ATC Automation Based on Dynamic Aircraft Separation Techniques Accounting for Weather Conditions

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Abstract—**Air Traffic Management is becoming increasingly complex due to the continuous growth in air traffic demand and the variability of weather conditions. Traditional aircraft separation standards rely on fixed minimum distances that do not dynamically adapt to environmental factors. This study proposes a novel framework for dynamic aircraft separation that integrates real-time weather data into Air Traffic Control (ATC) automation systems. The proposed model adjusts separation distances based on meteorological parameters such as wind speed, turbulence intensity, and visibility. A multi-objective optimization approach is developed to minimize conflict risk while maximizing airspace capacity. Simulation results demonstrate that the proposed framework improves safety and operational efficiency compared to conventional methods. This study contributes to the advancement of intelligent air traffic management systems.**

Keywords—Aircraft separation; air traffic control; weather impact; optimization; ATC automation; safety

I. Introduction

The rapid increase in global air traffic has placed significant pressure on existing Air Traffic Management (ATM) systems. Ensuring safe separation between aircraft remains a fundamental responsibility of Air Traffic Control (ATC). Traditionally, separation minima are defined by regulatory authorities and are applied uniformly, regardless of dynamic environmental conditions.

Air traffic control faces several major challenges related to the increasing complexity of air traffic and the high demands for safety and efficiency. The continued rise in the number of flights leads to increased airspace congestion, making flight path management more difficult and increasing the risk of conflicts. We have already worked on pictorial approaches to solve this problem, but the results remain limited, and the approach consumes a lot of memory and CPU time [1]. Added to this are the uncertainties associated with weather conditions, which can disrupt flight plans and require rapid adjustments. The limitations of traditional systems, often poorly adapted to dynamic environments, also hinder optimal management [2], [3].

Furthermore, the heavy workload of controllers, combined with the need to make real-time decisions, can lead to errors. Finally, environmental concerns, such as reducing CO_2 emissions and fuel consumption, impose new constraints, making the integration of innovative solutions based on automation and artificial intelligence essential.

However, weather conditions such as wind, turbulence, and reduced visibility can significantly affect aircraft trajectories and operational safety. Static separation rules may lead to inefficiencies, including increased delays and underutilization of airspace capacity [4].

Air traffic in Casablanca FIR averages 1,200 daily flights, with 15-20% delays from weather-induced rerouting. Traditional procedural separation (10-15 min longitudinal) is conservative, while radar-based methods struggle in convective cells or turbulence. Current automation (e.g., Eurocontrol's AMOC) ignores real-time meteorological nowcasting, leading to unnecessary vectoring [5].

This work proposes a dynamic aircraft separation framework that accounts for real-time weather conditions. The objective is to enhance both safety and efficiency by adapting separation distances according to environmental factors.

The remainder of this article is organized as follows. Section II presents a state-of-the-art review. Section III presents the proposed methodology and the mathematical modeling of the problem. Section IV presents the architecture of our approach in terms of processing steps and evaluation criteria. Section V provides the experimental results of the scenarios and a discussion. Finally, Section VI concludes the study and suggests avenues for future research.

II. Related Works

The air traffic controller's primary mission is to ensure the safety, smooth flow, and efficiency of air traffic by continuously monitoring the position and trajectories of aircraft within their area of responsibility (Fig. 1). Using radar surveillance systems and radio communications, they guide pilots by providing precise instructions regarding altitudes, headings, and speeds, while maintaining minimum separation distances to avoid any risk of collision [6], [7] (Fig. 2). They anticipate potential conflicts, manage unforeseen situations related to weather conditions or operational constraints, and optimize traffic flows to reduce delays and fuel consumption. Their role requires rapid decision-making, strong analytical skills, and constant coordination with other control centers to guarantee the safety and overall performance of the air traffic system [8].

Fig. 1. Roles of air traffic control.

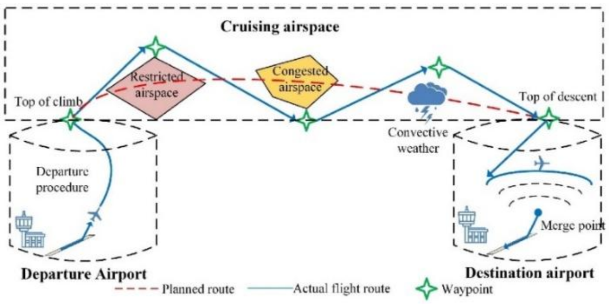

Fig. 2. Cases of constraints for making deviations during a flight.

