Being Fair or Efficient?
A Fairness-driven Modeling Extension to the Strategic Airport Slot Scheduling Problem

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Abstract

An increasing thrust of research has recently explored scheduling methods and models with a view to allocating efficiently scarce airport slots among competing airlines, a problem also known as strategic airport slot scheduling. Existing models have mainly placed the research focus on scheduling efficiency objectives, while it was only recently that fairness considerations were introduced in relevant literature. Borrowing principles from congestion pricing, our paper capitalizes on the conjecture that the intensity of congestion and delay phenomena are strongly affected not only by the demand volumes but also the temporal distribution and peaking characteristics of demand. Hence, we propose a fairness-informed extension of the strategic airport slot scheduling model aiming to ensure that each airline absorbs its "fair share" of congestion in the form of additional schedule displacement exerted onto other competing users. The results of the proposed model are demonstrated and validated in two IATA schedule coordinated airports in Portugal and Greece. The newly proposed fairness weights penalize mostly the "big contributors to congestion", assigning them with higher displacement weights on the basis of "the contributor pays" principle. Furthermore, we assess the "cost of fairness" by quantifying the impacts of fairness-driven scheduling on efficiency and various Level of Service indicators. The main findings of our research suggest that the adoption of the proposed fairness-driven scheduling approach may come at reasonable "cost" particularly at low or moderate fairness levels as compared to the previous "fairness indifferent" case.

Keywords: airport scheduling, slot allocation, schedule displacement, fairness

1. Introduction

Airports constitute critical nodes of the entire air transport system that are called to serve the steadily growing air transport operations and deal occasionally with severe network disruptions. This often triggers operational problems with aggravated propagation effects across the network (and vice versa) that are eventually reflected on manifold aspects of performance degradation of the ATM system. European (ECAC) flights increased by 2.8% in 2016 to 10.2 million flights, reaching pre-crisis 2008 traffic levels (Eurocontrol, 2017). At the same time, annual average all-cause departure delay amounted to 11.3 minutes per flight in ECAC region for 2016, while airline arrival punctuality decreased to 81% of flights arriving within 15 minutes or earlier than scheduled. Traffic forecasts illustrate bleak future prospects in terms of capacity pressures, congestion and level of service challenges for the entire air transport system. European congested airports operating at 80% or more of their capacity for more than 3 hours per day will increase from 6 airports in 2012 to 30 airports in 2035 for the most-likely traffic scenario (Eurocontrol, 2013). Under such future congestion levels, growing delay challenges will be experienced by an increasing number of airports especially during summer or external disturbances (e.g., weather disruption). This will, in turn, affect the system's ability to recover from disrupted states or even accommodating minor deviations from plan without rapidly accumulating delays, flight cancellations and unaccommodated demand.

The air transport industry has traditionally pursued three different, interdependent though, demand and capacity interventions (Jacquillat and Odoni, 2018): i) increasing capacity through new airport development or capacity expansion projects, ii) operational improvements or technological enhancements and iii) demand management interventions. Due to increasing physical limitations and safety considerations around the deteriorating gap between growing demand and available capacity, demand management interventions have been brought forward in practice and extensively studied by the research community during the last decade as an immediate, low-cost, sustainable solution to control over-capacity scheduling at congested airports during busy times or days. For a more detailed discussion of the capacity notions, key drivers and determinants, as well as capacity and operational delays modeling, the reader may also refer to Jacquillat and Odoni (2018) and Zografos *et al.* (2017).

Demand management interventions, being the broader subject of research addressed in this paper, cover a large variety of measures, instruments or rules aiming to manage the spatial and/or temporal profile of traffic and control access to congested airports or peak times either at operational (typically during the day of actual operations) or strategic level (few months before actual operations). The latter typically fall into three categories of interventions (or combinations thereof). First, schedule coordination measures (applied at airports worldwide outside the United States) set scheduling limits and control congestion by means of a complicated set of administrative rules and priorities (IATA, 2014). Second, congestion pricing has been the subject of extensive and long-standing transportation demand management research suggesting time-varying fee schemes as a self-controlling economic mechanism for airlines (or other transportation users) operating on the basis of levied congestion fees (Carlin and Park, 1970; Brueckner, 2002; Morrison and Winston, 2007). Third, market-based measures specify the capacity available for allocation and

invite competing users to reveal their valuations and bid for securing access to congested airports through different mechanisms, with the most popular in relevant research being the auctioning of part or the entire capacity, as well as primary and secondary trading. Market-based measures have received a great deal of consideration by both policy makers and researchers (NERA 2004; Ball *et al.*, 2006; Madas and Zografos, 2006; Mott MacDonald, 2006; Steer Davies Gleave, 2011). However, technical implementation difficulties, incompatibilities with the existing regulatory framework or even resistance from established industry players did not allow them to flourish into practice. As of today, market-based measures have been mainly examined as a supplementary (secondary allocation) mechanism to the primary allocation mechanism that is currently in place. Such hybrid schemes allocate a fixed amount of capacity with view to administrative rules and priorities (primary allocation), while secondarily introducing auctions or secondary trading to allocate the remaining capacity or adjust/correct inefficiencies of the initial allocation process (Steer Davies Gleave, 2011; Pellegrini *et al.*, 2012).

During the last decade or so, there has been an increasing thrust of research (Zografos *et al.*, 2017; Jacquillat and Odoni, 2018), within the broader area usually known as strategic airport slot allocation or scheduling, focusing directly on the mitigation of congestion well before the latter materializes at the day of operations. Relevant research efforts explore scheduling methods and pursue different modeling representations or extensions of the current IATA-based slot allocation framework (IATA, 2014). The strategic airport slot allocation problem aims to optimize the allocation of specific time intervals to the respective airlines' slot requests within a given scheduling season and has been modeled in existing literature with different underlying criteria and objectives. The first generation of models aimed at achieving scheduling efficiency by minimizing the "schedule delay" or "displacement" metric (both are now used interchangeably), a term originally cited by Koesters (2007). Schedule displacement stands for the absolute value of the difference between requested and allocated slot times (Koesters, 2007; Zografos *et al.*, 2012). The schedule displacement imposed on a slot request forces the movements (arrivals or departures) associated with the request under consideration to operate earlier or later than originally requested by that respective displacement amount. Zografos et al. (2012) modeled the strategic, single-airport, deterministic slot scheduling problem allocating requests for series of slots with view to the minimization of schedule delays. Building upon earlier modeling work, later research efforts (Castelli *et al.*, 2011; 2012; Corolli *et al.*, 2014; Pellegrini *et al.*, 2017; Benlic, 2018) enhanced or extended existing slot scheduling models for a network of airports with simultaneous consideration of schedule displacement objectives, with operational delays (Corolli *et al.*, 2014), unsatisfied requests (i.e., "missed allocations") (Pellegrini *et al.*, 2017) or deviations from commercially and operationally ideal pairs of slots (i.e., "shift costs") (Castelli *et al.*, 2012). In the U.S. context, Jacquillat and Odoni (2015) and Pyrgiotis and Odoni (2016) assessed the impact of non-monetary scheduling interventions by adjusting flight schedules based on airlines' requests, capacity utilization and airport on-time performance objectives (e.g., operational delay reduction).

More recent research efforts enriched efficiency objectives with acceptability and fairness considerations. The underlying motivation was that although total schedule displacement, as a primary scheduling objective, promotes the efficient utilization of available capacity, it cannot actually guarantee that the final slot allocation outcome

will be practically acceptable, especially in cases that displacement exceeds certain limits that may eventually jeopardize the operational feasibility and/or commercial viability of the airlines' master schedules. In response to these concerns, a new class of models combined schedule efficiency with acceptability objectives, with the latter being essentially modeled by means of the maximum schedule displacement metric as a proxy measure of the worst-case service level provided to airlines. Zografos *et al.* (2018) investigated the trade-off between scheduling efficiency and acceptability with particular emphasis placed on the minimization of the number of slots that "unacceptably" deviate from their original slot requests (i.e., "violated slot assignments"). Ribeiro et al. (2018) proposed a multi-objective scheduling model involving, *inter alia*, fairness criteria in the form of maximum displacement, as well as the number of rejected and displaced slots. Zografos and Jiang (2019) and Jacquillat and Vaze (2018) proposed fairness-informed modeling formulations postulating that the schedule displacement imposed on each airline should be proportional to the number of requested movements by that specific airline at either IATA schedule coordinated airports or U.S. airports, respectively. Another emerging stream of relevant slot scheduling research lies on the analysis of potential strategic behavior from the airlines that may find opportunities to conceal their actual scheduling preferences in order to reduce the number of their displaced flights (Vaze and Barnhart, 2012) or gain advantage over the competition through slot hoarding (Sheng *et al.*, 2019). In that respect, Castelli *et al.* (2012) introduced a fairness-enriched monetary compensation mechanism aiming to fairly redistribute displacement costs among airlines upon the elimination of historic slot holdings (i.e., grandfather rights).

Recent literature discussed above has shown that there are interesting opportunities for simultaneous consideration of scheduling efficiency with acceptability considerations. Although several fairness-informed modeling formulations of the strategic airport scheduling problem have been addressed in recent literature, these mostly capture alternative variations of the schedule displacement objective such as maximum displacement or the number of displaced slots. An inherent limitation of such fairness metrics is that they cannot account for the differing "contribution" to congestion from each individual airline. In that respect, the number of slots requested by each airline provides a measure of the volume/level of airline's demand and has been therefore treated by certain authors (Zografos and Jiang, 2019; Jacquillat and Vaze, 2018) as the major contributing factor in congestion in order to assign schedule displacement weights proportional to demand (i.e., number of slot requests). However, congestion impacts vary substantially with time on the grounds that slot requests during busy hours impose higher displacement on other users as compared to slots requested in off-peak hours.

In light of the above, it can be reasonably argued that a fair allocation outcome should *inter alia* ensure that airlines should "internalize" their "fair share" of total schedule displacement imposed on other airlines by taking into account not only the demand volume characteristics (i.e., number of requested movements), but also the peaking characteristics of their slot requests. Borrowing fundamental principles from congestion-based pricing (Brueckner, 2002; Fan and Odoni, 2002; Morrison and Winston, 2007), we propose a fairness-informed extension of the strategic airport slot scheduling model based on the conjecture that the intensity of congestion and the resulting displacement impacts are strongly affected by the volume, as well as the

temporal distribution and peaking characteristics of demand. Our model adopts the schedule efficiency objective weighted for the number of calendar days associated with a given slot request (i.e., slot series) in order to account for the multiplicative impact of the slot request. Most importantly, we introduce a novel fairness metric expressing the proportion of displacement that should be "internalized" by each airline on the basis of the additional displacement imposed by each airline's slots on all other airlines. Finally, we provide an exploration of various trade-offs between schedule efficiency, fairness, and several LOS-related indicators with the aim to assess compromises that relevant stakeholders (e.g., airlines, airports, slot coordinators) should be aware in the process of ensuring a fair slot allocation outcome. The proposed model is demonstrated and validated with real-world scheduling data in two IATA schedule coordinated (Level 3) airports in Portugal and Greece.

The remainder of this paper consists of four main sections. Section 2 presents the proposed model along with its underlying modeling concepts and the solution approach. Section 3 describes the computational experiments and the associated test problem and parameters. Section 4 discusses the results of the various model runs for a number of tested scenarios and capacity cases. It compares the displacement weights derived by the proposed model vis-à-vis other fairness-informed approaches proposed in existing literature. Furthermore, it demonstrates the implications of fairness on schedule efficiency and level of service indicators. The paper concludes with some overall remarks and directions for future research (Section 5), while it is complemented by a list of acronyms and references.

2. Proposed Model

This section introduces the basic concepts in the IATA slot allocation framework and their underlying modeling notations (Section 2.1), presents the proposed model formulation (Section 2.2) and outlines the displacement weight calculation process (Section 2.3).

2.1 Basic Concepts & Notations

The strategic airport slot allocation currently applied at congested airports worldwide outside the United States is driven by the IATA administrative, rule-based framework and its various adaptations or amendments (IATA, 2014; European Commission, 1993). Under this framework, the daily operating time of a slot-controlled (i.e., *schedule coordinated*) airport is broken down to time intervals of fixed length (usually 5-minute time windows used for scheduling purposes), named *coordination time intervals*. Schedule coordinated airports declare a number of available *slots* (i.e., permissions to schedule a landing or take-off) for certain periods of time (usually hourly) within a day, namely the airport's *declared capacity*, and then invite airlines to submit requests for permission to use the airport for a specific coordination interval (i.e., *slot request*) over a series of calendar days (i.e., *slot series*). The strategic airport slot allocation problem pertains to the scheduling of all airlines' slot requests on a schedule coordinated airport over a given scheduling horizon of approximately six months. The scheduling process is subject to operational constraints (e.g., declared capacity constraints), flight/aircraft connectivity constraints (e.g., turnaround time required to prepare the aircraft for a subsequent flight), as well as certain

administrative rules and priority classes. The latter involve different scheduling priorities, hence satisfying slot requests in the following order: i) historic usage rights (usually termed as "*grandfathered rights*"), namely, slots reserved by a given airline provided that they have been already utilized during the previous scheduling season, ii) slot requests for new entrants (i.e., airlines without substantial slot holdings in the airport under consideration) and iii) all remaining requests.

The airport slot allocation problem is defined by a set of airlines A placing slot requests R that span throughout the scheduling horizon D (the entire set of calendar days). The slot requests corresponding to arrivals are denoted by $R_{arr}(\subseteq R)$, while those referring to departures are denoted by $R_{dep}(\subseteq R)$. We denote by $T = \{0,1,..,n-1\}$ the set of coordination time intervals (with length equal to five minutes) during the active airport operating hours. Each slot request $r \in R$ involves a requested time interval $\tau_r \in T$, the type of movement (arrival vs. departure) and a set of calendar days D_r $(\subseteq D)$ over which the request is applicable. Hence, each request involves a set of requested movements on calendar days in D_r. The set of movements corresponding to a slot request r is denoted by M_r. The slot requests that are placed by airline $a \in A$ are denoted by R_a, while the corresponding requested movements associated to slot requests R_a are denoted by M_a. For instance, assume a slot request that involves an arrival at the airport at 08:00, every Monday within the time period from 21/05/2018 until 25/06/2018. Taking into account that the numbering of the calendar days starts (counting from 1) at 31/03/2018, the slot request is active for the following calendar days: 21/5 (day 52), 28/5 (day 59), 4/6 (day 66), 11/6 (day 73), 18/6 (day 80), 25/6 (day 87). Hence $D_r = \{59, 66, 73, 80, 87\}$. Moreover, this slot request involves six movements (arrivals) each one requested on the above calendar days at time 08:00. Assuming that the daily time horizon starts at 04:00 AM and the coordination time intervals are 5 minutes long, then (starting from 0) 08:00 corresponds to the 48th time interval.

