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A Survey on The Use of Generative AI in Aviation

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Abstract – The main goal of this research is to investigate the potential and current role of generative AI in improving and developing avionics systems, and aviation-related applications. Avionics, a vital part of aviation industry, consists of a set of equipment and electronic systems that operates the aircraft. Thus, development of these equipment is becoming increasingly difficult due to their complexity. In this manner, getting help from generative AI improves avionics systems and aviation applications in many areas from trajectory prediction, anomaly detection and data augmentation. This research aims to analyze current innovative solutions to the challenges faced in aviation applications exploring how generative AI models get integrated to them. This research's focus is to investigate best practices of generative AI used up to now to increase the effect of aviation.

Keywords – Generative Adversarial Networks (GANs), Variational Auto Encoders (VAEs), Aviation, Anomaly Detection, Trajectory Prediction

I. Introduction

In current world, Artificial Intelligence (AI) is integrating in many fields to make contributions, and aviation is one of them. This paper researches a special kind of AI called Generative AI (GenAI) and its contribution to Aviation industry. Generative AI, leveraging AI's analytical power, specifically advances aviation by generating predictive data and innovative solutions, thus bridging the gap between traditional AI capabilities and the dynamic needs of aviation safety and efficiency. Also, it helps making flying safer and more efficient, as an example, it can guess where an airplane should go, and find problems in aerospace before they happen. This paper is about the newest researches on GenAI in aviation. It analyzes different ways people are using GenAI and compares how these methods make contribution. In following sections, this paper thoroughly investigates the contributions of GenAI to the aviation industry, comparing various application areas to reveal GenAI's impacts and potentials in aviation.

II. Background Knowledge

This section delves into the fundamentals of generative AI, including key models like GANs and VAEs, and explores their application in aviation, from avionics systems to air traffic management.

A. Generative AI

Generative Artificial Intelligence (GenAI) is a sub-branch of AI, and it focuses on the ability of computers to generate original data. Generative AI models are based on deep learning and artificial neural networks, and they generally need huge datasets for training to generate new fake data. They try to generate realistic, unique and original data getting sense of given dataset. One example of generative AI could be thispersondoesntexist.com. This website generates different human faces that doesn't exist after every refresh. This Background knowledge part includes a brief introduction to fundamental generative AI models, aviation and how to integrate generative AI into aviation. [1],[2],[3]

B. Generative Adversarial Networks (GANS)

First, one of the most known models of generative AI is Generative Adversarial Networks (GANs). This model consists of two networks, a generator, and a discriminator. As the name implies, whereas generator's aim is to generate a new, realistic data just like the given dataset, the discriminator tries to correctly classify the real and fake data. Simply, discriminator gives generator feedback that indicates whether the generated data seems real or not. Then, generator uses this feedback to improve its work. Generator starts from random noise vector and tries to give more realistic output after every iteration. After every output of generator, discriminator gives feedback, and this adversarial process lasts until the generator fools the discriminator. At the end, when the loop terminated, discriminator identifies the fake generated data as real, and that means the generator successfully generated the realistic, original but fake data. So, it's clear that the generator and discriminator, two nets generated a realistic data in an adversarial way.

$$\min_G \max_D V(D,G) = E_{x\sim p_{data}(x)}[\log D(x)] + E_{z\sim p_z(z)}\left[\log\left(1 - D(G(z))\right)\right]$$

Formula.1

The GANs Formula.1 is explained by this paragraph. In formula, the Generator (G function) gets a random input and tries to transform it into a realistic data. (So, its output is a data) And, its aim is to minimize the classification accuracy, because classification was discriminator's work, and if the generated fake data is supposed as real by discriminator, it simply means that the generated data is successful and realistic. In this process, both networks do back-propagation to improve their outputs. Whereas the generator tries to improve its output using the feedback coming from discriminator, the discriminator also tries to improve the classification accuracy after every iteration. To explain the formula, we say that it's a min-max game, and while the generator tries to minimize the result of Formula.1, the discriminator tries to maximize it. (As a reminder, x is the real data, z is the random noise input. G function tries to transform the given data into the realistic data whereas the D function returns a probability of the given data to be real.) Thus, in this mathematical expression, we see two parts around the plus sign. Left hand side denotes the expected value of the logarithm of the probability that Discriminator correctly classifies the real data as real. At right hand side, similarly, G(z) was the generated fake data, and when it becomes D function's parameter, the D's output is simply the probability of Discriminator misclassified the fake data as real. So, when we subtract it from 1, then we can simply say that this part is the probability of discriminator correctly identifies the fake data as fake. And this is the expected value of it. So simply, Generator wants to minimize the value because if the value is minimum, then the generator successfully fools the discriminator, and means that the generated data is realistic. [4]

