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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 static and then 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 and the detection range of the radar. 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) 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. The Section 4.1. introduces the alternative path generation algorithm. Finally, Section 5. presents the results of the path change 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

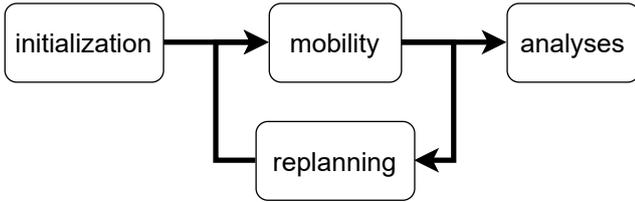


Fig. 1. The four-step simulation loop comprises the following stages: initialization, which initialize the stimulation environment; mobility and replanning moves of dynamic systems; analyses, which gathers the results of the simulation.

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.*¹⁾ and Xie *et al.*¹³⁾ 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^{3,6)} or a graph.^{5,7)}

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.^{4,12)} This approach is focused on tactical maneuvers and is usually solved thanks to optimal control.^{9,10)}

In the air, severe weather conditions are not the only obstacles. Some areas are prohibited, restricted or dangerous and therefore must be avoided.⁸⁾ 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.¹¹⁾ Guitart *et al.*²⁾ 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,⁷⁾ this work focuses on the automatic generation of a set of dissimilar paths based on weather information. The primary objective of our previous work⁷⁾ was to use strategic information to address tactical issues encountered in the en route airspace, a concern that

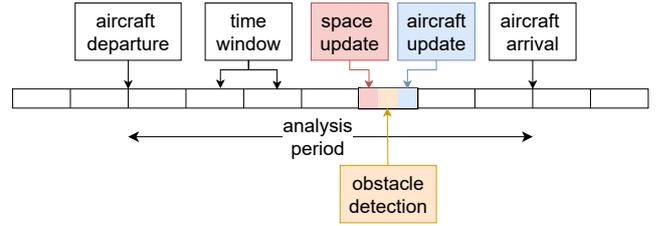


Fig. 2. The simulation time is divided into discrete intervals over the analysis period.

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
- 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 cell, with the time window being the temporal limit. In this

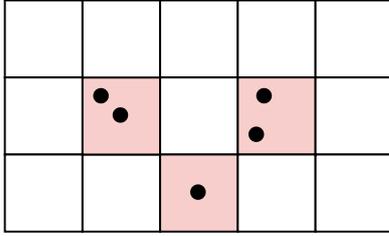


Fig. 3. The grid model of a flight level. The black dots represent the weather obstacles. When a grid cell contains at least one weather obstacle, all the cell is then considered as an obstacle and is colored in red.

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.

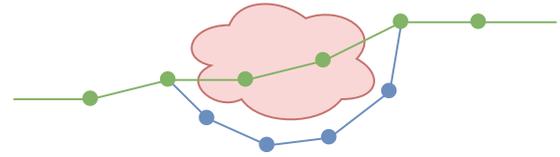
This approach can also be used to model weather information from air traffic controllers or any other useful pilot support system.

3.3.2. Replanner

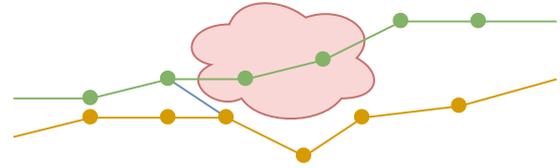
The map of the space generated by the radar system allows for the update of the flight plan followed by the aircraft. In this study, two kinds of replanning strategies are being compared.

The first one is the avoidance maneuver strategy (see Fig. 4a). When an obstacle is detected, the replanning strategy looks for the first available point on the trajectory and computes a new trajectory to this point that avoids the obstacle.

An alternative approach consists in shifting from the current flight plan to an alternative path that does not cross the obstacle (see Fig. 4b). This is achieved during the initialization step, when the alternatives paths connecting the origin to the destination are computed. 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.



(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).

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 article⁷⁾ cited in the references section.

4.1. Graph generation

The objective of this section is to generate a graph from scratch using the Rapidly-exploring Random Graph (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.

