

Review on Real-Time Flight Delay Forecasting using AI Techniques

Priya Lohat
Computer Science &
Engineering
Bansal Institute of Science and
Technology Bhopal, India

Mr. Virendra Khatakar
Assistant Professor
Computer Science &
Engineering
Bansal Institute of Science and
Technology Bhopal, India

Dr. Kailash Patidar
HOD
Computer Science &
Engineering
Bansal Institute of Science and
Technology Bhopal, India

Dr. Damodar Prasad Tiwari
Director
Bansal Institute of Science and
Technology Bhopal, India

Abstract : This review presents a comprehensive overview of real-time flight delay forecasting using Artificial Intelligence (AI) techniques. Flight delays are influenced by multiple dynamic factors, including weather conditions, air traffic congestion, airport operations, aircraft turnaround time, and historical flight patterns, making accurate prediction a challenging task. The review examines the application of Machine Learning (ML) and Deep Learning (DL) techniques such as Random Forest, Support Vector Machine, XGBoost, Artificial Neural Networks, Long Short-Term Memory networks, and hybrid AI models for predicting flight delays. It also discusses the role of real-time data from flight tracking systems, meteorological services, airport databases, and air traffic information in improving prediction accuracy. Various performance measures, datasets, input parameters, and forecasting approaches reported in existing studies are compared to identify their strengths and limitations. The review further highlights challenges related to data quality, model scalability, real-time processing, uncertainty, and generalization across different airports and flight routes. Overall, AI-based forecasting provides significant potential for developing reliable and responsive flight delay prediction systems that can support airlines, airports, and passengers in improving operational planning and decision-making.

IndexTerms – Flight Delay, AI Forecasting, Real-Time Prediction, Machine Learning, Deep Learning

I. INTRODUCTION

Flight transportation has become an essential component of modern mobility, supporting international trade, tourism, business activities, and passenger connectivity. However, flight delays remain a major operational challenge for airlines, airports, air traffic management authorities, and passengers. Delays can originate from several interconnected factors, including adverse weather, airport congestion, aircraft turnaround time, air traffic conditions, scheduling constraints, and delays propagated from preceding flights. Because these factors interact dynamically across the aviation network, predicting the occurrence and duration of a delay is a complex forecasting problem. Earlier research has therefore emphasized the importance of data-driven approaches for understanding the diverse factors contributing to flight delays and for developing more accurate prediction models [1].

The increasing availability of large-scale aviation datasets has encouraged the application of Artificial Intelligence (AI) and Machine Learning (ML) techniques to flight delay forecasting. Historical flight records can be combined with operational, temporal, airport, airline, and meteorological information to identify hidden relationships between input variables and delay outcomes. Traditional statistical approaches often face difficulties in representing the nonlinear and highly interconnected nature of aviation operations. In contrast, ML algorithms can learn complex relationships directly from historical observations and have consequently become an important research direction for flight delay prediction [2].

One of the important developments in this field is the use of ensemble learning and tree-based ML algorithms. Techniques such as Random Forest, Gradient Boosting, XGBoost, and related ensemble methods can process heterogeneous aviation data and capture nonlinear interactions among different delay-related variables. Studies have demonstrated the usefulness of Random Forest for short-term delay prediction, particularly when temporal and operational characteristics are incorporated into the model [3]. More recent research has also investigated enhanced feature engineering with Random Forest to improve the representation of factors associated with flight delays [4].

Deep Learning (DL) has further expanded the capabilities of flight delay forecasting by enabling models to learn complex temporal and spatial patterns from large datasets. Long Short-Term Memory (LSTM) networks are particularly relevant because flight operations contain sequential dependencies, such as aircraft rotations, previous-flight delays, airport congestion, and changing weather conditions. LSTM-based approaches have been investigated for predicting delays across sequences of flights and have also been combined with transfer learning to address situations where smaller airlines have limited training data [5].

Weather is another critical variable in real-time flight delay forecasting because changes in visibility, precipitation, wind, temperature, and other atmospheric conditions can directly influence airport and aircraft operations. Researchers have therefore investigated the fusion of flight and meteorological data with deep learning models. For example, deep convolutional neural network approaches have been developed by combining flight information with meteorological data to improve delay prediction, demonstrating the value of integrating external information sources into AI-based forecasting systems [6].

