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Optimal network-wide adjustments of initial airport slot allocations with connectivity and fairness objectives

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ABSTRACT

Due to serious demand-supply imbalances, many airports around the world are highly congested. Access to these highly congested (Level 3, coordinated) airports is controlled through the use of the IATA World Airport Slot allocation Guidelines (WASG). At an individual airport, slots requested by each airline are allocated at the airport under consideration independently without taking into account the interactions between slots allocated at different airports. However, in order for the air-transport network to operate seamlessly, ensuring network-wide connectivity of flights, and the interdependencies existing between the slots allocated at individual airports need to be considered. Several models have been proposed in the literature to deal with the optimum allocation of slots at a single airport. However, the literature currently does not adequately address the network-wide slot allocation problem. In this paper, we are introducing a novel approach to address the network-wide slot allocation problem. Our approach considers as an input the individual airport schedules generated during the slot allocation process at individual airports and optimally adjusts them to ensure network-wide flight connectivity by taking into account the interdependencies existing between flights connecting pairs of airports.

To this end, we propose bi-objective mathematical models, which consider schedule efficiency and inter-airline fairness objectives, and incorporate the importance that different airports have for the functioning of the air transport network, using the IATA connectivity indices and the betweenness centrality measures. We solve the proposed models using the $\varepsilon -$ constraint method to investigate trade-offs between network-wide schedule efficiency and fairness, and we investigate the effect of these trade-offs on the airlines and the airports. Results from the application of the proposed models to a test network suggest that the consideration of the contribution of the airports to network connectivity affect the way that the total network-wide schedule displacement is distributed among the airports. Specifically, we found that the use of the IATA connectivity index tends to allocate less schedule displacement to airports with frequent flights to many destinations, while the use of the betweenness centrality measure allocates less schedule displacement to airports that are more critical in ensuring the connectivity of other airports in the network.

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1. Introduction

Air transport plays an important role in the world-wide transportation of both passengers and freight. In 2017, the airlines carried 4.1 billion passengers and transported 56 million tons of freight on 37 million commercial flights. 3.5% of the gross domestic product worldwide, which corresponds to 2.7 trillion US dollars, belongs to aviation industry (The International Civil Aviation Organization, 2019). Within the European Union (EU) countries, 11.2% of the passengers are transported by air and from the EU to the rest of the world, 11.4% of the passengers use air transport to travel (European Commission, 2019). These figures demonstrate the importance and impact of aviation on the world-wide economy. It is also projected that global air passenger will grow in the range of 1.5% – 3.6% in the next 20 years (IATA, 2021c). Unfortunately, the rate of increase in the capacities of the airports has not kept up with this increase in demand, resulting in a supply-demand imbalance and highly congested airports (Odoni, 2020). In addition, the demand supply imbalance observed in airports around the world generate negative socio-economic and environmental impacts such as delays, emissions, and deterioration of service quality offered, affecting the travelling public, the airlines, the airports, and communities located in the vicinity of airports. Therefore, it is crucial to efficiently manage the demand and allocate efficiently the available scarce airport resources.

The International Air Transport Association (IATA) defines three categories of airports according to the congestion they experience (IATA, 2021a). Airports with sufficient capacity to meet the demand are classified as Level 1 airports, while airports facing congestion during certain periods of the day, week, or season, are designated as Level 2 (facilitated) airports. However, if the demand exceeds the airport's capacity during the scheduling period and an expansion of airport infrastructure to meet demand is not possible in the short term, then it is classified as Level 3 (coordinated) and the demand is managed through the slot allocation process, carried out by slot coordinator. The first step in the slot allocation process is to determine the declared capacity, also referred to as coordination parameters, of an airport. The capacity is expressed in *slots,* where a slot is defined as "a permission given by a coordinator for a planned operation to use the full range of airport infrastructure necessary to arrive or depart at a Level 3 airport on a specific date and time" (IATA, 2021a), and covers time intervals with a fixed duration, called *coordination time interval*. Declared capacity is a value showing a benchmark or a target, rather than a physical operational capacity, and it depends on several conditions such as weather, types of the runways in operation, types of aircraft movements, etc. (Odoni, 2020). Following the determination of an airport's coordination parameters, airlines submit their slot requests. Requests consisting of at least 5 slots for the same time on the same day-of-the-week are called *series* and they should be distributed as such throughout the season to ensure schedule regularity. The role of the slot coordinator in the slot allocation process is "to allocate slots to airlines and other aircraft operators in a neutral, transparent, and non-discriminatory way, on the basis of the applicable coordination parameters, and in accordance with the priority criteria of the WASG and any local guidelines and regulations" (IATA, 2021a). The slot allocation process is held twice each year to cover a 7-month and a 5-month period in summer and winter, respectively, each of which is called *scheduling season*.

To satisfy the capacity constraints of each airport, some requests may be displaced, meaning that they are allocated different slots from those originally requested. Since there might be other flights connected to those displaced flights, schedule inconsistencies might emerge for these flights, i.e., time difference between the departing and arriving flights at origin and destination airports may be smaller than the time needed to ensure flight connectivity. Thus, although these initial allocations are in line with the capacity availability of each individual airport, there may be inconsistencies in the network because of the connected flights. Subsequently, these initial slot allocations are adjusted to produce the final network-wide slot allocation.

Although coordinated airports correspond to around 6% of all airports in the world, they serve about 43% of all passengers travelling around the world (IATA, 2021b). As a consequence, the slot allocation problem has drawn the interest of the scientific community and optimization models have been proposed to address the single airport slot allocation problem (Zografos et al., 2012; Gillen et al., 2016; Zografos et al., 2017, 2018; Zografos and Jiang, 2019; Ribeiro et al., 2019a, 2019b; Fairbrother et al., 2020; Katsigiannis et al., 2021; Jorge et al., 2021), and the network level (Pellegrini et al., 2012; Castelli et al., 2012; Corolli et al., 2014; Pellegrini et al., 2017; Benlic, 2018) slot allocation problem. The single airport slot allocation problem deals with the allocation of slots independently at each airport, while the network-wide slot allocation problem aims to capture the interdependence among airports in allocating their slots (Zografos et al., 2017). Due to the complexity of the network-wide slot allocation problem, existing models use a simplified approach which considers only the primary slot allocation criteria and allocate the slots at all airports simultaneously considering the slot requests submitted by the airlines. As these models consider all requests that are submitted to all airports and allocate them simultaneously, the allocation process they are proposing is not in line with the IATA WASG, which require the allocation of slots at each airport individually. This makes the implementation of these models difficult under the current IATA slot allocation framework. Furthermore, this approach does not capture the local criteria used by different coordinators to address the issues and peculiarities emerging from the specific context at each airport, e.g., they do not consider secondary criteria, and do not take into account the differences between airports in relation to the importance of different types of criteria. This local information is not used by existing network level models.

In addition, the airports may have different contributions to the connectivity of the air transport network. For example, one airport may have connections to several airports and therefore, it may have a high importance in establishing the connectivity between several other airports. Connectivity plays an important role in the slot allocation process, too. The importance of global connectivity in the slot allocation process is reflected in the IATA WASG, which identifies the improvement of global connectivity as one of the objectives of the slot allocation process to eventually satisfy the needs of the passengers (IATA, 2021a). Therefore, although considering connectivity is essential in slot allocation, the existing network level models treat all airports uniformly, i.e., they do not recognize the importance that different types of airports play in the functioning of the global air transport system.

This paper proposes a novel approach to address these shortcomings of the existing network-level models. First, instead of simultaneous allocation of all requests to all airports, the outcome of the slot allocation at each individual airport is used as input for the network-level optimization problem. This is more in line with the process that is currently being used by IATA, which allocates slots at each airport independently and consequently provides the opportunity to consider local criteria and contextual factors at different airports. This approach allows the consideration of the local context, as well as the incorporation of primary and secondary criteria in making the initial slot allocation at individual airports and optimally adjusts the resulting individual airport schedules to ensure network-wide flight connectivity by taking into account the interdependencies between flights connecting pairs of airports. We also incorporate the importance of airports in the functioning of the air transport network, and we investigate how having airports with different importance affects the connectivity of the entire network and how the airports and airlines are affected. To this end, we propose bi-objective mathematical models using schedule efficiency and fairness objectives.

The paper is organized as follows. In Section 2, we review the existing literature on slot allocation problem at network level and we establish the contribution of this paper. In Section 3, the contribution of different types of airports in the functioning of the air-transport network is discussed through the use of the connectivity concept. In this context, different connectivity metrics introduced in the literature are discussed, leading to the selection of the metrics incorporated in the proposed models. Section 4 presents the proposed mathematical model, while Section 5 describes the solution approach. Computational experiments are presented in Section 6, and finally, Section 7 summarizes the findings and provides future research directions.

2. Related literature review

In this section, we review the literature focusing mostly on the relevant studies on network-level slot allocation while making references to the single airport models where necessary. We then conclude with the gaps in the existing literature and establishing the contributions of this study.

The slot allocation problem has been studied with various variants for single airports. On the other hand, the slot allocation problem at network level has not attracted as much attention as its single-airport counterpart. Single airport models have evolved from single objective models aiming to allocate slot requests to slots in such a way as to minimize the displacement, i.e., the absolute difference between the requested and allocated slot time (schedule efficiency) (Zografos et al., 2012), to bi-objective models considering schedule efficiency and fairness objectives (Zografos and Jiang, 2019; Jiang and Zografos, 2021; Fairbrother et al., 2020), to multi-objective models (Ribeiro et al., 2018; Katsigiannis et al., 2021; Katsigiannis and Zografos, 2021). Recently, Birolini et al. (2022) have included passenger-centric measures as objectives, such as the number of lost passengers due to infeasible connecting times, and the connecting times between the flights, aiming to minimize passenger inconvenience in addition to schedule displacement.

This paper focuses on the network-level slot allocation problem. Therefore, we are providing a more detailed discussion of the relevant network-level slot allocation literature to identify existing gaps and establish our contribution. Castelli et al. (2012) is the first work to formulate a mathematical model of the network-wide slot allocation problem. The model uses slot requests made for each airport to determine simultaneously the network-wide allocation of slots and the flight routes such that the sum of total displacement cost over all flights in the network and the cost of flight time deviation from the ideal flight time is minimized. The resulting integer programming model is solved using 100 randomly generated instances that simulate the air traffic demand over a portion of the European sky only for a 5-hour time horizon, including 2200 flights and a network of 60 airports. In a subsequent work, Pellegrini et al. (2012) propose two heuristic algorithms, namely Iterated Local Search and Variable Neighborhood Search to solve a similar problem with a different objective function, which firstly maximizes the number of flights to which slots are assigned, then minimizes the sum of overall displacement costs. They solve three sets of randomly generated instances with different sizes, with the largest having 30 airports and 29,835 flights, for a planning horizon of only 20 h. In both studies mentioned above, the experiments include a planning horizon of a limited time. Therefore, these models do not consider the entire scheduling season and the allocation of series of slots, which are key IATA slot allocation requirements. In addition, these models do not consider turnaround times, and the capacity constraints are applied only to the total movements, meaning that the model does not consider separately the capacity constraints associated with the arrivals and departures. In addition, Pellegrini et al. (2012) does not take into account the priorities associated with the satisfaction of different types of requests, which is another primary IATA slot allocation criterion.