It is also worth noting that the time intervals allocated to certain pairs of slot requests may be linked to each other. Two slot requests are considered as *linked* when the corresponding movements are operated by the same aircraft or they share common passengers on the same calendar day. An arrival is linked to a departure if the arrival precedes the departure and: i) the arriving aircraft is used for the departing movement or ii) arriving passengers have to transfer to the associated/linked departing movement. In both cases, the link between a pair of slot requests imposes a precedence constraint with lag time, since a minimum time difference must exist between the corresponding movements and this should be sufficient for facilitating the associated operations. Any pair of linked slot requests (r_1, r_2), $r_1, r_2 \in R$, where $\tau_{r_1} < \tau_{r_2}$, is stored in set P. The time intervals allocated to any pair of linked slot requests (r_1, r_2) should exceed a minimum time difference $s_{r_1 r_2}$. Moreover, the allocation of time intervals to slot requests should not violate the capacity constraints of the airport. It is assumed that no more than q_{td}^c movements of type c ($c \in C = \{0,1,2\}$, where 0 corresponds to arrivals, 1 to departures and 2 to both arrivals and departures) can be served by the airport within any time period $T_c^t = \{t, t+1, .., t+t_c-1\}$ of length t_c (e.g., 1 hour or the equivalent of 12 coordination time intervals). For instance, assume that the airport daily operating time is from 04:00 until 01:00 and the airport hourly capacity level involves up to 26 arrivals, 26 departures and 36 movements in total. This means that the schedule of slot requests should not violate

the capacity limits in any possible of hour of the day (e.g., 04:00-05:00, 04:05-5:05, 04:10-05:10).

Table 1 presents an excerpt of a list of slot requests submitted to a given airport. Each row of the table presents a pair of linked slot requests. As it can be observed from Table 1, the third row, highlighted with red border line, corresponds to a typical pair of linked slot requests. The first slot request (third row) corresponds to an arrival flight (2U5061) with requested time of arrival at 22:10. Its linked slot request corresponds to a departure flight (2U5062) with requested time of departure at 23:30. Both slot requests apply to each Friday (i.e., 0000500 or at the 5th weekday) on a 142-seating arrangement of a Boeing 738. Practically, each of the two slot requests creates 12 individual slot occurrences (every Friday) within the time period starting from July 3rd to September 18th (Table 1).

Arrival Flight No.	Departure Flight No.	From	To	Day of Operation	Seats	Aircraft Type	Requested Arrival Time	Requested Departure Time
2U5061	2U5062	03-Jul	18-Sep	0000500	142	738	2210	2330
4R3818	4R3819	27-Apr	01-Jun	1000000	150	319	0850	0935
4R3882	4R3883	27-Apr	08-Jun	1000000	150	319	1640	1725
4U0602	4U0603	29-Mar	26-Apr	0000007	156	319	1235	1305
4U0602	4U0603	30-Mar	01-May	1030500	156	319	1105	1135
4U0602	4U0603	31-Mar	28-Apr	0200000	156	319	1105	1135
4U0602	4U0603	02-Apr	02-May	0004060	156	319	1105	1135
4U0602	4U0603	03-May	18-Oct	0000007	156	319	1235	1305

Table 1: Excerpt of a Slot Request Table

2.2 Model Formulation

The objective of the proposed slot allocation problem is to determine a feasible slot schedule that minimizes the total displacement while simultaneously promoting a fair distribution of the total displacement among participating airlines. The proposed model treats total displacement as the sum of displacement over all movements instead of slot requests. Furthermore, it imposes the distribution of total displacement among the airlines $a \in A$ according to a pre-specified set of proportions π_a. With no loss of generality, we ignore any scheduling priority assigned to historic slot holdings (i.e., Grandfather Rights) or requests earmarked for new entrants. The proposed formulation is based on the general resource-constrained scheduling problem (Pritsker *et al.*, 1969). The decision variables of the proposed formulations are $x_{r\tau} \in \{0,1\}$, $r \in R$, $\tau \in T$, which take value 1 if slot request r is allocated coordination time interval τ, and 0 otherwise. We define the binary parameter $\delta_{rd}, r \in R, d \in D$ that takes value 1 if calendar day d belongs to the set of days D_r in which request r is active, and 0 otherwise. Moreover, we define parameter $\mu_{rc} \in \{0,1\}$, which takes value 1 if slot request r involves movements of type c, and 0 otherwise. For each airline $a \in A$, we assume a weight π_a that represents the proportion of displacement that should be allocated to airline $a \in A$. The values of π_a are set so as to impose fairness on the allocation of displacement among airlines. The procedure of calculating weights π_a is presented later in this section. The displacement ($f_{r\tau}$) of request $r \in R$ allocated to coordination time interval τ is defined as the difference between the requested time interval τ_r and the allocated time interval t, i.e., $f_{r\tau} = |\tau_r - \tau|$. Since this displacement is realized by every movement associated to slot

request r, we define the total displacement $F_{r\tau}$ as the sum of displacement over all the calendar days in D_r :

$$F_{r\tau} = \sum_{d \in D} f_{r\tau} \cdot \delta_{rd} \quad (1)$$

Hence forth, we will refer to this type of displacement as *aggregate displacement* in order to differentiate it from the term displacement used in existing literature. For instance, if a slot request involves 10 calendar days and has a displacement of 5 coordination time intervals, the aggregate displacement is equal to 50 coordination time intervals. The proposed formulation is given by (2)-(8):

$$(P1) \quad min\ Z_1(x) = \sum_{r \in R} \sum_{\tau \in T} x_{r\tau} \cdot F_{r\tau} \quad (2)$$

s.t.

$$\sum_{\tau \in T} x_{r\tau} = 1, \ \ \forall r \in R \quad (3)$$

$$\sum_{r \in R} \sum_{\tau \in T_c^s} \delta_{rd} \cdot \mu_{rc} \cdot x_{r\tau} \leq q_{td}^c, \ c \in C, \ d \in D, \ t \in T \quad (4)$$

$$\sum_{\tau \in \{0,1,..,k-1\}} x_{r_2\tau} + \sum_{\tau \in \{k-s_{r_1r_2},..,|T|-1\}} x_{r_1\tau} \leq 1, \ \ (r_1, r_2) \in P, \ r_1 \in R_{arr}, r_2 \in R_{dep} \ \ k \in \{s_{r_1r_2} \dots, |T|-1\} \quad (5)$$

$$\sum_{r \in R_a} \sum_{\tau \in T} x_{r\tau} \cdot F_{r\tau} \leq (1+\varepsilon)\pi_a \sum_{r \in R} \sum_{\tau \in T} x_{r\tau} \cdot F_{r\tau}, \ a \in A, and\ \pi_a \neq 0 \quad (6)$$

$$\sum_{r \in R_a} \sum_{\tau \in T} x_{r\tau} \cdot F_{r\tau} \geq (1-\varepsilon)\pi_a \sum_{r \in R} \sum_{\tau \in T} x_{r\tau} \cdot F_{r\tau}, \ a \in A\ and\ \pi_a \neq 0 \quad (7)$$

$$\sum_{r \in R_a} \sum_{\tau \in T} x_{r\tau} \cdot F_{r\tau} \leq (1-\varepsilon)\pi_{min} \sum_{r \in R} \sum_{\tau \in T} x_{r\tau} \cdot F_{r\tau}, \ a \in A, and\ \pi_a = 0 \quad (8)$$

$$x_{r\tau} \in \{0,1\} \quad (9)$$

where $\pi_{min} = min\{\pi_a : a \in A, \pi_a \neq 0\}$ and $\varepsilon \in (0,1)$ is a parameter that allows minor deviation from π_a. Objective function (2) expresses the aggregate displacement, that is, the total absolute difference between the requested and allocated time for the examined days of the planning horizon. Constraint (3) indicates that every slot request must be allocated to exactly one time interval. Constraint (4) implies that the number of movements of type c allocated to any time period of t_c length cannot exceed the corresponding capacity value q_{td}^c. Constraint (5) assures that if two slot requests are linked then they cannot be scheduled within a time period of length less than the minimum time difference. Hence, constraint (5) implies that the minimum time difference between the scheduled times of any pair of linked movements should be higher or equal to the minimum time difference. Constraints (3)-(5) are the same as in (Zografos *et al.*, 2012). Constraints (6) and (7) imply that the proportion of total aggregate displacement allocated to any airline a for which $\pi_a \neq 0$ should not deviate from π_α by $\pm(\varepsilon \cdot 100)$ %. The ε parameter essentially promotes the feasibility of the solution by providing some flexibility to accommodate displacement that is reasonably close ($\pm(\varepsilon \cdot 100)$ %) to the proportional displacement value (π_α) of each airline, respectively. Constraint (8) ensures that for any airline with $\pi_\alpha = 0$ (i.e., it does not contribute to congestion), its maximum possible share in displacement should not exceed the corresponding minimum value (π_{min}) that is allocated to any airline with $\pi_\alpha \neq 0$. This allows assigning some minor displacement ($\leq \pi_{min}$) even to airlines not contributing to congestion with view to promoting the solution feasibility.

It is worth noting that the constraint of "Grandfather Rights" can be readily addressed by directly scheduling the relevant slot requests to their requested time intervals. In terms of modelling, it means that incorporating the "Grandfather Rights" constraint in

the model requires just the update of the capacity values consumed by the relevant (scheduled in advance) slot requests. However, since the focus of our study is on fairness, we ignore this type of scheduling priority constraints.

2.3 Calculating Displacement Weights

A prerequisite for applying the proposed model ($P1$), is to estimate the newly proposed displacement weights, namely the corresponding values of π_α that should be assigned to each airline $a \in A$. We first calculate for each airline a the additional displacement caused by operating its slot requests in the airport. We employ a two-stage approach for this purpose. In the first stage, we solve the proposed model without the fairness constraints (6)-(8) and by excluding the slots requests of airline a. The emerging optimal aggregate displacement value is denoted as (Z_{opt}). At the subsequent stage, we solve (lexicographically) the model ($P2$) for the entire set of slot requests (including those of airline a) by using as a primary objective the minimization of the aggregate displacement assigned to the slot requests of airline $a \in A$, and, as a secondary objective, the minimization of the aggregate displacement of the remaining requests. The emerging value of the aggregate displacement ($Z_1^a(x) + Z_1^{na}(x)$) is then denoted by Z_a.

$$(P2) \quad lexmin(Z_1^a(x), Z_1^{na}(x)) \tag{10}$$

$$Z_1^a(x) = \sum_{d \in D} \sum_{r \in R_a} \sum_{\tau \in T} x_{r\tau} \cdot F_{r\tau} \tag{11}$$

$$Z_1^{na}(x) = \sum_{d \in D} \sum_{r \in R \setminus R_a} \sum_{\tau \in T} x_{r\tau} \cdot F_{r\tau} \tag{12}$$

s.t.

Constraints (3)-(5), (9)

We define the difference $B_a = Z_a - Z_{opt}$ as the additional displacement imposed by airline a on all other airlines competing for the same slot pool. This procedure is conducted separately for each airline. The newly proposed displacement weighting scheme (π_a) is given by (13).

$$\pi_a = \frac{B_a}{\sum_{a' \in A} B_{a'}}, \quad a \in A \tag{13}$$

Weight π_a expresses the actual airline-specific proportional contribution to congestion, namely the ratio of the additional schedule displacement imposed to the other airlines due to the slot requests of the respective airline $a \in A$, over the sum of the corresponding additional schedule displacement caused by all airlines.

3. Analysis Framework and Experiments

The computational experiments performed in this research work aim to: i) validate the proposed weighting scheme and ii) assess the scale of effect of imposing fairness in allocating slots. The former objective is achieved by verifying that it is not only the number of requests affecting the weight of an airline but also its requests on busy time intervals. This property of the proposed weighting scheme is verified by computing and comparing the airlines' fairness weights under a series of alternative scenarios in which the requests of a given airline are modified. We consider two extreme cases in which all requested times of an airline are moved either to time intervals where demand is below capacity or to time intervals where demand exceeds capacity. The expected outcome of the above experiments is that an airline's weight is expected to

increase/decrease when its requests are moved to busy/non busy time intervals, respectively.

The second objective of the proposed analysis is accommodated by solving various test problems for different levels of fairness sensitivity (i.e., values of ε) and capacity levels. Hence, this objective requires investigation in two parts. In the first part (Part I), we investigate the impacts of different fairness levels on a set of performance metrics at a given capacity level. In the second part (Part II), we assess the effect of fairness (for the lowest possible value of ε) on the proposed performance metrics under different capacity levels. We use three alternative capacity scenarios, representing hard, medium and loose capacity constraints, respectively. In both cases (Parts I and II), we measure the impact of imposing fairness in slot allocation on the basis of: i) the total aggregate displacement, ii) the maximum displacement assigned to any slot request and iii) a set of indicators founded on the assumption that each airline has maximum tolerance on the displacement received per request, denoted by ξ_r, $r \in R$. Hence, it is assumed that allocating a coordination time interval $\tau \notin [\tau_r - \xi_r, \tau_r + \xi_r]$ to slot request r of airline a would be considered by the airline as a *violated service* (Zografos *et al.*, 2018). The latter implies that the allocated time violates "unacceptably" the original slot request above certain acceptability thresholds or tolerance levels (ξ_r). If a request is allocated with a time interval within $[\tau_r - \xi_r, \tau_r + \xi_r]$, then the corresponding service of slot request is referred to as a *legitimate service* on the grounds that it ensures an acceptable level of service within the airline's tolerance limits. The displacement of a slot request receiving a legitimate service is called *legitimate displacement*. Moreover, if a slot request r is allocated with time interval $\tau > \tau_r + \xi_r$ or $\tau < \tau_r - \xi_r$, then the portion of displacement that spans after $\tau_r + \xi_r$ (i.e., $\tau - (\tau_r + \xi_r)$) or before $\tau_r - \xi_r$ (i.e., $(\tau_r - \xi_r) - \tau$) is called *excess displacement* and it is denoted by ($f_{r\tau}^e$). Formula (14) below provides the formal definition of $f_{r\tau}^e$.

$$f_{r\tau}^e = \begin{cases} \tau - (\tau_r + \xi_r), & \tau > \tau_r + \xi_r \\ \tau_r - \xi_r - \tau, & \tau < \tau_r - \xi_r \\ 0, & \tau \in [\tau_r - \xi_r, \tau_r + \xi_r] \end{cases} \tag{14}$$

Figure 1 illustrates the definition of the LoS indicators related to airlines' tolerance limits for a violated and a legitimate (non-violated) slot request. The example on the top of Figure 1 presents a violated service (i.e., a slot request that its allocated time is outside the airline's tolerance interval), while the non-violated service is presented at the bottom of Figure 1. It is worth noting that, in the case of the non-violated service, the total displacement coincides with the legitimate displacement, while the excess displacement equals to 0.

