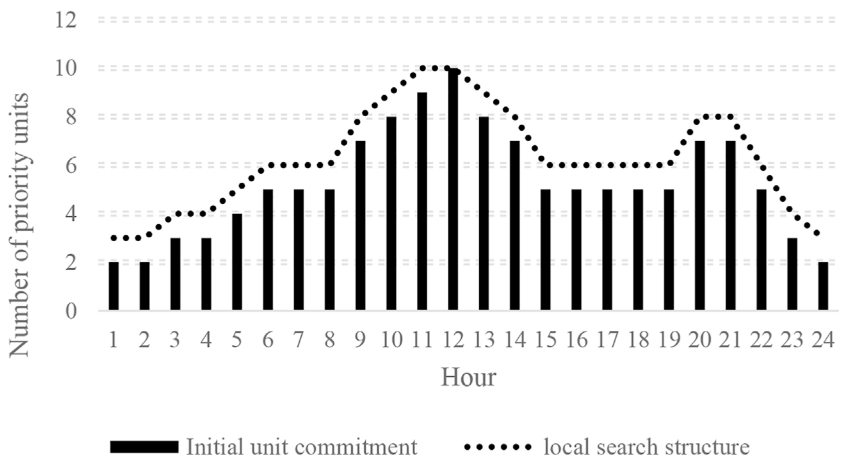

FIGURE 4
Initial unit commitment and their primary local search.

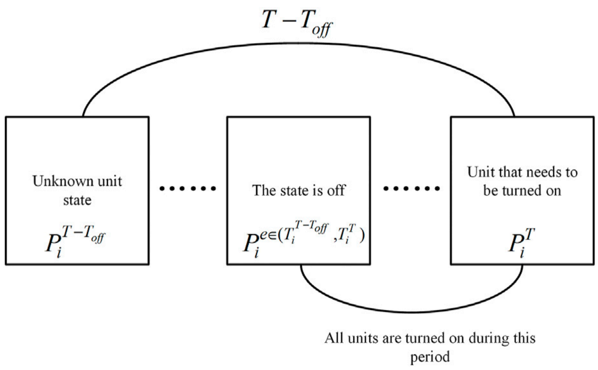

FIGURE 5
Flow chart for converting the unit to be started from the unit to be stopped.

According to the Eq. 6 to form the initial unit commitment, but in the process, to take into account for a certain period that the load is too heavy or subsequent unit start-up costs are too expensive to open, it is necessary to include opening a mandatory unit that must be turned off, to meet the requirements of load and the spinning reserve. While combining with the economic dispatch followed considering ramp rates constraints, it can appear that it does not satisfy Eq. 6. Therefore, to simplify the calculation, this paper first forms the bandwidth of an upward expansion unit, as shown in Figure 4. If the unit in sequence willing turn on is a mandatory unit that must be turned off, it is necessary to find the stopped time during the $T-T_{off}$ period and make it into the unit to be started, which will not add the unit start-up cost at the same time. However, redundant units may be generated during the $T-T_{off}$ period, thus it increases the operation cost. Therefore, the unit commitment of the $T-T_{off}$ period should be reconsidered according to the constraints of load and spinning reserve requirement, as shown in Figure 5. If Eq. 6 is still not satisfied, continue to expand one bandwidth, but ensure that the previous units still satisfy Eq. 8, i.e. execute loop Figure 5 until Eq. 6 is satisfied. Because the operation consumption function of the unit is a quadratic function, the Firefly Algorithm is used to find the best output balance for economic dispatch.

4 Application of LS-MFA in solving unit commitment problems

4.1 Bionic model of unit commitment problem

In this paper, fireflies in the population represent the unit output commitment of NT periods, expressed as follows:

$$\boldsymbol{P_{G,n}^k} = \left[\boldsymbol{P_{n,1}^k}, \boldsymbol{P_{n,2}^k}, \cdots, \boldsymbol{P_{n,T}^k}\right], \boldsymbol{n} = \mathbf{1}, \cdots, \boldsymbol{N_{firefly}} \tag{24}$$

