Research on the Problem of Sorting Parallel Runway Aircraft in Terminal Area Based on Genetic Algorithm

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Abstract. Serious air traffic congestion often occurs in busy airports and terminal areas, which seriously interferes with the normal operation of flights, resulting in a large number of flight delays, causing huge economic losses to airlines, and also affecting the safe operation of flights in the terminal area. This study takes the two-runway airport as the research object, establishes the parallel runway arrival flight sequencing model and designs the double-encoded genetic algorithm, uses a pair of chromosomes to determine the runway allocation and landing sequence number of the arriving flight, and arranges the flight landing sequence and the runway. The simulation experiments were carried out on 10 flights that were about to land at a certain time in the airport, the experimental results show that the algorithm achieves flight sorting and runway allocation optimization, compared with the current FCFS (First Come First Served) algorithm, it can effectively reduce flight delay time and improve the utilization efficiency of the airport terminal area.

1. Introduction

The development of China's civil aviation transportation industry has shown a continuous growth trend. In 2018, China's civil aviation completed a total transport turnover of 120.64 billion ton-kilometers, an increase of 11.4\% year-on-year; however, the increasing volume of civil aviation transportation not only brings considerable economic benefits, but also huge transport pressure. In 2018, the abnormal rate of civil aviation flights reached 19.87\%, and serious air traffic congestion often occurred in busy airports and terminal areas, which seriously interfered with the normal operation of flights. Terminal area flight sequencing is an air traffic flow management method to balances terminal area and runway capacity. By optimizing the sequencing method of incoming flights in the terminal area, the interval between adjacent flights and the delay time can be reduced, the traffic flow in the airspace of the terminal area can be improved, the airspace congestion in the airspace of the terminal area can be alleviated, and the airspace utilization rate can be improved, the flight delay can be alleviated, the cost of airlines can be saved, and the safe operation of the terminal area can be guaranteed.

In recent years, scholars have presented new trends in the study of the sequencing problem of incoming flights of the terminal area. [1-4] Scholars have studied different models and algorithms for the traffic management of terminal area, effectively optimizing the flight sequencing queue of terminal area and alleviating the traffic congestion in the terminal area [5-8]. Based on previous studies, this
study applies genetic algorithm to aircraft sequencing in airports with parallel runways in order to solve the problem of airport delay.

2. Modeling and algorithm design

2.1. Establishment of sequencing model for incoming flights

2.1.1. Objective function. Assume that the number of flights in the terminal area with a multi-runway busy airport is N, it can be expressed as $f = (1, 2, ..., N)$, $r = (1, 2, ..., R)$ is the number of airport runways, $g(i)$ represents the flight arriving at the i-th position after the flight queue optimization. The multi-runway sorting flight variable is defined as follows:

- $S_{ij}$: The time interval between two aircraft in front and rear of the same runway.
- $ET_{ir}$: The estimated landing time of flight $i$ on runway $r$, given by the flight schedule.
- $AT_{ir}$: The time when flight $i$ actually landed runway $r$, defined by Equation 1:

$$
T_{ir} = \begin{cases} 
\max \left( ET_{ir}, \left[ AT_{i-1,r} + S_{i,j} \right] \right) & \text{i-l, i landing on the same runway} \\
\max \left( ET_{ir}, \left[ AT_{i-1,r} + D_{i,j} \right] \right) & \text{i-l, i landing on different runways}
\end{cases} \tag{1}
$$

The objective function is based on the principle of minimizing the total delay time. The objective function is:

$$z = \min \sum_{i=1}^{N} AT_{ir} - ET_{ir} \tag{2}$$

2.1.2. Constraint conditions. Considering the restrictions on the number of runways and the interval of the wake during the sorting process, the constraints are as follows:

- $\sum_{i=1}^{N} \sum_{r=1}^{R} x_{ir} = N \tag{3}$
- $AT_{ir} - AT_{j} \geq S_{ij}$, $i,j = 1,2, ..., N(j>i) : r = 1,2, ..., R \tag{4}$
- $AT_{jr} - AT_{i} \geq D_{ij}$, $i,j = 1,2, ..., N(j>i) : r = 1,2, ..., R \tag{5}$
- $|i - z| \leq MPS$, $g(i) = z$, $i,z = 1,2, ..., N \tag{6}$

