Maximizing ATM Cost-efficiency by Flexible Provision of Airspace Capacity

Arne Strauss, Stefano Starita
Operational Research and Management Sciences, University of Warwick
Coventry, UK
arne.strauss; stefano.starita@wbs.ac.uk

Radosav Jovanovic, Nikola Ivanov
Division of Airports and Air Traffic Safety
University of Belgrade-Faculty of Transport and Traffic Engineering
Belgrade, Serbia
r.jovanovic; n.ivanov@sf.bg.ac.rs

Frank Fichert
Department of Tourism and Transportation
Worms University of Applied Sciences
Worms, Germany
fichert@hs-worms.de

***Abstract*—Inefficient airspace utilization together with an increasing demand make the European airspace network highly congested. This, in turn, generates significant delays and consequent cost increments. We propose to address this demand-capacity imbalance by introducing an optimization model which jointly decides on sector charges and capacities. This has to be embedded into a larger framework where we envisage a change in the Network Manager's (NM) role, from a *passive* mediator between Aircraft Operators (AOs) and Air Navigation Service Providers (ANSPs) to an *active* actor which purchases airspace capacity and sells trajectories. A case-study analysis is provided to highlight potential benefits of this approach.**

Keywords- ATM value-chain, optimization, sector charges, ATFM congestion, capacity management.

Foreword- *This work is envisaged as a part of SESAR 2020 Exploratory Research project COCTA. Opinions expressed in this work reflect the authors views only.*

I. Introduction

European Union airspace network is highly congested and fragmented. Furthermore, the European air traffic growth is expected to remain stable around 2.2% per year over the 2018-2022 period [7]. New policies should be implemented to encourage a safer and more efficient use of airspace. In this context, the COCTA project (Coordinated capacity ordering and trajectory pricing) aims at reshaping ATM environment by devising a new role for the Network Manager (NM).

Currently, the NM acts as a mere mediator between AOs and ANSPs, without having any significant economic instrument to affect capacity and demand. COCTA main idea is to shift this paradigm by letting the NM order capacities from Air Navigation Service Providers (ANSPs) and offer a menu of routes (priced according to opportunity costs) to AOs. In other words, the project suggests a shift from airspace-use charging to trajectory-use charging. With this acquired decision power, the NM will be able to influence AOs' behaviour so that overall network performance, seen as a combination of key indicators such as cost-efficiency, CO2 emissions, capacity utilization etc. can be optimized.

This project has received funding from the SESAR Joint Undertaking under grant agreement No 699326 under European Unions Horizon 2020 research and innovation programme

One of COCTA's objectives is to develop mathematical models which incorporate trajectory pricing, airspace capacity ordering and trajectory allocation. These models will be gradually made more sophisticated and complex by adding realistic assumptions (e.g., probabilistic models to simulate AOs' choice behaviour) and applying ideas that proved to be successful in other fields (e.g., flexible products).

Driven by this *increasing-complexity* approach, in this paper we introduce an optimization model which represents the first step and will be used as a benchmark in the upcoming research developments. The model embodies the main COCTA idea of simultaneously deciding on both sector charges and capacity.

The remainder of the paper is organised as follows: in Section 2 we briefly review past research works that dealt with capacity and pricing issues in ATM context. In Section 3 we propose a nonlinear version of our model, followed by the linearization approach implemented. In Section 4 we apply the model to a small artificial case study and compare the results with a model restricted to price decisions only so as to gauge the impact of controlling capacities as well. Finally, in Section 5 we provide conclusions and outline future research developments.

II. Background

ATM congestion problem has been widely studied during the last decades. The first papers on the topic considered ground delay assignments as a response to airport congestion [11, 15]. Afterwards, rescheduling was incorporated to tackle congestion at sector level as well [16, 1].