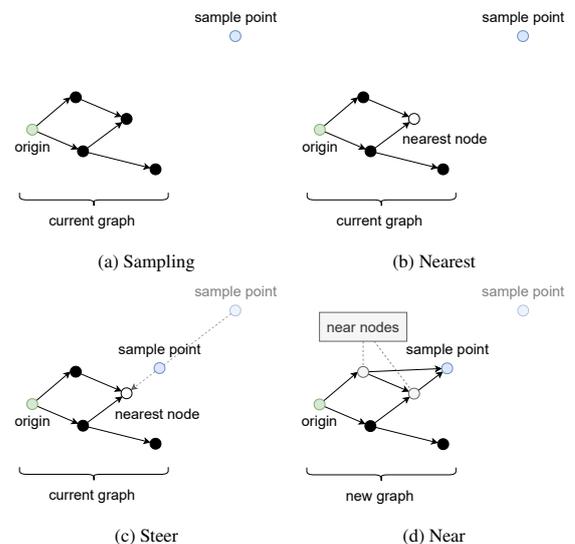


Fig. 5. The four main functions of the RRG algorithm are as follows: sampling, nearest, steer, and near.

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.

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. So, a final check must be made to ensure that there are no paths crossing obstacles.

In addition, if we have access to weather forecasts, 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.

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.

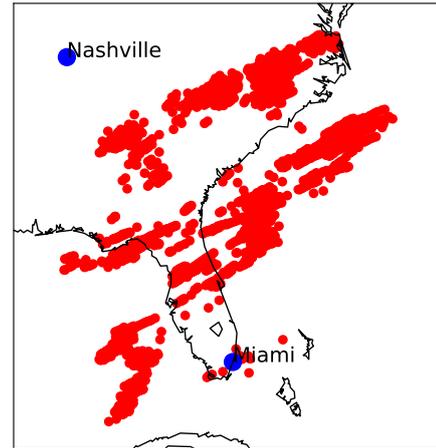


Fig. 6. Severe weather obstacles between Nashville and Miami cities the 26/02/2015.

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 simulation with static obstacles should perform at least one avoidance maneuver.

5.2. Plan change maneuver

This first work is devoted to the analysis of a plan change maneuver as presented in Fig. 4b. The approach is tested on both static and dynamic weather obstacles.

5.3. Static obstacles

In the first simulation, we wanted to simulate the dynamic movement of the aircraft in a space filled with static obstacles. This first experiment is exactly the scenario depicted in Fig. 6.

In this figure, we can observe clusters of obstacles. Even if the points may be a bit far from each other, they visually form a bloc and it would be abnormal to compute a path that crosses these blocs. In the simulation, we opted for a grid representation of the obstacles, so to apply the assumption we made earlier, we need to tune the size of the grid so that clusters of obstacles cannot be crossed.

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

Table 1. Parameters of the simulation with static obstacles.

σ_{cell}	η_{min}	η_{max}	n_g	α	β	$n_{samples}$
10 km	40 km	100 km	6	0.5	1	10 000
τ_{window}	Radius	Speed	Clusters	Kmeans		
10 min	100 km	800 km/h	300	2 000		

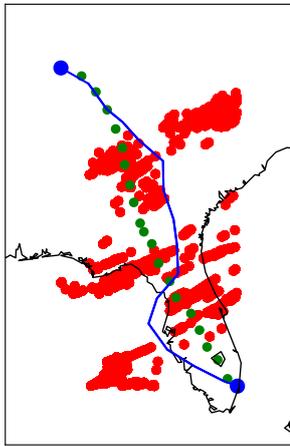


Fig. 7. Aircraft simulated trajectory using a plan change strategy in a space with static obstacles.

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.⁷⁾ The first column of the second table 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.

Fig. 7 shows the result found for this experiment. The largest blue dots are Nashville (top-left) and Miami (bottom-right). The green dots represent the shortest path connecting

Table 2. 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

the OD pair. This path is the initial flight plan followed by the aircraft. As we can see, this path passes through the obstacles. Confirming that the path computation is not based on any weather data. The blue line is the route taken by the aircraft. The blue path diverges from the green path meaning that the aircraft detects obstacles and change its plan. Furthermore, the blue path avoids all the obstacles on its path. It performed several dynamic path changes. The total travel time is 2 hours and 30 minutes whereas the flight typically took 1 hour and 46 minutes (average flight time performed by American Airline in flightradar24 at the average cruise speed of 500 kt which is equivalent to 926 km/h).

