Multi-objective Task Allocation Algorithm for Medical Scenarios Based on MOIACO*

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Abstract. With the increasing number of medical tasks, the existing medical robotic task allocation systems are facing significant pressure. This paper proposes a multi-objective optimization model based on goal programming to address this issue. The model prioritizes urgent medical tasks with the primary goal of minimizing task value loss, thereby reducing patient health risks. Additionally, it aims to minimize resource consumption to ensure task sustainability. To solve this model, an efficient multi-objective improved ant colony optimization algorithm(MOIACO) is proposed. This algorithm employs an adaptive heuristic function and a non-uniform pheromone initialization mechanism to guide task selection decisions, enhancing efficiency and accuracy. Experimental results demonstrate that the algorithm exhibits excellent convergence speed, solution quality, and flexibility in solving MRTAS problems, potentially reducing the burden on medical staff and improving the efficiency of medical institutions.

Keywords: Multi-objective Optimization · Task Allocation · MOIACO · Medical Scenarios.

1 INTRODUCTION

The development of multi-robot systems (MRS) has gone through several key phases, from the 1960s when the system was first proposed and investigated, through the 1980s and 1990s when it underwent full theoretical development, experimentation and application, to the early 21st century when it achieved a major technological breakthrough, and then in recent years when it entered the intelligence and autonomy phase. Early research focused on the autonomy and basic cooperation of individual robots, and with the development of distributed control and task assignment algorithms, multi-robot systems have gradually demonstrated significant value in application scenarios such as warehousing and logistics [1], search and rescue missions [2], unmanned aerial vehicle operation [3, 4]and medical care [5].

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In recent years, the application of MRS in the medical field has received extensive attention and in-depth research. Many researchers are committed to using robots to assist medical work, from surgical assistance robots [6] to hospital logistics robots [7], all of which show the great potential of multi-robot systems in improving medical efficiency and reducing manpower costs. However, the structure of medical robots is extremely complex and requires a specific environment for installation, which not only makes them extremely expensive to produce, but also results in high post-installation maintenance and manpower costs, inevitably leading to a significant increase in the cost of medical treatment for patients [8]. Against this background, Multi-Robot Task Allocation System (MRTAS) has become an important research direction, which aims to optimise robot resource utilisation and task execution efficiency, and make the system's efficiency and task completion optimal through reasonable task allocation [9], which can improve the efficiency and quality of medical services, reduce operational costs, and reduce the workload of healthcare workers.In addition, MRTAS is able to respond quickly to unexpected situations and emergencies, providing timely and effective medical rescue and support, thus ensuring the safety and health of patients. These advantages make MRTAS important in improving the management and operation of healthcare facilities.The solution methods of MRTAS can be classified into two main categories: exact methods and heuristic algorithms.Exact methods [10] aim to provide one or more optimal solutions to optimisation problems. For small task sizes, exact methods usually provide effective solutions. However, as the size of the problem increases, exact methods often face exponentially increasing computational costs and may be difficult to solve exactly. Heuristic algorithms represent an alternative to, for instance, large optimisation problems for which an optimal solution cannot be obtained within a reasonable time frame. This approach offers greater flexibility in practical applications and is particularly useful for problems that require resolution in real time on large numerical instances. Heuristic algorithms, which can rapidly provide solutions to problems, have been subjected to more thorough investigation than exact methods and have been demonstrated to constitute an effective basis for achieving suboptimal solutions.

In recent years, many researchers have focused on solving the MRTAS problem and proposed a variety of innovative heuristic algorithms. Chunmei Zhang et al proposed a distributed modal difference evolutionary algorithm [11] to solve the discrete problem.Nathan Lindsay et al proposed a task-oriented distributed allocation algorithm [12] to solve the task allocation problem in unmanned aerial systems, which can dynamically adjust the allocation result to adapt to the environmental changes, and is suitable for dynamic task allocation scenarios. Wei et al proposed a multi-objective particle swarm optimisation method [13] for collaborative multi-robot task allocation problems, which provides a competitive and general solution for multi-objective optimisation problems in continuous space.Javier G et al introduced a cooperative game theory framework [14] for multi-robot task allocation problems, demonstrating its superiority over traditional methods such as genetic algorithms across diverse problem instances.

