A Tabu-Based Multi-objective Particle Swarm Optimization for Irregular Flight Recovery Problem

Tianwei Zhou[1,2], Yichen Lai[1], Xiaojie Huang[1], Xumin Chen[1], and Huifen Zhong[1,3](✉)

[1] College of Management, Shenzhen University, Shenzhen 518060, China
zhonghf510520@163.com
[2] Great Bay Area International Institute for Innovation, Shenzhen University, Shenzhen 518060, China
[3] Faculty of Business and Administration, University of Macau, Macau 999078, China

Abstract. Air transportation is eminent for its fast speed and low cargo damage rate among other ways. However, it is greatly limited by emergent factors like bad weather and current COVID-19 epidemic, where irregular flights may occur. Confronted with the negative impact caused by irregular flight, it is vital to rearrange the preceding schedule to reduce the cost. To solve this problem, first, we established a multi-objective model considering cost and crew satisfaction simultaneously. Secondly, due to the complexity of irregular flight recovery problem, we proposed a tabu-based multi-objective particle swarm optimization introducing the idea of tabu search. Thirdly, we devised an encoding scheme focusing on the characteristic of the problem. Finally, we verified the superiority of the tabu-based multi-objective particle swarm optimization through the comparison against MOPSO by the experiment based on real-world data.

Keywords: Crew recovery · Irregular flight · Tabu-based multi-objective particle swarm optimization · Tabu search

1 Introduction

In the third year of facing COVID-19, the world is still suffering under the highly infectious variant Omicron. Though the dynamic clearing policy adopted by Chinese government reduces the loss greatly, the following lockdown and quarantine lead to flight circuit breaker mechanism. Moreover, weather anomaly generated by global warming may also cause irregular situation.

According to the Normal Statistical Method of Civil Aviation Flight [1] released by Civil Aviation Administration of China, normal flights can be defined as follows "flights depart 10 min or shorter after scheduled departure time without sliding back, veering or preparing for landing, or arrive within 10 min before scheduled arrival time." And irregular flights refer to those do not obey above conditions. Usually, the occurrence of irregular flight happens days or even hours before takeoff, which requires airline to

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recover it correctly and timely. The recovery is composed of route, flight, aircraft and crew recovery. And only crew recovery problem takes humanistic factors into account amongst them, which is a channel to exhibit airline's corporate responsibility and also a crucial means to improve onboard services. Hence the main question addressed in this paper is crew recovery problem.

Plenty of scholars have studied the irregular flight recovery problem from a wide variety of angles. Chutima et al. [2] considered cost, workload and pilots' preference at the same time. Wen et al. [3] took flight flying time variability into account. Zeighami et al. [4] and Zhou et al. [5] separately developed an algorithm based on alternating Lagrangian decomposition and ant colony algorithm in solving the problem. Doi et al. [6] and Quesnel et al. [7] respectively studied the impact of fair working time and crews' preferences on crew recovery problem. Antunes et al. [8] emphasized the robustness of schedule. Wen et al. [9] studied the relationship between manpower availability and crew scheduling strategies. Evler et al. [10] and Jin et al. [11] adopted rolling horizon algorithm and column generation method respectively in cope with the recovery problem. However, each of them indeed had come up with a way to either actualize the problem or speed the convergence velocity. In this paper, we introduced crew's satisfaction of work time to the previous single objective model of cost, which was highly associated with the efficiency and effectiveness of rearrangement. In addition, it also enriched the diversity of the original recovery problem.

When solving models with more than one objective, it usually fails to meet the demand of accuracy and timeliness by merely changing the multi-objective problem into single-objective one. And multi-objective algorithms, like MOPSO, can satisfy the needs of multiple objectives and show their merits like fewer adjustment parameters. However, it also inherits the shortcomings like easily falling into local optimum, which is the main focus of recent studies. Zhang et al. [12] developed a competitive mechanism to further improve the global and personal best particles. Luo et al. [13] introduced an indicator and direction vectors to enhance the capability of local exploration and maintain the non-dominated solution. Cui et al. [14] proposed a two-archive mechanism to emphasize convergence and diversity separately. Devaraj et al. [15] hybridized MOPSO and firefly algorithm to minimize the search space. Qu et al. [16] and Liang et al. [17] both introduced a self-organized based MOPSO to locate multiple Pareto optimal solutions. Liu et al. [18] used objective space division method to find Pbest and Gbest. Mohd et al. [19] hybridized dynamic boundary search method with MOPSO. Goyal et al. [20] came up with a hybrid algorithm of RSM (Response Surface Methodology) and MOPSO. Mahapatra et al. [21] introduced a hesitant fuzzy MOPSO algorithm to MORRA problem. Sellami et al. [22] suggested a MOPSO combined with MATPOWER toolbox. Whereas, recent studies in the field of MOPSO have only focused on the improvement of its internal mechanism and search methods, but few attempt to integrate other algorithms into MOPSO. Therefore, in this paper, we combined MOPSO with tabu search to improve the local optimum problem.

