Coordinated Capacity and Demand Management in a Redesigned ATM Value Chain

Strategic Network Capacity Planning under Demand Uncertainty

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***Abstract*— We present a model and a numerical example to analyse capacity decisions within a re-designed Air Traffic Management (ATM) value-chain. We assume a new role for the Network Manager (NM), having contractual relations with Air Navigation Service Providers (ANSPs) and Aircraft Operators (AOs). The NM orders en-route airspace capacity from ANSPs at strategic level and defines/adjusts sector opening schemes at pre-tactical level (capacity management). On the demand side, the NM offers trajectory products to AOs, which are defined based on both AOs' business/operational needs and network performance goals (demand management). In this context, we develop a mathematical model which underlines a part of this joint capacity and demand management process. The model aims at minimizing the sum of cost of capacity provision and cost of delays and re-routings, by managing airspace sector configuration over time and trajectory assignments. We use a realistic numerical study on a small-scale network to illustrate joint capacity and demand management decisions, as well as trade-offs between different performance indicators.**

Keywords- ATM value chain, network manager, capacity management, demand management.

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I. INTRODUCTION

In previous papers, we outlined a new concept of coordinated capacity ordering and trajectory pricing, referred to as COCTA [1], as well as an initial COCTA mathematical model [2]. In this concept, the Network Manager (NM) decides how much capacity units (we use sector hours) to order from each Air Navigation Service Provider (ANSP). On the demand side, the NM offers different trajectory products to Aircraft Operators (AO). Capacity and demand management (referred to as COCTA mechanism) are jointly performed by the NM to optimize a vector of network performance indicators.

In this paper, we present the redesigned ATM value-chain, roles and the institutional relations between the NM, ANSPs and AOs. We outline the timeline of capacity ordering: long-term (5 years) and strategic (6 months) capacity orders, as well as pre-tactical (7 days) decisions on sector opening schemes (sector configurations). The COCTA demand management elements (different trajectory products, trajectory prices and the underlying airport-pair charging principle) are not in the focus of this paper.

We outline a basic mathematical model that underpins a part of this coordinated capacity and demand management process. The model's objective is to minimize the overall cost imposed on AOs: cost of capacity provision and cost of delays and re-routings. Although the main goal is to improve cost-efficiency, we are also able to identify trade-offs between several performance indicators. A case study is used for testing and evaluating the model: it is large enough to allow interpretation and sense-checking of the results, and the traffic values are realistic representations of a part of the European network.

The remainder of the paper is structured as follows: Section II illustrates the COCTA concept, before we focus on the mathematical model in Section III. We present numerical results in Section IV and draw conclusions in Section V.

II. COCTA CONCEPT

COCTA is the first research project to consider coordinated en-route capacity and air traffic demand management decisions. A brief summary of relevant previous research efforts is provided in [2], and a more detailed capacity and demand management literature review is presented in [3].

A. Redesigned ATM value-chain

COCTA introduces substantial changes in the ATM value-chain [4] by mandating a new role for a network manager. The network manager:

- orders and allocates airspace capacities from ANSPs by applying demand driven capacity management and

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- manages demand by defining and offering different trajectory products at differentiated prices to AOs, mindful both of AOs' business/operational needs and required network performance levels.

These changes in institutional settings are necessary for a paradigm shift, introducing network-centric capacity ordering and allocation and departing from the traditional airspace-use charging to novel airport-pair (route) charging and trajectory pricing.

In this paper we do not focus on the demand side elements of COCTA. However, for the modelling we assume charges based on airport pairs. This assumption ensures that airlines do not have an incentive to deviate from the shortest route between two airports (for details, the reader is referred to [4]).

B. COCTA capacity and demand management process

The COCTA mechanism represents capacity and demand management measures in the COCTA process of optimizing network performance. Within the COCTA research, the mechanism is primarily designed for strategic (6 months in advance) and pre-tactical stage (7 days in advance), while the tactical stage is considered to a certain extent only. In addition, we also discuss long-term capacity planning (5 years) and ordering to improve the network performance.

1) Capacity management

Capacity management is carried out at the network level. Owing to long lead times involved in the capacity provision process [5] the COCTA network capacity planning and management process extends over a 5-year horizon. We assume a long term contract between the NM and ANSPs on an annual capacity budget. This capacity budget is based on long term traffic forecasts and serves as a foundation for an ANSP's decisions affecting capacity (e.g. staff training and technical equipment). For the sake of brevity, in this paper we focus on the strategic decision on capacity orders which the NM is taking six months in advance.

