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METHODS FOR SOLVING SOME PROBLEMS OF AIR TRAFFIC PLANNING AND REGULATION. PART I: Strategic Planning of 4D Trajectories

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Abstract: This paper considers the problems of improving the safety and efficiency of air traffic flows. Particular attention is paid to promising methods for detecting and resolving aircraft conflicts. These methods are classified. We study the problem of minimizing the number of potential conflicts with a promising air traffic control technology, the strategic deconfliction of 4D trajectories. We present a mathematical model to consider uncertainty in the strategic deconfliction of 4D trajectories, a corresponding formal statement as a mixed integer programming problem, and some approaches to solve this problem. Estimating the objective function requires calculating the number of potential conflicts between aircraft. Under uncertainty, this estimation involves a large amount of computations. We discuss an alternative approach to airspace capacity estimation based on air traffic complexity depending on the traffic structure and geometry of the airspace.

Keywords: air traffic management, strategic deconfliction of 4D trajectories, detection and resolution of aircraft conflicts.

INTRODUCTION

The expected growth of air traffic flows requires improving the air traffic management (ATM) system. The NextGen [1] and SESAR [2] projects are being implemented in the United States and Europe, respectively, to develop and adopt new ATM concepts. The strategic planning of 4D trajectories (three spatial coordinates and time) and keeping the assigned 4D trajectories with high accuracy by automated flight control systems will underlie the new ATM organization. This approach is expected to increase airspace capacity and the degree of automation of air traffic controllers with a high level of flight safety.

The main function of ATM systems is the separation of aircraft to ensure safe air traffic and detect and resolve aircraft conflicts. The following prescribed distances between aircraft must be observed outside airports: N_v (vertical separation) and N_h (horizontal separation). The airspace bounded by a cylinder around an aircraft (Fig. 1) should not contain other aircraft; otherwise, the aircraft are considered to be in potential conflict because the required minimum separation distance between them is violated.

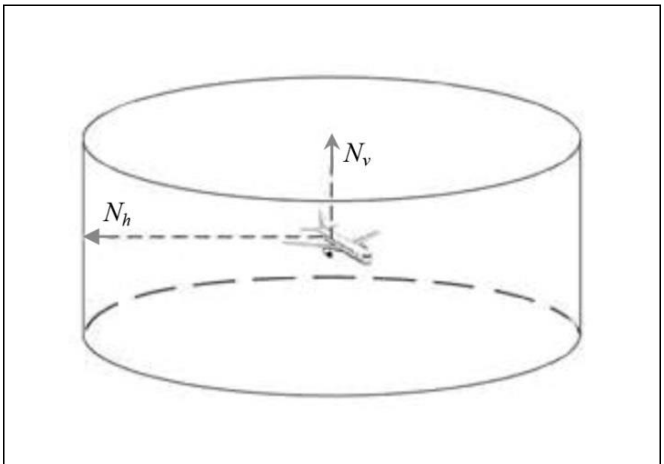

Fig. 1. A bounded space around the aircraft without other aircraft.

The concept of trajectory specification [3] was proposed during the development of ATM automation projects. Here, the basic idea is to limit the aircraft position at any flight time to a required volume of airspace. This space is defined by admissible deviations from a given reference 4D trajectory. Such deviations are dynamic and depend on the aircraft's flight characteristics and the flight situation. While all aircraft are within the admissible deviations from their reference trajectories, they have safe separation even in the case of failures in the ATM or data transmission systems on a calculated conflict-free horizon. This horizon is about 10–15 minutes.

The concept of trajectory specification should combine a ground component of the ATM system and an onboard flight control component. The onboard component forecasts a conflict-free trajectory considering aircraft flight parameters and the trajectories of surrounding aircraft. The forecasted trajectory is transmitted to the ground component and checked for potential conflicts with the currently assigned trajectories of other flights; if necessary, the forecasted trajectory is changed to resolve conflicts and is then transmitted back to the onboard component as its assigned trajectory [4].

In strategic planning, potential aircraft conflicts must be resolved in advance to avoid real-time tactical control due to an unexpected deviation from the assigned trajectory on the route.

This survey classifies conflict detection and resolution methods used in the existing ATM automation systems. We consider different approaches to minimizing the number of potential aircraft conflicts, including those with aircraft position uncertainty. For large-scale strategic trajectory planning in the European airspace, it is proposed to decrease air traffic complexity to reduce the computational complexity instead of calculating the numbers of aircraft and their potential conflicts. The capacity of large airports is a bottleneck of ATM systems. In this regard, a topical problem is to optimize the aircraft landing sequence: it will increase the efficiency of using the available infrastructure. Part II of the survey will cover a novel approach to these problems based on deep reinforcement learning.

1. CONFLICT DETECTION AND RESOLUTION METHODS

In manned aviation, a safe separation between aircraft is guaranteed by air traffic controllers. The Traffic alert and Collision Avoidance System (TCAS) is used onboard to prevent dangerous situations, and the Ground Proximity Warning System (GPWS) is used to warn pilots of the potential collision with the ground or another obstacle.

