Stochastic Air Traffic Flow Management for Demand and Capacity Balancing Under Capacity Uncertainty

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Abstract: This paper introduces an innovative approach to the synchronized demand-capacity balance with special focus on sector capacity uncertainty within a centrally controlled collaborative air traffic flow management (ATFM) framework. Further with previous study, the uncertainty in capacity is considered as a non-negligible issue regarding multiple reasons, like the impact of weather, the strike of air traffic controllers (ATCOs), the military use of airspace and the spatiotemporal distribution of nonscheduled flights, etc. These recessive factors affect the outcome of traffic flow optimization. In this research, the focus is placed on the impact of sector capacity uncertainty on demand and capacity balancing (DCB) optimization and ATFM, and multiple options, such as delay assignment and rerouting, are intended for regulating the traffic flow. A scenario optimization method for sector capacity in the presence of uncertainties is used to find the approximately optimal solution. The results show that the proposed approach can achieve better demand and capacity balancing and determine perfect integer solutions to ATFM problems, solving large-scale instances (24 h on seven capacity scenarios, with 6 255 flights and 8 949 trajectories) in 5—15 min. To the best of our knowledge, our experiment is the first to tackle large-scale instances of stochastic ATFM problems within the collaborative ATFM framework.

Key words: air traffic flow management; demand and capacity balancing; flight delays; sector capacity uncertainty; ground delay programs; probabilistic scenario trees

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0 Introduction

Air traffic delay has a significant impact on passengers' experience and may incur costs to airlines, causing massive disruptions to the air transportation network[1-3]. The International Air Transport Association (IATA) expects the overall traveler number to reach 4.0 billion by 2024, exceeding the pre-COVID-19 levels (103% of the 2019 total). However, flight delays are reported widely in airports around the world, attracting widespread attention from the public. Many organizations express a concern that the situations get worse to the extent that they have convened numerous workshops and organized diverse seminars to constantly update the technology and operational concept[4-5].

The core problem under the background arises from a long-standing imbalance between the demand and airspace capacity resources. Air traffic flow management (ATFM) is such a concept conducted to manage the flow of traffic in a manner that minimizes delays and maximizes the utilization of the entire airspace[6-8]. By tactically modifying the departure times and trajectories of flights, capacity-demand imbalance can be addressed[9-12], which occurs either when the capacity is reduced, or when the demand is high[13-15].

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Many countries are developing their ATFM programs and systems, such as the Ground Delay Programs (GDPs) and Airspace Flow Programs (AFPs) led by the Federal Aviation Administration (FAA, 2009). Eurocontrol has been proactively advancing the User Driven Prioritization Process (UDPP)[16] initiatives to provide increased flexibility for airspace users (AUs) to make their operations more cost-effective. Following such programs and initiatives, the industry gradually develops ATFM systems to guild the national traffic flow in a macroscopic view.

The development of the system was not achieved overnight. In 1986, about 12% of the flights in Europe were delayed by more than 15 min. By 1989, 25% of all flights were delayed by this amount at least. Hence, air traffic flow management units (ATFMU) were established in various states to regulate traffic flows and to match demand with capacity. Afterwards, the authorities realized that the control of flow on a regional basis would not solve the problems in a sense. The airspace was increasingly restricted, leading to more frequent delays[17].

It began to emerge that the only solution was to carry out flow management centrally, making the best possible use of all national airspace capacities available. Therefore, the European Organization accordingly set up the Central Flow Management Unit (CFMU). This organization oversees all instrument flight rule (IFR) flights, while the en-route airspace is further subdivided into approximately 70 area control centers (ACCs). Each ACC's airspace is segmented into different sectors managed by one or more air traffic controllers (ATCOs). Eurocontrol's Network Manager Operations Centre (NMOC), evolved from CFMU, has played an irreplaceable role in the further implementation of ATFM.

Other countries also attempted to develop national ATFM systems. Among them, China completed the establishment of National Air Traffic Flow Management Center (NTFS) after years of exploitation. By integrating NTFS with ATC, airlines, and airports in a uniformed collaborative platform, all national traffic flows can be fully optimized using a coherence algorithm. Japan launched Air Traffic Flow Management Center (ATFMC) in 1994 and extended it to Air Traffic Management Center (ATMC) accordingly in 2005. In Australia, provided by Airservices Australia, ATFM is based on the Ground Delay Program (GDP) deployed on various airports such as Sydney, Melbourne, Perth and Brisbane.

However, the above-mentioned initiatives and systems for flow management and for airspace sectorization may be not well coordinated or synchronized. Xu et al.[18] introduced a novel approach to the synchronized balance between demand and capacity in a proposed way of collaborative ATFM. The traffic regulation initiatives and a dynamic opening scheme were incorporated into a centralized optimization model for airspace configuration management. Nevertheless, regrettably some uncertainty factors were not considered through traffic flow optimization, and the deterministic model was proved not to be applicable in multiple scenarios which are incompatible with the reality. To improve the performance and robustness of the systems, uncertainty factors need to be taken into account in future work. Plus, stochastic programming has made significant progress in ATFM optimization during the decades[19-24], prompting us to think how to make our research go extra miles.

To better illustrate the benefits of this paper, we have summarized previous representative studies in stochastic ATFM problems in Table 1. From the prospective of methods, chance-constraint optimization, scenario optimization, and two-stage stochastic optimization are considered as typical methods. Most of the research demonstrates these methods through small sample experiments. Almost all of the research solely considers delay assignments (ground delay or airborne delay), and few simultaneously focuses on assigning delays and trajectory options. With the upcoming future operation concept (4D trajectory and free route airspace), conducting large-scale experiments to demonstrate demand and capacity balancing under capacity uncertainty is significant for ATM future operation.

In this paper, the main contributions and innovations are as follow:

(1) The previous study is further improved by taking the uncertainty of airspace capacities into account under a proposed collaborative ATFM framework for the synchronized balance between demand and capacity, which makes our research more complete.

Multiple strategies including delay assignment and rerouting are suggested for regulating the traffic flow. Compared to related studies (Table 1), synchronously adopting two strategies combined a scenario-based optimization method for enroute capacity with uncertainty in airspace is unprecedented, which indicates the importance of this study.

Table 1 Literature reviews and our main contribution

Items	Problem solving and innovation					This work
Author	Abdelghani et al.[20]	Fadil et al.[25]	Starita et al.[22]	Chen et al.[23]	Balakrishnan et al.[19]	
Method	Chance-constraint to approximate the optimal solution with a predetermined probabilistic confidence	Chance-constraint /scenario approach optimization method	Two stage stochastic optimization method/ a scalable decomposition approach	Chance-constrained optimization method/a polynomial approximation-based approach	Two-stage stochastic optimization method/ Mixed integer linear programming (MILP)	MILP
Focus	Airport capacity uncertainty	Sector capacity uncertainty	Sector capacity uncertainty/demand capacity uncertainty	Sector capacity uncertainty	Airport and sector capacity uncertainty	Sector capacity uncertainty/DCB
Strategy	Airborne holding and ground holding	Airborne holding and ground holding	Assigning delay and rerouting	Ground holding and airborne holding	Ground holding and airborne holding and reroutes	Ground holding and reroutes with delay minimization and green emission objective
Constraint	Airport and sector capacity constraint and other ATFM constraint	Airport and sector capacity constraints and other ATFM constraint	Sector capacity constraint and trajectory constraint	Airport and sector capacity constraint and other ATFM constraint	Airport and airspace sector capacity constraint and other ATFM constraints	Sector capacity constraint and trajectory constraint and other ATFM constraints
Experiment	4 airports +10 sectors	4 capacity scenario+10 sectors	15 ACCs+more than 1 000 flights	Small sizes examples/20 sectors and large-scale experiment 3 054 flights	Large scale experiment (17 500 flights/day, 370 airports and 375 airspace sectors+25 scenarios)	15 ACCs+224 operation sector+164 basic sector+6 255 flights+8 939 trajectories
Our main contribution	Our method focusses on assigning delays and trajectory options aiming at future operation concept, and a large-scale experiment is conducted to demonstrate the method					

(2) The previous demand and capacity balancing (DCB) model and collaborative DCB (C-DCB) model are finally updated to stochastic programming models, unified DCB (U-DCB) and unified collaborative DCB (UC-DCB), which is consistent with the concept of trajectory option set (TOS) in Collaborative Trajectory Options Program (CTOP). The study highlights future development of ATFM and ATM.

