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Crossing Waypoint Optimization in Free Route Airspace

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Abstract—With the imminent growth in air travel, ensuring the efficiency of airspace has become a necessity. This work addresses this specific concern, namely, the optimization of a Free Route Airspace (FRA). The FRA is a relatively recent concept applied into the European airspace. Even though this approach has the advantage of having the direct routing between origin and destination, there are still aspects that can be improved, regarding conflict handling and air traffic controllers' workload. To face this problem, we study the incorporation of Crossing Waypoints (CWs) into the FRA. These CWs will cluster the locations of conflicts, facilitating the controller's task. However, identifying their best locations and connections poses a challenge. Along this research, the problem of finding the optimal topology will be modeled in order to minimize potential conflicts between flights, reduce the workload on controllers, and decrease airlines' costs. This will lead to a multi-objective optimization problem, involving a balance between safety and fuel consumption. To find a solution to this issue, meta-heuristics algorithms were employed and compared (Particle Swarm Optimization, Simulated Annealing and Tabu Search). Initially the model will be validated in simple cases in order to compare the use of direct routing and the CW approach. Then the procedure is evaluated in a case-study of sector LFEEKF in Reims. Finally, we present a comparison between the algorithms to evaluate their individual performances.

Keywords—Crossing Waypoint Optimization; Free Route Airspace; Multi-objective optimization; Simulated Annealing;

I. INTRODUCTION

A. Motivation

As the number of civil aviation flights in Europe start returning to their pre-pandemic values [1], the air traffic rise seems to be an inevitable phenomenon. In Europe, the numbers seem pretty promising, as the passenger traffic in 2022 nearly doubled (compared to the year before), achieving just 21% below pre-pandemic volumes [2].

This growth will demand a higher capacity from the Air Route Network (ARN). Then, the optimization of this structure is essential to keep up this demand. In order to do so, Eurocontrol has already implemented Free Route Airspace (FRA) in some parts of the European Airspace.

A FRA is a specified airspace within which users may freely plan a route between a defined entry point and a defined exit point, with the possibility to route via intermediate (published or unpublished) significant points, without reference to the Air Traffic Service (ATS) route network. Within this airspace, flights still remain subject to Air Traffic Control (ATC) [3].

Despite the various benefits it offers for airlines and Air Traffic Management, the FRA has some aspects that can be improved. For example, a potential conflict can appear anywhere throughout the sector, broadening the attention area of the air traffic controllers. This high load of attention, and consequently, workload can jeopardize safety or lead to a limitation within ATC. Thus, the FRA approach still has some aspects to be improved regarding conflicts.

The main purpose of this work is to study the implementation of Crossing Waypoints (CWs) within a FRA, in order to face these challenges described before. Those CWs could even be activated when demand increases in order to structure the traffic for ATCOs to help them managing induced conflict. As a matter of fact, ATCOs are efficient when conflicts appear at the same location. CWs are a concept that have already been applied. Nevertheless, this paper searches the optimal positioning, connections and quantity of them, *i.e.* to achieve the optimal topology of the network to minimize the number of conflicts and the deviation of each flight. An assessment will be made regarding the number of CWs, their positions and the flow in each CW in order to optimize the building of the network. This will be done by conceiving a model to simulate and describe the network, and then applying an optimization algorithm to find the best locations of such CWs.

B. State of the Art

Over the past few years, various methods have been developed to address the CWO problem. In [4] the authors approached the problem as a multi-objective optimization, for which they had two objectives: minimize the total airline cost (TAC) and the total flight conflicts coefficient (TFCC). To tackle this issue, they joined the two sub problems transforming them into a single-

objective formation with a weighted sum of TAC and TFCC. They used the Particle Swarm Optimization algorithm to identify the optimal position of the CW and for the flow assignment component they applied the Floyd-Warshall algorithm ([4]).

The authors, K. Cai, J.Zhang, C. Zhou, tested the provided method in a comparative case study of the existing ARN operating in China's national airspace. The results showed a significant reduction of airline cost and flight conflicts. It should be noted that the topology of the network in this paper is fixed regarding the number of nodes and the regions of location of each node (a waypoint must be inside of a specified region imposed, usually in the core area of sectors).

