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WAKE VORTEX HAZARD CLASSIFICATION FOR CLOSE-PROXIMITY FORMATION FLIGHT USING LIDAR POINT CLOUD SIGNAL PROCESSING AND RISK TRAJECTORY ESTIMATION

Omais Alhatim^{1*}, Mohammad Khaleel Sallam Ma'aitah², S. Surya³, Zeeshan Baber⁴

¹KACST, Future Mobility Institute, Saudi Arabia, Riyadh. Email: oalhatim@kacst.gov.sa

²Robotics and Artificial Intelligence Engineering, Faculty of Engineering & Technology, Applied Science Private University, Amman, Jordan. Email: m_almaayta@asu.edu.jo

³Saveetha school of law, Simats, Chennai. Email: ssl@saveetha.com

⁴Institute of Business Management (IoBM), Karachi, Sindh, Pakistan. Email: zeeshankhan.cis@gmail.com

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Corresponding Author: Omais Alhatim

(oalhatim@kacst.gov.sa)

ABSTRACT

Wake vortex-induced encounters are one of the most poorly quantified hazards in close-proximity formation flight, in which following aircraft are within 50-400 meters of the lead aircraft and standard separation criteria as evaluated using solo-flight turbulence models do not represent the dynamic behavior of vortex decay and lateral off-centred behaviour at tight formation geometries. The current research paper introduces a framework of data-driven hazard classification and risk path estimation based on the LiDAR point cloud signal processing and trained to identify, describe, and predict the development of wake vortices under different atmospheric stratification but with different formation configurations. A dataset derived was composed of 94,000 LiDAR scan sequences at 20 Hz and 38 different formation flight conditions in crosswinds of 2.4 to 18.7 m/s, in altitudes 800 to 11,200 meters and five classes of aircraft weight, including regional turboprops up to wide-body jets. RAANSAC density adaptive segmentation pipeline was used to extract wake vortex cores in raw point cloud returns, which determines vortex core positions to within ± 0.34 meters and tangential velocity gradients with 1,840 radial measurement points in each scan. The extracted vortex signal information, such as circulation decay rate, lateral transport velocity, distance between vortex and vortex separation, atmospheric turbulence dissipation rate were formatted into spatiotemporal tensors and input to a stacked ensemble of gradient-boosted classifiers and a bidirectional LSTM forecasting head, which have a hazard classification accuracy of 96.2 percent across five risk levels and a 12-second forecast horizon of vortex path. The most important ensemble weighted predictors found by Shapley attribution were atmospheric stratification index and crosswind shear profile with classification weights of 34.7 and 28.3, respectively, and the vortex age, usually presumed to dominate in classical models, were found in the 3rd and 5th positions, respectively. The proposed framework improved false-safe classifications by 41 per cent and unnecessary separation events by 27 per cent which directly translated into fuel savings of about 3.2 per cent per hour of formation flight against current ICAO models of wake turbulence separation minima.

KEYWORDS: Wake vortex hazard classification, LiDAR point cloud processing, Formation flight safety, Bidirectional LSTM, Gradient boosting, Spatiotemporal signal tensors, Vortex trajectory estimation, Atmospheric stratification, RANSAC segmentation, Shapley attribution.

1. INTRODUCTION

Formation flight has been known as one of the most fuel-efficient operation configurations that can be used by both military and commercial aviation and it takes advantage of aerodynamic upwash of a lead aircraft to minimize induced drag of other aircraft [1]. Research in a range of echelon formations involving aircraft of various types has repeatedly shown a savings of between 5 per cent to 14 per cent in fuel consumption through operating in close-proximity echelon formations, with commercial fuel-saving initiatives like Airbus fello-fly project and the USAF large-scale efforts in echelon formation operations proving the feasibility in operations of this paradigm. Once such aerodynamic dividend cannot however be separated into the hazard that must be present: the trailing airplane must be operated in the wake vortices shedding regime of its leader, a hazard regime that the current international separation standards have not been designed or shown to face at such close scales [10].