(3) Large-scale instances (24 h on seven capacity scenarios, with 6 255 flights and 8 949 trajectories) can be realized through dynamic multi-stage DCB in 5—15 min. The decision-making process can be conducted based on the real departure time, instead of the scheduled one. Before this study, such large-scale experiments are rare. Overall, this research provides guidance for "precise" flow management in the future operation concept.

1 Motivation

In previous work[18,26-28], we proposed an approach combining multiple initiatives to an integrated DCB model, improving the efficiency of delay assignment. In follow-up work, it was demonstrated that incorporating rerouted strategy especially considering the identified hotspot areas could realize observable delay reduction in our experiment process. On this basis, an innovative approach for synchronized demand-capacity balancing was introduced through air traffic flow management. However, according to the workflow presented in Fig. 1, because many factors may have an impact on performance indicator, it is not feasible to directly calculate without considering recessive factors, or rather to say, uncertainty on the capacity side cannot be ignored.

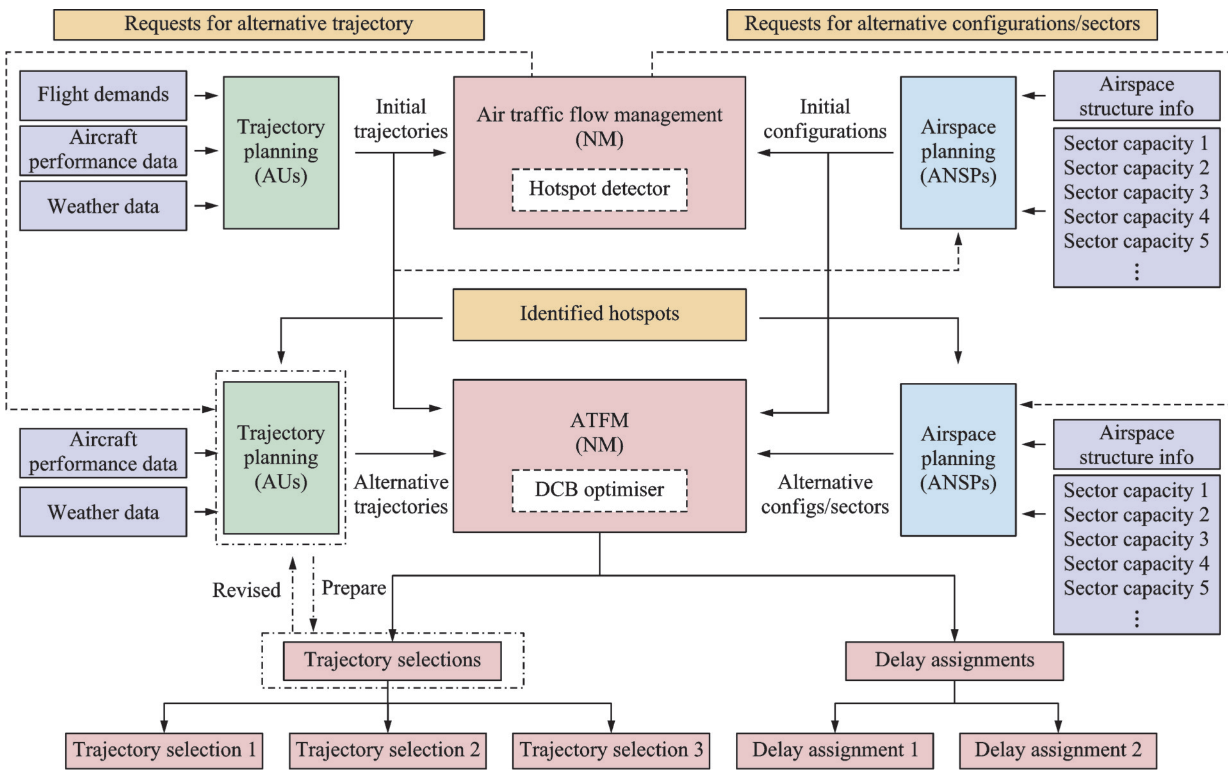


Fig.1 An overview of the architecture and workflow for the proposed model framework

Stochastic programming and robust optimization are the main techniques to address such issues. Much attentions have arisen in ATFM field where continuous efforts are made to explore these techniques to solve the uncertainty in ATFM optimization model from both demand and capacity sides[1]. The most difference between two optimization methods is how to deal with the uncertainty factors in the optimization process. For features of stochastic optimization, uncertainty is evaluated by assuming that the probability distribution can be acquired. In other words, accurate estimates can be performed based on its historical values. Nevertheless, optimizing strategy in robust optimization turns into finding the best solution in the worst-case scenario, which can result in a highly conservative solution. In this regard, both strategies make no difference to which has more advantages than the other. The most distinction between the two methods is dependent on optimization objectives. In this paper, stochastic optimization is adopted to solve the uncertainty on the capacity side. Our innovation beyond the previous relative research is solving large-scale stochastic ATFM problems in a more synchronous collaborative decision-making (CDM) framework, with delay assignment and alternative trajectories strategy into consideration simultaneously. To best of our knowledge, such exploration may be more appropriate for the real-world situation in the industry, which is beneficial to the future application to practical operation in ATM systems.

2 Problem Formulation

This section focuses on problem description and introduces an innovative model. As previously stated, the overall architecture is composed of a set of functional components, and the corresponding workflow diagram is presented in Fig.1. In CDM process, many stakeholders may participate in decision-making processes. Stakeholders, including AUs, ANSPs, network management (NM), functional airspace blocks (FABs) , national security areas (NSAs), are all involved in practical collaboration which derives from multi-participation. However, to better demonstrate the performance and benefits, the main stakeholders involved in this research are limited to the scope of ANSPs, AUs and network managers.

The European Network Operations Plan 2023—2027[29] presents the main operational requirements arising from the implementation of Network Strategic Projects. The free route airspace (FRA) will be gradually implemented by the network management board in the near future, cross-border operation will predominate in future ATM progress. Specially, our theoretical model can also contribute to future operation concept.

2.1 Problem description

ATFM problems are usually considered to be optimization problems related to resource constraints. Many studies adopt various strategies to achieve the same goal, minimizing the system delay. Common strategies encompass speed adjustment, rerouting, flight cancellation, flight overtaking, continued flights, etc. Current methods have been developed through a series of problems such as single airport holding, multi-airport holding, ground holding, ground delay, dynamic ground holding policy, and airborne holding. The actual operation of airlines here can be concisely illustrated by giving an example. Specifically, before a day of flight operation, an aircraft is scheduled to fly through specific routes to the destination airport. However, when it is ready to take off, some sectors are overload due to the imbalance between demand and capacity. If the aircraft continues flying on its original trajectory, the flight time will undoubtedly increase and the whole system will become inefficient because of congestion. Moreover, air traffic controllers in some sectors need to handle quite a number of flights. One particular phenomenon is that hotspots are sectors where demand for flights exceeds capacity. If we can detect such hotspots in advance and take actions to keep aircraft temporarily on the ground, the centralized systems will benefit from more reasonable arrangement.