Many research works were devoted to automating safe separation between aircraft and the corresponding methods. A central problem in these methods is the need to forecast aircraft trajectories. When predicting potential aircraft conflicts, it is necessary to consider random factors. Therefore, random processes-based methods were proposed for detecting potential conflicts of aircraft pairs; for details, see [5, 6]. For more complex air traffic scenarios, an interacting particle system algorithm was presented in [7]. The paper [8] considered aircraft conflict detection as a binary classification problem for the conflicts of several aircraft in free flight with arbitrarily chosen trajectories and speeds. The authors proposed a method for predicting conflicts in the short and medium term using pattern recognition.

The paper [9] compared over 100 conflict detection and resolution methods for manned and unmanned aircraft. The following conflict detection categories were introduced (Table 1).

Table 1

Categories of conflict detection methods

Surveillance	Centralized dependent Distributed dependent Independent
Trajectory propagation	State-Based Intent-Based
Predictability assumptions	Nominal Worst-Case Probabilistic

Aircraft surveillance can be centralized (through ATM systems from the ground) or distributed. In distributed dependent surveillance, the aircraft exchange their parameters (position, altitude, and identification data) via the Automatic Dependent Surveillance Broadcast (ADS-B) data channel without any intervention from the ground systems. Unmanned aerial vehicles use independent surveillance for static and dynamic obstacle detection (airborne systems and sensors not interacting with each other).

The future trajectories of an aircraft can be forecasted using their current state (state-based) or their nominal trajectories (intent-based). State-based trajectory propagation assumes a straight-line projection of the current aircraft position and velocity vector. However, if the future trajectory changes of all the aircraft involved are ignored, false alarms may occur and possible conflicts may be overlooked.

Future aircraft positions can be estimated using the nominal, worst-case, or probabilistic assumptions. The nominal estimate neglects uncertainties (i.e., the behavior of other aircraft or wind) and is generated for a short period. The worst-case estimate considers all possible trajectory changes due to uncertainties. However, this estimate is impractical in a real environment: it causes a lot of computations and many false alarms and, moreover, reduces the space for maneuvering. The probabilistic estimate is often employed instead. In this case, the probability of each possible trajectory change is considered based on the current position and the maximum turn and climb rates.

The conflict resolution categories are combined in Table 2.

Separation management (control) may be centralized or distributed. A centralized system provides a global solution to complex multi-actor problems. In manned aviation, ATM ensures centralized traffic safety. In a distributed system, separation is provided by individual aircraft. In a distributed conflict avoidance system, each aircraft considers neighboring aircraft only. Hence, this system is expected to have lower computational complexity. The growing number of unmanned aircraft is contributing to the development of distributed approaches as well. The main disadvantage of a distributed system is no global coordination for the surrounding traffic, which may negatively affect safety. As expected, introducing the ADS-B technology will guarantee safe aircraft separation in the air by a distributed conflict resolution system.

Centralized methods have two main categories: exact and heuristic (metaheuristic). The exact solution is often found using mixed integer linear programming. The first exact approach to global optimization was presented in 2002; see [10]. Two mixed integer linear programming models were proposed therein, the first one based on speed control and the second on heading control. The paper [11] introduced a two-stage approach in which the maximum number of conflicts is first resolved by speed control, and the remaining conflicts are resolved by direction control. The publication [12] reviewed the literature on exact approaches to conflict resolution. As emphasized by the authors, "… Mathematical Programming has a lot to say in the development of decision support tools for ATM, and, in particular, for aircraft deconfliction. However, after several decades of effort, current approaches still suffer from important limitations when it comes to their real application. ... Future approaches, other than meeting computational requirements due to the online nature of the problem, would need to consider a larger set of features than those of the models discussed here. These include, among others, the ability to handle uncertainty, accurate modeling of objectives such as energy consumption, robustness of the solution against failure, and integration with weather conditions."

An exact algorithm needs a high computing time, which makes it inapplicable in real life. Heuristic (metaheuristic) algorithms, although not guaranteeing optimality, are often employed to reduce execution times. Commonly used heuristic (metaheuristic) approaches include Variable Neighborhood Search (VNS) [13], Ant Colony Optimization [14], and Evolutionary Algorithms [15].

Distributed approaches have three main categories: prescribed, reactive, and explicitly negotiated. In the prescribed category, movement is coordinated in accordance with a pre-defined set of rules. In reactive methods, the maneuvering strategy is determined by the geometry of the conflict. Resolution methods in the explicitly negotiated category resolve conflicts based on explicit communication between aircraft [16]. However, in any negotiation, there is the risk of a deadlock, where aircraft communicate indefinitely without reaching an agreement. The number of interactions must be limited so that the aircraft cannot negotiate too long or wait indefinitely for data from another aircraft.

Table 2

Conflict resolution categories

Control	Method categories	Multi-Actor conflict resolution
Centralized	Exact Heuristic	Sequential Concurrent
Distributed	Prescribed Reactive Explicitly negotiated	Pairwise sequential Pairwise summed Joint solution

Table 3 presents the main features of conflict resolution maneuvers between the AFs.

Table 3

Conflict resolution maneuvering categories

Avoidance planning	Strategic Tactical Escape
Avoidance maneuver	Heading Speed Vertical Flight plan
Obstacle	Static Dynamic All
Optimization	Flight path Flight time Fuel/energy consumption

Depending on the time for which the avoidance maneuver is planned, forecasting can be:

– strategic (a long-range action that significantly changes the flight trajectory);

– tactical (a mid-range action that changes a small part of the flight trajectory);

– escape (a short-term maneuver that takes the aircraft to a safe location without additional consideration of the flight path).

