Research on optimization of manned robot swarm scheduling based on ant-sparrow algorithm

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Abstract. Considering the optimization problem of manned robot swarm scheduling in public environment, we constructed a demand-time-space-energy consumption scheduling model taking passenger waiting time and robot swarm energy consumption as optimization goals. This paper proposes an ant-sparrow algorithm based on the same number constraints colonies of ant and sparrow, which combines the advantages of ant colony algorithm great initial solution and the fast convergence speed of the sparrow search algorithm. After a limited number of initial iterations, the ant colony algorithm is transferred to the sparrow search algorithm. In order to increase the diversity of feasible solutions in the later stage of the ant-sparrow algorithm iteration, a divide-and-conquer strategy is introduced to divide the feasible solution sequence into the same small modules and solve them step by step. Applying it to the manned robot swarm scheduling service in the public environment, experiments show that the ant-sparrow algorithm introduced with a divide-and-conquer strategy can effectively improve the quality and convergence speed of feasible solutions.

1. Introduction
In recent years, the networked leasing business represented by shared transportation has been developing rapidly and has attracted widespread attention[1]. This has initiated the exploration of robotic swarm manned services in public environments. The coordinated operation of robot swarm deployed in public environment should meet the rapid response to the needs of passengers and minimize the energy consumption of the robot swarm. How to construct a collaborative robot swarm scheduling model and design a globally optimal and fast convergence algorithm is crucial for robotic swarm manned services scheduling problem[2].

At present, scholars have few researches on robotic manned services, and most of them are coordinated scheduling of cargo transportation[3-5]. The overall efficiency of cargo transportation is required to be high, while the individual response time of collaborative scheduling method does not need to be concerned. Aiming at the lack of parking space, traffic congestion, high energy consumption and high cost problems, Jelokhani[6] builds a spatiotemporal temporal matching model and proposes a new method based on GIS and ant colony, so as to find the best shared path and reduce traffic congestion better. In order to improve the flexibility and responsiveness of the flexible manufacturing system to customer needs, Maryam Mousavi et al.[7] adopt a hybrid GA-PSO method to evaluate the objective function value with the goal of optimizing the manufacturing time and the number of AGVs. The scheduling of numerical examples is evaluated before and after optimization, and the hybrid GA-PSO algorithm is superior to the other two algorithms. The multi-objective particle swarm algorithm, which is improved by Sasan Barak et al. to solve machine loading and unloading, long distribution time, low utilization of AGVs and high energy consumption problems in flexible
manufacturing systems, has improved the efficiency of the system[8]. For the flexible job shop scheduling problem with energy consumption constraint, Lei D et al.[9] propose the imperialist competitive algorithm (ICA) to reduce the delay time and the total energy consumption with the goal of Makespan, total delay time and total energy consumption, which reduce delay time and energy consumption. At present, genetic algorithm, particle swarm algorithm, ant colony algorithm, empire competition algorithm have made great progress in solving cooperative scheduling problems with complex constraints[10-11]. Inspired by the sparrow foraging and anti-predation mode, Xue J proposes the sparrow search algorithm with the characteristics of high solution efficiency and wide search range to solve the continuous function optimization problem. However, due to the lack of effective operators for discrete scheduling problems, there are still problems such as slow convergence, insufficient search range or easy to get stuck at locally optimal value.

The robot serves passengers, and the service environment is a dense crowd environment. The optimization goal must not only consider traditional scheduling constraints, but also take into account factors such as passenger tolerance, emotion, and patience. Inspired by the above research ideas of domestic and foreign scholars, the algorithm for the optimization of the robot carrier service scheduling problem should meet the short response time and the lowest global energy consumption. For this purpose, a new type of robot swarm scheduling method is explored, demand-time-space-energy consumption scheduling model is designed to solve the problem by the combination of ant colony algorithm and improved sparrow search algorithm, namely ant-sparrow algorithm.

2. Problem description and modeling

2.1. Description of the load task

The robots are denoted by the set $R = \{r_1, r_2, \cdots, r_m\}$, the total number is $M$, and the number of robots available for scheduling at the current moment is $m$. The passengers who need to carry the service are denoted by the set $P = \{p_1, p_2, \cdots, p_n\}$, and the number of passengers is $N$. The current state of the robot is denoted by the set $S = \{s_1, s_2, \cdots, s_j\}$. Robot $j$ empty is denoted by $s_j = 0$ and robot $j$ loaded by $s_j = 1$.

