Coordinated capacity and demand management in a redesigned Air Traffic Management value-chain

Abstract

We present a re-designed European Air Traffic Management value-chain, with a new role for the Network Manager, which coordinates capacity and demand management decisions, using economic instruments for both areas. A conceptual and mathematical model supports decision-making in that process, focusing on capacity management decisions taken at the strategic level. Total costs are minimized by jointly managing sector-opening schemes and trajectory assignments. A large-scale case study demonstrates clear trade-offs between the volume of capacity ordered and the scope of necessary demand management actions. In addition, the comparison against a baseline, which resembles the current system, shows that with the proposed concept less capacity is needed to serve the same demand, resulting in lower total cost for Aircraft Operators.

1 Challenges in the current Air Traffic Management value-chain

The current role of the Network Manager (NM) in the process of establishing a balance between air traffic demand and airspace/airport capacity in Europe is merely moderation between Aircraft Operators (AOs) and capacity providers, since the NM has limited instruments to influence either capacity or demand side planning decisions (EUROCONTROL NMOC, 2017). The European Commission (EC) also recognizes that the lack of the NM's clear executive powers in practice means that the NM 'tends to decide by consensus, which often results in weak compromises' (European Commission, 2013). The EC however stresses that an optimisation of the network performance necessitates an extended operating scope of actions by the NM (European Commission, 2013), a view also shared by one of the biggest airlines in Europe (Ryanair, 2018).

Although the NM initiates planning several months before the day of operations (EUROCONTROL NMOC, 2017), most of demand-capacity imbalance situations are still resolved on the day of operations by means of demand management actions, predominantly by delaying flights. For instance, total en-route Air Traffic Flow Management (ATFM) delay was 8.7 million minutes in Europe in 2016, for a traffic of more than 10 million flights (EUROCONTROL PRC, 2017). More than 55% of total en-route ATFM delay is attributed to (lack of) capacity and staffing reasons, while approximately half of that delay occurred during peak summer months: June, July and August 2016 (EUROCONTROL PRC, 2017). The Performance Review Commission (PRC) notes that the capacity requirements are frequently not met by some Area Control Centres (ACCs), but also that maximum capacity is not delivered at the times when it is needed (EUROCONTROL PRC, 2017).

One of the underlying causes for capacity/demand mismatch is seasonal traffic variability. If traffic is highly variable and there is limited flexibility to adjust the capacity provision according to actual demand, the result may be poor service quality or an underutilisation of resources (EUROCONTROL PRC, 2017). If addressed proactively, traffic variability can be mitigated or resolved to a certain degree by utilising previous experience, roster staffing levels to suit and to make more operational staff available by reducing ancillary tasks performed by Air Traffic Controllers (ATCOs) during the peak period (EUROCONTROL PRC, 2017). While delay costs occur when there is no sufficient capacity, better allocating or reducing spare capacity should also lead to lower costs of capacity provision for AOs.

AOs also attach great value to their flight planning flexibility and tend to reveal their route choice decisions only hours before the time of departure to benefit from up to date information. Although last moment route-choice cost savings could be at most a few hundred euros per flight (Altus, 2009; Cook and Tanner, 2012; Delgado, 2015), such behaviour reduces predictability for ANSPs and the NM. Namely, ANSPs plan their capacity weeks and months in advance, with only very limited and costly possibilities to adjust those at a short notice, especially upwards (Massacci and Nyrup, 2015). Therefore, ANSPs have to account not only for traffic variability, but also for traffic (un)predictability at a shorter notice, when planning their capacity provision. A consequence of this divorced planning horizons on a network level could be lower utilization of available capacities and/or higher costs imposed on other AOs, as well as likely deterioration of the network performance as a whole (Jovanović et al., 2015a). The fact that demand is inherently heterogeneous and that some AOs, in some cases, choose routes which seem to be inefficient (distance- or/and charges-wise) (Bucuroiu, 2016; Delgado, 2015), adds to the complexity of predicting AOs' route choice, with an adverse impact on the decision on adequate capacity provision.

Indeed, the current route charging scheme in Europe also plays a role in AOs' route choices, which are not always favourable for the environment and lead to an overall inefficient utilisation of airspace (Delgado, 2015). ANSPs still apply a rather simple charging structure without differentiation other than the aircraft Maximum Take-Off Weight (MTOW). In some areas, charges for air navigation services differ significantly between neighbouring areas. This may lead to environmentally detrimental outcomes, if an airline chooses a longer route due to lower charges (Delgado, 2015), but also to a shift of traffic from less towards more congested airspace (EUROCONTROL STATFOR, 2015).

Therefore, the trade-off between predictability for ANSPs and flexibility for AOs results in substantial and costly capacity buffers built into ANSP resource allocation. For instance, one ANSP estimated that approximately 5-10% of its capacity is actually 'reserved' to take care of all predictability and non-adherence issues arising in pre-tactical and tactical stages. Potential cost savings arising from a more predictable system are estimated to 45 million EUR per annum for that provider (EUROCONTROL, 2013a). Similarly, costly buffer times are built into AOs' schedules. For example, for AOs in the US approximately 6 billion USD was associated with schedule buffers (Ball et al., 2010), embedded to compensate for (a portion of) anticipated delays from all causes, while maintaining the on-time performance of flights and the operational reliability of schedules (Wu, 2005).

We recognize the issues of traffic variability and predictability and the need for capacity provision flexibility as some of the major challenges in today's ATM value-chain and propose a potential solution within the "Coordinated capacity ordering and trajectory pricing for better-performing ATM" - COCTA (acronym) framework. Within COCTA, we develop a concept to harmonize air traffic demand and airspace capacity by means of orchestrated application of economic instruments (incentives) on the demand as well as on the capacity side. The objective of COCTA is to propose and evaluate a redesigned ATM value-chain in which the NM coordinately asks for airspace capacity from ANSPs and offers trajectories at differentiated charges to AOs, aiming to optimize the overall network performance.

In the remainder of the paper we present the COCTA concept and its innovative elements (*vs.* state-of-the-art). We outline a modelling framework for strategic capacity management in Section 3, focusing on the NM's network-centric capacity ordering form ANSPs at strategic level. The mathematical model is presented in Section 4. We describe data, methodology and steps for model testing, as well as results in Section 5, followed by discussion and conclusions in Section 6.

2 Previous contributions and a way forward

2.1 Literature review

The vast majority of previous efforts in the field focus on administrative demand management actions at the tactical level, i.e. the day of operations, given the network capacity[1] (e.g. Lulli and Odoni, 2007; Bertsimas and Patterson, 1998; Agustin et al., 2012a, 2012b). On the other hand, there are only a handful of papers exploring the possibility to use economic measures to manage demand to manage demand (Jovanović et al., 2014). de Matos (2001) argues that certain potentials exist to employ price discrimination in the ATM system, while Deschinkel et al. (2002) investigate the possibility of influencing AOs' route choices (departure time and route) by differential sector pricing. A new Air Navigation Services (ANS) pricing rule taking into account, among else, the cost of congestion, is proposed by Raffarin (2004). A novel route charging method was recently proposed, called FRIDAY (Fixed Rate Incorporating Dynamic Allocation for optimal Yield). It assumes a single unit rate per city pair, which is expected, *inter alia*, to take away incentives for AOs to choose detours. It also proposes an accompanying mechanism for revenue redistribution among ANSPs (Verbeek and Visser, 2016).

Several previous Single European Sky ATM Research (SESAR) Long-Term and Innovative Research (WP-E) projects have addressed some related problems, which might, to a certain extent, be relevant in the context of COCTA research.

ACCHANGE, analysed, among other aspects, potential paths for change in ATM in Europe, using two-stage network congestion games (Blondiau et al., 2016). The results suggest that vertical integration between ANSPs and AOs may succeed in accelerating change as long as ANSPs are permitted to charge for improved quality, such as reduced congestion (Adler et al., 2014). The NEWO project investigated effects of various prioritisation criteria on network performance and delay propagation (Arranz et al., 2013). The ELSA project employed agent-based modelling to analyse interactions between the NM and AOs (strategic layer) and aircraft/pilot and ATCOs (tactical layer) (Bongiorno et al., 2015). The CASSIOPEA project is particularly worth noting for its finding that a strategy to reduce delay up to a residual delay of 10 minutes leads to 'significant costs savings when compared to the approach, widely used by AOs, of trying to eliminate all delay.' (Molina et al., 2014).

Probably the most relevant among recent research efforts in the field is the SATURN project ('Strategic Allocation of Traffic Using Redistribution in the Network'). The objective of SATURN was to propose and test realistic ways to use market-based demand management mechanisms to redistribute air traffic in the European airspace at the strategic level. To that end, several mechanisms have been developed (Bolić et al., 2014) – ranging from peak-load pricing (Bolić et al., 2017) to a conceptual model of cost-reflective intertemporal price discrimination application (Jovanović et al., 2015a), (Jovanović et al., 2015b). Some promising results have been obtained, yet, all SATURN mechanisms were developed under the assumption of strictly taking the capacity side as given. Consequently, improvements in financial cost-efficiency were impossible by definition, with possible benefits arising solely from trade-offs between cost of delays and costs of re-routings. Importantly, SATURN stakeholder consultation workshops provided a very useful feedback in terms of acceptability of economic-based demand-capacity balancing mechanisms. Among other aspects, it was revealed that differentiating charges based on quality of service might be a viable option from aircraft operators' perspective (SATURN Consortium, 2014).

A study produced by Steer Davies Gleave (SDG) for the EC investigates options for modulation of charges in the European airspace, with strong focus on implementation aspects (Steer Davies Gleave, 2015). The findings suggest that a fixed congestion supplement should be preferred over a differentiated unit rate. It is also suggested that incorporating economic and social costs in modulated charges would lead to prohibitively high route charges. As for price setting, the study recommends the use of several iterations rather than setting the price at single point in time. However, similar to SATURN, the SDG study tackles only the demand side of the

[1] For a comprehensive review of different formulations of airspace/airport congestion problem and mathematical modelling approach to tackle it, see Agustín et al. (2010).

problem, with strong stakeholders' (especially AOs') objections expressed to such approach employed (Steer Davies Gleave, 2015).