In [5] the authors attempt to optimize the location of the CW in a determined ARN, also taking into account the Prohibited, Restricted and Dangerous (PRD) areas. An adaptive method is used for this purpose, implementing an Artificial Potential Field (APF) model in order to minimize the total air route costs. The APF model would attract the CW towards the optimal route, which is the direct line between the origin and the destination. Contrarily, there would be repulsive forces from the airports and the PRD areas. They tested this approach in a real life controlled airspace environment and they observed a reduction in the number of conflicts, controller workload, cost-effectiveness indicators and delays.

Furthermore, in [6] the authors tried to optimize the location of CW and the links between them (Adjacency Matrix) and designed a multi-objective evolutionary algorithm called CoM-ARN. The principal objective of this work was to maximize airspace safety and minimize flight cost. Their results show that the CoM-ARN algorithm had an advantage over previous Multi-Objective Evolutionary Algorithms used for the optimization problem. Nevertheless they admitted that the number of nodes was constant.

In [7], even though the author's main purpose was different from CWO, he analyzed an intermediate case in which he optimized the location of the border waypoints between two Flight Information Regions (FIR). He managed to improve the location of the points by using the Interior Point Algorithm and the Global Search Algorithm from MATLAB. By applying this method, he succeeded in reducing the total path deviation from flights.

This paper explores the same topics to the ones mentioned above, using a distinct approach. The CWO problem will be tackled by introducing more flexible network topology. In other words, the solutions presented will include more decision variables. Our method will not only optimize the positions and connections of the CWs, but also the number of CWs used and the possibility for flows to be assigned to different paths.

The paper is organized as follows. Section 2 introduces the associated mathematical model that will simulate our ARN. The following section illustrates the interaction between our model

and the algorithm. Section 4 contains the results obtained using our methodology. Lastly, a conclusion is made summarizing the achievements of the work.

II. MODEL FORMULATION

A. Problem Description

Our airspace will be described by a set of inputs, \mathcal{O} , outputs, \mathcal{D} , and CW nodes, \mathcal{CW} . The first assumption made is that our FRA will be laid out in a specific rectangular area, in order to simplify the model. Later on, this simplification will be removed for the operational case study. The entry and exits nodes are located on the border of the considered area. Meanwhile, the CWs are located inside the area. This layout is shown in Figure 1.

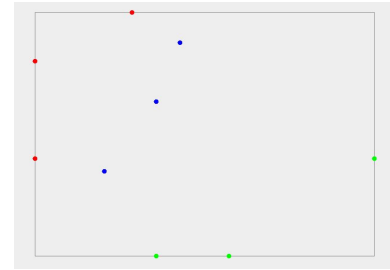


Figure 1. Airspace scheme with the graphical representation of the inputs, outputs and CWs (green, red and blue points, respectively). The gray lines represent the limit of the considered area.

It is noteworthy to mention that the airspace corresponds to sets of flight levels (FL). This was considered to follow the semi-circular rule, where airplanes that fly with an orientation between 0° and 179° must fly in a different FL than the flights having a route between 180° and 359° . So, in the representation of our model, the links between the nodes can be either black or pink. The black links will be the links from east to west (180° - 379°), while the pink links will be the links from west to east (0° - 179°).

The input/output nodes generate and transfer air traffic flow. In this paper we consider that the positions of this type of node will always be fixed. Contrarily, a CW can only transmit traffic flow without generating or absorbing any traffic and will have a position that can be modified.

In our model we will consider a set of routes. Each route will be characterized by an origin and a destination, in this case, an entry and an exit node. Every route will have a specific flow. A flow will represent the quantity of airplanes that can pass in a given amount of time. The flow of the routes will be constant throughout the simulation.

A flow can have one or two paths, which determines the trajectory of its respective route flow, always passing through a CW. In case of a route being spread across multiple paths, then each path will have a percentage of the flow that will represent the portion of flow that will pass through a specific CW.

So, given the positions of entry and exit nodes and the demand between these nodes, the main purpose of this work is to find the optimal number of CWs, their optimal position and the optimal path between them, in order to maximize airspace safety and minimize air route cost. Therefore, the CWO is considered as a multi-objective optimization problem. Since the positions of CWs can vary continuously in our airspace and the routes are assigned on the paths on the discrete domain, the optimization of the CW in the FRA is a mixed discrete-continuous problem.