When airline schedules are published, around six months in advance of a schedule season, the NM has more precise information on O&D pairs and respective times of operations. Based on this knowledge of traffic demand (scheduled flights represent more than 80% of total flights for several years now [6]) the NM can define capacity orders within the capacity budget sketched above. Therefore, about six months in advance, the NM refines its capacity order from ANSPs, aligned with the long-term order. The NM orders *capacity* from ANSPs, which is measured with sector-hours. The capacity management process continues after this decision, with options to slightly adjust the capacity order, in line with demand information received subsequently. However, in this paper we do not model these steps and more details can be found in [5].

2) Demand management

In the redesigned ATM value-chain, we propose a novel approach to demand management. The NM manages demand by defining and offering different trajectory products, at differentiated prices, to AOs. The NM aims to improve network efficiency by optimising the utilisation of the airspace capacity which has been ordered from the ANSPs. Therefore, trajectory products are tailored to improve network performance.

The demand management starts once the initial capacity order is made, i.e. six months before the day of operation. At that moment, the NM should have a good estimate of the cost of capacity to be recovered with airspace charges. This estimate will be used as a baseline to define base airport-pair charges.

III. Mathematical Model

A. Overview

In this paper, we define a mathematical model for the initial capacity ordering at strategic level and demonstrate the NM's decision-making using a small-scale, but realistic, example. We analyse principal trade-offs between capacity and demand management actions to improve overall cost-efficiency:

- Ordering (more) capacity, and thereby increasing the cost of capacity provision, to reduce costs of delaying or re-routing flights (uniformly termed *displacement costs* throughout the document) vs
- Delaying or re-routing flights in order not to increase the costs of capacity provision.

We assume that the NM's primary aim is to order capacities across the network to maximize cost-efficiency, i.e. to minimize the sum of capacity provision and displacement costs. In addition, we also examine trade-offs between different performance indicators.

B. Assumptions

1) Network, flights and trajectories

We consider a set of flights F flying over a network. Each flight f connects an origin (o) to a destination (d) airport (OD pair. Trajectories (3D) for each OD pair are chosen from a set R_{od} that contains several alternatives. Although the model can deal with 3D trajectories, in this paper, we consider trajectories only in the horizontal plane (2D - routes). The displacement cost is the additional cost if the route assigned is not an AO's first choice, i.e. if it is *displaced* in space and/or time. As outlined above, we assume that AOs prefer flying the shortest routes which are also the cheapest in the COCTA context (assuming zero wind condition). The displacement cost of trajectory r for a flight f is d_r^f. Finally, we use B to denote the route-sector-time incidence matrix ($b_{rst} = 1$ if route r uses sector s at time t, 0 otherwise).

2) Sector configurations

We consider several airspaces $a \in A$, with each airspace a composed by a set of elementary sectors $s \in S^a$. An airspace a has a known number of sector configurations at which it can operate. Let C^a be the set of these configurations, indexed by c. A configuration c is identified by a partition P^c. Elements of a partition are indexed by p, to represent how the airspace is split among air traffic controllers. In other words, an element p is a portion of the airspace, identified by a subset of elementary sectors $s \in S^p \subseteq S^a$. In our case study, we only consider horizontal divisions of airspace. However, the formulation of the model introduced is suitable to cope with vertical sectorisation.

Every element p in a partition has a capacity k_p denoting the maximum number of flights allowed to enter a sector, be it elementary or collapsed, per time period (commonly referred to as "entry counts"). A configuration is also defined by the number of sector-hours $\bar{h}_{ac}$which it consumes in every time period.

3) *Time Scales*

Two time scales are considered: a fine-scale used to describe trajectories and a coarse-scale used to model the dynamics of airspace configurations. Parameters $\bar{T}$ and $\bar{U}$ are the size of the fine-scale and coarse-scale time period, respectively. More specifically, $\bar{T}$ represents the minimum unit used to define trajectories (e.g., 5-10min) and $\bar{U}$ represents how often a sector configuration can change (e.g., 30-60min). For simplicity, we assume that a coarse-scale time period can be divided into an integer number of fine-scale time periods (i.e., $\bar{U}\%\bar{T} = 0$).

