Cross-border capacity planning in air traffic management under uncertainty

Jan-Rasmus Künnen¹, Arne K. Strauss*, Radosav Jovanović², Nikola Ivanov², Frank Fichert³, and Stefano Starita⁴

¹Chair of Demand Management and Sustainable Transport, WHU – Otto Beisheim School of Management, 56179 Vallendar, Germany
²Faculty of Transport and Traffic Engineering, University of Belgrade, 11000 Belgrade, Serbia
³Faculty of Tourism and Transport, Worms University of Applied Sciences, 67549 Worms, Germany
⁴Sasin School of Management, Chulalongkorn University, 10330 Bangkok, Thailand

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Abstract

In European air traffic management (ATM), it is an important decision how much capacity to provide for each airspace, and it has to be made months in advance of the departure day. Given the uncertainty in demand that may materialize until then along with variability in capacity provision (e.g., due to weather), a wrong decision can create high cost on the network in terms of necessary displacements (re-routings or delays). We propose a new cross-border capacity provision scheme in which some proportion of overall capacities can be flexibly deployed in any of the airspaces of the same alliance (at an increased unit cost). This allows us to hedge against the risk of capacity underprovision. Given this scheme, we seek to determine the optimum budget

*Corresponding author: arne.strauss@whu.edu
for capacities provided both locally and in cross-border sharing that results in the lowest expected network cost (i.e., capacity and displacement cost).

To determine optimum capacity levels, we need to solve a two-stage newsvendor problem: We first decide on capacities to provide for each airspace, and after uncertain demand and capacity provision disruptions have materialized, we need to decide on the routings of flights (including delays) and the sector opening scheme of each airspace to minimize cost. We propose a framework that balances exploration with exploitation in searching the most cost-efficient capacity levels (in the first stage), and use a heuristic to solve the routing and sector opening problem (in the second stage), which is \( \mathcal{NP} \)-hard.

We test our approach in a large-sized simulation study based on a real data covering around 2,800 flights across large parts of Western European airspace. We find that our approach significantly reduces network cost against a deterministic benchmark (using similar computational resources). Also, experiments on different setups for cross-border capacity sharing show that total cost can be reduced by 1.6%–2% if capacity is shared among neighboring airspaces - even though we require that each airspace has at least as much capacity under cross-border provision than without (this conservative assumption is to avoid substitution of expensive air traffic controllers with others from air navigation providers in countries with a lower wage level). In contrast, operating a central pool of air traffic controllers eligible to work across the network does not further improve performance since the higher capacity cost outweigh savings from delay and re-routings.

**Keywords:** air traffic management; capacity planning; simulation optimization

## 1 Introduction

We study a two-stage newsvendor problem in the context of air traffic management with cross-border capacity sharing. In the first stage, a network manager needs to decide on capacity levels to be delivered by each capacity provider for their respective airspaces locally, as well as on (more expensive) cross-border capacity that can be flexibly deployed in multiple airspaces. Cross-border capacity provision is intended to address underprovisions caused by random disturbances of demand (e.g., unusually high number of non-scheduled traffic) and capacity provision (e.g., triggered by weather events or unplanned air traffic controller absences). In the second stage, flight intentions by aircraft operators materialize and various sources of uncertainty are being resolved. The network manager needs to decide on demand management measures (delay or re-routing) and on the exact sector opening scheme for each airspace to minimize overall costs.
This problem is motivated by various on-going endeavours that advocate a strengthening of the role of the network manager and capacity sharing between air navigation service providers (ANSPs). At present, European ANSPs rely on their individual resources to deliver required capacity levels to meet demand on a day of operations. Since these resources mostly refer to the number of air traffic controllers (ATCOs) available and their rosters and shifts are planned several weeks in advance, there are usually very limited options to call in more ATCOs on short notice when additional capacity is needed on a day of operations. Note that in 2018 and 2019 one of the main reasons for delays in European airspace were related to air traffic control capacity and staffing (Eurocontrol (2019b, 2020a)). More specifically, about a quarter of en-route air traffic flow management (ATFM) delays—i.e., delays imposed by the Network Manager—was attributed to air traffic control staffing reasons, with an early indication that the (lack of) ATCOs could actually have even a higher impact than reported according to Eurocontrol (2020b). It is also worth noting that only a few ANSPs contribute to more than two thirds of ATFM delays in Europe.

One of the proposed remedies to recurring staffing issue is resource sharing between ANSPs—also referred to as the “capacity-on-demand” concept—which aims to increase resilience to disruptions by enabling a more dynamic temporary delegation of the provision of air traffic services to an alternate provider with spare capacity, as described in SESAR Joint Undertaking (2019). The Wise Persons Group (2019) also recommends the development of “capacity-on-demand” services, emphasising the need for improved flexibility and resilience in capacity provision. More recently, three European ATM doyens welcome the regulation proposal which strengthens the role of the network manager in European ATM by means of, inter alia, “putting the network manager in a position to manage the capacity brokering process, including the possibility to facilitate delegation of airspace” (Baumgartner et al., 2021). They moreover suggest that the network manager role should be further empowered with four key pan-European roles, including the role of capacity manager, which would, “based on pan-European demand-capacity balance analysis, decide on the best measures for a better balance including mandatory delegation of airspace from congested ANSPs to less congested neighbouring ANSPs” (Baumgartner et al., 2021).

Therefore, we focus on a future network manager which acts as a central decision maker and investigate different settings of cross-border capacity sharing with the objective of gaining insights into what might be promising avenues for future European air traffic management. It is important to emphasize that cross-border capacity sharing is not intended to reduce the cost of capacity provision (which differs dramatically between countries in Europe); instead,
it is intended to reduce the cost of re-routings and delays stemming from underprovision due to unforeseen events. Clearly, a proposal of substituting air traffic controllers in a high-wage country with controllers from a low-wage country will likely be politically not acceptable.

Our main contributions are (1) the development of a solution approach to the underpinning hard newsvendor problem that accounts for the stochastic nature of the problem using ideas from the domains of simulation optimization; (2) the application of this approach to a large case study using real flight and network/capacity data to obtain insights on how to implement cross-border sharing (central pool or several alliances of ANSPs). We find that our stochastic approach significantly improves—as one would expect—on benchmarks that optimize capacity based on deterministic problem instances. In particular, this makes the methodology suitable to assess the benefits of cross-border sharing given that we want to use the latter to hedge against the risk of capacity underprovision. We further find that—perhaps somewhat counter-intuitively—a central cross pool of controllers at the network manager is not the best setup but rather strategically chosen alliances of ANSPs return the lowest overall costs. This is promising since such alliances also are more likely to be established in practice than a central pool. Furthermore, despite the strong self-imposed constraint of requiring every airspace to have at least as much capacity under cross-border provision than without it (to make the concept politically more acceptable, as mentioned above), we still find that overall savings of 1.6%-2% are realistic, which would correspond to absolute annual cost savings of €5–10 million. These savings are estimated after accounting for higher unit cost of cross-border provision.

The paper is organized as follows: We review the relevant literature in §2 and provide a formal description of the problem in §3. In §4, we present a stochastic optimization approach to solve the problem efficiently and discuss a method to evaluate cross-border capacity provision. In §5, we provide different cross-border capacity settings and test them using the proposed methodology on a realistic-sized case study. We close with recommendations and managerial insights in §6.

2 Literature Review

Capacity sharing

While the idea of capacity resource sharing is not entirely new, to the best of authors knowledge, there are no academic papers which explore the potential benefits of such concept in ATM. While Ivanov et al. (2019) evaluate European ATM with a central network plan-
ner, they only argue that cross-border capacity provision could further improve total cost-efficiency of the system, but do not explore this option. Although there seem to be only several obstacles for the implementation of the “capacity-on-demand” concept (SESAR Joint Undertaking, 2019), in practice there are only very few examples. The report of the Directorate-General for Mobility and Transport (European Commission) (2020) distinguishes between four implementation scenarios for ATM data service provision (ADSP) and capacity-on-demand as part of the future European airspace architecture, namely: baseline, non-tactical, time critical and virtual centres scenarios (Fig. 29, p. 87). All of them, except the baseline scenario, might be relevant for the cross-border operations implementation. We therefore briefly discuss them below.