Firefly position updates are made by the following formula:

$$\begin{aligned}\boldsymbol{P_{m,t}^k} &= \boldsymbol{P_{m,t}^k}\left(\mathbf{1}-\boldsymbol{\beta^k}\right) + \boldsymbol{\beta^k}\cdot\boldsymbol{P_{n,t}^k}\\ &+\boldsymbol{\alpha^k}\left|\boldsymbol{P^{max}}-\boldsymbol{P^{min}}\right|\left(\boldsymbol{rand_{1\times NG}}(.)-\frac{\mathbf{1}}{\mathbf{2}}\right)\end{aligned} \tag{25}$$

Where: $P_{n,t}^k$ is the firefly whose brightness is higher than $P_{m,t}^k$. When there is no firefly whose brightness is greater than $P_{m,t}^k$ itself in the space around $P_{m,t}^k$, the position will be moved and updated randomly. Where:$P^{max} = [P_1{}^{max}, P_2{}^{max}, \cdots, P_{NG}{}^{max}]$, $P^{min} = [P_1{}^{min}, P_2{}^{min}, \cdots, P_{NG}{}^{min}]$.The Cartesian distance between the two units is expressed as follows:

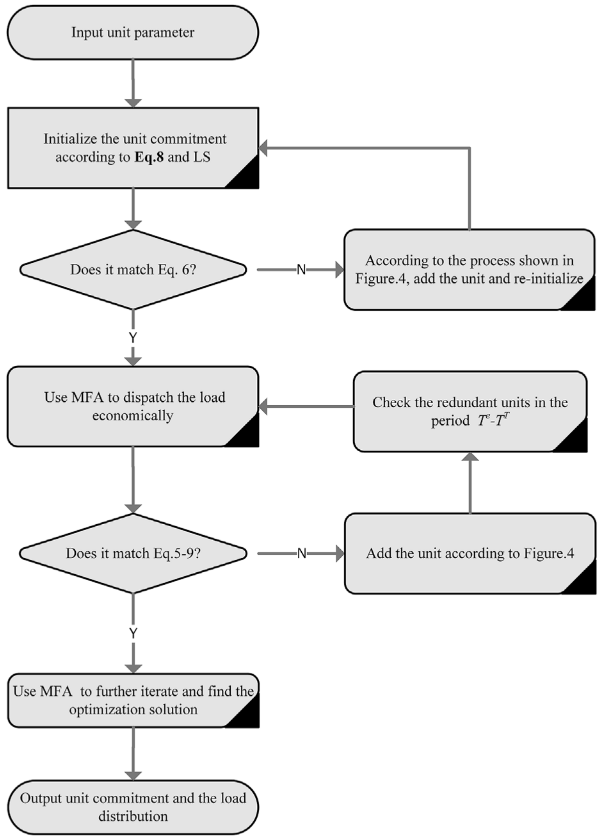

FIGURE 6
Overall flow chart for solving unit commitment problem.

TABLE 1 Unit parameters.

Unit parameters	**UNIT**									
	1	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**
$P_{i\max}/MW$	455	455	130	130	162	80	85	55	55	55
$P_{i\min}/MW$	150	150	20	20	25	20	25	10	10	10
$a_i/(/h)$	1,000	970	700	680	450	370	480	660	665	670
$b_i/(MWh)$	16.19	17.26	16.60	16.50	19.70	22.26	27.74	25.92	27.27	27.79
$c_i/(MW^2-h)$	0.48	0.31	2	2.11	3.98	7.12	7.9	4.13	2.22	1.73
min $up(h)$	8	8	5	5	6	3	3	1	1	1
min $down(h)$	8	8	5	5	6	3	3	1	1	1
hot start cost (\$)	4,500	5,000	550	560	900	170	260	30	30	30
cold start cost (\$)	9,000	10000	1,100	1,120	1800	340	520	60	60	60
cold start hours (h)	5	5	4	4	4	2	2	0	0	0
initial status (h)	8	8	-5	-5	-6	-3	-3	-1	-1	-1

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TABLE 2 Unit Commitment for 10-unit system.