The existing ICAO minima to separate wake turbulence, the regulatory basis of aircraft separation, were based on the empirical research of cruise-altitude, unaccompanied type flight, and encode a conservative, static model of vortex-decay which balances false-safe avoidance with operational efficiency in classical traffic management settings [2]. These models overlook dynamically coupled vortex-aircraft interactions, at the frequencies of 50-400 meters of a lead aircraft, where the vortex experienced by the trailing aircraft is no longer the far-field, old-fashioned vortex modeled by ICAO standards but a young, high-circulation structure, whose decadence pathology is no longer dominated by bulk climatological assumptions.

The basic scientific gap that drives the given study is that there exists no real-time sensor-based hazard intelligence layer able to describe the state of the wake vortices with a detailed spatiotemporal resolution, which is able to make safe, adaptive spacing decisions, during formation flight [3]. Doppler LiDAR systems on the ground have been shown to be able to determine the location of vortex cores and the magnitude of circulations with high fidelity in airport conditions, although their geometry does not allow them to be used in situations of airborne, dynamically evolving formations [4]. In contrast, Airborne LiDAR systems have the potential to have continuous, forward-looking vortex surveillance delivered by the very aircraft itself, which, combined with suitable signal processing and machine Learning inference pipelines, may form the basis of on board hazard intelligence system.

This paper provides a deep architecture of the wake vortex hazard classification and risk path prediction based on the airborne LiDAR point cloud signal processing. The pipeline includes a density adaptive RANSAC-based vortex core extraction framework, spatiotemporal feature tensor representation framework, five-tier hazard classified stacked ensemble classifier and 12 seconds vortex trajectory prediction based on a bidirectional LSTM pipeline. The system was trained and tested using the dataset of 94,000 LiDAR scan sequences in 38 different formation flight situations, five aircraft weight categories, and a wide array of atmospheric stratification and crosswind conditions [5]. Comparative benchmarking of ICAO minimum turbulence separation of the wake turbulence reveals both statistically significant progresses in safety and operational efficiency measurements.

2. LITERATURE REVIEW

Wake Vortex Physics in Formation Flight

Wake vortices are counter-rotating columnar structures shed from the wingtips of any finite-span lifting surface, representing the bound circulation of the wing transformed by Helmholtz's theorem into trailing free vorticity. In classical far-field encounters, the primary parameters governing encounter severity are initial circulation strength – itself a function of aircraft weight, wingspan, and airspeed – and vortex age, which determines the degree of viscous and turbulent decay experienced since shedding. The ICAO separation minima framework operationalizes these relationships through a static weight-class taxonomy mapping generator aircraft category to minimum separation distance for follower aircraft categories, encoding empirical decay curves derived from historical encounter data [12].

Close-proximity formation flight invalidates this framework along multiple axes. First, vortex age at encounter is dramatically reduced, at 200-meter following distance and 100 m/s airspeed, the trailing aircraft encounters a vortex approximately 2 seconds old, versus the 30-120 seconds of age implicit in conventional separation standards [6]. Second, the atmospheric environment experienced by both aircraft is effectively identical, eliminating the statistical smoothing of atmospheric variability that underpins legacy model uncertainty quantification. Third, the proximity of the trailing aircraft to the vortex system introduces aerodynamic coupling effects, most notably vortex deformation induced by the trailing aircraft's own upwash field, that are entirely absent from solo-flight models [8].

Lateral vortex transport, driven primarily by crosswind and the self-induced Biot-Savart velocity of the counter-rotating vortex pair, governs the spatial hazard geometry relative to the trailing aircraft's flight path. In stable atmospheric conditions, vortices may persist for 3–5 minutes and transport laterally by hundreds of meters, while in turbulent or convective environments rapid vortex decay may reduce the hazard window to under 30 seconds. Atmospheric stratification, quantified through the Brunt-Väisälä frequency or an equivalent stratification index, modulates both decay rate and the oscillatory (Crow instability) breakup behavior of the vortex pair, making it a first-order environmental predictor [7].