In addition to individual ML and DL models, recent studies have increasingly explored hybrid architectures that combine multiple learning mechanisms. Spatial and temporal dependencies are particularly important because congestion and delays at one airport can influence connected airports and subsequent flights. Hybrid models using spatial features, temporal representations, LSTM units, and Random Forest have therefore been developed to capture these dependencies more effectively [7]. Similarly, CNN-LSTM-based architectures have been investigated for simultaneously extracting spatial and temporal correlations before applying a classification model for final delay prediction [8].

The concept of real-time forecasting requires AI models to continuously process updated information rather than relying exclusively on historical data. Operational conditions can change rapidly because of weather disturbances, airport congestion, aircraft rotations, and unexpected disruptions. Recent research has consequently focused on models capable of using operational and meteorological information for timely prediction, while newer studies have also examined advanced architectures such as Liquid Neural Networks for weather-related flight delay classification [9]. Attention-based models have also been explored to identify important temporal points and direct and indirect delay factors, indicating the potential of deep learning for providing timely and operationally useful forecasts [10].

estimation, generalization across airports and airlines, and integration with live aviation information systems. Recent systematic reviews indicate that ensemble and deep learning models frequently provide strong predictive performance, but differences in datasets, prediction definitions, evaluation metrics, and deployment conditions make direct comparison difficult [11]. Furthermore, current research is increasingly examining explainability and calibrated predictions because aviation stakeholders require not only a predicted delay but also meaningful information about the reliability and factors behind that prediction [12].

II. BACKGROUND

Q. Zhong et al., [1] suggested a machine learning-based model to forecast and optimize civil aviation flight delays. Their model combined various algorithms in order to analyze operational, weather, and scheduling data. In the paper, the importance in addressing the question of how large-scale data fusion facilitates accuracy in the real-time delay prediction was emphasized. The authors showed that data preprocessing and feature engineering are important in enhancing the model performance. Their outcome revealed that prediction error was reduced highly as compared to regular regression models.

Zhong, Q [2] came up with a hybrid system of flight delay prediction which is applicable in the resource-constrained environment. The researcher used a hybrid of machine learning classifiers and regression models to strike a balance between the efficiency and the accuracy. They performed higher short-term delay estimation with real-world aviation datasets. The authors emphasized the significance of hybridization in order to optimize the predictive performance in case of limited hardware conditions. Their work is related to scalable and cost-effective ML deployment in the aviation analytics.

D. Schösser and J. Schönberger, [3] examined how short-term characteristics affect the performance of machine learning-based flight delay prediction models. European flight data was used to compare multiple algorithms including the Random Forest and Gradient Boosting. The researchers found out that the addition of brief weather and traffic variables to the study enhanced a considerable level of prediction. The model interpretability was also studied whereby the authors are focusing on explainable AI when handling operational applications. The authors determine that time-sensitive aspects are key to dynamic aviation.

M. Alfarhood et al., [4] were using machine learning to forecast flight delays in the Saudi Arabian Airlines. In their model, they took into account flight schedule, air traffic and environmental information and used to generate credible delays. The study established that compared to conventional approaches such as logistic regression, the use of ensemble based learning models is better. The authors stressed the regional customization to enhance flexibility of prediction

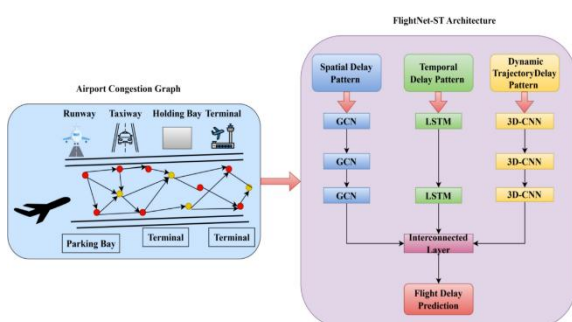


Figure 1: Flight Delay Architecture

Despite substantial progress, several challenges remain in developing reliable real-time flight delay forecasting systems. These include data quality, class imbalance, changing operational conditions, model interpretability, uncertainty

systems. Their solution offered practical information on the strategies of the airline and customer service.

