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Energy Management of a Power System for Economic Load Dispatch Using the Artificial Intelligent Algorithm

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Abstract: Economic Load Dispatch (ELD) is a key issue in power systems and its goal is to achieve minimum economic costs by allocating the output of generator units when satisfying the load demands and the operating constraints. As the dimension of the variables and the constraints increase, the traditional mathematical method is gradually not suitable for the ELD. This paper proposes an Improved Bird Swarm Algorithm (IBSA) to solve the ELD problem of a power system. By introducing the nonlinear cognitive and social coefficients, the proportion of individual learning and social learning of birds can be dynamically adjusted. In addition, the Levy flight strategy is added to the group between producers and beggars to increase the randomness. The performance of IBSA is verified via two systems consisting of 6 and 15 units, respectively, that take into account generation limitation, ramp rate limit, and prohibited operating zones. From the simulation results, the IBSA has shown excellent performance and robustness, which can be considered as a reliable solution for the ELD.

Keywords: Economic Load Dispatch; fuel cost; Improved Bird Swarm Algorithm; Levy flight strategy; prohibited operating zones; artificial intelligent algorithm

1. Introduction

With the continuous growth of the global economic scale, the consumption of traditional fossil energy and the demand for energy are gradually increasing year by year. As the contradiction between economic development and energy shortage gradually emerges, it is necessary to reduce energy cost per unit of GDP for the sustainable development of the economy. The power industry has a huge demand for fossil energy as the most important energy industry. In the power industry, it is important to reduce energy consumption cost and pollutant emission [1]. Therefore, reducing the fuel cost in the process of operation while satisfying the power supply reliability and power quality of the power system has always been the focus of electric power workers and scholars. Economic Load Dispatch (ELD) is an effective way to deal with the above problem [2].

The goal of ELD is to minimize the economic cost when considering the various constraints of power systems such as load balancing constraint, generation limitation, and ramp rate limit [3]. ELD is an effective dispatching strategy to enhance economic benefits under the condition of ensuring the safety and stability of power systems. The ELD problem is a classic type of constrained optimization problem consisting of objective function and constraints [4]. In the traditional ELD problem, the fuel cost function is modeled by a quadratic function, so the ELD problem can be transformed into a classical convex problem [5]. However, restricted by the valve point effect and prohibited operating zones in the actual power system, the traditional cost function becomes non-convex, which makes it difficult to optimize using traditional methods [6]. With the expansion of the power grid and increase of the constraint variables, the traditional mathematical programming method is prone to the problem of dimensionality disaster. In this case, intelligent algorithms gradually replace traditional mathematical methods. The intelligent optimization algorithm is inspired by natural experiences and does not need to consider the convexity of objective function. Compared with other traditional methods, it has the advantages of short solution time and high search efficiency. Therefore, intelligent algorithms have become common and effective approaches to solving the ELD problem [7].

Classical intelligent algorithms such as Particle Swarm Optimization (PSO) and Genetic Algorithm (GA) have been widely used in solving the ELD problem, and some new intelligent algorithms are also constantly applied over the last decade [8,9]. Bird Swarm Algorithm (BSA) is a new intelligent algorithm that is evolved by imitating the flight behavior of birds. The BSA has been tested and its performance is better than the classical PSO and Differential Evolution (DE) algorithms [10]. In this article, an Improved Bird Swarm Algorithm (IBSA) is put forward to further enhance the capability of BSA. By dynamically adjusting the proportion of cognitive behavior and social behavior and introducing the Levy flight strategy between the producers and beggars, the search ability of BSA can be further improved to avoid the phenomenon of premature. According to the experimental results of two classic economic dispatch cases, the capacity of IBSA in ELD is proved.

The structure of the paper is organized as follows: in Section 2, theoretical approaches and the literature review about ELD are provided. Section 3 describes the ELD problem. Section 4 introduces the principle of BSA and IBSA. In Section 5, the method of constraints handling is given. In Section 6, two case studies are presented and the detailed discussions on results are made. Section 7 gives the conclusions and future prospects.

2. Related Work

Economic dispatching of power systems has been mentioned since the 1920s. In the following decades, electric power and mathematics workers have conducted in-depth research on this issue and made many major breakthroughs. At present, the solution methods for the ELD are classified into two research directions: the traditional numerical method and intelligent algorithm. Traditional methods usually rely on mathematical tools for calculation, which mainly includes the lambda iterative method [11], dynamic programming [12], the Lagrange Relaxation (LR) method [13], linear programming [14], and quadratic programming [15]. In general, the above research methods are relatively mature and have been verified by many examples in engineering applications. However, these traditional methods cannot solve the ELD problem effectively as the size and constraints of the generator unit increase. In [16], Hemamalini and Simon used the Maclaurin series to replace the sine function caused by the valve point effect. This method reduces the calculation time, but the optimal solution obtained has a larger gap than with other intelligent algorithms. Traditional methods tend to produce the problem of dimensionality disaster in solving ELD problems, which will lead to a decrease in solving efficiency and accuracy. In addition, these methods have higher requirements on the mathematical properties of applied objects. Considering the existence of valve point effect and prohibited operating zones, the output of modern generators are characterized by high dimensionality and non-linearity. The traditional algorithms cannot handle such complex optimization problems due to dimensionality barriers and loss of precision.

Considering that the intelligent algorithm has a strong global search ability and has no high requirements of objective function, various intelligent algorithms have been widely used to get the best scheme of ELD. So far, the Grey Wolf Optimization algorithm (GWO) [17], differential evolution algorithm [18], Cuckoo Search Algorithm (CSA) [19], Immune Algorithm (IA) [20], Artificial Bee Colony (ABC) algorithm [21], Symbiotic Organisms Search (SOS) algorithm [22], Artificial Algae Algorithm (AAA) [23], Sine Cosine Algorithm (SCA) [24], Biogeography-Based Optimization (BBO) algorithm [25], and other intelligent algorithms have been applied in economic dispatching successively and achieved great prediction results.

When solving the optimization problems using intelligent algorithms, premature phenomena can occur and affect the accuracy of the solutions. Therefore, many improved algorithms have been proposed. Compared with the original version, the improved methods usually have better optimization performance. In [26], an Ameliorated Grey Wolf Optimization (AGWO) algorithm was proposed and the effect of AGWO was proved to be better than the original GWO on ELD. A modified chicken swarm algorithm that adds the differential factor of rooster and self-foraging factor to the chicks' group was proposed in [27]. The improved method is used to solve three ELD systems and has reduced fuel costs effectively. In [28], a Phase Particle Swarm Optimization algorithm (PPSO) was applied to a system with large-scale units and the experimental results prove the reliability of PPSO in different types of ELD problems. In [29] is an improved version of social spider algorithm in economic scheduling. The optimization ability of the algorithm is effectively improved by updating the radius formula and simplifying the control parameters of the algorithm. In [30] is presented a Modified Crow Search Algorithm (MCSA), which enhances the accuracy and robustness by making adaptive dynamic adjustments to the selection strategy and flight length of crows.

