Atmospheric Turbulence Prediction

Models for Safer Aircraft Navigation

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1. Introduction

The New Year of 1914 marked a milestone in aviation when Antony Habersack Jannus flew a twenty-three-minute-long scheduled flight with a passenger in Florida (Swopes, 2023). With the increase in passenger demands, the industry became a competitive business that should deliver cheap air travel with maximum safety and the best services. The weather and geography are two factors beyond the human ability to control and that affected safety. Clear Air Turbulence (CAT) is a meteorological phenomenon that arises due to the difference in the speed of air masses at high altitudes, especially higher than 15,000ft when flying across the boundary of two air masses. CAT occurs because of convective heating of air and is easy to miss on a clear and dry day, making it dangerous (Robert Graef, 2019). This paper presents several studies that use different numerical weather prediction (NWP) models and pilot report data to analyze and predict the weather and possible turbulences to plan aircraft routes efficiently. With the advancement in machine learning, the NWP models were combined with ML models and dimensionality reduction techniques to improve accuracy and latency.

Keywords: Clear Air Turbulence (CAT), Numerical Weather Prediction (NWP) model, Graphical Turbulence Guidance (GTG), Weather Research and Forecasting (WRF) model, Optical Turbulence (OT) model, XGBoost algorithm, random forest, SVC, PCA, K-means

2. Literature Review

The escalating demand for air travel has led to the growth of airlines and associated services. This escalation, however, has concurrently given rise to an increase in air traffic incidents, necessitating enhanced safety measures. In the year 1977, Lilly undertook a comprehensive investigation aimed at understanding large-scale, mesoscale, and turbulent-scale phenomena contributing to a downslope windstorm in Central Colorado on January 10th and 11th, 1972. Among the three analytical dimensions employed in this study, the documentation of aircraft hazards resulting from wave downdrafts and turbulence over mountainous terrains in adverse weather conditions marks the beginning of air turbulence analysis. According to Lilly's research findings, "the classical mechanism of shearing instability in the presence of stable thermal stratification was responsible for the generation of the turbulence, with the shear produced by the large amplitude and quasi-steady mountain wave" (Lilly, 1977).

In alignment with Lilly's precedent work, a comparable downslope windstorm incident in 1992 was observed and studied about the clear air turbulence (CAT) phenomenon with more technical improvements. The wind flow structures were collected from remote sensing using ground-based lidar of NOAA/ERL/ETL [1] which significantly improved the data contrary to the in-situ observations used before. The research concluded that the windstorm was a result of strong interactions between two distinctly different waveforms – flow-aligned internal gravity waves and crossflow jet stream undulations which are nearly orthogonal to each other. Their interactions led to numerous physical events and for the first time Horizontal Vortex Tubes (HVTs) and a penetrative downburst of CAT were documented (Clark, 2000).

Moving forward from the simulations for CAT events, Sharman et al (R. Sharman, 2006)introduced the Graphical Turbulence Guidance (GTG) system that focused on an automated procedure to forecast mid- and upper-level turbulence that affects aircraft. The Research Applications Laboratory (RAL) at NCAR and the NOAA's Earth System Research Laboratory (ESRL) took the initiative to develop and test the Integrated Turbulence Forecasting Algorithm (ITFA) which concentrated only on CAT related to jet streams and fronts at upper levels. ITFA was

[1] National Oceanic and Atmospheric Administration/Environmental Research Laboratories/Environmental Technology Laboratory

a blending of the Numerical Weather Models (NWPs) with the turbulence observations (i.e., the pilot reports) for predictions and was renamed GTG emphasizing the graphical nature of the output.

