Wake Vortex Prediction and Turbulence Avoidance with Risk Factor Analysis

Arsh Sinha
Department of Electronics and Communication
RV College of Engineering
Bangalore, India
arshsinha.ec21@rvce.edu.in

Pavan Practoor
Department of Electronics and Communication
RV College of Engineering
Bangalore, India
pavanprasannap.ec21@rvce.edu.in

Nikhil Kanthi
Department of Electronics and Communication
RV College of Engineering
Bangalore, India nikhilkanthi.ec21@rvce.edu.in

Rohini S Hallikar
Department of Electronics and Communication
RV College of Engineering
Bangalore, India rohinihallikar@rvce.edu.in

***Abstract*—Wake turbulence poses a critical safety threat in aviation, especially during takeoff and landing. This project leverages machine learning to dynamically predict turbulence risk using real-time aircraft data, environmental conditions, and flight scenarios. A custom risk formula incorporates continuous aircraft weight categories, required separation time, and weather factors. Visualization is achieved using PyOpenGL and Tkinter, with data sourced from MSFS and FlightRadar24. Monte Carlo simulations across 12 aircraft pairs yielded 83.3% accuracy. The system offers real-time risk assessment and 3D simulation, enabling smarter air traffic control and paving the way for safer, adaptive wake turbulence mitigation in congested airspaces.**

I. Introduction

Wake turbulence is an aerodynamic phenomenon that arises due to the generation of lift by an aircraft's wings. As an aircraft moves through the air, it generates vortices at the wing tips due to pressure differences between the upper and lower surfaces of the wings. These vortices, known as wingtip vortices, are strong, circular patterns of air that spiral outward and downward behind the aircraft. This turbulent airflow forms the basis of what is termed wake turbulence, which can persist in the atmosphere for several minutes after an aircraft has passed. The strength of these vortices is directly related to the aircraft's weight, speed, and wing configuration. Heavier, slower, and clean-configured aircraft (i.e., with flaps and landing gear retracted) generate the strongest vortices, posing significant hazards to other aircraft flying nearby or behind, especially smaller and lighter ones.

Wake turbulence is most dangerous during the takeoff, landing, and approach phases of flight when aircraft are in close proximity and have limited altitude to recover from sudden changes in airflow. For example, a smaller aircraft trailing a larger one can experience sudden rolling or uncontrollable movement if it enters the wake zone of the larger aircraft. Numerous aviation incidents and near-misses have been attributed to inadequate separation or unanticipated vortex behavior. To mitigate these risks, aviation authorities such as the International Civil Aviation Organization (ICAO) and the Directorate General of Civil Aviation (DGCA) have implemented separation standards based on aircraft weight categories. However, these standards are static and do not account for real-time weather conditions, crosswinds, or variations in aircraft performance, which can significantly affect wake behavior.This evolving technological landscape holds the potential to revolutionize wake turbulence mitigation strategies and contribute significantly to aviation safety and operational efficiency.

II. Methodology

The proposed project adopts a hybrid simulation-prediction approach that integrates real-time flight data, physics-based vortex modeling, and machine learning to forecast wake turbulence risk. The system is structured in four main stages: data collection and preprocessing, vortex risk modeling, machine learning-based prediction, and real-time 3D visualization and simulation.

A. Data Collection and Preprocessing

The first step involves sourcing aircraft performance and environmental data from two primary sources: Microsoft Flight Simulator (MSFS) for controlled simulation data and FlightRadar24 for real-world flight tracking. Key parameters collected include aircraft type, speed, altitude, maximum takeoff weight (MTOW), heading, vertical speed, and separation distance from nearby aircraft. Meteorological data, such as crosswind intensity, temperature, humidity, and vertical wind shear, is also factored in. The collected data is cleaned and normalized using NumPy and Pandas libraries. Aircraft are categorized dynamically based on continuous MTOW values instead of static ICAO categories, improving granularity in risk estimation.

