Strategic Cross-Border Capacity Planning Under Uncertainty

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***Abstract*—We evaluate a potential scenario for future Air Traffic Management (ATM) system in Europe and benefits it could bring to the Airspace Users, where a network manager (NM) has a mandate to manage capacity in the network and define capacity requirements to accommodate anticipated demand in a safe, efficient and environmentally friendly manner. In the considered scenario, the European airspace is still highly fragmented, i.e. capacity is provided by individual Air Navigation Service Providers (ANSPs) on a local/country level, but the assumption is that cross-border capacity provision is possible and is optimized in the capacity planning process led by the NM. Capacity planning usually starts a long time ahead of the day of operation to ensure that sufficient resources, including Air Traffic Control Officers (ATCOs) are available to safely manage traffic. At the time of making capacity decision, i.e. allocation of ATCO resources for a day of operation, one of the main challenges is considerable uncertainty regarding the demand: overall traffic volume and demand spatio-temporal distribution.**

The fundamental trade-off is between reducing the capacity provision cost (within-border and cross-border provision) at the expense of increasing expected displacement cost arising from re-routing or delays. To tackle this, we extend a decomposition approach that we proposed in [1] to allow capacity planning for cross-border provision. Furthermore, we present a numerical study based on real capacity and demand (traffic) data to study the effect of allowing cross-border capacity provision. The results suggest that there may be significant potential for cost reduction in cross-border control, especially for risk-averse decision makers.

***Keywords*—capacity ordering policies; cross-border capacity provision; integer programming applications; decomposition methods**

I. Introduction

Before the traffic downturn in 2020 due to the COVID19 pandemic, en-route Air Traffic Flow Management (ATFM) delays and share of en-route ATFM delayed flights in the European airspace have been increasing for several years [2]. Namely, total en-route ATFM delay increased from 7.2 million minutes in 2015 to 19.0 million minutes in 2018, with the share of en-route ATFM delayed flights increased from 3.9% in 2015 to 9.6% in 2018 (traffic volumes being 9.75 vs. 11.0 million flights in 2015 and 2018 respectively). Although the share of en-route ATFM delayed flights increased to 9.9% in 2019 (11.1 million flights in 2019), total en-route ATFM delay decreased to 17.2 million minutes [2].

Delays are not uniformly distributed in Europe across different ANSPs, and their respective airspaces; the Performance Review Commission (PRC) notes that only four of the most constraining ANSPs generated around two thirds of all en-route ATFM delay in 2019 [2]. ANSPs attributed around 75% of en-route ATFM delay to Air Traffic Control (ATC) categories (reasons): capacity, staffing and disruption [2]. However, the PRC suggests that this share could be as high as 90%, since some of ATFM delay attributed to adverse weather “occurred in the same sector configurations where the ANSPs have already flagged that the capacity constraints are due to the unavailability of qualified ATC staff (ATC staffing)” (a more detailed analysis on this issue is provided in [3]). Some of the most constraining ATC en-route sectors were collapsed sectors in the 2012–2019 period, meaning that additional sectors could have been opened, hence additional capacity provided, if ATCOs had been available [2]. ANSPs did not always deliver the maximum (presumably available) capacity at the time when it was needed, i.e. there were mismatches between the deployment of maximum capacity and the traffic demand, resulting in higher ATFM delays [4].

On the other hand, one of the reasons for the drop in delay in 2019 was attributed to the adoption of the enhanced NM/ANSP Network Measures for summer 2019 (eNM/S19) [2], [5]. Since it was neither possible to deploy more capacity due to lack of ATCOs nor to enable cross-border capacity provision, a subset of these measures aimed at alleviating traffic loads in already congested portions of airspace by re-routing flights in both horizontal and vertical plane, employing a network-centric perspective. Although these measures generated additional fuel burn and emissions (e.g. horizontal re-routings added 1.62 nautical miles of additional length per flight and 11 kg of additional fuel burn, on average), it was estimated that without them the delay levels could have doubled in 2019 vs 2018 [2].

The PRC concludes that a currently local-oriented capacity and demand management, should instead be network-oriented, i.e., managed by the NM with ANSPs and AUs collaborative efforts to find the best solution for the network as a whole [2]. The same recommendation is outlined in the report of the Wise Persons Group (WPG) on the future of the Single European Sky, stressing the importance of strengthening the role of the NM to actually manage the network [6]. It should be noted that AUs are also in favour of a more pro-active network management, especially in the light of strongly increasing ATFM delays in recent years [7], [8]. In addition, the SESAR Joint Undertaking Proposal on the future architecture of the European airspace (AAS), introduced a concept of "capacity-on-demand", which would enable a temporary delegation of the provision of air traffic services to an alternative provider with spare capacity [9].

