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RESEARCH ARTICLE

A Hybrid Discrete Artificial Bee Colony Algorithm for Imaging Satellite Mission Planning

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ABSTRACT Imaging satellite mission planning has received more and more attention as one of the core problems in the field of imaging satellite applications. In this paper, a hybrid discrete artificial bee colony (HDABC) algorithm is proposed to address this problem. The HDABC algorithm improves the three search phases of the basic artificial bee colony (ABC) algorithm to make them applicable to the discrete satellite mission planning problem. In the employed bee search phase, the population is divided and a multi-strategy search equation mechanism is used to balance the exploration and development of the algorithm. In the following bee search phase, two kinds of neighborhood search operators are designed based on the problem characteristics to further improve the fitness values of the better solutions. In the scout bee search phase, a migration operator and an immigration operator are introduced to improve the fitness values of the worse solutions and promote the exchange of different subpopulations to achieve co-evolution. In the experimental part, orthogonal experimental design is used to determine the appropriate algorithm parameters. Simulation experiments are carried out to test problems of different sizes. The experimental results show that the proposed HDABC algorithm shows good performance.

INDEX TERMS Artificial bee colony algorithm, imaging satellite, mission planning.

I. INTRODUCTION

Imaging satellites usually operate in specific orbits, and when they transit over the observation target, they image the target by carrying spaceborne remote sensors such as visible light, hyperspectral, synthetic aperture radar, and infrared, and store the acquired target image information temporarily in the spaceborne memory. When they transit the ground station, the data will be transmitted down at a selected time, and the data will be processed by relevant departments and then sent to users. Due to its special geographical position, the imaging satellite has the advantages of being free from the restriction of national region and wide observation range, which make it widely used in military, civil and commercial fields. In recent years, with the continuous development of the application of satellite earth observation, on the one hand, the number and types of orbiting imaging satellites are increasing gradually; on the other hand, the demands of users in various fields are constantly increasing, showing complex and diverse characteristics. Therefore, it is necessary to make overall arrangements for imaging satellite resources to meet the needs of users to the maximum extent and improve the utilization rate of satellite resources. As a key supporting technology in the field of satellite application control, imaging satellite mission planning has become an important research direction in space applications. The research on imaging satellite mission planning can provide technical support for engineering practice and has high practical application value.

The imaging satellite mission planning is a typical non-deterministic polynomial hard (NP-Hard) problem [1]. With the increase of the scale of missions and resources, the complexity of solving the problem also rises sharply. At present, the algorithms to solve the problem can be divided into three categories: exact algorithm, heuristic algorithm and intelligent optimization algorithm.

1) Exact algorithm. Han et al. [2] proposed a solution framework based on column generation, whose basic idea is to obtain the optimal solution of relaxation problem by

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using column generation algorithm. Hu et al. [3] established a mixed integer planning model for the multi-satellite collaborative mission planning problem and proposed a branch pricing solution algorithm, in which dynamic planning and heuristic algorithms are designed separately for subproblem solving to accelerate the solution speed. Liu et al. [4] used a multilevel path reduction dynamic planning method to deal with the satellite mission planning problem and obtained optimal solutions in small and medium-sized problems. The exact algorithm can obtain the optimal mission planning scheme by means of mathematical analysis. However, due to its computational complexity, the solution efficiency is low. Especially for large-scale task planning problems, Lagrange relaxation, column generation and branch pricing are needed to disassemble the search space to improve the solution efficiency.

2) Heuristic algorithms. Wang et al. [5] designed a task flexibility factor based on time window length, task duration and task weight, and proposed a heuristic algorithm based on priority and conflict avoidance, supplemented by priority backtracking. Xu et al. [6] designed two types of heuristic factors, priority system benefit and priority opportunity cost, to guide the solution construction. Chen et al. [7] designed a conflict degree heuristic factor with the number and length of time window overlapping periods and task weights, and designed a solution generation algorithm based on time greed and weight greed. The heuristic algorithm is mainly based on the domain knowledge of satellite mission planning to design heuristic factors to guide the construction of solutions. Compared with the exact algorithm, the heuristic algorithm is easy to implement and has high solving efficiency.

3) Intelligent optimization algorithms. Intelligent optimization algorithm, generated by simulating the operation mechanism of natural phenomena, has the characteristics of simple, effective and strong universality. It is one of the most commonly used solving algorithms, such as genetic algorithm [8], [9], tabu search algorithm [10], [11], simulated annealing algorithm [12], [13]and ant colony algorithm [14], [15], which have been widely used in the field of satellite mission planning. Zheng et al. [16] designed iterative rules based on termination algebra and jump conditions by referring to the advantages of dynamic mutation strategy and adaptive mutation strategy, so as to overcome the shortcomings of traditional genetic algorithms, such as easy to fall into local optimization and long solving time. Gao et al. [17] introduced the tabu search method and Metropolis rule into the mutation operation of genetic algorithm to accelerate the convergence speed of the algorithm and improve the probability of finding the optimal solution. Habet et al. [10] mapped the satellite mission planning problem into a constraint satisfaction optimization problem and performed the construction of the taboo search neighborhood by partial enumeration based on insertion trial. Ding et al. [18] proposed a multi-objective variable neighborhood simulated annealing algorithm, designed coding and decoding rules, variable neighborhood search methods, and selection and elimination mechanisms to achieve sliding optimization of the imaging moments of the observation mission, which improves both the completion of the observation mission and the imaging quality. Yu et al. [19] established a satellite mission planning model considering the mission synthesis mechanism and used an improved ant colony algorithm to solve the problem. By inserting Insert search operators into the ant colony algorithm, local optimization was carried out in the optimal solutions of each generation to improve the quality of the solutions.

In general, at present, researchers mostly use intelligent optimization algorithms to solve the problem of satellite mission planning. Classical algorithms such as genetic algorithm, tabu search algorithm and simulated annealing algorithm have been widely used in the field of satellite mission planning, and related researches mainly focus on population structure, neighborhood structure, and escape mode structure [20]. In fact, the above algorithms have natural advantages in solving satellite mission planning problems. Satellite mission planning problem is a kind of typical discrete optimization problem whose solution space is discrete. The main operators of genetic algorithm, tabu search algorithm and simulated annealing algorithm can directly operate on discrete coded solutions to generate new neighborhood solutions. But it should also be noted that the above algorithm also has some limitations. A good intelligent optimization algorithm should have two characteristics: exploration and development. Exploration means that the algorithm jumps out of the local area to search for optimization in the whole solution space to enhance the diversity of solutions. Development refers to optimizing a local area in order to find the best solution. The global optimization ability of genetic algorithm is strong, but the local optimization ability is insufficient. Tabu search algorithm, on the contrary, has strong local optimization ability and weak global optimization ability. As a very effective means to solve optimization problems, intelligent optimization algorithm has been widely concerned by researchers. At present, many advanced intelligent optimization algorithms have been produced, and scholars have tried to apply them to their own research fields and made some beneficial explorations, such as: brain storm optimization [21], differential evolution algorithm [22], biogeography algorithm [23], multi-verse optimizer [24], grey wolf optimizer [25] and Seagull optimization algorithm [26], etc. At the same time, it should be noted that most of the current intelligent algorithms were first proposed for continuous optimization problems, which need to be discretized before they can be applied to discrete optimization problems such as satellite mission planning.