Robots are distributed in certain locations in the terminal building. In order to make the robot resources reasonably utilized, in the $(t + \Delta t)$ time period, the passengers who need to be served and idle robots are placed in the scheduling pool for dispatch. Then in the scheduling pool, there is a limited set $N_m$ of manned mission plans, and each passenger needs to be bound to a robot. According to the robot and passenger's location and robot status information, robots are assigned by the system to serve the passengers. Assuming that $r_j$ is assigned to $p_i$, the scheme of manned mission is defined as $A = \{(x_j, y_j), p_i(x_i, y_i), z_{ij} = 1, s_j = 0, \forall r_j \in R, \forall p_i \in P, \forall s_j \in S\}$. Among them, current position of the robot are denoted by $r_j(x_j, y_j)$, current position of the passenger $p_i(x_i, y_i)$, the position coordinates of the j-th robot are denoted by $r_j(x_j, y_j)$, the position coordinates of the i-th person are denoted by $p_i(x_i, y_i)$.

2.2. Robot population scheduling model

Define $z = (z_{ij})_{n \times m}$, $z_{ij}$ as 0, 1 variables, the i-th passenger carried by the j-th robot is denoted by $z_{ij} = 1$, and the i-th passenger not carried by the j-th robot is denoted by $z_{ij} = 0$. Define $[\text{len}, \text{wid}]$ as the robot moveable range, in the movable area, the length is denoted by $\text{len}$ and the width is denoted by $\text{wid}$. Define $\text{L} = (l_{ij})_{n \times m}$, the Manhattan distance between the i-th passenger and the j-th robot is denoted by $l_{ij}$. The road condition factor is denoted by $\delta(\text{route}*)$, which depends on the passenger density $\rho$ of the current road section. Define $v = (v_{ij})_{n \times m}$, the speed of the j-th robot travels to the i-th passenger is
denoted by \( v_j \). Define \( U = (u_{ij})_{n \times m} \), \( I = (i_{ij})_{n \times m} \), voltage and current of the j-th robot are respectively denoted by \( u_{ij} \) and \( i_{ij} \).

The following demand-time-space-energy scheduling model is constructed by this paper, which includes the objective function and constraints.

\[
\begin{align*}
\min f &= w_1 \sum_{i=1}^{m} \sum_{j=1}^{n} l_{ij} z_{ij} + w_2 \sum_{j=1}^{n} z_{ij} \int_0^{t_j} \delta(\text{route}^*) u_{ij} i_{ij} dt + w_3 \sum_{i=1}^{m} z_{ij} i_{ij} / v_j \\
\text{St. } &\text{net}_s = \{p_i(x_i, y_i), r_j(x_j, y_j)\}, \forall p_i \in P, \forall r_j \in R \\
m &= \sum_{j=1}^{m} s_j, \forall s_j \in S \\
l_{ij} &= \min\{g(\text{net}_1) \cup g(\text{net}_2) \cdots \cup g(\text{net}_j)\} C \\
\sum_{j=1}^{n} z_{ij} &= \max \left\{ \sum_{j=1}^{m} l_{ij} \right\} (i = 1, 2 \cdots m) \\
\sum_{j=1}^{n} z_{ij} &= 1, (i = 1, 2 \cdots n) \\
\sum_{i=1}^{n} z_{ij} &= 1, (j = 1, 2 \cdots m) \\
z_{ij} &= 0 \ or \ 1, (i = 1, 2 \cdots n; j = 1, 2 \cdots m) \\
0 \leq x_{pi} \leq \text{len}, \forall p_i \in P \\
0 \leq y_{pi} \leq \text{wid}, \forall p_i \in P \\
0 \leq x_{rj} \leq \text{len}, \forall r_j \in R \\
0 \leq y_{rj} \leq \text{wid}, \forall r_j \in R
\end{align*}
\]
ant-sparrow algorithm is designed to solve the discrete scheduling optimization problem based on the constraint of the same number of ant colonies and sparrow colonies.