The application of the hybrid algorithm is also a hot topic in the ELD. Compared to the single algorithm, the hybrid algorithm can give full play to the ability of each sub-algorithm and usually have a more comprehensive optimization ability. In [31], an algorithm combing PSO and harmony search algorithm was presented. The simulation results from four different standard test systems show that the hybrid method is superior to the single algorithm. In [32] is proposed a cuckoo search algorithm combining differential evolution strategy. The introduction of the mutation scheme improved the search efficiency and quality of the solution. In [33], a hybrid method that combines the imperialist competition algorithm and sequential quadratic programming was presented. This hybrid method can overcome the premature phenomena of the original algorithm and solve complex constrained optimization problems effectively. Considering the accuracy of traditional GA cannot be guaranteed when solving the ELD problem, a GA-PSO hybrid algorithm was proposed [34]. The introduction of PSO improves the convergence accuracy of GA and reduces the running time significantly. In general, the intelligent algorithm has gradually replaced the traditional mathematical method with its advantages of high accuracy and high efficiency. The improved algorithms and hybrid algorithms have also gained more attention gradually because of their superiority in improving the optimization effect.

Bird Swarm Algorithm (BSA) was proposed in 2016, which draws on the flight behavior of birds. The birds can constantly seek the best solution through foraging behavior, vigilance behavior, and migration behavior. Through the above three behaviors, the BSA has excellent convergence speed and search efficiency. Since proposed, the BSA has been applied in the field of wind speed prediction [35], Travel Salesman Problem (TSP) [36], distribution network planning [37], and target detection [38]. By combining the advantages of PSO and DE strategy and introducing Gaussian mutation through a certain frequency, the BSA has excellent global and local optimization capabilities. In this study, the IBSA is presented to solve the ELD problem of power systems. The nonlinear cognitive factors and social factors are adopted to enhance the optimization performance in the IBSA. Besides, the Levy flight strategy is introduced to increase diversity. For proving the effectiveness of IBSA, two cases with 6 and 15 generators units are tested in the case of considering a smooth cost curve. Through a detailed analysis of test results and comparison with other algorithms, it is demonstrated that the IBSA can provide a stable and economic dispatching scheme for the power system.

3. Problem Description

3.1. *Objective Function*

By allocating the output of units reasonably, the operating costs can be significantly reduced. The cost model is simplified below:

$$\min(F_T) = \min\sum_{i=1}^{N} F_i(P_{Gi}) \tag{1}$$

where F_T indicates the total fuel cost, N represents the total number of generator units, P_{Gi} is the active power output of the i-th generator, and $F_i(P_{Gi})$ means the corresponding fuel consumption cost of the i-th generator, and can be expressed a power-dependent quadratic polynomial:

$$F_i(P_{Gi}) = a_i(P_{Gi}) + b_i(P_{Gi}) + c_i \tag{2}$$

where a_i, b_i, and c_i represent the fuel cost coefficient. When the intake valve of the turbomachine is suddenly opened, the resulting "valve point effect" can be generally represented as sinusoidal function. This sinusoidal function will be added to the traditional quadratic polynomial fuel cost function, that is:

$$F_i(P_{Gi}) = \alpha_i(P_{Gi})^2 + b_i(P_{Gi}) + c_i + \left|d_i \sin(e_i(P_{Gi}^{\min} - P_{Gi}))\right| \tag{3}$$

where $P_{Gi}^{\min}$ represents the lower limit of output power of the i-th generator and d_i and e_i mean the cost coefficients.

3.2. *Constraints*

3.2.1. Balance Constraints

Power balance constraints are the most critical constraints in the operation of the generator unit. If the constraint is not met, it will lead to paralysis of the power system and seriously threaten the reliability of the system operation. This constraint can be summarized whereby the total output of all generator units must be equal to the sum of load and transmission loss. That is,

$$\sum_{i=1}^{N} P_{Gi} = P_D + P_L \tag{4}$$

$$P_L = \sum_{i=1}^{N}\sum_{j=1}^{N} P_{Gi}B_{ij}P_{Gj} + \sum_{i=1}^{N} B_{i0}P_{Gi} + B_{00} \tag{5}$$

where P_D represents the load of the system, P_L represents the transmission loss, and B_{ij}, B_{i0}, and B_{00} are called the loss parameter or B parameter.

3.2.2. The Generation Constraints

The output of each generator will be limited in a certain operating range to guarantee the system stability, which is the necessary condition for the safe operation of the generator units. The constraints are represented as follow:

$$P_{Gi}^{\min} \le P_{Gi} \le P_{Gi}^{\max} \tag{6}$$

where $P_{Gi}^{\min}$ and $P_{Gi}^{\max}$ represent the upper and lower limits of the power output of the i-th generator unit, respectively.

3.2.3. Ramp Rate Limit

Within a time period, the power variation is limited by the operation of the generator. This constraint is described below:

$$-DR_i \leq P_{Gi} - P_{Gi(t-1)} \leq UR_i \tag{7}$$

where UR_i and DR_i are ramp-up and ramp-down rate limits of the i-th generator unit. $P_{Gi(t-1)}$ is the active power output of the i-th generator unit at the previous interval.

3.2.4. Prohibited Operating Zones Limits

The bearings of the generator will produce severe vibration when the generator runs to some zones. Therefore, the power output should be adjusted to avoid prohibited operating zones during actual operation. The prohibited operating zones limits are listed below:

$$\begin{cases} P_{Gi}^{\min} \leq P_{Gi} \leq \underline{P}_{Gi}^{1} \\ \overline{P}_{Gi1}^{k-1} \leq P_{Gi} \leq \underline{P}_{Gi}^{k}, \quad k = 2, 3, \ldots, n_Z \\ \overline{P}_{Gi}^{nz} \leq P_{Gi} \leq P_{Gi}^{\max} \end{cases} \tag{8}$$

where $\underline{P}_{Gi}^{k}$ represents the lower limits of the i-th generator in the j-th prohibited operating zone. $\overline{P}_{Gi}^{k}$ represents the upper limits of the i-th generator in the j-th prohibited operating zone, and n_Z is the number of the prohibited zones.

4. Proposed Method

In this section, the principle of BSA and IBSA is introduced in detail. The improvement strategies contain: (1) Dynamic cognitive and social coefficients; (2) Levy flight strategy.