The main contributions of this paper include three parts. First, the crew recovery model would be closer to real-world situation after we considered the satisfaction of crew members besides recovery cost. Secondly, we proposed a tabu-based multi-objective particle swarm optimization enabling the primary algorithm to overcome the local optimum problem. Thirdly, we established a coding scheme based on the characteristics of the problem.

The paper has been organized in the following way. Section 2 states the multi-objective model. Section 3 describes the tabu-based multi-objective particle swarm optimization. Section 4 explains the encoding scheme. Section 5 presents the simulation results against comparative algorithms. Section 6 concludes the paper and points out the future directions.

2 Model of Multi-objective Crew Recovery Problem

This section describes the model of crew recovery problem. The model considering cost and satisfaction is listed below. Table 1 explains the meaning of parameters displayed in the mathematical model.

Table 1. Definition of symbols

Symbols	Meaning of symbols
F	Set of flight
K	Set of crew member's number
A	Set of crew base
P	Set of crew task pairing
i	Subscripts of flight, $i \in F$
j	Subscripts of crew task list, $j \in P$
a	Subscripts of airport, $a \in A$
k	Superscripts of crew, $k \in K$
p	Subscripts of flight sequence executed by crew k, $p = 1, 2, \cdots n$
c_i	Cost of canceling flight i
h_a	Number of flights for airport a executing original schedule after recovery
d_j^k	Cost of crew k executing crew task list j
s_j, f_j	Start and finish time of crew task list j
PVN	Sum of vacation of all members
x_j^k	Whether crew k executes task list j
y_i	Whether flight i is canceled
a_{ij}	Whether flight i is contained in crew task list j
b_{pa}, e_{pa}	Whether the p^{th} task is started or ended at airport a
x_j^k	The j^{th} task executed by crew k
t_j^k	Working time possessed by the j^{th} task executed by crew k
$\overline{t^k}$	Average working time executed by crew k, $\overline{t^k} = \sum_{j\in P} x_j^k t_j^k / \sum_{j\in P} x_j^k$

$$\min Z_1 = \sum_{k \in K} \sum_{j \in P} d_j^k x_j^k + \sum_{i \in F} c_i y_i \tag{1}$$

$$\min Z_2 = \sum_{k \in K} \sum_{j \in P} \left(x_j^k t_j^k - x_j^k \overline{t^k}\right)^2 \tag{2}$$

Our model includes two objective functions. Objective function (1) demands the lowest executing cost and canceling cost. Objective function (2) requires the minimum of crew member's worktime variance, which means the fairness of the worktime of each crew is preferred.

$$s.t. \sum_{k \in K} \sum_{j \in P} a_{ij} x_j^k + y_i = 1 \ \forall i \in F \tag{3}$$

$$\sum_{k \in K} x_j^k \leq 1, \ \forall j \in P \tag{4}$$

$$\sum_{j \in P} x_j^k (f_j - s_j) \leq 100, \ \forall k \in K \tag{5}$$

$$\left| x_{j+1}^k s_{j+1} - x_j^k f_j \right| \geq x_j^k x_{j+1}^k \ \ \forall k \in K, \, j \in P \tag{6}$$

$$x_p^k b_{pa} = x_{p+1}^k e_{(p+1)a}, \ \forall k \in K, \ \forall a \in A, \ p \in Z \tag{7}$$

Constraint (3) ensures each flight can only be executed by single crew, or canceled. Constraint (4) guarantees each crew can execute at most one task list. Constraint (5) requires the duration of crew executing task every month is less than 100 h. Constraint (6) restricts the rest time of crew between two consecutive tasks is more than 1 h. Constraint (7) ensures the ending airport of preceding task is the same as the following task's airport.

3 Improved Multi-objective Particle Swarm Algorithm

In this section, we present our tabu-based multi-objective particle swarm algorithm, abbreviated as MOPSO-TS, which combining the primary MOPSO and tabu search.

