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Using The Heuristic Genetic Algorithm in Multi-runway Aircraft Landing Scheduling

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Abstract

Flights landing scheduling problem is an NP-hard problem, the article presents a heuristic genetic algorithm for multi-runway flights landing scheduling problem. The algorithm is based on a single chromosome coding and dynamic way flights runway allocation, then selects the center gene by the information entropy of each gene, and uses variation of the local search method to solve the slow convergence and easy to fall into local optimum of genetic algorithm. Compared with traditional genetic algorithm, the method can quickly give the better flight approach and landing order to reduce flight delays by the experimental results.

Keywords: *heuristic, genetic algorithm, information entropy, local search*

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1. Introduction

Nowadays, contradictions between the sharp increase of air traffic demand and the limited airspace resources are getting more and more intense. How to improve the automation level of Aircraft Landing problem (Aircraft Landing problem, ALP) has become a problem which desperately need to be solved, also gradually attracts more and more scholars’ attention, and they put forward a lot of optimization solutions. However, there are no perfect theories and methods have been formed because of the complexity of the ALP problem itself. At present, the airport flight dispatching of the terminal area is manual control mode. Controllers estimate the time the plane arrived at the specified location (Estimated Time, ET) in the base of relevant data such as the speed, altitude, latitude and longitude, and history data of the airplane. Then they use the first come, first serve (FCFS) algorithm for aircraft landing scheduling. This kind of scheduling depends entirely on the controller's experience and judgment, lacks of scientific nature, turns out it’s already been able to adapt to modern air traffic demand. Besides, when flight flow densely, it cause great pressure on controllers which is prone to more scheduling difficulties [1]. In recent years, with in-depth study of intelligent bionic algorithm, it applies more and more on aircraft landing scheduling. A theory: aircraft scheduling control based on genetic algorithm suggested by V.H.L.Cheng [2] in 1999 had realized multiple runway ALP problems by using double chromosome coding. In the basement of that, literature [3] and literature [4] put forward a new method: to encode flights and runway respectively and accomplish much more flights partial genetic search is adopted to accomplish the aircraft landing scheduling of multiple flights and runway. The literature [5] put up to encode the plane type to reduce coding space, improve the search efficiency. Literature [6-9], respectively, using the genetic algorithm based on rolling time domain and the collaborative scheduling strategy for solving and optimizing the problems of ALS. Above methods all code in different ways, but they all take random selection in the process of genetic variation and it lacks of effective learning mechanism, with slow convergence speed and high time complexity besides it’s easy to fall into local optimal fault [10]. This paper proposes a heuristic genetic algorithm to solve the problem of ALS, through the calculation of information entropy of gene location [11], and to improve the algorithm convergence speed by comparing the process of combination between mutations and mobile mutations. Compared with traditional genetic algorithm, this kind of mutation genetic local search algorithm based on information entropy can solve ALS effectively. Not only the algorithm have quick convergence quality, also can get high quality solutions.

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The remainder of this paper is organized as follows: Section2 introduces the mathematical model of ALP problem, our proposed methods are described in detail in Section 3, this is followed by the experimental description and the corresponding results obtained in Section 4, and in Section 5 the related work conclusions and future work are presented.

2. Mathematical Model of ALP Problem

ALP question designed to find one of the plane's landing orders, the order meet landing minimum interval, and make the plane the minimum total delay time, the mathematical model is described as fallows:

A for flights landing sequence (A = {1, 2,..., n}); R for available landing runways (R = {1, 2,..., m}); Matrix M for the minimum time interval that different aircraft types must meet, according to the international practice, aircraft can be divided into heavy machine (H), large (L) and small (S); Matrix T indicates the earliest time when the runway is available for the next flight landing, Tij means the earliest time when runway i is available for airplane type j, among them (i = {1,..., m}; j = {1, 2, 3}), matrix T is initialized to null; ETA means the plane's estimated time of arrival, ETAij means the time when ith flight arrive in j th runway (I = {1,..., n}; j = {1,..., m}); X represents the actual landing time of this plane (X = {1, 2,..., n}); Flight delay is defined as the time difference between the actual landing time and the earliest arrival time when airplane arrive the runway, so the mathematical model of ALP is described as follows:

$$\text{Min} \quad Y = \sum_{i=1}^{n} (x_i - \min(ETA_{ik})) \tag{1}$$

In which k= {1,……,m}.

3. Heuristic Genetic Algorithm

Heuristic genetic algorithm includes the following steps, as shown in Figure 1. First step: selecting random chromosome coding of flight sequence, then distribute the runway under the safe interval, and calculate each chromosome fitness; The second step: using the roulette to select the offspring; The third step: carrying on the substring exchange hybridization; The fourth step: calculate the information entropy to determine center gene for local search.