B. Input Data

Our model will receive the following information

- Number of entry nodes, N_{in} ;
- Number of exit nodes, N_{out} ;
- Location of the entry/exit nodes;
- Minimum and maximum number of CWs, N_{min} , N_{max} , respectively;
- Flows between each entry and exit points;
- Entry and exit speeds in each entry/exit node;
- Shape of the considered area.

C. Decision Variables

The model that we propose gathers together three decision variables. The first one is the number of CWs used, N_{cw} . The second one is the position of each CW, represented by the following vector:

$$P = \{p_1, p_2, \dots, p_{N_{max}}\} \quad \forall p_i \in P, p_i = (x_i, y_i)$$

Finally, the last variable contains the percentage of the flow that will pass at a specific CW. This variable will be represented by a 3D matrix, in which the entry point, exit point and CW used represent the 1st, 2nd and 3rd dimension, respectively. In (1), a 2D matrix was used to represent this decision variable, in order to simplify the visual illustration.

$$L = \begin{bmatrix} l_{11} & l_{12} & \dots & l_{1N_{max}} \\ l_{21} & l_{22} & \dots & l_{2N_{max}} \\ \dots & \dots & \dots & \dots \\ l_{N_R1} & l_{N_R2} & \dots & l_{N_RN_{max}} \end{bmatrix} \quad (1)$$

where N_R is the number of routes between entries and exits, i.e., $N_R = N_{in}N_{out}$. In the illustration the variable l_{ij} will contain the percentage of flow from route i that passes through the CW j . Meanwhile, in the 3D matrix, l_{ijk} will represent the percentage of the flow between the entry i and the exit j , that passes by the CW k .

We define the decision variable vector as:

$$x = (N_{cw}, P, L)$$

D. Objective Function

As mentioned before, the objective function of the model is to maximize safety and minimize flight costs. Safety is measured by induced number of conflicts. A conflict is a predicted convergence between two aircraft, which violate the separation minima (5 NM horizontally and 1000 ft vertically) during the flight [8] as it is illustrated in Figure 2.

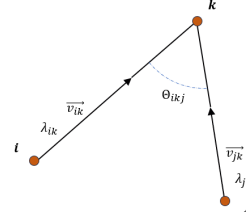


Figure 2. Representation of a convergent conflict.

In order to calculate the number of conflicts, (2) was applied.

$$\phi_k = \sum_{\substack{i,j \in \mathcal{F}_k \\ j \neq k}} 2R \frac{\sqrt{v_{jk}^2 - 2v_{jk}v_{ik}\cos\theta + v_{ik}^2}}{v_{jk}v_{ik}\sin\theta} \lambda_{jk}\lambda_{ik}, \quad (2)$$

where $R = 5\text{NM}$ and \mathcal{F}_i represents the adjacent nodes connected to node i with an inbound link. Formula (2) measures the average number of conflicts at a given crossing point. In this formula v represent the average speeds of the flows λ and θ is the crossing angle.

Regarding the second objective, we use as metric the deviation of the selected path with respect to the direct path between the entry and exit points of the route, δ . In (3) the difference between the two trajectories is multiplied with the flow of the route. This is due to the fact that the deviation of a route with more airplanes has a bigger impact in cost than the same deviation for a smaller flow.

$$\delta_{ij} = (d_{dev} - d_{direct})\lambda_{ij}l_{ijk} \quad (3)$$

$$d_{dev} - d_{direct} = \|p_i - p_k\| + \|p_k - p_j\| - \|p_j - p_i\|$$

where $i \in \mathcal{O}$, $j \in \mathcal{D}$ and $k \in \mathcal{CW}$.

Taking into account these two criteria we obtain the objective function of the model in (4). The purpose is to minimize it, reducing the number of conflicts and the deviation of flights from all the ARN.

$$\min f = \alpha \sum_{i \in \mathcal{CW} \cup \mathcal{D}} \phi_i + (1 - \alpha) \sum_{i \in \mathcal{O}} \sum_{j \in \mathcal{D}} \delta_{ij}. \quad (4)$$

It should be noted that a weighting factor α has been added to merge the two criteria into a single objective function. A technique commonly referred to as scalarization. The value of

α will denote the importance of the safety factor with regard to the economical.

E. Constraints

Following the analysis of the CWO model, the subsequent constraints were established:

1) Minimum distance between CW

The CWs must have a safety distance between them, in order to avoid creating more conflicts directly between CWs.

$$d_{ij} \geq D_{wpmin} \iff \|p_i - p_j\| \geq D_{wpmin}$$

where $i, j \in CW$.

