A Distributed Metaheuristic Approach for Complexity Reduction in Air Traffic for Strategic 4D Trajectory Optimization

Paveen Juntama, Supatcha Chaimatanan, Sameer Alam, Daniel Delahaye

A Distributed Metaheuristic Approach for Complexity Reduction in Air Traffic for Strategic 4D Trajectory Optimization

Paveen Juntama
OPTIM Research Lab
Ecole National d'Aviation Civile (ENAC)
Toulouse, France
paveen.juntama@enac.fr

Supatcha Chaimatanan
SOAR Research Lab
Geo-Informatics and Space Development Agency (GISTDA)
Thailand
supatcha@gistda.or.th

Sameer Alam
Air Traffic Management Research Institute (ATMRI)
Nanyang Technological University
Singapore
sameer.alam@ntu.edu.sg

Daniel Delahaye
OPTIM Research Lab
Ecole National d'Aviation Civile (ENAC)
Toulouse, France
daniel@recherche.enac.fr

***Abstract*—This paper presents a new challenge on the strategic 4D trajectory optimization problem with the evaluation of air traffic complexity by using the geometric-based intrinsic complexity measure called König metric. The demonstration of König metric shows the potential that the algorithm can capture the disorganized traffic which represents the difficulty of maintaining situational awareness as expected by the air traffic controller. We reformulate the optimization problem with two trajectory separation approaches including delaying flight departure time and allocating the new flight level subject to limited delay time of departure, limited changes of flight levels and fuel consumption constraints. We propose our solution to solve daily traffic demands in the regional French airspace. The resolution process uses the distributed metaheuristic algorithm to optimize aircraft trajectories in 4D environment with the objective of finding the optimal air traffic complexity. The experimental results shows the reduction of maximum complexity more than 95% with average delay of 2.69 minutes. The optimized trajectories can save fuel more than 80 000 kg. The proposed algorithm not only reduces the air traffic complexity but also maintain its distribution in traffic. The research results represent further steps towards taking other trajectory separations methods and aircraft trajectory uncertainties into account, developing our approach at the continental scale as well as adapting it in the pre-tactical and tactical planning phase.**

***Index Terms*—air traffic complexity, intrinsic metrics, könig metric, strategic 4d trajectory optimization, fuel consumption, distributed metaheuristic**

I. Introduction

Air traffic demands increasing on air transportation system can downgrade quality of air traffic service in the near future. Following the annual report in 2018 [1], the average European traffic was 30 168 flights per day with maximum traffic demands over 37 000 daily flights. Meanwhile, ATC capacity, en-route weather and ATC staffing were the major causes of en-route delays. Dealing with this traffic demands, air traffic controllers encounter the difficulties to separate all aircraft in the control sector and to maintain an efficient air traffic flow. However, flight planning operations is required before a day of operation to minimize airspace congestion that can reduce control workload within a sector. Network Management Operations Centre (NMOC), previously known as the Central Flow Management Unit (CFMU) is the operational unit of Eurocontrol and responsible for optimizing aircraft trajectories from tactical to strategic planning phase in European airspace.

One key element of two major ATM initiatives, Single European Sky ATM Research (SESAR) and Next Generation (NextGen), to support future traffic demands is 4D Trajectory Based Operations (TBO). TBO makes air traffic becomes much more predictable in allowing conflict detection and resolution by proposing the alternative flightplans in strategic phase and traffic advisory in tactical phase. Over the past decade, most research in strategic 4D trajectory planning has emphasized the use of conflict detection as the principle objective evaluation in the optimization problem. The question then arises whether as to the resolution algorithm based on conflict evaluation is compatible with general strategies of the air traffic controller. So far, very little attention has been paid to the role of air traffic controller.

In recent years, SESAR addresses the performance-driven balancing of en-route traffic demand and ATM capacity under the Advanced Demand and Capacity Balancing (DCB) project. Relevant to capacity management processes, the aim of this project is to offer the controller a solution that presents a traffic situation compatible with his capabilities. The promising key in the literature to overcome this problem is air traffic complexity metrics.

Air traffic complexity is a concept introduced to measure the difficulty of controlling the air traffic situation. This was originally introduced with the purpose of assessing whether an air traffic configuration may cause unsustainable ATC workload and providing guidelines on how to obtain more manageable sectors by reconfiguring the airspace and by modifying traffic patterns. According to many attempts on development of complexity metrics [2], [3], the complexity evaluation on a long term prediction horizon have a potential to identify congested areas and support strategic flight plan optimization, whereas the complexity evaluation on a mid/short term horizon can help to identify encounter situations that are critical for distributed conflict resolution operations.

This paper assesses the significance of strategic 4D trajectory optimization with air traffic complexity evaluation. We propose delaying departure time and allocating the new flight level approaches to aircraft for minimizing traffic complexity in airspace. Moreover, the distributed metaheuristic algorithm is adapted to this problem. Empirical studies using real initiate flightplans in French airspace show that the proposed methods are benefit to solve the strategic 4D trajectory planning in terms of efficiency (computation time and speed of convergence) and efficacy (complexity reduction and distribution and less fuel consumption). The paper is organized as follows: Section II presents the previous related works. Section III gives the problem formulation of the strategic 4D trajectory optimization. Section IV describes our purposed methods. Section V represent our implementation. Section VI reports the experimental results and discussion. Finally, Section VII concludes the paper as well as indicates the next research steps.

