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Aviation maintenance technician scheduling with personnel satisfaction based on interactive multi-swarm bacterial foraging optimization

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Abstract

This study focuses on the challenges of aviation maintenance technician (AMT) scheduling and constructs a model based on personnel satisfaction and the parallel execution of aircraft maintenance tasks. To obtain the scheduling scheme from the constructed NP-hard model, an interactive multi-swarm bacterial foraging optimization (IMSBFO) algorithm is proposed using multi-swarm coevolution, structural recombination, and three information interactive mechanisms among individuals. Moreover, considering the distributed feature of the AMT scheduling problem, a specific mechanism is designed to convert continuous solution to a binary AMT scheduling scheme. Finally, a series of comparative experiments highlight the efficiency and superiority of our proposed IMSBFO algorithm, and the optimal scheduling scheme owns the delicate balance between the work and rest time.

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KEYWORDS
aircraft maintenance, aviation maintenance technician scheduling, bacterial foraging optimization, multi-swarm, personnel satisfaction

1 | INTRODUCTION

Considering the advancement of the aviation industry, the improvement of fleet size and major airlines stimulates an increasing demand for aircraft maintenance, repair, and overhaul (MRO).[1] Owing to the high proportion of maintenance cost in the aviation industry, most airlines adopt the outsourcing MRO service from aircraft maintenance companies to reduce cost and ensure the safety level of aircrafts. In 2012, the proportion of outsourcing business has reached 45%, which is an increase of 20% compared with that of the mid-1990s.[2] In addition to cost control, personnel satisfaction of maintenance technicians, with the great influence on service quality and company's reputation, has become a key issue for improvement in a company's soft power.

According to statistics, satisfying requirements, such as flexible work arrangements, fairness, and reasonable shifts, and personnel preferences can often stimulate the staff and improve work quality.[3] Existing literature on airline employee scheduling problem, especially on crew pairing problem (CPP) and crew rostering problem (CRP), often has impact factors, such as cost, personnel preference, and fairness.[4–8] Compared with the crew, aviation maintenance technicians (AMTs) are often under greater work pressure, higher work intensity, and harsher working conditions.[9] However, only a few scholars pay attention to the AMT scheduling problem. Qin et al.[1] considered maintenance technician scheduling and constructed a total cost function using the labor cost. Chen et al.[3] focused on the fairness of the workload distribution of maintenance technicians while considering the labor cost. Empirically, very few studies consider personnel satisfaction on the AMTs scheduling problem. Moreover, to simplify the mathematical model of the AMT scheduling problem, Qin et al.[1] and Chen et al.[3] assumed that the maintenance tasks of all aircrafts in the hangar have been prearranged, and the model is designed from three dimensions, including shift, task, and technician. Nevertheless, practically, each aircraft waiting to be repaired owns a corresponding work card. When all aircraft maintenance tasks are executed in parallel, it is necessary to match all maintenance technicians and aircrafts according to the work card. Hence, in this study, we consider the aircraft as a separate dimension to obtain a more practical maintenance technician scheduling scheme based on personnel satisfaction.

AMT scheduling is a distributed and challenging NP-hard problem. It is difficult to provide an efficient AMT scheduling scheme using mathematical methods, especially for a large-scale condition. However, heuristic algorithms are suitable for complex NP-hard problems.[1,3,7–13] For example, Chen et al.[3] took the minimization of labor cost and maximization of workload allocation fairness as the optimization objectives and used tabu search techniques to obtain the optimal solution for the aircraft maintenance technician allocation problem. Deveci et al.[10] used the genetic algorithm (GA) with hill climbing to solve the simple CPP.

Compared with widespread heuristic algorithms, such as GA,[14–17] particle swarm optimization (PSO),[18–20] and ant colony optimization (ACO),[21–23] bacterial foraging optimization (BFO),[24–26] as a new swarm intelligence algorithm, has shown great potential in solving complex global optimization problems. Previous studies on the improvement of BFO mainly focused on the combination of hybrid algorithms,[27] parameter adjustment,[28] operation modification,[29] and information interaction.[30,31] However, the aforementioned studies are based on single bacterial swarm and often stuck in a limited searching scope and dimension disaster.[32,33] Considering these problems, the multi-swarm strategy has been successfully utilized in some previous studies. Chen et al.[32] extended the single swarm BFO to the multi-swarm model, which emphasized the communication among multiple bacterial populations and increased the diversity of the algorithm. Chatzis and Koukas[33] combined the swarming dynamics of PSO using BFO and used different swarms to optimize designated components of the solution vectors with a better convergence performance.

On the basis of the above discussions, this study focuses on the AMT scheduling problem with outsource strategy. The interactive multi-swarm bacterial foraging optimization (IMSBFO) algorithm is proposed, and the application of heuristic algorithm is expanded to task–technician assignment problem. The contributions of this study mainly focus on three aspects.

- First, we creatively measure the satisfaction of AMTs using work preference, working overtime, continuous participation in shifts, and fairness concern. These are acceptable and applicable to both aircraft maintenance companies and AMTs.
- Second, we analyze the AMT scheduling problem from four dimensions: aircraft, shift, task, and technician and design a concrete and novel AMT scheduling model, considering both manpower cost and work satisfaction. Moreover, based on the parallel and one-to-one characteristics of the constructed model, a highly cohesive task–technician coding scheme is created.
- Third, we propose the IMSBFO algorithm for solving the AMT scheduling problem. The IMSBFO algorithm is designed by modifying the nested relationship among chemotaxis, reproduction, and elimination/dispersal operations in the BFO and enriching the approaches of information interaction among individuals, including the multi-swarm coevolution, structural recombination, mutual aid and information interactive mechanism between biological swarms, and the mutual aid and competition mechanism within a swarm.

The rest of the paper is structured as follows: Section 2 details the problem of AMT scheduling and explains the relevant variables; Section 3 provides sufficient details of the proposed IMSBFO algorithm. In Section 4, the coding mechanism and how to apply the proposed algorithm to solve the model are illustrated. Section 5 presents the computational results based on the comparative experiments conducted. Finally, the conclusion and our future study are outlined in Section 6.

2 | PROBLEM DESCRIPTION AND FORMULATION

We visited Guangzhou Baiyun International Airport, China Southern Airlines, and Shenzhen Airlines to understand the actual demand for AMTs and interview their senior managers. According to the interviews, this section introduces the constructed assignment model in three steps. First, the AMT scheduling problem is described, and the related variables are defined. Thereafter, the objective function is proposed based on personnel satisfaction. Finally, the constraints are given with detailed explanations.

2.1 | Problem descriptions

In most aircraft maintenance companies, aircrafts parked need to go through a series of maintenance works. Each maintenance work has a work card listing detailed tasks. The work card is compiled by the maintenance company according to the aircraft manufacturer's documents and maintenance requirements of a specific aircraft. All the maintenance tasks are carried out chronologically and neither must be skipped or missed. According to Chen et al.'s,[3] the maintenance tasks that need to be completed by more than one technician are divided into several subtasks using a sequence relationship, and a technician can complete only one subtask. Moreover, each maintenance technician has a license level, each maintenance task holds specific requirements for the license level of the maintenance technician, and it takes different times for each maintenance technician to complete different maintenance tasks. For instance, considering the same task, some technicians may need 7 or 8 h, whereas others only need 2 or 3 h. Maintenance technicians with higher level licenses tend to have higher wages.

There are two kinds of AMTs: route maintenance and regular maintenance technicians. Route maintenance technicians are mainly responsible for routine inspection before and after flight maintenance procedures and troubleshooting after landing every night. This study is one of the most arduous during maintenance procedures, with long working hours, high error probability, and high pressure. Regular maintenance technicians are mainly responsible for regular large-scale in-depth inspection of aircrafts, which is divided into A, C, D categories and other categories. In this study, we mainly focus on the scheduling problem of route maintenance technicians. To meet the operational needs and improve the utilization of the aircrafts, aircraft maintenance work continuously for 24 h. Therefore, AMTs usually adopt a shift working system, where 1 day is divided into three shifts, namely, morning, middle, and night shifts (each of which is about 8 h).

To clearly express the mathematical model of the AMT scheduling problem, we list the parameters and variables involved in the model in Tables 1 and 2.