Against this background, we propose and evaluate a concept of a potential future ATM system where both the WPG recommendation for strengthening the role of the NM to manage capacity (and demand) and the AAS capacity-on-demand in a form of cross-border capacity provision are implemented. On the capacity side, the NM makes strategic capacity decision for the day of operations regarding the level of capacity required in the network, including the need for cross-border capacity provision. At the tactical level, the NM makes a decision which sector configurations will be opened for each ANSP, taking into account resources allocated at the strategic level. The NM makes capacity decisions jointly with demand management decisions, i.e., decisions how to re-distribute demand in temporal and spatial dimensions (where and when needed).

Previous academic work which tackled the issue of demand-capacity imbalance considering application of both capacity and demand measures in a coordinated fashion is very limited. Besides the SESAR Exploratory Research project COCTA [10] which dealt with this challenge (without considering cross-border capacity provision), the authors of this paper are only aware of the work carried out in the SESAR project APACHE [11]. They used a mixed integer programming model to balance capacity and demand and reached the same conclusion as in COCTA: not only the system delays could be largely reduced, but also the ATC operational costs and the required total capacity provisions [11].

The main contribution of this paper lies in demonstrating that overall cost-efficiency could be improved by incorporating cross-border capacity considerations already in the strategic planning phase. This may seem somewhat counter-intuitive since we assume that cross-border capacity comes at a cost per sector-hour which is at least as high as the cost of the highest within-border sector-hour, such that one might expect that it will be better to invest more in local capacity so as to deal with capacity shortages (and the resulting displacement costs). However, we demonstrate that cross-border provision can be overall beneficial since it allows us to temporarily increase capacity in an airspace that otherwise would not have sufficient capacity to deal with traffic peaks. We show that our earlier capacity planning methodology developed in [1] (as part of the COCTA project) can be easily adjusted so as to be able to handle cross-border planning.

The paper is structured as follows: section II has been directly taken from our earlier work [1] so as to define the problem formulation. In Section III, we extend this methodology to the case of cross-border capacity planning. We provide numerical results for this extension in Section IV and conclude in Section V.

II. Problem Statement

We define an ATM system where a network manager has a mandate to manage capacity and demand, that is, to make capacity requirement decisions (for each area control centre (ACC) in the network) and decisions on delaying or re-routing flights and flows. The problem is posed as a somewhat stylized process over two stages; the objective is to minimize the cost borne by airspace users, that is, capacity provision costs and displacement costs (both re-routing and delay incurs displacement costs).

In the first stage, the NM plans how many sector-hours will be required for each airspace for a specific day in the future, which in practice corresponds to the strategic planning phase. At this stage, the NM has information on scheduled flights, e.g. origin and destination airport and timetables. There is only some probabilistic information regarding non-scheduled flights available, meaning that we have the ability to sample non-scheduled flights. We assume for some uncertainty in the capacity provision as well, meaning that ANSPs might not be able to provide the planned nominal capacity of sectors on the day of operations. Based on assessment on potential future materialization of traffic (scheduled and non-scheduled flights) and uncertainties in capacity provision, the NM makes capacity requirement decision, measured in sector-hours for individual ANSPs (airspaces).

In the second stage, which corresponds to the day of operations, the uncertain information regarding non-scheduled flights (number of flights, their origins and destinations as well as desired departure times) and capacity (reductions) is revealed. In the light of this information, the NM decides on re-routing or delaying flights on the demand side, and on the exact sector opening scheme for each airspace, subject to the fixed "capacity budget" from the first stage. Structurally, the problem is related to the well-known newsvendor problem (see [12]). In the following, we offer a rigorous definition of this problem.

Consider multiple airspaces $a \in A$, each with a finite number of possible sector configurations $c \in C^a$. For a given configuration c, we have a set of sectors $p \in P^c$ that form the elements of the configuration. Each of these sectors p is either an elementary sector or consists of multiple elementary sectors merged together (referred to as a collapsed sector). Each sector p has a fixed nominal capacity of K_p flights that may enter that sector within a given time period $u \in U$. The time periods in U span the day of operation on a uniform grid with spacing chosen such that it is possible to change the configuration of an airspace from one time period to the next (say, 1 hour). This is motivated by current practice where a required capacity profile for the following summer season is defined on an hourly basis and ACCs may even change sector configurations more frequently than that [13]. Opening configuration c in airspace a for one time period requires $\bar{h}_{ac}$ sector-hours.