Hour	Load (MW)	UNIT									
		1	2	3	4	5	6	7	8	9	10
1	700	1	1	0	0	0	0	0	0	0	0
2	750	1	1	0	0	0	0	0	0	0	0
3	850	1	1	0	0	1	0	0	0	0	0
4	950	1	1	0	0	1	0	0	0	0	0
5	1,000	1	1	0	1	1	0	0	0	0	0
6	1,100	1	1	1	1	1	0	0	0	0	0
7	1,150	1	1	1	1	1	0	0	0	0	0
8	1,200	1	1	1	1	1	0	0	0	0	0
9	1,300	1	1	1	1	1	1	1	0	0	0
10	1,400	1	1	1	1	1	1	1	1	0	0
11	1,450	1	1	1	1	1	1	1	1	1	0
12	1,500	1	1	1	1	1	1	1	1	1	1
13	1,400	1	1	1	1	1	1	1	1	0	0
14	1,300	1	1	1	1	1	1	1	0	0	0
15	1,200	1	1	1	1	1	0	0	0	0	0
16	1,050	1	1	1	1	1	0	0	0	0	0
17	1,000	1	1	1	1	1	0	0	0	0	0
18	1,100	1	1	1	1	1	0	0	0	0	0
19	1,200	1	1	1	1	1	0	0	0	0	0
20	1,400	1	1	1	1	1	1	1	1	0	0
21	1,300	1	1	1	1	1	1	1	0	0	0
22	1,100	1	1	0	0	1	1	1	0	0	0
23	900	1	1	0	0	0	1	0	0	0	0
24	800	1	1	0	0	0	0	0	0	0	0

$$r^k_{mn,t} = \sqrt{\sum_{i=1}^{NG}\left(P^k_{n,t,i} - P^k_{m,t,i}\right)^2} \tag{26}$$

4.2 Flow chart of the solving process

The flow chart of the optimization solving process can be shown in Figure 6.

Step 1: The unit parameters, load, and spinning reserve requirement are the first input.

Step 2: The initial unit commitment is determined according to the maximum unit output, Eq. 8, and the method of local structure construction, and whether it meets the load and spinning reserve requirement of the unit is considered, i.e. Eq. 6. If Eq.6 is satisfied, go to Step 4.

Step 3: If not, according to the process shown in Figure 4 and Eq. 8, restarting the units in the previous period makes the units will be opened into units to be available, and initialize the firefly population of the reopened units again to eliminate redundant units. Then repeat Step 2.

Step 4: When Eq. 6 is met, MFA is used to carry out economic dispatch corresponding to this unit commitment. However, since ramp rate limits should be considered in the process of economic dispatch, other units in the same segment need to be opened again to meet the load and spinning reserve requirement. Therefore, if Eqs 5–9 is not satisfied, go to Step 5, otherwise, go to Step 6.

Step 5: In this step, Figure 4 should be used again. Initialize the firefly population of the reopened units again to eliminate redundant units, until the units satisfy Eqs 5–9 again. Then, repeat Step.4.

Step 6: In this step, MFA is used to further optimize the iteration of the population, including unit commitment and economic dispatch, and the "self-comparison" strategy is used to prevent the iteration from deviating from the optimal value.

TABLE 3 Economic Dispatch for 10-unit system.

Hour	UNIT									
	1	2	3	4	5	6	7	8	9	10
1	455	245	0	0	0	0	0	0	0	0
2	455	295	0	0	0	0	0	0	0	0
3	455	370	0	0	25	0	0	0	0	0
4	455	455	0	0	40	0	0	0	0	0
5	455	390	0	130	25	0	0	0	0	0
6	455	360	130	130	25	0	0	0	0	0
7	455	410	130	130	25	0	0	0	0	0
8	455	455	130	130	30	0	0	0	0	0
9	455	455	130	130	85	20	25	0	0	0
10	455	455	130	130	162	33	25	10	0	0
11	455	455	130	130	162	73	25	10	10	0
12	455	455	130	130	162	80	25	43	10	10
13	455	455	130	130	162	33	25	10	0	0
14	455	455	130	130	85	20	25	0	0	0
15	455	455	130	130	30	0	0	0	0	0
16	455	310	130	130	25	0	0	0	0	0
17	455	260	130	130	25	0	0	0	0	0
18	455	360	130	130	25	0	0	0	0	0
19	455	455	130	130	30	0	0	0	0	0
20	455	455	130	130	162	33	25	10	0	0
21	455	455	130	130	85	20	25	0	0	0
22	455	455	0	0	145	20	25	0	0	0
23	455	420	0	0	25	0	0	0	0	0
24	455	345	0	0	0	0	0	0	0	0

TABLE 4 Optimal operating cost per hour for 10-unit system.