Despite the popularity of the topic, the use of economic instrument such as peak load pricing, congestion charges etc.

has been somewhat neglected in this context. [6] proposed a sector pricing model aimed at obtaining results as close as possible to an optimal route-slot allocation target. They used a Logit model to estimate AOs' behaviour. They finally implemented a simulated annealing algorithm to obtain approximate solutions efficiently. [12] proposed a new pricing scheme aimed at obtaining an equilibrium where AOs choices are optimal both individually and from a social point of view. [4] evaluate a slot allocation mechanism when an airport or a sector is congested. They considered the possibility for airlines to pay so that delay is reduced. They applied their policy to small-scale real life case studies, comparing it against the First Planned First Served allocation policy. [3] introduced a bi-level formulation to compute the Unit Rate imposed by a single ANSP to the flights passing through its charging zone. The model assumed that ANSP aims at maximizing its profits and airlines choose the minimum cost route. [10] investigated the problem of introducing time-dependent sector charges to balance the network traffic at a minimal cost for airspace users. They proposed a bi-level assignment model representing system's and users' perspectives. [8] studied the issue of late flight plans submissions. This problem increases uncertainty and results in inefficient resource allocations. They proposed a pricing scheme based on the concept of *rewarding predictability* (i.e., penalties are introduced for late filing). They assumed that Airline Operators (AOs) deterministically choose the least-cost route. This assumption was subsequently relaxed in [9] where AOs' choice behaviour became stochastic. [5] provided a background on how routes are charged in Europe and analyse length and cost of routes submitted in the past. The work emphasized that AOs are likely to choose shortest path routes. Longer routes are considered only when adjacent areas have significantly different prices. [2] introduced a bi-level model to implement a peak-load pricing scheme. The model aimed at identifying congested sectors in the airspace and consequently applying charges to induce AOs to reroute their traffic over less congested sectors.
To the best of authors' knowledge our model represents the first attempt at developing an optimization approach to identify optimal trajectory prices and sector capacity levels in a congested airspace network.

III. Optimization Model

In this section we study a simplified price and capacity optimization problem on a network composed of a set of Air Traffic Control (ATC) sectors and a set of flights, over a fixed time horizon (such as a single day). The purpose is to demonstrate the benefits of jointly controlling sectors' charges and capacities as compared to only controlling charges. Whilst the model features rather simplified assumptions, such as a known fixed unit cost of capacity provision for a given number of (elementary) sectors opened, it shall quantify potential benefits of controlling both capacity and price and as such motivate the research on more sophisticated models undertaken in the COCTA project.

To model the problem we make the following assumptions:

- The basic time period is small enough so that all flights will spend it entirely within one sector (i.e., time intervals are not split between sectors).
- A feasible route is a route that can be assigned without breaching the capacity limitation of any of the sectors involved.
- AOs choose the cheapest available route from a set of feasible routes.
- The *displacement* cost of a route is a cost parameter defined to rank routes for each flight. *Displacement* cost of favourite routes is 0. These costs are estimated by the NM, using information such as historical route choices, aircraft type, fuel consumption, length of the route etc.
- The NM is revenue neutral, i.e. its aim is to fully recover operating costs without making any additional profit.
- We seek to minimize the cost of ANS provision and displacement cost.
- The NM sets route prices by dynamically fixing per-sector charges.
- Each sector can operate at different capacity levels, meaning that the NM can actively decide on what capacity limitation adopting for a sector. For simplicity, we assume that all sectors have the same number of levels. This assumption can be relaxed with small changes in the formulation.
- Each capacity level has associated operating cost[1].

The optimization model uses the following notation:

- U length of the flight horizon
- $u \in \{1, ..., U\}$ elementary time periods
- $f \in F$ set of flights
- R^f is the set of routes to f, indexed by r
- S is the set of sectors, indexed by s
- A route r is an ordered sequence of (s, u) sector-time couples
- L number of capacity levels
- $l \in \{1, ..., L\}$ level index
- k_{sl} is the maximum number of flights allowed to fly over sector s when s operates at level l
- c_{slu} is the cost of operating sector s at level l and time u
- A is the route-sector-time incidence matrix, with

$$a_{rsu} = \begin{cases} 1 \text{ if route } r \text{ uses sector } s \text{ at time } u; \\ \\ 0 \text{ otherwise} \end{cases}$$

- d_r^f is the displacement cost of route r for flight f

[1]Note that increasing capacity level actually corresponds to opening a new ATC sector, i.e. adding two new controllers, hence step-like cost increase.