C. *Model Formulation*

Under the assumptions summarized in the previous section, we can now formulate the optimization model. The notation used is summarized in the following table:

Sets:

O	Set of origin-destination pairs
F, F_{od}	Respectively, the set of all flights and the set of flights connecting od
R_{od}	The set of routes connecting od
T	Fine-scale time horizon
U	Coarse-scale time horizon
A	Set of airspaces
C^a, S^a	Set of configurations and elementary sectors for airspace a
P^c	Partition of elementary sectors corresponding to a configuration
S^p	Subset of elementary sectors forming a collapsed sector within a configuration

Indices:

f	Flights
od	Origin and destination airports
t	Fine-scale time index
u	Coarse-scale time index
r	Route
a	Airspace
c, c'	Airspace's configuration
p	Airspace sector (collapsed or elementary)
s	Elementary sector

Parameters:

ρ_a	Variable cost of providing one sector-time unit for airspace a
k_p	Maximum capacity of airspace portion p
q_a	Fixed cost of airspace a
h_a	Number of sector-time units available at airspace a
$\bar{h}_{ac}$	Number of sector-time units consumed by airspace a working in configuration c
$\bar{T}$	Length (min) of a fine-scale time unit
$\bar{U}$	Length (min) of a coarse-scale time unit
d_r^f	Displacement cost of route r for flight f
gd_r	Ground delay for route r
to_f	Flight f scheduled take off time
$b_{rsu}(to_f)$	Is equal to 1 if route r uses sector s at time u, assuming take off to_f, 0 otherwise
l_r	Length of route r expressed as number of time periods t

Variables:

$$z_{acu} = \begin{cases} 1, & \text{if airspace } a \text{ configuration is } c \text{ at time } u \\ 0, & \text{otherwise} \end{cases}$$

$$y_r^f = \begin{cases} 1, & \text{if flight } f \text{ is assigned to route } r \\ 0, & \text{otherwise} \end{cases}$$

The problem of identifying optimal Airspaces Configurations and Demand Management (ACDM) is formulated below as a linear program:

$$\min_{z,y} \sum_{a \in A} \left(q_a + \rho_a \sum_{u \in U} \sum_{c \in C^a} \bar{h}_{ac} z_{acu}\right) + \sum_{f \in F} \sum_{r \in R_{od_f}} d_r^f y_r^f \quad (1)$$

$$\text{s.t.} \sum_{r \in R_{od_f}} y_r^f = 1 \qquad \forall f \in F \quad (2)$$

$$\sum_{c \in C^a} z_{acu} = 1 \qquad \forall a \in A, u \in U \quad (3)$$

$$\sum_{f \in F} \sum_{r \in R_{od_f}} \sum_{s \in S^p} b_{rsu}(to_f + gd_r)\, y_r^f \le K_p z_{acu} + |F| \sum_{c' \neq c} z_{ac'u} \qquad \forall a \in A, c \in C^a, p \in P^c, u \in U \quad (4)$$

$$\sum_{u \in U} \sum_{c \in C} \bar{h}_{ac} z_{acu} \le h_a \qquad \forall a \in A \quad (5)$$

$$z_{acu} \in \{0,1\} \qquad \forall a \in A, c \in C^a, \quad (6)$$

$$y_r^f \in \{0,1\} \qquad \forall f \in F, r \in R_{od_f} \quad (7)$$

The objective (1) aims to minimize capacity and displacement cost. Constraints (2) ensure that each flight must be assigned to one and only one route. Constraints (3) state that one operating sector configuration must be defined at any time, for each airspace. Inequalities (4) set the capacity limitations across the network. More specifically, if partition p belongs to configuration c and c is chosen as configuration at time u (i.e., $z_{acu} = 1$), then no more than K_p aircraft can enter sectors identified by p, in period u. However, if c is not chosen, then the term $|F| \sum_{c' \neq c} z_{ac'u}$ guarantees that the constraint is no longer binding. To compute the number of flights entering a sector in period u, we need to consider the actual take off time given by to_f plus the ground delay gd_r (based on assigned trajectory r). Inequalities (5) are the sector-hours budget constraints for each airspace that accounts for the fixed budget. Finally, (6)-(7) define the limitations for the decision variables.

IV. Numerical Results

We demonstrate fundamental trade-offs in the NM's decision-making process of initial capacity ordering at strategic level, using a small-scale example. We assume that the NM purchases capacity from ANSPs about six months in advance, with limited (and costly) options for later capacity adaptations. As mentioned earlier, these capacity orders have to be based on traffic forecasts. However, for only approximately 80% of all flights (basically most scheduled flights), information on OD pairs as well as flight times is available. Therefore, the NM has to balance the risk of ordering too much capacity (and thus overspending) with the risk of ordering too little capacity (endangering stable service), using different rules for decision making.

A. *Case Study Design*

The network considered consists of five ANSPs represented by different colours in Figure 1. Four ANSPs have two elementary sectors each, while the central ANSP has three. The sectors' 30-minute capacities range between 16 and 19. For the simulation we have to assume costs of capacity provision (see Appendix A).