Hour	1	2	3	4	5	6
COST/h	13683.12975	14554.49975	17709.4485	18597.66775	20580.0195	23487.0445
HOUR	7	8	9	10	11	12
COST/h	23261.9795	24150.34075	28111.056	30117.5503	31976.0611	33950.22152
HOUR	13	14	15	16	17	18
COST/h	30057.5503	27251.056	24150.34075	21513.6595	20641.8245	22387.0445
HOUR	19	20	21	22	23	24
COST/h	24150.34075	30547.5503	27251.056	22735.521	17684.6935	15427.41975

5 Simulation results and analysis

In this essay, the example of 10 units in literature (Kazarlis et al., 1996) for a 24-hour period is first adopted. The unit parameters are provided in Table 1, which includes the maximum active power output of the unit i in the period t, the minimum active power output of the unit i in the period t, the fuel cost coefficients of the conventional generator set i, the minimum up-down time, and the initial continuous uptime of units. Table 2 presents the unit commitment in the 24-hour period and the load demand by LS-MFA for a 10-unit system. As can be seen from the table, the unit commitment belongs to the local structure formed in Figure 4. And it conforms to the minimum up-down time limits. Table 3 shows the economic dispatch of unit commitment in Table 2. Further analysis showed that the units with a good economy will not only be put into priority, but also be arranged to run at full load as far as possible.

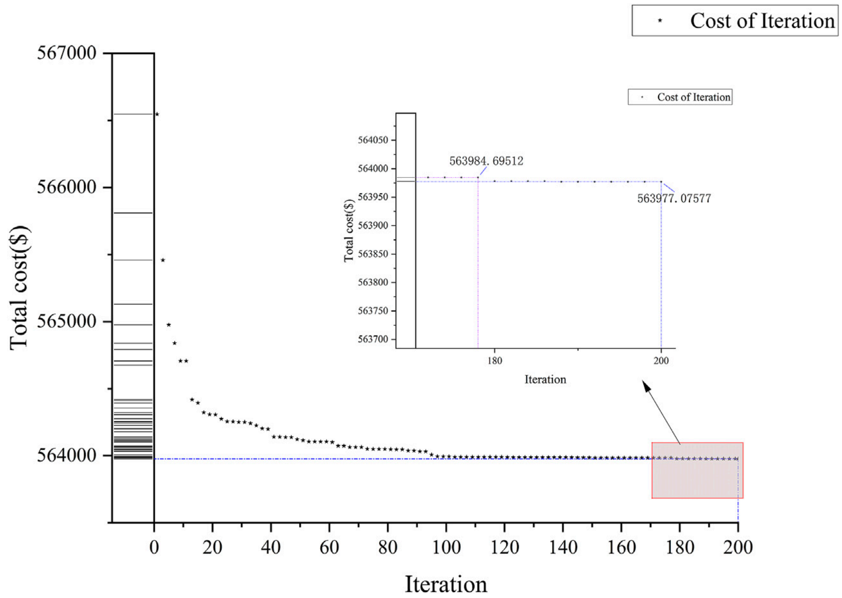

FIGURE 7
The iterative optimization of LS-MFA.

TABLE 5 Comparison of total cost with reported optimization techniques for 10-unit system.

Methods	Total production costs ($)	Cost difference (%)	Methods	Total production costs ($)	Cost difference (%)
BGOA	563,027	−0.1684	BF	564,842	0.1534
SFLA	563,937	−0.0071	ABFMO	565,136	0.2055
HPSO	563,942	−0.0062	ALR	565,508	0.2715
ELR	563,977	0.0000	DPSO	565,804	0.3239
GAUC	563,977	0.0000	LR	565,825	0.3277
BDEr	563,989	0.0021	GA	565,825	0.3277
DPLR	564,049	0.0128	PSO-LR	565,869	0.3355
BPSOGWO	564,402	0.0754	ICGA	566,404	0.4303
BGWO	564,549	0.1014	BCGA	567,367	0.6011
EP	564,551	0.1018	ABC	641,303	13.7108
BCS	564,673	0.1234	LS-MFA	563,977	0.0000
LRGA	564,800	0.1459			

Meanwhile, it satisfies the load demand, the spinning reserve requirement, and the ramp rate. The results obtained from the preliminary analysis of optimal operating cost per hour are set out in Table 4.