4.1. Bird Swarm Algorithm

The BSA is a simplification of group behavior and intelligence interaction of birds. The main rules of BSA are simplified as follows [39]:

1. Individuals in the population can randomly switch between foraging behavior and vigilance behavior.
2. When foraging, each individual will store and update the optimal foraging information, and this information can be shared.
3. When keeping vigilance, each individual in the swarm intends to gather to the center position, and the behavior would be influenced by the other birds. The individuals who consume more food have more opportunities to reach the center than other individuals.
4. Birds would fly to another location regularly. During the migration process, the individual who has the highest reserves would become producers, while the individual who has the lowest reserves would become beggars. The remaining birds would become producers or beggars randomly.
5. The producers seek the food by itself, while the beggars randomly track a producer to hunt for food.

In Rule 2, the position updating formula of the birds in foraging behavior can be described below:

$$x_{i,j}^{t+1} = x_{i,j}^{t} + (p_{i,j} - x_{i,j}^{t}) \times C \times rand(0,1) + (g_j - x_{i,j}^{t}) \times S \times rand(0,1) \tag{9}$$

where $j \in [1, 2 \cdots d]$, d is the dimension, $x_{i,j}^{t} (i = 1, 2, \ldots n)$ represents the j-th dimension of the position of i-th bird at t-th iteration, and $p_{i,j}$ means the optimal previous position of the i-th bird. g_j represents the optimal previous position in the swarm, and C $(C > 0)$ and S $(S > 0)$ are the cognitive and social coefficients.

In Rule 3, the formulas of the birds in vigilance behavior are shown below:

$$x_{i,j}^{t+1} = x_{i,j}^{t} + A_1(F_{mean}^{j} - x_{i,j}^{t}) \times rand(0,1) + A_2(p_{k,j} - x_{i,j}^{t}) \times rand(-1,1) \tag{10}$$

$$A_1 = a_1 \times \exp(-\frac{F_i}{F_{sum} + \varepsilon} \times N) \tag{11}$$

$$A_2 = a_2 \times \exp(\frac{F_i - F_k}{|F_k - F_i| + \varepsilon} \times N \times \frac{F_k}{F_{sum} + \varepsilon}) \tag{12}$$

where $k(k \neq i)$ represents a positive integer in (1,*N*), $\varepsilon \to 0^+$. F_i is the best fitness value of the *i*-th bird. F_{sum} represents the sum of the swarm fitness value, F_{mean}^{j} is the *j*-th dimension of the center position of the whole swarm, and a_1 and a_2 are two positive constants, which are randomly chosen between 0 and 2.

In Rule 4, the swarm will migrate at a fixed frequency. From a mathematical perspective, it can be described that the bird swarm will perform a new position updating formula at every migration cycle FQ in the iteration process. The behaviors of producers and beggars can be described below:

$$x_{i,j}^{t+1} = x_{i,j}^{t} + x_{i,j}^{t} \times randn(0,1) \tag{13}$$

$$x_{i,j}^{t+1} = x_{i,j}^{t} + (x_{k,j}^{t} - x_{i,j}^{t}) \times FL \times rand(0,1) \tag{14}$$

where $FL \in [0,2]$ is the following coefficient, and $randn(0,1)$ represents a random number subject to the Gaussian distribution with mean 0 and standard deviation 1.

4.2. Improved Bird Swarm Algorithm

The group is in the foraging state during most of the time of the search process, so ensuring the efficiency of foraging is essential for finding the optimal solution. The cognitive and social accelerated coefficients are used to adjust the proportion of individual learning and social learning. The coefficients used in the original algorithm are fixed values, which cannot dynamically adjust the cognitive behavior and group behavior of birds. Therefore, the dynamic cognitive and social coefficients are introduced. The cognitive coefficient takes a larger value in the early stage. As the search progresses, the cognitive coefficient is gradually reduced to a certain value, while the social coefficient is gradually increasing. By controlling the change of the two coefficients, the algorithm can balance global and local search capabilities during the search process. The two dynamic coefficients are indicated as follows:

$$C = 1 + 0.5 * \sin[\frac{\pi}{2}(1 - \frac{t}{T_{\max}})] \tag{15}$$

$$S = 1 + 0.5 * \sin(\frac{\pi t}{2T_{\max}}) \tag{16}$$

where $T_{\max}$ is the maximum number of iteration.

In addition, the Levy flight strategy is introduced for the birds between the producers and beggars, which can increase the randomness and diversity of the population. As a random walk strategy, the Levy flight can effectively expand the search range and avoid falling into local optimal points. The formula after introducing Levy flight strategy is shown below:

$$x_i{}^{t+1} = Le'vy(d) \times x_i{}^{t} + x_i{}^{t} \tag{17}$$

where d is the dimension of the position of birds.

The formula of Levy flight is expressed below:

$$Le'vy(x) = 0.01 \times \frac{r_1 \times \sigma}{|r_2|^{\frac{1}{\beta}}} \tag{18}$$

$$\sigma = \left(\frac{\Gamma(1+\beta) \times \sin(\frac{\pi\beta}{2})}{\Gamma(\frac{1+\beta}{2}) \times \beta \times 2^{(\frac{\beta-1}{2})}} \right)^{1/\beta} \tag{19}$$

where $r_1,\ r_2 \in [0,1]$ are two stochastic numbers: $\beta = 1.5$, and $\Gamma(x) = (x-1)!$

When the birds are in the flight behavior, the bird swarm is first sorted by fitness values from small to large. Then the top 10% of birds are chosen as producers and the last 60% of birds are chosen as beggars. Finally, the remaining 30% of birds are adjusted according to the Levy flight strategy. The pseudo code of IBSA is introduced in Algorithm 1.

Algorithm 1 Improved Bird Swarm Algorithm (IBSA)

```
Initialize related parameters including population number N, maximum iteration number
M, flight frequency FQ, and probability of foraging P
t = 0; Perform the initialization and evaluate the fitness values
Record the best individual and corresponding fitness value
while (t < M)
Update the C and S using Formulas (15) and (16)
  if (t% FQ ≠ 0)
    for i = 1:N
      if rand < P
          Update position using Formula (9)
      else
          Update position using Formula (10)
      end if      end for
   else
      Sort the birds by fitness value from small to large
      Update the position of the top 10% birds using Formula (13)
      Update the position of the last 60% birds using Formula (14)
      Update the position of remaining birds by Formula (17)
   end if
   Evaluate new solutions
   Update optimal individual
   Update the optimal individual of the population and its fitness value
   t = t + 1;
   end while
 Output best solution
```

4.3. Verification and Comparison

In Table 1, five benchmark functions are selected for testing the performance of IBSA. In addition, the IBSA is compared with the original BSA, PSO, and DE. The experiment is simulated by MATLAB 2017a. The number of population and iteration is set to 30 and 500. Four algorithms run 30 independent trials. The specific parameters are listed in Table 2. The statistical results obtained are shown in Table 3.

Table 1. Benchmark functions.

