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Economic dispatch using modified bat algorithm

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Due to the frequent opening and shutting of turbine valves in the power system, valve point effect (VPE) that makes the economic dispatching (ED) problem non-linear, non-smooth and non-convex may be generated. Moreover, various constraints appear in the operation process, such as network transmission loss, and power balance during unit operation, which make it more difficult to find the global optimum through traditional mathematical methods. Nowadays, intelligent algorithms have successfully become a useful optimization tool to deal with nonlinear problems. In this paper, an improved bat algorithm (IBA), into which random black hole strategy and Gaussian mutation are introduced, is proposed to solve the ED problem. Furthermore, the random black hole strategy can enhance the diversity of the population and improve the convergence speed of IBA. Gaussian mutation is adopted to help jumping out of the local optimum. IBA is tested in 50 and 100 dimensions on 10 sets of well-known benchmark functions respectively, and compared with the methods in literature to verify its feasibility. Then, three different scales economic dispatching problems (3 units, 13 units, 40 units) are solved by this method, which further proves its effectiveness. The results show that IBA has obvious advantages and practical application value compared with other optimization methods.

KEYWORDS

static economic dispatch1, bat algorithm2, random black hole strategy3, gaussian mutation4, valve point effects5

1 Introduction

Economic Dispatch problem is a typical optimization problem in power system operation and has been one of the hot topics of research in recent years. The objective of the ED problem is to find the appropriate generation value to minimize the cost of generation while satisfying the equation and inequality constraints that may arise in power system operation (Ma et al., 2017; Chen and Tang, 2022). Generally, the thermal power unit would be affected by the valve point effect, which make the ED problem be a complex optimization problem with non-smooth, non-linear, non-convex and non-differentiable. There are two general methods to solve this problem: one is the classical mathematical method, such as quadratic programming, nonlinear programming, etc., and the other is the intelligent optimization algorithm, such as genetic algorithm, particle swarm algorithm, etc. (Singh and Dhillon, 2019; Yang et al., 2021). The former

FIGURE 1
Cost function with and without valve point effect.
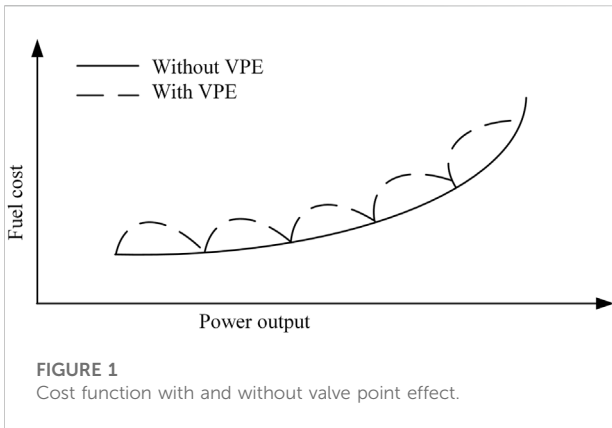
requires continuous differentiable function, which is obviously not suitable for the practical application scene. However, the latter has no special requirements on the objective function, so this paper chooses intelligent optimization algorithm instead of classical mathematical method to solve the ED problem.

In recent years, with the rapid development of intelligent optimization algorithms, more and more scholars are using it to solve ED problems (Niu et al., 2014; Dou and Qin, 2020). grey wolf optimization (GWO) (Singh and Dhillon, 2019), sailfish algorithm (SFA) (Li et al., 2021), fireworks algorithm (FWA) (Zare et al., 2021), whale optimization algorithm (WOA) (Medani et al., 2018), artificial bee colony algorithm (ABC) (Hassan et al., 2020), ant colony optimization (ACO) (Zhou et al., 2017), social spider algorithm (SSA) (Adhvaryyu and Adhvaryyu, 2020), marine predator algorithm (MPA) (Pan et al., 2021), ant lion optimizer (ALO) (Mouassa et al., 2017), bat algorithm (BA) (Rugema et al., 2021), and other optimization algorithms have

been applied to the solution of ED problems. Ref. (Singh and Dhillon, 2021) proposes an improved directed bat optimizer with contrastive learning to solve the minimization power scheduling problem, and the results show that the proposed algorithm is a potential algorithm to solve the ED problem. An improved hybrid particle swarm optimization algorithm based on PSO and HPSOBA is proposed to solve economic dispatch problems containing conventional as well as hybrid and renewable energy sources. The results demonstrate the superior performance of the developed algorithm in terms of fuel cost reduction, faster convergence and computation time (Ellahi et al., 2021). Ref. (Guerraiche et al., 2021) presents a bat algorithm combined with a generalized evolutionary wandering algorithm to solve the multi-objective redundancy design problem with series-parallel power systems. A chaotic bat algorithm based on chaotic sequence improvement is applied to solve optimal reactive power scheduling problems with small, medium and large scale power systems. Simulation results reveal the effectiveness and interference resistance of the chaotic bat algorithm for solving such problems (MugemanyiQu et al., 2020). Ref. (Liang et al., 2018) proposes a bat optimization algorithm based on a combination of chaotic mapping and stochastic black hole model for solving economic dispatch problems in power systems, and the effectiveness of the proposed method is illustrated on three test cases.

The bat algorithm (BA) has the advantages of few parameters and fast convergence, so it is more often used in various power system problems (Xu and Xiang, 2021). However, the convergence speed of BA algorithm is too fast, which leads it to fall into local optimum easily. From this, a new improved BA (IBA) algorithm is proposed in this paper. To address the problem that the original BA algorithm

Step 1:Initialization, random generation of bat population X_i and speed v_i.

Step 2:Initialization, randomly generated pulse rate r_i, loudness A_i and frequency f_i.

Step 3:While (t < Maximum iteration)

A new solution can be generated by changing the frequency, and the speed and position can be updated by equation **(6) – (8).**

Step 4:If rand > the pulse rate r_i

New local solutions can be generated around a random optimal solution by using **Formula (9)**

Otherwise, new solutions can be generated by random flight

Step 5:If rand $<A_i$ & $f(X_i)<f(X_*)$

Accept the new solution and increase r_i and decrease A_i by formula **(10) – (11)**

Otherwise, compare the size of bats and find the current optimal solution X_*

End, and output the optimal solution X_*
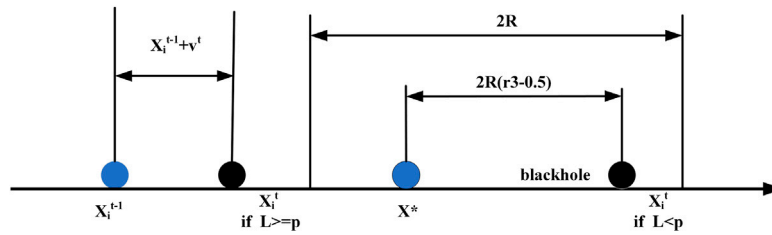
FIGURE 2
Pseudo codes of BA.

FIGURE 3
Position X_i^{t-1} updated by random black holes.

Step 1:Initialization, random generation of bat population X_i and speed v_i.

Step 2:Initialization, randomly generated pulse rate r_i, loudness A_i and frequency f_i.