We define the following set of decision variables:

- $y_r^f = \begin{cases} 1 \text{ if } f \text{ chooses } r; \\ 0 \text{ otherwise} \end{cases}$
- $z_{slu} = \begin{cases} 1 \text{ if } s \text{ operates at level } l \text{ at time } u; \\ 0 \text{ otherwise} \end{cases}$
- p_{su} is the price charged for sector s at time u

A non linear formulation of the route pricing problem under least-cost choice assumption (RPLC) is given as follows:

$$\text{[RPLC]} \ \min \sum_{f \in F} \sum_{r \in R^f} y_r^f (d_r^f + \sum_{s \in S} \sum_{u \leq U} a_{rsu} p_{su}) \tag{1}$$

$$\text{s.t.} \sum_{r \in R^f} y_r^f = 1 \quad \forall f \in F \tag{2}$$

$$\sum_{l \leq L} z_{slu} = 1 \quad \forall s \in S, u \leq U \tag{3}$$

$$\sum_{f \in F} \sum_{r \in R^f} a_{rsu} y_r^f \leq \sum_{l \leq L} z_{slu} k_{sl} \tag{4}$$
$$\forall s \in S, u \leq U$$

$$\sum_{f \in F} \sum_{r \in R^f} a_{rsu} y_r^f p_{su} \geq \sum_{l \leq L} c_{slu} z_{sl} \tag{5}$$
$$\forall s \in S, u \leq U$$

$$\sum_{f \in F} \sum_{r \in R^f} y_r^f \sum_{s \in S} \sum_{u \leq U} a_{rsu} p_{su} \geq \tag{6}$$
$$\sum_{s \in S} \sum_{l \leq L} \sum_{u \leq U} c_{slu} z_{slu}$$

$$y_r^f \in \{0,1\} \quad \forall f \in F, r \in R^f \tag{7}$$

$$z_{slu} \in \{0,1\} \quad \forall s \in S, l \leq L, u \leq U \tag{8}$$

$$p_{su} \geq 0 \quad \forall f \in F, r \in R^f, s \in S, u \leq U. \tag{9}$$

The objective function (1) aims at minimizing the overall costs faced by airlines, computed as routes' prices plus displacement costs. Equalities (2) enforce that each flight must be assigned to exactly one route. Constraints (3) state that each sector can only operate at one level per period. Constraints (4) are the capacity limitations for each sector-period couple. Constraints (5) guarantee that the revenue collected by charging all flights choosing a route going through s at time u should cover the operating cost of sector s at time u. This lower bound is introduced to avoid unrealistic cases where only a few sectors are overcharged and the rest are free to fly over. Inequality (6) states that total revenue must fully cover capacity provision costs of the network. Note that each flight is assigned the cheapest available route in the optimal solution, thus representing AOs that always choose the cheapest available route. Constraints (7) and (9) are restrictions for variables y, z and p.

The RPLC formulation is non linear in both the objective function (1) and constraints (5), (6). A linear reformulation can be obtained by introducing one large constant M and the additional variables $p_{rsu}^f = a_{rsu} y_r^f p_{su}$.

In words, p_{rsu}^f is equal to the sector price p_{su} if f chooses r and r crosses s at time u; 0 otherwise.

A linear formulation of RPLC (RPLC2) is given as follows:

$$\text{[RPLC2]} \ \min \sum_{f \in F} \sum_{r \in R^f} (d_r^f y_r^f + \sum_{s \in S} \sum_{u \leq U} p_{rsu}^f) \tag{10}$$

$$\text{s.t. } (2) - (4)$$

$$\sum_{f \in F} \sum_{r \in R^f} p_{rsu}^f \geq \sum_{l \leq L} c_{slu} z_{slu} \tag{11}$$
$$\forall s \in S, u \leq U$$

$$\sum_{f \in F} \sum_{r \in R^f} \sum_{s \in S} \sum_{u \leq U} p_{rsu}^f \geq \tag{12}$$
$$\sum_{s \in S} \sum_{l \leq L} \sum_{u \leq U} c_{slu} z_{slu}$$

$$p_{rsu}^f \geq a_{rsu} p_{su} + M(y_r^f - 1) \tag{13}$$
$$\forall f \in F, r \in R^f, s \in S, u \leq U$$