In practice, there is supply-side uncertainty due to factors that affect capacity provision, such as weather conditions, military activity, strikes of air traffic controllers etc. We assume that we do not know the true distribution that governs the materialization of supply-side uncertainty; however, we do have a uniform distribution over a finite collection $\mathcal{K}$ of capacity disruption scenarios $K \in \mathcal{K}$ where some sectors are operating at a fraction of their nominal capacities. We assume that this distribution can be used to approximate the true (unknown) distribution of capacity disruption scenarios. We only observe in period 2 which capacity scenario K we are facing.

Furthermore, there is also demand-side uncertainty over the number and details of non-scheduled flights in period 1 that only gets resolved in period 2. Similarly to modeling the capacity disruption scenarios, we assume that we do not know the true distribution that governs the materialization of non-scheduled flights but that we do have a uniform distribution over a finite collection of flight scenarios which we assume to approximate the true distribution. Both collections are known in period 1; for instance, this could be defined as the collection of historic operating capacities and non-scheduled flights. We augment the collection of non-scheduled flights scenarios $\mathcal{F}$ by adding a fixed and known set of scheduled flights to every scenario of non-scheduled flights; the resulting collection of flight scenarios is denoted by $\mathcal{F}$. In other words, every element $F \in \mathcal{F}$ is a set of flights, and the elements only differ by the non-scheduled flights; the scheduled flights are the same in each of them. Note that traffic scenario F relates only to the number of flights, their origins and destinations, planned departure time, and a set of trajectory options R_f for every flight f that represent different demand management measures of re-routing or delaying flight f, including the option for the shortest route without delay. The traffic scenario does not determine the trajectories.

Both sources of uncertainty are paired to form scenarios $S = (F^S, K^S)$. Scenarios are collected in set $\mathcal{S}$. In the following, we write the expectation over scenarios S in the understanding that uncertainty only pertains to non-scheduled flights and capacity scenarios. For a given flight f, route $r \in R_f$, time period $u \in U$ and a sector p, we define $b_{frpu} \in \{0, 1\}$ to be equal to 1 if route r uses sector p at time u, and otherwise 0. Each of these route options $r \in R_f$ comes with an associated displacement cost d_{fr} that reflects the additional fuel cost and delay costs incurred relative to the shortest distance at no delay (d_{fr} for the latter is set to zero). As such, we incorporate not only cost to the ANSP, but also costs to airspace users. The aim is to reduce overall costs.

We face a trade-off between achieving cost savings by decreasing capacity provision cost in stage 1, and increasing costs by potentially increased need for demand management measures depending on the realization of non-scheduled flights and unexpected shortfalls of capacity in some parts of the airspace. In stage 1, we need to decide on how much capacity budget $\mathbf{h} = (h_a)_{a \in A}$ in terms of sector-hours to acquire for the different airspaces (at unit cost γ_a for each airspace a). In stage 2, we then decide on the sector opening scheme by setting $z_{acu} = 1$ if airspace a gets configuration c at time u, and 0 otherwise. This sector opening scheme is subject to the fixed capacity budget $\mathbf{h}$. Furthermore, we decide on demand management measures in stage 2: $y_{fr} = 1$ represents assigning flight f to route $r \in R_f$, and 0 otherwise. We summarize the notation in Table I.

TABLE I. OVERVIEW OF NOTATION.

Sets:	
F	Flight scenario (scheduled and non-scheduled flights)
$\mathcal{F}$	Finite collection of flight scenarios F
K	Capacity scenario (some sector capacities may be reduced)
$\mathcal{K}$	Finite collection of capacity scenarios K
S	Short-hand notation for pair (F^S, K^S)
$\mathcal{S}$	Finite collection of uncertain scenarios S
R_f	Finite set of re-routing and delay options available to flight f
U	Set of time periods covering the day of operation
A	Set of airspaces
C^a	Set of configurations for airspace a
P^c	Partition of sectors corresponding to a configuration c
Indices:	
f	Flights
u	Time index
r	Route option, fixed in both spatial and temporal terms
a	Airspace
c	Airspace's configuration
p	Airspace sector
Parameters:	
$\gamma = (\gamma_a)_{a \in A}$	Unit cost of one sector hour for airspace a
κ_p^S	Maximum capacity of airspace sector p under scenario K^S
$\mathbf{h} = (h_a)_{a \in A}$	Budgets of available sector-hours for all airspaces $a \in A$
$\bar{h}_{ac}$	Sector-hours used and provided by airspace a in configuration c per time unit
$\bar{h}_{ac}^x$	Sector-hours used by airspace a but provided through cross-border control in configuration c per time unit
d_{fr}	Displacement cost of route r for flight f
$b_{frpu} \in \{0, 1\}$	Indicates whether route r uses sector p at time u
Variables:	
$z_{acu} \in \{0, 1\}$	Indicator: configuration c open in airspace a in time period u
$y_{fr} \in \{0, 1\}$	Indicator: flight f assigned to route r