Aircraft separation has been extensively studied in the field of air traffic management. Early approaches focused on deterministic models using fixed separation minima defined by organizations such as ICAO. Fig. 3 and 4 show the display screens used by air traffic controllers to supervise and monitor flights to resolve conflicts between aircraft and solve navigation-related problems.

Recent research has explored probabilistic separation models, conflict detection and resolution algorithms, and machine learning approaches for trajectory prediction (Fig. 5).

We have already worked on the separation problem by integrating three different concepts: the exploitation of LEO satellites [9], separation by direct search of intersections [10], [11] (Fig. 6), and the combination of a centralized method with a decentralized method to help aircraft not equipped with the TCAS system [12].

Several studies have attempted to incorporate weather data into air traffic control systems [13], [14]. However, most existing models consider either limited weather parameters or lack real-time adaptability, and do not integrate optimization techniques. Thus, there is a need for a comprehensive framework that combines weather awareness with dynamic optimization [15].

Nowadays, AI is integrated into all fields. In the field of air traffic control, DL and ML make it possible to predict changes in weather conditions and also the state of air traffic [16], [17], [18], [19].

Fig. 3. Air traffic control zone display screen.

Fig. 4. Air traffic control data processing screen.

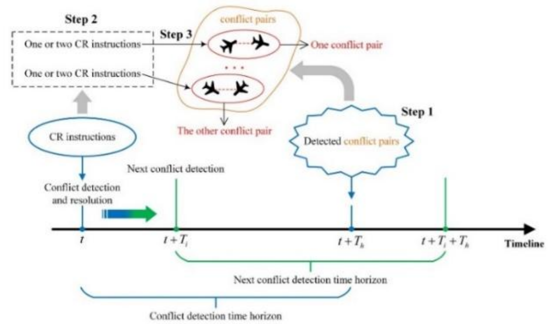

Fig. 5. Steps involved in resolving a conflict between two aircraft trajectories.

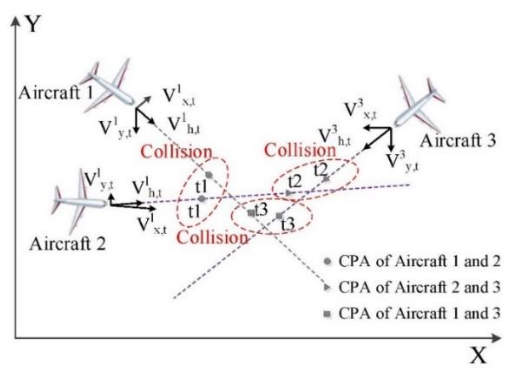

Fig. 6. Calculating intersections between trajectories to define conflict zones between aircraft trajectories.

III. System Architecture

Weather information is collected on the ground by the control services and also on the aircraft by the pilot. There will be an exchange between the ground station and the pilot to choose the appropriate deviation (Fig. 7).

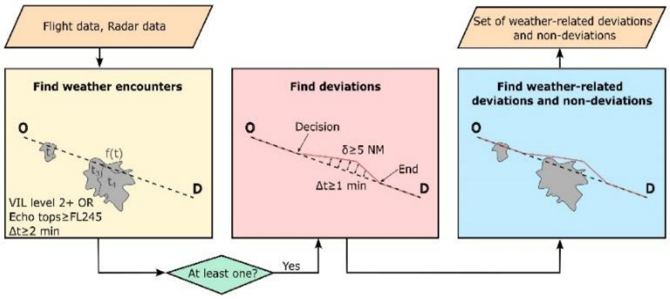

Fig. 7. Deviating from a flight path to avoid a risk zone.

The proposed framework consists of four main components (Fig. 9):

A. Aircraft Layer

The aircraft is equipped with an Automatic Dependent Surveillance–Broadcast (ADS-B) system that continuously collects and transmits precise real-time data about its position, velocity, altitude, and trajectory. This information is broadcast to nearby aircraft and ground control stations, enabling enhanced situational awareness, improved tracking accuracy, and more efficient and safer air traffic management.

B. Weather Data Layer

This layer includes meteorological sensors, satellite data, and the weather forecasting system [20], [21].