Corolli et al. (2014) consider the uncertainty in the definition of the declared capacity. However, their model does not consider the allocation of series of slots throughout the scheduling season, and the priority rules associated with the allocation of different types of requests in the slot allocation optimization process. The problem instance solved considers the allocation of slots only for four calendar days, which is not in line with the IATA slot allocation guidelines.

Pellegrini et al. (2017) introduce a model considering an objective of minimizing the number of flights that cannot be allocated, then the total displacement cost of allocated slots is optimized. Furthermore, they propose two variants of the model to consider fairness between airlines. In the first variant, a linear combination of the costs incurred to the average and to the most penalized airline is minimized, whereas the second variant normalizes the cost encountered by each airline according to the number of requests that have been submitted by each airline. The results are obtained by solving the proposed mathematical programs in CPLEX solver using an instance with 152 airports and 32,665 requests. The shortcoming of this paper is that they do not consider the series of slots as the experiments cover only a single day of operations.

The major shortcomings of the papers discussed above is that they do not consider the allocation of series of slots as they are using scheduling horizons ranging from few hours to four days. Consideration of the entire season is a key IATA slot allocation requirement (IATA, 2021a) as it influences the quality of the resulting schedule by ensuring schedule regularity throughout the scheduling season

(Zografos et al., 2012; Fairbrother and Zografos, 2021). Therefore, these studies present a disadvantage in terms of adhering to schedule regularity. On the other hand, the consideration of series of slots exacerbates the complexity of the problem and its computational requirements.

This shortcoming has been addressed by Benlic (2018), who studies the slot allocation problem at network level by extending the single airport slot allocation model proposed by Zografos et al. (2012). In addition to the constraints regarding the allocation of series of slots for the entire season, and to the turnaround time and rolling capacity constraints for different types of movements introduced in (Zografos et al., 2012), this model incorporates constraints to ensure the connectivity of flights in the network. A construction heuristic algorithm is used to solve the resulting model. The proposed algorithm is applied to a set of randomly generated instances with different sizes. This study does not consider initial allocations at each airport and therefore does not take into account the local context and the criteria used to allocate slots at each airport, making the implementation of this model difficult in practice. Furthermore, it does not differentiate among the airports in the network with respect to their role in the functioning of the network, i.e., contribution of different types of the airports in the connectivity of the network.

Due to the complexity of the problem, emerging from the simultaneous consideration of the slot requests at network level, the existing studies at network-level problem use simplified approaches, in which not all the criteria suggested by IATA WASG are considered. They allocate the slots at all airports simultaneously, only by extending the single airport models by introducing flight connectivity constraints. However, this approach results in considering the IATA WASG rules very macroscopically, making their applicability questionable. IATA suggests two types of criteria for slot allocation, primary and secondary. While the first category covers addressing the priorities among the requests, e.g., historic and new entrant slots, and the priorities that should be given to year-round operations, secondary criteria take into account other factors such as the effective period of operation, operational factors at the airports, and connectivity (IATA, 2021a). In addition, European Commission suggests specific consideration for slot requests associated with routes connecting airports located in isolated or developing regions of the European Union Member States (European Commission, 2023). This constitutes an additional request priority referred to as Public Service Obligations (PSO), which pre-empts other requests, and is used to guarantee the connectivity of these disadvantaged regions (Katsigiannis and Zografos, 2021). The existing network-level slot allocation models apply mostly the primary criteria in all airports. On the other hand, the coordinators apply the secondary criteria and local guidelines as needed according to the special requirements of the airport under consideration, when they apply them at the individual airports. The models that consider these additional criteria, such as fairness (Zografos and Jiang, 2019), type of the consumer service and market served, e.g., flights on highly competitive markets, long-haul flights, international flights, and home-carrier flights may be of importance (Ribeiro et al., 2021; Jorge et al., 2021); network connectivity, e.g., flights with a high number of connecting passengers may be important in slot allocation decisions (Jacquillat and Odoni, 2017); and local guidelines that may prevent operational delays (Katsigiannis and Zografos, 2023), can be used to solve the single airport slot allocation problem at different airports according to their needs in terms of the criteria to be used, and the outcomes of these models can be utilized in the solution of the network-level problem. This will ensure a more realistic representation of the problem.

This paper contributes to the existing literature in three ways: First, we propose a model which considers the initial slot allocations at each individual airport, instead of the slot requests. The use of the initial allocations ensures that the allocations at each airport are optimized taking into account the local context; it can be detailed enough to consider primary and secondary criteria and local guidelines; it can consider airside and landside capacity constraints, and it adheres to the IATA guidelines. To this end, our model optimally adjusts the initial slot allocations to meet the needs of the airlines at the network level. It aims at systematically and consistently ensuring optimality of adjustments for the whole scheduling season. Second, considering the topology of the air transportation network and the importance of different airports in the functioning of the network, we aim at increasing the network connectivity by integrating in the proposed optimization model measures expressing the contribution of different airports to the network connectivity. This new feature fills another gap in the slot allocation literature and helps establishing the network connectivity by constructing a network-wide schedule, which is suitable for both the connected flights and passengers while maintaining the schedule efficiency. It incorporates inter-airline fairness at network level and introduces three alternative bi-objective formulations that allow decision makers to gain insights about the trade-offs between slot allocation efficiency, inter-airline fairness, inter-flight fairness (as a proxy for passenger fairness), and airport fairness, while considering different indices, IATA connectivity index, and betweenness centrality index, expressing the importance of different airports in the functioning of the air transport network. Finally, we solve the proposed model using an instance adapted from a real-world data for an entire planning season ensuring that schedule regularity is established, and we give managerial insights regarding the effect of the network structure on the network-wide slot allocation decisions.

3. Problem definition

In this section, we elaborate on the characteristics of the problem in terms of both the slot allocation and the importance of the airports in the connectivity of the air transport network.

3.1. Network connectivity

Network connectivity is an important concept in the aviation industry, and it is defined by IATA as a measure of "how well a country is connected to cities around the world" (IATA, 2020). It helps countries to participate in the global trade, supports tourism flows, and overall plays a significant role in global economy. Connectivity is an important factor in the slot allocation process, too, as the IATA Worldwide Slot Guidelines highlight that improving global connectivity is one of the objectives of the slot allocation, and they stress that coordinators should try to develop airport route network and connectivity to meet the needs of the passengers and shippers (IATA, 2021a). Therefore, our approach takes into account the importance of the airports in establishing the connectivity of the network. To achieve this, we first elaborate on how to represent and quantify the importance of the airports in the air transport network. We then solve the network-level slot allocation problem by considering these importance measures.

A variety of indices have been proposed in the literature to express the importance of different airports in the functioning of the air transport network. Allroggen et al. (2015) propose GCI (Global Connectivity Index) to make classifications of the airports at global level in terms of how much they contribute to flights that are frequent, convenient for the passengers, i.e., non-stop or one-stop with short connecting times, and that go to quality destinations, e.g., close to economically attractive markets. Redondi et al. (2021) use connectivity notion to estimate the market shares of the itineraries, aiming to predict passenger behavior to be used as a guidance in allocating air traffic flows. For that, they compare the performances of several connectivity indices using similar characteristics to those in Allroggen et al. (2015) and of a logit-based calibrated index. Guimerà et al. (2005) use the betweenness centrality, one of the node centrality measures (Opsahl et al., 2010), which measures the extent to which an airport lies on the paths connecting other pairs of airports, to find the most central airports. Suau-Sanchez et al. (2016) investigate self-connectivity, which is defined as travelling without a connecting ticket, e.g., with tickets purchased separately. They found out that betweenness centrality measure, which quantifies how much an airport is able to funnel the passenger flow in the network (Opsahl et al., 2010), has the largest impact on the potential for self-connectivity. In other words, the airports with high betweenness centrality are more likely to attract passengers who plan their transfers by themselves outside the boundaries of the existing connected flights. Therefore, betweenness centrality is a relevant measure for representing the importance of the airports with regards to the connectivity of the network, thus we turned our attention to this metric. The details regarding the network representation and how the betweenness centrality in this study is calculated are explained in Appendix A.

IATA also proposes a connectivity index, which extends the degree centrality measure by considering the number of available annual seats to each destination between 2014 and 2019, then weighting it by the size of the destination airport in terms of number of passengers handled at that airport in each year. Abbreviated by ICI_i to stand for the IATA connectivity index for airport i, this metric is formulated as follows:

$$ICI_i = \sum_{j \in D_i} s_j * w_j \tag{1}$$

where D_i, s_j and w_j stand for the set of airports connected to airport i, annual number of seats from airport i to airport j, and the size of airport j, defined as the annual number of passengers handled at airport j, respectively. This index measures the degree of integration of an airport into the global air transport network (IATA, 2020) and addresses the centrality from another aspect using the number of passengers transported between airports. Therefore, we turn our attention to these centrality measures and use betweenness centrality and IATA connectivity index in our computations.

3.2. Network level slot allocation model (NL-SAM)

In this section, we first introduce the problem with its parameters and present the constraints, then we present three objective functions to be used in different settings according to the decision maker's criteria.

3.2.1. Network level slot allocation problem (NL-SAP) definition

NL-SAP addresses the optimal adjustment of the initial slot allocations by incorporating the importance of the airports in connectivity of the air transport network, such that connectivity of the flights in the network is ensured and schedule efficiency is maintained. As per IATA requirements, the NL-SAP is solved over a scheduling season, i.e., for the days between the last Sundays of March and October for the summer season and the remaining days of the year for the winter season. Let D be the set of planning days, each consisting of a set of q coordination time intervals, $T = [0, \ldots q-1]$. A request series $m \in M$ is a set of arrival or departure requests such that at least 5 slots are allocated for the same time on the same day-of-the-week, distributed regularly in the same season. Individual requests can also be defined as series of requests by defining a parameter which specifies whether a request operates on a particular day or not.