The non-tactical scenarios are essentially the planned delegation of air traffic services (such as for night-time operations, etc.). These arrangements can be long-term and fixed. In contrast, the time-critical implementation scenarios capture “time-critical contingency applications” (e.g., ANSP system failure, workforce sickness, security-related events etc.) and “dynamic time-critical cross-border delegation of operations” (e.g., planned dynamic resectorisation between two providers when the exact hours of such operation are not known). The latter is actually the rationale behind the ongoing FINEST project, the Finnish-Estonian dynamic cross-border sectorisation. [Directorate-General for Mobility and Transport (European Commission) (2020), pp. 91–92]. FINEST is predicated on a common ATM system between ANSPs of Finland and Estonia, which enables a switching of sectors between two area control centers and full interoperability. The virtual centers scenarios, finally, assume decoupling ATM data services, such as flight data, radar, and weather information, from the physical controller working position. This is an obvious enabler for fuller capacity-on-demand concept (dynamic optimisation), on local, regional or network level. Some existing arrangements in Europe already show certain features of the virtual center concept according to Directorate-General for Mobility and Transport (European Commission) (2020), p. 94: the planned geographically-decoupled provision of ATM data services from Maastricht Upper Area Control Center for SloveniaControl or within the Swiss ANSP Skyguide, the operation of a virtual center serving both Zurich and Geneva ACCs. In our work, we investigate cross-border designs aligned with the time-critical application scenario and with the virtual center scenarios (and compare it with the scenario of having no cross-border control).

Whilst we are not aware of any academic publications on cross-border capacity sharing in air traffic management, there is work in electricity markets that analyzes cross-border capacity balancing, see Baldursson et al. (2018). They consider three scenarios concerning
sharing agreements: either no sharing at all, exchange of electricity across borders and lastly a common reserve that multiple countries can draw on (similar to our considered designs of no cross-border sharing, sharing within certain alliances and a central pool that can be used in any airspace). They find that a focus on overall social welfare (rather than the individual players’ costs) is important to incentivise collaboration. This aligns with our choice of assuming a central planner seeking to minimize overall costs (capacity provision and displacement/delay costs) whilst insuring that no capacity provider has less capacity than without capacity sharing to ensure their collaboration. Adler et al. (2020) investigate collaboration specifically in the air traffic domain using a game theoretic approach. They assume that ANSPs seek to maximize profits by pricing their services subject to certain regulations imposed on them. In our framework, we assume that a central network manager decides on capacity levels with the aim of minimizing overall costs as mentioned above; by centrally procuring capacity provision, ANSPs do not charge air space users any more but rather just deliver capacity based on their contract with the network manager (NM). The financial risk of not being able to cover the capacity expenses would accordingly also rest with the NM, as would the competence for route charging (see Künnen and Strauss (2021) for a dynamic pricing methodology in this context). This assumption of a stronger role for the NM in Europe was first proposed by Ivanov et al. (2019). Amongst others, this role foresees that the NM coordinates capacity provision in the network and decides on capacity levels for each airspace in line with anticipated demand.

Newsvendor problem

Structurally, the planning problem that we consider is known as newsboy or newsvendor problem in the inventory management literature. The basic version of this problem is to decide on what quantity of products to order so as to sell them later at an a priori unknown profit (since this will depend on materialization of uncertain demand). Various variations of this problem have been studied over the past decades, see Khouja (1999) and Qin et al. (2011) for reviews. In our context, we assume that demand for air navigation services is independent of our capacity decision such that we do not need to model interactions between the two. This seems justifiable since in practice demand is largely driven by the flight schedule which in turn depends on end customer demand and airport slot availability (but not on en-route airspace capacity). We also make the simplifying assumption that the unit price of capacity, which we measure in sector-hours, is constant and only differentiated based on whether it can be deployed cross-border or locally only. Another feature of newsvendor problems is
how the risk attitude of the decision maker is modelled. We settle on the classic assumption of risk-neutrality (meaning that we optimize expected costs) because we assume that the capacity decisions are modelled for a short period only (e.g., a single day) and would be taken frequently.

Sample Average Approximation

The main challenge of our problem is that the evaluation of the expectation is expensive. For such problems, sample average approximation (SAA) had been proposed by Kleywegt et al. (2002), who also show that the optimal solution based on SAA converges to the true optimal value with probability 1. The idea is essentially to replace the expectation with a finite sample average – that then represents a deterministic function – and that accordingly can be minimized using deterministic optimization methods. In particular, SAA approaches usually require estimates of the gradient of the objective function so as to employ gradient-based numerical optimization techniques. For an introduction to SAA approaches, see Kim et al. (2015). In our application, the objective is discontinuous and sub-gradients would be computationally very expensive so that we need a derivative-free approach. Theoretical properties (in particular, bounds on SAA’s accuracy) of a data-driven newsvendor were more recently studied by Levi et al. (2015). We adopt a random search method called the ‘asymptotical optimal set (AOS) framework’ of Hu and Andradóttir (2019) that has been designed specifically for minimization of an expectation over a discrete or continuous domain that cannot be evaluated exactly. This framework does not require gradients and has the attractive theoretical feature that, as the name suggests, it ensures asymptotical optimality in that the best point in the candidate set converges almost surely to the global optimum, and other suboptimal candidates will ultimately be eliminated from the candidate set with probability 1. It improves on the Adaptive Search with Resampling approach of Andradóttir and Prudius (2010) by including a method of discarding inferior points from the pool of candidates; this is particularly important in our application since the computational effort of re-evaluating a solution is significant.

Deterministic approach

In a model closest to our work, Starita et al. (2020) tackle the same strategic capacity planning model for European ATM. They propose a heuristic approach to determine capacity level for a given demand and capacity scenario. The authors also develop different policies that define how the individual optimal capacity levels (also referred to as “capacity budgets”) across
numerous scenarios can be combined into one capacity decision. In contrast to their approach that starts with a number of known scenarios of the future and results in a suggested capacity budget decision, we start from capacity budget decisions and work towards better decisions by learning the quality of each decision on random scenarios in a way that focuses most computational effort on the most promising solutions. Furthermore, new budget decisions are being discovered and investigated in the AOS framework that we employ. Approaching the problem as a stochastic learning problem is particularly important since we want to study cross-border capacity provision as a means to hedge against the risk of underprovision. Using the approach of Starita et al. (2020) would mean that we start with a deterministic flight scenario with all uncertainties resolved; in that case, there is no need any more for (the more expensive) cross-border control since we can simply adjust the local capacities accordingly. To the best of our knowledge, no other research has yet been carried out to study the strategic capacity provision problem.

3 Problem Statement

In this section, we define the two-stages newsvendor problem under consideration, show that evaluation of the objective at the second stage is both noisy and expensive, and thus set the stage for the proposed learning approach in the next section.

We consider the problem \( \min_{x \in \mathcal{X}} f(x) \), where \( f(x) = \mathbb{E}_S(G(x,S)) + c^T x \); \( x \) is a vector of capacity allocations to airspaces (measured in sector-hours) out of the finite set of designs \( \mathcal{X} \); \( S \) represents a random scenario for the materialization of demand and potential capacity provision disturbances; \( G(x,S) \) is the displacement cost function given scenario \( S \) and capacity budgets \( x \); and the capacity unit costs are given in vector \( c \). Displacement cost represents the cost of re-routing and/or delaying flights. The exact evaluation of \( f(x) \) is impossible due to the expectation over a complex distribution of scenarios, combined with the fact that even a single objective function observation \( G(x,S) + c^T x \) is expensive, since \( G(x,S) \) is a large integer program. Moreover, \( G(x,S) \) is not continuous in \( x \), which means that we are not able to construct derivatives at all feasible solutions.

The domain \( \mathcal{X} \) of potential solutions can be considered to be finite because for each unit time interval (e.g. 30 minutes), each airspace has only a finite number of potential configurations that it can operate in, and each configuration corresponds to a fixed number of sector hours. In other words, one can enumerate all combinations of configurations that an airspace may have over the course of a day, and correspondingly would have the number
of sector hours that would be required for each such combination, meaning that the optimal solution must be in this finite set. Of course, the cardinality of $\mathcal{X}$ is very high and therefore it is computationally intractable to explore the entire domain.

However, we do not need to explore the entire domain anyway since at the strategic planning stage we already have information on flights from scheduled carriers; uncertainty in the spatio-temporal distribution of demand mainly stems from non-scheduled flights and capacity provision disruption (due to weather or sickness-related absences of ATCOs). Non-scheduled flights usually amount to no more than 20% of total traffic, so the majority of traffic is known in advance and the overall pattern in terms of likely congested airspaces is known. This allows us to define a sensible search space $\mathcal{X}$ within certain maximum and minimum bounds of sector hours along each dimension.