3.1 Primary MOPSO

Multi-objective particle swarm optimization is based on single-objective PSO, finding global excellent solution set through establishing non-dominant solution set and selecting one particle in non-dominant set as guiding solution. Through randomizing the location of each point, iterating and updating towards different directions and broadly exploring the unknown space, a Pareto front will be obtained finally.

3.2 Tabu-Based Multi-objective Particle Swarm Algorithm

Due to MOPSO's drawback of prematurity and local optima, we introduced tabu search to the primary MOPSO.

Tabu search algorithm is an iterative search algorithm simulating human intelligence. It can avoid roundabout searching by setting up tabu list and tabu principle, therefore escape from local optimal point and enhance the ability of global search.

Targeting at the shortcoming of MOPSO, we combine the MOPSO with tabu search. Since the initial solution shows a great impact on the effectiveness of tabu search algorithm, firstly, we introduce tabu search algorithm after optimizing iteratively by MOPSO. Then updating the tabu list on the basis of comparatively excellent group which is constituted by non-dominant solution and partly dominant solution. And searching in the neighborhood until the terminal condition is met. The process in detail is presented in Fig. 1 and the improvement is circled in red.

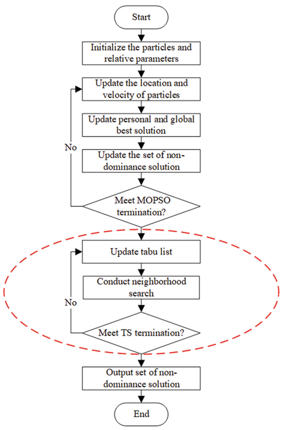

Fig. 1. Flow chart of MOPSO with tabu search

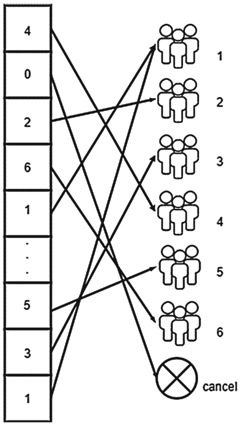

Fig. 2. Encoding scheme of crew recovery problem

3.3 Tests and Results

Intending to verify the performance of MOPSO-TS, we adopted the ZDT1, ZDT2 and ZDT3 as test functions forwarded by famous scholar Deb [23].

This paper compared MOPSO-TS with primary MOPSO under the same test functions and conditions, and evaluated these algorithms through IGD and HV. Table 2 shows the average number of each index after 30 times of independent experiments.

Table 2. Results of test functions

Test function	Index	MOPSO	MOPSO-TS
ZDT1	IGD	9.57E−03	6.56E−03
	HV	7.11E−01	7.15E−01
ZDT2	IGD	9.21E−03	6.54E−03
	HV	4.17E−01	4.40E−01
ZDT3	IGD	1.21E−02	8.18E−03
	HV	5.95E−01	5.97E−01

According to the table, the Pareto fronts concluded by MOPSO-TS in the three test functions are all better than MOPSO. And among the algorithms, MOPSO-TS has the smallest IGD and biggest HV, indicating that MOPSO-TS is better in convergency, diversity and overall performance.

4 Encoding Scheme

According to the model and the characteristic of the problem, we adopted the encoding scheme in Fig. 2.

Each particle in the group represents one scheduling scheme. The number of particle's dimension refers to the total number of flights. For each dimension which equals to k, it represents the corresponding flight is executed by the k^{th} crew. If the dimension value is 0, it means the flight is canceled.

Table 3. Primary flight schedule

Flight	Departure airport	Arrival airport	Departure time	Arrival time	Flying time
1481	BOS	CLE	730	930	158
1519	BOS	GSO	1015	1210	155
1687	CLE	BOS	740	940	156
789	CLE	EWR	1100	1225	119
1867	CLE	GSO	1335	1450	113
1609	CLE	GSO	1650	1805	112
1568	CLE	GSO	2150	2305	110
1601	EWR	GSO	700	843	117
1779	EWR	GSO	830	1015	121
1690	EWR	CLE	955	1134	124
1531	EWR	GSO	1155	1330	130
1431	EWR	GSO	1300	1440	136
1626	GSO	EWR	1220	1353	129
1670	GSO	CLE	1240	1355	124
1678	GSO	CLE	1545	1700	108
1591	GSO	CLE	1630	1758	121
1720	GSO	CLE	1725	1843	116
1698	GSO	EWR	1825	1957	130

5 Experiments and Results

In this section, we simulated the rescheduling process due to the cancelation of certain flight under the force majeure like inclement weather and natural disaster on MATLAB2020a, while balancing the minimal recovery cost and even worktime.