2.2 | Objective function

Considering the characteristics of the maintenance tasks, working overtime or even working on weekends is quite common and AMTs are often under great pressure. Moreover, part of the maintenance work is carried out outdoors in a noisy environment. To stimulate the AMTs and guarantee maintenance quality, the fairness of workload distribution and task preference of AMTs are of great concern.

However, few studies consider both manpower cost and personnel satisfaction in the AMT scheduling problem. In this section, in view of the real demands of AMTs, we present the created optimization objective of aircraft maintenance companies with personnel satisfaction.

$$\min \sum_{\forall i \in A} Weightiness_i \cdot (C_{\mathrm{mp}} + C_{\mathrm{wd}} + C_{\mathrm{pws}}), \tag{1}$$

$$C_{\mathrm{mp}} = \sum_{m \in M} \sum_{t \in T} \sum_{s \in S} z_{mt,is} \cdot \theta m, \tag{2}$$

$$C_{\mathrm{wd}} = penalty_1 \cdot \sum_{t \in T} \max\left\{ \sum_{m \in M} \sum_{s \in S} z_{mt,is} \cdot l_{mt,is} - d_{it}, 0 \right\}, \tag{3}$$

TABLE 1 Definition of parameters

Variables	Meaning of parameters
A	Set of aircrafts waiting for maintenance services within a considered time period
M	Set of AMTs waiting to be assigned maintenance tasks
T	Set of shifts throughout the whole maintenance period
S_{it}	Set of tasks of aircraft i during shift t
S	Set of tasks waiting to be maintained
Q	Set of license level of technicians
θ_m	Cost of technician m per shift
$\tau_{mt,is}$	Preference cost of technician m to task s of aircraft i during shift t
$l_{mt,is}$	Time required for technician m to finish task s of aircraft i during shift t
avg	Average working time of M technicians in the whole maintenance period
CSN_m	Number of times technician m works in two consecutive shifts throughout the whole maintenance period
d_{it}	Scheduled delivery time of aircraft i in shift t
h_m	Working time of technician m stipulated in the labor contract
PD_{is}	Preorder tasks of task s on aircraft i
e_{mq}	Technician m with license q
m_{qs}	Task s can be assigned to technicians with license q

TABLE 2 Definition of the binary variables

Variables	Meaning of variables
$z_{mt,is}$	1, if technician m is assigned to task s of aircraft i during shift t 0, otherwise
a_m	1, if technician m is available 0, otherwise
y_{ist}	1, if task s of aircraft i can be performed during shift t 0, otherwise
$f_{is'}$	1, if task s' of aircraft i is complicated 0, otherwise
s_{it}	1, if maintenance service of aircraft i during shift t does not start 0, otherwise
$overwork_m$	1, if technician m works overtime 0, otherwise
f_{it}	1, if maintenance service of aircraft i during shift t is complicated 0, otherwise

$$C_{\mathrm{pws}} = C_{\mathrm{wp}} + C_{\mathrm{wo}} + C_{\mathrm{cs}} + C_{\mathrm{fc}}, \tag{4}$$

$$C_{\mathrm{wp}} = penalty_2 \cdot \sum_{m \in M} \sum_{t \in T} \sum_{s \in S} z_{mt,is} \cdot \tau_{mt,is}, \tag{5}$$

$$C_{\mathrm{wo}} = penalty_3 \cdot \sum_{m \in M} overwork_m \cdot \max\left\{ \sum_{t \in T} \sum_{s \in S} z_{mt,is} \cdot l_{mt,is} - h_m, 0 \right\}, \tag{6}$$

$$C_{\mathrm{cs}} = penalty_4 \cdot \sum_{m \in M} CSN_m, \tag{7}$$

$$C_{\mathrm{fc}} = penalty_5 \cdot \left[\frac{1}{m} \sum_{m \in M} \left(\sum_{t \in T} \sum_{s \in S} z_{mt,is} \cdot l_{mt,is} - avg \right)^2 \right]. \tag{8}$$

From the perspective of aircraft maintenance company, the optimization objective of this study consists of manpower cost C_{mp}, work delay cost C_{wd}, and personnel work satisfaction cost C_{ps} as shown in (1). $Weightiness_i$ refers to the cost weightiness of aircraft i, and $penalty_k$ $(k \in \{1, 2, 3, 4, 5\})$ is the coefficient of the corresponding cost.

The manpower cost C_{mp}, which represents the cost of all the AMTs calculated based on each shift during the maintenance cycle, is obtained by formula (2). If the tasks in a shift cannot be completed on time, it is likely that the maintenance work cannot be delivered on time, making the aircraft maintenance company bear the cost of work delay. Formula (3) illustrates the formulation of work delay cost C_{wd}, representing the cost of timeout, where the completion time of all the tasks exceeds the specified end time of the shift. The function of personnel work satisfaction cost C_{pws} is presented in formula (4). This includes work preference cost C_{wp}, working overtime cost C_{wo}, continuous shifts cost C_{cs}, and fairness concern cost C_{fc}. Each maintenance technician has a different preference for each maintenance task. We divide the work preference of each technician into different levels, and calculate the work preference cost C_{wp} according to the specific preference $\tau_{mt,is}$ of all the AMTs using formula (5). Moreover, according to the interview with the AMTs, frequent overtime and continuous work are the key reasons for tired feelings and impaired concentration. Therefore, working overtime cost C_{wo} and continuous shifts cost C_{cs} are included in the total cost. In this study, working overtime cost C_{wo} is determined by the sum of working overtime in (6), and continuous shifts cost C_{cs}, which is presented by the total number of times where the AMTs participate in two consecutive shifts in (7). Furthermore, fairness of maintenance time allocation considerably affects personnel satisfaction. Formula (8) utilizes fairness concern cost C_{fc} to describe this phenomenon.

2.3 | Constraints

After receiving aircraft maintenance orders, aircraft maintenance companies often need to allocate maintenance technicians reasonably according to the current arrangement of the maintenance technicians and specific situation of the aircraft maintenance tasks. In most cases, one aircraft maintenance cycle is composed of several consecutive shifts. One shift lasts for 8 h, and one working day includes three consecutive shifts. When assigning the AMTs, a series of constraints are supposed to be satisfied, including the constraints that require orderly execution of the maintenance tasks. The constraints restrict technician allocation in line with practical significance and are used to ensure that the maintenance work is completed on time.

First, the maintenance tasks on each aircraft are conducted in sequence. In Shift t, Task s, and its subsequent maintenance tasks can be performed only when all the presequence maintenance tasks PD_{is} on Aircraft i have been completed. The above relationships are defined in formula (9), where y_{ist} indicates whether Task s on Aircraft i in Shift t can be conducted, and $f_{is'}$ represents whether the tasks before Task s on Aircraft i has been completed.

$$y_{ist} \leq \frac{1}{|PD_{is}|} \cdot \sum_{s' \in PD_{is}} f_{is'}, \qquad \forall i \in A, \forall s \in S_{it}, \forall t \in T. \tag{9}$$

Second, technicians will not be assigned to aircrafts that have not yet submitted maintenance requests and that have indicated that all maintenance tasks have been completed. We restrict the above two situations using (10), where s_{it} measures whether the first task of Aircraft i has been started, and f_{it} refers to whether all maintenance tasks of Aircraft i have been completed.

$$\begin{aligned} y_{ist} &\leq 1 - s_{it}, \qquad \forall i \in A, \forall t \in T, \forall s \in S_{it}, \\ y_{ist} &\leq 1 - f_{it}, \qquad \forall i \in A, \forall t \in T, \forall s \in S_{it}. \end{aligned} \tag{10}$$

Moreover, (11) and (12) demonstrate whether a technician can be assigned to a particular task. Formula (11) indicates that the technicians can only be assigned to maintenance tasks that are allowed to be conducted, and (12) defines that only technicians in idle conditions can be assigned maintenance tasks. $z_{mt,is}$ denotes whether Technician m is assigned to complete Task s on Aircraft i in Shift t and a_m represents the availability of Technician m.

$$z_{mt,is} \leq y_{ist}, \qquad \forall i \in A, \forall t \in T, \forall m \in M, \forall s \in S_{it}, \tag{11}$$

$$z_{mt,is} \leq a_m, \qquad \forall i \in A, \forall t \in T, \forall m \in M, \forall s \in S_{it}. \tag{12}$$