LiDAR Remote Sensing of Wake Vortices

Coherent Doppler LiDAR has become the leading ground-based technology to characterize wake vortex at airports with operational systems in operation at major airports in London Heathrow, Frankfurt and Dallas/Fort Worth to support reduced separation programs [8]. These systems observe the radial component of atmospheric motion through the Doppler shift of laser light reflected backscattered by aerosol particles entrained in the core of a vortex which allows the reconstruction of the tangential velocity profile of the vortex, therefore, the magnitude of circulation. In low turbulence conditions ground based systems are routinely able to resolve the vortex core position to ± 0.5 meters as well as measure the circulation with less than 5% uncertainty.

Airborne LiDAR systems are more challenging to sense. The very fact that the scan platform itself is in motion through the atmospheric medium, and that it is not moving transversely to its flight path, but along it; the vortex system under consideration is no longer cutting through it, but following it; and signal processing needs to cope with the dynamic nature of the vortex structure pattern between adjacent scans [12]. Literature on airborne vortex sensing has mostly focused on pulsed direct-detection LiDAR to measure cloud and aerosol profiles instead of coherent Doppler to measure velocities, and the issue of extracting the core of the vortex out of point clouds in air has been addressed rather systematically rarely.

Atmospheric Hazard Classification with Classical Machine Learning.

In recent years, the use of machine learning to provide weather and turbulence hazard classification in aviation has been greatly accelerated by the

evolution of ensemble-based and deep learning architecture that can take advantage of high-dimensional, time-structured sensor data. XGBoost and lightGBM are examples of gradient-boosted decision tree ensembles that have shown excellent performance on tabular atmospheric feature data, both in predictive accuracy and interpretable features with SHapley Additive exPlanation (SHAP) techniques [9]. Recurrent neural network designs, the long short-term memory network and its bidirectional counterparts have been shown to be useful in time-varying prediction of atmospheric state variables such as turbulence intensity, icing severity and evolving convective hazards.

Earlier studies on predicting the existence of wake vortices have mainly utilised physics-enhanced statistical models, including the DLR Wake Vortex Prediction and Monitoring System (WSVBS) and the Aircraft Vortex Spacing System (AVOSS) of the FAA both of which use explicit atmospheric measurements inputs and parametric equations of vortex evolution [10]. Wholly data-based methods of classifying vortex hazards, especially methods that use raw LiDAR point cloud returns, as opposed to more processed vortex state projections, is an under-investigated approach that can potentially capture non-linear interactions of features not discernible using physics-parameterized models.

Dataset Construction and Experimental Configuration

Data Collection Platform and Sensor Configuration

This dataset was obtained with a forward-facing coherent Doppler LiDAR system with wavelength of 1.55 μm that was chosen due to aerosol backscatter coefficient being high compared to lower wavelengths at the lower troposphere, and being eye-safety compliant. The LiDAR system was set to scan in a conical fashion with a half-angle of 15 degrees resulting in complete azimuthal scans at a repetition rate of 20 Hz [11]. This arrangement provided densities of point clouds of about 4,200 returns per scan at a nominal point separation of 0.8 meters along the radial axis and 0.6 meters along the azimuth at the nominal operational range of between 150 and 350 meters. GPS/INS Onboard integrated with post-processing accuracy of ± 0.12 meters was used to provide the platform motion compensation required to achieve point cloud georeferencing accuracy [10].

Simultaneous measurements of airspeed, angle of attack and sideslip angle were obtained at 100 Hz on

an onboard five-hole probe; a flush air data system that provided static and dynamic pressure at the fuselage surface; and a turbulence dissipation rate estimator that was based on the longitudinal wind velocity power spectral density using the inertial subrange method. Formation geometry was incessantly logged by the differential GPS between leading and trailing planes at 10 Hz which gave ground-truth age of the vortex and the geometry between airplanes against which the LiDAR-derived readings could be compared [12].

Scenarios and Classes of Aircraft 3.2.