Maneuvers to keep the necessary separation between aircraft can be based on changing the current heading, speed, altitude, or flight plan. The number of maneuvers performed and the deviation from the original trajectory should be minimal; the solution must be found within the available time before losing the minimum aircraft separation.

As stated in [9], most models currently include tactical planning, distributed control, and nominal trajectory propagation based on the current state of all aircraft involved. How do the existing methods work in particular traffic scenarios? The answer to this question is needed to determine further ways to improve the methods.

2. MINIMIZING THE NUMBER OF POTENTIAL CONFLICTS

2.1. An aircraft position uncertainty model

Consider discretized 4D trajectories, i.e., sequences of 4D coordinates describing the aircraft trajectory: (x, y, z, t), where x, y, and z are latitude, longitude, and altitude, and t denotes time.

The aircraft trajectory can be affected by many random factors (e.g., wind) as well as tracking, navigation, and control errors.

For strategic trajectory planning, the authors [17] modeled the aircraft position with the uncertainty in the horizontal plane along the trajectory. In addition to the horizontal uncertainty, the same authors [18] considered the uncertainties of flight altitude and the arrival time at a given point.

The mathematical model of the aircraft position uncertainty has the following form (Fig. 2).

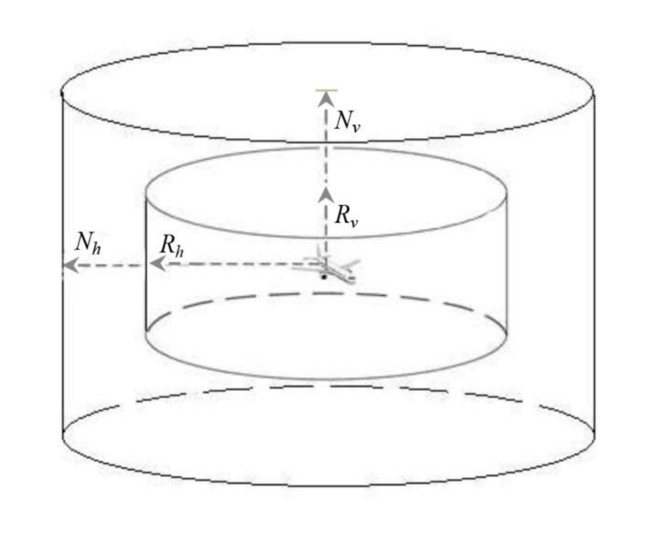

Fig. 2. A bounded space around the aircraft with uncertainty.

Due to the uncertainty, at a time *t*, the aircraft can be in a circle of a given radius R_h with the center (x, y) in the horizontal plane:

$$\left\{\left(x^r, y^r\right) : \left(x^r - x\right)^2 + \left(y^r - y\right)^2 \le R_h^{\,2}\right\}.$$

Therefore, the radius of safe minimum separation of the aircraft in the horizontal plane increases by the radius of uncertainty:

$$N_h^r = N_h + R_h.$$

Similarly, the uncertainty of the aircraft position in the vertical plane is determined by the radius of uncertainty R_v:

$$\left|z - z^r\right| \le R_v .$$

Thus, the safe minimum separation distance in the vertical plane considering the uncertainty is

$$N_v^r = N_v + R_v .$$

The arrival time uncertainty is determined by t_E, the maximum time error.

The real arrival time t^r considering the uncertainty belongs to the following interval:

$$t^r \in [t - t_E, t + t_E].$$

Given the uncertainty, a potential conflict between trajectories α and β may arise if the three conditions

- $\sqrt{(x_P - x_Q)^2 + (y_P - y_Q)^2} < N_h^r$,
- $|z_P - z_Q| < N_v^r$,
- $|t_P - t_Q| < 2t_E$,

hold at points $P = (x_P, y_P, z_P, t_P)$ and $Q = (x_Q, y_Q, z_Q, t_Q)$ on these trajectories.

Figure 3 shows the intersection of trajectories in the horizontal plane.

Figure 4 presents possible trajectory intersection scenario for aircraft α and β in time. The upper time axis corresponds to the arrival time of aircraft α at point *P*. Below are four possible positions of aircraft β on the time axis of its arrival at point *Q*. In cases a) and b), a potential conflict is possible, unlike cases c) and d).

The set of uncertainties implicitly describes all possible aircraft interaction scenarios (the worst-case approach).

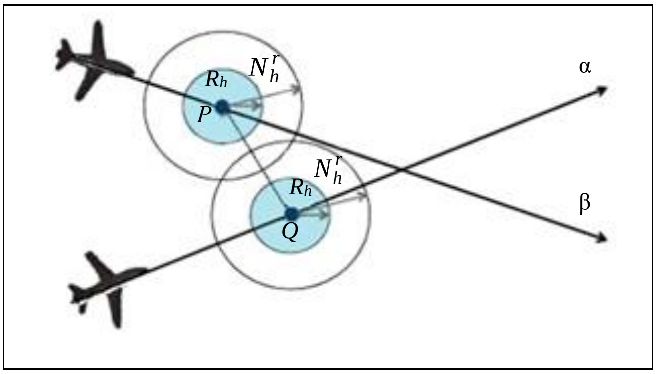

Fig. 3. The intersection of trajectories in the horizontal plane.

