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An Integrated Flight Scheduling Design and Allocation Method Considering Multiple Stakeholders' Interests

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Abstract. Compared to the Worldwide Airport Slot Guidelines and Regulations, China's current flight scheduling management method lacked a balanced consideration of the actual interests of multiple stakeholders including airlines, passengers, airports, and air traffic control. Therefore, this study proposed an integrated flight scheduling design and allocation model that accounts for the interests of multiple stakeholders' interests. Firstly, a comprehensive evaluation framework for flight scheduling management under multi-stakeholder interests is established. Then, based on this framework, an integrated flight scheduling allocation model is developed utilizing an enhanced particle swarm optimization algorithm. Simulation results demonstrate that this proposed model can provide a efficiency allocation to airline fleet resources and the interests of other multiple stakeholders.

Keywords: air traffic flow management, flight scheduling, evaluation metrics, particle swarm optimization

1. Introduction

Since 1947, IATA has conducted a biennial Slot Conference, introducing a series of Airport Slot Guidelines. The latest version of Worldwide Airport Slots Guidelines (WASG) was released in July 2022[1]. It comprehensively explains key concepts and terms across policies, principles, and processes. It covers the classification of slot-coordinated airports, critical allocation principles and priorities, stakeholder responsibilities, flight schedule allocation timelines, and slot use distribution.

Based on these regulations, the Federal Aviation Administration's Air Traffic Organization has set up a Slot Management Office responsible for flight schedule management[2]. FAA appoints coordinators for level 3 airports and schedule facilitators for level 2 airports to manage these airports[3]. On the other hand, the European Union has established general rules for public airport slot allocation through Council Regulation 95/93 and multiple amendments[4]. In coordinated airports, a Flight Schedule Coordination Committee is composed of representatives from airlines, agencies, air traffic management, airport operators, among others. The airport categorization rules are similar to the three categories proposed by WASG. At coordinated airports, a Flight Schedule Management Committee adjusts supply-demand conflicts based on airport capacity and airline requirements, proposes allocation suggestions, and flight schedule coordinators approve plans. In facilitated coordinated airports, flight schedule coordinators propose landing and take-off schedules based on available airport capacity for adoption and implementation by airport authorities and carriers. Meanwhile, at non-coordinated airports, slot allocation follows a 'first-come, first-served' principle.

Compared to established overseas management procedures, China's flight schedule management methods still exhibit certain deficiencies in addressing market competitiveness for new entrant carriers and flexibility in secondary allocation. Additionally, while the flight schedule management methods possess well-defined rules quantifying slot efficiency compared to the Worldwide Airport Slot Guidelines and European Council regulations, the corresponding metrics entail limited scope. This limitation to some extent constrains airlines' flexibility in responding to market changes during actual scheduling, lacking a balanced consideration of the actual interests of airlines, passengers, airports, and air traffic management stakeholders.

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The previous studies have traditionally focused on optimizing flight schedules for specific individual stakeholders or a limited subset thereof. Marieta incorporates pilot satisfaction as a constraint, aiming to minimize the operational costs of the airline within this constraint[5]. Li et al. devise a multi-objective optimization model considering fairness across multiple airports to optimize the entire multi-airport system's flight schedule. The optimization objectives involve minimizing the overall flight schedule displacement while addressing the maximum deviation between fairness and absolute fairness[6]. The predominant approach in algorithmic solutions relies on heuristic algorithms. Geng et al. designed an improved simulated annealing algorithm (SAA) to solve the proposed multiobjective optimization problem[7]. Xu et al. proposed a column generation procedure as well as a sequential variable neighborhood search (VNS) heuristic to solve models for large-scale airline instances[8]. Anshori et al. applied Genetic Algorithm (GA) and Particle Swarm Optimization (PSO) for the optimization model to select optimal pairings covering all flight numbers[9].

The remainder of this paper is organized as follows: Section 2 describes a set of indicators for flight schedule under multi-stakeholder interests. Section 3 outlines the construction of integrated flight schedule design model and proposal of an enhanced algorithm based on particle swarm optimization. Section 4 details the simulation experiment performed to test our model, and conclusions are presented in Section 5.

2. Evaluation Framework under Multiple Stakeholder Interests

Flight schedule management evaluation is a comprehensive system engineering endeavour. Establishing a metrics system is fundamental to conducting evaluations, as the scientific and rational basis directly impacts the accuracy of assessment outcomes. Flight schedules play a critical role in airline planning, airport connectivity, air traffic operational efficiency, and passenger travel demands. Consequently, within the corresponding evaluation metrics system, there exist both quantitative and qualitative factors. These factors interplay and constrain each other. The proposed flight schedule management evaluation metrics system, which considers multiple stakeholders' interests, provides a foundational basis and guidance for subsequent flight schedule management and optimization. The construction of a hierarchical metrics system involves analysing the interrelations and distinctions among stakeholders' interests. This process includes categorizing and stratifying metrics. Furthermore, the constructed evaluation metrics system needs to adequately showcase the characteristics of stakeholders' perspectives on flight schedule management, facilitating the quantification of various metrics.

