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Efficient Aircraft Arrival Sequencing Given Airport Gate Assignment

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The aircraft sequencing problem has been well discussed in many variants over the years; and during this time, the problem has changed from a standalone optimization problem to an embedded problem. At hub airports, aircraft sequencing influences passengers' available connecting times. Short connections could benefit from a modification of the arrival or departure sequence. In our work, we have developed a bilevel optimization problem that combines the aircraft sequencing problem and the airport gate assignment problem at hub airports to make connections more efficient. The decision on the gate assignments is made at the upper level, whereas the efficient aircraft arrival sequencing is addressed at the lower level. Methods for solving this kind of large-scale bilevel optimization problem by considering a full day of operation and dynamically changing traffic situations have yet to be researched. In this paper, we focus on efficient aircraft sequencing by taking into consideration gate assignments, and we propose a multiobjective mixed integer linear program that is solved by an interactive method and considers the (contradicting) objectives of competing airlines and the air traffic control. The capabilities of our approach are demonstrated by modeling and solving a real-case scenario for Munich Airport.

Nomenclature

A	=	set of arriving and departing aircraft
A_{AGAP}	=	set of aircraft considered in airport gate assignment problem
A_{arr}	=	set of arriving aircraft
A_{dep}	=	set of departing aircraft
A'	=	set of airlines
a	=	virtual leading aircraft in a sequence
b_{arr}	=	vector of optimal runway assignments for aircraft in A_{arr}
b_{dep}	=	vector of optimal runway assignments for aircraft in A_{dep}
b_i	=	assigned runway to aircraft i
$c_{\mathrm{FF},i}$	=	costs incurred from fuel flow by aircraft i, U.S. dollars/s
cat_i	=	wake-turbulence category of aircraft i
c_i^y	=	costs incurred from a missed deadline y by aircraft i, U.S. dollars
D	=	set of edges
d_i	=	decision allocation, delay of aircraft i
E'	=	evaluation matrix
$\mathrm{ETA0}_{i,\min}$	=	earliest $\mathrm{ETA0}_i$ of aircraft i among all runways in use
$\mathrm{ETA0}_{\max}$	=	latest earliest time of arrival among all aircraft in a sequence
$\mathrm{ETA0}_i^b$	=	earliest time of arrival of aircraft i at runway b
$\overline{\mathrm{ETSC}}$	=	modified estimated time of stand clearance
f	=	objective function
g_i^*	=	most preferred objective function articulated by aircraft i
h	=	number of objective functions
i	=	aircraft index
$-i$	=	competing aircraft to aircraft i belonging to airline i'
i'	=	airline index
$-i'$	=	competing airline to airline i
i''	=	index of airline–individual sequence
k	=	vector of stand assignments
l_{arr}	=	vector of optimal times of arrival for aircraft in A_{arr}, s
l_{dep}	=	vector of optimal times of departure for aircraft in A_{dep}, s
l_i	=	decision allocation, landing time of aircraft i, s
$l_{i,\mathrm{ref}}$	=	decision allocation, landing time of aircraft i, reference sequence, s
$l_{\max}^{\mathrm{FCFS}}$	=	landing time of the last aircraft in sequence, s
M_{ij}^c	=	big-M factor for aircraft i and j linked to runway c
m	=	number of aircraft
m'	=	number of airlines
m''	=	number of airline–individual sequences
n	=	number of stands
q	=	virtual trailing aircraft in a sequence
R	=	set of runways in use
r	=	number of runways in use
SEQ'	=	set of airline–individual sequences
sep_{ij}	=	separation time between two aircraft, i and j, s
$\mathrm{sep}_{\max}(i)$	=	maximum separation time among all aircraft pairings in a sequence for aircraft i, s
sep'_{ij}	=	separation distance between two aircraft, i and j, m
$\mathrm{seq}_{\mathrm{ref}}^*$	=	reference sequence
seq^*	=	optimal sequence, solution of the multiobjective aircraft sequencing problem
t_{in}	=	taxi-in time, s
t_{opt}	=	start time of a bilevel optimization run
t_{out}	=	taxi-out time, s
t_{ta}	=	turnaround time, s
$t_i^{b,y}$	=	time coefficient for aircraft i, runway b, and deadline y, s
$t_{\mathrm{in},i}^b$	=	taxi-in time from arrival runway b to stand k of aircraft i, s
$t_{\mathrm{occ},i}^b$	=	runway occupancy time of aircraft i using runway b, s
$v_{\mathrm{GS},i}$	=	ground speed of aircraft i, m/s
x	=	decision vector of the upper level
x_0	=	initial point7
$x_i^{b,y}$	=	decision allocation, aircraft i assigned to runway b misses deadline y
x_i^y	=	decision allocation, aircraft i misses deadline y
x_{ij}^{bc}	=	decision allocation, aircraft i on runway b is linked to aircraft j on runway c
x^*	=	optimal decision vector of the upper level
y	=	decision vector of the lower level/index of deadline
Y_i	=	set of deadlines for aircraft i
y^*	=	optimal decision vector of the lower level

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z_i	=	number of deadlines for aircraft i
z^*	=	ideal objective vector
Θ	=	upper bound, s

I. Introduction

IN OUR work, we focus on optimizing connections at major hub airports by minimizing the connection time for passengers. Passengers wish to experience a seamless and comfortable connection within a short timeframe. However, the reality may differ significantly from the passenger's wish, and making a connection can be become a challenge. One aim of hub airports and airlines is to continuously improve the connection experience. This can only be achieved if all stakeholders work together closely and make optimal decisions by considering their own objectives as well as a common operational objective. One way to improve the connection process is to modify the sequence of arriving and departing aircraft in such way that aircraft participating in connections with only a short timeframe are prioritized. However, air traffic control (ATC) treats every aircraft equally. The *first-come, first-served* (FCFS) principle applies. Another approach is to minimize the walking time from the arrival gate to the gate of the onward flight. The gate assignment is made either by the airport operator or the airlines at major hub airports. In this context, there is usually no advanced and automated exchange of preferences between participating stakeholders for optimizing decision making.

Optimal operational decisions can be made by modeling and solving mathematical optimization problems. In aiming to improve the connection experience, it is necessary to focus on the most important aspects, i.e., the airport infrastructure, passenger flows, and the sequencing of arriving/departing aircraft. The challenge is that there is a high degree of complexity and interdependency. Therefore, not all aspects can be simultaneously considered in a single optimization problem. Furthermore, the time domain is against us: a solution has to be provided within a short timeframe. Over the years, sophisticated models and solving techniques have been developed to resolve these optimization problems. However, a large number of them only address single optimization aspects. Our work is focused on the optimization of connections at hub airports. Disruptions may lead to additional costs for airlines. The competition in airline business demands a continuous improvement of processes. For this reason, our work aims at developing a novel approach in decision making to reduce the impact of disruption for a hub airline. Key elements of our approach in decision making are the provision of special passenger services, the reassignment of stands, or even a modification of the arrival and departure sequence. Although the proposed optimization approach is not limited to a certain airport, a case study is performed for terminal 2 at Munich Airport, which is rated as Europe's only five-star airport [1]. For terminal 2, the minimum connection time starts at only 30 min for flights within the Schengen area. In 2018 and before the COVID-19 crisis, a proportion of 30% of all departing flights was delayed [2]. Proportions of 52 and 8% of the delays were caused by the airlines and the airport operator, respectively ([3] p. 29). Not only the weak on-time performance but also the airport operator's commitment to a high level of service quality require action.

At Munich Airport, there are five arrival and departure peaks spread over a day. For terminal 2, there are a total of about 500 aircraft that we must assign to stands, as well as position in an arrival or departure sequence. In the event of a major delay, when the available connection times tend to decrease, the sequence of arriving and departing aircraft can be modified to lessen the impact of the delay. Swiss International Air Lines influences the arrival sequencing by prescribing a controlled time of arrival to selected aircraft at peak times (Ref. [4] p. 91). Modified sequencing, tailored by an airline, mitigates the risk of stand reassignment. At Munich Airport, gates are usually assigned to European flights more than 1 h before the expected arrival. If a delay becomes critical for connections, not only may a stand reassignment be initiated for the delayed aircraft but also for other aircraft to which passengers connect. To minimize costs and walking times for passengers resulting from gate changes, we apply mathematical optimization methods: an optimal assignment of the gates or stands to a set of aircraft is the solution of the airport gate assignment problem (AGAP). The more aircraft are affected by delays, the more aircraft must be considered in the AGAP, resulting in an increase in complexity and in the size of the optimization problems encountered. With regard to the time domain, an exact solution of the AGAP cannot be expected in polynomial time due to the immense number of combinations [5]. Without considering operational restrictions, we have

$$m!\binom{n}{m}$$

combinations. In our optimization, we consider stands instead of gates because this takes the ground infrastructure into account. Furthermore, we do not optimize the stand assignment for all aircraft of the day at once because arrival and departure times are subject to delay. Instead, we solve subproblems in which we assign up to 65 aircraft to stands at peak times. In each subproblem, we always consider the full number of 253 stands. Consequently, we can only expect to find, at the least, a satisfactory solution due to the immense number of combinations for a given timeframe. An aerodrome chart and an apron chart are provided in Figs. 1 and 2, respectively. Note that Fig. 2 shows less than 253 stands. For modeling reasons, some stands are duplicated to consider different walking times that result from security and border controls if required. Please refer to Ref. [6] for more information about the modeling. To improve the connection process, we developed a bilevel optimization problem that combines the AGAP in its upper level and the optimization of the arrival and departure sequencing in its lower level. For the AGAP, we use a hybrid optimization approach, based on a binary quadratic assignment problem (QAP) and a Nash equilibrium problem, to assign stands to aircraft [6]. Our bilevel optimization problem makes use of a sophisticated terminal and taxiway model. The walking times of the passengers, travel times by bus to or from apron stands, and the taxi times of aircraft are precisely determined by an underlying digraph. Furthermore, we consider the availability of ground vehicles and special services that are offered at Munich Airport [7].

In this paper, we focus on modeling and solving of the multi-objective aircraft arrival sequencing problem in the lower level for a

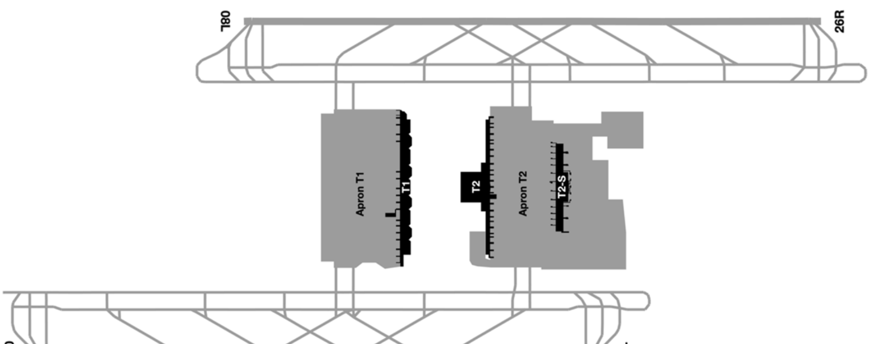


Fig. 1 Aerodrome chart of Munich Airport depicting the locations of terminals T1, T2, and T2-satellite; essential aprons; taxiways; and the parallel runway system.

