

## WORST-CASE ROBUST MODEL OF MULTI-PERIOD AIRPORT GROUP COORDINATED FLIGHT TIMETABLE

JIANZHONG YAN AND MINGHUA HU\*

**ABSTRACT.** This paper introduces a robust optimization model for multi-period airport group coordinated flight timetable (MPAGCFT) with worst-case travel time. It assigns all arrival and departure flights of each period for different airports to their unique time slots in an uncertain environment to prevent conflicts between them at any waypoints. Furthermore, some real-world constraints such as maximum delay time for each flight etc. have also been taken into account in proposed model. The objective aims at minimizing total deviations between planned and actual time for all flights. The solutions are found by applying RSOME solver. Finally, a case study of four airports in China is given to verify the feasibility of our study, by analyzing the impact of the uncertainty parameter budget on optimal schedules.

### 1. INTRODUCTION

An airport group network includes comprises a collection of airports, shared waypoints, and the connections that link them together. There are some flights scheduled to take off or land at their planned times at the airport, where an arrival flight fly from the shared waypoint at a time to the airport at planned loading time, while each departure flight fly from the airport at their planned take-off times to the shared waypoint at a time. Obviously, no coordination of all arrival and departure flights between different airports and a shared waypoint may cause them to pass though this waypoint within a safe interval, resulting in some flights must hover for a while to make sure the safe fly corridor. In such case, these delayed flights simultaneously generate additional fuel consumption and carbon emissions. Compared with a single airport flight timetable (SAFT), airport group coordinated flight timetable (AGCFT) can improve time slot resource allocation efficiency to minimize flight delays and mitigate carbon emissions, by coordinating arrival and departure times of related flights at various airports to mitigate conflicts at the same waypoints [18, 27, 28, 32, 46]. The solution scale of AGCFT is larger than that of SAFT, which has been proved to be a NP-hard problem [9]. Therefore, AGCFT have attracted the attention of many scholars and engineers.

At present, most of the existing literature studies the problem of single- period AGCFT, which aims at only generate one day's flight schedule for a week's one, by assuming that any flight operates on seven days in a week [14, 33]. However, some

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\*Corresponding author.

flights do not operate every day of the week, resulting in multi- period AGCFT fit better than single- period AGCFT in practice. Existing literatures of multi- period AGCFT could be further divided into two categories: (1) the same arrival and departure time of the flight on seven days in a week [5]; (2) the changed arrival and departure time of the flight on seven days in a week [4]. Obviously, the seven-day schedule of the first category can be generated as a whole, while the schedule for each day of the week of the second category can be generated separately. Although the operation efficiency of the former is not as high as that of the latter, it is more in line with the travel habits of civil aviation passengers. However, existing studies have mainly focus on multi- period AGCFT with certain flight time and ignored the effect of uncertainty on model performance, which makes the schedule difficult to be applied in practice [11, 22, 31]. Therefore, it is essential to investigate robust optimization model for multi- period AGCFT with worst-case flight time.

The primary contribution of our research aimed at proposing a robust optimization model for MPAGCFT with worst-case flight time. The two tasks of this study conclude: 1) Determination of the optimal schedules for MPAGCFT by simultaneously assigning all arrival and departure flights of each period for different airports to their unique time slots to avoid potential conflicts at all shared waypoint, by taking into account some real-world constraints such as maximum delay time for each flight etc. as well as spatiotemporal distribution of flight times between airports and waypoints. 2) Creation of robust optimization model for MPAGCFT by assuming worst-case flight time to discuss the influence of uncertainty of flight time on the schedules. Finally, a case study is applied to generate optimal schedules and the validity of this study is verified by comparing with the traditional model.

The rest of this paper is organized as follows. Section 2 briefly reviews the related literatures on airport flight timetable. Section 3 introduces the notions of MPAGCFT and explains the formulation of proposed model. Section 4 gives a real instance to verify the feasibility of this study. Finally, concluding remarks and future work are discussed in Section 5.

## 2. LITERATURE REVIEW

Airport flight timetable allocation stands as one of the paramount components within Air Traffic Flow Management (ATFM) [11, 22, 27, 28, 31, 46]. Historically, a plethora of scholars have extensively scrutinized slot allocation issues, primarily focusing on two domains: single airports and airport clusters. Concerning single airport schedule allocation, Zografos et al. [50] initially proposed the objective function for timetable allocation: minimizing the total absolute deviation between requested and allocated time intervals (also referred to as planned delay [29]). The research findings of this model indicate that announcing capacity increments can significantly ameliorate the objective function, thereby enhancing timetable allocation efficiency. Subsequent studies have expanded considerations to encompass total planned displacement, such as maximum planned displacement [34], fairness [3, 21, 48], and anticipated operational delays [10, 47]. These objectives are often considered in conjunction with other factors, as exemplified by Zografos et al. [47], who integrated the acceptability of flight schedules into their model. Research indicates that by diminishing the efficiency of flight schedules, their utilization intensity can

be heightened. Building upon prior research, Fairbrother and Zografos [13] introduced a demand-based fairness index, which, although more aligned with the actual operational requirements of airlines, lacks preference features. Following suit, Katsigiannis and Zografos [23] introduced a time flexibility index to reflect airline preferences. Ribeiro et al. [36] further refined the objectives into minimizing total displaced timetables, maximizing displacement, total displacement, and the number of flights displaced, assigning weighted values to prioritize these objectives, thereby better reflecting airline preferences. Noteworthy is the innovative approach of this model, which employs a dictionary-based sequence to address each priority issue, thus capturing dependencies between different time timetables. Similarly, Jacquilla and Vaze [20] proposed a dictionary framework based on efficiency, fairness, and punctuality. Owing to the vast and intricate nature of flight schedule data, additional model-solving methodologies include heuristic algorithms [6, 7, 24, 33, 40, 43] as well as the Deferred Acceptance (DA) algorithm [23], column-and-row generation algorithms [50], two-stage approaches [15], and the  $\varepsilon$ -constraint method [16]. In recent years, scholars have delved deeper into the multi-objective functions for timetable allocation at single airports. For instance, Zografos and Jiang [48] proposed a multi-objective optimization model considering efficiency, fairness, and airport accessibility. Katsigiannis et al. [23, 25] extended the work of Fairbrother and Zografos [13], proposing a multi-objective optimization model considering minimum and maximum displacement and fairness. Kerama and Zografos [26] introduced an optimization model considering efficiency, fairness, flexibility, and regularity of flight schedules. Although these studies address the multi-objective and multi-level issues of airport flight schedules and adhere to corresponding policies and regulations, they overlook the relationships between relevant stakeholders in practical applications.

Research indicates that studying a single airport within a complex network environment can better capture the interactions among airports, airlines, and passengers [1, 19, 37]. For instance, Sheng et al. [38] investigated the uncertainty in airport cluster demand by describing subjective predictions and market equilibrium of various stakeholders, including ticket prices, flight sizes, private information, differences in flight schedules, time value, route selection, and passenger utility. After determining the departure time of flights from the departure airport, it is imperative to simultaneously confirm the arrival time of these flights at the destination airport. Research on flight schedule allocation in airport clusters can effectively grasp the substitutability, temporal and spatial complementarity, and interdependence between timetables [35, 49] which are unattainable at single airports. Castelli et al. [8] initially proposed the flight schedule allocation problem for airport clusters, aiming to minimize the cost deviation between allocated flight schedules and ideal schedules. However, this model did not consider existing scheduling rules (a limitation addressed in the study by Benlic [5]) and was only applicable to specific flights at specific times, neglecting scheduling issues for entire seasons or series of time periods. Subsequently, Corolli [10] extended Zografos et al.'s single airport cluster model by proposing a two-stage stochastic programming model with recourse rights, which for the first time considered capacity uncertainty at the airport cluster level, applicable to flight schedule requests for four different days. Nevertheless, it overlooked grandfather rights. Fairbrother and Zografos [14] proposed

a novel timetable allocation model that allows flexible operations throughout the scheduling season, effectively reducing planned displacement, but it is only suitable for small to medium-sized airports. Following this, Pellegrini et al. [32] introduced a model capable of handling all flight schedule requests in Europe, addressing flight scheduling for the entire season. Similar to single airport timetable allocation issues, most studies also employ heuristic algorithms [2, 18, 33] to address timetable allocation problems in airport clusters.