To ensure that all maintenance tasks of each aircraft can be completed before the delivery time, we define formula (13). This demonstrates that in Shift t, the completion time of all tasks on Aircraft i cannot exceed the specified end time of the shift. $l_{mt,is}$ indicates time required for Technician m to finish Task s of Aircraft i during Shift t, and d_t is the scheduled end time of Shift t.

$$\sum_{m \in M} \sum_{s \in S_{it}} z_{mt,is} \cdot l_{mt,is} \leq d_t, \quad \forall i \in A, \forall t \in T. \tag{13}$$

In addition, AMTs have different levels of maintenance licenses. When assigning technicians to aircraft maintenance tasks, each maintenance task has specific requirements for the level of maintenance license. Only a maintenance technician with a license level higher than or equal to the required level is qualified to claim the maintenance task. Formula (14) shows that when assigning technicians, the license level of Technician m shall not be lower than the license level required by Task s on Aircraft i. e_{mq} refers to Technician m with License q, and m_{qs} indicates that Task s can be assigned to technicians with License q. We assume that each subtask is completed by only one maintenance technician in (15).

$$z_{mt,is} \leq e_{mq} m_{qs}, \quad \forall i \in A, \forall t \in T, \forall m \in M, \forall s \in S_{it}, \forall q \in Q, \tag{14}$$

$$\sum_{m \in M} z_{mt,is} = 1, \quad \forall i \in A, \forall t \in T, \forall s \in S_{it}. \tag{15}$$

Finally, to ensure that the AMTs have sufficient rest time, the work time allocation of the technicians needs reasonable scheduling. In general, a technician cannot participate in the maintenance work of consecutive shifts, to ensure work efficiency.[1] Additionally, the total working time of Technician m shall not exceed the time h_m stipulated in the labor contract. Formulas (16) and (17) define the continuous shifts constraint and working overtime constraint, respectively.

$$\sum_{s \in S_{it}} z_{mt,is} \cdot \sum_{s \in S_{it}} z_{m(t+1),is} = 0, \qquad \forall i \in A, \forall t \in T, \forall m \in M, \tag{16}$$

$$\sum_{i \in A} \sum_{t \in T} \sum_{s \in S_{it}} z_{mt,is} \cdot l_{mt,is} \leq h_m, \qquad \forall m \in M. \tag{17}$$

3 | INTERACTIVE MULTI-SWARM BACTERIAL FORAGING OPTIMIZATION

This section introduces the proposed IMSBFO algorithm in detail. Compared with the original BFO,[24] IMSBFO is improved mainly from aspects of the swarm division and structure adjustment, including multi-swarm coevolution strategy, structural recombination, and information interactive mechanisms.

3.1 | Multi-swarm coevolution strategy

Inspired by the coevolution mechanism of natural species, a bacterial multi-swarm coevolution strategy is proposed. This includes the coevolution modes of mutualism symbiosis and intraspecific competition in biology to improve the global search ability of the IMSBFO.

In traditional BFO, individuals are all in a single swarm, leaving a time-consuming problem. To overcome this problem, in this study, the whole swarm is divided into several subswarms. Each individual in a subswarm represents a solution, and each subswarm represents a subsolution space. In search of optimal solutions, the optimal individuals within the swarm and those among the swarms will be retained to assist in information exchange within and between the swarms. At the same time, each individual will gradually approach the positions of the current optimal individuals and those away from the poor position.

3.2 | Structural recombination

Unlike the original BFO, in IMSBFO, the traditional three-level nested loop composed of chemotaxis, reproduction, and elimination/dispersal operations are broken, and these three operations are operated sequentially. Each individual will carry out chemotaxis, reproduction, and elimination/dispersal operations one of another during the iterative optimization process.

3.2.1 | Chemotaxis

Chemotaxis mainly simulates the swimming and tumbling movements of *Escherichia coli*. First, the bacteria tumble according to a random direction and step size. They also determine whether the current tumble direction is an effective flip direction by calculating and comparing the fitness values before and after the tumble. If it is effective, the swimming operation will continue in this direction; otherwise, the comparison will go on within limited iterations.

3.2.2 | Reproduction and elimination/dispersal

Considering the reproduction operation, the first half of the optimal individuals sorted according to the fitness value will be retained, and the second half of the individuals will be replaced by the first half of the optimal individuals. Because the IMSBFO removes the three-layer nested loops, the reproduction operation is designed to be intergenerational, executed to avoid premature convergence.

In the elimination/dispersal operation, all the bacteria have a fixed probability of death and have a fixed probability to migrate to the position with a better fitness value. The dead bacteria will be replaced by randomly generated new ones.

Therefore, the phenomenon of "natural selection, survival of the fittest" caused by reproduction and elimination/dispersal is considered as a form of intraspecific competition.

3.3 | Information interactive mechanisms

Information interaction is a common form of intraspecific mutualism. Biological individuals often decide their behaviors through the obtained information to obtain better resources and avoid adverse factors. According to the relationship among the interacted individuals, information interaction can be divided into two categories: information interaction within a subswarm and information interaction among subswarms.

3.3.1 | Information interaction within a subswarm

Within a subswarm, each individual can interact with its two neighbors (according to the order in the initialization process) or any other random individual with a predefined probability and learn from the best individual. In addition, the swarm's optimal individual and historical positions of each individual are important references for individual evolution. Information interaction within a swarm can be divided into four categories.

Interact with the optimal neighbor

To improve the convergence performance of the algorithm, when individual i interacts with the neighboring individuals in subswarm j, the fitness values corresponding to its two neighbors and the individual itself are compared. Individual i will learn from its neighbor N_{ij}^t only when N_{ij}^t holds the best fitness value among those three individuals.

Interact with a random individual

To increase the diversity of solutions in a search space and avoid falling into local optimal solutions, each bacterial individual i has the opportunity to interact with a random individual R_j^t in subswarm j.

Interact with the suboptimal individual

According to the order of individual fitness value, the optimal individual position in subswarm j is retained, and the corresponding individual position is recorded as $Cbest_j^t$. Thereafter, other individuals in subswarm j will approach this individual during the foraging process to obtain a higher fitness value.

Interact based on self-historical optimal position

The self-historical optimal position $Pbest_{ij}^t$ of individual i in subswarm j reflects the life course of its interaction with the surrounding environment and other individuals. Thus, $Pbest_{ij}^t$ is retained as part of the new location information.

3.3.2 | Information interaction among subswarms

Information interactions also exist among different bacterial swarms. In the iterations, the positions of subswarm optimal individuals are recorded. Thereafter, the global optimal individual $Gbest^t$ is obtained, considering the fitness values of the subswarm optimal individuals. Each individual will learn from the global optimal solution of the whole swarm while interacting with one another in the subswarms.

3.3.3 | Learning strategies for effective information

We take a certain individual i in subswarm j in iteration t as the reference, and this is defined by P_{ij}^t. Thereafter, the bacterial individuals that can interact with individual i can be divided into five groups, including the optimal neighbor of individual i in subswarm j, a random individual in subswarm j, optimal individual in subswarm j, historical self-optimal individual, and global optimal individual. On the basis of the five types of bacterial individuals above, we propose the learning strategies for effective information. These strategies are presented below. α_k and β_k, $k \in \{1, 2\}$ are the random learning factors.

- *Strategy I*: Learn from both the optimal neighbor N_{ij}^t of individual i or a random individual R_j^t in subswarm j.

$$P_{ij}^{t+1} = \begin{cases} N_{ij}^t, & P_{ij}^t > N_{ij}^t, \\ R_j^t, & P_{ij}^t < N_{ij}^t, \end{cases} \tag{18}$$

$$N_{ij}^t = \min\{P_{(i-1)j}^t, P_{(i+1)j}^t\}. \tag{19}$$

- *Strategy II*: Learn from both the historical self-optimal individual $Pbest_{ij}^t$ and random individual R_j^t in subswarm j.

$$P_{ij}^{t+1} = P_{ij}^t + \alpha_1\left(Pbest_{ij}^t - P_{ij}^t\right) + \beta_1\left(R_j^t - P_{ij}^t\right). \tag{20}$$

- *Strategy III*: Learn from both the global optimal individual $Gbest^t$ and suboptimal individual $Cbest_j^t$ in subswarm j.

$$P_{ij}^{t+1} = P_{ij}^t + \alpha_2\left(Gbest^t - P_{ij}^t\right) + \beta_2\left(Cbest_j^t - P_{ij}^t\right). \tag{21}$$

Figure 1 presents the three strategies above and clearly illustrates the information interactive mechanisms within and among subswarms. The flowchart of IMSBFO is demonstrated in Figure 2 to show the structural reorganization of chemotaxis, reproduction, and elimination/dispersal operations, and three learning strategies for effective information.