C. Variational Autoencoders

Another important methodology for generating data is Variational Autoencoders. VAEs are another type of autoencoder that reconstructs datasets. Particularly, VAEs contain an encoder transforms each data point in the dataset into a lower-dimensional latent space to represent a probability distribution from which these data points can be generated, and a decoder that takes points from this latent space and generates data like the data points in the original dataset. The key feature of VAEs is the ability to model the probability distribution from which data points are generated, rather than replicating the data points exactly. This allows VAEs to use the learned distribution to create new, unique non-existing data points that just like the given dataset. About evaluation metrics, the loss function of VAEs consists of two terms: reconstruction loss and regularization loss. The reconstruction loss measures how close the data produced by the decoder is to the original data, while the regularization loss ensures that the latent space is smooth and continuous, so similar data points are positioned close to each other in the latent space. [5]

Generative Adversarial Networks (GANs) and Variational Autoencoders (VAEs) are the fundamental methods of innovative and flexible approaches in artificial intelligence. However, the potential of these technologies extends far beyond these models alone, as they can be expanded and enhanced through integration with other AI techniques. For instance, Generative Adversarial Imitation Learning extends the capabilities of GANs by combining deep learning and imitation learning techniques. Similarly, Deep Generative Convolutional Recurrent Neural Networks integrate the strengths of convolutional and recurrent neural networks with generative models. Approaches like Conditional Generative Adversarial Networks (CGANs) expand the applications of GANs by enabling controlled data generation. These developments demonstrate that fundamental generative models can be transformed into much more powerful and specialized AI solutions when combined with various AI techniques. Such innovative combinations allow generative AI to go beyond merely mimicking existing datasets, enabling the modelling of more complex and realistic scenarios. This is particularly enhancing the potential of generative AI in sectors like aviation, which needs high technology and continuous innovation.[6],[7],[8],[9]

D. Avionics Systems

Avionics, literally means that the electronics equipment used in aircrafts. (Airplanes, helicopters, artificial satellites, and spacecraft etc.) To illustrate, the flight computers, hydraulic systems, fire detectors and gyroscope are the avionics in the airplane. Avionics are used to handle the control, communication, and navigation of aircrafts. To delve into deeper, let's explore some of these systems in detail. Firstly, Control systems are one of the most significant avionics systems that follows the pilot's commands and controls the movement of the plane to prevent possible problems during the flight. Secondly, communication systems that enable voice and data communication are a must for aircrafts that need to be in constant communication with ground stations to ensure air traffic control. Furthermore, avionics uses navigation systems like Global Positioning System (GPS) to determine the location of aircraft and optimize the route planning. Moreover, Surveillance and Safety Systems are used by avionics to monitor and evaluate some parameters instantly. (Engine performance, fuel consumption, weather conditions etc.) Also, these systems are used to detect dangerous situations and warn the pilot. Lastly, Autopilot systems are important avionics components that keeps airplanes flying on a set course and helps pilots maintain a high level of control. These systems support pilots on long-range flights and in specific weather conditions. [10]

E. Air Traffic Management

Air Traffic Management refers to the integrated management of all elements that facilitate aircraft movement, both on the ground and in the air. This system plays a crucial role in ensuring the safe, efficient, and orderly flow of air traffic. One key element within ATM is the management of aircraft trajectories. The trajectory of an aircraft refers to the path it follows throughout its flight, considering both spatial dimensions (latitude, longitude, altitude) and time. In air traffic management, understanding and predicting these trajectories is vital for several reasons such as safety, efficiency and preserving orderliness.

III. PRESENT STUDIES

This section outlines current research and applications of Generative AI in aviation, focusing on air traffic management, anomaly detection, and data augmentation, highlighting their advancements and challenges in enhancing safety, efficiency, and predictive capabilities in the sector.

A. Air Traffic Management

Generative Artificial Intelligence (GenAI) presents a transformative opportunity in trajectory prediction within Air Traffic Management. GenAI can significantly increase reliability of trajectory forecasts with ease. These advanced AI models, through their deep learning capabilities, can analyze vast arrays of historical and real-time flight data to generate highly accurate predictions of aircraft trajectories. This ability is particularly useful in complex situations involving dense air traffic or rapidly changing environmental conditions, such as adverse weather.