The problem of minimizing the number of potential conflicts in strategic trajectory planning consists in the following. Consider a set of all 4D flight trajectories for a given day on the national or continental scale. For each flight, known data include:

- the set of possible routes in the horizontal plane,
- the set of possible altitudes,
- the set of possible departure times,
- the parameters of the uncertainty of the aircraft position and arrival time.

Potential conflicts between aircraft can be resolved in different ways: by changing departure times, speeds, flight altitudes or horizontal trajectories of the aircraft involved in the conflict, or by combining these methods.

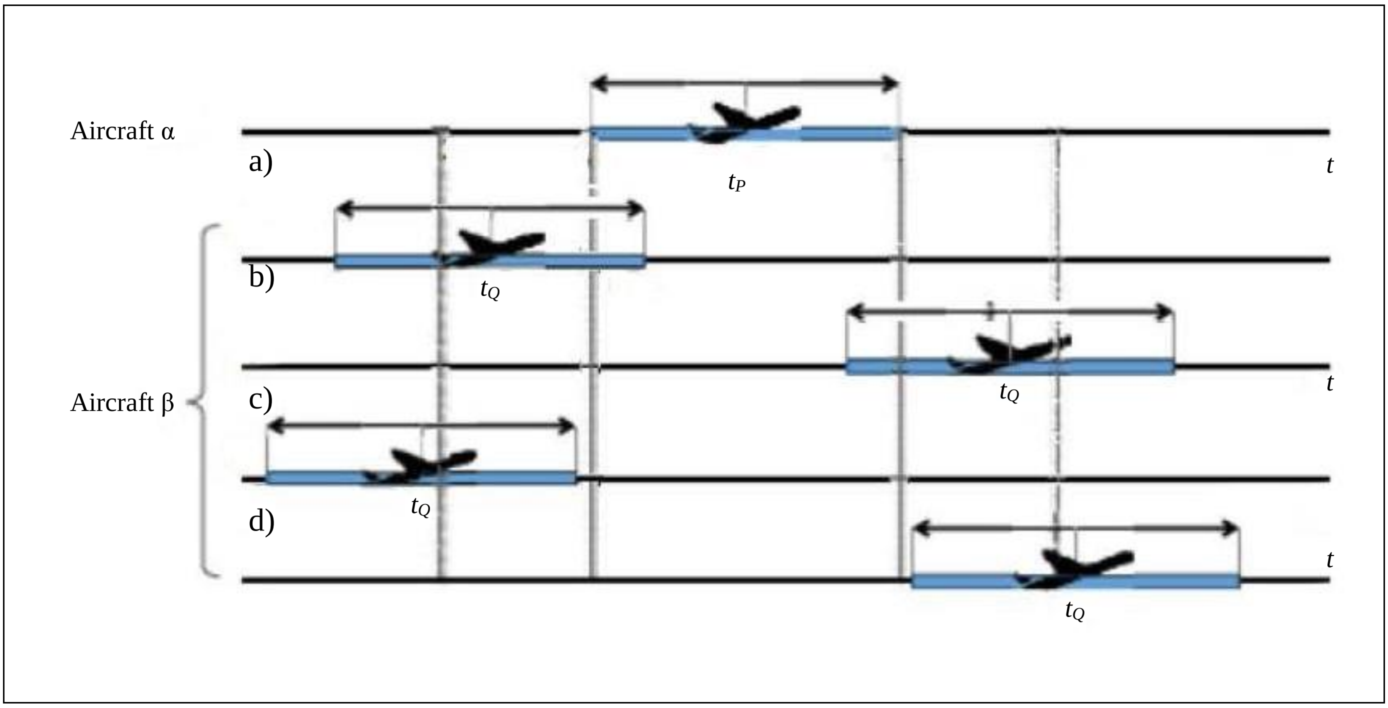

Fig. 4. Possible trajectory intersection scenarios in time.

The goal is to find an alternative set of 4D trajectories with the minimum number of potential conflicts.

The problem of minimizing the number of potential conflicts was formalized as mixed integer linear and nonlinear programming problems. However, due to a large number of conflicts, variables, and constraints, high memory and computation time requirements prevent from obtaining optimal solutions. As a result, different approaches and heuristic methods were proposed for approximate solution of the problem.

2.2. Minimizing the number of potential airspace conflicts by changing departure times

When organizing air traffic, the capacity constraints of airspace sectors along the route (the maximum number of aircraft entering the sector in a given period) must be satisfied.

One of the easiest ways to reduce the load on the ATM system is to shift flights if the capacity constraints of the airspace sectors on the route are exceeded. However, flight shifts may cause problems for airlines, so they should be minimized.

The paper [19] proposed a departure time correction approach based on modeling possible conflicts between any two aircraft and resolving all conflicts instead of satisfying the sector capacity constraints. However, the necessary separation between the aircraft will remain only if the aircraft can accurately follow the planned 4D trajectories. When the uncertainty of departure and navigation times is introduced, the number of required shifts increases rapidly, so other methods of minimizing the number of potential conflicts are also needed.

