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Collaborative Task Allocation Problem in Laboratory Equipment Maintenance in Universities

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Abstract. Given the increasing demand for laboratory equipment management in universities, especially the increasingly complex equipment management, the traditional equipment management system can no longer meet the management needs of universities. Therefore, it is very important to optimize the university's equipment management system. The allocation of laboratory equipment maintenance tasks in the laboratory equipment management system of universities is a very critical link. Its effective solution is crucial to ensure the normal operation of laboratory equipment and the reasonable allocation of maintenance resources. This study proposes a double coding adaptive genetic algorithm to optimize the allocation of laboratory equipment maintenance tasks in universities to achieve the optimal allocation of resources and minimize maintenance costs. The work allocation scheme is iteratively optimized by a dual-coding strategy and definition of adaptive crossover and mutation operators. The experimental results of this study show that the algorithm can find the approximate optimal task allocation scheme within a reasonable time, which improves the efficiency and accuracy of laboratory equipment maintenance. In addition, compared with the traditional allocation method, the algorithm in this paper shows stronger flexibility and robustness when dealing with large-scale complex problems.

Key words: GA, laboratory equipment maintenance, task allocation,universities, DCA_GA

1. Introduction

With the continuous development of modern scientific research, the frequency and complexity of laboratory equipment in universities are increasing. The stable operation of laboratory equipment not only directly affects the smooth progress of teachers' and students' experiments, but also the accuracy of experimental results, and involves the coordinated progress of multiple research teams and experimental projects. Moreover, the maintenance tasks of laboratory equipment are usually complex and diverse, involving multiple links and collaboration between multiple university departments. Therefore, equipment maintenance is particularly important.

This study investigated and analyzed several Chinese universities and found that there are two main methods for laboratory equipment maintenance: manual recording

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and information management. When teachers and students find equipment abnormalities, they report to the laboratory administrator, who manually records the maintenance needs and assigns the corresponding maintenance tasks based on experience. This method often seems inadequate when faced with a large number of equipment and complex collaborative maintenance needs. The information management method has indeed changed the way laboratory administrators work, and they no longer need to manually record maintenance information. Since maintenance tasks need to match the skills of maintenance personnel, improper allocation may lead to increased maintenance time and error risks. In addition, if capable maintenance personnel are not fully utilized, maintenance tasks may be delayed. Combined with these problems, it will hurt the overall operating efficiency of the laboratory. A good task allocation and scheduling method becomes very important.

Therefore, this study hopes to determine the constraints of equipment maintenance task allocation and resource scheduling based on the actual characteristics of university laboratory equipment maintenance and design a reasonable maintenance task allocation method to optimize the university laboratory equipment management system and shorten the maintenance task execution time.

2. Related Work

Before introducing the work proposed in this paper, related research on the collaborative task allocation problem in laboratory equipment maintenance is first conducted to provide the necessary background and reference. In this section, this study reviews the existing equipment maintenance task allocation methods, aiming to describe the impact of different allocation strategies on equipment maintenance efficiency and management costs.

2.1. Method for Allocating Equipment Maintenance Tasks in Universities

Task allocation is also called assignment problem [1]. Task allocation method refers to the rules that should be followed or the methods adopted when allocating tasks [2]. In terms of laboratory equipment maintenance, combined with the survey of surrounding schools and relevant literature, the following three maintenance task allocation methods can be summarized:

a. Manual decision-making

Many schools usually rely on laboratory administrators or relevant personnel to make manual decisions when equipment fails. That is, when the equipment fails, the laboratory manager or relevant personnel repairs it through the maintenance master they contacted. Although this method is flexible, it is easily affected by personal experience and judgment, which may lead to inefficient maintenance or improper selection.

b. Simple scheduling tools

Some university laboratories use spreadsheets or documents to record and track maintenance tasks. These tools help administrators view the maintenance history of equipment, current task status, and future maintenance plans.