It is widely acknowledged that the primary objective of flight timetable allocation is to mitigate flight delays, a process heavily influenced by multifaceted factors including capacity constraints (both in airspace and at airports), runway availability, air traffic density, among others. Concurrently, schedule coordinators encounter significant uncertainty when making decisions, encompassing capacity constraints (both in airspace and at airports), flight durations, prediction intervals, adverse weather conditions, and operational demands from various departments [45]. In response to this prevailing uncertainty, numerous scholars have embarked on modeling endeavors. For instance, Wang and Zhao [41] endeavored to minimize strategic deviation costs and potential operational congestion by formulating a flight schedule allocation model for airport networks under uncertain capacity conditions, accounting for airline preferences. However, this model fell short in analyzing the ramifications of external capacity fluctuations on decision-making, opting instead for a direct utilization of weighted averages within a single-stage model. Wang et al. [42] delved into the allocation of flight schedules under flight time uncertainty at 15-minute intervals while maintaining fixed capacity constraints. Although this model encapsulated network effects and the cascading repercussions of consecutive flights within airport networks, it neglected to address the nuances of periodic flights and the propagation of delays. Liu et al. [30] amalgamated the salient features of the aforementioned models by adopting 5-minute intervals to curtail delay propagation and alleviate cascading reactions within airport networks through the judicious control of capacity constraints. The secondary phase of this model treated the tally of flight delays within a specified timeframe as a continuous variable, thereby facilitating decision-making under worst-case capacity scenarios and enhancing predictive flexibility across multiple operational days. However, the literature reviewed herein is not devoid of shortcomings: firstly, the examined models delved into flight schedules within specified temporal boundaries without broaching the subject of flight cycle dynamics; secondly, while these models grappled with uncertainty surrounding airport capacity, they remained silent on the fluctuating nature of airspace capacity stemming from flight time uncertainties. One prominent avenue for addressing uncertainty optimization models lies in the adoption of chance constraints. In the context of flight schedule allocation applications, Delahaye and Wang [11] underscored that chance constraints were introduced to address fixed capacity constraints within airport networks, proffering a flight schedule allocation method for airport networks. This model minimized total flight displacement within airport networks while converting departure/arrival point constraints into chance constraints, thereby accommodating a spectrum of capacity constraints. Subsequently, Wang et al. [44] delved into the airspace capacity requirements resulting from flight time uncertainty,

employing chance constraints to tackle this uncertainty. The above research indicates that uncertainty optimization models, as opposed to deterministic optimization models, can provide robust and efficient solutions for flight schedule allocation in airport clusters, offering important reference tools for slot coordinators.

Although a few researchers have successfully studied a variety of models and methods for SAFT/AGCFT, the following three problems deserve further investigation:

(1) Most of the existing studies mainly focused on single- period AGCFT to generate one day's flight schedule for a week's timetable, neglecting some flights do not operate every day of the week. Although multi- period AGCFT fit better than single- period AGCFT in practice, related studies on multi- period AGCFT are scarce [4, 5, 12, 14, 33].

(2) Existing studies have mainly focus on SAFT/AGCFT with uncertain flight time or airport capacity. However, they can not solve the robustness and anti-interference of scheduling scheme under uncertain environment, which makes the schedule difficult to be applied in practice. Therefore, it is important to explore a robust optimization model for multi- period AGCFT with worst-case flight time [17, 39].

### 3. ROBUST OPTIMIZATION FRAMEWORK FOR MPAGCFT

**3.1. Description of the problem.** A MPAGCFT network topology contains some nodes (i.e., airports or waypoints) and edges between them, where an airport could link several shared waypoints, and a shared waypoint can also connect multiple airports. There are many flights at each airport in seven days of a week, which involve planned take-off or landing times, types (arrival or departure flight), shared waypoints as well as maximum delay times etc. The 1440 minutes of the day are divided into 288 time slots at 5-minute intervals. All flights at each airport need to be assigned to their unique time slots in seven days of a week. Furthermore, the quantity of flights at an airport or a waypoint designated for a specific time slot in seven days of a week is less than its capacity. Moreover, interval variables are employed to represent the uncertain flight times, which may be influenced by adverse weather conditions and other factors. The primary objective of this paper is to identify the optimal relationship among the network layout of MPAGCFT, the spatial and temporal distribution of flights across various airports, as well as the uncertainties associated with flight duration, scheduling, and overall system costs.

The objective of this study is to present a worst-case robust model designed to assign all flights in seven days of a week to their specific time slots to minimize the total deviations in their arrival and departure times between planned and actual schedules. To ensure that our model aligns with real-world scenarios, the primary assumptions are outlined as follows:

- (1) The basic information of all arrival and departure flights at each airport in seven days of a week can be obtained in advance.
- (2) The capacity of airports or waypoints for each time slot in seven days of the week is also known in advance.
- (3) The estimated intervals for flight times can be derived through analysis of flight operation data.