2.2. Genetic algorithm design of incoming flight sequencing

(1) Coding scheme

An airport flight zone level 4F, with two parallel runways, is coded by a double structure based on runway allocation, and each chromosome consists of an upstream code and a downstream code. The upstream code indicates the order of landing of the arriving flight, the downstream code indicates the runway number of the flight allocation, and the upstream and downstream codes are encoded in integer form. Take two runways and six flights as an example. The coding method is shown in the following table.
Table 1. Double structure coding method.

| Flight number | 1 | 2 | 3 | 4 | 5 | 6 |
|---------------|---|---|---|---|---|---|
| Runway number | 1 | 2 | 2 | 1 | 2 | 1 |

(2) Initialization of the population
After the chromosome coding is completed, an initial population must be generated as the starting solution, so the number of initialized populations is first determined. In general, the number of flights determines the number of populations. This article sets the initial population size to 100. The algorithm adopts a partially random method when setting the initial population, and adds a part of the FCFS sequence. Even in the worst case, the optimization result is better than the FCFS sequence.

(3) Fitness function

\[ f = \frac{1}{\sum_{i=1}^{N} (AT_i - ET_i)} \]  

(7)

The fitness function here is the reciprocal of the total delay time, and each flight sequence corresponds to a different actual arrival time, so the delay time is also different. For different flight sequences, the shorter the delay time, the greater the fitness value, which represents a better sorting result, and is also conducive to the next selection operation.

(4) Select operation

The selection operation selects individuals from the population with a certain probability to add to the new individual group in the next iteration. The probability that the individual is selected is related to the fitness value of the individual. The higher the fitness value of an individual, the better the individual is, and the higher the probability of being selected to join the next iteration.

(5) Cross operation

The upstream code of the cross operation is determined by means of partial mapping hybridization, and the downstream code value of the sub-individual is determined according to the correspondence between the downstream code and the upstream code in the parent individual. As shown in Table 2, the two positions of the parent chromosomes P1, P2 are arbitrarily selected for intersection, such as position 3 and position 6.

Table 2. Parent chromosome.

| P1    | 6 | 5 | 2 | 8 | 7 | 4 | 1 | 3 |
|-------|---|---|---|---|---|---|---|---|
|       | 2 | 2 | 1 | 1 | 2 | 1 | 2 | 1 |
| P2    | 5 | 4 | 6 | 3 | 7 | 8 | 2 | 1 |
|       | 2 | 1 | 2 | 1 | 1 | 2 | 1 | 2 |

The data of the upstream code between the two individual positions 3 and 6 of the parent generation are crossed, and the individuals who obtain the children are: S1: (5 | 6 3 7 8 | 1 #); S2: (5 # | 2 8 7 4 | 1 ).

After crossing, the non-repeated Numbers in the same individual are retained, and there are duplicate flight numbers, that is, the conflicting numbers (with # position) use the partial mapping method to eliminate the conflict, that is, the mapping is performed by using the correspondence relationship of the intermediate segments. The result is: S1: (2 5 | 6 3 7 8 | 1 4); S2: (5 3 | 2 8 7 4 | 6 1).
According to the correspondence between the downstream code and the upstream code in the parent generation individual, the downstream code value of the child is obtained, and finally the chromosomes of the children S1 and S2 after the cross operation are obtained, as shown in Table 3.

| Table 3. Filial generation chromosome. |
|---------------------------------------|
| S1                                   |
| 2 5 6 3 7 8 1 4                      |
| 1 2 2 1 2 1 2 1                      |
| S2                                   |
| 5 3 2 8 7 4 6 1                      |
| 2 1 1 2 1 1 2 2                      |

(6) Mutation operation
The mutation operation takes two points randomly selected in the upstream code of the parent generation chromosome and swaps them, while the downstream code position remains unchanged. For example, select position 4 and position 7, as shown in Table 4.

| Table 4. Chromosomal variation. |
|---------------------------------|
| P1                              |
| 7 3 6 4 1 2 5 8                 |
| 2 1 2 2 1 2 1 1                 |
| After chromosomal variation:    |
| P2                              |
| 7 3 6 2 1 4 5 8                 |
| 2 1 2 2 1 2 1 1                 |