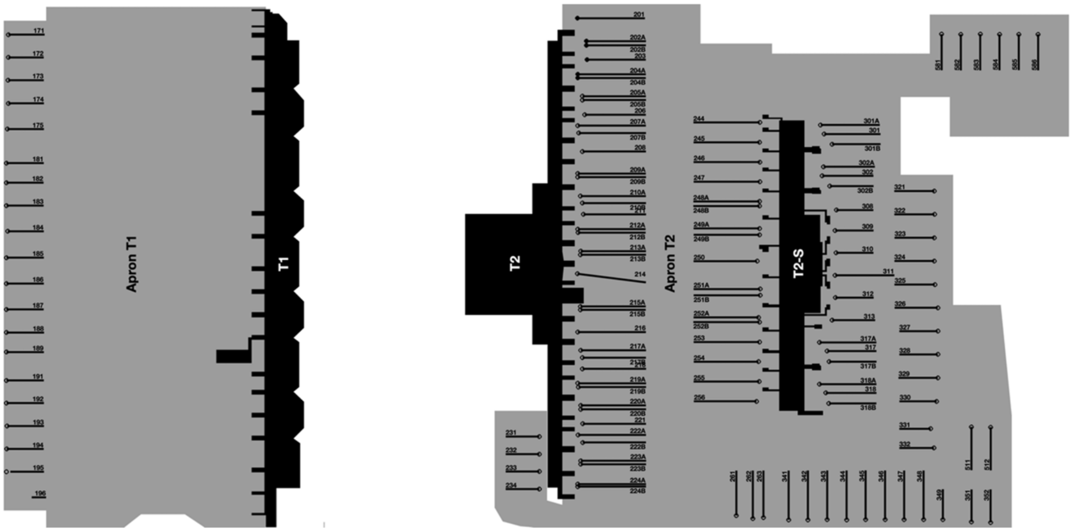


Fig. 2 Apron chart of Munich Airport, depicting the main building (T2) and the satellite (T2-S) of terminal 2. Terminal 2 is used by the Lufthansa Group and its partners. Terminal 1 is used by all other airlines.

parallel independent runway system. We propose an interactive method that can optimize arrival sequences taking into consideration the operational objectives of (hub) airlines and the ATC. We model the underlying sequencing problem as a multiobjective mixed integer linear program (MOMILP) for a given stand assignment.

II. Related Works

Over the years, many variants of the aircraft sequencing problem[†] (ASP) have been discussed in detail. Early studies [8–10] addressed the modeling and solving of the classic ASP for a single runway, whereas more recent studies have instead focused on a multiobjective optimization for multiple runways at major (hub) airports [11–13]. Nowadays, the ASP is no longer a standalone optimization problem rather an embedded problem because more and more shared information has been made available to stakeholders, and this is combined with the ongoing continuous requirement for all participants to operate more efficiently. Nevertheless, stakeholders usually have different and even contradicting objectives. This results in multiobjective optimization problems. In Ref. [14], a multiobjective mixed integer linear program (MILP) for the aircraft arrival and departure scheduling on multiple runways is proposed that addresses the simultaneous minimization of delay and the maximization of runway utilization. A valuable review of literature on the modeling and solving of the ASP from a mathematical point of view is provided in Ref. [14].

Furthermore, we must also consider the procedures in ATC and their impact on the ASP. The point of merge system is one approach for establishing a sequence. At airports with high traffic densities, multiple merge points usually exist, which makes optimal sequencing difficult. In Ref. [15], single-objective and multiobjective programming models are proposed to minimize the total fuel consumption, total flight time, and total delay including taxi times. These models are tailored to the needs of a terminal maneuvering area with a parallel-point merge system, and they were demonstrated for the multiple runway system of Istanbul Airport. Furthermore, the reassignment of aircraft to different runways was addressed in the decision making. Hence, the optimal ground routing of aircraft must also be considered. The establishment of a sequence is the task of ATC. However, the optimization should not only consider the objectives of ATC. A bilevel optimization is proposed in Ref. [16]. A trajectory optimization is performed in the lower level to minimize fuel consumption, whereas an optimal sequence is determined in the upper level.

Over recent years, the classic ASP has changed from a standalone optimization problem to an embedded problem. However, the combination of the ASP and AGAP into a bilevel optimization problem constitutes a gap in the research. The most important reasons for this are the following:

1) Consideration is only required for airports at which connections are expected.

2) The AGAP is performed by the airline or airport/terminal operator, whereas the ASP is performed by ATC; an information exchange mechanism for collaborative decision making may not exist.

3) The fair treatment of competing airlines must be ensured.

This paper focuses on the modifications to the classic ASP that are aligned with a consideration of the decisions made in the AGAP, and it proposes an interactive method for optimizing arrival sequences at hub airports. In Sec. III, we first give a brief introduction to the structure of the underlying bilevel optimization problem. In Sec. IV, we summarize the basics of modeling the ASP as a single-objective MILP. Later in this section, we introduce the required objective functions. In Sec. V, we give a brief outline of multiobjective optimization. Then, in Sec. VI, we present our approach for determining efficient sequences based on the commonly encountered steps of interactive methods for solving multiobjective optimization problems. Finally, we present the results of a case study in Sec. VII. The capabilities of the proposed interactive method are compared to the sequences that are obtained from applying the FCFS principle and maximizing the runway capacity.

III. Problem Description

Bilevel programming supposes that a leader (upper level) has control over the decision variable $x \in X \subset R^n$ and that a follower (lower level) has control over the decision variable $y \in Y \subset R^m$. The leader goes first and selects an x in an attempt to optimize their objective function $F(x, y(x))$ subject to some constraints of $G(x, y) \leq 0$. The follower observes the leader's actions and reacts by selecting a y to optimize their objective function $f(x, y)$, subject to some constraints of $g(x, y) \leq 0$ in the y variable for the value of x chosen. The notation $y(x)$ stresses the fact that the leader's decision is implicit in the y decision variable (Ref. [17] p. 48).

A. Airport Gate Assignment Problem

Figure 3 shows the structure of our bilevel optimization problem with the AGAP in the upper level and the ASP in the lower level. The AGAP as the leader goes first and determines a gate/stand assignment as the solution of the underlying biobjective QAP. Remember that we consider stands instead of gates in our model because we consider the aircraft wingspan and the transportation time by passenger buses from/to apron stands, which depend only on the stands. Minimizing the walking time and minimizing the monetary costs are two contradicting

[†]In the literature, the aircraft sequencing problem is also known as the aircraft landing problem or as aircraft arrival and departure scheduling. The latter also includes the optimization of departing aircraft.

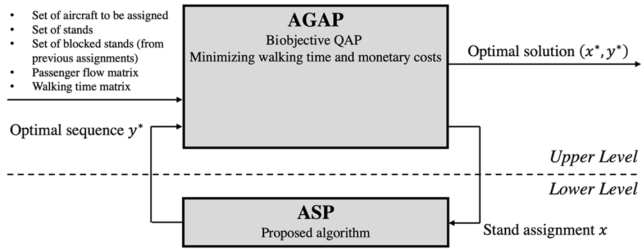


Fig. 3 Bilevel structure.

objective functions when we consider Munich Airport. When minimizing monetary costs, aircraft are usually assigned to stands close to the runways because of reduced taxi times, and hence lower fuel costs; whereas the minimization of the walking time usually leads to stand assignments at the centers of the terminal buildings. Therefore, the resulting stand assignment x is a compromise between the two objective functions. To determine x, we proceed as follows: we start by minimizing monetary costs first. Based on this solution, which is an ideal objective vector of the biobjective optimization problem, we modify this stand assignment in order to reduce the walking time. We make use of a daily monetary budget that is spent over a day to modify the stand assignments in favor of reduced walking time. In particular, we prioritize short connection timeframes and connections having large passenger flows. The prime input data to the AGAP are the set of aircraft to be assigned, the set of available/blocked stands, and the walking times between all stands. Furthermore, the passenger flow matrix provides us with the number of embarking and disembarking passengers. To address the high-quality standards at Munich Airport and the provision of special services to frequent flyers, we consider four loyalty levels[‡] in our optimization model. For example, for passengers awarded the highest loyalty level, we have to consider special transportation services in the AGAP. For information on how to model and solve the AGAP, we refer to Refs. [6,7].

B. Bilevel Structure

The AGAP provides the ASP with the initial solution x, which is the stand assignment for all aircraft that belong to the hub airline. An optimization of the stand assignments for all other aircraft is not considered. However, the stand assignments for all other aircraft are known to the AGAP to avoid invalid assignments. Based on x, we use the proposed algorithm to determine an optimal solution/sequence y^*. Finally, the AGAP evaluates its performance and determines its final stand assignment x^* based on y^*. Note that we do not process all arrivals, departures, and turnarounds of the day at once. Instead, we process subproblems and consider only aircraft that will arrive or depart over a time horizon of 40 min. The sets A_{arr}, A_{dep}, and A_{AGAP} to which we assign stands are usually different because of the given time horizon and the encountered airlines.

In the following, the aim is to familiarize ourselves with the information flow within our bilevel optimization problem, as depicted in Fig. 4. Here, we consider only the most important variables and parameters that influence both optimization problems. To begin with, the AGAP (as the leader) determines the initial solution x. At this time, the estimated time of stand blocking (ETSB), estimated time of stand clearance (ETSC), and $\overline{\text{ETSC}}$ are not yet known. By an $\overline{\text{ETSC}}$, we denote a modification to the ETSC, which may result from sequence optimization. At this time, the scheduled time of stand blocking (STSB) and scheduled time of stand clearance (STSC) are used to determine the initial solution x. Furthermore, an initial point x_0 (pre-assignment of stands) based on the STSB and STSC is passed to the AGAP to increase the solver performance.

The ASP observes the stand assignment and reacts by selecting an optimal solution/sequence y^* based on x. In our work, all arriving and departing aircraft are metered at the runway threshold. This allows us to consider arrivals and departures within the same ASP. However, in the following, we differentiate between arriving and departing aircraft because some interdependencies exist that are of interest to us. Note that there are $m!(r^m)$ combinations to order the aircraft in a sequence.

The earliest time of arrival (ETA0) and the earliest time of departure (ETD0) for all aircraft in A_{arr} and A_{dep}, respectively, are known. To determine the ETA0, we analyze the aircraft trajectory. Furthermore, in order to determine the ETD0, all taxi times between all runways and stands are known. For the sake of ease, in this subsection, we simply aim to minimize fuel costs. The arrival runway assignment b_{arr} allows us to determine the taxi-in time t_{in} by considering k. Now, the ETSB and ETSC can be calculated. The ETSB is the sum of l_{arr} and the taxi-in time. The ETSC is the sum of the ETSB and the duration of the turnaround t_{ta}:

$$\text{ETSB} := l_{\text{arr}}(b_{\text{arr}}) + t_{\text{in}}(k, b_{\text{arr}}) \tag{1}$$

$$\text{ETSC} := \text{ETSB} + t_{ta} \tag{2}$$

Some dependency is observed between the two optimization problems: the ASP aims to minimize the fuel consumption to get to the stands, which were assigned in the upper level. Simultaneously, the ETSB and ETSC as variables of the upper level are affected by the decision y^* made in the lower level because the ETSB and ETSC depend on the optimal time of arrival and the taxi time. During the optimization runs, the STSB and STSC are substituted by the ETSB and ETSC, respectively. Furthermore, departures must also be considered. Again, we consider scenarios with more than one runway in use. The earliest estimated time of departure for all runways in use is calculated from the ETSC and the taxi-out time:

$$\text{ETD0} := \text{ETSC} + t_{\text{out}}(k, b_{\text{dep}}) \tag{3}$$

Finally, the ASP provides us with the vector of the optimal times of departure l_{dep} and the vector of the optimal runway assignment b_{dep} in addition to l_{arr} and b_{arr}. As a consequence, the optimal solution y^* may cause a time gap. For this reason, we have to evaluate the ETSC. The time gap can be used as a taxi buffer or for an extended stay at the stand if it has not yet been blocked by another aircraft. To reduce fuel costs, we favor an extended stay in our approach. The modified ETSC under consideration of the departure time and the taxi-out time is denoted by $\overline{\text{ETSC}}$ and determined as follows:

$$\overline{\text{ETSC}} := l_{\text{dep}}(b_{\text{dep}}) - t_{\text{out}}(k, b_{\text{dep}}) \tag{4}$$

C. Simulation Horizon and Uncertainty

In the ASP, we consider arriving and departing aircraft up to 40 min in advance from t_{opt}. This set time horizon allows us to consider almost all aircraft inbound to Munich: even short-haul flights that just departed. A bilevel optimization run is limited to 10 min. A new optimization run is initiated every 10 min with updated ETA0/ETD0. The remaining flight time is determined from trajectory predictions. For operational reasons, we restrict modifications to the sequence as follows: a change to the runway assignment is only allowed if the remaining flight time is not less than 15 min, and no modifications are allowed if the remaining flight time is less than 10 min. For departing aircraft, we apply less restrictions: a change to the optimal time of departure or to the assigned runway is allowed until 5 min before the ETSC.