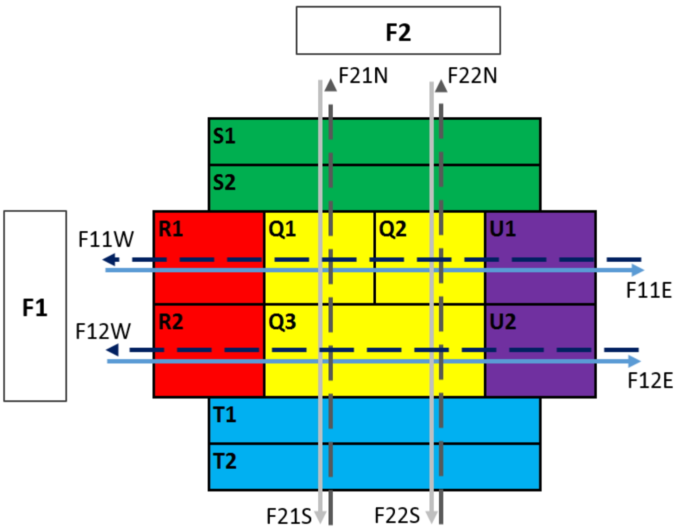

Figure 1. Network structure

There are two main traffic flows: F1 (east and west) and F2 (south and north). There are several sub-flows with indicated shortest routes in Figure 1. We assume that the F1 is a more dominant flow, with approximately two times more flights than the flow F2. Also, eastern flows are more dominant than western, as well as southern compared to northern flows.

We observe two hours of traffic in the given network with up to 150 flights in this time window; traffic closer to the upper bound is particularly challenging for the network.

We consider three aircraft sizes: small (E145), medium (A320) and large (B752).

Since we demonstrate initial capacity ordering six months in advance, we assume around 80% of demand is known to the NM. Therefore, we fix 120 scheduled flights (traditional and low-cost carriers) for which the NM has information on OD airport pairs, timetables and aircraft size (no cancellations of scheduled flights assumed).

Up to 30 flights, i.e. around 20% of demand, is *uncertain demand* (charter and cargo non-schedule, business aviation, other). We randomly choose between 1 and 30 *uncertain* flights: left-skewed probability distribution, with expected mean 20. The left skew is purposely introduced to study a challenging problem (i.e., the share of uncertain demand is likely to be significant). A distribution with a positive skew would reduce the impact of uncertain demand, hence making the simulation approach less of interest. One traffic sample with 30 *uncertain flights* and 120 schedule flights (150 in total) is shown in Figure 2.

Once the number of flights is selected using Monte Carlo simulation, aircraft sizes are assigned to uncertain flights. The average shares of small, medium and large aircraft are 30%, 60% and 10%, respectively. Flights are then assigned to different flows, preserving the share of flights on each flow.

Shortest routes are the cheapest in the COCTA context and, as such, preferred by AOs. If a flight cannot be assigned to the shortest route at the desired time of departure, the NM either delays it (up to 30 minutes) or reroutes it (up to 40NM).

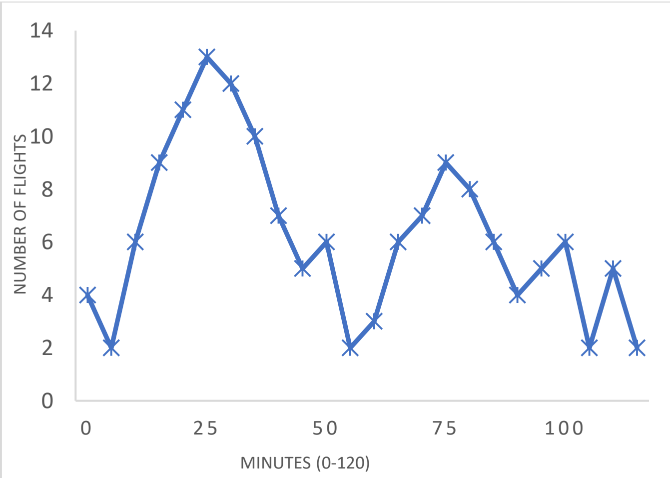

Figure 2. One traffic sample with 150 flights (30 *uncertain flights*)

B. Model testing steps

The NM anticipates scheduled flights as planned plus additional *uncertain* flights. However, the NM cannot know how many *uncertain* flights there will be, nor where or when they will appear. To decide on capacity ordering, the NM simulates many different *uncertain* demand materialisations, as explained above. Based on the results of the simulation, the NM decides on the amount of capacity ordered.