In the following, we assume that this process has been completed to identify the domain $\mathcal{X}$. We then need to identify the best solution $x^* \in \mathcal{X}$ with a limited computational budget that we measure in terms of the maximal number of objective function evaluations.

We need some additional notation in order to fully specify the objective function. First, a solution $x := [(x_a)_{a \in A}; (x_g^0)_{g \in G}]$ consists of sector-hour budgets $x_a$ for each airspace $a$ that can only be used for that airspace, as well as sector-hour budgets $x_g^0$ for each cross-border alliance $g \in G$, where $G$ denotes the index set of all such alliances. Alliance $g$ consists of airspaces $a \in A_g \subseteq A$. We distinguish between the physical allocation of capacity within the headquarters of an ANSP in an airspace (meaning where the controller would actually be based), and where their workforce is being virtually deployed. This difference is important since we assume, perhaps conservatively, that cross-border provision would only be politically acceptable if no ANSP would have labour displaced, i.e. if each airspace $a$ has at least as many sector-hours physically assigned as they would have if there were no cross-border sharing at all. The latter capacity is denoted by $\bar{x}_a$ and serves as a static parameter in the model (having been calculated by a previous model run without cross-border allowance). Furthermore, for practical and potentially operational reasons (such as ATCO licence maintenance) we also assume that all ANSPs within an alliance need to provision the same number of sector-hours $x_g^0$ of cross-border capacity. This budget may be deployed within their own airspace or to support another ANSP in the alliance. We require that each airspace’s total capacity budget must be no less than this threshold capacity $\bar{x}_a$:

$$\bar{x}_a \leq x_a + x_g^0 \quad \forall a \in A,$$

where $g$ corresponds to the alliance that features airspace $a$ (so $a \in A_g$).
It is a separate decision where the cross-border capacity $x^0_g$ of each airspace in alliance $g$ will be used; we denote the number of sector hours that will be virtually deployed in airspace $a$ as $h^0_a$ and require

$$\sum_{a \in A_k} h^0_a \leq |A_k| x^0_g \quad \forall \ g \in G,$$

so $x^0_g = 10$ would mean that each airspace plans for 10 sector hours cross-border provision at their location which can then be flexibly used in any airspace $a \in A_g$ within the alliance according to our allocation $h^0_a$. Let $z_{acu}$ indicate that airspace $a$ is run in configuration $c$ in time period $u$, and $\bar{h}_{ac}$ denotes the number of sector hours required to run configuration $c$ in airspace $a$ for one period of time. Then the capacity constraints of the airspaces can be stated as

$$\sum_{u \in U} \sum_{c \in C^a} \bar{h}_{ac} z_{acu} \leq x_a + h^0_a \quad \forall \ a \in A.$$

Due to this requirement of the physical cross-border provision at each airspace having to be the same, the cost coefficient $c_g$ of $x^0_g$ is simply the sum of all unit cross-border costs over all airspaces $a \in A_g$.

We now can define the displacement cost function $G(x, S)$ in the objective, which expresses the minimal displacement cost incurred under capacities $x$ in scenario $S$ (recall that displacement cost refers to the cost of re-routing or delaying flights):

$$G(x, S) = \min_{y,z} \sum_{f \in F_t} \sum_{r \in R^f} d_f^r y^f_r$$

s.t. (1–3)

$$\sum_{f \in F_t} \sum_{r \in R^f} \sum_{e \in E^p} b_{freu} y^f_r z_{acu} \leq \kappa_l \quad a \in A, c \in C^a, l \in L^c, u \in U$$

$$\sum_{c \in C^a} z_{acu} = 1 \quad a \in A, u \in U$$

$$\sum_{r \in R^f} y^f_r = 1 \quad f \in F$$

$$h^0_a \geq 0 \quad \forall \ a \in A$$

$$y^f_r \in \{0, 1\} \quad f \in F, r \in R^f$$

$$z_{acu} \in \{0, 1\} \quad a \in A, c \in C^a, u \in U.$$

The objective function minimizes total flight displacement cost for all the flights in the scenario $S$. The decision variable $y^f_r$ assign flight $f$ to route $r$. Constraints (5) ensure that
the sector capacity is not exceeded: if we operate under configuration $c$ at $u$, we restrict the capacity of any sector $l$ in $L^c$ to $\kappa_l$. Constraints (6) enforce that each airspace operates under one configuration at any time, and constraints (7) require that exactly one route is assigned to each flight.

If the evaluation of $G(x, S)$ were easy, we could simply evaluate each solution $x$ for a large sample of scenarios and then substitute the expectation in the newsvendor problem with the sample average. However, Künnen and Strauss (2021) show that this problem is NP-hard such that fully exploring the whole solution space is computationally not practical. Therefore, we propose to use a learning framework to decide which solutions to evaluate how often given a fixed computational budget as described in the following section.

4 Learning Approach

Our goal is to find a capacity budget $x^*$ that we confidently believe to lead to low expected network costs across random scenarios $S \in \mathcal{S}$. In the following, we denote by $f(x, S)$ the network cost generated by budget $x$ in scenario $S$, i.e., $f(x, S) = G(x, S) + c^T x$. Here, any scenario $S = (F^S, W^S)$ constitutes a materialization of traffic $F^S$ due to unknown demand from non-scheduled flights, and capacity $W^S$ due to uncertain provision of capacity services (e.g., from weather or ATCO shortages). Note that $W^S$ impacts both the actual available sector-hours $x^S$ and the actual sector capacities $\kappa^S$. To find a high-quality capacity decision $x^*$ in the sense as outlined above, we use a framework that balances the exploration of new budgets $x$ with the exploitation of existing budgets (meaning to measure $f(x, S)$ for promising candidates $x$ on additional scenarios $S$ to increase our confidence in the average performance); see §4.1. We propose an efficient method to evaluate $f(x, S)$ in each measurement step, see §4.2.

4.1 Framework

We base our approach on the Asymptotically Optimal Set framework by Hu and Andradóttir (2019), which we adjust to our problem. The procedure seeks to determine an optimal capacity decision $x^*$ given solution space $\mathcal{X}$, and is summarized in Algorithm 1. The idea is that we iteratively develop a pool $\mathcal{X}_j^* \subset \mathcal{X}$ of promising solutions (where $j$ is the number of sampled solutions $x$), which is reduced to solution $x^*$ over time. In each iteration $i$ we either evaluate a new candidate $x \in \mathcal{X} \setminus \mathcal{X}_j^*$, or re-assess an existing candidate from this pool on a new scenario $S \in \mathcal{S}$. To trade off exploration with exploitation, we need to decide how
frequently we sample new solutions. Over time we want to explore new solutions less and less frequently to ensure that more effort can be spent on evaluating the quality of encountered promising solutions. As suggested by Hu and Andradóttir (2019), we sample new solutions at iterations $i = \lfloor j^{1.5} \rfloor$, and resample existing solutions otherwise.

Algorithm 1 Exploration-exploitation framework to seek optimum capacity

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Input: Scenarios $S$, solution space $X$, sampling, resampling
1: Initialize: $i = 0$, $j = 1$, $X_0^* = \emptyset$, $\hat{f}_0(x^*) = M$ (large number)
2: while $\exists x \in X_j^* : N(x) < N_{max}$ do
3:     $i = i + 1$
4:     if $i = \lfloor j^{1.5} \rfloor$ then
5:         Select $x \in X$ based on sampling strategy, evaluate $f(x, S_1)$ and set $j = j + 1$
6:     else
7:         $X_j^* = X_{j-1}^* \cup \{x\}$, $\hat{f}_i(x) = f(x, S_1)$, $N(x) = 1$
8:         end if
9:     for $x \in X_j^*$ (ensure minimum amount of resampling) do
10:        if $N(x) < \lceil j^{0.5} \rceil$ then
11:            Set $n = \lceil j^{0.5} \rceil - N(x)$ and evaluate $f(x, S_{N(x)+1}), \ldots, f(X, S_{N(x)+n})$
12:            Set $\hat{f}_i(x) = \frac{\hat{f}_{i-1}(x)N(x) + \sum_{k=1}^{n} f(x, S_{N(x)+k})}{N(x)+n}$, and $N(x) = N(x) + 1$
13:        end if
14:    end for
15:    for $x \in X_j^*$ (discard poor solutions) do
16:        if $\hat{f}_i(x) - \hat{f}_i(x^*) > \lambda / j^{0.15}$ then
17:            $X_j^* = X_j^* \setminus \{x\}$
18:        end if
19:    end for
20: else
21:     Select $x \in X_j^*$ based on re-sampling strategy and evaluate $f(x, S_{N(x)+1})$
22:     Set $\hat{f}_i(x) = \frac{\hat{f}_{i-1}(x)N(x) + f(X, S_{N(x)+1})}{N(x)+1}$, and $N(x) = N(x) + 1$
23:     Update $x_i^* = \arg \min_{x \in X_i^*} \hat{f}_i(x)$ and
24: end if
25: end while
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Output: Capacity budget $x_i^*$ with network cost $\hat{f}_i(x^*)$