We use a point mass model to determine the trajectories of the arriving aircraft. The planned routes are known to the ASP, which determines the ETA0 based on the present position, a generic cruise/descent profile, and the wind vectors at the start of an optimization run. We use wind data from Ref. [18], which provide us with wind vectors for every full hour. To allow for uncertainty, the actual positions of the aircraft in every optimization run are subjected to disturbance. To create disturbance, we use the mean of the wind vectors of the present and the preceding hours for the determination of the actual position. The influence of deviations is mitigated with

[‡]In accordance with Lufthansa's frequent flyer program, the levels are HON circle member (level 1), senator (level 2), and frequent traveler (level 3). Passengers without frequent flyer status are assigned to level 4.

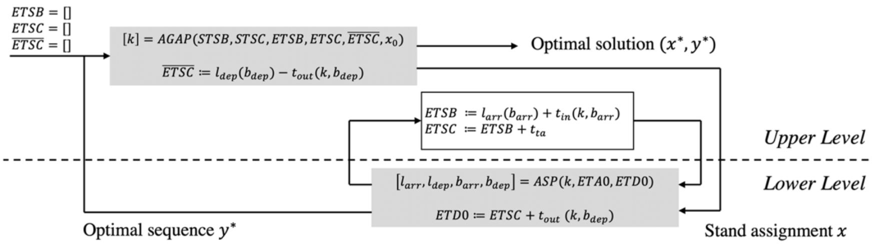


Fig. 4 Information flow.

each new optimization run. The required runtime of a bilevel optimization problem depends on the size of the underlying problems. It takes about 2 min to construct the MOMILP and another 5 min to solve the ASP using our algorithm. Another 3 min are required for the evaluation of the stand assignment based on y^*. Thus, we can initiate a new optimization run only every 10 min.

Note that the main objective of our bilevel optimization problem is to ensure a seamless connection process, and it is supposed to be used as a tactical tool to make a decision on runway assignment and the order of aircraft in a sequence given the stand assignment. Although we consider arriving and departing aircraft in our bilevel optimization problem, we propose an algorithm that has been especially developed to optimize runway assignment and arrival times for arriving aircraft within a sequence of arriving and departing aircraft by taking into consideration the stand assignment. For this reason, we consider only arriving aircraft in this paper.

IV. Basic Modeling of the Aircraft Sequencing Problem

An applicable approach for determining an optimal sequence is to model and solve a traveling salesman problem with time windows. Aircraft are the "customers" in this scenario. A salesman (the air traffic control) must determine the optimal path to visit all customers, one after the other. The earliest and latest arrival times of the aircraft define the time windows. A formulation of this problem is provided in Ref. [19].

We define the set of nodes (the aircraft) that we must assign to a position in a sequence by $A \coloneqq \{1, \dots, m\}$. The set of edges is defined by $D = A \times A$ and refers to the separation distances between all aircraft. We consider a total number of m aircraft and two virtual aircraft, a and q, as the start and end nodes of our complete digraph $G(A, D)$. The two virtual aircraft, a and q, precede or follow all aircraft $i = 1, \dots, m$, respectively. Hence, there is a fixed start node and end node, which reduce the complexity of the MILP. We extend the set of nodes and edges by $\tilde{A} \coloneqq A \cup \{a, q\}$ and

$$\tilde{D} \coloneqq D \cup \{(a, m), (m, q) | \forall m \in A\}$$

The weight of an edge refers to the separation time sep_{ij} between two aircraft, i and j. A separation between aircraft a and i or between aircraft i and q need not be established, assuming $\mathrm{sep}_{ai} = \mathrm{sep}_{iq} \coloneqq 0$. Wake separation minima are defined according to the International Civil Aviation Organization (ICAO) wake-turbulence categories of *light, medium, heavy*, and *super*. A maximum separation does not usually exist. However, the definition of an upper bound might be useful for operational and numerical reasons. In Ref. [19], the edges are extended by a time component $t \in [a_i, b_i]$ for all nodes $i = 1, \dots, m$. The modified edge $((i, t)(j, t'))$ refers to the path segment from nodes i to j, departing at time t and arriving at $t' \coloneqq \max\{t + \mathrm{sep}_{ij}, a_j\}$. The resulting separation refers to the costs and is given by $c_{ij} = t + \mathrm{sep}_{ij} - a_j$. We adopt this approach in our model and build up the sequence with reference to the runway threshold. The solution of the underlying MILP is the landing time $l_i \in \mathbb{N}_o$, the assigned runway, and the position in a sequence for all aircraft $i = 1, \dots, m$.

Furthermore, we define the earliest estimated arrival time $\mathrm{ETA0}_i$ for all aircraft $i = 1, \dots, m$, which refers to the time an aircraft could pass the runway threshold without imposing operational restrictions such as the separation minima. Defining a maximum landing time as an upper bound is useful for operational reasons and might be helpful to the solver: an applicable way is to build up an initial sequence using the FCFS principle. The landing time of the last aircraft in sequence $l_{\max}^{\mathrm{FCFS}}$ based on the FCFS principle is used as an upper bound in the model. Furthermore, we must consider the runway system and its connection to the airway network. The $\mathrm{ETA0}_i$ usually varies from runway to runway. For this reason, a differentiation must be made. For Munich Airport, we have to consider two independent parallel runways. Hence, the decision making in our model is extended to the set of runways in use R. Consequently, we introduce a lower bound and an upper bound for the landing time by $l_i \in [\mathrm{ETA0}_{i,\min}, l_{\max}^{\mathrm{FCFS}}]$ for all aircraft $i = 1, \dots, m$. By $\mathrm{ETA0}_{i,\min}$, we denote the earliest $\mathrm{ETA0}_i$ for aircraft i among all runways in use, $b = 1, \dots, r$. The earliest estimated arrival time of aircraft i at runway b is denoted by $\mathrm{ETA0}_i^b$ and is determined from aircraft-descent-trajectory calculations starting at the top of descent. The route is known. Based on the route, the airway network, the wind vectors, and an optional delay, the $\mathrm{ETA0}_i^b$ can be determined for all aircraft and runways in use. From the true airspeed profile and the wind vectors, we can calculate the ground speed v_{GS}. Furthermore, we know the wake separation minima sep'_{ij} in the distance unit defined by the ICAO, as well as the wake-turbulence categories cat_i and cat_j of the preceding aircraft i and following aircraft j. Hence, we can calculate the separation minima $\mathrm{sep}_{ij}(\mathrm{sep}'_{ij}, \mathrm{cat}_i, \mathrm{cat}_j, v_{\mathrm{GS},j})$ in the units of time. For the sake of ease, we assume that all aircraft $i = 1, \dots, m$, have the same ground speed profile from 10 min before arrival because they follow the transition to final approach. Thus, we are able to formulate the MILP based on the previous knowledge. In a first step, we introduce the decision variables and restrictions of the basic model. Different objective functions require us to extend the number of decision variables and restrictions. The extensions are elaborated on in Sec. IV.C.

A. Decision Variables

Our task is to determine a set of edges $D' \cap D \neq \varnothing$ between all nodes $i = 1, \dots, m$ that minimizes a certain objective function f. An edge links aircraft i on runway b with aircraft j on runway c. We introduce the binary decision variables $x_{ij}^{bc} \in \{0, 1\}$, $i, j \in \{a, 1, \dots, m, q\}$; $i \neq j$; $i \neq q$; $j \neq a$; b, and $c \in \{a, 1, \dots, r, q\}$, which can be interpreted as follows: if $x_{ij}^{bc} \coloneqq 1 \rightarrow$ aircraft i on runway b is linked with aircraft j on runway c. However, no link exists if $x_{ij}^{bc} \coloneqq 0$. Furthermore, the decision variable $l_i \in \mathbb{N}_o$ is introduced for all aircraft $i = 1, \dots, m$.

B. Restrictions

The first four restrictions [Eqs. (5–8)] apply to the flow network. We must satisfy the restriction that for all nodes $i = 1, \dots, m$, the number of edges going into a node equals the number of edges coming out of it. In our case, the allowable number of edges is exactly one for either direction of flow. However, this applies only to all aircraft $i = 1, \dots, m$. Because we use virtual aircraft, we must ensure that aircraft a precedes all aircraft and aircraft q follows all aircraft $i = 1, \dots, m$. Hence, aircraft a is a source that has only outgoing flow and aircraft q is a sink that has only incoming flow:

$$\sum_{j \in \{1,\dots,m,q\}, j \neq i}^{m} \sum_{b=1}^{r} \sum_{c \in \{1,\dots,r,q\}}^{r} x_{ij}^{bc} = 1 \quad \forall\ i = 1, \dots, m \tag{5}$$

$$\sum_{i\in\{a,1,\ldots,m\},i\neq j}^{m} \sum_{b\in\{a,1,\ldots,r\}}^{r} \sum_{c=1}^{r} x_{ij}^{bc} = 1 \quad \forall\ j = 1,\ldots,m \tag{6}$$

$$\sum_{j=1}^{m} \sum_{c=1}^{r} x_{aj}^{ac} = 1 \tag{7}$$

$$\sum_{i=1}^{m} \sum_{b=1}^{r} x_{iq}^{bq} = 1 \tag{8}$$

Note that we do not have to assign a *real* runway to a virtual aircraft. Hence, we denote the virtual runway assigned to aircraft a and q by runways a and q, respectively. The use of a virtual runway allows us to define a single start node and a single end node; this saves two decision variables, and no conditions have to be introduced that govern the correct runway assignment to virtual aircraft. Because we consider more than one runway, we must ensure that the edge into a node and the edge out of it point at the same runway for a given aircraft. As described earlier in this paper, the edge x_{ij}^{bd} links aircraft i on runway b with aircraft j on runway d. For a valid network flow, runway b must be selected for the edge out and the edge into aircraft i. The restriction is expressed as

$$\begin{gathered}\sum_{j\in\{1,\ldots,m,q\},i\neq j}^{m} \sum_{d\in\{1,\ldots,r,q\}}^{r} \sum_{e\in\{a,1,\ldots,r\}}^{r} x_{ij}^{bd} - x_{ji}^{eb} = 0 \\ \forall\ i \in \{1,\ldots,m\}; \quad \forall\ b = 1,\ldots,r\end{gathered} \tag{9}$$