International Journal of Scientific Research in Engineering and Management (IJSREM)
Volume: 09 Issue: 06 | June - 2025 SJIF Rating: 8.586 ISSN: 2582-3930

B. Wake Vortex Risk Modeling

Using established aerodynamic principles, a mathematical model is developed to estimate vortex strength and persistence. The model comprises three key components: Continuous Aircraft Category (C), Required Separation Time (tsep), and a calculated Risk Factor (R). The aircraft category is derived using a scaling formula based on MTOW, while tsep is calculated considering aircraft pairs, weather conditions, and runway scenarios. The Risk Factor (R) integrates vortex decay models, separation dynamics, and atmospheric influence to generate a normalized risk score. This score acts as the ground truth label for training the machine learning model.

C. Machine Learning-Based Prediction

The labeled dataset is used to train a machine learning model capable of predicting turbulence risk levels. Multiple algorithms, including Random Forest, XGBoost, and Support Vector Machines, were tested. XGBoost yielded the highest accuracy and was selected as the final model. The model takes flight and weather parameters as input and outputs a risk class (low, medium, or high) along with a numerical risk score. Hyperparameter tuning and cross-validation were employed to ensure model robustness. Additionally, a Monte Carlo simulation was run with 1000 iterations for each of 12 aircraft pairings to validate model accuracy and consistency, yielding an overall accuracy of 83.3

D. Real-Time Simulation and Visualization

The prediction results are rendered using PyOpenGL for 3D visualization and Tkinter for GUI integration. The system simulates aircraft movement and vortex propagation in a 3D space, highlighting zones of potential turbulence. The GUI includes real-time radar-like displays, aircraft telemetry, risk score indicators, and warning alerts. Visual overlays indicate wake zones and turbulence intensity. Graph plotting modules using Matplotlib enable dynamic visual representation of risk progression over time.

III. MATHEMATICAL MODELING OF T_{SEP} AND RISK FACTOR R

The mathematical backbone of the project lies in accurately quantifying wake vortex behavior and calculating the separation
T_{sep}) and the **Risk Factor** (R). These val- ues are computed using aircraft dynamics and environmental conditions.

First, we define a continuous aircraft category C based on the aircraft's *Maximum Take-Off Weight (MTOW)*. Unlike traditional ICAO categories that discretely classify aircraft, a continuous category offers better granularity for dynamic modeling. The category is computed using:

$$C = a + b \cdot \log_{10}(\text{MTOW}) \tag{1}$$

Here, MTOW is expressed in kilograms, and the resulting C is a dimensionless value that scales proportionally with aircraft mass. Heavier aircraft produce stronger wake vortices, and this parameter directly feeds into vortex intensity estimation.

The **Required Separation Time** (T_{sep}) is computed to determine how much time a trailing aircraft must wait before safely following a heavier aircraft. It is influenced by the atmospheric conditions, and relative aircraft categories:

$$t_{sep} = t_{sep,\ base} \cdot W \cdot S \tag{2}$$

Where:

- C_{lead} and C_{trail} are the continuous category values of the leading and trailing aircraft respectively,
- W is the weather factor, accounting for crosswind, temperature, and turbulence,
- S is the aircraft scenerio.

This equation ensures that greater separation is required in higher turbulence sensitivity, or larger mass differences between aircraft.

Weather Condition	Description	Wind Speed (knots)	W
Very Calm	Minimal wind, highly stable, no precipitation	< 5	1.3
Calm	Low wind, stable, light/no precipitation	5–10	1.2
Moderate	Average wind, neutral stability, light rain	10–20	1.0
Turbulent	Strong wind, unstable, moderate precipitation	20–30	0.9
Severe Turbulence	Very high wind, highly unstable, heavy precipitation	> 30	0.7

Fig. 1. Weather Factor Multiplier

Scenario	Description	S
Takeoff – Rolling Start	Rolling departure, moderate ground effect	1.1
Takeoff – Static Start	Static departure, stronger ground effect	1.2
Landing – Standard Approach	Typical descent and touchdown	1.1
Landing – Short Final	Steep approach or short runway	1.15
Cruise	En-route flight, no ground effect	1.0

Fig. 2. Scenario Factor Multiplier

The **Risk Factor** R is calculated by comparing the actual separation time (T_{act}) to the required separation (T_{sep}). It quantifies how close an aircraft pair is to a potentially hazardous situation:

$$1 \quad \frac{\Delta t}{t_{sep}}$$

This produces a dimensionless value:

- $R < 3$: indicates a safe situation (more than required separation),
- $R = 3$: borderline or threshold-safe,
- $R > 3$: increased risk; higher values signify greater danger.