**3.2. Notations.** A few preliminary definitions and notations are given in Table 1.

TABLE 1. Definitions and notations of MPAGCFT model

Index:	
$k$	Each time slot index
$i$	Each flight index
$a$	Each airport index
$w$	Each shared waypoint index
$s$	Each day index
Sets:	
$A$	All airports
$K$	All time slots
$N$	All shared waypoints
$S$	Seven days of a week
$F_{a,s}^{\text{Out}}$	All flights leaving from airport $a$ on a day $s$
$F_{a,s}^{\text{In}}$	All flights arriving at airport $a$ on a day $s$
$F_{a,w,s}^{\text{Out}}$	All flights leaving from airport $a$ flying though waypoint $w$ on a day $s$
$F_{a,w,s}^{\text{In}}$	All flights arriving at airport $a$ flying though waypoint $w$ on a day $s$
Parameters:	
$T_i^s$	The scheduled time slot of arrival or departure flight $i$ on a day $s$
$d_i^s$	Maximization deviation in arrival or departure time slot of flight $i$ on a day $s$
$C_{a,s}^k$	Airport $a$ 's total capacity of time slot $k$ on a day $s$
$C_{a,s}^{15}$	Airport $a$ 's total capacity during 15 min on a day $s$
$C_{a,s}^{30}$	Airport $a$ 's total capacity during 30 min on a day $s$
$C_{a,s}^{60}$	Airport $a$ 's total capacity during 60 min on a day $s$
$C_{a,s}^{k,\text{In}}$	Airport $a$ 's total arrival capacity of time slot $k$ on a day $s$
$C_{a,s}^{15,\text{In}}$	Airport $a$ 's total arrival capacity during 15 min on a day $s$
$C_{a,s}^{30,\text{In}}$	Airport $a$ 's total arrival capacity during 30 min on a day $s$
$C_{a,s}^{60,\text{In}}$	Airport $a$ 's total arrival capacity during 60 min on a day $s$
$C_{a,s}^{k,\text{Out}}$	Airport $a$ 's total departure capacity of time slot $k$ on a day $s$
$C_{a,s}^{15,\text{Out}}$	Airport $a$ 's total departure capacity during 15 min on a day $s$
$C_{a,s}^{30,\text{Out}}$	Airport $a$ 's total departure capacity during 30 min on a day $s$
$C_{a,s}^{60,\text{Out}}$	Airport $a$ 's total departure capacity during 60 min on a day $s$
$Q_{w,s}^k$	Waypoint $w$ 's total capacity of time slot $k$ on a day $s$
$Q_{w,s}^{15}$	Waypoint $w$ 's total capacity during 15 min on a day $s$
$Q_{w,s}^{30}$	Waypoint $w$ 's total capacity during 30 min on a day $s$
$Q_{w,s}^{60}$	Waypoint $w$ 's total capacity during 60 min on a day $s$
$Q_{w,s}^{k,\text{In}}$	Waypoint $w$ 's total arrival capacity of time slot $k$ on a day $s$
$Q_{w,s}^{15,\text{In}}$	Waypoint $w$ 's total arrival capacity during 15 min on a day $s$
$Q_{w,s}^{30,\text{In}}$	Waypoint $w$ 's total arrival capacity during 30 min on a day $s$
$Q_{w,s}^{60,\text{In}}$	Waypoint $w$ 's total arrival capacity during 60 min on a day $s$
$Q_{w,s}^{k,\text{Out}}$	Waypoint $w$ 's total departure capacity of time slot $k$ on a day $s$

TABLE 1. (Continued)

Parameters:	
$Q_{w,s}^{15,Out}$	Waypoint $w$ 's total departure capacity during 15 min on a day $s$
$Q_{w,s}^{30,Out}$	Waypoint $w$ 's total departure capacity during 30 min on a day $s$
$Q_{w,s}^{60,Out}$	Waypoint $w$ 's total departure capacity during 60 min on a day $s$
$T_{aw}^s$	Flying time from airport $a$ to waypoint $w$ on a day $s$
$\bar{T}_{aw}^s$	Average flying time from airport $a$ to waypoint $w$ on a day $s$
$\hat{T}_{aw}^s$	Deviation of flying time from airport $a$ to waypoint $w$ on a day $s$
Decision variables:	
$h_{ik}^s$	Whether each flight $i$ will be allocated to time slot $k$ on a day $s$ or not

**3.3. Formulation.** A novel 0–1 robust model of MPAGCFT with worst-case flight time could be firstly outlined as follows:

$$(3.1) \quad \text{Min } f = \sum_{\forall s \in S} \sum_{\forall a \in A} \sum_{\forall i \in F_{a,s}^{Out} \cup F_{a,s}^{In}} \sum_{\forall k \in K} h_{ik}^s (k - T_i^s)$$

S.t:

$$(3.2) \quad \sum_{\forall k \in K} h_{ik}^s = 1, \quad \forall i \in F_{a,s}^{Out} \cup F_{a,s}^{In}, \quad \forall a \in A, \quad \forall s \in S$$

$$(3.3) \quad 0 \leq h_{ik}^s (k - T_i^s) \leq d_i^s, \quad \forall i \in F_{a,s}^{Out} \cup F_{a,s}^{In}, \quad \forall a \in A, \quad \forall k \in K, \quad \forall s \in S$$

$$(3.4) \quad \sum_{\forall i \in F_{a,s}^{Out} \cup F_{a,s}^{In}} h_{ik}^s \leq C_{a,s}^k, \quad \forall k \in K, \quad \forall a \in A, \quad \forall s \in S$$

$$(3.5) \quad \sum_{\forall i \in F_{a,s}^{Out} \cup F_{a,s}^{In}} \sum_{j=0}^2 h_{i(k+j)}^s \leq C_{a,s}^{15}, \quad \forall k \in K, \quad \forall a \in A, \quad \forall s \in S$$

$$(3.6) \quad \sum_{\forall i \in F_{a,s}^{Out} \cup F_{a,s}^{In}} \sum_{j=0}^5 h_{i(k+j)}^s \leq C_{a,s}^{30}, \quad \forall k \in K, \quad \forall a \in A, \quad \forall s \in S$$

$$(3.7) \quad \sum_{\forall i \in F_{a,s}^{Out} \cup F_{a,s}^{In}} \sum_{j=0}^{11} h_{i(k+j)}^s \leq C_{a,s}^{60}, \quad \forall k \in K, \quad \forall a \in A, \quad \forall s \in S$$

$$(3.8) \quad \sum_{\forall i \in F_{a,s}^{In}} h_{ik}^s \leq C_{a,s}^{k,In}, \quad \forall k \in K, \quad \forall a \in A, \quad \forall s \in S$$

$$(3.9) \quad \sum_{\forall i \in F_{a,s}^{In}} \sum_{j=0}^2 h_{i(k+j)}^s \leq C_{a,s}^{15,In}, \quad \forall k \in K, \quad \forall a \in A, \quad \forall s \in S$$

$$(3.10) \quad \sum_{\forall i \in F_{a,s}^{In}} \sum_{j=0}^5 h_{i(k+j)}^s \leq C_{a,s}^{30,In}, \quad \forall k \in K, \quad \forall a \in A, \quad \forall s \in S$$

$$(3.11) \quad \sum_{\forall i \in F_{a,s}^{\text{In}}} \sum_{j=0}^{11} h_{i(k+j)}^s \leq C_{a,s}^{60,\text{In}}, \quad \forall k \in K, \quad \forall a \in A, \quad \forall s \in S$$

$$(3.12) \quad \sum_{\forall i \in F_{a,s}^{\text{Out}}} h_{ik}^s \leq C_{a,s}^{k,\text{Out}}, \quad \forall k \in K, \quad \forall a \in A, \quad \forall s \in S$$

$$(3.13) \quad \sum_{\forall i \in F_{a,s}^{\text{Out}}} \sum_{j=0}^2 h_{i(k+j)}^s \leq C_{a,s}^{15,\text{Out}}, \quad \forall k \in K, \quad \forall a \in A, \quad \forall s \in S$$

$$(3.14) \quad \sum_{\forall i \in F_{a,s}^{\text{Out}}} \sum_{j=0}^5 h_{i(k+j)}^s \leq C_{a,s}^{30,\text{Out}}, \quad \forall k \in K, \quad \forall a \in A, \quad \forall s \in S$$

$$(3.15) \quad \sum_{\forall i \in F_{a,s}^{\text{Out}}} \sum_{j=0}^{11} h_{i(k+j)}^s \leq C_{a,s}^{60,\text{Out}}, \quad \forall k \in K, \quad \forall a \in A, \quad \forall s \in S$$

$$(3.16) \quad \sum_{\forall a \in A} \left[ \sum_{\forall i \in F_{a,w,s}^{\text{Out}}} h_{i(k-T_{aw}^s+j)}^s + \sum_{\forall i \in F_{a,w,s}^{\text{In}}} h_{i(k+T_{aw}^s+j)}^s \right] \leq Q_{w,s}^k, \\ \forall w \in N, \quad \forall k \in K, \quad \forall s \in S$$