Hu et al. [11] introduces TPGAN (Trajectory Prediction GAN, a type of CGAN), and uses this architecture in 3 different models:

-Conv1D-TPGAN: Recognized for its high precision in trajectory prediction, showcasing the lowest MAE for all coordinates (x: 0.070086, y: 0.055173, z: 0.041097) and excelling in distribution distance metrics (IS, FID, MMD2). It employs UpSampleCNN blocks in time series modeling which, combined with its computational efficiency (as seen in Table III), makes it highly suitable for real-time applications like ATC decision making, where both speed and accuracy are crucial.

-Conv2D-TPGAN: Leverages a creative method by transforming time series data into RGB images for prediction, marking an innovative step in data representation. While it shows a slightly higher MAE (x: 0.084744, y: 0.068838, z: 0.048685) and distribution distance metrics than the Conv1D-TPGAN, indicating a marginal drop in precision, it remains a competitive alternative, particularly where the novel image-based approach may offer unique benefits.

-LSTM-TPGAN: Employs an Encoder-Decoder LSTM structure, beneficial for capturing complex temporal sequences and dependencies. It provides better predictions in speed and heading attributes than CNN-based models but shows higher mean absolute errors (MAE) in all dimensions (x: 0.083811, y: 0.073732, z: 0.046562) and suffers from increased accumulated errors over extended prediction horizons compared to CGAN-based models, positioning it as less accurate for longer-term forecasts but valuable where understanding intricate patterns over time is crucial.

In summary, while Conv1D-TPGAN outperforms the others in accuracy and computational performance, making it the most suitable for real-time short-term trajectory prediction tasks, the LSTM-TPGAN's strength lies in its ability to decipher complex temporal patterns, which can be essential for applications involving extended period predictions and trend analysis, despite higher computational demands and error rates. The choice of architecture should be dictated by the specific demands of the application, with Conv1D-TPGAN being the preferred choice for tasks requiring high accuracy and immediate processing speed, but with LSTM-TPGAN providing added value for complex, time-extended pattern recognition.

Secondly, Pham et al. [12] focuses on predicting the movements of airplanes im-mediately after landing and take-off on airstrips, one of the areas with the most intense airplane traffic. The authors chose this model because of GAIL’s strength in mimicking actual taxi-speed behaviors, handling complex traffic scenarios, and outperforming baseline models in accuracy. Additionally, GAIL's ability to learn from complex stochastic environments without explicit reward functions makes it particularly suitable for the dynamic and unpredictable nature of airport ground movements. Nonetheless, its requirement for substantial training data and computational expense are notable drawbacks. Specifically, it achieved a spatial completion of up to 97.1% for arrivals and 88.3% for departures. In terms of temporal completion, the model showed stable performance with low Root Mean Square Error (RMSE) of 16.8 seconds for arrivals and 32.4 seconds for departures and Mean Absolute Percentage Error (MAPE) of 4.4\% for arrivals and 7.6% for departures. These results indicate that the model's errors are substantially lower (72% for arrivals and 48% for departures) compared to other baseline models, highlighting its impressive accuracy in replicating aircraft taxiing behavior. This superiority stems not only from GAIL's algorithmic robustness but also from its effective capture and replication of nuanced traffic interactions and taxi-speed variations, which are often oversimplified or overlooked in other models.

Liu et al. propose an innovative methodology for predicting 4D aircraft trajectories in their study [13]. To allow the model account for various uncertainties (such as wind, temperature, and convective weather conditions) that are crucial for predicting aircraft paths in real-time scenarios, the model uniquely combines long short-term memory (LSTM) networks for sequence prediction with convolutional neural layers to process high-dimensional weather data effectively. Also, a tree-based matching algorithm to correlate weather conditions with aircraft trajectory data is used with model because the system is designed to run in real-time, and it should be able to process large datasets swiftly. Furthermore, the advanced predictive capabilities of this system allow it to model trajectories as conditional Gaussian mixtures, generating probabilistic forecasts that consider multiple potential future states. This feature significantly enhances its utility in strategic decision-making within air traffic control, enabling a dynamic response to varying operational and environmental conditions. The modular design incorporates an encoder-decoder framework where the encoder LSTM processes the flight plan data into a compressed representation, which is then decoded by the LSTM decoder integrated with convolutional layers to predict the actual flight trajectories. This setup effectively captures temporal and spatial dependencies critical for accurate predictions. Lastly the experimental results from the study "Predicting Aircraft Trajectories: A Deep Generative Convolutional Recurrent Neural Networks Approach" demonstrate that the model achieves an average point-wise horizontal error of 49.60 nautical miles and a trajectory-wise vertical error of 2861.38 feet. These outcomes confirm the model's robust predictive capability, particularly for standard operational conditions, although deviations in trajectory predictions, particularly for flights with unusual departure procedures, highlight areas for further refinement.