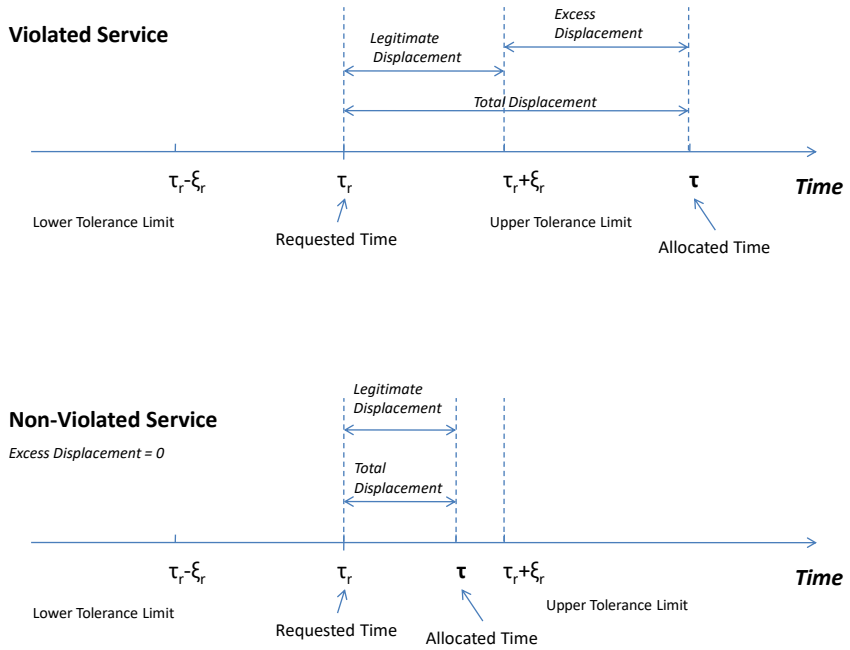


Figure 1: Examples of LoS Metrics
(defined for a violated and a non-violated slot request)

Overall, the indicators used to express the Level of Service in our analysis are presented below:

- *Average Excess Displacement (per Movement)*: this is the ratio of the sum of the excess displacement (i.e., *Total Excess Displacement*) over the number of movements experiencing violated service. This indicator exhibits some similarities with the Average Delay per Delayed Flight (ADD) metric broadly used by Eurocontrol's CODA for operational ATM delays in ECAC airports (Eurocontrol, 2017).

- *% of Violated Movements*: this is the ratio of the number of movements experiencing violated service (i.e., the allocated time interval is outside $[\tau_r - \xi_r, \tau_r + \xi_r]$) over the total number of movements.

- *Maximum Request Displacement*: this corresponds to the maximum displacement imposed on any slot request as a measure of the "worst-case" service scenario for the users of a given congested airport (Zografos *et al.*, 2018).

In the remainder of this section, we define the test problems and data sets used for our experiments (Section 3.1), and describe the analysis process for assessing the proposed weighting scheme (Section 3.2) and the fairness impacts (Section 3.3).

3.1 Test Problems and Parameters

The test problems used for the above types of assessment pertain to a medium-sized, national hub airport in Portugal (called PRA from now on) and a small, regional airport in Greece (called GRA). PRA accommodated over 29 million passengers and 216,000 aircraft movements, with GRA serving more than 3 million passengers and 19,000 aircraft movements in 2018. For slot scheduling purposes, both airports are

designated as schedule coordinated (Level 3) airports for the summer scheduling season (due to seasonality effects, GRA is schedule coordinated only for the summer scheduling season). Data were granted by the respective slot coordination authorities in Portugal and Greece and included requested slot data and capacity parameters for the summer scheduling season of 2009. Table 2 provides a summary of the main slot scheduling data for both airports under consideration.

Test Airports	Number of Airlines	Number of Slot Requests	Hourly Declared Capacity Parameters
PRA – Schedule Coordinated (Level 3)	56	896 requests (32,916 movements) (Summer Scheduling Season 2009)	Current Declared Capacity 26 DEP (per 60 min.) 26 ARR (per 60 min.) 36 MVMTS (per 60 min.) Low Capacity Scenario 24 DEP (per 60 min.) 24 ARR (per 60 min.) 32 MVMTS (per 60 min.) High Capacity Scenario 29 DEP (per 60 min.) 29 ARR (per 60 min.) 40 MVMTS (per 60 min.)
GRA – Schedule Coordinated (Level 3) (only for the summer scheduling season)	39	526 requests (3,407 movements) (Summer Scheduling Season 2009)	Current Declared Capacity 4 DEP (per 60 min.) 6 ARR (per 60 min.) 10 MVMTS (per 60 min.) Low Capacity Scenario 4 DEP (per 60 min.) 4 ARR (per 60 min.) 8 MVMTS (per 60 min.) High Capacity Scenario 6 DEP (per 60 min.) 6 ARR (per 60 min.) 12 MVMTS (per 60 min.)

Table 2: Slot Scheduling Data for PRA Airport

The test problems involve 896 slot requests (32,916 movements) placed by 56 airlines in PRA and 526 slot requests (3,407 movements) placed by 39 airlines in GRA for the period between March 29 and May 31, 2009. Figure 2 presents the distribution of demand (expressed by the number of requested movements per 15 minutes) at PRA and GRA. The presented demand level per 15 minutes (Figure 2) corresponds to the maximum value of 15-minute demand throughout all calendar days in the scheduling horizon under consideration.

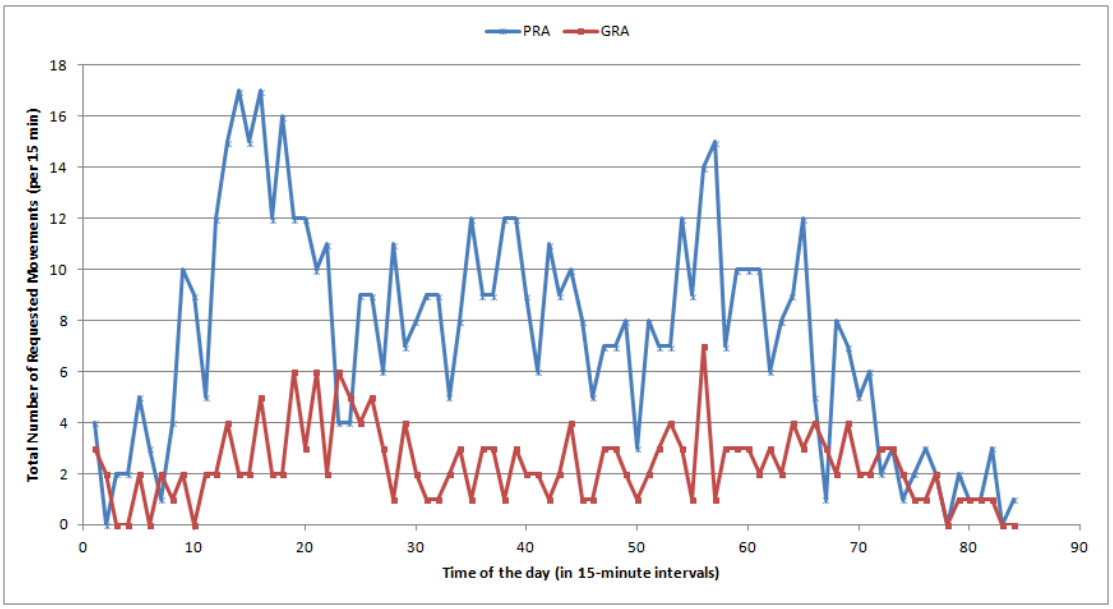


Figure 2: Demand profile for PRA and GRA
(maximum number of requested movements per 15 minutes
throughout the scheduling horizon)

All experiments were performed on an Intel Core 3.60 GHz computer with 64-bit Windows operating system and 16GB RAM.

3.2 Assessing the Displacement Weighting Scheme

In this type of assessment, we initially compute the newly proposed fairness-driven displacement weights (π_a) based on the three examined capacity levels for PRA and GRA, respectively. For simplicity, we will make reference to each of the tested capacity cases by the triplet (ARR, DEP, TOT), e.g., (26,26,36) or (4,6,10). Although capacity levels for arrivals and departures are further controlled by tighter constraints on the total number of movements (MVMTS), as well as rolling capacity constraints per unit of time (e.g., 15 min., 30 min., 60 min.), we only consider hourly rolling capacity constraints. Then, we compare the newly proposed fairness-driven displacement weights (π_a) against weights previously addressed in relevant literature (Zografos and Jiang, 2019). In addition, we explore whether and how the airlines' displacement weights are affected by the peaking characteristics of each airline's demand. Stated otherwise, we investigate changes in displacement weights when the requested time intervals of a given airline are shifted from busy periods to non-busy periods and vice versa. This series of experiments aims to verify that the displacement weight of an airline is affected by the demand profile of its requested time intervals. It is expected that requesting time intervals at off-peak hours would imply for airline lower displacement weights as compared to requesting the same number of movements at busy hours. To validate this statement, we select two airlines for each airport: one airline requesting times intervals at low-demand periods (below capacity) and one having many requests on intervals with high demand (above capacity). For each airline, we shift requested time intervals between periods of high and low demand respectively (for the same total number of requests) and then recalculate the corresponding airlines weights to assess how displacement weights change in response to these temporal modifications of the demand's profile. The worst case

computational times for calculating the airlines weights for the PRA and GRA were 37 hours and 2.5 hours, respectively.

3.3 Assessing the Fairness Impact

The objective of this type of analysis is the assessment of the impact of introducing fairness in airport slot allocation by comparing the results (on the basis of the aforementioned performance metrics) of fairness-indifferent scheduling of slot requests with the corresponding results when fairness constraints are taken into account (fairness-sensitive case). This type of analysis is accommodated by solving various instances of a test problem for different levels of fairness (Part I) and capacity levels (Part II).

Measuring Fairness Impact

In both cases (Parts I and II), we measure the impact of imposing fairness in slot allocation by comparing the values of the proposed metrics under two different cases: with versus without the fairness constraints. The metrics under study are the average total aggregate displacement, the average excess displacement, the percentage of violated slot requests, and the maximum displacement. The assessment of each metric is performed through the following types of experiments:

E1. Average Aggregate Displacement Assessment. We compare the solutions of models $(P1)$ and $(P1')$, where the model $(P1')$ is the model $(P1)$ without constraints (6)-(8). The optimal solutions are denoted by $x^*_{(P1)}$ and $x^*_{(P1')}$ and they represent the fairness-sensitive and fairness-indifferent schedules that optimize the total aggregate schedule displacement. Their total aggregate displacement values are $z^*_{(P1)}$ and $z^*_{(P1')}$, respectively. Hence, the average aggregate displacement in both cases emerges as the ratio of $z^*_{(P1)}$ and $z^*_{(P1')}$ over the total number of movements.

E2. Excess Displacement Assessment. We compare the excess displacement values of the solutions of models $(P3)$ and $(P3')$ presented below.

$(P3)$ $\quad lexmin\ (Z_1(x), Z_3(x))$

Where

$$Z_3(x) = \sum_{d\in D}\sum_{r\in R}\sum_{\tau\in T} x_{r\tau}\cdot f^e_{r\tau}\cdot \delta_{rd} \tag{15}$$

s.t.

Constraints (3)-(9)

$(P3')$ $\quad lexmin\ (Z_1(x), Z_3(x))$

s.t.

Constraints (3)-(5), (9)

The objective function $Z_3(x)$ in (14) expresses the total excess displacement of solution x. Therefore, model $(P3)$ aims to determine a fairness-sensitive schedule of minimum total aggregate displacement that minimizes the total excess displacement. Stated otherwise, among alternative solutions with minimum total aggregate displacement, it determines the one with the minimum excess displacement. The model $(P3')$ provides a fairness-indifferent schedule of minimum aggregate displacement that minimizes the total excess displacement accordingly. Hence, the

average aggregate displacement in both cases emerges as the ratio of $z_{3^*_{(P3)}}$ and $z_{3^*_{(P3')}}$ over the total number of movements with non-zero excess displacement.

E3. Violated Service Assessment. We compare the violated service values of the solutions of models $(P4)$ and $(P4')$ presented below.

$(P4)$ $lexmin\ (Z_1(x), Z_4(y))$

Where

$$Z_4(y) = \sum_{r \in R} y_r \tag{16}$$

s.t.

Constraints (3)-(9)

$$(\sum_{\tau \in T} x_{r\tau})\tau - (\tau_r - \xi_r) \geq \frac{1}{2} - y_r|T|\,, \quad r \in R \tag{17}$$

$$(\tau_r + \xi_r) - \sum_{\tau \in T} x_{r\tau}\,\tau \geq -y_r|T|\,, \quad r \in R \tag{18}$$

$$(\tau_r + \xi_r) - \sum_{\tau \in T} x_{r\tau}\,\tau \leq -\frac{1}{2} + (1 - w_r)|\mathrm{T}| \quad r \in R \tag{19}$$

$$\sum_{\tau \in T} x_{r\tau}\,\tau - (\tau_r - \xi_r) \leq \frac{1}{2} + (1 - v_r)|\mathrm{T}| \quad r \in R \tag{20}$$

$$y_r \leq w_r + v_r \quad r \in R \tag{21}$$

$(P4')$ $lexmin\ (Z_1(x), Z_4(x, y))$

s.t.

Constraints (3)-(5), (9), (17)-(21)

where y_r are binary variables that take value 1 if slot request r is violated, and 0 otherwise. These variables are defined in the model based on the following supporting variables: i) binary variables w_r which take value 0, if the time interval allocated to request r is earlier than $(\tau_r + \xi_r)$ and 1 otherwise and ii) binary variables v_r which take value 0 if the time interval allocated to request r is later than $(\tau_r - \xi_r)$ and 1 otherwise. It is worth noting that if either w_r or v_r takes value 1, then the relevant request r is violated, i.e., $y_r = 1$. Objective function $Z_4(y)$ expresses the total number of slot requests receiving violated service. Constraints (17)-(21) are borrowed from Zografos *et al.* (2018). The objective of model $(P4)$ is to determine a fairness-sensitive schedule of minimum aggregate displacement that minimizes the total number of slot requests receiving violated service. The model $(P4')$ aims to provide the corresponding fairness-indifferent schedule. Hence, the value of the metric percentage of violated services in both cases is calculated by the ratio of $z_{4^*_{(P4)}}$ and $z_{4^*_{(P4')}}$ over the total number requested movements.

E4. Maximum Displacement Assessment. We compare the maximum displacement values of the solutions of models $(P5)$ and $(P5')$ presented below.

$(P5)$ $lexmin\ (Z_1(x), Z_5(y))$

where

$$Z_5(y) = y \tag{22}$$

s.t.

$\sum_{t \in T} x_{rt} f_{rt} \leq y, \;\; r \in R$ (23)

Constraints (3)-(9)

$y \geq 0$ (24)

$(P5')$ $lexmin\ (Z_1(x), Z_5(x, y))$

s.t.