Kim et al (Kim J., 2014) modified the Graphical Turbulence Guidance (GTG) system by evaluating a time-lagged ensemble of energy dissipation rate (EDR)[2]--scale turbulence metrics and applied it to air traffic management (ATM) planning. The modifications included a finer horizontal grid, a time-lagged ensemble forecast, and probabilistic information for the ATM instead of a deterministic one. The modified GTG system from the study by Kim et al derived 10 turbulence diagnostics from three time-lagged ensemble members to get a total of 30 different turbulence forecasts. On application of the model to different events that occurred already due to convective clouds and/or jet streams over mountain regions proved to have higher accuracy than the then-existing deterministic model.

The atmospheric turbulence and meteorological conditions often affect the observed data especially collected using ground-based techniques and free-space optical communication. Rafalimanana et al (Rafalimanana A., 2022) modeled predictions based on NCAR's Advanced Research Weather Research and Forecasting (WRF) model which predicts the refractive index of the transmission layers beforehand by injecting into an optical turbulence model (OT) so as to adjust on the observation data using the basic atmospheric physics parameters – pressure, temperature, relative humidity, wind speed, and wind direction.

Yoshimura et al reproduced a CAT event that occurred on 30th December 2020 using a regional NWP model with a resolution of 35 m (Yoshimura, 2023). The simulation of the model was validated by comparing virtual flight turbulence with the onboard reports during the CAT event.

[2] The rate of the turbulent kinetic energy (TKE) transfer from large- to small-scale eddies. (Kim J., 2014)

The study derived numerical solutions or replications of the event, simulated Boeing 787 aircraft motion through the calculated CAT space, and compared it with the real experience. The regional NWP model could reproduce the turbulence in realistic scales and match it with the flight data.

With the advancement in scopes for machine learning models, there was a series of research that employed different data-driven ML models in place of the complex NWP models. Williams developed a random forest classifier model (also KNN and LR) that fuses data from turbulence reports from different aircraft to produce a real-time diagnosis of turbulence associated with thunderstorms and other causes (Williams, 2013). Further, using a collection of conventional turbulence indices from a regional NWP model, the XGBoost[3] algorithm was applied to the turbulence forecasts (Hon K. K., 2020).

3. Technical Review

In the paper, Lilly introduces intricate details pertaining to wind speed and direction, pressure differentials relative to sea level, surface pressure, and temperature profiles. These data were meticulously collected over varying durations, ranging from days to months and extending up to an impressive eight-year span within the specified region of interest. The paper encompasses a sophisticated blend of mathematical and physical analyses applied to diverse parameters, rendering it an indispensable resource for subsequent investigations within the field (Lilly, 1977).

Clark et al (Clark, 2000) uses four levels of grid refinement for simulations of the CAT using the Clark-Hall Model. The large-scale domain was a 25.6 km horizontal grid over 820 km by 820 km with mesoscale analyses every three hours over the continental United States. The innermost

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XGBoost: [3] eXtreme Gradient Boosting

domain used a 200 m horizontal grid and focused on the turbulence over a region of 48 km on a side by 12.7 km vertically. The model used 0900 UTC MAPS analysis data, which updated the model's outermost boundary every three hours throughout the simulation. The simulation projected momentum, temperature, and moisture fields onto the outermost 25.6 km grid. On the establishment of all the domains, the simulation was run until 1500 UTC with the last 30 minutes giving the highest resolution on adding the finest domain.

The GTG (R. Sharman, 2006) system revolutionized the forecast models with its graphical approach. GTG represents the large-scale features of the atmosphere from the National Centers for Environmental Prediction's rapid Update Cycle (RUC-2) NWP model for its higher effective vertical resolution. The system integrates various weighted turbulence diagnostics in real-time upon receiving enough pilot reports and is updated with every RUC model update.