To be more specific, during trajectory planning, pilots obtain initial trajectory data from air traffic flow management units based on flights demands, aircraft performance data, and weather data. The initial trajectory may not be the final trajectory owing to adjustments in the tactical stage by ATFM (network manager in Europe). The DCB optimizer prefers to modify the trajectory data based on the time-varying hotspots across the whole airspace. Thus, new trajectories are generated to provide to pilots or airspace users. Such hotspots are overload sectors. After this, pilots can choose more economical and environmentally friendly trajectories to save fuel and the whole air traffic management system will benefit from reduced delays. Network managers get sector capacity information from the perspective of airspace planning. ANSPs provide initial configurations to network managers, and as operational situations change, some sectors will be closed and parts of sectors will be merged to an integrated sector. This paper hence focuses on the impact of sector capacity uncertainty on DCB optimization and ATFM.

Two strategies are considered in this paper, delay assignment and trajectory sections, which are utilized in a collaborative ATFM framework. Collaborative techniques require the participation of multiple stakeholders, processing multidimensional information including weather data, aircraft performance data, and flight demand to generate initial trajectories. The DCB model is proposed in this research for data calculation and result optimization, which are finally fed back to the initial planning process.

2.2 Collaborative ATFM framework under capacity uncertainty

The workflow is depicted in Fig.1. The methodology is dedicated to generating two strategies: Delay assignment and alternative trajectory options. The collaborative process consists of five parts as follows:

(1) Initial scheduling of user-preferred trajectory.

(2) Initial scheduling of airspace configuration.

(3) Detection of time-varying hotspot airspaces.

(4) Submission of alternative trajectory options.

(5) Integrated optimization model for synchronized DCB.

As the main topic is to solve the uncertainty factors from the perspective of sector capacity, the transformation of sector capacity to different capacity scenarios is considered. It is worth noting that trajectory selections involve revising the initial trajectory planning, so as to achieve more economical and environmentally friendly trajectories. Beyond this, this paper conducts seven scenarios in the instances in contrast to only one certainty scenario in the previous work. These scenarios are merely a demonstration and expected to have wider practical applications in future research.

2.2.1 Delay assignment

Delay assignment (DAS) strategy goes back a long way. At the very beginning, it is part of Ground Delay Programs (GDPs) in the United States. With the development of GDPs, nowadays DAS is run exclusively in Unified Delay Program (UDP) mode. Besides, DAS as an optimization strategy can be implemented at pre-tactile and tactical levels[30]. A typically tool namely ratio by schedule (RBS) adopts the strategy to deal with slot management in Europe, which minimizes system-level delays by explicitly assigning delays to specific flights. The required delay can be transformed into ground delay prior departure. In some studies, airborne delay and ground delay can both be used, but in this case, only ground delay is considered, which means to determine the airborne flight time. Fig.2 illustrates the DAS strategy.

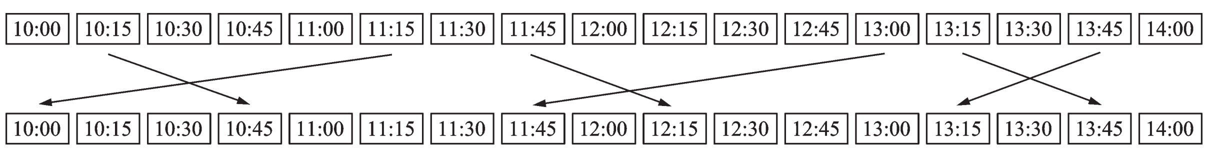


Fig.2 DAS strategy schematic diagram

2.2.2 Alternative trajectory options

Another strategy utilized in this study is placed on alternative trajectory options. Compared to DAS, alternative trajectory options provide another view to minimize the system delay, offering more choices to airspace users. Facing the hotspot areas, pilots get relevant information in advance to avoid the congestion routes before departure. The section process is illustrated in Figs.3, 4. In Fig.3, pilots can choose the red route based on the initial trajectory normally planned by the demand. However, with some sectors overload, the red route may not be the best choice as many traversed sectors change to severe overload from slight overload, as shown in Fig.4. In this case, pilots may choose the green route to quickly adapt to the actual operational situa-

Fig.3 Schematic diagram of assigning delay and alternative trajectory option

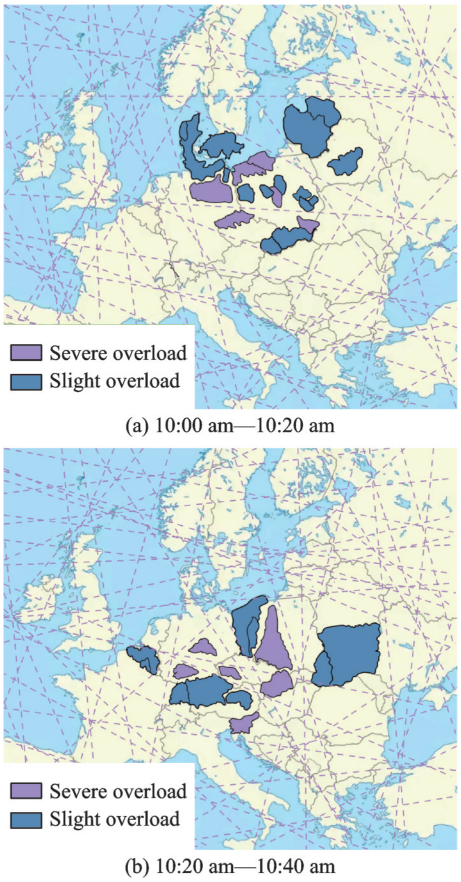


Fig.4 Time-varying projected hotspot volumes identified across the airspace network

tion. If hotspot avoidance information is obtained, pilots can avoid such hotspot areas in advance, and AUs can flexibly reschedule their trajectories to save more fuel.

2.3 Constraints

There are different types of constraints in this study, mainly derived from the capacity side and the demand side. Typical constraints are also introduced in the proposed model such as trajectory constraint and location of flights constraint. Beyond this, variables should satisfy the binary constraint.

(1) Sector capacity constraint

The capacity constraint guarantees that demand does not exceed its capacity. By limiting the number of aircraft within the specific sector, resources utilization can be more efficient.

(2) Operation constraint

With respect to estimate time of arrival (ETA), prescript range of calculated time of arrival (CTA) at each control point for each flight is specified. Meanwhile, timeline continuity is insured by appropriate equation. In the end, a decision-making factor is used to ensure the airborne flight time remains unchanged from the initial time scheduled.

2.4 Capacity uncertainty

The sector capacity depends on the weather conditions such as the visibility, cloud ceiling and the location of thunderstorms, which are classified into uncertainty factors[31].

Many studies have discussed the issues of uncertainty, some focus on dynamic multi-stage[19], and a few present a new method[23]. In particular, some studies solely consider airport uncertainty[32], whereas some literatures place emphasis on sector uncertainty[25], and a number of works consider more uncertainty from both sides on demand and capacity[33-34]. But some papers conduct case study only from one side[35]. Groundbreaking work[36] and early pioneering work[37] involve methods and rerouting strategy. Recent limited research concentrates on performance analysis combined strategy[38].