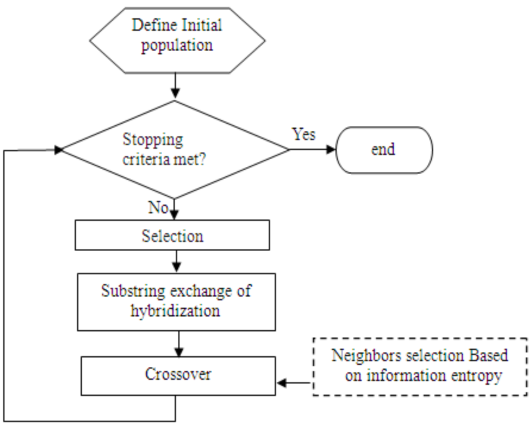

Figure 1. Heuristic Genetic Algorithm Flowchart

3.1. Encoding

There are several encoding for using genetic algorithm to solve multi runway scheduling problem. For example double chromosome coding representation for both flight sequence and runway assignment; Single chromosome coding representation flight sequence, runway assignment, or aircraft types.

3.1.1. Double Chromosome Coding

Double chromosome coding is used in which a chromosome means the flight landing sequence, while the other one represents the runway assignment. The correspondence between flights and runways is decided by the genes which have the same location in the double chromosome coding, for example, as the following double chromosome coding:

6	3	11	12	5	1	4	7	10	8	9	2
1	3	1	2	3	1	2	3	3	3	1	2

The number 6 is in the first gene locus of the first chromosome, while the number 1 is in the first gene locus of the second chromosome. Thus flight "6" will be landing on the first runway. This encoding method is easier to decode, but compared to a single chromosome encoding method, the solution space will be increased m^n times, while m represents the number of runways, n represents the number of flights to be landed.

3.1.2. Single Chromosome Coding Representation Flight Sequence

Randomly selecting flight landing sequence, using 1,... , n the way of random code, using the experimental data in the literature [4] of 3 runways 12 flights. For a random coding t is:

6 3 11 12 5 1 4 7 10 8 9 2

According to the landing order, ETA, and aircraft type to determine the landing runway and delay time:

For *i*=1 to n

Calculate the earliest time for landing current flight t_i , and assign the appropriate runway;

Reset matrix T;

Calculate their delay times and the total delay time;

End for

3.1.3. Single Chromosome Coding Representation Runway Assignment

The length of the chromosome which representation runway assignment is the number of flights to be landed, and the range of the loci in this chromosome is [1, m], while m represents the number of runways. Also using the experimental data in the literature [4] of 3 runways 12 flights. For a random coding t is:

1 3 1 2 3 1 2 3 3 3 1 2

According to the runway assignment, ETA, and aircraft type to determine the landing order and delay time:

For *i*=1 to n

Select flight which is the first to reach the runway t_i for landing;

Reset matrix T;

Calculate their delay times and the total delay time;

End for

3.1.4. Single Chromosome Coding Representation Aircraft Types

The length of the chromosome which representation aircraft types also is the number of flights to be landed, and the range of the loci in this chromosome is [1, r], while r represents the number of aircraft types. Also using the experimental data in the literature [4] which has three aircraft types. For a random coding t is:

1 3 1 2 3 1 2 3 3 3 1 2

According to the aircraft types and ETA to determine the landing order and delay time:
For *i*=1 to n
Select flight which has the same type with the i-th loci and first to reach;
Assign runway and landing;
Reset matrix T;
Calculate their delay times and the total delay time;
End for

3.2. Fitness Function

The optimal solution of ALS is the scheduling order contributes to minimum delay time, the shorter the delay time is, and the chromosome is more outstanding, so the adaptive value function is defined as follows:

$$f = \sum_{i=1}^{n} 1/(x_i - \min(ETA_{ik})) \tag{2}$$

In which k = {1,... … , m}.