2.3. Minimizing the number of potential conflicts by speed regulation

The authors [20] studied the possibility of minimizing the number of potential conflicts based on speed regulation in a small range (from –6% to +3% of the initial speed) along the initial aircraft trajectories. Two mixed integer optimization models for resolving potential aircraft conflicts based on speed regulation were proposed, and the solution yielded by the general COUENNE solver was discussed in [21]. However, for large dimensions of the problem, high memory and time requirements prevent from obtaining optimal solutions. The authors presented a heuristic procedure to calculate a solution of satisfactory quality by decomposing the problem into subproblems with a small number of aircraft for which an optimal solution can be computed. The concept of a cluster was introduced in [22]. It involves the assumption that in real situations, only small aircraft groups with close trajectories potentially come into conflict among all the trajectories of numerous aircraft. Then such local solutions are combined.

2.4. Minimizing the number of potential airspace conflicts by changing the planned trajectory in the horizontal plane

The paper [23] proposed a method for changing the originally planned trajectories in the horizontal plane to minimize the number of potential conflicts. The trajectory of aircraft $i = 1, \ldots, N$ is changed by adding M waypoints uniformly arranged along it (Fig. 5):

$$w = \{w_i^j\},\ j = 1, \ldots, M.$$

At these points, the aircraft is supposed to deviate laterally from the original trajectory.

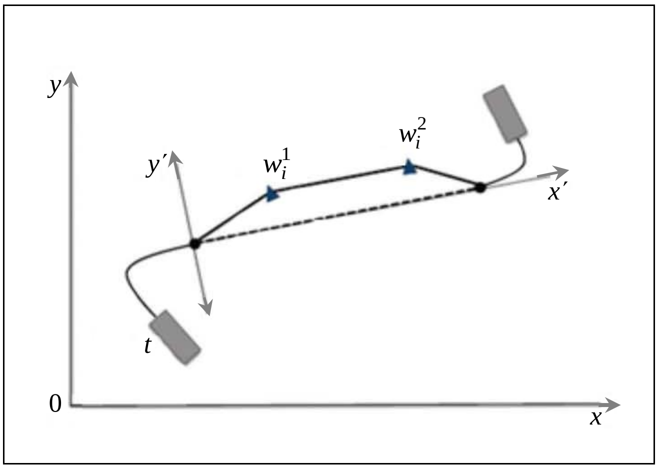

Fig. 5. Additional waypoints.

To avoid sharp turns, the virtual waypoints should not be placed very close to each other.

The lateral deviation is limited so that the route length will not exceed given thresholds. For example, in the case of M = 2 virtual waypoints and K = 7 admissible deviations, we obtain 7^2 = 49 possible routes (Fig. 6).

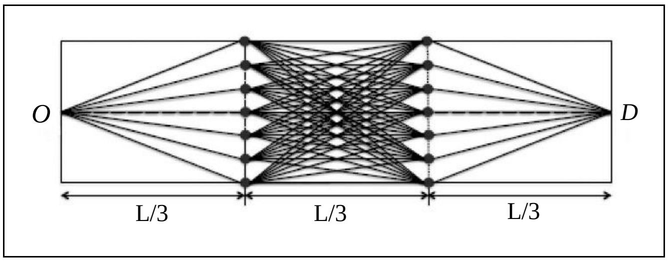

Fig. 6. Possible routes.

The maximum admissible lateral deviation is limited so that the increase in the length of the original trajectory will not exceed a user threshold within the range $w_{i,y}^{j} \in [-a_i, a_i]$, where $w_{i,y}^{j}$ denotes the coordinate *y* of the *j*th virtual waypoint.

2.5. Stating the mixed integer programming problem

The number of potential conflicts among *N* discretized 4D trajectories of aircraft can be minimized by solving a mixed integer programming problem [18].

The solution variables are represented as

$$u = (\delta, \omega, l)$$

with the following notations: $\delta = (\delta_1, \delta_2, \ldots, \delta_N)$, where δ_i is the departure time shift, chosen from a uniformly discretized interval $[\delta_{i,\min}, \delta_{i,\max}]$; $t_i = t_{i,0} + \delta_i$ is the departure time of aircraft *i*, where $t_{i,0}$ is the planned departure time; $\omega = (\omega_1, \omega_2, \ldots, \omega_N)$, where ω_i is the coordinates of additional waypoints; $l = (l_1, l_2, \ldots, l_N)$, where l_i is the altitude shift of aircraft *i*; $i = \overline{1, N}$.

Let $\Phi_i(u)$ be the number of potential conflicts encountered by aircraft *i*. The problem is to minimize the total number of potential conflicts, i.e., the objective function

$$\sum_{i=1}^{N} \Phi_i(u).$$

Due to the noncontinuous solution space, the solution time grows exponentially with increasing the problem dimension *N*. In addition, the solution variables are not independent because of interactions between flights.

This combinatorial optimization problem is *NP*-hard.

To estimate the objective function, it is necessary to detect potential aircraft conflicts. Detecting conflicts between trajectories with tolerances requires significantly more computation than without them. For nonzero tolerances, at any given time, each point in the bounded airspace for one flight must be at a sufficient distance from each point in the bounded airspace for another flight. Conflict detection algorithms must operate almost in real time.

An effective conflict detection algorithm should avoid unnecessary calculations when the separation between the aircraft is much greater than the minimum value (either vertically, horizontally, or temporally).

A conflict detection scheme based on airspace discretization using a 4D spatiotemporal grid was proposed in [23]. This grid is a series of 3D grids with time discretization (Fig. 7).