Furthermore, we must ensure the separation minima. The separation minima depend on a certain aircraft pairing in the sequence: preceding aircraft i and following aircraft j. Because we do not know the sequence in advance (because this is the solution we wish to obtain), a distinction between cases must be made. This leads to a quadratic restriction that cannot be solved by the *CPLEX* solver, which we use for our simulations. Therefore, a linearization must be initiated. We use the *big-M* linearization for linearizing it. For further information about the method, please refer to Refs. [7,20]. We add the following inequality constraint that ensures sufficient separation:

$$\begin{gathered}l_i - l_j + M_{ij}^{c} x_{ij}^{bc} \le \Theta - \mathrm{ETA0}_j^c \\ \forall\ i,j \in \{1,\ldots,m\}, i \neq j, \quad \forall\ b,c \in \{1,\ldots,r\}\end{gathered} \tag{10}$$

We define the big-M factor by

$$M_{ij}^{c} \coloneqq \Theta - \mathrm{ETA0}_j^c + \mathrm{sep}_{ij} \tag{11}$$

Furthermore, we must introduce an upper bound Θ that completes the threshold. For numerical reasons, the value of the big-M factor should be kept as low as possible. Hence, the value of Θ must be kept as low as possible. A lower bound of Θ is the landing time of the last aircraft $l_{\max}$ in the sequence that we do not know in advance. However, we can use $l_{\max}^{\mathrm{FCFS}}$ as an approximation. The upper bound is the maximum value that cannot be exceeded by any solution. This maximum value refers to the worst case when we apply the greatest separation minima $\mathrm{sep}_{\max}(i)$ among all occurring wake categories in a sequence for all aircraft pairings. The upper bound Θ is determined according to

$$\begin{aligned}l_{\max} &\le \mathrm{ETA0}_{\max} + \sum_{i=1}^{m-1} \mathrm{sep}_{\max}(i) \\ &\le \mathrm{ETA0}_{\max} + \sum_{i=1}^{m} \mathrm{sep}_{\max}(i) - \mathrm{sep}_{\min}(i) = \Theta \\ \mathrm{ETA0}_i^b &\le l_i \le \Theta \quad \forall\ i \in \{1,\ldots,m\}, \quad \forall\ b \in \{1,\ldots,r\}\end{aligned} \tag{12}$$

Furthermore, we must ensure that an aircraft cannot land before $\mathrm{ETA0}_i^b$. Therefore, we add the following constraint:

$$\sum_{j=1}^{m} \sum_{b=1}^{r} \sum_{c=1}^{r} -l_i + \mathrm{ETA0}_i^b x_{ji}^{cb} \le 0 \quad \forall\ i \in \{1,\ldots,m\} \tag{13}$$

Up until now, we have ensured the establishment of the separation between all aircraft on a single runway by means of restriction (10). However, in the case of an independent parallel runway system, when the lateral separation minima between two runways is reduced to zero, we must add another constraint that ensures the establishment of a longitudinal separation between two aircraft heading for the same runway. Without introducing the new restriction, we would fulfill a separation of 0 s between aircraft i on runway b and aircraft j on runway c. Similarly, we would fulfill a separation of 0 s from aircraft j on runway c to a third aircraft k on runway b. However, no longitudinal separation is established between aircraft i on runway b and aircraft k on runway b. This situation is depicted in Fig. 5.

For this reason, we consider the triangle constellation of aircraft i, j, and k in order to ensure the longitudinal separation. The separation is ensured by introducing a restriction to the difference between l_k and l_i. Every time a triangle constellation is fulfilled, the separation sep_{ik} must be established between aircraft i and k. The resulting *trigger* is modeled by introducing the binary decision variable $x_{ik}^{bb} \in \{0,1\}$ for every triangle constellation of aircraft i and k on runway b. Note that the landing times l_i for all aircraft $i = 1,\ldots,m$ are still determined by restriction (10). The restriction thus becomes

$$\begin{gathered}x_{ij}^{bc} + x_{jk}^{cb} - x_{ik}^{bb} \le 1 \\ \forall\ i,j,k \in \{1,\ldots,m\}, i \neq j, j \neq k \\ \forall\ b,c \in \{1,\ldots,r\}, b \neq c\end{gathered} \tag{14}$$

The introduction of this restriction requires us to add $r(m^2 - m)$ decision variables. Unfortunately, the separation sep_{ik} is not yet ensured. As stated previously, the restriction only applies if the triangle constellation is fulfilled for aircraft i and k. Therefore, we must add another restriction that enables the triangle constellation:

$$\begin{gathered}l_i - l_k + (\Theta + \mathrm{sep}_{ik}) x_{ik}^{bb} + \underbrace{(-\Theta - \mathrm{sep}_{ik})}_{(*)} \le -\mathrm{sep}_{ik} \\ \forall\, i,k \in \{1,\ldots,m\}, i \neq k, \quad \forall\, b \in \{1,\ldots,r\}\end{gathered} \tag{15}$$

In the case of $x_{ik}^{bb} \coloneqq 0$, no longitudinal separation needs to be ensured between aircraft i and k. The compensation term $(*)$ disables the restriction. However, for of $x_{ik}^{bb} \coloneqq 1$, a cancellation of ε is observed, which enables the restriction. In Table 1, we specify the number of constraints of our basic model.

Note that we do not need to add constraints for subtour elimination because we use two fixed virtual aircraft a and q at the start and the end of the sequence. Furthermore, we require a minimum separation time of 1 s between two aircraft landing on independent runways to avoid subtours.

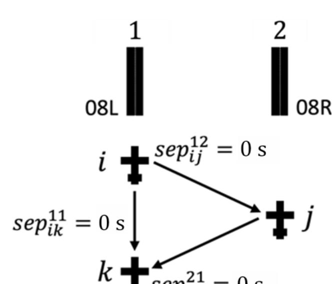


Fig. 5 Triangle constellation of aircraft. Invalid longitudinal separation between aircraft i and k resulting from a separation of 0 s between two independent runways.

Table 1 Number of constraints

Constraint	Number of constraints
(5)+(6)+(13)	$\mathcal{O}(3m)$
(7)+(8)	$\mathcal{O}(2)$
(9)	$\mathcal{O}(mr)$
(10)	$\mathcal{O}(mr^2 - 2mr)$
(14)+(15)	$\mathcal{O}((m^2 - m)(m - 2)r + 2(m^2 - m))$

C. Objective Function

Our work considers terminal 2 of Munich Airport. Terminal 2 consists of a main building and a satellite, which are used by the Lufthansa Group and its partners. In 2019, the Lufthansa Group had a market share of 68% at Munich Airport [21]. The objective in the upper problem (AGAP) is to ensure comfortable connections within a short timeframe. Therefore, and allowing for any delays, we must determine gate pairings to ensure short connection times. If there are critical connections, another option is to modify the arrival and departure sequences to reduce delay. However, this influences other flights. Where sequences comprise only Lufthansa aircraft, a modification seems reasonable. As soon as competitors join the sequence, their interests could be undermined. Furthermore, environmental and capacity aspects must also be considered. In reality, we deal with a modest number of stakeholders with common, different, or even contradicting objectives. This leads to a multiobjective optimization problem. In Table 2, we list the objective functions considered in our work. In most cases, the objective functions require us to add additional decision variables and restrictions to the basic model.

Maximizing capacity f_1 is primary objective of air traffic control, whereas minimizing the total fuel consumption f_5 and delay with respect to ETA0 f_2 are in the primary environmental and airline objective. As soon as it is also desirable to consider the optimization of gate assignments in the upper level, we must consider delay in our decision making. The obvious objective is to minimize the total delay in respect of the critical time of stand blocking (CTSB), which refers to the latest arrival time of an aircraft at its assigned stand that still allows the passengers to make their connection in time. The CTSB of aircraft i depends on all connections to all other aircraft to which a passenger flow exists. Because other aircraft might also be delayed, the CTSB must be updated over the simulation time. In the event of severe disruption, some passengers may not make their connections. Delaying onward flights is an option but may propagate the delay. Providing exclusive bus services to passengers of critical connections is another option that is available at Munich Airport. However, this results in additional monetary costs. Missed connections result in rebooking: in some cases, the airline may even have to pay for compensation and accommodation. Consequently, a decision must be made about the selection of available options. This leads to a minimization of the impact of delay (f_4). Whereas f_1, f_2, and f_3 minimize time costs, objective functions f_4 and f_5 minimize monetary costs. Simultaneous evaluation of time and monetary costs is not straightforward. After all, the interests of competitors and infrastructure providers must also be considered. For these reasons, we determine an optimal sequence by balancing the interests using a multiobjective optimization approach. In the following, we introduce the objective functions f_1 to f_5.

Table 2 Additional restrictions and decision variables' different objective functions

	Objective function	Number of additional restrictions	Number of additional decision variables
f_1	Maximize runway capacity	m	1
f_2	Minimize sum of delay with respect to ETA0	$(mr) + 2m$	$(mr) + m$
f_3	Minimize sum of delay with respect to the critical time of stand blocking	$(mr) + 2m$	$(mr) + m$
f_4	Minimize impact of delay	$\sum_{i=1}^{m} 2z_i + rz_i$	$\sum_{i=1}^{m} rz_i + z_i$
f_5	Minimize total fuel consumption	——	——

1. *Objective Function f_1*

Maximizing the capacity relates to maximizing the arrival flow, which is equivalent to minimizing the landing time of the last aircraft in sequence. This objective function is normally used by ATC at times when a high traffic density is encountered. For this reason, we must add the decision variable $l_{\max} \in \mathbb{N}_o$ to our basic problem. The objective function f_1 thus becomes

$$f_1 : l_{\max} \to \min \tag{16}$$

Furthermore, we must add the following constraint, which allows us to determine $l_{\max}$:

$$l_i - l_{\max} \le 0 \quad \forall\ i \in \{1, \dots, m\} \tag{17}$$

Note that the last aircraft's time of landing is minimized. However, the times of landing of all other preceding aircraft are not necessarily minimized: A delay to the ETA0, and hence a gap between aircraft in the sequence, may occur.

2. *Objective Functions f_2 and f_3*

We can either sum the delay with reference to the ETA0 or to the CTSB. The structure is equivalent. Because we consider the taxi times and the ETA0 for different runways, we must add $(mr + m)$ decision variables and two restrictions for all aircraft $i = 1, \dots, m$: Let us introduce the binary decision variable x_i^b: if $x_i^b := 1$, aircraft i arrives on runway b. Remember that the ETA0 and taxi times may vary from runway to runway. For this reason, a differentiation must be drawn for all runways $b = 1, \dots, r$. Furthermore, another case distinction must be made for the selected objective function:

$$\Omega_i^b := \begin{cases} -\mathrm{ETA0}_i^b, & \mathrm{ETA0} \to \min \\ -(\mathrm{CTSB}_i - t_{occ,i}^b + t_{\mathrm{in},i}^{bk}), & CTSB \to \min \end{cases} \tag{18}$$

The parameters $t_{occ,i}^b \in \mathbb{N}_o$ and $t_{\mathrm{in},i}^{bk} \in \mathbb{N}_o$ denote the runway occupancy time and the taxi-in time, respectively. Note that these parameters and CTSB_i are downlink parameters from the upper level. Because we use a detailed digraph of the runway and taxiway system, the times are determined based on the ICAO wake-turbulence categories of light, medium, heavy, and super. Large wide-body aircraft usually need more time for taxiing than small narrow-body aircraft.