4 | SOLUTION BASED ON THE IMSBFO

To overcome the complex AMT scheduling model and build a bridge between binary task–technician matching problem and continuous IMSBFO algorithm, this section mainly introduces the detailed parallel technician assignment rules, encoding scheme, and corresponding transformation mechanisms.

4.1 | Parallel technician assignment rules

Contrasting from the AMT scheduling method in the existing literature,[1,3] we consider the aircraft as a separate dimension to carry out technician assignment for practical convenience. Regarding each aircraft, the assignment of maintenance technicians is performed in parallel. Specifically, maintenance technicians cannot carry out maintenance work on multiple aircrafts simultaneously, and all aircrafts share a fixed number of

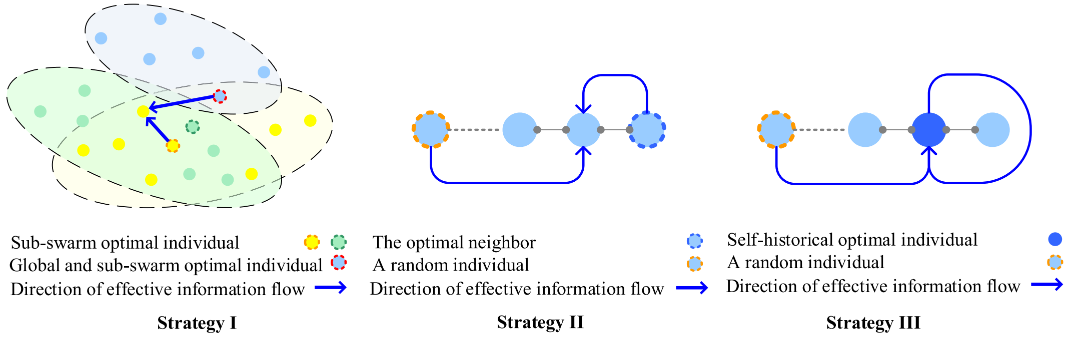

FIGURE 1 Model of information interaction [Color figure can be viewed at wileyonlinelibrary.com]

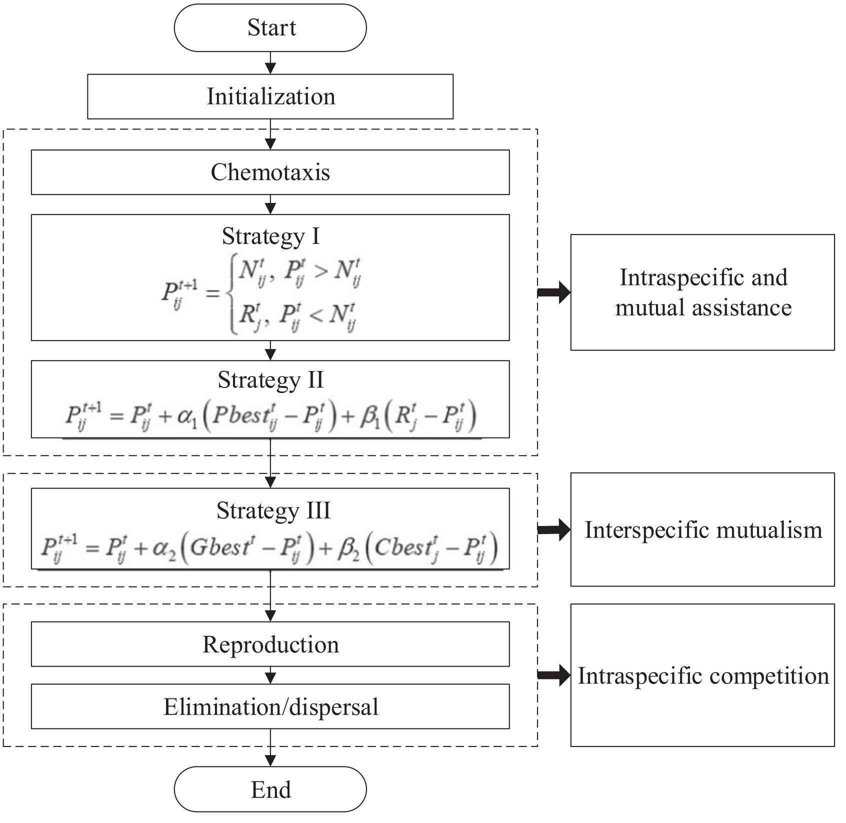

FIGURE 2 Flowchart of interactive multi-swarm bacterial foraging optimization (IMSBFO)

maintenance technicians. Therefore, we formulate two technician assignment rules below to compactly implement the parallel aircraft maintenance tasks:

- The maintenance technicians in a working state cannot be assigned.
- The maintenance technicians who cannot meet the requirements of maintenance task license levels cannot be assigned.

On the basis of the two rules above, supposing there are several aircrafts in the hangar, each aircraft has a task sequence in a specific shift. When assigning AMTs, we first set a virtual timer and task counter for each aircraft, and assign the first task to the aircrafts according to the start time of the maintenance work. After the first task–technician matching is predetermined, the time for the specific maintenance technician to complete the task is recorded in the timer of the aircraft, and the value of the corresponding task counter is increased by one unit. In the subsequent assignment operations, we select the aircraft that completes the current task first, according to the timers and task counters of all aircrafts, and assign a technician to the task of this aircraft. For each aircraft, when the value of task counter reaches its actual task quantity, it means that all maintenance works have been completed, and no technician will be needed. To better illustrate the task–technician matching procedure, the relationships among tasks, technicians, virtual timer, and task counter are illustrated in Figure 3.

4.2 | Encoding scheme

To realize the combination of the model and algorithm, we encode the task–technician assignment as shown in Table 3. In shift t, the value of position (M, S_{it}), for example, $z_{mt,is}$ in the maintenance task–technician allocation table of aircraft i is 0 or 1 (shown in Table 3). "$z_{mt,is} = 1$" indicates that Task s of Aircraft i is assigned to maintenance Technician m in Shift t. Because one maintenance task can only be completed by one maintenance technician, the value of only one position in each column of Table 3 is "1." Each individual represents a solution in the whole solution set space, recording the maintenance task–technician assignment in all shifts and on all aircrafts.

4.3 | Transformation mechanisms in encoding scheme

In this study, the IMSBFO algorithm is used to optimize the location of an individual in a subswarm. In the optimization process, the partial evolution of an individual and its conversion process are shown in Tables 4 and 5, respectively. The red number indicates the working maintenance technicians, the gray shading indicates that the maintenance technician level is lower than the license requirement, and the yellow shading indicates the selected maintenance technician. In particular, to ensure that the working maintenance technicians are not assigned to other maintenance tasks, the corresponding positions of the working maintenance technicians are forced to be "0."