The size of the grid cells is determined by the separation norms of the aircraft in the corresponding measurements. The aircraft position is associated with the corresponding cell in the 4D grid. Each cell in this grid has 3^3 = 27 neighbor cells, including the cell itself. Potential conflicts can be detected by checking 27 neighbor cells for each non-empty cell of the grid.

A potential conflict is detected if either one cell is occupied by different aircraft or neighbor cells are occupied by different aircraft.

The authors [24] implemented a conflict detection algorithm on a graphics processing unit (GPU). As declared, the algorithm reduces the computation time by two orders of magnitude compared to the CPU-based implementation.

2.6. Estimating air traffic complexity

An alternative approach to estimating airspace capacity can be related not to the number of aircraft and their conflicts but air traffic complexity. It depends on the traffic structure and the geometry of the airspace [25].

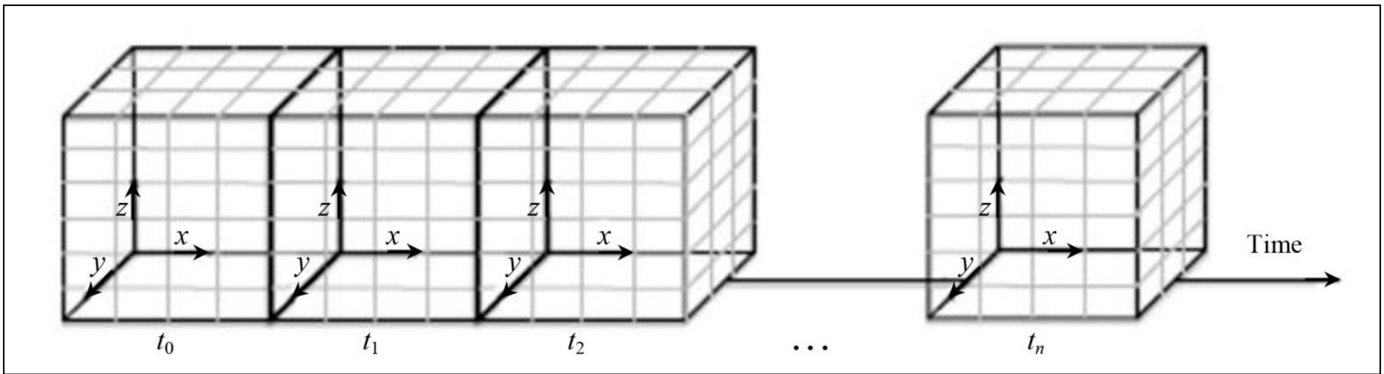

Fig. 7. Airspace discretization.

The complexity index based on a linear dynamic system is adapted to estimate traffic congestion over a complete horizon. Traffic complexity in the current flight situation can be measured using the vectors of aircraft position and speed instead of simply calculating the number of aircraft.

Assume that at a given time, there are several aircraft in a given area. For each aircraft, we consider two observation vectors: the position measurement $X_i = \left[x_i\, y_i\, z_i\right]^{\mathrm{T}}$ and the speed measurement $V_i = \left[v_{x_i}\, v_{y_i}\, v_{z_i}\right]^{\mathrm{T}}$.

To calculate the local complexity in the current flight situation, we represent it as a linear dynamic system. The motion equation has the form

$$\dot{X}_i = AX_i + B$$

with the following notations: $\dot{X}_i$ is the estimated velocity vector associated with each point in the state space; X_i is the position vector; the coefficient matrix A is a linear mapping from $\dot{X}_i$ into X_i; finally, the vector B describes the static behavior of the system.

To determine the exact dynamic system best matching the observations in the state space, it is necessary to find a matrix A and a vector B that minimize the error between the velocity observations and the estimated velocity vectors.

The detailed calculation of the matrix A and vector B was described in [26].

Based on the matrix A and its eigenvalues, the local complexity metric is defined as follows:

- The metric is the sum of the absolute values of the negative real parts of the eigenvalues.
- If none of the eigenvalues has a negative real part, the metric will be zero.

This metric characterizes the intensity of the convergence trend in the current flight situation at a given time.

If the metric is zero, then the complexity is zero; hence, diverging aircraft will not lead to air traffic conflicts. A non-zero value of this metric indicates of a risk of potential conflicts: a higher value means a greater level of risk.

Consider the local complexity metric $\psi_{i,k}$ for the ith aircraft on the kth trajectory sample. To obtain it, the process begins with determining the air traffic situation around the ith aircraft by considering the neighbor aircraft in the horizontal and vertical planes. The speeds and positions of neighbor aircraft are considered to calculate the local complexity metric.

We denote by

$$\Lambda_{i,k} = \left\{\lambda_{i,k}^{(1)}, \lambda_{i,k}^{(2)}, \ldots, \lambda_{i,k}^{(N_e)}\right\}$$

the set of eigenvalues of the matrix A for the ith aircraft on the kth trajectory sample. Then

$$\psi_{i,k} = \sum_{n \in \mathcal{N}} |\operatorname{Re}\{\lambda_{i,k}^{(n)}|, \mathcal{N} = \left\{n : \operatorname{Re}\left\{\lambda_{i,k}^{(n)}\right\} < 0\right\}.$$

The local complexity along the trajectory of the ith aircraft is given by

$$\psi_i = \sum_{k=1}^{N_i} \psi_{i,k},$$

where N_i denotes the number of trajectory samples for the ith aircraft.