But because the difference of individual adaptive value is bigger in the initial stages of algorithm, excellent fitness may be far greater than other chromosomes which cause these excellent chromosomes account for a big part of parent object when we establish the parent generation. It leads to the algorithm become easier to premature convergence to local optimal solution. On the other hand, in the late algorithm due to the difference of individuals' fitness value in the population fitness is getting smaller, which makes the algorithm easy to appear stagnation phenomenon. During all these experiments, we linear transform the fitness function, and ensure that after the transformation, the average adaptive value is equal to the original one, and the maximum fitness value is equal to c times the original average fitness value, where c is a predefined constant. When the population number is 20-100, number c often take a value of 1.2 ~ 2. It can effectively overcome these shortcomings. Linear transform the fitness function as follows:

$$f^* = a \bullet f + b \tag{3}$$

Where $a = \dfrac{(c-1) f_{avg}}{f_{\max} - f_{avg}}$, and $b = \dfrac{(f_{\max} - c \bullet f_{avg}) f_{avg}}{f_{\max} - f_{avg}}$

3.3. Selection

The selection process makes use of roulette algorithm based on adaptive value choice. Algorithm process is as follows:
Begin
For i=1 to n do
r=random(1);
While(r>q_j) do j++
Select the *j* th chromosome;
End while
End for
End

3.4. Substring Exchange of Hybridization

Algorithm base on substring exchange hybridization of method [12] proposed by Cheng, Gen and Tsujimura, then come up with the deterministic substring exchange hybrid method.

Step 1: randomly generate two intersection Numbers, exchange of the two substring be determined by the intersection to get two offspring;

Step 2: to compare the 2 substring, determine the redundant or missing genes of offspring;

Step 3: remove redundant genes, and in accordance with the way from left to right, add missing gene into the offspring.

Specific operation is as follows: set random numbers 3 and 5.

(1 , 3 , |4 , 2 , 5 , | 6 , 8 , 9 , 7)
(3 , 1 , |2 , 7 , 8 , | 4 , 5 , 9 , 6)

Exchange the position of 2 substrings:

(1 , 3 , |2 , 7 , 8 , | 6 , 8 , 9 , 7)
(3 , 1 , |4 , 2 , 5 , | 4 , 5 , 9 , 6)

Compare 2 substring that child 1 is short of 4 and 5, but with redundant 7 and 8, and child 2 is missing 7 and 8, but with extra 4 and 5.

(1 , 3 , |2 , 7 , 8 , | 6 , 4 , 9 , 5)
(3 , 1 , |4 , 2 , 5 , | 7 , 8 , 9 , 6)

3.5. Local Adjacent Mutation Based on Information Entropy

The traditional mutation in genetic algorithm is randomly operated. This paper defines the information entropy combining with the characteristics of ALP. The fitness function of ALP is calculated by the various genes of flight's delay time, so the definition of flight delays is its information entropy of the gene.

Definition 1: set (A = {1, 2... n}) as the chromosome coding, the information entropy of i gene are as follows:

$$t_i = x_i - \min(ETA_{ik}) \tag{4}$$

In which k = {1,... …, m}

Local adjacent mutation operations are as follows:

begin

while i < specific number n do

Choose the gene with maximum information entropy as the center; make it exchange one by one with i genes in front of it, and generating new chromosomes; Evaluation of new chromosome; If the chromosomes better than other current chromosomes, set it as current chromosome; i =i+ 1

end while

end

4. Simulation Experiment

4.1. Experimental Data

Three sets of data are using for testing the algorithm. The first set of data using a set of flights from one airport, and the data has 37 flights and one runway. Another two sets of data from literature [4].

Using literature [4] the 3 runways/12 flights model as the experimental data, the ETA data and aircraft type are as follows:

Table 1. The Literature [4] 12 Flights 3 Runways Data

Flight	Type	Runway1	Runwa2	Runway3
1	H	12	11	10
2	S	15	17	19
3	H	7	9	8
4	H	6	7	8
5	L	10	13	15
6	H	7	6	5
7	L	15	17	19
8	H	7	8	9
9	S	6	7	8
10	H	9	12	15
11	H	6	5	4
12	L	9	7	6

The second column of Table 1 represents the type of each aircraft (i.e. H stands for heavy, L for large, and S for small). The third to fifth columns of Table 1 represent the earliest landing time (ETAik) of aircraft i landing on runway k.

The third experimental data has 5 runways /20 flights also from the literature 4 as follows:

Table 2. The Third Experimental Data

Flight	Type	Run1	Run2	Run3	Run4	Run5
1	H	12	11	10	10	9
2	L	15	17	19	18	18
3	H	7	9	8	7	8
4	H	6	7	8	7	8
5	S	10	13	15	15	14
6	H	7	6	5	6	5
7	L	15	17	19	19	18
8	H	7	8	9	8	9
9	H	6	7	8	7	8
10	S	9	12	15	15	14
11	H	6	5	4	6	6
12	L	9	7	6	9	8
13	S	7	8	9	7	8
14	L	6	7	8	7	8
15	H	9	8	7	8	9
16	S	10	11	10	10	11
17	L	6	7	8	6	7
18	L	9	8	7	8	7
19	H	7	8	9	7	9
20	L	9	10	11	9	10

The second column of Table 2 represents the type of each aircraft (i.e. H stands for heavy, L for large, and S for small). The third to seventh columns of Table 2 represent the earliest landing time (ETA_{ik}) of aircraft i landing on runway k.