Artificial bee colony (ABC) algorithm is a relatively novel swarm intelligence algorithm, which simulates the intelligent foraging behavior of bee colonies in nature, and has the characteristics of high searching performance and easy implementation. The ABC algorithm is optimized through the employed bee phase, following bee phase and scout bee phase. The employed bees conduct global optimization, and the following bees further develop the better solutions, while the scout bees timely stop the development of the worse solutions. The three phases are interrelated, taking into account the exploration and development of the algorithm. This unique optimization mechanism is widely concerned by researchers. In recent years, many improved versions have been proposed, most of which focus on designing new solution search equations [27], [28], [29], [30], [31], [32]. Peng et al. [27] proposed a solution search strategy guided by the best neighbor to enhance the development ability of ABC algorithm. Zhou et al. [28] proposed an improved ABC algorithm based on multi-elite guidance to achieve a better balance between exploration and development. Inspired by particle swarm optimization algorithm, Zhu and Kwong [29] incorporated the global optimal solution into the solution search equation, with the purpose of utilizing valuable information in the global optimal solution to enhance development.

In order to further expand the application range of artificial bee colony algorithm, researchers improved the basic artificial bee colony algorithm and proposed the discrete artificial bee colony algorithm to successfully apply it to discrete optimization problems, such as multi-sensor resource scheduling problem [33], secondary allocation problem [34], single machine scheduling problem [35], flow shop scheduling problem [36], etc. The calculation results show that compared with other existing intelligent optimization algorithms, the improved discrete ABC algorithm can produce good results in discrete optimization problems. At present, there are not many literatures that use the discrete ABC algorithm to solve the satellite mission planning problem. Therefore, this paper intends to apply the discrete ABC algorithm to solve the imaging satellite mission planning problem.

In this paper, a hybrid discrete artificial bee colony (HDABC) algorithm is proposed for the imaging satellite mission planning problem. HDABC algorithm improves the three search phases of ABC algorithm and discretizes them to make them applicable to the satellite mission planning problem. In the employed bee search phase, the population is divided and a multi-strategy search equation mechanism is used to balance the exploration and development of the algorithm. In the following bee search phase, two kinds of neighborhood search operators are designed based on the problem characteristics to further improve the fitness values of the better solutions. In the scout bee search phase, a migration operator and an immigration operator are introduced to improve the fitness values of the worse solutions and promote the exchange of different subpopulations to achieve co-evolution.

II. MODELING OF IMAGING SATELLITE MISSION PLANNING PROBLEMS

A. SYMBOL DEFINITION

In order to facilitate the description of the problem, the relevant symbol definitions are first given, as shown in table 1.

TABLE 1. Symbols and their meanings.

Symbol	Meaning
$T_{schedule}=[T_s,T_e]$	Planning time period, T_s is the planning start time, T_e is the planning end time.
$S=\{S_1,S_2\cdots S_M\}$	Set of imaging satellites, a total of M satellites.
$Mission=\{m_1,m_2\cdots m_N\}$	Set of imaging tasks, N tasks in total.
$TW_{i,j}^k=\left[tws_{i,j}^k,twe_{i,j}^k\right]$	The kth visible time window of satellite j for mission i, $tws_{i,j}^k$ is the start time of the time window and $twe_{i,j}^k$ is the end time of the time window.
$TS_{i,j}^k=\left[ts_{i,j}^k,te_{i,j}^k\right]$	The actual observation time of satellite j for mission i at the kth visible time window, $ts_{i,j}^k$ is the start time and $te_{i,j}^k$ is the end time.
v_i	Observation benefit for mission i.
dur_i	Observation duration of mission i.
st_{i_1,i_2}	Adjustment time of remote sensors during continuous satellite missions.
td_i	Storage capacity occupied by mission i.
T_j^{free}	Available power-on time of satellite j in the current orbital lap.
D_j^{free}	Available storage capacity of satellite j in the current orbital lap.
x_i^j	Decision variable, if satellite j observes mission i, the value is 1; otherwise, it is 0.

B. PROBLEM DESCRIPTION AND BASIC ASSUMPTIONS

The multi-imaging satellite mission planning problem can be described as the cooperative imaging of N missions by M satellites within a certain planning period. By finding reasonable values of decision variables, the earth observation scheme of the satellite can maximize the earth observation benefits on the premise that all constraints can be satisfied.

In order to facilitate the modeling of the problem, the following reasonable simplifications and basic assumptions are made in this paper based on the consideration of actual satellite systems.

1) The imaging satellites can all work normally during the mission planning cycle.

2) The satellites involved in the planning carry only one on-board remote sensor and have the ability of side swing.

3) The imaging targets are all point targets after processing.

4) Regardless of data transmission mission planning, it is assumed that data transmission resources are sufficient and the satellite has the opportunity to transmit data down and release memory within each orbital lap.

C. CONSTRAINTS ON THE PROBLEM

1) Each mission can be executed at most once.

$$\sum_{j=1}^{M} x_i^j \le 1, \quad \forall i \in Mission \tag{1}$$

2) The actual execution time window of the mission must be within the satellite's visible time window to the target.

$$ts^k_{i,j} \geq tws^k_{i,j}, \quad te^k_{i,j} \leq twe^k_{i,j} \tag{2}$$

3) The same satellite must satisfy the attitude adjustment time constraint for two consecutive missions.

$$te^k_{i1,j} + st_{i1,i2} \leq te^k_{i2,j} \tag{3}$$

4) Energy constraint. The duration of mission observation cannot exceed the available power-on time of satellite in the current orbital lap.

$$x^j_i = \begin{cases} 0, & dur_i > T^{free}_j \\ 1, & dur_i \leq T^{free}_j \end{cases} \tag{4}$$

5) Data storage constraints. The storage capacity occupied by the mission cannot exceed the storage capacity available for satellite's current lap.

$$x^j_i = \begin{cases} 0, & td_i > D^{free}_j \\ 1, & td_i \leq D^{free}_j \end{cases} \tag{5}$$

D. OBJECTIVE FUNCTION

The imaging satellite mission planning problem is a typical multi-objective optimization problem with different optimization objectives for different application scenarios. In this paper, the objective function is designed by considering the mission benefit and the mission completion rate comprehensively as follows.

$$f_1 = (\sum_i^N \sum_j^M x^j_i \times v_i) / \sum_i^N v_i \tag{6}$$

$$f_2 = (\sum_i^N \sum_j^M x^j_i)/N \tag{7}$$

$$f = \alpha \times f_1 + (1 - \alpha) \times f_2 \tag{8}$$

Equation (6) represents the first planning objective: the mission benefit, which is the ratio between the benefit of completed missions and the benefit of total missions. Equation (7) represents the second planning objective: mission completion rate, which is the ratio of the number of completed missions to the total mission number. Equation (8) is the objective function of this paper, which takes the mission benefit and mission completion rate into comprehensive consideration, where α denotes the weight of the first planning objective and satisfies $0 < \alpha < 1$.

III. THE BASIC ABC ALGORITHM

The ABC algorithm is a colony intelligence algorithm that simulates the intelligent foraging behavior of a bee colony. In this algorithm, each honey source represents a feasible solution to the problem, and the bees are divided into employed bees, following bees and scout bees according to their division of labor, corresponding to the three search phases of the algorithm. The bees perform different activities according to their respective division of labor and share information to complete the problem search process. The basic phases are as follows.

A. INITIALIZATION

Assuming that the problem dimension is D, any solution can be represented by a D-dimensional array, e.g., $X_i = (x^1_i, x^2_i, \cdots x^D_i)$. Each dimension of the solution is generated randomly in the search space according to the following equation.

$$x^j_i = x^j_{\min} + r(x^j_{\max} - x^j_{\min}) \tag{9}$$

where $x^j_{\min}$ and $x^j_{\max}$ represent the minimum and maximum values of the jth dimension of the solution, $j = 1, 2 \cdots D$, $i = 1, 2 \cdots N$, N is the population size, and r is a random number and $r \in (-1, 1)$.

