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Strategic Path Change Maneuvers for Weather Obstacle Avoidance in Aviation*

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Weather avoidance algorithms play a crucial role in significantly enhancing aircraft safety during flight operations, particularly in the presence of severe weather conditions. This paper presents a novel obstacle avoidance strategy based on the use of alternative paths to circumvent obstacles during the cruise phase. The objective of this study is to assess the benefits of using strategic information to address tactical avoidance issues. Firstly, the new strategy is simulated in a dynamic space populated with weather obstacles. Subsequently, the proposed strategy is compared to a classical avoidance maneuver in several dynamic simulations, varying the size of the obstacles. The results show that including strategic information on dynamic rerouting can be of significant benefit to both the pilot and air traffic controller, providing a supportive decision-making tool for bad weather avoidance.

Key Words: Weather Avoidance Algorithm, Alternative Trajectory, Simulation

1. Introduction

A few hours before departure, the pilots prepare their flight plan by taking into account atmospheric conditions which are not fully deterministic. Weather conditions can postpone flights for minutes or even hours. In extreme cases, these conditions threaten aircraft safety and may lead to accidents. To reduce their adverse effects on civil aviation, it is really important to analyze these factors and their associated consequences. With accurate predictions, we can then use this knowledge to enhance aircraft routing.

Optimizing aircraft's trajectory is a crucial issue in air transportation. To reduce fuel usage, airlines develop methodologies to optimize flight routes. This route planning considers both the aircraft's capabilities and anticipated meteorological conditions. Pilots adhere to this route as closely as possible. However, unforeseen events such as meteorological obstacles or airspace conflicts can interfere with the planned route. In these scenarios, pilots guided by air traffic controllers must address severe weather conditions or resolve conflicts with other aircraft. These solutions need to be found quickly; hence they are barely optimal. Furthermore, in critical situations, quick responses can be challenging, and automation might assist. Our approach for solving this issue involves pre-flight generation of alternative cruise paths.

Free Route Airspace (FRA)[1,2] represents a novel approach to air traffic management, offering pilots enhanced flexibility and more options for flight planning between airports. The application of FRA rules starts after the initial departure constraints and ends with the arrival into the terminal area of the destination airport. Weather avoidance algorithms play a crucial role for enhancing aircraft safety during flight, particularly in the face of stormy weather conditions.

Tactical avoidance maneuvers entail a temporary deviation from the trajectory to circumvent obstacles, followed by a return to the original trajectory. However, such an approach addresses a local problem with a solution computed based on local information only. This kind of approach may result in excessive travel time, which could be reduced through the implementation of more efficient maneuvers.

This paper presents a novel obstacle avoidance strategy that considers global information to compute efficient cruise avoidance trajectories when obstacles are detected on the flight plan. The provision of this information should enable a reduction in the impact of avoidance maneuvers on the total flight time. The following assumptions are considered in this paper:

- aircraft can operate in FRA conditions,
- alternative trajectories can be flown by the aircraft,
- flight level and aircraft speed are constant,
- aircraft have access to real-time weather data.

The paper is organized as follows: Section 2 presents some previous related works on route planning and dynamic avoidance route generation methods. Then, Section 3 details the simulation framework used to simulate the flights. Section 4 introduces the alternative path generation algorithm. Finally, Section 5 presents the results of the path change

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strategy and a comparison with the classical avoidance maneuver is given.

2. Previous Related Work

2.1. Route planning

Prior to departure from an airport, the airline in charge of a flight must submit a flight plan. This flight plan describes the route that the aircraft will follow. The flight plan is the result of an optimization process that respects several constraints. The combination of these constraints with the uncertainty linked to the weather makes the computation of such a flight plan a very complex task.

Different approaches have been developed to tackle this problem. The airspace can be sampled, after which graph theory algorithms such as Dijkstra or A* can be applied to compute the least-cost path, which avoids obstacles. This approach is detailed in by Bokadia et al.[3] and Xie et al.[4] Another approach uses a sampling-based algorithm. In contrast to the preceding methodology, this approach starts by generating sample points within the free space and then build a tree[5,6] or a graph.[7,8]

The flight plan is calculated based on weather forecasts and historical data. However, the weather conditions available at departure may differ from the prediction, resulting in dynamic adjustments.