The analysis involved 38 different formation flight situations in three years in several geographic

locations and seasons to have diversities in the atmosphere. Lead aircraft were represented by five weight classes namely, Class I (regional turboprop, 8,000-16,000 kg maximum takeoff weight), Class II (regional jet, 20,000-40,000 kg maximum takeoff weight), Class III (single-aisle narrow-body, 60,000-85,000 kg maximum takeoff weight), Class IV (twin-aisle wide-body, 150,000-250,000 kg maximum takeoff weight). The formation after distances varied between 52 and 398 meters and the crosswind elements at the altitude of flight were between 2.4 and 18.7 m/s. Coverage, as demonstrated in table 1, was 800-11,200 meters with the planetary boundary layer, free troposphere and tropopause transition regimes with significantly different vortex decay regimes.

Table 1. Summary of scenario classes, lead aircraft types, number of formations, LiDAR sequences collected, and altitude ranges across 38 formation flight scenarios.

Scenario Class	Lead Aircraft Type	Formations	LiDAR Sequences	Alt. Range (m)
Class I	Regional Turboprop	6	11,200	800-3,500
Class II	Regional Jet	7	16,800	1,200-6,000
Class III	Narrow-Body	10	24,000	3,000-9,500
Class IV	Wide-Body	9	22,400	5,000-11,200
Class V	Heavy Wide-Body	6	19,600	6,000-11,200
Total	All Classes	38	94,000	800-11,200

Atmospheric Stratification Characterization

Radiosonde profiles released in a 50km radius and a 90 minutes each formation flight window characterized atmospheric stratifications at the scenario altitude and time with supplements by ECMWF ERA5 reanalysis gridded fields on a horizontal resolution of 0.25 degrees. The stratification index SI that has been applied in this paper is defined as the square of Brunt-Vaisala frequency N^2 calculated as the ratio of vertical potential temperature gradient in the 200-meter layer at the center of flight altitude to give a measurement of atmospheric stability, which is strongly stable ($SI > 0.8$), neutral ($0.2 < SI < 0.4$) and convective/unstable ($SI < 0.1$). The difference between wind vectors in the air 50 meters above and below flight level was used as the crosswind shear profile with the ratio of the vortex initial circulation given to obtain a non-dimensional shear parameter [9].

Signal Processing and Feature Extraction Methodology.

Density-Adaptive RANSAC Vortex Core Segmentation.

Each scan produced raw LiDAR point clouds which were preprocessed in a five-stage pipeline. First, it performed platform motion compensation based on the angular rate and INS derived velocity

measurements in order to transform all returns to a shared inertial reference frame [15]. Second, the atmospheric backscatter filtering eliminated powder of signal-to-noise ratio less than 6 dB, eliminating noise contamination with relatively low costs of degrading vortex core sampling density [13]. Third, a k-nearest-neighbor ($k=12$) spatial density analysis technique revealed high-density structures against the background aerosol field of lower density the vortex cores.

The core extraction of the vortex was applied by a density-adaptive form of the Random Sample Consensus (RANSAC) algorithm with adjustments to a Rankine combined vortex velocity profile to radial velocity measurements obtained along a set of candidate scan planes [12]. The adaptation added the density-dependent inlier threshold which adjusted the fitting tolerance automatically to the dependence on the local point density, avoiding the algorithm to fit spurious coherent structures in atmospheric layer regions or contaminated with thin clouds [8]. The optimization problem reduced the sum of squared residuals between the measured radial velocity and the Rankine profile prediction, and the vortex core position, core radius and peak tangential velocity were used as free parameters. It converged in 3.4 iterations each scan on average, which is far less than is necessary to run at 20 Hz in real time.

Comparison to the ground-truth vortex positions formed by the differential GPS geometry and

independent estimates of vortex age indicated vortex core position resolutions of ± 0.34 meters (95 th percentile error) regardless of the scenario and regardless of the weather category with slightly poorer results (± 0.61 meters) in the Class I turboprop scenarios where weaker initial circulation produced lower signal-to-noise contrast [14]. A gradient in tangential velocity was determined in 1,840 radial measurement points per scan offering adequate resolution in the radial direction to describe the vortex core structure in terms of the viscous core region and remote-field potential flow regime.

Construction of Hull Spatiotemporal Feature Tensor.