B. EMPLOYED BEE PHASE

All employed bees generate a new candidate solution around the current solution according to the following equation.

$$v^j_i = x^j_i + \varphi(x^j_i - x^j_k) \tag{10}$$

where $V_i = (v^1_i, v^2_i, \cdots v^D_i)$ is the newly generated candidate solution, φ is a random number and $\varphi \in (-1, 1)$, and $X_k = (x^1_k, x^2_k, \cdots x^D_k)$ is a randomly selected individual from the population that is different from the current solution. When a new candidate solution is generated, the employed bee evaluates it and updates the current solution if the new solution is better than the current solution, otherwise the current solution is retained.

C. FOLLOWING BEES PHASE

The employed bee shares the information of the nectar source with the following bee after completing the search, and the following bee uses a roulette strategy to select a suitable solution for its exploitation according to the quality of the solution. The selection probability of any solution is calculated according to the following equation.

$$P_i = \frac{fit_i}{\sum_{n=1}^N fit_n} \tag{11}$$

where fit_i is the fitness value of the i th solution. The following bee mines the selected solution by using (10). If the new solution is better than the current one, the current one will be updated; otherwise, the current one will be retained.

D. SCOUT BEE PHASE

The algorithm records the iterations of each solution. when a solution reaches a certain number of iterations and its quality still cannot be improved, the employed bee will be transformed into the scout bee, which will generate a new solution to replace the original individual by using (9).

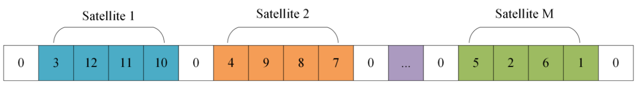

FIGURE 1. Encoding schematic.

IV. HYBRID DISCRETE ARTTIFICIAL BEE COLONY ALGORITHM

The basic ABC algorithm, with its simple structure, easy implementation and fast convergence, has been widely used in optimization problems, but it is still challenged in solving some complex optimization problems. On the one hand, the basic ABC algorithm is stronger than exploration and weaker than development. Intelligent optimization algorithms generally have common characteristics, namely exploration and development. Equation (9) and (10) are the search equations used in the basic ABC algorithm. Equation (10) is to search the current solution neighborhood based on the randomly selected solution, which makes the search blind. Equation (9) is to randomly generate feasible solutions in the solution space, which is a pure exploration behavior. On the other hand, the basic ABC algorithm belongs to numerical optimization algorithm, which is mostly used for solving continuous domain optimization problems. However, in reality, there are a large number of discrete domain optimization problems similar to satellite mission planning. If the search equation in the standard algorithm is directly applied, a large number of illegal solutions will be generated, and it takes a lot of time to legalize the solutions.

Based on the above analysis, this paper proposes the HDABC algorithm to solve the satellite mission planning problem. The HDABC algorithm improves the three search phases of the basic ABC algorithm and discretizes it to make it applicable to the satellite mission planning problem.

A. ENCODING AND DECODING

The integer encoding mechanism of satellite-mission, which is more intuitive to the solution expression, is used to solve the satellite mission planning problem. For a satellite mission planning problem with M satellites and T imaging missions, the encoding of one of the feasible solutions is shown in Fig. 1. The whole code is composed of different satellite segments. A certain satellite segment is the imaging missions undertaken by the satellite. The number 0 is used to distinguish different satellite segments.

The coding mode of satellite-mission does not directly specify a specific observation window for a specific mission, but the actual observation window is specified during decoding. The specific operation mode is as follows:

Take out the number of the current mission and the number of the satellite executing the mission, traverse all observation windows of the current mission on the current satellite, and conduct constraint detection in turn. If an observation window meets all constraints, specify the corresponding window for the mission and set its decision variable as 1, and then arrange the next mission. If all windows fail to pass the constraint detection, then the mission cannot be completed and its decision variable is set to 0. After traversing all the missions on the current solution, the fitness value of the solution is calculated according to the decision variables of each mission, namely the objective function value.

B. INITIALIZATION

A sequence containing T task numbers is randomly generated, and a random balanced allocation strategy is adopted to determine the satellite segment to which the task belongs, that is, each satellite segment performs at least $(T//M)$ missions, and then $(T - M(T//M))$ satellite segment is randomly selected, and the number of missions performed by these satellite segments is $((T//M) + 1)$.

C. IMPROVED EMPLOYED BEE SEARCH PHASE

The multi-strategy search equation mechanism is used to improve the employed bee search phase of the basic ABC algorithm, taking into account the exploration and development of the algorithm.

1) MULTI-STRATEGY SEARCH EQUATION MECHANISM

The basic ABC algorithm uses (10) to search around the current solution in the employed bee phase. Equation (10) modifies the current solution by randomly selecting an individual in the population. Therefore, searching by (10) has randomness, which is suitable for exploration but not conducive to development. In fact, the information of elite solutions in the population can often provide some guidance for the search of the current solution. For example, in particle swarm optimization algorithm, particles can effectively improve their own fitness value by tracking the best solution of individual history and the best solution of the population. Many researchers have modified the search equation of the basic ABC algorithm based on this point, mainly emphasizing the use of population optimal and elite solutions to enhance the exploitation capability of the algorithm. It should be noted that although the use of optimal and elite solutions can improve the search efficiency and facilitate exploitation, it can also weaken the diversity of the population and lead to premature convergence of the algorithm. To balance the exploration and development of the algorithm, the multi-strategy search equation mechanism is used in the employed bee search phase.

(1) Random search mechanism. The random search strategy should make the algorithm explore the whole search space, and the search equation should have strong exploration ability. In this paper, the search equation of the basic ABC algorithm is modified by using (12) [37].

$$v_i^j = x_{r1}^j + \varphi(x_{r1}^j - x_{r2}^j) \tag{12}$$

where $X_{r1} = (x_{r1}^1, x_{r1}^2, \cdots x_{r1}^D)$ and $X_{r2} = (x_{r2}^1, x_{r2}^2, \cdots x_{r2}^D)$ are two different individuals randomly selected from the population and both different from the current solution X_i, φ is the guiding factor, and $\varphi \in (0, 1)$, and $V_i = (v_i^1, v_i^2, \cdots v_i^D)$ is the updated individual. Thus the equation has the opportunity to be explored in any direction, which is beneficial to the diversity of the population.

(2) Search mechanism based on the maximum access level. In this search mechanism, a memory function is introduced for the employed bees. The employed bees no longer randomly select the solution in the population to update the current solution. Each employed bee sets the access level for nectar sources other than its own. The longer a source has not been visited, the higher its access level, and the more likely the employed bee will choose that source to update the current source. If there are nectar sources with the same access level, the source with the higher fitness value will be chosen. The search equation is modified as follows.

$$v_i^j = x_i^j + \varphi(x_s^j - x_i^j) \tag{13}$$

where $X_s = (x_s^1, x_s^2, \cdots x_s^D)$ is the solution with the highest access level and the highest fitness value, and the other parameters have the same meaning as in (12).

(3) Search mechanism based on optimal solution guidance. Inspired by the idea of individual tracking the extremum of the swarm in particle swarm optimization algorithm, the employed bee has the ability to find the global optimal solution and update the current solution under the guidance of the optimal solution. The search equation is modified as follows.

$$v_i^j = x_i^j + \varphi(x_{best}^j - x_i^j) \tag{14}$$

where $X_{best} = (x_{best}^1, x_{best}^2, \cdots x_{best}^D)$ is the global optimal solution and the other parameters have the same meaning as in (12).