Constraints (3)-(5), (9), (23)

The objective function $Z_5(y)$ in (22) expresses the maximum displacement assigned to any slot request. Constraint (23) implies that the non-negative variable y is higher than the displacement assigned to any slot request. Hence, minimizing $Z_5(y)$ implies that y coincides with the maximum over all displacements assigned to slot requests. Solving model $(P5)$ leads to a fairness-sensitive schedule of minimum aggregate displacement that minimizes the maximum displacement given to any slot request. On the other hand, the model $(P5')$ provides a fairness-indifferent schedule of minimum aggregate displacement that minimizes the maximum displacement as well. The value of this metric under both cases (Fairness-sensitive vs Fairness-indifferent) coincides with $z_{5_{(P5)}}^*$ and $z_{5_{(P5')}}^*$ respectively.

Experiments

It is evident that in experiments E1-E4 we measure the impact of fairness on the proposed performance metrics by comparing the fairness-indifferent vs. fairness-sensitive optimum (with respect to total aggregate displacement) solutions on each of these metrics. In Part I analysis, the proposed experiments are iterated for different values of ε at the current capacity level/scenario. On the other hand, within the framework of Part II analysis, each of the above experiments is executed separately for each alternative capacity scenario (and the tightest possible fairness level). Each of the above lexicographic models is solved in two stages: i) we initially solve the problem using only the primary objective functions leading to z_1^* and ii) we then solve the model using as a single objective the secondary objective function and adding the constraint $Z_1(x) \leq z_1^*$. All mathematical models are solved with Cplex 12.6. The worst computational time of the runs performed for the PRA and GRA were 152 minutes and 15 minutes, respectively.

The first set of scenario runs experiments with decreasing values of the ε parameter (at a given capacity level) in order to quantify the impact of fairness on the optimal solution (total aggregate displacement). The fairness constraints (6)-(8) remain practically inactive for large values of ε, thus resembling the "fairness-indifferent" (FI) case. On the other hand, small values of the ε parameter (close to zero) imply small deviations allowed from the fairness-driven displacement weights, hence triggering the tightness of the fairness constraints. At the outset, it can be claimed that the ε parameter serves as a proxy of fairness in that it controls the tightness of the fairness-related constraints. Having said that, the impact of decreasing values of the ε parameter on the optimal aggregate displacement values can be reasonably viewed as the "cost of fairness". As part of our analysis, the first set of scenario runs involves an exploration of five different values of the ε parameter (i.e., $\varepsilon = 0.15$, 0.2, 0.3, 0.4 and 0.50), including the "fairness indifferent" (FI) case, at the current declared capacity

levels of both airports, namely (26,26,36) in PRA and (4,6,10) in GRA. The second set of scenario runs aims to explore the sensitivity of the solution at varying capacity levels. It is empirically expected that higher capacity levels render more slots available for allocation, hence reducing congestion and displacement metrics accordingly (with the opposite being also true). For the purposes of our analysis here, the second set of scenario runs has been conducted for the tightest value of ε (i.e., 0.15) at three different capacity levels, namely (24,24,32), (26,26,36) and (29,29,40) for PRA and (4,4,8), (4,6,10) and (6,6,12) for GRA.

Two additional fundamental scheduling parameters that are employed in our model are the coordination time interval and the minimum time difference (e.g., turnaround time). The former stands for the duration of the primary time window used for scheduling purposes and was set to 5 minutes. This practically means that airlines submit requests for slots on a 5-minute basis so that an airline posing an arrival request at time interval 12 would imply a requested arrival movement operated at 01:00 am. Similarly, schedule displacement metrics are also measured and aggregated at the level of the coordination time interval. For example, a displacement of 150 intervals imposed on a certain airline would imply that the requested slots of this particular airline are assigned with 150 intervals of displacement or 150*5 minutes, namely 750 minutes. The minimum turnaround time is also measured in 5-minute intervals and set equal to 6 coordination time intervals (i.e., 30 minutes). Although a relevant time difference exists in connected flights as well, we will not consider such pairs in our analysis. Henceforth, the time difference refers to the turnaround time for a pair of linked slot requests. In all runs, we explicitly take into account the multiplicative displacement effect of a slot request throughout the entire scheduling season. Therefore, each slot request is penalized with a displacement weight on the basis of all its occurrences throughout the period that the request is regularly valid. Finally, the maximum tolerance limit (ξ_r) of airlines above which an allocated (but violated) slot is considered unacceptably displaced (i.e., excess displacement) is assumed to be 1 hour (i.e., 12 intervals). The maximum tolerance limit of 1 hour is considered realistic on the grounds that it cannot drastically affect the feasibility of airlines' master/network schedules, given the intensive schedule padding already incorporated in their schedules as a resilience measure against operational delays (or schedule displacement accordingly).

4. Discussion of Results

This section aims to present the results of the model runs for the various scenarios discussed below. It is structured into two main sub-sections. Section 4.1 investigates the proposed displacement weights for assigning a given "displacement budget" fairly and reasonably among competing airlines as compared to other approaches proposed in existing literature (Section 4.1.1). Moreover, a validation of the newly proposed weight scheme is presented in Section 4.1.2. Finally, Section 4.2 discusses the implications of fairness ("cost of fairness") on aggregate schedule displacement and level of service indicators.

4.1 Displacement Weights

4.1.1 Comparative Analysis of Displacement Weights

Existing literature in slot scheduling has basically addressed fairness considerations by introducing a fairness constraint aiming to ensure that each airline will absorb a schedule displacement that is proportional to the number of slots (or movements) requested by the airline under consideration over the total number of requested slots (or movements). This essentially defines the displacement weight that each airline should be "assigned" at a certain schedule coordinated airport. This displacement weight associates the assigned displacement with the number of requested operations. In effect, it provides a clear disincentive to "over-activity" of airlines that may be tempted to secure desired slots by requesting much more slots than those actually aimed for.

In the herewith proposed displacement weighting scheme, each airline is assigned with an aggregate schedule displacement that is proportional to its actual airline-specific congestion impact (π_a). In that respect, airlines will not be over-penalized for requested slots that may be operated at off-peak times. On the other hand, other airlines will not be under-penalized for slots requested under extreme peaking conditions. At the outset, our computational approach for obtaining displacement weights captures not only the demand volume (how many slots?), but also the temporal distribution and peaking characteristics of demand (when are slots requested?) in order to estimate their actual "congestion footprint" in the form of schedule displacement imposed on other airport users / airlines.

In the analysis that follows (Figures 3a-b), the newly proposed ("NEW") displacement weights (i.e., proportional to the aggregate displacement imposed on other users) are presented for the three examined capacity cases at both PRA and GRA, namely (24,24,32), (26,26,36) and (29,29,40) for PRA and (4,4,8), (4,6,10) and (6,6,12) for GRA. The corresponding "NEW Weights (32)", "NEW Weights (36)" and "NEW Weights (40)" for PRA (Figure 3a) and "NEW Weights (8)", "NEW Weights (10)", and "NEW Weights (12)" for GRA (Figure 3b) are compared against weights previously ("PRE Weights") adopted in literature (i.e., proportional to the number of requested movements) (Zografos and Jiang, 2019). Unlike with weights based on the number of requested slots that are assumed to be independent of capacity, the newly proposed weights differ with capacity levels since the displacement imposed on other airlines is reduced (increased) as a result of relaxing (tightening) capacity constraints. This can be reasonably expected by the fact that as capacity increases more slots become available for allocation with a relief effect in terms of congestion and displacement.

Figures 3a-b provide a comparative analysis of new versus previous displacement weights (vertical axis), with the latter demonstrating a linear relationship with the number of requested movements (horizontal axis). In both cases, airlines split between those penalized with the new displacement scheme (i.e., points above the line indicated with red color), those favored (i.e., points below the line indicated with green color), and the large majority of airlines concentrating around the area of negligible difference among the two proposed weight schemes (i.e., the congested area at the lower left part of the figure).

Another interesting observation stems from the fact that airlines with a similar number of requests are assigned with significantly different displacement weights in the new scheme. For example, as far as PRA is concerned (Figure 3a), Airline 48 (requesting 512 movements) obtains a weight between 4.3% and 5.48%, while Airline 9 (513 requested movements) is assigned with a displacement weight between 2.25% and 2.52%, with reference to different capacity cases. The corresponding weight on the previous scheme would be roughly 1.56% for any airline requesting approximately 510 movements. Similarly, Airlines 5, 13 and 54, requesting movements in the range of 260-280, obtain a new displacement weight in the order of 2.1-2.4%, while Airlines 8 and 24, with 256 and 257 movements respectively, are assigned with a displacement weight in the order of 0-0.6%. The corresponding weight on the previous scheme would be roughly 0.8% for any airline requesting around 260 movements. Interestingly, the displacement weights for Airline 25 (770 movements) are comparable (in the range of 1-1.5%) to the weights for Airline 47 (40 movements) and Airline 1 (318 movements). Last but not least, the new weighting scheme favors Airline 16 (not illustrated in Figure 3a, being an outlier in terms of the number of requested movements with 21,712 requested movements). Airline 16 obtains a new displacement weight between 34% and 38% as compared to the previous displacement reaching 66% (further investigation of this apparently paradoxical situation follows in the subsequent paragraphs). On the other hand, the second most active airline in the airport (i.e., Airline 28 with 1,722 requested movements) is among the penalized airlines based on the new displacement scheme. In particular, the displacement weights for Airline 28 range between 7.8-9% in the new displacement scheme, with the corresponding previous weights being amounted to 5.23%.

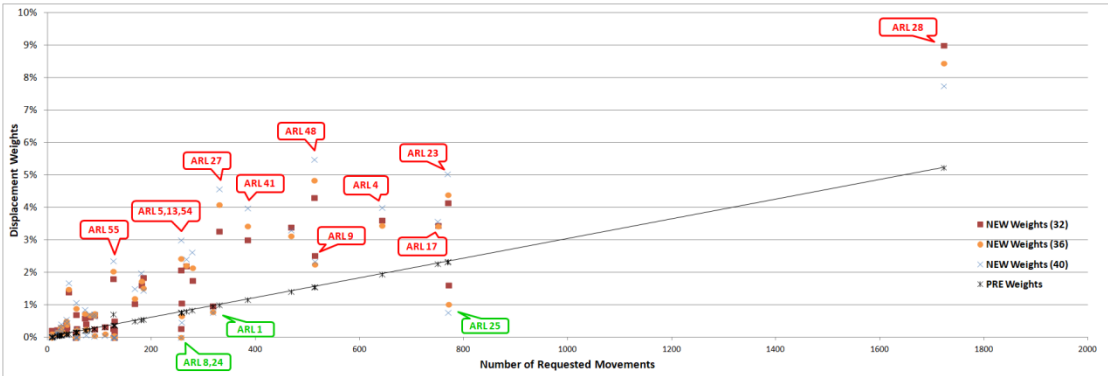


Figure 3a: Comparison between NEW and PRE Displacement Weights (PRA)

Quite similar findings can be observed in GRA (Figure 3b) with respect to the comparison between previous and new displacement weights. For example, Airline 21 with 120 movements obtains a weight between 5.2% and 8%, while for comparable number of movements (100 movements), Airline 24 is assigned with a displacement weight in the order of 2-2.5% for the various capacity cases examined. The corresponding weight on the previous scheme would be roughly 3-3.5% for any airline requesting approximately 100-120 movements. In a similar context, Airlines 0 and 29 have comparable number of movements (278 and 262 movements respectively), but are assigned with different displacement weights in the new scheme (14.2% vs. 11%) compared to roughly 8% in the previous scheme. Moreover, the displacement weights for Airline 36 (568 movements) are quite comparable (in the range of 18-31%) to those of Airline 19, despite the substantially different number of requested movements (568 movements for Airline 36 vs. 882 movements for Airline

19). Finally, Airline 19, the major operator in GRA, is slightly favored by the new weighting scheme at low capacity levels, hence being assigned with displacement weights in the order of 18-21% as compared to previous displacement weights of about 26%. The previous analysis at both PRA and GRA provides plausible evidence on the justification of a weighting scheme that will vary with the actual congestion or displacement impact, regardless of the intensity or volume of demand per se.

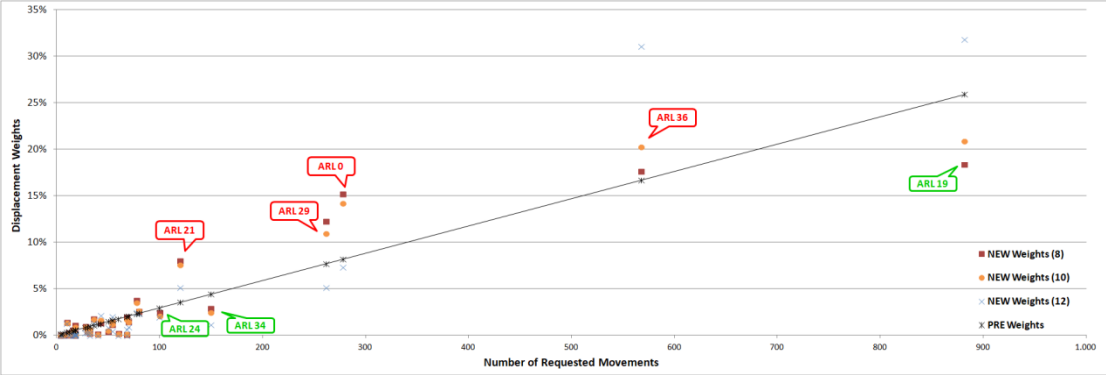
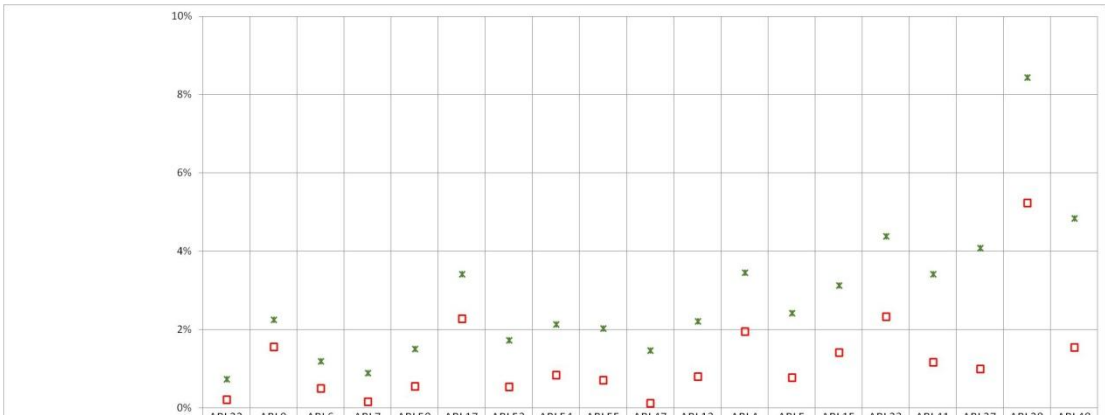


Figure 3b: Comparison between NEW and PRE Displacement Weights (GRA)

An essential conclusion from the previous analysis is that airlines may be assigned with different displacement weights on the basis of the intensity of actual congestion (additional displacement) they cause on the entire system (other airlines). This is due to the fact that the actual congestion impact is not necessarily associated with the degree of activity (i.e., number of slot requests), but it should also take into account the temporal distribution and peaking characteristics of each airline's demand. In order to verify this intuitive hypothesis, we proceed with additional analysis aiming to investigate whether the new weight scheme exhibits reasonable and operationally desirable behavior with respect to airlines penalized or favored in relation to the previously suggested weight scheme (i.e., proportional to the number of requested slots) (Zografos and Jiang, 2019). In the subsequent analysis (Figures 4a-c and Figures 5a-b), the newly proposed ("NEW") and previously suggested ("PRE") displacement weights are presented for the currently applied declared capacity scenario at each airport, that is (26, 26, 36) for PRA and (4, 6, 10) for GRA. We split the figure in parts in order to facilitate the readability of the displacement weights for the entire set of airlines (horizontal axis). Airlines are sorted in the horizontal axis by the magnitude of difference between the NEW and PRE weight scheme. In addition to PRE and NEW weights, two important metrics are also presented (in the data table enclosed below): i) the percentage of movements per airline that their requested time interval lies in periods where demand exceeds capacity (% of movements in busy periods) and ii) the number of movements per airline (# of movements).

