Research and Realization of Grouping Collection Algorithm of Infrared Cage Heating Circuit for Spacecraft Vacuum Thermal Test

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Abstract. In the process of spacecraft thermal test, the infrared cage is mainly used to simulate the heat flow outside the space. In the design, the infrared cage is divided into several heating zones corresponding to the spacecraft. The heating strip of the infrared cage is divided into heating circuits, the heating circuits are grouped and collected, and the infrared cage heating node table is defined as an important basis for controlling the infrared cage. At present, there is a single method of grouping and gathering heating circuits, which is mostly limited by manual adjustment based on experience and lack of automation. In order to solve the shortcomings of the existing technology, this paper adopts the genetic algorithm hybrid BFD based on reinforcement learning to group and collect the heating circuits, and optimize the design results according to the constraints. The user interaction interface is designed to facilitate the user to do further analysis. Thereby improving the level of business automation, optimizing working procedures and reducing costs.

1. Introduction
The vacuum thermal environment test can effectively check the reliability of spacecraft products and plays a very important role in the spacecraft development process. During the thermal test of the spacecraft, the infrared cage is mainly used to simulate the heat flow outside the space[1]. In the design, the infrared cage is divided into several heating zones corresponding to the spacecraft. The heating strip of the infrared cage is divided into heating circuits, the heating circuits are grouped and collected, and the infrared cage heating node table is defined as an important basis for controlling the infrared cage. In the design process, various factors such as the capacity of the main plug, the length of the transition cable, and the number of power supplies used need to be considered. The current method is mainly based on personal experience to manually design, lack of automation, and easily cause a waste of resources.

In order to solve the shortcomings of the current technology, this paper uses the genetic hybrid BFD (Descending Best Adaptation Algorithm) algorithm based on reinforcement learning to replace the manual electric equipment design. By setting the corresponding initial parameters of the genetic algorithm, using the reinforcement learning method, the optimal genetic algorithm parameters are automatically learned according to the entropy index, and combined with the BFD method for grouping and pooling, so as to obtain the optimal result. In addition, the user interaction interface is completed through MATLAB GUI (Graphical User Interface), and the process of cyclically running the packing algorithm is designed in the main program. Before each run, the user manually enters
2. Solutions and data modeling

2.1. Solution
According to the grouping and collection of infrared cage heating circuits, the design of infrared cage electrical installation can be simplified into a one-dimensional packing problem. Taking into account the characteristics of the NP (complete) problem in the boxing problem, when the scale of the problem gradually increases, the phenomenon of "combination explosion" will occur when the traditional search technology is used to solve this type of problem[2].

After investigating and comparing solutions to the one-dimensional packing problem, this article uses a hybrid GA-BFD algorithm to solve the problem of grouping and gathering of infrared cage heating circuits. At the same time, by further introducing RL (Reinforcement learning) to optimize the GA algorithm, it solves the problems of premature convergence and slow convergence of traditional genetic algorithms. The multi-strategy selection genetic algorithm based on reinforcement learning can increase the diversity of the population, effectively avoid the problem of premature convergence of the genetic algorithm, and combine the diversity of the population with the operation mechanism of the algorithm, so as to maintain the diversity of the population in an appropriate range. Improve the adaptability and generalization ability of genetic algorithm[3]. According to the above-mentioned problem description, the heating loop grouping algorithm algorithm adopts modular design, thereby increasing the reliability, flexibility and subsequent scalability of the system. It mainly includes the following functional modules:

- **Data formatting module**: This functional module is mainly responsible for formatting input and output files. According to the effective heating circuit information, the input and output data are processed in a predetermined format.
- **Model analysis module**: This functional module is mainly responsible for the analysis and classification of problem models, and pre-packing processing using adaptive algorithms, so as to generate effective items and box models.
- **Genetic algorithm module**: This functional module is mainly responsible for effectively providing a basic solution set for solving the packing problem through genetic coding and mathematical optimization methods based on the processed box data and item data.
- **Reinforcement learning modules**: This functional module is responsible for further control of the genetic algorithm parameters using the neural network reinforcement learning method to obtain the optimal genetic algorithm parameters, so that the packing result can maximize the performance index.
- **Human-computer interaction module**: The function module mainly provides a graphical user interface for users, generates corresponding formatted file output, and provides the numerical relationship between related parameters and output results.