In order to solve the drawback that single search equation exploration and exploitation could not be combined, a multi-strategy search equation mechanism is introduced. Accordingly, in order to apply the above search mechanism, the island model is adopted, and the population is divided into class I, class II, and class III islands according to the individual fitness values, with a ratio of 3:4:3. For class I island, the search mechanism based on optimal solution guidance is used to focus on exploitation and improve the convergence speed and accuracy. For class II island, the search mechanism based on the maximum access level is used to give consideration to exploration and development, which has a good convergence effect and a certain ability to jump out of the local optimal. For class III island, random search mechanism is adopted to explore emphatically and maintain the diversity of the population.

2) SEARCH EQUATION DISCRETIZATION

The above search equations are mainly used in continuous space optimization problems. If they are directly applied to discrete optimization problems such as satellite mission planning, a large number of illegal solutions will be generated. Therefore, this paper redefines the operators in the equation to discretize the search equation [38]. The search equations all have the structure of $v_i^j = x_i^j + \varphi(y_i^j - x_i^j)$, and the relevant operators are redefined as follows.

$$m_i^j = \varphi(y_i^j - x_i^j) \quad \forall j = 1 \dots D \tag{15}$$

$$m_i^j = \begin{cases} mutation(x_i^j) & if\ \varphi < rand \\ y_i^j & if\ \varphi \geq rand \end{cases} \tag{16}$$

$$v_i^j = multi\_point\_crossover(x_i^i, m_i^i) \quad \forall j = 1 \dots D \tag{17}$$

where $mutation(x_i^j)$ is a variation operation, which means the current mission randomly exchanges its position with another task, φ is a bootstrap factor, and $\varphi \in (0, 1)$, and $multi\_point\_crossover(x_i^i, m_i^i)$ is a multi-point crossover operation. m_i^j and v_i^j are generated involving the replacement of some elements in x_i^j. The mission number in this paper is unique, and directly performing the above operation will result in the same mission number in the solution. Therefore, when executing the replacement operation, we first examine whether the replaced task a is the same as the replaced task b in x_i^i. If not, we find the location of task a in x_i^i and copy task b to that location, and then execute the replacement operation afterwards.

D. IMPROVED FOLLOWING BEE SEARCH PHASE

After the employed bee search phase, the following bee uses a roulette to select the solutions for secondary development. In this paper, two kinds of neighborhood search operators are designed based on the characteristics of the problem, namely mission insertion/replacement within the satellite segment and mission replacement between the satellite segments. These two neighborhood search operators are executed successively for the selected solutions.

1) MISSION INSERTION/REPLACEMENT WITHIN SATELLITE SEGMENT

The satellite segments of the current solution are traversed. In a certain satellite segment, the uncompleted missions whose value of the decision variable is 0 are found, and the missions are sorted from largest to smallest according to the observation benefit. Take out missions successively. If the mission has no observation window on the satellite, the position of the mission will not be changed. If there are observation windows, the windows will be investigated in turn. If the mission can be inserted into an observation window without conflict, that is, the insertion of the mission does not affect the execution of its adjacent missions, then the observation window is assigned to it and it is placed in the corresponding position. If none of the windows can insert the mission without conflict, then the arranged missions affected by the mission in each observation window will be evaluated. Assuming that the benefit of the mission is v_1 and the benefit of the missions that cannot be executed in a certain window due to the insertion of the mission is v_2, then the observation window with the maximum positive value of $v_1 - v_2$ is designated for the task and the task is placed in the corresponding position. If neither of the above is possible, the position of the mission within the current satellite segment is not changed.

2) MISSION REPLACEMENT BETWEEN SATELLITE SEGMENTS

After the current solution has undergone the neighborhood search operator based on mission insertion/replacement within the satellite segment, the fitness value of the solution will be further improved. At this time, there are two kinds of missions that have not been executed in each satellite segment. The mission has no observation window on the current satellite, or there is a large overlap between the observation window of the mission and the observation window of the currently executed missions. In these two cases, it is difficult for the unexecuted missions to be executed in the current satellite segment, and the mission replacement operator between satellite segments is executed. The specific operation is to take out the unexecuted missions in each satellite segment to form a mission pool, and each satellite segment in turn randomly selects the unexecuted missions from other satellite segments.

E. IMPROVED SCOUT BEE SEARCH PHASE

In the basic ABC algorithm, the solutions that reach a certain number of iterations and the quality cannot be improved are removed in the scout bee search phase, and new solutions are randomly generated in the solution space by using (9). Although this is beneficial to exploration, the quality of the new solution cannot be guaranteed because it is randomly generated. For complex high-dimensional discrete optimization problems, the quality of the new solution generated randomly at the late stage of evolution is also difficult to be improved in a short time. Therefore, the scout bee search phase is redesigned by introducing the migration operator and the immigration operator. By carrying out the migration operation and the immigration operator after every G iteration, on the one hand, the low-quality solution is improved, and on the other hand, the communication between the islands is promoted to achieve co-evolution.

The migration operator is one of the main operators of the biogeography-based optimization (BBO) algorithm. It is carried out among all solutions, so that different solutions can share information. Different from the BBO algorithm, this paper has divided the population into three types of islands. Different from the biogeography optimization algorithm, this paper has divided the population into three types of islands. Since the purpose of migration operation is to improve the quality of inferior solutions through high-quality solutions, the migration operation between islands in this paper is unidirectional, that is, class I island migrates to class II island, and class II island migrates to class III island. When performing the migration operation, it is necessary to first calculate the immigration rate λ_k and emigration rate μ_k of individuals. It should be noted that the migration operation defined in this paper takes place between different types of islands, so the calculation of the immigration rate and emigration rate are relative to a certain type of island. In this paper, In this paper, a hyperbolic tangential deformation mobility model [39] which matches the migration law of species in nature is adopted to calculate the immigration rate and emigration rate. The calculation method is as follows.

$$\lambda_k = \frac{I}{2} \cdot (-\frac{e^{(k-n/2)} - e^{(-k+n/2)}}{e^{(k-n/2)} + e^{(-k+n/2)}} + 1) \tag{18}$$

$$\mu_k = \frac{E}{2} \cdot (\frac{e^{(k-n/2)} - e^{(-k+n/2)}}{e^{(k-n/2)} + e^{(-k+n/2)}} + 1) \tag{19}$$

where, I and E are the defined maximum immigration rate and emigration rate, n is the maximum number of species on a certain type of island, k is the number of species on the current island of this type, and k=n-i, and i is the fitness ranking of the island on its type of island. Taking the migration from class II to class III islands as an example, firstly, the individual X_i is selected from class III islands by using (18); secondly, the individual Y_k is selected from class II islands by using the roulette method according to (19); finally, (20) is used to update the individual X_i.

$$z_i^j = x_i^j + \varphi(y_k^j - x_i^j) \tag{20}$$

where $Z_i = (z_i^1, z_i^2, \cdots z_i^D)$ is the updated individual. This paper does not use the individual renewal equation of the basic BBO algorithm, but uses the equation similar to the employed bee search phase to achieve the renewal of individuals with poor fitness value.

Islands with poor overall fitness value in evolution, such as class III islands, may produce relatively potential solutions, but the search equation adopted by them is of great randomness. Such random search is difficult to develop a better solution than the current solution, or even produce a solution of no use value. In order to further develop this type of solution and to facilitate the exchange between different islands, an immigration operator is introduced in this paper, that is, class III islands transport the best individual of this type islands to class II islands and replace any non-optimal individual from class II islands. Similarly, class II islands transport the best individuals of this type islands to class I islands and replace any non-optimal individuals from class I islands.