Let $x_i^b := 1$; a delay occurs if $l_i + \Omega_i^b x_i^b > 0$. Once again, we must introduce a new decision variable $d_i \in \mathbb{N}_o$ for all aircraft $i = 1, \dots, m$, which acts as a delay compensator in the new restriction that we must add:

$$\sum_{b=1}^{r} l_i + \Omega_i^b x_i^b - d_i \le 0$$
$$\forall\ i \in \{1, \dots, m\}, x_i^b \in \{0, 1\}, d_i \in \mathbb{N}_o \tag{19}$$

This constraint requires us to add two more constraints to indicate the correct runway:

$$\sum_{j=1}^{m} \sum_{c=1}^{r} x_{ij}^{bc} - x_i^b = 0$$
$$\forall\ i \in \{1, \dots, m\}, i \ne j, \quad \forall\ b \in \{1, \dots, r\} \tag{20}$$

$$\sum_{b=1}^{r} x_i^b = 1 \quad \forall\ i \in \{1, \dots, m\} \tag{21}$$

The objective function f is given by

$$f_{2,3}: d_i \to \min \tag{22}$$

3. Objective Function f_4

Until now, we have minimized objective functions with respect to time. When minimizing the impact of delay, we usually focus on monetary costs. To do so, it is necessary to look at the passenger flows and consider the costs an airline will incur if passengers miss their flights. If passengers miss their flights, they will usually be rebooked onto the next flight. In the best-case scenario, seats are available and no monetary costs are incurred. However, we may also encounter situations in which airlines will have to pay compensation and for accommodation if there is a major delay or journey disruption. In the following, we modify our model to make it possible to minimize the monetary costs for an airline. Again, decisions must be made in the lower level based on the gate assignment in the upper level. The gate assignments and the resulting taxi times for aircraft and connection times for passengers are known. Note that adjustments of the gate assignments are made in the upper level based on the solution of the lower level for the last iteration performed. Furthermore, any delays to the onward flights have already been considered in the upper level such that the CTSBs are fixed for all aircraft $i = 1, \ldots, m$. If we focus on aircraft i, not all passengers will connect to the same onward flight. Some passengers will have more time to make their connections than others. Furthermore, the impact of delay may vary from connection to connection. For this reason, we make a case differentiation by temporal gradation. We define deadlines for the arrival times of an aircraft. If an aircraft arrives later than a given deadline, at least one connection will be missed and costs will result. We define $y = 1, \ldots, z_i$ deadlines $t_i^{b,y} \in \mathbb{N}_o$ for all aircraft $i = 1, \ldots, m$ and for all runways $b = 1, \ldots, r$. For aircraft i, the set of deadlines is denoted by Y_i. Recall that our research relates to a parallel runway system, and thus the taxi times vary from runway to runway. Based on the preceding considerations, the deadlines are individual for all aircraft and runways; moreover, they are input from the upper level and known in advance. A deadline is missed if $l_i > t_i^{b,y}$. Furthermore, we add the binary decision variable $x_i^{b,y} \in \{0, 1\}$. If $x_i^{b,y} := 1$, aircraft i uses runway b and deadline y applies. Costs resulting from a missed deadline are triggered by constraint (23). Again, we use an upper bound $\tilde{\Theta}$ as a threshold that can never be exceeded. We have already introduced Θ in Eq. (12). However, we cannot use this value in the event of a delay because it might be too small to ensure that constraint (23) is fulfilled. Therefore, based on Eq. (24), we determine $\tilde{\Theta}$ as the maximum value of either Θ or a deadline that has the maximum value for $t_i^{b,y}$ from all aircraft $i = 1, \ldots, m$ and all runways $b = 1, \ldots, r$:

$$\sum_{b=1}^{r} l_i - t_i^{b,y} x_i^{b,y} - \tilde{\Theta} x_i^y \le 0$$
$$\forall\ i \in \{1, \ldots, m\}, \quad \forall\ y \in \{1, \ldots, z_i\}$$
$$t_i^{b,y} \in \mathbb{N}_o, x_i^{b,y} \in \{0, 1\}, x_i^y \in \{0, 1\} \tag{23}$$

$$\tilde{\Theta} = \max\left\{\Theta, \max_{\substack{b\in\{1,\ldots,r\}\\ i\in\{1,\ldots,m\}\\ y\in\{1,\ldots,z_i\}}} t_i^{b,y}\right\} \tag{24}$$

Analogous to constraints (20) and (21), we must introduce a further two constraints to indicate the correct runway:

$$\sum_{j=1}^{m}\sum_{c=1}^{r} x_{ij}^{bc} - x_i^{b,y} = 0$$
$$\forall\ i \in \{1,\ldots,m\}, i \ne j, \quad \forall\ b \in \{1,\ldots,r\}, \quad \forall\ y \in \{1,\ldots,z_i\} \tag{25}$$

$$\sum_{b=1}^{r} x_i^{b,y} = 1 \quad \forall\ i \in \{1, \ldots, m\}, \quad \forall\ y \in \{1, \ldots, z_i\} \tag{26}$$

We also introduce the cost coefficient $c_i^y \in \mathbb{N}_o$, which gives the costs if deadline $t_i^{b,y} \in Y_i$ is missed by aircraft i. Finally, the impact of a delay is minimized by the following objective function:

$$f_4: c_i^y x_i^y \to \min \tag{27}$$

Table 2 quantifies the number of decision variables and constraints to be added. The number of deadlines must be carefully selected to avoid increases in complexity and runtime.

4. Objective Function f_5

The total fuel consumption is another essential objective function to be considered. In general, the lowest fuel consumption (FC) is expected during descent. A precise estimation of the FC is difficult because it depends on a series of influences such as the aircraft mass and the specific FC of the engines. The average fuel flow (FF) of a modern midsize aircraft equipped with two turbofan engines is about 600 kg/h of fuel for an unrestricted descent from FL390 to the ground, whereas the FF of a large wide-body aircraft powered by four engines is about 1500 kg/h ([22] p. 167). The quantified FF refers to a descent in idle thrust. Therefore, a surcharge must be added for holdings and staggering during approach. A precise quantification is, however, not possible. For this reason, we define an average FF according to the ICAO wake-turbulence categories of light, medium, heavy, and super; and we assume that the surcharge is linear and proportional to the average FF. Hence, the surcharge does not have an influence on the objective function.

We introduce the FF coefficient $c_{\mathrm{FF},i} \in \mathbb{N}_o$. There are no modifications to the basic restrictions. The objective function f thus follows:

$$f_5: c_{\mathrm{FF},i} l_i \to \min \tag{28}$$

V. Multiobjective Optimization

In this section, we give a brief outline of multiobjective optimization based on Ref. [23]. For further information, we refer the reader to Ref. [23]. In multiobjective optimization, we consider at least two ($h \ge 2$) conflicting objective functions $f_i: \mathbb{R}^n \to \mathbb{R}$ that we wish to minimize simultaneously; the problem can be formulated as

$$\min_{x\in X}(f_1(x), f_2(x), \ldots, f_h(x)) \tag{29}$$

The set X is the nonempty feasible set of decision vectors. The decision vectors $x = (x_1, x_2, \ldots, x_n)^T$ belong to X. The feasible set X is usually defined by constraints. Objective vectors are images of the decision vectors and consist of objective function values

$$z = f(x) = (f_1(x), f_2(x), \ldots, f_h(x))^T$$

In fact, a feasible solution that minimizes all conflicting objective functions simultaneously does not normally exist. For this reason, we deem objective vectors to be optimal if none of their components can be improved without deteriorating at least one of the other components. Hence, a decision vector $x^* \in X$ is deemed Pareto optimal if there is no other decision vector that dominates it.

The solution methods are classified into the four following classes according to the role of the decision maker (DM) in the solution process: 1) a priori methods, 2) a posteriori methods, 3) no preference method, and 4) interactive methods.

In a priori methods, the DM articulates preference information before starting the solution process; whereas in a posteriori methods, a set of Pareto-optimal solutions is first generated and then the DM selects the most preferred solution among them. High computational loads are a major drawback of a posteriori methods because the solution process cannot benefit from articulated preference in advance. In no-preference methods, the DM does not take part in the solution process: instead of asking for preferences, some assumptions are made.

In interactive methods, an iterative solution algorithm (commonly consisting of six steps) is formed and repeated, typically several times. After each iteration, the DM is provided with some (updated) information. Furthermore, the DM is asked to specify (updated) preference information. The iterative process allows the DM to adjust preferences. Simultaneously, the DM can learn about the interdependencies in the problem and about the DM's own preferences. Furthermore, the successful application of interactive methods relies on the circumstances that the DM must be available and willing to actively participate in the solution process and direct it according to their preferences.

The commonly encountered steps of interactive methods can be briefly outlined in the following algorithm:

1) Initialization: calculate ideal and approximated nadir objective vectors and show them to the DM.
2) Generation of a Pareto-optimal starting point.
3) Provision of preference information by the DM.
4) Generation of new Pareto-optimal solutions according to the provided preferences.
5) Selection of the most preferred solution by the DM.
6) Stop if the DM so desires; if not, go to step 3.

VI. Interactive Method for Aircraft Sequencing

In Sec. IV, we introduced a model to determine an optimal sequence for a parallel runway system under consideration of a single objective function. However, different (operational) objectives will be encountered for hub airlines and other users if the aircraft gate assignment and aircraft sequencing are to be simultaneously optimized. Furthermore, operational conditions at an airport will change over the course of a day because delay will have to be considered. Therefore, continuous adjustments to gate assignment and aircraft sequencing must be made. Moreover, the time domain is a constraining factor: feasible solutions must be provided to the AGAP and ASP within a fixed (limited) time. For these reasons, we decided to use an interactive method to optimize the aircraft sequence because this allows us to make adjustments in each iteration by taking into consideration the current state of operations. Air traffic control is the DM and articulates preferences according to the current state of operations by taking into consideration the gate assignments and the (operational) objectives of the aircraft and their respective airlines. The interaction of the DM is considered as the interface between the AGAP and the ASP, and therefore between the upper and lower levels in our bilevel optimization problem. In this section, we introduce our interactive method based on the steps 1 to 6, which were described in Sec. V. However, steps 2 and 3 were merged because operational preferences articulated by ATC and the airlines are known a priori as input information from the upper level. Note that an example is provided in Sec. VII. Although about 25 to 65 aircraft are continuously considered in the lower level, a scenario consisting of only 12 aircraft is chosen deliberately to get familiar with all features of the algorithm.

A. First Step: Initialization

To begin with, we calculate the ideal objective vector $z^* \in \mathbb{R}^h$. Its components are obtained by minimizing each of the h objective functions individually [23]. The solution of the AGAP (upper level) provides us with the stand assignments and the expected delay costs, from which we can set up our objective functions. Note that the costs for all aircraft $i = 1, \ldots, m$ are minimized during this step. At larger hub airports and at peak times, an optimal sequence must be determined for $m \geq 10$ aircraft simultaneously. The runtime to solve the underlying MILP may increase exponentially with the number of aircraft. Furthermore, a preprocessing time of more than 5 min will be encountered if $m \geq 40$. We found out that providing the CPLEX solver with an initial point reduces the preprocessing time to less than 30 s. A sequence that is established by using the FCFS principle can be used as an initial point. However, in our work, the original problem is divided into subproblems and solved by CPLEX in order to determine a more advantageous initial point as compared to the FCFS principle. We first sort the aircraft by their ETA0 in ascending order and divide the original problem into subproblems consisting of m_{sub} aircraft if $m \geq 12$. Our simulations show that dividing the original problem into subproblems is favorable if $m \geq 12$. Starting with the first subproblem, which encompasses the aircraft that have the earliest ETA0 among all m aircraft, we obtain the first subsequence. The time of landing of the last aircraft in the first subsequence is used to update the ETA0 of the aircraft in the following subproblem because they cannot arrive before the last aircraft of the previous subproblem has landed. This is done for all subproblems. Next, we generate an initial point from the solutions of the subproblems and use it to solve the original problem of m aircraft. After minimizing each of the h objective functions individually, the ideal objective vector z^* is shown to the DM.