For task allocation in medical scenarios, Gautham P proposed a distributed algorithm [5] based on auction and consensus principle, which improves the task processing efficiency and reduces the communication bandwidth requirement. Ma et al. proposed a discrete difference particle swarm algorithm and mathematical model [15] to deal with multi-intelligent body task allocation problem in epidemic scenarios. Most of the above studies proposed some efficient objective optimisation algorithms, but rarely considered the priority of the objective tasks. It is crucial to consider the priority when allocating tasks in hospital scenarios because it is related to the safety and health of patients, which ensures that emergencies are handled in a timely manner, prevents deterioration of condition, optimises the efficiency of the use of human and equipment resources, reduces the waiting time of patients, and improves the quality of service.

Ant Colony Optimisation (ACO) [16] is a meta-heuristic method inspired by the pheromone tracking behaviour of a number of real ant species.ACO was originally designed to solve single-objective combinatorial optimisation problems [17].Grayna Starzec proposed a two-dimensional pheromone-based ACO algorithm for solving single-objective transport problems [18]. It can benefit from the ability to encode more information in a more complex pheromone structure.Due to the remarkable results achieved on these problems [19], the ACO algorithm was soon extended to solve problems with more complex features, especially multi-objective functions. Manuel et al. proposed an auto-configurable multi-objective ant colony optimisation algorithm frameworkto solve multi-objective optimisation problems [20] , which greatly simplified the process. Chen et al. proposed an effective multi-objective ant colony algorithm [21] to address the challenge of collaborative task allocation for heterogeneous unmanned aerial vehicles. The algorithm incorporates a novel pheromone updating mechanism and four newly defined heuristics, which enhance the convergence speed and search efficiency of the algorithm.

In this paper, we constructed a resource consumption model and a task benefit model for MRTAS of medical services. We then adopted the idea of goal programming in operations research to solve the problem hierarchically. Finally, we considered the actual problem, set the priority of medical tasks. A multi-objective improved ant colony optimisation (MOIACO) is proposed as a solution to the model. In conclusion, the contributions of this paper can be summarised as follows:(1) In the medical service scenario, the MRTAS mathematical model is introduced, which minimises the loss of task value and minimises the resource consumption by setting the medical task priority mechanism.(2) Considering the urgency and task complexity in the medical environment, a new heuristic information and pheromone updating strategy is designed, the discrete ant colony algorithm is improved by combining global and local search, and a pheromone concentration adaptive mechanism is introduced to dynamically adjust the initial pheromone concentration according to the task priority to improve the adaptability and efficiency of the algorithm in a dynamic and high-demand environment.(3) The establishment of an objective prioritisation mechanism to ensure the minimisation of loss of task value, on the basis of which the minimisation of resource consumption of sub-priority objectives is further optimised. This approach not only effectively solves the multi-objective optimisation problem, but also provides a more flexible and easy-to-interpret optimisation scheme, enabling decision makers to make better trade-offs and choices.An objective hierarchical mechanism is established to ensure that high-priority objectives (i.e. minimising task value loss) are given priority, on the basis of which sub-priority objectives (i.e. minimising resource consumption) are further optimised. This approach not only effectively solves the multi-objective optimisation problem, but also provides a more flexible and easily interpretable optimisation scheme, enabling decision makers to make better trade-offs and choices.

The remainder of the paper is organised as follows: a multi-objective optimisation model for MRTAS is presented in Section II. Section III provides a brief introduction to the basic framework of MOIACO and describes the implementation of the algorithm in detail. Section IV presents extensive experimental data and analyses. Section V presents the conclusions of this study.

2 MULTI-OBJECTIVE OPTIMISATION MODEL FOR MRTAS

In the context of healthcare services, there often exist multiple conflicting optimization objectives. When executing tasks, MRTAS need to consider these objectives comprehensively. This paper proposes a goal-based approach aimed at minimizing both the task value loss and resource consumption incurred by robot task execution in healthcare settings. By employing goal programming, it becomes feasible to address multiple conflicting objectives simultaneously, ensuring that the optimization process prioritizes the most critical objectives.