At iterations $i$ where $i \neq \lfloor j^{1.5} \rfloor$, we sample a new candidate $x$ according to a pre-defined sampling strategy. To ensure that we cover the entire solution space, we use Latin Hypercube Sampling, which is described in the appendix. We then need to decide whether to accept $x$ into the pool of promising candidates, or whether to discard it. For this purpose, we define
a benchmark scenario $S_1$ without disturbances, i.e. we set $|F^{S_1}|$ to the average number of expected flights, and $W^{S_1}$ such that $x^{S_1} = x$ and $\kappa^{S_1} = \kappa$. We then accept a solution $x$ into the pool if the objective function value $f(x, S_1)$ at is at most $\lambda$ worse that our current best candidate, i.e. $f(x, S_1) - \hat{f}_i(x^*_i - 1) < \lambda$, where $\hat{f}_i(x)$ denotes the average objective value of $x$ at iteration $i$. Furthermore, if sufficiently many objective function evaluations have been conducted, we discard existing solutions based on a rejection threshold. More specifically, if $j$ candidates have been evaluated, we discard solutions $x \in X^*_j$ if $\hat{f}_i(x) - \hat{f}_i(x^*_i - 1) > \lambda/j^{0.15}$. This threshold is used to remove candidates from the pool who no longer look sufficiently promising. Note that $\lambda/j^{0.15}$ gets increasingly stringent so as to reduce the pool eventually to the optimal solution. To ensure convergence, a minimum amount of re-sampling is required throughout the procedure. We require for the number of evaluations $N(x)$ of any candidate $x$ that $N(x) \geq \lceil j^{0.5} \rceil$, and determine further objective function values for $x$ if the condition is not fulfilled.

At iterations $i$ where $i \neq \lceil j^{1.5} \rceil$, we re-sample an existing candidate $x \in X^*_j$ according to a pre-defined resampling strategy. We use an epsilon greedy approach: we sample with probability $\sigma(j) := 0.99/j^{0.5}$ a solution $x \in X^*_j$ randomly, and with probability $1 - \sigma(j)$ we choose $x := x^*_i$ (where $x^*_i$ is the minimal currently known average cost solution). We then evaluate $f(x, S)$ for a randomly chosen scenario $S$ and update average objective function value $\hat{f}_i(x)$ and evaluation count $N(x)$ accordingly. We stop the procedure if we have evaluated all candidates in the current pool over $N^{\text{max}}$ scenarios. We choose this stopping condition because a) we do not observe large variations in $\hat{f}(x)$ after a certain amount of evaluations, and b) there are often many very good candidates with similar $\hat{f}(x)$ in the pool (for large $j$), so reducing the pool further until only one candidate remains is not beneficial.

One advantage of the proposed framework is that only two parameters ($\lambda$ and $N^{\text{max}}$) need to be set according to the problem at hand (see §5.1). However, the effectiveness and efficiency of the procedure depend on how well and how fast we can evaluate network cost $f(x, S)$ for any budget $x$ and scenario $S$, which we discuss below.

### 4.2 Cost Evaluation for Given Solution and Given Scenario

In order to evaluate $G(x, S)$ for any candidate capacity budget $x$ under traffic and capacity scenario $S$, we need to solve the integer program that underpins $G(x, S)$. However, this problem is $\mathcal{NP}$-hard since it represents an instance of the Multidimensional Multiple Choice Knapsack Problem (MMKP) as shown by Künnen and Strauss (2021). In fact, in order to determine an exact solution, we would need to solve an MMKP (i.e., the routing problem)
for each of the $\prod_a |C^a|^{|U|}$ possible combinations of airspace configurations. Following the approach in Künen and Strauss (2021), we separate the sector-opening problem from the routing problem to find an approximate solution $G(x, S) \approx D(x, F^S, W^S)$ in polynomial time. More specifically, we conduct two steps to determine displacement cost $D(x, F^S, W^S)$, which are detailed in the following subsections:

1. Determine best candidate configuration $C'(x, F^S, W^S)$ given the capacity budget $x$, traffic scenario $F^S$ and uncertainty around capacity provision $W^S$, see §4.2.1;

2. Determine routing of flights with lowest cost $D(C', F^S, W^S)$ given the candidate configuration $C'$, see §4.2.2.

### 4.2.1 Finding best candidate configuration

In a first step, we want to determine candidate configuration $C' = \{c_{au} : a \in A, u \in U\}$, which consists of individual configurations $c_{au}$ for each airspace and operating time. For this purpose, we first assign each flight to its shortest route, i.e., the route with zero displacement cost; a positive cost is incurred if a flight is “displaced” in time (delayed) or in space (re-routed). We assume that this traffic assignment (represented by allocation $y$) gives us a good indication of where capacity is required in the network. Given traffic assignment $y$, we can compute the capacity shortage $k_{acu}$ for each airspace $a$, configuration $c \in C^a$ and time unit $u$. We define capacity shortage as the number of flights that exceed sector capacity limits, i.e., $k_{acu} := \sum_{l \in L^a} \left( \sum_{e \in E^l} \sum_{f \in F^S} \sum_{r \in R^f} b_{freu}y_{fr} - \kappa_{S}^{f} \right)^+$, where $x^+ := \max\{x, 0\}$. We then determine configuration $c_{au}$ for each airspace $a$ and time $u$ as the feasible configuration with the lowest total capacity shortage by solving the following ‘configuration integer linear program’ (CILP):

\[
\begin{align*}
\text{(CILP)} \quad \min_z & \quad \sum_{a,c,u} k_{acu}z_{acu} \\
\text{s.t.} & \quad \sum_{u} \sum_{c \in C^a} \tilde{h}_{ac}z_{acu} \leq x^+_a \\
& \quad \sum_{c \in C^a} z_{acu} = 1 \\
& \quad z_{acu} \in \{0, 1\}
\end{align*}
\]

In particular, $c_{au}'$ is given by the configuration for which $y_{ac'u} = 1$ for each airspace $a$ and operating time $u$. It is easy to see that the CILP decomposes by airspace; we denote this
decomposition by CILP-d. Even after decomposition the resulting problem still represents a multiple choice knapsack problem (MCKP), which is NP-hard. However, as there are typically no more than tens of configuration options per European area control center in each time unit, the number is sufficiently low so that the problem can be solved exactly in reasonable time. If larger airspaces need to be accounted for, or if the number of operating time units make the problem intractable, we would revert to heuristic approaches for the MCKP, such as the one proposed in Pisinger (1995).

To model cross-border capacity provision, the approach outlined above for determining $C'$ needs to be adjusted to allow for sharing of capacities among two or more airspaces. Recall that $a \in A^g \subseteq A$ ($g \in G$) represent the airspaces in cross-border alliance $g$ among which capacities can be shared. We explicitly allow $A^g = A$ to evaluate the case where capacities are shared across the entire network. If cross-border capacity provision is not permitted in certain airspaces, we combine these airspaces in alliance $g'$ and set $x^0_{g'} := 0$. We can obtain the sector opening scheme under cross-border capacity provision by solving the following mixed integer linear program (which we could decompose by sharing alliance $g$):

\[
\text{(XCILP)} \quad \min_{h^0, z} \sum_{a,c,u} k_{acu} z_{acu} \\
\text{s.t. (8c), (8d)} \\
\sum_u \sum_{c \in C^a} \hat{h}_{ac} z_{acu} \leq x^0_a + h^0_a \quad a \in A \quad (9b) \\
\sum_{a \in A^g} h^0_a \leq |A^g| x^0_{g} \quad g \in G \quad (9c) \\
h^0_a \geq 0 \quad a \in A. \quad (9d)
\]

4.2.2 Determine lowest displacement cost with given configuration

After having determined configuration set $C'$, we apply the MMKP-based heuristic proposed in Künnen and Strauss (2021) to determine the routing of flights with lowest displacement cost $D(C', F^S, W^S)$. The approach is summarized in Algorithm 2. We initialize the routing procedure by assigning each flight $f \in F^S$ to the route with lowest displacement cost. Let $L' = \{l \in L' : c' \in C'\}$ be the sectors defined by $C'$. To establish a feasible solution, we then iteratively reassign flights on the most congested sector $l^*$ until all sectors $l \in L'$ are within capacity limits $\kappa^S_l$ (which depend on $W^S$). To decide which flight to reassign to another route, we compute a decision parameter $\gamma f$ that weighs the change in displacement cost with the change in capacity usage on the most congested sector. Finally, we test if we can use
potential spare capacities to further improve this feasible solution. For that purpose, any flight \( f \) and route \( r \) is reassigned from current route \( r' \) to \( r \), if this reassignment improves displacement cost while keeping the routing feasible.