No	Function	Dim	Bounds	Optimum
1	$f_1(x) = \sum_{i=1}^{n} x_i^2$	30	[−100,100]	0
2	$f_2(x) = \sum_{i=1}^{n} \lvert x_i\rvert + \prod_{i=1}^{n} \lvert x_i\rvert$	30	[−10,10]	0
3	$f_3(x) = \sum_{i=1}^{n} \left[x_i{}^2 - 10\cos(2\pi x_i) + 10\right]$	30	[−5.12,5.12]	0
4	$f_4(x) = -20\exp(-0.2\sqrt{\frac{1}{n}\sum_{i=1}^{n} x_i{}^2} - \exp\left[\frac{1}{n}\sum_{i=1}^{n}\cos(2\pi x_i)\right] + 20 + e$	30	[−32,32]	0
5	$f_5(x) = \frac{1}{4000}\sum_{i=1}^{n} x_i{}^2 - \prod_{i=1}^{n}\cos(\frac{x_i}{\sqrt{i}}) + 1$	30	[−600,600]	0

Table 2. The parameters of different algorithms.

Algorithm	Parameters
PSO	w = 0.729, C1= C2 = 1.49445
DE	F = 0.6, CR = 0.9
BSA	FQ = 5, C = S = 1.5, a1 = a2 = 1, FL ∈ [0.5,0.9], P ∈ [0.8,1]
IBSA	FQ = 5, C ∈ [1.5,1], S ∈ [1,1.5], a1 = a2 = 1, FL ∈ [0.5,0.9], P ∈ [0.8,1]

Table 3. The statistical results of different algorithms.

No	Algorithm	Best	Worst	Mean	Std	Time (s)
1	PSO	89.05	1293.70	421.99	264.19	25.19
	DE	0.02	0.32	0.11	0.07	41.03
	BSA	7.74×10^{-242}	1.75×10^{-218}	6.05×10^{-220}	3.20×10^{-219}	20.98
	IBSA	3.50×10^{-273}	3.21×10^{-239}	1.14×10^{-240}	5.86×10^{-240}	17.43
2	PSO	5.76	20.86	11.01	2.98	26.60
	DE	1.68×10^{-5}	0.02	0.001	0.005	47.45
	BSA	9.59×10^{-121}	1.99×10^{-109}	8.51×10^{-112}	8.51×10^{-112}	17.32
	IBSA	1.79×10^{-138}	9.59×10^{-124}	3.21×10^{-125}	1.75×10^{-122}	17.76
3	PSO	46.13	113.81	77.35	16.08	23.68
	DE	143.55	232.27	208.15	18.73	53.11
	BSA	0	0	0	0	15.33
	IBSA	0	0	0	0	16.31
4	PSO	5.70	9.84	7.11	1.02	43.90
	DE	0.078	19.95	4.59	7.42	86.80
	BSA	8.88×10^{-16}	8.88×10^{-16}	8.88×10^{-16}	0	15.61
	IBSA	8.88×10^{-16}	8.88×10^{-16}	8.88×10^{-16}	0	16.38
5	PSO	1.66	8.79	4.14	1.79	34.63
	DE	0.04	0.78	0.28	0.18	85.26
	BSA	0	0	0	0	21.19
	IBSA	0	0	0	0	20.44

From the test results in Table 3, the optimal value, worst value, average value, standard deviation, and calculation time of IBSA and BSA are far superior to PSO and DE, which also confirms the superiority of BSA. Compared to the original BSA, the IBSA has shown better search capability. In the 30 trials, the total time spent on IBSA and BSA is almost the same, which indicates that the improved strategy does not increase the amount of computation of the original algorithm.

5. Constraints Handling

The penalty function method is an effective way of dealing with a multi-constrained optimization problem. The penalty function method applies the sequence unconstrained minimizing technique and has the advantages of simple principle and low requirements. By the penalty function, the ELD problem can be transformed into an unconstrained problem [40]. By adding the difference of the load balancing equation, the cost function and the load constraint can be integrated into a penalty function as the objective function. The penalty factor P is employed to control the punishment degree when the constraint is not satisfied [41]. The objective function is set below:

$$\text{Objective function} = \min\sum_{i=1}^{N} F_i(P_{Gi}) + P * \left(\sum_{i=1}^{N} P_{Gi} - P_D - P_L\right)^2 \tag{20}$$

When penalty factor P takes a larger positive constant, it can effectively reduce the amount of violation of load balancing constraints. The search range can be set by the range of power generation constraints when the ramp rate limits are not considered. When considering the ramp rate limit, these two constraints can be combined to formulate a new operating constraint and the new constraints are obtained, that is:

$$\max(P_{Gi}^{\min}, P_{Gi(t-1)} - DR_i) \leq P_{Gi} \leq \min(P_{Gi(t-1)} + UR_i, P_{Gi}^{\max}) \tag{21}$$

When the particles move to the prohibited operating zone, the positions of particles can be reset to the feasible domain. Through the above operations, it can be guaranteed that the obtained solution always satisfies the running constraint. The flow chart for solving ELD with IBSA is shown in Figure 1.