The method proposed demonstrated its efficacy in a complex study case with static obstacles by dynamically modifying the aircraft flight plan, resulting in complete obstacle avoidance for the Nashville-Miami flight.

5.4. Dynamic obstacles

In this second 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. 8 and Fig. 9.

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. 8. Subsequently, the aircraft avoids the obstacle on the right side, as illustrated in Fig. 9. 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. The small (resp. large) maneuver resulted in a travel time of 2 hours and 10 minutes (resp. 2 hours and 20 minutes). 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 altered from the static simulation are presented in Table 2a and Table 2b. It can be observed that three parameters have undergone a change between the two simulations. The

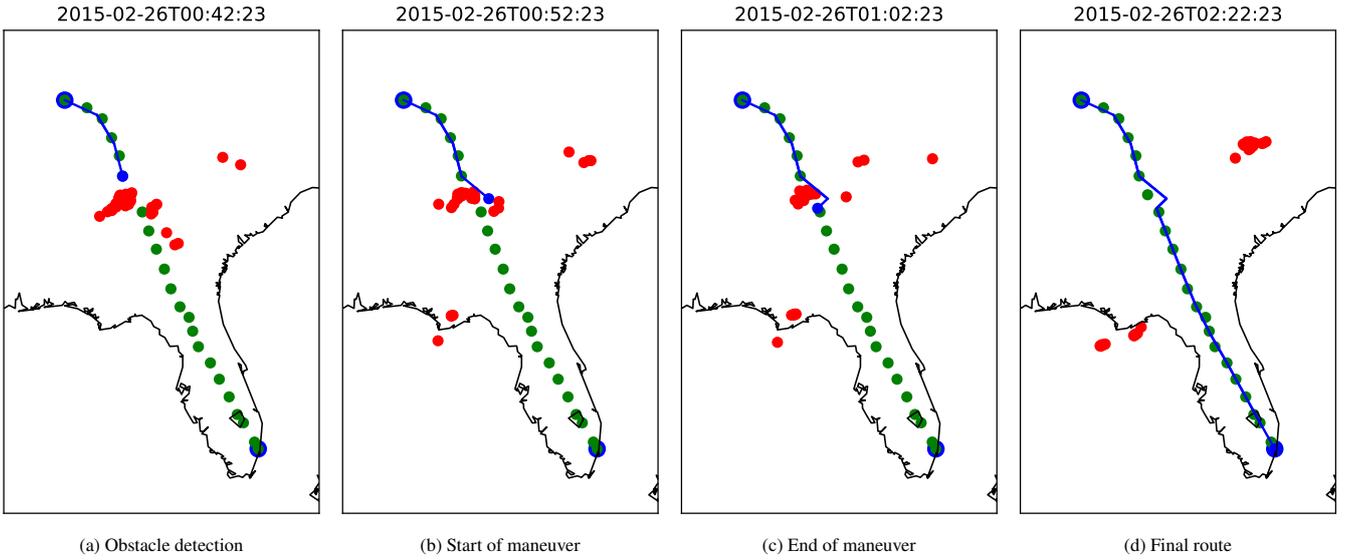


Fig. 8. Small obstacle path change maneuver.