This paper proposes several categories of indicators from five dimensions: air traffic control, airlines, airports, ground services and passengers. It constructs an evaluation index system for flight schedule management that considers the interests of multiple parties, as illustrated in Fig. 1.

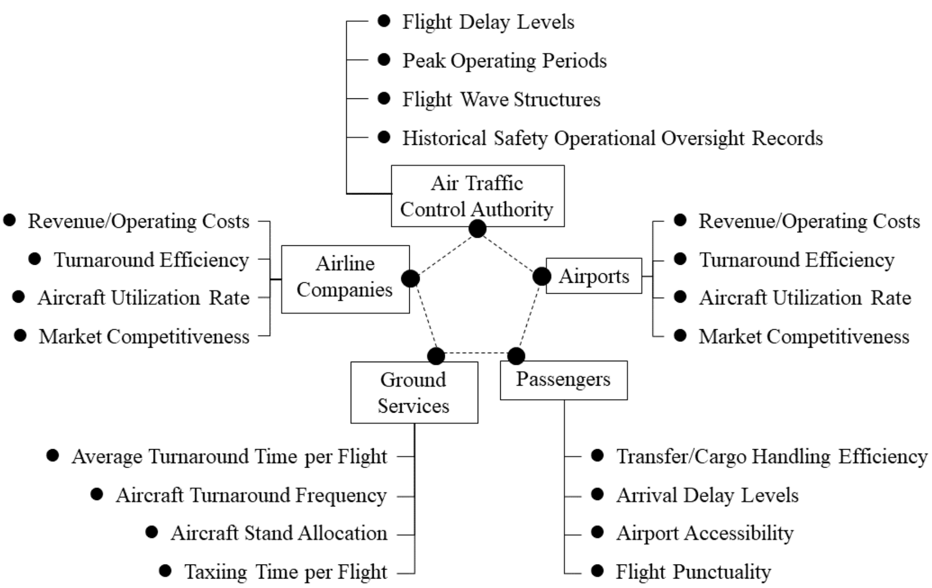

Fig. 1: Evaluation Metrics for Flight Schedule Management under Multi-Stakeholder Interests

3. Integrated Flight Scheduling Model and Solution

Model for integrated flight schedule design and assignment is given by (1)–(14). If the aircraft fleet k operates flights f_1 and f_2 consecutively, the binary variable $x_{f_1 f_2}^k$ equals 1; otherwise, it equals 0. At this point, these two flights constitute valid edges in the flight connection network $G(V,E)$, meeting the transfer time and airport connectivity requirements, namely, $(f_1, f_2) \in E$. The binary variable z_f equals 1 if flight f is not selected to operate, and it equals 0 otherwise. The continuous variable h_i characterizes the number of passengers travelling in itinerary i. The continuous variable v_f characterizes the temporal configuration coefficient weight associated with flight f within the civil aviation industry.

The objective function (1) aims to maximize airline profits. The average fare for itinerary $i \in I$ is characterized by $fare_i$. The parameter $c_{f_1}^k$ represents the operation cost of aircraft fleet $k \in K$ executing flight f_1.

$$\max \sum_{i \in I} fare_i h_i - \sum_{k \in K} \sum_{(f_1, f_2) \in E} c_{f_1}^k x_{f_1 f_2}^k \tag{1}$$

Constraint (2) is a flow balance constraint to ensure that the inflow and outflow at each flight node are equal. As this model is intended to design weekly recurrent flight schedules, there is no need to add virtual start and end nodes.

$$\sum_{f_2:(f_1, f_2) \in E} x_{f_1, f_2}^k - \sum_{f_2:(f_2, f_1) \in E} x_{f_1, f_2}^k = 0, \forall k \in K, f_1 \in F \tag{2}$$

Constraint (3) ensures the allocation of aircraft to fly flights with historical priority. Correspondingly, constraint (4) selects the remaining flight slots within the selective flight slot pool.

$$\sum_{k \in K} \sum_{f_2:(f_1, f_2) \in E} x_{f_1 f_2}^k = 1, \forall f_1 \in F^H \tag{3}$$

$$\sum_{k \in K} \sum_{f_2:(f_1, f_2) \in E} x_{f_1 f_2}^k \le z_f, \forall f_1 \in F / F^H \tag{4}$$

where F^H represents the set of flights with historical priority.