A request pair $(m_1,m_2) \in P$ involves an arrival movement and its connected departure movement which are operated by the same aircraft at the same airport. Therefore, they should be scheduled considering the turnaround time of the aircraft, l_{m_1,m_2}. A request pair $(o, d) \in L$ involves a departure movement from an origin airportand its corresponding arrival movement at the destination airport. To establish the network-level flight schedule consistency, the departure movement at the origin airport and the following arrival movement at the destination airport must be assigned compatible slots considering the flight time between these airports, t_{od}.

The capacity is declared in slots over a sequence of consecutive time periods and expressed for arrivals, departures, and total movements. Therefore, the number of slots that can be allocated is limited by these capacities.

We are given as input a set of schedules for each airport in the network, which have been constructed independently in the initial slot allocation. The aim of this problem is to ensure flight connectivity throughout the network i.e., the slots at origin and destination airports are allocated considering the flight times, while optimizing schedule performance objective(s). Let y_m denote the slot index request $m \in M$ has been initially allocated to. In ensuring feasibility, the slots that have been allocated at each airport may be displaced and their displacement might be either positive or negative, which are denoted by the variables x_m^+ and x_m^-, respectively, or it may stay as it is if there is no need for adjustment. To illustrate this, Table 1 shows a toy example with two airports over a 10-minute interval. Let

Table 1
Example of schedule adjustment.

Airport 1			Airport 2		
Request	Movement	Initial schedule	Request	Movement	Initial schedule
–	–	09:50 (118)	1	Arrival	10:50 (130)
–	–	09:55 (119)	–	–	10:55 (131)
1	Departure	10:00 (120)	2	Arrival	11:00 (132)

Table 2
Notation.

Symbol	Definition
Sets	
A	Set of airports in the network
R	Set of airlines that place requests on the network of airports
M	Set of requests over all airports of the network, each of which is either an arrival or a departure movement.
M_a	Subset of requests from M that need to be allocated a slot at airport $a \in A$
M_r	Subset of requests from M that are requested by airline $r \in R$
P	Set of request pairs (m_1,m_2) where $m_2 \in M$ stands for the departure movement followed by the arrival movement $m_1 \in M$ by the same aircraft at the same airport
L	Set of flight legs where each leg $o, d \in M$ is a pair involving a departure request o at an origin airport, and the following arrival request d at a destination airport in the network of airports
D	Set of calendar days within the scheduling period
D_m	Set of days for which request $m \in M$ is scheduled
T	Set of coordination time intervals per day, $\{0, 1, \ldots q-1\}$
$C(a)$	Set of capacity constraints at airport $a \in A$
T_c^s	Set of consecutive coordination time intervals over which the constraint is checked, where $T_c^s = \{t \in T, s \le t \le s + t_c\}$ for a specified time $s \in T_c = \{t \in T,\ t < q - t_c + 1\}$
Parameters	
t_c	Duration of a capacity constraint $c \in C(a)$ at airport $a \in A$
u_c^{dt}	Value of capacity constraint $c \in C(a)$ at airport $a \in A$ for day $d \in D$ and coordination time interval $t \in T_c$
k_m^d	1, if request $m \in M$ operates on day $d \in D$, and 0, otherwise
b_m^c	Units of capacity $c \in C(a)$ of airport $a \in A$ consumed by request $m \in M$. This parameter is set to 1 if the constraint is applied to arrivals (departures) or to total movements if the request is an arrival (departure) movement and it is set to 0, otherwise.
$l_{m_1 m_2}$	Turnaround time between an arrival movement $m_1 \in M$ and the corresponding departure movement $m_2 \in M$ of the same aircraft
t_{od}	Flight time that can be assigned between an origin airport o $\in$ A and a destination airport $d \in$ A
t_m	Time interval allocated to request $m \in$ M in the primary slot allocation
f_m^t	Displacement from assigning slot $t \in$ T to request $m \in$ M, $\lvert t - t_m \rvert$
m_o,m_d	Origin and destination airports of request $m \in$ M
c_m	Centrality metric incurred for request $m \in$ M
c_a	Centrality metric of airport $a \in A$
$\lvert M_r \rvert$	The number of flights airline $r \in R$ operates, defined as $\lvert M_r \rvert = \sum_{m \in M_r} D_m$
Decision Variables	
y_m	The time interval to which request $m \in$ M is reallocated
x_m^+	Positive displacement of request $m \in$ M
x_m^-	Negative displacement of request $m \in$ M
x_m^t	1, if request $m \in$ M is reallocated to time interval $t \in$ T, 0 otherwise
dis_m	Total displacement allocated to request $m \in$ M, including the number of operating days request m operates
d_r	Total displacement allocated to the requests of airline $r \in R$, defined as $d_r = \sum_{m \in M_r} dis_m$
Δ	Total schedule displacement of all requests at all airports in the network
z	Maximum displacement any request is allocated at any airport in the network
ρ_r	Fairness metric of airline $r \in R$
f	Fairness objective of the network

us consider a coordination time interval of 5 min, a capacity of 1 for all movements at both airports and let the flight time between these airports be 1 h. Between 09:50 and 10:00, Airport 1 has one departure scheduled at 10:00, whose destination is Airport 2, and its corresponding arrival is scheduled at 10:50. Airport 2 has another arrival scheduled at 11:00. The slot indices are shown in the parenthesis assuming that the first slot belongs to the interval 00:00–00:05, i.e., $y_{1-dep} = 120$ and $y_{1-arr} = 130$. Since the flight time is 1 h and the difference between the departure and the arrival is 50 min, there should be a shift of 2 slots to make this schedule feasible. There are two possibilities here: 1) shifting departure movement at Airport 1 to 09:50 ($x_{1-dep}^- = 2$), or 2) shifting departure movement at Airport 1 to 09:55 ($x_{1-dep}^- = 1$) and shifting arrival movement at Airport 2 to 10:55 ($x_{1-arr}^+ = 1$). Both options result in a total difference of 2 slots compared to the initial schedule. However, if the decision maker would like to avoid changes at Airport 2, then option 1 would be preferable.

Table 2 presents the sets, parameters, and decision variables used in the mathematical model. Note that, according to the IATA

Guidelines, it is required that all flights belonging to the same series of slots, i.e., slots for the same flight on the same day of the week, at least five times over the season, should be given a slot at the same time of the day (IATA, 2021a). Therefore, our formulation requires that all slots belonging to a series are allocated exactly at the same time, i.e., all y_m variables have the same value for all the requests in the series.

3.2.2. Network level slot scheduling objectives

The problem can be solved using different objective functions according to the decision maker's criteria and requirements. Schedule efficiency is a commonly used criterion for both single airport and network models. It can be expressed by displacement-based measures, where displacement refers to the difference between the requested and allocated slots, including total displacement over all flights (Zografos et al., 2012; Ribeiro et al., 2018; Katsigiannis et al., 2021) and maximum displacement across all flights (Jacquillat and Odoni 2015; Zografos et al., 2018; Ribeiro et al., 2018). Another objective that has been considered in airport slot allocation is fairness, which measures how equitably the resulting displacements are allocated among the airlines (Zografos and Jiang, 2019; Jiang and Zografos 2021; Fairbrother et al., 2020). In NL-SAP, we consider a schedule efficiency measure and an inter-flight fairness measure, which are the network-wide total displacement over all requests at all airports in the network, and the maximum displacement any request receives at any airport in the network, as well as a fairness measure, which considers all flights operated by each airline at all airports in the network. Note that, although we are using the same concepts with the above-mentioned studies, we are extending the definition of each objective such that they measure the network-wide level properties. Efficiency objective is extended to network-wide efficiency by aggregating all flights over the network. Similarly, fairness should be thought as network-wide fairness as it is tackled considering all the flights of each airline over the entire network.

3.2.2.1. Total displacement objective. We define the total displacement of a request as the absolute difference between its initially allocated slot, i.e., in the primary allocations, and the newly allocated slot, weighted by the number of days the request under consideration is planned to operate (Ribeiro et al., al.,2018). Therefore, we include the number of days a flight operates within the season in the displacement calculation. If request m is allocated a slot $t \in T$, i.e., $x_m^t = 1$, the resulting displacement from its initially allocated slot, t_m, is calculated as $f_m^t = |t - t_m|$. We can then define the displacement each request m is allocated as expressed in Eq. (2).

$$dis_m = \sum_{t \in T} |D_m| f_m^t \, x_m^t \tag{2}$$

To calculate the network-wide total displacement, all requests operated at all airports in the network are considered. As each airport has a different importance in the air transport network with regards to connectivity of the network, to incorporate this important aspect of the problem, the displacements are weighted by the centrality measures considering the airports in which the flights operate. The aim of this is to improve the connectivity of the network by increasing the scheduling efficiency of the airports that play a pivotal role in establishing the connectivity of the network.

Let c_{m_o} and c_{m_d} be the connectivity metrics of the origin and destination airports flight m operates. Considering the importance of both airports, we propose a weight of $c_m = c_{m_o} + c_{m_d}$ for the displacement of request m, if one of the airports is not coordinated. However, if the request is between two coordinated airports, meaning that both departure and arrival flights are allocated slots, then we use the connectivity metric of the corresponding airport, i.e., the metrics of the origin and destination airports are used for the departure and arrival flights, respectively. The reason behind using the connectivity metric of only one airport is that, because both departure and arrival requests are included in the set of requests, summation of the metrics of both airports results in double-counting the measures. Then the schedule efficiency in terms of the total displacement at all airports in the network can be expressed as follows:

$$\Delta = \sum_{m \in M} c_m dis_m \tag{3}$$

3.2.2.2. Maximum displacement objective. In addition to the overall schedule efficiency at network level, one may consider minimizing the maximum displacement any flight is allocated at any airport in the network. This ensures that none of the flights receive a disproportionally high displacement, as it may lead to increased discrepancies in the network due to the connected flights, and it provides a guaranteed worst-case service level in the network for all flights. This objective has been motivated by the inter-flight equity concerns since it minimizes the displacement that any flight is incurred and has been used in several studies including Jacquillat and Odoni (2015), Pyrgiotis and Odoni (2016), Jacquillat and Vaze (2018) and Zografos et al. (2018) for the single airport models, and it can be used as a proxy of passenger fairness. The maximum displacement is considered as the actual displacement for each flight and includes neither the connectivity measures nor the total number of days the flight operates, i.e., it is the absolute value of the difference between the initial and final allocations. It is therefore expressed as follows:

$$z = \max_{m \in M} \left\{ f_m^t x_m^t \right\} \tag{4}$$

3.2.2.3. Inter-Airline fairness objective. Finally, to facilitate the fairness between airlines, we have extended the single airport fairness measure introduced in Zografos and Jiang (2019) to a network-wide fairness measure. The metric considers the displacements of the requests over the entire network. It includes all flights of all airlines, operated at all airports in the network. Let ρ_r be the fairness metric of airline r, which is defined as follows:

$$\rho_r = \frac{\frac{d_r}{\sum_{r\in R} d_r}}{\frac{|M_r|}{\sum_{r\in R}|M_r|}} \tag{5}$$

where total displacement of airline r is $d_r = \sum_{m\in M_r} dis_m$, and the number of flights airline r operates is $|M_r| = \sum_{m\in M_r} D_m$. According to this fairness metric, a fairly treated airline has a fairness value of 1. A favored airline has a fairness value which is smaller than 1, i.e., the percentage of the displacement allocated to this airline is smaller than its portion in the total number of requests in the network. Similarly, a disfavored airline has a fairness value that is greater than 1.