2.2. Avoidance maneuver

In order to model weather avoidance maneuvers, it is necessary to simulate the system dynamics. The aircraft may be able to access regular weather information thanks to different radar devices. This data can take two different forms: real weather data, or tactical forecasts. Based on these new data, the pilot can update the aircraft trajectory accordingly in order to minimize the detour.[9,10] This approach is focused on tactical maneuvers and is usually solved thanks to optimal control.[11,12]

In the air, severe weather conditions are not the only obstacles. Some areas are prohibited, restricted or dangerous and therefore must be avoided.[13] In addition to such regions, the other flights in the airspace must be also avoided too. This problem is known as aircraft deconfliction. One possible approach to model this problem is to use mixed integer linear programming and to solve it with commercial software.[14] Guitart et al.[15] propose a collaborative solution framework to design, for a foreseen set of flights, efficient trajectories taking into account weather conditions while avoiding traffic conflicts.

All the previously described methods dynamically recompute the "best response" to the last collected information. In contrast to our previous work,[8] this work focuses on the automatic generation of a set of dissimilar paths based on weather information. The primary objective of our previous work[8] was to use strategic information to address tactical issues encountered in the en route airspace, a concern that is also addressed in this work. The aim of this research is to quantify the benefits of strategic information on dynamic rerouting when an obstacle occurs on the flight plan.

3. Simulation Framework

The simulation loop, which is used to simulate the aircraft trajectory in a dynamic airspace, is presented in Fig. 1. This loop is composed of four main components: initialization, mobility, replanning, and analyses. In the initialization step, the data is loaded and the objects required to run the simulation are created. This step also defines the simulation period, departure time of the aircraft, and flight plan. In the mobility bloc, the obstacles are updated according to the weather data and the aircraft is moved in accordance with its flight plan. The set of moving obstacles and aircraft will be designed as a dynamic systems. If an obstacle is detected on the aircraft flight plan, replanning is triggered. During the replanning phase, a new plan is generated based on the current weather conditions. The simulation will then end when the aircraft reaches its destination. Once this occurs, all the data collected during the simulation can be analyzed.

3.1. Time window

This simulation package simulates the positions of dynamic systems over a time period designated as the analysis period. This analysis period is defined by the departure time of the aircraft from the departing airport and the arrival time at the destination airport. This period is divided into several time windows, as illustrated in Fig. 2. The duration of a time window is typically in minutes, with a range of 5 to 15 minutes. The dynamic systems (airspace and aircraft) are updated at each time window. The updating process involves computing the positions of these systems at the end of the time window based on the current state of the simulation.

3.2. Airspace

We assume that the aircraft is flying at a constant flight level. We model the airspace as a two-dimensional grid, where each cell represents a specific area.

The cell is activated during the designated time window if there is at least one weather obstacle contained within such a

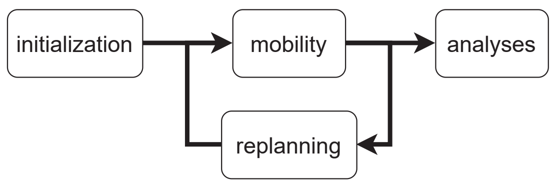


Fig. 1. The four-step simulation loop comprises the following stages: initialization, which initialize the stimulation environment; mobility and replanning moves of dynamic systems; analyses, which gathers the results of the simulation.

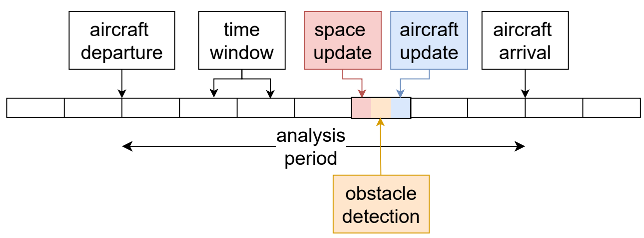


Fig. 2. The simulation time is divided into discrete intervals over the analysis period.

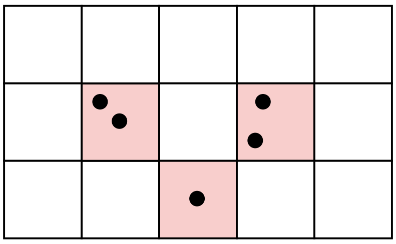
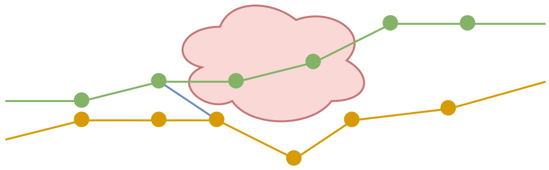


Fig. 3. The grid model of a flight level. The black dots represent the weather obstacles. When a grid cell contains at least one weather obstacle, all the cell is then considered as an obstacle and is colored in red.