Moreover, in recent years, separation management[39], trajectory prediction[40], and conflict management[41], have been incorporated into ATFM, and new techniques, like reinforcement learning[42], are applied to accelerate solution time[43]. Distributed management is renewed and updated to central authority-controlled pattern in ATFM problems[44]. Review papers in this field can also be found[45].

Above analysis reveals the sources of uncertainty. The probability of each scenario is mainly dependent on weather forecasting. To be specific, we have retracted the data from Ventusky (Weather Forecast Maps) to acquire the weather conditions of our experimental day (on 5 February 2017) in French airspace. We also carried out some surveys and measurements on that day, finding the weather changed to low visibility with rain starting from 12 pm. That is the reason why 70% of the scenario trees changed to "bad weather", and 30% to "good weather" since there was a 30% probability of no rain from 12 pm according to weather forecasting. Additionally, postmortem analysis was conducted, indicating the accuracy of the scenario information. However, in actual operation, weather forecasting may not be accurate. Most of weather forecasting shows meteorological change by the probability. Therefore, our scenario trees can show such probability of each scenario based on the information acquired in advance. The scenario tree information is displayed in detail in Fig.5, where S1—S7 represent scenarios 1—7.

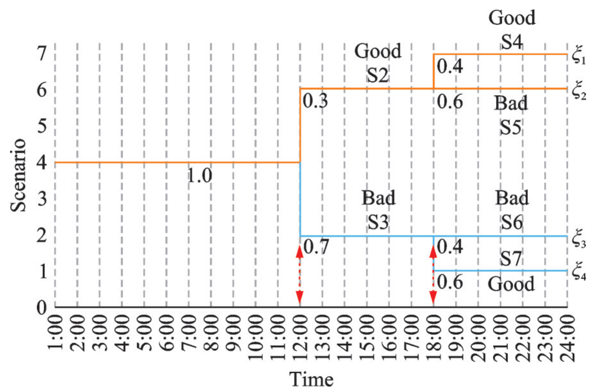


Fig.5 Example of a scenario tree with seven scenarios

The distribution probabilities are 0.4 and 0.6 for scenarios 2 and 3. Scenario 2 is divided into scenarios 4 and 5 with the probabilities of 0.7 and 0.3. Scenario 3 is divided into scenarios 6 and 7 with the probabilities of 0.6 and 0.4. The process occurs after 6 pm. Notably, optimization was performed three times. In the beginning, the DCB optimizer performed before departure of all the flights, which could be regarded as the pre-tactical stage. Optimization was still carried on when some flights took off at 12 pm. At 6 pm, the DCB was performed again to optimize the remaining flights.

2.5 Time-window

In our model, different time window can be set to specify the maximal delay time that can be assigned to each flight. This parameter affects the problem dimension in the simulation. We set time window as 360 min and 120 min with our two models in follow-up large-scale experiments.

2.6 Nomenclature

The nomenclatures in this study are concluded as follows.

$f\in F$ Set of flights

$j\in J$ Set of elementary sectors

$k\in K$ Set of trajectory options

$t\in T$ Set of time moments

$\tau\in\Upsilon$ Set of time periods

$l\in L$ Set of operating sectors

$\xi\in\Xi$ Set of different scenarios

$s\in S$ Set of multi-stage

K_f Subset of trajectory options submitted by flight f

J_f^k Subset of elementary sectors flight f (or trajectory k) traverses

$T_f^{k,j}$ Subset of time feasible for flight f (or trajectory k) entering elementary sector j

$\Upsilon(\tau)$ Subset of time moments subject to time period τ

L_τ Subset of operating sectors opened in time period τ

L_j Subset of operating sectors constructed by elementary sector j

$J_{f,l}^{k,\tau}$ The first elementary sector for flight f (or trajectory k) that functions in operating sector l in time period τ

$J_f^k(i)$ The ith elementary sector for flight f (or trajectory k)

$\overline{T_f^{k,j}}$ Upper bound of feasible time window $T_f^{k,j}$

$\underline{T_f^{k,j}}$ Lower bound of feasible time window $T_f^{k,j}$

$\underline{T_f^{k,j}}$ Lower bound of feasible time window $T_f^{k,j}$

$r_f^{k,j}$ Estimated arrival time of flight f (or trajectory k) entering elementary sector j

$\hat{t}_f^{k,jj'}$ Scheduled flight time of segment jj' for flight f (or the kth trajectory)

c_l^τ Capacity of operating sector l during time period τ

d_f^k Extra fuel consumption for the kth trajectory of flight f

e_f^k Extra route charges for the kth trajectory of flight f

α Unit cost of performing ground delay

γ Unit cost of fuel consumption

3 Stochastic Optimization Model

This section presents the variant models U-DCB and UC-DCB, which are based on the previous baseline model DCB. U-DCB is a model for multi-scenarios demand and capacity balancing while UC-DCB is a variant model considering an additional strategy of rerouting. The two variant models are illustrated in detail below, as shown in Table 2, which summarizes the main features (or initia-

Table 2 Initiatives of the two model variants considered in this study

Model	Delay	Alternative trajectory option
U-DCB	√	—
UC-DCB	√	√

tive) activated in each model.

3.1 Model U-DCB

Model DCB aims at balancing demand under various capacity scenarios through assigning ground delay to flights. A set of fixed airspace opening schemes are considered, which are planned in early stages based on the historical traffic flow. In this study, by considering future trajectory-based operations, CTAs are imposed along the trajectory with each control point. To assign the CTAs, a set of decision variables are identified as follows.

Compared with the model presented in Refs.[18, 28], only ground holding is considered, not airborne holding in this paper.

Firstly, we set a decision variable x in the model, as follow

$$x_{f,t}^{j,\xi,s}=\begin{cases}1 & \text{If flight } f \text{ enters elementary sector } j \text{ by time } t \text{ within stage } s \text{ under scenarios}(\xi)\\ 0 & \text{Otherwise}\end{cases}$$

The objective function Eq.(1) of model DCB is to minimize the total delay of the system. The CTA is imposed to each flight at control point using constraint Eq.(2).

$$\min \underbrace{\sum_{\xi\in\Xi}P(\xi)}_{\text{Scenario}}\times\sum_{s\in S_\xi}\sum_{f\in F}\sum_{j=J_f}\sum_{t\in T_f^j}(t-r_f^j)(x_{f,t}^{j,s}-x_{f,t-1}^{j,s}) \tag{1}$$

$$\text{s.t.}\quad x_{f,\underline{T}_f^j-1}^{j,\xi,s}=0,\ x_{f,\overline{T}_f^j}^{j,\xi,s}=1$$
$$\forall f\in F,\forall j\in J_f,\forall\xi\in\Xi,\forall s\in S_\xi \tag{2}$$

$$x_{f,t}^{j,\xi,s}-x_{f,t-1}^{j,\xi,s}\geqslant 0$$
$$\forall f\in F,\forall j\in J_f,\forall t\in T_f^j,\forall\xi\in\Xi,\forall s\in S_\xi \tag{3}$$

$$x_{f,t+\bar{t}_f^{jj'}}^{j',\xi,s}-x_{f,t}^{j,\xi,s}=0$$
$$\forall f\in F,\forall t\in T_f^j,j=J_f(i),\forall s\in S_\xi,$$
$$j'=J_f(i+1):\forall i\in[1,n_f) \tag{4}$$

$$\sum_{\xi\in\Xi}P(\xi)\times\sum_{s\in S_\xi}\sum_{f\in F}\sum_{j=J_{f,l}^{\tau}}\sum_{t\in T_f^j\cap r(\tau)}x_{f,t}^{j,\xi,s}-x_{f,t-1}^{j,\xi,s}\leqslant c_l^{\xi,s}(\tau)$$
$$\forall l\in L_\tau,\forall\tau\in r,\forall s\in S_\xi,\forall\xi\in\Xi \tag{5}$$

$$x_{f,t}^{j,\xi,s}\in\{0,1\}\quad\forall f\in F,\forall j\in J_f,\forall t\in T_f^j,\forall s\in S_\xi \tag{6}$$

Constraint (3) guarantees the timeline continuity of the decision variables (recall the “by” time concept), similar to the previous work[18]. As the U-DCB model only considers ground delay, constraint (4) ensures that the airborne (segment) flight time remains unchanged from the initial time scheduled.