$$(3.17) \quad \sum_{\forall a \in A} \left[ \sum_{\forall i \in F_{a,w,s}^{\text{Out}}} \sum_{j=0}^2 h_{i(k-T_{aw}^s+j)}^s + \sum_{\forall i \in F_{a,w,s}^{\text{In}}} \sum_{j=0}^2 h_{i(k+T_{aw}^s+j)}^s \right] \leq Q_{w,s}^{15}, \\ \forall w \in N, \quad \forall k \in K, \quad \forall s \in S$$

$$(3.18) \quad \sum_{\forall a \in A} \left[ \sum_{\forall i \in F_{a,w,s}^{\text{Out}}} \sum_{j=0}^5 h_{i(k-T_{aw}^s+j)}^s + \sum_{\forall i \in F_{a,w,s}^{\text{In}}} \sum_{j=0}^5 h_{i(k+T_{aw}^s+j)}^s \right] \leq Q_{w,s}^{30}, \\ \forall w \in N, \quad \forall k \in K, \quad \forall s \in S$$

$$(3.19) \quad \sum_{\forall a \in A} \left[ \sum_{\forall i \in F_{a,w,s}^{\text{Out}}} \sum_{j=0}^{11} h_{i(k-T_{aw}^s+j)}^s + \sum_{\forall i \in F_{a,w,s}^{\text{In}}} \sum_{j=0}^{11} h_{i(k+T_{aw}^s+j)}^s \right] \leq Q_{w,s}^{60}, \\ \forall w \in N, \quad \forall k \in K, \quad \forall s \in S$$

$$(3.20) \quad \sum_{\forall a \in A} \left[ \sum_{\forall i \in F_{a,w,s}^{\text{Out}}} h_{i(k-T_{aw}^s+j)}^s \right] \leq Q_{w,s}^{k,\text{Out}}, \quad \forall w \in N, \quad \forall k \in K, \quad \forall s \in S$$

$$(3.21) \quad \sum_{\forall a \in A} \left[ \sum_{\forall i \in F_{a,w,s}^{\text{Out}}} \sum_{j=0}^2 h_{i(k-T_{aw}^s+j)}^s \right] \leq Q_{w,s}^{15,\text{Out}}, \quad \forall w \in N, \quad \forall k \in K, \quad \forall s \in S$$

$$(3.22) \quad \sum_{\forall a \in A} \left[ \sum_{\forall i \in F_{a,w,s}^{\text{Out}}} \sum_{j=0}^5 h_{i(k-T_{aw}^s+j)}^s \right] \leq Q_{w,s}^{30,\text{Out}}, \quad \forall w \in N, \quad \forall k \in K, \quad \forall s \in S$$



$$(3.23) \quad \sum_{\forall a \in A} \left[ \sum_{\forall i \in F_{a,w,s}^{\text{Out}}} \sum_{j=0}^{11} h_{i(k-T_{aw}^s+j)}^s \right] \leq Q_{w,s}^{60,\text{Out}}, \quad \forall w \in N, \quad \forall k \in K, \quad \forall s \in S$$

$$(3.24) \quad \sum_{\forall a \in A} \left[ \sum_{\forall i \in F_{a,w,s}^{\text{In}}} h_{i(k+T_{aw}^s+j)}^s \right] \leq Q_{w,s}^{k,\text{In}}, \quad \forall w \in N, \quad \forall k \in K, \quad \forall s \in S$$

$$(3.25) \quad \sum_{\forall a \in A} \left[ \sum_{\forall i \in F_{a,w,s}^{\text{In}}} \sum_{j=0}^2 h_{i(k+T_{aw}^s+j)}^s \right] \leq Q_{w,s}^{15,\text{In}}, \quad \forall w \in N, \quad \forall k \in K, \quad \forall s \in S$$

$$(3.26) \quad \sum_{\forall a \in A} \left[ \sum_{\forall i \in F_{a,w,s}^{\text{In}}} \sum_{j=0}^5 h_{i(k+T_{aw}^s+j)}^s \right] \leq Q_{w,s}^{30,\text{In}}, \quad \forall w \in N, \quad \forall k \in K, \quad \forall s \in S$$

$$(3.27) \quad \sum_{\forall a \in A} \left[ \sum_{\forall i \in F_{a,w,s}^{\text{In}}} \sum_{j=0}^{11} h_{i(k+T_{aw}^s+j)}^s \right] \leq Q_{w,s}^{60,\text{In}}, \quad \forall w \in N, \quad \forall k \in K, \quad \forall s \in S$$

The objective function (3.1) aims at minimizing the total deviations between planned and actual times for all flights across various airports in seven days of a week. Constraint (3.2) mandates that all flights must be assigned to their unique slot times in a day of a week. Constraint (3.3) mandates. Constraints (3.4)–(3.7) establish that overall quantity of arrival and departure flights at the airport in any 5/min/15min/30min/60min in a day of a week cannot exceed its certain threshold. Constraints (3.8)–(3.11) establish that overall quantity of arrival flights at the airport in any 5/min/15min/30min/60min in a day of a week cannot exceed its certain threshold. Constraints (3.12)–(3.15) establish that overall quantity of departure flights at the airport in any 5/min/15min/30min/60min in a day of a week cannot exceed its certain threshold. Constraints (3.16)–(3.19) stipulate that overall quantity of arrival and departure flights passing through the waypoint in any 5/min/15min/30min/60min in a day of a week must also adhere to established thresholds. Constraints (3.20)–(3.23) reinforce limitations on total number of departure flights at the airport in any 5/min/15min/30min/60min in a day of a week. Constraints (3.24)–(3.27) reiterate restrictions concerning arrival flights at the airport in any 5/min/15min/30min/60min in a day of a week.

To deal with MPAGCFT with random flying time, the affine term  $\ddot{T}_{aw}^s + \hat{T}_{aw}^s z$  is used to depict its uncertainty in the interval  $[\ddot{T}_{aw}^s - \hat{T}_{aw}^s, \ddot{T}_{aw}^s + \hat{T}_{aw}^s]$ , where the stochastic parameter  $z$  lies in the uncertainty set  $\mathbb{Z} = \{z : \|z\|_\infty \leq 1, \|z\|_1 \leq \Gamma\}$ , and  $\Gamma$  presents the budget of uncertainty in flight time. The robust model of MPAGCFT is described as below.

$$(3.28) \quad \text{Minmax}_{z \in \mathbb{Z}} f = \sum_{\forall s \in S} \sum_{\forall a \in A} \sum_{\forall i \in F_{a,s}^{\text{Out}} \cup F_{a,s}^{\text{In}}} \sum_{\forall k \in K} h_{ik}^s (k - T_i^s)$$

S.t:

(3.29)

$$\sum_{\forall a \in A} \left[ \sum_{\forall i \in F_{a,w,s}^{\text{Out}}} h_{i(k - [\ddot{T}_{aw}^s + \hat{T}_{aw}^s z] + j)}^s + \sum_{\forall i \in F_{a,w,s}^{\text{In}}} h_{i(k + [\ddot{T}_{aw}^s + \hat{T}_{aw}^s z] + j)}^s \right] \leq Q_{w,s}^k,$$

$\forall w \in N, \forall k \in K, \forall s \in S$

(3.30)

$$\sum_{\forall a \in A} \left[ \sum_{\forall i \in F_{a,w,s}^{\text{Out}}} \sum_{j=0}^2 h_{i(k - [\ddot{T}_{aw}^s + \hat{T}_{aw}^s z] + j)}^s + \sum_{\forall i \in F_{a,w,s}^{\text{In}}} \sum_{j=0}^2 h_{i(k + [\ddot{T}_{aw}^s + \hat{T}_{aw}^s z] + j)}^s \right] \leq Q_{w,s}^{15},$$