The computational analysis can be divided in two steps: Scenario Identification (SI) and Scenario Test (ST).

The SI step consists of iteratively sampling the uncertain demand and subsequently solving the unconstrained (referring to constraint (5)) ACDM model. The solution will suggest the optimal number of sector hours needed for each ANSP to accommodate the demand. This number will be directly obtained from z_{acu} variables. The procedure is repeated for a pre-determined number of iterations. Consequently, the output of SI will be a set of sector-hours budgets. With this set, the challenge is to identify a criterion to choose which budget should finally be implemented (i.e. how many sector hours should be ordered from each ANSP). In this analysis, we will consider and compare several decision criteria.

Sector Hours Identification

Set *Counter* = 0;
REPEAT
Generate flight demand based on the rules defined in X;
Solve unconstrained ACDM;
Retrieve optimal solution and store the number of sector hours for each airspace;
Counter = *Counter* + 1;
UNTIL *Counter*=NUM_ITERATIONS;

Once a budget has been chosen, a second simulation (ST) is run to test its robustness. Similarly, as in SI, at each step the uncertain demand is sampled and ACDM is solved. The sole difference is that ACDM now has a budget limitation set by vector $\boldsymbol{h}^*$ (left-hand side of constraint (5)).

Sector Hours Test

Select budget to test $\boldsymbol{h}^*$
Set *Counter* = 0;
REPEAT
Generate flight demand ;
Solve ACDM with $\bar{\boldsymbol{h}} = \boldsymbol{h}^*$;
Store optimal solution;
Counter = *Counter* + 1;
UNTIL *Counter*=NUM_ITERATIONS;

In each iteration optimal solutions are stored so that the budget can be evaluated by assessing performance parameters such as displacement cost or number of heavily delayed flights.

C. Results

Building upon the results of SI, we have selected and tested eight representative network capacity ordering scenarios, Table 1. All scenarios except MAX-PLUS have materialised at least once in the Simulation step 1, i.e. each of those seven scenarios was cost-optimal for some possible traffic materialisation, assuming, importantly, coordinated (centralised) capacity and demand management in place. To that end, the MAX (as well as MAX2 and MAX3) scenarios could arguably be interpreted as a decision of a conservative (delay-averse) Network Manager. In other words, these scenarios would be selected if the NM aims at having enough capacity to efficiently deal with all the uncertain scenarios it has foreseen, On the other hand, the MIN (as well as MIN2 and MIN3) scenarios could be seen as a decision of an 'optimistic' Network Manager. The FREQ scenario could be seen as the most-likely appropriate one. The network capacity budgets range between 11.5 (MIN scenario) and 15 sector-hours (MAX-PLUS scenario). Those eight scenarios account for 89.6% of all outcomes of SI. The FREQ scenario itself is a cost-optimal outcome in more than two thirds of all cases (step 1).

The MAX-PLUS scenario, on the other hand, is intentionally constructed with somewhat more generous capacity budgets compared to the MAX scenario. One might argue that such a scenario could be the outcome of an independent capacity-decision-making of individual delay-averse ANSPs. Under such an assumption, the MAX-PLUS scenario might represent a valuable benchmark to assess the effects on network performance of various centrally-coordinated capacity provision scenarios.

Concerning the resulting traffic assignment, there are, on average, between 55 (MAX and MAX-PLUS scenario) and 63 (MIN scenario) displaced flights, meaning that, on average, the remaining 75-83 flights are assigned to the shortest routes with no delay (Table II). Average delay per delayed flight expectedly is reduced with increasing capacity budgets: from 9.5 minutes (MIN) to 7.4 minutes (MAX and MAX-PLUS).

TABLE I. CAPACITY ORDERING SCENARIOS TESTED (ALL VALUES IN *SECTOR HOURS*)

Scenario outcome	ANSP					Total capacity budget
	R	S	U	T	Q	
MIN	2.5	2	2	2	3	**11.5**
MIN2	2.5	2	2	2	3.5	**12**
MIN3	2.5	2	2.5	2	3	**12**
FREQ	2.5	2	2.5	2	3.5	**12.5**
MAX2	3	2	2.5	2	3.5	**13**
MAX3	3	2	2.5	2.5	3.5	**13.5**
MAX	3	2	3	2.5	3.5	**14**
MAX-PLUS	3.5	2	3	2.5	4	**15**

The observed tradeoffs between the amount of capacity provided and displacement costs are intuitively expected across seven capacity-coordinated scenarios (i.e. all but MAX-PLUS), Figure 3. The difference in capacity costs (excluding structural capacity cost) between MIN and MAX scenarios is some 3,100 EUR (14%). That difference is more than offset by the decrease in average displacement cost: from 12,583 EUR in MIN to 7,759 EUR in MAX, with also notably higher variance of displacement costs in scenarios with scarcest capacity budgets, Table II (column 5). The total cost minimum is found in the FREQ scenario (capacity budget of 12.5 sector-hours), which thus represents, on average, the least expensive combination of capacity provision costs and displacement costs.