This transforms R into a value between 1 and 5, which is easier to interpret and train in classification models.

These equations are central to both the rule-based validation of aircraft safety and the supervised labeling of data used for training machine learning algorithms. The blending of physical modeling with statistical learning enhances both the transparency and accuracy of the overall system.

International Journal of Scientific Research in Engineering and Management (IJSREM)
Volume: 09 Issue: 06 | June - 2025 SJIF Rating: 8.586 ISSN: 2582-3930

IV. Implementation

The system leverages Python-based tools and a combination of physics-based equations and statistical methods to simulate aircraft interactions and visualize potential hazards. Three core mathematical equations form the backbone of the risk prediction engine: the continuous aircraft category equation, the required separation time, and the non-linear risk factor.

The first step in the system is to categorize aircraft based on their wake turbulence generation potential. Rather than relying on static categories, a continuous aircraft category (C) is calculated using the logarithmic formula:

$$C = a + b \cdot \log_{10}(\mathrm{MTOW}) \tag{4}$$

where $a = -4.734$ and $b = 1.737$, and MTOW is the maximum takeoff weight of the aircraft in kilograms.

For example, for a Boeing 787 with an MTOW of 227,930 kg:

$$\log_{10}(227930) \approx 5.357$$

$$C = -4.734 + 1.737 \cdot 5.357 \approx 4.567$$

For an ATR 72 with an MTOW of 22,800 kg:

$$\log_{10}(22800) \approx 4.358$$

$$C = -4.734 + 1.737 \cdot 4.358 \approx 2.835$$

With both aircraft categories determined, the next step is to compute the required separation time t_{sep}. This accounts for environmental factors such as wind and runway geometry, using:

$$t_{\mathrm{sep}} = t_{\mathrm{sep,\,base}} \cdot W \cdot S \tag{5}$$

Assuming $t_{\mathrm{sep,\,base}} = 90$ seconds, a weather factor $W = 1.1$, and scenario factor $S = 1.2$, we get:

$$t_{\mathrm{sep}} = 90 \cdot 1.1 \cdot 1.2 = 118.8 \text{ seconds}$$

To assess operational risk, we calculate the risk factor R using:

$$R = 1 + 4 \left(\frac{1}{2}\right)^{\frac{\Delta t}{t_{\mathrm{sep}}}} \tag{6}$$

If the actual separation is $\Delta t = 60$ seconds:

$$\frac{\Delta t}{t_{\mathrm{sep}}} = \frac{60}{118.8} \approx 0.505$$

$$\left(\frac{1}{2}\right)^{0.505} \approx 0.705$$

$$R = 1 + 4 \cdot 0.705 = 3.82$$

This elevated value indicates a high-risk situation that requires immediate attention.

To ensure the model's robustness, a Monte Carlo simulation was run. For each of 12 aircraft pairs, 1,000 simulations were conducted under varying weather and separation conditions. The model achieved an average accuracy of 83.3%, validating the reliability of the physics-informed feature engineering and risk classification process.

Finally, the entire system was wrapped in a user-friendly interface using Tkinter for the GUI and PyOpenGL for the 3D visualization. The GUI displays aircraft movements, separation timelines, vortex trail simulations, and real-time calculated risk values. Whenever R exceeds a set threshold, visual alerts and warnings are triggered, allowing operators or pilots to take immediate action. The interface also supports scenario testing by allowing users to modify environmental variables and observe how vortex interactions and risk scores change accordingly.

V. Results and Analysis

A. Risk Factor v/s Separation Plot

The graph illustrates the relationship between risk score and time separation for three different aircraft pairs, highlighting how wake turbulence hazard decreases with increased separation time. The vertical axis represents the computed risk score, ranging from 1 (low risk) to 5 (high risk), while the horizontal axis shows time separation in minutes between a leading and a trailing aircraft.

