Multi-objective Collaborative Optimization for Scheduling Aircraft Landing on Closely Spaced Parallel Runways Based on Genetic Algorithms

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Abstract: A scheduling model of closely spaced parallel runways for arrival aircraft was proposed, with multi-objections of the minimum flight delay cost, the maximum airport capacity, the minimum workload of air traffic controller and the maximum fairness of airlines' scheduling. The time interval between two runways and changes of aircraft landing order were taken as the constraints. Genetic algorithm was used to solve the model, and the model constrained unit delay cost of the aircraft with multiple flight tasks to reduce its delay influence range. Each objective function value or the fitness of particle unsatisfied the constrain condition would be punished. Finally, one hub of a domestic airport was introduced to verify the algorithm and the model. The results showed that the genetic algorithm presented strong convergence and timeliness for solving constraint multi-objective aircraft landing problem on closely spaced parallel runways, and the optimization results were better than that of actual scheduling.

Key words: air transportation; runway scheduling; closely spaced parallel runways; genetic algorithm; multi-objections

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0 Introduction

The growth rate of airport capacity has been lagged behind the increasing aviation demand. Some busy airports expanded runways to tackle this problem. Compared with other configurations, closely spaced parallel runways (CSPR), i. e., runways spaced less than 762 m, could better improve the capacity of runway system, as well as hold more flexibility for aircraft landing [1]. Therefore, the CSPR's expansion has become the first choice to alleviate the capacity-demand contradiction. However, inadequate research on CSPR and the stronger impact of the wake flow between aircraft on CSPR renders scheduling aircraft on CSPR a great challenge. So far, related studies covered three aspects as follows:

(1) CSPR's capacity: Capacity calculation model [2] and evaluation model [3], method for enhancing capacity [4-5] and the relationship between runways operation modes and the theoretical capacity [6].

(2) Approach procedure to CSPR: Hammer et al. and Eftek et al. proposed paired approach procedures[7-8]; Domino et al. analyzed the paired approach procedure's feasibility [9] and Sun et al. investigated its collision risk [10]; and Mundra et al. analyzed the paired approach procedure's advantages and the required hardware[11].

(3) Influence of wake turbulence and its countermeasures: Rad [12] developed a concept of dynamic separations using wake vortex predictions, in order to reduce the wake effects. Rossow et al. [13] analyzed the propagation mechanism

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of the wake flow from a dynamic view and proposed a method to evaluate the influence of wake turbulence; Tian et al. [1] studied the time intervals of aircraft landing on CSPR when the operational characteristic of wake turbulence was the worst.

However, the research on CSPR had two problems:

(1) Static state. Runway capacity, approach mode and the influence of wake turbulence were confined to theoretical research. Therefore, the research results could not be directly applied to practical scheduling.

(2) One-sidedness. Almost all researchers confined to study a part of the factors influencing runway scheduling. However, practical runway scheduling was a complex optimization problem and it was affected by various factors.

Many studies, domestic and abroad, on aircraft arrival sequencing problems, have accomplished both theoretically and practically. But those works mainly focused on how to sequence the landing aircraft [14-16] and improve its efficiency [17-18], without studying multi-objective optimization problem.

Therefore, a CSPR scheduling model was proposed to improve the operating efficiency of CSPR, and therefore to ease the demand-supply contradiction. The genetic algorithm was introduced to solve the model. The model was designed to obtain four objectives: the minimum delay cost, the maximum runway capacity, the best fairness among airlines and the minimum workload of air traffic controllers.

1 Modeling

Aircraft landing is defined as assigning landing runway and landing time to certain aircraft belonging to some airlines at one time window. The goal of aircraft landing is to balance the demand and the supply, and to minimize the operation cost. Scheduling is completed coordinately by three parts: airlines, airport and air traffic control department. Safety holds the highest priority during scheduling; economy the second, and fairness the third. Targeting at the three goals, airports should serve as many aircraft as possible within limited time span while increasing aviation business charges. Throughout this procedure, air traffic controllers would face a critical challenge, because the operating safety of airport terminal can be improved by reducing the workload of controllers while the number of aircraft landing on the runways is increased. Therefore, we comprehensively considered the interests among the departments when scheduling aircraft.