Table 5 is presented to illustrate the transformation process compared with Table 4. Considering each column in the table, among the maintenance technicians who are idle and whose license levels are higher than the task requirement level, set the position with the largest corresponding value as "1" and the rest as "0." For example, regarding Task 3 of Aircraft i in Shift t, only maintenance

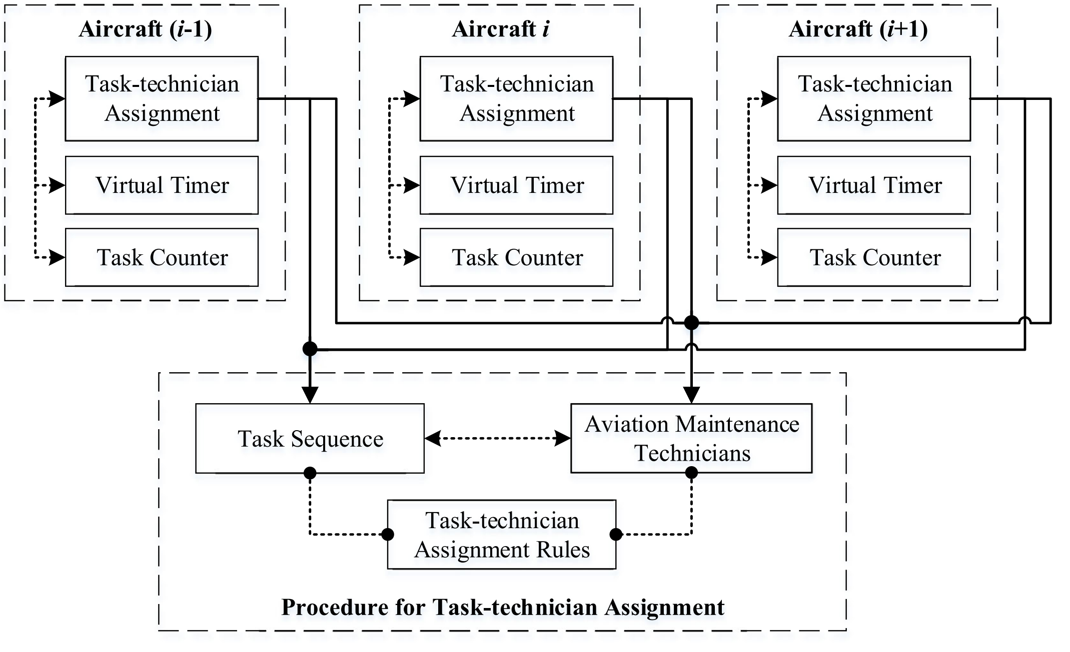

FIGURE 3 Relationships between parallel technician assignment rules [Color figure can be viewed at wileyonlinelibrary.com]

TABLE 3 Encoding scheme

	Technician No.	Shift 1/8 h			Shift 2/8 h				Shift 3/8 h		
		Task 1	Task 2	Task 3	Task 1	Task 2	Task 3	Task 4	Task 1	Task 2	Task 3
Aircraft *i*	*M*1	0	0	0	1	0	0	0	0	0	1
	*M*2	0	0	1	0	0	0	1	0	0	0
	*M*3	0	0	0	0	0	0	0	1	0	0
	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮
	*M*11	1	1	0	0	0	0	0	0	1	0

TABLE 4 Continuous encoding mechanism

Aircraft No.	Technician No.	Shift 1 /8h Task 1	Shift 1 /8h Task 2	Shift 1 /8h Task 3	Shift 2 /8h Task 1	Shift 2 /8h Task 2	Shift 2 /8h Task 3	Shift 2 /8h Task 4	Shift 3 /8h Task 1	Shift 3 /8h Task 2	Shift 3 /8h Task 3
	*M*1	0	0.95	0	0.99	0	0.63	0	0.96	0.39	0.05
	*M*2	0	0.94	0	0.15	0	1.00	0	0.20	0.98	0.80
	*M*3	0	0.65	0	0.60	0	1.00	0	0.18	0.10	0.34
	*M*4	0	0.31	0	1.00	0	0.94	0	0.93	0.95	0.32
	*M*5	0.86	0.68	0	0.44	0.89	0.06	0	**0**	0.22	0.50
*A*1	*M*6	0.89	0.17	0	0.31	1.00	0.74	0	0.23	**0**	**0**
	*M*7	0.58	0.35	0	**0**	0.31	0.02	0	0.46	0.05	0.78
	*M*8	0.81	0.06	0.01	0.10	**0**	**0**	0.85	0.43	0.44	0.53
	*M*9	0.40	**0**	**0**	0.22	0.68	0.68	0.32	0.75	0.49	0.21
	*M*10	0.01	0.19	0.39	0.98	1.00	0.63	0.87	0.26	0.27	0.39
	*M*11	0.99	0.46	0.97	0.20	0.30	0.06	0.66	0.81	0.31	0.30
	*M*1	0.46	0	0.68	0.35	0	0.45	0.48	0	0.28	0
	*M*2	0.86	0	0.33	0.90	0	0.36	0.81	0	**0**	0
	*M*3	0.85	0	0.20	0.87	0	**0**	0.32	0	0.23	0
	*M*4	0.65	0	0.75	**0**	0	1.00	0.95	0	0.35	0
	*M*5	0.14	0.18	0.45	0.62	0.05	0.08	0.99	0.64	0.06	0
*A*2	*M*6	0.10	0.14	0.88	0.51	0.65	0.30	0.21	0.98	0.98	0
	*M*7	0.96	0.20	1.00	0.43	0.60	0.89	0.09	0.29	0.67	0
	*M*8	0.48	0.24	0.12	0.98	1.00	0.79	0.67	0.84	0.14	0.17
	*M*9	0.40	0.26	0.46	0.80	0.18	0.42	0.96	0.20	0.50	1.00
	*M*10	0.13	0.10	0.41	0.36	0.99	0.33	**0**	0.25	0.29	0.78
	*M*11	**0**	**0**	**0**	0.97	0.54	0.26	0.63	0.42	0.86	0.16

technicians *M*8, *M*9, *M*10, and *M*11 meet the license-level requirements, and maintenance technicians *M*7 and *M*10 are in the working state. Therefore, maintenance technician *M*9, with the largest continuous value of 0.15, is selected as the allocation object of maintenance Task 3.

5 | EXPERIMENTS AND RESULTS

In this section, we design six groups of experiments with different scales to test the efficiency of the IMSBFO for our considered AMT scheduling problem.

The data of aircrafts, maintenance tasks, and maintenance technicians used in the experiment are generated based on interviews of aircraft maintenance companies (such as ST Aerospace Guangzhou Aviation Services) and Reference [3]. In our experiments, the number of aircrafts is $A \in \{2, 4, 6\}$, the number of maintenance technicians is $M \in \{11, 15, 19\}$, and the number of shifts is $T \in \{3, 5, 7, 10\}$. The license level of AMTs is $Q \in \{1, 2, 3\}$ and the corresponding labor costs are 0.5, 1, and 1.5 per hour. The specific value of A, M, T, and S is shown

TABLE 5 Binary encoding mechanism

Aircraft No.	Technician No.	Shift t /8h Task 1	Shift t /8h Task 2	Shift t /8h Task 3	Shift 2 /8h Task 1	Shift 2 /8h Task 2	Shift 2 /8h Task 3	Shift 2 /8h Task 4	Shift 3 /8h Task 1	Shift 3 /8h Task 2	Shift 3 /8h Task 3
	*M*1	0	1	0	0	0	0	0	1	0	0
	*M*2	0	0	0	0	0	0	0	0	1	1
	*M*3	0	0	0	0	0	1	0	0	0	0
	*M*4	0	0	0	1	0	0	0	0	0	0
	*M*5	0	0	0	0	0	0	0	0	0	0
*A*1	*M*6	0	0	0	0	0	0	0	0	0	0
	*M*7	0	0	0	0	0	0	0	0	0	0
	*M*8	0	0	0	0	0	0	0	0	0	0
	*M*9	0	0	0	0	0	0	0	0	0	0
	*M*10	0	0	0	0	1	0	1	0	0	0
	*M*11	1	0	1	0	0	0	0	0	0	0
	*M*1	0	0	0	0	0	0	0	0	0	0
	*M*2	0	0	0	0	0	0	0	0	0	0
	*M*3	0	0	0	0	0	0	0	0	0	0
	*M*4	0	0	0	0	0	1	0	0	0	0
	*M*5	0	0	0	0	0	0	1	0	0	0
*A*2	*M*6	0	0	0	0	0	0	0	1	1	0
	*M*7	1	0	1	0	0	0	0	0	0	0
	*M*8	0	0	0	1	1	0	0	0	0	0
	*M*9	0	1	0	0	0	0	0	0	0	1
	*M*10	0	0	0	0	0	0	0	0	0	0
	*M*11	0	0	0	0	0	0	0	0	0	0

TABLE 6 Number of aircrafts (*A*), technicians (*M*), shifts (*T*), and tasks (*S*)

Instances	***A***	***M***	***T***	***S***
Instance 1	2	11 (4, 3, 4)	3	10 (3, 4, 3)
Instance 2	2	11 (4, 3, 4)	5	14 (3, 4, 3, 2, 2)
Instance 3	4	15 (5, 5, 5)	5	14 (3, 4, 3, 2, 2)
Instance 4	4	15 (5, 5, 5)	7	18 (3, 4, 3, 2, 2, 2, 2)
Instance 5	6	19 (7, 6, 6)	7	18 (3, 4, 3, 2, 2, 2, 2)
Instance 6	6	19 (7, 6, 6)	10	25 (3, 4, 3, 2, 2, 2, 2, 2, 3, 2)

in Table 6. Taking Instance 1 as an example, the number of AMTs whose license levels are 1, 2, and 3 is 4, 3, and 4, respectively. There are three shifts, for Instance, 1, and the corresponding number of tasks in each shift is 3, 4, and 3. The time for the AMTs to complete each maintenance task is given as a fixed real number between 1 and 3, and the corresponding maintenance task preference is given as a fixed integer between 1 and 3. Particularly, each shift lasts for 8 h, and the working time of an AMT shall not exceed 8 h/day.