The optimization problem that we tackle can be written as the minimization of expected displacement cost and capacity cost over all possible scenarios S by deciding on the capacity budget $\mathbf{h}$:

$$\min_{\mathbf{h} \geq 0} \mathbb{E}_S[G(S|\mathbf{h})] + \gamma^T \mathbf{h}, \tag{1}$$

where $G(S|\mathbf{h})$ represents the minimum displacement cost to accommodate flight scenario F^S under capacity budgets $\mathbf{h}$, given capacities K^S. The superscript T denotes the transpose of a vector. To ensure feasibility of $G(S|\mathbf{h})$, we add a dummy configuration c_0 that requires no capacity ($\bar{h}_{ac_0} = 0$ for all a), is used by a dummy route $r_0 \in R_f$ for all flights $f \in F$, and its single sector $p \in P^{c_0}$ has capacity $\kappa_p = |F|$ regardless of the capacity scenario materialization. Using this dummy route incurs a high penalty cost which can be interpreted as the cost of displacing a flight beyond the planning horizon. With this construct, the displacement cost function $G(S|\mathbf{h})$ for a given flight scenario F^S and a given capacity scenario K^S, is defined by a deterministic integer program:

$$G(S|\mathbf{h}) = \min_{\mathbf{y},\mathbf{z}} \sum_{f\in F^S} \sum_{r\in R_f} d_{fr} y_{fr}$$

$$\text{s.t.} \sum_{f\in F^S} \sum_{r\in R_f} b_{frpu} y_{fr} z_{acu} \leq \kappa_p^S$$

$$\forall\, a \in A, c \in C^a, p \in P^c\; u \in U \qquad (2)$$

$$\sum_{u\in U} \sum_{c\in C^a} \bar{h}_{ac} z_{acu} \leq h_a \qquad \forall\, a \in A \qquad (3)$$

$$\sum_{r\in R_f} y_{fr} = 1 \qquad \forall f \in F^S \qquad (4)$$

$$\sum_{c\in C^a} z_{acu} = 1 \qquad \forall a \in A, u \in U \qquad (5)$$

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

$$y_{fr} \in \{0,1\} \qquad \forall f \in F^S, r \in R_f. \qquad (7)$$

The objective of $G(S|\mathbf{h})$ is to minimize displacement and penalty costs, subject to (2): used capacity in a given sector and time period being less than maximum capacity; (3): total capacity usage to not exceed the capacity budget $\mathbf{h}$; (4): every flight being assigned to exactly one trajectory; (5): every airspace a having exactly one configuration at every time u; and binary constraints (6–7). Note that constraint (2) is non-linear; a standard linearization of this constraint requires to introduce a new set of binary variables n_{fracu} replacing the products $y_{fr}z_{acu}$, together with a new set of constraints to enforce equivalence. This approach provides a tight relaxation but is not scalable for this problem. As an example, a medium-sized network with 10 airspaces, 10 configurations, 100 flights with 10 routes, studied over 2 time periods, requires 200,000 additional variables and 600,000 additional constraints. Consequently, in order to solve $G(S|\mathbf{h})$ directly (for small instances), we replace constraints (2) with:

$$\sum_{f\in F^S} \sum_{r\in R_f} b_{frpu} y_{fr} \leq \kappa_p^S z_{acu} + |F^S| \sum_{c'\neq c} z_{ac'u}$$

$$\forall a \in A, c \in C^a, p \in P^c, u \in U. \qquad (8)$$

Constraints (8) have a loose linear programming relaxation but, at least for small instances, they allow solving of $G(S|\mathbf{h})$ with commercial solvers like CPLEX as discussed in the numerical results section. We represent $G(S|\mathbf{h})$ with the non-linear constraints (2) because we use them in our proposed decomposition approach.

In summary, (1) is a type of newsvendor problem that is difficult to solve even for moderately-sized instances due to the challenges in evaluating the expectation. We do not have a closed-form expression of the distribution that underpins the realizations of non-scheduled flights, and we need to solve a large binary program for every such realization to evaluate the costs in stage 2. We use the solution approach proposed in our earlier work [1].