3.1. Convergence analysis of Ant-Sparrow optimization algorithm

The discrete optimization problem is described as

\[ Zg = \min_{x \in S} \{ g(x) \} \]

among them, \( x \) are denoted as \( n \)-dimensional vector of solutions in the feasible region \( S \). \( g(x) \) is fitness functions in the feasible region \( S \). * , \( \min_{x \in S} g(x) \) \( = \) \( g(x^*) \). The optimal fitness value is denoted by \( g(x^*) \).

The construction algorithm of the next generation of sparrow swarm is denoted by the following expression:

\[
D = \begin{pmatrix}
d_{i1} & d_{i2} & \cdots & d_{iN} \\
d_{21} & d_{22} & \cdots & d_{2N} \\
\vdots & \vdots & \ddots & \vdots \\
d_{M1} & d_{M2} & \cdots & d_{MN}
\end{pmatrix}
\]

(13)

Where, \( 0 \leq d_{ij} \leq 1 \), \( \sum_{j=1}^{M} d_{ij} = 1 \), \( i, j = 1, 2, \cdots, M \).

**Definition 1** If the stochastic process corresponding to the ant-sparrow algorithm is denoted by \( \{X(k)\}_{k=1}^{\infty} \) and the state space is denoted by \( Y \) and satisfies \( \forall X(k) \in Y \), then the stochastic process \( \{X(k)\}_{k=1}^{\infty} (\forall X(k) \in Y) \) is identified to have Markovianity.

**Proof 1** Due to \( X(k+1) = DX(k) \), the next generation of sparrow swarm is selected from the pool of sparrow swarm formed by \( X(k) \) and \( X(k+1) \). Therefore, \( \forall Y \subseteq Y \), then, \( P(X(k+1) \in Y \mid X(0), \cdots, X(k)) = P(X(k+1) \in Y \mid X(k)), k = 1, 2, \cdots \). As a result, \( \{X(k)\}_{k=1}^{\infty} \) at the state of \( (k+1) \)-th generation \( X'(k+1) \) is determined only by the state \( X(k) \) at the \( k \)-th generation. Eventually, \( \{X(k)\}_{k=1}^{\infty} \) is proved to have Markovianity.

**Definition 2** Given a Markov process \( \{X(k)\}_{k=1}^{\infty} (\forall X(k) \in Y) \), the optimal state is denoted as \( Y^* \subseteq Y \), then \( P(X'(k+1) \in Y^* \mid X(k) \in Y^*) = 0 \), \( \{X(k)\}_{k=1}^{\infty} \) is denoted as the Markov process with the absorbing state property.

**Proof 2** The next generation of sparrow swarm is selected by the ant-sparrow algorithm using a divide-and-conquer strategy to select the best individuals from the previous generation of sparrow swarm and the new sparrow swarm. Thus, the best feasible solution for each iteration will be selected and copied to the next generation. Hence, once the optimal solution \( x^* \in X(k) \) is searched by the ant-sparrow algorithm after the \( k \)-th iteration, then the optimal solution \( x^* \) is also included in the sparrow swarm \( X'(k+1) \) at the \( (k+1) \)-th iteration, \( X^* \in X'(k+1) \). Therefore, \( \{X(k)\}_{k=1}^{\infty} \) can be proved to satisfy the properties of absorbing state Markov process.

**Definition 3** The ant-sparrow algorithm corresponds to the stochastic process \( \{X(k)\}_{k=1}^{\infty} \), \( (\forall X(k) \in Y) \), \( Y^* \subseteq Y \), the optimal state is denoted as \( Y^* \), if \( \forall X(0) \in Y \), \( \lim_{k \to \infty} P(X(k) \in Y^*) = 1 \), then the ant-sparrow algorithm converges with probability 1.

**Proof 3** Because of \( \exists k' \geq 0 \), when \( k > k' \), \( P(X(k) \in Y^* \mid X(k-l) \in Y^*) = 0 \), therefore, \( P(X(k) \in Y^* \mid X(k-l) \in Y^*) \leq 1 - \delta_k \). Suppose \( p_{mm}(k) = \prod_{l=0}^{k-1} P(X(k) \in Y^* \mid X(k) \in Y^*) \), it can be
derived that \( \lim_{k \to +\infty} P_{\text{not}}(k) \leq \prod_{k=0}^{\infty} (1 - \delta_k) \). Also because of \( \prod_{k=0}^{\infty} (1 - \delta_k) = 0 \), then \( \lim_{k \to +\infty} P_{\text{not}}(k) = 0 \). Therefore, the ant-sparrow algorithm reaches the optimal state at least once when the number of iterations tends to infinity.