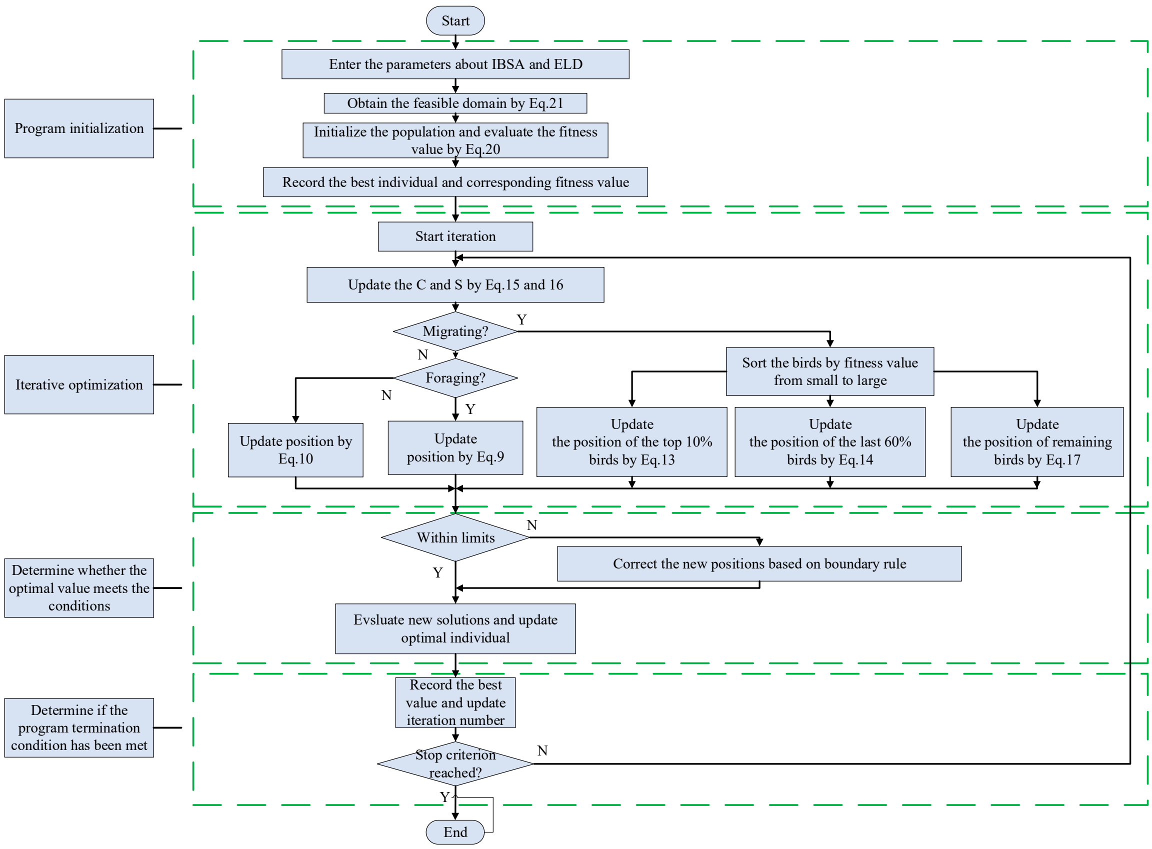

Figure 1. Flowchart of the IBSA for solving the Economic Load Dispatch (ELD) problem.

6. Case Study

In this section, two test systems are introduced to comprehensively evaluate the performance of IBSA. In these two case systems, there are 6 and 15 generator units respectively, and the ramp rate constraint and prohibited operating zone are considered. All experiments are carried out on MATLAB 2017a. The operating environment is a PC with Intel (R) Core (TM) i5-4200U CPU @ 1.6 GHz 2.3 GHz and the operating system is Windows 7. Each case is run 40 times independently, and the optimal value, average value, maximum value, and standard deviation of the fuel cost are recorded. The penalty factor is 100. The parameters of BSA and IBSA are set as follows: the number of population is 100, the number of iterations is 1000, migration frequency FQ is 5, and other parameters are set to default values.

6.1. Case 1

This system is a classic case in ELD, which adopts the smooth fuel cost curve [42]. This case study consists of 6 generating units, 46 transmission lines, and 26 buses [43]. The power load demand is 1263 MW, and the detailed parameters of the generator units are given in Table 4. The loss coefficients B with 100-MVA base capacity are given in Appendix A. The algorithms including GA [44], PSO [44], SA [45], MTS [45], NPSO-LRS [46], PSO-LRS [46], and CBA [47] have been applied to solve this issue. The optimum experimental results are given in Table 5. Table 6 provides the statistical values in the 40 experiments.

From Table 5, the minimum fuel cost of IBSA and BSA is 15,448.98 ($/h), which is the smallest in all algorithms. In addition, the BSA has the same cost value as the IBSA, which proves the performance of the original algorithm. From the obtained result of power output, the errors of the power balance equations of BSA and IBSA are 0.067 MW. Relative to the load of 1263 MW, the error can be negligible. From the data listed in Table 6, the four indicators of the IBSA are superior to other algorithms and have obvious improvements, especially the maximum cost and standard deviation. Figure 2 shows the fuel cost values with BSA and IBSA in 40 replicate experiments. It can be seen directly that the results with IBSA is small, which varies between 15,449.00 ($/h) and 15,448.98 ($/h). Conversely, the results obtained by BSA are highly volatile. In all 40 repeated trials, the proposed method shows good robustness and stability. Figure 3 shows the convergence curves of BSA and IBSA when obtaining the optimal solution. Compared with BSA, the convergence curve of IBSA is smoother and the downward trend is more obvious. So, the IBSA has better convergence characteristics than BSA. To sum up, the IBSA has better performance and can a generate better solution for ELD.

Table 4. The detailed generator unit data of System 1.

Unit	P_{max} (MW)	P_{min} (MW)	a_i (\$/MW^{2}h)	b_i (\$/MWh)	c_i (\$/h)	UR_i (MW/h)	DR_i (MW/h)	P_i (MW)	Prohibited Zones
G1	500	100	7.0×10^{-3}	7.0	240	80	120	440	[210,240], [350,380]
G2	200	50	9.5×10^{-3}	10.0	200	50	90	170	[90,110], [140,160]
G3	300	80	9.0×10^{-3}	8.5	220	65	100	200	[150,170], [210,240]
G4	150	50	9.0×10^{-3}	11.0	200	50	90	150	[80,90], [110,120]
G5	200	50	8.0×10^{-3}	10.5	220	50	90	190	[90,110], [140,150]
G6	120	50	7.5×10^{-3}	12.0	190	50	90	110	[75,85], [100,105]

Table 5. Dispatch results of System 1.

Unit	GA	PSO	MTS	SA	NPSO-LRS	PSO-LRS	CBA	BSA	IBSA
G1	474.80	447.49	448.12	478.12	446.96	447.44	447.41	447.49	447.48
G2	178.63	173.32	172.80	163.02	173.39	173.34	172.82	173.30	173.30
G3	262.20	263.47	262.59	261.71	262.34	263.36	264.07	264.44	263.44
G4	134.28	139.05	136.96	125.76	139.51	139.12	139.24	139.05	139.05
G5	151.90	165.47	168.20	153.70	164.70	165.50	165.65	165.47	165.46
G6	74.18	87.12	87.33	93.79	89.01	87.16	86.76	87.12	87.12
Total Power Generation (MW)	1276.03	1276.01	1276.02	1276.13	1275.94	1275.95	1275.98	1275.88	1275.88
Ploss (MW)	13.02	12.95	13.02	13.13	12.93	12.95	12.98	12.95	12.95
Total Generation Cost (\$/h)	15,459.00	15,450.00	15,450.06	15,461.10	15,450.00	15,450.00	15,450.23	15,448.98	15,448.98

Table 6. Statistical results of multiple methods in System 1.