In general, costs due to separation procedures would not occur if all aircraft could arrive at the ETA0 because this time refers to an unrestricted landing time. Hence, in general, the aim of all aircraft is to arrive at the ETA0. The objective function f_1 aims to make the time of landing of the last aircraft in the sequence as early as possible. However, the landing times of all other aircraft may not equal the ETA0, although this is indeed possible. Consequently, avoidable gaps occur. For this reason, we finally improve l_i toward the ETA0$_i$ for all aircraft $i = 1, \ldots, m$ in order to eliminate gaps. This step is essential when solving subproblems for f_4 because the landing times l_i tend to adopt values approaching the upper bound Θ. This problem is further complicated by deadlines approaching Θ. Consequently, a solution for the preceding subproblems may not be found because the updated ETA0 will shrink the solution space. Therefore, the elimination of gaps or waiving of the upper bound Θ represent two options for overcoming this issue.

B. Second Step: Generation of a Reference Sequence

The first step provides us with the optimal sequences for each objective function individually. The information obtained from each sequence is the landing time l_i and the assigned runway b_i for all aircraft $i = 1, \ldots, m$. According to the steps described in Ref. [23], a Pareto-optimal starting point must be generated. Because we must ensure a fair sequencing process among competing airlines and must also consider the interest of ATC, the starting point is not Pareto optimal in our work. In the second step, the DM is provided with the information about the most preferred objective function of each aircraft $i \in \{1, \ldots, m\}$. Furthermore, the preferences are known in advance as input information from the upper level. This is why we merged steps 2 and 3.

Remember that we also consider the AGAP in our work. Therefore, the aim of aircraft i is not necessarily to land at the ETA0$_i$. We must also consider the taxi time to the assigned gate or stand. Depending on the selected aircraft stand, landing on another runway at a later l_i might be more efficient because of a shorter taxi time. This is usually the case when l_i approaches a deadline. If not, landing at ETA0$_i$ is anticipated to be most efficient. In our work, we determine a reference sequence $\mathrm{seq}^*_{\mathrm{ref}}$ instead of a Pareto-optimal solution. For the second step, each aircraft $i \in \{1, \ldots, m\}$ articulates its most preferred objective function g^*_i among all h objective functions. It can occur that the landing time l_i and the assigned runway b_i of aircraft i are the same for another objective function. We provide an example: for a given scenario, Table 3 lists the landing time l_i and assigned runway (RWY) b_i for all aircraft $i = 1, \ldots, m$ and all objective functions $g = 1, \ldots, h$. Except for f_4, aircraft 5 lands at $l_i = 332$ s on runway 08R. Therefore, aircraft 5 would also agree on $(f_1 - f_3)$ and f_5. The reference sequence $\mathrm{seq}^*_{\mathrm{ref}}$ is determined based on the score rating. For each aircraft $i \in \{1, \ldots, m\}$, the DM casts one vote for each objective function $g \in \{1, \ldots, h\}$ if $l^g_i = l^{g*}_i$ and $b^g_i = b^{g*}_i$. Therefore, the DM must cast at least one vote and at most h votes for aircraft i. The objective function that obtains the highest score is selected as $\mathrm{seq}^*_{\mathrm{ref}}$. By $l_{i,\mathrm{ref}}$ and $b_{i,\mathrm{ref}}$, we denote the landing time and the assigned runway of aircraft i in $\mathrm{seq}^*_{\mathrm{ref}}$, respectively. In the event that more than one objective function has the same score, the DM is allowed to cast one vote to ensure clear voting.

C. Third Step: Airline–Individual Improvements

In the third step, we address the interests of the participating airlines. This step corresponds to step 4 of the algorithm introduced

Table 3 Resulting sequences from optimization for considered objective functions f_1 to f_5

Aircraft index i	$f_1: l_i^1(\mathrm{s})/\mathrm{RWY}$	$f_2: l_i^2(\mathrm{s})/\mathrm{RWY}$	$f_3: l_i^3(\mathrm{s})/\mathrm{RWY}$	$f_4: l_i^4(\mathrm{s})/\mathrm{RWY}$	$f_5: l_i^5(\mathrm{s})/\mathrm{RWY}$
1	0/08R	0/08R	690/08R	0/08R	0/08R
2	259/08R	259/08R	259/08R	394/08L	259/08R
3	423/08R	423/08R	758/08R	1,144/08R	423/08R
4	237/08L	237/08L	666/08L	556/08L	237/08L
5	332/08R	332/08R	332/08R	467/08L	332/08R
6	603/08R	512/08R	485/08R	970/08R	489/08R
7	690/08R	734/08L	584/08R	734/08L	588/08R
8	552/08L	790/08R	755/08L	790/08R	552/08L
9	485/08L	485/08L	485/08L	1,076/08R	485/08L
10	689/08L	654/08R	577/08L	923/08L	643/08L
11	536/08R	563/08L	871/08R	903/08R	701/08R
12	621/08L	342/08L	342/08L	855/08L	358/08L

in Sec. V. The reference sequence $\mathrm{seq}^*_{\mathrm{ref}}$ determined during the second step is based on a fair voting procedure. This corresponds to an equal treatment of all aircraft. However, our work concentrates on hub airports. Therefore, a sequence usually consists of more than one aircraft belonging to a certain airline. Our approach enables a reoptimization/processing of $\mathrm{seq}^*_{\mathrm{ref}}$ to address the operational interests of airlines and simultaneously ensures the equal treatment of the aircraft of competing airlines. Again, ATC acts as the DM in the third step.

To begin with, we identify the airlines $i' = 1, \ldots, m'$ of all aircraft $i = 1, \ldots, m$. The set of airlines is denoted by A'. A competitor airline of airline i' is denoted by $-i' = -1, \ldots, -m'_{i'}$ and an aircraft of a competitor airline is denoted by $-i = -1, \ldots, -m_i$. For all airlines $i' = 1, \ldots, m'$, we again determine an optimal sequence in a manner almost identical to the first step. However, we combine the objective functions f_4 and f_5 at this time because total monetary costs are considered at this time. The objective function thus follows:

$$f_6 := f_4 + f_5 \tag{30}$$

The set of airline–individual sequences is denoted by SEQ'. Again, the solution is the information about the landing time $\tilde{l}_i$ and the assigned runway $\tilde{b}_i$ for all $i = 1, \ldots, m$. For the optimization problem of airline i', we add restrictions ensuring that the (new) landing time $\tilde{l}_{-i}$ is equal to or is less than $l_{-i,\mathrm{ref}}$ if aircraft $-i$ belongs to airline $-i'$. This restriction ensures that a competitor is not placed in a less favorable situation as compared to $\mathrm{seq}^*_{\mathrm{ref}}$. Furthermore, we consider only the costs of airline i' in f_6. Finally, we reduce $\tilde{l}_i$ toward $\mathrm{ETA0}_i$ for all aircraft $i = 1, \ldots, m$ in order to eliminate gaps.

D. Fourth Step: Determination of the Optimal Sequence

During the third step, we determined an airline–individual sequence for all airlines $i' = 1, \ldots, m'$. For the fourth step, we select the final solution seq^* from all sequences in SEQ'. This step corresponds to step 5 of the algorithm introduced in Sec. V. To ensure fair competition, we attempt to select a sequence that is Pareto optimal. In general, we will find only a few airlines in a sequence. An airline–individual improvement for airline i' can only be achieved if there is more than one aircraft that belongs to airline i'. Therefore, we process an airline–individual improvement only for airline i' if there is more than one aircraft of this airline in a sequence. Consequently, we determine m'' airline–individual sequences. Note that an aircraft $-i$ of a competing airline $-i'$ may benefit from the airline–individual optimization of airline i' because we require $\tilde{l}_{-i} \le l_{-i,\mathrm{ref}}$ as a restriction introduced in the third step. For an airline i', some aircraft may benefit from an airline–individual improvement with respect to $l_{i,\mathrm{ref}}$, and others will not. For these reasons, the DM only counts the aircraft that can improve.

First, for all airline–individual sequences $i'' = 1, \ldots, m''$, we count the number of aircraft that can improve. Therefore, the condition $\tilde{l}_i < l_{i,\mathrm{ref}}$ is required for aircraft i. We define the evaluation matrix $E' = A' \times \mathrm{SEQ}'$. An entry in E' is denoted by $e'_{i',i''}$ and gives the number of aircraft that belong to airline i' and that can improve if the airline–individual sequence i'' is selected. From E', we determine the Pareto-optimal solution(s) seq^* from all sequences $i'' = 1, \ldots, m''$ so that no airline i' can improve without deteriorating the landing time of at least one aircraft $-i$ of a competing airline $-i'$. This sequence is the solution of the fourth step. However, it may occur that there is more than one Pareto-optimal solution. In this case, the DM is asked to select the preferred sequence among them.

Solving a multiobjective optimization problem interactively is a constructive process in which the DM steers the solution process. The DM is either provided with new preference information or solutions from which they select the preferred one. In this sense, it is more appropriate to speak about a psychological convergence in interactive methods rather than a mathematical convergence [23].

Finally, the upper level is provided with the solution of the ASP. The DM of the upper level analyzes the impact of the sequencing on the gate assignment. If the gate assignment turns out to be infeasible or if there is still sufficient time, the interactive solution process is restarted with the second step and updated information from the upper level.

VII. Simulations and Results

A. General Considerations and Scenario Description

To solve the optimization problem, we implemented a model in a MATLAB environment. Based on MATLAB 2019b, we use IBM CPLEX 12.9 to solve the underlying optimization problems on a 2017 model iMac Pro with a 2.3 GHz 18-core Intel Xeon W processor and with 32 GB and 2666 MHz of DDR4 RAM.

To perform simulations, the following basic properties of the arriving aircraft must be known: 1) the aircraft type and its ICAO wake-turbulence category, 2) the ETAO for all runways in use, 3) the aircraft stand, and 4) the airline.