Lastly, there are a few relevant SESAR H2020 research projects which address some aspects relevant for the COCTA research. The INTUIT project's aim is to explore a potential use of visual analytics, machine learning and systems modelling techniques to improve understanding of the cause-effect relationships between different performance indicators in ATM. Marcos et al. (2017) propose a visual analytics and machine learning approach for the prediction of airline route choices in the pre-tactical planning phase and demonstrate some improvements compared to the tool ("PREDICT") currently used by the Network Manager. Similarly, the APACHE project proposes a new framework to assess ATM performance in Europe to capture interdependencies between KPAs at different modelling scales (micro, meso and macro) (Prats et al., 2017). The DART project evaluates the suitability of applying big data techniques for predicting multiple correlated aircraft trajectories based on data driven models and accounting for ATM network complexity effects. For example, Esther Calvo et al. (2017) address a trajectory prediction and demand-capacity imbalance problem at pre-tactical stage by means of machine learning and agent-based modelling methods. First, they demonstrate that aircraft trajectories can be predicted with a certain level of accuracy during pre-tactical phase based on historical data (individual trajectory prediction). Second, the authors demonstrate how agent-based modelling methods can help in trajectory forecasting when anticipated demand exceeds available capacity, taking into account interactions among trajectories, considered as self-interested agents that aim to minimize their delays and resolve demand-capacity imbalances. The results based on a case study in a Spanish airspace for a day of operations (~4,000 flights) indicate that the proposed approach could establish a demand-capacity balance in a decentralised manner with very low delay overall.

To the best of our knowledge, COCTA is the first research attempt to explore options for coordinated capacity and demand management decisions, employing economic instruments and incentives, at the strategic and the pre-tactical levels in a redesigned ATM value-chain. In one of the first COCTA-related publications, Starita et al. (2016) formulate a problem of jointly finding route prices, which are linked to the capacity level provided, and route assignments to minimise total cost for AOs. The authors developed a non-linear mathematical model, based on simplified assumptions regarding capacity provision, and demonstrate basic trade-offs between providing more capacity or re-routing flights using an academic example. In Starita et al. (2017), the authors develop a new (linear) mathematical model to support capacity ordering decision making. As a measure of capacity (budget), the authors use total sector-hours provided by capacity providers and demonstrate (two-step) capacity ordering using an artificial small-scale example (~150 flights flying over an airspace within jurisdiction of five ANSPs within a 2-hour window).

In this paper, we further develop the COCTA concept compared to the previous research, make more realistic assumptions regarding capacity provision, revise the mathematical model formulation and test it using a large-scale case study based on real data.

3 COCTA Air Traffic Management value-chain

3.1 Key novel aspects

We envisage a new role for the Network Manager, mandating it to co-ordinately take capacity and demand management decisions and actions. This change is supported by a redesigned ATM value-chain, in which the NM has contractual relationships with ANSPs and AOs, with the responsibility to optimise network performance, as defined by policy makers, Figure 1. Policy objectives might include acceptable ranges of network performance indicators, including areas of cost-efficiency, capacity, environment, equity, etc.

One of the key proposed changes on the capacity side concerns the relationship between the NM and the ANSPs[2]. In the proposed setting, the NM asks for airspace capacities in line with expected network demand, employing a network-centred, demand driven approach, as opposed to the current piecemeal supply driven practice, often tailored to accommodate local/ANSP traffic peaks (EUROCONTROL, 2013b). The COCTA capacity management process has long-, medium- and short-term phases, involving negotiations between the NM and ANSPs about capacity which should be provided in respective periods and eventually delivered on the day of operations.

On the demand side, COCTA introduces an airport-pair based charging principle to incentivise more predictable route choices. Within the COCTA concept, the base charge for a flight between two airports, i.e. the charge without applying additional demand management incentives, only depends on the MTOW of an aircraft. Building upon capacity ordered and applying the airport-pair charging principle, the NM defines different trajectory products and offers them at differentiated charges to AOs, thus employing economic (incentives) measures to manage demand. Mindful of AOs business needs and preferences, the NM defines trajectory products in such manner to influence their trajectory (route) choice to establish demand-capacity balance in a network (performance) optimal manner.

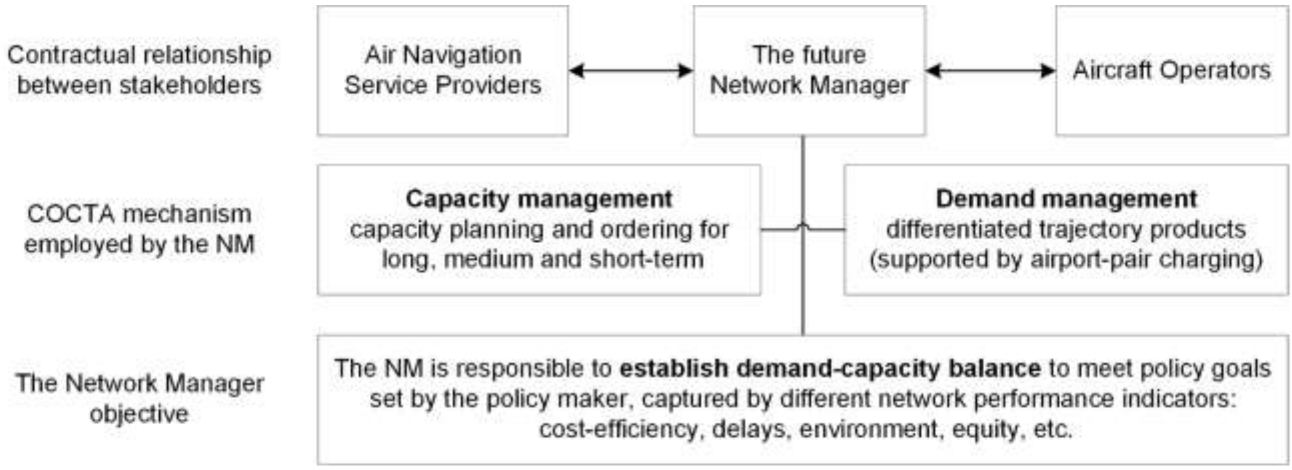


Figure 1.Re-designed ATM value chain

3.2 An overview of the COCTA capacity and demand management process

The COCTA mechanism combines capacity and demand management actions to optimise network performance. Within the COCTA framework, the mechanism is primarily designed for the strategic (six months in advance) and the pre-tactical stages (seven days in advance), while the tactical stage is considered to a certain extent only. In addition, we also discuss long-term (five years) capacity planning and ordering.

The NM carries out capacity management at the network level. Due to long lead times related to the capacity planning process(Tobaruela et al., 2013), the COCTA network capacity management spans over a 5-year horizon. Similar to the current practice, we assume that the NM and the ANSPs agree on a nominal capacity profile (NCP) which needs to be delivered over the long-term (EUROCONTROL, 2018a), with the difference that this agreement is based on a contract within the COCTA concept. This capacity profile is based on long-term traffic forecasts and serves as a foundation for ANSP's decisions affecting capacity (e.g. staff training and technical equipment). There are different options to define a measure and metrics for the NCP: total number of sector-hours (± margin) for each year, planned peak-day sector-opening scheme profile, ACC sustainable capacity during peak hours (which is currently being used in practice, EUROCONTROL (2013b)), etc. Although

[2] Within the general COCTA context, airports are involved as fairly passive capacity providers. As such they are not explicitly included into the modelling.

choosing a measure and metrics for the NCP is not the major focus of COCTA research, we recognise the importance of long-term capacity planning on cost-efficiency and other performance indicators. This process determines staffing, with ATCOs being the main resource of a centre, and strongly impacts airspace sectorisation and sector-opening sequences (Tobaruela et al., 2013).

When AOs publish schedules, around six months in advance of a schedule season, the NM has more precise information on O&D pairs and respective times of operations. Based on information of scheduled traffic and accounting for a portion of non-scheduled demand - which is associated with a higher level of uncertainty in terms of O&D pairs, times of operations and overall traffic levels - the NM defines capacity orders within the capacity profile sketched above. Therefore, about six months in advance before the schedule season, the NM refines its planning and specifies its capacity orders, aligned with the long-term order. Depending on the assumed flexibility of capacity provision in terms of ANSPs' staffing practices, e.g. how much in advance ATCOs rostering is fixed, the NM can define its initial order as a sector-opening scheme for a day of operations (less flexible variant) or as a total number of sector-hours to be delivered on that day, including the maximum number of sectors to be opened and the duration at maximum configuration (more flexible variant). The capacity management process continues after this decision, with an option to slightly adjust the initial capacity order, in line with flight intentions information received/updated subsequently, again, depending on the assumed flexibility of capacity provision.

In general, the potential for reducing the costs of capacity provision depends (amongst others) on the specific staffing agreements and working regulations of each individual ANSP. On a pre-tactical level, only few options for improving cost-efficiency exist, in particular reducing the number of ATCOs working overtime (and thereby receiving overtime premia) or reducing the number of staff on stand-by. In the strategic phase, an improved capacity planning might reduce the total number of ATCO hours needed during a specific period (e.g. one year), influencing total ATCO employment and thereby personnel costs. Again, the costs per ATCO-hour on duty (as well as the share of ATCO costs on total costs) differ significantly between European ANSPs (EUROCONTROL 2017). In our modelling we assume that ANS are provided by ATCOs employed by the ANSPs responsible for specific parts of the airspace. A more flexible provision of capacity, in particular cross-border provision of ANS, would increase the flexibility of the entire system and expectedly enable further cost savings which are not included into the analysis in this paper.

In the redesigned ATM value-chain, we also foresee a novel approach to demand management, which becomes trajectory (product) management. The trajectory management process (lifecycle) starts at the strategic level and spans until a flight has been executed. Again, in the current COCTA concept, we focus on the strategic and pre-tactical phases.

At the strategic level, demand management is used by the NM primarily to establish a cost-efficient balance between demand and capacity. Namely, the NM evaluates if it is more cost-efficient to delay or re-route flights in certain parts of the network, instead of asking ANSPs to provide more capacity. Moreover, in some parts of the network and during certain periods (peak hours), demand profile might be such that even maximum (structural) capacity might not be sufficient to accommodate anticipated demand without delays (or re-routings). Therefore, using available information on flight intentions (scheduled carriers) and anticipated/forecasted level and spatio-temporal distribution of non-scheduled flights (e.g. charters), the NM evaluates what is the scope of demand management actions, combined with capacity management, which minimises total cost to AOs. As a result of this analysis, the NM has information on capacity needed per ANSP and the scope of delays and re-routings of flights/flows in the network, which establishes a cost-efficient balance between anticipated demand and capacity ordered.