Later, Kim et al (Kim J., 2014)modified the GTG system using a time-lagged ensemble of NWP forecasts. These forecasts provide probabilistic information about turbulence likelihood using turbulence diagnostics. Moreover, they implemented a high-resolution NWP model with 3 km horizontal grid spacing which covers the Contiguous United States (CONUS) to predict the effects of convection and give better representations of mountain waves and CAT sources. The study uses the Advanced Research version of the Weather Research and Forecasting Model (ARW) adapted from the NOAA's High-Resolution Rapid Refresh (HRRR) operational system. The model extends to 20hPa with 50 vertical layers with about 500 m vertical grid spacing in the Upper Troposphere and Lower Stratosphere (UTLS). The model used the Pleiades supercomputer at the NASA Ames Research Center with a run time of one hour using 500 cores to complete one model with forecast outputs in every 15 minutes for six hours. Further, the EDR metrics were evaluated using the probability of detection “yes” for the EDR >= 0.22 $m^{2/3}$ s^{-1} or “no” for the EDR <= 0.01 $m^{2/3}$ s^{-1} (PODY/N).

Optimal Turbulence prediction blending the WRF and OT models (Rafalimanana A., 2022) could achieve predictions of almost 24 hours. The simulations are run 12 – 18 hours before the time for which the prediction is anticipated. Three Planetary Boundary Layer (PBL) schemes and two Land Surface Models (LSM) were tested and compared to find the optimal WRF design. The WRF model has a vertical grid with 46 levels with a resolution decreasing slowly with height, with thickness ranging from 10 m at the highest layer located at 50hPa (~20 km above mean sea level) to 1150 m at the bottom layer. The data used in this study was gathered from the Cerro Pachón[4] campaign for the meteorological parameters. The radio soundings data profile ranges from ground to 25 km with a high vertical resolution of 4 – 7 m. The WRF model predictions were compared with this data and gave an MRE under 6.4%.

The Clear Air Turbulence event of 2020 over Tokyo was resolved by employing a mesoscale NWP model (Yoshimura, 2023). The research required data for three different steps. The NWP model simulated the event with horizontal resolutions of 500 m, 250 m, 70 m, and 35 m. It generated initial and boundary conditions for the coarse resolution based on JMA-MSM analysis data which was updated every three hours with 5 km resolution by the Japan Meteorological Agency. A 2D flight simulation was applied based on the NWP results and other meteorological data such as wind speed. Thirdly, data was three aircraft that encountered maximum turbulence at every second interval was collected and validated with the flight simulation data.

[4] During the Cerro Pachón campaign, 46 radio-sounding balloons were launched to measure vertical profiles of pressure, temperature, wind speed, wind direction, relative humidity, and refractive index structure constant C_n^2 (Rafalimanana A., 2022).

The machine learning approach enabled the extraction of insights based on data from previous episodes and embedding them in weather prediction models. Williams used data from ground-based Doppler radar, geostationary satellite imagery, lightning detection network, and other derived features (Williams, 2013). The model followed the standard training and testing phases and eventually performance evaluation using the ROC[5] curves. The XGBoost model (Hon K. K., 2020) also combined data from pilot reports and turbulence indices from the NWP model. The algorithm was implemented on Python which is a supervised learning model with large data sets based on iterative ensembles of regression trees with gradient boosting and covered data from a 1-year period. An advanced model, the LiDAR[6] turbulence identification model, based on XGBoost and a conditional generative adversarial network (CGAN) was designed based on the Keras framework that utilized Neural network layers to reduce the dimensionality of the data set and enabled a backpropagation technique that significantly reduced false alarms on turbulence predictions (Zhuang Z., 2023).

4. Obstacles

The data employed for the analysis and comprehension of the 1977 downslope windstorm were derived from in-situ recordings conducted by two NCAR[7] aircraft, as documented by Lilly in 1977. While informative, these observations faced limitations in accurately mapping intricate wind flow structures, temperature variations, and turbulence characteristics (Lilly, 1977). In the subsequent study in 1992, these limitations were addressed through the utilization of ground-based lidar observations. However, owing to the inherently three-dimensional nature of windstorms, the

[5] ROC: Receiver Operating Characteristic – The plot of True Positives versus False Positives in predictions

[6] LiDAR: Doppler light Detection and Ranging is a remote sensing method for measuring atmospheric parameters in the lower troposphere.