In this study, minimizing task value loss is designated as the primary optimization objective, aiming to prioritize urgent medical rescue tasks, mitigate human health losses, and enhance the overall value of robot task execution systems. Subsequently, the secondary objective focuses on minimizing resource consumption while maintaining the minimization of task value loss as a prerequisite. This secondary objective aims to further optimize resource utilization efficiency, reduce resource consumption rates, and ensure the sustainability of robot task execution systems. By adopting this approach, the model can effectively tackle multi-objective optimization problems, providing flexible optimization solutions that empower decision-makers to strike a balance and make informed choices. All parameters in the default model are known, and Table 1 lists the relevant indexes, sets, parameters and variables used in this section.The model is given by Eqs. (1), (2) and constraints (3) to (13).

$$\min F = a \sum_{j=1}^{T} d_j^+ + b d_c^+ \tag{1}$$

$$R = T = N \tag{2}$$

st.

Task Value Loss Model:

$$f_1 = \sum_{j=1}^{T} u_j v_j \prod_{i=1}^{R} (1 - q_{ij} x_{ij}) \tag{3}$$

$$u_j v_j \prod_{i=1}^{R} (1 - q_{ij} x_{xj}) + d_j^- - d_j^+ = 0 \quad for \;\; i = 1, 2, \cdots, R \tag{4}$$

Resource Consumption Model:

$$f_2 = \sum_{i=1}^{R} \sum_{j=1}^{T} c_{ij} x_{ij} \tag{5}$$

$$\sum_{i=1}^{R} \sum_{j=1}^{T} c_{ij} x_{ij} + d_c^- - d_c^+ = C_{ideal} \quad for \;\; i = 1, 2, \cdots, R \tag{6}$$

Task Assignment Constraint:

$$\sum_{i=1}^{R} x_{ij} = 1 \quad for \;\; j = 1, 2, \cdots, T \tag{7}$$

Robot Assignment Constraint:

$$\sum_{j=1}^{T} x_{ij} = 1 \quad for \;\; i = 1, 2, \cdots, R \tag{8}$$

Robot Workload Constraint:

$$\sum_{j=1}^{T} w_{ij} x_{ij} \leq k_i \quad for \;\; i = 1, 2, \cdots, R \tag{9}$$

Time Constraint:

$$\sum_{j=1}^{T} t_j x_{ij} \leq Time_i \quad for \;\; i = 1, 2, \cdots, R \tag{10}$$

Priority Constraint:

$$a > b \tag{11}$$

$$a + b = 1 \tag{12}$$

Binary Decision Variable:

$$x_{ij} = \begin{cases} 1 & , if \;\; robot \;\; i \;\; is \;\; assigned \;\; to \;\; task \;\; j \\ 0 & , others \end{cases} \tag{13}$$

Table 1: Mathematical Model Parameters

Symbol	Description
R	Number of robots
T	Number of tasks
w_{ij}	Workload of robot i on task j
c_{ij}	Resource consumption of robot i on task j
t_j	Execution time of task j
k_i	Maximum workload of robot i
p_{ij}	Success probability of robot i on task j
v_j	Value of completing task j
u_j	Priority of task j
d_j^+, d_j^-	Value loss deviation variables of task j
d_c^+, d_c^-	Resource consumption deviation variables
C_{ideal}	Ideal resource consumption value
x_{ij}	Binary variable indicating if robot i performs task j

The symbols R and T represent the number of robots and the number of tasks, respectively. The individual robots and tasks are denoted by the symbols i and j, respectively.The following equation shows that the number of robots is equal to the number of tasks. The weight parameters a and b are used to balance the task value loss and resource consumption.The objective function (1) minimizes both task value loss and resource consumption of MRTAS while ensuring task allocation quality. Deviation variables d_j^+ and d_j^- represent cases where task completion value exceeds or falls below expected values, while d_c^- and d_c^+ denote instances of actual resource consumption below or above expectations. The main reason for using only d_j^+ and not considering d_j^- in the objective function (1) is that we are more concerned with the additional cost or loss of the uncompleted task rather than the loss of value of the completed task. And the emphasis is on cases where actual resource consumption exceeds expectations (d_c^+), given the potential for cost escalation or resource scarcity in health care. Constraints (11) and (12) prioritise minimising task value loss while considering the rationality of resource consumption, with weight normalisation ensuring a combined weight of 1 for task value loss and resource consumption. Equation (2) maintains the integrity and consistency of task scheduling, thereby aligning the model with real world scenarios.