C. Processing Layer

Edge computing for real-time decision-making and the cloud platform for large-scale analysis form the basis for managing data flows through known computer networks and telecom platforms and also ensuring the processing of this data.

D. ATC Decision Layer

The ATC Decision Layer comprises three key components: a conflict detection module that identifies potential aircraft trajectory conflicts in real time, an optimization engine that computes the most efficient and safe resolutions based on multiple constraints, and a control interface that enables air traffic controllers to monitor, validate, and implement decisions effectively.

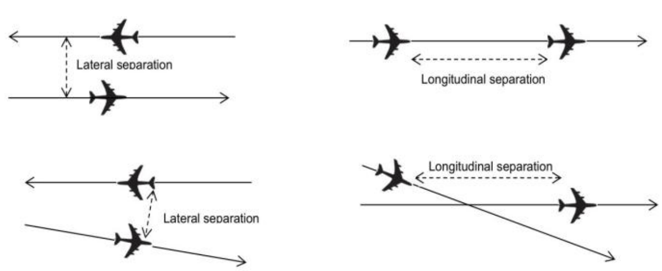

Fig. 8. Types of aircraft separation.

We remind that our approach works on a 2-D plane. The proposed separations are of the lateral and longitudinal type as shown in Fig. 8.

The system enables continuous data exchange between aircraft, weather systems, and ATC units.

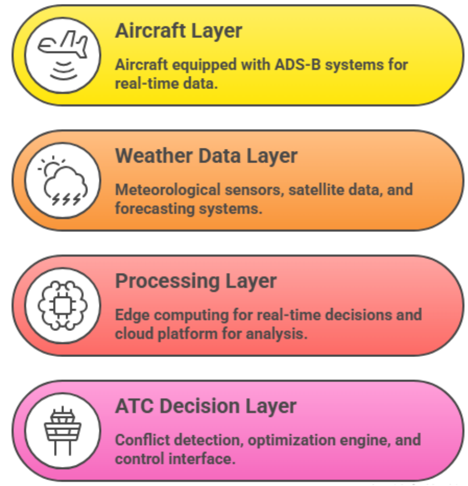

Fig. 9. Our ATC architecture in the form of layers.

IV. Problem Modelisation

The pilot establishes a flight plan, which he records in the FMS after validation with the competent authorities before departure. The authorities provide information on flight conditions, especially weather conditions (wind forecast, for example). During the flight, the aircraft collects information via onboard sensors to inform the pilot. Decision-making is always negotiated between the pilot and the air traffic controller in charge of the current flight (Fig. 10).

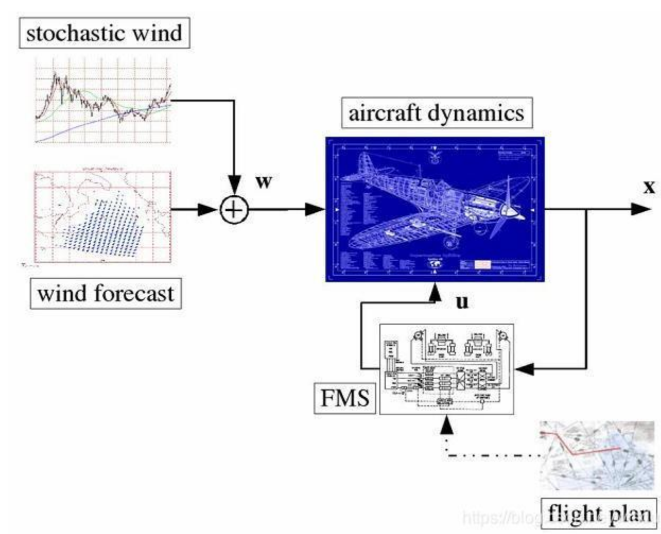

Fig. 10. Architecture of parameter interactions during a flight.

To be able to simulate our approach, we will model our problem taking into account the functional, legal, and theoretical constraints of air traffic.