Step 3:Set the black hole threshold p and radius R

Step 4:while (t < Maximum iteration)

New solutions can be generated by changing the frequency. The speed can be updated by formula **(6) and (7),** and the position can be updated by Formula **(12)**

Step 5:If rand > the pulse rate r_i

A new solution can be generated according to formula **(13)**

Otherwise, new solution can be generated by surrounding the optimal solution according to Formula (9)

Step 6:If rand <A_i & $f(X_i) < f(X_*)$

Accept the new solution and increase r_i and decrease A_i by formula (10) - (11)

Otherwise, compare the size of bats and find the current optimal solution X_*

End, and output the optimal solution X_*

FIGURE 4
Pseudo code of IBA.

easily falls into local optimum, two improvements are made to the BA algorithm: first, Random black hole strategy is used to increase the diversity of the algorithm and accelerate the convergence speed; second, Gaussian mutation is introduced to reduce the local optimum probability and improve the global search capability. To verify the effectiveness of IBA, we tested it on 10 sets of benchmark functions and three different sizes of ED problems and compared it with other methods in the literature, and the results show that IBA has a high convergence accuracy and can obtain better optimization results compared with other algorithms.

The rest of the paper is organized as follows. Section 2 describes in detail the mathematical model of the ED problem. Section 3 introduces the standard BA algorithm and proposes IBA. Section 4 evaluates comprehensively the performance of the IBA on benchmark functions. Section 5 gives the summary of the work and makes some briefings to the later research work.

2 Problem statement

The economic dispatch problem is the task of allocating reasonably the output of each unit under the premise of meeting various constraints in power system operation, so as to achieve the goal of minimizing the total generation cost of the power system.

2.1 SED problem formulation

The SED problem is mainly considered in this paper, which can be described as a cost minimization problem, and its objective function is defined as:

$$\text{Min} \sum_{i=1}^{N} F_i(P_i) \tag{1}$$

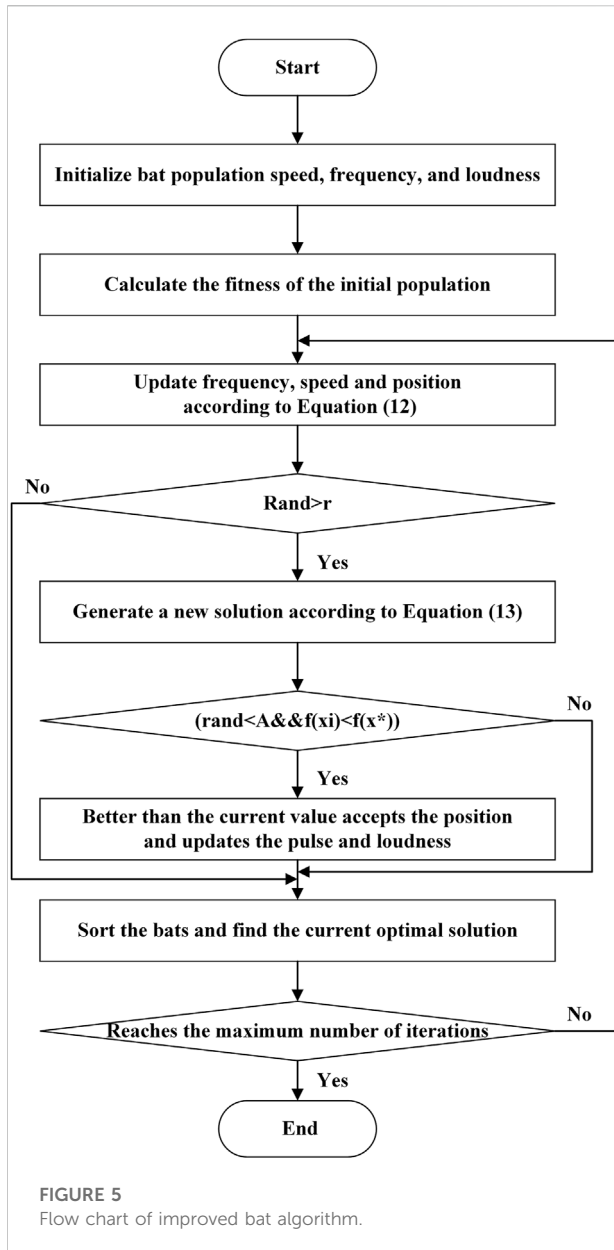where $F_i(P_i)$ is the fuel cost function of the ith unit and P_i is the output power generated by the ith unit.

FIGURE 5
Flow chart of improved bat algorithm.

TABLE 1 Description of single-modal benchmark function.

Function	Dim	Range	Minf
$F1(x) = \sum_{i=1}^{n} x_i^2$	50	$[-100, 100]$	0
$F2(x) = \sum_{i=1}^{n} |x_i| + \sum_{i=1}^{n} |x_i|$	50	$[-10, 10]$	0
$F3(x) = \sum_{i=1}^{n} \left(\sum_{j=1}^{i} x_j\right)^2$	50	$[-100, 100]$	0
$F4(x) = \max\{|x_i|, 1 \le i \le n\}$	50	$[-100, 100]$	0
$F5(x) = \sum_{i=1}^{n-1} [100(x_{i+1} - x_i^2)^2 + (x_i - 1)^2]$	50	$[-30, 30]$	0
$F6(x) = \sum_{i=1}^{n} ([x_i + 0.5])^2$	50	$[-100, 100]$	0

In real life, the power system produces VPE because of the steam turbine in the power system. Whenever the steam valve is

turned on or off, which could change the input and output characteristics of the unit. Therefore, the fuel cost function has two forms: one is a quadratic function without VPE defined as Eq. 2, the other with VPE is described as Eq. 3.

$$F(P_i) = \sum_{i=1}^{N} a_i + b_i P_i + c_i P_i^2 \tag{2}$$

$$F(P_i) = \sum_{i=1}^{N} \{a_i + b_i P_i + c_i P_i^2 + |d_i \sin[e_i(P_i^{min} - P_i)]|\} \tag{3}$$

where a_i, b_i, and c_i are the fuel-cost coefficients of the ith unit, d_i and e_i are the fuel cost-coefficients of the ith unit with valve point effects. In addition, the cost functions without and with VPE are shown in Figure 1. In this paper, Eq. 3 is used as the cost function.

2.2 Constraints

(a) Power balance constraints

$$\sum_{i=1}^{N} P_i - P_L = P_D \tag{4}$$

where P_D is the total system load demand, and P_L is the transmission loss. While power network is concentrated, thus P_L is ignored in this paper.

(b) Generating capacity constraints

$$P_i^{min} \le P_i \le P_i^{max} \tag{5}$$

where P_i^{max} and P_i^{min} are the maximum and minimum power outputs of the ith unit.

3 Improved bat algorithm

3.1 Conventional bat algorithm

Bat algorithm (BA) is a heuristic search algorithm based on group intelligence proposed by Yang in 2010, which mimics the behavior of miniature bats to find small insects as prey or avoid obstacles through echolocation system. Furthermore, bats perform various activities through echolocation, which can be summarized as follows (Yang, 2010).

(a) Miniature bats can use echolocation to measure distance and distinguish between prey and obstacles.
(b) Miniature bats make random flight catch prey at a certain speed v_i, fixed frequency f_{min}, variable wavelength λ and loudness A_0. Furthermore, the emissivity $\varepsilon \in [0, 1]$ can be adjusted. Meanwhile, the frequency and wavelength of the pulses are related to the distance to the prey.