Method	Generation Cost for Different Algorithm ($/h)			
	Maximum Cost	Minimum Cost	Average Cost	Standard Deviation
GA	15,524.00	15,459.00	15,469.00	-
PSO	15,492.00	15,450.00	15,454.00	-
MTS	15,453.64	15,450.06	15,451.17	0.92
SA	15,545.50	15,461.10	15,488.98	28.36
NPSO-LRS	15,452.00	15,450.00	15,450.50	-
PSO-LRS	15,455.00	15,450.00	15,454.00	-
CBA	15,518.65	15,450.23	15,454.76	2.96
BSA	15,458.98	15,448.98	15,449.73	2.02
IBSA	15,449.00	15,448.98	15,448.98	4.30×10^{-3}

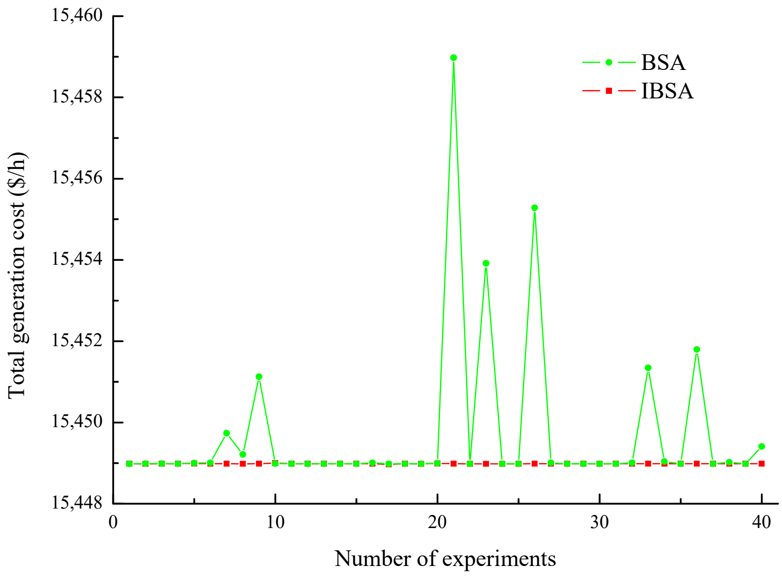

Figure 2. Distribution of results with BSA and IBSA in System 1.

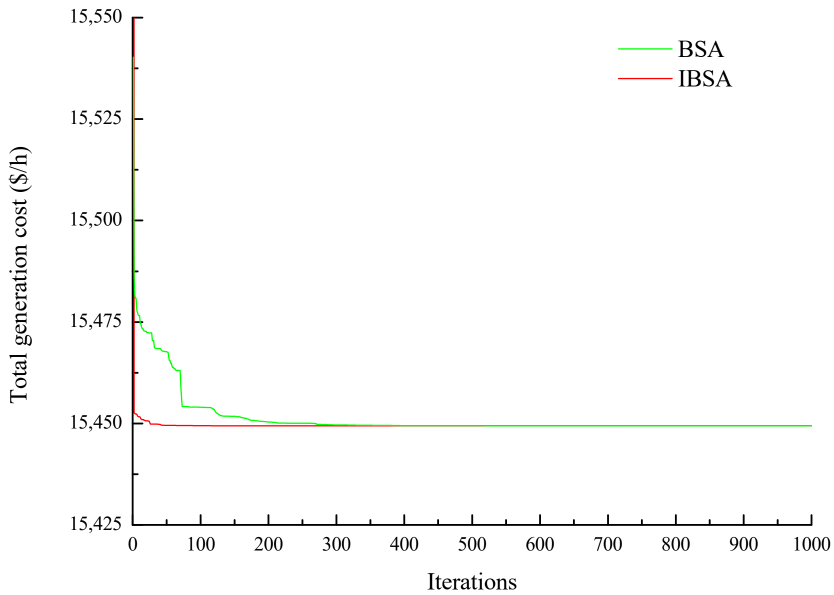

Figure 3. Convergence curve of Bird Swarm Algorithm (BSA) and IBSA in System 1.

6.2. Case 2

The second system contains 15 generators with prohibited operating zone constraints [48]. The load demand is 2630 MW and the transmission loss coefficients are given in Appendix B. Table 7 shows the detailed parameter of System 2. GA [44], PSO [44], MTS [45], APSO [49], SGA [50], and AIS [51] have also been used to solve this case. In Table 8, the best solutions of different algorithms are given. The statistical results of multiple algorithms are provided in Table 9.

Table 7. The detailed generator unit data of System 2.

Unit	P_{max} (MW)	P_{min} (MW)	a_i (\$/MW^{2}h)	b_i (\$/MWh)	c_i (\$/h)	UR_i (MW/h)	DR_i (MW/h)	P_i (MW)	Prohibited Zones
G1	455	150	2.99×10^{-4}	10.1	671	80	120	400	
G2	455	150	1.83×10^{-4}	10.2	574	80	120	300	[185,225], [305,335], [420,450]
G3	130	20	1.13×10^{-3}	8.8	374	130	130	105	
G4	130	20	1.13×10^{-3}	8.8	374	130	130	100	
G5	470	150	2.05×10^{-4}	10.4	461	80	120	90	[180,00], [305,35], [390,42]
G6	460	135	3.01×10^{-4}	10.1	630	80	120	400	[230,55], [365,95], [430,455]
G7	465	135	3.64×10^{-4}	9.8	548	80	120	350	
G8	300	60	3.38×10^{-4}	11.2	227	65	100	95	
G9	162	25	8.07×10^{-4}	11.2	173	60	100	105	
G10	160	25	1.20×10^{-3}	10.7	175	60	100	110	
G11	80	20	3.59×10^{-3}	10.2	186	80	80	60	
G12	80	20	5.51×10^{-3}	9.9	230	80	80	40	[30,40], [55,65]
G13	85	25	3.71×10^{-4}	13.1	225	80	80	30	
G14	55	15	1.93×10^{-3}	12.1	309	55	55	20	
G15	55	15	4.45×10^{-3}	12.4	323	55	55	20	

Table 8. Dispatch results of System 2.

Unit	GA	PSO	MTS	APSO	SGA	AIS	BSA	IBSA
G1	415.31	455.00	453.99	455.00	455.00	441.15	455.00	455.00
G2	359.72	380.00	379.74	380.01	380.00	409.58	380.00	379.99
G3	104.42	130.00	130.00	130.00	130.00	117.29	130.00	130.00
G4	74.98	130.00	129.92	126.52	130.00	131.25	130.00	130.00
G5	380.28	170.00	168.08	170.01	170.00	151.01	170.00	170.00
G6	426.79	460.00	460.00	460.00	460.00	466.25	460.00	459.99
G7	341.31	430.00	429.22	428.28	430.00	423.36	430.00	430.00
G8	124.78	60.00	104.30	60.00	106.25	99.94	60.00	71.71
G9	133.14	30.04	35.03	25.00	25.00	110.68	70.57	58.88
G10	89.25	159.91	155.88	159.78	160.00	100.22	160.00	159.99
G11	60.05	80.00	79.89	80.00	80.00	32.05	80.00	79.99
G12	49.99	80.00	79.90	80.00	80.00	78.81	80.00	80.00
G13	38.77	25.00	25.02	33.70	25.00	23.56	25.00	25.00
G14	41.94	55.00	15.25	55.00	15.00	40.25	15.00	25.00
G15	22.64	15.00	15.07	15.00	15.00	36.90	15.00	15.00
Total Power Output (MW)	2668.40	2659.96	2661.36	2658.32	2661.30	2662.04	2660.56	2660.59
Ploss (MW)	38.27	30.02	31.35	28.36	31.25	32.40	30.62	30.65
Total Generation Cost (\$/h)	33,113.00	32,735.45	32,716.87	32,742.77	32,711.00	32,854.00	32,706.90	32,703.72

Table 9. Statistical results of multiple methods in System 2.