Although there are several fairness objectives to assess the fairness between airlines (Jiang and Zografos, 2021), we incorporate a fairness objective, which minimizes the maximum difference between the fairness metric of an airline and the average fairness metric of all airlines. The use of this objective ensures that the worst treated airline (in terms of satisfying its requests) is not far away from the average fairness of all airlines. By making a comparison with the average treatment, the airlines can assess how fairly they are treated (Jiang and Zografos, 2021). Minimizing the maximum value of the absolute differences from the average fairness prevents large deviations and makes sure that the airlines are treated similarly (Zografos and Jiang, 2019). The fairness objective is then defined as follows:

$$f = \max_{r\in R}\left|\rho_r - \frac{\sum_{r\in R}\rho_r}{|R|}\right| \tag{6}$$

3.2.3. Constraints

Having defined the notation and the characteristics of the problem, we can now define the constraints as follows:

3.2.3.1. Slot allocation constraints. This set of constraints define the variables y_m to be the adjusted slot times, which are the sum of the initially assigned slots and the adjustments made. These constraints are also used to establish the relationship between x_m^t and y_m variables. Specifically, constraints (7) define the variable y_m as the adjusted time slot with respect to the initially allocated slot. If request m is allocated a slot at time interval t, then x_m^t for the corresponding time interval should be 1, which is ensured by constraints (8). Since among all x_m^t variables, only the one corresponding to the adjusted time slot t can take value of 1, other assignment variables are forced to be 0, which is guaranteed by constraints (9).

$$y_m = t_m + x_m^+ - x_m^- \quad m \in M \tag{7}$$

$$y_m = \sum_{t\in T} t\, x_m^t \quad m \in M \tag{8}$$

$$\sum_{t\in T} x_m^t = 1 \quad m \in M \tag{9}$$

3.2.3.2. Flight connectivity constraints. Constraints (10) guarantee that the difference between the slots allocated to a pair of requests associated with the same aircraft, i.e., the arrival and the following departure request at the same airport, is equal to the required turnaround time. Similarly, constraints (11) ensure a compatible allocation of slots belonging to requests with aircraft rotations, i.e., successive flights at different airports, by scheduling the departure at the origin airport and the corresponding arrival at the destination airport considering the flight time between the airports.

$$y_{m_2} - y_{m_1} = l_{m_1 m_2} \quad m_1, m_2 \in P \tag{10}$$

$$y_d - y_o = t_{od} \quad o, d \in L \tag{11}$$

3.2.3.3. Airport capacity constraints. All slot adjustments should be made such that the declared airport capacities are respected. Constraints (12) enforce rolling capacity constraints for arrivals, departures, and total movements.

$$\sum_{m\in M(a)} \sum_{t\in T_c^s} k_m^d b_m^c x_m^t \le u_c^{ds} \quad a \in A,\ c \in C(a),\ d \in D,\ s \in T_c \tag{12}$$

3.2.4. Mathematical formulations of the network level slot allocation model (NL-SAM)

In this study, we are proposing two bi-objective formulations, which help examining the trade-offs between two sets of potentially conflicting objectives. The first model analyses the trade-off between the total displacement and the maximum displacement allowed for any flight in the network, while the second model investigates the total displacement and the inter-airline fairness. The trade-offs are expressed by the efficient solutions of the corresponding bi-objective model and are represented by the corresponding Pareto frontiers.

3.2.4.1. NL-SAM/MTD. The first model investigates the trade-off between 1) maximum displacement any flight is allocated and 2) total displacement over all flights at all airports in the network. Therefore, we name the model as NL-SAM/MTD, in which MTD stands for maximum and total displacement objectives used in this model. It is formulated as follows:

$$\begin{array}{ll} \textit{minimize} & (z, \Delta) \\ \textit{subject to} & \\ & \text{Constraints} \quad (7) - (12) \end{array} \tag{13}$$

$$z \geq (y_m - t_m) \qquad m \in M \tag{14}$$

$$z \geq (-y_m + t_m) \qquad m \in M \tag{15}$$

$$x_m^t \in \{0, 1\} \qquad m \in M, \ t \in T \tag{16}$$

$$y_m, \ x_m^+, \ x_m^- \geq 0 \qquad m \in M \tag{17}$$

$$z \geq 0 \tag{18}$$

where constraints (17) and (18) establish the definition of variable z by making sure that for each request, the absolute value of the difference between the initially allocated slot and the adjusted slot does not exceed z.

3.2.4.2. NL-SAM/FTD. The second model analyses the trade-off between 1) inter-airline fairness and 2) total displacement over all flights at all airports in the network. This model is abbreviated as NL-SAM/FTD, in which FTD represents the fairness and total displacement objectives. NL-SAM/FTD can be formulated as follows:

$$\begin{array}{ll} \textit{minimize} & (f, \Delta) \\ \textit{subject to} & \\ & \textit{Constraints} \ (7) - (12), \ (16), \ (17) \end{array} \tag{19}$$

4. Solution methodology

The ε-constraint method was selected to solve the resulting bi-objective optimization problems. The ε-constraint method converts one of the objectives into a constraint and solves the problem as a single-objective problem. It has the ability to generate the entire set of efficient solutions without requiring decision makers to articulate their ad-hoc preferences in relation to the considered objectives. The generated frontiers provide decision makers information regarding the trade-off existing between the competing objectives, and on the basis of this information, the decision maker(s) can select the preferred solution for implementation. This method has been successfully implemented for the slot allocation problems (Zografos et al., 2018; Fairbrother et al., 2020; Zografos and Jiang, 2019; Katsigiannis et al., 2021). The steps of the solution methodology for the NL-SAM/FTD can be summarized as follows:

1 A single-objective model is constructed by removing the fairness objective, f, and the problem is solved to minimize the total displacement. The results of this solution are substituted into Eq. (5) to calculate the fairness metric of each airline. Then the fairness objective of this solution is calculated by using Eq. (6), which is assumed to be the initial value of ε.

2 A new single-objective model is constructed using Δ as the objective function, the constraints (7)–(12), (16), (17) and the following parametric constraint: $f \leq \varepsilon$. However, since f is a nonlinear function of x_m^t, this constraint is linearized following the same steps in Zografos and Jiang (2019), by multiplying both sides of the equation by the total displacement. The linearized constraint becomes:

$$\left| \frac{\frac{\sum_{m \in M_r} dis_m}{|M_r|}}{\sum_{r \in R} |M_r|} - \frac{\sum_{r \in R} \frac{\frac{\sum_{m \in M_r} dis_m}{|M_r|}}{\sum_{r \in R} |M_r|}}{|R|} \right| \leq \varepsilon \sum_{m \in M} dis_m, \ r \in R \tag{20}$$

3 The model in Step 2 is solved iteratively by decreasing the value of ε by a step size, δ, i.e., ε is updated at each iteration as ε = ε − δ, until there is no feasible solution for the current value of ε.

The solutions obtained through these steps lead to the Pareto frontier for the bi-objective problem. The same procedure is followed for the NL-SAM/MTD, by replacing the fairness constraint expressed by Eq. (20) with the maximum displacement objective expressed by Eq. (21).

$$z \leq \varepsilon \tag{21}$$

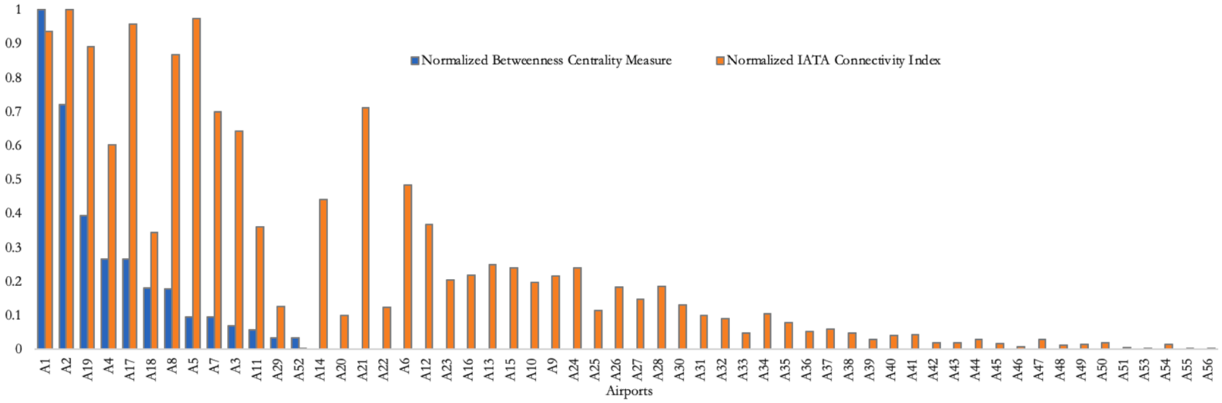


Fig. 1. Distribution of the normalized IATA connectivity and betweenness centrality index for the network of airports under consideration.

5. Computational study

To demonstrate the implementation of proposed models, we need a dataset which includes the initial allocations made at the individual airports comprising the network. In addition, we need historical flight data for the calculation of connectivity metrics. To this effect, we use two data sets: the first is a synthetic data set generated based on a real initial slot allocation data for the coordinated and facilitated airports in Brazil, available in the slot coordination database of Brazilian National Civil Aviation Agency (ANAC, 2021). We have made some assumptions and modifications to the original data in relation to the attributes we are using in this problem. The network includes 56 national airports, 16 of which are either facilitated or coordinated airports. These 16 airports are included in our optimization model, i.e., the slots at these airports are optimized. Although there is no slot allocation at Level 2 airports, we chose to include them in the optimization as the changes in the schedules may cause schedule disruptions at these airports if they belong to the congested hours. Since we do not have the allocation information about the airports outside Brazil, we only consider the coordinated and facilitated airports within the Brazilian network. For example, if there is a flight between Airport A in Brazil and Airport B in Germany, which are both coordinated airports and normally both departure and arrival movements of this flight should be included in the optimization, we only consider the departure movement in Airport A, and we do not include the displacement encountered at airport B in our objective function. Therefore, the value of our objective function involves only the displacements encountered at the airports in the domestic network. Appendix B presents the network of Brazilian airports considered in this study, along with the corresponding number of flights, which are based on synthetic data. More details on how the synthetic initial slot allocation dataset was generated and its content can be found in https://doi.org/10.17635/lancaster/researchdata/634.