Bastas et al. [14] has an experimental study in which they integrate GAIL with clustering and classification for a comprehensive data-driven trajectory prediction framework. They aim to produce accurate long-term predictions and make model adapt well to different trajectory patterns. Mimicking expert-level trajectory shaping, (The researchers use a data-driven approach to imitation learning, where AI models attempt to emulate expert strategies in trajectory shaping.) the unique integration of GAIL enables the model to learn complex trajectory patterns from historical data. Given the diverse nature of flight paths and conditions, adaptability to various flight patterns is significant, and Bastas et al. show their model’s adaptability as an advantage. However, while the method requires a significant amount of historical data, it is designed to address complex trajectories, including those as aircraft approach their destination, though these scenarios present more challenges due to increased maneuvering and other dynamic factors. As shown in their experiments that showed big improvements compared to traditional methods, (especially in dealing with complicated situations in air traffic control) one of the major contributions of this study is its framework that captures the subtle nuances of aircraft trajectory management, making it a robust tool for enhancing the predictability and efficiency of Air Traffic Management systems. In their experimental evaluation, Bastas et al. reported that the future trajectory classifier achieved an impressive average accuracy of 97.6%, with a standard deviation of just 0.94%, highlighting its effectiveness in the pre-tactical stages of aircraft trajectory prediction.

The study by Krauth et al. [15] adapts VAEs with Temporal Convolutional Networks to focus on trajectory prediction in Terminal Maneuvering Areas. This research innovates by applying Variational Autoencoders enhanced with Temporal Convolutional Networks to model 4-dimensional aircraft trajectories within TMAs. (TCNs are used to enhance the VAE's ability to model the sequential data effectively.) The core achievement of this study lies in its adaptation of the VAE architecture, integrated with TCN, to effectively capture the complex and variable patterns of aircraft trajectories near airports. These patterns often deviate from nominal due to dynamic factors like air traffic control decisions and changing environmental conditions. Also, the highlighted strength of the model is the ability to handle high variability and complexity in trajectory data due to the sophisticated temporal and spatial dependencies modeled by the TCN components. This capability makes it particularly suited for real-time application. The VAE architecture also utilizes a Variational Mixture of Posteriors (VampPrior), which not only facilitates the generation of diverse, realistic trajectories but also ensures that generated trajectories conform to the statistical distributions observed in real flight data. For accuracy, TCVAE showed an e-distance of 0.0103, significantly lower than the Gaussian Mixture Model's 0.059. So, at the end, the authors highlighted the superior capability of TCVAE.

In their unique approach in the field of Aircraft Trajectory Prediction, Hashemi et al. [16] uses GANs enhanced by blockchain technology for added security. Whereas this approach aims to support the resilience of the models against adversarial attacks, it also predicts aircraft trajectories using variables like latitude, longitude, altitude, heading, speed, and time. To enhance data security and safeguard the trajectory predictions against tampering and fraudulent activities, blockchain served as a Ledger Technology to securely store the trajectory forecasts. Moreover, adding to securing the integrity of the data, the combined use of GANs and blockchain technology also demonstrates high accuracy in trajectory prediction, with the GAN model achieving a training accuracy of 96.5% and a testing accuracy of 92.1%, thereby confirming the efficacy of this advanced approach in maintaining high standards of prediction reliability and precision.