(a) Avoidance maneuver (blue path) around an obstacle (red cloud).



(b) Plan change maneuver (blue link) to an alternative path (orange path).

Fig. 4. Two obstacle avoidance strategies for circumventing a weather obstacle (red cloud) detected on the aircraft route (green path).

cell, with the time window being the temporal limit. In this model, the range of the weather obstacle is equivalent to the size of the cell it has triggered (see Fig. 3).

3.3. Aircraft

The aircraft is one of two dynamic systems whose positions evolve during the simulation. At each simulation time window, the position of the aircraft is updated based on spatial information. This information is collected by the "radar" of the aircraft. If the radar detects an obstacle on the route, the aircraft computes a new route to avoid the obstacle.

3.3.1. Radar

The radar is the system in our model that allows the aircraft to obtain information from the surrounding environment while it is in motion. The radar performs two main tasks. Firstly, it has access to the space data and therefore knows where the weather obstacles are currently located for the time window (this information is coming from the real weather radar of the aircraft). Secondly, thanks to the TCAS system it has access of the position and speed of the current aircraft and the positions of the weather obstacles in a given range. Based on this information, it can predict potential conflicts. This approach can also be used to model weather information from air traffic controllers or any other useful pilot support system.

3.3.2. Replanner

The map of the space generated by the radar system allows for the update of the flight plan followed by the aircraft. In this study, two kinds of replanning strategies are being compared.

The first one is the avoidance maneuver strategy (see Fig. 4a). When an obstacle is detected in the radar range, the replanning is triggered. This strategy starts by identifying the points on the flight plan that are behind the obstacle. Then, alternative routes are computed between the aircraft position and those points. The route selected to avoid the obstacle is the shortest.

An alternative to the one described previously consists in shifting from the current flight plan to an alternative route that does not cross the obstacle (see Fig. 4b). The computation of the alternative routes between the origin and the destination airports is done during the initialization step. The flight plan followed by the aircraft is the shortest route among those alternatives. The route shifting is implemented the following way: firstly, we identify the shortest route that avoids the obstacle, and then compute the closest node to aircraft position on this alternative respecting flight constraints. Unlike the avoidance maneuver, there is no need to return to the initial flight plan, as the alternative path has been validated before the departure by the airline company in terms of flight operation constraints, travel time, fuel consumption, etc. The only reason to return to that route would be that this route becomes the best solution to avoid an obstacle later on the flight.

4. Alternative Path Generation Algorithm

The objective of this study is to analyze through simulations the relevance of computing alternative paths at a strategic level for tactical situations. To do so, we compute the alternative paths and the flight plan in the initialization step (see Fig. 1). In this section, we present a brief overview of the alternative trajectories generation process. Further details on the method can be found in the article[8] cited in the references section.

4.1. Graph generation

The objective of this section is to generate a graph from scratch using the RRG algorithm.

The algorithm can generate multiple paths between two points by sampling the space and can be easily adapted to consider constraints. This algorithm is repeated many times with four functions until a criterion is met. These functions are presented in Fig. 5.

The sampling function randomly generates a sample point in the space. The nearest function then identifies the node in the current graph that is the closest to the sample point. If the closest node and the sample point are too far apart, the steer function brings the sample point closer to the graph. Finally, the near function computes the set of nodes that are the closest to the sample point.

Once all four functions have been performed, the graph is updated. The update entails connecting the near nodes to the sample node. As a result of the iterative application of these functions, the size of the graph increases linearly with the number of iterations but the number of links increases exponentially.