TABLE 2 Description of multimodal benchmark function.

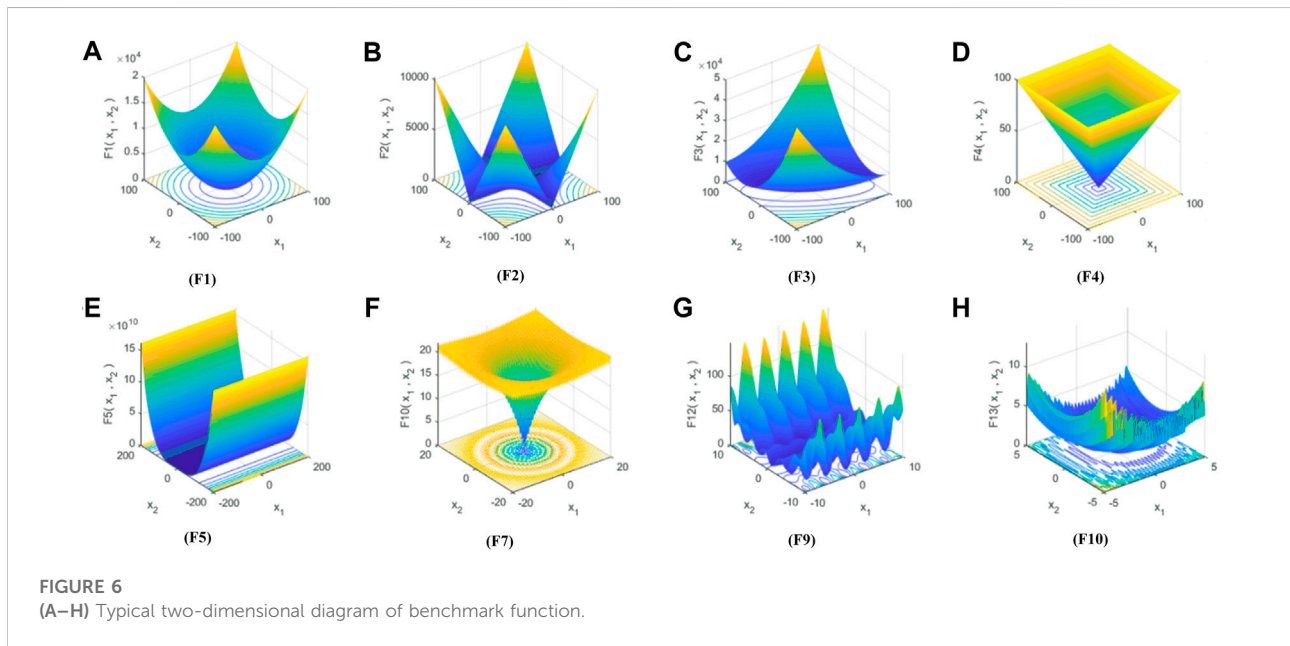| Function	Dim	Range	Minf
$F7(x) = -20\exp\left(-0.2\sqrt{\frac{1}{n}\sum_{i=1}^{n}x_i^2}\right) - \exp\left(\frac{1}{n}\sum_{i=1}^{n}\cos(2\pi x_i)\right) + 20 + e$	50	[−5.2, 5.12]	0
$F8(x) = \frac{1}{4000}\sum_{i=1}^{n}x_i^2 - \prod_{i=1}^{n}\cos\left(\frac{x_i}{\sqrt{i}}\right) + 1$	50	[−32, 32]	0
$F9(x) = \frac{\pi}{n}\{10\sin(\pi y_1) + \sum_{i=1}^{n-1}(y_i-1)^2[1+10\sin^2(\pi y_{i+1})] + (y_n-1)^2\} + \sum_{i=1}^{n}u(x_i, 10, 100, 4)$	50	[−600, 600]	0
$y_i = 1 + \frac{x_i+1}{4}$			
$u(x_i, a, k, m) = \begin{cases} k(x_i-a)^m & x_i > a \\ 0 & -a < x_i < a \\ k(-x_i-a)^m & x_i < -a \end{cases}$			
$F10(x) = 0.1\{\sin^2(3\pi x_1) + \sum_{i=1}^{n}(x_i-1)^2[1+\sin^2(3\pi x_i+1)] + (x_n-1)^2[1+\sin^2(2\pi x_n)]\} + \sum_{i=1}^{n}u(x_i, 5, 100, 4)$	50	[−50, 50]	0

FIGURE 6
(A–H) Typical two-dimensional diagram of benchmark function.

(c) Here, the loudness may be anywhere from a big positive A_0 to a constant value A_{min} of the minimum.

Like most evolutionary algorithms, the population $X_{i,j}$ ($i = 1, 2, ..., N; j = 1, 2, ..., D$) of BA is composed of N individuals with D variable. In D dimensional search space, each bat adjusts its frequency f before updating its speed, and then updates its speed according to its current speed and the distance between its current position and the current optimal position. The position and speed are updated as follows:

$$f_i = f_{min} + \beta(f_{max} - f_{min}) \quad (6)$$

$$v_i^t = v_i^{t-1} + f_i(X_i^t - X_*) \quad (7)$$

$$X_i^t = X_i^{t-1} + v^t \quad (8)$$

where f_i is the frequency of the ith bat, f_{min} is the minimum frequency, f_{max} is the maximum frequency. For convenience,

$f_{min} = 0$, $f_{max} = 100$, as described in reference (Yang, 2010). β is a uniformly distributed random number in [0, 1], X_* is the current global optimal position.

If the random number is greater than the pulse number, bats can carry out random flight. The formula for random flight is as follows:

$$X_{new} = X_{old} + \epsilon A^t \quad (9)$$

where ϵ is a random number in [−1, 1], A^t is the average loudness of all bats at t^{th} iteration. With the iteration going on, the loudness and rate of pulse emission need to be updated accordingly, and the formulas are as follows:

$$A_i^{t+1} = \alpha A_i^t \quad (10)$$

$$r_i^{t+1} = r_i^0(1 - \exp(-\gamma t)) \quad (11)$$

TABLE 3 Comparison of the results (Dim=50,FES=4e+5).