Algorithm 2 MMKP-based heuristic for routing problem

Input: Configuration \( C' \), traffic scenario \( F^S \) and capacity uncertainty \( W^S \)

1: **Initialize:** Set \( r'_f := \arg\min_{r \in R^f} d_l^f \) for \( f \in F^S \), Lagrange Multiplier \( \mu_l := 0 \) for \( l \in L' \)
2: **Establish feasible solution:** Iterate until \( \bar{k}_l \leq 1 \forall l \in L' \)
3: Compute relative “weight” \( w_{frl} = \sum_{l \in E^l} b_{fru}/k_l^S \) for \( f \in F^S, r \in R^f, l \in L' \)
4: Compute relative capacity shortage \( k_l = \sum_{f \in F^S} w_{frl} \) and set \( l^* := \arg\max_l k_l \).
5: For flights with \( w_{frl^*} > w_{frl} \) on \( l^* \), store \( \gamma^f_r = \frac{d^f_l - d^f_{l^*} - \sum_{l \in L'} \mu_l(w_{frl} - w_{frl^*})}{w_{frl^*} - w_{frl}} \) for \( r \in R^f \).
6: Determine flight and route with lowest \( \gamma^f_r \), update \( r'_f = r \) and \( \mu_{alu}^* = \mu_{alu} + \gamma^f_r \)
7: **Improve feasible solution:** Iterate until no further improvement found, i.e., \( \delta = \emptyset \)
8: For flights and routes with \( d^f_{l^*} > d^f_l \) and \( k_l - w_{frl} + w_{frl^*} \leq 1, l \in L' \), store \( \delta^f_l = d^f_{l^*} - d^f_l \).
9: Find flight and route with largest \( \delta^f_l \) and update \( r'_f := r \).

Output: Routing \( R^* = \{r'_f : f \in F^S \} \) and displacement cost \( D^* = \sum_{r \in R^*} d_r \)

As shown in Moser et al. (1997), Algorithm 2 has complexity \( \mathcal{O}(m(n-o)^2 + mn) \), where \( m = |L'| \) is total number of sectors given configuration \( C' \), \( n = \sum_{f \in F^S} |R^f| \) is total number of flight-route combinations, and \( o = |F^S| \) is total number of flights. Given this complexity, evaluating \( D(C', F^S, W^S) \) is still computationally very expensive for larger networks and traffic scenarios. Therefore, we use Algorithm 2 to generate a large number of observations \( \hat{D} \) given certain capacity budgets, traffic scenarios and capacity uncertainties, and apply a linear regression to approximate \( D \). In particular, we estimate \( D \) based on the capacity shortages \( k_{acu} \) that a certain capacity budget and traffic and capacity scenario generates:

\[
\hat{D}(C', F^S, W^S) = \beta_0 + \sum_{a \in A} \beta_a \sum_u k_{acu}.
\]  

(10)

The idea is that the number of excess flights directly influences the required amount of reallocations of flights to alternative routes, and thus the size of total displacement cost. This choice of explanatory variable also offers another benefit: Since the CILP is decomposable by airspace, the solution with minimum excess flights \( k_{acu} \) will also be the one with minimum cost estimate (based on (10)). However, the XCILP can only be decomposed by alliance \( g \) (not by airspace \( a \)) because we allow capacities to be shared among airspaces in an alliance. Therefore, we may encounter cases where the solution with minimum excess flights does not provide minimum cost. To avoid this, we use parameters \( (\beta_a)_{a \in A} \) as weights in the objective
function of the XCILP to directly optimize over cost. In particular, we replace function (9a) in the XCILP to get:

\[(\text{XCILP}^*) \min_{h_0,z} \sum_{a,c,u} \beta_a k_{acu} z_{acu} \]

\[\text{s.t. (9b), (9c), (9d)}.\]

We denote the decomposition by alliances of the XCILP* by XCILP-d*. Overall, the CILP-d with regression (10) (and XCILP-d* for cross-border capacity provision) provide us with cost estimate \(\hat{D}\) for any given capacity budget and scenario. We use this estimate in each iteration of Algorithm 1 to evaluate \(f(x, S) = \hat{D}(C', F^S, W^S) + c^T x\). Since we can separately determine estimates \(\hat{D}\) for each airspace (or alliance in the case of cross-border capacity provision), we also run Algorithm 1 individually for each airspace (and alliance), which significantly speeds up the solving process. To further improve the estimates \(\hat{D}\), we could re-run Algorithm 2 and update parameters \(\beta\) after a fixed amount of iterations, using only budgets \(x\) that are close to the current optimum. However, we decide not to apply this updating procedure because (a) re-applying Algorithm 2 consumes sizable computational resources, and (b) the variation in displacement cost by scenario is too large to warrant a more exact cost estimate per scenario.

5 Numerical Results

The objective of our research is two-fold: (1) We want to assess the performance of our stochastic optimization approach in finding optimal strategic capacity levels for each airspace, and (2) to guide decision-makers towards an operationable and effective design of cross-border capacity provision. In order to assess the value of cross-border capacity provision, we need a case study of sufficient size (both in terms of time horizon and number of airspaces) such that cross-border services may actually be demanded. For this purpose, we use a case study based on real flight data covering a 6-hour time period on the busiest day of 2016, see §5.1. We discuss results of our numerical experiments on our stochastic approach and on cross-border capacity sharing in §5.2 and §5.3, respectively.
5.1 Case study description

We use the network data based on the large case study in Starita et al. (2020) and increase the considered time horizon and the number of flights. The real dataset covers large parts of en-route airspace in Western Europe and was obtained using Eurocontrol’s Demand Data Repository (DDR2) service. On the capacity side, the case study includes 15 area control centers (i.e., airspaces) across 8 ANSPs, which consist of 177 elementary sectors in total. These elementary sectors are combined in various ways to form a total of 173 different configurations, which were selected among the most frequently used ones in 2016. Figure 1 shows exemplary scheduled traffic across the considered network at a specific point in time.

The capacity cost used in the case study are average ATCO cost per sector-hour for each ANSP, computed based on Eurocontrol (2019a). We treat these cost as variable cost in the simulations because fewer sector-hours will lead to fewer ATCOs and therefore lower ATM service provision cost in the long run. To define the solution space $\mathcal{X}$, we determine the minimum sector-hours $\underline{x}_a$ and maximum sector-hours $\bar{x}_a$ ($a \in A$) that each airspace operated based on historic data; we then have $\mathcal{X} = \{x \in [\underline{x}_a, \bar{x}_a]_{a \in A}, x \in \mathbb{N}^{\mid A\mid}\}$.

![Figure 1: Air network for large case study with scheduled flights at a specific point in time.](image)

On the demand side, the data includes all flights in the selected network on September 9, 2016, the busiest day in European airspace that year. For the simulation, we restrict the time frame to 9am – 3pm (to cover at least one full shift; note that shift lengths differ between control centers), and select the 2,260 scheduled flights crossing the network during
this time. Among the remaining flights in the dataset we randomly choose 2,500 to serve as a pool of non-scheduled flights. To create the traffic scenarios, we uniformly sample from this pool a number of non-scheduled flights, where the number of flights is drawn from a normal distribution with mean of 540 (to generate on average 20% non-scheduled traffic) and standard deviation of 200. Each traffic scenario $F^S$ then consists of all 2,260 scheduled flights and a sample of non-scheduled traffic, giving on average 2,800 total flights. Each flight in the dataset has a reference (shortest) route with zero displacement cost and up to 12 different (in the horizontal or vertical plane) alternative routing options. Reference and alternative routes were generated using Eurocontrol’s Network Strategic Tool (NEST) based on the last filed flight plan for every flight in a dataset. For the shortest route, we add three potential delay options: 10, 20 and 30 minutes. A flight can only be subject to one demand management measure: either delay or re-routing (this also keeps the number of total routing alternatives low). To further reduce solution time of the model (especially Algorithm 2), we pre-process the routes of all scheduled flights and keep only frequently used route options. Displacement costs are computed for each flight and route option separately and consist of delay and re-routing cost. Delay costs are derived from Cook and Tanner (2015) and they differ by aircraft type and increase non-linearly with the duration of delay, while re-routing costs include mainly additional fuel costs, but also crew and passenger cost (estimated based on Cook and Tanner (2015); Eurocontrol (2018)).