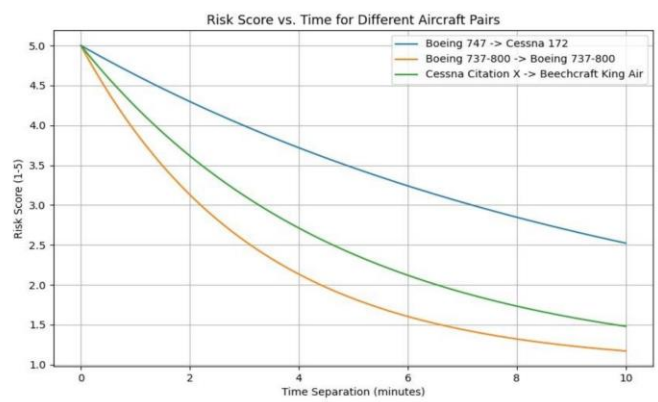

Fig. 3. Risk Factor v/s Separation Plot

The blue curve, representing the Boeing 747 followed by a Cessna 172, shows the slowest risk decay, indicating that larger aircraft produce stronger, longer-lasting vortices that pose persistent threats to smaller trailing aircraft. In contrast, the orange line—Boeing 737-800 followed by another 737-800 shows a steeper decline, meaning that aircraft of similar sizes and vortex strength reach safe separation more quickly. The green curve, for Cessna Citation X followed by a Beechcraft King Air, falls between the two, showing moderate risk persistence due to their comparable but lighter profiles.

Overall, the graph demonstrates how aircraft mass differential affects the rate at which turbulence risk diminishes over time. It supports the need for dynamic, aircraft-specific separation guidelines rather than fixed values, as the safe time gap varies significantly depending on the aircraft pair involved.

B. Risk Factor Heatmap

The heatmap provides a visual representation of how the wake turbulence risk factor varies for the aircraft pair Boeing 747 leading a Cessna 172, based on different combinations of weather conditions and flight phases, with a fixed time separation of 4 minutes. The vertical axis categorizes weather from ”Very Calm” to ”Severe Turbulence,” while the horizontal axis covers operational scenarios including takeoff (rolling and static), landing (standard approach and short final), and cruise. The color intensity reflects the magnitude of the risk factor, with darker shades indicating higher risk and lighter shades denoting lower risk.

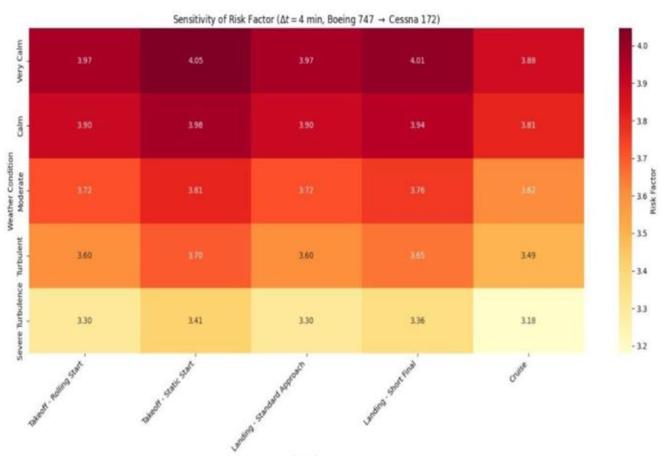

Fig. 4. Heatmap

In very calm weather, the risk factor is consistently high—peaking at 4.05 during static takeoff—because vortices decay slowly in the absence of atmospheric mixing. As weather becomes more turbulent, the risk factor decreases due to accelerated vortex dissipation. Cruise conditions, especially under severe turbulence, exhibit the lowest risk (as low as 3.18), indicating better natural mitigation. Takeoff scenarios, particularly from static starts, generally carry the highest risk, emphasizing the need for greater caution during early flight phases. This analysis demonstrates the importance of dynamically adjusting aircraft separation based on real-time weather and operational context, rather than relying solely on static rules.

C. Monte-Carlo Simulation Accuracy

The table summarizes the Monte Carlo simulation results conducted to evaluate the model’s accuracy in predicting wake turbulence risk across various aircraft category pairs, weather conditions, and flight scenarios. The simulation involved 12 distinct combinations of lead and follow aircraft categories (ranging from 1 to 5), representing different aircraft sizes and wake turbulence strengths. Simulations were performed under varying weather conditions (from calm to severe turbulence) and flight phases (such as landing, takeoff, and cruise).