No	Result	Methods							
		IBA	QBA	CBA	PSOBA	MSCA	ISCA	IISCA	WPBOA
F1	Mean	0	6.38E+02	1.26E+05	1.27E+05	1.67E+05	1.67E+05	1.67E+05	4.49E+03
	Std test	0	2.51E+03	9.04E+03	1.21E+04	2.07E+04	2.05E+04	2.08E+04	3.06E+02
		–	1	1	1	1	1	1	1
F2	Mean	3.56E-256	3.70E+11	3.03E+18	9.97E+18	2.23E+34	7.68E+33	1.12E+34	3.86E+01
	Std test	0	2.03E+12	1.04E+19	2.68E+19	4.82E+35	8.23E+34	1.74E+35	1.26E+00
		–	1	1	1	1	1	1	1
F3	Mean	0	3.17E+03	3.31E+05	3.16E+05	4.45E+06	4.19E+06	4.58E+06	9.93E+03
	Std test	0	1.64E+04	1.07E+05	7.47E+04	5.13E+06	5.40E+06	5.35E+06	1.80E+03
		–	1	1	1	1	1	1	1
F4	Mean	1.22E-256	4.37E+00	9.12E+01	9.11E+01	9.82E+01	9.80E+01	9.80E+01	1.77E+01
	Std test	0	7.69E+00	2.29E+00	3.21E+00	1.80E+00	1.78E+00	1.99E+00	0.38E+00
		–	1	1	1	1	1	1	1
F5	Mean	4.85E+01	2.01E+05	5.16E+08	5.12E+08	7.92E+08	7.97E+08	7.92E+08	6.78E+05
	Std test	0.01E+00	1.08E+06	6.39E+07	5.58E+07	1.60E+08	1.54E+08	1.58E+08	1.58E+08
		–	1	1	0	1	1	1	1
F6	Mean	1.25E+01	2.31E+03	1.21E+05	1.29E+05	1.67E+05	1.66E+05	1.68E+05	4.51E+03
	Std test	0	8.58E+03	1.47E+04	1.18E+04	2.07E+04	2.06E+04	2.06E+04	2.98E+02
		–	1	1	0	1	1	1	1
F7	Mean	4.44E-15	1.33E+00	2.07E+01	2.07E+01	2.12E+01	2.12E+01	2.12E+01	1.07E+01
	Std test	0	3.69E+00	0.08E+00	0.10E+00	0.17E+00	0.17E+00	0.16E+00	0.24E+00
		–	1	1	1	1	1	1	
F8	Mean	0	1.87E+01	1.17E+03	1.10E+03	1.49E+03	1.48E+03	1.50E+03	4.12E+01
	Std test	0	8.37E+01	9.11E+01	9.82E+01	1.91E+02	1.87E+02	1.99E+02	3.36E+00
		–	1	1	1	1	1	1	1
F9	Mean	1.47E+00	8.00E+02	1.19E+09	1.19E+09	2.06E+09	2.03E+09	2.09E+09	2.31E+01
	Std test	7.36E-16	4.35E+03	2.07E+08	1.87E+08	4.70E+08	4.41E+08	4.61E+08	2.09E+00
		–	1	1	-1	1	1	1	1
F10	Mean	0.39E+00	6.34E+04	2.31E+09	2.25E+09	3.72E+09	3.68E+09	3.70E+09	8.59E+04
	Std test	0.06E+00	2.61E+05	3.52E+08	3.07E+08	7.93E+08	7.21E+08	8.07E+08	2.54E+04
		–	1	1	0	1	1	1	1

where α and γ are constants, $\alpha = \gamma = 0.9$, as described in reference (Yang, 2010). A_i^0 and r_i^0 are random number in $[1, 2]$ and random number in $[0, 1]$, respectively.

The pseudo code of bat algorithm (Yang, 2010) is shown in Figure 2.

3.2 Improved bat algorithm proposed

BA algorithm can be regarded as a reduced version of particle swarm. In addition to adding frequency to control bat flight speed, two variables of pulse rate r_i and loudness A_i are added. It also removes the fact that particle swarm optimization can move towards local and global optimal positions, which leads to faster convergence, but it is easy to fall into local optimization, which is

its disadvantage. Therefore, based on the above deficiencies, some strategies need to be modified to get out of the local optimal problem and improve the performance of the BA algorithm.

This section proposes a new and improved bat algorithm for SED problem. Firstly, the random black hole strategy is used to update the bat position randomly, and then the Gaussian distribution function is used to jump out of the local optimum. In summary, two major improvements to IBA can be described as follows.

3.2.1 Random black hole strategy

According to the black hole theory, particles could be absorbed by the black hole within a certain range, namely capture, but may also be spit out with a certain probability by the black hole, namely escape. Suppose that the bat swarm is a swarm of particles, and a

TABLE 4 Comparison of the results (Dim=100,FES=4e+5).

No	Result	Methods							
		IBA	QBA	CBA	PSOBA	MSCA	ISCA	IISCA	WPBOA
F1	Mean	0	9.25E+03	2.73E+05	2.76E+05	3.32E+05	3.34E+05	3.32E+05	1.01E+04
	Std test	0	2.33E+04	1.33E+04	1.64E+04	3.05E+04	3.02E+04	2.84E+04	4.78E+02
		–	1	1	1	1	1	1	1
F2	Mean	1.26E-255	1.42E+34	5.48E+45	8.37E+45	8.94E+64	1.79E+66	1.29E+64	8.29E+01
	Std test	0	7.80E+34	2.78E+46	4.05E+46	1.18E+66	3.10E+67	1.26E+65	1.96E+00
		–	1	1	1	1	1	1	1
F3	Mean	0	7.36E+04	1.18E+06	1.41E+06	1.65E+07	1.59E+07	1.78E+07	3.97E+04
	Std test	0	2.44E+05	3.55E+05	5.65E+05	2.08E+07	1.83E+07	2.02E+07	6.60E+03
		–	1	1	1	1	1	1	1
F4	Mean	1.39E-252	4.71E+00	9.60E+01	9.56E+01	9.90E+01	9.90E+01	9.90E+01	1.85E+01
	Std test	0	9.17E+00	1.55E+00	1.00E+00	1.02E+00	0.91E+00	1.00E+01	2.30E-02
		–	1	1	1	1	1	1	1
F5	Mean	9.80E+01	6.28E+06	1.19E+09	1.17E+09	1.61E+09	1.60E+09	1.63E+09	1.63E+06
	Std test	0.02E+00	2.55eE07	8.69E+07	1.01E+08	2.05E+08	2.14E+08	2.17E+08	1.51E+05
		–	1	1	0	1	1	1	1
F6	Mean	2.50E+01	2.25E+03	2.79E+05	2.78E+05	3.34E+05	3.33E+05	3.35E+05	9.99E+03
	Std test	0	4.33E+03	1.57E+04	1.60E+04	2.86E+04	2.98E+04	2.30E+04	4.75E+02
		–	1	1	0	1	1	1	1
F7	Mean	4.44E-15	2.92E+00	2.09E+01	2.09E+01	2.12E+01	2.12E+01	2.12E+01	1.10E+01
	Std test	0	5.21E+00	0.08E+00	0.06E+00	0.11E+00	0.10E+00	0.10E+00	0.47E+00
		–	1	1	1	1	1	1	1
F8	Mean	0	7.93E+01	2.46E+03	2.51E+03	3.00E+03	3.01E+03	2.98E+03	8.89E+01
	Std test	0	1.50E+02	1.47E+02	1.47E+02	2.76E+02	2.71E+02	2.61E+02	5.46E+00
		–	1	1	1	1	1	1	1
F9	Mean	1.33E+00	2.62E+05	2.83E+09	2.87E+09	4.08E+09	4.08E+09	4.07E+09	2.70E+01
	Std test	1.30E-16	1.14E+06	3.23E+08	2.41E+08	6.49E+08	6.18E+08	6.58E+08	1.74E+01
		–	1	1	-1	1	1	1	1
F10	Mean	0.92E+00	3.02E+06	5.44E+09	5.42E+09	7.38E+09	7.44E+09	7.44E+09	2.53E+05
	Std test	0.12E+00	1.14E+07	5.78E+08	4.49E+08	1.07E+09	1.07E+09	1.10E+09	3.70E+04
		–	1	1	1	1	1	1	1

bat near the current optimal bat is a black hole. The radius of the black hole is R. Within radius R, bats are captured by the black hole, but those caught still have a chance to escape. Introducing the random black hole strategy, if bats are captured, is conducive to accelerating the convergence; Conversely, it can increase the diversity of the population (Chen and Cheng, 2013; Zong et al., 2016; Liang et al., 2018; LV et al., 2019). The principle of the random black hole model is shown in Figure 3.