We compare the IMSBFO to other heuristic algorithms, including BFO,[24] bacterial colony optimization (BCO),[34] swarm intelligence bacterial colony optimization (SiBFO),[35] PSO,[18] CLPSO,[36] and GA.[14] In each experiment, we gradually expand one or more of the number of aircrafts, AMTs, shifts, and maintenance tasks. Particularly, during the algorithm comparison, the same group of experiments uses the same data. This indicates that we can observe the adaptability and superiority of the proposed IMSBFO algorithm to AMT scheduling problem.

5.1 | Parameter settings

To better illustrate the superiority of the designed IMSBFO algorithm in the AMT scheduling problem, the parameters of each comparison algorithm are selected using a large number of pre-experiments. The number of individuals N_p is 30, and that of the fitness function evaluations (*Fes*) in IMSBFO, BFO, BCO, SiBFO, PSO, CLPSO, and GA is 30,000. The elimination probabilities P_{ed} in IMSBFO, BFO, and SiBFO are set to 0.25. Details of the parameter settings are listed as follows:

- In IMSBFO, the number of subswarms is 5, $N_{\mathrm{s}} = 10$, $C_{\mathrm{start}} = 0.2$, $C_{\mathrm{end}} = 0.01$, and that of the iterations between two reproduction operations is $F_{\mathrm{re}} = 10$. The number of generations between two reproduction operations is set to 200.
- Considering BFO, the number of chemotaxis, reproduction, elimination/dispersal, and swimming are $N_{\mathrm{c}} = 1000$, $N_{\mathrm{r}} = 5$, $N_{\mathrm{e}} = 2$, and $N_{\mathrm{s}} = 4$, respectively. The chemotaxis step $C = 0.1$.

With regard to BCO, $N_{\mathrm{c}} = 1000$, $N_{\mathrm{s}} = 50$, $C_{\mathrm{start}} = 0.2$, and $C_{\mathrm{end}} = 0.01$.

- Regarding SiBFO, the number of iterations between two reproduction operations is $F_{\mathrm{re}} = 200$, and that of the swimming operations is $N_{\mathrm{s}} = 4$. The chemotaxis step $C = 0.1$.
- In PSO, the learning factors c_1, c_2 are set to 2, and the inertia weight $w = 0.9$.
- In CLPSO, the learning factor $c = 1.49445$, and the inertia weight $w_0 = 0.9$, $w_1 = 0.4$.
- In GA, the crossover probability and mutation probability are $p_{\mathrm{c}} = 0.95$ and $p_{\mathrm{m}} = 0.1$, respectively.

5.2 | Experimental results and comparative analysis

To illustrate the efficiency of the proposed the IMSBFO, BFO, BCO, SiBFO, PSO, CLPSO, and GA algorithms are utilized as the comparison algorithms, and six groups of experiments with parameters listed in Table 6 are conducted 10 times. Figures 4 and 5 are the convergence curves and boxplots drawn according to the mean value of the total costs, respectively. Table 7 lists the maximum, minimum, mean value, and standard deviation of the optimal total cost obtained by the above seven algorithms in all the experiments.

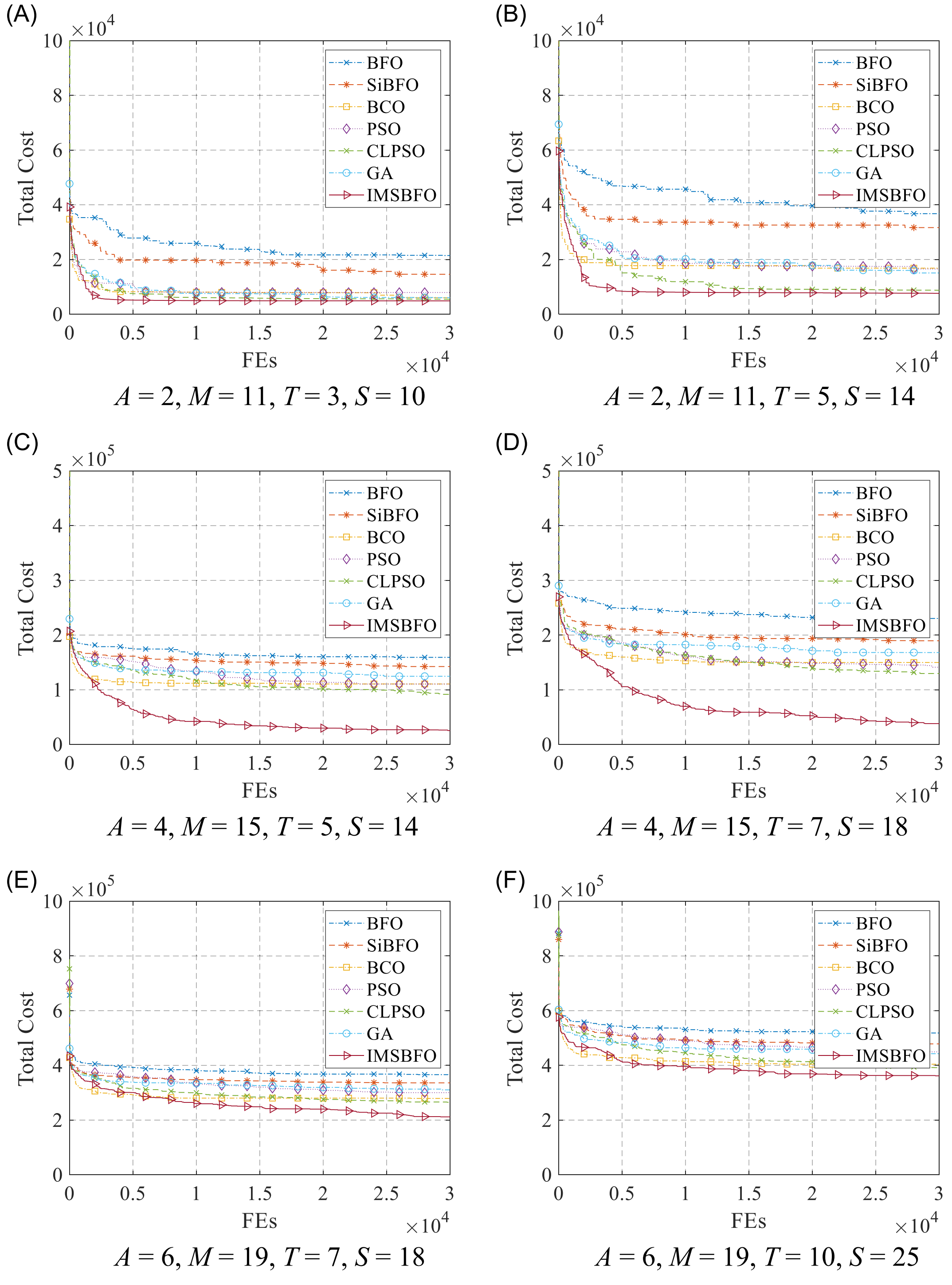

FIGURE 4 Convergence curves of the objective function based on the BFO, SiBFO, BCO, PSO, CLPSO, GA, and IMSBFO algorithms. ACO, ant colony optimization; BCO, bacterial colony optimization; BFO, bacterial colony optimization; CLPSO, comprehensive learning particle swarm optimizer; GA, genetic algorithm; IMSBFO, interactive multi-swarm bacterial foraging optimization; PSO, particle swarm optimization; SiBFO, swarm intelligence bacterial colony optimization [Color figure can be viewed at wileyonlinelibrary.com]