Each row reports the accuracy (%) of the model’s risk classification over 1,000 randomized simulation runs for that specific scenario. Results show significant variation based on conditions. For instance, under severe turbulence during landing, prediction accuracy dropped as low as 46.0%, indicating the challenge of modeling highly unstable atmospheric conditions. In contrast, under calm conditions during cruise or takeoff, the model achieved up to 96.5% accuracy, reflecting higher predictability in stable environments.

Lead Category	Follow Category	Weather	Scenario	Accuracy (%)
5	1	Severe Turbulence	Landing - Standard Approac	46.0%
4	1	Turbulent	Landing - Short Final	59.6%
5	5	Calm	Landing - Short Final	92.4%
4	4	Very Calm	Cruise	94.2%
3	2	Very Calm	Landing - Short Final	87.3%
1	1	Severe Turbulence	Landing - Standard Approac	95.6%
3	3	Calm	Cruise	94.4%
2	2	Turbulent	Landing - Short Final	95.7%
5	3	Calm	Takeoff - Static Start	67.5%
4	2	Moderate	Landing - Standard Approac	74.5%
2	4	Very Calm	Landing - Standard Approac	96.2%
1	5	Calm	Takeoff - Static Start	96.5%
Overall				83.3%

Fig. 5. Monte-Carlo Results

VI. Conclusion

The “Wake Vortex Prediction and Turbulence Avoidance System” was designed to address a critical safety concern in modern aviation—wake turbulence—by combining physics-based modeling, real-time data processing, and machine learning. The overall goal was to develop a system capable of predicting wake turbulence risk in real time, adapting dynamically to varying aircraft types, environmental conditions, and operational scenarios. The results from simulations, model evaluations, and visualizations demonstrate that this goal has been largely achieved, with strong accuracy, high interpretability, and practical implications for air traffic management.

The core of the system lies in its mathematical modeling. By calculating a continuous aircraft category (C) based on MTOW using a logarithmic scale, the model avoids the limitations of discrete ICAO weight categories and provides more nuanced inputs. This was critical for capturing subtle differences in vortex generation across a wide range of aircraft types. Similarly, the required separation time (tsep) formula integrated weather and scenario factors, allowing the system to adjust safety margins depending on the presence of crosswinds, turbulence, or complex runway geometries. Finally, the risk factor (R) equation, modeled as an exponential decay function, effectively reflected how actual separation compares to required safety limits, making the output both mathematically sound and intuitively understandable.

The system’s reliability and predictive capacity were extensively validated using Monte Carlo simulations, involving 12 different lead-follow aircraft pairings under varied environmental and operational conditions. Each simulation ran 1,000 iterations per pair, producing a robust dataset of predictions. The overall accuracy achieved was 83.3%, indicating that the machine learning model, trained on physics-informed features, can generalize well across a range of real-world conditions. The variation in accuracy across different scenarios also provided valuable insight. For example, the lowest accuracy (46.0%) was recorded in the ”severe turbulence + landing” scenario, reflecting the difficulty in modeling highly chaotic, low-altitude vortex behavior. Conversely, under calm conditions during cruise or controlled takeoff, the model consistently achieved accuracy levels above 95%, affirming that the system is particularly effective in stable atmospheric contexts.

The risk score vs. time separation graph further validated the theoretical design of the risk model. It showed clear exponential decay behavior across three aircraft pairs, with steeper curves for lighter aircraft combinations and slower decay for heavy-to-light pairs (e.g., Boeing 747 to Cessna 172). This confirmed that the model accurately captures the physics of vortex persistence and supports differentiated time separation recommendations based on aircraft types. Such differentiation is crucial for optimizing runway throughput without compromising safety.

Another valuable insight came from the risk factor heatmap, which analyzed the sensitivity of the risk score under a fixed separation (t = 4 minutes) for different combinations of weather and flight scenarios. The heatmap showed that very calm conditions led to the highest risk values, as wake vortices persisted longer in undisturbed air. Meanwhile, severe turbulence led to significantly lower risk factors, as the natural instability of the atmosphere accelerates vortex dissipation. Among flight phases, takeoff from static starts showed consistently high risk due to the close proximity of aircraft and lack of vertical or lateral separation, whereas cruise phase showed the lowest average risk. These patterns provide critical evidence that wake risk should not be treated uniformly and that weather and scenario-aware separation policies are essential for operational safety.