To simplify the problem, we assumed that: Firstly, aircraft parking time was within 2 h and the serving time of departure lounge bridges was within 1 h. Security charge of the cargo was zero. Secondly, runway occupying time of all aircraft was 45 s. Finally, the basic information of the aircraft was given.

1.1 Objective functions

The flights here are divided into two kinds: multi-tasking flights and single-tasking flights. The aircraft of the former will have other missions in h. So, the minimum delay cost Z_1 is given as

$$\min Z_1 = \sum_{i=1}^{N} C_{f_i} = \sum_{i=1}^{N} \begin{cases} c_{f_i}(T_{f_i} - t_{f_i})^{1+\varepsilon} & E_{f_i} \leqslant t_{f_i} \leqslant T_{f_i} \\ \varphi_{f_i} c_{f_i}(t_{f_i} - T_{f_i})^{1+\varepsilon} + \\ \lambda_{f_i}(1-\varphi_{f_i}) c_{f_i}(t_{f_i} - T_{f_i})^{1+\varepsilon} & T_{f_i} \leqslant t_{f_i} \leqslant L_{f_i} \end{cases} \tag{1}$$

where N is the number of landing aircraft; C_{f_i} the delay cost of flight f_i, which is related to its unit time delay cost c_{f_i} and delay time; $\varepsilon=0.5$ the coefficient of super-liner growth. t_{f_i}, T_{f_i}, L_{f_i} and E_{f_i} indicate the actual landing time, the target landing time, the latest landing time and the earliest landing time, respectively. If the aircraft of flight f_i has only one fly mission at the airport, the flight is defined as unique tasking flight and $\varphi_{f_i}=1$; otherwise the flight is multi-tasking flight and $\varphi_{f_i}=0$. λ_{f_i} is the penalty coefficient of the unit time delay cost of multi-tasking flight and is obtained by

$$\lambda_{f_i} = 1 + \frac{ca_{f_i}}{c_{f_i}} \tag{2}$$

where ca_{f_i} is the unit time delay cost of aircraft executing flight f_i.

Runway capacity Z_2 is defined as the number of flights landing on the runway within 1 h. So, the maximum runway capacity is given by

$$\max Z_2 = \frac{60(N-1)}{\max_i t_{f_i} - \min_i t_{f_i}} \tag{3}$$

The change number of landing order is used to measure the workload of air traffic controllers Z_3 here, so the minimum workload is given by

$$\min Z_3 = \sum_i |D_{f_i} - D^{\#}_{f_i}| \tag{4}$$

where D_{f_i} is actual landing order and $D^{\#}_{f_i}$ is target landing order.

The best fairness is given by

$$\min Z_4 = \max_{a \in A} |X_a - Y_a| \tag{5}$$

where Z_4 represents the fairness. X_a and Y_a are the proportion of delay cost of flights and the proportion of aviation business charges belonging to airline a, and they are described as

$$X_a = \frac{\sum_{f_i \in F_a} C_{f_i}}{\sum_{f_i \in F} C_{f_i}} \tag{6}$$

$$Y_a = \frac{U_a}{\sum_{a \in A} U_a} \tag{7}$$

where F is a set of flights and F_a a set of aircraft belonging to airline a; U_a the aviation business charges of airline and A a set of airlines, $a \in A$.

1.2 Constraint formulations

$$E_{f_i} \leqslant t_{f_i} \leqslant L_{f_i} \tag{8}$$

$$\sum_{r \in \mathbf{R}} \xi_{f_i r} = 1 \tag{9}$$

Eq.(8) illustrates constrains for all flights landing time, and Eq.(9) the constraints of each flight with only one runway. R is a set of runways. If flight f_i lands on runway r, $\xi_{f_i r}=1$; otherwise $\xi_{f_i r}=0$.

The aircraft here are divided into three types according to the strength of their wake flow: Heavy (H), Middle (M) and Light (L). The landing time interval between the leading aircraft and the trailing is not less than the minimum time interval, and also not less than runway occupying time. The constraint is given by

$$60 * (t_{f_j} - t_{f_i}) \geqslant \max(\sigma_{\langle f_i, f_j \rangle} S_{\langle f_i, f_j \rangle} + (1-\sigma_{\langle f_i, f_j \rangle}) s_{\langle f_i, f_j \rangle}, 45) - Md_{\langle f_i, f_j \rangle} \quad \forall i \neq j \tag{10}$$

where $S_{\langle f_i, f_j \rangle}$ represents the separation time between flights f_i and f_j on the same runway and $s_{\langle f_i, f_j \rangle}$ the separation time between flights f_i and f_j on different runway. If flights f_i and f_j land on the same runway, $\sigma_{\langle f_i, f_j \rangle}=1$, otherwise $\sigma_{\langle f_i, f_j \rangle}=0$. If flight f_i lands on the runway after f_j, $d_{\langle f_i, f_j \rangle}=1$, otherwise $d_{\langle f_i, f_j \rangle}=0$. M is a great positive number.