The position updating formula by the random black hole strategy can be formulated as follows:

$$X_i^t = \begin{cases} X_i^{t-1} + v^t, & L \geq p \\ X_* + 2R(r_3 - 0.5), & L < p \end{cases} \quad (12)$$

where R is the radius of the black hole, r_3, L and p are all random numbers in $[0, 1]$. And the threshold p represents the capture capability of the black hole. If $L < p$, bats are attracted to the black hole.

3.2.2 Gaussian mutation

Since the bat algorithm itself is easy to fall into local optimum, in view of this, Gaussian distribution function is introduced to help IBA to escape from local optimum (Kaur and Narang, 2019; Xie et al., 2021), which is depicted below:

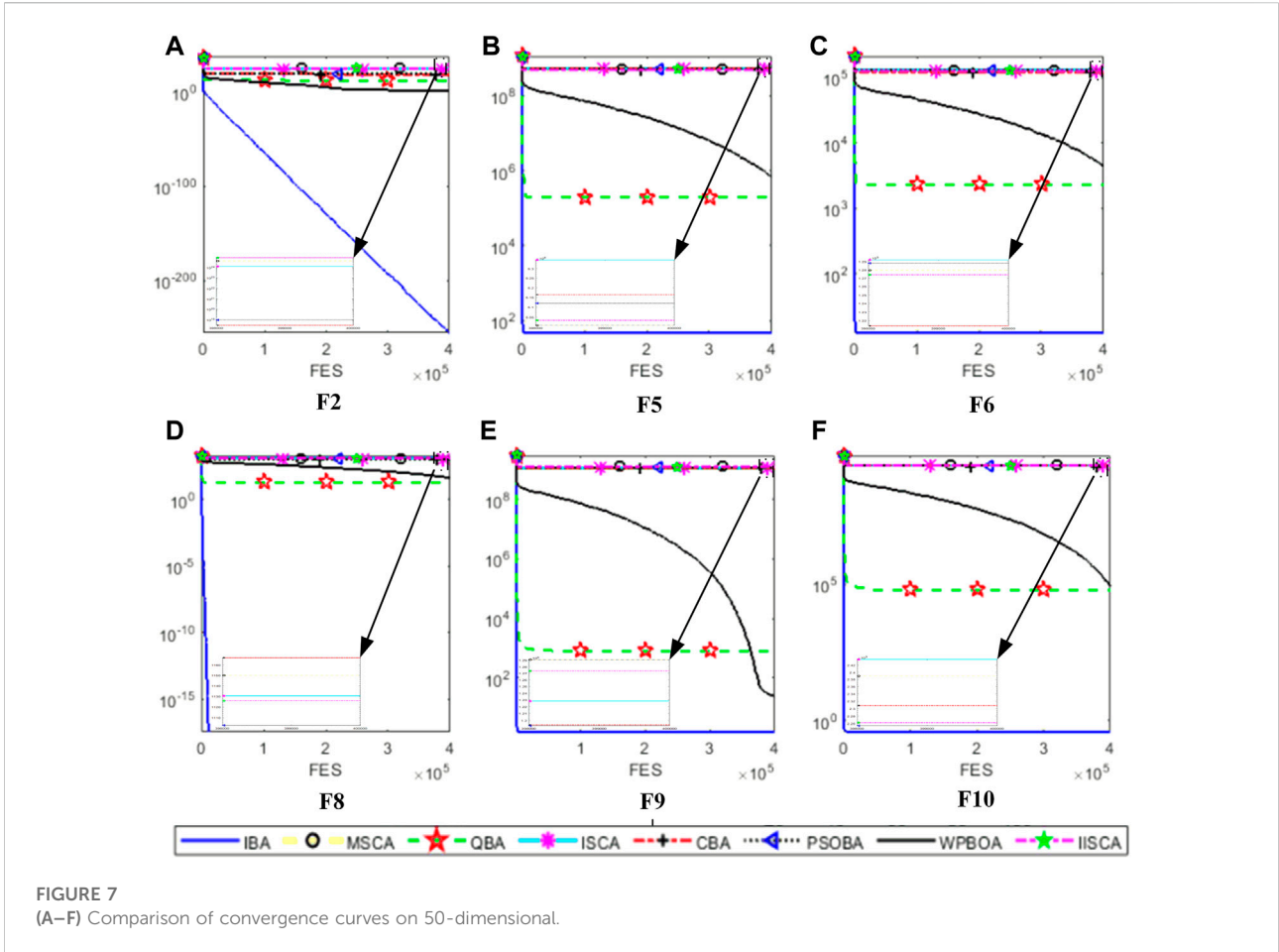$$X_i^t = X_i^t \cdot (0.5 + \tau \cdot N(0, 1)) \quad (13)$$

FIGURE 7
(A–F) Comparison of convergence curves on 50-dimensional.

TABLE 5 Results of case I with 850 mw load demand (3-unit system with valve point effect).

Evolution method	Minimum cost ($)	Maximum cost ($)	Mean cost ($)	Mean time (sec.)
CEP (Sinha et al., 2003)	8234.07	8241.83	8235.97	20.46
FEP (Sinha et al., 2003)	8234.07	8241.78	8234.24	4.54
MFEP (Sinha et al., 2003)	8234.08	8241.80	8234.71	8.00
IFEP (Sinha et al., 2003)	8234.07	8234.54	8234.16	6.78
CBA	8241.67	8488.02	8369.66	0.0083
PSOBA	8258.91	8520.68	8396.10	0.0085
MSCA	8240.94	8964.43	8610.91	0.0048
ISCA	8234.14	8943.21	8626.42	0.0043
IISCA	8251.76	8957.13	8622.12	0.0039
BA	8234.22	8242.16	8241.90	0.0079
IBA	**4638.06**	**6705.63**	**5099.38**	0.0081

Bold value denotes the best result.

where X_i^t is the position of ith bat at the tth iteration, τ is a random number in $[0, 1]$, and $N(0, 1)$ represents the normal distribution with mean value of 0 and variance of 1.

The pseudo code of the improved bat algorithm is shown in Figure 4.