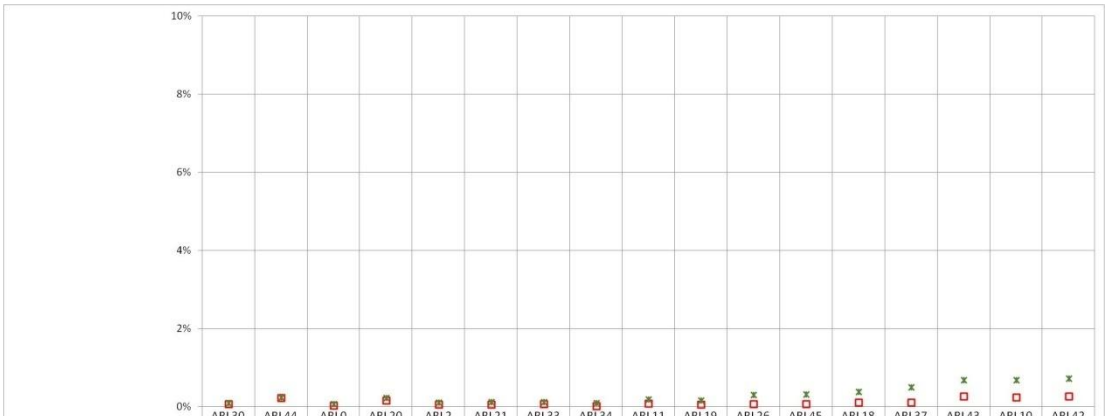
Figure 4a presents the airlines penalized by the new weight scheme as compared to PRE weights. Most of the penalized airlines exhibit more than double weights in the new weight scheme. It should be, however, observed that penalized airlines have a large part of their movements requested in periods of high demand (exceeding capacity). For example, the NEW weights for Airlines 55, 41, 27 and 48 increase by a factor of three, but all these airlines request more than 60% of their movements in peak periods. An interesting case relates particularly to Airline 55 (Figure 4a). Although its PRE weight was relatively low at 0.72% (basically due to the small number of requested movements), the corresponding NEW displacement weight is

significantly higher reaching 2.03%. This can be reasonably attributed to the fact that almost all movements of Airline 55 (i.e., 94.5%) are requested in busy periods. On the other hand, displacement weights are somewhat indifferent or with negligible differences between the previous and the new weight scheme for several airlines presented in Figure 4b. Finally, the newly proposed weight scheme tends to favour airlines requesting time intervals in periods of low demand (below capacity). This statement can be observed for Airlines 8, 39, 36, 32, 14, 51, 31, 40 etc. demonstrating significantly lower displacement weights compared to the corresponding PRE weights (Figure 4c). It is worth noting that the previously listed favoured airlines do not place any slot request in peak periods (i.e., 0% of requested movements in high demand periods). An interesting outlier in the previous analysis was Airline 16, representing the most favoured airline under the new weight scheme (38.22%) as compared to previous weights (65.96%) (Figure 4c). As a matter of fact, Airline 16, having established a significant foothold in PRA, has been over-penalized for its entire slot portfolio (21,712 requested movements) under the previous weight scheme, despite the fact that only 42% of its requests were placed in highly congested periods.



	ARL22	ARL9	ARL6	ARL7	ARL50	ARL17	ARL53	ARL54	ARL55	ARL47	ARL13	ARL4	ARL5	ARL15	ARL23	ARL41	ARL27	ARL28	ARL48
PRE Weights	0.22%	1.56%	0.51%	0.17%	0.56%	2.28%	0.55%	0.84%	0.72%	0.12%	0.81%	1.95%	0.78%	1.42%	2.34%	1.17%	1.00%	5.23%	1.56%
NEW Weights (36)	0.73%	2.25%	1.20%	0.90%	1.51%	3.42%	1.74%	2.13%	2.03%	1.48%	2.21%	3.45%	2.42%	3.13%	4.38%	3.42%	4.08%	8.43%	4.85%
% of movements in busy periods	100.00%	37.82%	33.53%	92.73%	46.20%	41.07%	75.00%	42.45%	94.49%	50.00%	48.12%	36.70%	50.00%	41.03%	33.29%	60.68%	97.58%	46.63%	69.53%
# of movements	72	513	167	55	184	750	180	278	236	40	266	643	256	468	769	384	330	1,722	512

Figure 4a: Additional Investigation of NEW Displacement Weights for PRA (26,26,36) (Part a)



	ARL30	ARL44	ARL0	ARL20	ARL2	ARL21	ARL33	ARL34	ARL11	ARL19	ARL26	ARL45	ARL18	ARL37	ARL43	ARL10	ARL42
PRE Weights	0.07%	0.22%	0.03%	0.17%	0.05%	0.05%	0.07%	0.02%	0.08%	0.05%	0.08%	0.08%	0.11%	0.11%	0.27%	0.25%	0.27%
NEW Weights (36)	0.09%	0.25%	0.07%	0.23%	0.12%	0.12%	0.13%	0.10%	0.19%	0.17%	0.30%	0.32%	0.39%	0.50%	0.68%	0.68%	0.72%
% of movements in busy periods	16.67%	37.84%	50.00%	33.93%	50.00%	50.00%	27.27%	0.00%	0.00%	50.00%	32.00%	50.00%	51.35%	50.00%	90.00%	77.78%	50.00%
# of movements	24	74	10	56	18	18	22	8	27	18	25	26	37	36	90	81	90

Figure 4b: Additional Investigation of NEW Displacement Weights for PRA (26,26,36) (Part b)

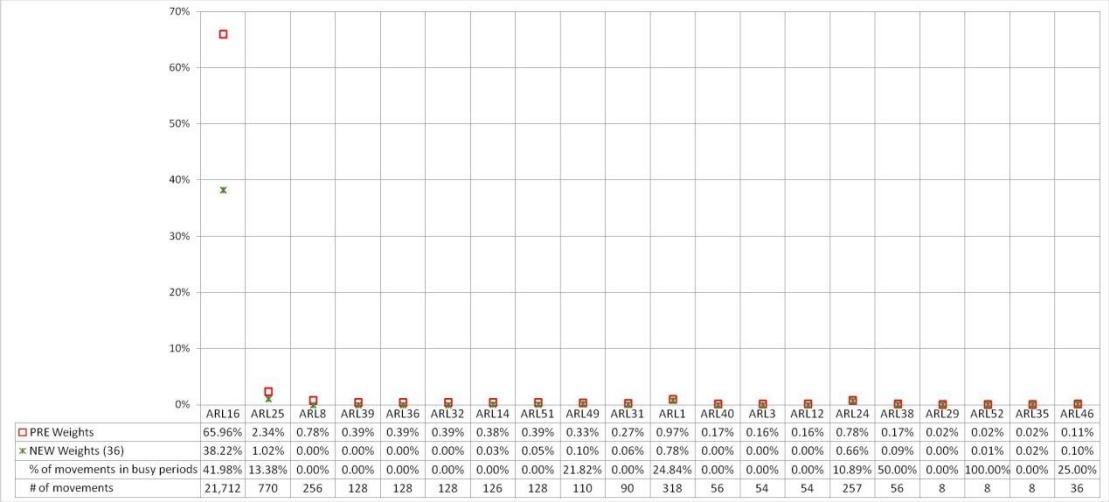
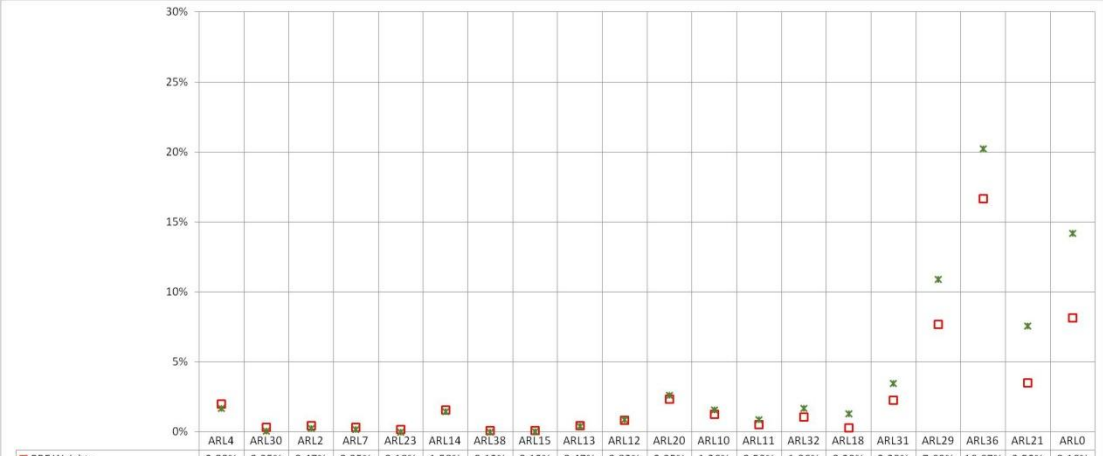


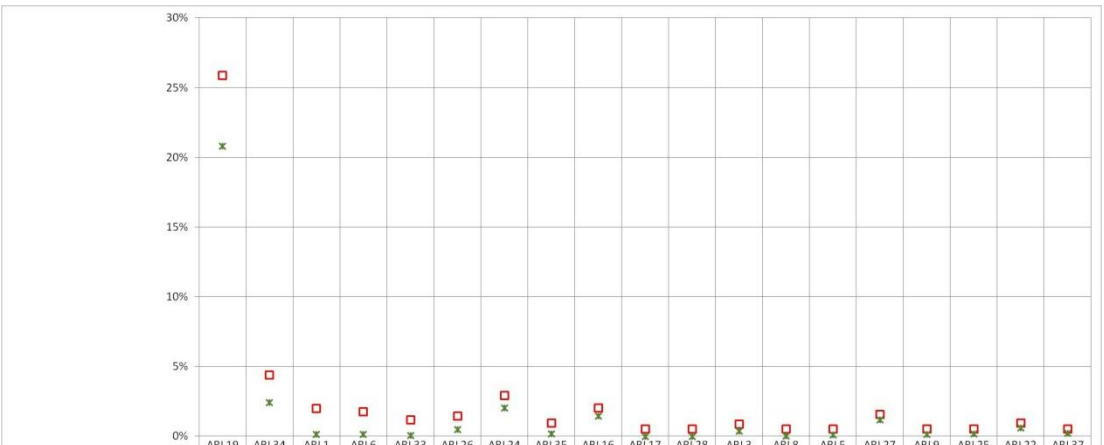
Figure 4c: Additional Investigation of NEW Displacement Weights for PRA (26,26,36) (Part c)

Figures 5a-b compare and investigate further the previous (PRE) and newly proposed (NEW) displacement weights calculated for the current capacity scenario (4,6,10) at GRA. A similar observation with the PRA case is that NEW weights are significantly higher than the corresponding PRE weights for airlines requesting a substantial part of their slots in high demand (busy) periods (Figure 5a). For example, Airlines 18, 31 and 21 exhibit substantial increases in the new weight scheme accounting for the fact that they request more than 50% of their total movements during peak periods (Figure 5a). More specifically, Airline 18 exhibits very low activity in GRA (i.e., 10 movements), thus receiving a PRE weight of 0.29% (Figure 5a). The NEW weight is, however, at much higher levels (1.3%), since all (100%) of the movements of Airline 18 are requested in busy periods. On the other hand, notably lower NEW displacement weights (compared with the corresponding PRE weights) can be observed for airlines that do not request any (0%) movements in high demand periods (e.g., Airlines, 1, 6, 33, 26, 35, 17, 28) (Figure 5b). Finally, Airline 19 represents a major operator in GRA, requesting 25.89% of the airport's total movements, hence being assigned with the equivalent displacement weight (25.89%) according to the PRE weight scheme (Figure 5b). Interestingly, the NEW weight for Airline 19 is substantially lower (20.83%), requesting only 2.7% of its movements in high demand periods.