The minimum time intervals between two aircrafts landing on the same runway are shown in Table 1.

Table 1 Minimum separation times between two aircraft on the same runway Unit: s

Leading	Following		
	H	M	L
H	99	133	196
M	74	107	131
L	74	80	98

The minimum time intervals between two aircraft landing on different runways are obtained through the relationship between the long term planning capacity of single runway and that of closely spaced parallel runways, shown as Table 2.

Table 2 Minimum separation times between two aircraft on different runway Unit: s

Leading	Following		
	H	M	L
H	51	68	100
M	38	55	67
L	38	41	50

Actual runway capacity is not larger than the ultimate capacity, and it is constrained as

$$Z_2 \leqslant V \tag{11}$$

where V is the ultimate capacity of runways.

Eq.(12) demonstrated the change number of aircraft landing order

$$|D_{f_i} - D^{\#}_{f_i}| \leqslant \text{Reset} \tag{12}$$

$$M \gg 0; \quad i,j = 1,\cdots,N \tag{13}$$

where Reset is the maximum change value of landing order.

2 Genetic Algorithm

2.1 Double chromosome encoding

Each chromosome consists of two chromatids: one chromatid encodes the landing time, and the other the landing runway, as shown in Fig. 1.

Time	…	t_{fi}	…	t_{fi}	…
Runway	…	0	…	1	…

Fig. 1 Double chromosome coding

2.2 Weighted average method

The weighted average method is divided into two kinds: one is punishing each objective function value, and the other is punishing the fitness. The former is simply called SFWM, and the latter is GFWM. The processes are shown as follows:

(1) The process of SFWM

① Calculate each objective function value, and punish each value of the particle violating the constraints. For example, if particle e_k violates the constraints, and the number is m, each value z_i will be set into $z_i + m * (\mathrm{fix}(\log_{10} z_i) + 1)$, where $\mathrm{fix}(\log_{10} z_i)$ represents the magnitude of z_i.

② Normalize the objective function values according to the mapminmax function of MATLAB, and the fitness is equal to the weighted sum of all normalized objective function values.

(2) The process of GFWM

① Calculate each objective function value and normalize each one.

② Assign the weighted sum of the normalized values to the fitness. If the particle violates the constraints, then punish its fitness.

2.3 Operating steps of genetic algorithm

Step 1 Population initialization: Create matrix $\boldsymbol{P}$ one column of full rank to ensure the diversity of initial population. The row is equal to $2N$, and the column is n, where n is the population size.

Step 2 Calculate the fitness and assign the value of matrix $\boldsymbol{P}$ to matrix $\boldsymbol{P}'$.

Step 3 Selection: Sort all particles of initial population in descending order of their fitness values, and the top 80% particles are chosen as the next generation individuals candidate and assigned to matrix $\boldsymbol{O}$.

Step 4 Crossover: Assign the matrix $\boldsymbol{P}'$ to $\boldsymbol{P}''$. Randomly generate one array $W = w_1 w_2 \cdots w_i \cdots w_{2N}$. The crossover process is operated as follows:

(1) If $w_i = 1$, index$=\boldsymbol{P}'(\boldsymbol{i}, \boldsymbol{k})$, $\boldsymbol{P}'(i, k) = \boldsymbol{P}'(i, n+1-k)$ and $\boldsymbol{P}'(i, n+1-k) =$ index.

(2) If $w_i = 0$, corresponding position values of the mating particles are not changed.

Step 5 Mutation: Randomly generate one number, and the mutation process is operated as:

(1) If the number is less than the mutation probability, generate one positive integer l between 0 and $2N$.

① If the positive integer l is odd, randomly generate one integer x between -30 and 30 and assign it to $\boldsymbol{P}''(l, k)$.