For the sake of completeness, we briefly elaborate on trajectory management from the strategic to the pre-tactical stage, without explicitly addressing it in this paper (due to the scope of the paper and the complexity of this aspect within the COCTA demand management process).

After the initial capacity order, the NM starts defining trajectory products to incentivise AOs' route/trajectory choice to maintain, to the extent possible, the strategically established balance between demand and capacity, which minimises total cost to AOs. Therefore, the NM steers demand by defining and offering to AOs different trajectory products, at differentiated prices. These products are, for the sake of simplicity, labelled Standard Trajectory (ST), Discounted Trajectory (DT) and Premium Trajectory (PT). For instance, ST is associated to the shortest route between two airports, including relatively narrow and pre-agreed spatio-temporal trajectory margins, potentially needed for trajectory fine tuning at a later stage (e.g. shortly before take-off). This product comes at a base charge and is tailored for flights/flows which are not likely, based on strategic assessment, to be subject to demand management actions. On the other hand, by choosing DT, an AO gets a lower charge compared to ST, but delegates the decision to the NM to delay or re-route its flight within pre-agreed margins (wider than those for ST), if needed. With PT, AOs have an option for last minute trajectory changes, either in space or time, within agreed margins; this option comes at a higher charge compared to the ST. To sum up, the NM offers different trajectory products, which are also subject to negotiation with AOs, at differentiated charges, to incentivise AOs' trajectory/route choices to the extent possible, to achieve required network performance.

In Table 1, we provide a brief overview of the process as a whole.

Table 1. The COCTA capacity and demand management process summary

Phase	**Time before day of operations**	**Demand management**	**Capacity management**	**Transactions / products**
Long-term	5 years (rolling plan)	The NM forecasts demand and assesses impact of future traffic on overall network performance with currently available capacity.		Network performance indicators
			The NM evaluates if more capacity should be provided and agrees with ANSPs on capacity to be provided in the next five years (rolling plan).	Nominal capacity profile
Strategic	~ 1 year		Based on published schedules, the NM defines capacity order for the following schedule season, within the limits of nominal capacity profile (any deviation is negotiated with ANSPs).	Capacity (ordered for a schedule season or a year)
	~ 1 year – 1 week	The NM defines trajectory products and starts offering them to AOs. AOs negotiate and book trajectories from the NM. The NM adapts the products and prices if needed.		Trajectory products
	~ 1 year – 1 week		The NM asks ANSPs to adjust capacity in line with updated spatio-temporal demand profile, if needed (depending on assumed flexibility in capacity provision).	Capacity order adjustments

Pre-tactical	1 week – day-1		The NM makes final decision on sector-opening scheme, subject to consultation with ANSPs (very limited options for further capacity adjustments).	Sector-opening scheme
	1 week – day-1	The NM and AOs negotiate about trajectory products to be adjusted (if needed).		Trajectory products adjustments
Tactical	Day of operations	Final trajectories are defined and agreed, in line with chosen trajectory products.		Final trajectories

The main focus of this paper is on the strategic decision on capacity orders which the NM is taking several months (up to a year) in advance of a day of operations. We demonstrate how the NM makes strategic capacity ordering decisions, determining the sector-opening scheme (SOSc) for a day of operation. In addition, we show to which degree the COCTA concept may reduce the cost of capacity provision by comparing the COCTA concept against a modelled baseline which we elaborate on in the following sections.

4 Mathematical model

4.1 Conceptual model

We analyse principal trade-offs between capacity and demand management actions to improve overall cost-efficiency:

- asking for higher capacity provision, versus
- delaying or re-routing flights.

Ordering more capacity entails higher capacity provision costs, but a reduction in costs associated with delaying or re-routing (so-called *displacement costs*), and vice versa. The mathematical model introduced in this section aims to balance this trade-off so as to minimise overall cost. Note that this optimisation is not intended for operational flight assignments, but serves a basis for defining trajectory products, as well as to inform the strategic capacity ordering decision well in advance of the planned day of operation.

On the capacity side, we assume that each ANSP has defined how its volume of airspace is divided into elementary sectors and how these can be combined in predefined ways to form (sector) configurations, with different number of sectors open/active in a configuration. The more sectors are open in a configuration, the more capacity an ANSP can offer, up to the point where maximum number of sectors is open (structural capacity limit). By asking for more sectors to be opened during a certain period, the NM effectively increases capacity, but also the cost of capacity provision. As a unit cost of capacity provision, we use the cost of opening one sector for one period. In our case, this period is 30 minutes long, since sector configurations are typically not changed more frequently than every half an hour. Cost of capacity provision is borne by AOs, through airspace charges. Although the costs of capacity provision are fixed on the actual day of operations (as outlined in section 3.2), we treat ATCO costs per sector half-hour as variable costs in our modelling. Since the NM and the ANSPs have agreed on the provision of a capacity (budget) over a longer period (e.g. six months or one year), using parts of this total capacity reduces the capacity which is available in the remainder of this period, thereby causing opportunity costs. Moreover, decreasing the average number of sector hours opened per day decreases also the total staff requirements. Consequently, although there is no immediate cost effect of reducing the number of sector hours on one day, the aggregated reduction enables the ANSPs to reduce total staff costs.

On the demand side, we assume that AOs prefer flying the shortest routes which are also the cheapest in the COCTA context (assuming zero wind condition)[3]. Delaying a flight or re-routing it from the shortest route, incurs a ("displacement") cost to the AO, while we assume that changing a flight level for a flight (up to one level higher or lower) does not affect the AO's operational cost. We assume that displacement cost depends on the scope of demand management action (non-linear), i.e. length of delay or re-routing, and aircraft type.

Therefore, the NM jointly decides on which SOSc will be ordered from each ANSP and which flights/flows will be delayed or re-routed across the network to maximize cost-efficiency, i.e. to minimize the sum of the cost of capacity provision and displacement cost.

4.2 Terminology and notations

We consider several en-route airspaces $a \in A$, with each airspace a composed by a set of elementary sectors $s \in S^a$. Let C^a be the set of configurations, indexed by c. A sector configuration c is identified by a partition P^c. Elements of a partition are indexed by p, to represent how the airspace is split, i.e. how elementary sectors are combined (collapsed) to form configurations. In other words, an element p is a portion of the airspace, identified by a subset of elementary sectors $s \in S^p \subseteq S^a$; this sector which is formed from elementary sectors is called collapsed sector. Every element p in a partition has a capacity k_p denoting the maximum number of flights allowed to enter a sector, be it elementary or collapsed, per time period (commonly referred to as "entry counts"). Capacity cost (variable) is linked to the number of sectors open and the duration they are active (open), with each airspace $a \in A$ having its unit cost of opening one sector for one period ρ_a. Finally, we use B to denote the route-configuration-time incidence matrix: $b_{frpu} = 1$ if route r uses elementary or collapsed sector p at time u, 0 otherwise.

We consider a set of flights F in a network. Each flight f connects an origin (o) to a destination (d) airport (O&D pair). Trajectories for each flight are chosen from a set R_f which contains several alternatives. We stress that this set R_f is assumed to be pre-determined by the exogenously given trajectories (more details in the data Section 5.1). The displacement cost of trajectory r for a flight f is d_r^f.

A fine-scale discrete time axis is used to define trajectories, and a coarse-scale one to model the dynamics of airspace configurations. The time unit used to define trajectories is 5 minutes, whereas the one used for sector configuration corresponds to 30 minutes.

4.3 Mathematical model formulation

The notation used to formulate the COCTA mathematical model is summarized below:

Sets:

F	The set of all flights
R_f	The set of trajectories available to flight f
U	Set of all coarse-scale time periods
A	Set of airspaces
C^a, S^a	Set of configurations and elementary sectors for airspace a
P^c	Partition of elementary sectors corresponding to a configuration
S^p	Subset of elementary sectors forming a collapsed sector within a configuration

[3] This assumption appears valid for short and medium-haul flights, e.g. intra-European flights, for which wind is less influential on trajectory choice. For long(er)-haul routes, like trans-Atlantic flights, shortest route might not be the cheapest option, therefore AOs have to be eventually offered more flexibility and left with an option to decide on their final trajectory shortly before take-off.

Indices:

f	Flights
u	Coarse-scale time index
r	Trajectory
a	Airspace
c, c'	Airspace’s configuration
p	Airspace sector (elementary or collapsed)
s	Elementary sector

Parameters:

ρ_a	Variable cost of providing one sector-time unit for airspace a
k_p	Maximum capacity of airspace portion p
$\bar{h}_{ac}$	Number of sector-time units consumed by airspace a operating in configuration c
d_r^f	Displacement cost of trajectory r for flight f
$B = [b_{frpu}]$	Matrix element b_{frpu} is equal to 1 if trajectory r of flight f uses elementary or collapsed sector p at time u, 0 otherwise

Variables:

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

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

The joint sector configuration and flight assignment problem is formulated below as a linear binary program:

$$\min_{z,y} \sum_{a \in A} \rho_a \sum_{u \in U} \sum_{c \in C^a} \bar{h}_{ac} z_{acu} + \sum_{f \in F} \sum_{r \in R_f} d_r^f y_r^f \tag{1}$$

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

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

$$\sum_{f \in F} \sum_{r \in R_f} b_{frpu}\, y_r^f \leq K_p z_{acu} + |F| \sum_{c' \neq c} z_{ac'u} \qquad \forall a \in A, \; c \in C^a, \; p \in P^c, \; u \in U \tag{4}$$

$$z_{acu} \in \{0,1\} \qquad \forall a \in A, \; c \in C^a, \; u \in U \tag{5}$$

$$y_r^f \in \{0,1\} \qquad \forall f \in F \; r \in R_f \tag{6}$$

The objective (1) aims to minimize capacity and displacement cost. The constraint (2) ensures that each flight must be assigned to one and only one trajectory. The constraint (3) states that one configuration must be defined (active) at any time, for each airspace. The inequalities (4) set the capacity limitations across the network. More specifically, if a partition p belongs to a configuration c in a given airspace a, and c is chosen as an active configuration in this airspace at time u (i.e., $z_{acu} = 1$), then no more than K_p aircraft can enter the sector p in period u. However, if c is not chosen, then the term $|F|\sum_{c' \neq c} z_{ac'u}$ guarantees that the constraint is no longer binding. This so-called "Big M" approach may lead to poor linear programming relaxations and more efficient formulation is possible, however, the problem (using either formulation) still would be intractable even for commercial solvers at large scale. Therefore, we stick to this representation as it easier to read. The left-hand side of the constraint computes the total number of flights entering a sector in period u. Finally, (5) - (6) define the binary nature of the decision variables.