In their article [17] Olive et al. aims to light the way for how autoencoding models enhance the interpretability of trajectory data in Air Traffic Management (ATM) and trajectory data analysis, and why using Generative AI becomes a necessity for ATM ensuring that AI models are trustworthy and comprehensible to human operators in addition to being effective. Unlike other research in Air Traffic Management that focuses on generating or predicting trajectories, Olive et al. concentrate on enhancing the explainability of how trajectories are analyzed and understood through autoencoding models. Researchers' aim in here is to show how Autoencoders could affect Aircraft Traffic Management with referring their advantages and limitations. The study highlights the major advantages of variational autoencoders in Aviation, including enhanced interpretability and realistic trajectory predictions, enabling intuitive, visual interpretations of complex trajectory patterns and enhancing operational understanding and decision-making. However, the study also acknowledges limitations, including the complexity of applying these models in dynamic ATM environments, the potential oversimplification due to reliance on visual tools, and the high dependency on quality of the training dataset. Despite these challenges, the study points to the potential for these models to offer more realistic trajectory predictions, which could significantly aid in strategic decision-making processes within ATM, and future research will focus on refining these visual explanation methods and expanding their applicability to more complex ATM scenarios.

B. *Anomaly Detection*

While GenAI has proven its effectiveness in enhancing trajectory prediction with remarkable accuracy and handling complex scenarios, it's also useful in Anomaly detection. This section delves into another critical aspect of air safety and efficiency: anomaly detection in flights.

This section starts with study of Du et al. [18] which introduces a GANs model that's specialized for anomaly detection in aerospace datasets (GANomaly). A key advantage of Ganomaly is its ability to use unsupervised learning to detect anomalies without the need for a large set of labeled abnormal data. This is particularly beneficial in the aerospace industry because acquiring labeled data for all types of potential anomalies is impractical or impossible. This method is favored because traditional methods are labor-intensive and insufficient for real-time accuracy, and there's an imbalance in the availability of normal versus abnormal samples in aerospace datasets. GANomaly consists fundamental Generative Adversarial Nets, and an encoder adding to them. (an encoder-decoder-encoder architecture within the GAN setup) In this approach, the idea of GANomaly is that normal data and abnormal data will be processed differently by the Encoder & Generator pair. This architecture allows the system to capture the underlying relationships of data within its potential space, making it adept at recognizing anomalies in complex aerospace data. The encoder-decoder-encoder sequence enhances the model's ability to distinguish between normal and abnormal data by comparing the latent spaces of the input and reconstructed output. (If the data can be easily reconstructed by the pair, then the output shows the input is normal. But in case of the pair reconstructs the input poorly, then the output shows the input is abnormal.) As stated, the method achieved an F1 score of 0.978 and an AUC of 0.9840 for the Statlog Shuttle dataset.

Also with a similar approach, Memarzadeh et al. [19] use Convolutional Variational Auto-Encoder (CVAEs) in their study to detect anomalies in high-dimensional time-series data from flight operations in unsupervised manner. CVAEs use the reconstruction error obtained by comparing the latent spaces of input and reconstructed data to classify data above a set threshold in the training data as anomalies. As an advantage, the Convolutional Variational Auto-Encoder (CVAE) offers an unsupervised approach to anomaly detection in complex and high-dimensional time-series data without labeling processes. This method demonstrates superior capabilities in identifying subtle and intricate anomalies, and significantly outperforms traditional autoencoders in precision and recall metrics. Furthermore, the flexibility of the CVAE is enhanced by the strategic tuning of the hyperparameter β, which allows for precise adjustment of the model's sensitivity to anomalies, optimizing performance across various datasets. This adaptability is critical in environments where anomaly characteristics can differ markedly, making CVAE a robust choice for diverse operational settings.

Furthermore, Campbell et al. [20] use a Recurrent Neural Network-based Conditional Variational Autoencoder (RNN-CVAE) to identify and predict loss-of-control (LOC) events in aircraft. A significant contribution of this work is the introduction of a technique to assess changes in the latent space using the Jensen-Shannon distance gradient, offering insights into impending shifts in the aircraft's flight envelope status. This method provides a novel approach to predicting LOC states by examining the minute variations within the model's encoding of flight data. The study used the NASA T-2 aircraft, which was equipped with comprehensive sensor arrays to capture detailed flight data across various high-risk maneuvers. The collected data were then used to train the CVAE models to recognize patterns indicative of LOC states based on two key metrics: Reconstruction Probability and Gaussian Shift. The system's effectiveness was measured by its true positive rate of detecting actual LOC events and its ability to reduce false alarms through adjustable detection thresholds and the CVAE models demonstrated a high degree of accuracy, with the GRU-CVAE variant showing superior performance in distinguishing between LOC and non-LOC states. The models were effective in real-time monitoring, achieving a true positive rate of 97%.