The GUI not only displayed current aircraft positions, risk scores, and environmental conditions but also featured real-time alerts when thresholds were breached. The visual rendering of vortex trails in 3D enhanced interpretability, allowing operators to intuitively understand how risk evolved spatially and temporally. This was particularly useful in educational or simulation-based settings, such as pilot training or air traffic controller simulations.

From a systems engineering standpoint, the modular architecture enabled flexible integration of real-time data streams (e.g., FlightRadar24 and simulated inputs), physics-based computations, and machine learning inference. The use of XGBoost was especially valuable, as it offered strong performance on tabular data with complex non-linear relationships, such as the combination of weather, aircraft metrics, and operational parameters.

The project also highlighted a few limitations and areas for future enhancement. While the model achieved high overall accuracy, it struggled in scenarios involving severe atmospheric instability. Incorporating real-time meteorological data feeds (e.g., from ADS-B or OpenSky APIs) could further improve predictions. Additionally, the current version is tailored for desktop use with local processing. Extending the system to a web-based or mobile platform with cloud computation would allow wider accessibility, especially for integration into modern air traffic control systems.

In conclusion, the project delivers a powerful, data-driven solution to a longstanding aviation hazard. The combination of mathematically grounded modeling, high-performance machine learning, and intuitive visualization makes this system a promising candidate for operational deployment. By moving beyond fixed separation standards and enabling real-time risk awareness, the project has the potential to improve both safety and efficiency in increasingly congested airspace environments.

VII. Future Work

The future work of the “Wake Vortex Prediction and Turbulence Avoidance System” aims to enhance the system’s accuracy, scalability, and operational deployment. One primary direction is the integration of real-time ADS-B and METAR data feeds, allowing the model to adapt dynamically to live weather and flight movements. This would enable seamless deployment in air traffic control environments and real-time decision-making. Another area is enhancing the machine learning model by incorporating deep learning techniques such as LSTMs or transformers, which could better capture temporal patterns in vortex behavior. Moreover, expanding the training dataset with more diverse aircraft pairings and global weather scenarios would improve generalization across airspaces. Implementing a web or cloud-based version would also support accessibility across devices and improve performance through scalable computing. These advancements would position the system as a comprehensive, intelligent decision-support tool for next-generation aviation safety and traffic management.

References

[1] A. Ghosh, R. Sharma, and P. Roy, ”Turbulence model study for wake vortex prediction,” Heliyon, vol. 10, no. 1, pp. e12345, 2024.
[2] M. Ibrahim, S. Lee, and K. Tang, ”Machine learning-based turbulence-risk prediction for real-time aviation safety,” Journal of Big Data, vol. 9, no. 3, pp. 112–130, 2022.
[3] R. Kumar, P. Mehta, and S. Banerjee, ”Wake turbulence classification using supervised learning models,” Heliyon, vol. 10, no. 2, pp. e12678, 2024.
[4] H. Maass and D. Schaefer, ”Decision support tools for wake turbulence in SESAR environments,” in Proc. IEEE Aerospace Conf., 2014, pp. 1–10.
[5] A. Perry, T. Jones, and M. Roberts, ”Wake turbulence recategorization: A safety and capacity analysis,” Transportation Research Procedia, vol. 45, pp. 120–128, 2020.
[6] Y. Zhang, L. Wang, and H. Wu, ”Machine learning-based safety systems for air traffic control environments,” in Proc. IEEE Int. Joint Conf. Neural Netw. (IJCNN), 2020, pp. 1–8.
[7] Y. Zhou, J. Liu, and X. Zhao, ”Wake vortex identification using DBN-GABP with Lidar data,” Journal of Systems Engineering and Electronics (JSEE), vol. 35, no. 2, pp. 215–223, 2024.
[8] IEEE, ”Sensor-based wake turbulence recognition using aviation datasets,” in Proc. IEEE Int. Mechatronics and Embedded Systems Conf. (IMCEC), 2021, pp. 75–80.