c. Introduction of information platforms

With the development of information technology, more and more schools have begun to adopt information platforms to manage equipment maintenance. References [3] proposed to manage equipment through information technology. Literature [4][5] proposed to design a laboratory equipment management system. When laboratory equipment fails, the user (such as a laboratory technician or teacher) fills in relevant information through the system, such as the equipment name, fault type, and occurrence time. The laboratory administrator logs in to the platform to review the fault information. According to the fault description, the laboratory administrator fills in the maintenance task order. At this time, the platform only records and manages the task order and checks the list of maintenance personnel. One solution is that the administrator contacts the maintenance personnel. The administrator contacts the maintenance personnel through the maintenance personnel contact information displayed on the platform to communicate the maintenance time and requirements. The maintenance personnel arrives at the site for maintenance. After the maintenance is completed, the laboratory administrator updates the platform maintenance task status and records the maintenance content. Another solution is that the maintenance personnel log in to the platform to view the tasks by themselves. That is, the maintenance personnel need to log in to the platform regularly to view the pending maintenance tasks, select appropriate tasks, and arrange the maintenance time by themselves.

The above allocation method has obvious shortcomings. For example, when faced with complex equipment failures and diverse maintenance needs, manual decision-making makes it difficult to make reasonable judgments quickly, which leads to delays in maintenance tasks and idle equipment; simple scheduling tools can easily miss or record maintenance information incorrectly; information management frees laboratory managers from manual and simple scheduling methods, but still stays on simple query and summary work, often unable to fully consider complex task requirements and maintenance personnel's skills. Therefore, these allocation methods make it difficult to effectively optimize maintenance task allocation. To solve these problems, it is very necessary to study the task allocation problem in "equipment maintenance" in university laboratories. The maintenance task allocation problem will be described in detail below.

2.2. Description of the Equipment Maintenance Task Allocation Problem in Colleges and Universities

With the rapid development of computer technology, the complexity of tasks to be processed in production is getting higher and higher. It is an inevitable trend for multiple maintenance personnel to cooperate to complete a task [6]. The maintenance tasks of university laboratory equipment usually consist of multiple continuous maintenance processes. Especially for complex laboratory equipment, the maintenance process has a strict operation sequence and clear time requirements. Only when all technicians involved in maintenance across disciplines and departments work together in accordance with the standardized maintenance plan can they ensure the normal operation of the equipment and achieve collaborative maintenance, thereby maximizing the use of laboratory resources.

When equipment in university laboratories needs maintenance, collaborative maintenance tasks need to be considered when executing this maintenance process. For example, a computer storing important data in the laboratory has a hard disk failure. First, the maintenance process of the computer is decomposed into two tasks: replacing the hard disk and recovering data. Then the maintenance plan is implemented under a unified maintenance standard. Finally, the tasks are assigned to the corresponding maintenance personnel according to the required skills, that is, the task of replacing the hard disk of this computer equipment is assigned to the hardware maintenance personnel, and the maintenance tasks of data recovery and backup are assigned to data recovery experts. Through collaborative cooperation, computer maintenance tasks are completed to ensure data integrity and normal operation of the system. However, in equipment maintenance, there are usually many maintenance personnel who have the skills to repair a certain task at the same time. Therefore, in the process of dividing equipment maintenance into subsets according to maintenance tasks, this paper considers the skills of maintenance personnel as the target and establishes a 0-1 integer programming model under the constraint of time. Assume that a certain equipment needs maintenance, which is divided into n maintenance task subsets to be completed, the formula is expressed as: $\{n_1,n_2,..n_n\}$, there is m maintenance personnel, the formula is expressed as $\{m_1,m_2...m_m\}$. Different subsets of tasks for the same equipment are assigned to maintenance personnel with matching skills, thus completing collaborative maintenance.