$\forall w \in N, \forall k \in K, \forall s \in S$

(3.31)

$$\sum_{\forall a \in A} \left[ \sum_{\forall i \in F_{a,w,s}^{\text{Out}}} \sum_{j=0}^5 h_{i(k - [\ddot{T}_{aw}^s + \hat{T}_{aw}^s z] + j)}^s + \sum_{\forall i \in F_{a,w,s}^{\text{In}}} \sum_{j=0}^5 h_{i(k + [\ddot{T}_{aw}^s + \hat{T}_{aw}^s z] + j)}^s \right] \leq Q_{w,s}^{30},$$

$\forall w \in N, \forall k \in K, \forall s \in S$

(3.32)

$$\sum_{\forall a \in A} \left[ \sum_{\forall i \in F_{a,w,s}^{\text{Out}}} \sum_{j=0}^{11} h_{i(k - [\ddot{T}_{aw}^s + \hat{T}_{aw}^s z] + j)}^s + \sum_{\forall i \in F_{a,w,s}^{\text{In}}} \sum_{j=0}^{11} h_{i(k + [\ddot{T}_{aw}^s + \hat{T}_{aw}^s z] + j)}^s \right] \leq Q_{w,s}^{60},$$

$\forall w \in N, \forall k \in K, \forall s \in S$

(3.33)

$$\sum_{\forall a \in A} \left[ \sum_{\forall i \in F_{a,w,s}^{\text{Out}}} h_{i(k - [\ddot{T}_{aw}^s + \hat{T}_{aw}^s z] + j)}^s \right] \leq Q_{w,s}^{k,\text{Out}}, \quad \forall w \in N, \forall k \in K, \forall s \in S$$

(3.34)

$$\sum_{\forall a \in A} \left[ \sum_{\forall i \in F_{a,w,s}^{\text{Out}}} \sum_{j=0}^2 h_{i(k - [\ddot{T}_{aw}^s + \hat{T}_{aw}^s z] + j)}^s \right] \leq Q_{w,s}^{15,\text{Out}}, \quad \forall w \in N, \forall k \in K, \forall s \in S$$

(3.35)

$$\sum_{\forall a \in A} \left[ \sum_{\forall i \in F_{a,w,s}^{\text{Out}}} \sum_{j=0}^5 h_{i(k - [\ddot{T}_{aw}^s + \hat{T}_{aw}^s z] + j)}^s \right] \leq Q_{w,s}^{30,\text{Out}}, \quad \forall w \in N, \forall k \in K, \forall s \in S$$

(3.36)

$$\sum_{\forall a \in A} \left[ \sum_{\forall i \in F_{a,w,s}^{\text{Out}}} \sum_{j=0}^{11} h_{i(k - [\ddot{T}_{aw}^s + \hat{T}_{aw}^s z] + j)}^s \right] \leq Q_{w,s}^{60,\text{Out}}, \quad \forall w \in N, \forall k \in K, \forall s \in S$$

(3.37)

$$\sum_{\forall a \in A} \left[ \sum_{\forall i \in F_{a,w,s}^{\text{In}}} h_{i(k + [\ddot{T}_{aw}^s + \hat{T}_{aw}^s z] + j)}^s \right] \leq Q_{w,s}^{k,\text{In}}, \quad \forall w \in N, \forall k \in K, \forall s \in S$$

(3.38)

$$\sum_{\forall a \in A} \left[ \sum_{\forall i \in F_{a,w,s}^{\text{In}}} \sum_{j=0}^2 h_{i(k+[\ddot{T}_{aw}^s + \hat{T}_{aw}^s z] + j)}^s \right] \leq Q_{w,s}^{15,\text{In}}, \quad \forall w \in N, \quad \forall k \in K, \quad \forall s \in S$$

(3.39)

$$\sum_{\forall a \in A} \left[ \sum_{\forall i \in F_{a,w,s}^{\text{In}}} \sum_{j=0}^5 h_{i(k+[\ddot{T}_{aw}^s + \hat{T}_{aw}^s z] + j)}^s \right] \leq Q_{w,s}^{30,\text{In}}, \quad \forall w \in N, \quad \forall k \in K, \quad \forall s \in S$$

(3.40)

$$\sum_{\forall a \in A} \left[ \sum_{\forall i \in F_{a,w,s}^{\text{In}}} \sum_{j=0}^{11} h_{i(k+[\ddot{T}_{aw}^s + \hat{T}_{aw}^s z] + j)}^s \right] \leq Q_{w,s}^{60,\text{In}}, \quad \forall w \in N, \quad \forall k \in K, \quad \forall s \in S$$

The other constraints are the same as above. Objective function (3.28) presents worst-case of objective function (3.1). Constraints (3.29)–(3.40) present worst-cases of constraints (3.16)–(3.27).

#### 4. SOLUTION METHOD

As above mentioned, MPAGCFT could be further divided into Model 1 with the same arrival/ departure time of a flight on all days and Model 2 with its changed arrival/departure time on different days. Model 1 can be directly solved by using RSOME solver generate a 7-day flight schedule, and Model 2 will be solved seven times by the RSOME solver to generate a daily flight schedule. A data-driven framework for solving MPAGCFT is given in Figure 1. After analyzing the flight information on seven days in a week of each airport in an airport group, their busy shared waypoints are determined and their upper and lower bounds of flight times are obtained. The solutions of Model 1 and Model 2 are obtained based on their inputs and budget of uncertainty parameter.

#### 5. EXAMPLE STUDY

**5.1. Data preparation.** A total of 2547 flights between August 1, 2023 to August 7, 2023 in MPAGCFT network of four airports in Beijing-Tianjin-Hebei region, China, seen in Figure 2, is utilized to demonstrate the validity of this study. Tables 2 and 3 depict all flights of four airports as well as them between airports and waypoints on each day of a week. There are a total of 2035, 2547, 2020, 2253, 2041, 2127 and 2064 arrival and departure flights between Monday and Sunday, where 56.3%, 52.45%, 56.5%, 55.9%, 5.61%, 54.3%, 56.4% of those flights fly through these busy waypoints in these seven days. Other parameters are set as:  $d_i = 120$  min,  $C_a^{15\text{min}} = 3C_a^k$ ,  $C_a^{30\text{min}} = 6C_a^k$ ,  $C_a^{60\text{min}} = 12C_a^k$ ,  $Q_w^k = 4$ ,  $Q_w^{15\text{min}} = 3Q_w^k$ ,  $Q_w^{30\text{min}} = 6Q_w^k$ ,  $Q_w^{60\text{min}} = 12Q_w^k$ ,  $\Gamma = 0$ .