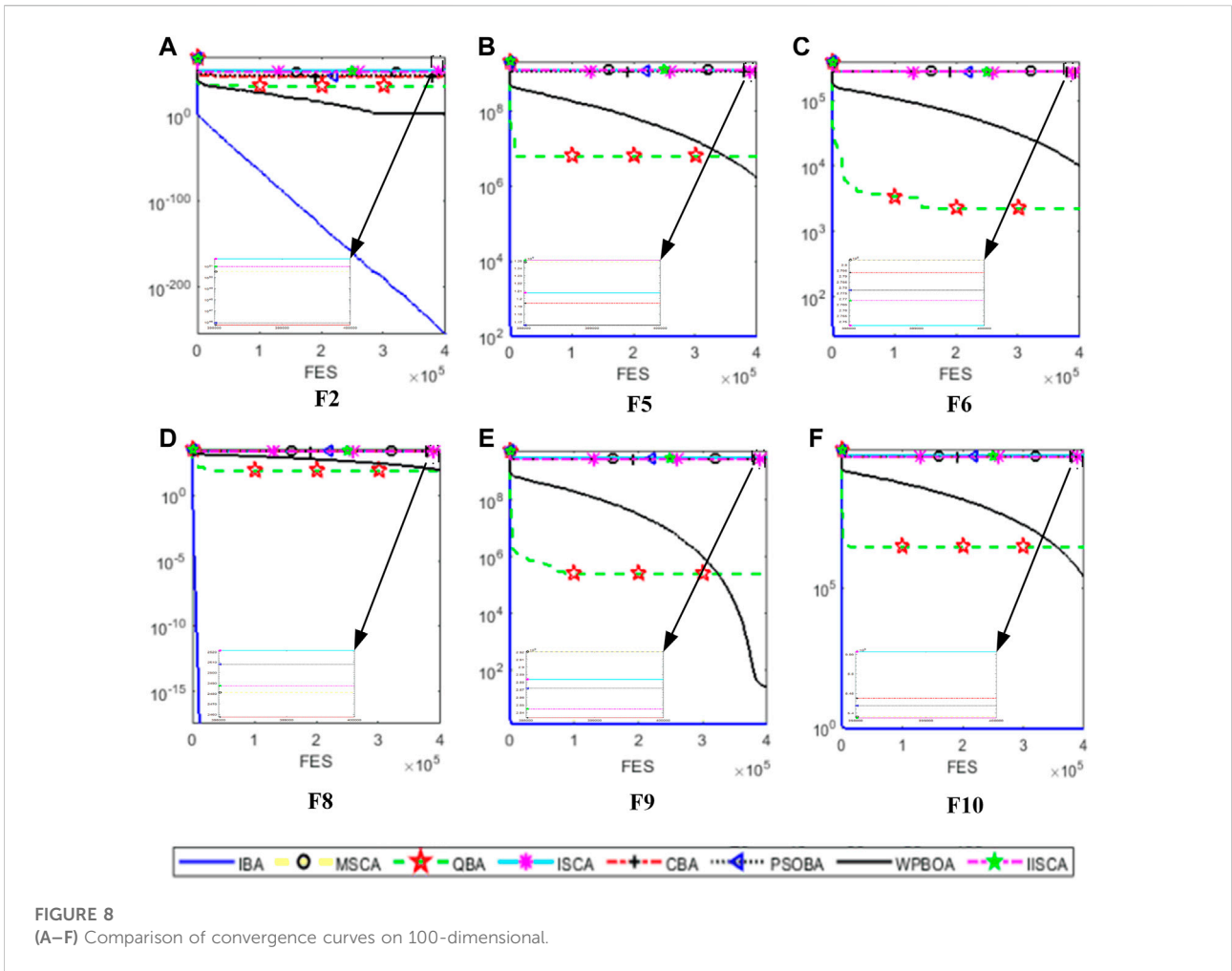The flow chart of the improved bat algorithm is shown in Figure 5.

FIGURE 8
(A–F) Comparison of convergence curves on 100-dimensional.

TABLE 6 Distribution of best results of 3 unit SED problems.

Unit	1	2	3
Output(MW)	396.2894	53.7106	400.0000
Fuel cost($)	4638.06		

4 Experimental analysis

This section conducts simulation experiments based on 10 commonly used benchmark functions (Mirjalili and Lewis, 2016). Firstly, the definitions of these 10 functions are given in Table 1 and Table 2, and then IBA performance is compared with other seven algorithms including CBA (Adarsh et al., 2016), QBA (Zhu et al., 2016), PSOBA (Tchapda et al., 2017), WPBOA (Guo et al., 2021), MSCA (Wang and Lu, 2021), ISCA (Zadehparizi and Jam, 2022) and IISCA (Long et al., 2019). All experiments in this study are conducted in a PC with Windows 10 system, 3.8 GHz Intel Core, 8 GB RAM, and MATLAB R2018b.

Generally speaking, benchmark functions can be divided into four groups: single-modal, multimodal, fixed dimensional multimodal and composite functions. In this paper, the performance of the proposed IBA method is analyzed and verified by using single-mode and multi-mode functions. The definitions of single-mode and multi-mode benchmark functions are listed in Tables 1 and 2, respectively. Figure 6 shows a typical two-dimensional diagram of some benchmark functions in this paper. Among these 10 benchmarks, F1 to F6 are unimodal functions, and the unimodal function has only one optimal value. However, for the multi-modal functions F7 to F10, the number of local minima increases as the problem dimension increases. In order to make a fair comparison between different algorithms, the function evaluation number (FES) (Kazikova et al., 2021) is utilized to measure the running time of the algorithm. All test functions in this paper have the same FES when searching for the global minimum.

TABLE 7 Results of case 2 with load demand of 1800 MW (13 unit system with valve point effect).

Evolution method	Minimum cost ($)	Maximum cost ($)	Mean cost ($)	Mean time (sec.)
CEP (Sinha et al., 2003)	18048.21	18404.04	18190.32	294.96
FEP (Sinha et al., 2003)	18018.00	18453.82	18200.79	168.11
MFEP (Sinha et al., 2003)	18028.09	18416.89	18192.00	317.12
IFEP (Sinha et al., 2003)	17994.07	18267.42	18127.06	157.43
PSO (Victoire and Jeyakumar, 2004)	18030.72	–	18205.78	77.37
ABC (Hemamalini and Simon, 2010)	17963.86	17995.11	17987.22	16.39
HGA (He et al., 2008)	17963.83	–	17988.04	8.48
CBA (Zhu et al., 2016)	17963.83	17995.2256	17965.4889	0.97
PSOBA (Guo et al., 2021)	18533.4	19656.8	19189.1	–
MSCA	18475.19	19935.18	19324.68	0.2400
ISCA	18532.86	19843.64	19325.93	0.1706
IISCA	18572.49	19964.21	19335.33	0.1737
BA	18163.26	18285.85	18264.41	1.0335
IBA	11396.51	11971.64	11768.75	1.1043

–Indicates data not available in the corresponding literature; Bold value denotes the best result.

TABLE 8 Distribution of best results of 13 unit problems.

Unit	1	2	3	4	5	6	7
Output(MW)	449.5160	150.6522	208.1061	157.6421	108.7338	169.6950	94.3623
Unit	8	9	10	11	12	13	
Output(MW)	136.7151	60.0000	57.8553	83.0436	65.6161	58.0623	
Fuel cost($)	11396.51						

TABLE 9 Results of case III with 10500 MW load demand (40 unit system with valve point effect).