2) Minimum distance between CW and Entry/Exit nodes

A CW must not be too close to an entry or an exit point to give a margin of manoeuvring to the aircraft. Also, the CW must be inside the sector. For a rectangular sector we have:

$$\begin{aligned} x_{min} + D_{bord} &\leq x_i \leq x_{max} - D_{bord} \\ y_{min} + D_{bord} &\leq y_i \leq y_{max} - D_{bord} \end{aligned}$$

where $i \in CW$ and D_{bord} is the minimum distance between the border of the sector and a CW. It is noteworthy to mention that the condition imposed above is just for the assumption that the FRA under discussion is considered rectangular. In the case of Reims' section case study the condition would be just $p_i \in A'$, where A' is the area of the airspace with a margin of D_{bord} . The value of such a margin is fixed at 10NM.

3) Limited number of conflicts per CW

The number of conflicts associated to a given CW must be limited since the controller in charge can not be overloaded.

$$\phi_i \leq N_{cmax}$$

where $i \in CW$ and N_{cmax} is the maximum number of conflicts that a controller can handle for a given waypoint. The value of N_{cmax} has been fixed at 15 conflicts per hour.

4) Flow Balance

This condition will guarantee that the global entry flow at the entry nodes will be equal to the entry flow of the CWs:

$$\sum_{j \in \mathcal{D}} \lambda_{ij} = \sum_{k \in CW} \lambda_{ik}, \quad \forall i \in \mathcal{O}$$

Additionally, the total exit flow at the exit nodes will be equal to the exit flow of the CW:

$$\sum_{i \in \mathcal{O}} \lambda_{ij} = \sum_{k \in CW} \lambda_{kj}, \quad \forall j \in \mathcal{D}.$$

These two constraints insure that all flows will pass through the available CW, and also that the total flow will be maintained.

5) Flow conservation

This condition guarantees that the entry flow on a CW will be the same as the exit flow.

$$\sum_{j \in \mathcal{D}} \lambda_{kj} = \sum_{i \in \mathcal{O}} \lambda_{ik}, \quad \forall k \in CW$$

6) Entering/Exiting angle range

In order to avoid too small crossing angles between flows we keep only large enough crossing angle. In the same way, in order to avoid to sharp turn on the paths, we restrict the heading changes for each waypoint.

$$\Theta_{min} \leq \Theta_{ij} \leq \Theta_{max}$$

where i, j are entry/exit links from the same node k ($k \in \mathcal{I} \cup \mathcal{O} \cup CW$). The values of Θ_{min} and Θ_{max} chosen were 30° and 120° respectively.

III. ALGORITHM IMPLEMENTATION

A. Evaluation-based Simulation

The resolution process of the CWO consists of an a evaluation-based simulation. This evaluation can be divided into two main parts: the simulation evaluation process and the optimization algorithm. The interaction between these two parts will produce a potential solution for the problem. The optimization algorithm controls the set of decision variables, X . Meanwhile, the simulation environment will receive these state decisions with the aim of evaluating them through the simulation process, then used by the optimization algorithm for improving the decision variables in the next steps.

B. Neighborhood

In order to apply the SA algorithm [9] the neighborhood operator had to be adapted to the CWO problem. To do so, we used three methods to generate a neighbor, each one related to the modification of one of the decision variables. The first type of generator changes the number of CW used, by randomly choosing a number between N_{min} and N_{max} . The second type involves changing the position of a random CW. The chosen waypoint will be moved through a predetermined distance (5 NM) with a random direction. Finally, the last type corresponds to the change of L , in other words, the links between the CW and the origins/destinations. A random route (R) and a random CW will be chosen. Then, a specified percentage step (5%) will be added or subtracted to the percentage of flow of R retained by that CW. Later on, another random CW will be chosen and modified with the objective of maintaining the total flow of R (maintaining it in 100%), which is distributed between the CWs. The Figure 3 shows an example of this operator being applied.

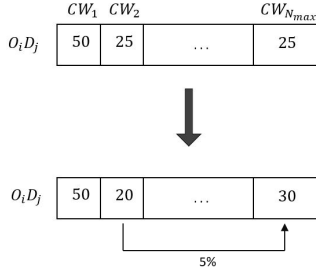


Figure 3. Example of the neighbor operator for L with a step of 5%.