4.4 Computational methods

Computational runtime is a crucial aspect of this modelling approach. Our model as presented so far is challenging to solve even with a commercial solver when large instances are considered. For this reason, we tested several heuristic approaches to solve the model. The main challenge is a large number of possible combination of configurations, but also a large number of potential different trajectories for each flight. After intensive testing, we selected a heuristic approach, which we briefly describe below.

In the initial step, we open all elementary sectors, that is, start with maximum sectors open (capacity provided) for every period u. Then, we assign flights to preferred (shortest) trajectories. Note that a demand profile might be such that it exceeds maximum capacity in some elementary sectors s in periods u. After assignment, we obtain the traffic counts θ_{su}^{0} for each open sector s and time period u, that is, how many flights entered each elementary sector in each time period. Then, for each pair (a, u), we select a configuration associated with the lowest cost (i.e. minimum sectors open) which provides enough capacity for the given traffic ($k_p > \theta_{su}^{0}$). This is done by fully enumerating configurations starting from the one with lowest cost, that is, lowest number of sectors. As soon as a configuration which provides enough capacity for the traffic in the airspace considered is found, the enumeration stops. If, however, there is no configuration in an airspace with enough capacity for the traffic at a given time, the configuration minimising the gap between traffic and capacity is selected. A new feasible trajectory assignment is then found by solving the optimization model with capacity decisions fixed. The output of the initial step is a solution with the minimum displacement cost achievable (given the airspaces structural capacity constraint). However, the capacity cost returned can be very high.

Therefore, a second empirical step is implemented to try to reduce the capacity cost while trading with displacement cost. The basic idea is to identify when the network is close to congestion and apply minor changes to the capacity configurations around those time periods. At this stage, this is done empirically by looking at the peaks in the demand profile. Formally, for each airspace (a, u) pairs deemed as congested (capacity utilisation >90%), the traffic count θ_{su}^{it} ($\forall\ s \in S^a$) is decremented by a pre-determined number of flights; in our experiments, the modifications γ are empirically set to 5, 10 and 20 flights. Practically, these flights are delayed and will enter the affected airspaces in the time periods after congestion. With the new temporal distribution of flights in the network, we run the enumeration algorithm to identify the new least cost configurations for each pair (a, u). Optimization is then used to find the flight-to-trajectory assignments and measure the displacement cost, given the fixed capacity. This procedure is repeated while increasing the magnitude of the traffic modifications and storing the best solution. The procedure stops after the solution cannot be improved by a threshold margin or when the time for computation expires.

It should be noted that we also use the COCTA mathematical model and algorithm in the Baseline (reference) scenario, but with different model settings, as explained in section 5.2.1.

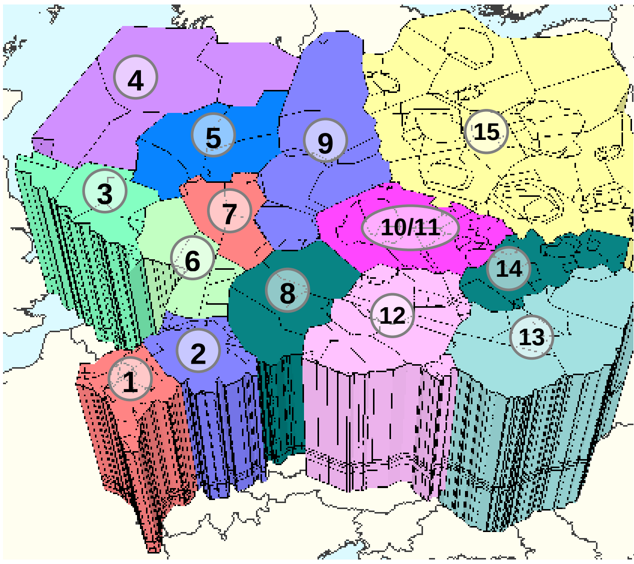
5 Numerical results

5.1 Large-scale case study data

For our case study, we use real data, obtained from EUROCONTROL's service Demand Data Repository (DDR2), using EUROCONTROL Network Strategic Tool (NEST). The large-scale case study includes airspaces in central and Western Europe, covering eight ANSPs and 15 ACCs/sector groups (Figure 2. Case study airspace, ACCs and sector groups [Source: EUROCONTROL NEST]). For instance, Karlsruhe Upper Area Centre (UAC) is divided into four sector groups: East, West, South and Central, each with its own sectorisation and sector configurations. The COCTA concept is primarily developed for the en-route airspace and therefore, most of the selected ACCs provide ANS services primarily in the upper airspace. We choose between configurations that were used by ACCs in 2016 and select those that were most frequently used. We select configurations with different number of sectors: in total, we have 173 different configurations for 15 ACCs/sector groups (Figure 2. Case study airspace, ACCs and sector groups [Source: EUROCONTROL NEST]).

The ANSP cost data used in the model is based on cost and capacity information provided in the ATM Cost-Effectiveness Benchmarking Report (EUROCONTROL, 2017). Since some ANSPs in our case study changed their sectorisation over the last years (which also has an influence on costs per sector hour), we only use the most recent data available (2015). For each ANSP in the case study, we calculated the average ATCO costs per sector hour based on the average number of ACC ATCOs on duty per sector hour and the average employment costs per ATCO hour (in the case of Germany we used operational data for ACC Karlsruhe only). We treat these average ATCO costs per sector hour as variable costs in our model.

To obtain a challenging set of flights, the busiest day on record in 2016 - 9th September, with a total of 34,594 flights in the European airspace, was chosen for the case study. In the COCTA context, the ANS charging scheme favours shortest routes, therefore, we first use NEST to generate shortest routes for the traffic sample based on last filed flight plans (many flights have already filed shortest plannable routes). We then generate alternative trajectory options for each flight, using NEST, both in horizontal and vertical plane, crossing different elementary sectors. In the end, the final traffic sample consists of 11,211 individual flights (shortest trajectories), plus 49,685 additional (spatial) trajectory options. We also consider several levels of delays (e.g. 5, 10, 15, etc. minutes) for flights as well, thus further increasing the number of different 4D flight options. We consider delays only for shortest routes, i.e. we apply only one demand management measure per flight (delay or re-routing). To estimate delay and re-routing costs per aircraft type we make use of findings presented in Cook and Tanner (2015) and EUROCONTROL (2018). Scheduled flights make around 85% of total demand in the case study traffic sample, while the remaining 15% are non-scheduled, in line with the annual averages (EUROCONTROL PRC, 2017).



No.	ACC/Sector group	Min/Max Sectors open	Number of configurations
1	Genève UAC	1/6	11
2	Zurich UAC	1/5	7
3	MUAC Brussels	1/6	10
4	MUAC Deco	1/6	7
5	MUAC Hannover	1/7	12
6	Karlsruhe West	1/8	11
7	Karlsruhe Central	1/9	13
8	Karlsruhe South	1/8	13
9	Karlsruhe East	1/9	13
10	Praha UAC	1/5	8
11	Praha CTA	1/5	6
12	Wien ACC	2/12	21
13	Budapest	1/7	7
14	Bratislava	1/5	8
15	Warszawa	1/10	26

Figure 2. Case study airspace, ACCs and sector groups [Source: EUROCONTROL NEST]

5.2 COCTA model evaluation methodology

We test and evaluate the COCTA concept/model to:

1) Compare the COCTA results, i.e. capacity required for a given traffic demand and associated network performance indicators, against a modelled Baseline, which mimics the current system (described in the next section).

2) Demonstrate the NM's capacity ordering decision-making, that is, asking for sector-opening schemes from ANSPs for a day of operations in the schedule season.

5.2.1 COCTA model evaluation: comparison against a modelled Baseline

For the sake of comparison, we define a Baseline scenario which should mimic, to the extent possible, the current practice of capacity planning. To facilitate fair comparison, for the Baseline we use the same COCTA model, but with different assumptions/model settings, which are in line with the current practice. Namely, we assume that the NM also tries to find the most cost-efficient solution in the Baseline scenario, with the difference that the NM considers delays as a primary demand management measure, without considering re-routings (EUROCONTROL, 2013b). This means that the Baseline scenario *de facto* relies upon the same capacity management principles as the COCTA case, while demand management in the Baseline is primarily focused on delaying flights; re-routings of limited length (up to 2NM only) are considered only when the model cannot find a feasible solution by delaying flights solely. The reason for having the same capacity management mechanism assumed in both scenarios is that replicating individual ANSP's capacity management/planning practices is not trivial. Also, using the available real data on capacity provision is not appropriate for comparison purposes, since the capacity decisions in practice are affected by many non-nominal conditions (disruptions) and limitations (e.g. ATCOs available) which are challenging to replicate. It should finally be noted that by assuming COCTA-like capacity-management principles in the Baseline, we arguably remain on the conservative side concerning the estimated COCTA cost-efficiency benefits.

The comparison is performed as follows. The NM examines how much capacity, provided by means of a specific sector-opening scheme – SOSc, is needed for different traffic levels in the network and assesses network performance associated with capacity decisions for both scenarios (COCTA and Baseline). As input for both scenarios, we have a range of different traffic levels anticipated in a schedule season. Based on typical seasonal traffic patterns and anticipated flow variations, both on local and network level, the NM has a good estimate of how many flights could be expected (EUROCONTROL STATFOR, 2018). In our experiments, we vary number of flights between 8,300 and 11,211 (maximum number of flights), using a uniform distribution. Each flight from the set of flights has an equal chance to be sampled, which increases variability of traffic flows, and we randomly choose 200 different traffic samples. For each of these traffic samples, we run the model in COCTA and Baseline scenarios to obtain results: sector-opening schemes for each ANSP, cost of capacity provision, scope of delays and re-routings, etc. Note that although both COCTA and Baseline scenario use the same capacity management mechanism, the resulting capacity ordered might be different, due to different demand management mechanism used.