Evolution method	Minimum cost ($)	Maximum cost ($)	Mean cost ($)	Mean time (sec.)
CEP (Sinha et al., 2003)	123488.29	126902.89	124793.48	1956.93
FEP (Sinha et al., 2003)	122679.71	127245.59	124119.37	1039.16
MFEP (Sinha et al., 2003)	122647.57	124356.47	123489.74	2196.10
IFEP (Sinha et al., 2003)	122624.35	125740.63	123382.00	1167.35
PSO (Sa-Ngiamvibool et al., 2011)	121830.68	122083.17	121962.57	87.37
ABC (Hemamalini and Simon, 2010)	121441.03	122123.77	121995.82	32.45
PSO-LRS (Selvakumar and Thanushkodi, 2007)	122035.79	123461.67	122558.45	15.86
ACO (Pothiya et al., 2010)	121532.41	121679.64	121606.45	52.45
NPSO-LRS (Selvakumar and Thanushkodi, 2007)	121664.43	122981.59	122209.31	16.81
CBA (Zhu et al., 2016)	121412.54	121436.15	121418.98	1.55
PSOBA (Guo et al., 2021)	130426.80	158797.70	141211.00	–
MSCA	130479.70	164826.97	150981.54	1.3584
ISCA	131114.88	165120.63	151137.64	0.4090
IISCA	132162.18	166503.30	150849.64	0.4386
BA	116533.87	124641.86	119686.50	6.0295
IBA	75502.17	79210.95	77501.25	5.0169

–Indicates data not available in the corresponding literature; Bold value denotes the best result.

TABLE 10 Distribution of best results of 40 unit problems.

| Unit	Output (MW)	Unit	Output (MW)	Unit	Output (MW)	Unit	Output (MW)
1	42.4405	11	362.8970	21	473.4723	31	110.0000
2	61.9452	12	367.8126	22	474.2985	32	110.0000
3	79.5318	13	422.2350	23	105.9820	33	110.0000
4	83.9341	14	182.4522	24	27.0412	34	507.2215
5	97.0000	15	493.0717	25	86.7288	35	375.0000
6	132.8338	16	472.9907	26	59.1070	36	375.0000
7	300.0000	17	550.0000	27	190.0000	37	377.4806
8	300.0000	18	550.0000	28	114.2801	38	430.6044
9	228.9456	19	532.7167	29	104.5628	39	106.8364
10	284.9755	20	508.7328	30	126.7891	40	181.0801
Fuel cost($)	75502.17						
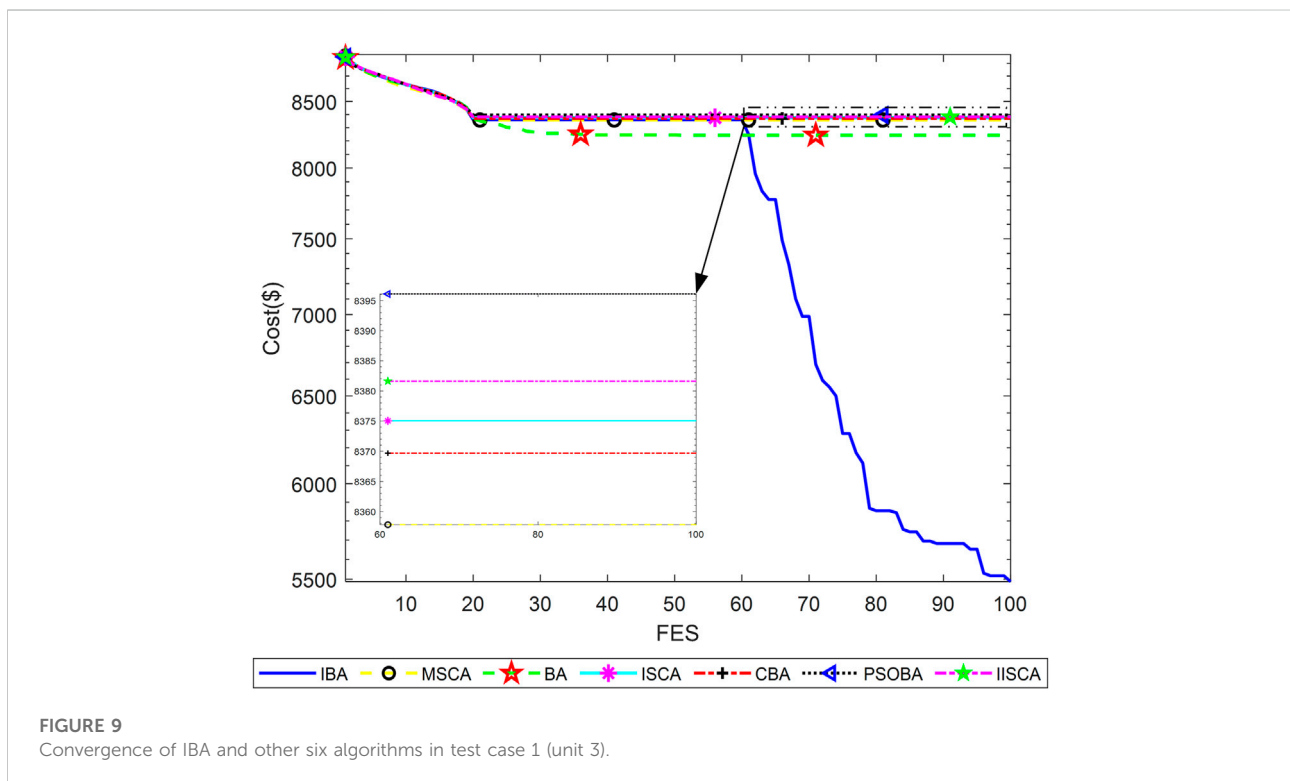
FIGURE 9
Convergence of IBA and other six algorithms in test case 1 (unit 3).

4.1 Performance verification of IBA

IBA method is further evaluated on 10 benchmark functions and compared with other seven methods the above mentioned. In this paper, Wilcoxon signed rank test (Yang et al., 2021) is utilized to compare the differences between IBA and other algorithms in the literature, and the significant level α is set to 0.05, max_FESs on 10 benchmark functions under 50 and 100 dimensions are all 4E+05. In order to obtain better results, each algorithm runs independently for 30 times. The population sizes of IBA and the other seven methods are all **N** 20, and the other parameters of the seven methods are derived from the literature.