$$p_{rsu}^f \leq a_{rsu} p_{su} \tag{14}$$
$$\forall f \in F, r \in R^f, s \in S, u \leq U$$

$$p_{rsu}^f \leq M y_r^f \tag{15}$$
$$\forall f \in F, r \in R^f, s \in S, u \leq U$$

$$p_{rsu}^f \geq 0 \tag{16}$$
$$\forall f \in F, r \in R^f, s \in S, u \leq U$$

$$(7) - (9).$$

Constraints (11) and (12) represent the linearization of constraints (5) and (6), respectively. The set of inequalities (13)-(16) are introduced to define variables p_{rsu}^f.

IV. Case Study Analysis

In this section we test our model with a small case study based on [13]. To highlight the potential benefits of our ideas we perform a comparison with fixed-capacity, price-change approaches. Price only policies can be easily implemented as a special cases of RPLC2 where only one capacity level is considered for each sector (two levels if we consider the possibility that sectors can be closed). All analysis has been conducted using programming language C combined with

Cplex 12.6 libraries.

In Figure 1 the airspace network under consideration is shown, along with routes. The small network has 5 sectors: R, Q, S, T, U. The problem is studied over a 60 minute time horizon. For simplicity, we focus on 5 minutes long time periods. Having such a small time period can be considered unrealistic, given that we are deciding on sectors' capacities. The issue can be easily addressed by imposing that a sector must remain on a capacity level for a certain number of periods. For instance, in the following analysis we assume that sectors cannot change capacity level for 15 minutes (i.e., 3 time periods).

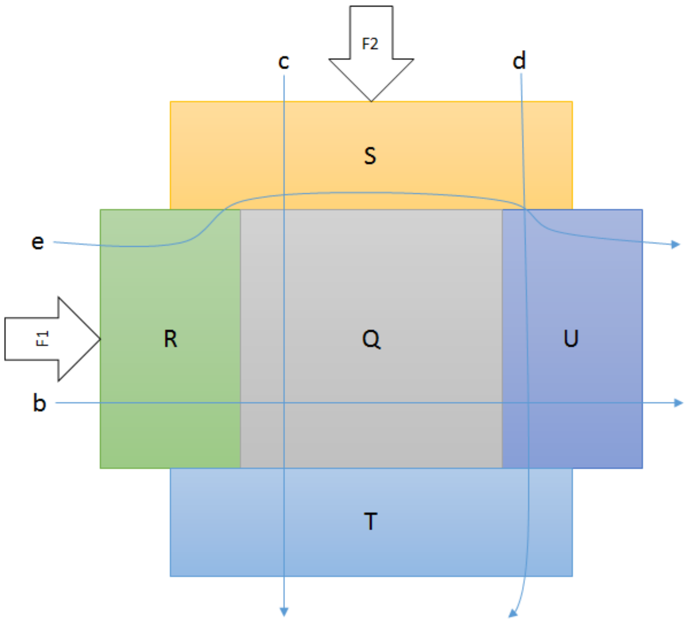

Figure 1. Air route network

We consider two traffic flows: $F1$ and $F2$. Each flow is made of 5 flights entering the airspace under consideration at the same time. Table I shows the details of routes available for each flow. Note that both shortest routes (b and c) enter the same sector (Q) at the same time. This is done to introduce a bottleneck in the network which could lead to congestion.

TABLE I
AVAILABLE ROUTES

Flow	Route	Time spent on sector S(min)			Length(min)
F1	b	R(20)	Q(20)	U(15)	55
F1	e	R(20)	S(20)	U(20)	60
F2	c	S(20)	Q(20)	T(15)	55
F2	d	S(20)	U(20)	T(20)	60

Based on linear relationship between airline operating costs and flight length [14], assuming constant speed, we estimate operating costs as a function of flight duration, using Block Hour Operating Costs (BHOC) per aircraft type.

We assume heterogeneous demand by considering 3 different types of aircraft: Boeing 777-200 (B772), Airbus 321 (A321) and Embraer 145LR (E145). Aircraft distribution per flow is as follows: two B772 and three A321 for flow F1; two A321 and three E145 for flow F2. Displacement costs (Table II) are obtained for each flow and aircraft by subtracting the cost of the cheapest route from route costs (e.g., displacement cost of route e, for E145, is given by 1170-1073).

