Research on Reloading Airdrop Strategy Based on Multi-Objective Programming

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Abstract: In order to realize the rapid assembly of equipment, it is necessary to use formation for airdrop. When the formation aircraft are too close to each other, the wake of the front aircraft may affect the safety of the rear aircraft and the cargo. In order to make the landing point of the rear aircraft and the target point as small as possible and the landing time as close as possible. In this paper, a multi-objective optimization problem with target distance and landing time as objective functions is established. After analyzing the specific flight problems and establishing a series of constraints, a suitable intelligent optimization algorithm-genetic algorithm is selected to solve the multi-objective problems.

1 INTRODUCTION

In modern war, the key to determine victory or defeat in a war is the rapid transfer and delivery of military equipment and materials. The heavy load airdrop with medium and large transport aircraft as the transport platform has become an important strategic action. The so-called heavy airdrop refers to the use of large transport aircraft and parachute landing equipment to quickly drop heavy weapons and equipment from a certain height to the designated ground. As the main way for airborne troops to carry out airborne combat weapons, ammunition, vehicles and other follow-up supplies, it plays a key role in the deployment of airborne troops in depth and breaking through the enemy defense line.

The main factors that affect the safety and accuracy of airdrop include the local meteorological conditions (temperature, pressure, air density), the position of the aircraft, the driving distance in the cargo deck, the loss height of the cargo deck, the steady descent rate of the cargo deck, and the time from the cargo to the landing. With the new changes in the battlefield environment, to meet the needs of future airdrop operations, heavy air drop is being given new requirements and new connotations, among which the precision of heavy air drop point will become a trend.

2 PROBLEM ANALYSIS

2.1 Analysis of Maximum Wake Intensity

Assuming that the aircraft speed v, aircraft gravity G, and air density ρ are all known. So, the lift coefficient of the aircraft is

$$G_y = \frac{G}{144\rho v^2}. \quad (1)$$

If the radius r_w and spacing of the vortex core L_w are known, the maximum intensity of the trailing vortex Γ_0 and the maximum tangential velocity of the trailing vortex circumference V_{max} can be obtained.

$$\Gamma_0 = \frac{G}{\rho v L_w} \quad (2)$$

$$V_{max} = \frac{\Gamma_0}{2\pi r_w} \quad (3)$$

2.2 Analysis of Wake Fully Formed Position

The complete formation distance of the forward tail vortex is

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$$S = \frac{13.85384 \cdot \lambda}{C_y}. \tag{4}$$

The initial sinking velocity of the wake vortex is

$$V_d = \frac{\Gamma_0}{2\pi L_w}. \tag{5}$$

Then the sinking height of the wake vortex can be calculated as follow.

$$\Delta H = S\frac{C_y}{\pi}\left(\frac{1}{\lambda} + 0.025\right) + \frac{\Gamma_0}{2\pi L_w} \tag{6}$$

Wake vortex formation time is

$$T = \frac{S}{v} \tag{7}$$

2.3 The Relation Between the Rear Wing Tip and the Forward Tail Vortex

The transverse distance between the section where the aircraft is located and the boundary of the tail vortex is

$$L_k = L_{lr} - \frac{3L_w}{8S}\left(L_{fb} + 47\right). \tag{8}$$

The sinking height of the forward tail vortex at the rear wing tip is

$$H_1 = L_{fb}\frac{C_y}{\pi}\left(0.025 + \frac{1}{\lambda}\right) + V_{下}\frac{L_{fb}}{v}. \tag{9}$$

The linear distance between the aircraft and the tail vortex boundary is

$$r = \sqrt{L_k^2 + \left(H_1 + h\right)^2}. \tag{10}$$

The intensity of the tail vortex attenuation to the position of the rear wing tip is

$$v_\theta\left(r,t\right) = \frac{\Gamma_0 e^{-0.05t}}{2\pi r}\frac{r^2}{r^2 + \left(r_w + 0.5\sqrt{t}\right)^2}. \tag{11}$$