III. Extension to Cross-border Provision

Let us turn to the case where cross-border capacity provision is possible. We assume that the potential cooperation arrangements are known (in the sense of which ACC could provide capacity with whom), and likewise the costs of cross-border provision per sector hour is assumed to be known and higher than within-border capacity provision. The higher costs stems from the requirement that air traffic controllers need to be specifically trained to handle sectors in foreign airspace. Let us assume that there is a central pool of air traffic controllers (measured again in sector-hours) that we can draw on to manage high traffic hotspots. This simplifies exposition, and it represents the advantageous situation of the NM being very flexible in when and where local capacity is supported. However, it is straight-forward to extend the framework to the case of other collaboration arrangements in the form of multiple pools of capacity that can be used only in certain airspaces.

As before, we seek to minimize expected cost by deciding on the budget of sector hours for each airspace as well as for the cross-border budget:

$$\min_{\mathbf{h}\geq 0} \quad \mathbb{E}_S\left[G\left(S|\mathbf{h}\right)\right] + \gamma^T \mathbf{h},$$

where $G\left(S \mid \mathbf{h}\right)$ represents the minimum displacement costs stemming from demand management measures and $\gamma^T \mathbf{h}$ represents the costs of capacity provision. The decision vector $\mathbf{h}$ contains also the budget h^x for cross-border provision. This budget can be used to run configurations in different airspaces that have at least one remote-controlled sector. We split the cross-border budget h^x into allocations x_a to different airspaces such that (for any airspace a) the consumed cross-border capacity does not exceed its allocation: $\sum_{u\in U} \sum_{c\in C^{a,x}} \bar{h}^x_{ac} z^S_{acu} \leq x_a$, where $C^{a,x}$ denotes the set of configurations of airspace a featuring at least one remote-controlled sector.

With this, we can formulate the optimization problem to determine the displacement cost $G(S|\mathbf{h})$ under scenario S given capacity budgets $\mathbf{h}$:

$$G(S|\mathbf{h}) = \min_{y,z} \sum_{f\in F^S} \sum_{r\in R_f} d_{fr} y_{fr}$$

$$s.t. \sum_{f\in F^S} \sum_{r\in R_f} b_{frpu} y_{fr} z_{acu} \leq \kappa_p^S$$

$$\forall a \in A, c \in C^a, p \in P^c, u \in U$$

$$\sum_{a\in A} x_a \leq h^x$$

$$\sum_{u\in U} \sum_{c\in C^a} \bar{h}_{ac} z_{acu} \leq h_a, \quad \forall a \in A$$

$$\sum_{u\in U} \sum_{c\in C^{a,x}} \bar{h}^x_{ac} z_{acu} \leq x_a \quad \forall a \in A$$

$$\sum_{r \in R_f} y_{fr} = 1, \quad \forall f \in F^S$$
$$\sum_{a \in C^a} z_{acu} = 1, \quad \forall a \in A, u \in U$$
$$x_a \geq 0 \quad \forall a \in A$$
$$y_{fr} \in \{0,1\}, \quad \forall f \in F^S, r \in R_f$$
$$z_{acu} \in \{0,1\}, \quad \forall a \in A, c \in C^a, u \in U.$$

Taking the same route as above, we approximate the problem by looking for the minimum cost solutions for several sampled scenarios (so as to make the problem deterministic and thus less complex), and then determine an approximate solution to the original problem by consolidating the set of solutions into a single recommended one.

To do so, the key realisation is that we can include cross-border implications through the definition of a configuration c. We assume that the maximum capacity configuration of an airspace is not used without cross-border provision because otherwise an ACC would need to commit to a large number of ATCOs (that are however only all needed in few peak times). Therefore, we model the maximum capacity configurations to have one or several sectors controlled from a foreign ANSP.

Whilst the cost for a configuration with a cross-border controlled sector will be higher than if there is no cross-border controlled sector, this configuration would have more sectors open than otherwise available for that airspace (since cross-border would only be invoked when the domestic ANSP cannot support the traffic any more). The idea is to only make use of cross-sector configurations to adjust to traffic peaks, so that despite having higher service provision costs, we save on delay and re-routing.