**5.2. Results.** There is a total deviation of 5106 slots for assigning all flights on these seven days to their actual time slots in the optimal solution of Model 1. As seen in Tables 2 and 3, the result shows that: (1) For the four airports on any given day, the larger degree of imbalance between supply and demand of an airport it is

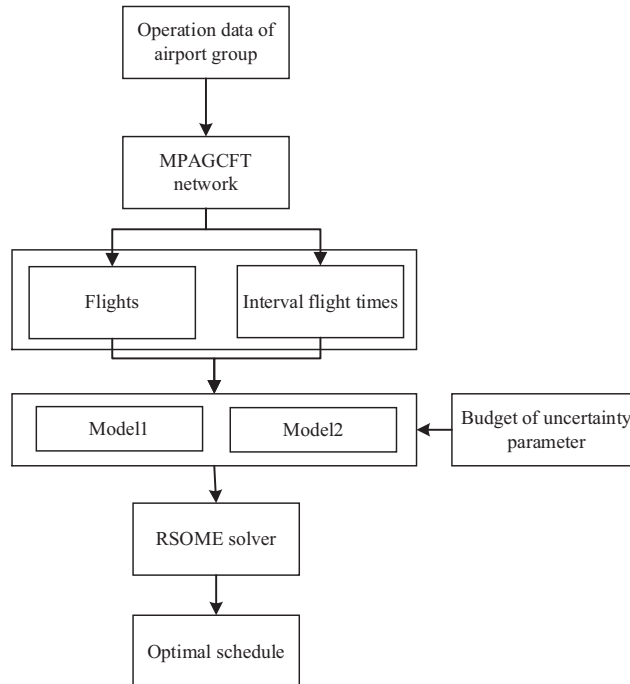


FIGURE 1. A data-driven framework for solving MPAGCFT

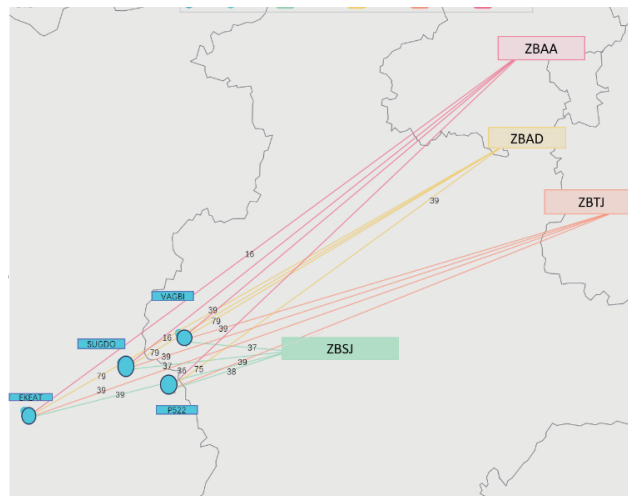


FIGURE 2. Layout of MPAGCFT network

the largest, and deviations between planned and actual time for all flights. They are ranked in descending order as ZBAD, ZBAA, ZBTJ and ZBSJ. (2) For an airport on a different day, the more flights on a given day, the greater imbalance between supply and demand, resulting in more deviations between planned and actual time for all flights. They are ranked in descending order as Tuesday, Thursday, Saturday, Friday, Monday, Wednesday and Sunday.

TABLE 2. Flights of airports and waypoints airports

Airport		Number of flights						
Name	$C_a^k$	Monday	Tuesday	Wednesday	Thursday	Friday	Saturday	Sunday
ZBAA	8	588	805	574	636	588	571	583
ZBAD	6	934	1043	932	981	944	941	955
ZBTJ	4	337	455	337	415	339	398	340
ZBSJ	2	176	244	177	221	170	217	186

TABLE 3. Flights between four airports and waypoints

Airport		WayPoint						
Name	Name	Number of flights						
		Monday	Tuesday	Wednesday	Thursday	Friday	Saturday	Sunday
ZBAA	P522	111	126	108	115	109	101	106
	P86	78	91	73	81	77	65	76
	VAGBI	107	126	103	116	105	102	105
	DPX	77	92	77	86	79	74	80
ZBAD	P522	87	98	90	96	89	91	90
	P86	142	151	142	145	142	134	144
	VAGBI	113	125	112	120	116	117	115
	DPX	132	146	134	138	136	127	139
ZBTJ	P522	59	69	58	67	57	63	56
	P86	40	50	40	47	41	45	41
	VAGBI	58	70	57	67	55	63	56
	DPX	29	38	30	37	29	33	31
ZBSJ	P522	40	54	40	49	38	49	44
	P86	20	30	21	29	19	26	23
	VAGBI	40	52	42	49	39	49	42
	DPX	14	19	14	18	14	16	16

TABLE 4. Basic information of the optimal solution for Model 1

Airport	Total delay time/Number of flights not delayed or more than 30 minutes						
	Monday	Tuesday	Wednesday	Thursday	Friday	Saturday	Sunday
ZBAA	37/553/0	200/673/0	30/545/0	42/597/0	33/557/0	34/538/0	32/552/0
ZBAD	549/679/13	963/725/32	539/678/14	688/700/19	558/685/14	637/684/16	520/694/13
ZBTJ	14/324/0	75/402/0	12/325/0	40/379/0	15/325/0	32/368/0	17/325/0
ZBSJ	2/174/0	13/233/0	2/175/0	8/214/0	3/167/0	7/211/0	4/182/0

Furthermore, Table 5 compares difference in optimal solutions the of Model 1 and Model 2. Compared with Model 1, total deviation, number of flights not delayed, number of flights delayed more than 30 minutes and number of flights delayed more than 60 minutes of Model 2 are reduced by 18.7%, 14.2%, 40.7% and 35.5%,

TABLE 5. Comparison of model A and model B

Scenarios		Model 1	Model 2	Gap
Total deviation (time slots)		5106	4302	18.7%
Number of flights delayed	No delay	12664	11093	14.2%
	More than 30 minutes	121	86	40.7%
	More than 60 minutes	42	31	35.5%

respectively. However, passengers expect the same flight to be constant at departure or arrival time on seven days of a week, thus Model 1 is more realistic than Model 2.

**5.3. Sensitivity analysis.** Figure 3 analyzes the effect of degree of uncertainty on the model performance. The heightened degree of uncertainty has resulted in an expanded time window for flight duration. This, in turn, diminishes the solution space that accommodates all relaxation variables, ultimately leading to a suboptimal solution. Obviously, if changed time window of the flight time does not reduce the solution space, the optimal solution stays the same.

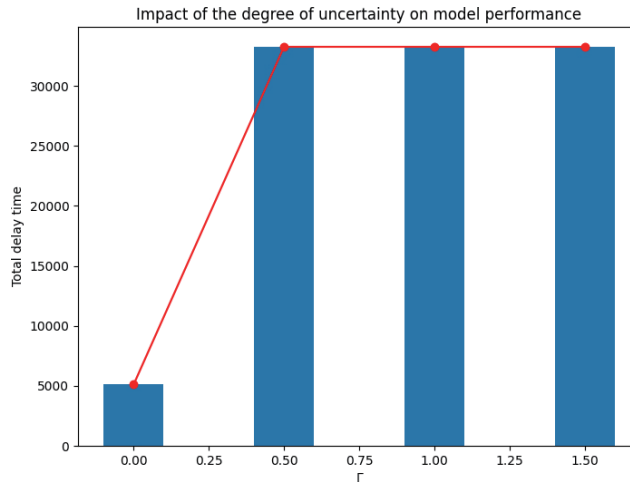


FIGURE 3. Comparison of optimal schedules under various degrees of uncertainty

Figure 4 analyzes how different airport capacity affect the result. The enhancement of airport capacity can lead to reduction in the total deviation of time until the threshold is reached. This is due to the fact that the enhancement of airport capacity has allowed some flights not to be delayed. When the capacity of a time slot is greater than number of flights assigned to this time slot, total deviation of time is a fixed value, decided by some factors such as waypoint capacity.

Figure 5 analyzes the effect of different waypoint capacity on the result. As waypoint capacity increases, the total deviation time gradually decreases. When the threshold is reached, it will remain the same. The reason for this phenomenon is similar to that of Figure 4.