TABLE II
ROUTE COSTS

	Route	Route cost	Displacement cost
B772	b	5346	0
B772	e	5832	486
A321	b	2558	0
A321	e	2791	233
A321	c	2558	0
A321	d	2791	233
E145	b	1073	0
E145	e	1170	97

For each sector we consider three capacity levels as listed in table III:

TABLE III
SECTORS CAPACITY LEVELS

	Level 0		Level 1		Level 2		Level 3	
Sector	Cap	Cost	Cap	Cost	Cap	Cost	Cap	Cost
R	0	0	4	333	6	500	8	667
Q	0	0	4	333	6	500	8	667
S	0	0	4	333	6	500	8	667
T	0	0	4	333	6	500	8	667
U	0	0	4	333	6	500	8	667

Level 0 is used to represent a closed sector. In level 1, capacity limitations are chosen to simulate a scarce-resources configuration. For instance, assuming that all flights choose the cheapest route (b for F1 and c for F2), this will lead to a demand of 10 flights over sector Q, as opposed to its capacity of 4. Unit cost of controlling any specific volume of airspace (sector) considered is assumed to increase linearly with capacity provided, being: 4000 EUR/h for Level 1, 6000 EUR/h for Level 2, and 8000 EUR/h for Level 3 capacity. These assumptions are made to provide a simple and explanatory example.

a) Displacement cost vs Capacity cost tradeoff: Figure 2 provides details on the optimal capacity levels chosen by RPLC2. Capacity of sector Q (which the reader will recall being the network's bottleneck) is increased from 4 to 6 during the time interval (20-40 min) in which the sector is congested.

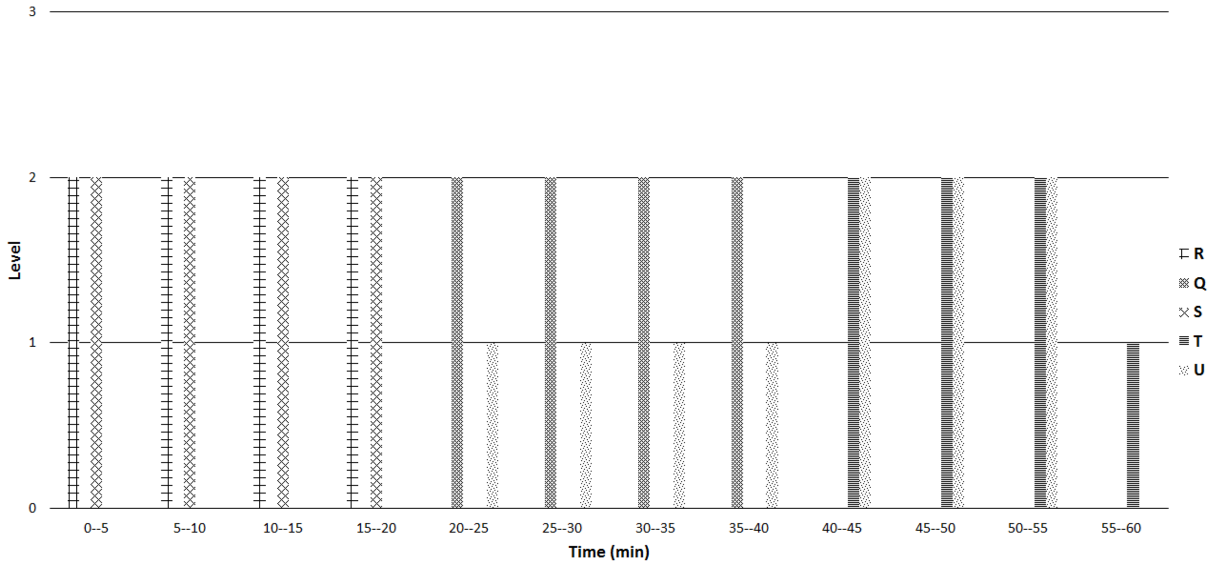

Figure 2. Sector-Level across the time horizon

In every period, with the exception of the last one, there are only 2 sectors open. More specifically, during the first 20 minutes, capacities of sectors R and S are increased to level 2 to accommodate 10 flights entering the airpsace under investigation. In the following 20 minutes, R and S are replaced by Q (level 2) and U (level 1). Finally T and U are open at level 2. Note that, flights assigned to their favourite route will exit the airspace 5 minutes earlier. Consequently, only one sector is left open in the last period to accommodate flights assigned to non-favourite routes.