II. Previous related works

A. Strategic 4D trajectory optimization

In the framework of aircraft trajectory optimization, several different actions can be used to optimize 4D trajectories with various objectives such as solving potential conflicts, improve flight efficiencies, minimize overall delays etc. The commonly used actions are as follows:

- modifying departure time;
- speed regulation;
- traffic rerouting and;
- assigning the alternative flight level

Deterministic and meta-heuristics algorithms have been widely adopted in the conflict resolution approach to generate near-optimal aircraft trajectories. Durand et al. [4] propose two trajectory maneuvers: modifying the heading and the flight level. En-route conflicts between trajectories are solved by the genetic algorithm (GA). Erzberger et al. [5] propose the resolution algorithm that generates several candidate trajectories and then select the best of them. The construction of resolution trajectories is based on three types of maneuvers: modifying altitude, horizontal route and speed profile. Dougui et al. [6] propose a Light Propagation Algorithm (LPA) which is based on the different refractions of light. The potential conflicts are solved using a Branch-and-Bound (B&B) algorithm. Other research has also investigated the use of hybrid metaheuristic for the planning of 4D aircraft trajectories [7], [8].

Chaimatanan et al. [8] propose a strategic trajectory planning methodology to minimize the interaction between aircraft. The aircraft is separated from others by modifying the shapes of trajectory and delaying flight departure times. For the interaction detection scheme, the hashing subdivision is used to map each 4D cell to the one-dimensional hash table index. For each trajectory, any other trajectory from other aircraft fallen into the same cell and neighboring cell, is considered as a single count of interaction. However, the aircraft speed vector is not used in this approach. A hybrid metaheuristic algorithm using the hill-climbing and the simulated annealing was proposed to generate interaction-free trajectories in French and European airspace.

B. Complexity metrics

The Dynamic Density [9]–[11] was firstly developed by NASA. It consists in measuring a set of traffic characteristics (number of changes in direction, changes in speed, changes in altitude, etc.) and the workload experienced by a controller, then carrying out linear regression in order to adjust the model to the experienced workload as precisely as possible. The mentioned characteristics are not sufficient to describe the complexity associated with airspace. The difficulty in determining reliable workload measures has been a motivation for developing new evaluation approaches of complexity that are independent from traffic characteristics, such as the fractal dimension [12], the input-output approach [13], and the intrinsic complexity [14], [15].

Intrinsic complexity metrics were introduced with the purpose of capturing the level of disorder as well the organization structure of the air traffic distribution. Breil et al. [16] applied the convergence indicator to build the complexity map of aircraft 4D trajectories in the congested area. The objective in this work is to rebuild the temporary route networks for reducing the traffic complexity in the tactical planning phase.

In this paper, we contribute to the application of the strategic 4D trajectory planning. We propose an alternative, the mathematical formulation of this application. We focus on a new objective function: to minimize the maximum complexity of aircraft trajectories and to maintain the complexity distribution of all trajectories. As inspired by König's theorem [17], we develop the new complexity metric in the 4D environment for the objective function. We also propose the distributed metaheuristic algorithm by introducing the distributed optimization approach.

III. Strategic 4D trajectory optimization problem

The problem in this work is to determine optimized 4D trajectories where aircraft can fly in the airspace with the optimal air traffic complexity. In this section, we start from

modeling complexity measurement in 4D environment and then reformulate the optimization problem. This problem enables two following opportunities to separate aircraft trajectories: delaying time of departure and allocating the new flight level subject to the limited delay time, limited changes of flight level and the fuel consumption constraints.

A. Complexity measurement in 4D environment

Given 4D trajectory X_i of aircraft i representing a set of sampled 4D coordinates (x, y, z, t) and the speed vectors (v_x, v_y, v_z) derived from each coordinate. As we can see in Fig. 1, we construct the 4D window from the sampled coordinate. Each 4D window represents its own coordinate and neighbors' coordinates. We then calculate the complexity (as proposed in Section IV) from these coordinates.

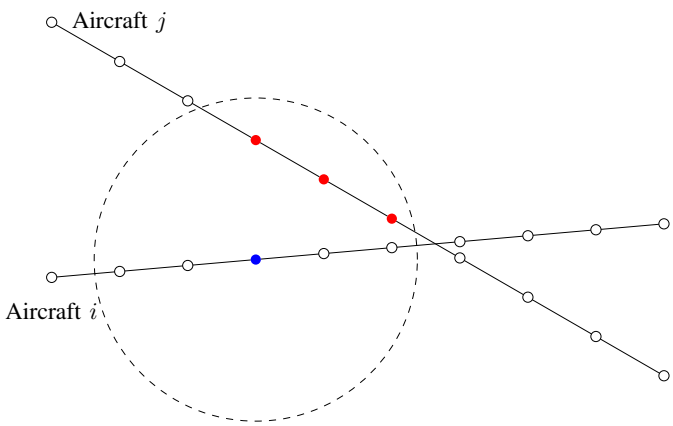

Fig. 1: Example measurement of air traffic complexity for the trajectory of aircraft i within the 4D window

The aggregated complexity Ψ_i of the aircraft i calculated from its full trajectory can be expressed as follows:

$$\Psi_i = \sum_{k=1}^{N_i} \Psi_{ik} \tag{1}$$

Therefore, the maximum complexity Ψ_{max} determined from all aircraft in airspace is computed as follows:

$$\Psi_{max} = \max\{\Psi_1, \Psi_2, ..., \Psi_N\} \tag{2}$$

where N is a number of aircraft and N_i is a number of 4D coordinates

B. Decision variables

Departure time delay: The first separation option is delaying time of departure with δ_i for each flight i from the initial departure time t_i given in its initial flightplan. Once the flight i is selected for this option, the new departure time is expressed as follows:

$$\hat{t}_i = t_i + \delta_i \tag{3}$$

Changes of the flight level: The next separation option represents allocating the new flight level with a number of steps l_i for the flight i from the initial flight level h_i so that the new allocated flight level can be expressed following:

$$\hat{h}_i = h_i + l_i \tag{4}$$

Regarding to the instrument flight rules (IFR), the aircraft cruises eastbound with the odd flight level, whereas the westbound aircraft cruises at the even numbered flight level. Therefore, the aircraft can change its flight level in the same direction with the step of 2000 ft.