Table 3 and Table 4 summarize the average results, standard deviation and Wilcoxon signed rank test results of 30 independent runs on 50 and 100 dimensional benchmark functions. The best results of the average and standard deviation are marked in bold. When the test = 1, 0 and −1, IBA is superior,
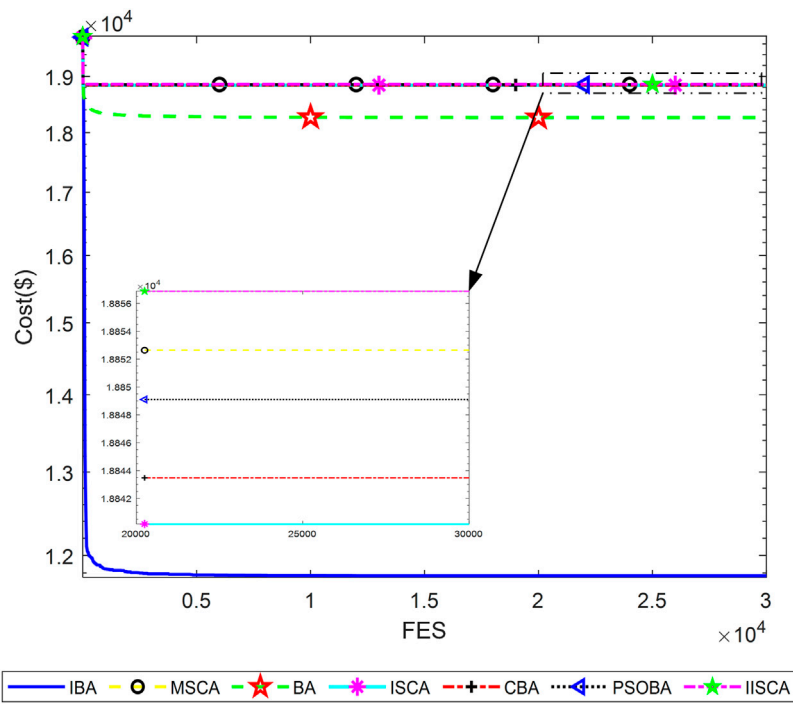
FIGURE 10
Convergence of IBA and other six algorithms in test case 2 (unit 13).
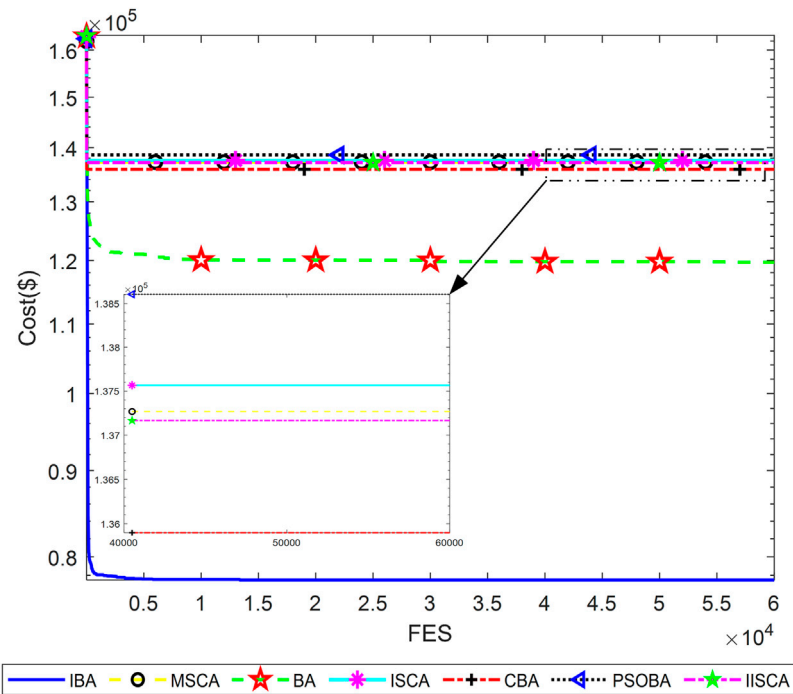

FIGURE 11
Convergence of IBA and other six algorithms in test case 3 (unit 40).

equivalent and lower than the methods in the above literature respectively. Among the 10 benchmark functions solved by IBA, the results of three functions (F1, F3, and F8) reach the theoretical optimal value, which is better than CBA, QBA, PSOBA, WPBOA, MSCA, ISCA, and IISCA. The results of the other seven functions that do not reach the theoretical optimal value are significantly better than the results of the compared algorithms, and are closer to the theoretical optimal value. The Wilcoxon signed rank test is used to test IBA and the methods in the literature. The results show that IBA is better than most algorithms compared. Equally unsurprisingly, only IBA can obtain optimal solutions or suboptimal solutions with the scale of the problems. It can be seen that the improved IBA algorithm has higher computation accuracy. In the case of statistical results, no method is better than the proposed IBA. In order to more intuitively express the convergence rate of IBA, Figure 7 and Figure 8 show the convergence characteristic curves of the average value of 30 independent tests of six functions. It can be seen from the figure that five algorithms are very close on some benchmark functions, which look like a curve. However, the convergence curves of IBA are all located at the bottom of the figure with the fastest convergence speed and the highest calculation accuracy. It can be concluded that IBA algorithm proposed in this paper is better than the algorithms in the literature, which shows that IBA has strong optimization ability. To sum up, it proves that IBA not only has high precision, but strong stability.

4.2 Application to SED

Three power system cases considering the valve point effects from the reference, that are as follows: 1) 3 units and power load demand 850MW; 2) 13 units and power load demand 1800MW; 3) 40 units and power load demand 10500 MW. The details of the three cases can be obtained from reference (Sinha et al., 2003; Niu et al., 2014). All test data are from the literature published for fair comparison. Furthermore, termination criteria max_FESs of 3-unit, 13-unit, and 40-unit systems are respectively set to 100, 30000, and 60000.

The results of minimum, maximum, average cost and average calculation time are shown in Table 5, Table 7 and Table 9. The best results of three cases obtained by IBA are better than all other algorithms. Even the maximum fuel costs of IBA is better than the method in the literature. Although the computation time of IBA is not as fast as other algorithms, its results are still competitive. Table 6, Table 8, and Table 10 show the dispatch of the best results obtained by IBA meeting all constraints. Therefore, it can be concluded that IBA is effective to solve the SED problem. Figure 9, Figure 10, and Figure 11 show the convergence curves of IBA algorithm and other algorithms. It can be seen that compared with other algorithms, IBA can jump out of the local optimum and find the global optimum quickly. From

the above discussion, it is evident that the improved BA is effective, for which the detailed reasons are listed as the following: First, Random black hole strategy disables the population to be gathered in the process of evolution to some extent, which further improves the convergence of the IBA; second, Gaussian mutation is adopted in IBA to increase its ability of local search and to improve the quality of the solution. In brief, IBA algorithm overcomes the poor local search capability and the precocious phenomena of the traditional BA, and also effectively improves the global search ability of the BA.

5 Conclusion

This paper proposes an improved bat algorithm (IBA) with random black hole strategy and Gaussian mutation. Random black hole strategy can make the algorithm converge quickly and increase the population diversity. Gaussian mutation can improve the global search ability of the IBA. Furthermore, IBA is tested on ten benchmark functions compared with the algorithms from the literature. The results show that the performance of IBA algorithm has been improved significantly. Finally, the proposed IBA method is used to solve three different scale of power system problems, in which valve point effect and power balance constraints are considered. The experimental results show that for the SED problem with valve point effect, IBA has better effect on the SED problem in terms of fast convergence speed and high-quality solution. In addition, the good performance of IBA also shows its potential in solving large-scale optimization problems. To sum up, it can be proved that IBA has achieved satisfactory results on benchmark function and SED problem, and provides a competitive alternative to solve nonlinear and nonconvex optimization problems. Furthermore, the combination of large-scale and renewable resources is also a topic for future research.

Data availability statement

The datasets presented in this article are not readily available because these datasets are also a part of the ongoing study. Requests to access the datasets should be directed to XM, mouxiaolin@sztu.edu.cn.

Author contributions

WY and XM designed experiments; RL and YY carried out experiments; RL and YY analyzed experimental results and wrote the manuscript.

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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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Supplementary material

The Supplementary Material for this article can be found online at: https://www.frontiersin.org/articles/10.3389/fenrg.2022.977883/full#supplementary-material

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