A 47 scalar quantities feature vector was calculated for the result of each processed scan and sorted into half a dozen physical groups (vortex geometry, core position, core radius, vortex pair separation distance, core height above terrain, circulation, transport dynamics, lateral drift velocity, vertical drift velocity, drift acceleration, lateral drift standard deviation over 10-scan window, atmospheric state, stratification index, crosswind magnitude, crosswind shear parameter, turbulence dissipation rate, relative humidity at flight altitude, formation geometry, following distance, lateral offset, vertical offset [15].

Tensors of shape $[T \times F]$, where $T = 60$ (history length of 3s at 20 Hz) and $F = 47$ features, were pooled together to form feature vectors of a single scan, and then the subsequent scan, and so on, to create a spatiotemporal representation of the features to be inputted into the bidirectional LSTM, with enough temporal history to resolve vortex evolution patterns and still making the full computationally manageable to run on board [11]. The feature normalization was performed using a robust scaler (median and interquartile range) to the training split to ensure that scale distortion due to outliers is minimized, while the scaling parameters were kept class-specific to each of the atmospheric strata classifications to reflect the fact that feature distributions are very different in stable and unstable atmospheric conditions [14].

In this category, hazards are classified based on the taxonomies of the hazard parameters to which they are most closely related. 4.3 Hazard Classification Taxonomy Hazards are categorized under different taxonomies of the hazard parameters to which they most closely relate [16].

There were five hazard risk levels which were determined through the worst-case coefficient of a roll moment which the next airplane of the same

weight category would roll and hit the characterized system of vortex. Tier 0 (Green: Negligible) is below 5 percent of maximum aileron authority induced roll, Tier 1 (Yellow: Marginal) is between 5 and 20 percent, Tier 2 (Amber: Moderate), is between 20 and 40 percent, Tier 3 (Orange: Severe) is between 40 and 70 percent, and Tier 4 (Red: Catastrophic) is greater than 70 percent. Post-flight ankle examination through the combination of measured vortex circulation, subsequent airplane aerodynamic specifications, and the vortex encounter simulation code created as part of the NASA Aircraft Vortex Spacing System program assigned labels of ground-truth tier.

Model Architecture and Training

Gradient-Boosted Ensemble Classifier is a machine learning model that uses a series of boosted tree models to classify input data points. 5.1 Gradient-Boosted Ensemble Classifier Gradient-Boosted Ensemble Classifier is an example of machine learning that classifies each input data point using a sequence of boosted tree models.

The hazard classification module has been applied as an ensemble consisting of three base classifiers, which are an XGBoost model trained on the full 47-dimensional feature vector with 800 trees and maximum depth 6; a LightGBM model with gradient-based one-side sampling and 1,200 leaves; and a CatBoost model with ordered boosting to mitigate prediction shift in the time-ordered training split. The output of a base classifier (class probability vectors) was concatenated and inputted into a meta-learner, which was a logistic regression, trained on the training split through stratified 5-fold cross-validation. The Bayesian optimization (150 evaluations per base model) was used to minimize a weighted log-loss, which weighting down false-safe classifications (Tier 0 assigned to Tier 3 encounter) by 4 times the weighting down false-alarm classifications (Tier 3/4 assigned to Tier 0 encounter) to represent the asymmetric safety implications of the two types of error [17].

Two-way LSTM Trajectory Forecasting Head.

The 12-second vortex trajectory predictor component was based on the bi-directional LSTM architecture that works with the $[60 \times 47]$ spatiotemporal cube input. The bidirectional encoder had two LSTM layers of 256 hidden units, and the sequence was fed in both forward and reverse time directions and the resultant hidden state vectors were combined. The 512-dimensional composite representation was fed through a two-layer fully connected decoder with 256 and 128 units

respectively (ReLU activations, 0.3 dropout), which generated a prediction tensor of $[240 \times 2]$ of the lateral and vertical displacement of the individual vortex cores at 20 Hz over the next 12 seconds. The Huber loss was used to train the model, which is less sensitive to misaligned outlier trajectories, and the Adam optimizer was used, with an initial learning rate of 3×10^{-4} and a cosine annealing schedule of 120 epochs. The 8 NVIDIA A100 GPUs were used to train on a distributed cluster in data-parallel training with a time of approximately 14 hours [17].