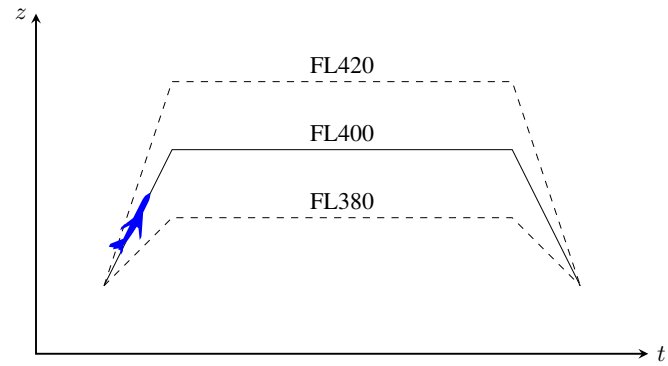

Fig. 2: Flight level modification: the solid line represents the initial flight level; two dashed lines represent the alternative flight levels

C. Problem constraints

Throughout this problem, the constraints should be defined as follows:

Limited departure time delay: We can manage the overall flight delay by giving the maximum delay time of departure to each flight. The delay time δ_i has the unit of slot. The minimum duration of each slot is the minimum sampling time of traffic data. The range of departure time slots can be expressed as follows:

$$\delta_i \in \{0, ..., \delta_{max} - 1, \delta_{max}\} \tag{5}$$

Limited changes of flight level: We define the restricted changes of flight level in the symmetrical range as follows:

$$l_i \in \{-l_{max}, -l_{max} + 1, ..., 0, ..., l_{max} - 1, l_{max}\} \tag{6}$$

Fuel consumption regulation: We consider the effects of altitude on aircraft fuel consumption. Refer to the Base of Aircraft Data (BADA) database version 3.6, we analyze the typical aircraft's fuel consumption at each flight level for three different phases of flight as shown in Fig. 3. There are different trends for climb, cruise and descent phases. The climbing aircraft starts off consuming more fuels than others and then decreases steadily on higher altitude. After FL450, the fuel consumption rates fall adequately. The cruising aircraft tends to increase its fuel consumption on higher altitude until FL380 and then follows the same trend as the climbing aircraft. Finally, the fuel consumption in the descent phase

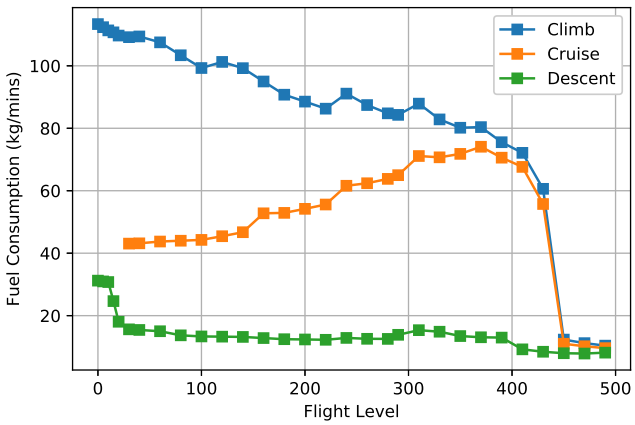

Fig. 3: Average fuel consumption of typical commercial aircraft categorized by 3 different phases of flight with the evolution of the flight level

remains steady during terminal maneuvering area (TMA) and en-route operations. Overall, the climbing operation consumes the highest fuels whereas the descending operation requires less fuels for all flight levels.

In order to give the fuel consumption constraint to the aircraft, we regulate the changes of flight level by restricting that the aircraft can consume fuel less than or equal to its fuel consumption from its initial flightplan. Given c_i the fuel consumption of aircraft i during its flight time. The new restricted fuel consumption can be written as follows:

$$\hat{c}_i(\hat{h}_i) = c_i(h_i + l_i) \leq c_i(h_i) \tag{7}$$

D. Mathematical formulation

Finally, the strategic 4D trajectory optimization problem can be formulated as follows:

$$\begin{aligned}
&\text{given} && L = \begin{bmatrix} l_1 & l_2 & \dots & l_N \end{bmatrix} \\
& && \Delta = \begin{bmatrix} \delta_1 & \delta_2 & \dots & \delta_N \end{bmatrix} \\
&\underset{L,\Delta}{\text{minimize}} && \Psi(L, \Delta) \\
&\text{s.t.} && -l_{\text{max}} \leq l_i \leq l_{\text{max}} && , l_i \in \mathbb{Z} \\
& && 0 \leq \delta_i \leq \delta_{\text{max}} && , \delta_i \in \mathbb{R} \\
& && c_i(h_i + l_i) \leq c_i(h_i) \\
& && l_i + \delta_i \in \{l_i, \delta_i\}
\end{aligned}$$

IV. Proposed methods

In this paper, we propose the following methods to achieve the strategic 4D trajectory optimization problem: determination of complexity using the König metric, the 4D complexity evaluation scheme and the distributed metaheuristic algorithm.

A. König metric

The method consists in calculating kinetic moment of each aircraft around the barycenter calculated from aircraft in an interested area. This metric allows us to quantify the disordered structure in translation and in rotation of a set of speed vectors [15].