When a neighbor is generated we must choose one of the methods mentioned above. It should be noted that the methods of generation have different probabilities of being chosen throughout the cooling process. At the beginning, when the temperature is high, it is more probable of creating a neighbor with a modification in N_{cw} than any other type. When the temperature is lower, the probability of creating a neighbor with a modification in P becomes the most likely to happen. Finally, at the the lowest temperatures, the modification of L becomes the most probable. These shifting probabilities were chosen due to the fact that a change in N_{cw} modifies also P and L indirectly. So, a change in N_{cw} has a bigger impact in the modification in the topology of our ARN than in the rest of the decision variables. Consequently, a modification in this will be more adequate in the phase of exploration. Meanwhile, the modification in L is more suitable in the phase of exploitation, *i.e.* when the temperatures are lower.

C. Penalizations

Some constraints were applied directly to the decision variables, like the flow balance and the redistribution of flow. The rest of them were addressed using penalization. This method was used in order to have a deeper exploration of the state space.

This relaxation consists in adding the terms to the objective function with the goal of penalizing the violation of a constraint. So, in practice, the objective function will be

$$\min f + \tau \zeta \quad (5)$$

where f is the original objective function seen in (4), ζ is the penalization term and $\tau = 1 - \text{ratio temperature}$. τ will be an indicator of the system temperature. Its value will increase as the temperature decreases. Based on this trick, at the beginning of the process, the algorithm can explore a wider range of solutions, even though some of them do not respect the constraints. At the exploitation phase, the algorithm will start penalizing more the constraints with the aim of obtaining a solution that respects them. Our penalization term can be broken down into

$$\zeta = \beta_1 c_1 + \beta_2 c_2 + \beta_3 c_3 + \beta_4 c_4 + \beta_5 c_5 + \beta_\eta \eta \quad (6)$$

where all β are penalty parameters to be set by the user. Each parameter c represents a constraint violation. It is crucial to highlight that the constraints are non-negative. c_1 is the distance between CWs. This constraint was explained in section II-E, and it can be calculated using the following expression $c_1 = \max(0, D_{wpm} - d_{ij})$, where $i, j \in CW$. Regarding c_2 , this parameter will contain the total number of angles between routes in every node that are not within the acceptable value, as it was described in constraint 5.

Furthermore, another element was added to the objective function: the sum square of the conflicts in each CW, c_3 . This was included due to the need to balance the workload in each CW. When we try to minimize the square sum of them, the variance of our conflicts will tend to decrease, reaching the objective of having a balanced workload for every CW. In addition to that the violation of distance between CW and entry/exit points was added as c_4 . Regarding c_5 , this constraint imposes the limit of conflicts per CW.

While performing the first tests, a factor that initially was not taken into account appeared: undesired intersections. In this work an undesired intersection is considered as any intersection between routes at the same FL that does not occur in a CW. This corresponds to link crossings at the same FL. To face this issue and try to minimize the number of undesired intersections, η , a penalization parameter was added. This parameter measures the quality of flow crossings out of CWs.

IV. RESULTS

Initially it was decided to test the model using simple cases, in order to check the model's coherence and have an initial comparison with the direct routing method. Later on, it was decided to apply the model to a real case scenario.

A. Performance Metrics

As it was remarked in the implementation, our model's priorities are safety and fuel saving. In the optimization algorithm, we primarily use the total number of conflicts and the total deviation of flights to quantify these elements in the objective function. However, in the results section, different metrics were applied. This modification aims to enhance the readability and comprehension of the solutions for the readers.

Safety will be defined by two metrics: the Average Number of Conflicts per Flight (ϕ_{avg}), and the total number of undesired intersections (η). Meanwhile, fuel saving will be characterized by the Average Flight Deviation (θ_{avg}). Therefore, the two averages will give an awareness of the solution's impact on each flight. In addition to that the number of undesired intersections will help to analyze the global safety of the sector.

B. Simple Cases

To test our approach, one decided to implement three simple scenarios, a case of 3x2 (three entries and two exits), a 3x3 and a 4x4 using the display of Figure 1. For these three cases, the minimum and maximum number of CWs used were two and six, respectively. The results can be observed in Table I.. It should be noted that the time budget used for these tests were 30 seconds for the grid 3x2 and 3x3, and 60 seconds for the 4x4.