To model a real-life setting, we need to account for both demand- and capacity-side uncertainties. Demand-side uncertainty stems from non-scheduled flights, in terms of total number of such flights and where and when they appear in the network, which is modeled through our traffic scenarios $F^S$ described above. For capacity-side uncertainty $W^S$ we distinguish between internal (ATCO shortages) and external (e.g., adverse weather) effects. This distinction is particularly important because internal effects can be mitigated, at least partly, through cross-border capacity provision while external effects cannot. To estimate internal effects, we analyse ATFM regulations due to ATCO staffing reasons in the considered network. An ATFM regulation is issued when demand exceeds capacity in an airspace volume for a period of time. We partially rely on analysis of 2016 ATFM regulation data to derive frequencies of ATC staffing regulation occurrences for each airspace in the case study, which we show in the appendix. External effects can sometimes severely reduce capacities in an affected airspace for a certain amount of time, which is why we apply a more differentiated probability distribution here. Again, based on historical ATFM regulation data, we assume that the capacity of any one elementary sector (and the collapsed sector containing it), is
reduced to 90% in 10% of cases, to 70% in another 10% of cases and to 50% in 5% of cases.

Finally, two parameters in Algorithm 1 ($\lambda$ and $N^{max}$) need to be tailored to our case study. Parameter $\lambda$ determines which candidates we accept into the pool, and which ones we discard (after a certain amount of evaluations). We decide to only accept candidates into the pool that stay within 20% of the current minimal cost solution. Accordingly, we set $\lambda := 2,000$ when running Algorithm 1 for each airspace (in the case without cross-border sharing), and $\lambda := 4,000$ when running it for each alliance (if cross-border sharing is allowed). Furthermore, we set $N^{max} := 300$ since we do not observe significant changes in $f(x, S)$ if we evaluate more than 300 scenarios.

5.2 Value of stochastic approach

5.2.1 Simulation setting and evaluation

To analyze whether the stochastic approach leads to better capacity planning decisions, we compare it with a deterministic benchmark procedure, which we describe below. The quality of a capacity management decision is assessed based on the expected total network cost (both displacement and capacity cost) that it creates. We test the approaches on the regular setting without cross-border capacity provision, i.e., all airspaces can only use their own, local capacities to manage traffic demand. In the stochastic approach, we determine optimal capacity budget $x^* = (x^*_a)_{a \in A}$ using Algorithm 1 as discussed in §4. In this process, we use a fixed set of 300 traffic and capacity scenarios (stored in $S_1$) on which each candidate budget is evaluated. In the deterministic approach, we determine optimal budgets $x^{S^*} = (x^{S^*_a})_{a \in A}$ separately for each scenario. For each scenario, we evaluate $f(x_a, S)$ for all $x_a \in X_a$ and setting $x^{S^*_a} := \arg\min_{x_a \in X_a} f(x_a, S)$. We solve $x^{S^*}$ using this procedure for as many scenarios $S \in S_B \subseteq S_1$ as we use in the stochastic approach (on average per candidate) to determine $x^*$. After evaluating all scenarios, we find the benchmark capacity budget $x^{B*} = (x^{S^*_a})_a$, using the policy that performed best in Starita et al. (2020), namely the so-called risk-based policy that they proposed to choose a solution from a pool of candidates. More specifically, we choose each $x^{S^*_a}$ among all $x^{S^*_a}$ ($S \in S_B$) such that the probability that any other budget $x^{S^*}$ (for $S \neq S'$) has higher capacity in airspace $a$ is less than a given $\epsilon$ (which is set to 0.2).

Once the capacity budgets $x^*$ and $x^{B*}$ have been determined, we assess their performance on a different set of 50 traffic and capacity scenarios (stored in $S_2$) by using the CILP and Algorithm 2. Here, we use Algorithm 2 instead of regression (10) to determine displacement cost in order to test the budgets on the most exact estimates. The simulations are run using
Amazon Web Services (AWS) Batch with 4 CPU and 30GB RAM.

5.2.2 Discussion of results

Before we discuss the performance of the stochastic and benchmark approaches to minimize network cost, we comment on efficiency and effectiveness of regression (10) to approximate displacement cost $G(x, S)$ for a given budget $x$ and scenario $S$. For this purpose, we compare the cost estimates from regression (10) on 2,280 instances (each instance is a combination of budget and scenario) against costs determined through Algorithm 2. With a mean absolute error of 6,191 (or 6.4% of average displacement cost) and $R^2$ of 0.96, we confirm that regression (10) adequately approximates displacement cost for our purpose. To illustrate the relationship, we show in Figure 2 the correlation between capacity shortages (aggregated across airspaces and time for purpose of illustration) and displacement cost based on Algorithm 2 for all instances.

![Figure 2: Correlation between total capacity shortage and displacement cost. (n = 2280)](image)

Applying regression (10) instead of Algorithm 2 (together with the CILP-d) to estimate displacement cost significantly reduces our solution time. For the case study at hand, we manage to reduce average run time for one instance (i.e., combination of budget and scenario) from over 20 minutes to under one second, including running the CILP-d.

Table 1 summarizes the simulation results for the capacity decisions $x^*$ and $x^{B*}$ of the stochastic and deterministic approach on 50 scenarios, without capacity sharing. We note that the number of flights that cannot be assigned to non-dummy routes is well below 1% (on average across all scenarios) for both solution approaches, which shows that almost all flights
can be routed within the given time frame and network conditions. Overall, the stochastically determined capacity leads to significantly lower network cost than the benchmark capacity decision, since the capacity cost savings of €3,332 outweigh the higher displacement cost.

Figure 3 shows the performance of the stochastic versus deterministic capacity decision ($x^*$ and $x^{B*}$) for each of the 50 evaluated traffic and capacity scenarios. We see that the stochastic solution creates lower network cost than the deterministic solution in all but one of the 50 scenarios. The average cost reduction of €2,364 represents savings of 1.6% on total network cost.

### Table 1. Simulation results for solution approaches over 50 scenarios.

<table>
<thead>
<tr>
<th>Approach</th>
<th>Capacity cost</th>
<th>Displ. cost</th>
<th>Network cost</th>
<th>Not assigned</th>
<th>Run time</th>
</tr>
</thead>
<tbody>
<tr>
<td>Stochastic</td>
<td>133,336</td>
<td>8,294</td>
<td>141,630 ± 5,608</td>
<td>0.23%</td>
<td>96 min.</td>
</tr>
<tr>
<td>Deterministic</td>
<td>136,668</td>
<td>7,326</td>
<td>143,994 ± 5,161</td>
<td>0.22%</td>
<td>128 min.</td>
</tr>
<tr>
<td>Difference</td>
<td>3,332</td>
<td>-968</td>
<td>2,364 ± 1,157*</td>
<td>-0.01%</td>
<td>32 min.</td>
</tr>
</tbody>
</table>

* Significant at 95% confidence level.

Next to cost, an important consideration for the network manager (or ANSPs in the case of decentralized decision-making) is the speed with which capacity decisions can be made. With the proposed stochastic approach we manage to determine capacity decision $x^*$ in under two hours, which warrants the method for practical application. Note that since we decompose the problem by airspace, we could also parallelize the process by solving $x^*_a$ for each airspace simultaneously, which would further reduce the run time to around 10 minutes. A further advantage is that due to this decomposition, our approach is fully scalable to any number of airspaces in the network. Without this level of scalability, we would not be able to evaluate networks that are large enough such that cross-border capacity sharing may be beneficial.