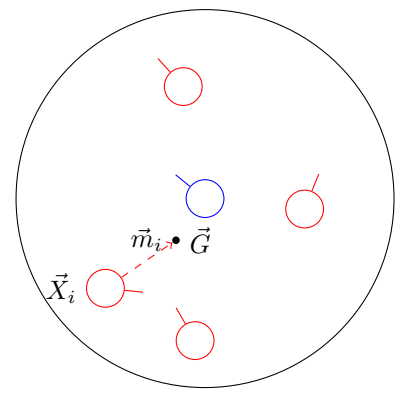

Fig. 4: König space representing the aircraft vectors $\vec{X}_i$, the center of gravity $\vec{G}$ and the kinetic moment $\vec{m}_i$

For each aircraft i represented in the considered area, the center of gravity or barycenter is computed from all aircraft positions:

$$\vec{G} = \frac{1}{N} \sum_{i \in D} \vec{X} \tag{8}$$

The normalized kinetic moment of aircraft i is defined by:

$$\vec{m}_i = \frac{1}{\left\| \vec{d}_{iG} \right\|} \left(\vec{V}_i \wedge \vec{d}_{iG} \right) \tag{9}$$

where $\vec{d}_{iG}$ is a relative distance from aircraft i to the center of gravity G. Therefore, the average kinetic moment can be given by:

$$\vec{M}_G = \frac{1}{N} \sum_{i \in D} \vec{m}_i \tag{10}$$

The covariance matrix of the normalized kinetic moment is expressed as follows:

$$COV_M = \frac{1}{N} \sum_{i \in D} \left(\vec{m}_i - \vec{M}_G \right) \cdot \left(\vec{m}_i - \vec{M}_G \right)^T \tag{11}$$

The disorder associated to the normalized kinetic moment D can be defined by:

$$D = \sqrt{\| COV_M \|_T} \tag{12}$$

From the previous definition, when D has very small value compared to average normalized kinetic moment, $\left\| \vec{M}_G \right\|$, it means that the aircraft are organized in rotation movement.

The normalized König metric which can varied from 0 to 1 is proposed as follows:

$$\Psi = \frac{D}{D + \left\| \vec{M}_G \right\|} \tag{13}$$

B. 4D Complexity Evaluation Scheme

The set of 4D coordinates from all trajectories are all stored into 4D cell with size of 5 NM in horizontal, 1000 ft in vertical and 15 seconds in time. Each cell is indexed by the hash key used for locating data in the hash table. The computed hash key is associated with the 4D cell. The 4D coordinate can be retrieved from the hash table with the complexity $\mathcal{O}(n) = 1$. To calculate the König metric Ψ_{ik} for the coordinate k of aircraft i, we start from searching for neighborhood 4D coordinates of other aircraft around the current 4D coordinate as shown in Fig. 5. These points allow us to construct the small König space and then determine their center of gravity and normalized kinetic moments. As we can see from the example of aircraft i in Fig. 6, the small König space is constructed from the first sampled 4D coordinate for computing the metric at $k = 0$ where k is the number of sampled coordinate in the trajectory. After sliding from the first to the last coordinate of the aircraft i, As depicted in Fig. 7, we can present the evolution of the complexity for each coordinate. This evolution shows that the coordinates of aircraft j, which is the neighbor of aircraft i, exist in the König space from $k = 2$ to $k = 9$. When the position and speed of both aircraft appears to be diverged, the traffic disorder becomes disappeared in the König space. Here we can adapt (13) to calculate the complexity in each König space as follows:

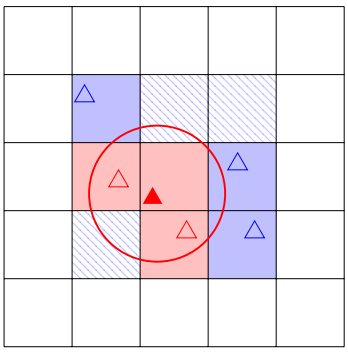

Fig. 5: Neighborhood filtering for possible trajectory pairs

$$\Psi_{ik} = \frac{D_{ik}}{D_{ik} + \left\| \vec{M}_G^{ik} \right\|} \tag{14}$$

Finally, we can apply this equation for all 4D trajectories and then calculate the maximum air traffic complexity from all aircraft by using (2).

C. Distributed Metaheuristic Optimization Algorithm

The optimization approach relies on a generic Simulated Annealing (SA). SA algorithm proposed by Kirkpatrick et al. in 1993, is a global optimization algorithm which is suitable for NP-hard problems [8]. This algorithm is inspired by the metallurgical annealing process. In this natural process, under controlled conditions, a material is heated up and slowly cooled down to increase the size of the crystals in the material and reduce their defects in order to improve the material's strength and durability.