Training, Validation and Test Protocol.

Data splitting was based on a scenario-stratified protocol: training (26 scenarios, 63800 sequences), validation (6 scenarios, 14400 sequences), and test (6 scenarios, 15800 sequences) splits were divided by situations and assigned each situation to one of these splits. Such splitting at the level of scenarios ensured that the temporal autocorrelation within a scenario did not artificially inflate the metrics of validation and test performance - this is a serious issue to consider since the acquisition rate at 20 Hz yields around 1,200 consecutive and highly correlated samples within a minute of flight [18]. The test split

was not used at all until end model evaluation, where no hyperparameter or architecture choices were made based on test split performance.

3. RESULTS

The performance of the hazard classification module is categorized into 6.1 Hazard Classification Performance.

The stacked ensemble classifier had an overall accuracy of 96.2% on the held-out test split both in the five risk tiers and a macro-averaged F1 score of 0.951, as shown in table 2. The Tier 0 (F1 = 0.978) and Tier 4 (F1 = 0.961) resulted in the highest-level performance (as the physical distinguishing feature of the extreme cases) and the lowest performance in Tier 2 (F1 = 0.931), where the moderate-hazard regime was the most natural ambiguous between the adjacent tiers. The confusion matrix also showed that the most common error was adjacent-tier errors (Tier 2 predicted Tier 1 or Tier 3), and not distant-tier errors, a behaviorally-conservative failure mode due to the asymmetric loss weighting. None of the Tier 4 (catastrophic) experiences were categorized as Tier 0 or Tier 1 in the test set, indicating a rate of zero critical false-safe errors on the test data.

Table 2. Classification performance metrics (precision, recall, F1 score, and support) of the stacked ensemble classifier across five wake turbulence hazard risk tiers on the held-out test set.

Risk Tier	Label	Precision	Recall	F1 Score	Support
Tier 0	Negligible	0.982	0.974	0.978	4,820
Tier 1	Marginal	0.961	0.948	0.954	3,910
Tier 2	Moderate	0.924	0.938	0.931	3,240
Tier 3	Severe	0.953	0.967	0.960	2,680
Tier 4	Catastrophic	0.971	0.952	0.961	1,150
Macro Avg.	—	0.958	0.956	0.951 (F1)	15,800

Vortex Trajectory Prediction Accuracy

Bidirectional LSTM predictor head was able to make vortex core position forecast error of 1.8 meters at 12 secs forecast time with error increasing almost linearly with forecast time, with a minimum error of 0.6 meters at the 2 secs forecast time up to the maximum of 1.8 meters at 12 secs forecast time. The prediction accuracy was highly influenced by the stratification growth in the atmosphere: in the stable conditions ($SI > 0.6$) where the motion of the vortices is quasi-deterministic and controlled by the self-induced velocity of the vortex pair, the 12-second RMSE had the value of 1.2 meters. At neutral conditions ($0.2 < SI < 0.4$), 12-second RMSE had an average of 1.9 meters, which indicates the higher contribution of turbulent transport fluctuation. RMSE of 2.7 meters in convective conditions ($SI < 0.1$) is owed to the vortex trajectory deviations, which are rapid and turbulence dominated and difficult to all

physical and data-driven prediction methods.

Division of the prediction error into components, lateral displacement prediction (RMSE = 1.4 m at 12 s) was better than vertical displacement prediction (RMSE = 2.1 m at 12 s), which is in agreement with the physical concept that lateral vortex transport is mainly determined by the comparatively predictable crosswind and self-induced velocity fields and vertical transport is determined by the variability of atmospheric convective structure that is not fully represented by the scalar stratification index [20].

Feature Attribution with Shapley.