The second set of data used for the calculation of the IATA connectivity indices and betweenness centrality measures contains data on the flights operated during the summer scheduling season of 2019, i.e., between 31 March 2019 and 26 October 2019. This information was obtained from the database of Brazil's National Civil Aviation Agency (ANAC, 2021) through the R package, **flightsbr**, which was developed by the Institute for Applied Economic Research (Ipea), Brazil (Pereira, R.H.M., 2022). The calculated IATA connectivity indices and betweenness centrality measures used in the computational study can be found in https://doi.org/10.17635/lancaster/researchdata/634.

Note that, our model follows the most recent IATA WSGA, which assigns the highest priority to the satisfaction of the historic slots, then establishing a slot pool of all other requests that includes new entrant requests, non-new-entrant requests, and requests for changes to historic slots, which are treated holistically (IATA, 2021a). Therefore, we first allocate slots to the historic requests, update the coordination parameters accordingly, then all other requests are optimized at the same time. Regarding the capacity constraints, although the model is able to capture the capacity limits on a rolling-time basis, the capacities are declared for each hour in the data. Therefore, the number of movements is restricted for an hourly basis.

5.1. Calculation of the connectivity metrics

Using the flight data obtained from the database of Brazil's Civil Aviation Agency (ANAC, 2021), we construct a directed weighted network, where the arc weights are assumed to be the total number of flights in the considered season. As discussed in Appendix A, the distance of an arc, i.e., the convenience of using that connection, is calculated as the reverse of the weight, and the most convenient path between each airport is calculated using these distance measures. Then the betweenness centrality measures are calculated using Eq. (A1). For the IATA connectivity index, the number of outbound seats between each airport is calculated using the flights in the considered season. To calculate the weight of an airport, which is originally the annual number of passengers handled at that airport, we again use the information of the flights between the airports in the dataset, i.e., only the passengers coming from or going to an airport in the dataset are included in the calculation. Then the IATA connectivity index is calculated using Eq. (1).

Fig. 1 illustrates the normalized IATA connectivity indices and betweenness centrality measures for the network of airports under consideration. Because the betweenness centrality is based on whether an airport is on the "shortest paths" between other airport pairs,

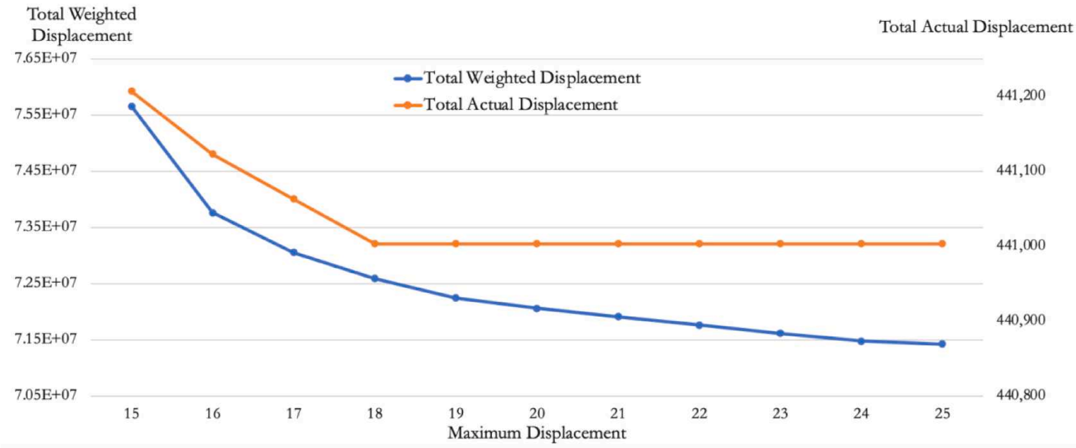


Fig. 2. Trade-off between total and maximum displacement when using betweenness centrality measures.

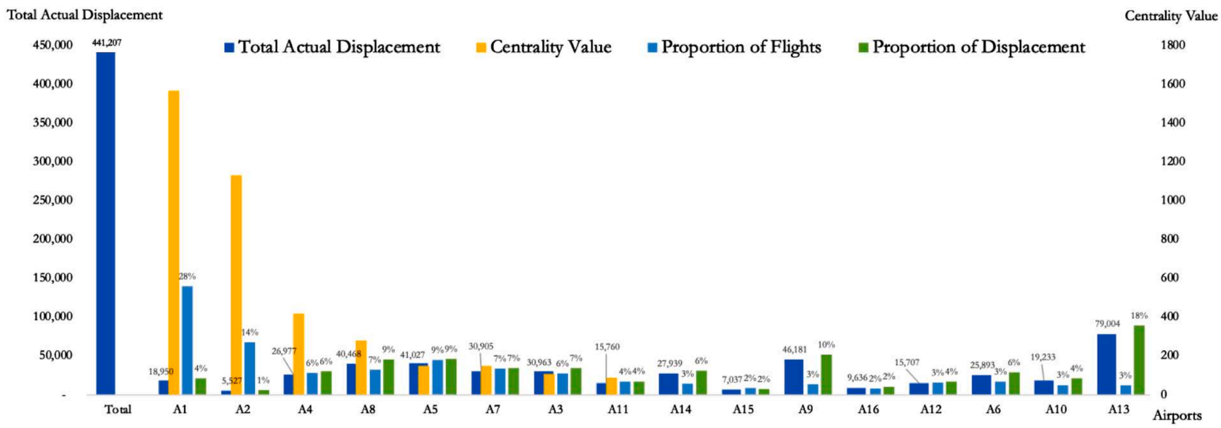


Fig. 3. Distribution of total actual displacement among the airports.

some airports, which are not part of the "shortest paths" in the network, may have zero betweenness centrality value. In fact, many of the coordinated airports have zero betweenness centrality measure value, whereas some non-coordinated airports have positive values. This supports our approach of considering the centrality values of both airports in weighting the displacement of a request. For example, for a departure flight going from a Level 3 airport to a Level 1 airport, the model gives more importance to that flight if it goes to an airport with higher centrality value compared to another airport with lower centrality value. Therefore, to take into account the displacement of slots at the airports with "0" centrality value, we assign a very small centrality value to these airports.

5.2. Results

This section presents the results of the proposed models for studying trade-offs between total and maximum displacement, as well as between total displacement and inter-airline fairness. For both models, the following three variants are examined: i) flight displacements are weighted using the betweenness centrality index of each airport ii) flight displacements are weighted using the IATA connectivity index of each airport, and iii) flight displacements are not weighted, i.e., the actual (unweighted) total displacement is minimized. To identify these variants, we use in the model title the acronyms BC, IC, and UW, to signify the model variant that uses betweenness centrality measures, IATA connectivity indices, and unweighted displacements, respectively. The coordination time interval is assumed 5 min. The models are solved by CPLEX 12.10 solver on a workstation with Intel Xeon E5 2.60 GHz processor and 32 GB RAM using the default settings.

5.2.1. Results of NL-SAM/MTD: maximum – total displacement trade-off

In this section, we present the results of the three variants of the NL-SAM/MTD model.

5.2.1.1. Results of NL-SAM/MTD/BC: using betweenness centrality measures. In this variant of the proposed model, we use the

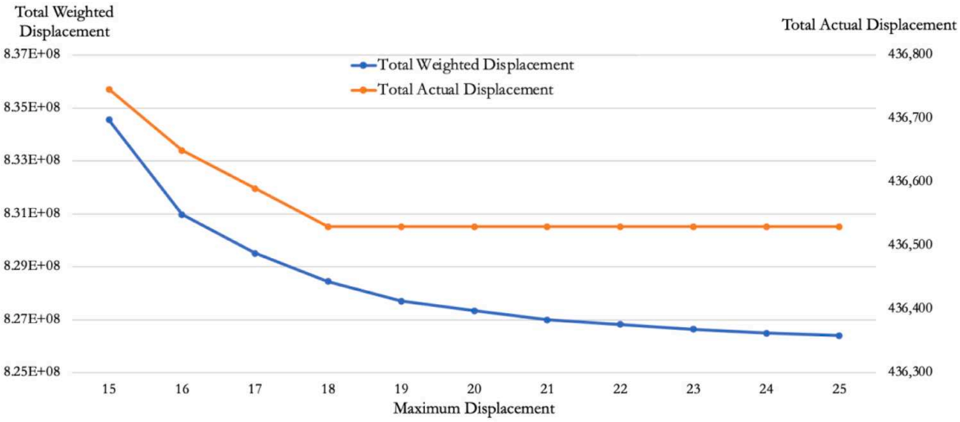


Fig. 4. Trade-off between total and maximum displacement when using IATA connectivity indices.

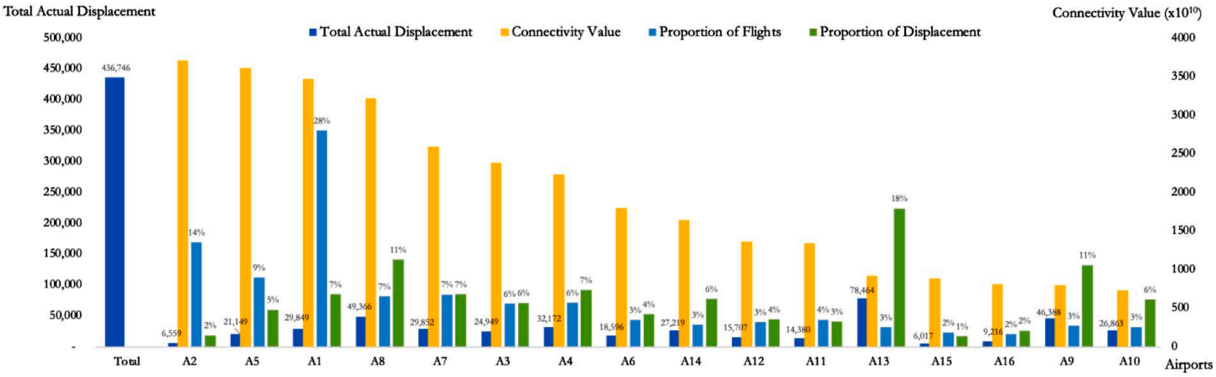


Fig. 5. Distribution of total actual displacement among the airports.

betweenness centrality measures, b_i, in calculating the coefficients c_m, as explained in Section 3.2.2.1. The relationship between the maximum and total displacement is depicted in Fig. 2, where the displacements are expressed in 5 min intervals. We also report the associated unweighted displacements of these solutions of NL-SAM/MTD/BC, which are the actual displacement values obtained by summing up the displacements all flights receive in the corresponding solution. The average computational time required to achieve these optimal solutions is 317.2 s.