The total complexity for all aircraft in the airspace is calculated as follows:

$$\psi = \sum_{i=1}^{N} \psi_i = \sum_{i=1}^{N} \sum_{k=1}^{N_i} \psi_{i,k}.$$

2.7. A hybrid metaheuristic approach to the problem

The paper [18] proposed a simulated annealing algorithm to minimize the number of potential aircraft conflicts. However, it requires very many estimates of the objective function and, consequently, a huge amount of computations. A local heuristic search method was integrated into the simulated annealing method to accelerate convergence.

The hybrid metaheuristic approach is based on the classical simulated annealing algorithm and two different local search modules. Local search activates search around a potential candidate solution; simulated annealing allows exploring the solution space with avoiding local minima by allowing random solutions that worsen the objective function value. The proposed hybrid algorithm combines the simulated annealing and local search algorithms: local search is treated as an inner loop of the simulated annealing procedure executed under certain conditions.

The simulated annealing algorithm consists in the following. First, the objective function Φ_C is estimated for the current solution. Then a new solution is generated for a randomly selected flight number to be modified. If this solution improves the objective function value, it is accepted. Otherwise, it is accepted with the probability $e^{-\Delta\Phi/T}$, where $\Delta\Phi = \Phi_N - \Phi_C$ is the difference of the objective function values for the new N and current C states. When the maximum number n_T of iterations is reached at a given temperature T, the temperature is reduced according to a user schedule, and the process is repeated up to a predefined final temperature T_{final}.

Local search modules are heuristic methods; a new solution is accepted only when decreasing the objective function value. The process is repeated until no further improvements are found or the maximum number $n_{T_{LOC}}$ of iterations is reached.

Two local search modules correspond to two strategies:

– search intensification along one particular trajectory,

– search intensification along all trajectories interacting with the selected one.

To generate a new solution, it is determined whether to change the location of the waypoints or the departure time. In general, solution search with changing the departure time is preferable: it will not increase fuel consumption. However, according to empirical tests, restricting the search procedure to changing the departure time only requires an unreasonable computational time. Therefore, a user-defined parameter P_w is introduced to control the probability of changing the waypoint location, and the probability of changing the departure time is set equal to $1-P_w$.

The key factor in tuning this hybrid algorithm is compromising between the exploration and exploitation of the solution space, i.e., reaching a good tradeoff between the fine convergence to local minima and the computational time spent exploring the entire search space.

2.8. Simulation results

The proposed algorithm was tested on air traffic data of the European airspace [18]. Two local search strategies were investigated and compared. According to numerical results, the sequential use of both strategies, first for one particular trajectory and then for all trajectories interacting with it, requires 40% less computation time than using each strategy separately.

The effect of the number of virtual waypoints on the resolution time was also investigated. Despite increasing the richness of the solution space, using more virtual waypoints increases the number of variants in the search space. As a result, computation time grows and the trajectories include undesirable zigzags.

In addition, numerical results demonstrated that shifting the departure time only is insufficient to obtain solutions without potential conflicts. Similarly, changing the trajectory shape only is insufficient as well, requiring an unreasonable computational time. When departure time shifts and trajectory shifts are both allowed, the richness of the solution space increases and an optimal solution (without interaction) can be obtained in much less computational time.

The effect of optimization constraints (the maximum shift in departure time and the maximum increase in route length) was also studied. Quite expectedly, relaxing such constraints allows solving the problem in less computation time.

CONCLUSIONS

For several decades, extensive research was conducted on decision support automation in ATM systems. Mathematical models developed for this problem either minimize the number of potential conflicts between 4D aircraft trajectories or redistribute aircraft flows to reduce airspace congestion. The number of potential aircraft conflicts is often decreased using one or several methods as follows: shifting flight departure times, regulating airspeeds, changing flight trajectories, and changing flight altitude.

As shown, minimizing the number of potential aircraft conflicts is an *NP*-hard problem. Consequently, various metaheuristic algorithms emerged to solve it. A hybrid metaheuristic approach based on the simulated annealing algorithm, improved by local search methods, was developed for the strategic planning of air traffic flows considering the uncertainty of aircraft positions.

The complexity and scale of minimizing the number of potential conflicts in airspace require new approaches to this problem. Some publications in recent years have been devoted to deep reinforcement learning methods for improving the safety and efficiency of air traffic. These publications will be discussed in part II of this survey.