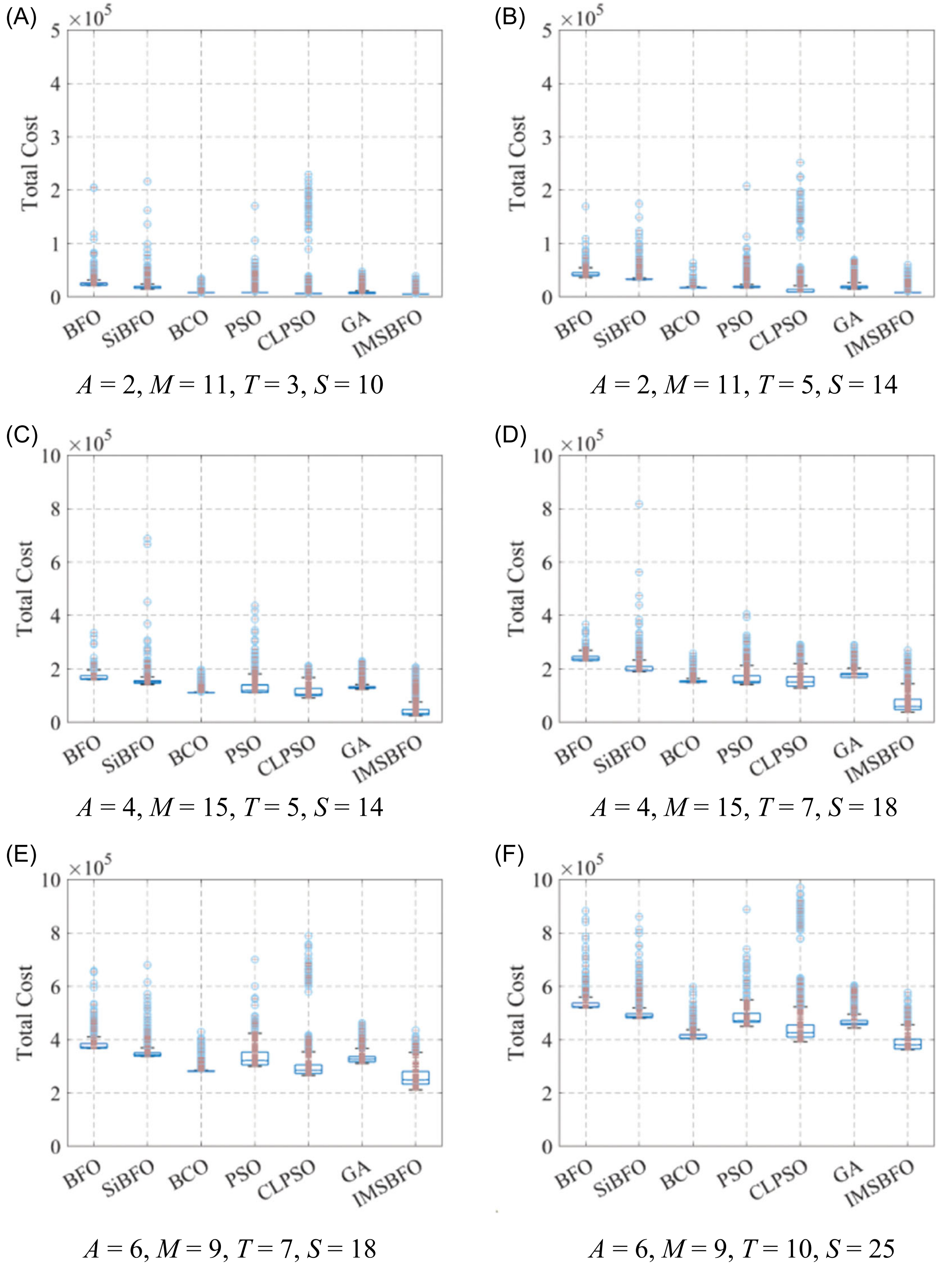

FIGURE 5 Boxplots of the objective function based on the seven algorithms. ACO, ant colony optimization; BCO, bacterial colony optimization; BFO, bacterial colony optimization; CLPSO, comprehensive learning particle swarm optimizer; GA, genetic algorithm; IMSBFO, interactive multi-swarm bacterial foraging optimization; PSO, particle swarm optimization; SiBFO, swarm intelligence bacterial colony optimization [Color figure can be viewed at wileyonlinelibrary.com]

TABLE 7 Comparisons of MCBFO with the other optimization algorithms on the total cost

Instance		BFO	SiBFO	BCO	PSO	CLPSO	GA	IMSBFO
1	*max*	27,238	26,867	6936	16,052	6936	6512	**5028**
	min	16,185	6188	5308	5586	5308	4997	**4601**
	mean	21,452	14,598	5997	7920	5997	6051	**4862**
	std	5112	6343	660	4091	660	451	**145**
2	*max*	41,706	40,597	20,432	29,169	20,432	19941	**8078**
	min	19,976	19,778	9799	8988	9799	9574	**7056**
	mean	36,743	31,660	16,829	16,520	16,829	15063	**7630**
	std	7234	7233	4541	8192	4541	4905	**358**
3	*max*	178,530	159,210	128,530	165,930	128,530	147230	**46,400**
	min	138,660	119,000	87,369	68,036	87,369	99461	**13,916**
	mean	159,310	142,480	110,640	110,490	110,640	124710	**25,467**
	std	13,574	15,330	12,195	27,915	12,195	13905	**9935**
4	*max*	263,290	203,920	174,300	163,400	174,300	183900	**50,572**
	min	183,880	154,120	132,060	112,620	132,060	146410	**19,062**
	mean	230,410	189,590	149,030	141,300	149,030	168090	**38,155**
	std	23,437	15,643	16,264	17,385	16,264	13110	**10,411**
5	*max*	386,280	343,790	323,480	353,320	323,480	326110	**281,060**
	min	334,160	314,480	240,970	251,920	240,970	296280	**151,890**
	mean	366,140	336,230	279,390	300,320	279,390	310540	**211,820**
	std	16,777	**9078**	24,987	34,860	24,987	9317	51,202
6	*max*	568,880	503,960	442,670	516,200	442,670	468030	**405,810**
	min	475,560	448,190	364,490	402,610	364,490	418390	**326,010**
	mean	518,420	478,690	404,350	449,480	404,350	442640	**361,810**
	std	29,687	20,482	20,810	38,169	20,810	**17895**	27,771

Abbreviations: ACO, ant colony optimization; BCO, bacterial colony optimization; BFO, bacterial colony optimization; CLPSO, comprehensive learning particle swarm optimizer; GA, genetic algorithm; IMSBFO, interactive multis-warm bacterial foraging optimization; MCBFO, multi-colony bacterial foraging optimization; PSO, particle swarm optimization; SiBFO, swarm intelligence bacterial colony optimization.

Note: The bold values in Table 7 refer to the optimal values among seven algorithms when comparing the maximum, minimum, mean and standard deviation of total costs.

First, considering the optimizing ability demonstrated in Figure 4, among the six groups of experiments, IMSBFO can find the scheduling scheme with the minimum total cost, followed by CLPSO, BCO, PSO, and GA. BFO shows the worst performance. Considering the increase in the number of shifts and tasks, the optimal total cost of each algorithm becomes larger, whereas the increase in the total maintenance cost with the IMSBFO algorithm is the smallest. When the number of shifts and tasks remain the same, and the number of aircrafts and maintenance technicians increases, compared with other algorithms, the IMSBFO can still get the minimum total cost.

Considering the convergence performance, when the scale of the problem is relatively small, such as (A) and (B) in Figure 4, the IMSBFO, BCO, PSO, and GA converge faster than the BFO, SiBFO, and CLPSO, and IMSBFO holds the fastest speed. Because the scale tends to be larger, such as (C)–(F) in Figure 4, compared with other algorithms, the convergence speed of IMSBFO is slower. Even at that point, the IMSBFO can still provide AMTs scheduling scheme with the lowest cost.