Table I: Features Included in Original Dataset [1]

Sr No	Feature Type	Description
1	Flight	Year, Month, Day of Month, Day of Week, Air line, Flight Number, Origin, Destination, Scheduled Departure Time, Scheduled Arrival Time, Departure Delay, Arrival Delay, Number of Seats
2	Weather	Temperature (2m), Relative Humidity (2m), Dew point (2m), Surface Pressure, Precipitation, Rain, Snowfall, Cloudcover (Low, Mid, High), Wind Speed (10m,100m), Wind Direction (10m, 100m), Wind Gusts (10m)

A. A. B. Shukri et al., [5] used Naive Bayes algorithm to forecast flight delays of airlines using sample of historical flight operations. The experiment was to pick the features and test the model based on such performance measures as accuracy and precision. Naive bayes was very effective in classification of delays, although the classification was done in smaller datasets due to its simplicity. The authors came to the conclusion that preprocessing and noise elimination of the data are necessary to enhance the reliability of the models. Having worked with them, we can see how lightweight algorithms can be useful in quick deployment in airline systems.

Randivsky et al., [6] made a comparative analysis of Random Forest, SVM and Naive Bayes algorithms in optimization tasks with sentiment analysis. The findings of the study, though text-based, are applicable in aviation delay prediction, specifically, in the context of the model efficiency and accuracy. They showed that SVM has a better generalization property on multidimensional data. Hybridization of models proved to enhance similarity of classification. Their methodology favors development of powerful hybrid models of predictive analytics.

Enhancement of sentiment analysis with LSTM networks on stemming techniques of U.S.-based Twitter data was done by S. Sahu et al., [7]. Their approach proved the strength of the sequence-based learning models to deal with the time-related information. Despite the fact that the study was focused on social media, its preprocessing and model optimization principles are very applicable in predicting flight delays. The LSTM architecture had covered chain dependence very well, much-like the time patterns in flight activities. The

authors have emphasized that the tandem of text and temporal aspects of forecasting increases the accuracy of real-time predictions.

A. K. Chanchal and S. K. Pandey, [8] offered a literature review of flight delay prediction with the different techniques of machine learning. The paper has evaluated regression, classification, and ensemble forecasting of delay in aviation systems. They have found out that data-driven models are highly important compared to statistical and simulation-based approaches. Imbalance of data, records missing, and overfitting were other issues that were addressed by the authors. Their discussion drew attention to the possibility of hybrid ML methods to obtain a more accurate prediction and flexibility.

Table II: Previous Work Comparison [1]

Model	Accuracy (%)	Precision (%)	Recall (%)	F1-Score (%)
Random Forest [1]	92.4	98.3	86.2	91.9
Ajayi et al. [5]	86.2	86.9	74.2	81.2
Kiliç and Sallan [3]	75.0	45.0	88.0	60.0
Chakrabarty et al. [2]	79.7	76.0	80.0	74.0

K. Vijay et al., [9] presented a flight delay prediction model based on a combination of temporal convolutional networks (TCN) with traditional machine learning. Their hybrid system was also capable of capturing the dependence on flight parameters that were both be it static and temporal. The TCN-based model performed better than traditional neural networks in delay prediction using real-world data. The authors indicated the versatility and scalability of deep learning systems to real-time architectures. Their results reveal the usefulness of the combination of time-series modeling towards better aviation analytics.

At S. Addu et al, [10], the aim was to forecast flight delay with the help of machine learning models that were developed using previous flight data. Several algorithms such as DT, RF and SVM were compared in the study. Their conclusion is that ensemble models continuously greater generalization and strength in large scales. The authors also addressed the issues of hyperparameter tuning and data normalization in order to improve performance. Their findings suggested that machine learning can be useful in real-time delay management.

S. S. Pophale et al., [11] modeled and forecasted flight delays through a combination of the supervised machine learning algorithms. Their analysis noted that delay time depends on the weather, time of departure and air traffic. They tested the Linear Regression, the SVM, and KNN models and concluded that hybrid approaches yielded higher accuracy. The authors pointed out the importance of preprocessing and cross-validation as a way of reducing overfitting. Their work is useful in the deployment of predictive systems in aviation networks.