Constraint (5) enforces the capacity constraint. Notably, constraint (5) differs to our previous work in which multiple scenarios are integrated into the deterministic capacity constraint model. To better eliminate the impact of inconsistency between the capacity entity (operating sector) and the control point (elementary sector), a commonly used rule is adopted, that is, only the first entry (control point) into an operating sector is counted for each flight (or trajectory).

Finally, all decision variables should be subject to the binary constraint (6).

3.2 Model UC-DCB

Model UC-DCB is based on the U-DCB model and evolved from the C-DCB model introduced previously[18,28,46-48]. It incorporates more contribution from AUs' side (alternation trajectory options). AUs can submit a number of alternative trajectories for the affected flights in the initially planned trajectories. UC-DCB model is an enhanced model which can copy with more complex scenarios. As stated before, our research mainly contributes to extending our model to multiple scenarios under capacity uncertainty. The centralized optimization model seeks an optimal distribution of trajectory selections and delay assignments across all the flights.

Besides the decision variable $x_{f,t}^{k,j,\xi}$, an extra decision variable k is further determined to represent trajectory options

$$z_{f,s}^{k,\xi}=\begin{cases}1 & \text{If the } k\text{th trajectory of flight } f' \text{ is choosen within stage } s \text{ under scenarios}(\xi)\\ 0 & \text{Otherwise}\end{cases}$$

In this sense, all the control points and associated CTAs are bonded with the kth trajectory, instead of the flight. Simultaneously, the decision variable $x_{f,t}^{k,j}$ is introduced to assign the delay to specific fights as

$$x_{f,t,s}^{k,j,\xi}=\begin{cases}1 & \text{If the } k\text{th trajectory of flight } f' \text{ enters elementary sector } j \text{ by time } t \text{ within stage } s \text{ under scenarios}(\xi)\\ 0 & \text{Otherwise}\end{cases}$$

The above two sets of decision variables are linked together, and the delay (if any) will be imposed on each particular flight instead of the selected trajectories.

$$\min \underbrace{\sum_{\xi\in\Xi} P(\xi)}_{\text{Scenario}}\times\left[\underbrace{\sum_{s\in S_\xi}\sum_{f\in F}\sum_{k\in K_f}\sum_{j=J_f}\sum_{t\in T_f^{k,j}}\alpha(t-r_f^{k,j})(x_{f,t}^{k,j,s}-x_{f,t-1}^{k,j,s})}_{\text{Delay}}+\underbrace{\sum_{s\in S_\xi}\sum_{f\in F}\sum_{k\in K_f}(\gamma d_f^k+e_f^k)z_f^{k,s}}_{\text{Alternative trajectory}}\right] \tag{7}$$

In this paper, the fuel consumption d_f^k and route charges e_f^k are considered as the trajectory related costs. The objective function Eq.(7) is to minimize the total delay costs and the extra costs incurred from diverting the flights to their alternative trajectories under different capacity scenarios.

$$\text{s.t.} \sum_{k\in K_f} z_{f,s}^{k,\xi}=1 \quad \forall f\in F,\forall\xi\in\Xi,\forall s\in S_\xi \tag{8}$$

$$x_{f,T_f^{k,j}}^{k,j,\xi,s}-1=0,\ x_{f,T_f^{k,j}}^{k,j,\xi,s}=z_{f,s}^{k,\xi}$$
$$\forall f\in F,\forall k\in K_f,\forall j\in J_f^k,\ \forall\xi\in\Xi,\forall s\in S_\xi \tag{9}$$

$$x_{f,t,s}^{k,j,\xi}-x_{f,t-1,s}^{k,j,\xi}\geqslant 0$$
$$\forall f\in F,\forall k\in K_f,\forall j\in J_f^k,\forall t\in T_f^{k,j},\forall\xi\in\Xi,\forall s\in S_\xi \tag{10}$$

$$x_{f,t+\hat{t}_f^{k,jj'},s}^{k,j',\xi}-x_{f,t,s}^{k,j,\xi}=0$$
$$\forall f\in F,\forall k\in K_f,\forall j\in J_f^k,\forall t\in T_f^{k,j},\forall\xi\in\Xi,$$
$$\forall s\in S_\xi, j'=J_f(i+1):\forall i\in[1,n_f) \tag{11}$$

$$\sum_{\xi\in\Xi}P(\xi)\times$$
$$\sum_{s\in S_\xi}\sum_{f\in F}\sum_{k\in K_f}\sum_{j=J_{f,l}^{k,\tau}}\sum_{t\in T_f^{k,j}\cap r(\tau)} x_{f,t,s}^{k,j,\xi}-x_{f,t-1,s}^{k,j,\xi}\leqslant c_l^{\xi,s}(\tau)$$
$$\forall l\in L_\tau,\forall\tau\in r,\forall\xi\in\Xi,\forall s\in S_\xi \tag{12}$$

$$x_{f,t,s}^{k,j,\xi}\in\{0,1\}$$
$$\forall f\in F,\forall k\in K_f,\forall j\in J_f,\forall t\in T_f^j,\forall\xi\in\Xi,\forall s\in S_\xi \tag{13}$$

$$z_{f,s}^{k,\xi}\in\{0,1\} \quad \forall f\in F,\forall k\in K_f,\forall\xi\in\Xi,\forall s\in S_\xi \tag{14}$$

To ensure that only one trajectory is chosen for each flight from the set of its submitted trajectory options (K_f), we present constraint (8) and revise the previous constraint (2) that extends the upper bound to the decision variable $z_f^{k,\xi}$. This suggests that we revise the feasible time window, and we present it in constraint (9). Constraint (10) remains the same as constraint (3) to represent the concept of time continuity. Similarly, constraint (11) is close to constraint (4) to keep the airborne flight time unchanged in the model. Constraint (12) realizes the demand all along exceeds the capacity under multiple capacity scenarios, with alternative trajectory options in consideration. Constraints (13) and (14) are binary constraints, which ensure the decision variable is binary.

4 Case Study

Numerical computations have been performed with respect to the two models. Eurocontrol's Demand Data Repository version 2 (DDR2) is used to demonstrate our study. Results have been compared between the two model variants through a three-stage optimization process (one day ago, at 12 pm and 6 pm) to illustrate how traffic flow optimization and airspace configuration scheduling are harmonized under capacity uncertainty.

4.1 Experimental setup

Consistent with our previous work, the experimental scenario is focused on the French airspace with 24 hours' traffic, which includes 6 255 planned flights, 15 ACCs, 1 511 configurations, 164 elementary sectors and 431 operating sectors. The airspace environment dataset is retrieved from the Eurocontrol DDR2 database in a typical day in February, 2017. An in-house trajectory planning tool is employed to generate trajectory data after calculating information related to the initial flight demand, meteorology, and hotspot avoidance. The unit time is set up to 1 min during computation. The maximum of grounding holding is set up to 60 min.