Figure 4 visualizes an exemplary path of Algorithm 1 to determine the capacity decision $x^*$ (shown for airspace EDUUUTAS). We see that the procedure converges quickly towards a good solution, with only small variations in the recommended capacity level after around 700 iterations.
5.3 Value of cross-border provision

5.3.1 Cross-border concepts and evaluation

To provide guidance to decision-makers on how to design a potential cross-border capacity provision scheme in European ATM, we test three different design options:

1. No capacity sharing (Local): As in §5.2, we assume that all airspaces can only rely on their own, local capacities to manage traffic demand, as is currently the case.

2. Capacity sharing across pre-defined alliances (Regional): We define a finite set of alliances among which capacities can be shared. If an airspace belongs to an alliance with cross-border capacity sharing, it can leverage the cross-border capacity of its alliance, next to its own capacity, to manage traffic demand.

3. Capacity sharing across the entire network (Global): Apart from using their own capacity, each airspace can leverage a central pool of ATCOs that are eligible to work across the network ("Super-ATCOs") to manage traffic demand.

For the regional design, we compare the two setups as shown in Table 2. Both setups are developed based on practical relevance, i.e., we pool together airspaces with similar infrastructure, geography and marginal cost. While we require in setup A that each alliance contains at most two airspaces (apart from the three Maastricht airspaces), we pool up to four airspaces in setup B.
Apart from the geographic setup, an important consideration in designing a cross-border scheme are marginal cost for cross-border capacity services. For the *global* setting, we assume that the so-called “Super-ATCOs” will need to earn at least the amount the best-paid ATCOs receive in the network. Therefore, we require $\rho_g = \max_{a \in A} \rho_a$ for variable capacity cost $\rho_g$ of alliance $g$. Without this condition, cross-border capacity sharing could be used to reduce capacity cost by “outsourcing” ATM service provision to airspaces with lower rates. Instead, we intend to employ it as a mean to hedge against displacement cost uncertainty. For the *regional* setting, we require that the cost per sector-hour of providing cross-border service is at least as high as the average cost among the airspaces in which capacity is shared, i.e.,

$$\rho_g = (1 + \delta) \frac{\sum_{a \in A^g} \rho_a}{|A^g|} \quad g \in G.$$  

In this case, we do not charge the maximum cost within the alliance because “outsourcing” is prevented through condition (1). However, we require $\delta > 0$ since we assume that if an ATCO is eligible to work in an airspace outside its own, she will need to be reimbursed for the additional effort and training associated with this task. In particular, we set $\delta := 0.1$ in the baseline case, and compare different markups in a sensitivity analysis.

To model the cross-border settings, we apply the (XCILP-d*) to determine the best candidate configuration for each budget $x$ and alliance $g$ given solution space $X_g$, where
Table 2. Geographic setups for regional cross-border setting.

Setup A

<table>
<thead>
<tr>
<th>Alliance</th>
<th>Airspaces</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>EDUUUTAC (G. Central)</td>
</tr>
<tr>
<td></td>
<td>EDUUUTAE (G. East)</td>
</tr>
<tr>
<td>2</td>
<td>EDUUUTAS (G. South)</td>
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<td>LZBBCTA (Slovakia)</td>
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<td>LHCCCTA (Hungary)</td>
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<td></td>
<td>LSAZUTA (Switzerland)</td>
</tr>
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<td>7</td>
<td>EDYYBUTA (Maastricht)</td>
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<td></td>
<td>EDYYDUTA (Maastricht)</td>
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<td>EDYYHUTA (Maastricht)</td>
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Setup B

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<tr>
<td></td>
<td>EDYYHUTA (Maastricht)</td>
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</table>

Germany abbreviated as “G.”

\[ \mathcal{X}_g = \{ x \in [x_a, \bar{x}_a]_{a \in A^g}, x \in \mathbb{N}^{\lvert A^g \rvert}, x^0 \in [\underline{x}_g^0, \bar{x}_g^0], x^0 \in \mathbb{N} \}. \] We define \( A^g, \underline{x}_g^0 \) and \( \bar{x}_g^0 \) as follows (note that \( x_a, \bar{x}_a \) for \( a \in A \) is given by the case study, see §5.1): For the global setting, we set \( G = \{ g_1 \}, A^{g_1} = A, \underline{x}_{g_1}^0 = 0 \) and \( \bar{x}_{g_1}^0(x) = \sum_{a \in A} (\bar{x}_a - x_a) / \lvert A \rvert \). This way, we ensure that the sum of local and cross-border hours in each airspace do not exceed the maximum limit \( \bar{x}_a \) (\( a \in A \)). Otherwise, part of the benefit of using cross-border services would be attributable to exceeding the limits set for the local setting. For the regional setting, we define sets \( G \) and \( A^g(g \in G) \) according to Table 2. In order to fulfill condition (1) for budgets \( x \), we set \( \underline{x}_g^0(x) = \max_{a \in A^g} (\bar{x}_a - x_a)^+ \) and \( \bar{x}_g^0(x) = \min_{a \in A^g} \bar{x}_a - x_a \) for \( g \in G \). As discussed in §5.2.1, we assess the performance of each of the proposed cross-border settings with a two-staged simulation study: We first determine budget \( x^* \) using Algorithm 1 (using scenarios in \( S_1 \)), and test its performance using the XCILP* and Algorithm 2 (on a new set of scenarios in \( S_2 \)). Again, simulations are run using AWS Batch with 4 CPU and 30GB RAM.
5.3.2 Discussion of results

The table below compares the cost performance in the simulation of the local, regional (setups A and B) and global setting for cross-border capacity, based on the network described in §5.1. The overall results are rather stable across the settings. Each of the three cross-border settings is able to reduce total network cost by €2,400 to €2,800 (around 1.6% to 2.0%) against the local setting. In the case that capacities are shared across the entire network (global setting), the high cost of cross-border services leads to rather low amounts of cross-border capacity to be provided and thus no large improvements over the regional setting. If the observed cost savings could be realized across the entire European airspace with over 25,000 daily flights (i.e., 10 times the flights considered in the simulation), and across all 365 days of the year, a cross-border concept could cut network cost by about €7–10 million per year.

Table 3. Simulation results of cross-border settings over 50 scenarios.

<table>
<thead>
<tr>
<th>Setting</th>
<th>Capacity cost</th>
<th>Displ. cost</th>
<th>Network cost</th>
<th>Difference to Local</th>
<th>Run time</th>
</tr>
</thead>
<tbody>
<tr>
<td>Local</td>
<td>133,336</td>
<td>8,294</td>
<td>141,630 ± 5,608</td>
<td>-</td>
<td>96 min.</td>
</tr>
<tr>
<td>Regional A</td>
<td>134,283</td>
<td>4,572</td>
<td>138,855 ± 3,911</td>
<td>-2,775</td>
<td>245 min.</td>
</tr>
<tr>
<td>Regional B</td>
<td>134,569</td>
<td>4,702</td>
<td>139,271 ± 3,841</td>
<td>-2,359</td>
<td>251 min.</td>
</tr>
<tr>
<td>Global</td>
<td>134,611</td>
<td>4,229</td>
<td>138,840 ± 3,150</td>
<td>-2,790</td>
<td>583 min.</td>
</tr>
</tbody>
</table>

We also see from the results that cross-border sharing is an effective means to reduce the variation in network cost (from 5,608 to under 4,000 in the simulation). This benefit of cross-border sharing (next to average cost reduction) is important because a lower variation implies a more stable network performance and thus higher reliability of service provision to airspace users (e.g., airlines). As expected, the solution time for the cross-border settings are somewhat longer than for the local setting, where we decompose the process by airspace. In particular, we require around 6 hours to determine capacity decisions in the regional setting. Here, the process can be parallelized by solving it simultaneously for each alliance $g \in G$, which reduces the solution time to around 35 minutes for setup A and 50 minutes for setup B. Solution time for the global setting is around 10 hours; and since we use only one alliance, the process cannot be parallelized.

The savings in all cross-border settings are generated exclusively by reducing the average displacement cost rather than by reducing capacities. This is particularly relevant because lower re-routing cost (which make up over 90% of displacement cost in the case study) also imply lower greenhouse gas emissions from reduced fuel burn. If an additional cost for emissions was considered in the displacement cost estimation, this would further increase
the potential benefit reaped through cross-border capacity provision. Figure 5 shows how the displacement cost vary by scenario for the different cross-border settings. We find that all cross-border settings behave rather similarly across the scenarios, and are able to reduce displacement cost especially when the cost in the local setting deteriorate. While cost without cross-border sharing increase up to 20,000 or more, the cost with cross-border sharing stay below 10,000 for all but two scenarios. We also compare the performance to a lower bound on displacement cost, which we obtain by setting $x_a^* := \bar{x}_a (a \in A)$. We find that the with cross-border sharing we are in fact able to realize large parts of the total cost reduction potential (on average over 50%) between local setting and lower bound.