The stacked ensemble classifier was used in SHAP (SHapley Additive exPlanings) analysis in order to estimate the average contribution made by each feature to classification output. Stratification index (SI) in the atmosphere turned out to be the most influential predictor with 34.7 percent of total mean absolute SHAP value - which inverts the implicit legacy model

assumption that vortex age is the first most important decay predictor [19]. Crosswind shear profile came second at 28.3% indicating the importance of near-field wind shear in controlling lateral transport and development history of the Crow instability that can

dissipate high risk structures of vortexes very fast. The third largest value was the vortex age with values at 19.1, then peak tangential velocity (8.4) and distance between vortex pairs (4.6) and the rest of the 39 features at 4.9, s mentioned in table 3.

Table 3. SHAP feature attribution rankings and legacy model assumptions for the top five predictors in the stacked ensemble classifier.

Feature	SHAP Contribution (%)	Rank	Legacy Model Assumption
Atmospheric Stratification Index (SI)	34.7%	1st	Not modeled
Crosswind Shear Profile	28.3%	2nd	Secondary factor
Vortex Age	19.1%	3rd	Primary factor
Peak Tangential Velocity	8.4%	4th	Implicit via weight class
Vortex Pair Separation Distance	4.6%	5th	Not modeled
All Other Features (39)	4.9%	–	–

Comparative Benchmarking Against ICAO Standards

The 15,800 test sequences were directly compared between the classifications provided in the proposed framework and the ICAO wake turbulence separation minima model and ICAO classifications were calculated by using the standard weight-class separation rules using the aircraft type of the ground-truth object and an estimate of the vortex age based on following distance and airspeed. The proposed framework cut false-safe cases, cases in which the ICAO model had the Tier 0 (safe) label, by 41% compared to ICAO, which is an important contribution to improving hazards critical to safety. At the same time, unnecessary separation events, which were ICAO Tier 3 or Tier 4 but ground truth was Tier 0 or Tier 1, were also decreased by 27 percent, or the 3.2 percent per-hour fuel savings estimate based on decreased formation spacing conservatism [15].

4. DISCUSSION

The result that stratification index of the atmosphere is giving 34.7 percent of the weight in classification, which is significantly higher than vortex age at 19.1 valid, has significant implications on both practice and development of the regulatory framework. The vortex age effect which prevails in legacy model predictions in the formation flight regime, in which the encounter must necessarily be with a young vortex (1-10 seconds old depending upon following distance and airspeed), is squeezed into a small band with only a limited discrimination capability [16]. In comparison, the stratification state of the atmosphere defines whether that young vortex is short-lived (unstable conditions) or retained with approximately initial circulation (strongly stable conditions), and produces a first-order hazard modulation, which ranges an order of magnitude

between typical atmospheric states.

This has a direct implication on operational decision making in formation flight management systems. A formation working at a fixed following distance in calm atmospheric conditions can be exposed to a risk two or three levels greater than the same formation at the same following distance in convective conditions; the reverse of the intuitive expectation that clear stable air is always the safest place to operate [11]. The formation flight management systems with atmospheric stratification knowledge would be able to change adaptively after the distance or vertical deflection to maintain a specified risk level under different atmospheric conditions, substituting the fixed separation minima of the current frameworks with a risk-calibrated spacing algorithm [15].

The second highest-ranking predictor, crosswind shear profile, represents the difference in velocity of wind across the core height of the vortex, that contributes to the asymmetric lateral transport of two counter-rotating vortex tubes. The vortices are dragged off in different rates in high shear conditions, and they quickly grow apart and trigger the long-wave Crow instability which causes vortex connections and break up. This process offers a physical explanation of the counter-intuitive observed resultant characteristic of moderate crosswind shear conditions that result in lower hazard classification compared to low-shear conditions of a similar age: the accelerated vortage-decay pathway proposed by shear-driven Crow instability can destroy a high-hazard vortex structure within seconds following its formation prior to the following aircraft arriving at the vortex position.

The operational implication is that real-time crosswind shear measurement, which is offered by the onboard five-hole probe system at 100 Hz in the study platform gives a high-value input signal, which substantially enhances the hazard

classification fidelity as compared to bulk crosswind magnitude alone [19]. High-bandwidth wind shear measurement should be considered as an integral part of formation flight management systems as opposed to pre-flight atmospheric profiling data because shear layers at the lower troposphere have small spatial scales.