With the aim of presenting the optimization process, Figure 7 shows the trend of 200 iterations of the optimization process. From the figure, the results have been smooth around the 100th iteration. And it can be seen from the whisker diagram of the ordinate axis, that in the initial iterations of the optimization, convergence speed is quick, and most of the results are concentrated around the optimal solution, this phenomenon also confirms the improvement in both in the random movement factor α and the attractiveness β, namely in the initial iterations of the optimization needs larger random movement factor and enough stable attractiveness to find the optimal solution, and as the iteration goes on, the decrease of random movement factor α is beneficial to the optimization in a small range, and in this process, the attractiveness function is dynamic, which ensures the convergence speed and the diversity of the population and avoids premature convergence. Finally, from the enlarged image about the last period of the iteration, at 178th, the cost

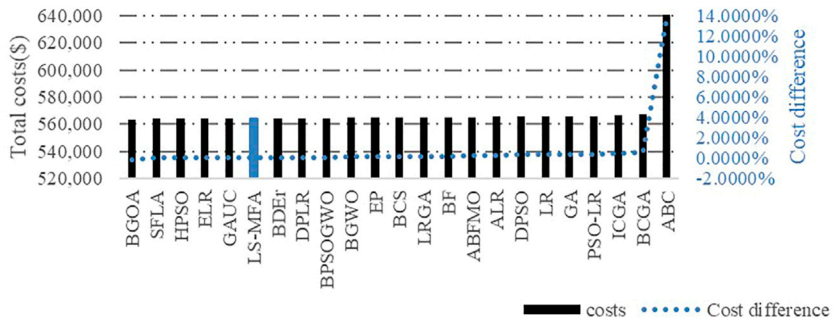

FIGURE 8
Comparison of total cost with reported optimization techniques for 10-unit system.

TABLE 6 Comparison of total cost with reported optimization techniques for 20-unit system.

Methods	Total production costs ($)	Cost difference (%)	Methods	Total production costs ($)	Cost difference (%)
BGOA	1,120,470	−0.2517	LR	1,130,660	0.6555
LRGA	1,122,622	−0.0601	ABFMO	1,131,551	0.7348
ELR	1,123,297	0.0000	BDEr	1,132,763	0.8427
EP	1,125,494	0.1956	BGWO	1,140,027	1.4894
GAUC	1,125,516	0.1975	BCS	1,142,930	1.7478
GA	1,126,243	0.2623	BPSOGWO	1,145,016	1.9335
ALR	1,126,720	0.3047	LS-MFA	1,123,297	0.0000
DPLR	1,128,098	0.4274			

TABLE 7 Comparison of total cost with reported optimization techniques for 40-unit system.

Methods	Total production costs ($)	Cost difference (%)	Methods	Total production costs ($)	Cost difference (%)
BGOA	2,240,277	0.0000	LR	2,258,503	0.8136
LRGA	2,242,178	0.0849	ABFMO	2,265,867	1.1423
ELR	2,244,237	0.1768	BDEr	2,291,992	2.3084
EP	2,249,093	0.3935	BGWO	2,298,588	2.6028
GAUC	2,249,715	0.4213	BCS	2,305,632	2.9173
ALR	2,249,790	0.4246	BPSOGWO	2,311,725	3.1892
GA	2,251,911	0.5193	LS-MFA	2,240,277	0.0000
DPLR	2,256,195	0.7105			

is 563984$. It is worth mentioning that at 180th the cost converges on 563977$, and the trend is stable.