It should be noted that since we are dealing with metaheuristic algorithms, the results are going to be described using the mean (\bar{x}) and the standard deviation (σ). This is due to the use of random and stochastic processes in this type of algorithms. Computing the mean and standard deviation helps evaluating on how robust the algorithm is to different initial configurations and its overall performance. For the results, 10 iterations of each algorithm were made in order to obtain these measurements. Examples of the optimal CW placement found by the SA algorithm can be seen in the Figure 4.

Additionally, it is worth noting that in these simple cases we exclusively applied SA. This deliberate choice was made to initially assess whether the CWO approach demonstrated potential to enhance any of the metrics with respect to the direct route method, before introducing any additional algorithm.

TABLE I. RESULTS IN DIFFERENT SIMPLE CASES. VALUES OF THE AVERAGE NUMBER OF CONFLICTS PER FLIGHT (ϕ_{avg}), AVERAGE FLIGHT DEVIATION (θ_{avg}), AND THE TOTAL NUMBER OF UNDESIRE INTERSECTIONS (η)

	ϕ_{avg} [Ac/h]		θ_{avg} [NM/Ac]		η	
	\bar{x}	σ	\bar{x}	σ	\bar{x}	σ
Grid 3x2						
SA	0.334	0.046	33.2038	2.374	1.2	1.1662
direct	0.1763	0.00	0.00	0.00	3	0
Grid 3x3						
SA	0.412	0.025	72.317	5.232	7.2	1.7204
direct	0.466	0.00	0.00	0.00	9	0
Grid 4x4						
SA	0.788	0.124	86.8929	7.533	6.46	1.362
direct	0.748	0.00	0.00	0.00	12	0

At first sight of Table I., it is clear that the use of CWs is going to affect negatively the θ_{avg} . The concept itself of CW makes the increase in deviation a necessary factor in order to apply it properly. However, the goal of this optimization is not to obtain the most profitable ARN, but rather the safest one, while managing to reduce the most the impact on the routes.

Regarding safety, there is a noticeable enhancement in η . It manages to be reduced by 50% in some cases. Nevertheless, the parameter ϕ_{avg} is generally increased significantly by using CWs. It seems that this difference in ϕ_{avg} is reduced when the network grows (more entries & exits), which infers a possibility of improvement when the network becomes more complex. This inference will be confirmed in the case study. This shows that the CWO has a potential to simplify the controllers' job by concentrating the workload in some specific area.

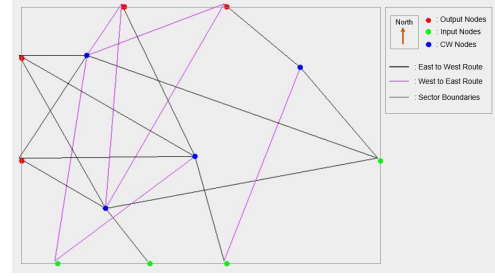


Figure 4. Example of a solution obtained by SA for the grid 4x4.

C. Reims LFEEKF Sector Case

Once the model has been tested and validated with simple cases, it was decided to test the model with a real case. The algorithm was applied to a subsection of France's UIR, more specifically Reims' section . Reims' airspace can be divided according to Figure 6 [10].

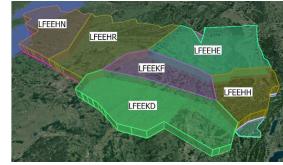


Figure 5. Reims ACC Sectorisation. [11]

The sector LFEEKF was chosen due to its simple geometry and location (center of the Reims Area Control Center). This sector contains 14 corners, from which 11 will be considered as entry and exit nodes. It was admitted that the total demand would be of 150 aircraft/hour for the whole center, which is approximately the average of a peak day traffic in 2019, [12]. It was decided to use this value to design a topology to support a high demand in the network.

1) Initial Results: The sector was designed and inserted in the model of the simulation environment, for which the results are illustrated in Figures 6 and Table II. In addition to the SA, Taboo Search (TS) [13] and Particles Swarm Optimization (PSO) [14] are also applied on this problem. It must be noted that the time budget chosen for this test is 150 seconds.

TABLE II. RESULTS IN THE REIMS LFEEKF SECTOR.