F. FLOW OF HYBRID DISCRETE ARTIFICIAL BEE COLONY ALGORITHM

The general flow of the hybrid discrete artificial bee colony algorithm is obtained based on the above description as follows.

step1: Set the population size N, the maximum number of iterations MaxG, the guiding factor φ, the number of iterations between executing the scout bee search phase, initialize the population, calculate the fitness value of the initial population, and classify each individual in the population into three types of islands according to the fitness value, and let the number of iterations g=1.

step2: If the number of iterations g is greater than MaxG, output the optimal solution.

step3: The employed bees uses a multi-strategy search equation mechanism to generate new solutions, and replaces the current solution when the new solution is better than the current solution.

step4: The following bees use roulette rule to select the better solution to execute the neighborhood search operator.

step5: Determine whether to carry out the scout bee search phase. If so, go to step6; if not, go to step7

step6: The scout bees implement the migration operator and the immigration operator to improve the poor solution and promote the communication between different islands.

step7: Let g=g+1, calculate the fitness value of each solution, record the global optimal solution, go to step2.

G. ANALYSIS OF THE ALGORITHM COMPLEXITY

In the standard ABC algorithm, it mainly includes the following key operations: parameter setting, population initialization, employed bee search phase, following bee search phase and scout bee search phase. Let the population size be N, the maximum number of iterations be $T_{\max}$, and both the number of employed bees and the number of following bees be N. The time complexity of the three search phases is $O(N)$. Then, the total time complexity of the algorithm is $O(3T_{\max}N)+O(N)+O(1)$, where, $O(3T_{\max}N)$ is the time complexity of $T_{\max}$ iterations of the three search stages, $O(1)$ is the time complexity of parameter setting, and $O(N)$ is the time complexity of population initialization. In the HDABC algorithm designed in this paper, the main phases that affect the time complexity are the improved employed bee search phase and the improved scout bee search phase. In the improved employed search phase, the population is divided into three parts and three search strategies are performed respectively. In the improved scout bee search phase, the scout bee search phase runs every G generation, which reduces the time complexity compared to the original scout bee search phase. Suppose the population numbers of the three populations are N_1, N_2 and N_3 respectively, and meet $N_1 + N_2 + N_3 = N_{pop}$, then the total time complexity of the HDABC algorithm can be calculated as $O(T_{\max}(2N_{pop} + N_{pop}//G)) + O(N_{pop}) + O(1)$. It can be seen that the main difference between the time complexity of the HDABC algorithm and the standard ABC algorithm is the population size, and both are at the same quantity level. Therefore, the HDABC algorithm does not improve the solving effect at the cost of improving the time complexity.

In terms of space complexity, the main factor that leads to the difference between the storage space required by HDABC algorithm and standard ABC algorithm is also population size. Assume that the standard ABC algorithm requires N storage space, and the HDABC algorithm requires N_{pop} storage space. Generally speaking, the population size of the HDABC algorithm is larger than that of the standard ABC algorithm because it adopts three search mechanisms, but the spatial complexity of the two algorithms is still at the same quantity level, so the HDABC algorithm has little influence on the spatial complexity of the standard ABC algorithm.

TABLE 2. Orbital parameters of the seed satellite.

SA	E	I	RAAN	AP	TA
7103.14	0	98.295	20.714	0	0

TABLE 3. Levels of each parameter.

Parameter	Parameter level			
	1	2	3	4
N	40	80	120	160
φ	0.2	0.4	0.6	0.8
G	5	10	15	20

V. SIMULATION EXPERIMENT

At present, there is no recognized test set for imaging satellite mission planning. In this paper, random task generation is adopted to verify the algorithm. A Walker constellation consisting of 12 imaging satellites is established. The satellites adopt sun-synchronous orbits and are evenly distributed in 4 orbital planes. The satellite's position in space is defined by six orbital parameters: semimajor axis (SA), eccentricity (E), inclination (I), right ascension of the ascending node (RAAN), Argument of periapsis (AP), and true anomaly (TA). The orbital parameters of the seed satellite are shown in Table 2.

A total of 6 image missions are set, and the mission sizes are 100, 150, 200, 250, 300 and 400 respectively. All missions are randomly generated in the range of $70^{\circ}S \sim 70^{\circ}N$, $180^{\circ}W \sim 180^{\circ}E$, and the mission benefit is randomly generated in the range of 1 to 10. The start time of the simulation scenario is 12 Oct 2022 04:00:00 (UTCG) for one day.

A. DETERMINATION OF ALGORITHM PARAMETERS

The HDABC algorithm involves three relatively important parameters, the population size N, the guiding factor φ and the interval generation G, all of which can affect the operation effect of the algorithm. With the increase of population size, the profit value obtained by the algorithm gradually increases. However, the increase of the profit brought by too large population size is not obvious, and the optimization time of the algorithm will be increased. For the guiding factor φ, if it is too small, the current solution will lack the guidance of the elite solution, the randomness of search is large, and the convergence effect is not good; if it is too large, the current solution will inherit too much information from the elite solution, but at the same time it will sacrifice the diversity of the population. For the interval algebra G, if it is too small, the migration operator and the immigration operator are executed too frequently, which will increase the running time of the algorithm and affect the operation of the search mechanism of the island itself; if it is too large, it is not conducive to the spread of island population diversity, the improvement of the poor solution and the development of the better solution.

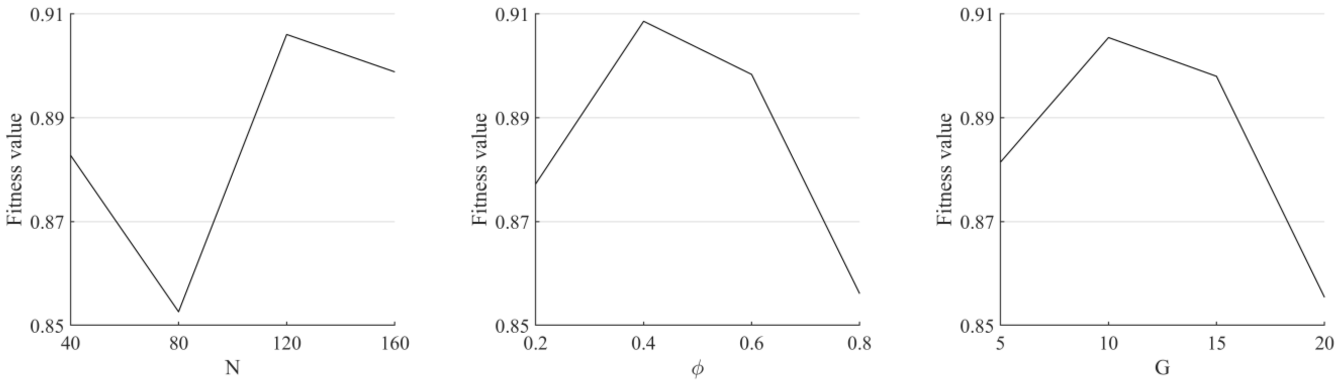

FIGURE 2. Trend graph of fitness values at different parameter levels.

TABLE 4. Results of the orthogonal experiment.

	Parameter level			fitness value
Trial number	N	φ	G	
1	1	1	1	0.867
2	1	2	2	0.916
3	1	3	3	0.930
4	1	4	4	0.818
5	2	1	2	0.903
6	2	2	1	0.849
7	2	3	4	0.836
8	2	4	3	0.821
9	3	1	3	0.896
10	3	2	4	0.924
11	3	3	1	0.914
12	3	4	2	0.889
13	4	1	4	0.843
14	4	2	3	0.945
15	4	3	2	0.912
16	4	4	1	0.896

In this paper, the maximum number of iterations is set to 500, the task size is 200, and the other parameters have 5 levels as shown in Table 3, which are determined by experimental design. The orthogonal experiment layout $L_{16}(4^5)$ with two dummy parameters is selected for the experimental analysis of 3 parameters and 5 levels, and the experimental results are shown in Table 4.