In their study, Ahn et al. [21] uses two distinct models, GANomaly and VAE, and evaluates them. The study examines the models' performance in distinguishing between normal and abnormal data in various operational scenarios, employing a semi-supervised learning framework and 1D-CNN for feature extraction. GANomaly outperforms VAE, especially in complex scenarios where the difference between normal and abnormal data is not distinct, due to its dual approach of minimizing reconstruction errors and Jensen-Shannon divergence. In contrast, VAE struggles in scenarios with inherent noise, where it can mistakenly generate abnormal samples from normal data. The paper concludes that while GANomaly demonstrates superior results, enhancements and the application of real-world data are essential for advancing anomaly detection capabilities in spacecraft systems.

In their study, Guo et al. [22] presents an approach for Automatic Dependent Surveillance-Broadcast (ADS-B) systems using a hybrid model combining Variational Autoencoders (VAE) and Long Short-Term Memory networks (LSTM). Addressing the vulnerabilities in ADS-B data, which lacks encryption and authentication, the VAE-LSTM model effectively captures the temporal dependencies inherent in the sequential ADS-B data to enhance anomaly detection. The model architecture integrates LSTM cells in both encoder and decoder components, facilitating the learning and reconstruction of ADS-B data distributions based on reconstruction probabilities. Experiments conducted with real-world ADS-B data sourced from Flightradar24 demonstrate that the VAE-LSTM model surpasses both traditional methods like PCA and OC-SVM, and similar deep learning models in detecting anomalies, as evidenced by higher ROC-AUC and PRC-AUC scores. This study underscores the potential of using advanced machine learning techniques to improve the safety and reliability of air traffic management systems by enabling more accurate anomaly detection.

For most of the articles and methods analyzed in this research, the main problem is insufficient existing data. Like that, in the study of Lu Yang [23] tackle the pervasive challenge of insufficient data in AI-driven aircraft engine vibration analysis. Initially, a Support Vector Machine (SVM) classifier was used, which recorded limited success with an F1-score of 77% for positives and 56% for negatives, primarily due to a small sample size. To address this, the authors implemented CGAN to generate synthetic data that closely mimics the real operational data, effectively enlarging the training dataset. This approach significantly enhanced the SVM classifier's performance, elevating the F1-scores to 84% for positive cases and 81% for negative cases, while also improving precision and recall. The use of CGAN not only augmented the dataset but also crucially refined the accuracy of the analysis model, underpinning its potential in predictive maintenance and flight safety enhancement.

C. Data Augmentation

With above example, one more contribution of Generative AI is noted. The main problem about using Generative AI with Aviation is insufficient existing data because in Aviation industry, collecting more and more data is generally expensive and time consuming. So, in below Table I, some researches are shown they use Generative AI to supplement their existing dataset within the aviation industry.

Table I. Data Augmentation for Aviation-Related Applica

tions.

Study	Problem
[24]	Limited condition monitoring data for aircraft engine maintenance prediction
[25]	Insufficient and diverse image resources that provide aviation-related applications, such as navigation, surveillance, terrain analysis, and infrastructure planning
[26]	Insufficient quality text data for civil aviation radiotelephony communication
[27]	Enhancing wireless channel recognition in aerospace communication systems with generating synthetic data
[28]	Traditional methods often face limited fault data samples in the evaluation of aeroengine performance

IV. CRITICAL ANALYSIS

Following section is the exploration of current studies in Section 3. Section 4 provides a critical analysis, comparing methodologies and highlighting the optimal applications of Generative AI in aviation scenarios.

A. Air Traffic Management

Articles with similar goals in same field show that if the aim is to achieve real-time trajectory prediction, particularly less complex scenarios, to establish balance between computational efficiency and predictive accuracy, VAEs might be more suitable instead of GAIL or GANs because of simpler complexity of them. The preference for VAEs in these instances stems from their effective handling of uncertainty and their robustness in generating diverse, plausible trajectory samples without the computational overhead associated with more complex models.

On the other hand, in scenarios with complex air traffic and variable speeds, GAIL is suggested by research because of its ability to mimic real-world behaviors and accurately modeling busy aerospace. This model's strengths lie in its imitation learning framework, which excels in complex stochastic environments where nuanced interactions and behaviors must be replicated with high fidelity.