	ARL4	ARL30	ARL2	ARL7	ARL23	ARL14	ARL38	ARL15	ARL13	ARL12	ARL20	ARL10	ARL11	ARL32	ARL18	ARL31	ARL29	ARL36	ARL21	ARL0
PRE Weights	2.00%	0.35%	0.47%	0.35%	0.18%	1.58%	0.12%	0.12%	0.47%	0.82%	2.35%	1.26%	0.53%	1.06%	0.29%	2.29%	7.69%	16.67%	3.52%	8.16%
NEW Weights (10)	1.70%	0.06%	0.27%	0.17%	0.00%	1.45%	0.00%	0.02%	0.42%	0.90%	2.63%	1.59%	0.87%	1.70%	1.30%	3.46%	10.92%	20.24%	7.58%	14.19%
% of movements in busy periods	13.24%	0.00%	6.25%	41.67%	0.00%	0.00%	0.00%	0.00%	6.25%	10.71%	18.75%	0.00%	16.67%	33.33%	100.00%	50.00%	31.30%	6.69%	65.83%	38.13%
# of movements	68	12	16	12	6	54	4	4	16	28	80	43	18	36	10	78	262	568	120	278

Figure 5a: Additional Investigation of NEW Displacement Weights for GRA (4,6,10) (Part a)



	ARL19	ARL34	ARL1	ARL6	ARL33	ARL26	ARL24	ARL35	ARL16	ARL17	ARL28	ARL3	ARL8	ARL5	ARL27	ARL9	ARL25	ARL22	ARL37
PRE Weights	25.89%	4.40%	2.00%	1.76%	1.17%	1.47%	2.94%	0.94%	2.05%	0.53%	0.53%	0.88%	0.53%	0.53%	1.58%	0.53%	0.53%	0.94%	0.53%
NEW Weights (10)	20.83%	2.43%	0.13%	0.13%	0.08%	0.48%	2.04%	0.17%	1.45%	0.00%	0.00%	0.36%	0.05%	0.09%	1.18%	0.13%	0.18%	0.59%	0.20%
% of movements in busy periods	2.72%	8.00%	0.00%	0.00%	0.00%	0.00%	3.00%	0.00%	14.29%	0.00%	0.00%	3.33%	0.00%	0.00%	18.52%	0.00%	0.00%	15.63%	0.00%
# of movements	882	150	68	60	40	50	100	32	70	18	18	30	18	18	54	18	18	32	18

Figure 5b: Additional Investigation of NEW Displacement Weights for GRA (4,6,10) (Part b)

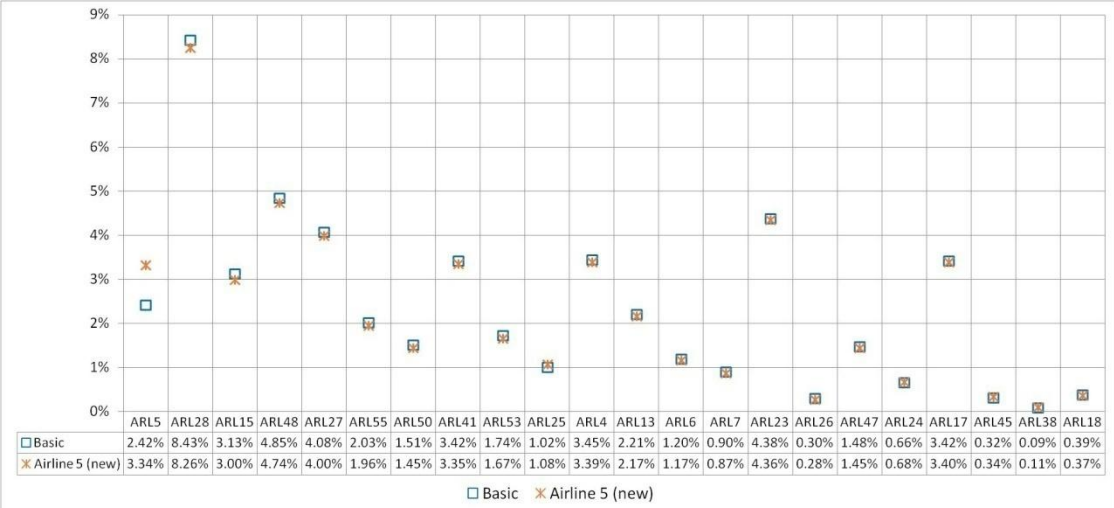
It can be reasonably derived from the above that certain airlines generate severe congestion and schedule displacement impacts by opting for slots in the highest peak periods of the days/hours of the scheduling season. As a result, under the new weight scheme, these airlines are penalized with larger portions of the overall schedule displacement in line with their actual contribution in that displacement (i.e., "the contributor pays" principle). On the other hand, other airlines distribute better their requested operations throughout the entire scheduling season and request fewer slots in congested periods, hence being favored by a smaller portion of the displacement penalty.

4.1.2 Validation of the Proposed Displacement Weight Scheme

In this section, we perform additional experiments with the aim to validate whether the proposed displacement weight scheme effectively captures the temporal dimension and peaking profile of airlines' slot requests. More specifically, we run two alternative validation scenarios at the declared capacity levels (i.e., (26,26,36),

(4,6,10)) for both problem instances (i.e., PRA, GRA): i) slots requested by an airline during off-peak intervals are shifted to peak periods and ii) slots requested by an airline during peak intervals are shifted to off-peak periods. In both cases, we thereafter assess the effect on displacement weights after rescheduling ("new" scenario) as compared to the original ("basic") scenario.

As far as PRA (26,26,36) is concerned, the rescheduling scenarios involve shifting requests for Airline 5 (Figures 6a-b) and Airline 28 (Figures 7a-b). Airline 5 has only 4 slot requests pertaining to 256 movements in total. The requested time intervals for 2 of its requests are placed in periods where demand is below capacity. We carefully selected time intervals so that all requested times are shifted to busy periods (where demand exceeds capacity). The displacement weights calculated under the "basic" scenario and the rescheduling scenario of Airline's 5 requests ("Airline 5 new") are presented in Figures 6a-b (airlines are sorted in the horizontal axis in decreasing order based on the difference between the two scenarios). Figure 6a includes the airlines' weights changing by at least 0.01 (from the basic to the airline 5 scenario), while Figure 6b presents the airlines' weights changing by less than 0.01. It can be easily verified from Figure 6a that the displacement weight of Airline 5 increases from 2.42% (basic scenario) to 3.34% when its off-peak requests are moved to high demand periods.



	ARL5	ARL28	ARL15	ARL48	ARL27	ARL55	ARL50	ARL41	ARL53	ARL25	ARL4	ARL13	ARL6	ARL7	ARL23	ARL26	ARL47	ARL24	ARL17	ARL45	ARL38	ARL18
Basic	2.42%	8.43%	3.13%	4.85%	4.08%	2.03%	1.51%	3.42%	1.74%	1.02%	3.45%	2.21%	1.20%	0.90%	4.38%	0.30%	1.48%	0.66%	3.42%	0.32%	0.09%	0.39%
Airline 5 (new)	3.34%	8.26%	3.00%	4.74%	4.00%	1.96%	1.45%	3.35%	1.67%	1.08%	3.39%	2.17%	1.17%	0.87%	4.36%	0.28%	1.45%	0.68%	3.40%	0.34%	0.11%	0.37%

Figure 6a: Displacement Weights for the Basic Scenario and the Rescheduling of Airline 5 Requests to Busy Periods of PRA (26,26,36) (Part a)

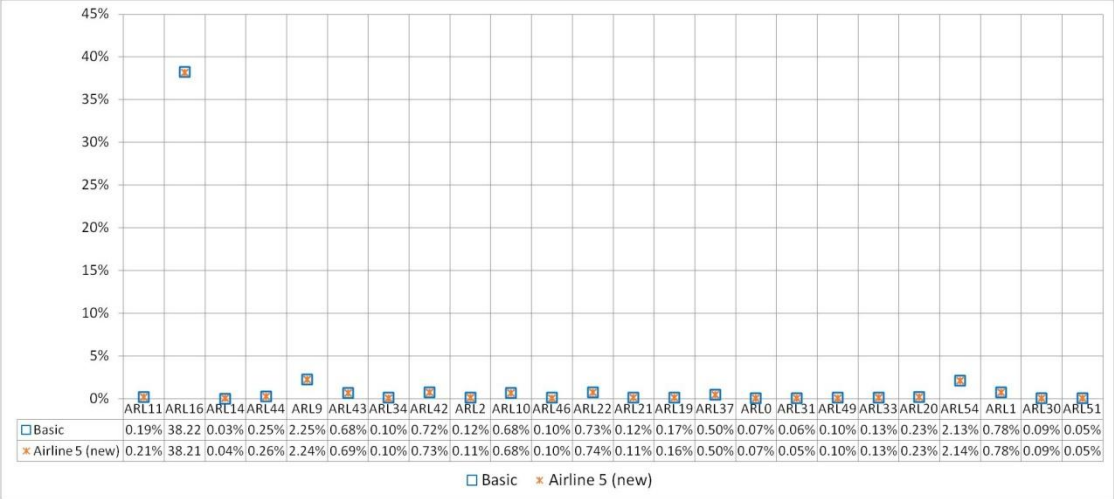


Figure 6b: Displacement Weights for the Basic Scenario and the Rescheduling of Airline 5 Requests to Busy Periods of PRA (26,26,36) (Part b)

On the other hand, Airline 28 has 88 requests involving 1,722 movements. We modify the temporal distribution of Airline's 28 requests so that all of its requested movements are placed in non-busy periods. As it was reasonably expected, the displacement weight of Airline 28 drops sharply from 8.43% (basic scenario) to 0.68% as a result of the rescheduling of its requests to off-peak periods (Figure 7a).

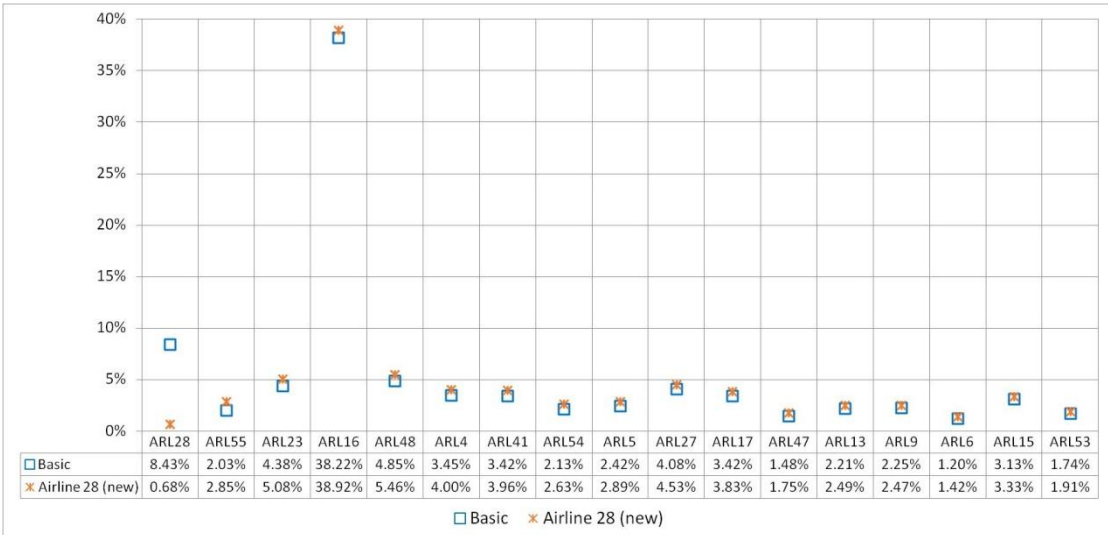


Figure 7a: Displacement Weights for the Basic Scenario and the Rescheduling of Airline 28 Requests to Non-Busy Periods of PRA (26,26,36) (Part a)

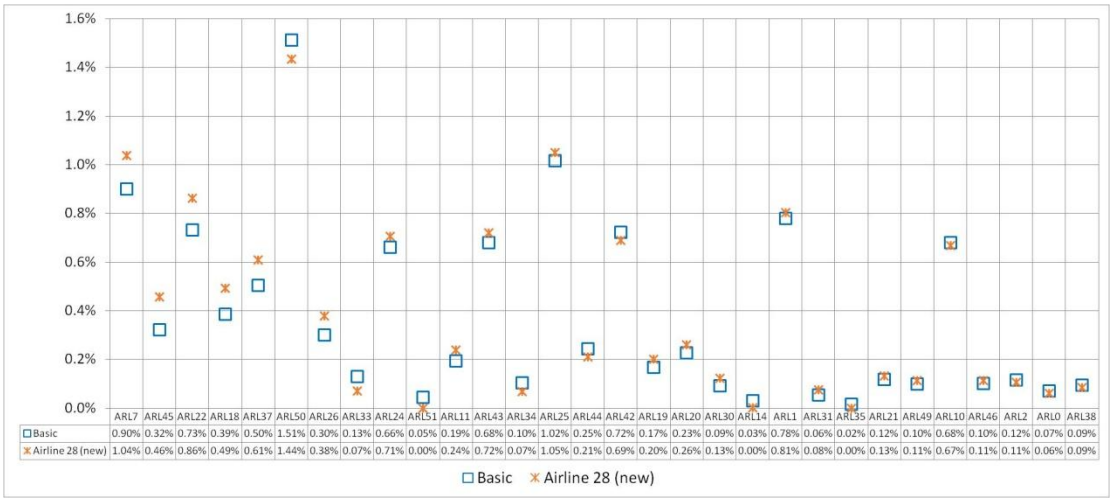


Figure 7b: Displacement Weights for the Basic Scenario and the Rescheduling of Airline 28 Requests to Non-Busy Periods of PRA (26,26,36) (Part b)

Similar validation experiments were also conducted for GRA (4,6,10), in which the rescheduling scenarios involve shifting requests for Airline 17 (Figures 8a-b) and Airline 29 (Figures 9a-b). In particular, Airline 17 has 4 slot requests involving 180 movements in total. All requested time intervals for Airline 17 are placed in non-busy periods (demand is below capacity). We carefully selected time intervals so that all requested times are now shifted to periods where demand exceeds capacity. It can be easily verified from Figure 8b that the displacement weight of Airline 17 increases from 0% (basic scenario) to 0.72% when its (off-peak) requests are moved to high demand periods.