Constraint (5) computes the weight scores v_{f_1} for time slots within the flight slot pool using a nonlinear function $eval(\cdot)$, and constraints (6) and (7) compare these scores against potential flight slot scores submitted by other airlines to determine the feasibility of operating the corresponding flights.

$$v_{f_1} \ge eval\left(x_{f_1 f_2}^k\right), \forall k \in K, f_1 \in F / F^H \tag{5}$$

$$v_f \ge \overline{v_f} - M\left(1 - z_f\right), \forall f \in F \tag{6}$$

$$v_f \le \overline{v_f} + M z_f, \forall f \in F \tag{7}$$

where the parameter M is a sufficiently large constant.

Constraint (8) represents fleet resource constraints, limiting the number of available aircraft for each fleet. Constraint (9) stands for aircraft capacity constraints, ensuring that the number of passengers allocated to a flight does not exceed the seat limit of the allocated aircraft type.

$$\sum_{(f_1, f_2) \in E} x_{f_1 f_2}^k \le N_k, \forall k \in K \tag{8}$$

$$\sum_{i \in I} \theta_{i,f} h_i \le \sum_{k \in K} Cap_k \sum_{f_2:(f_1, f_2) \in E} x_{f_1 f_2}^k, \forall f \in F \tag{9}$$

where N_k represents the available number of aircrafts for each aircraft fleet. The parameter Cap_k represents the number of seats (capacity) in aircraft k. If itinerary i involves flight f, the binary variable $\theta_{i,f}$ equals 1; otherwise, it equals 0.

Constraint (10) specifies the maximum number of passengers Λ_m that can be allocated on the same market's travel itinerary. Based on the utility value μ_i of travel itineraries, constraint (11) introduces a discrete choice model to compute the number of passengers that can be allocated to each itinerary based on their utility values.

$$\sum_{i \in I_m} h_i + h_m = \Lambda_m, \forall m \in M \tag{10}$$

$$\frac{h_i}{u_i} - \frac{h_m}{u_m} \leq 0, \forall m \in M, i \in I_m \tag{11}$$

where h_m represents the number of passengers travelling in other airline companies. The set of passengers is represented by M , and the set of passenger itineraries is represented by I_m.

Constraint (12) further stipulates that when flight schedules related to travel itineraries are not operated, passengers cannot be allocated to those itineraries. Finally, constraints (13) and (14) define the maximum take-off/landing slots available to airlines at each time slot s in airport a, denoted as $DC_{a,s}$ and $AC_{a,s}$ respectively.

$$\sum_{f_2 \in F} \sum_{i \in I_{f_1, f_2}} h_i \leq M z_{f_1}, \forall f_1 \in F \tag{12}$$

$$\sum_{k \in K} \sum_{f_1 \in F_{as}^D} \sum_{f_2 : (f_1, f_2) \in E} x_{f_1 f_2}^k \leq DC_{a,s}, \forall a \in A, s \in S \tag{13}$$

$$\sum_{k \in K} \sum_{f_1 \in F_{as}^A} \sum_{f_2 : (f_1, f_2) \in E} x_{f_1 f_2}^k \leq AC_{a,s}, \forall a \in A, s \in S \tag{14}$$

where the parameter $DC_{a,s}$ represents the maximum number of departure slots available in each time slot s at Airport A, and the parameter $AC_{a,s}$ represents the maximum number of arrival slots available in each time slot s at Airport A.

Due to the mixed linear and nonlinear constraints in the aforementioned model, representing a nonlinear integer maximization problem with a large dataset, traditional linear programming methods are less efficient. Therefore, this segment is designed to utilize an improved Particle Swarm Optimization (PSO) algorithm based on integrated flight scheduling and assignment to solve the model.

While Particle Swarm Optimization (PSO)[10] boasts rapid convergence and high generality, it faces challenges such as premature convergence and reduced efficiency in later iterations. Hence, we integrated the principles of Genetic Algorithm crossover and mutation operators into the original algorithm[11]. This involves performing crossover and mutation operations on individuals and the swarm's extremities, considering optimization capability and particle feasibility. We introduced evolutionary crossover and repair operators to ensure particles consistently adhere to constraint limitations, expanding the iterative search space, allowing particles to explore beyond current optimal positions, thereby increasing the likelihood of finding superior values. The algorithm flowchart is illustrated in Figure 2.

4. Simulation and Results

In this section, we report empirical results for the proposed models and solution techniques. The solution framework is implemented in MATLAB and executed on a computer with 2.10GHz AMD Ryzen 5 3550H CPU and Windows 11 operating system.