TABLE II. NETWORK PERFORMANCE INIDICATORS UNDER DIFFERENT CAPACITY-ORDERING SCENARIOS TESTED

1	2	3	4	5	6	7	8	9	10	11
Scenario Outcome	**Capacity budget (sector-hours)**	**Fixed capacity cost in EUR**	**Variable capacity cost in EUR (average)**	**Average displacement cost in EUR [st. dev.]**	**Total cost in EUR (average)**	**Average number of displaced flights [st. dev.]**	**Total delay (minutes)**	**Average delay (minutes) per delayed flight (average)**	**Number of flights delayed ≥20min (average)**	**Relative incidence (% of all) sector-periods with utilisation ≥85%**
MIN	**11.5**	6,080	15,990	12,583 [3,203]	34,653	63.5 [6.6]	526	9.5	6.0	32.4
MIN2	**12**	6,385	16,782	11487 [3,442]	34,654	60.3 [7.2]	507	9.3	4.6	31.1
MIN3	**12**	6,330	16,624	9,905 [1,727]	32,859	63.9 [7.4]	372	8.1	2.1	28.1
FREQ	**12.5**	6,635	17,541	8,280 [1,591]	32,456	56.4 [7.3]	336	7.8	1.3	27.9
MAX2	**13**	6,885	17,769	7,954 [1,293]	32,608	55.6 [6.6]	314	7.6	1.1	27.4
MAX3	**13.5**	7,135	17,886	7, 771 [1,074]	32,792	54.9 [6.0]	301	7.5	1.0	27.6
MAX	**14**	7,385	17,891	7,759 [1,057]	33,036	55.0 [6.0]	300	7.4	1.0	27.6
MAX-PLUS	**15**	7,940	17,935	7,713 [1,016]	33,588	54.7 [5.8]	298	7.4	1.0	27.4