Equation (3) computes total expected task value loss F_1, where $\prod_{i=1}^{R}(1-q_{ij}x_{ij})$ represents the probability of task j not being completed by any robot, and v_j denotes task j's value. Equation (4) represents task value loss model constraints, aiming to minimize total expected task value loss F_1. Hence, equation (4) ensures the task value loss model meets expectations through the constraint $d_j^- - d_j^+ = 0$. Equation (5) calculates total resource consumption by all robots, while equation (6) represents resource consumption model constraints. Here, ensuring total system resource consumption F_2 matches ideal consumption C_{ideal} is essential. Thus, equation (6) ensures system resource consumption model compliance with expectations through the constraint $d_c^- - d_c^+ = 0$. Constraints (7) and (8) guarantee each task is assigned to one robot and each robot is allocated one task. Constraint (9) prevents robot workload exceeding maximum available capacity, while constraint (10) limits robot working time. Constraint (13) indicates whether robot i executes task j.

3 MOIACO ALGORITHM

This paper presents a multi-objective improved ant colony (MOIACO) algorithm, specifically designed to address the multi-robot task allocation problem in the context of the aforementioned medical scenario. The adaptive heuristic function dynamically adjusts the search direction of the ants based on the task priority, and the non-uniform pheromone initialisation motivates the ants to explore the solution space more extensively at the early stage of the search. The pseudo-code for the MOIACO algorithm is provided in Algorithm 1. Relevant parameters are detailed in Table 2, and Fig.1 illustrates the flowchart of the MOIACO algorithm.

Table 2: Parameter Values and Results

Symbol	Description
tabu_list	Used to record the tasks that each ant has done
m	Number of ants in the colony
Iter_max	Maximum number of algorithm iterations
ρ	Rate at which pheromone evaporates
Q	Pheromone enhancement coefficient
τ_0	Initial value of pheromone
$\Delta\tau$	Increment value of the pheromone
α	Weighting factor for pheromone information
β	Weighting factor for heuristic information
k	A proportional constant used to adjust the initial pheromone value.
d_j^+, d_j^-	Variables representing task value loss
d_c^+, d_c^-	Variables representing resource consumption deviation

3.1 Adaptive Pheromone Initialization

In the original ACO algorithm, the heuristic function is calculated solely on the basis of the inverse of the distance between the optional nodes, without consideration of task-related factors. This results in the ACO algorithm exhibiting deficiencies in task assignment, rendering it incapable of effectively addressing the urgency and diversity of medical tasks. Consequently, the overall efficiency and accuracy of task assignment are diminished. To address this issue, an adaptive heuristic function has been introduced that considers a range of factors,