Since the stochastic process \( \{X^M(k)\}_{k=0}^{\infty} \) corresponding to the ant-sparrow algorithm is an absorbing Markov process. According to Definition 2, \( P\{X^M(k) \in Y^* \mid X^M(k-1) \in Y^*\} = 0, k = 1, 2, \ldots \). The following is obtained from the full probability formula.

\[
P\{X^M(k) \in Y^*\} = P\{X^M(k) \notin Y^* \mid X^M(k-1) \notin Y^*\} \cdot P\{X^M(k) \notin Y^* \mid X^M(k-1) \notin Y^*\} + P\{X^M(k) \notin Y^* \mid X^M(k-1) \in Y^*\} \cdot P\{X^M(k-1) \in Y^*\}
\]

\[
= P\{X^M(0) \notin Y^*\} \cdot \prod_{k=0}^{\infty} P\{X^M(k+1) \notin Y^* \mid X^M(k) \notin Y^*\}
\]

\[
= P\{X^M(0) \notin Y^*\} \cdot \lim_{k \to +\infty} P_{\text{not}}(k)
\]

\[
= 1 - P\{X^M(0) \in Y^*\} \cdot \lim_{k \to +\infty} P_{\text{not}}(k) = 1
\]

In summary, definition 3 is proven to be true and the ant-sparrow algorithm is convergent.

3.2. Introduction of divide-and-conquer strategy

Inspired by the partitioning idea of the quick sort algorithm, the divide-and-conquer strategy is introduced into the position transformation phase of the sparrow swarm, which is the partitioning of the feasible solution sequence into smaller scale identical modules and solving them step by step. "Conquering" is used in the quick sort algorithm to compare values within an array, while in this paper it is used to sparrow individual fitness function values. The schematic diagram of sequence ID swapping based on the divide-and-conquer strategy is shown in figure 1.

![Figure 1. Schematic diagram of ID swap based on divide-and-conquer strategy.](image-url)
3.3. Step of Ant-Sparrow optimization algorithm

Figure 2 shows the steps of the ant-sparrow algorithm to solve the manned robotic swarm scheduling model.

![Ant-sparrow algorithm flow chart](image)

Figure 2. Ant-sparrow algorithm flow chart.

4. Simulation experiments and results analysis

![Domestic airport terminal floor plan](image)

Figure 3. Domestic airport terminal floor plan.
The experiment takes a domestic airport terminal as an example. Figure 3 shows a domestic airport terminal floor plan drawn by MATLAB. In order to verify the performance when solving the robot collaborative scheduling problem, the experiment was conducted between the ant-sparrow algorithm and other six multi-objective optimization algorithms, such as GA, PSO, ACA and SSA. To ensure better fairness, the population size of each algorithm is set to 100, and the number of iterations is set to 300. Each algorithm is coded in the same way as the ant-sparrow algorithm.

It is known that the annual throughput of an airport is about 100 million passengers, that is, the daily throughput is about 270,000 passengers. It can be seen that the daily throughput of a certain terminal is about 90,000, and the number of passengers arriving within 2 minutes at a certain time is about 50 to 75. The experiment is implemented in a certain terminal. At a certain moment, the demand for passenger flow in 2 minutes is assumed to be N1=20, and the number of idle robots is assumed to be M1=40 in experiment 1. The demand under the same conditions is assumed to be N2=20, and the number of idle robots is assumed to be M2=40 in experiment 2.

4.1. Experimental results and analysis

The following are the simulation conditions of this experiment. The traveling speed of the robot is 1~4 times the walking speed of the passenger, which is determined by $v = \text{ave} + \text{dev} \times \text{rand}(1)$. Among them, the average speed of the robot is recorded as $\text{ave}$, which is 2.5m/s. The variance is represented by the $\text{dev}$ table, which is 1.5.