In the U-DCB model, the sector opening scheme has been already planned (according to the DDR2), and the number of concerned operating sectors is only 224 in total. For the UC-DCB model, the same airspace setting is utilized as in the DCB model, along with the modified strategy. With

86 time-varying hotspot areas identified, there are 1 305 lateral and 1 379 vertical alternative trajectories generated.

Other assumptions and parameters setting in the experiments are as follows: (1) The unit cost of delay α covers all time relevant delay costs and is constant (i.e., 5 €/min), which is also the same for different flights; (2) the unit cost of fuel consumption γ is 0.5 €/kg; (3) the route charges are calculated based on the previous data; (4) AUs are willing to share the detailed costs of their alternative trajectories; (5) the unit cost for the ANSP to open an operating sector δ for 60 min is 100 €; (6) the capacity overload is set to 10% on the extreme situation.

The time window is an important parameter to control the maximal delay that can be assigned to each flight in the U-DCB model and the UC-DCB model. It affects notably the problem dimensions, as presented in Tables 3, 4.

Table 3 Problem dimensions and computational times for U-DCB

Parameter	Stage 1	Stage 2	Stage 3-1	Stage 3-2
Variables	12 392 347	16 226 289	6 993 841	7 380 457
Equations	22 459 267	29 417 378	12 669 179	13 391 971
Non-zeros	47 518 810	62 197 655	26 747 825	28 253 683
Presolved variables	103 105	134 897	61 150	61 369
Presolved equations	159 193	208 674	95 215	95 328
MIP solution time/s	198.20	277.98	117.48	105.33
Final LP solution time/s	19.28	33.95	10.70	11.58
Presolve time/s	11.03	19.42	6.25	7.63
Time window/min	360			

Table 4 Problem dimensions and computational times for UC-DCB

Parameter	Stage 1	Stage 2	Stage 3-1	Stage 3-2
Variables	6 423 766	12 847 531	12 847 531	12 847 531
Equations	11 689 487	23 378 972	23 378 967	23 378 973
Non-zeros	24 715 157	49 429 943	49 428 909	49 430 313
Presolved variables	197 174	234 163	234 163	234 163
Presolved equations	5 469 395	358 171	358 149	358 140
MIP solution time/s	60.91	154.30	244.59	423.14
Final LP solution time/s	8.03	30.09	32.38	27.78
Presolve time/s	4.44	16.78	17.27	16.75
Time window/min	120			

In our experiment, GAMS v27.3 software is used as the modelling tool and cplex optimizer as the solver. The experiment is performed on a platform of the 11th Gen Intel(R) Core (TM) i5-1130G7 @ 1.10 GHz 1.80 GHz CPU computer with 16 GB of RAM and the Windows system. The schematic diagram of simulation is described in Fig.6.

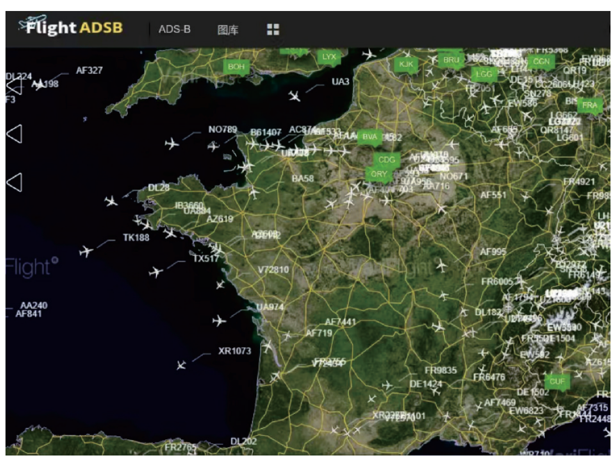
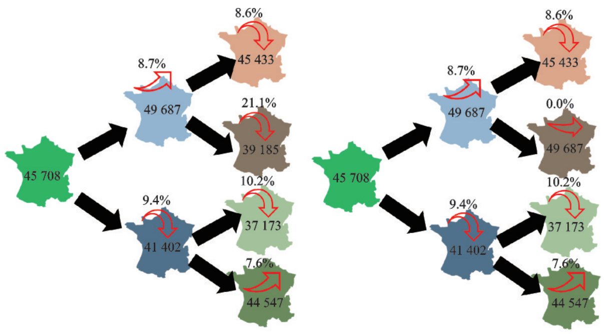


Fig.6 Large-scale experiment for a typical day on the French airspace (schematic diagram from Variflight)

The experiment involves seven scenarios, with each scenario corresponding to various capacity values. A process diagram is displayed in Fig.7 to illus-



(a) U-DCB experimental capacity scenarios (b) UC-DCB experimental capacity scenarios

Fig.7 Flow diagram of change of capacity scenarios

trate the design for capacity change. The values in small French airspace map represent the capacity value in each scenario.

The models' presolve time and solution time and other setting for U-DCB and UC-DCB are organized in Tables 3, 4. It can be observed that most of the computing effort has been spent to find an optimal solution. Tables 5, 6 exhibit the complete process of different optimization stages.

For U-DCB, the solution time reaches 22 s and 46 s compared to the initial stage of 53 s and the second stage of 111 s. With continuous optimization process, variables, equations and non-zeros reduce while the time window remains as 360 min. Generation time significantly reduces from 2 min to 0.03 s with the less variable at the follow-up stage. For the UC-DCB simulation, tendency nearly remains the same as U-DCB with less variable and equations at the follow-up stage, and the solution time and the generation time tend to be less compared to the upper stage.

Table 5 Overall result comparisons for the U-DCB model of seven scenarios

Parameter	Scenario 1	Scenario 2	Scenario 3	Scenario 4	Scenario 5	Scenario 6	Scenario 7
Total delays/min	185 263	59 103	111 435	5 775	14 607	28 344	14 612
Delayed flights	1 353	651	1 029	230	344	473	323
Initial trajectory				6 255			
Capacity provision	45 708	49 687	41 402	45 433	39 185	37 173	44 547
Opened sectors	1 098	1 098	1 098	1 098	1 098	1 098	1 098
Pre-demand(upper stage)	—	34 233	34 233	22 412	22 412	22 412	22 412
Post-demand	34 233	22 412	22 412	9 660	9 660	10 194	10 194
Capacity load/%	74.90	45.10	54.13	21.26	24.65	27.42	22.88

Table 6 Overall result comparisons for the UC-DCB model of seven scenarios

Parameter	Scenario 1	Scenario 2	Scenario 3	Scenario 4	Scenario 5	Scenario 6	Scenario 7
Total delays/min	3 287	2 157	10 836	5 350	22 301	68 518	14 080
Delayed flights	410	288	820	536	1 300	2 137	800
Initial trajectory				6 255			
Capacity provision	45 708	49 687	41 402	45 433	49 687	37 173	44 547
Opened sectors	1 098	1 098	1 098	1 098	1 098	1 098	1 098
Post-demand-o1	30 047	34 112	29 581	30 660	29 148	28 652	29 932
Post-demand-o2	1 696	1 107	2 156	1 451	2 574	2 966	2 015
Post-demand-o3	2 195	1 715	2 089	1 885	2 008	2 079	1 979
Capacity load/%	65.74	68.65	71.45	67.48	58.66	77.08	67.19