The dataset originates from a division of China Eastern Airlines, a prominent legacy carrier in China. The airline's fleet comprises three distinct aircraft models (A319, A320, A321). A compilation of four practical test scenarios has been curated from the operational schedule of this airline in December 2019. Table 1 presents a comprehensive breakdown of these four test cases. Specifically, the initial six columns introduce the planning horizon, flight count, aircraft count, vertices, and edges within the flight connection network. Additionally, the last three columns respectively denote the count of flights necessitating re-timing, the number of passenger itineraries, and the quantity of optional flights. In terms of passenger itinerary related data, data from Ctrip, a Chinese online travel agency, is used to derive ticket fares of different airlines for different markets.

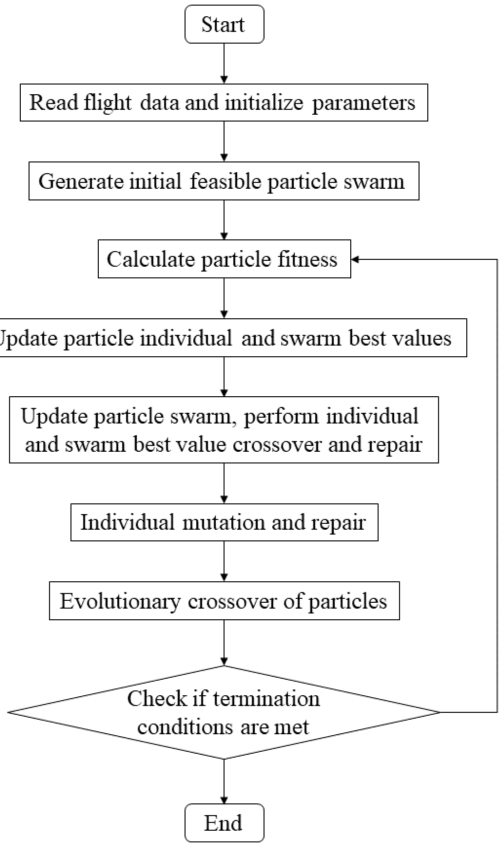

Fig. 2: Enhanced PSO Algorithm Flowchart

Table 1: Characteristics of four test instances

No.	Horizon	Flights	A/C	Nodes	Edges	Re-timing	Itineraries	Optional flights
1	1 day	210	48	679	23722	109	298	19
2	2 days	451	49	1397	102162	245	618	41
3	3 days	680	51	2125	187698	376	938	50
4	4 days	918	49	2884	269376	510	1286	102

Experiments are carried out for the four instances using enhanced PSO algorithm to derive the optimal solutions and branch-and-bound[12] for integer solutions. We first present the benchmark results using enhanced PSO algorithm presented in Section 4 with 24 h maximum solving time (12 h for enhanced PSO and 12 h for branch-and-bound). The details of the results are shown in Table 6. The number of iterations taken by enhanced PSO algorithm is shown in column ePSO iter. Opt Obj and Opt time indicate the objective function value and the corresponding solution time. In order to get integer solution, branch-and-bound is applied. A lower bound of the optimal integer solution is derived by branch-and-bound. Finally, the relaxation rate is reported in column RR to denote the relative gap between optimal solution and integer solution from branch-and-bound.

Table 2: Computation results of integrated flight schedule design and assignment Model using enhanced PSO Algorithm

No.	ePSO iter	Opt Obj	Opt time/s	Branch-and-bound	Total time/s	RR/%
1	149	10763253	16.56	10731821	18.15	0.29
2	829	23543876	928.40	22376485	43293.32	4.96
3	2159	34885637	43200.00	29187365	86400.00	16.33
4	1723	46637441	43200.00	14563223	86400.00	68.77

From the results presented in Table 2, it is evident that the improved particle swarm optimization algorithm effectively solves the model. This algorithm adeptly handles relatively simpler problems like Example 1 and Example 2. Moreover, when dealing with larger instances such as Example 3 and Example 4, viable solutions are still achievable. In such cases, the branch-and-bound method plays a significant role in assisting in the search for approximate feasible solutions. The outcomes indicate that, in Example 3 with a larger fleet scale, airlines exhibit higher profits primarily due to the increment in flight routes without a pronounced surge in the number of aircraft, thereby elevating the airline's flight scheduling costs.

5. Conclusions

In this paper, an evaluation framework of flight scheduling under multiple stakeholder interests which include air traffic control, airlines, airports, ground services and passengers was proposed. Then an integrated flight schedule design and allocation model was built. This model takes into account historical priority of operating aircraft, fleet resource constraints, aircraft capacity limitations, passenger volumes, and other functionalities. To solve this model, an enhanced particle swarm optimization algorithm which integrate genetic algorithm crossover and mutation operators was used. Finally, the datasets collected from China Eastern Airlines is used to demonstrate the feasibility of the proposed algorithm. The simulation results shows that this model can serve as a basis for airlines to select appropriate crew members when scheduling flight plans in the aviation industry.

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