5. LIMITATIONS

There are a number of limitations of the present study that deserve being mentioned explicitly. To begin with, the data set, representing 38 scenarios and 94,000 scan sequences, is not representative of all the types of airborne LiDAR configurations that can be implemented in commercial formation flight systems since it was only collected on one leading-aircraft platform. The data set is not shown to be representative of the range of airborne LiDAR configuration realizations that can be deployed. Second, there is uncertainty in the ground-truth hazard tier labels based on post-flight vortex encounter simulation based on the parameterization of the simulation model, especially in the aerodynamic reaction of the subsequent aircraft to non-uniform vortex structures of intricate complexity [20].

Third, the 12-second forecast horizon of tactical spacing is probably not adequate in the management of strategic formations that need prediction horizons of 30-60 seconds. An increase in the forecast horizon is likely to drastically augment prediction RMSE, specially in neutral and convective weather circumstances in which vortex path stochasticity escalates very fast. Fourth, existing model lacks any aerodynamic modeling of the interaction between the trailing aircraft and the vortex structure; an event that grows important at a trailing distance less than about 80 meters and can enhance the speed at which vortices are dissipated compared to the uncoupled scenario taken here [11].

The suggested framework is intended to be deployed as an onboard hazard intelligence layer on a formation flight management system, and works in parallel with the main flight management computer, and provides hazard tier and trajectory forecast outputs to the flight crew on a dedicated situational awareness display. The computation time of real-time inference, about 12 ms per 20 Hz scan cycle of the joint RANSAC segmentation, feature extraction, ensemble classification, and LSTM forecasting architecture on an embedded GPU accelerator, is within the computational ability of the current-generation avionics processing architectures [14].

Connection with existing formation flight automation systems, including the USAF Surfing

Aircraft Vortices for Energy (SAVE) program autopilot and the autopilot response operational standards contemplated by Airbus and others in commercial formation flight automation development, would need a standard hazard tier communication interface and agreed standards of operation response to Tier 3 and Tier 4 classifications. The 41 percent cut in false-safe classification and 27 percent cut in false-separation events in the framework offer a quantitative foundation of regulatory involvement because adaptive spacing based on real-time LiDAR hazard information may assist in a significant decrease in conservative separation buffers with no deterioration or enhancement in absolute safety routines.

6. CONCLUSION

This paper has provided an overview of a data-driven wake vortex hazard classification and risk trajectory prediction framework in the context of close-proximity formation flight that is based upon airborne LiDAR point cloud signal processing and has been trained on a 94,000 scan sequences dataset of 38 formation scenarios with five aircraft weight categories and a wide varying weather regime. The model attains 96.2% success in hazards classification at five levels of risk and vortex trajectory projection over a 12 second horizon +1.8 meters - performance levels that translate directly and squarely to both measurable real-world operational benefits.

The Shapley attribution analysis demonstrates that the most important predictors of formation flight wake vortex hazard are atmospheric stratification index and profile of crosswind shear which contribute 63 and 19 percent of classification weight, respectively, compared to vortex age, a finding that undermines the underlying assumption of legacy ICAO separation models and leads to an entirely new way of thinking about the adaptive separation of formations. These results not only suggest the technical design of airborne hazard intelligence systems but also suggest the regulatory and certification frameworks of operation in the formation flight regime where the demonstrated deficiency of the weight-class-based separation minima at low Reynolds number is provided with quantitative incentive of sensor-driven adaptive separation standards.

The direction to which the future research can be divided is as follows: extension of the dataset to include wider varieties of trailing aircraft and formation geometry, vortex models that are aerodynamically coupled to capture the interaction between the trailing aircraft and the wake, the

formation flight management system autopilots should be integrated to study to characterize the end-to-end safety and efficiency benefit of adaptive LiDAR-guided spacing in realistic operational conditions. The architecture is a deployable platform to next-generation formation flight hazard

intelligence, and has direct applicability to military echelon operations, commercial fuel-efficient formation programs as well as the future urban air mobility corridors where the formation-like proximity operations are expected to be common place.

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