![Figure 5: Displacement cost for different cross-border settings across 50 scenarios.](image)

In Figure 6 we illustrate how cross-border capacity provision helps increase the flexibility with which capacities can be adjusted within an alliance. The capacities used by the two Swiss airspaces (LSAZUTA and LSAGUTA) change frequently across the 50 scenarios, to adjust to the materialized demand and capacity provision.

While cross-border capacity provision can work to improve network performance, this comes at a cost. For that purpose, we want to determine what influence the marginal cost of cross-border sharing has on the value of such a service. We conduct a sensitivity analysis with increased cost markups $\delta := 0.2$ for setup A of the Regional setting, see Table 4. While we still observe a cost improvement if cross-border services come at a markup of 20% instead of 10%, the total saving reduces from 2,775 to 964. In particular, given the higher marginal
cost of the service, less cross-border capacities are provided and the displacement cost saving reduces by almost 1,000 compared to the setting with 10% markup.

5.4 Limitations

The proposed methodology features some limitations. Firstly, while Algorithm 1 is scalable in terms of the number of airspaces in the network, it does not scale for the number of airspaces contained in each alliance if cross-border sharing is allowed. This is due to the fact that we cannot decompose XCILP* by airspace, but only by alliance. In addition, in order to determine the regression parameters required for Algorithm 1, we need to run Algorithm 2 to generate a sufficiently large number of displacement cost observations. This procedure works adequately for the case study at hand, but does not scale well for much larger networks. Secondly, we base our regression on estimates of displacement cost obtained from a heuristic...
Table 4. Sensitivity analysis of *regional* setup A over 50 scenarios.

<table>
<thead>
<tr>
<th>Setting</th>
<th>Capacity cost</th>
<th>Displ. cost</th>
<th>Network cost</th>
<th>Difference to <em>local</em></th>
</tr>
</thead>
<tbody>
<tr>
<td><em>Local</em></td>
<td>133,336</td>
<td>8,294</td>
<td>141,630 ± 5,608</td>
<td>-</td>
</tr>
<tr>
<td><em>Regional A (10%)</em></td>
<td>134,283</td>
<td>4,572</td>
<td>138,855 ± 3,911</td>
<td>-2,775</td>
</tr>
<tr>
<td><em>Regional A (20%)</em></td>
<td>135,131</td>
<td>5,535</td>
<td>140,667 ± 3,755</td>
<td>-964</td>
</tr>
</tbody>
</table>

procedure, which can only approximate these cost. This limits the quality of cost estimates obtained through regression (10). Furthermore, there are several assumptions made in the evaluation of the methodology that may limit the generalizability of results. On the one hand, we assume that higher sector-hour cost will lead to higher total ATCO cost in the long-term. However, this effect may only materialize inflexibly, since ATCOs are hired and trained years before becoming operational. On the other hand, we use a time horizon of 6 hours on one day to make strategic decisions (with regards to capacity levels and cross-border concepts). The capacity levels will however need to be judged based on the performance over a sustained period of time. Finally, further practical considerations such as rostering practices for ATCOs are neglected in our simulation, but may have an impact on how well the strategic decision translates into better network cost performance.

6 Conclusions

In European ATM, we observe large demand-capacity imbalances due to static capacities paired with large uncertainties with regards to demand and capacity provision. To reduce the impact of these imbalances, we propose a cross-border capacity provision scheme in which capacities can be shared among airspaces. We develop an efficient, scalable approach to determine capacity budgets for each airspace that perform well across various scenarios (of demand and capacity uncertainty). A simulation study on a realistic-sized network with around 2,800 flights shows that the stochastically determined capacity decision significantly outperforms a deterministic benchmark. We use this approach to test different cross-border capacity settings, and find in the case study that cross-border sharing can reduce network cost by about 1.6–2%. As additional benefits, cross-border capacity provision can lead to a more stable network performance (by reducing variation in displacement cost) and lower fuel emissions (by reducing reroutings in the network). The reduction potential does however depend on the additional marginal cost of cross-border services. Finally, we find in the simulation that regional alliances of two or more airspaces suffice to realize the potential
from cross-border sharing. In contrast, a network-wide capacity sharing scheme does not improve performance much further, given the higher capacity cost for such a service.

**Author Statement**


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**References**


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Appendix

7 Latin Hypercube Sampling

This section describes the Latin Hypercube Sampling procedure used to build random capacity samples. Each iteration of this algorithm generates $\bar{\eta}$ different samples, stored into a $\bar{\eta} \times |A|$ matrix, $X$. Let us also define $A^a = \{\bar{x}_{a_{\text{min}}}^a, \bar{x}_{a_{\text{min}}}^a + \epsilon, \bar{x}_{a_{\text{min}}}^a + 2\epsilon, ..., \bar{x}_{a_{\text{max}}}^a\}$, with $\epsilon = (\bar{x}_{a_{\text{max}}}^a - \bar{x}_{a_{\text{min}}}^a)/\bar{\eta}$. Values $\bar{x}_{a_{\text{min}}}^a$ and $\bar{x}_{a_{\text{max}}}^a$ represents the minimum and maximum number of sector hours for airspace $a$. These values are defined by the structure of the airspace’s configurations and the length of the time horizon.

Algorithm 3 Latin Hypercube Sampling

for $\eta = 1$ to $\bar{\eta}$ do
    $A \leftarrow A$
    while $A \neq \emptyset$ do
        $a$ is uniformly drawn and removed from $A$
        $\bar{x}_a$ is uniformly drawn and removed from $A^a$
        $X[\eta][a] = \bar{x}_a$
    end while
end for
return $X$
## 8 Case study data

Table 5. Capacity-side network characteristics in the case study

<table>
<thead>
<tr>
<th>Airspace</th>
<th>Elementary sectors</th>
<th>Collapsed sectors</th>
<th>Configurations</th>
<th>Probability of ATFM regulation</th>
</tr>
</thead>
<tbody>
<tr>
<td>EDUUUTAC</td>
<td>11</td>
<td>14</td>
<td>13</td>
<td>10.8%</td>
</tr>
<tr>
<td>EDUUUTAE</td>
<td>10</td>
<td>14</td>
<td>13</td>
<td>8.3%</td>
</tr>
<tr>
<td>EDUUUTAS</td>
<td>12</td>
<td>29</td>
<td>13</td>
<td>41.6%</td>
</tr>
<tr>
<td>EDUUUTAW</td>
<td>10</td>
<td>12</td>
<td>11</td>
<td>2.5%</td>
</tr>
<tr>
<td>EDYYBUTA</td>
<td>8</td>
<td>13</td>
<td>10</td>
<td>0.0%</td>
</tr>
<tr>
<td>EDYYDUTA</td>
<td>9</td>
<td>12</td>
<td>7</td>
<td>0.0%</td>
</tr>
<tr>
<td>EDYHYUTA</td>
<td>12</td>
<td>19</td>
<td>12</td>
<td>0.0%</td>
</tr>
<tr>
<td>EPWWCTA</td>
<td>18</td>
<td>77</td>
<td>26</td>
<td>56.8%</td>
</tr>
<tr>
<td>LHCCCTA</td>
<td>10</td>
<td>24</td>
<td>7</td>
<td>0.0%</td>
</tr>
<tr>
<td>LKAACTA</td>
<td>6</td>
<td>9</td>
<td>6</td>
<td>0.2%</td>
</tr>
<tr>
<td>LKAUATA</td>
<td>6</td>
<td>9</td>
<td>8</td>
<td>0.0%</td>
</tr>
<tr>
<td>LOVVCTA</td>
<td>26</td>
<td>58</td>
<td>21</td>
<td>1.2%</td>
</tr>
<tr>
<td>LSAGUTA</td>
<td>6</td>
<td>9</td>
<td>11</td>
<td>3.1%</td>
</tr>
<tr>
<td>LSAZUTA</td>
<td>6</td>
<td>7</td>
<td>7</td>
<td>0.3%</td>
</tr>
<tr>
<td>LZBBCTA</td>
<td>27</td>
<td>69</td>
<td>8</td>
<td>0.0%</td>
</tr>
</tbody>
</table>