	ϕ_{avg} [Ac/h]		θ_{avg} [NM/Ac]		η	
	\bar{x}	σ	\bar{x}	σ	\bar{x}	σ
SA	0.251	0.029	25.24	1.23	40.60	10.26
TS	1.272	0.344	19.25	3.34	90.53	25.68
PSO	0.556	0.042	30.22	1.78	52.51	8.14
direct	0.62	0.00	0.00	0.00	87	0

At a first glance, one can observe a significant difference between TS and the other methods. It seems that the algorithm,

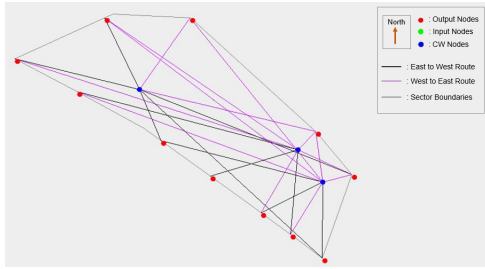


Figure 6. Topology of a solution obtained by SA in LFEEKF sector.

due to its noticeable variability, did not have the time or the exploration capacity to find a more adequate solution. This will be examined deeper in the time budget analysis. Thus, in terms of consistency, TS demonstrated the worst performance for this time budget, giving it a significant disadvantage.

Regarding safety, it is evident that the SA has a better performance in the number of conflicts and the number of undesired intersections, lowering these metrics approximately 50% with respect to the classical FRA approach.

It is also evident that the average number of conflicts has significantly decreased as well as the number of undesired intersections. Also, as seen in the simple cases, the increase in safety implies an increase in the detouring of flights, so we verify an average detouring of approximately 30 nautical miles per flight. This result shows that the use of CW can improve the efficiency of an ARN regarding safety and workload for controllers with a lower number of undesired intersections compared to the direct route approach.

In spite of various tests, it was not possible to achieve a solution where there were no undesired intersections. A main cause for this issue can be the fact that this model only admits a path using just one CW. This assumption limited the solutions' space. A possible approach for this limitation will be mentioned in the last section.

2) *Time Budget Analysis:* Although Table II. showed at first glance that the PSO and SA had the best performance between the algorithms regarding safety, it is essential to perform a time budget analysis. This evaluation consists in carrying out various tests with different time budgets. This approach will permit us to see the evolution of each algorithm performance along time. This way, one can check if the superiority of PSO and SA is still significant.

For this evaluation a range of time budget where chosen between 20s and 200s (time for which all the objective function values are already stabilized). Figure 7 illustrates the global performance analysis.

Figure 7 puts in evidence some key aspects. Firstly, the algorithms managed to decrease the objective function value effectively. Secondly, a considerable difference can be observed between the standard deviation of TS and the rest. Finally, it is

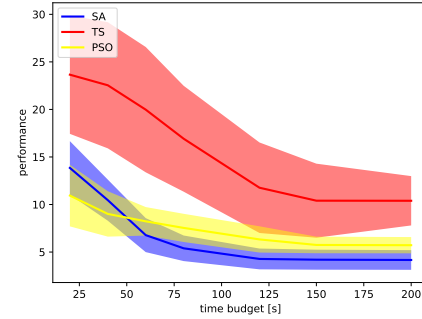


Figure 7. Global performance with respect to time budget. Comparison of algorithms' \bar{x} (solid line) and σ (translucent areas).

visible that initially the performance of the PSO is the best but, as the time budget increases, it is surpassed by the SA. In order to deepen our analysis, an evaluation of the evolution of the main criteria of the objective function was done. This is illustrated in Figure 8.