3 MODELING

3.1 Constructing Objective Function

In order to ensure that the front and rear cargo are as close as possible, we can make the two aircraft in the formation of heavy aircraft as close as possible, that is,

$$\min \sqrt{L_{lr}^2 + L_{fb}^2 + h^2} \tag{12}$$

If the relative position vector of two aircraft is $X = \left[L_{lr},\ L_{fb},\ h\right]^T$, then the above formula can be expressed as the L-2 norm of X.

$$\min \quad \left\|X\right\|_2 \tag{13}$$

The difference between the delivery time of the aircraft formation is Δt. In order to ensure that the landing time of the cargo before and after the aircraft is as close as possible, there is

$$\min \quad \Delta t \tag{14}$$

3.2 Constructing Constraints

Considering the safety of air delivery, the following constraints are formulated.

1) The steady decline rate of the cargo platform shall not exceed $8m/s$, that is

$$v \le 8. \tag{15}$$

2) The tangential wind speed of the cargo platform subject to the wake shall not exceed $2m/s$, that is

$$v_\theta\left(r,t\right) = \frac{\Gamma_0 e^{-0.05t}}{2\pi r}\frac{r^2}{r^2 + \left(r_w + 0.5\sqrt{t}\right)^2} \le 2. \tag{16}$$

3) The relative distance between aircraft is greater than 0, that is

$$\left\|X\right\|_2 > 0. \tag{17}$$

3.3 Constructing Constraints

So, a multi-objective optimization model of formation is obtained

$$\begin{aligned} &\min \left\|X\right\|_2 \\ &\min \Delta t \\ \text{s.t.}\quad & v_\theta\left(r,t\right) = \frac{\Gamma_0 e^{-0.05t}}{2\pi r}\frac{r^2}{r^2 + \left(r_w + 0.5\sqrt{t}\right)^2} \le 2 \\ & \left\|X\right\|_2 > 0 \end{aligned} \tag{18}$$

In order to obtain the solution, the linear weighting method is used to transform the multi-objective problem into a single-objective problem, that is,

$$\min \quad \omega_1\left\|X\right\|_2 + \omega_2\Delta t \tag{19}$$

4 SIMULATED ANNEALING ALGORITHM

Simulated annealing algorithm is a heuristic algorithm designed to randomly search the global optimal solution in the feasible solution space by combining probabilistic jump characteristics.

If the new feasible solution x_j is found to be better than the current feasible solution x_i, the new feasible solution is accepted. Otherwise, the *Metropolis* criterion determines whether to accept the new feasible solution. In order not to reject directly, define the acceptance probability P. P lies between [0,1], and measures the distance between $f\left(x_j\right)$ and $f\left(x_i\right)$. The closer is the distance, the larger is P. Here we make assumptions.

$$P \propto \exp\left(-\left|f\left(x_j\right)-f\left(x_i\right)\right|\right) \tag{20}$$

In order to improve the efficiency of the algorithm, in the early stage of the algorithm search, it is necessary to improve the scope of the algorithm search to avoid falling into local optimal. In the later stage of the search, it is necessary to reduce the search scope of the algorithm as much as possible. That is, it just searches locally, because at this time it is close to the global optimal. We make a deformation of the above formula (20).

$$P \propto \exp\left(-C_t\left|f\left(x_j\right)-f\left(x_i\right)\right|\right) \tag{21}$$

C_t in the formula (21) can be regarded as a time-dependent coefficient. Then the probability P of the algorithm accepting the new feasible solution establishes a relationship with the time parameter.

If t is small in the early stage of search, and the search scope is large enough, then the corresponding P needs to be larger. And C_t is set to be negatively correlated with P, so it should be small. If P is smaller in the late search period, C_t should be larger. Obviously, the longer time goes, the bigger C_t gets.

The flow of the search process is as follows.

1) Generate an initial solution A randomly, and calculate the objective function $f\left(A\right)$ corresponding to the initial solution.

2) A solution B is generated near the initial solution according to the probability mechanism, and the objective function $f\left(B\right)$ corresponding to the new solution B is calculated.

3) If $f\left(B\right) > f\left(A\right)$, the new solution overwrites the original solution and repeat the above steps.