[7] National Center for Atmospheric Research

conventional wave-breaking windstorm model prevalent at that time proved inadequate, as highlighted by Clark in 2000 (Clark, 2000).

The GTG system provided useful information for strategic planning to avoid turbulence, however, faced some inconsistency issues related to the NWP models used, the resolutions of the model, and the errors associated with the resolvable scales. Further, the GTG system uses the pilot reports for modeling and model fitting which are subject to misrepresentations due to the involvement of human judgment. Moreover, the inability to deal with large data to improve accuracy also affected the quality of predictions (R. Sharman, 2006). Kim et al gave notable improvement on the GTG system however lacked a 3D optimization of routes that could minimize the fuel and travel time. Moreover, the high latency of the forecast had to be dealt with to provide real-time predictions (Kim J., 2014).

The Optical Turbulence model implementation on the WRF model (Rafalimanana A., 2022) gave a satisfactory outcome on turbulence predictions and a seasonal analysis that spots the turbulence using the gradient of potential temperature, however, the work calls for improvement in wind speed and direction forecasts within the atmospheric boundary layer. This requires a more large and complete measurement data set containing vertical profiles of meteorological parameters for broadening the analysis.

The simulation of the CAT event of December 2020 in Tokyo lacked the pitching rate control data embedded in the aircraft which was an obstacle in improving the accuracy of reproducing the event (Yoshimura, 2023). The machine learning models employed using the random forest classifier model (Williams, 2013) and XGBoost algorithm (Hon K. K., 2020) lack the ability to detect the turbulence occurrence date (Mizuno, 2022) which is dealt with by recent models that implement PCA and other techniques.

5. Recent and Future Work

5.1. Case Study

The recent studies using machine learning of CAT forecasts, like the previous ones, utilize data from pilot reports about turbulences and weather prediction models. With the advancement in data analysis as in data handling methods like big data storage and usage and complex libraries to handle data and computations, the ML models emerged to be more sophisticated. Mizuno et al. devised an algorithm that conducted a PCA analysis on meteorological data that reduced the dimensionality of the data and implemented a Support Vector classification model. The research also studied and compared their predictions with the turbulences experienced by flights from Matsumoto Airport whose geographical location makes it susceptible to turbulences caused by mountain waves. The part that makes this experiment unique is that the data collectors were not pilots but the researchers themselves! Apart from SVC, a risk cluster calculation was also conducted based on the collected data using the K-means method. The study could successfully predict the turbulence days and levels and was verified using weather maps later. This experiment and ML model could predict even less frequent turbulence events (Mizuno, 2022).

5.2. Course of Action

Even though the modern ML models are promising, they require expansion of the data domain and a better understanding of seasonal influences on the weather. Most of the research is locally centered and cannot be used to generalize or expand beyond the specific region (Mizuno, 2022). Moreover, the models tend to give false alarms and inaccurate classifications that affect the time and efficiency of aircraft companies. Each model or approach tends to provide an advantage over the other, however fails to give a complete solution that meets the standards of aircraft navigation. A model that could give a combination of desired features will be the goal for all improvements in the future.

6. Conclusion

The recent research in the forecasting of turbulences and other weather phenomena has given prediction models with high accuracy and fewer false alarms. Many airline companies are adapting these models to ensure a safer experience for their customers. Turbulence forecasting involves a deep understanding of complex fluid dynamics and weather patterns. The improvements in any prediction model involve domain knowledge and statistical skills. The ML models allow the predictions with minimal subject knowledge which can be interpreted and embedded for forecasting by experts in the field. The research area has a great scope when the field expertise, machine learning knowledge, and business goals are combined. With the availability of big data from weather stations, radar systems, and pilot reports and the infrastructure to store and high computational power to analyze this volume of high-velocity data, air turbulence could no longer stand in the way of air traffic safety.

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