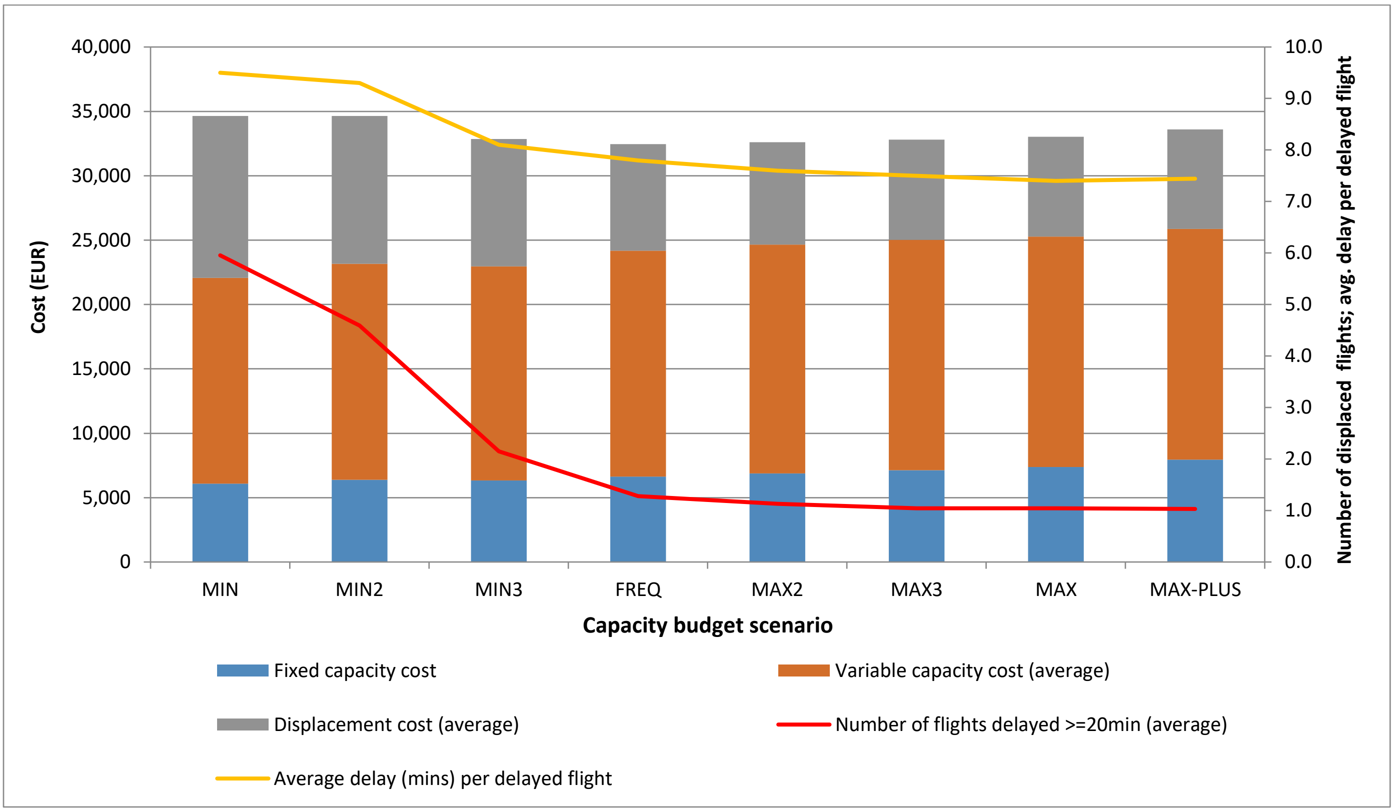

Figure 3. Key network performance tradeoffs: capacity costs vs. displacement indicators

The MIN scenario is on average 6.8% more costly than FREQ, whereas MAX is 1.8% more costly than the FREQ scenario. The MAX2 scenario (with extra 0.5 hours bought from ANSP R compared to FREQ capacity order) is only 0.4% more costly than FREQ. Importantly, the benchmark scenario (MAX-PLUS) does not perform better than most of the other seven capacity-coordinated scenarios (quite oppositely, only MIN and MIN2 are, on average, more costly than MAX-PLUS). Starting from the MAX scenario capacity order as a baseline, the addition of 0.5 sector-hours from ANSPs R and Q each, resulting in MAX-PLUS scenario, does not improve cost-efficiency, since it yields only a very small reduction in displacement cost, which is more than offset by the associated increase in capacity costs. The MAX-PLUS scenario is, on average, 3.5% more costly than the FREQ scenario, and 1.7% more costly than MAX scenario. This seems to highlight that a central coordination approach is generally more advantageous than having every ANSP deciding independently, with a delay-averse approach employed.

Environmental performance, measured via extra CO_2 emitted (compared to shortest routes), is solely driven by re-routings (with re-routing larger aircraft being more harmful, *ceteris paribus*). The scenarios with lowest capacity orders perform better than the others in this respect. Among the four most generous-capacity scenarios, FREQ is the best performer concerning CO_2 emissions. MAX-PLUS on average yields the same amount of CO_2 emissions as MAX and MAX-3 scenarios.

Concerning the right end of the distribution of delayed flights, which can be interpreted also as a rough proxy for equity (fairness), the average number of flights delayed by ≥20 minutes rapidly decreases with capacity increase, Figure 3. It should nevertheless be noted that, owing to the cost-minimisation objective, practically all long re-routings are applied on small and medium-sized aircraft, while the average number of long re-routings applied on large aircraft is close to zero.

On a related matter, it should be noted that large aircraft by far most frequently get assigned the optimal (shortest) trajectory, with this frequency ranging between 79% in MIN scenario and 88% in FREQ, MAX, MAX2 and MAX3 scenarios. This means that only between one in five and one in nine large aircraft are expected to get displaced, on average. The percentages of shortest route assignments are notably lower for medium-sized aircraft (ranging between 53% and 64% in different scenarios), and in particular for small aircraft (40-46%). Finally, reflecting on performance of the MAX-PLUS scenario in this respect, adding further capacity compared to MAX scenario, does not yield any tangible benefits.

Another interesting aspect concerns the robustness of different capacity ordering scenarios, in terms of ability to absorb (withstand) certain deviations from assumed traffic parameters while obeying capacity constraints. In this regard, more generous capacity budgets expectedly perform somewhat better than scarcer ones, measured by relative incidence of sector-periods with capacity utilisation ≥85%, Table II. This indicator peaks at 32.4% in the MIN scenario, meaning that nearly a third of all sector-periods are expected to experience quite high utilisation of their declared capacities.