Landing must be depending on the type of aircraft and landing sequence satisfy certain time intervals, landing minimum wake separation standards in Table 3. As shown, depending on the respective types of the leading and trailing airplanes requesting a landing (heavy, large or small), different separation times are required. For instance, a large aircraft following a small aircraft requires only one unit of separation time, while a small aircraft trailing a heavy aircraft will require two units.

Table 3. The Requirements for Aircraft Separation

Leading	Trailing Heavy	Large	Small
Heavy	1	1.5	2
Large	1	1.5	1.5
Small	1	1	1

4.2. Experimental Method

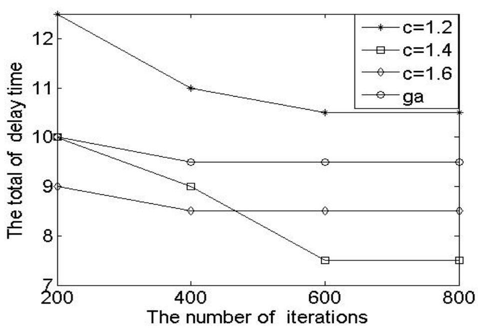

Figure 2. The Analysis of c Value Sensitivity

Experiment 1 using the same initial population, its size is 50, using the formula (3) as a fitness function, the c value, respectively, are 1.2, 1.4, 1.6 in iterative 200,400,600 and 800 times to obtain the best delay time, hybrid probability value is defined as 0.25, the mutation probability value defined as 0.1, with the method of random variable, and using the formula (2) as the fitness function of genetic algorithm. The result is shown in Figure 2.

Analysis from the result of the experiment, when the c value is 1.2, The algorithm converge slowly at first, while when the c value is 1.6, or use formula (2) as the genetic algorithm, though at first algorithm converges faster, but prone to stagnation phenomenon in the late algorithm. When c value is 1.4 it is easier to get the optimal solution.

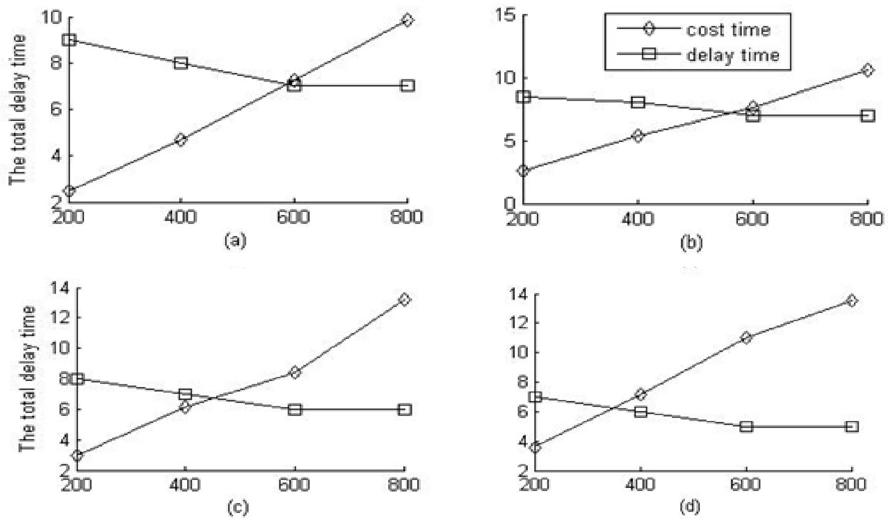

Figure 3. Different Neighbor Search Results

Experiment 2 applies adjacent variation based on information entropy. C value is defined as 1.4, search scope is respectively 2, 3, 4, 5 to correspond (a), (b), (c), and (d) in Figure 3, hybrid probability value is 0.25, the mutation probability value is 0.1, the four algorithms using the single chromosome coding representation flight sequence and the same initial population, its size is 50. Iterate respectively, 200, 400, 600 and 800 times to obtain minimum delay and consuming time. The experimental result is the average after the program run ten times.

Analysis from the result of the experiment shows that when the neighboring search scope is smaller, the slower the convergence speed gets, the more likely it is to get the optimal solution, at the same time, the time of consumption is more. As shown in Figure 3(d) when the neighboring search range is 5, the algorithm will get a better solution at the 200th time. Due to the number of initial population is 50, when the iteration repeats 600 times, all the algorithms converge to the optimal solution.