② If the positive integer l is even, $\boldsymbol{P}''(l, k)$ is equal to its opposite.

(2) If the number is not less than the mutation probability, do not perform mutation operation.

Step 6 Update population: The matrix $\boldsymbol{Q}$ is equal to the combination of matrix $\boldsymbol{O}$, $\boldsymbol{P}'$ and $\boldsymbol{P}''$. Firstly, delete the same column of matrix $\boldsymbol{Q}$ to protect the diversity of the population, and assign the remaining column to matrix $\boldsymbol{Q}'$. Secondly, calculate the fitness of matrix $\boldsymbol{Q}'$ and sort it in descending order. Finally, select the top n particles and assign them to matrix $\boldsymbol{P}$.

Step 7 Stop and output the optimal solution if the maximum generation number is achieved. Otherwise, go to Step 2.

3 Results

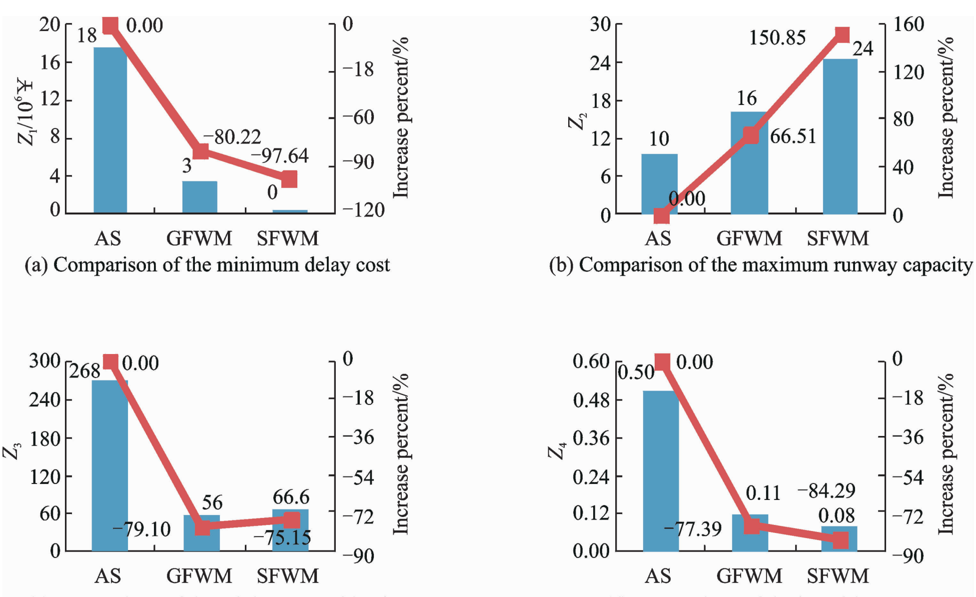
The genetic algorithms presented above were implemented in MATLAB on a 3.40 GHz PC with 8 192 MB memory. The parameters of the simulation experiment were set as: $n = 100$, Reset$=3$; the maximum iterative algebra was 100 and the mutation probability was equal to 0.01. The weight values of each objective function were equal to 0.4, 0.3, 0.15 and 0.15, respectively. We took one hub airport as an example to analyze the model, and some information of the flights were shown in Table 3.

Table 3 Sample data of flights

Flight No.	$D^{\#}_{f_i}$	T_{f_i}	t_{f_i}	Type	Flight No.	$D^{\#}_{f_i}$	T_{f_i}	T_{f_i}	Type	Flight No.	$D^{\#}_{f_i}$	T_{f_i}	T_{f_i}	Type
MU212	1	8:15	7:49	M	MU5506	14	9:25	9:54	M	CZ6521	27	9:45	9:33	M
AY057	2	8:20	7:56	H	BA169	15	9:25	11:44	H	SU208	28	9:45	10:29	H
CA1965	3	8:35	8:30	M	MU517	16	9:30	9:00	M	KE893	29	9:45	9:38	H
HO1276	4	8:50	9:08	M	CA8953	17	9:30	9:04	M	MU294	30	9:45	10:12	M
MU2881	5	8:55	9:08	M	CI581	18	9:30	9:14	H	FM9070	31	9:50	10:17	M
MU5586	6	8:55	8:52	M	MU2402	19	9:35	9:36	M	MU521	32	9:50	9:45	M
GE332	7	8:55	8:37	M	MU5544	20	9:35	9:17	M	MU726	33	9:50	9:47	M
MU5512	8	9:00	9:19	M	MU5660	21	9:35	9:13	M	PR338	34	9:50	9:40	M
FM9258	9	9:15	10:11	M	FM9328	22	9:40	9:27	M	MU5052	35	9:50	9:42	H
MU5534	10	9:15	9:02	M	FM9402	23	9:40	9:44	M	MU5342	36	9:55	9:28	M
MU5286	11	9:20	9:15	M	MU5468	24	9:40	9:19	M	FM9308	37	9:55	9:33	M
MU5466	12	9:20	9:09	M	KE875	25	9:40	9:24	M	MU5183	38	9:55	9:05	M
VS250	13	9:20	9:11	H	3U8971	26	9:45	9:31	M	HU7205	39	10:00	9:39	M