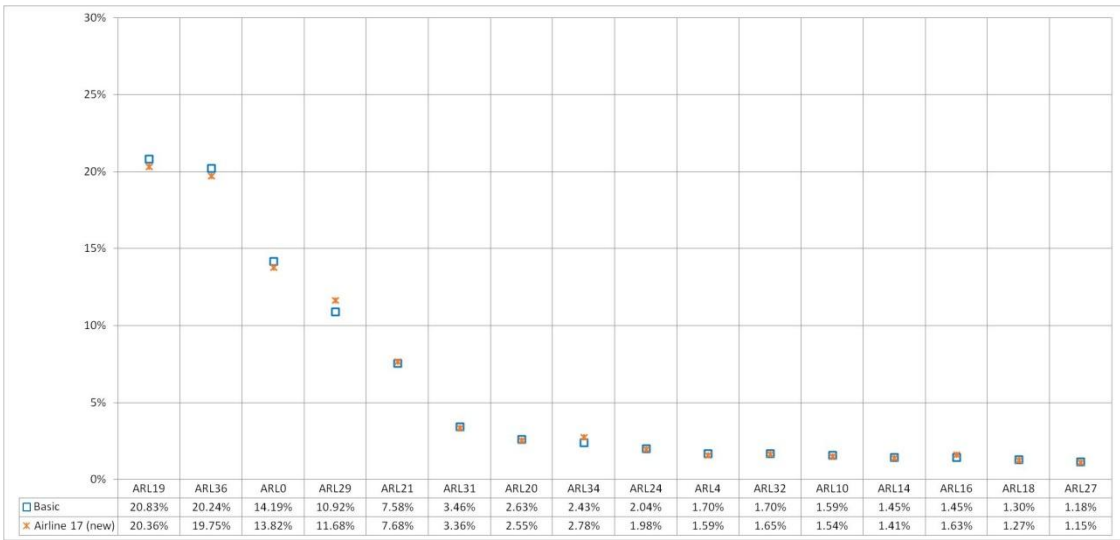
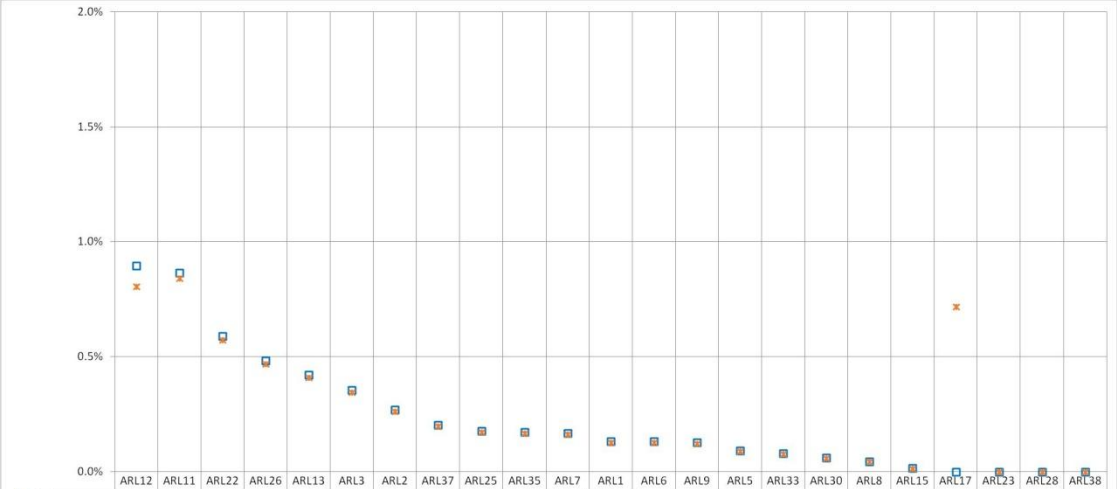


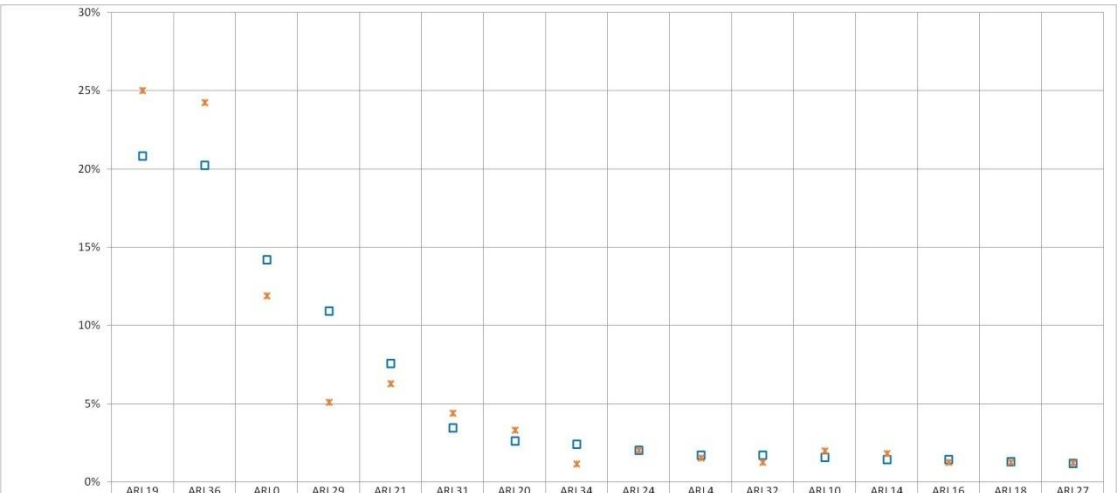
Figure 8a: Displacement Weights for the Basic Scenario and the Rescheduling of Airline 17 Requests to Busy Periods of GRA (4,6,10) (Part a)



	ARL12	ARL11	ARL22	ARL26	ARL13	ARL3	ARL2	ARL37	ARL25	ARL35	ARL7	ARL1	ARL6	ARL9	ARL5	ARL33	ARL30	ARL8	ARL15	ARL17	ARL23	ARL28	ARL38
Basic	0.90%	0.87%	0.59%	0.48%	0.42%	0.36%	0.27%	0.20%	0.18%	0.17%	0.17%	0.13%	0.13%	0.13%	0.09%	0.08%	0.06%	0.05%	0.02%	0.00%	0.00%	0.00%	0.00%
Airline 17 (new)	0.81%	0.84%	0.57%	0.47%	0.41%	0.35%	0.26%	0.20%	0.17%	0.17%	0.16%	0.13%	0.13%	0.12%	0.09%	0.08%	0.06%	0.04%	0.01%	0.72%	0.00%	0.00%	0.00%

Figure 8b: Displacement Weights for the Basic Scenario and the Rescheduling of Airline 17 Requests to Busy Periods of GRA (4,6,10) (Part b)

On the contrary, Airline 29 has 87 requests accounting for 626 movements in total (of which 32% are requested in busy periods). We changed the requested time intervals of Airline 29 so that all of its slot requests are placed in non-busy time periods. As a result, the displacement weight of Airline 29 (Figure 9a) rapidly decreases from 10.92% (basic scenario) to 5.1% when its (peak) requests are shifted to off-peak periods.



	ARL19	ARL36	ARL0	ARL29	ARL21	ARL31	ARL20	ARL34	ARL24	ARL4	ARL32	ARL10	ARL14	ARL16	ARL18	ARL27
Basic	20.83%	20.24%	14.19%	10.92%	7.58%	3.46%	2.63%	2.43%	2.04%	1.70%	1.70%	1.59%	1.45%	1.45%	1.30%	1.18%
Airline 29 (new)	25.01%	24.24%	11.92%	5.10%	6.29%	4.39%	3.31%	1.17%	2.02%	1.55%	1.27%	2.01%	1.84%	1.26%	1.25%	1.24%

Figure 9a: Displacement Weights for the Basic Scenario and the Rescheduling of Airline 29 Requests to Busy Periods of GRA (4,6,10) (Part a)

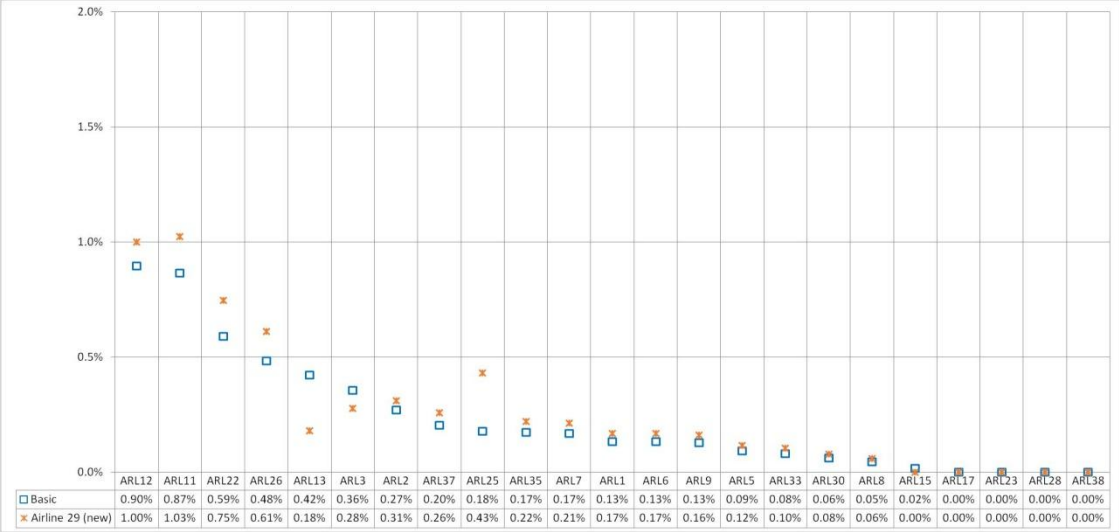


Figure 9b: Displacement Weights for the Basic Scenario and the Rescheduling of Airline 29 Requests to Busy Periods of GRA (4,6,10) (Part b)

At the outset, the selected validation scenarios at both problem instances (i.e., PRA, GRA) confirm the proper functioning of the newly proposed displacement weight scheme in relation to the peaking characteristics of airlines' slot requests. The new displacement weights respond adequately by penalizing those airlines concentrating their demand in busy periods, while simultaneously favoring other airlines distributing their requested slots in off-peak periods.

4.2 Fairness Impacts

In this section, we aim to quantify the "cost of fairness" by estimating the impacts of fairness-driven scheduling on certain level of service indicators under various capacity scenarios for both tested airports. In doing so, we first examine the results of the proposed model for decreasing values of ε at a given capacity level, the one corresponding to declared capacity (26,26,36) for PRA (Table 3 and Figure 10) and (4,6,10) for GRA (Table 4 and Figure 11). As part of the first type of scenario runs, we test the impact of five different values of the ε parameter (i.e., $\varepsilon = 0.15$, 0.2, 0.3, 0.4, 0.50), including the "fairness indifferent" (FI) case, for both airports.

Total displacement metrics (Figures 10-11) are deteriorating when moving from the "fairness indifferent (FI)" case (i.e., solution of the model without fairness considerations / constraints) to tighter fairness cases (i.e., decreasing values of ε). As far as PRA is concerned (Table 3 and Figure 10), the total aggregate displacement increases from 38,230 intervals (FI case) to 42,306 intervals for ε = 0.5, accounting for an increase of roughly 10.7%. It is interesting to observe that fairness-driven scheduling imposes a deterioration of approximately 21% in total aggregate displacement for the tightest fairness case (ε = 0.15) at PRA. The impact of fairness-driven scheduling of GRA (Table 4 and Figure 11) seems to be almost negligible for ε = 0.5 (i.e., less than 3% increase in total aggregate displacement), but it becomes much more vivid in the tightest fairness case (ε = 0.15), accounting for an increase in total aggregate displacement in the order of 34%. It can be, therefore, claimed that the compromise in total aggregate displacement is not that great particularly at loose

fairness levels (e.g., ε = 0.5) such that fairness considerations are really worth incorporating in the scheduling process.

PRA Capacity Level (26,26,36)	Total Aggregate Displacement (intervals)	Total Excess Displacement (intervals)	% of Violated Movements	Maximum Request Displacement	Average Excess Displacement per Movement (intervals)
Fairness Indifferent (FI)	38,230	3,527	0.92%	26	5.20
ε = 0.50	42,306	1,869	1.14%	151	3.50
ε = 0.40	43,460	2,091	1.16%	171	4.00
ε = 0.30	44,641	1,864	1.16%	152	3.20
ε = 0.20	45,769	1,997	0.94%	197	2.90
ε = 0.15	46,144	2,008	1.18%	208	3.10

Table 3: Impact of Fairness on Scheduling Efficiency and LoS Metrics (PRA)

GRA Capacity Level (4,6,10)	Total Aggregate Displacement (intervals)	Total Excess Displacement (intervals)	% of Violated Movements	Maximum Request Displacement	Average Excess Displacement per Movement (intervals)
Fairness Indifferent (FI)	10,876	3,346	6.11%	44	15.14
ε = 0.50	11,179	3,063	5.02%	54	15.47
ε = 0.40	11,978	2,935	5.08%	36	16.04
ε = 0.30	12,899	2,935	5.31%	55	16.04
ε = 0.20	13,974	3,025	5.34%	37	16.09
ε = 0.15	14,581	2,935	5.28%	45	16.04

Table 4: Impact of Fairness on Scheduling Efficiency and LoS Metrics (GRA)

Another interesting observation stems from the fact that increases in total aggregate displacement as a result of tighter fairness constraints do not seem to pass on to total excess displacement at both PRA (Table 3 and Figure 10) and GRA (Table 4 and Figure 11). In particular, the incorporation of fairness constraints at PRA would result in a decrease of roughly 43% (from 3,527 to 2,008 intervals) in total excess displacement at a level of ε = 0.15. The situation is quite similar for GRA (Table 4 and Figure 11), where the application of fairness constraints would practically leave excess displacement almost unaffected (again with slight downward trends). Similar downward trends are also observed in average excess displacement values of both airports under consideration.

With respect to PRA, the application of tighter fairness constraints (i.e., decreasing values of ε) does not substantially affect the percentage of violated movements (Table 3 and Figure 10). As a matter of fact, the percentage of violated movements at PRA remains almost stable at about 1% under all fairness levels (including the FI case). However, the maximum request displacement is substantially affected by fairness, ranging between 151 and 208 intervals at the various fairness levels as compared to 26 intervals for the FI case (Table 3 and Figure 10). As far as GRA is concerned (Table 4 and Figure 11), violated slots demonstrate a slight decrease from 6.11% (FI case) to 5.28% (ε = 0.15), with the impact on maximum request displacement being practically negligible.

It derives from the previous analysis that a fairness-driven scheduling may come at reasonable "cost" in terms of total aggregate displacement especially at loose or moderate fairness levels for both PRA and GRA. Fairness considerations in the scheduling process would not drastically affect the percentage of violated movements, demonstrating some slight increase at PRA and decrease at GRA while moving towards tighter fairness levels. Moreover, it would reduce total excess displacement at both airports by probably shifting displaced slots in the legitimate area (by modifying

excess to legitimate displacement). Particularly at PRA, substantial deteriorating effects are observed in terms of maximum request displacement. The latter may indicate that certain over-displaced slots will be further displaced due to their strong peaking characteristics. At the outset, for a small, regional airport "spoke" (e.g., GRA) without transfer operations or intensive head-to-head scheduling of flights, the application of fairness-driven scheduling would normally come at the expense of some reasonable increases in the total aggregate displacement through increases in legitimate (acceptable or non-excess) displacement of regularly displaced slots. On top of increases in total aggregate and legitimate displacement, for a medium or large airport (e.g., PRA) with intensive hub operations and persistent peaking characteristics, there is sufficient indication that displacement penalties will be further inflated for those (violated) slots that are already excessively displaced. In other words, fairness impacts at larger and more congested airports would become more acute especially for big contributors to congestion, with the latter observation being in alignment with the stated focus of the proposed weight scheme.