D. Zhang et al., [12] constructed a ST-GCN to estimate the delays in high-speed trains. The model was the best representation of spatial and temporal dependencies, which can be applied to air traffic delays forecasting. The research authors established that the graph-based neural networks are more effective in dynamic environments than the time-series models. Their model can be extended to the prediction of flight delays by modelling the networks of airports as spatio-temporal graphs. This study highlights the increasing role of deep learning to transportation systems.

P. Hu et al., [13] suggested a model which is a SVM based model, to predict flight arrival delays using civil aviation data. The paper used the meteorological, operational, and scheduling parameters to improve the accuracy of the model. It was found that SVM was better at both regression and classification related tasks than other schemes. The authors were more focused on the kernel selection and optimization of the parameters to improve on generalization. Their study confirms the effectiveness of SVM in prediction of delays and advocates its usage in conjunction with other structures.

III. CHALLENGES

Real-time flight delay forecasting using AI techniques faces several challenges because flight operations are influenced by highly dynamic, uncertain, and interconnected factors. Weather conditions, air traffic congestion, airport capacity, aircraft turnaround time, crew availability, previous-flight delays, and unexpected operational disruptions can change rapidly and affect prediction accuracy. In addition, aviation datasets may contain missing, inconsistent, imbalanced, or delayed information, while AI models trained on historical data may not perform equally well under new operational conditions. The integration of multiple real-time data sources and the requirement for fast predictions further increase system complexity. Therefore, developing a reliable flight delay forecasting system requires careful consideration of data quality, temporal dependencies, model adaptability, interpretability, and computational efficiency.

1. Dynamic and Uncertain Operational Conditions

Flight operations continuously change because of weather, air traffic, airport congestion, aircraft availability, and operational disruptions. A model trained on historical conditions may encounter situations that were not present in its training data. This makes it difficult to maintain consistent prediction performance in real-time environments.

2. Data Quality and Availability

AI models require large amounts of reliable and relevant data for effective training and forecasting. Flight datasets may contain missing values, duplicate records, inconsistent formats, and incomplete operational information. Delayed availability of real-time data can also reduce the usefulness of predictions when immediate decisions are required.

3. Integration of Multiple Data Sources

Accurate forecasting often requires combining flight schedules, historical delays, weather information, airport conditions, air traffic data, and aircraft-related information. These sources may have different formats, update frequencies, and levels of accuracy. Integrating them into a single real-time prediction framework is therefore technically challenging.

4. Temporal and Sequential Dependencies

Flight delays are not independent events. A delay in one flight can affect the aircraft's next flight and subsequently influence other flights in the network. AI models must therefore capture short-term and long-term temporal dependencies to understand how previous operational events influence future delays.

5. Class Imbalance

In many flight datasets, the number of normal flights can be significantly higher than the number of flights experiencing severe delays. This imbalance can cause an AI model to favor the majority class and perform poorly when identifying delayed flights. Appropriate sampling, feature engineering, and evaluation techniques are required to address this problem.

6. Real-Time Computational Requirements

A real-time forecasting system must process continuously changing information and generate predictions within a short period. Complex deep learning and hybrid models may require substantial computational resources for training and inference. Maintaining low prediction latency while preserving model accuracy is therefore an important challenge.

7. Model Generalization and Adaptability

A model developed using data from one airport, airline, or geographical region may not perform similarly in another operational environment. Differences in airport infrastructure, flight schedules, weather patterns, traffic volume, and airline practices can affect model performance. AI systems should therefore be adaptable to changing conditions and capable of learning from newly available data.

8. Model Interpretability and Reliability

Many advanced AI models, particularly deep learning and hybrid architectures, can produce accurate predictions while providing limited explanation of how the prediction was obtained. Aviation stakeholders may need to understand whether weather, congestion, previous delays, or other factors contributed to a forecast. Improving interpretability, uncertainty estimation, and prediction reliability is therefore important for practical deployment of AI-based flight delay forecasting systems.