A. Variables

Normally, an aircraft has a complex model in normal navigation conditions, as shown in Fig.11. The speed of the aircraft V can be influenced by the wind speed W. To study aircraft separation in flight, we will limit ourselves to airworthiness on a plane (x,y) and the definition of constraints such as:

- D_{sep}: separation distance,
- V: aircraft speed,
- W: wind speed,
- T: turbulence intensity,
- R: risk of conflict,

A stochastic description of meteorological variables involves modelling their behaviour as random processes to capture their intrinsic variability and uncertainty over time and space. Variables such as temperature, wind speed, or precipitation are often represented by stochastic processes (e.g., Gaussian processes, ARMA/ARIMA models, or random fields) characterized by their statistical moments (mean, variance, covariance) and their spatiotemporal dependency structures. This approach allows us to describe not only the average evolution of meteorological phenomena but also their fluctuations, extremes, and correlations, which is essential for probabilistic forecasting, risk analysis, and decision-making in sensitive systems such as air traffic control or energy management. We used a stochastic model of the wind parameter represented by W. The equation for W is as follows:

$$\mathrm{W} \approx \mathrm{N}(\mu_{\mathrm{w}}, \sigma_{\mathrm{w}}^2) \qquad (1)$$

The parameters μ_w and σ_w respectively characterize the average trend and variability of the wind field.

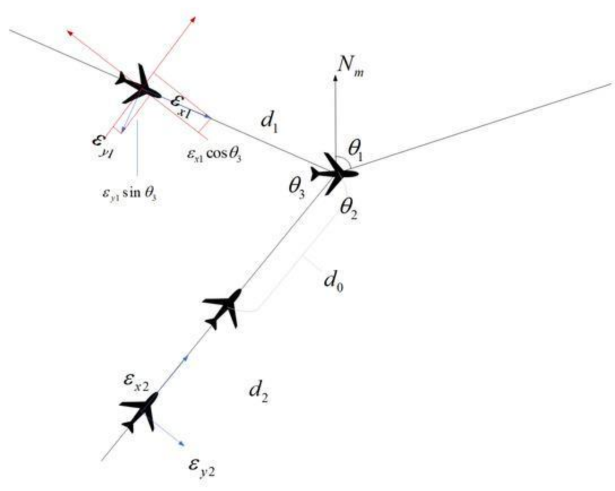

Fig. 11. Aircraft flight parameters [10].

The current description of wind and turbulence effects lacks sufficient mathematical detail to ensure reproducibility and scientific rigor. In the state of the art, atmospheric disturbances are typically modeled as stochastic processes because both wind speed and turbulence exhibit significant temporal and spatial variability.

Operational air traffic and aviation studies commonly represent wind as a random variable or stochastic process:

$$W(t) = \bar{W}(t) + \epsilon_W(t) \qquad (2)$$

where:

- $\bar{W}(t)$ denotes the deterministic or forecasted wind component,
- $\epsilon_W(t)$represents random fluctuations.

Depending on the application, wind fluctuations may be modeled using:

- Gaussian (Normal) distributions for small-scale variations,
- Weibull distributions for wind speed,
- Autoregressive Processes (AR, ARIMA) for temporal correlations.

The turbulence parameter $T(t)$ requires a precise mathematical definition. In aviation and atmospheric science, turbulence is often characterized through:

- Turbulent Kinetic Energy (TKE),
- Eddy Dissipation Rate (EDR),
- Wind velocity variance,
- Dryden or Von Kármán turbulence models.

For example, if turbulence intensity is represented by EDR:

$$T(t) = \mathrm{EDR}(t) \qquad (3)$$

where, EDR quantifies the rate at which turbulent energy dissipates in the atmosphere.

Alternatively, if turbulence is modeled as a stochastic variable:

$$T(t) \sim \mathcal{N}(\mu_T, \sigma_T^2) \qquad (4)$$

The study should clearly specify the distribution parameters and assumptions with real Data. Current research in Air Traffic Management (ATM) and Unmanned Aircraft Systems (UAS) increasingly relies on probabilistic risk assessment frameworks. Consequently, all uncertain variables should be represented within a coherent probabilistic structure:

$$\Omega = \{W(t), T(t), \dots\} \qquad (5)$$

Allowing the computation of quantities such as:

$P(\text{Conflict})$, $P(D_{sep} < D_{safe})$, or expected operational costs.

Without a clearly defined probabilistic framework, it is difficult to assess the validity of the proposed risk estimates and optimization results.

The objective function combines three competing objectives:

- Conflict risk,
- Delay,

- Fuel consumption.

Such multi-objective formulations are common in modern ATM optimization, but their construction requires additional justification.