Fig. 2 illustrates all the objective function values obtained by three kinds of algorithms, where "AS" is the abbreviation for actual scheduling of the airport. Taking the values of AS as the reference, the percentage increase of the objective function value is shown in the secondary vertical axis of Fig. 2.

Fig. 2 indicates that delay cost of genetic algorithm is significantly less than that of AS, and runway capacity of the former is obviously improved. In particular, runway capacity of SFWM is nearly 2.5 times of that of AS. The reduction of delay cost is beneficial to airline's operation. The improvement of runway capacity can not only increase airport revenue, but also improve the operating efficiency of runway surface and the safety of air transportation. The fairness of the two methods was increased by 77.39% and 84.29%, respectively. The increase of the fairness can weaken monopoly of some airlines to promote harmonious development of aviation transportation market. There were 39 aircrafts waiting for landing within the scheduling time window. If the change number of landing order of all aircraft was



(a) Comparison of the minimum delay cost
(b) Comparison of the maximum runway capacity
(c) Comparison of the minimum workload
(d) Comparison of the best fairness

Fig. 2 Objective values obtained by three different methods the maximum, i. e., 3, the total change number would be equal to 117. Fig. 2 shows that AS is equal to 268. So the scheme of AS was not suitable to the model here. However, the schemes obtained by the two kinds of genetic algorithm met Eq. (12) in section 1. 3. Table 4 shows the objective function values in different cases.

Table 4 Results in different simulation conditions

Simulation result	SFWM				GFWM			
	Z_1	Z_2	Z_3	Z_4	Z_1	Z_2	Z_3	Z_4
The best Z_1	29 535	23	70	0.098	278 073	16	46	0.063
The best Z_2	52 970	26	36	0.097	413 145	18	62	0.063
The best Z_3	52 970	26	36	0.097	342 692	16	44	0.074
The best Z_4	37 127	23	72	0.053	278 073	16	46	0.063

The following conclusions can be summarized from Table 4:

(1) When Z_1 is optimal, i. e.: the value of Z_1 is the minimum, the delay cost is the minimum. However, runway capacity is the minimum, and the value of Z_4 of SFWM is the maximum, i. e., the fairness of scheduling is the worst. On the contrary, that of GFWM is the minimum, i. e., the fairness was the best.

(2) When runway capacity is the maximum, the value of Z_3 of SFWM is also optimal. However, delay cost is the maximum, and the second method has the maximum workload and delay cost.

(3) When the value of Z_3 is the minimum, it represents the workload is the minimum. The first method also has the optimal Z_2. The second method has the minimum runway capacity and the worst fairness.

(4) When Z_4 is optimal, it represents the fairness is the best. Delay cost of the second method is the minimum. However, two methods have the minimum runway capacity. And the workload of first method is the maximum.

The conclusions presented above indicate an almost negative correlation between delay cost and runway capacity.

According to the three evaluation grades: excellent(ex), average(av) and poor(po), the data of Table 4 can be translated into those in Table 5.

Table 5 Evaluation grades from Table 4

Simulation result	SFWM				GFWM			
	Z_1	Z_2	Z_3	Z_4	Z_1	Z_2	Z_3	Z_4
The best Z_1	ex	po	av	po	ex	po	av	ex
The best Z_2	po	ex	ext	av	po	ex	po	ex
The best Z_3	po	ex	ext	av	av	po	ex	po
The best Z_4	av	po	po	ext	ext	po	av	ex

The three evaluation grades were respectively assigned to 3, 2 and 1, and thus the scores of two methods are shown in Table 6.