In the underpinning stochastic problem, this cross-border capacity pool serves as a hedge against the risk of underprovision of capacity in any airspace without us having to pre-commit all capacity to individual airspaces. In the deterministic problem $G(S)$ for a given scenario S, we only have a benefit from configurations with cross-border controlled sectors if traffic is such that we need the configurations' high capacity throughput in order to avoid displacement costs that are larger than the additional cost of capacity. This deterministic problem $G(S)$ with cross-border control is given by:

$$G(S) = \min_{\mathbf{y},\mathbf{z}} \sum_{a \in A} \sum_{c \in C^a} \sum_{u \in U} \gamma_{ac} z_{acu} + \sum_{f \in F^S} \sum_{r \in R_f} d_{fr} y_{fr}$$
$$\text{s.t.} \sum_{f \in F^S} \sum_{r \in R_f} b_{frpu} y_{fr} z_{acu} \leq \kappa_p^S z_{acu}$$
$$\forall a \in A, c \in C^a, p \in P^c \, u \in U$$
$$\sum_{r \in R_f} y_{fr} = 1 \qquad \forall f \in F^S$$
$$\sum_{c \in C^a} z_{acu} = 1 \qquad \forall a \in A, u \in U$$
$$z_{acu} \in \{0,1\} \qquad \forall a \in A, c \in C^a, u \in U$$
$$y_{fr} \in \{0,1\} \qquad \forall f \in F^S, r \in R_f.$$

The cost coefficient γ_{ac} represents the cost of configuration c for one time period; otherwise, the formulation is exactly as in the original solution approach in [1]. Therefore, we can use the same methodology to solve this problem efficiently for the cross-border provision case as well. Solving this problem for a single scenario S gives us the budget of h_a^S for each airspace a as before. The cross-border budget is given by $h^{x,S} := \sum_{a \in A} \sum_{u \in U} \sum_{c \in C^{a,x}} \bar{h}_{ac}^x z_{acu}^S$, where $C^{a,x}$ is the set of configurations of airspace a that feature at least one remote-controlled sector, and h_{ac}^x denotes the number of sector-hours needed from the central pool to run this configuration for one time unit. The policy to consolidate the solutions is introduced below.

IV. Numerical Experiments

We demonstrate the ability of this approach to deal with cross-border capacity planning by conducting a numerical case study based on real flight data. Sector configurations that were adapted from real sector data and modified so as to reflect cross-border control. The aim is to gain insights into the general impact that the inclusion of cross-border control may have compared to working without it.

A. Decision Policy

The foresight approach will produce a set of solutions $\mathbf{h}^S$ for different scenarios S. However, we still require a consensus function that maps from this collection of solutions to a single one to be used. We refer to such a consensus function as a policy; for our experiments, we used the best-performing policy reported in our earlier work [1]. This policy is defined as follows:

$\epsilon = x\%$: In the risk-based policy, the capacity decision is obtained by setting $\mathbf{h}^*$ such that the sample probability of encountering a flight scenario in which we had better planned for more capacity in at least one airspace is less than a given ϵ, i.e. Prob$(\mathbf{h} \not\leq \mathbf{h}^*) < \epsilon$, where the sample probability distribution of $\mathbf{h}$ has been computed by the perfect foresight approach over scenarios $S \in \mathcal{S}$ with step-size $\alpha = 10^{-9}$ (small due to scaling issues). The ϵ policy is tested with $\epsilon \in \{0.01, 0.05, 0.10, 0.20\}$. Setting ϵ to large values such as 0.10 or 0.20 reflects an increasing willingness to accept the risk of making capacity decisions which could work poorly under a significant number of traffic scenarios. On the other extreme, setting ϵ to smaller values such as 0.01 or 0.05 represents less risk and thus is more appropriate for risk-averse decision makers.

B. Data Description

We use real capacity and demand data, which we obtained via the EUROCONTROL Demand Data Repository service using the EUROCONTROL Network Strategic Tool (NEST). The selected region includes en-route airspace in Central and Western Europe, including eight ANSPs and 15 ACCs/sector groups. It covers a large part of the so-called core area (e.g., MUAC and Germany) of the European airspace, as well as a part of airspace that is not as congested (e.g Polish and Slovakian airspace). Based on historical usage of configurations in 2016, for each ACC or sector group, we selected configurations with different numbers of sectors that were most frequently used: in total, we have 173 different configurations for the 15 ACCs/sector groups. We calculated average ATCO costs per sector-hour for the different ANSPs, and in one case for an ACC, based on [14]. We treat those costs as variable costs at the strategic level (although ATCO costs might be considered fixed costs in the short term, reducing the daily number of ATCO hours will reduce the total number of ATCOs needed for ANS provision, consequently reducing staff costs). For cross-border capacity provision, we assume that the cost per sector-hour is either equal to or 10% higher than the MUAC sector-hour (the highest among ANSPs/ACCs in study).