Algorithm 1 MOIACO (Multi-Objective improved Ant Colony Optimization)

```
Initialize parameters (R, T, u, q, c, t, v, k, time_limit, alpha, beta, rho, g, tau_0,
Iter_max, m)
Initialize pheromone matrix (tau) with initial value tau_0 of size T x T
for each iteration from 1 to Iter_max do
  Update dynamic task and resource states
  for each ant from 1 to m do
    Initialize ant position and tabu list
    Allowable task set allowed_tasks = 0, 1, ..., T-1
    Solution solution = [-1, -1, ..., -1] (size T)
    for each robot from 1 to R do
      if allowed_tasks is empty then
        break
      end if
      Current task current_task = -1
      for step within range(T) do
        Assign task to robot solution[task] = robot
        Update current task current_task = task
        Remove task from allowed_tasks
        Add task to tabu list
      end for
    end for
    Add solution to solutions list
  end for
  Update global best solution and global best objective function values
  Local pheromone update:
  for each edge (i, j) do
    tau[i][j] = (1 − rho) · tau[i][j] + rho · tau_0
  end for
  Compute deviation variables:
  Calculate task value loss and resource consumption deviation based on task
  values and resource consumption
  Update global pheromone:
  Calculate delta_tau based on objective function values
  for each edge (i, j) do
    tau[i][j] = (1 − rho) · tau[i][j] + rho · delta_tau
  end for
  Adaptive pheromone update:
  for each edge (i, j) do
    if (i, j) is in pre-selected area then
      tau[i][j] = tau_max
    else
      tau[i][j] = tau_min
    end if
  end for
  Check if solution satisfies constraints:
  if solution does not satisfy constraints then
    Reset pheromone matrix tau and tabu list, and restart current iteration
  end if
end for
Output global best solution and global best objective function values
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including task priority, task success probability, task resource consumption, and task execution time. The heuristic function thus designed can better guide individual ants' decision-making in task selection, enabling them to more accurately assess the priority and adaptability of each optional node. This improves the purpose and efficiency of the algorithm. Concurrently, the design of this adaptive heuristic function enables the algorithm to more effectively adapt to the urgency and diversity of medical tasks, thereby enhancing the overall efficiency and accuracy of task allocation.The proposed adaptive heuristic function is expressed by Eq. (14).

$$\eta_{ij} = \frac{u_{ij} q_{ij}}{c_{ij} t_j} \tag{14}$$

The heuristic information is calculated by integrating factors representing the importance of tasks and their likelihood of success. Specifically, the numerator of the heuristic information consists of the task priority u_j and the execution success probability q_{ij}, reflecting the significance of tasks and their likelihood of completion. Meanwhile, the denominator comprises the resource consumption c_{ij} and the task execution time t_j, representing the cost and duration of task completion. Consequently, ants are inclined to select task nodes with higher priority and success probability, along with lower resource consumption and execution time when choosing the next task node. This enhances the efficiency and accuracy of task allocation.

3.2 State Transition Probability Rule

In traditional ant colony algorithms, the state transition probability rule serves as a fundamental component, guiding ants in selecting the next task. We employ this rule to compute the probability of ants transitioning from one task to another based on the priority of tasks and the historical concentration of pheromones along the paths. Specifically, at the position of ant k on task e, the determination of whether to move from task e to task f is governed by the computation of the state transition probability P_{ef}^k. The probability in question is given by Eq. (15).

$$P_{ef}^k = \begin{cases} \frac{(\tau_{ef})^\alpha (\eta_{ef})^\beta}{\sum\limits_{f \in \text{allowed}_k} (\tau_{ef})^\alpha (\eta_{ef})^\beta}, & \text{if } f \in \text{allowed}_k \\ 0, & \text{otherwise} \end{cases} \tag{15}$$

Here, τ_{ef} denotes the concentration of pheromones on the path from task e to task f, and η_{ef} represents the heuristic information. Parameters α and β respectively denote the relative importance of pheromone concentration and heuristic information in task selection. Through this rule, we achieve a better balance between task priority and historical experience along paths, thereby enhancing the efficiency and performance of medical task allocation.

3.3 Non-uniform Pheromone Initialization

In the initialization phase of the original ACO, pheromones are usually uniformly distributed across all paths during the initialization phase. This uniform

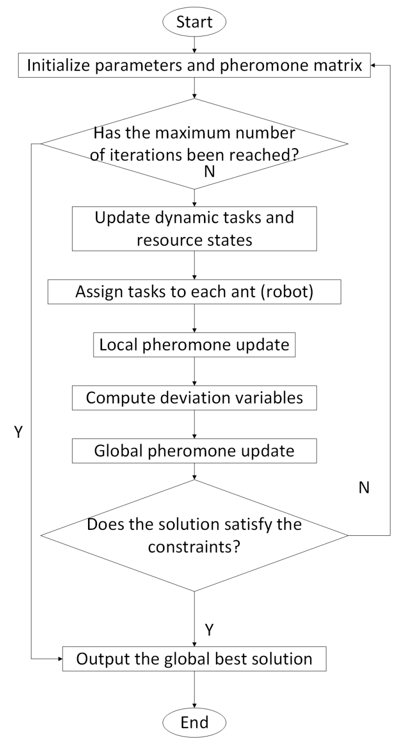


Fig. 1: Flowchart of MOIACO algorithm