Analysis from the Figure 4, the encode 2 using Single chromosome coding representation flight sequence has best result, while the encode 1 using the double chromosome coding has the worst result. The other two encoding, encode 3 using Single chromosome coding representation runway assignment, and encode 4 using Single chromosome coding representation aircraft types, are very easy to fall into difficulties search elements, and the results are far away with the optimal solution. Table 4 shows the best scheduling order on data 2 while using the single chromosome coding representation flight sequence. The first column of Table 4 represents the aircraft landing sequence, the second column of Table 4 represents the earliest achieved time of corresponding flight on all runway. While the forth column (STA) represents the achieved time of corresponding flight on the assigned runway, which is listed in the fourth column, and the fifth column represents the delay time of corresponding flight. While Table 5 shows the best scheduling order on data 3 while using the single chromosome coding representation flight sequence.

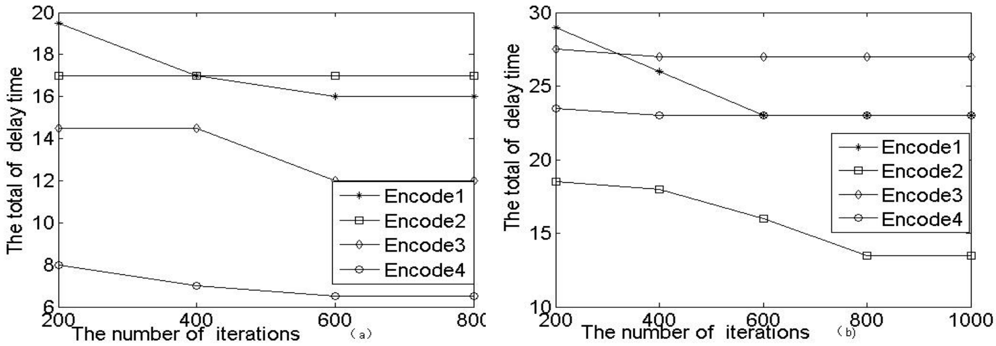

Figure 4. Different Encoding Results

Experiments 3 tested four different encoding, respectively, using data 2 and data 3, c value is defined as 1.4, and search scope is 3. Initial population size is 50, using the formula (3) as a fitness function. Hybrid probability value is 0.25; the mutation probability value is 0.1. Iterate respectively, 200, 400, 600 and 800 times to obtain minimum delay and consuming time. The experimental result is the average after the program run ten times. The result is shown in Figure 4, Figure 4(a) using data 2, and Figure 4(b) using data 3. Encode 1 using the double chromosome coding, encode 2 using Single chromosome coding representation flight sequence, encode 3 using Single chromosome coding representation runway assignment, and encode4 using Single chromosome coding representation aircraft types.

Table 4. The Best Scheduling Order on Data 2

Flight	ETA	RUNWAY	STA	DELAY
11	4	3	4	0
4	6	1	6	0
3	7	1	7	0
6	5	3	5	0
10	9	1	9	0
5	10	1	10.5	0.5
12	6	3	6.5	0.5
2	15	1	15	0
8	7	2	8	1
7	15	1	16	1
9	6	3	8	2
1	10	3	10	0

Table 5. The Best Scheduling Order on Data 3

Flight order	ETA	RUNWAY	STA	DELAY
11	4	3	4	0
4	6	1	6	0
6	5	3	5	0
19	7	1	7	0
10	9	1	9	0
16	10	1	10	0
12	6	3	6.5	0.5
9	6	2	7	1
2	15	1	15	0
5	10	2	13	3
18	7	5	7	0
15	7	3	7.5	0.5
17	6	4	6	0
13	7	4	7.5	0.5
14	6	4	8.5	2.5
20	9	4	10	1.
7	15	1	16.5	1.5
3	7	5	8	1
8	7	3	8.5	1.5
1	9	5	9	0

5. Conclusion

Combining with ALS practical problems, we put forward a heuristic genetic algorithm. This algorithm adopts the single chromosome coding scheme, using the linear transformation to adjust fitness function, and avoid algorithm from keeping local optimum at first or stays stagnation in late stage, meanwhile, adjacent mutation search based on information entropy makes the algorithm quickly obtain the optimal solution, and realize the optimization of aircraft landing scheduling. The experimental results show that compared with the traditional genetic algorithm, new algorithm is able to improve the operation efficiency effectively, prevent local optimum, while reducing the total delay in the process of landing. In the future, it can be combined with ALS and takes a further research on flight departure and arrival flight cooperatively.

Acknowledgements

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