We observe that as the value of the maximum allowable displacement increases, both weighted and unweighted total displacements decrease. However, when the maximum displacement value is greater than 18 (five-minute intervals, i.e., 90 min), the value of the actual total displacement remains constant. From Fig. 2, we can also infer that there is no strong trade-off between total and maximum displacement. Specifically, a 20% increase in maximum displacement (from 15 to 18 5-minute intervals) produces only a 0.05% improvement in the total actual displacement.

We further analyze the solution with maximum displacement of 15, 5-minute intervals to identify potential patterns regarding the distribution of displacement among the airports.

Fig. 3 shows the distribution of the total actual displacement among the airports along with the proportion of flights operated in these airports, the proportion of total displacement associated with each airport, and the centrality values for each airport. It is evident that the two airports with the highest betweenness centrality values (A1, A2) receive a much lower percentage of actual total displacement as compared to the percentage of the flights operated in these two airports.

5.2.1.2. Results of NL-SAM/MTD/IC: using IATA connectivity indices. In this variant of the model, we use the IATA connectivity indices, ICI_i, for calculating the c_m coefficients. Fig. 4 shows the efficient frontier between maximum and total displacements as well as the actual total displacement values of the corresponding solutions. The optimal solutions are obtained in 314.2 s, on average.

We observe a similar behavior with the solutions obtained when betweenness centrality measures are used. The trade-off between maximum and total displacements again is not very pronounced. Therefore, we again select the solution with the maximum displacement of 15 to analyze the details on airport level, which are illustrated in Fig. 5.

Regarding the distribution of total displacement among the various airports, we observe that the airports with the three highest IATA connectivity values (A2, A5, A1) receive a much lower percentage of actual total displacement as compared to the percentage of

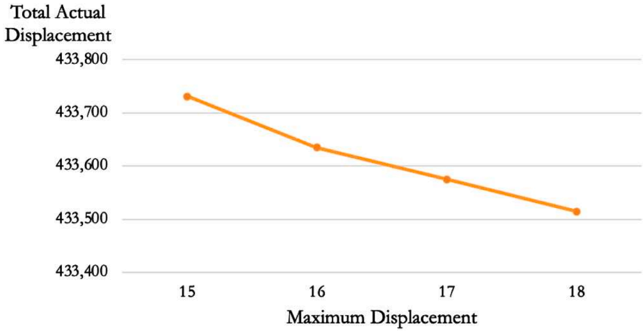


Fig. 6. Trade-off between total and maximum displacement when connectivity metrics are not used.

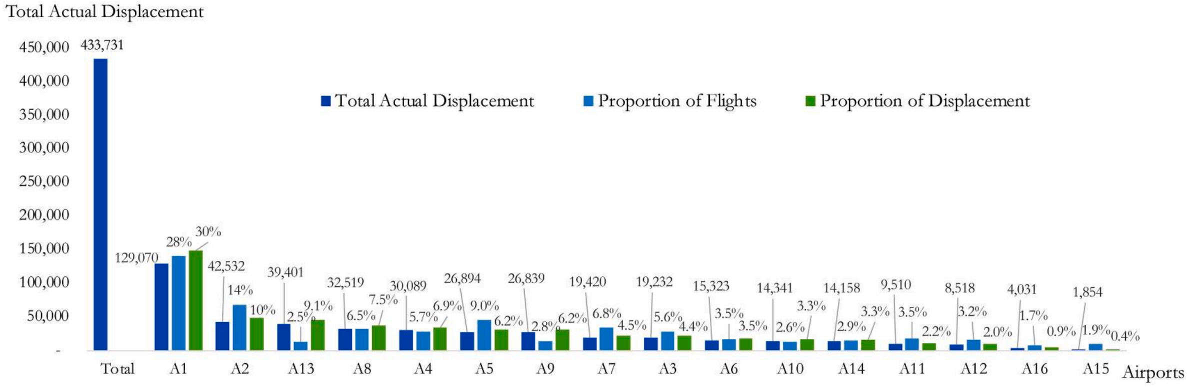


Fig. 7. Distribution of total actual displacement among the airports.

Table 3
Comparison of proportion of flights and proportion of displacement at each airport for each model.

Airports in decreasing order of BC	% Flights	% Displacement		
		NL-SAM/MTD/BC	NL-SAM/MTD/IC	NL-SAM/MTD/UW
A1	**28.1%**	**4.3%**	**6.8%**	**29.8%**
A2	**13.6%**	**1.3%**	**1.5%**	**9.8%**
A4	**5.7%**	**6.1%**	**7.4%**	**6.9%**
A8	6.5%	9.2%	11.3%	7.5%
A5	**9.0%**	**9.3%**	**4.8%**	**6.2%**
A7	6.8%	7.0%	6.8%	4.5%
A3	5.6%	7.0%	5.7%	4.4%
A11	3.5%	3.6%	3.3%	2.2%
A14	2.9%	6.3%	6.2%	3.3%
A15	1.9%	1.6%	1.4%	0.4%
A9	2.8%	10.5%	10.6%	6.2%
A16	1.7%	2.2%	2.1%	0.9%
A12	3.2%	3.6%	3.6%	2.0%
A6	3.5%	5.9%	4.3%	3.5%
A10	2.6%	4.4%	6.2%	3.3%
A13	2.5%	17.9%	18.0%	9.1%

the flights operated in these three airports.

5.2.1.3. Results of NL-SAM/MTD/UW: without considering connectivity metrics. In this subsection, we present the solutions obtained by solving the model without weighting the displacements, i.e., the trade-off between the maximum and actual total displacements is investigated. The efficient frontier is depicted in Fig. 6.

The average computational time for these solutions is 332.4 s. As shown in Fig. 6, although the trade-off between two objectives is not strong, similar to the previous cases, the extreme points of the efficient frontier are attained when the maximum displacement is 15 and 18. Furthermore, the distribution of the total displacement, as shown in Fig. 7, is quite different than those obtained in the previous

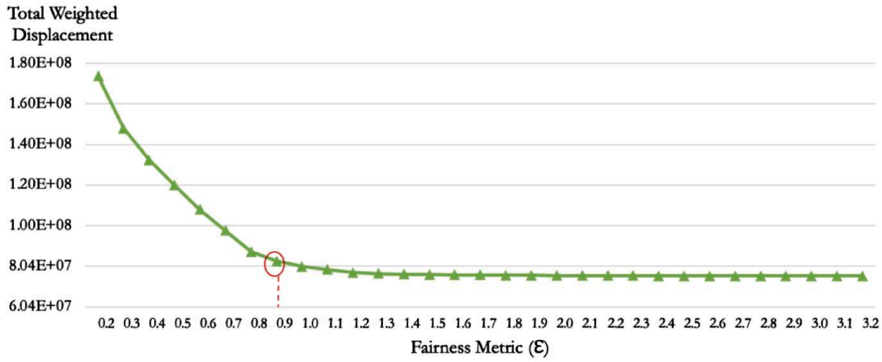
Table 4
Displacement per displaced flight at each airport for the solutions with maximum displacement of 15 for each model.

Airport	NL-SAM/MTD/BC	NL-SAM/MTD/IC	NL-SAM/MTD/UW
A1	2.57	2.35	3.07
A2	1.82	1.73	1.90
A3	3.45	3.47	3.13
A4	2.45	2.67	2.72
A5	1.93	1.49	1.71
A6	3.55	2.94	2.98
A7	1.73	1.72	1.81
A8	3.45	3.69	3.34
A9	10.44	11.43	7.33
A10	4.12	5.00	4.60
A11	1.64	1.68	1.82
A12	2.40	2.40	2.11
A13	11.86	11.94	8.81
A14	3.55	3.45	2.73
A15	1.88	1.96	1.53
A16	2.07	2.17	1.54
Variance	**9.18**	**10.46**	**4.36**

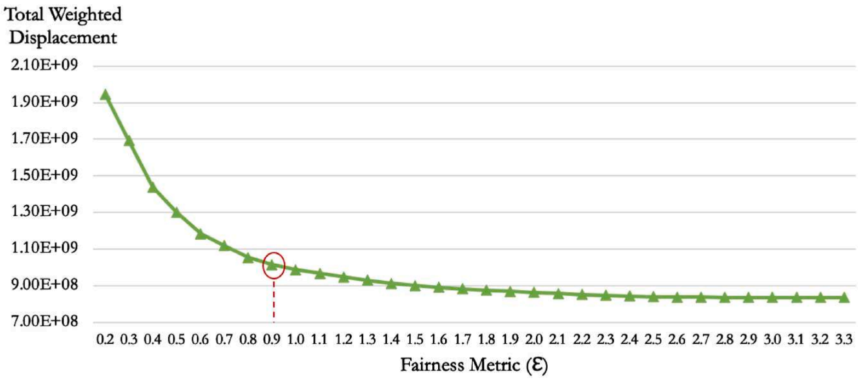
two variants. In this model variant we observe that due to the fact that all airports are treated equally, i.e., no betweenness centrality or IATA connectivity coefficients are used, the airports with the highest betweenness centrality (A1, A2) and IATA connectivity indices (A2, A5, A1) are not "protected" in terms of the allocation of displacement.

5.2.1.4. Comparison of different model variants. In this section, we compare the three model variants discussed above, i.e., NL-SAM/MTD/BC, NL-SAM/MTD/IC and NL-SAM/MTD/UW. It is clear that, all cases have very similar total actual displacement values, with the solution of Variant 3, which does not use connectivity or centrality metrics, having the best value. The results of Variants 1 and 2, where displacements are weighted using the betweenness centrality measures and IATA connectivity indices, respectively, have 1.7% and 0.7% higher total un-weighted displacement as compared to the total un-weighted displacement of Variant 3. It is worth mentioning that there is not a strong trade-off between the total and maximum displacement values in all variants. On the other hand, there is a clear difference between these variants in terms of how the proportion of displacement values are distributed among the airports. In Table 3, the airports are listed in decreasing order of their betweenness centrality values in the first column, the second column reports percentage of flights corresponding to each airport and the following columns present the percentage of displacement received by the flights operated at the airports in each model variant, based on the solutions with maximum displacement of 15 slots. It is observed that the two most central airports A1, A2, experience an increase of the percentage actual (unweighted) displacement in the unweighted model as compared to the percentage actual displacement of the models using betweenness centrality values; while A1, A2 and A5 experience an increase in the allocated percentage of actual displacement in the unweighted model as compared to the model using IATA indices. The rest of the airports have in the unweighted model less or equal percent displacement as compared to the weighted models. Therefore, one can argue that the weighted models are "protecting" the airports (A1, A2), and (A1, A2, A5) that play an important role in the functioning of the network in terms of centrality and connectivity respectively, by transferring the displacement to less central or less connected airports. Furthermore, as Table 4 suggests, in the unweighted model the distribution of the displacements per displaced request has smaller variability, indicating a fairer distribution of displacement among the airports.