2.2. Data modeling
According to the grouping and collection of the infrared cage heating circuit, the corresponding problem description is given:

When the constraints are met, the weight combination of the total number of heating cables used and the cable length should be as few as possible. The constraint condition is that the upper limit of the total capacity of each loop combination is 15, that is, the capacity of each box is 15. According to the problem description, the following optimization problem model is established.

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- Known constant $C = \{C_1, C_2, \ldots, C_n\}$ is the loop set. Each constant $C_i$ contains spatial position information (center point position, angle, height), as well as the number of loops and the zone where the loop is located.
• Variable $B = \{B_1, B_2, \ldots, B_m\}$ is the collection of all boxes (plugs).
• The variable $P_0 = \begin{cases} 1, & C_i \text{ is in } B_j \\ 0, & C_i \text{ is not in } B_j \end{cases}$ is the current loop packing situation.

Further describe the objective function of the problem: $\min M$ means the total number of plugs is the least, $\min L$ represents the shortest cable length.

The optimization goal can be expressed as: $P = a \cdot (\text{Number of boxes}) + (1-a) \cdot (\text{Total cable length})$, among them, $a$ is the adjustment coefficient of the objective function.

The algorithm input is the information of all heating circuits, including all heating circuit spatial location information (X, Y, Z), zone information (such as A zone, B zone, etc.), as shown in Figure 1.

3. Hybrid GA-BFD Algorithm

The hybrid GA-BFD algorithm combines the advantages of the GA algorithm and the BFD algorithm, and uses the BFD algorithm to introduce a local search process to find the local optimal solution corresponding to each individual in the current environment, so as to achieve the purpose of improving the overall performance of the group. The feasible solution range of GA algorithm is further reduced, and the packing result is obtained. After using the above-mentioned decoding process on the chromosome encoding string, the packing scheme shown conforms to the idea of approximate algorithm, and the sum of the volume of each box does not exceed its prescribed volume. As the scale of the problem expands, the search space for optimization problems expands sharply, and sometimes it is difficult or even impossible to get the exact optimal solution using enumeration on current computers. For such complex problems, genetic algorithm is one of the best tools to find such satisfactory solutions. The main steps of the decoding process of the hybrid GA-BFD algorithm can be described as follows:

• Step 1: Items are arranged in descending order of size;
• Step 2: Use genetic algorithm to solve, get a better solution;
• Step 3: Use the BFD idea to further optimize the solution.

The characteristics of this hybrid genetic algorithm are mainly reflected in the following two aspects:

• A partial search process is introduced. Based on the phenotype corresponding to each individual in the group, a local search is performed to find the local optimal solution corresponding to each individual in the current environment, so as to achieve the purpose of improving the overall performance of the group.
• Increase the code conversion operation process. For the local optimal solutions obtained in the local search process, they are transformed into new individuals through the encoding process, so that the next generation of genetic evolution operations can be performed based on a new population with better performance.

| Block name (representing area) | Algorithm input data |
|--------------------------------|----------------------|
| Partitions name (representative) | Heating circuit name | Spatial location center | Heating circuit resistance |
| AI-1                          | AI-1-1               | X | Y | Z |
| AI-2                          | AI-2-1               | 0.98 | 0.413 | -0.354 | 8.6Ω |
| AI-3                          | AI-2-2               | 0.657 | 0.856 | -0.354 | 8.6Ω |
| AI-4                          | AI-3-1               | 0.43 | 0.99 | -0.354 | 8.6Ω |
| AI-4                          | AI-3-2               | 0.657 | 0.856 | -0.354 | 8.6Ω |

Figure 1. Figure with short caption (caption centred).
4. RLGA-BFD algorithm

The Reinforcement Learning (RL), also known as Reinforcement Learning, Evaluation Learning, or Reinforcement Learning, is one of the paradigms and methodologies of machine learning, used to describe and solve the problem of how agents interact with the environment through learning Strategies to maximize returns or achieve specific goals. On the basis of the hybrid GA-BFD algorithm, by further introducing RL to optimize the GA algorithm, the problem of premature convergence and slow convergence speed of traditional genetic algorithms is solved. The multi-strategy selection genetic algorithm based on reinforcement learning can increase the diversity of the population and effectively avoid the premature convergence problem of genetic algorithm. Combine the diversity of the population with the operating mechanism of the algorithm, thereby maintaining the diversity of the population in an appropriate range, and improving the adaptability and generalization ability of the genetic algorithm, as shown in Figure 2-4.