Controlling a fixed level of a variable, the fitness values under that level are averaged as the fitness value of the algorithm under that variable. The influence of this variable level on the fitness value of the algorithm is drawn, as shown in Fig.2. Based on the results of this experiment, the population size N is taken as 120, the guiding factor φ is taken as 0.5, and the interval generation G is taken as 10.

B. ALGORITHM COMPARISON

The algorithms in this paper are tested on problems of different scales with the discrete artificial bee colony algorithm (DABC), the improved genetic algorithm (IGA) [17], and the improved discrete particle swarm algorithm (IDPSO) [40], respectively. Each algorithm is run 20 times on each problem scale to record the best fitness value (BF) and the average fitness value (AF), and the results are shown in Table 5. From Table 5, When the problem scale is small, satellite resources are relatively sufficient, and all the four algorithms are capable of finding a better planning scheme. When the problem scale gradually increases, satellite resources become strained and the conflict between missions gradually increases. At this time, the difference between the four algorithms' searching ability gradually appears. In general, the HDABC algorithm achieves better best fitness values and average fitness values than the other three algorithms for six problem sizes. In terms of average fitness values, as the problem size increases, the HDABC algorithm achieves average fitness values that are 6.3%, 7.4%, 9.5%, 16.9%, 19.2%, and 22.3% higher compared to the DABC algorithm; 3.7%, 4.4%, 5.6%, 6.6%, 9.3%, and 12.7% higher compared to the IGA algorithm; 1.3%, 1.5%, 2.8%, 4.1%, 5.5%, and 8.7% higher compared to IDPSO. In terms of the best fitness value, the HDABC algorithm achieves best fitness values that are 4.9%, 7.2%, 9.3%, 16.1%, 18.9% and 20.7% higher compared to the DABC algorithm; 2.9%, 4.4%, 5.3%, 6.3%, 9.1% and 11.3% higher compared to the IGA algorithm; 0, 1.4%, 2.3%, 3.8%, 5.2% and 7.8% higher compared to IDPSO. It can be seen that with the increase of problem scale, the advantages of HDABC algorithm are more obvious than other algorithms.

In order to demonstrate the statistical significance of the experimental results, the average fitness values obtained by the HDABC algorithm are statistically tested with the average fitness value obtained by the other three algorithms at the 95% confidence level, and the results are shown in Table 6. It can be seen from Table 6 that p values of different scales are all less than 0.05, indicating significant differences between algorithms. With the increase of the problem scale,

TABLE 5. The results of algorithm comparison experiment.

Problem scale	HDABC		DABC		IGA		IDPSO	
	BF	AF	BF	AF	BF	AF	BF	AF
100	1.000	1.000	0.951	0.937	0.971	0.963	1.000	0.987
150	0.977	0.969	0.906	0.897	0.934	0.926	0.963	0.954
200	0.942	0.922	0.854	0.834	0.892	0.870	0.920	0.896
250	0.915	0.889	0.763	0.739	0.856	0.830	0.879	0.852
300	0.870	0.832	0.705	0.672	0.791	0.754	0.825	0.786
400	0.772	0.721	0.612	0.560	0.685	0.632	0.712	0.658

TABLE 6. Statistical tests at 95% confidence level.

Problem scale	HDABC-DABC		HDABC-IGA		HDABC-IDPSO	
	Z	p-value	Z	p-value	Z	p-value
100	2.065	0.040	2.013	0.045	1.961	0.049
150	2.113	0.036	2.052	0.041	2.023	0.043
200	2.162	0.031	2.093	0.037	2.061	0.039
250	2.223	0.027	2.132	0.333	2.110	0.035
300	2.271	0.023	2.184	0.030	2.142	0.032
400	2.312	0.020	2.212	0.027	2.195	0.029

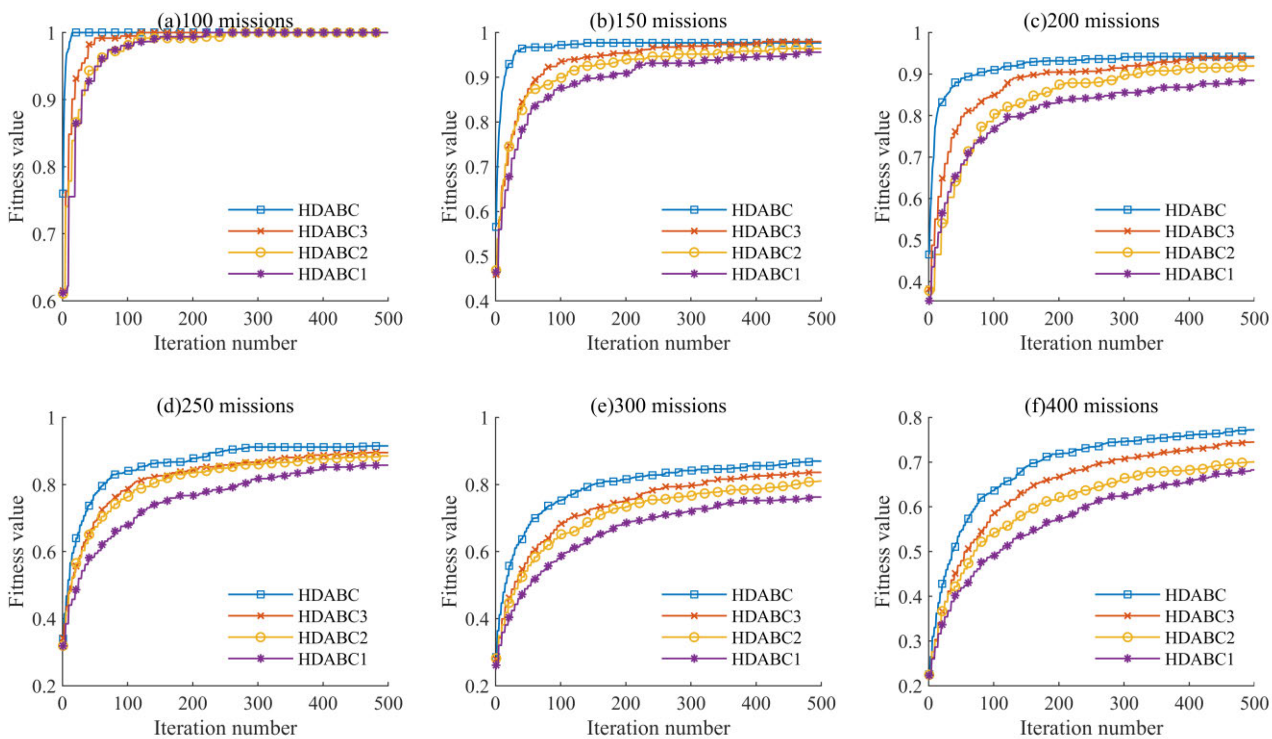

FIGURE 3. Comparison of HDABC algorithm using different strategies.

the differences among algorithms also increase, which further confirms the good performance of the HDABC algorithm in solving the imaging satellite mission planning problem studied in this paper.