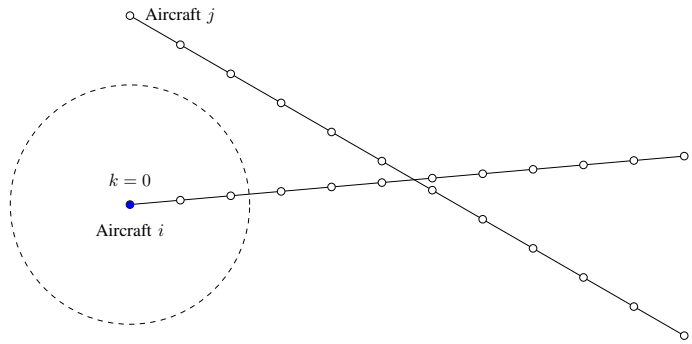

Fig. 6: Complexity evaluation representing the König space at the first 4D coordinate of aircraft i

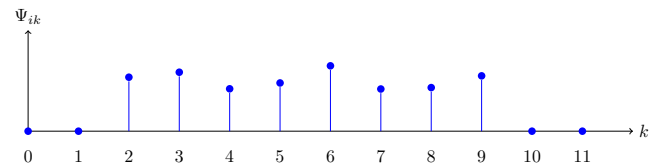

Fig. 7: Evolution of König metric for the full trajectory evaluation of aircraft i

Throughout mathematical optimization problems, each configuration of a decision set in the search space represents a different internal energy of the system. Heating the system leads to a relaxation of the acceptance criteria in order to take samples from the search space. When the system cools down, the acceptance criteria of samples is reduced so that movements are enhanced. Once the system has cooled, the configuration will represent a sample at or near a global optimum.

In this paper, we reformulate the SA algorithm in the distributed way. We independently apply neighborhood configuration and cooling process to every decision from N decisions with the temperature T_k for each iteration k. The temperature which is considered as a control parameter, decreases in each transition by following the geometric cooling process with $T_{k+1} := \alpha T_k$ where α is the cool down factor. Instead of evaluating all decisions, we evaluate each decision with its previous cost value γ under the Metropolis criterion. This criterion helps the system to always accepts the better decision and to avoid a local minima. The aggregated objective value can be derived from the aggregation function A (min, max, sum, etc.) depending on the problem context. To avoid modifying the decisions which are not able to disturb the aggregated objective value γ^*, we can regulate the system with the aggregation factor β. The algorithm below provides a pseudocode listing of the Distributed Metaheuristic Optimization (DMO) algorithm for minimizing the aggregated cost function.

Algorithm 1 Distributed Metaheuristic Optimization (DMO)

init T_0
$D = \{d_i | 1 < i < N\}$
$\Gamma = \{\gamma_i = eval(d_i) | 1 < i < N\}$
$T := T_0, k := 0$
repeat
  $\gamma^* = A(\Gamma_k)$
  for $i = 1 \rightarrow N$ **do**
    if $\gamma_i > \beta\gamma^*$ **then**
      $\tilde{d}_i = change(d_i)$
      $\tilde{\gamma}_i = eval(\tilde{d}_i)$
      if $\tilde{\gamma}_i < \gamma_i$ **then**
        $d_i \leftarrow \tilde{d}_i$
      else
        $d_i \leftarrow \tilde{d}_i$ with probability $\exp\left(\frac{\gamma_i - \tilde{\gamma}_i}{T}\right)$
  $T := \alpha T$
  $k := k + 1$
until $k = M$
return D^*

V. Implementation

This section presents implementation steps following the proposed algorithm from the step importing the simulated data simulated from initial flightplans until the final step to export the optimized flightplans.

A. Pre-processing

At first, the program starts reading the file containing the list of flights and their trajectory data. All existed aircraft coordinates are manipulated and stored in the hash table. Secondly, we construct the decision set $D = \{d_1, d_2, ..., d_N\}$ where the decision d_i represents the decision variables (δ_i, l_i) and its cost value γ_i of the flight i. The decision variables are all assigned with the initial value of 0 and the cost value is the air traffic complexity of each aircraft trajectory ($\gamma_i \leftarrow \Psi_i$) whose value is calculated from (III-D).

B. Optimization Process

The heating up process is started and the output from this process provides us with the initial temperature T_0 required to start the cooling down process. We can calculate this temperature by first randomly generating 100 deteriorating transformations and then by evaluating the average variations $E[\Delta\gamma]$, of the objective function values. The initial temperature T_0, is then computed from the expression: $T_0 = \frac{E[\Delta\gamma]}{\ln \tau}$, where τ is the initial acceptance rate of degrading solutions (which it is empirically set).

The cooling down process can be launched using the initial temperature T_0 from the heating up process. An adequate number of iterations required for reaching to an equilibrium is constant and pre-defined by the user.

We follow the proposed algorithm described in the previous section and then adapt it to our problem as depicted in Fig. 8. According to the objective function in this problem,