Capacity planned at the strategic level is often not provided on the day of operations for many different reasons. Some of these reasons exhibit some regularities and could be anticipated/planned well in advance, while other are not easy to predict. We partially rely on historical ATFM regulations to derive a uniform probability distribution over sectors that a random sector in an ACC will have capacity reduction by 10%, 30%, or 50% or will be closed for flights entirely (zero-rate entry count). We use the same distribution as in [1]. To avoid creating overly restrictive capacity scenarios, we limit the number of sectors per ACC with reduced capacity. We also limit the maximum number of sectors which can be opened by several ACCs, namely Wien ACC, Karlsruhe ACC (Central) and MUAC, unless cross-border capacity provision is employed.

We selected 9th September 2016, the busiest day in 2016, to obtain demand/flight data. A subset of morning schedule flights and all non-scheduled flights on the selected day (which crossed the study airspace) create our flight dataset. The final demand set, i.e. flight scenario, consists of 1,200 scheduled flights (fixed) and 211 non-scheduled flights randomly selected from a pool of 1569 flights. As a result, in each demand scenario 15% of flights are non-scheduled. Note that we uniformly distribute entry times of non-scheduled flights into the selected airspace, since they are polled from the entire day, while we test our model only for a period of 2 hours in the morning. Flights can be either delayed or rerouted (only one demand management measure per flight. Delay and rerouting costs are calculated based on [15], [16]. Delay costs are non-linear with time, while re-routing costs include fuel costs, crew costs, soft and hard passenger costs, as well as maintenance costs [15]. Delay options are discrete and the same for each flight, namely, 5, 15, 30 or 45 minutes. Each flight has a number of alternative spatial trajectories: up to 3 nautical miles longer than the shortest and one flight level higher or below the one from flight plan (if feasible), all generated using the NEST and last filed flight plan for each flight.

C. Implementation

Set $\mathcal{S}$, representing the collection of scenarios anticipated by the decision maker, is populated with 100 scenarios. Once a policy is obtained, its performance is assessed with a simulation. Specifically, for a given policy budget $\mathbf{h}$, scenarios S are iteratively sampled and the cost performance is measured by solving the problem $G(S|\mathbf{h})$ to optimality via CPLEX commercial solver. Each simulation is run for 100 iterations.

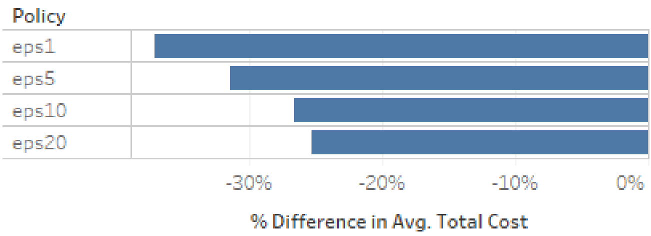

Figure 1. Percentage reduction of total cost when using cross-border provision relative to not using cross-border provision per policy (based on 300 scenarios for evaluation)

We consider *low* and *high* uncertainty simulation settings. In the first, scenarios are sampled from the same pool used to devise the policies (i.e., $\mathcal{S}$). In the latter, 200 additional scenarios are added. In other words, in the *high* uncertainty case we assume that the decision maker does not anticipate all scenarios that may happen. We obtain policies under the following assumptions:

- No cross-border provision.
- Cross-border sector-hours available at the cost of the most expensive ACC.

D. Findings

The results confirm that enabling cross-border capacity provision has a significant potential of reducing the average overall costs (capacity costs along with displacement costs), see Figure 1. The more risk-averse the policy, the higher the savings: this is because cross-border provision acts as an insurance against disruptions (such as capacity shortages or higher-than usual non-scheduled flight activity). As can be seen in Figure 2, using cross-border provision allows to drastically reduce average displacement costs whilst hardly increasing capacity costs. Also, the relative savings of more risk-averse policies are larger than without cross-border provision, suggesting that cross-border provision is particularly useful for risk-averse decision makers. The lowest risk policy $\epsilon = 1\%$ is the best-performing policy.

Inclusion of cross-border control may also lead to more robust cost performance in the face of traffic uncertainties as illustrated in Figure 3. We would expect that average total costs will increase as traffic uncertainty is increased (by drawing on 300 evaluation scenarios rather than just 100); this is indeed the case without cross-border provision. However, with cross-border provision the average cost remains about the same as we are able to handle the uncertainty with the flexibility that cross-border provision gains us.