Finally, an interesting albeit not surprising situation concerns the comparison of the MIN2 and MIN3 scenarios, which have the same total capacity budget (12 sector-hours each), but those are slightly differently distributed across ANSPs, see Table I above. More specifically, starting from the MIN scenario as a baseline, the decision whether extra 0.5 sector-hours are ordered from ANSP Q (leading to Scenario MIN2) or from ANSP U (leading to Scenario MIN3) quite notably affects the resulting network performance. Whereas the additional capacity cost is similar in both cases, the effects on displacement costs and environmental performance are remarkably different. More specifically, enabling extra capacity in ANSP Q does not have a positive net effect on total cost (i.e. the reduction in displacement cost is not sufficient to offset the increased capacity cost), but at the same time it leads to the by far most environmentally efficient outcome across all scenarios tested. Conversely, ordering extra 0.5 sector-hours from ANSP U notably decreases both the displacement cost (average value as well as the standard deviation) and the total cost, see Table II, but at the same time results in the worst-CO_2 score across all scenarios tested.

A possible comparison baseline, corresponding to the present state of affairs in Europe, should assume airspace-based charges and consequently some longer routes chosen by AOs even when sufficient capacities are available to support shortest-route options [7]. Concerning the capacity provision matter itself, one might argue that the present insufficient coordination between ANSPs in a strategic timeframe could effectively be closest to the MAX-PLUS scenario tested (strategic dimensioning of capacities against local traffic peaks). This is more likely to be true concerning structural costs and maximum capacity provision costs (see Appendix), than concerning sector hour provision costs (since structural capacities, albeit charged for, are often not delivered on the day of operations [5]). Thus, while maximum capacity provision is nowadays arguably paid for (by AOs), the full operational benefits thereof are not necessarily extracted. The latter implies that the typically delivered capacity levels (and thus also associated displacement costs) are arguably closer to MIN2, MIN3 or FREQ scenario, while the charges more likely reflect the MAX-PLUS, MAX or MAX-3 scenario examined. This further implies that the cost-efficiency benefits estimated in our small case study are most likely on a conservative side.

V. CONCLUSION AND OUTLOOK

We have developed a systematic approach to illustrate the impact of trading off costs of capacity provision versus cost of displacement in the context of a small case study. Compared to previous papers, one major addition is the introduction of a realistic portion of uncertain demand, allowing to analyse the NM's decision making on capacity ordering.

The small numerical example offers insight into the effects of timely (well in advance) coordinated capacity provision (network-centric approach), and centralised demand management, with (still) effectively no active route charging approach in force. The results obtained confirm the existence of intuitively expected performance tradeoffs associated with different airspace capacity levels provided across the network.

The methodological approach employed enables to estimate the likely effects of incremental changes in capacity provided in different network segments. For instance, ordering an extra sector-hour from ANSP (sector) A vs. ordering it from ANSP B vs. do-nothing option, as in the above-discussed case of MIN2 vs. MIN3 vs. MIN scenarios.

It should be mentioned that experiments with flatter demand pattern over time were also run, in order to understand and quantify the dependency of results upon the extent of traffic "peakiness". The results indicate a possibly tangible impact of traffic profile *per se*, first of all concerning the incidence (frequency) of demand management actions needed, and the associated costs thereof. Due to space constraints in this paper, for more details we refer the interested reader to ref. [8].

Future work will, *inter alia*, address the interdependencies between higher strategic displacements and airport capacity restrictions (slots).

Finally, we have been operating in a single-objective framework so far, while only monitoring the impact on key performance indicators other than total cost. In forthcoming work, we intend to test incorporation of other objectives as well to provide more comprehensive results.

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VI. APPENDIX A: CAPACITY AND DISPLACEMENT COST

Since the capacity decision is made six months in advance, a large share of total cost is considered to be fixed cost, called structural capacity costs. The variable part of capacity provision costs is called sector hour provision cost, Table III. However, since the ANSP cannot cease its operation (i.e. has to operate at minimum capacity at any time) the minimum cot for a time period of two hours is the sum of the structural capacity costs plus the product of minimum capacity and the sector hour capacity provision cost. For the numerical example we assumed different costs for neighbouring ANSPs, a situation which can be found in many parts of the European airspace. For more details, refer to ref. [8]. Regarding the displacement cost per aircraft type, we rely on findings in [9].

TABLE III. COST OF CAPACITY PROVISION

	Q	T	R	U	S
Maximum sectors simultaneously open	3	2	2	2	2
Minimum capacity (sector-hours per 2 hours)	2	2	2	2	2
q_a Structural capacity cost (EUR per 2 hours)	5,000	4,000	4,000	4,000	4,000
ρ_a Sector hour provision cost (EUR per active ½ sector hour)	920	570	750	650	460