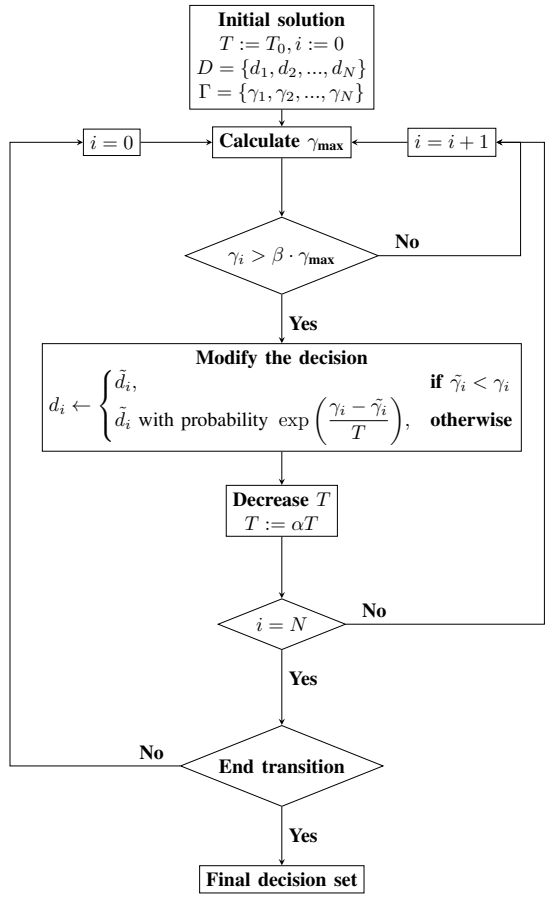

Fig. 8: Adaptation of the DMO algorithm to the optimization process

we use the maximum cost value $\gamma_{\max}$ as the aggregated objective value of the DMO algorithm. If the cost value of the current decision is greater than $\beta\gamma_{\max}$, the program will modify this decision variable under the Metropolis criterion. The modification of decision d_i aims to modify either the new flight level or the departure time delay with the user-defined probabilities P_{FL} and P_{delay} respectively where $P_{\text{FL}} + P_{\text{delay}} = 1$. These trajectory separation approaches also respect the limited departure time delay and the limited changes of the flight level. Concerning the flight level decision, the algorithm consults the BADA performance data in order to select the available changes of flight level subject to the fuel consumption as previously detailed in Section III. The algorithm below provides a pseudocode listing of the decision strategy associated with this modification:

Algorithm 2 Decision strategy

input $d_i(t_i, l_i)$
if $P_{\text{FL}} < random(0, 1) \leq P_{\text{delay}}$ **then**
  $t_i \leftarrow \tilde{t}_i$
else
  $l_i \leftarrow \tilde{l}_i$ **where** $\hat{c}_i(h_i + l_i) - c_i(h_i) \leq 0$
return $\tilde{d}_i$

If the decision is not accepted by the Metropolis criterion, the *comeback* operation will return the modified decision back to the previous one as shown in Fig. 9. The modification operation repeats with the same temperature T_k until the last decision d_N for the iteration k. For every iteration, the temperature decreases with the geometric cooling schedule as described in the DMO algorithm description. After the final iteration, the program exports the optimized trajectories and the final decision set.

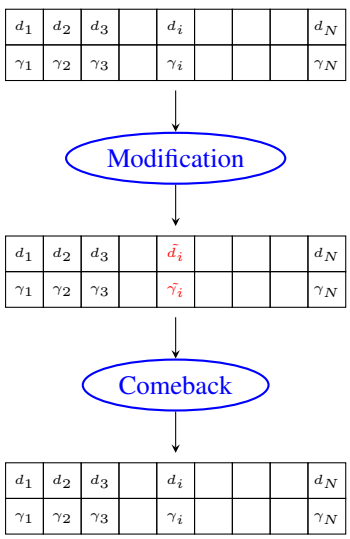

Fig. 9: The *comeback* operation triggered in the cooling process when the Metropolis criterion does not accept the modified decision

VI. Results

A. Experimental Data and Configuration

By assessing the performance of our model and algorithm, 1000 regional trajectories provided by A Complete Air Traffic Simulator (CATS) are used in our experiment. In our resolution approach, we implemented the DMO algorithm adopted to our problem with Java on Ubuntu system with 2.7 GHz processor and 8 GB memory. The parameters are detailed in Table I. Before starting, initial trajectories represent the maximum complexity based on König metric with the value of 405.82. The complexity map of initial trajectories can be visualized in Fig. 10.

Parameters	**Value**
Trajectory update rates, Δt	15 seconds
Horizontal grid size, $\Delta x, \Delta y$	5 NM
Altitude grid size, Δz	1 000 ft
Limited delay time of departure, δ_{max}	30 minutes
Limited changes of flight level, l_{max}	2
Probability for delaying time of departure, P_{delay}	0.3
Probability for allocating the new flight level, P_{FL}	0.7

TABLE I: Parameters

Regarding with this problem, the initial parameters of the DMO algorithm are configured, with an initial acceptance rate

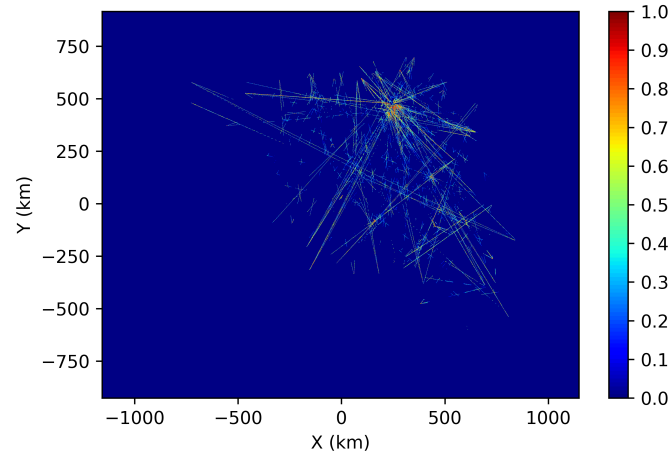

Fig. 10: Complexity map based on König metric for 1000 initial trajectories in horizontal plane

$\tau = 0.8$, a geometric cooling schedule with $\alpha = 0.99$ and 1000 transitions. In this problem, we also empirically set the aggregation factor $\beta = 0.95$.

B. Numerical Results

As can be seen in Table II, our algorithm performs the reduction of maximum complexity based on König metric at 15.04, the average complexity of 4.23, the average delay of 2.69 minutes. Meanwhile, our algorithm can also performs with the computation time of 37.54 seconds. Concerning the flight performance, we can save fuel 88 993.5 kg or 1.16 % comparing with the initial trajectories.