So far in the analysis, we always assumed that a cross-border sector hour comes at the cost of a sector hour of the most expensive airspace. We also conducted some experiments on increasing this cost further by 10% and 20%, respectively. For the latter, cross-border capacity is too expensive such that it never gets procured in our optimization. At the cost rate of 110% the cost of a sector hours of the most expensive airspace, only under the most risk averse policy $\epsilon = 1\%$ some cross-border budget is ordered, leading to similar cost savings as in the 100% cost case. Accordingly, there will be a maximum

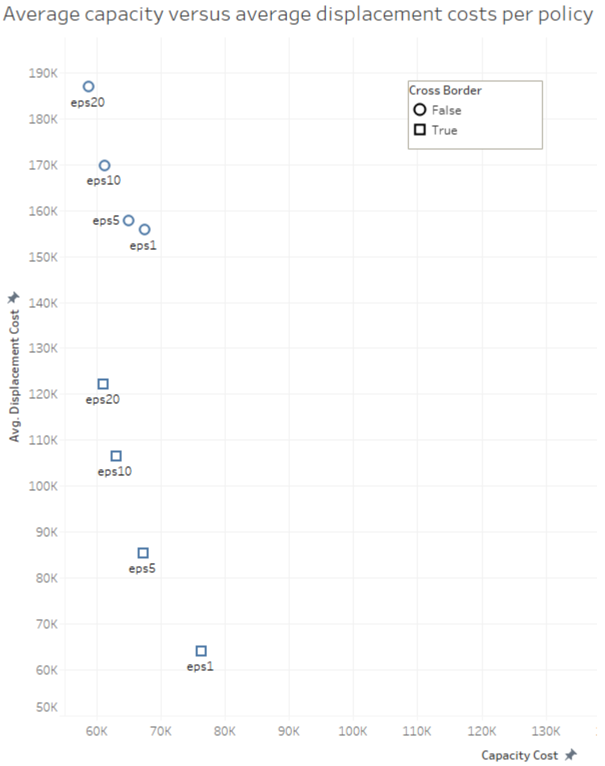

Figure 2. Using cross-border provision leads also to improved performance of the more risk-averse policies relative to riskier ones (apart from lowering total costs overall). Based on 300 evaluation scenarios.

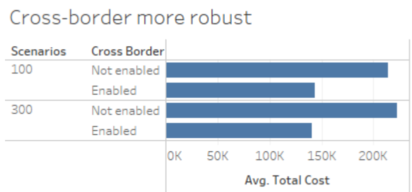

Figure 3. Cross-border provision may lead to more robust cost performance in the face of increased uncertainty (100 evaluation scenarios means low, 300 scenarios means high traffic uncertainty).

cost for cross-border provision beyond which the latter is no longer beneficial. A precise analysis into these cost figures is not sensible on the basis of our case study but would be an interesting topic for future research.

Except for reducing the total cost to airspace users, the cross-border provision also improves environmental performance in our case study. For instance, if we look at the $\epsilon = 1\%$ policy, the inclusion of cross-border at the 100% cost rate on average reduces the extra distance flown by 38%: from 561nm to 348nm. Even at the 110% cost rate, the extra distance is still substantially reduced – by 30% vs. the no-cross-border scenario, which is a highly indicative finding. Similarly, the number of heavily delayed flights seems to be tangibly reduced by the inclusion of cross-border provision. Looking again at the $\epsilon = 1\%$ policy, this number drops from an average of 20.9 (median 7) without cross-border, to 13.2 (median 4) at the 100% cost rate, and 14.6 (median 6) if the 110% cost rate is assumed. This is a very important initial indicator for fairness of the solution, knowing the strong non-linearity of delay costs with delay duration.

Clearly, the results of a numerical study will depend on the choice of parameters, and ours is not different. A critical setting is the magnitude of the penalty cost for flights that need to be delayed beyond the considered planning horizon. As such, the presented results are to be understood as illustration of the approach in an academic setting; however, the data were based as much as possible on available real flight and sector data.

The main insight gained from the numerical experiments is that cross-border provision leads to particularly strong cost performance improvements for more risk-averse decision makers, which is a promising feature.

V. Conclusion

For a setting in which the network manager can centrally plan air navigation service capacity, we present a methodological approach on how to optimize capacity budgets for each airspace alongside cross-border capacity budgets. The findings on a small case study suggest that there may be significant potential for cost reduction in cross-border control, especially for risk-averse decision makers, as long as it can be offered at 'reasonable' rates that do not exceed the regular cost of capacity dramatically. Cross-border capacity provision acts as a hedge against the risk of underprovision and its flexibility has the promise to lead to more robust cost performance in the face of traffic uncertainty.

In future work, we plan to expand on this work by considering larger cases as well as tackling the problem with a stochastic solution approach.

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