During the experiment, in order to ensure the fairness of the experimental results, each algorithm is run independently on each experiment 20 times. Table 1 shows the running results of each algorithm. Among them, the optimal value is represented by $f^*$, the worst value is represented by $f^w$, the average value is represented by $\bar{f}$, the average running time is represented by $\bar{t}$, the known optimal solution is represented by $u$, the deviation rate is represented by $\psi$, $\psi = (f^* - f^w) / f^u$.

| Category | Algorithms | $f^*$  | $f^w$  | $\bar{f}$ | $\bar{t}$ | $\psi$ | $\bar{t}/s$ |
|----------|------------|-------|-------|----------|---------|--------|----------|
| Experiment 1 | GA         | 16789 | 13826 | 15678   | 1.08    | 3.4    |          |
|           | PSO        | 8966  | 7797  | 8254    | 0.18    | 4.3    |          |
|           | ACA        | 6634  | 7033  | 7326    | 0.06    | 18.5   |          |
|           | SSA        | 8096  | 7185  | 7741    | 0.08    | 4.6    |          |
|           | AC-SSA     | 7092  | 6787  | 6953    | 0.02    | 4.1    |          |
| Experiment 2 | GA         | 26023 | 24335 | 25064   | 1.07    | 2.2    |          |
|           | PSO        | 12211 | 12471 | 11903   | 0.06    | 5.9    |          |
|           | ACA        | 11750 | 14753 | 14965   | 0.26    | 36.5   |          |
|           | SSA        | 13953 | 12584 | 13058   | 0.07    | 4.5    |          |
|           | AC-SSA     | 13671 | 12098 | 12846   | 0.03    | 4.3    |          |

The result of experiment 1 shows that the deviation rate $\psi$ of the ant-sparrow algorithm is 0.02, which is lower than that of other algorithms. The average running time of the ant-sparrow algorithm is 4.1s, which is lower than the running time of other algorithms except GA. However, the optimal solution quality of GA is far inferior to the ant-sparrow algorithm.
Figure 4. Comparison of fitness values of various algorithms.

It can be seen from Figure 4 that the ant-sparrow algorithm iterated 46 times to reach the optimum in experiment 1. The ant-sparrow algorithm converges to the optimum at a speed of 88 iterations in experiment 2. The convergence speed of the ant-sparrow algorithm and the quality of the solution are significantly better than other algorithms. Due to the divide-and-conquer strategy is used in the ant-sparrow algorithm to divide the feasible solution sequence into smaller-scale identical modules. This not only speeds up the convergence speed of the algorithm, but also improves the quality of feasible solutions.

### Table 2. Energy required for each optimization algorithm.

| Category | Algorithm | GA | PSO | ACA | SSA | AC-SSA |
|----------|-----------|----|-----|-----|-----|--------|
|          | Indicators | $E_a / kw·h (10^2)$ | $\varphi$ | $E_a / kw·h (10^2)$ | $\varphi$ |
| Experiment 1 | GA | 45.690 | 46.8% | 81.48 | 64.3% |
| Experiment 1 | PSO | 34.17 | 9.8% | 50.08 | 0.9% |
| Experiment 1 | ACA | 34.289 | 10.2% | 61.642 | 24.3% |
| Experiment 1 | SSA | 3.302 | 0.01% | 52.9 | 6.7% |
| Experiment 1 | AC-SSA | 3.112 | - | 49.593 | - |

Table 2 shows the energy consumption values required by different optimization algorithms to solve the scheduling model. Among them, $\varphi$ represents the ratio of the energy consumption value of the ant-sparrow algorithm solution model compared to the energy consumption value of other algorithms. $\varphi=(E_a - E_i) / E_i, (a = 1,2,3,4)$, the energy consumption value of each algorithm is denoted by $E_a$. The energy consumption required to solve the scheduling model by the ant-sparrow algorithm is lower than that of other algorithms.

### 5. Conclusion

Starting from the problem of collaborative scheduling of robot swarms, the Demand-Time-Space-Energy scheduling model is constructed in this paper. In order to solve the robotic swarm scheduling model, the ant-sparrow algorithm not only integrates the characteristics of the better initial solution of the ant colony algorithm, but also absorbs the advantages of the fast convergence speed of the sparrow search algorithm. Compared with other classic algorithms, the ant-sparrow algorithm can achieve the best solution quality under the premise of ensuring fast convergence. The ant-sparrow algorithm has practical significance for the research and application of multi-objective optimization problems.
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