Table 4. Primary crew schedule

Crew	Flight number	Departure airport	Arrival airport	Departure time	Arrival time	Flying time
E1	1601	EWR	GSO	700	843	117
	1626	GSO	EWR	1220	1353	129
E2	1779	EWR	GSO	830	1015	121
	1670	GSO	CLE	1240	1355	124
	1609	CLE	GSO	1650	1805	112
E3	1690	EWR	CLE	955	1134	124
	1867	CLE	GSO	1335	1450	113
	1678	GSO	CLE	1545	1700	108
E4	1531	EWR	GSO	1155	1330	130
	1591	GSO	CLE	1630	1758	110
	1568	CLE	GSO	2150	2305	110
E5	1687	CLE	BOS	740	940	156
	1519	BOS	GSO	1015	1210	155
	1698	GSO	EWR	1825	1957	130
E6	1481	BOS	CLE	730	930	158
	789	CLE	EWR	1100	1225	119
	1431	EWR	GSO	1300	1440	136
	1720	GSO	CLE	1725	1843	116

5.1 Parameter Setting

This paper used data in Table 3 and Table 4 [24] to verify the performance of MOPSO-TS in solving irregular flight recovery problem, involving 18 flights and 6 crews. The total flying time must be less than 100 h and the gap between two continual flights is ought to be longer than one hour. The canceling cost is 100 thousand yuan and switching cost is 20 thousand yuan. Table 5 is the detailed parameter setting of MOPSO-TS. To simulate abnormal situation, we assume that flight 1720 is canceled due to epidemic.

Table 5. Parameters of algorithm

Symbols	Meaning	Value
	MOPSO-related	
I	Maximum iteration time	2000
D	Dimension of particle	17

(*continued*)

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Symbols	Meaning	Value
NP	Number of particles	100
NR	Number of repository	100
NC	Number of candidate	150
W	Inertia weight	0.9
$Wdamp$	Inertia weight damping rate	0.9
v_{max}; v_{min}	Lower and upper bound of variables	6;0
c_1	Personal learning coefficient	1.5
c_2	Global learning coefficient	1.5
	Tabu Search-related	
TI	Maximum iteration time of tabu search	500
mu	Mutation rate	0.7
nGrid	Number of grid per dimension	7
Alpha	Inflation rate	0.1
Beta	Leader selection pressure	2
Gamma	Deletion selection pressure	2
TL	Tabu length	9

5.2 Experiment Result

We adopted MOPSO-TS and MOPSO to solve the problem independently for thirty times, and compared the Pareto Front of them. Pareto front has many points, and we

Table 6. Recovered crew schedule

Crew	Flight number	Departure airport	Arrival airport	Departure time	Arrival time	Flying time
E1	1601	EWR	GSO	700	843	117
	1670	GSO	CLE	1240	1355	129
	1609	CLE	GSO	1650	1805	112
E2	1779	EWR	GSO	830	1015	121
	1626	GSO	EWR	1220	1353	124
E3	1690	EWR	CLE	955	1134	156
	1867	CLE	GSO	1335	1450	155
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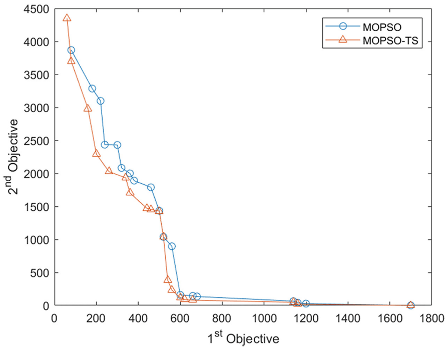

Fig. 3. The Pareto Front of MOPSO-TS, MOPSO

choose one of the point with the lowest cost to exhibit the specific recovery scheme, which is shown as Table 6.

According to the Pareto Front curves in Fig. 3, the front of MOPSO-TS was closer to the bottom left of target space than MOPSO, which demonstrated MOPSO-TS performed better in the solution of our model.

6 Conclusions and Future Directions

In this paper, we studied irregular flight recovery problem, created a multi-objective model considering the fare and satisfaction concurrently and proposed an improved multi-objective particle swarm optimization hybridizing tabu search. In the future, we will apply our algorithm to other problems with multiple objectives and come up with new elements to enrich our model.

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