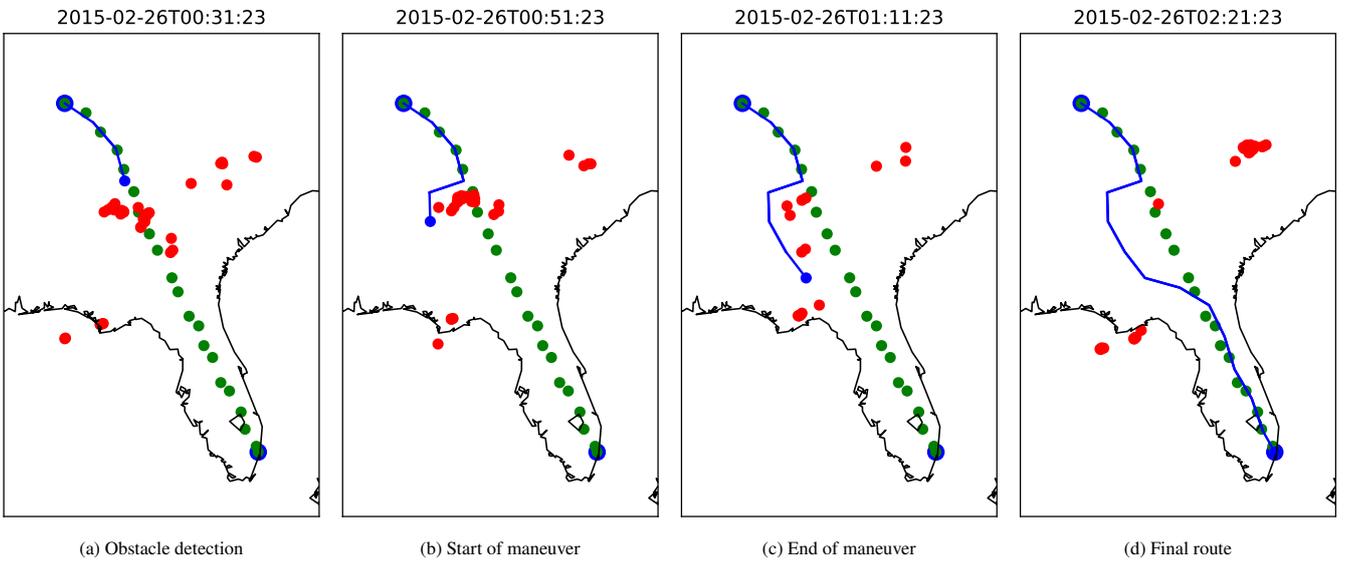


Fig. 9. Large obstacle path change maneuver.

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 demonstrated strong efficiency even in dynamic scenarios, effectively identifying viable alternatives that circumvent the tactical obstacles encountered during flight.

5.5. Comparison with avoidance maneuver

The two preceding studies demonstrate that a strategic pre-computation 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.

Approximately 400 000 simulations were conducted with weather conditions corresponding to 26/02/2015. In each simulation, two aircraft are modeled with two distinct strategies, with the same kind of radar. One of the aircraft performs an avoidance maneuver when encountering an obstacle, while the other alters its flight plan. All aircraft started their journey from Nashville, with the same initial flight plan, in order to connect the OD pair. From the 400 000 simulations conducted, only 20 000 yielded results where both aircraft performed at least one maneuver and where the travel times differed. Furthermore, the size of the obstacles, the departure time from Nashville and the radar detection range are varied for each simulation. The remaining simulation parameters are identical to those used in Table 2a of the aforementioned reference.

Table 3. Comparison between avoidance and path change travel times.