distribution often fails to differentiate between task priorities, causing ants to randomly select tasks in the initial stage and search paths blindly, which reduces the efficiency and performance of the algorithm. However, in medical scenarios, task priority is crucial for task execution. To enhance the algorithm's awareness of task priority, this study introduces a non-uniform pheromone initialization mechanism [22]. This mechanism ensures that high-priority tasks receive higher initial pheromone concentrations, thereby attracting ants to these tasks more quickly and improving the algorithm's selection and processing capability for high-priority tasks. The proposed non-uniform pheromone initialization expression is given by Eq. (16).

The proportional constant, denoted by the symbol g, is employed to adjust the initial pheromone value. By selecting an appropriate value for g, the initial pheromone concentration can be ensured to be within a reasonable range. For instance, if the task priorities range from 1 to 10 and the desired initial pheromone concentration range is [0, 1], then g can be set to 0.1. The pheromone increment $\Delta\tau_{ef}$ is calculated based on the priority u_j of task j, as shown in Eq. (17).

$$\tau_{ef}(initial) = g \cdot u_j \tag{16}$$

$$\Delta\tau_{ef} = \frac{Qu_j}{\sum_{j=1}^{N} u_j} \tag{17}$$

The following experiments illustrate the advanced nature and rationality of the MOIACO framework. The algorithm exhibits faster convergence speed and superior global values.

4 EXPERIMENTAL SETUP AND RESULTS ANALYSIS

In medical scenarios, the timeliness and complexity of tasks often make it difficult for traditional algorithms to effectively solve the multi-robot task assignment problem. Therefore, we propose the MOIACO algorithm. In the experimental part of MOIACO, we have designed a series of experiments to comprehensively evaluate the performance and applicability of the improved ACO optimisation algorithm for multi-robot task allocation systems in medical scenarios. These experiments aim to provide an effective solution to the medical task allocation problem and provide reliable theoretical support and practical guidance for real-world applications.

First, we conducted parameter tuning experiments focusing on the key parameters in the ACO algorithm.In the algorithm experiments, to ensure the accuracy of the results, we fixed other variables and focused on adjusting the ranges of several key parameters. The parameter α was chosen to range between 1 and 3 to evaluate the impact of pheromone intensity on ant behavior at different levels. A lower α value indicates a smaller effect of pheromone, while a higher α value indicates a larger effect, thus allowing us to find the optimal balance point. The range for β was set between 2 and 5 to investigate the varying influence of heuristic information on ant decision-making behavior. A lower β value reduces the impact of heuristic information, whereas a higher β value enhances its effect. The range for ρ was set from 0.5 to 0.7 to adjust the rate of pheromone evaporation. A higher ρ value results in faster pheromone decay, while a lower ρ value leads to a longer retention time of pheromones, thus optimizing the pheromone update effect. Finally, the range for Q was set from 1 to 5 to control the magnitude of pheromone increment. A higher Q value increases the pheromone concentration, which may accelerate the convergence of the algorithm. By adjusting these parameter ranges, we can systematically evaluate their impact on algorithm performance and identify the optimal parameter combination to enhance overall algorithm performance.

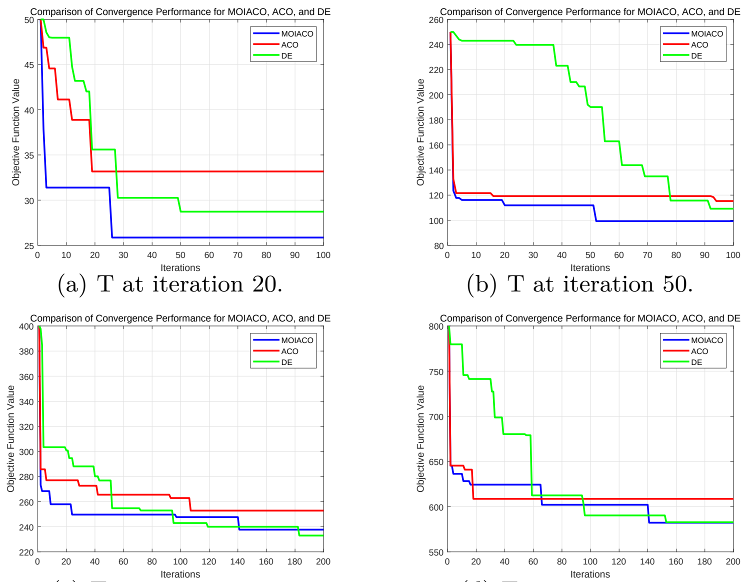
Next, task-size experiments were conducted using the previously selected parameters. The algorithm parameters, task attributes, and robot attributes were held constant, while the number of tasks varied across nine different values, ranging from 40 to 200. For each task size, twenty independent runs were performed, recording the optimal objective function values. The mean, standard deviation, minimum, and maximum values were calculated for each set of task sizes. By limiting the maximum function evaluation time to 10,000 runs, we controlled the algorithm's running time to ensure timely results while avoiding excessively long runs. This experimental design allows for evaluating the algorithms' performance under different task sizes and provides guidance for scaling up in real-world applications.

Table 3: Experimental Results for Different Task Counts

Task Count	Mean	Standard Deviation	Minimum	Maximum
40	89.1393	10.5326	78.8106	95.0829
60	152.0720	10.9255	128.5607	172.5526
80	204.2384	15.2454	194.7862	220.5234
100	242.9256	15.1698	236.7611	256.2717
120	339.3589	17.9601	300.3750	369.1772
140	406.0688	21.6547	365.3570	439.0107
160	460.6674	17.2234	433.2594	495.7829
180	531.0143	30.9735	485.1256	587.3427
200	594.0329	22.6477	558.3181	615.4454