3. Methods

3.1. Model Building

Different from the general task allocation problem, due to the urgency of laboratory equipment maintenance tasks, it is not required that each maintenance personnel be assigned a task, nor is it limited to assigning a maintenance personnel to only one task. The mathematical model of laboratory equipment maintenance tasks can be described as follows:

Assume that a certain equipment contains a subset of n maintenance tasks and there are m maintenance personnel in the logistics department. Let T_{ij} represent the time required for maintenance personnel i to complete task j. X is the task allocation matrix. When maintenance personnel i performs task j, $X_{ij}=1$, otherwise the task is performed by others. The objective function means finding the solution with the shortest time to complete all tasks in the allocation solution.

$$\text{Minimize } F = \sum_{j=1}^{n} \sum_{i=1}^{m} X_{ij}T_{ij} \tag{1}$$

The task allocation target in formula (1) must satisfy the following constraint (formula 2). This constraint means that each task needs to be completed by someone, and only one person is required to complete it.

$$\sum_{i=1}^{m} X_{ij} \text{ , } X_{ij} \in \{0,1\} \quad {}_{i=1,2,\ldots,n} \tag{2}$$

3.2. Problem Analysis

The 0-1 integer programming model is a classic model in operations research and is widely used in various optimization problems [7]. In this model, each variable can only take 0 or 1, which usually represents two choices of decision, such as whether to select a task or resource. This problem is usually used to describe some discrete decision problems, such as task allocation and scheduling problems. Literature [7] pointed out that the existing solutions include:

Traditional exact solutions. For example, complete enumeration method, dynamic programming method, backtracking method, etc. This type of method is suitable for small-scale problems. The solution space of task allocation problem is n^m. It is not feasible to use this type of method to find the optimal solution because the calculation is too large and unrealistic.

Approximate algorithms. For example, greedy algorithms. These algorithms are based only on the current local information and do not consider the global information of the overall problem. In this way, some potentially better solutions may be ignored because they need to make a seemingly bad choice at the current stage. Greedy algorithms are usually used when the problem is small in scale or simple in structure, and the local optimal solution is close to the global optimal solution.

Intelligent optimization algorithm. It is the most widely used method for solving task allocation problems. Intelligent algorithms generally solve optimization problems, including genetic algorithms, ant colony algorithms, simulated annealing algorithms, etc. Genetic algorithms can solve approximate optimal solutions in complex spaces, so they are applied by many scholars to task allocation and scheduling [8].

3.3. Design of Double-Encoding Adaptive Genetic Algorithm

Literature [9] proposed a genetic algorithm to solve the problem of equipment repair task allocation. However, traditional genetic algorithms often have problems such as complex coding, high randomness in the selection of the initial population, and easy precocity. Therefore, the adaptive genetic algorithm proposed in the literature [10] is superior to the traditional genetic algorithm in terms of accuracy and convergence speed. Literature [11] proposed a two-dimensional coding method that can effectively reduce redundant search/solution space compared to the traditional one-dimensional coding method.

These studies are all improved based on genetic algorithms, and the optimization effect has been improved to a certain extent, but all of them are based on the objective function of the given task cost or the shortest time. When allocating laboratory equipment maintenance tasks in colleges and universities, there are many types of equipment and complex technologies, involving multiple professional fields. Therefore, in addition to considering the maintenance time, it is also necessary to pay attention to the professional knowledge of maintenance personnel. Therefore, this study aims to minimize the total completion time of the task and the professional ability of maintenance personnel based on the characteristics of laboratory equipment maintenance in colleges and universities. A Double Encoding Adaptive Genetic Algorithm (DEA_GA) is proposed. Firstly, a double chromosome encoding strategy is used to deal with task allocation and maintenance personnel skills to solve the problem of complex coding of traditional genetic algorithms; secondly, to solve the problem that GA is prone to fall into local optimality, the crossover rate and mutation rate are dynamically adjusted during the algorithm operation; finally, the algorithm is used to solve the problem of collaborative task allocation of equipment maintenance in university laboratories.