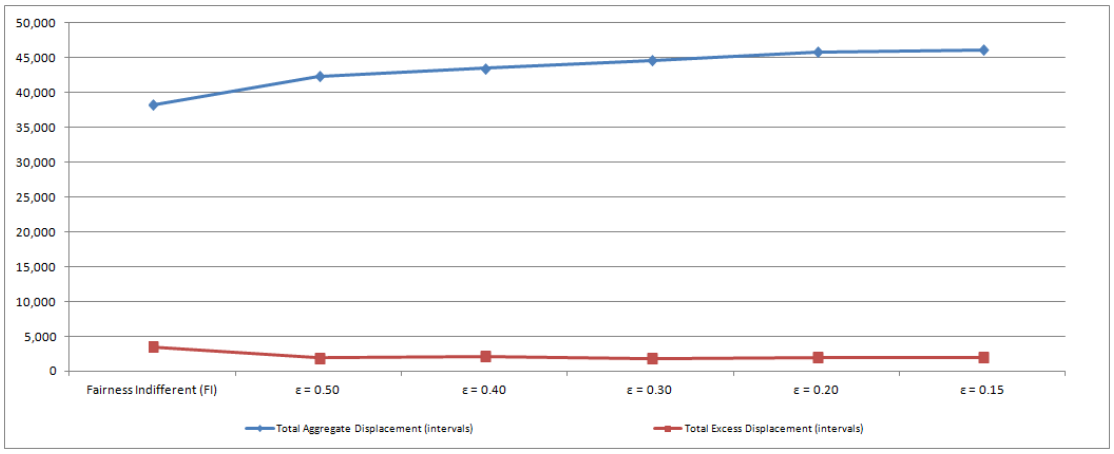


Figure 10: Total Displacement Metrics at Different Levels of Fairness (PRA)

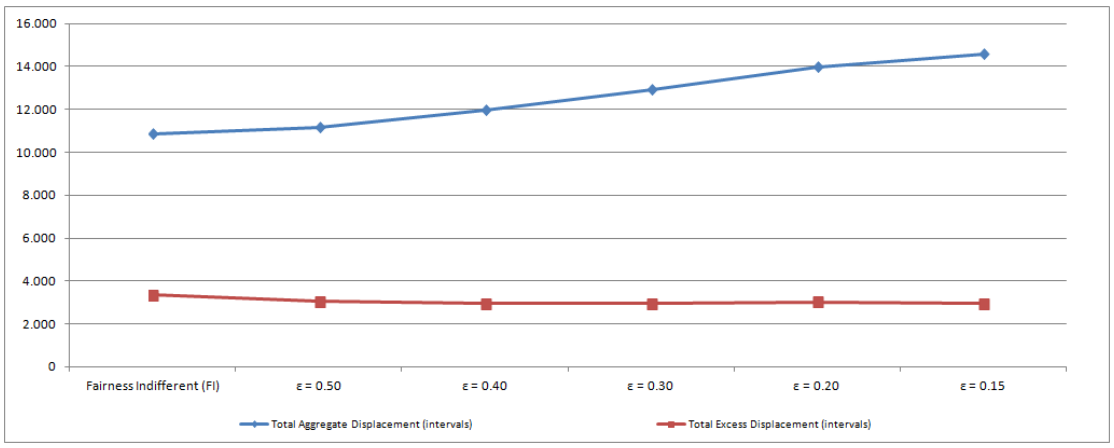


Figure 11: Total Displacement Metrics at Different Levels of Fairness (GRA)

As part of the second type of scenario runs, we conduct a sensitivity analysis of the displacement metrics/results at three different capacity levels (i.e., (24,24,32), (26,26,36), (29,29,40) for PRA, and (4,4,8), (4,6,10), (6,6,12) for GRA) at the tightest fairness case (i.e., $\varepsilon = 0.15$). The results demonstrate clearly the highly influential role of capacity on congestion and displacement at both PRA (Table 5) and GRA (Table 6).

PRA Fairness Level (ε = 0.15)	Total Aggregate Displacement (intervals)	Total Excess Displacement (intervals)	% of Violated Movements	Maximum Request Displacement	Average Excess Displacement per Movement (intervals)
Capacity (24,24,32)	68,844	6,509	2.75%	38	6.78
Capacity (26,26,36)	46,144	2,008	1.18%	26	3.20
Capacity (29,29,40)	22,349	1,656	1.04%	24	4.09

Table 5: Impact of Capacity on Scheduling Efficiency and LoS Metrics (PRA)

GRA Fairness Level (ε = 0.15)	Total Aggregate Displacement (intervals)	Total Excess Displacement (intervals)	% of Violated Movements	Maximum Request Displacement	Average Excess Displacement per Movement (intervals)
Capacity (4,4,8)	16,620	3,683	6.16%	148	15.61
Capacity (4,6,10)	14,581	2,935	5.28%	45	16.04
Capacity (6,6,12)	9,546	2,748	4.52%	34	17.96

Table 6: Impact of Capacity on Scheduling Efficiency and LoS Metrics (GRA)

Reasonable increases in declared capacity at a level of 10-20% may reduce total displacement metrics by 30-50% (Figures 12-13). Similarly, such a capacity expansion would substantially reduce the percentage of violated movements at both airports. The benefits of capacity increase from existing declared capacity to the high-capacity scenario for PRA would reflect on all total displacement metrics with the most notable being an approximate 52% decrease in total aggregate displacement (35% decrease for GRA) and 17.5% decrease in total excess displacement (6.5% decrease for GRA). Moreover, the percentage of violated movements would decrease by roughly 12.5% at PRA (i.e., 1.04% of movements) and 14.5% at GRA (i.e., 4.52% of movements). Positive impacts on maximum request displacement would range between 8% at PRA (i.e., 24 intervals) and 24.5% at GRA (i.e., 34 intervals). These findings essentially validate our empirical intuition that the availability of additional capacity would free up more slots that would be able to alleviate displacement impacts and congestion implications, hence better satisfying slot requests particularly during peak demand periods.

As discussed above, higher capacity levels are also behind the reduction of the percentage of violated movements at both PRA and GRA (Tables 5-6). This practically indicates that certain violated movements shift into the acceptable/legitimate displacement "area" due to the availability of additional slots for allocation among previously violated slot requests. On the other hand, some interesting observations can be made with regard to the impacts on excess displacement. The reduction of the percentage of violated movements positively affects total excess displacement as a result of additional capacity and slots available for allocation. However, at the same time, average excess displacement values remain at relatively stable levels at both airports regardless of increases in capacity levels. Violated movements will still suffer on average an excess displacement between 20 and 35 minutes (i.e., 4-7 intervals) at PRA and between 75 and 90 minutes (i.e., 15-18 intervals) at GRA on top of the maximum tolerance limit ($\xi_r = 12$ intervals or 60 minutes) within which a movement is considered acceptably displaced. Besides, average excess displacement demonstrates some irregular or non-systematic behavior with respect to capacity increases. This can be practically attributed to the fact that total excess displacement will be shared among a smaller "pool" of violated movements as capacity increases. Furthermore, despite some incremental increases in

capacity, these may not free up sufficient "room" for better satisfying slots requested at over-congested periods.

At the outset, increases in capacity create favorable conditions for drastically reducing total displacement impacts. There will be a larger number of movements that will be acceptably displaced as capacity increases. On the other hand, fewer slots will be unacceptably displaced at notably high excess displacement values, while more drastic capacity expansion projects seem to be required in order to deal with the remaining persistently violated slots during over-congested periods.

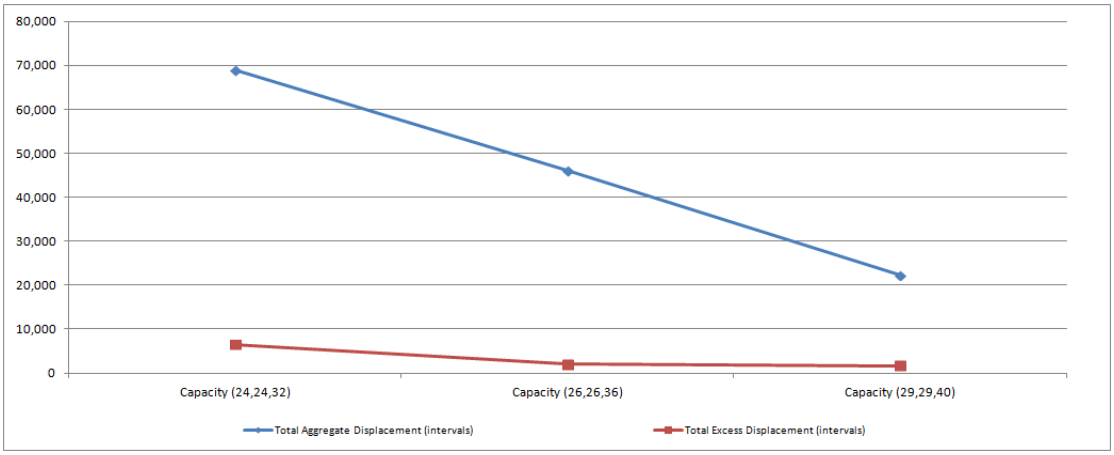


Figure 12: Total Displacement Metrics at Different Capacity Levels (PRA)

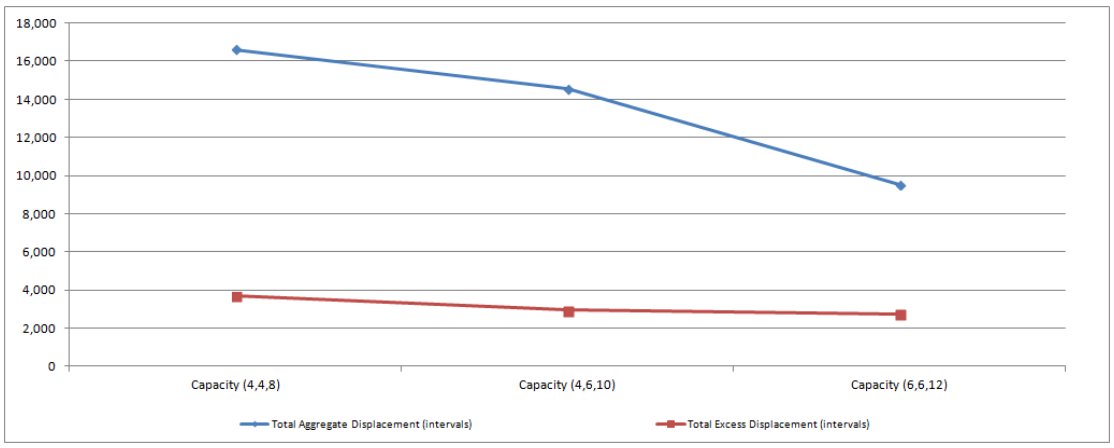


Figure 13: Total Displacement Metrics at Different Capacity Levels (GRA)

5. Conclusions

The strategic airport slot scheduling problem has increasingly drawn the attention of the research community, policy makers and professionals in the airport community. Existing research has placed the main focus on scheduling efficiency and acceptability criteria, but there is still ample room for further investigation of fairness-driven objectives. In this paper, we proposed a fairness-informed modeling extension of the strategic single-airport slot scheduling problem based on the general resource-constrained scheduling problem. Our model involved an enhanced version of the total aggregate displacement objective, weighted for the number of movements associated with a given slot request, but it also incorporated a fairness metric expressing the

proportion of displacement that should be "internalized" by each airline on the basis of the displacement imposed on all other airlines. The objective of the proposed slot scheduling model was to determine a feasible slot schedule minimizing total displacement while simultaneously promoting a fair distribution of the total displacement among competing airlines. As part of the new fairness-enriched schedule, airlines were assigned with their "fair share" of total schedule displacement by taking into account not only the demand volume characteristics, but also the peaking characteristics of their slot requests and subsequently their "contribution" to actual congestion of the entire system.

The proposed model was solved for two IATA schedule coordinated (Level 3) airports, a medium-sized, national hub airport in Portugal and a small, regional airport in Greece, with real-world scheduling data for the summer scheduling season of 2009. The analysis of the estimated fairness-driven weights provided plausible evidence on the justification of a weighting scheme that would vary with the actual congestion or displacement impact of a slot request. Airlines were assigned with different displacement weights on the basis of the intensity of actual congestion (additional displacement) caused on the entire system (other airlines) rather than the degree of activity (i.e., number of requested slots or movements). As a result, the proposed displacement weight scheme penalized "big contributors" to congestion by assigning weights on the basis of "the contributor pays" principle. Another interesting finding was that the proposed fairness-driven scheduling might come at reasonable "cost" in terms of total aggregate displacement particularly at low or moderate fairness levels. Interestingly, a comparison between the previous, "fairness indifferent" case and the various fairness cases examined in our analysis suggested that the application of the proposed fairness scheme would "cost" approximately a 11% increase in total aggregate displacement at low fairness levels ($\varepsilon = 0.5$) and 21% at the tightest fairness level ($\varepsilon = 0.15$) for PRA. The corresponding trade-off at GRA would result in an increase in total aggregate displacement ranging between 3% at low fairness levels ($\varepsilon = 0.5$) and 34% at the tightest fairness case ($\varepsilon = 0.15$).

Future research in the strategic slot scheduling problem can be channeled into three major streams. First, the exploration of airline-specific maximum tolerance levels, either as an aggregate airline metric or even per request/movement of each airline, would deserve further research. Alternative metrics expressing scheduling efficiency need to be also investigated in combination with the proposed fairness-driven modeling extension. The incorporation of a squared metric of total aggregate displacement would penalize the assignment of large displacements to slot requests, hence dealing with certain over-displaced requests still appearing in the scheduling results. Second, alternative viable modeling formulations and heuristic solution algorithms for the network problem merit further exploration by capitalizing on the experience derived from the single-airport slot scheduling models. A major challenge in addressing slot allocation for a network of airports pertains to the huge size of the emerging scheduling problem and the interrelations between the schedules at different airports. It is evident that the capacity and turnaround constraints of a given airport may affect the schedule of another airport. Last but not least, further research will be required in order to elicit the actual market-driven slot valuations of airlines that would potentially act as an alternative congestion management scheme. In the same line of research, it is worth investigating alternative methods aiming to provide monetary approximations of displacement weights that may feed into a congestion-

based pricing scheme. Needless to say that any market-driven or pure pricing scheme needs to be also viewed and assessed under the prism of various operational and economic efficiency criteria (e.g., length of flight, type of aircraft, load factors, operational/queuing delays, scheduling feasibility and flexibility at network level), in conjunction with fairness considerations (e.g., fair distribution of displacement, access to new entrants) and social priorities (e.g., social mobility, safeguarding access to small communities).

List of Acronyms

ADD	Average Delay per Delayed Flight (on Departure or Arrival)
ARL	Airline
ARR	Arrival(s)
ATM	Air Traffic Management
CODA	Central Office for Delay Analysis
DEP	Departure(s)
DIFF	Difference between PRE and NEW displacement weighting scheme
ECAC	European Civil Aviation Conference
EU	European Union
FAV	Airlines favoured by the newly proposed displacement weighting scheme
FI	Fairness indifferent case (model solution without fairness considerations)
GRA	Small, regional airport in Greece
IATA	International Air Transport Association
LOS	Level of Service
MVMTS	(Aircraft) Movements
NEW	Newly proposed displacement weights (our proposed model)
PEN	Airlines penalized by the newly proposed displacement weighting scheme
PRA	Medium-sized, national hub airport in Portugal
PRE	Displacement weights previously adopted in existing literature (i.e., proportional to the number of requested slots)
TOT	Total number of movements, including both arrivals and departures

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