Furthermore, the most preferred objective function g_i^* must be articulated by aircraft i if aircraft i wants to participate in the airline–individual improvement. Even if g_i^* is not available for aircraft i, the third and fourth steps can be processed for all other aircraft that have submitted g_i^* to ATC. Based on the distance to go, we calculate the ETAO for each runway by taking into consideration of the airway structure and the airspeed profile of the aircraft. We use the wind data from Ref. [18] to determine the ground speed profile and the runways in use. Taxi times are determined based on a digraph. The information about the aircraft stands and the costs resulting from missed deadlines is input from the upper level of our bilevel optimization problem. If an alternative flight on the same day cannot be offered to a passenger, the airline must pay for accommodation. According to the passenger's loyalty level, we assume costs of 100 U.S. dollars (USD) (level 3 and 4) or 150 USD (level 1 and 2) per passenger per night. In July 2019, a search on several booking websites was performed to quantify the average costs. A standard guest room in the towns of Schwaig and Halbergmoos is assigned to passengers of levels 3 and 4, whereas an executive double room at Novotel Munich Airport is assigned to passengers of levels 1 and 2. There is a complimentary transfer to the hotels. Furthermore, we assume fuel costs of 0.60 USD/kg [24]. Based on the fuel consumption quantified in Sec. IV, we have fuel costs of 0.102 and 0.252 USD/s for aircraft in categories of medium and heavy, respectively. The passenger flow matrix provides us with the itineraries for all passengers. For the sake of ease, we assume that the origin of the inbound flight and the destination of the onward flight are the start and the end of the itinerary, respectively. The costs for compensations are determined by Ref. [25] based on the total distance, the total delay, and the exchange rate. For more details on the conditions for compensation, please refer to [25]. Note that all compensations are stated in euros in Ref. [25]. The exchange rate is retrieved from Ref. [26]. Furthermore, if an onward flight is missed, we assume that no costs are incurred for an alternative flight. A reasonable determination of these costs is beyond the scope of our work at this stage. Furthermore, an airline is required to provide passengers with meal vouchers if a major delay occurs. Instead of meal vouchers, the Lufthansa Group provides drinks and snacks at the service counters: costs are negligible for the provided service. Passengers of loyalty levels 1, 2, and 3 are invited to use the airline lounges. The deadlines are listed in Table 4. A deadline refers to the latest arrival time at the assigned stand in order to not miss a connection. Note that the deadlines are defined for full minutes and only for airline 1 because airlines 2 and 3 do not use Munich Airport as a hub.

In the following, we present the results of our simulations, by way of example, for an arrival sequence consisting of 12 aircraft belonging to three airlines, which are differentiated by their indices. The runways in use are 08L ($b := 1$) and 08R ($b := 2$). Table 5 lists the aircraft and their properties. Note that the big-M factors should be selected as little as possible because of numerical issues. For this reason, we subtract all values of the ETA0 by the earliest $\mathrm{ETA0}_{\min}$ among all aircraft $i = 1, \ldots, m$ and among all runways $b = 1, \ldots, r$. In our example, aircraft 1 has the earliest $\mathrm{ETA0}_{\min}$ of 162 s if it lands on runway 08R: hence, $\mathrm{ETA0}_1^2 := 0$ s. Note that all values listed in Table 5 have already subtracted 162 s.

B. First Step: Initialization

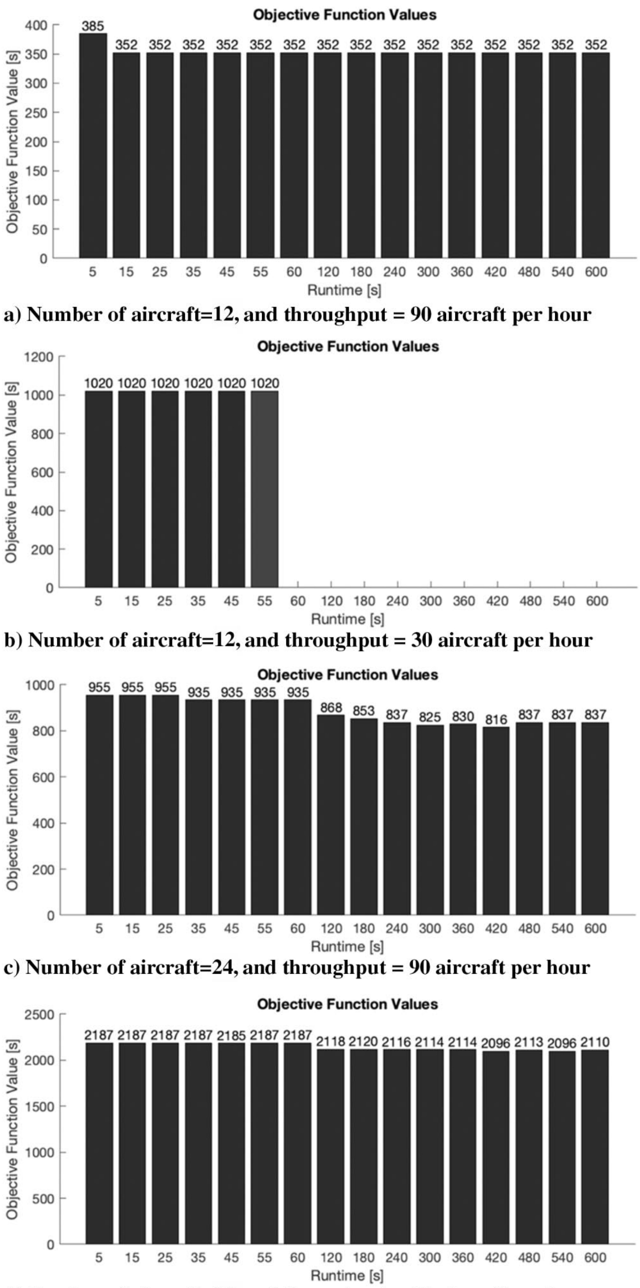
As a first step, we calculate the ideal objective vector $z^* \in \mathbb{R}^h$ as described in Sec. V. Hence, we model the ASP as an MILP and solve it for all h objective functions individually. The resulting sequences are depicted in Table 3. To achieve the maximum utilization of all 18 cores of our iMac Pro and to reduce communication time, we solve all MILPs in parallel. Hence, CPLEX uses at least three cores to solve each MILP. Furthermore, we divide each MILP into four subproblems of three aircraft each. In general, we set a time limit in order not to exceed the given runtime. An exact solution was determined within less than 250 s for all subproblems in our simulation. A valid solution is usually determined within a couple of seconds. However, a general assumption as to the runtime cannot be made. For benchmarking purposes, the objective function values were determined for different runtimes in the range of 5 to 600 s. A total of 300 scenarios with 12 to 24 aircraft were solved for throughputs in the range of 30 to 90 aircraft per hour. The objective functions f_1 to f_5 were considered. The solution search was repeated for a given runtime because CPLEX does not output the objective function value at given time steps. An exact solution was determined for only seven out of 300 scenarios. The throughput was about 30 aircraft per hour in these scenarios. For throughputs of 90 aircraft per hour and higher, the determination of an exact solution cannot be expected in a short time. We extended the runtime to 24 h for five scenarios. Nevertheless, an exact solution was not determined in this time. Note that a runtime of more than 600 s is not practicable under consideration of the intended application. In Fig. 6, the results are shown for four scenarios in which the capacity was maximized. In general, increasing the runtime should lead to an objective function value that is closer to the exact solution. However, this was not observed for some scenarios. Compare the objective function values in Fig. 6c for the runtimes of 420 and 480 s: a higher objective function value was obtained at 480 s. For all scenarios, an improvement of more than 8%, as compared to the objective function value obtained at 120 s, was not observed for runtimes exceeding 120 s. Figures 6a and 6b show the results for two scenarios with 12 aircraft. For a high throughput of 90 aircraft per hour, the objective function value did not improve after 15 s of runtime. Compared with this, in Fig. 6b, an exact solution was obtained for a runtime of 55 s and for a low throughput of 30 aircraft per hour. In Figs. 6c and 6d, the results are shown for two scenarios with 24 aircraft. From an operational point of view, an at least satisfying objective function value was obtained within 120 s for all scenarios and for the objective functions f_1 to f_5.

Table 4 Deadlines defined by airline 1

	First deadline			Second deadline		
Aircraft index i	Time, s	Costs incurred, USD	No. of affected passengers	Time, s	Costs incurred, USD	No. of affected passengers
1	——	——	——	——	——	——
2	——	——	——	——	——	——
3	660	400	2	——	——	——
4	——	——	——	——	——	——
5	540	150	1	——	——	——
6	840	400	4	960	300	2
7	1,080	200	2	——	——	——
8	720	400	4	——	——	——
9	——	——	——	——	——	——

Table 5 Aircraft properties

				ETA0, s		ETA0 at stand, s	
Aircraft index i	Airline index i'	Wake-turbulence category	Stand	RWY 08L	RWY 08R	RWY 08L	RWY 08R
1	1	Medium	261	234	0	533	317
2	1	Medium	256	394	259	699	583
3	1	Heavy	222A	593	422	871	749
4	1	Heavy	254	237	299	547	665
5	1	Heavy	318	467	307	911	836
6	1	Heavy	219A	493	485	820	872
7	1	Heavy	215A	734	522	1,119	979
8	1	Heavy	250	515	790	927	1,279
9	1	Medium	231	485	695	850	1,091
10	2	Heavy	——	577	654	——	——
11	3	Medium	——	563	509	——	——
12	3	Medium	——	342	404	——	——



a) Number of aircraft=12, and throughput = 90 aircraft per hour

b) Number of aircraft=12, and throughput = 30 aircraft per hour

c) Number of aircraft=24, and throughput = 90 aircraft per hour

d) Number of aircraft=24, and throughput = 30 aircraft per hour

Fig. 6 Course of objective function values obtained for different runtimes. The capacity is maximized.

In our scenario, airline 1 is the only airline that uses Munich Airport as a hub. Therefore, costs arising from missed deadlines only apply to this airline. Aircraft 2 and 8, belonging to airline 1, are delayed and are about to miss deadlines. In Table 3, column 5 (f_4), we can see the prioritization of these two aircraft. Consequently, the intended prioritization of aircraft by minimizing the impact of delay (f_4) leads to an increase of the landing time ($l_{\max} \coloneqq 1144s$) of the last aircraft in sequence.

C. Second Step: Generation of a Reference Sequence

For the second step, each aircraft $i \in \{1, \ldots, m\}$ can articulate its most preferred objective function g^* from all h objective functions if it wishes to. The reference sequence $\text{seq}^*_{\text{ref}}$ is determined based on a score rating. Aircraft that are about to miss deadlines will select the sequence referring to f_4. All other aircraft will select a sequence that ensures a landing at $l_{\min}$. Table 3 lists l_i^g for all aircraft $i = 1, \ldots, m$ and for all objective functions $g = 1, \ldots, h$. For each aircraft $i \in \{1, \ldots, m\}$, the DM casts one vote for each objective function $g \in \{1, \ldots, h\}$ if $l_i^g = l_i^{g*}$ and $b_i^g = b_i^{g*}$. The voted l_i^g are underlined.

As we can see from Table 3, each of the objective functions f_1 to f_3 counts a total of six votes, and f_5 counts five votes. As stated before, aircraft 2 and 8 are the only aircraft that select f_4 due to deadlines. We count three votes for f_4, with two among them from aircraft 2 and 8. There are three objective functions that obtained the highest number of votes, which is six. In this case, ATC as the DM is allowed to select its most preferred solution among them. In our case, the DM selects the sequence that refers to the lowest $l_{\max}$. Therefore, the sequence referring to f_1 is selected by the DM as the most preferred reference sequence $\text{seq}^*_{\text{ref}}$ in our scenario.

D. Third Step: Airline–Individual Improvements

In the third step, we address the interests all involved airlines $i' = 1, \ldots, m'$. We select f_6 and require that $\tilde{l}_{-i}$ of aircraft $-i$ must not exceed $l_{-i,\text{ref}}$. Remember that f_6 considers only the costs of airline i'. For airlines 1 and 2, an improvement is obtained over $\text{seq}^*_{\text{ref}}$. However, airline 3 cannot benefit from an airline–individual improvement. The resulting sequences for airlines 1 and 2 are shown in Tables 6 and 7, respectively. For airline 1, aircraft 6 and 7 can improve their landing time, whereas aircraft 8 and 9 land later as compared to $\text{seq}^*_{\text{ref}}$. However, airline 1 will benefit from this optimization in terms of total costs. Furthermore, all aircraft of competing airlines 2 and 3 also benefit from the airline–individual improvement of airline 1 and land earlier than $\text{seq}^*_{\text{ref}}$. Note that the landing time (676 s) of the last aircraft (aircraft 9) is less than the landing time (690 s) obtained for f_1 in the first step. Recall the set time limit in the first step. In the third step, the airline–individual improvement is provided with the solution of the first step as an initial point. Therefore, a further improvement is achieved.