5. Algorithm design and implementation

For the boxing problem, generally speaking, the fitness function is transformed from the objective function. The fitness function in this algorithm is the total cable length and the total number of plugs. The goal is to minimize the number of boxes used and the total cable length.

Most of the traditional multi-objective optimization problems are transformed into a single objective to measure the diversity of the solution, and the obtained diversity value is often not accurate enough. Research on the diversity of multi-objective optimization function solutions, the method currently adopted is to evaluate the distribution degree of frontier solutions with Pareto property. Generally, the more uniform the solution distribution, the better the diversity of the solutions obtained. In this paper, the method of information entropy is used to measure the diversity of solutions, combined with reinforcement learning to dynamically determine the parameters of the genetic algorithm, and further optimize the solution, thereby improving the packing performance.

The descending best fit algorithm is used to calculate the fitness function of the genetic algorithm. It arranges the items in descending order according to certain rules and puts them into the feasible box with the smallest remaining capacity. If the current item cannot be put into any initialized box, put it in a new box. The algorithm introduces a local search process to find the local optimal solution corresponding to each individual in the current environment, so as to achieve the purpose of improving the overall performance of the group and further reduce the range of feasible solutions of the genetic algorithm.

Furthermore, the reinforcement learning is used to cooperate with the genetic algorithm and the descending optimal adaptation algorithm, and the reinforcement learning is trained in advance, and the best genetic algorithm crossover rate and mutation rate value are obtained by the method of finding the maximum entropy population. Under this value, the diversity of genetic algorithms can be guaranteed, the performance of genetic algorithms can be optimized, and the "premature" problem that is common...
in typical genetic algorithms can be solved. That is, individuals in the population lose their diversity prematurely in the iteration, resulting in slow convergence or convergence to a local extreme in the later stage of evolution, which affects the performance of the algorithm.

5.1. Software interface
In order to facilitate the user’s operation of the software, a user interaction interface is designed using MATLAB GUI. The process of cyclically running the packing algorithm is designed in the main program. Before each run, the user manually enters different parameters. At the end of the run, the statistical results of the evolution process are output through the dialog box, which is convenient for the user to do further analysis. To start basic operation, the program needs to be initialized first. The initialization work includes obtaining input data and algorithm parameters, calculating chromosome byte length, allocating data space, initializing random number generator and generating initial population, and outputting initial generation statistics. Then optimize the boxing to calculate the fitness, selection probability and cumulative probability, and get the final result.

5.2. Test Results
The test data has a total of 813 heating circuits, and each circuit information includes structure information, circuit name, spatial coordinate information, etc. Set the relevant parameters in the user interface, the software will optimize according to the designed packing algorithm, get the corresponding result, and output the specified file location. The output result is shown in screenshot 6. The test data has a total of 813 heating circuits, and each circuit information includes structure information, circuit name, spatial coordinate information, etc. Set the relevant parameters in the user interface.

6. Conclusions
According to the above results, the automatic grouping problem of heating circuits, as a kind of packing problem, has important research value. Based on the latest research results, this paper further conducts theoretical discussion and methodological research on the main issues of the intelligent hybrid heuristic algorithm in the boxing problem method, proposes a new intelligent boxing algorithm, and has achieved good experimental results, mainly including the following content:

- **Aiming at the packing problem, the BFD method and basic genetic algorithm are introduced into the research field of packing problem, and through program simulation, it is verified that this idea is effective for solving the packing problem.**

- **On the basis of the basic genetic algorithm, the reinforcement learning algorithm is integrated, and the algorithm automatically finds the optimal population through machine learning, thereby improving the generalization ability and adaptability of the algorithm, and is more optimized than the basic genetic algorithm when solving the box-packing problem. Many of them have high practicability. This kind of research ideas and methods provide a good reference experience and reference basis for the research of other complex problems.**
• Use Matlab GUI programming to realize the application program based on the user's visual input and output. It has a good user interface and high portability, which makes the system have a certain practical application prospect.

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