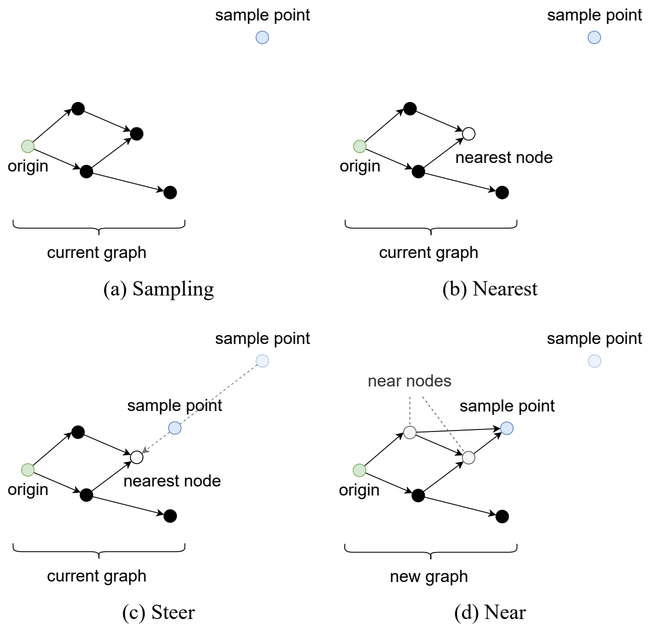


Fig. 5. The four main functions of the Rapidly-exploring Random Graph (RRG) algorithm are as follows: sampling, nearest, steer, and near.

4.2. k-means clustering

The process of generating graphs is repeated multiple times in order to obtain graphs with distinct alternatives. However, this results in a concatenated graph with numerous nodes. The clustering of small groups of nodes in a limited space is not significant. For example, if one node from a group is located in a weather zone, the other nodes in the group will also be in this area. If some nodes are not, they will still be too close to the obstacle to be used as alternatives. Consequently, we propose the merging of these nodes into a single centroid node.

The k-means algorithm was selected for this clustering processing due to its unsupervised nature and single parameter requirement (number of clusters). Furthermore, the absence of outliers in the data is guaranteed, as all points belong to at least one path, which have been generated by the RRG algorithm.

4.3. Filtering process

The clustering step can generate centroids in weather obstacles. Therefore, it is relevant to remove the routes whose centroids cross obstacles.

In addition, if we have access to any other weather data (forecasts for instance), we can include this information in the filtering process. This would reduce the memory requirements and the running time to compute the best alternative when an obstacle is detected on the route.

This process must be applied carefully for memory usage reasons. The weather data used for the path generation and forecasts are very uncertain. Thus, there is no guaranty that the routes identified before departure would still be operational during the flight as weather conditions change. Here, we recommend keeping a high number of alternative routes with diversity to be prepared for as many scenarios as possible.

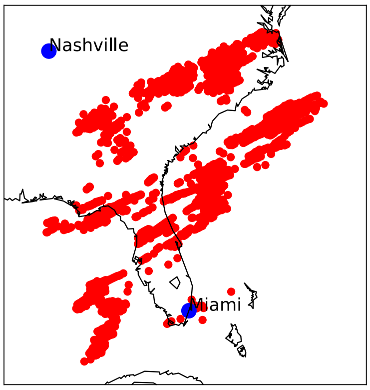


Fig. 6. Severe weather obstacles between Nashville and Miami cities on the 26/02/2015.

5. Results

5.1. Data

In order to perform the simulations, this simulator requires time series weather data. However, these data are difficult to obtain, particularly when the time step is small (less than an hour).

For this study, we utilize the data from the Severe Weather Data Inventory (SWDI) database, which is a repository of severe weather records for the United States. Severe weather represents a significant risk to both people and property. Fast updrafts during strong thunderstorms can cause frozen precipitation, which can result in significant damage and harm.

The SWDI records originate from various sources within the National Climatic Data Center archive and encompass a range of weather phenomena. We have used a 2015 extract that includes hail detections, which provide insight of the probability and severity of the event. The dataset comprises event-level records of storm cells that are likely to produce hail. The dataset comprises a total of 10,824,080 individual storm cells.

To challenge our method, we needed an Origin-Destination (OD) airport pair on a day with multiple obstacles. We have chosen the OD connecting Nashville to Miami on the 26/02/2015. The global weather obstacles of this day are presented in Fig. 6. The obstacles are distributed mainly in two rows and the distribution in these rows are not uniform which will allow avoidance maneuvers. Besides, the direct route between OD pair crosses the obstacles, therefore the simulations should perform at least one avoidance maneuver.

5.2. Dynamic obstacles

This first work is devoted to the analysis of a plan change maneuver as presented in Fig. 4b. The approach is tested on dynamic weather obstacles corresponding to 26/02/2015.

Besides, during the initialization step, no prior weather information is used to compute the set of alternative paths connecting the OD pair. The initial flight plan is the shortest path in this set. The aircraft is equipped with a radar system that has access to the real time space state. For this first study, the radar is capable to detect obstacle collisions up to 100 km ahead. When an obstacle is detected, the replanner selects the shortest alternative that avoids the obstacle if one is available, otherwise the decision is left to the pilot. This is the limit of such a decision support tool in operational situations. However, an extension could be to change the strategy to an avoidance maneuver.