Interestingly, no level 3 increments are considered leading to some flights (4) flying non-favorite routes. This is a consequence of the trade-off between displacement costs and capacity increment costs. To further inspect this issue, in Figure 3 we plot the overall displacement costs while incrementing the number of flights (starting from flights with higher displacement costs) assigned to their favourite route. At the same time, the graph shows the cost increment needed to provide proper capacity at sector Q. In accordance with the results obtained with RPLC2, the graph shows that it is cost-effective to increment Q's capacity up to 6 (level 2). Any further increment will be inefficient as capacity costs outgrow significantly displacement cost reductions.

In the following paragraphs we report on our findings of comparing different policies so as to highlight potential benefits of implementing our approach. Table IV gives an outline of the policies used to benchmark RPLC2: DPFC (Dynamic Pricing with Fixed Capacities) is a dynamic pricing policy which decides sector charges over time assuming fixed known capacities. SPFC (Static Pricing with Fixed Capacities) is the static version of DPFC, i.e. sector charges do not change over time while capacities are again considered constant.

TABLE IV
POLICIES TESTED

	Policy acronym		
	RPLC2	DPFC	SPFC
Pricing	Dynamic	Dynamic	Static
Capacities	Level-based	Fixed	Fixed

b) RPLC2 vs DPFC: In this analysis we compare our model with the policy that decides on time and sector-based price only while assuming fixed capacities. Sectors capacities are set equal to limitations imposed by level 2 (fixing to level 1 would lead to an unfeasible problem). In Table V we compare the optimal flight-to-route assignments obtained by the two approaches.

TABLE V
DPFC VS RPLC2 FLIGHT-ROUTE ASSIGNMENTS

	DPFC		RPLC2	
Flight	Route	Favourite	Route	Favorite
B772	b	YES	b	YES
B772	b	YES	b	YES
A321	b	YES	b	YES
A321	b	YES	b	YES
A321	b	YES	b	YES
A321	d	NO	d	NO
A321	c	YES	c	YES
E145	d	NO	d	NO
E145	d	NO	d	NO
E145	d	NO	d	NO
	Total cost	12024	Total cost	11189