This comparison could reflect a long(er)-term capacity ordering decision implication on overall network performance. Since a very large number of iterations is needed to make sound capacity ordering decisions, we present the results from 200 iterations and then demonstrate the capacity ordering decision based on model testing for a representative day in the network.

5.2.2 COCTA model evaluation: capacity ordering for a representative day

We demonstrate the NM's capacity ordering decision-making in the COCTA context, that is, asking for sector-opening schemes from ANSPs for a day of operations in the schedule season.

For any specific day of operations, the NM assumes that scheduled flights will materialise as planned whereas there is a degree of uncertainty associated with a number of non-scheduled flights expected for the day of operations. As an example, we use a busy Friday traffic (pattern), anticipating that the total number of flights will be 11,000 including ± 2% traffic variability. Out of these 11,000 flights, approximately 85% are scheduled, while we assume that variability, again in terms of traffic levels and spatio-temporal distribution in the network, originates from the remaining 15% of non-scheduled demand. We use all scheduled flights from the dataset (9,642 in total) as fixed and randomly choose between 1,130 and 1,569 flights from the non-scheduled flights in dataset (there are 1,569 such flights in total). Again, we select 200 different traffic samples to be used as input for model testing. For any traffic sample, we solve the COCTA optimisation model (1-6). The solution is used to identify the SOSc ($\boldsymbol{z}$ variables) together with several performance indicators (e.g., displacement cost, CO2 emissions etc.) resulting from the flight-to-route assignments ($\boldsymbol{y}$ variables). The objective is to collect a list of SOSc for different demand levels. Basically, in order to establish a cost-efficient demand-capacity balance the NM assesses the effects of traffic variability on the capacity needed, in terms of overall traffic levels and spatio-temporal distribution of non-scheduled flights. We subsequently define different scenarios by grouping (clustering) similar results of individual iterations. We refer to this step as Scenario Identification (SI) step, which as an output has different capacity ordering (SOSc) policies, associated with distinct network performance levels.

Then the NM evaluates capacity ordering decisions, that is, different SOSc ordered and associated network performance under different traffic scenarios ("*what if*"). This is the Scenario Testing (ST) step in which the NM tests the performance (including robustness) of each of the identified scenarios in the previous step. Basically, the NM evaluates the effects of his capacity decision if the actual traffic on the day of operations is on the low, "medium" or on the higher side of expected levels. In our case, we assume that "low" traffic means 10,856 flights, "high" is 11,176 flights and "expected" or "medium" is 11,075 flights. Again, for each of these expected traffic levels, we sample non-scheduled flights as in the SI step to serve as input for model testing. Also, we now have a specific SOSc for each ordering policy chosen in the SI step to be also used as input for the COCTA model testing. Basically, the COCTA model is used just to find optimal demand management decisions to minimise cost of delays and re-routings for a traffic sample, given the capacity. Finally, the NM can compare results (network performance) for the pre-defined set of SOSc and decide on the final capacity for each ANSP/ACC.

5.3 Results

5.3.1 Results of COCTA model evaluation: comparison against a modelled Baseline

We start with the individual results of 200 iterations, which correspond to 200 different traffic materialisations, uniformly distributed between "low" (8,300 flights) and "high" (11,211 flights) demand. The number of flights in the COCTA and the Baseline scenario does not differ, since we are using the same demand across scenarios, which ensures fair comparison between them. The summary of the results for 200 iterations for the Baseline and the COCTA scenario are presented in Table 2.

Since we chose the busiest day in the network in 2016, in the Baseline scenario we can see very high delays associated with high demand (Table 2). Moreover, in some instances the heuristics was not able to find a feasible solution, assuming ground delays limited to 90 minutes. For that reason, after extensive testing, we had to allow re-routings of up to 2NM in the Baseline scenario so that all the demand could be accommodated. As expected, the average number of delayed flights and total delay overall are also significantly lower in the COCTA scenario than in the Baseline scenario (independent-samples Mann-Whitney U Test[4], p=.000 across all

[4] Since the results (data) are not normally distributed (Kolmogorov-Smirnov and Shapiro-Wilk tests) and variances are not the same (Levene's test for equality of variances), we use non-parametric Mann-Whitney U test (Connolly, 2011) to thoroughly compare network performance between the two. As a note, non-parametric test generally have lower power

delay categories). The equity indicator for very long delays also heavily favours systematic and centralised application of re-routings, as there are no severely delayed flights in the COCTA scenario.

In the present ATM system, re-routings are not considered in the capacity planning phase (EUROCONTROL, 2013b), but are executed in a form of mandatory (re-routing) scenarios on the day of operation to avoid excessive ATFM delays (EUROCONTROL NMOC, 2017). Therefore, in this case of very high delays, the Baseline scenario is not a realistic representation of demand materialisation, but merely a consequence of limited capacity in the network and limited demand management actions undertaken at the strategic stage.

It is also worth noting that, in the present system, AOs are not always in favour of re-routings (EUROCONTROL, 2015), not just because of the additional cost, but because there is no network-wide assessment of scenarios' impact (Woodland, 2018). More specifically, AOs seem to be concerned that ANSPs use mandatory re-routing scenarios primarily as a tool to reduce ATFM delays to meet their local delay targets (EUROCONTROL, 2015).

On the other hand, in the COCTA ATM value-chain, with airport pair pricing and trajectory charging introduced, re-routing becomes a network-centric instrument to effectively establish a demand-capacity balance, with clear benefits for AOs overall. They allow the NM as a central planner to spread the demand in the network in such a manner that the total cost is lower in the COCTA scenario, compared to the Baseline.

Table 2. Comparison of Scenarios: Baseline and COCTA – Key Performance Indicators

Performance indicators	Baseline			COCTA		
	Min	Average [St.Dev]	Max	Min	Average [St.Dev]	Max
Number of flights in the demand scenario	8,302	9,743 [872]	11,194	8,302	9,743 [872]	11,194
Total cost (capacity + displacement) [EUR]	756,939	1,035,165 [269,411]	2,333,510	752,144	884,681 [81,534]	1,025,670
Capacity cost (only variable) [EUR]	747,843	886,410 [80.270]	1,010,570	747,965	863,107 [65,397]	966,855
Displacement cost [EUR]	1,979	148,755 [204.580]	1,336,160	2,729	21,574 [17,057]	61,184
Total number of sector half-hours used	2,384	2,831 [263]	3,242	2,387	2,755 [212]	3,095
Number of displaced flights	64	768 [556]	2,173	156	531 [286]	1,097
Number of delayed flights	30	629 [508]	1,953	6	85 [65]	219
Total delay (min)	170	7,390 [8,026]	40,045	40	478 [368]	1,255
Average delay per delayed flight (min)	5.58	9.56 [2.81]	20.57	5.00	5.23 [0.43]	7.86
Num of flights delayed 5min	28	354 [212]	752	5	80 [60]	203
Num of flights delayed 15min	2	214 [214]	715	0	5 [5]	20
Num of flights delayed 30min	0	35 [54]	232	0	0	1
Num of flights delayed 45min	0	19 [31]	221	0	0	0
Num of flights delayed 60min	0	2	70	0	0	0

for statistical inference compared to parametric tests (like t-test); for instance, when the alternative hypothesis is true, non-parametric tests may be less likely to reject the null hypothesis (Connolly, 2011).

Performance indicators	Baseline			COCTA		
	Min	Average [St.Dev]	Max	Min	Average [St.Dev]	Max
		[8]				
Num of flights delayed 90min	0	4 [9]	62	0	0	0
Average re-routing per re-routed flight (NM)	1	1 [0.6]	1	2.68	5.62 [5.82]	7.78
Extra CO_2 (kg)	752	2,970 [1,176]	5,152	7,729	46,315 [34,865]	128,317

However, the COCTA mechanism makes far more frequent use of spatial displacement (re-routings), with about 450 re-routed flights on average (=531 displaced minus 85 delayed flights), corresponding to 4.6% of all flights. Consequently, the CO_2 emission due to additional mileage is notably higher in the COCTA scenario. The distribution of spatial deviations from the shortest plannable route in the COCTA scenario is however strongly right-skewed, with re-routings being up to 7.5NM for 75% of all re-routed flights, and up to 30NM for 99% of all re-routed flights (Figure 3). Maximum re-routing length allowed is 50NM, with only 100 flights, counting together across all 200 iterations, being re-routed more than 45NM.

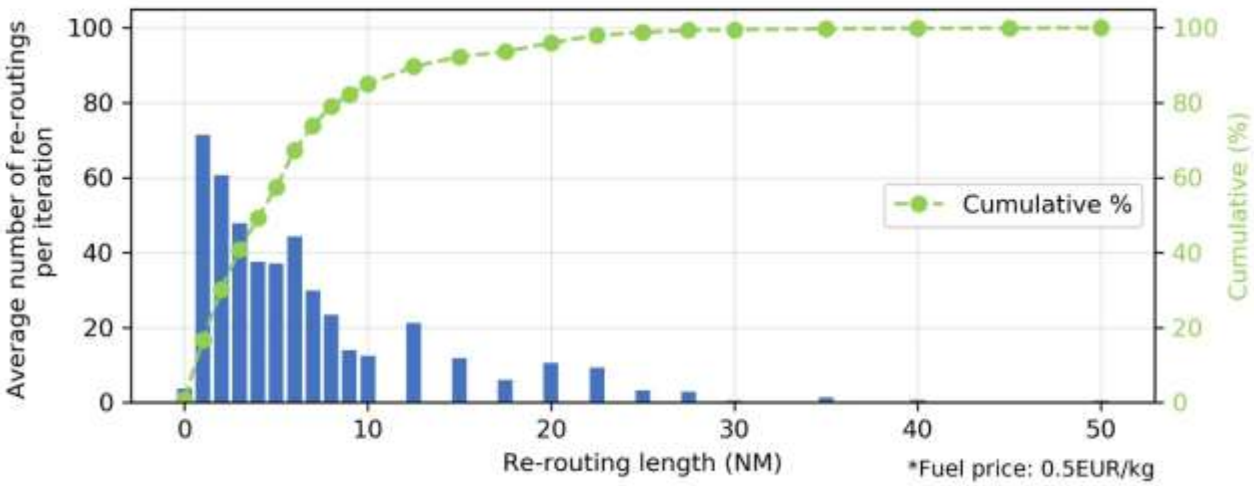


Figure 3. Average number of re-routings and distances per iteration (COCTA scenario, 200 iterations)

We also evaluate the COCTA model using a “high fuel” price of 1 EUR/kg (whereas the Table 2 results were obtained using 0.5EUR/kg). A high fuel price increases the cost of re-routings, since fuel costs make roughly 50-60% of total re-routing cost for turbo-prop and 75% for jet aircraft (Cook and Tanner, 2015). In general, cost of re-routings increases in a super-linear way with millage, with higher gradients of change associated with larger aircraft. However, the results of COCTA model testing using the same demand, but with higher fuel price, are almost identical with the results obtained with a lower fuel price, with only few minor differences. Displacement cost is higher, which is a consequence of higher re-routing costs, due to higher fuel price. We also observe the expected trade-off between “attractiveness” of re-routing vs. delay: when the fuel price goes up, the number of re-routed flights goes down and the number of delayed flights goes up. Consequently, additional CO_2 emissions decline with fewer re-routings in the “high” fuel scenario. However, the higher delay in the “high” fuel price scenario is caused by a higher number of flights delayed by only 5 minutes. Although the difference seems to be statistically significant (Mann-Whitney U test $p<0.05$), the difference in absolute terms is only a few percent.