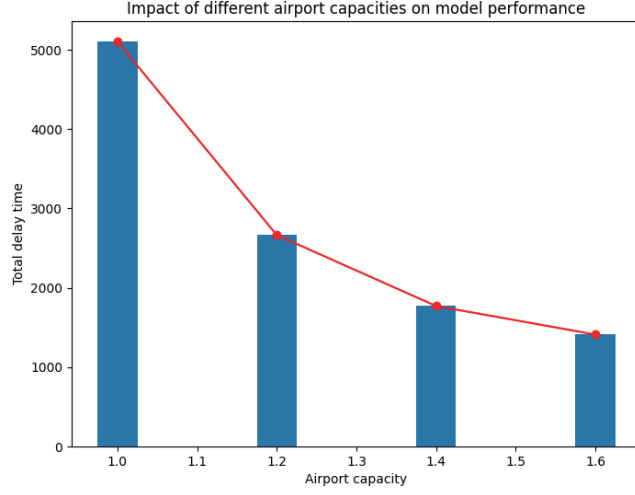


FIGURE 4. Comparison of optimal schedules under various airport capacities

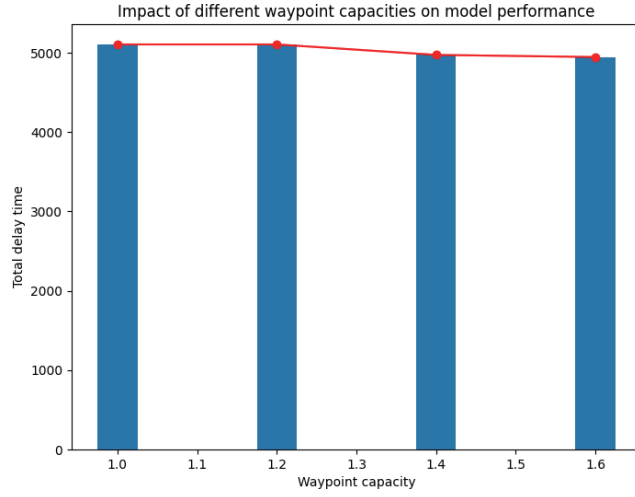


FIGURE 5. Comparison of optimal schedules under various waypoint capacities

## 6. CONCLUSIONS

This paper develops a worst-case robust model for MPAGCFT with uncertain flight time to identify optimal relationship between network layout of MPAGCFT, space-time distribution of flights at different airports, the uncertainties associated with flight durations, schedule and overall system costs. Furthermore, some pragmatic constraints such as airport and waypoint capacity as well as maximum delay time are also considered in proposed model. The solutions are derived utilizing RSOME. Finally, a real example is presented to validate practicality of this research.

The key findings of this study are summarized as follows:

(1) For the infeasible timetable with number of flights at some periods being more than their airport or waypoint capacities, our study, the same as the traditional AGCFT model, also adjusts arrival and departure time of some flights to make number of flights for all periods less than the airport or waypoint capacities, so that the infeasible timetable becomes a feasible timetable.

(2) Compared with single- period AGCFT, MPAGCFT could generate a viable 7-day schedule based on the differences in flight schedules for the seven days of the week. Obviously, the greater the imbalance between supply and demand at an airport, the greater its flight deviation. Similarly, the greater the imbalance between supply and demand on a given day, the greater the flight deviation.

(3) Although total deviation times for all flights of Model 1 is larger than that of Model 2, the former is closer to reality than the latter, which is in line with passengers' travel habits.

However, our model has two major shortcomings: (1) it only considers minimum objective of deviations between planned and actual time for all flights, ignoring the impact of airline and airport fairness on the schedule; (2) many real-world constraints such as schedule of new flights, dynamic allocation of airport or waypoint capacity etc. are neglected. Expanding our model to a multi-objective framework with many pragmatic constraints will be the focus of our future work.

## REFERENCES

- [1] N. Adler, *Hub-spoke network choice under competition with an application to western europe*, Transp. Sci. **39** (2005), 58–72.
- [2] A. Agogino and J. Rios, *Robustness of two air traffic scheduling approaches to departure uncertainty*, in: Proceedings of 2011 IEEE/AIAA 30th Digital Avionics Systems Conference, IEEE, October 2011, pp. 16–20.
- [3] K. N. Androutsopoulos and M. A. Madas, *Being fair or efficient? A fairness-driven modeling extension to the strategic airport slot scheduling problem*, Transp. Res. Part E: Logist. Transp. Rev. **130** (2019), 37–60.
- [4] K. N. Androutsopoulos, E. G. Manousakis and M. A. Madas, *Modeling and solving a bi-objective airport slot scheduling problem*, Eur. J. Oper. Res. **284** (2020), 135–151.
- [5] U. Benlic, *Heuristic search for allocation of slots at network level*, Transp. Res. Part C: Emerg. Technol. **86** (2018), 488–509.
- [6] E. K. Burke, S. Petrovic and R. Qu, *Case-based heuristic selection for timetabling problems*, J. Sched. **9** (2006), 115–132.
- [7] B. Capozzi, S. Atkins and S. Choi, *Towards optimal routing and scheduling of metroplex operations*, in: Proceedings of 9th AIAA Aviation Technology, Integration and Operations Conference (ATIO), AIAA, June 2009: 7037.
- [8] L. Castelli, P. Pellegrini and R. Pesenti, *Airport slot allocation in europe: economic efficiency and fairness*, Int. J. Reven. Manag. **6** (2012): 28.
- [9] T. B. Cooper and J. H. Kingston, *The complexity of timetable construction problems*, in: Proceedings of Lecture Notes in Computer Science, Springer Berlin Heidelberg, June 1996, pp. 281–295.
- [10] L. Corolli, G. Lulli and L. Ntamo, *The time slot allocation problem under uncertain capacity*, Transp. Res. Part C: Emerg. Technol. **46** (2014), 16–29.
- [11] D. Delahaye and Y. Wang, *Slot allocation in a multi-airport system under flying time uncertainty*, in: Proceedings of International Workshop on ATM/CNS, Springer, October 2022, pp. 119–126.
- [12] B. Dijk, B. F. Santos and J. P. Pita, *The recoverable robust stand allocation problem: a gru airport case study*, OR Spectr. **41** (2018), 615–639.