IV. CONCLUSION

The reviewed studies demonstrate that Artificial Intelligence and Machine Learning techniques have significant potential for real-time flight delay forecasting by learning complex relationships among historical flight patterns, weather conditions, airport operations, air traffic, and delay propagation factors. Traditional statistical methods provide useful foundations for understanding delay distributions, while modern approaches such as Random Forest, Gradient Boosting, Artificial Neural Networks, Genetic Algorithm-based models, and Deep Learning can capture nonlinear and temporal relationships more effectively. The literature also indicates that integrating multiple real-time data sources and developing hybrid models can improve the ability to forecast both delay occurrence and delay duration. However, challenges related to data quality, real-time processing, class imbalance, model interpretability, changing operational conditions, and generalization across airports remain important research gaps. Future research should therefore focus on adaptive, explainable, and computationally efficient AI frameworks capable of continuously processing real-time aviation data and providing reliable flight delay forecasts for effective operational planning and decision-making.

REFERENCES

1. Q. Zhong, Y. Yu, Y. Huang et al., "Prediction and Optimization of Civil Aviation Flight Delays Based on Machine Learning Algorithms," *Int. J. Comput. Intell. Syst.*, vol. 18, art. no. 189, 2025.
2. Zhong, Q., Yu, Y., Huang, Y. et al. Prediction and Optimization of Civil Aviation Flight Delays Based on Machine Learning Algorithms. *Int J Comput Intell Syst* 18, 189 (2025). <https://doi.org/10.1007/s44196-025-00932-2>.
3. Q. Li, R. Jing, and Z. S. Dong, "Flight delay prediction with priority information of weather and non-weather features," *IEEE Transactions on Intelligent Transportation Systems*, vol. 24, no. 7, pp. 7149–7165, 2023.
4. R. T. Reddy, P. Basa Pati, K. Deepa, and S. T. Sangeetha, "Flight delay prediction using machine learning," in 2023 IEEE 8th International Conference for Convergence in Technology (I2CT), pp. 1–5, 2023.
5. D. J. D. P, and J. R. L., "Flight Delay Prediction using GANN - An Improved Artificial Neural Network Model Integrating Genetic Algorithm," in 2023 International Conference on Advances in Computing, Communication and Applied Informatics (ACCAI), pp. 1–10, 2023.
6. Z. Wang, H. Liu and F. Chu, "Flight Arrival Delay Time Prediction Based on Machine Learning," 2022 3rd Asia Conference on Computers and Communications (ACCC), Shanghai, China, 2022, pp. 35-39, doi: 10.1109/ACCC58361.2022.00013.
7. N. L. Kalyani, G. Jeshmitha, B. S. Sai U. M. Samanvitha, J. Mahesh, and B. Kiranmayee, "Machine learning model - based prediction of flight delay," in 2020 Fourth International Conference on I-SMAC (IoT in Social, Mobile, Analytics and Cloud) (I-SMAC), pp. 577–581, 2020.
8. N. Chakrabarty, T. Kundu, S. Dandapat, A. Sarkar, and D. K. Kole, "Flight arrival delay prediction using gradient boosting classifier," in *Emerging Technologies in Data Mining and Information Security: Proceedings of IEMIS 2018, Volume 2*, pp. 651–659, Springer, 2019.
9. A. Vaswani, N. Shazeer, N. Parmar, J. Uszkoreit, L. Jones, A. N. Gomez, L. u. Kaiser, and I. Polosukhin, "Attention is all you need," in *Advances in Neural Information Processing Systems (I. Guyon, U. V. Luxburg, S. Bengio, H. Wallach, R. Fergus, S. Vishwanathan, and R. Garnett, eds.)*, vol. 30, Curran Associates, Inc., 2017.
10. M. Baluch, T. Bergstra, and M. El-Hajj, "Complex analysis of united states flight data using a data mining approach," in 2017 IEEE 7th Annual Computing and Communication Workshop and Conference (CCWC), pp. 1–6, 2017.
11. Y. Tu, M. O. Ball, and W. S. Jank, "Estimating flight departure delay distributions-a statistical approach with long-term trend and short-term pattern," *Journal of the American Statistical Association*, vol. 103, no. 481, pp. 112–125, 2008.
12. L. Schaefer and D. Millner, "Flight delay propagation analysis with the detailed policy assessment tool," in 2001 IEEE International Conference on Systems, Man and Cybernetics. e-Systems and e-Man for Cybernetics in Cyberspace (Cat.No.01CH37236), vol. 2, pp. 1299–1303 vol. 2, 2001.