The boxplots in Figure 5 illustrate that IMSBFO is the best in terms of the average, quantile, or minimum distribution of the mean value of the total cost in all the iterations. In general, the distribution of all the solutions obtained by the IMSBFO is most concentrated and closer to the optimal solution. Regarding the problem expansion, the concentration of PSO is improved, and it even surpasses the IMSBFO in (B) and (C); nonetheless, its ability to search the optimal solution is weaker than the IMSBFO. As visualized in Table 7, the IMSBFO surpasses the other five algorithms, considering the maximum and minimum mean values of total cost in the six groups of experiments. This highlights the searching superiority of the proposed algorithm. Moreover, in Instances 1–4, the standard deviation of total cost obtained by the IMSBFO is the smallest, whereas in Instance 5 and 6, when the problem scale becomes larger, the standard deviations of the total cost obtained by the SiBFO and GA are lower than that by the IMSBFO. This is because when the scheduling model is relatively simple with a smaller A, M, T, and S, the optimization process is easier to realize, and the IMSBFO can find the optimal solution more quickly with a lower standard deviation using its strong searching ability. When A, M, T, and S increase, the optimization process becomes complex, and the standard deviation of the results decreases. Considering the SiBFO and GA, the solutions obtained in most experiments are approximate solutions with a large gap in the optimal solution, leading to lower standard deviations.

The following examples are given to describe a specific AMT scheduling scheme. When $A = 3$, $M = 11$, $T = 3$, and $S = 10$, the AMT scheduling scheme obtained by the IMSBFO is shown in Tables 8 and 9. This illustrates the maintenance technician assigned to each aircraft maintenance task and the corresponding working time. The data in Table 8

TABLE 8 Task–technician assignment scheme based on the IMSBFO

	Shift *t*/8 h			**Shift *t*/8 h**				**Shift *t*/8 h**		
Aircraft No.	***S*1**	***S*2**	***S*3**	***S*1**	***S*2**	***S*3**	***S*4**	***S*1**	***S*2**	***S*3**
*A*1	5	4	10	1	8	8	8	2	4	4
*A*2	9	9	9	11	7	3	1	6	6	10
*A*3	10	2	5	3	11	11	7	5	2	6

Abbreviation: IMSBFO, interactive multi-swarm bacterial foraging optimization.

TABLE 9 Corresponding maintenance time

	Shift *t*/8 h			**Shift *t*/8 h**				**Shift *t*/8 h**		
Aircraft No.	***S*1**	***S*2**	***S*3**	***S*1**	***S*2**	***S*3**	***S*4**	***S*1**	***S*2**	***S*3**
*A*1	2.3	1.9	2.3	2.1	1.5	1.2	2.7	2.5	2.5	3
*A*2	2	2.2	1.5	1.1	2.9	2.5	2	2.2	1.6	2.5
*A*3	2	2.5	2.5	2.7	2.5	1.5	2.3	2.4	2.6	3

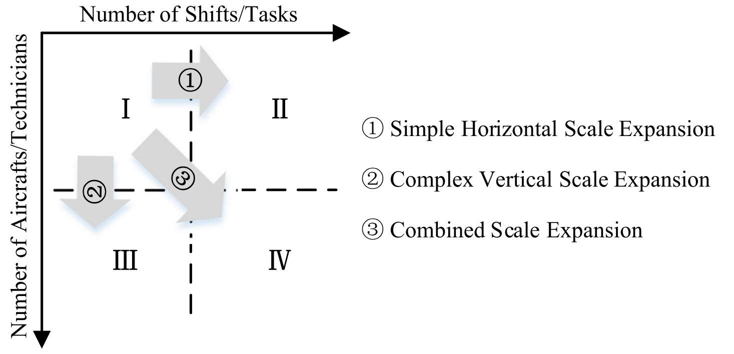

FIGURE 6 Three approaches to expand the scale of the problems [Color figure can be viewed at wileyonlinelibrary.com]

indicate that the results of the IMSBFO algorithm tend to minimize the number of maintenance technicians participating in the same shift. For example, in the first shift, technician *M*9 performs three tasks, and technicians *M*5 and *M*10 perform two tasks, respectively. This arrangement aims to provide as many AMTs as possible for the subsequent shifts and guarantee the rest time of the AMTs who do not participate in the maintenance work of the current shift. This is in line with the needs of improving the efficiency of technician utilization during the enterprise interview.

5.3 | Model-scale analysis

The scale of this model is determined by four dimensions (e.g., aircraft, technician, shift, and task). In Table 3, the ordinate contains aircraft and maintenance technicians, and the abscissa contains shifts and maintenance tasks. Compared with the latter, the number of aircrafts and maintenance technicians directly affects the number of parallel tasks and corresponding technician assignment ability, which is the key factor affecting model complexity. Therefore, considering the expansion of the ordinate and abscissa, we divide the process of problem expansion into three approaches: simple horizontal-, complex vertical-, and combined-scale expansions.

Figure 6 demonstrates how the three-problem scales expand using three arrows. We divide the coordinate system into four distinct regions: I–IV, according to the number of aircrafts/AMTs and shifts/maintenance tasks.

5.3.1 | Analysis of the simple horizontal-scale expansion

The process from region I to II can be represented by comparing (A) and (B), (C) and (D), and (E) and (F) in Figure 4. We find that when the number of aircrafts and AMTs remain unchanged, whereas the number of shifts and maintenance tasks increases, the total cost increases slightly. It is equivalent to the assignment of technicians for a constant number of maintenance tasks. The only difference is the number of shifts and tasks. During the solution process, the constraints will not be changed. Consequently, the fluctuation in the total cost mainly reflects the variation of the manpower cost.

5.3.2 | Analysis of the complex vertical-scale expansion

The process from region Ⅰ to Ⅲ can be represented by comparing (B) and (C), and (D) and (E) in Figure 4. When keeping the number of shifts and tasks constant and increasing the number of aircrafts and maintenance technicians, the total cost becomes larger. It is equivalent to the number of tasks performed in parallel increases; nevertheless, it will face more constraints in technician assignment because of the increase in working AMTs. In addition, if there are not enough maintenance technicians, it will lead to problems, such as unfair workload distribution, overtime work, and so forth, resulting in greater total cost increasement.

5.3.3 | Analysis of the combined-scale expansion

The process from region Ⅰ to Ⅳ can be represented by comparing (A), (C), and (E); (B), (D), and (F) in Figure 4. When the number of aircrafts, AMTs, shifts, and tasks increase, the total cost of the scheduling model will rise to the largest margin. For a larger-scale problem, the optimization process becomes more complex, and it becomes more difficult to find the optimal scheduling solution. At the same time, with the increase in the maintenance technicians and extension of working hours, the manpower cost will increase, and the satisfaction of the technicians and the fairness concern of workload will become more difficult to realize.

6 | CONCLUSIONS AND FUTURE DIRECTIONS

Contrasting from the existing models that ignore the dimension of aircraft when assigning AMTs, this study comes up with a more compassionate scheduling scheme, considering personnel work satisfaction from four dimensions of aircraft, shift, maintenance task, and technician. Thereafter, inspired by the mechanism of interspecific mutual assistance, mutualism, and competition in biology, the IMSBFO algorithm is proposed based on the ideas of multi-swarm coevolution, information interactive mechanism, and structure recombination. Then, we design six different scale experiments to compare the optimization performance of seven algorithms, including IMSBFO. The simulation results imply that compared with other algorithms, the IMSBFO algorithm has a faster convergence speed, stronger optimizing ability, and better adaptability. Through the scale expansion analysis, we find that the increase in total cost caused by the increase number of aircrafts is much higher than that caused by the increase number of shifts and tasks.

In the future, we will further explore the AMT scheduling problem under dynamic maintenance orders. In addition, we will try to design a multi-objective heuristic algorithm based on the IMSBFO and apply it to solve the multi-objective AMT scheduling problem.

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CONFLICT OF INTERESTS

The authors declare that there is no conflict of interests.

AUTHOR CONTRIBUTIONS

Conceptualization: Ben Niu, Tianwei Zhou, and Bowen Xue. *Methodology*: Bowen Xue, Tianwei Zhou, and Mijat Kustudic. *Validation*: Mijat Kustudic. *Formal analysis*: Bowen Xue, Ben Niu, and Tianwei Zhou. *Writing—original draft preparation*: Bowen Xue and Ben Niu. *Writing—review and editing*: Tianwei Zhou. *Project administration*: Tianwei Zhou. *Funding acquisition*: Ben Niu. All authors have read and agreed on the published version of the manuscript.

DATA AVAILABILITY STATEMENT

All relevant data have been placed in the paper.

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