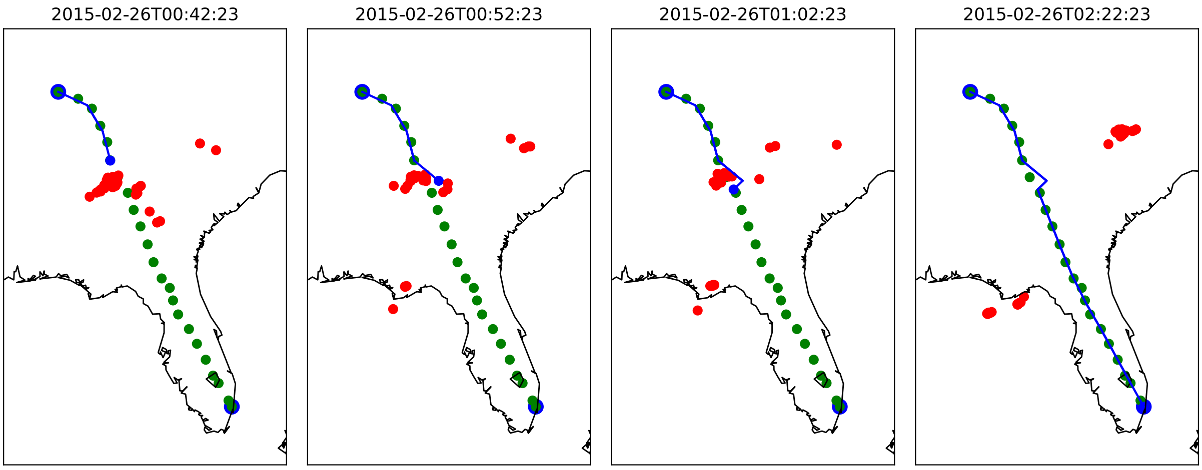
The parameters used for this simulation can be found in Table 1. σ_{cell} is the size of the cell. η_{min}, η_{max} is the range where the parameter η varies. This parameter is involved in the steering function of RRG. It sets the distance between the nearest node and the moved sample point (see Fig. 5). n_g is the number of graphs generated at the initialization. α is the coefficient fixing the lower bound radius when identifying the near nodes, and β is also a coefficient used to compute semi minor axis of the ellipse whose foci are the OD pair. We use an ellipse to limit the space where the random points are generated. $n_{samples}$ is the number of random points generated by the RRG algorithm in the space. For more details on these parameters, the reader can refer to the article.[8] The first column of Table 1 is the time window, which is the duration between two simulation iterations. The radius fixes the range of detection of obstacles. Then, there is the number of clusters used for the k-means and the associated number of iterations.

Table 1. Parameters of the two dynamic path change maneuvers.

(a) Small maneuver.						
σ_{cell}	η_{min}	η_{max}	n_g	α	β	$n_{samples}$
10 km	40 km	100 km	6	0.5	1	10,000
(b) Large maneuver.						
σ_{cell}	η_{min}	η_{max}	n_g	α	β	$n_{samples}$
25 km	40 km	100 km	6	0.7	1	30,000

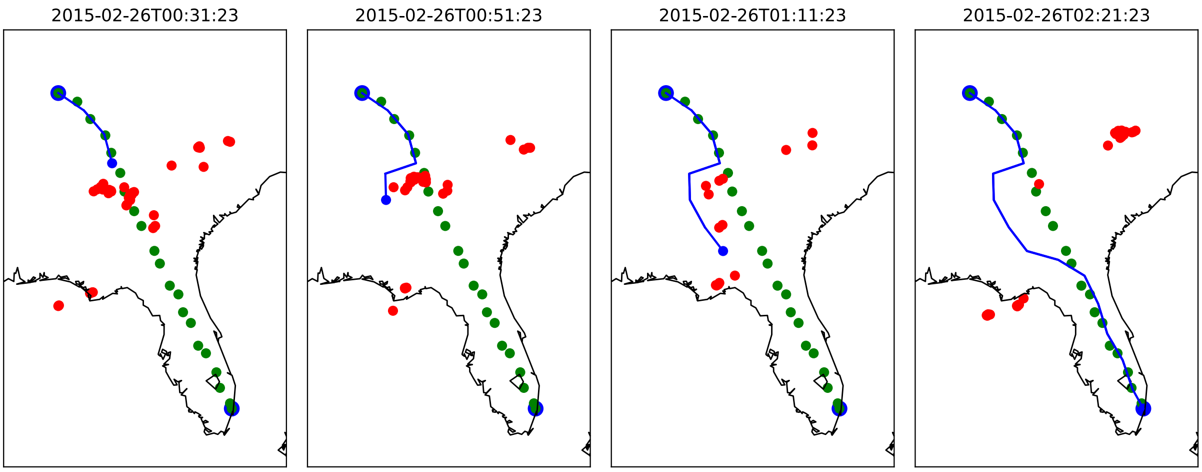
In this simulation, the aircraft is moving in a dynamic space. The positions of all the obstacles are updated every ten minutes, which is the size of the time window.