Table 6 Evaluation scores of the scheme

Simulation result	SFWM	GFWM
The best Z_1	7	9
The best Z_2	9	8
The best Z_3	9	7
The best Z_4	7	9

Some conclusions can be drawn from Table 6: Firstly, the comprehensive score of SFWM is higher when Z_2 and Z_3 are optimal. A higher score indicates the scheme is more suitable for putting into practice. Secondly, the comprehensive scores of GFWM is higher when Z_1 and Z_4 are optimal. Therefore, decision makers can select the appropriate scheduling scheme according to different scheduling environment.

The convergence was an effective medium to test intelligent algorithm, and the variation of fitness values could excellently reflect it, which are shown in Figs. 3, 4.

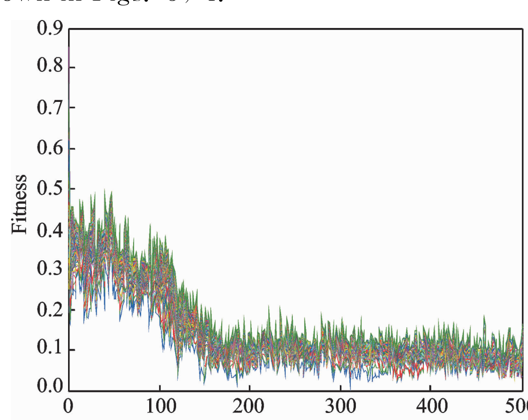


Fig. 3 Fitness values of SFWM in each generation

Figs. 3, 4 indicate that the two kinds of genetic algorithms both have excellent convergence with declining fitness. In addition, the convergence of the latter is better than that of the first

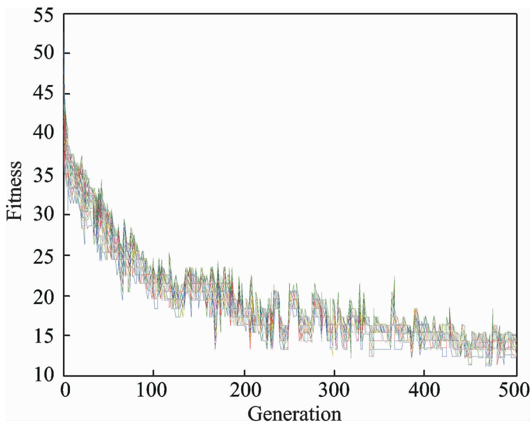


Fig. 4 Fitness values of GFWM in each generation

one, because its curve becomes more smooth.

Program running time is a standard to measure the efficiency of the algorithm. Parts of program running times are shown in Fig. 5.

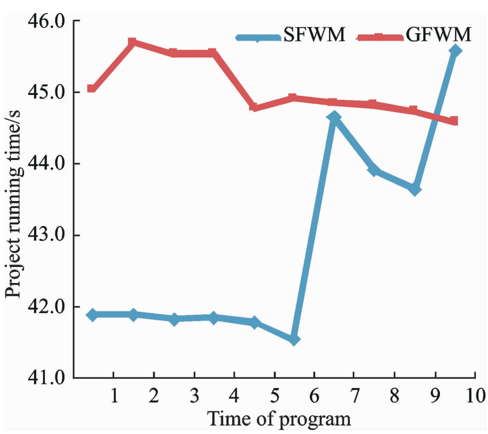


Fig. 5 Running time of the program

Fig. 5 shows that the running time of the program of SFWM was shorter than that of GFWM. The average running time of SFWM was equal to 42.9 s, and it was 2.2 s shorter than that of GFWM. The shorter the running time is, the more conductive putting into practice and improving the dynamics of flight scheduling is.

4 Conclusions

We transformed the minimum time intervals between two aircrafts landing on the same runway into those on different runways, then the model with multi-objections for aircraft landing on CSPR was proposed. The delay cost of multi-tasking flights was punished to weaken the influence on the next task. Finally, two kinds of penalty mechanisms were used to deal with multi-objective functions, and the following conclusions were summarized from the simulation.

(1) The solution of genetic algorithm is more outstanding than that of AS.

(2) Genetic algorithm based on SFWM is more suitable to solve the model than the other one.