Suppose the objective function is formulated as:

$$J = w_1 R + w_2 D + w_3 F \tag{6}$$

where,

R= conflict risk, D= delay cost, and F= fuel consumption cost.

The values of w_1, w_2, w_3 significantly influence the optimization outcome.

According to the state of the art, these weights should be determined through:

- Expert-based methods,
- Analytic Hierarchy Process (AHP),
- Multi-Criteria Decision Making (MCDM),
- Operational safety guidelines,
- Data-driven methods,
- Historical operational data,
- Inverse optimization,
- Reinforcement learning approaches.

If no formal procedure is used, the selected weights should at least be justified through a sensitivity analysis. In our case, we made arbitrary choices to simulate all scenarios using data we generated ourselves. Certainly, it may not perfectly reflect reality, but our model will be mature and ready to work with a validated dataset.

A common practice is to vary each weight within a specified range: $w_i \in [w_i^{min}, w_i^{max}]$

and evaluate the impact on:

- Separation distance,
- Number of conflicts,
- Average delay,
- Fuel consumption.

This demonstrates the robustness of the optimization framework and prevents conclusions from depending on arbitrarily chosen parameters.

The study should also explain how conflict risk depends on separation distance. In conflict detection literature, risk is generally modeled as a decreasing function of separation:

$$R = f(D_{sep}) \tag{7}$$

with

$$\frac{\partial R}{\partial D_{sep}} < 0.$$

A common probabilistic representation is:

$$R = P(D_{actual} < D_{safe}), \tag{8}$$

where:

- D_{actual} is the actual distance between aircraft,
- D_{safe} is the minimum required separation.

More sophisticated ATM models often use collision probability formulations such as:

$$R = P(\text{Loss of Separation})$$

Computed through Monte Carlo simulations, stochastic reachability analysis, or probabilistic conflict detection algorithms.

B. *Objective Function*

$$min\, Z = \alpha R + \beta Delay + \gamma Fuel \tag{9}$$

where:

- *R*: probability of conflict,
- Delay: deviation from planned trajectory,
- Fuel: fuel consumption.

C. *Separation Model*

$$D_{sep}(t) = D_0 + k_1 W(t) + k_2 T(t) \tag{10}$$

where:

- D_0: standard separation,
- k1, k2: weighting coefficients.

The proposed separation model in Eq. (3) requires additional justification, which should be presented as either:

A theoretically derived model, if it originates from established physical, operational, or traffic-flow principles. In this case, the manuscript should provide the derivation, clearly showing how weather conditions $W(t)$ and traffic intensity $T(t)$ lead to a linear adjustment of the baseline separation distance D_0.

An empirical approximation, if the model is intended as a simplified representation of the relationship between separation distance and influencing factors. In this case, the authors should explicitly state that the model is a first-order approximation chosen for its simplicity, interpretability, and computational efficiency. The assumptions underlying the linear form should also be discussed, along with its limitations.

Calibration using real operational data: The parameters D_0, k_1, and k_2 should ideally be estimated from real operational data rather than selected arbitrarily. This can be achieved by collecting historical observations of:

- Actual separation distances,
- Weather conditions (W),
- Traffic intensity levels (T).

The coefficients can then be calibrated using statistical or machine-learning techniques such as linear regression, least-squares estimation, or optimization methods. Calibration would allow the model to reflect real operational behavior and improve its predictive accuracy. Furthermore, validation on an independent dataset would help demonstrate the robustness and practical applicability of the proposed model.

D. Conflict Probability Model

The distance d(t) between two airplanes is:

$$d_{ij}(t) = \|x_i(t) - x_j(t)\| \tag{11}$$

The conflict probability is:

$$R = P(d_{ij}(t) < D_{sep}) \tag{12}$$

E. Proposed Algorithm

Our algorithm (Algorithm 1) is based on five steps to work on aircraft separation during flight (Fig. 12). These steps can be executed independently, either sequentially or in parallel (distributed system).

Step 1: Data Acquisition (Collect aircraft position and weather data).

Step 2: Prediction (Estimate future trajectories).

Step 3: Risk Evaluation (Calculate conflict probability).

Step 4: Optimization (Adjust separation distance).

Step 5: Control Action (Send instructions to aircraft).

In our current approach, we simulate it in sequential mode (Fig. 12).