4.2 Comparison of model results

The results of main indicators are presented in Tables 5, 6. For the U-DCB model, ground holding is only a strategy to balance between capacity and demand, which in a sense, requires a huge number of delays. This is mainly because we enforce constraints in all operating sectors, which is not in line with the real case. For the change of scenario 1 to scenario 2 and scenario 3, the capacity goes up to 108.7% and down to 90.6%, respectively, and total delayed flights and total delays respond to such change, with total delays from 185 263 min to

59 103 min from scenario 1 to scenario 2. Same as our intuition, the capacity increase releases much more resources which play a vital role in delay assignments strategy. For stage 1, because it executes DCB from the beginning of the selected day, more flights are planned to receive the assigned slots. For stage 2, the focus is placed on scenario 2 and scenario 3, with some flights already taking off, especially the morning flights. Compared with stage 3, total delays and delayed flights are further reduced to 5 775 min and 230 flights on scenario 4, 14 607 min and 344 flights on scenario 5, 28 344 min and 473 flights on scenario 6 as well as 14 612 min and 323 flights on scenario 6. The reason is similar to the first comparison, however departure of flights tends to be more in this stage. The results echo our intuition that the potentially optimization space becomes less since much more flights have departed with multi-stage optimization process moving forward. For different capacity scenarios, more delays must be enforced if capacity is reduced. The results have proven that our model is beneficial. In our study, the baseline DCB model is evolved to U-DCB model to achieve a "precise" optimization process through various stages.

Notably, the opened sectors remain the same as the sector reduction strategy is not considered in our model. The capacity load reduces from stage 1 to stage 3.

The UC-DCB experiment is different from the U-DCB. Although the capacity provision is nearly the same as that of U-DCB (except for scenario 5), the results of post-demand are diverse compared to U-DCB model. More flights choose o2(the alternative route 2) or o3 (the alternative route 3) route from stage 1 to stage 3, while less flights choose o1 route (the original route). Meanwhile, total delays and total delayed flights increase, which is inconsistent with the U-DCB process. The most possible reason is that, in the UC-DCB experiment, our model considers not only the assigning delay strategy, but also trajectory options with the objective of minimizing the systems delays and consumption costs. In this way , flights should determine the lowest cost way to choose a trajectory. Therefore, the UC-DCB leads to more delays on the ground on the follow-up stage because there are already more flights in the route, making subsequent flights more difficult to choose a proper route. The second reason may be the capacity. For scenario 6 and scenario 7, capacity is reduced, which may lead to scarcity of resources.

4.3 Demand and capacity situations

With the above analysis, we further present specific analysis of demand and capacity situations in Figs.8—10.

In Fig.8, imbalance of demand and capacity is remarkably improved when executing the DCB model or C-DCB model. Before optimization of our model, the initial situation is that demand on some sectors exceeds its capacity. After the DCB implementation, a more balance on the demand and capacity can be achieved. The part where demand exceeds the capacity is optimized through the ground delay program. Simultaneously, demand and capacity reach balancing after C-DCB optimization, which is

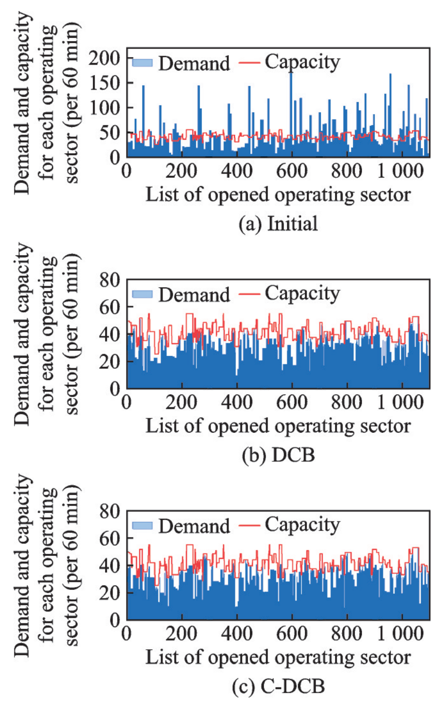
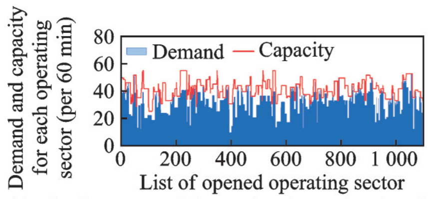
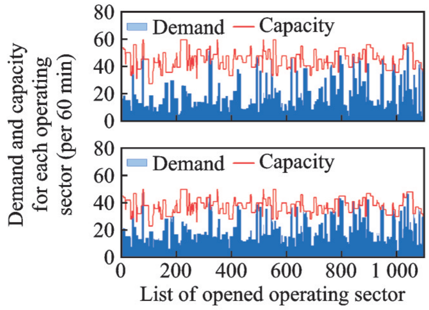


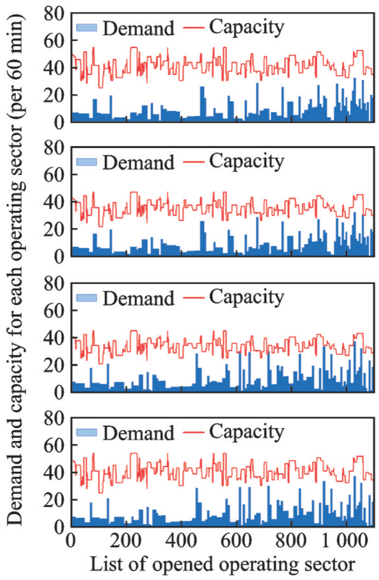
Fig.8 Demand and capacity situations (for each operating sector across the day) with respect to the initial case (i.e., pre-regulation) and the second models after execution (i.e., post-regulation)



(a) The first stage of demand and capacity situations (for each operating sector) with respect to the U-DCB

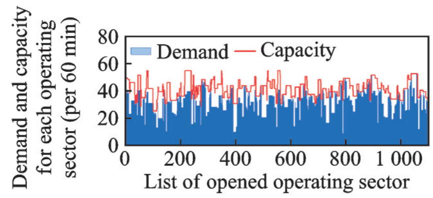


(b) The second stage of demand and capacity situations (for each operating sector) with respect to the U-DCB

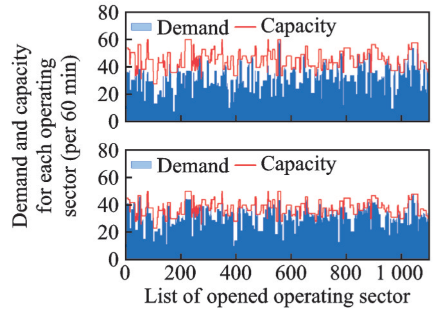


(c) The third stage of demand and capacity situations (for each operating sector) with respect to the U-DCB

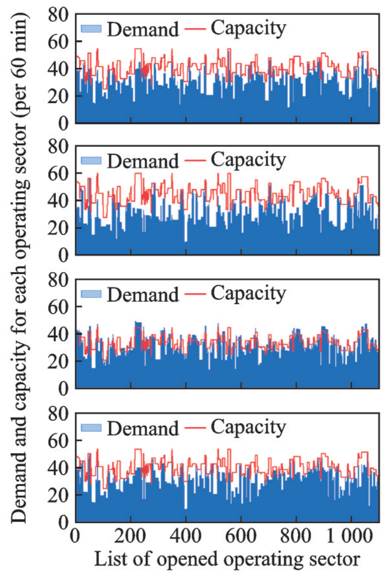
Fig.9 Demand and capacity situations (for each operating sector across the day) with respect to the U-DCB and the seven scenarios results after execution



(a) The first stage of demand and capacity situations (for each operating sector) with respect to the UC-DCB



(b) The second stage of demand and capacity situations (for each operating sector) with respect to the UC-DCB



(c) The third stage of demand and capacity situations (for each operating sector) with respect to the UC-DCB

Fig.10 Demand and capacity situations (for each operating sector across the day) with respect to the UC-DCB and the seven scenarios results after execution

mentioned in our previous work. In Fig.9, by updating DCB to U-DCB, the better demand and capacity balancing at all stages can be realized. Demand reduces with departure of more flights already and demand and capacity balancing is successfully accomplished on each scenario though different scenarios match diverse capacities. Moreover, demand and capacity balancing is also accomplished when conducting another trajectory options strategy with dynamic optimization method of probabilistic scenario trees. The large-scale experiment shows the proposed method can be applied to national-scale air traffic flow management.