In order to further illustrate the advantages and practicability of LS-MFA, the clustering results of the other twenty-two methods of DPLR, ALR, ELR (Ongsakul and Petcharaks, 2004), LR, GA (Kazarlis et al., 1996),EP (Juste, 1999), LRGA (Cheng and Liu, 2000), GAUC(Yamashiro, 2001), DPSO(Gaing, 2004), ICGA, BCGA(Damousis et al., 2004), BF(Eslamian et al., 2009), PSO-LR (Balci and Valenzuela, 2004), SLFA (Ebrahimi et al., 2011), HPSO(Ting et al., 2006), BGOA (Shahid et al., 2021), ABC(Kokare and Tade, 2018), ABFMO(Pan et al., 2021), BCS(Reddy Surender, 2017), BDEr (Kamboj et al., 2017), BGWO(Panwar et al., 2018), BPSOGWO(Kamboj, 2016) which are shown in Table 5, meanwhile, the results are compared with the result of LS-MFA, obtaining the cost difference. Figure 8 visualizes the comparison, ranking several methods using operating costs as

TABLE 8 Comparison of total cost with reported optimization techniques for 60-unit system.

Methods	Total production costs ($)	Cost difference (%)	Methods	Total production costs ($)	Cost difference (%)
BGOA	3,356,574	−0.2056	LR	3,394,066	0.9090
ELR	3,363,491	0.0000	ABFMO	3,397,162	1.0011
LRGA	3,371,079	0.2256	BDEr	3,451,346	2.6120
ALR	3,371,188	0.2288	BGWO	3,460,080	2.8717
EP	3,371,611	0.2414	BCS	3,464,932	3.0159
GAUC	3,375,065	0.3441	BPSOGWO	3,478,950	3.4327
GA	3,376,625	0.3905	LS-MFA	3,363,491	0.0000
DPLR	3,384,293	0.6185			

TABLE 9 Comparison of total cost with reported optimization techniques for 80-unit system.

Methods	Total production costs ($)	Cost difference (%)	Methods	Total production costs ($)	Cost difference (%)
BGOA	4,475,407	0.0000	LR	4,526,022	1.1310
ELR	4,485,633	0.2285	ABFMO	4,531,605	1.2557
ALR	4,494,487	0.4263	BDEr	4,616,190	3.1457
EP	4,498,479	0.5155	BGWO	4,622,671	3.2905
LRGA	4,501,844	0.5907	BCS	4,625,838	3.3613
GA	4,504,933	0.6597	BPSOGWO	4,645,223	3.7944
GAUC	4,505,614	0.6750	LS-MFA	4,475,407	0.0000
DPLR	4,512,391	0.8264			

TABLE 10 Comparison of total cost with reported optimization techniques for 100-unit system.

Methods	Total production costs ($)	Cost difference (%)	Methods	Total production costs ($)	Cost difference (%)
BGOA	5,596,414	−0.1380	LR	5,657,277	0.9481
ELR	5,605,678	0.0273	ABFMO	5,660,087	0.9982
LRGA	5,613,127	0.1603	BDEr	5,776,923	3.0830
ALR	5,615,893	0.2096	BGWO	5,786,794	3.2592
EP	5,623,885	0.3522	BCS	5,788,367	3.2872
GAUC	5,626,514	0.3991	BPSOGWO	5,812,001	3.7090
GA	5,627,437	0.4156	LS-MFA	5,604,146	0.0000
DPLR	5,640,488	0.6485			

the primary axis (black) and cost differences (blue) as the secondary axis. By checking the output obtained from SLFA, whose cost is better than LS-MFA, we find that although the cost is 563937$, it does not meet the load demand in the period of T = 22. What is striking about the figures in Figure 8 is that LS-MFA proposed in this paper has good optimization performance, is better than most methodologies, and is worthy of consideration by researchers in future work studies.

In order to further demonstrate the good performance of LS-MFA, the 20,40,60,80,100-unit systems are used to verify. The 20, 40, 60, 80, and 100-unit data are obtained by duplicating the base case (ten units), whereas the load demands are adjusted in proportion to the system size. And the comparisons of the larger systems are shown in. Meanwhile, for a more intuitive comparison, the methods are sorted. Figures 9–13 visualize the comparison, ranking several methods using operating costs as the primary axis (black) and cost differences (blue) as the secondary axis. Figures 10, 12 present that LS-MFA acquires the best data in 40-unit and 80-unit.