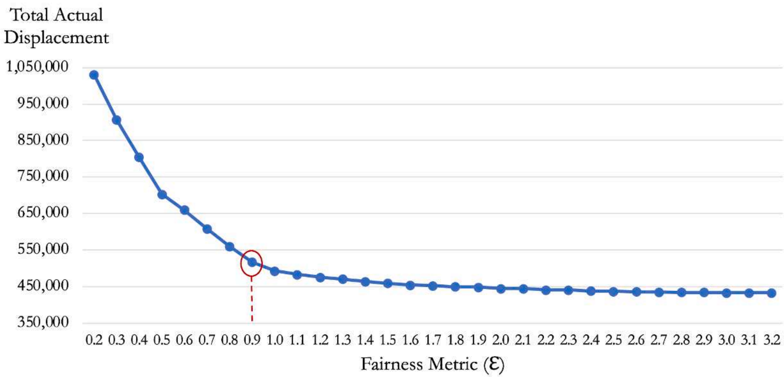
These comparisons shed light on the decision making process with respect to different decision making preferences. If the decision makers seek to develop a schedule that minimizes the total actual displacement and are indifferent on how this total displacement is distributed among the airports in the network under consideration, then the variant 3, the one that does not consider the connectivity metrics of the airports, is more appropriate to be used as it generates slightly lower displacement (1.7% and 0.7% for variant 1 and 2, respectively) as compared to the other two variants. However, if the decision makers want to influence the distribution of displacement of the flights throughout the network, i.e., to assign proportionally less displacement to airports that exhibit high betweenness centrality (A1, A2) or high IATA connectivity (A1, A2, A5), then the variants 1 and 2, respectively are more preferable. The choice of the measure expressing the airport importance to be used also depends on the decision makers' preferences, as different measures of connectivity may capture different aspects of connectivity such as travel time, travel cost, the number of connections, the number of destinations served, frequency of flights, etc. (IATA, 2020). The IATA connectivity index is an extension to the degree centrality measure, which represents the importance of an airport in terms of its local centrality. It reflects the extent an airport is connected to the rest of the air transport network in terms of the number of passengers departing from that airport. Therefore, it is suitable for a decision making policy which prioritizes the airports with frequent flights to many destinations. On the other hand, betweenness centrality is a measure of global centrality, i.e., it shows how well an airport connects other airports in the network. It also identifies the airports, whose isolation, including closure of those airports as well as operational disruptions at those airports, is most critical to the robustness of the air transport network in terms of its resilience to these failures (Lordan et al., 2014). Therefore, for a decision policy which gives a higher importance to the connectivity of the airports with the others, to the convenience of self-connecting passengers as well as to the network stability, using betweenness centrality measures is more appropriate.



a. Betweenness centrality measures are used



b. IATA connectivity indices are used



c. Connectivity metrics are not used

Fig. 8. Efficient frontiers for the fairness and total displacement trade-off.

5.2.2. *Results of NL-SAM/FTD: fairness – total displacement trade-off*

This subsection investigates the trade-off between the total displacement and inter-airline fairness measured by the fairness objective presented in Section 3.2.2.3. Again, we perform three sets of experiments using the corresponding versions of the NL-SAM. We solve the models allowing a maximum of 15 5-minute intervals, which is the minimum value of the maximum displacement for all variants. The step size to update ε at each iteration of the ε-constraint method, δ, is assumed 0.1 as in Katsigiannis et al. (2021). Note that, a time limit of 7200 s is applied for these experiments as adding the fairness constraints increases the complexity of the problem and the time required to find the optimal solution was hours. Therefore, the solutions reported are the best bounds obtained after 2 h. Fig. 8 shows the trade-offs between fairness and total displacement for each variant. The red circles indicate the knee points of the corresponding curves. This is the point of diminishing returns in terms of total displacement savings, i.e., huge sacrifices in fairness produce insignificant total displacement gains. In all variants, there is a stronger trade-off between two objectives in this model,

Table 5
Distribution of total displacement among airlines.

Airlines	Betweenness centrality measures	IATA connectivity indices	Without connectivity indices
R23	125,477	125,117	125,057
R6	123,811	122,596	121,441
R20	118,533	116,067	115,647
R30	62,886	62,466	61,626
R29	7050	7050	6510
R35	3240	3240	3240
R39	150	150	150
R55	60	60	60

Table 6
Comparison of proportion of flights and displacement at each airport for each model.

Airports in decreasing order of BC	% flights		% Displacement	
		NL-SAM/FTD/BC	NL-SAM/FTD/IC	NL-SAM/FTD/UW
A1	**28.1%**	**2.4%**	**10.5%**	**38.1%**
A2	**13.6%**	**0.7%**	**1.8%**	**11.7%**
A4	**5.7%**	**3.4%**	**6.4%**	**6.4%**
A8	**6.5%**	**5.3%**	**10.2%**	**7.7%**
A5	**9.0%**	**5.0%**	**4.0%**	**6.0%**
A7	6.8%	5.1%	6.5%	4.5%
A3	5.6%	6.2%	5.4%	3.4%
A11	3.5%	2.7%	3.6%	3.2%
A14	2.9%	7.9%	5.3%	2.9%
A15	1.9%	4.9%	1.2%	0.3%
A9	2.8%	12.0%	12.5%	2.7%
A16	1.7%	1.9%	1.9%	1.2%
A12	3.2%	4.4%	3.1%	1.4%
A6	3.5%	12.0%	4.0%	3.5%
A10	2.6%	11.6%	8.5%	3.4%
A13	2.5%	14.3%	15.1%	3.4%

compared to the NL-SAM/MTD model.

The details from the comparison of the solutions attained at the knee points, which represent a good compromise in terms of fairness and total displacement, and at the optimal total displacement points are discussed below.

5.2.2.1. Results of NL-SAM/FTD/BC: using betweenness centrality measures. When the betweenness centrality measures are used as coefficients, 72% improvement in the fairness metric, from 3.2 to 0.9, results in 82.9% deterioration in total actual displacement from 441,207 to 807,052.

It is worth noting that at the optimal total displacement point, the displacements are shared only by 8 airlines, while the remaining 47 airlines receive no displacement. On the other hand, at the knee point, the fairness metric takes value of 0.9 and 32 airlines share the total displacement. Clearly, a significant sacrifice of total actual displacement is needed to have a fairer allocation, while at the same time the flights of 32 out of the 55 airlines in the network are displaced.

5.2.2.2. Results of NL-SAM/FTD/IC: using IATA connectivity indices. In this variant, we are using the IATA connectivity index to weight the displacements at each airport. Comparing the solutions obtained at the knee point, where the fairness metric is 0.9, and at the optimal total weighted displacement point, 72% improvement in fairness metric deteriorates the total actual displacement by 19.1% from 436,746 to 520,021. While in the former solution all 55 airlines receive some displacement, at the optimal total displacement point, only 8 airlines are allocated a displacement, which are the same airlines in the NL-SAM/FTD/BC model.

5.2.2.3. Results of NL-SAM/FTD/UW: without considering connectivity metrics. When neither of the connectivity metrics are used in the objective function, the knee point of the fairness-displacement curve corresponds to a fairness metric value of 0.9 and to a total actual displacement of 515,650, which represents 18.9% deterioration (increase in displacement) as compared to the value of the actual displacement at the optimal displacement point. The displacements are again distributed to 8 airlines, which coincide with the airlines which experience displacement of their flights in the previous models, while in the solution that corresponds to the knee point of the displacement-fairness curve the flights of all 55 airlines are displaced.

5.2.2.4. Comparison of different variants. In this part, we discuss the three model variants NL-SAM/FTD/BC, NL-SAM/FTD/IC and NL-SAM/FTD/UW. Considering the solutions attained at the optimal total displacement points, when the connectivity metrics are used, the more central airports are allocated proportionally less displacement, while in the model that does not differentiate the airports according to their importance in the functioning of the network (un-weighted displacement model), the more central and more connected airports are not "protected". In all cases the airlines have very similar total actual displacement values, which is summarized in Table 5. On the other hand, these are distributed among the airports very differently. For example, for the airline R23, when betweenness centrality measures are used, 2% and 3% of the total displacement allocated to this airline are shared by its flights operated at A1 and A2, which are the first two airports with the highest betweenness centrality values, respectively. On the other hand, these airports are allocated 23% and 24% of the total displacement, respectively, when connectivity metrics are not used. Similarly, when IATA connectivity indices are used, A2 and A1, having the first and third highest connectivity values, receive 3.6% and 4.2% of the total displacement allocated to R23, respectively. This observation, i.e., that the percent displacement of the airlines allocated to the airports with high betweenness centrality and high connectivity, A1 and A2, is increasing significantly in the case of the NL-SAM/FTD/UW as compared to other models, holds for the remaining three airlines R6, R20, and R30, which along with R23, collectively represent 90% of the flights in the network.

It is worth noting that the average displacement per displaced flight for the same fairness level differ among the three model variants, i.e., at the solutions obtained at the knee points, it is 4.9, 3.5 and 3.2 for the models using betweenness centrality and IATA connectivity, and for that not using these metrics. However, the model variants that take into account the connectivity of the airports in the form of the IATA index or the betweenness centrality measure allocates proportionally less displacement to the flights operated at airports that play an important role on the network connectivity, and consequently protects the passengers that have connected flights through these airports. Table 6 presents for each airport, its proportion of flights and the proportion of displacement it is allocated at the solutions attained at the knee points in each model variant. A similar behavior to that in NL-SAM/MTD models is observed here. When using betweenness centrality values, the two airports with the highest centrality values, i.e., A1 and A2, are allocated proportionally less displacement compared to the model that does not weight the displacements. Similarly, when using IATA connectivity metrics, A1, A2 and A5 have proportionally less displacement, while for the other airports, the unweighted model has less percentage values. Therefore, one can argue that the displacement in the network is pushed to the less central or less connected airports. Stated otherwise, the choice of the models that weights displacement with any of the two connectivity indices is more beneficial for the passengers transferring through these airports, but these choices deteriorate the overall system efficiency compared to the model that does not consider the connectivity of the airports.