Finally, we present the improvement of capacity load for U-DCB model with seven scenarios from stage 1 to stage 3 in Fig.11, which explains capacity load distribution for 1 098 sectors. Notably, not only the average capacity load decreases, but also most of the sectors (75%) in stage 3 have their capacity loads less than 30%. This number for stage 2 is greater than 30%. On the other side, most of sectors in the U-DCB model at stage 3 appear a capacity load less than 10% (with a limited 0% cases), which is fairly low, and sometimes is an unexpected from the aspect of safety.

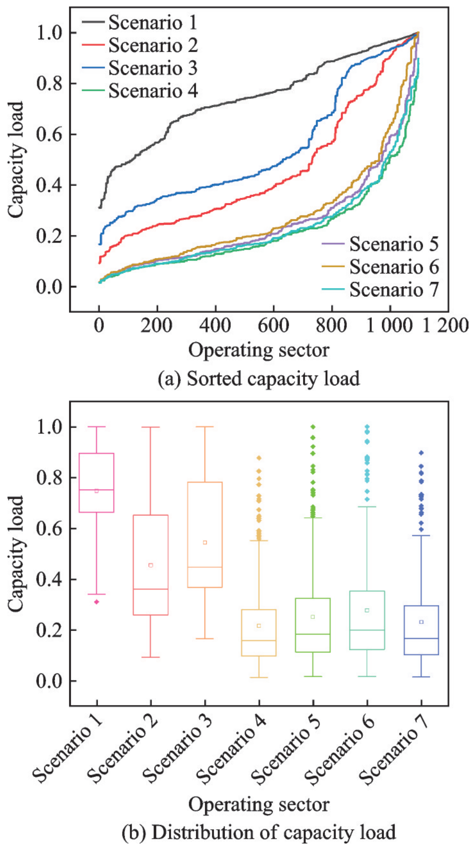


Fig.11 Final capacity load (i.e., demand and capacity ratio) in seven scenarios

4.4 Comparative experiment

For further improvement, a comparative experiment is conducted in this section. In a prior study, scenario tree was used to define the uncertainty in sector capacity. For comparison, a probability distribution function is used to address the uncertainty in capacity. With the simulation of a probability distribution, a chance-constrained method of optimization is used to set the equation in a certainty probability. To be more specific, the probability of airspace capacity is simulated, the mean value is set to zero, and the standard deviation is set to 0.033. The overview of probability distribution of capacity is shown in Fig.12. In this case, the capacity constraint is established and a certain probability should be satisfied for the capacity constraint. The comparative results are shown in Table 7.

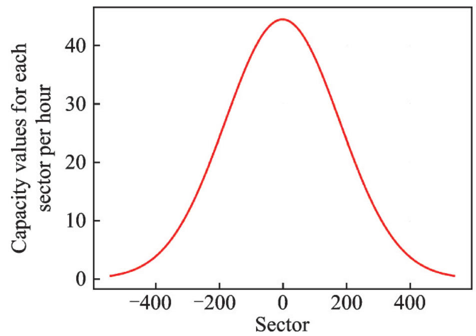


Fig.12 Curve of simulated capacity distribution

Table 7 Comparative results

Parameter	Scenario tree to solve UC-DCB	Probability distribution function to solve UC-DCB
Total delay/min	3 287	3 412
Delayed flights	410	423
Initial trajectory	6 255	
Capacity	45 708	45 708
Total solution time	17 min	13 s

In this comparative experiment, it is unexpected to find out that if probability distribution function is used to solve UC-DCB model, the total delays and delayed flights will increase. To balance demand with capacity, it is necessary to delay more flights on the ground. The use of scenario tree to calculate simple multiple scenarios would lead to a better solution even in case of a large-scale ATFM problem. However, scenario tree method has an obvious disadvantage in total solution time. In our comparative experiment, it takes 17 min to find the optimal solution if scenario tree is used to solve UC-DCB. In comparison, it takes only 13 s when probability distribution function is used. The results illustrate the need to conduct future study for improvement.

5 Conclusions

We demonstrate a dynamic multi-stage approach of probabilistic scenario trees with a collaborative ATFM strategy, by mainly considering the uncertainty in capacity. The enhanced model can copy with more complex scenarios, which is more appropriate to real-world situations. The traffic regulation initiatives are incorporated into our centralized optimization model with the specific strategy (assigning ground holding and alternative trajectory options). Comparing the results from our previous work, delayed flights and total delays reduce significantly with baseline DCB model, realizing demand and capacity balancing on each scenario, which shows the improvement to our previous work. More meaningfully, our experiment is the first to tackle large-scale instances of stochastic ATFM problems within a collaborative ATFM framework.

The main contributions of this research include not only making the previous work more complete. More importantly, the DCB model and the C-DCB model are finally updated to stochastic programming model U-DCB and UC-DCB, which is consistent to the concept of trajectory option set (TOS) in Collaborative Trajectory Options Program (CTOP). The paper underlines future development of ATFM and ATM, and provides guidance for "precise" flow management in the future operation concept.

However, more improvement may be needed in the future. The aim of this research is to better balance the demand and capacity in a more harmonized way. Additionally, the scenario structure will definitely become more complex if more scenarios are considered. This problem can be addressed in a follow-up work. Moreover, more experiments can be conducted in the future to make our study more complete. It is expected that scenario probabilities may be determined more realistically, and different kinds of uncertainty sources along with sector capacity can be taken into account using the scenario optimization approach. Flight demand is also an uncertain element in ATFM and can be considered in future research.

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容量不确定性下空中交通流量管理的需求与容量平衡

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摘要：引入了一种创新方法，实现了协同空中交通流量管理框架下扇区容量不确定性的需求与容量平衡。受极端天气、空军活动、管制员工作负荷等不可忽视的隐性因素影响，空域容量具有不确定性，进而影响流量管理优化结果。本文重点研究了扇区容量不确定性对需求与容量平衡优化，以及对空中交通流量管理优化的影响。在协同流量管理框架下实施多种策略，如延误指派和改航绕飞等管理交通流。进而提出了一种场景优化方法解决扇区容量的不确定性。结果显示，所提方法可以实现更好的需求与容量的平衡，并在空中交通流量管理问题中得到近似最优解，解决大规模的流量优化实例（24 h下的7个容量场景，6 255个航班以及8 949条航迹）只需要5～15 min。本文实验计算是已知的首次在协同流量管理框架下解决大规模随机性空中交通流量管理问题的有效实例。

关键词：空中交通流量管理；需求与容量平衡；航班延误；扇区容量不确定性；地面等待；场景决策树