a. Double Encoding Method

Most of the traditional genetic algorithms use single chromosome encoding, that is, the gene sequence of an individual represents the distribution of tasks, and each individual is a task-to-personnel arrangement. There are multiple task points, which are randomly arranged to form a sequence, and breakpoints are added to the sequence to represent different tasks or resource allocations. When the breakpoints are inserted at inappropriate positions, the solution with high fitness will be destroyed, destroying the optimal solution for task allocation. The dual encoding strategy represents the solution as two chromosomes, which represent the task allocation chromosome and the maintenance personnel skill chromosome respectively. Suppose there is an equipment maintenance allocation problem with three tasks T1, T2, T3, T4, and T5, and three maintenance personnel W1, W2, and W3 with the required skills need to be allocated. Each maintenance personnel can have specific skills, and the skill chromosome is represented by 0 and 1, where 1 means that the skill is possessed and 0 means that the skill is not possessed (as shown in Figure 1). This strategy runs each chromosome independently, thereby providing a larger solution space and search capability, while better adapting to changes in the problem.

$$\begin{bmatrix} 10010 \\ 01001 \\ 00100 \end{bmatrix} \qquad \begin{bmatrix} 11010 \\ 01111 \\ 10101 \end{bmatrix}$$

Task allocation chromosome Skill chromosome

Figure 1. Double coding chromosomes

b. Fitness Function

The design of the fitness function is based on the objective function. Usually in minimization problems, the fitness function is inversely proportional to the objective function value, that is, the smaller the objective value, the higher the fitness. Therefore, the fitness function is constructed as shown in Formula 3:

$$\text{fitness} = \frac{1}{1 + \sum_{j=1}^{n} \sum_{i=1}^{m} X_{ij} T_{ij}} \tag{3}$$

This design ensures that the fitness function is positive and inversely proportional to the target value. The smaller the target value, the larger the fitness value, which is conducive to finding a solution that minimizes the objective function.

c. Initial Population Generation

Normally, the population size N is 30 individuals. A set of 2*N task allocation schemes is randomly generated. The fitness value of each task allocation scheme is evaluated using formula (1), and the fitness values are sorted. The first 30 individuals with higher fitness are selected to form the initial population.

d. Genetic Operators

(1) Selection operator

This paper chooses Roulette Wheel Selection, which is a probabilistic selection method in which the probability of each individual being selected is proportional to its fitness value. In other words, individuals with higher fitness values have a greater probability of being selected.

(2) Adaptive crossover and mutation operator

The adaptive crossover operator dynamically adjusts the crossover probability according to the fitness of individuals in the population, with the goal of exploring more solution spaces. For individuals with higher fitness, the crossover probability can be reduced to reduce the possibility of destroying high-quality gene combinations. For individuals with lower fitness, the crossover probability can be increased to increase the chance of new individuals appearing, thereby increasing diversity and avoiding premature convergence of the population. This article introduces the improved crossover operator formula from the literature [12] as follows:

$$p_c = \begin{cases} p_{c\_min} + \left(\frac{1}{1+e^{-(\bar{f}-f_{max})}}\right) * (p_{c\_max} - p_{c\_min}) & \text{if } f_{max} \geq \bar{f} \\ p_{c\_max} & \text{if } f_{max} < \bar{f} \end{cases} \tag{4}$$

The purpose of using the adaptive mutation operator in this study is to maintain the diversity of individuals to avoid falling into the local optimum and to avoid excessive mutations that cause low fitness. For individuals with high fitness, the mutation probability is reduced to protect high-quality gene individuals from being destroyed. For individuals with low fitness, the mutation probability is increased to increase the diversity of individuals, which helps to jump out of the local optimal solution. This paper introduces the improved mutation operator formula of the literature [12] as follows:

$$p_m = \begin{cases} p_{m\_min} + \left(\frac{1}{1+e^{-(\bar{f}-f_{max})}}\right) * (p_{m\_max} - p_{m\_min}) & \text{if } f_{max} \geq \bar{f} \\ p_{m\_max} & \text{if } f_{max} < \bar{f} \end{cases} \tag{5}$$

In formula (4), p_{c_max} and p_{c_min} are the upper and lower limits of the crossover probability. In formula (5), p_{m_max} and p_{m_min} are the upper and lower limits of the mutation probability. f_{max} is the highest fitness in the previous population, and is the average fitness of the current population. f_i is the fitness of individual i. According to the description in the literature [12], the algorithm has the best performance when p_{c_max}=0.8, p_{c_min}=0.08, p_{m_max}=0.1, p_{m_min}=0.02.