As can be seen by the above results, the result obtained by LS - MFA is better than most methods, and in the process of

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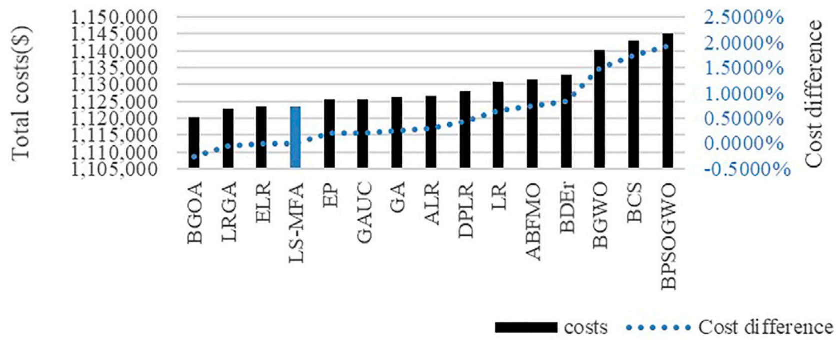

FIGURE 9
Comparison of total cost with reported optimization techniques for 20-unit system.

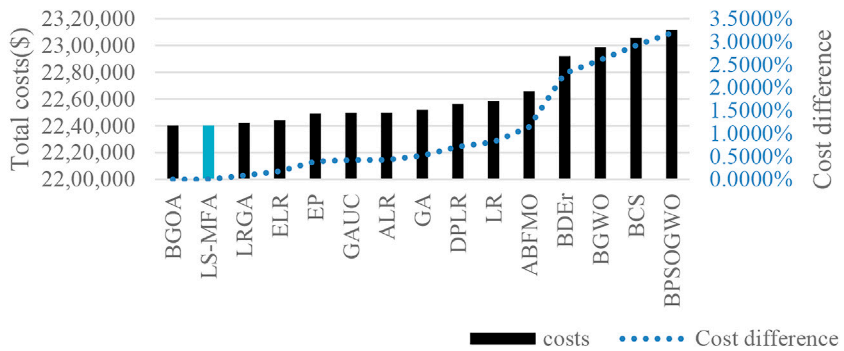

FIGURE 10
Comparison of total cost with reported optimization techniques for 40-unit system.

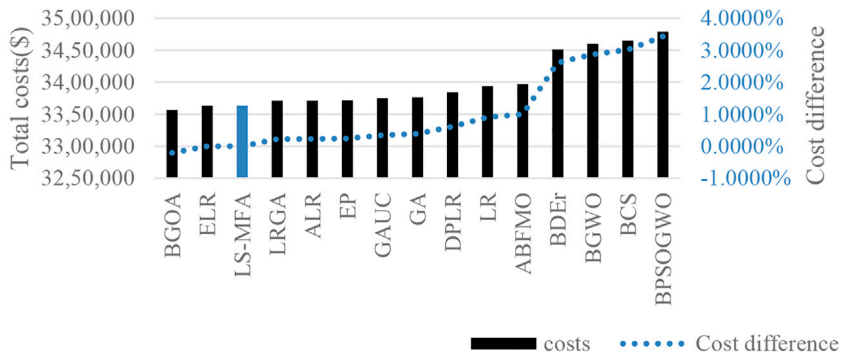

FIGURE 11
Comparison of total cost with reported optimization techniques for 60-unit system.

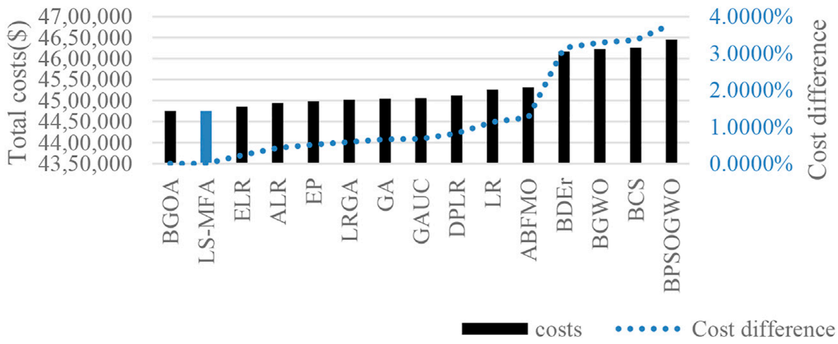

FIGURE 12
Comparison of total cost with reported optimization techniques for 80-unit system.