Basically, the differences at strategic level between “high” and “low” fuel price are marginal and observable only in few network performance indicators, with relatively weak statistical significance. There are several reasons for similar results from model testing with different fuel prices. First, more than two thirds of alternative routes are shorter than 20 NM in our case study, so the cost differences are not as high, compared to cost of capacity provision and cost of delays. Also, in cases of high demand in the network, longer delays instead of re-routings are no longer a more cost-efficient demand management option, since cost of delays increase in a non-linear fashion with delay minutes. Lastly, although we have more than 50,000 different 3D trajectory options for individual flights in our case study, there might be other viable options in some portions of airspace, which we are not able to generate *a priori* using NEST.

Moving on to other performance areas, COCTA coordinated capacity and demand management allows the same traffic to be handled with significantly fewer sector hours overall (Mann-Whitney U Test $p=0.001$), with difference being 38 sector-hours, or about 2.8%, on average, with however much larger difference for higher demand cases (up to 74 sector-hours, or 4.7% higher capacity spending in the Baseline).

As presented in Table 2, total cost in the COCTA scenario is almost 15% lower compared to the Baseline scenario. This difference mainly arises from higher displacement cost in the Baseline scenario and only partially due to higher cost of capacity provision. This is not unexpected though, since the capacity management in the Baseline scenario is coordinated network-wide (using the COCTA capacity mechanism). Mann-Whitney U test shows significant differences in total cost, capacity costs and displacement costs ($p<0.05$).

Figure 4 shows that the cost-efficiency performance of the COCTA and the Baseline scenario is broadly comparable for low and moderate demand volumes, i.e. until about 10,000 flights. For higher demand materialisations total cost in the Baseline scenario starts increasing in a non-linear way, whereas in the COCTA scenario the linear relationship between traffic volume and total costs continues. The cost-efficiency gap between the two thus increases with the demand increase, owing primarily to dramatic growth in the displacement costs in the Baseline scenario. This again is a consequence of the range of demand management measures available in the Baseline scenario, and of strong non-linearity of at-gate delay costs (Cook and Tanner, 2015), especially for delays in excess of 30 minutes, which are far more frequently imposed in the Baseline scenario (Table 2).

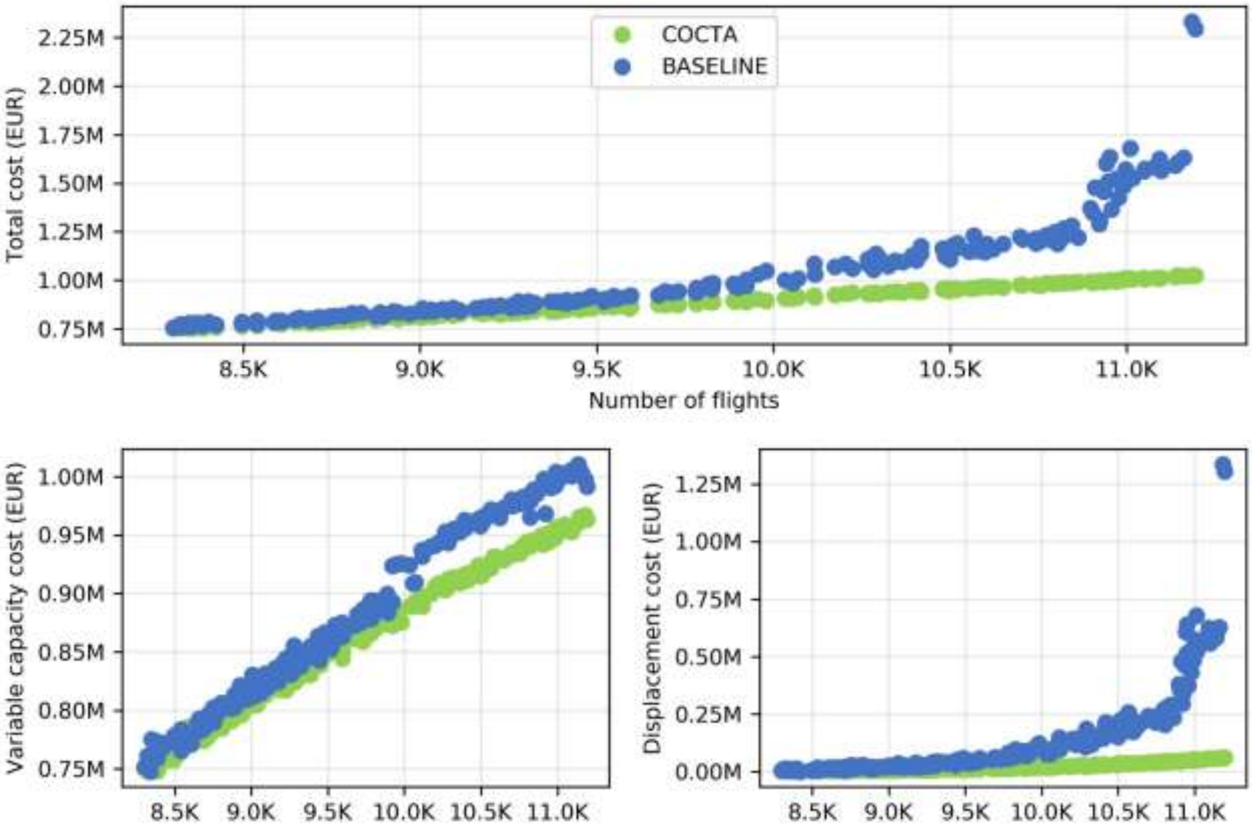


Figure 4. Comparison between Baseline and COCTA total cost-efficiency (capacity and displacement costs)

However, COCTA also outperforms the Baseline in terms of capacity usage, i.e. it persistently spends fewer sector-hours than the Baseline to accommodate the same demand volume. This is notable for demand above 10,000 flights, since a Mann-Whitney U Test shows no significant difference at 5% level (p=.070) between capacity costs for demand lower than 10,000 flights (again, owing to coordinated capacity management).

This comparative analysis suggests a substantial added value of the extensive spatial demand management measures applied in COCTA, resulting in better use of available capacities and yielding remarkably better cost-efficiency than in the Baseline scenario, as observed in the strategic planning stage. Unsurprisingly, this comes at a cost of somewhat increased CO_2 emissions due to more extensive re-routings applied in COCTA: about 4.45kg extra CO_2 per flight, on average, equivalent to 1.4kg extra fuel burned per flight.

Capacity (sector-hours) needed to cost-efficiently handle various levels of traffic in the case study network, linearly increases with traffic for both scenarios[5], Figure 5. Up to 10,000 flights, there are no significant differences between sector-hours needed. With more than 10,000 flights in the network, the number of displaced flights increases non-linearly in the Baseline scenario, compared to a linear increase in the COCTA scenario (Figure 5).

[5] This linear relationship between traffic levels and sector hours is also noticeable in practice; based on DDR data obtained via NEST, we can see than some ACCs, like Geneva and Maastricht adapt their sector-opening schemes in line with demand. However, some other ACCs do not adapt their sector-opening schemes closely in line with demand, thus deviating from linear relation (and potentially suggesting that their efficiency can be improved).

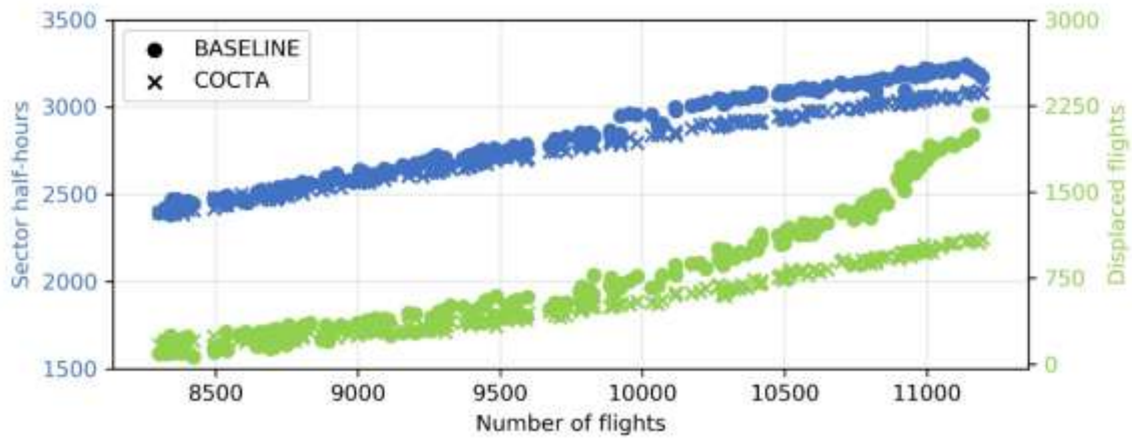


Figure 5. Capacity required and displaced flights comparison between Baseline and COCTA

From 10,000 flights and above, the Baseline scenario also needs more sector hours than COCTA, as confirmed by Mann-Whitney U test (p=.000). Moreover, the Baseline scenario uses configurations with more sectors than COCTA (Figure 6).