Obstacle (m)	Radar (m)	Avoidance						Path change					
		lwb	q1	q2	avg	q3	uwb	lwb	q1	q2	avg	q3	uwb
10 000	100 000	7 800	7 800	7 800	7 708	7 800	7 800	7 200	7 200	7 200	7 461	7 800	8 400
10 000	110 000	7 800	7 800	7 800	7 699	7 800	7 800	7 200	7 200	7 200	7 427	7 800	8 400
10 000	120 000	7 200	7 200	7 800	7 669	7 800	8 400	7 200	7 200	7 200	7 443	7 800	8 400
10 000	130 000	7 800	7 800	7 800	7 686	7 800	7 800	7 200	7 200	7 200	7 418	7 800	8 400
15 000	100 000	7 800	7 800	7 800	7 709	7 800	7 800	7 200	7 200	7 200	7 472	7 800	8 400
15 000	110 000	7 200	7 200	7 800	7 674	7 800	8 400	7 200	7 200	7 200	7 466	7 800	8 400
15 000	120 000	7 200	7 200	7 800	7 677	7 800	8 400	7 200	7 200	7 200	7 471	7 800	8 400
15 000	130 000	7 800	7 800	7 800	7 689	7 800	7 800	7 200	7 200	7 200	7 440	7 800	8 400
20 000	100 000	7 800	7 800	7 800	7 700	7 800	7 800	7 200	7 200	7 200	7 485	7 800	8 400
20 000	110 000	7 200	7 200	7 800	7 668	7 800	8 400	7 200	7 200	7 200	7 493	7 800	8 400
20 000	120 000	7 200	7 200	7 800	7 686	7 800	8 400	7 200	7 200	7 200	7 491	7 800	8 400
20 000	130 000	7 200	7 200	7 800	7 683	7 800	8 400	7 200	7 200	7 200	7 481	7 800	8 400
25 000	100 000	7 200	7 200	7 800	7 671	7 800	8 400	7 200	7 200	7 200	7 517	7 800	8 400
25 000	110 000	7 200	7 200	7 800	7 681	7 800	8 400	7 200	7 200	7 200	7 482	7 800	8 400
25 000	120 000	7 200	7 200	7 800	7 686	7 800	8 400	7 200	7 200	7 200	7 478	7 800	8 400
25 000	130 000	7 200	7 200	7 800	7 690	7 800	8 400	7 200	7 200	7 200	7 482	7 800	8 400
30 000	100 000	7 200	7 200	7 800	7 695	7 800	8 400	7 200	7 200	7 200	7 525	7 800	8 400
30 000	110 000	7 200	7 200	7 800	7 657	7 800	8 400	7 200	7 200	7 200	7 550	7 800	8 400
30 000	120 000	7 200	7 200	7 800	7 686	7 800	8 400	7 200	7 200	7 200	7 508	7 800	8 400
30 000	130 000	7 200	7 200	7 800	7 704	7 800	8 400	7 200	7 200	7 200	7 503	7 800	8 400
35 000	100 000	7 200	7 200	7 800	7 686	7 800	8 400	7 200	7 200	7 200	7 518	7 800	8 400
35 000	110 000	7 200	7 200	7 800	7 664	7 800	8 400	7 200	7 200	7 200	7 538	7 800	8 400
35 000	120 000	7 800	7 800	7 800	7 703	7 800	7 800	7 200	7 200	7 200	7 493	7 800	8 400
35 000	130 000	7 800	7 800	7 800	7 691	7 800	7 800	7 200	7 200	7 200	7 477	7 800	8 400

The statistical results of the simulations are presented in Table 3. The first and second columns represent the size of the cells and the detection range of the radar respectively. Both values are expressed in meters. 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 quartiles, and the mean are lower for the path change strategy. The third quartile is identical for both strategies. Finally, the uwb value is lower for the avoidance maneuver.

The average efficiency of the path change strategy is higher than that of the avoidance maneuver. The difference in efficiency is typically 200 seconds, which is approximately three minutes. However, the most significant finding is that the third quartile of the path change strategy is equal to the second quartile of the avoidance strategy. This indicates that 75% of flights based on the path change strategy complete the flight in less than 7800 seconds, whereas only 50% complete the trip in the same amount of time with the avoidance strategy. It can be concluded that, in general, the path change is more efficient than the avoidance maneuver. However, for some cases, the path change is ten minutes slower than the avoidance maneuver, which represents the difference between the uwb travel times.

Subsequently, the number of maneuvers executed by both

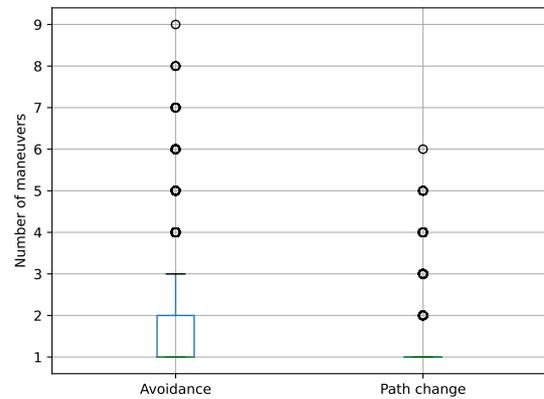


Fig. 10. Comparison of the number of maneuvers performed by avoidance and path change strategies.

strategies across all 20 000 simulations presented in Fig. 10 is compared. In the case of avoidance maneuver, the lwb and mean values are equal to one, while the third quartile is two and the uwb is three. Conversely, the uwb value for the path change strategy is equal to one. Consequently, the latter strategy is generally associated with a lower number of maneuvers than the former.

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 is 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 static space populated with weather obstacles representative of a typical day. Subsequently, the same 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 and the detection range of the radar. 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 is reduced when the plan is altered in response to the occurrence of an obstacle on the route.

Such a strategy benefits 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 reduced, thereby reducing potential sources of stress and fatigue for the pilot. Finally, this strategy minimizes the fuel consumption required to avoid the obstacle.

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.

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