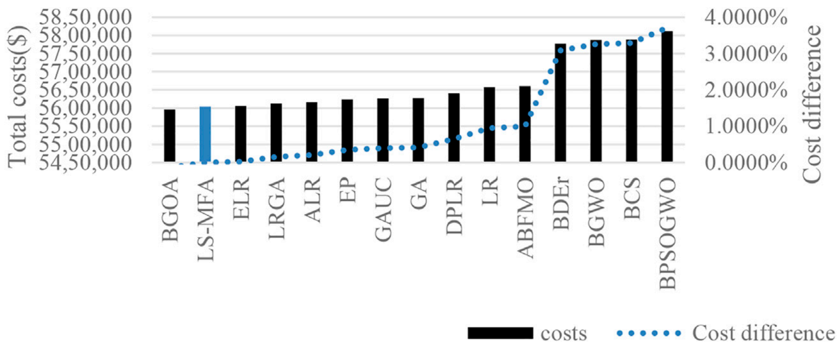

FIGURE 13
Comparison of total cost with reported optimization techniques for 100-unit system.

optimization, compared with the mixed-integer nonlinear programming, the use of local search avoids the dimension disaster, and improves convergence speed. Meanwhile, few parameters using the firefly algorithm program and strong randomness make the optimization not too premature and effectively prevent the local convergence. The improvement of the Firefly algorithm itself makes the final results tend to be stable, and the results obtained are well.

6 Conclusions and future work

In the process of the optimization problem of the power system, the unit commitment problem is always the top priority. And its economic dispatch power system is efficient, safe, stable, and economic operation indispensable safeguard. By finding the optimum commitment, the electric power industry of a country can not only get considerable income but also alleviate the problems of energy shortage and environmental pollution in today's era. Meanwhile, it is a powerful catalyst to promote the implementation of sustainable a development strategy.

Unit Commitment of electric power system and the economic dispatch problem is discrete and continuous variables of the nonconvex, nonlinear, multi-dimensional. Besides, the distribution of the process is complex. Therefore, only set up accurate realistic models of the actual working state of the power grid, can we obtain more conducive for the further optimization and development of the power system. The focus of this paper lies in:

1) Use dynamic α factor to further improve the optimization of the FA.
2) The self-adjustment strategy is used to prevent the target value from deviating from the optimal solution due to iteration.
3) A tolerance mechanism was adopted to modify the infeasible solution to the feasible region and increase the population diversity.
4) Combined with the Local Search method, the "pit-jumping strategy" is adopted to determine the unit commitment, which not only ensures the diversity of unit commitment solutions but also avoids dimension disaster to a certain extent.

5) The Firefly Algorithm combined with the Local Search method can be found through the simulation results that its unit commitment and economic dispatch results are not inferior to other algorithms

In the future, the author will strive to improve LS-MFA and add an integrated energy management system, including combining heat and power generation (CHP), wind and hydropower units, and battery energy storage systems, so as to make it meet the modern energy needs.

In recent years, the living level has continuously improved, and people are no longer taking the environmental problem for granted, we must adhere to the new concept of development, sustainable development. So when solving the UC problem, the power system should not only consider whether or not the operation efficiency, the cost is considerable, and incorporated into the new energy. Beyond that, some uncontrollable factors should be taken into account, such as inaccurate load prediction, failure of output unit start and stop, accidents in the transmission process, and the probability of interference factors that may occur. And finally, the objective function and each constraint probability are calculated to build a scheduling model in line with the actual operation situation. That is, to say, the premise of our pursuit of economic benefits is to protect nature and build an energy-conserving society.

Data availability statement

The original contributions presented in the study are included in the article/supplementary material, further inquiries can be directed to the corresponding author.

Author contributions

All authors listed have made a substantial, direct, and intellectual contribution to the work and approved it for publication.

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Conflict of interest

The authors declare that the research was conducted in the absence of any commercial or financial relationships that could be construed as a potential conflict of interest.

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