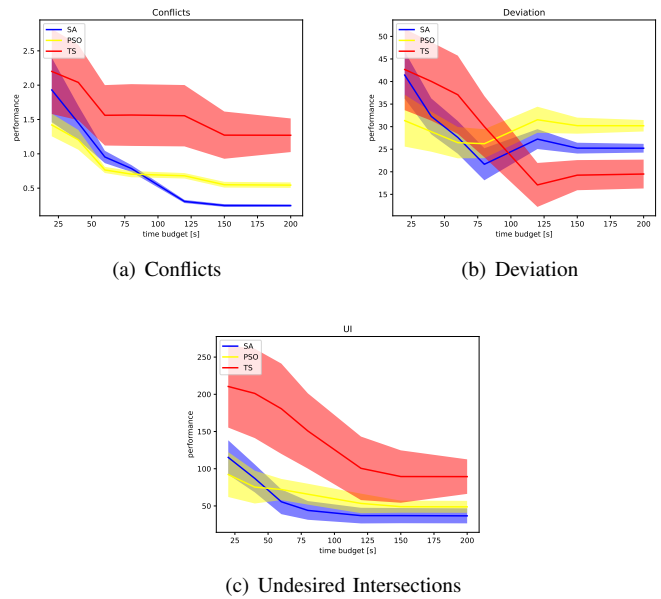


Figure 8. Performance of individual metrics with respect to time budget. Comparison of algorithms' \bar{x} (solid line) and σ (translucent areas).

Using a weighted sum function as the objective function of our multi objective problem, it is evident that although the number of iterations increases, some metrics do not necessarily perform better (decrease), specially in the route deviation, as illustrated in Figure 8. This occurs because the algorithm finds a better global solution, which means that it could have worsened one characteristic, but the others have been enhanced so much so that the overall score decreased. It is evident that, using our

objective function, our algorithms give a huge priority towards the conflicts and the undesired intersections.

We observe that there is a considerable difference between TS and the other approaches. Initially, the assumption was that the TS low performance could be attributed to not allocating enough time. However, as the results of Figure 7 indicated performance stagnation, this option was dismissed. It seems that the TS exploitation phase is not as exhaustive as the other two alternatives, leading to a high variability of the solutions given, *i.e.* a high value of σ . The randomization employed in the initial states is not being attenuated by the algorithm's exploitation phase. In another words, the algorithm is not able to converge into the same solutions.

Meanwhile, the PSO and SA manage to reduce their variability significantly, achieving an average conflict rate below 1 Ac/h and a η below a 100. It is seen that the performance of PSO is the best for few iterations. Later on, when the time budget is higher than 50 seconds approximately, SA outperforms the PSO. So, the PSO starts with a good performance due to its swarm exploration strategy, which is pretty efficient. The fact of creating $N_{particles}$ makes that the algorithm explores more states initially. Nevertheless, as time budget increases, SA improves more, this can be justified by two factors. The first is that SA's exploration phase is more efficient. This is attributed to the capability of SA to use a greater number of iterations to explore a given solution, in contrast to PSO, which employs significantly fewer iterations per solution.

Secondly, the PSO exploration strategy seems to stagnate thanks to the influence of the population trapped in local minima. This way, the velocity of the swarm tend to converge towards the area of the solution space, not arriving to the same level of SA. Therefore, PSO can manage to be an adequate solver for a low budget simulation, while SA will be fitter for a high budget simulation were our main priority is performance.

V. CONCLUSIONS

The model proposed in this paper offers an improvement regarding the classical FRA model. The model tends to increase safety by lowering the number of potential conflicts in the considered area, and concentrating these conflicts within the CWs. This improvement will decrease the workload of the air traffic controllers, while trying to minimize routes' deviations.

The optimization problem has been modeled as a CWO, where the decision variables are the number of CWs, their positions and the percentage of flow of each route that passes through each CW. With these variables our model simulates the decision variables and return the number of conflicts within the sector from each CW, and the average deviation of each route. Then, the problem is solved by using SA, PSO or TS algorithms which aims to minimize the objective function. The objective function

was designed to minimize the total number of potential conflicts, undesired intersections and the total deviation of the routes.

The results of this approach showed that the use of well placed CW can improve the performance of a sector, even though there will always be an increase in the distance traveled by all the flights. However, the total number of conflicts and undesired intersections can be reduced significantly. In addition to that, the potential conflicts will be less scattered throughout the sector, improving the work of the controller.

Despite the positive results, some points still have the possibility of being improved. Firstly, although our method reduced the number of undesired intersections, it was not possible to reduce it to zero in a real case scenario. A proposal to achieve this is to explore more types of topologies, since the flow in our simulator can only be routed through a single CW. Furthermore, some new factors could be added to the model like the existence of PRD zones or the use of more than two FLs in the sector. Moreover, another interesting approach would be the implementation of a multi-objective algorithm like NSGA-II. Finally, the model should be tested with more airspace examples with different geometries and demands, increasing the confidence in the methods developed. All of these proposals could lead to a more adapted model to different types of airspace sectors and a better structure of our ARN.

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