The distribution of the obstacles is not uniform in either space or time. In order to account for the presence of obstacles along the flight path, the aircraft is simulated departing at midnight. The outcomes of the two simulations are presented in Fig. 7 and Fig. 8.



(a) Obstacle detection (b) Start of maneuver (c) End of maneuver (d) Final route

Fig. 7. Small obstacle path change maneuver.



(a) Obstacle detection (b) Start of maneuver (c) End of maneuver (d) Final route

Fig. 8. Large obstacle path change maneuver.

In both simulations, the aircraft is avoiding the obstacles in a consistent manner. Initially, the aircraft avoids the obstacle on the left side, as illustrated in Fig. 7. Subsequently, the aircraft avoids the obstacle on the right side, as illustrated in Fig. 8. In the initial simulation, the aircraft traverses a narrow corridor between two weather obstacles, subsequently adhering closely to its original trajectory. In the second example, the aircraft performs a significant avoidance maneuver on the right and subsequently returns to a trajectory that is almost similar to its original plan. These two examples have shown that our strategy is capable of generating different solutions (right and left side maneuvers) to tackle the obstacle problem. In these simulations, the original flight plan is different. The simulations have been run independently with different parameters. Therefore, the set of alternative routes is also different. In this context, the best solution found when the obstacle was detected was a left side maneuver for the small maneuver and right side for the large maneuver. The route change occurs when the radar detects an obstacle, as indicated by the deviation of the blue trajectory (aircraft trajectory) from the green trajectory (flight plan). Although it may seem that the trajectory returns to the initial path after avoiding the obstacle, it is essential to clarify that the avoidance path and the original trajectory are not identical; some overlap may exist among the alternative paths, but they remain distinct. Additionally, the flight times for the maneuvers are approximately 2 hours and 10 minutes for the small maneuver and 2 hours and 20 minutes for the large maneuver, with each scenario involving a single maneuver. These two examples simulate two different levels of maneuver complexity for the pilot. For both examples the proposed algorithm found relevant maneuvers. Furthermore, the parameters that have been used for the simulation are presented in Table 1a and Table 1b. It can be observed that three parameters have undergone a change between the two simulations. The dimensions of the cells, α and $n_{samples}$ were augmented. The size of the cell has no impact on the paths computed; it only reduces the number of alternatives when the obstacle is detected. However, it is obvious that the values of α and the number of samples have a direct impact on the paths computed. As the value of α increases, the paths computed become more diverse from one another. Conversely, the number of paths increases with the value of $n_{samples}$.

The method proposed demonstrated its efficacy in a complex study case with dynamic obstacles by swiftly adapting the aircraft flight plan, resulting in successful avoidance of tactical challenges during the flight.

5.3. Comparison with avoidance maneuver

The two preceding studies demonstrate that a strategic precomputation of alternative paths can be highly beneficial in avoiding obstacles in tactical situations in the en route airspace. The objective of the following work is to quantify the benefit of the aforementioned method in comparison to a classical avoidance maneuver.

The initial analysis entails a comparison of the travel times for both strategies within a specified scenario. In this particular scenario, the cell size was fixed at 10 km, while the aircraft speed and radar range were set to 220 m/s and 140 km, respectively. To ensure the robustness of the results, the scenario was run multiple times, with each iteration using the same flight plan for both strategies. The RRG algorithm was also employed to calculate the avoidance trajectory as part of the avoidance strategy. The results of the simulations are presented in Fig. 9.