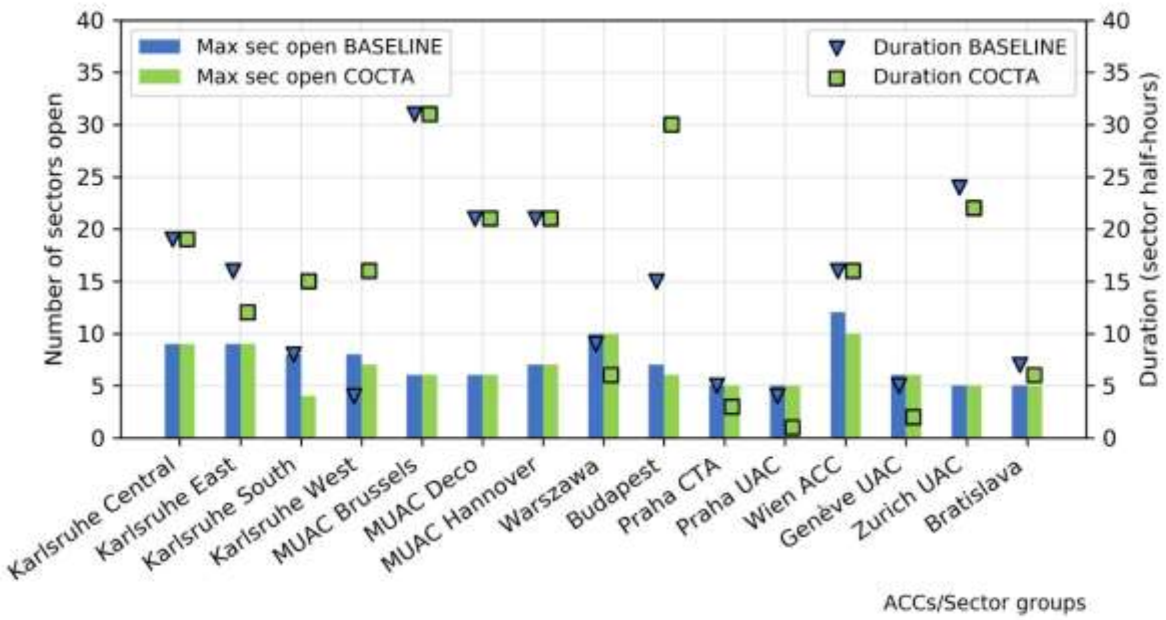


Figure 6. Maximum sectors open and duration (sector half-hours) at maximum configuration

Distribution of sector half-hours across ACCs is shown in Figure 7 – ACCs like Vienna and Karlsruhe Central have higher variation in capacity, while some others, like Bratislava, have much lower variability.

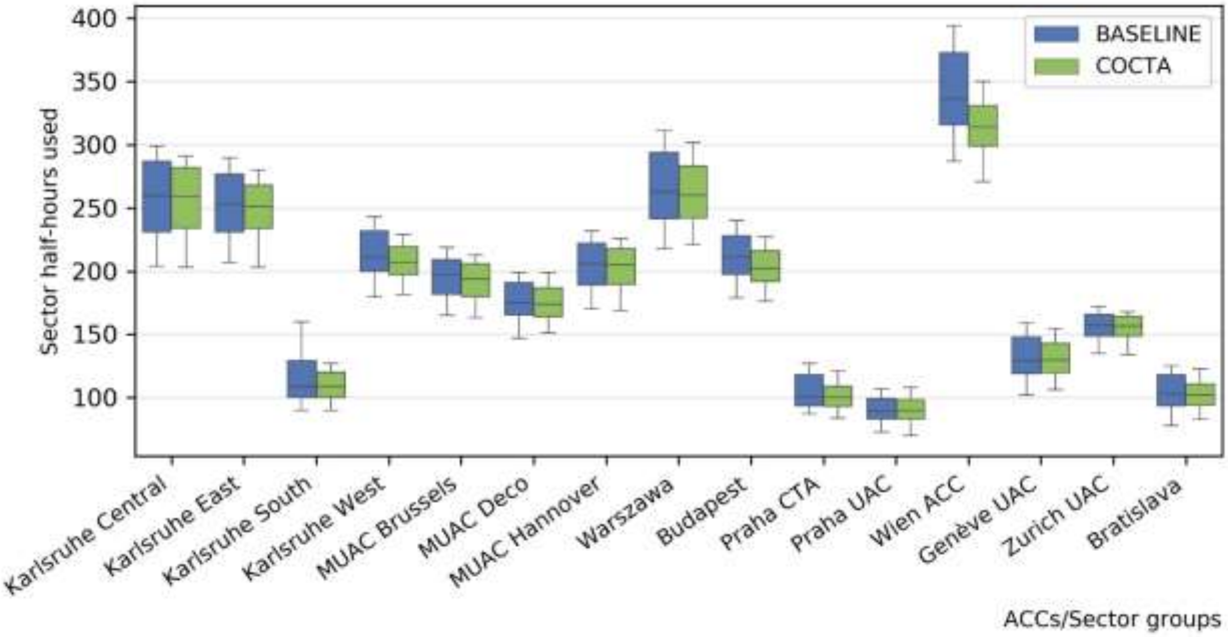


Figure 7. Sector half hour periods across ACCs for COCTA and Baseline scenarios

The analyses so far compared the COCTA and the Baseline scenario over a wide range of demand levels expected to materialize in the network during a schedule season (and/or years), accounting for a high level of traffic variability (in terms of number of flights and spatio-temporal distribution). This might serve as a starting point for the NM to assess required capacity profiles during the season, or even for a longer period, for all ACCs. We observe a very strong correlation between the number of flights and almost all the other variables (KPIs) monitored, usually higher than 0.9. This indicates that the number of flights is a very strong driver and predictor not just for the capacity required in the coming period (see Figure 5) but also for the network performance overall. The NM, therefore, can base its capacity orders, even in the long term, upon the expected traffic growth in the network. Potentially, the NM could conclude that some ACCs might need to increase their maximum number of sectors or provide the maximum capacity level for a longer period. Since we do not have reliable information on the current "limits" for maximum capacity levels and for how long they can be provided by each ACC, we cannot test and evaluate if that is the case.

5.4 COCTA model evaluation: capacity ordering for a representative day

5.4.1 Scenario Identification

To demonstrate capacity ordering decisions taken by the NM, that is, sector-opening schemes for ACCs, we use a representative day in the network. We consider a moderate level of traffic variability, i.e. assume that all scheduled flights will materialize as planned, with only a portion of demand (non-scheduled) being "stochastic". We demonstrate this process for a busy Friday traffic (pattern), anticipating that the total number of flights will be 11,000 including ± 2% traffic variability. Out of 11,000 flights, approximately 85% are scheduled (and deterministic), while we assume that variability, again in terms of traffic levels and spatio-temporal distribution in the network, originates from the remaining 15% of non-scheduled demand.

Based on model output (active sector configurations over time per each ACC) for 200 runs of the model, within a relatively narrow range of high demand materialisations, we obtained the distribution of SOSc for each ACC for the entire day. Building upon obtained sector-opening schemes for each ACC for each 30-minute time window (i.e. 48 periods in the day), we defined four representative SOScs to be used for the second stage analysis, i.e. for the strategic scenario testing:

- MIN: representing the sector-opening schemes providing as low as possible capacities which still, on average, allows for accommodating the expected demand.
- Q1: broadly corresponding to the first quartile (25th percentile) of the capacity provided per each ACC and each 30-min period. This is a slightly more generous capacity-policy than MIN, expected to result in higher costs of capacity provision but also improved delay and environmental performance, on average.
- MEDIAN: broadly corresponding to the median (50th percentile) of the capacity provided per each ACC and each 30-min period, aiming to broadly represent an "average" case.
- MAX: Meant to reflect the most conservative capacity policy, taking for each ACC and each 30-min period the maximum observed number of opened sectors. This arguably mimics planning for the highest-demand scenario, with likely redundancies in some ACCs. It is thus not intuitively clear if (or how often) gains from reduction of displacement costs would offset the higher capacity provision costs.

In Table 3, we present the network performance results, which correspond to the generated SOSc. It should be noted that the difference between the MIN and MAX scenario is 167.5 sector-hours, that is, MAX SOSc provides, overall, 11.7% more sector-hours than the MIN SOSc (Table 3). Furthermore, MAX adds six more sectors opened at maximum configuration compared to MIN, which might also have longer-term cost implications.

With the MIN SOSc we get 35% of unfeasible solutions, meaning that there are 35% demand materialisations which cannot be accommodated by such SOSc when a maximum at-gate delay of 90 minutes is assumed. With the Q1 SOSc only 5% of the demand profiles turn out to be too challenging for the available capacities and the predefined range of available demand management actions, Table 3.

Whereas there is quite a sharp performance improvement between the MIN and the Q1 SOSc, in particular concerning total delay, the incidence of lengthy delays and the CO_2 emissions, the improvement gradient notably slows down between the Q1 and MEDIAN SOSc, and effectively diminishes between the MEDIAN and the MAX SOSc, except for slight CO_2 emission reduction (Table 3).

With MEDIAN and MAX SOSc we get feasible solutions for every random demand sample, the summary results of which are presented in Table 3. The MEDIAN SOSc spends a 4.8% lower overall capacity than the MAX SOSc.

With respect to total cost-efficiency (capacity and displacement cost), we can clearly observe the improvements from MIN to Q1 and MEDIAN, owing to larger decline in displacement cost than increase in capacity cost (Figure 8). Adding more capacity on top of MEDIAN in this case leads to further lowering displacement cost, but at the expense of higher total cost, due to higher cost of capacity provision (Figure 8).