- [13] J. Fairbrother and K. G. Zografos, *Introducing flexibility and demand-based fairness in slot scheduling decisions*, in: Proceedings of Odysseus conference, Sardinia, June 2018, pp. 23–29.
- [14] J. Fairbrother and K. G. Zografos, *Optimal scheduling of slots with season segmentation*, Eur. J. Oper. Res. **291** (2021), 961–982.
- [15] J. Fairbrother, K. G. Zografos and K. D. Glazebrook, *A slot-scheduling mechanism at congested airports that incorporates efficiency, fairness, and airline preferences*, Transp. Sci. **54** (2020), 115–138.
- [16] H. Feng, R. Hu, D. Wang, J. Zhang and C. Wu, *Bi-objective airport slot scheduling considering scheduling efficiency and noise abatement*, Transp. Res. Part D: Transp. Environ. **115** (2023): 103591.
- [17] Y. S. Gök, S. Padrón, M. Tomasella, D. Guimarans and C. Ozturk, *Constraint-based robust planning and scheduling of airport apron operations through simheuristics*, Ann. Oper. Res. **320** (2022), 795–830.
- [18] F. B. Hafner, *Improving airline schedule reliability using a strategic multi-objective runway slot assignment search heuristic*, Master's thesis, University of Central Florida, 2008.
- [19] S. Hong and P. T. Harker, *Air traffic network equilibrium: Toward frequency, price and slot priority analysis*, Transp. Res. Part B: Methodol. **26** (1992), 307–323.
- [20] A. Jacquillat and V. Vaze, *Interairline equity in airport scheduling interventions*, Transp. Sci. **52** (2018), 941–964.
- [21] Y. Jiang and K. G. Zografos, *A decision making framework for incorporating fairness in allocating slots at capacity-constrained airports*, Transp. Res. Part C: Emerg. Technol. **126** (2021): 103039.
- [22] F. Ju, K. Cai, Y. Yang and Y. Gao, *A scenario-based optimization approach to robust estimation of airport capacity*, in: Proceedings of 2015 IEEE 18th International Conference on Intelligent Transportation Systems, IEEE, September 2015, pp. 2066–2071.
- [23] F. A. Katsigiannis and K. G. Zografos, *Optimising airport slot allocation considering flight-scheduling flexibility and total airport capacity constraints*, Transp. Res. Part B: Methodol. **146** (2021), 50–87.
- [24] F. A. Katsigiannis and K. G. Zografos, *Multi-objective airport slot scheduling incorporating operational delays and multi-stakeholder preferences*, Transp. Res. Part C: Emerg. Technol. **152** (2023): 104156.
- [25] F. A. Katsigiannis, K. G. Zografos and J. Fairbrother, *Modelling and solving the airport slot-scheduling problem with multi-objective, multi-level considerations*, Transp. Res. Part C: Emerg. Technol. **124** (2021), 102914.
- [26] T. Kerama and K. G. Zografos, *A multi-objective framework for investigating airport schedule efficiency, fairness, flexibility, and regularity trade-offs*, in: Proceedings of International Workshop on Freight Transportation and Logistics, ODYSSEUS, May 2022, pp. 24–32.
- [27] M. Keskin and K. Zografos, *Modeling and solving the network-wide airport slot allocation problem with connectivity, efficiency and fairness considerations*, SSRN Electron. J. (2022), DOI: 10.2139/ssrn.4180320.
- [28] M. Keskin and K. G. Zografos, *Optimal network-wide adjustments of initial airport slot allocations with connectivity and fairness objectives*, Transp. Res. Part B: Methodol. **178** (2023): 102801.
- [29] D. Koesters, *Airport scheduling performance—an approach to evaluate the airport scheduling process by using scheduled delays as quality criterion*, in: Proceedings of the Air Transport Research Society (ATRS) annual world conference, UNO Aviation Institute, June 2007, pp. 23–27.
- [30] W. Liu, Q. Zhao and D. Delahaye, *Research on slot allocation for airport network in the presence of uncertainty*, J. Air Transp. Manag. **104** (2022): 102269.
- [31] K. K. H. Ng, C. K. M. Lee, F. T. S. Chan and Y. Qin, *Robust aircraft sequencing and scheduling problem with arrival/departure delay using the min-max regret approach*, Transp. Res. Part E: Logist. Transp. Rev. **106** (2017), 115–136.

- [32] P. Pellegrini, T. Bolić, L. Castelli and R. Pesenti, *Sosta: An effective model for the simultaneous optimisation of airport slot allocation*, Transp. Res. Part E: Logist. Transp. Rev. **99** (2017), 34–53.
- [33] P. Pellegrini, L. Castelli and R. Pesenti, *Metaheuristic algorithms for the simultaneous slot allocation problem*, IET Intell. Transp. Syst. **6** (2012), 453–462.
- [34] N. Pyrgiotis and A. Odoni, *On the impact of scheduling limits: A case study at newark liberty international airport*, Transp. Sci. **50** (2016), 150–165.
- [35] S. J. Rassenti and R. L. Bulfin, *A combinatorial auction mechanism for airport time slot allocation*, Bell J. Econ. **13** (1982), 402–417.
- [36] N. A. Ribeiro, A. Jacquillat, A. P. Antunes, A. R. Odoni and J. P. Pita, *An optimization approach for airport slot allocation under iata guidelines*, Transp. Res. Part B: Methodol. **112** (2018), 132–156.
- [37] B. Saraswati and S. Hanaoka, *Airport–airline cooperation under commercial revenue sharing agreements: A network approach*, Transp. Res. Part E: Logist. Transp. Rev. **70** (2014), 17–33.
- [38] D. Sheng, Z. C. Li, Y. B. Xiao and X. W. Fu, *Slot auction in an airport network with demand uncertainty*, Transp. Res. Part E: Logist. Transp. Rev. **82** (2015), 79–100.
- [39] C. Tan and J. He, *Robust airport gate assignment based on the analysis of flight arrival time*, Math. Prob. Eng. **2021** (2021): 6693127.
- [40] P. B. M. Vranas, *Optimal slot allocation for european air traffic flow management*, Air Traffic Control Q. **4** (1996), 249–280.
- [41] D. Wang and Q. Zhao, *A simultaneous optimization model for airport network slot allocation under uncertain capacity*, Sustain. **12** (2020): 5512.
- [42] K. Wang and A. Jacquillat, *A stochastic integer programming approach to air traffic scheduling and operations*, Oper. Res. **68** (2020), 1375–1402.
- [43] S. Wang, J. H. Drake, J. Fairbrother and J. R. Woodward, *A constructive heuristic approach for single airport slot allocation problems*, in: Proceedings of 2019 IEEE Symposium Series on Computational Intelligence (SSCI), IEEE, December 2019, pp. 1171–1178.
- [44] Y. Wang, C. Liu, H. Wang and V. Duong, *Slot allocation for a multiple-airport system considering airspace capacity and flying time uncertainty*, Transp. Res. Part C: Emerg. Technol. **153** (2023): 104185.
- [45] C. Wanke, M. Callaham, D. Greenbaum and A. Masalonis, *Measuring uncertainty in airspace demand predictions for traffic flow management applications*, in: Proceedings of AIAA Guidance, Navigation, and Control Conference and Exhibit, AIAA, June 2003, pp. 5708–5716.
- [46] M. Wei, Y. Xiong and B. Sun, *Spatial effects of urban economic activities on airports’ passenger throughputs: A case study of thirteen cities and nine airports in the Beijing-Tianjin-Hebei region, China*, J. Air Transp. Manag. **125** (2025): 102765.
- [47] K. G. Zografos, K. N. Androutsopoulos and M. A. Madas, *Minding the gap: Optimizing airport schedule displacement and acceptability*, Transp. Res. Part A: Policy Pract. **114** (2018), 203–221.
- [48] K. Zografos and Y. Jiang, *Modelling and solving the airport slot scheduling problem with efficiency, fairness, and accessibility considerations*, in: Proceedings of TRISTAN Symposium, Academia, June 2016, pp. 13–16.
- [49] K. G. Zografos, M. A. Madas and K. N. Androutsopoulos, *Increasing airport capacity utilisation through optimum slot scheduling: review of current developments and identification of future needs*, J. Sched. **20** (2016), 3–24.
- [50] K. G. Zografos, Y. Salouras and M. A. Madas, *Dealing with the efficient allocation of scarce resources at congested airports*, Transp. Res. Part C: Emerg. Technol. **21** (2012), 244–256.

J. Z. YAN

College of Civil Aviation, Nanjing University of Aeronautics and Astronautics, Nanjing 213332, China; Operation Management Center, ATMB, CAAC, Beijing 100022, China

*E-mail address:* `yanjianzhong2024@163.com`

M. H. HU

Operation Management Center, ATMB, CAAC, Beijing 100022, China

*E-mail address:* `minghuahu@nuaa.edu.cn`