REFERENCES

1. *The Next Generation Air Transportation System (NextGen). Concept of Operations*, Joint Planning & Development Office, Washington, DC, 2011.
2. *Sesar Joint Undertake. European ATM Master Plan*, Brussels: SESAR, 2020.
3. Paielli, R.A., Trajectory Specification for High-Capacity Air Traffic Control, *Journal of Aerospace Computing, Information, and Communication*, 2005, vol. 2, no. 9, pp. 361–385. DOI: 10.2514/1.12335.
4. Paielli, R.A. and Erzberger, H., Trajectory Specification for Terminal Airspace: Conflict Detection and Resolution, *Journal of Air Transportation*, 2019, vol. 27, no. 2.
5. Paielli, R.A. and Erzberger, H., Conflict Probability Estimation for Free Flight, *Journal of Guidance, Control, and Dynamics*, 1997, vol. 20, no. 3, pp. 588–596.
6. Paielli, R.A. and Erzberger, H., Conflict Probability Estimation Generalized to Non-level Flight, *Air Traffic Control Quarterly*, 1999, vol. 7, no. 3, pp. 195–222.
7. Jacquemart, D. and Morio, J., Adaptive Interacting Particle System Algorithm for Aircraft Conflict Probability Estimation, *Aerospace Science and Technology*, 2016, vol. 55, pp. 431–438.
8. Jiang, X.R., Wen, X.X., Wu, M.G., et al., A SVM Approach of Aircraft Conflict Detection in Free Flight, *Journal of Advanced Transportation*, 2018, no. 4, pp. 1–9.

9. Ribeiro, M., Ellerbroek, J., and Hoekstra, J., Review of Conflict Resolution Methods for Manned and Unmanned Aviation, *Aerospace*, 2020, vol. 7, no. 79. DOI: 10.3390/aerospace7060079.
10. Pallottino, L., Feron, E., and Bicchi, A., Conflict Resolution Problems for Air Traffic Management Systems Solved with Mixed Integer Programming, *IEEE Transactions on Intelligent Transportation Systems*, 2002, no. 3, pp. 3–11.
11. Cafieri, S. and Omheni, R., Mixed-Integer Nonlinear Programming for Aircraft Conflict Avoidance by Sequentially Applying Velocity and Heading Angle Changes, *European Journal of Operational Research*, 2017, vol. 260, pp. 283–290.
12. Pelegrın, M. and d'Ambrosio, C., Airspace Conflict Resolution: A Unifying Mathematical Framework and Review, *HAL*, 2021. URL: https://hal.archives-ouvertes.fr/hal-02902566/.
13. Alonso-Ayuso, A., Escudero, L.F., Martin-Campo, F.J., and Mladenovic, N., A VNS Metaheuristic for Solving the Aircraft Conflict Detection and Resolution Problem by Performing Turn Changes, *Journal of Global Optimization*, 2014, vol. 63, pp. 583–596.
14. Liu, H., Liu, F., Zhang, X., et al., Aircraft Conflict Resolution Method Based on Hybrid Ant Colony Optimization and Artificial Potential Field, *Science China Information Sciences*, 2018, vol. 61, art. no. 129103.
15. Allignol, C., Barnier, N., Durand, N., and Alliot, J.M., A New Framework for Solving En Route Conflicts, *Air Traffic Control Quarterly*, 2013, vol. 21, no. 3, pp. 233–253. DOI: 10.2514/atcg.21.3.233.
16. Sislak, D., Volf, P., and Pechoucek, M., Agent-Based Cooperative Decentralized Airplane-Collision Avoidance, *IEEE Transactions on Intelligent Transportation Systems*, 2011, vol. 12, pp. 36–46.
17. Chaimatanan, S., Delahaye, D., and Mongeau, M., A Hybrid Metaheuristic Optimization Algorithm for Strategic Planning of 4D Aircraft Trajectories at the Continental Scale, *IEEE Computational Intelligence Magazine*, 2014, vol. 9, no. 4, pp. 46–61.
18. Chaimatanan, S., Delahaye, D., and Mongeau, M., Aircraft 4D Trajectories Planning under Uncertainties, *Proceedings of 2015 IEEE Symposium Series on Computational Intelligence* (SSCI 2015), Cape Town, 2015, pp. 51–58.
19. Barnier, N. and Allignol, C., 4D - Trajectory Deconfliction Through Departure Time Adjustment, *8th USA/Europe Air Traffic Management Research and Development Seminar (ATM 2009)*, Napa, 2009.
20. Cafieri, S. and Durand, N., Aircraft Deconfliction with Speed Regulation: New Models from Mixed-Integer Optimization, *Journal of Global Optimization*, 2014, vol. 58, no. 4, pp. 613–629.
21. Belotti, P., Lee, J., Liberti, L., et al., Branching and Bounds Tightening Techniques for Non-convex MINLP, *Optimization Methods and Software*, 2009, vol. 24(4), pp. 597–634.
22. Granger, G. and Durand, N., A Traffic Complexity Approach through Cluster Analysis, *Proceedings of the 5th ATM Research and Development Seminar*, Budapest, 2003.
23. Chaimatanan, S., Delahaye, D., and Mongeau, M., Strategic Deconfliction of Aircraft Trajectories, *2nd International Conference on Interdisciplinary Science for Innovative Air Traffic Management (ISIATM 2013)*, Toulouse, 2013.
24. Alligier, R., Durand, N., and Alligier, G., Efficient Conflict Detection for Conflict Resolution, *8th International Conference on Research in Air Transportation (ICRAT 2018)*, Castelldefels, 2018.
25. Delahaye, D. and Puechmorel, S., New Trends in Air Traffic Complexity, *ENRI International Workshop on ATM/CNS (EIWAC)*, Tokyo, 2009, pp. 55–60.
26. Delahaye, D., Paimblanc, P., Puechmorel, S., et al., A New Air Traffic Complexity Metric Based on Dynamical System Modeling, *IEEE/AIAA 21st Digital Avionics Systems Conference*, vol. 1, Irvine, 2002.

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