The findings, presented in Table 3, indicate that as the number of tasks increases, the average, minimum, and maximum objective function values all exhibit an upward trend. This suggests that the employed algorithm excels at handling more tasks and can optimize the objective function more effectively in complex scenarios. Additionally, the standard deviation of the objective function values increases with the number of tasks, indicating that the algorithm maintains a certain degree of stability and adaptability when addressing larger-scale problems. These results further underscore the algorithm's superiority in managing complex tasks.

Finally, algorithmic comparison experiments were conducted to evaluate the performance of MOIACO against other commonly used task allocation algorithms, including the difference evolutionary algorithmDE and the original ACO algorithm. The specific results are presented in Fig.2. Figures a-d illustrate the convergence curves of the three algorithms under T = 20, 50, 100 and 200, respectively. The data presented above demonstrate that MOIACO consistently exhibits excellent performance under different task allocation scales. The algorithm's high convergence probability and low objective function value indicate a significant advantage in task allocation. Irrespective of the size of the task, MOIACO converges rapidly and identifies the optimal solution, thereby demonstrating excellent adaptability and efficiency. In contrast, the original ACO algorithm and the DE algorithm perform poorly at certain task sizes.



(a) T at iteration 20. (b) T at iteration 50.

(c) T at iteration 100. (d) T at iteration 200.

Fig. 2: Comparison of Convergence Performance for MOIACO, ACO, and DE

Table 4: Experimental Results of Different Algorithms

Algorithm	Mean	Standard Deviation	Average Runtime (s)
DE	259.227	18.4741	**344.745**
MOIACO	**242.9256**	**15.1698**	644.745
ACO	284.912	19.4615	659.65

Then,the performance of the three algorithms was compared at T=100, as shown in Table 4. The study reveals that in the medical robot task allocation system, the MOIACO algorithm exhibits a significantly lower average objective function value compared to the other algorithms, indicating its clear advantages in minimizing task value loss and cost expenditure. A lower objective function value corresponds to reduced task value loss and cost expenditure, suggesting that the MOIACO algorithm may more effectively reduce resource consumption and risk in medical robot task allocation processes, thereby enhancing system efficiency and sustainability. Furthermore, the relatively low standard deviation of the MOIACO algorithm indicates its higher stability. This suggests that the MOIACO algorithm can consistently perform well under different environments and conditions, thereby enhancing its reliability and practicality.

In this study, parameters such as task values, the probability of robot task completion, and robot workload are assumed to be predetermined. All experiments took place on a 64-bit operating system with an x64 processor, equipped with an Intel(R) Core(TM) i5-8265U CPU @ 1.60 GHz (with a maximum frequency of 1.80 GHz) and 8 GB of RAM. MATLAB R2022b served as the programming environment.

5 CONCLUSION

This study proposes a novel multi-objective optimization model tailored for MRTAS to address the escalating demand for efficient task allocation in medical settings. The model employs goal programming to prioritize urgent medical tasks while minimizing task value loss and optimizing resource utilization. To effectively manage the model, we introduce a multi-objective improved ant colony optimization algorithm that integrates an adaptive heuristic function and a non-uniform pheromone initialization mechanism.

The experimental results demonstrate several significant advantages of the proposed method: Firstly, it significantly improves the efficiency and accuracy of MRTAS task allocation by prioritizing critical tasks and optimizing resource allocation. Secondly, the algorithm exhibits excellent performance, with empirical validation showing fast convergence rates and superior solution quality. Additionally, by minimizing task value loss and optimizing resource utilization, the method ensures the sustainability of task execution in healthcare environments.

In summary, this study effectively addresses the critical issue of optimizing task allocation within MRTAS. By introducing an innovative optimization model and a highly efficient algorithm, it achieves the goals of streamlining the operational dynamics of medical robotic systems, enhancing system efficiency and sustainability, thereby reducing the burden on healthcare professionals and improving the quality of healthcare services. The results indicate that the MOIACO algorithm has significant potential and practical value in enhancing the efficiency, stability, and sustainability of medical robotic task allocation systems.

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