4. Simulation Experiments and Discussions

Assume that a device in a university's laboratory in China breaks down. The device has a subset of 7 maintenance tasks (tasks 1 to 7) that must be completed as soon as possible to ensure normal use of teaching and scientific research. There are 5 maintenance personnel (maintenance personnel 1 to 6). The time cost matrix of the task is shown in Table 1. The numbers represent the time to perform the task, the 1 in the brackets represents the skill to perform the task, and the blank indicates that the task cannot be performed.

In order to verify the correctness of the improved algorithm, this paper uses the exhaustive method, genetic algorithm and DEA_GA to conduct experiments on the above cases, and obtains that the shortest maintenance time is 35. This consistency shows that the DEA_GA algorithm is theoretically correct and can find the optimal solution.

Further analysis shows that as the problem size increases, the calculation time of the algorithm also increases accordingly. The data provided in Table 2 illustrates the average computation time for problems of different sizes. These data not only confirm the usefulness of the DEA_GA algorithm in solving these problems, but also demonstrate its significant scalability and efficiency advantages when dealing with larger-scale problems.

Table 1. Task time cost matrix

People/Task	1	2	3	4	5	6	7
1	30(1)	40(1)	36(1)	18(1)	15(1)	18(1)	
2	40 (1)	43 (1)	33 (1)	15 (1)		38 (1)	39 (1)
3	47 (1)		52 (1)	25 (1)	11 (1)	35 (1)	10 (1)
4	61 (1)	64 (1)		37 (1)	28 (1)		49 (1)
5		22 (1)	13 (1)	15 (1)	46 (1)	70 (1)	61 (1)
6	16(1)		81(1)		54(1)	73(1)	31(1)

Table 2. Comparison of simulation results of different algorithms

Problem size (Number of people * number of tasks)	Exhaustive search time	GA time	DEA_GA
6*7	55.8ms	80.33ms	79.95ms
6*10	13788ms	98.28ms	95.17
10*10	10^6 (Estimated by 6*10)	99.45ms	96.62ms

Observation results show that compared with traditional genetic algorithms and exhaustive methods, the calculation time of the DEA_GA algorithm increases sharply with the increase in problem size, showing a non-linear growth trend. In contrast, the time required for the DEA_GA algorithm to solve the problem increases relatively slowly, indicating its superiority and stability when dealing with the increase in problem size. Especially when the problem size reaches the order of 6 × 10, the computing time advantage of this algorithm begins to appear significantly, and as the problem size further expands, this advantage becomes more prominent.

5. Conclusion

In this study, by designing dual coding, adaptive crossover, and mutation operators, the DEA_GA algorithm can iteratively search and optimize the allocation plan for laboratory equipment maintenance tasks. Experimental results show that the DEA_GA algorithm can not only find an approximately optimal solution within a reasonable time but also significantly improve the efficiency and accuracy of laboratory equipment maintenance. In addition, compared with traditional allocation methods, this algorithm shows greater flexibility and robustness when dealing with large-scale and complex problems.

In summary, this study confirms the practicability and efficiency of the DEA_GA algorithm in laboratory equipment maintenance task allocation and provides a solid theoretical and practical foundation for the use of genetic algorithms in a wider range of practical applications in the future. As the size of the problem increases, the advantages of the DEA_GA algorithm will become more obvious, making it an ideal choice for solving large-scale complex optimization problems.

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