C. ANALYSIS OF ALGORITHM VALIDITY

The HDABC algorithm, the hybrid discrete artificial bee colony algorithm without multi-strategy search equation mechanism (HDABC1), the hybrid discrete artificial bee colony algorithm without two kinds of neighborhood search operators (HDABC2), and the hybrid discrete artificial bee colony algorithm without migration and immigration operators (HDABC3) are respectively run in the six scale problems, and the results are shown in Fig.3. As can be seen from Fig.3, when the problem size is small, all the four algorithms can achieve good planning results. With the increase of the scale of the problem, the advantages of HDABC algorithm are gradually highlighted. Its optimal solution and convergence are better than the other three algorithms, and the other three algorithms all fall into the local optimal value due to different degrees of premature convergence. In summary, the three improvement strategies have influence on algorithm performance from large to small: the multi-strategy search equation mechanism, the neighborhood search strategy, migration operator and an immigration operator. Therefore, the design of three strategies in the HDABC algorithm can take into account the exploration and development of the algorithm, make it out of the local optimal solution, and further improve the performance of the algorithm.

VI. CONCLUSION

Aiming at the problem of mission planning for imaging satellite, a mission planning model for imaging satellite is established by considering the mission benefit and the mission completion rate comprehensively, and a HDABC algorithm is proposed to solve the model. The HDABC algorithm improves the three search phases of the standard ABC algorithm and discretized it to make it suitable for satellite mission planning. In the employed bee search phase, the multi-strategy search equation mechanism is used to explore and develop the algorithm. In the following bee search phase, two neighborhood search operators are designed based on the problem characteristics. In the scout bee search phase, a migration and an immigration operator are introduced to improve the fitness values of poor solutions and promote the communication of different subpopulations. Experimental results show that the proposed algorithm has certain advantages in solving satellite mission planning problems.

Facing the future, imaging satellite mission planning still has a lot of research content worth paying attention to. As for the imaging mission itself, it shows the characteristics of large scale, multi-type and dynamic arrival. On the one hand, the increase in users of various types of satellites will inevitably bring about a large number of multi-type imaging tasks, such as visible, hyperspectral and radar images. How to combine multi-type imaging satellites for mission planning is worth discussing. On the other hand, in the actual mission planning, some urgent imaging missions may arrive at any time, and these urgent imaging tasks often need to be executed in a short time. For this kind of task, heuristic method is used to adjust the planning scheme. However, when the dynamic arrival of the task becomes normal, this method will make the existing scheme be modified repeatedly, resulting in a sharp decline in the optimization of the scheme.

We believe that distributed satellite mission planning may provide a way to solve the above problems. At present, satellite mission planning mostly belongs to ground centralized planning. This kind of planning requires a ground control center with all the satellite information. After completing the mission planning based on the status of the in-orbit satellite, the ground control center sends the instructions to the satellites, and the satellites complete the relevant actions according to the instructions. In the future, with the smooth communication link and the development of intelligent satellites, distributed satellite mission planning may be widely used. In the distributed satellite mission planning, the satellites first realize the reasonable assignment of missions through negotiation, and then the satellites can call the planning algorithm according to their own state to carry out reasonable planning of their own missions. Distributed satellite mission planning has advantages in dealing with large scale, multi-type and dynamic arrival imaging missions. On the one hand, the imaging missions has been decomposed to the level of single satellite, which greatly reduces the difficulty of solving. On the other hand, satellites can receive missions in real time and plan them online, which is suitable for handling missions that arrive dynamically. However, the implementation of distributed satellite mission planning is based on efficient intersatellite and satellite-ground communication links, which may not be available at the present stage. But we can make some useful exploration and do some valuable work in satellite negotiation model and mission planning algorithms.

REFERENCES

[1] N. G. Hall and M. J. Magazine, "Maximizing the value of a space mission," *Eur. J. Oper. Res.*, vol. 78, no. 2, pp. 224–241, Oct. 1994, doi: 10.1016/0377-2217(94)90385-9.

[2] C. Han, X. Wang, G. Song, and R. Leus, "Scheduling multiple agile Earth observation satellites with multiple observations," 2018, *arXiv:1812.00203*.

[3] X. Hu, W. Zhu, B. An, P. Jin, and W. Xia, "A branch and price algorithm for EOS constellation imaging and downloading integrated scheduling problem," *Comput. Oper. Res.*, vol. 104, pp. 74–89, Apr. 2019, doi: 10.1016/j.cor.2018.12.007.

[4] Z. Liu, Z. Feng, and Z. Ren, "Route-reduction-based dynamic programming for large-scale satellite range scheduling problem," *Eng. Optim.*, vol. 51, no. 11, pp. 1944–1964, Nov. 2019, doi: 10.1080/0305215x.2018.1558445.

[5] P. Wang, G. Reinelt, P. Gao, and Y. Tan, "A model, a heuristic and a decision support system to solve the scheduling problem of an earth observing satellite constellation," *Comput. Ind. Eng.*, vol. 61, no. 2, pp. 322–335, Sep. 2011, doi: 10.1016/j.cie.2011.02.015.

[6] R. Xu, H. Chen, X. Liang, and H. Wang, "Priority-based constructive algorithms for scheduling agile earth observation satellites with total priority maximization," *Expert Syst. Appl.*, vol. 51, pp. 195–206, Jun. 2016, doi: 10.1016/j.eswa.2015.12.039.

[7] X. Chen, G. Reinelt, G. Dai, and A. Spitz, "A mixed integer linear programming model for multi-satellite scheduling," *Eur. J. Oper. Res.*, vol. 275, no. 2, pp. 694–707, 2019, doi: 10.1016/j.ejor.2018.11.058.

[8] L. H. Mao, Q. Deng, R. N. Liu, and X. L. Kong, "A critical path genetic algorithm for multi-star simulation scheduling," *J. Syst. Simul.*, vol. 33, no. 1, pp. 205–214, May 2021, doi: 10.16182/j.issn1004731x.joss.19-0301.

[9] L. Zhao, S. Wang, Y. Hao, and Y. Wang, "Energy-dependent mission planning for agile Earth observation satellite," *J. Aerosp. Eng.*, vol. 32, no. 1, Jan. 2019, Art. no. 04018118, doi: 10.1061/(asce)as.1943-5525.0000949.

[10] D. Habet, M. Vasquez, and Y. Vimont, "Bounding the optimum for the problem of scheduling the photographs of an agile Earth observing satellite," *Comput. Optim. Appl.*, vol. 47, no. 2, pp. 307–333, Nov. 2008, doi: 10.1007/s10589-008-9220-7.

[11] A. Sarkheyli, A. Bagheri, B. Ghorbani-Vaghei, and R. Askari-Moghadam, "Using an effective Tabu search in interactive resources scheduling problem for LEO satellites missions," *Aerosp. Sci. Technol.*, vol. 29, no. 1, pp. 287–295, Aug. 2013, doi: 10.1016/j.ast.2013.04.001.

[12] X. Wang, Y. Gu, G. Wu, and J. R. Woodward, "Robust scheduling for multiple agile Earth observation satellites under cloud coverage uncertainty," *Comput. Ind. Eng.*, vol. 156, Jun. 2021, Art. no. 107292, doi: 10.1016/j.cie.2021.107292.

[13] L. He, X. Liu, G. Laporte, Y. Chen, and Y. Chen, "An improved adaptive large neighborhood search algorithm for multiple agile satellites scheduling," *Comput. Oper. Res.*, vol. 100, pp. 12–25, Dec. 2018, doi: 10.1016/j.cor.2018.06.020.

[14] C. Yang, Q. R. Zhou, and H. Wang, "Study of modeling and optimization algorithms for multi-satellite multitasking assignment problems," *Aerosp. Control. Appl.*, vol. 48, no. 5, pp. 39–46, Oct. 2022.

[15] W. Zhu, X. Hu, W. Xia, and H. Sun, "A three-phase solution method for the scheduling problem of using Earth observation satellites to observe polygon requests," *Comput. Ind. Eng.*, vol. 130, pp. 97–107, Apr. 2019, doi: 10.1016/j.cie.2019.02.014.