(3) Genetic algorithm has strong convergence, and the program running time is shorter. So it has a good practical value.

However, some relevant parameters of genetic algorithm are mainly determined through the experimental simulation. It needs to be studied further.

References:

[1] TIAN Yong, SUN Jia, WAN Lili, et al. Separation determining method of closely spaced parallel runways [J]. Journal of Traffic and Transportation Engineering, 2013, 13(1):70-76. (in Chinese)

[2] TAO mei, NIE Rutu, ZHAO Weijing. Capacity of closely-spaced parallel runways using dependent approach procedures [J]. Journal of Transportation Systems Engineering and Information Technology, 2014, 6(14): 182-193. (in Chinese)

[3] PENG Y, WEI G, JUN Q S. Capacity analysis for parallel runway through agent-based simulation [J]. Mathematical Problems in Engineering, 2013.

[4] JANIC M. Steeper approach procedure for increasing ultimate capacity of closely spaced parallel runways [J]. Transportation Research Record: Journal of the Transportation Research Board, 2015:81-89.

[5] GUO H Q, ZHU J F. Calculation models of capacity and delay for closely spaced parallel runway [J]. Journal of Traffic and Transportation Engineering, 2008, 4: 10-16.

[6] Gu Zhengbing. Study on instrument operation modes for closely spaced parallel runways of HONG-QIAO airport [J]. Journal of Civil Aviation University of China, 2010, 28(5): 21-24. (in Chinese)

[7] HAMMER J B. Case study of paired approach procedure to closely spaced parallel runways [J]. Air Traffic Control Quarterly, 2000, 8(3):223-252.

[8] EFTEK ARI R, HAMMER J B, HAVENS D A, et al. Feasibility analyses for paired approach procedures for closely spaced parallel runways[C]// IEEE

Integrated Communications, Navigation and Surveillance Conference (ICNS), 2011. Venice: IEEE, 2011:1-14.

[9] DOMINO D, TUOMEY D, STASSEN H P, et al. Paired approaches to closely spaced runways: Results of pilot and ATC simulation[C]//Digital Avionics Systems Conference (DASC), 2014 IEEE/AIAA 33rd. [S. l.]: IEEE, 2014: 1B2-1-1B2-15.

[10] SUN Jia, TIAN Yong. Collision risk analysis of closely spaced parallel runways under parallel dependent approach procedure[J]. Journal of Harbin University of Commerce (Natural Sciences Edition), 2014, 2(30):241-245. (in Chinese)

[11] MUNDRA A D, COOPER W W, SMITH A P, et al. Potential benefits of a paired approach procedure to closely parallel runways in instrument and marginal visual conditions[C]// IEEE Digital Avionics Systems Conference. St. Paul: IEEE, 2008: 10-27.

[12] RAD T, SCHÖNHALS S, HECKER P. Dynamic separation minima coupled with wake vortex predictions in dependent runway configurations [J]. Proceedings of the Institution of Mechanical Engineers, Part G: Journal of aerospace engineering, 2014, 228 (8): 1450-1457.

[13] ROSSOW V J, MEYN L A. Guidelines for avoiding vortex wakes during use of closely spaced parallel runways [C] // 26th AIAA Applied Aerodynamics Conference. Honolulu, Hawall:[s. n.],2008.

[14] HU Minghua, MA Yuanyuan, TIAN Wen, et al. Optimized sequencing and scheduling approach for arrival traffic flow at complex terminal area[J]. Journal of Nanjing University of Aeronautics & Astronautics, 2015,47(4):459-466. (in Chinese)

[15] WU Y, SUN L, QU X. A sequencing model for a team of aircraft landing on the carrier[J]. Aerospace Science and Technology, 2016, 54: 72-87.

[16] JI X P, CAO X B, TANG K. Sequence searching and evaluation: a unified approach for aircraft arrival sequencing and scheduling problems [J]. Memetic Computing, 2015: 1-15.

[17] JIANG Y, YANG Y B, ZHOU H. Innovative predatory search algorithm for aircraft arrival sequencing and scheduling problems[J]. Transactions of Nanjing University of Aeronautics & Astronautics, 2010,27 (4):361-366.

[18] FURINI F, KIDD M P, Persiani C A, et al. Improved rolling horizon approaches to the aircraft sequencing problem[J]. Journal of Scheduling, 2015, 18(5): 435-447.

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