Method	Generation Cost for Different Algorithm (\$/h)			
	Maximum Cost	Minimum Cost	Average Cost	Standard Deviation
GA	33,337.00	33,113.00	33,228.00	-
PSO	32,910.73	32,735.45	32,825.43	62.72
MTS	32,796.15	32,716.87	32,767.21	17.51
APSO	-	32,742.77	32,976.68	133.92
SGA	33,005.00	32,711.00	32,802.00	35.58
AIS	32,892.00	32,854.00	32,873.25	10.80
BSA	33,098.99	32,706.90	32,778.87	81.38
IBSA	32,704.10	32,703.72	32,703.84	0.18

From Table 8, the minimum cost acquired by IBSA is significantly lower than other algorithms including BSA and the error of the power balance equation is at an acceptable level. From Table 9, the optimal value, maximum value, mean value, and standard deviation of the cost of IBSA are significantly reduced compared with other algorithms, which confirms its accuracy and stability. Figure 4 shows the cost of 40 repetitive experiments in Case 2. Clearly, the results of IBSA vary between 32,704.10 ($/h) and 32,703.72 ($/h), which shows its high robustness. The results obtained by the BSA show great volatility. As indicated in Figure 5, the convergence rate of IBSA is much better than the original algorithm, and the convergence curve is smoother. The conclusions obtained in System 2 are consistent with those obtained in System 1, which shows the good effect of IBSA for different test systems.

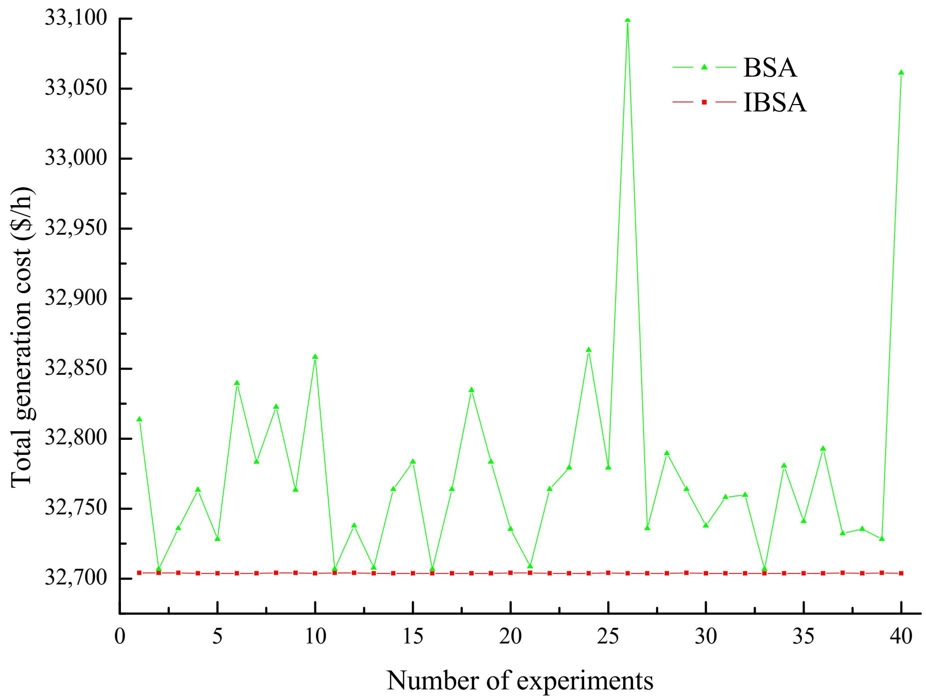

Figure 4. Distribution of results with BSA and IBSA in System 2.

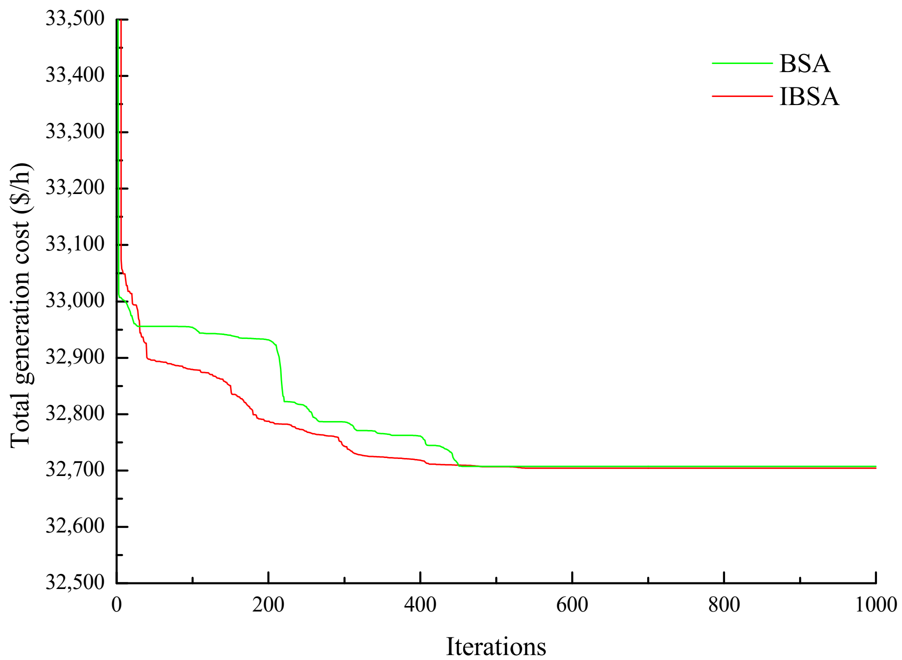

Figure 5. Convergence curve of BSA and IBSA in System 2.

7. Conclusions

The ELD problem is an important optimization problem in power systems and has the characteristics of discontinuity, nonlinearity, and multiple constraints. With the emergence of prohibited operating zones, traditional analysis methods cannot solve non-convex problems. Therefore, intelligent algorithms have gradually been applied. However, the intelligent algorithm may have occurred prematurely and the quality of the solution cannot be guaranteed. Since the performance of the algorithm has a great impact on the accuracy and robustness of results, it is very important to select the appropriate intelligent algorithm. In this paper, the IBSA is proposed to solve the ELD problem. By dynamically adjusting the learning factor and introducing the Levy flight strategy, the convergence and stability of IBSA have been improved as a whole. According to the five benchmark functions given, the accuracy and stability of the IBSA are confirmed compared to other algorithms and the calculation time of IBSA is much smaller than PSO and DE. Compared to BSA, the time spent by IBSA has not increased, which shows that the modified strategy does not sacrifice the search efficiency and increase search costs.