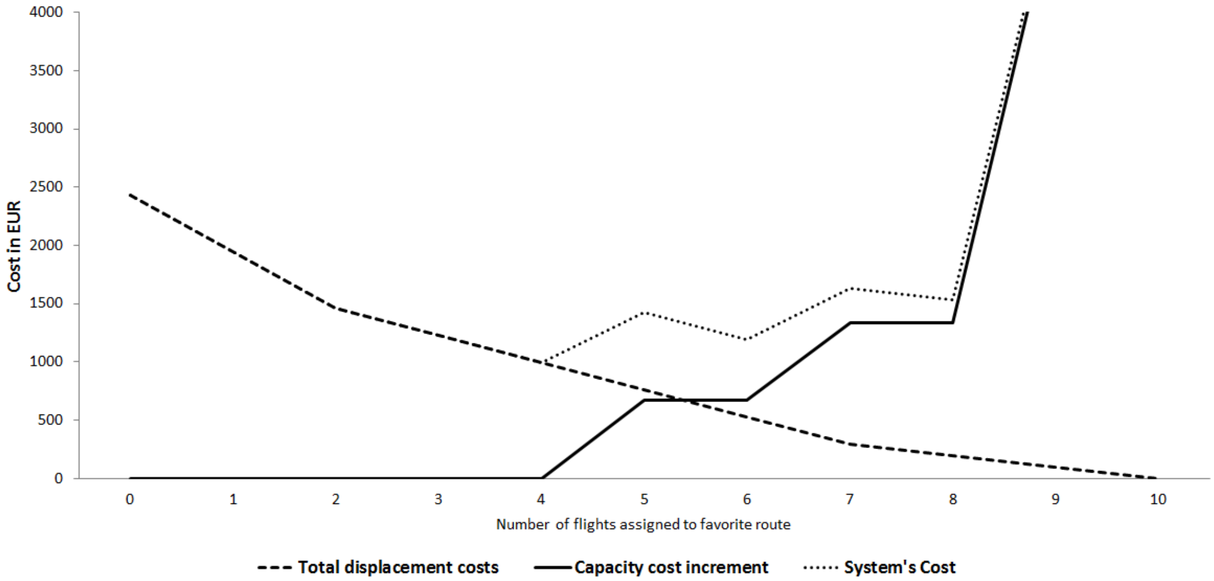

Figure 3. Trade off between displacement and capacity costs

The table shows that both policies return the same flight assignments. Nonetheless, with the flexibility of dynamically adjusting capacity levels, RPLC2 reduce the overall cost by 6.9%.

Not surprisingly, priority is given to flights with higher displacement costs (i.e., B772 and A321).

c) RPLC2 vs SPFC: Another interesting feature of RPLC2 is that sector prices do not have to be fixed across the time horizon. To assess the impact of dynamic pricing, we perform a comparison with SPFC policy.

TABLE VI
SPFC VS RPLC2 FLIGHT-ROUTE ASSIGNMENTS

	SPFC		RPLC2	
Flight	Route	Favourite	Route	Favorite
B772	b	YES	b	YES
B772	b	YES	b	YES
A321	b	YES	b	YES
A321	b	YES	b	YES
A321	b	YES	b	YES
A321	c	NO	d	NO
A321	c	NO	c	YES
E145	c	NO	d	NO
E145	c	NO	d	NO
E145	c	NO	d	NO
	Total cost	12257	Total cost	11189

As expected, SPFC performances are worse than DPFC, given the lack of flexibility on price decisions over time. Table VI shows the SPFC policy assigns one flight less (5 instead of 6) to its favourite route. The advantage of using RPLC2 over SPFC is clear, with a total cost 8.7% smaller. To sum up, results of the two comparison show that dynamic pricing (already considered in the literature) has some potential on its own, but joint capacity and pricing control might be much more powerful.

d) Sector charges analysis: Finally, to deepen the understanding of the three policies investigated, Table VII provides an overview of sector charges they have generated.

SPFC charges same prices for all sectors and, by definition, these prices are constant over time. The table also highlights how DPFC distributes resources in a less efficient way compared to RPLC2. In fact, both charges at sectors T and U have significant variations from 100 to 125. This is caused by the number of flights using these sectors which drops from 4 to 3. Conversely, RPLC2 provides a more efficient distribution which is reflected by smaller fluctuations on sector charges.

V. CONCLUSIONS AND FUTURE STEPS

In this paper we introduced an optimization model to simultaneously assign dynamic sector charges and decide on airspace capacity provided. The model was applied to a small network. Results show that this approach has the potential to lead to a more cost-efficient utilization of network resources compared to price-only solutions. It should finally be noted that, while the assumed unit cost of capacity provision is fairly realistic, the unrealistically thin traffic flows, under the assumed full cost recovery regime, make consequent per-flight sector charges excessively high. More realistic traffic intensities would mean lower sector charges and would affect the tradeoff between capacity cost and displacement cost, illustrated in Figure 3.

TABLE VII
SECTOR CHARGES OVER TIME

	R			Q			S			T			U		
T(min)	RPLC2	DPFC	SPFC	RPLC2	DPFC	SPFC	RPLC2	DPFC	SPFC	RPLC2	DPFC	SPFC	RPLC2	DPFC	SPFC
0–5	100	100	100	0	0	100	100	100	100	0	0	100	0	0	100
5–10	100	100	100	0	0	100	100	100	100	0	0	100	0	0	100
10–15	100	100	100	0	0	100	100	100	100	0	0	100	0	0	100
15–20	100	100	100	0	0	100	100	100	100	0	0	100	0	0	100
20–25	0	0	100	83.33	83.33	100	0	0	100	0	0	100	83.33	125	100
25–30	0	0	100	83.33	83.33	100	0	0	100	0	0	100	83.33	125	100
30–35	0	0	100	83.33	83.33	100	0	0	100	0	0	100	83.33	125	100
35–40	0	0	100	83.33	83.33	100	0	0	100	100	100	100	83.33	125	100
40–45	0	0	100	0	0	100	0	0	100	100	100	100	100	100	100
45–50	0	0	100	0	0	100	0	0	100	100	100	100	100	100	100
50–55	0	0	100	0	0	100	0	0	100	100	100	100	100	100	100
55–60	0	0	100	0	0	100	0	0	100	83.33	125	100	0	0	100