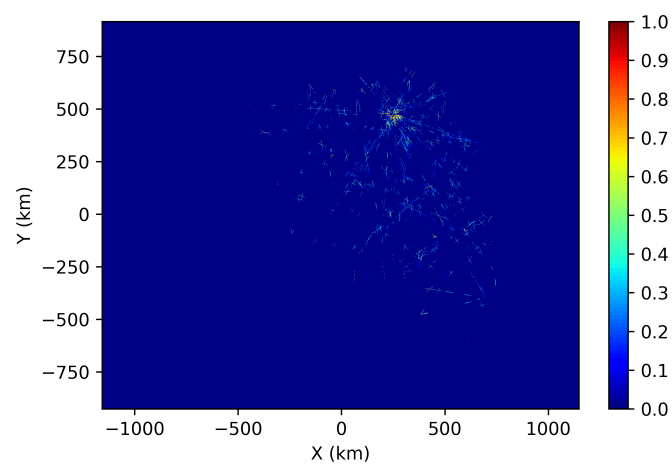

Fig. 11: Complexity map based on König metric for 1000 optimized trajectories in horizontal plane

Comparing with Fig. 10, Fig. 11 shows the complexity map of 1000 trajectories after the optimization process. Remaining complexity from this strategic phase can manage and solve in

TABLE II: Numerical results of 1000 optimized trajectories after the optimization process compared with the initial trajectories

Data	Max Complexity	Average Complexity	Complexity Distribution	Average delay	Fuel Consumption	Computation Time
Initial Trajectories	405.82	23.64	42.03	0.0	7 648 919.2 kg	-
Optimized Trajectories	15.04	4.23	4.21	2.69 mins	7 559 925.7 kg	37.54 seconds

the pre-tactical and tactical phase so that allows to significantly mitigate the controller's workload. The comparison of air traffic complexity between the initial and optimized 1000 trajectories is visualized in Fig. 12. This visualization shows that the DMO algorithm can reduce the overall complexity and maintain the complexity distribution of the traffic. Fig. 13 represents the comparison of fuel consumption between initial and optimized flightplans categorized by three different phases of flight. Due to utilization of upper cruising flight levels after optimizing trajectories, the fuel consumption rises in climb phase. In contrast to the cruising phase, the aircraft becomes less in fuel consumption when it stays on the upper flight level. Finally, we assess the performance of the DMO algorithm by comparing it with the distributed logistic optimization (DLO) algorithm. This algorithm is constructed from DMO algorithm by disabling the Metropolis criterion. The evolution of the aggregated objective value γ^* until the final iteration is compared in Fig. 16. The DMO algorithm yields a better solution and converges significantly faster than the DLO algorithm does.

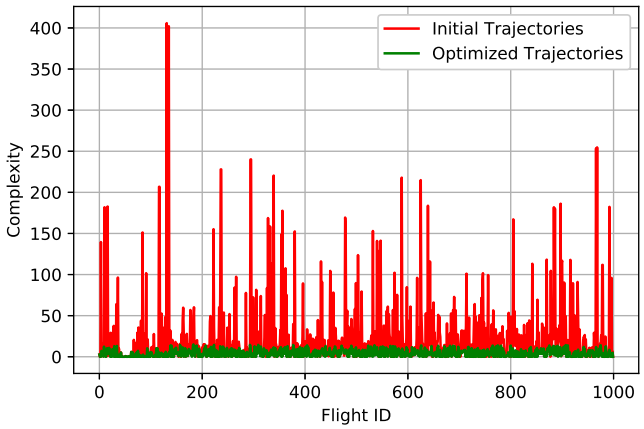

Fig. 12: Complexity map based on König metric for 1000 optimized trajectories in horizontal plane

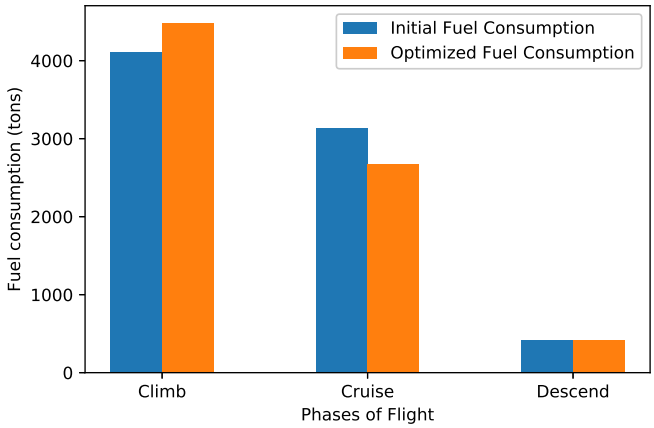

Fig. 13: Comparison of fuel consumption before and after the optimization process categorized by three different phases of flight

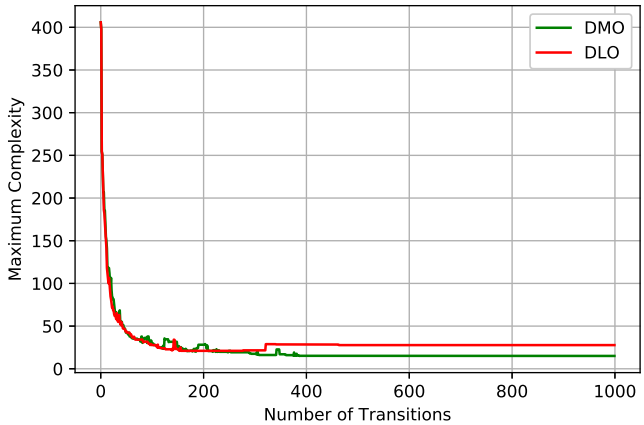

Fig. 14: Comparison of convergence between the DMO algorithm and the logistic optimization (without the Metropolis criterion)