Table 3. COCTA scenario identification for a representative day

Performance indicators	SOSc scenario			
	MIN	Q1	MEDIAN	MAX
Capacity (sector-halfhours)	2,873	2,974	3,062	3,208
Sum of peak ACC configurations (sectors)	94	96	99	100
Feasibility	0.65	0.95	1	1
Variable capacity cost	902,520	933,166	957,516	998,004
Average capacity cost per flight (EUR)	81.6	84.3	86.5	90.1
Average total cost per flight (EUR)	117.2	95.7	91.7	95.1
Displacement cost (EUR) [st.dev]	394,866 [187,081]	126,901 [99,572]	57,877 [5,482]	55,678 [4,091]
Number of displaced flights [st.dev]	1,233 [118]	1,072 [61]	1,074 [55]	1,041 [53]
Total delay (min) [st.dev]	6,961 [3,132]	2,423 [1,806]	1,201 [126]	1,208 [103]
Average delay per flight (min) [st.dev]	0.63 [0.28]	0.22 [0.16]	0.108 [0.011]	0.109 [0.009]
Average delay per delayed flight (min)	17.4	9.3	5.82	5.79
Average number of flights delayed 15-30 (min)	102.2	34.3	16.1	16.5
Average number of flights delayed 45+ (min)	68.8	15.9	0.2	-
Extra CO2 (kg) [st.dev]	168,393 [28,500]	130,900 [21,665]	119,852 [8,896]	115,720 [7,542]

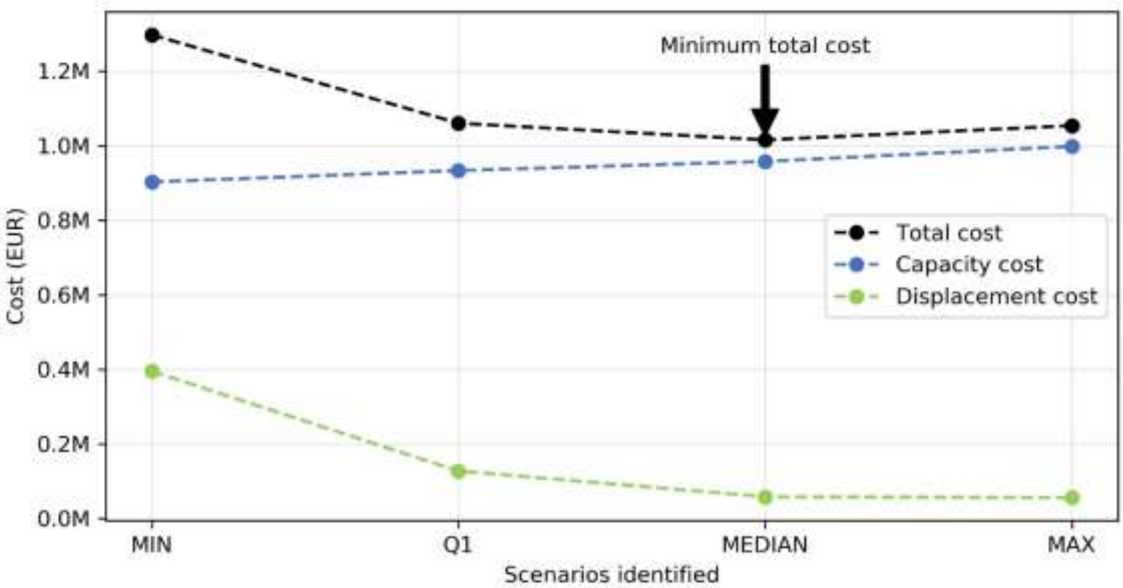


Figure 8. Capacity and displacement cost trade-off between different scenarios

5.4.2 Scenario testing

Based on the results from the Scenario Identification step, we proceed with testing and evaluating in more detail only the MEDIAN and the MAX sector-opening schemes, since those were able to accommodate all flights in each iteration. In this step, the NM assesses fixed sector opening schemes (MEDIAN and MAX) for each ACC, for the same traffic levels and assumed variability in the SI step. We run 100 iterations, with different non-scheduled traffic materialisations in the network, and summarize our results in Table 4.

Table 4 suggests that the MEDIAN SOSc, on average, performs 3.6% better than the MAX scenario in terms of total cost (variable cost of capacity provision plus displacement cost) and that the difference is statistically significant (Mann-Whitney U Test p=.000). This is because the increment in displacement costs, owing to scarcer capacity in MEDIAN, is on average lower than the corresponding cost of additional capacity provided in the MAX SOSc. On the other hand, there is no significant difference between displacement cost in MEDIAN and MAX scenarios at 5% level (Mann-Whitney U Test p=0.070).

Table 4. Scenario testing: network performance for COCTA MEDIAN and MAX SOSc

Performance indicators	MEDIAN			MAX		
	Low	Medium [St.dev]	High	Low	Medium [St.dev]	High
Number of flights in the demand scenario	10,856	11,075 [0]	11,176	10,856	11,075 [0]	11,176
Total cost (capacity + displacement) [EUR]	1,004,890	1,015,393 [5,482]	1,029,210	1,044,590	1,053,682 [4,091]	1,058,120
Capacity cost (only variable) [EUR]	957,516	957,516 [0]	957,516	998,004	998,004 [0]	998,004
Displacement cost (EUR)	47,371	57,877 [5,482]	71,693	46,590	55,678 [4,091]	60,121
Total number of sector half-hours used	3,062	3,062 [0]	3,062	3,208	3,208 [0]	3,208
Number of displaced flights	950	1,074 [55]	1,152	922	1,041 [53]	1,105
Number of delayed flights	176	206 [15]	234	174	209 [16]	233
Total delay (min)	990	1,201 [126]	1,565	1,000	1,208 [103]	1,375
Average delay per flight (min)	0.091	0.108 [0.011]	0.140	0.092	0.109 [0.009]	0.123
Average delay per delayed flight (min)	5.50	5.82 [0.23]	6.69	5.49	5.79 [0.11]	5.94
Num of flights delayed 5 min	161	190 [12]	205	174	192 [13]	233
Num of flights delayed 15min	9	16.0 [3.5]	25	9	16.4 [3.1]	21
Num of flights delayed 30min	0.0	0.1 [0.45]	2.0	0.0	0.05 [0.22]	1.0
Num of flights delayed 45min	0.0	0.1 [0.31]	1.0	0.0	0.0 [0.00]	0.0

Performance indicators	MEDIAN			MAX		
	Low	Medium [St.dev]	High	Low	Medium [St.dev]	High
Extra CO_2 emitted (kg)	101,323	119,852 [8,896]	135,294	98,678	115,720 [7,542]	123,478

The remaining indicators are, on average, typically only marginally better in the MAX scenario than in the MEDIAN, with however somewhat higher dispersion of values (measured via standard deviation) in the MEDIAN scenario, which is expected given the scarcer capacity, owing to the impact of most challenging demand materialisations. The capacity decision of the NM ultimately depends on its objective function. If the NM is supposed to minimize overall costs, the MEDIAN scenario should be chosen. However, if a very strong emphasis is put on some other KPIs, e.g. minimizing CO2 emissions, the MAX scenario might be preferable.

6 Discussion and conclusions

In this paper, we outline the proposed changes in the ATM value-chain and briefly explain the COCTA concept of a combined capacity and demand management process. We present in detail the COCTA mathematical model and an approach to solve it. For model testing and evaluation of the COCTA concept, we use a large-scale case study based on real data. We include the large portion of central and western Europe, covering eight ANSPs, that is, 15 ACCs/sector groups, with more than 170 different sector-opening schemes available. The demand consists of more than 11,200 individual flights for the entire day, with almost 50,000 different trajectory (re-routing) options. We calculate costs of capacity provision, delays and re-routings, to serve as input parameters for model testing and evaluation.

The idea to balance demand and capacity on a sooner-than-tactical level (day of operations) in a deterministic context clearly has its limitations, owing to a number of uncertainties and variabilities inherent to air transport system (Ball et al., 2005), stemming from both demand and supply side. Nevertheless, although the proposed COCTA concept presently does not include the tactical phase, but focuses on strategic and pre-tactical phase, it establishes a framework preceding the day of operations, which will be integrated in our future research.

Setting the scene for model testing is not trivial in this case, so we elaborate in detail different levels and steps, as well as different scenarios. We start with model testing at the strategic level for the case with high traffic variability, both in terms of overall traffic levels and their spatio-temporal distribution in the network. We compared the model results against a Baseline scenario, which reflects the current system to the extent possible. Based on the results from model testing, we can infer that by coordinated capacity and demand management, the NM is able to achieve better network performance in cost-efficiency, capacity and equity performance areas compared to the Baseline, which could have a long(er)-term impact. Unsurprisingly, the Baseline scenario had seemingly better performance in the environment area (lower CO_2 emissions), owing to assumed Baseline demand management options (i.e. ground delays predominantly). The results also show how the COCTA mechanism makes trade-offs between ordering more capacity, thus increasing cost of capacity provision and lowering displacement cost, and *vice versa*.

We proceed with the COCTA model testing and demonstrate the NM's capacity ordering for a representative day in a schedule season, now assuming a lower level of traffic variability. This level has two different testing steps: scenario identification and scenario testing. Basically, the NM evaluates the capacity needed based on anticipated traffic materialisation in the network, identifies scenarios based on initial results, and then tests those scenarios and compares them against each other. Finally, the NM, based on its objective function, decides on the sector-opening scheme to be ordered, that is, asked for and negotiated, from ANSPs.

The results of extensive COCTA concept (model) testing are promising, especially concerning the overall cost-efficiency, indicating that coordinated capacity and demand management actions, within a redesigned ATM value-chain, might be the right step forward.

However, after its initial capacity order, the NM has to define trajectory products and prices thereof, to govern AO's trajectory choice towards a “system optimum” which is defined at the strategic level. This requires modelling AO's choices, when presented a range of trajectory products at differentiated prices. Also, one of the options for the NM would be to refine its initial capacity order, e.g. to order more capacity (sector-hours) from some ACCs, but at a higher price compared to the initial order. Moreover, decisions taken at the strategic level have to be further tested at the pre-tactical and tactical level, especially in cases when the assumptions from the strategic level no longer hold; for instance, traffic does not materialize as anticipated or an ACC cannot deliver capacity ordered. It would further be interesting to examine the effect of variability concerning take-off times. For instance, adding an uncertainty interval, e.g. (-5 minutes, +10 minutes) around published (scheduled) take-off times would enable assessment of robustness of different capacity orders we analysed in this paper, providing a valuable additional performance indicator. These are some of the immediate future research directions.

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