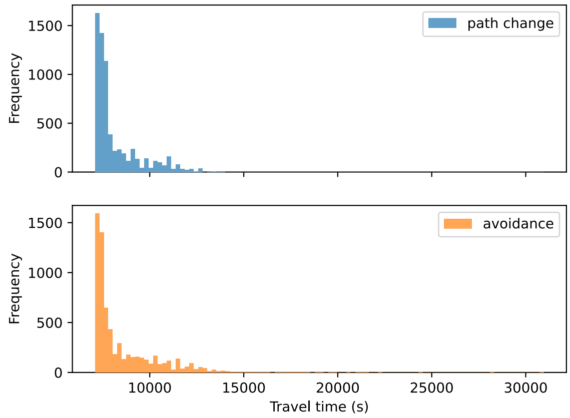


Fig. 9. Distribution of travel times for path change and avoidance strategies with a cell size of 10 km.

The comparison of the travel time distributions reveals a high degree of similarity. However, it is noteworthy that the third bar exhibits a significantly higher frequency in the path change strategy compared to the avoidance strategy. This indicates that for this specific travel time range, a greater number of aircraft exhibited a travel time within that range when using the path change strategy in comparison to the aircraft using the avoidance strategy. The mean travel time for path change and avoidance strategies is 8,146 and 8,516 seconds, respectively. The difference between the two values is 370 seconds, which is equivalent to approximately 6 minutes. On average, the path change is faster than the avoidance approach to avoid obstacles.

In the second part of the analysis, we simulate scenarios with different obstacle sizes keeping all the other parameters unchanged. From all the simulations run, 34,066 yielded results where both aircraft performed at least one maneuver and where the travel times differed.

The statistical results of the simulations are presented in Table 2. The first represents the size of the cells. The value is expressed in meters. The second column represents the number of simulations where the two strategies generate different travel times. The aforementioned columns were employed to categorize the simulations. The following columns present the lower whisker bound (lwb), first and second quartiles, mean, third quartile, and upper whisker bound (uwb) values of the travel times in seconds of both strategies.

The results indicate that the lwb, first and second quartile, mean, third quartile, and the uwb of the path change strategy are lower for all scenarios tested. With the exception of the initial row, the lwb are in close proximity to one another for both strategies. The difference in time is equivalent to dozens of seconds. With regard to the first quartile, the temporal dis-

Table 2. Comparison between avoidance and path change travel times.

Obstacle size	Simulations	Path change						Avoidance					
		lwb	q1	q2	avg	q3	uwb	lwb	q1	q2	avg	q3	uwb
10,000	2,966	8,951.00	10,561.00	11,050.00	11,019.76	11,637.75	13,249.00	10,318.00	11,877.50	12,331.00	12,301.35	12,929.00	14,483.00
15,000	3,416	7,131.00	7,839.00	8,074.00	8,310.25	8,649.00	9,834.00	7,156.00	8,495.75	9,105.00	9,395.76	9,741.25	11,582.00
20,000	5,940	7,086.00	7,210.00	7,271.00	7,367.47	7,402.00	7,683.00	7,090.00	7,292.00	7,566.50	8,558.93	8,565.25	10,475.00
25,000	5,516	7,072.00	7,204.00	7,264.00	7,314.79	7,380.00	7,630.00	7,096.00	7,247.00	7,393.50	8,098.48	7,986.25	9,095.00
30,000	5,736	7,082.00	7,212.00	7,280.00	7,306.16	7,373.00	7,612.00	7,102.00	7,240.00	7,343.00	7,872.98	7,491.00	7,867.00
35,000	5,645	7,073.00	7,223.00	7,287.00	7,298.99	7,366.00	7,534.00	7,098.00	7,235.00	7,310.00	7,544.09	7,405.00	7,657.00
40,000	4,847	7,083.00	7,228.00	7,294.00	7,304.12	7,373.00	7,581.00	7,118.00	7,248.00	7,328.00	7,560.96	7,431.00	7,687.00

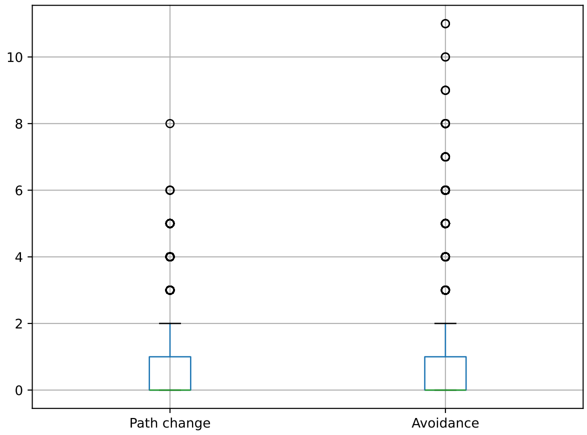


Fig. 10. Comparison of the number of maneuvers performed by avoidance and path change strategies.