VII. Conclusion

In this paper, we introduced a methodology to address the strategic planning of aircraft trajectory in the framework of trajectory based operation. We proposed the intrinsic based metric for complexity evaluation of aircraft 4D trajectories. König metric implemented under 4D environment can identify disorganized patterns of air traffic. We then formulated the problem the strategic 4D trajectory planning with two strategies: delaying time of departure and allocating the new flight level subject to limited time delay, limited changes of the flight level and fuel consumption constraints. We studied the altitude effects on the fuel consumption for typical commercial aircraft by analyzing performance data on the BADA database and then formulated the mathematical constraint to the optimization problem. Experimental results based on the real traffic situation represent the potential of the proposed methods. The distributed metaheuristic algorithm produces the optimized flightplans with shortened air traffic complexity, flexible complexity distribution and improved aircraft fuel efficiencies within the acceptable computation

time. Concisely, the numerical representation of complexity metric opens the new challenges of 4D trajectory fine-tuning approaches in pre-tactical and tactical phases for developing the promising robust 4D trajectory planning methods.

VIII. Future works

The significant results in this work open new perspectives with the future research on following that can be taken into account:

- **Trajectory modification**: we proposed changing flight level and departure time in this work. Other methods such as speed regulation and horizontal trajectory deviation can be considered for the future investigation.
- **Improvement of resolution algorithm**: The rise of machine learning algorithms opens the further challenges on combining them with our proposed metaheuristic approach.
- **Uncertainty**: Predicting air traffic complexity under uncertainty caused from departure airports, weather information and other disruptive factors can be applied in next investigation.
- **Short term 4D trajectory optimization**: the evidence in this study concerning the way of capturing disorganized traffic by our proposed complexity metric can allow us to identify encounter situations that are critical for tactical conflict resolution operations

IX. Acknowledgment

This research is partially supported by NTU-CAAS Research Grant M4062429.052 by Air Traffic Management Research Institute, School of Mechanical and Aerospace Engineering, Nanyang Technological University, Singapore

References

[1] "Annual Network Operation Report 2018," EUROCONTROL, Main Report, Mar. 2019.

[2] M. Prandini, V. Putta, and J. Hu, "Air traffic complexity in future Air Traffic Management systems," *Journal of Aerospace Operations*, no. 3, pp. 281–299, 2012.

[3] B. Hilburn, "Cognitive Complexity in Air Traffic Control - A Literature Review," EUROCONTROL, Tech. Rep. 2004-007EEC Note 2004/04, Jan. 2014.

[4] N. Durand, J.-M. Alliot, and J. Noailles, "Automatic aircraft conflict resolution using genetic algorithms," in *Proceedings of the 1996 ACM symposium on Applied Computing - SAC '96*. Philadelphia, Pennsylvania, United States: ACM Press, 1996, pp. 289–298.

[5] H. Erzberger, T. A. Lauderdale, and Y.-C. Chu, "Automated conflict resolution, arrival management, and weather avoidance for air traffic management," *Proceedings of the Institution of Mechanical Engineers, Part G: Journal of Aerospace Engineering*, vol. 226, no. 8, pp. 930–949, Aug. 2012.

[6] N. E. Dougui, D. Delahaye, S. Puechmorel, and M. Mongeau, "A new method for generating optimal conflict free 4d trajectory," in *ICRAT 2010, 4th International Conference on Research in Air Transportation*, Budapest, Jun. 2010, pp. 185–191.

[7] S. Alam, L. T. Bui, H. A. Abbass, and M. Barlow, "Pareto meta-heuristics for generating safe flight trajectories under weather hazards," in *Simulated Evolution and Learning*. Berlin, Heidelberg: Springer Berlin Heidelberg, 2006, pp. 829–836.

[8] S. Chaimatanan, D. Delahaye, and M. Mongeau, "Hybrid metaheuristic for air traffic management with uncertainty," in *Recent developments of metaheuristics*, ser. Operations Research/Computer Science Interfaces Series, F. Y. Lionel Amodeo, El-Ghazali Talbi, Ed., 2018, vol. 62, pp. 219–251.

[9] I. Wyndemere, "An evaluation of air traffic control complexity," NASA Ames Research Center, Moffet Field, CA, Tech. Rep. NASA-2-14284, Oct. 1996.

[10] I. V. S. Laudeman, "Dynamic Density: An Air Traffic Management Metric," Tech. Rep. NASA-TM-1998-112226, Apr. 1998.

[11] B. Sridhar, "Airspace Complexity and its Application in Air Traffic Management," Orlando, FL, United States, Jan. 1998.

[12] S. Mondoloni and D. Liang, "Airspace Fractal Dimensions and Applications," Dec. 2001.

[13] M. Prandini, L. Piroddi, S. Puechmorel, and S. Brázdilová, "Complexity metrics applicable to autonomous aircraft," SESAR: Brussels, Belgium, Tech. Rep., Jan. 2009.

[14] D. Delahaye and S. Puechmorel, "Air Traffic Complexity: Towards an Intrinsic Metric," Jan. 2000.

[15] D. Delahaye, P. Paimblanc, S. Puechmorel, J. Histon, and R. Hansman, "A new air traffic complexity metric based on dynamical system modelization," in *Proceedings. The 21st Digital Avionics Systems Conference*, vol. 1. Irvine, CA, USA: IEEE, 2002, pp. 4A2–1–4A2–12.

[16] R. Breil, D. Delahaye, L. Lapasset, and E. Féron, "Multi-agent Systems to Help Managing Air Traffic Structure," *Journal of Aerospace Operations (ISSN : 2211-0038)*, Sep. 2017.

[17] H. Essen, "Average Angular Velocity," *European Journal of Physics*, vol. 14, no. 5, pp. 201–205, Sep. 1993, arXiv: physics/0401146.