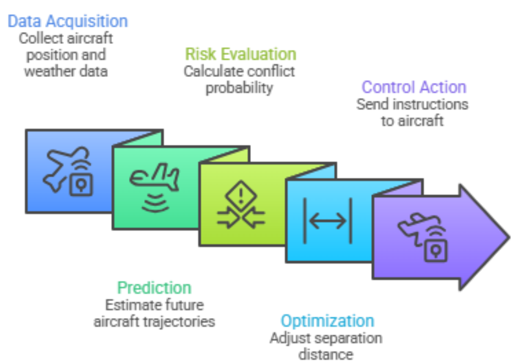

Fig. 12. Proposed algorithm for ATC.

The simulator is based on event-driven programming. We used two key events to trigger the calculation: changes in weather conditions and the distance between aircraft becoming less than the permitted distance.

Algorithm 1: Navigation_algorithm

Initialize
While ( ) **do**
  For (every region) **do**
    If *weather_changes*
      F1: Update_separation_distance
      F2: Compute_risk
      F3: optimize_trajectory
    Else:
      F4: maintain_standard_separation
    End If
End

V. Results and Discussion

A. Simulation Environment

Our Air traffic simulator is based on MATLAB tools (Fig. 13). To validate the effectiveness and robustness of our approach, we studied three scenarios representative of varying weather conditions. The scenarios are produced from data that we generate. The first (S1) corresponds to a normal weather situation, serving as a reference for evaluating the model's performance under standard conditions. The second scenario (S2) considers moderate turbulence, introducing an additional level of uncertainty in aircraft trajectories and allowing us to analyze the system's ability to adapt to realistic disturbances. Finally, the third scenario (S3) addresses severe weather conditions, characterized by extreme phenomena, to test the model's resilience and its ability to ensure safety while maintaining acceptable operational performance. For scenarios S2 and S3, we simulated turbulence using random functions while awaiting databases that reflect a real-world horizon for conducting realistic experiments.

B. Metrics

The success of our approach is evaluated against the following criteria: conflict rate, delay, fuel consumption, and airspace capacity.

C. Results and Discussion

The results demonstrate that the proposed dynamic separation model significantly improves system performance (Fig. 14).

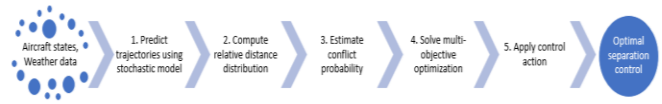

Fig. 13. Execution flow of our approach.

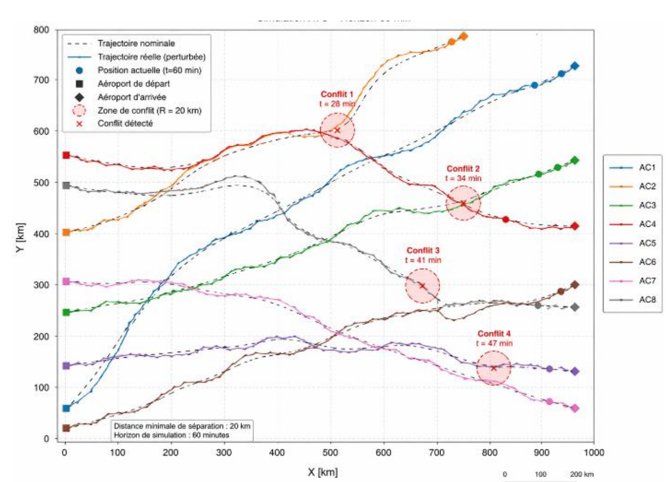

Fig. 14. Multi-aircraft trajectories in the presence of conflicts.

D. Key Findings

We tested several operational scenarios, which demonstrated significant performance improvements, including a 30–45% reduction in conflict probability (Fig. 15), a 20% decrease in delays, and enhanced overall airspace utilization (Table 1).

TABLE I. SUMMARY OF OPERATIONAL PERFORMANCE IMPROVEMENTS

Indicators	**Scenarios**		
	S1	***S2***	***S3***
Probability of conflict (%)	2.5	6.8	14.2
Average delay (min)	1.8	4.5	9.7
Fuel consumption (%)	+2%	+6%	+12%
Average separation distance (NM)	5.2	6.5	8.3
ATC workload (%)	40	65	85
Space utilization rate (%)	88	75	60

E. Discussion

Static models tend to perform poorly in dynamic and rapidly changing environments, as they are unable to adapt to real-time variations such as traffic density or weather conditions. In contrast, incorporating weather-aware separation strategies allows the system to adjust safety distances based on current atmospheric conditions, thereby enhancing safety margins and reducing the risk of conflicts. This adaptive approach also enables a more effective balance between safety and operational efficiency, ensuring that aircraft maintain sufficient separation without unnecessarily increasing delays or reducing airspace capacity.