For airline 2, the total costs are reduced by assigning an earlier landing time to aircraft 12 and a later one to aircraft 11. For the competitors, aircraft 6 and 7 of airline 1 and the sole aircraft of airline 3 can improve their landing times.

However, an improvement for airline 3 cannot be obtained. A major reason here is that the landing times of all aircraft that belong to competing airlines must not exceed the landing times assigned in $\text{seq}^*_{\text{ref}}$. Hence, there is no space for improvement. In general, the chance of improvements increases with an increasing number of aircraft of a certain airline in a sequence.

E. Fourth Step: Determination of the Optimal Sequence

In the third step, we determined an airline–individual sequence for all airlines $i' = 1, \ldots, m'$. In the fourth step, the DM selects the

Table 6 Airline–individual improvement for airline 1

	RWY 08L			RWY 08R		
Sequence position	Aircraft index i	l_i, s	$l_{i,\text{ref}}$, s	Aircraft index	l_i, s	$l_{i,\text{ref}}$, s
1	4	237	237	1	0	0
2	12	424	621	2	259	259
3	6	493	603	5	332	332
4	8	582	552	3	423	423
5	9	676	485	11	509	536
6	——	——	——	7	584	690
7	——	——	——	10	675	689

Table 7 Airline–individual improvement for airline 2

	RWY 08L			RWY 08R		
Sequence position	Aircraft index i	l_i, s	$l_{i,\mathrm{ref}}$, s	Aircraft index	l_i, s	$l_{i,\mathrm{ref}}$, s
1	4	237	237	1	0	0
2	12	342	621	2	259	259
3	9	485	485	5	332	332
4	8	552	552	3	423	423
5	10	643	689	6	512	603
6	——	——	——	7	611	690
7	——	——	——	11	724	536

preferred sequence seq*. All airlines were able to improve the landing times of at least one aircraft. A total of five aircraft can improve their landing times in the airline–individual improvement for airline 1, as compared to only four aircraft for airline 2. For this reason, the airline–individual improvement for airline 1 is our final solution seq*. Remember that we do not consider aircraft that land at a later landing time as compared to the $\mathrm{seq}^*_{\mathrm{ref}}$ in the fourth step. A major reason here is that a later landing time does not necessarily lead to an increase in total costs because we must also consider the objectives of the upper level of our optimization problems. Therefore, a later landing time may even lead to reduced total costs.

F. Benchmarking

Our work focuses on minimizing the total monetary costs of hub airlines. For this reason, we compare the objective function values of f_4 and f_5 obtained from our case study, applying an interactive method (Table 8) against the ones that we obtain from applying the FCFS principle (Table 9) and maximizing the runway capacity f_1 (Table 10), which is in the interest of ATC. Furthermore, maximizing the runway capacity is selected as the objective of the reference sequence. Furthermore, the main properties of the resulting sequences are provided in Tables 8–10. In our case study, we assume that the majority of aircraft are delayed and the airline has to pay for accommodations if passengers miss their flights. The resulting costs $\tilde{c}_i^4$ are listed for all aircraft $i = 1, \ldots, m$. Similarly, the resulting fuel costs $\tilde{c}_i^5$ are listed for all aircraft $i = 1, \ldots, m$.

Considering the fuel costs, the results show that there is only a marginal difference in the objective function values between the three sequences. Aircraft 10 to 12 do not belong to the hub airline. Remember that our method ensures that the landing times of aircraft belonging to competing airlines should not be later than the ones determined for the reference sequence. For the interactive method, aircraft 10 to 12 even save fuel as compared to the reference sequence.

Costs resulting from missed connections are only considered for the hub airline. Therefore, no costs occur for aircraft 10 to 12, $\tilde{c}_{10}^4 = \tilde{c}_{11}^4 = \tilde{c}_{12}^4 = 0$. Compared to the reference sequence, the resulting costs are almost halved. Applying the FCFS principle also results in higher costs (1550 USD) as compared to our interactive method (950 USD).

Note that for the reference sequence, the deadlines set at 840 and 960 s are missed by aircraft 6, which arrives at the stand at 990 s: costs of 700 USD are incurred. For the FCFS principle, the costs are reduced to 400 USD because only one deadline is missed. However, no costs are incurred for the interactive method because aircraft 6 arrives at the stand at 820 s. Hence, no deadlines are missed.

Table 8 Sequence by interactive method

Aircraft index i	Landing time l_i, s	Runway	ETA at stand, s	Costs of delay $\tilde{c}_i^4$, USD	Fuel costs $\tilde{c}_i^5$, USD
1	0	08R	317	0	0
2	259	08R	583	0	26
3	423	08R	750	400	107
4	237	08L	547	0	60
5	332	08R	861	150	84
6	493	08L	820	0	124
7	584	08R	1041	0	147
8	582	08L	994	400	147
9	676	08L	1041	0	69
10	675	08R	——	0	170
11	509	08R	——	0	52
12	424	08L	——	0	43
Totals	——	——	——	= 950	= 1029

Table 9 Sequence by FCFS principle

Aircraft index i	Landing time l_i, s	Runway	ETA at stand, s	Costs of delay $\tilde{c}_i^4$, USD	Fuel costs $\tilde{c}_i^5$, USD
1	0	08R	317	0	0
2	259	08R	583	0	26
3	422	08R	749	400	106
4	237	08L	547	0	60
5	329	08R	858	150	83
6	515	08R	902	400	130
7	701	08R	1158	200	177
8	555	08L	967	400	140
9	485	08L	850	0	50
10	648	08L	——	0	163
11	631	08R	——	0	64
12	353	08L	——	0	36
Totals	——	——	——	1550	1035

Table 10 Reference sequence (maximizing capacity)

Aircraft index i	Landing time l_i, s	Runway	ETA at stand, s	Costs of delay $\tilde{c}_i^4$, USD	Fuel costs $\tilde{c}_i^5$, USD
1	0	08R	317	0	0
2	259	08R	583	0	26
3	423	08R	750	400	107
4	237	08L	547	0	60
5	332	08R	861	150	84
6	603	08R	990	700	152
7	690	08R	1147	200	174
8	552	08L	964	400	139
9	485	08L	850	0	49
10	689	08L	——	0	174
11	536	08R	——	0	55
12	621	08L	——	0	63
Totals	——	——	——	1850	1083

We analyzed a total of 500 scenarios for benchmarking purposes. In the scenario, we consider all scheduled arrivals and departures on 30 July 2019 during the last traffic peak of the day from 2000 to 2245 hrs. During this time, there were 86 arrivals and 79 departures. Furthermore, a total of 65 aircraft was considered in the AGAP. The scenarios were solved by the proposed bilevel approach. For each scenario, a unique passenger flow matrix using a stochastic approach was created. Furthermore, the ETA0 and deadlines were determined stochastically for throughputs of 30, 45, 60, 75, and 90 aircraft per hour. Therefore, a total of 100 scenarios were analyzed for each listed throughput. A throughput of 90 aircraft per hour was only encountered at a traffic peak. The normalized improvement in total costs, which is calculated as (total monetary costs interactive method)–(total monetary costs of reference sequence/total monetary costs of reference sequence) which is is used to compare the results. The results are shown in Table 11. For a throughput of 30 aircraft per hour, an improvement is only observed in 15 out of 100 scenarios. The number of scenarios for which an improvement is observed tends to increase with an increase in throughput. However, more improvements are counted for a throughput of 45 aircraft per hour (36 of them) as compared to 60 aircraft per hour (24 of them) in our benchmarking. Significant improvements are only observed for higher throughputs: an improvement of up to 78% was observed in the benchmarking.

Note that major costs result from missed connections. The number of passengers missing their connections is also an important factor that increases costs. Supposing that, due to a technical issue, a fully booked Airbus A380 with 509 passengers on board arrives more than 3 h late from a flight with a distance of at least 3500 km, the airline has to pay a compensation of 600 euros to each passenger. Obviously, high savings can be made by preventing such occurrences. If we have no delays or a low arrival traffic density, our interactive method does not usually reduce costs as compared to the reference sequence. Furthermore, in six out of 100 scenarios, and only for a low throughput of 30 aircraft per hour, we observed higher total monetary costs of the reference sequence as compared to the sequence that is established by the FCFS principle. A maximum increase of 15% in total monetary costs is observed. Our investigations show that this is caused by aircraft with early ETA0s and for which deadlines close to the ETA0 exist. Therefore, the proposed algorithm may benefit from the consideration of the FCFS principle in the interactive methods in further research.

VIII. Conclusions

Over the years, many variants of the ASP have been discussed in detail. However, the combination of the aircraft sequencing and the airport gate assignment in a bilevel optimization problem has not previously been researched. In this paper, The focused was on efficient arrival sequencing for parallel independent runway systems at hub airports under consideration of the operational interests of hub airlines and other users. An interactive method was used to solve the underlying MOMILP. Air traffic control is the decision maker and steers the solution process within the interactive method. The capabilities of the current algorithm are demonstrated for a real-case scenario at Munich Airport. A major advance of the proposed approach is that only basic operational data are required. Six objective functions were considered. As a minimum, the types of the arriving aircraft, their ETA0s, and the wake-turbulence category are known. This information is at least sufficient to determine an optimal sequence with respect to maximizing the capacity. For all other objective functions, f_2 to f_6, the optimization problems can be solved independently to obtain the ideal objective vector. Even if operational information about some aircraft is not (yet) known, a reference sequence can be determined by default data.

Airlines can decide if they participate in the airline–individual improvement or not. The current algorithm ensures that the operational interests of competing airlines are not undermined. The final solution is the preferred sequence among all airline–individually improved sequences that ensure Pareto optimality. The ASP can still be performed by ATC. Deadlines and their associated costs, as well as the assigned stands, must be provided by the airlines. The ATC acts as a confidential and independent stakeholder. Data on operational objectives and costs associated with deadlines are exclusively processed by ATC. The current case studies show that an exact solution for a scenario with 12 aircraft can be obtained within the given timeframe of 5 min using an iMac Pro with an 18-core processor. However, setting a time limit at least provides a satisfactory solution for larger scenarios. A gap tolerance of 20% is usually reached within a couple of seconds. However, a general assumption on the runtime is not possible and depends on the scenarios. Another major advantage is that for the first and third steps, all optimization problems can be solved in parallel. Therefore, large problems can still be considered in due time. In this work, more than 500 scenarios were analyzed. It was found that the current interactive method can save up to 78% of the total monetary costs. A major drawback of the proposed approach is the limited consideration of uncertainty at the current stage of this

Table 11 Normalized improvement in total monetary costs over reference sequence

	Frequency of scenarios by normalized improvement, %															
Throughput, aircraft/h	0	5	10	15	20	25	30	35	40	45	50	55	60	65	70	75
30	85	11	2	1	1	0	0	0	0	0	0	0	0	0	0	0
45	64	28	1	0	1	0	0	2	0	0	0	3	1	0	0	0
60	76	21	1	0	0	1	0	0	1	0	0	0	0	0	0	0
75	58	32	2	0	1	1	1	1	0	0	1	1	1	1	0	0
90	58	25	1	4	0	1	3	1	1	1	0	1	0	1	0	3

work. The ETA0 is usually subject to deviations. At the moment, an update of the ETA0 at the beginning of an optimization run is the only measure to consider uncertainty.

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