We aim at applying this problem to an example based on real data. This will require working with larger time periods and developing a more accurate function to evaluate capacity provision costs.

We foresee development of proposed initial model, both in terms of relaxing some of the assumptions made and increasing the complexity of model itself; for instance, by encompassing other aspects of network performance indicators in the objective function. The aim is to develop a sophisticated tool to decide on capacity levels and trajectory prices, while incorporating the choice-based (routes) aspects to mimic typical AOs' behavior, so as to optimize the system's performance (expressed as a vector of performance indicators). Developing more complicated mathematical models will also require to devise efficient solution approaches to tackle problems of realistic size.

REFERENCES

[1] D. Bertsimas and S. S. Patterson. The air traffic flow management problem with enroute capacities. *Operations research*, 46(3):406–422, 1998.

[2] L. Castelli, T. Bolić, S. Costanzo, D. Rigonat, É. Marcotte, and G. Tanner. Modulation of en-route charges to redistribute traffic in the european airspace. *Fifth SESAR Innovation Days*, 2015.

[3] L. Castelli, M. Labbé, and A. Violin. A Network Pricing Formulation for the revenue maximization of European Air Navigation Service Providers. *Transportation Research Part C: Emerging Technologies*, 33:214–226, 2013.

[4] L. Castelli, R. Pesenti, and A. Ranieri. The design of a market mechanism to allocate air traffic flow management slots. *Transportation research part C: Emerging technologies*, 19(5):931–943, 2011.

[5] L. Delgado. European route choice determinants. *11th USA/Europe Air Traffic Management Research and Development Seminar*, 2015.

[6] K. Deschinkel, J. L. Farges, and D. Delahaye. Optimizing and assigning price levels for air traffic management. *Transportation Research Part E: Logistics and Transportation Review*, 38(3-4):221–237, 2002.

[7] Eurocontrol. Eurocontrol seven-year forecast febraury 2016. Accessed: 16-09-2016.

[8] R. Jovanović, O. Babić, and V. Tošić. Pricing to reconcile predictability, efficiency and equity in ATM. *11th USA/Europe Air Traffic Management Research and Development Seminar*, 2015.

[9] R. Jovanović, O. Babić, M. Živanovic, and V. Tošić. Efficiency vs. Flexibility in ATM: Can Pricing Help? *Proceendings of the Fifth SESAR Innovation Days*, pages 1–8, 2015.

[10] R. Jovanović, V. Tošić, M. Čangalović, and M. Stanojević. Anticipatory modulation of air navigation charges to balance the use of airspace network capacities. *Transportation Research Part A: Policy and Practice*, 61:84–99, 2014.

[11] A. R. Odoni. *Flow Control of Congested Networks*, chapter The Flow Management Problem in Air Traffic Control, pages 269–288. Springer-Verlag, 1987.

[12] M. Raffarin. Congestion in european airspace. *Journal of Transport Economics and Policy (JTEP)*, 38(1):109–125, 2004.

[13] SATURN-Consortium. Pricing mechanism. Deliverable, SATURN Consortium, 2014. D3.1.

[14] W. M. Swan and N. Adler. Aircraft trip cost parameters: A function of stage length and seat capacity. *Transportation Research Part E: Logistics and Transportation Review*, 42(2):105–115, 2006.

[15] M. Terrab and A. R. Odoni. Strategic flow management for air traffic control. *Operations Research*, 41(1):138–152, 1993.

[16] V. Tošić, O. Babić, M. Čangalović, and D. Hohlacov. A model to solve en route air traffic flow management problem: A temporal and spatial case. *In Proceeding of the 1st USA/Europe Air Traffic Management Seminar. Saclay, France*, 1997.