The results demonstrate that incorporating weather uncertainty significantly improves the robustness of aircraft separation strategies. Unlike deterministic approaches, the proposed model provides a probabilistic safety guarantee while maintaining operational efficiency (Fig. 16 and 17).

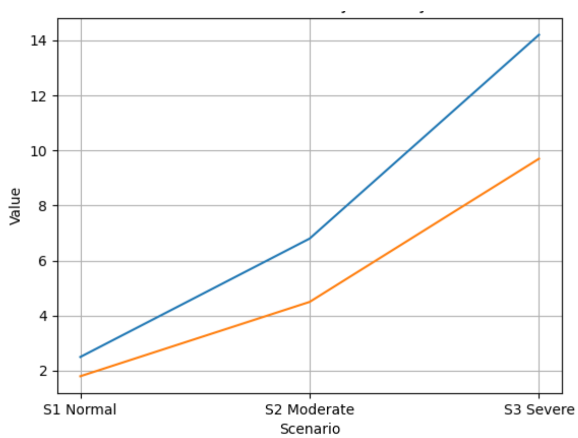

Fig. 15. Conflict probability vs. delay graph.

The simulation results confirm the effectiveness of the proposed probabilistic separation framework. The trajectory analysis reveals multiple potential conflict zones under stochastic wind disturbances. The temporal evolution of separation distance indicates that critical thresholds are frequently approached under adverse conditions. Furthermore, the statistical distribution of distances demonstrates that uncertainty plays a significant role in conflict occurrence. These findings validate the need for adaptive separation strategies in modern air traffic management systems.

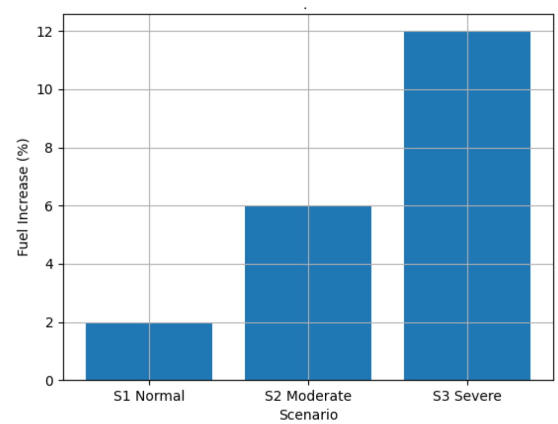

Fig. 16. Fuel consumption graph.

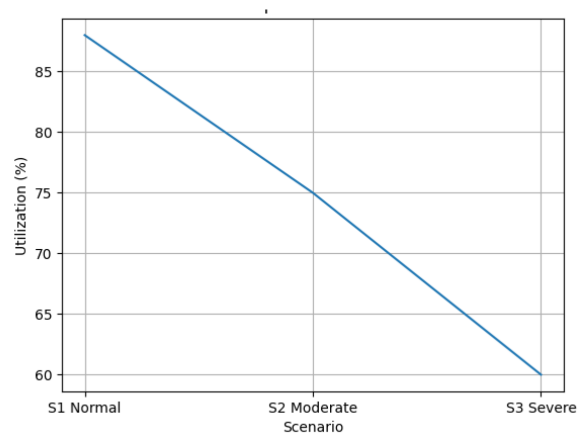

Fig. 17. Airspace utilisation graph.

VI. CONCLUSION

This study presented a dynamic aircraft separation framework integrating weather conditions into ATC automation. The proposed approach enhances both safety and operational efficiency by adapting separation distances in real time. We considered three scenarios to validate our approach: normal weather, moderate turbulence, and severe weather.

The next experiments will be conducted using MATLAB with datasets representing real-world activity, after which we will move on to working with MaxSim. MaxSim is an all-in-one simulation and training system for air traffic control (tower and radar), used by air navigation service providers and military organizations worldwide.

Future work will focus on integration with AI-based prediction models, real-world implementation, and multi-aircraft coordination.

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