crepancy between the two initial scenarios is 1,317 and 656 seconds, respectively. The time difference for the remaining scenarios is approximately dozens of seconds. A comparison of the second quartile of the two strategies reveals that, for the first two scenarios, the time difference is approximately 1,000 seconds; for the two following scenarios, it equals several hundred; and for the other scenarios, it is closer to 40 seconds. On average, the path change strategy is faster, and the time difference varies between several hundred and a thousand seconds. The trend for the third quartile is analogous to the trend of the average. In conclusion, the time discrepancy between the two strategies increases progressively. When a comparison is made between the initial scenarios, the time difference is measured in thousands of seconds. For the subsequent scenarios, the time discrepancy is measured in hundreds of seconds.

It can be concluded that, in general, the path change is more efficient than the avoidance maneuver.

Subsequent analysis of the results indicated that the number of maneuvers executed by both strategies across all 34,066 simulations was highly comparable. The results of this study are presented in Fig. 10. The median is null, the third quartile is equal to 1, and the maximum number of maneuvers is 2. The difference lies in the outliers, where we can see more values above the uwb for the flight following the avoidance strategy than for the flight using a path change strategy. In addition to their substantial number, the outliers that employ the avoidance strategy generate a greater number of maneuvers than the outliers that use the path change strategy. Nevertheless, this finding alone is insufficient to draw definitive conclusions regarding the efficacy of our method in comparison to the avoidance strategy with respect to this particular criterion. The presence of outliers indicates the occurrence of exceptional behaviors, which complicates the interpretation of results.

Irrespective of the magnitude of the obstacles encountered during the simulations, the number of maneuvers required to circumvent them is typically minimal. In 50% of the cases, no maneuvers are necessary, while in 75% of instances, a single maneuver is sufficient. In the remaining cases, two maneuvers are required.

The execution of a limited number of maneuvers is advantageous for the pilot, as it simplifies the flight conditions, particularly in terms of reducing stress and fatigue, and the probability of failures, thereby enhancing the safety of the flight. Furthermore, the execution of maneuvers results in an increase in fuel consumption. By reducing the number of maneuvers, the aircraft could be able to preserve fuel and extend its range.

6. Conclusion

This paper presents a new obstacle avoidance strategy based on strategic alternative path computation. The classical avoidance strategy avoids an obstacle and then returns to the original flight plan. Conversely, the path change strategy involves shifting the flight plan that is currently in the vicinity of a weather obstacle to an alternative path that avoids the obstacle and continues along that route.

In the initial section of this paper, we present the simulation framework that was used to simulate aircraft cruise trajectories. Subsequently, the results of the simulations were presented. This section was divided into three parts. Firstly, the path change strategy was simulated in a specific scenario to visualize the kind of routes it can generate. Subsequently, the aforementioned strategy was simulated in a dynamic space where the obstacle positions were updated according to the data. Finally, we compare the avoidance and path change strategies in several dynamic simulations, varying the size of the obstacles. The results of each test demonstrate the efficacy of the path change strategy in addressing these issues. It can be observed that the travel times are typically shorter and the number of maneuvers remains constant when the plan is altered in response to the occurrence of an obstacle on the route.

Such a strategy benefit to both the pilot and air traffic controller, providing a supportive decision-making tool in FRA conditions. Furthermore, this strategy offers a number of advantages. Firstly, it mitigates the impact of tactical unexpected events on the flight schedule. Consequently, the number of maneuvers required is low, thereby reducing potential sources of stress and fatigue for the pilot.

Finally, while this strategy may offer potential benefits in terms of fuel consumption, a thorough discussion of optimality is necessary to substantiate this claim. This discussion must take into account various factors, such as flight routes and maneuver operations.

The current version of the simulation does not consider weather forecasts in the computation of the alternatives. Furthermore, the maneuver is performed as soon as an obstacle is detected. Optimizing the maneuver decision and integrating forecasts could potentially enhance the simulation in future work. Further analysis should be conducted to examine the fuel efficiency of both maneuvering strategies in relation to the aircraft's movement, with the incorporation of weather forecasts. In this study, we have limited our consideration to 2D airspace. An extension to this could integrate 3D airspace, including the volume of weather obstacles and enabling altitude changes for avoidance. Finally, it would be relevant to simulate the maneuvering strategies in an airspace with multiple flights that may come into conflict.

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