If $f\left(B\right) \le f\left(A\right)$, it calculates the probability of accepting the newer solution B, that is $P_t = \exp\left(-\left|f\left(B\right)-f\left(A\right)\right|\right)\times C_t$. Then it randomly generates number $r \in \left[0,1\right]$. If $r < P$, the initial solution A is overwritten by the new solution B. And the above steps are repeated. Otherwise, it returns to the second step. A newer solution B_1 is re-generate near the initial solution, and it continues to iterate.

However, there is a problem in the above process, that is, the setting of key coefficient C_t. So we define the initial temperature $T_0 = 100$. According to thermodynamics, the formula for temperature drop is

$$T_{t+1} = \alpha T_t \tag{22}$$

In the formula (22), α is usually 0.95, then the temperature at time t is

$$T_t = \alpha^t T_0 = 100 \times 0.95^t \tag{23}$$

To ensure that C_t increases about t, we have

$$C_t = \frac{1}{T_t} = \frac{1}{100 \times 0.95^t} \tag{24}$$

Then

$$P_t = \exp\left(\frac{\left|f\left(B\right)-f\left(A\right)\right|}{T_t}\right) = \exp\left(\frac{\left|f\left(B\right)-f\left(A\right)\right|}{100 \times 0.95^t}\right) \tag{25}$$

Let $\Delta f = \left|f\left(B\right)-f\left(A\right)\right|$, when the temperature is constant, the smaller Δf is, the greater the probability P_t is. That is, the smaller the difference from the existing solution is, the greater the possibility of accepting the newer solution is. When Δf is constant, the higher the temperature is, the greater the acceptance probability is. Therefore, it is easier to accept the newer solution when the temperature is high in the early stage of search.

5 SIMULATION CALCULATION

The theoretical basis of Monte Carlo method is the law of large numbers. The law of large number describes the results of a considerable number of repeated experiments, and according to this law, the larger the number of samples, the closer the average will be to the true value.

One type of Monte Carlo method is that the problem can be converted into some random distribution of characteristic numbers, such as the probability of a random event, or the expected value of a random variable. By random sampling method, the probability of random events is estimated by the frequency of occurrence, or the numerical characteristics of random variables are estimated by the numerical characteristics of sampling, and it is used as the solution of the problem. Here the initial solution is selected based on Monte Carlo simulation.

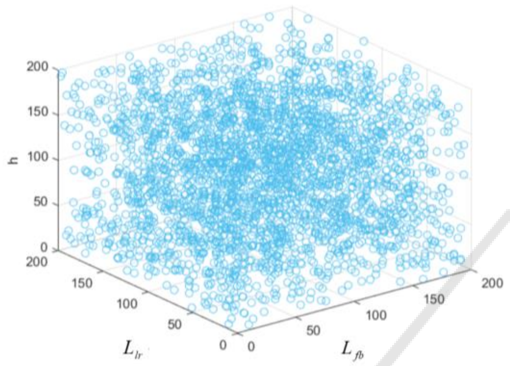

Figure 1: Initial value solution selection based on Monte Carlo simulation.

Under the condition that $r_w = 0.989$, $L_w = 38.84$, $G = 130 \cdot e^3$, $v = 88.8$, temperature is 18 C^0 and air pressure is 1014 *hpa*. The optimal model is solved by MATLAB, shown in figure2.

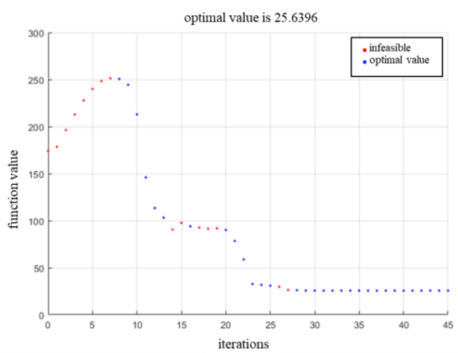

Figure 2: Optimization procedure.

The optimal function value obtained is 25.6396, and the optimal solution is $X = [8.459, 0.5131, 0.5666]^T$. The time difference between the front and back engines is 17.1458s, which is in good agreement with the actual situation.

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