3. Analysis of simulation results
The parallel runway of the airport A uses an independent parallel instrument approach, and the two parallel runways are set as independent operation state, that is, the time interval $D_{ij}=0$ for the flight to land on different runways. The algorithm was verified by taking 10 flights as an example. Table 5 shows the initial flight data of 10 flights that will be landed on the A airport one day:

| Table 5. Initial flight data. |
|------------------------------|
| Flight number | Model | Expected to arrive at the runway 1 time | Expected to arrive at the runway 2 time |
|----------------|-------|----------------------------------------|----------------------------------------|
| 1              | H     | 58                                     | 116                                    |
| 2              | H     | 58                                     | 116                                    |
| 3              | H     | 58                                     | 116                                    |
| 4              | H     | 58                                     | 116                                    |
| 5              | H     | 116                                    | 54                                     |
| 6              | S     | 198                                    | 432                                    |
| 7              | S     | 198                                    | 432                                    |
| 8              | H     | 311                                    | 303                                    |
| 9              | L     | 643                                    | 763                                    |
| 10             | L     | 643                                    | 763                                    |

This paper calls the MATLAB genetic algorithm toolbox and sets the initial population size to 40, the maximum evolution algebra to 100, the flight crossover probability $pcf=0.6$ runway crossover probability $pcr=0.6$, the flight variation probability $pcf=0.06$, and the runway variation probability $pcr=0.06$. MPS=3. The results of the flight genetic algorithm are shown in Table 7.
### Table 6. FCFS algorithm flight sequencing results.

| Runway 1 | Runway 2 |
|----------|----------|
| Number and model | $ET_{ir}$ | $AT_{ir}$ | $T_{del}$ | Number and model | $ET_{ir}$ | $AT_{ir}$ | $T_{del}$ |
| 1 (H) | 58 | 58 | 0 | 5 (H) | 116 | 116 | 0 |
| 2 (H) | 58 | 122 | 74 | 8 (H) | 311 | 311 | 0 |
| 3 (H) | 58 | 210 | 152 |
| 4 (H) | 58 | 325 | 267 |
| 6 (S) | 198 | 413 | 166 |
| 7 (S) | 198 | 485 | 238 |
| 9 (L) | 643 | 643 | 0 |
| 10 (L) | 643 | 747 | 104 |
| **Total delay time:** | | | 1001 |

### Table 7. Sequencing results of genetic algorithm.

| Runway 1 | Runway 2 |
|----------|----------|
| Number and model | $ET_{ir}$ | $AT_{ir}$ | $T_{delay}$ | Number and model | $ET_{ir}$ | $AT_{ir}$ | $T_{delay}$ |
| 2 (H) | 58 | 58 | 0 | 5 (H) | 58 | 58 | 0 |
| 3 (H) | 58 | 132 | 74 | 1 (H) | 58 | 152 | 94 |
| 7 (S) | 198 | 250 | 52 | 4 (H) | 58 | 246 | 188 |
| 6 (S) | 198 | 348 | 150 | 8 (H) | 311 | 350 | 39 |
| 10 (L) | 643 | 643 | 0 |
| 9 (L) | 643 | 718 | 75 |
| **Total delay time:** | | | 672 |

The total flight delay time optimized by the algorithm is 672 seconds, and the first-come-first-served (FCFS) algorithm has a total delay time of 1001 seconds. The comparison between the total flight delay time and the first-come-first-served service (FCFS) algorithm optimized by the algorithm is shown in Figure 1. It can be seen from the simulation results that optimizing the order of arrival flights and the allocation of runways can effectively reduce flight delay time and improve air traffic control efficiency.

![Figure 1. Comparison of FCFS algorithm and genetic algorithm ranking results.](image)

### 4. Conclusion

This study established a model of sequencing the incoming flights in the terminal area, based on the model of sequencing the incoming flights in the terminal area, combined with the 10 flights of the A-airport dual-runway during a certain period of time, the double structure coding based on the runway allocation is used to solve the model. Finally, according to the comparison between the FCFS algorithm and the genetic algorithm, it is concluded that the optimized algorithm greatly reduces the delay time and improves the airspace usage. Compared with the first-come-first-served (FCFS)
algorithm, the genetic algorithm designed in this paper not only effectively reduces flight delay time, but also has better real-time performance, improves air traffic control efficiency, and the congestion of busy airport terminal areas can be alleviated to some extent.

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