Therefore, one conclusion emerging from these results is that the NL-SAM/FTD/UW model is more suitable when the decision policy does not seek to influence the distribution of total displacement among the airports. On the other hand, for a policy which gives a higher importance to the airports that play important role in functioning of the network, using these metrics, i.e., betweenness centrality is more suitable. Similar to the NL-SAM/MTD models, the selection of the connectivity metric in NL-SAM/FTD models also depends on the decision making criteria. If the decision makers would like to favor the airports, which play an important hub role to connect several airports, i.e., with high betweenness centrality values, then using the model NL-SAM/FTD/BC would result in the desirable outcome. Similarly, if it is desired that the airports with dense connections with several airports, offering many flights from and to several locations, i.e., with high IATA connectivity indices, are favored, then using NL-SAM/FTD/IC would produce this outcome. However, both models sacrifice from the actual displacement each flight receives when considering the fairness. Therefore, if the airports are not to be differentiated, then the most suitable model is NL-SAM/FTD/UW to achieve both the fairness between the airlines and a lower average displacement per displaced flight.

6. Conclusions

In this study, we have developed and solved two bi-objective models for allocating slots for a network of airports. The overall aim is to construct a solution with minimum deviation from the initial schedules resulted from the allocation of slots at individual airports by considering the importance of the airports in the functioning of the network. We expressed the importance of the airports through the consideration of two metrics, namely the betweenness centrality measure and the connectivity index proposed by IATA. The former considers the importance of the airports in ensuring connectivity with other pairs of airports in the network, whereas the latter gives higher importance to the airports with many outgoing flights to destination airports that handle many flights. We used these metrics as coefficients to weight the displacements in the objective function such that the displacements are encouraged to be distributed among the airports with low effect in the network. We have also formulated a model that does not consider the importance of the airports in the functioning of the network, which provides a more equitable distribution of the schedule adjustments among the airports. We then investigated the trade-off between the total weighted displacement and both the maximum actual displacement and the fairness among the airlines. The ε-constraint method was used to solve the proposed bi-objective models.

We performed an extensive computational study using a synthetic data from the domestic Brazilian air network. The case study results have demonstrated that using the connectivity metrics has a major effect on the distribution of the total displacement among the airports although the network-wide total displacement itself is not affected significantly. The distribution of the displacements among the airports changes dramatically depending on the connectivity metric used. Our analysis regarding the use of inter-flight fairness suggests that there is no strong trade-off between total displacement and inter-flight fairness. This means that a fairer network-wide schedule can be produced without sacrificing the efficiency of the allocation expressed through the minimization of the total displacement. When the connectivity indices are considered along with the inter-airline fairness, we observe a strong trade-off between fairness and the total weighted displacement. The results of the case study suggest that the airports with the highest centrality and connectivity values receive proportionally less total displacement with respect to the number of flights they operate. Therefore, connectivity values can be used to steer the solutions to the desired direction. Which metric to use in the modelling depends on the decision makers' strategy regarding the importance of the airports in the network. A decision policy which gives higher importance to the airports serving as hubs between many airports and to maintaining the resilience of the network against possible interruptions may use betweenness centrality measures. However, if the decision makers require that the airports with higher traffic volume to several destinations receive less displacement, then IATA connectivity measures may be used.

The presented results relate to the case study under consideration. Further research is needed to provide additional empirical evidence of the patterns regarding the distribution of displacement among airports and airlines. Future work may incorporate the preferences of airlines regarding the allocation of their schedule displacement to different flights at different airports. Furthermore, additional metrics expressing the importance of the airports in the functioning of the air transport network can be investigated. More disaggregate passenger-centric metrics can be incorporated in the proposed models to better reflect the passengers' connectivity requirements. One can also embed the connectivity metrics within the optimization problem, e.g., treating them endogenously such that the decisions also affect the connectivity of the network. For example, the model proposed by Birolini et al. (2022) can be used for the initial slot allocation at the individual airports, and at the second level our proposed model with appropriate maximum acceptable displacement constraints, similar to those introduced in Zografos et al. (2018) or the Timing Flexibility Indicator (TFI) introduced in Katsigiannis and Zografos (2021), can be used to optimally adjust the initial single airport allocations to produce optimum network wide slot allocations. In addition, investigating a larger network could bring more insights to the addressed problem. In this direction the development of efficient heuristics provides a fruitful direction for future research.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Acknowledgments

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Appendix A. Calculation of Betweenness Centrality

Let g_{jk} and $g_{jk}(i)$ be the number of shortest paths between airports $j \in A$ and $k \in A$, and among these shortest paths, the number of those passing from airport $i \in A$, respectively. Then the betweenness centrality of airport i, can be defined as follows:

$$b_i = \sum_{j,k \in A | j,k \neq i} \frac{g_{jk}(i)}{g_{jk}} \tag{A1}$$

In the air transport network, vertices and edges represent the airports, and the connections between the airports by non-stop flights, respectively. Early studies represent the links as binary states, i.e., the airports are either connected or not (Barrat et al., 2004). However, the relationship between two airports is much more complex than being simply connected to each other. For example, if there are five flights per week between airports A and B, and only one flight between airports A and C, one could argue that the relationship between A and B is much stronger than that between A and C. Similarly, if the number of total available seats per week is 200 and 100 between A and B and A and C, respectively, then one could again argue that having more seats is a sign of a stronger relationship, and the connection between A and B is stronger than that between A and C. Therefore, the edges can be associated with different attributes which represent the relationship between the vertices they connect, so they can be weighted.

In a binary network, the shortest path between two nodes is the path with minimum number of edges linking these nodes, and total

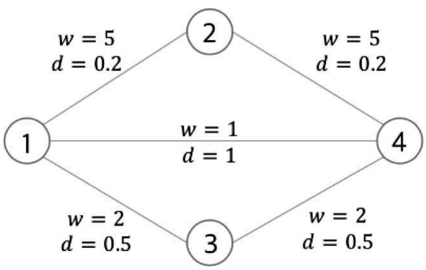

Fig. A1. Illustration of alternative connections in a small network of four airports.

distance of the shortest path is the number of edges on this path. However, the air transport network is indeed a weighted network, as each connection is different. This difference could be defined using several measures, including total number of flights or total number of available seats in a season, flight time, etc. In this study, we assume the edge weight as the total number of flights in the scheduling season. Then, one needs to define the distances of the edges. Here, we assume that the distance of an edge is the reverse of its weight. For instance, if the weight of an edge is 10, then its distance could be assigned as 0.1. Therefore, the links that provide more flights in a season constitute "shorter paths". Note that length of an arc or distance here is used as a measure expressing the convenience offered by different airports. The "shortest path" can be interpreted as the most convenient way of getting connected, and therefore it should not be confused with the shortest path in terms of physical distance. Fig. A1 illustrates a small network of 4 airports, where the edges have different weights, denoted with w, and different lengths, denoted with d. For a passenger who wants to travel from 1 to 4, there are three possible paths. Although there is a direct flight, its frequency is low compared to the flights on other two paths. Among these two paths, 1–2-4 is the one offering the most frequent flights. Therefore, this path is the most convenient among others, in terms of the number of available flights throughout the season, with an imaginary "total distance" of 0.4. In our calculations, we use this approach to find the shortest paths between airports.

Appendix B. Details of the Numerical Instance

Fig. B1 illustrates the structure of the network consisting of 16 airports considered in our problem, where an arc between a pair of these airports is created if a flight is operated between them. Note that, the nodes representing the locations of some airports are slightly relocated compared to their real locations so that the arcs are more visible.

Table B1 lists the number of requested series for each airport in the dataset. All numbers are accompanied by the corresponding number of flights in the parentheses. Furthermore, the number of requested series between the coordinated and facilitated airports is 2908, which corresponds to 149,583 flights.

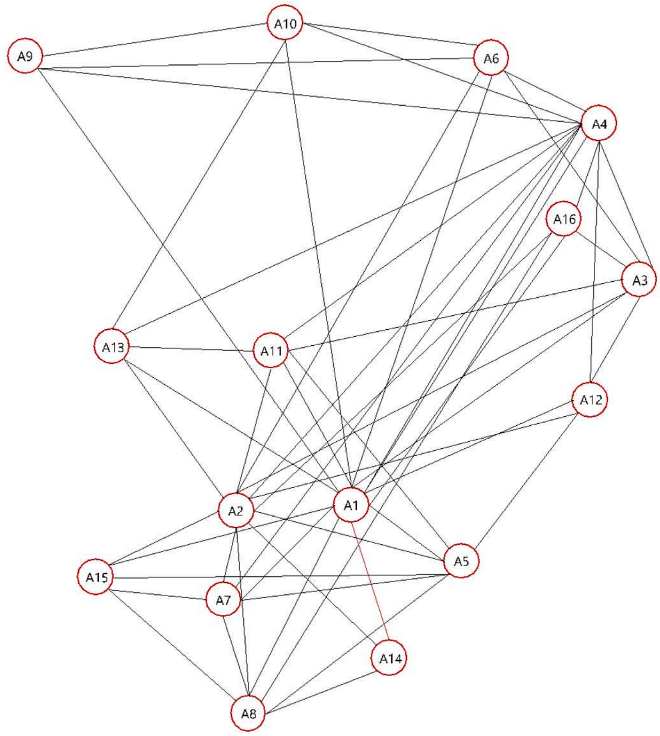

Fig. B1. Illustration of the network used in the computational study.

Table B1
Details of slot requests for each airport in the synthetic dataset.

Airports	Historic slots	Other slots in the slot pool	Total
A1	504 (44,011)	1236 (134,006)	1740 (178,017)
A2	334 (32,611)	573 (64,918)	907 (97,529)
A3	137 (6657)	427 (26,886)	564 (33,543)
A4	156 (12,622)	317 (27,399)	473 (40,021)
A5	78 (6991)	383 (43,096)	461 (50,087)
A6	101 (4191)	299 (16,669)	400 (20,860)
A7	62 (4861)	340 (32,516)	402 (37,377)
A8	61 (4925)	288 (31,272)	349 (36,197)
A9	108 (5726)	172 (13,274)	280 (19,000)
A10	57 (5066)	166 (12,386)	223 (17,452)
A11	17 (2370)	191 (16,881)	208 (19,251)
A12	21 (1543)	162 (15,339)	183 (16,882)
A13	40 (4554)	132 (12,109)	172 (16,663)
A14	27 (2828)	124 (13,918)	151 (16,746)
A15	6 (480)	105 (8926)	111 (9406)
A16	10 (964)	93 (7893)	103 (8857)

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