[16] Z. Zheng, J. Guo, and E. Gill, "Swarm satellite mission scheduling & planning using hybrid dynamic mutation genetic algorithm," *Acta Astronaut.*, vol. 137, pp. 243–253, Aug. 2017, doi: 10.1016/j.actaastro.2017.04.027.

[17] X. Gao, Y. Guo, G. Ma, H. Zhang, and W. Li, "Agile satellite autonomous observation mission planning using hybrid genetic algorithm," *J. Harbin Inst. Technol.*, vol. 53, no. 12, pp. 1–9, Oct. 2021.

[18] Y. N. Ding, Y. B. Liu, S. Y. Wang, and C. J. Lei, "A multi-target variable-neighborhood simulated annealing algorithm and mission planning method for imaging constellations," *J. Astronaut.*, vol. 43, no. 12, pp. 1686–1695, Dec. 2022.

[19] J. Yu, W. Y. Yang, X. L. Liu, and L. L. Xing, "Imaging satellite intensive mission synthesis method and its scheduling algorithm," *J. Huazhong Univ. Sci. Technol.*, vol. 49, no. 10, pp. 73–78, Jun. 2021, doi: 10.13245/j.hust.211012.

[20] X. X. Hu, W. Xia, P. Jin, and W. M. Zhu, *Mission planning Theory and Methods for Imaging Satellites*. Beijing, China: Science Press, 2021, pp. 16–21.

[21] L. B. Ma, S. Cheng, and Y. H. Shi, "Enhancing learning efficiency of brain storm optimization via orthogonal learning design," *IEEE Trans. Syst., Man, Cybern., Syst.*, vol. 51, no. 11, pp. 1–20, Nov. 2021, doi: 10.1109/TSMC.2020.2963943.

[22] K. Yu, J. Liang, B. Qu, Y. Luo, and C. Yue, "Dynamic selection preference-assisted constrained multiobjective differential evolution," *IEEE Trans. Syst., Man, Cybern., Syst.*, vol. 52, no. 5, pp. 2954–2965, May 2022, doi: 10.1109/TSMC.2021.3061698.

[23] H. Ren, C. Guo, R. Yang, and S. Wang, "Fault diagnosis of electric rudder based on self-organizing differential hybrid biogeography algorithm optimized neural network," *Measurement*, vol. 208, Feb. 2023, Art. no. 112355, doi: 10.1016/J.MEASUREMENT.2022.112355.

[24] M. Yaghoubi and A. Maroosi, "Simulation and modeling of an improved multi-verse optimization algorithm for QoS-aware web service composition with service level agreements in the cloud environments," *Simul. Model. Pract. Theory*, vol. 103, Sep. 2020, Art. no. 102090, doi: 10.1016/j.simpat.2020.102090.

[25] S. Ayub, S. M. Ayob, C. W. Tan, S. M. Arif, M. Taimoor, L. Aziz, A. L. Bukar, Q. Al-Tashi, and R. Ayop, "Multi-criteria energy management with preference induced load scheduling using grey wolf optimizer," *Sustainability*, vol. 15, no. 2, p. 957, Jan. 2023, doi: 10.3390/SU15020957.

[26] P. Krishnadoss, V. Poornachary, P. Krishnamoorthy, and L. Shanmugam, "Improvised seagull optimization algorithm for scheduling tasks in heterogeneous cloud environment," *Comput., Mater. Continua*, vol. 74, no. 2, pp. 3166–3173, Oct. 2022, doi: 10.32604/CMC.2023.031614.

[27] H. Peng, C. Deng, and Z. Wu, "Best neighbor-guided artificial bee colony algorithm for continuous optimization problems," *Soft Comput.*, vol. 23, no. 18, pp. 8723–8740, Sep. 2019, doi: 10.1007/s00500-018-3473-6.

[28] X. Zhou, J. Lu, J. Huang, M. Zhong, and M. Wang, "Enhancing artificial bee colony algorithm with multi-elite guidance," *Inf. Sci.*, vol. 543, pp. 242–258, Jan. 2021, doi: 10.1016/j.ins.2020.07.037.

[29] G. Zhu and S. Kwong, "Gbest-guided artificial bee colony algorithm for numerical function optimization," *Appl. Math. Comput.*, vol. 217, no. 7, pp. 3166–3173, Dec. 2010, doi: 10.1016/j.amc.2010.08.049.

[30] B. Akay and D. Karaboga, "A modified Artificial Bee Colony algorithm for real-parameter optimization," *Inf. Sci.*, vol. 192, no. 1, pp. 120–142, Apr. 2012, doi: 10.1016/j.ins.2010.07.015.

[31] H. Peng, C. Wang, Y. Han, W. Xiao, X. Zhou, and Z. Wu, "Micro multi-strategy multi-objective artificial bee colony algorithm for microgrid energy optimization," *Future Gener. Comput. Syst.*, vol. 131, pp. 59–74, Jun. 2022, doi: 10.1016/J.FUTURE.2022.01.011.

[32] X. Zhou, Z. Wu, H. Wang, and S. Rahnamayan, "Gaussian bare-bones artificial bee colony algorithm," *Soft Comput.*, vol. 20, no. 3, pp. 907–924, 2016, doi: 10.1007/s00500-014-1549-5.

[33] W. Liu, C. Liu, X. Guo, S. He, and L. Fan, "Solving the multisensor resource scheduling problem for missile early warning by a hybrid discrete artificial bee colony algorithm," *J. Sensors*, vol. 2022, pp. 1–16, Oct. 2022, doi: 10.1155/2022/5094415.

[34] Z.-Y. Peng, Y.-J. Huang, Y.-B. Zhong, N. Jiang, R. Khaled, and W.-W. Li, "A discrete artificial bee colony algorithm for quadratic assignment problem," *J. High Speed Netw.*, vol. 28, no. 2, pp. 131–141, May 2022, doi: 10.3233/JHS-220684.

[35] J. Jia, C. Lu, and L. Yin, "Energy saving in single-machine scheduling management: An improved multi-objective model based on discrete artificial bee colony algorithm," *Symmetry*, vol. 14, no. 3, p. 561, Mar. 2022, doi: 10.3390/SYM14030561.

[36] H. Li, X. Li, and L. Gao, "A discrete artificial bee colony algorithm for the distributed heterogeneous no-wait flowshop scheduling problem," *Appl. Soft Comput.*, vol. 100, Mar. 2021, Art. no. 106946, doi: 10.1016/j.asoc.2020.106946.

[37] W.-F. Gao, S.-Y. Liu, and L.-L. Huang, "A novel artificial bee colony algorithm based on modified search equation and orthogonal learning," *IEEE Trans. Cybern.*, vol. 43, no. 3, pp. 1011–1024, Jun. 2013, doi: 10.1109/TSMCB.2012.2222373.

[38] M. Masdari, S. Barshande, and S. Ozdemir, "CDABC: Chaotic discrete artificial bee colony algorithm for multi-level clustering in large-scale WSNs," *J. Supercomput.*, vol. 75, no. 11, pp. 7174–7208, Jun. 2019, doi: 10.1007/s11227-019-02933-3.

[39] Y. P. Wang, Z. J. Zhang, Z. H. Yan, and Y. Z. Jin, "Biogeography optimization algorithm based on improved mobility model," *J. Comput. Appl.*, vol. 39, no. 9, pp. 2511–2516, May 2019.

[40] Y.-A. Fan and C.-K. Liang, "Hybrid discrete particle swarm optimization algorithm with genetic operators for target coverage problem in directional wireless sensor networks," *Appl. Sci.*, vol. 12, no. 17, p. 8503, Aug. 2022, doi: 10.3390/APP12178503.

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