Also, in terminal maneuvering areas with highly traffic again, VAEs combined with Temporal Convolutional Networks are advised due to their ability in processing complex, multi-dimensional data. This approach leverages the TCNs' capability to process multi-dimensional data effectively, capturing both temporal and spatial dependencies critical in high-density areas.

For short-term and long-term discussion, two articles explain their methodologies for each. In short-term prediction needs, a fully trained CGAN model that gives output in one go is suggested because of its power in preventing cumulative error accumulation. On the other hand, GAIL with clustering and classification is now suggested for long-term predictions. Because of the generated model’s adaptation to various trajectory patterns, GAIL is chosen for long-term predictions by the authors. Noting that, whereas both articles need significant amounts of quality historical data, they suffer from high complexity.

The fields where data security is crucial, the GANs implementation with blockchain leads the way. Utilizing GANs secured by Blockchain technology provides an added layer of data integrity and resistance to adversarial attacks.

Table II that shows limitations and advantages of methods is provided for this section.

Table II. The Advantages and Limitations of Air Traffic Management Applications

Method	Advantages	Limitations	Best Use Scenario
VAEs	Handles uncertainty effectively, generates diverse samples, Lower computational requirements	Less effective in highly complex scenarios	Real-time predictions in less complex traffic scenarios
GAIL	Mimics real-world behavior accurately, excels in complex environments	- High computational demand, requires substantial training data	Complex traffic scenarios with variable speeds
CGAN	-Outputs predictions in one iteration	May not handle long-term dependencies well	Short-term trajectory predictions
GAIL with Clustering and Classification	Adapts to various trajectory patterns, Suitable for long-term predictions	High complexity, Extensive data requirement	Long-term trajectory predictions
VAEs with TCNs	Captures temporal and spatial dependencies, Processes complex multidimensional data effectively	Complexity increases with additional structures	Terminal maneuvering areas with high traffic density
GANs with Blockchain	Ensures data integrity and security, resistant to adversarial attacks	Higher resource consumption	Scenarios where data security is crucial

B. Anomaly Detection

In this section, we critically evaluate the strengths and weaknesses of various generative AI methodologies employed in anomaly detection within the aviation sector.

Table III. The Advantages and Limitations of Anomaly Detection Applications

Method	Advantages	Limitations
GANomaly	Effective unsupervised learning	Sensitive to input data quality
Convolutional VAEs	Handles high-dimensional data well, Flexible through hyperparameter tuning	Dependency on correct hyperparameter settings, Challenges in distinguishing true anomalies from outliers
RNN-CVAE	Suitable for sequential data	Prone to overfitting, long training times and complex model maintenance

V. DISCUSSION & FUTURE WORK

The integration of Generative AI into aviation, as explored in this research, shows a new technology's transformative potential in Aviation industry, especially enhancing air traffic management, anomaly detection, and supplementing data for aviation-related datasets. However, the field is still newborn, with limited but growing examples, generally from Chinese research.

The need for pilot projects with aviation authorities to test these GenAI models or integrating them in other fields of Aviation for especially real-world scenarios should be highlighted. They would provide invaluable insights into the practicalities and challenges of GenAI integration in operational environments and help these technologies and researchers about them for broader application and improvement.

Currently, most researchers that use Generative AI in aviation is from China, but as contribution of these technologies shown and, understanding of these technologies grow, a global expansion will be anticipated. This spread will likely lead to more di-verse applications and innovations, driven by different needs and challenges faced by the aviation industry worldwide.

Future research about Generative AI in Aviation can focus on developing AI models that balance computational efficiency with predictive accuracy especially for real-time applications as it's generally stated real-time complexity is the issue for applications. Also, Generative AI's role in aviation could be significantly enhanced through integration with cutting-edge technologies. For example, Blockchain technology adding a new layer of security and data integrity was a critical example for it.

VI. CONCLUSION

In conclusion, this paper has provided a comprehensive overview of the research on the application of Generative AI (GenAI) in the aviation industry, especially in Air Traffic Management and Anomaly detection of aircrafts. Through an in-depth analysis of current research and their diverse applications, GenAI demonstrates significant potential in improving the safety, effectiveness, and dependability of aviation activities. The studies examined in this paper reveal that GenAI is not a theoretical concept but a practical tool contributing aviation field. How-ever, as it's shown, this field is still in its infancy. This initial focus presents both a challenge and an opportunity for global research communities to further explore and expand upon these initial findings.

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