In order to deal with the constraints, the penalty function has been adopted. Besides, two test cases containing 6 and 15 units, respectively, are used to verify the capability and robustness of IBSA. The two cases consider the line loss, the ramp rate limit, and the prohibited operating zone limit. In 40 repeated and independent experiments, the IBSA shows good performance. Among the four statistical indicators given, the optimal value, maximum value, average value, and standard deviation of the result obtained by IBSA in these two cases are superior to other algorithms. In addition, the convergence characteristics of IBSA are far better than the original algorithm. The robustness and convergence accuracy has been significantly improved, which proves the effectiveness of the improvement measures. When the constraint is complex and the cost function is not convex, the conventional method such as equal consumed energy increase ratio law cannot be applied to solve such an equation. The proposed method shows strong superiority in solving such problems and can provide a feasible and effective reference scheme.

To sum up, the IBSA can obtain a better optimization scheme in solving the ELD problem. However, the proposed method only tests the classic cases and does not carry out in-depth research on the actual scheduling problem. Therefore, the research on large-scale scheduling problems should be strengthened to solve practical engineering problems. In future work, IBSA can also be used in other fields. In addition, different penalty function methods can be tried to handle the constraint problem.

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Appendix A

$$B_1 = 0.01 * \begin{bmatrix} 0.0017 & 0.0012 & 0.0007 & -0.0001 & -0.0005 & -0.0002; \\ 0.0012 & 0.0014 & 0.0009 & 0.0001 & -0.0006 & -0.0001; \\ 0.0007 & 0.0009 & 0.0031 & 0.0000 & -0.0010 & -0.0006; \\ -0.0001 & 0.0001 & 0.0000 & 0.0024 & -0.0006 & -0.0008; \\ -0.0005 & -0.0006 & -0.0010 & -0.0006 & 0.0129 & -0.0002; \\ -0.0002 & -0.0001 & -0.0006 & -0.0008 & -0.0002 & 0.0150; \end{bmatrix}$$

$$B_2 = 0.001 * [-0.3908\ -0.1297\ 0.7047\ 0.0591\ 0.2161\ -0.6635]$$

$$B_3 = 0.56$$

Appendix B

$$B_1 = \begin{bmatrix}
0.0014 & 0.0012 & 0.0007 & -0.0001 & -0.0003 & -0.0001 & -0.0001 & -0.0001 & -0.0003 & -0.0005 & -0.0003 & -0.0002 & 0.0004 & 0.0003 & -0.0001 \\
0.0012 & 0.0015 & 0.0013 & 0.0000 & -0.0005 & -0.0002 & 0.0000 & 0.0001 & -0.0002 & -0.0004 & -0.0004 & -0.0000 & 0.0004 & 0.0010 & -0.0002 \\
0.0007 & 0.0013 & 0.0076 & -0.0001 & -0.0013 & -0.0009 & -0.0001 & 0.0000 & -0.0008 & -0.0012 & -0.0017 & -0.0000 & -0.0026 & 0.0111 & -0.0028 \\
-0.0001 & 0.000 & -0.0001 & 0.0034 & -0.0007 & -0.0004 & 0.0011 & 0.0050 & 0.0029 & 0.0032 & -0.0011 & -0.0000 & 0.0001 & 0.0001 & -0.0026 \\
-0.0003 & -0.0005 & -0.0013 & -0.0007 & 0.009 & 0.0014 & -0.0003 & -0.0012 & -0.001 & -0.0013 & 0.0007 & -0.0002 & -0.0002 & -0.0024 & -0.0003 \\
-0.0001 & -0.00023 & -0.0009 & -0.0004 & 0.0014 & 0.0016 & -0.000 & -0.0006 & -0.0005 & -0.0008 & 0.0011 & -0.0001 & -0.0002 & -0.0017 & 0.0003 \\
-0.0001 & 0.000 & -0.0001 & 0.0011 & -0.0003 & -0.000 & 0.0015 & 0.0017 & 0.0015 & 0.0009 & -0.0005 & 0.0007 & -0.000 & -0.0002 & -0.0008 \\
-0.0001 & 0.0001 & 0.000 & 0.005 & -0.0012 & -0.0006 & 0.0017 & 0.0168 & 0.0082 & 0.0079 & -0.0023 & -0.0036 & 0.0001 & 0.0005 & -0.0078 \\
-0.0003 & -0.0002 & -0.0008 & 0.0029 & -0.001 & -0.0005 & 0.0015 & 0.0082 & 0.0129 & 0.0116 & -0.0021 & -0.0025 & 0.0007 & -0.0012 & -0.0072 \\
-0.0005 & -0.0004 & -0.0012 & 0.0032 & -0.0013 & -0.0008 & 0.0009 & 0.0079 & 0.0116 & 0.02 & -0.0027 & -0.0034 & 0.0009 & -0.0011 & -0.0088 \\
-0.0003 & -0.0004 & -0.0017 & -0.0011 & 0.0007 & 0.0011 & -0.0005 & -0.0023 & -0.0021 & -0.0027 & 0.014 & 0.0001 & 0.0004 & -0.0038 & 0.0168 \\
-0.0002 & -0.000 & -0.0000 & -0.000 & -0.0002 & -0.0001 & 0.0007 & -0.0036 & -0.0025 & -0.0034 & 0.0001 & 0.0054 & -0.0001 & -0.0004 & 0.0028 \\
0.0004 & 0.0004 & -0.0026 & 0.0001 & -0.0002 & -0.0002 & -0.000 & 0.0001 & 0.0007 & 0.0009 & 0.0004 & -0.0001 & 0.0103 & -0.0101 & 0.0028 \\
0.0003 & 0.001 & 0.0111 & 0.0001 & -0.0024 & -0.0017 & -0.0002 & 0.0005 & -0.0012 & -0.0011 & -0.0038 & -0.0004 & -0.0101 & 0.0578 & -0.0094 \\
-0.0001 & -0.0002 & -0.0028 & -0.0026 & -0.0003 & 0.0003 & -0.0008 & -0.0078 & -0.0072 & -0.0088 & 0.0168 & 0.0028 & 0.0028 & -0.0094 & 0.1283
\end{bmatrix}$$

$$B_2 = [-0.0001\ -0.0002\ 0.0028\ -0.0001\ 0.0001\ -0.0003\ -0.0002\ -0.0002\ 0.0006\ 0.0039\ -0.0017\ 0.0000\ -0.0032\ 0.0067\ -0.0064]$$

$$B_3 = 0.0055$$

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