Archives available at journals.mriindia.com

Open Access International Journal of Science and Engineering

ISSN: 2456-3293

Volume 9 Issue 03, 2026

FLIGHVISION PRO: A Dashboard-Driven System for Flight Delay Prediction and Dynamic Fare Optimization with Real-Time Visualization

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Peer Review Information

Submission: 10 Feb 2026

Revision: 26 Feb 2026

Acceptance: 11 March 2026

Keywords

Flight Delay Prediction, Dashboard Analytics, Ensemble Machine Learning, Dynamic Fare Optimization, Real-Time Visualization, Aviation Analytics System, Interactive Dashboard, Control Center, Predictive Decision Support, Offline-Capable System

Abstract

Airline operations are highly sensitive to disruptions caused by weather conditions, air traffic congestion, and operational constraints. Most existing systems monitor these factors but respond only after delays occur, resulting in inefficient decision-making. To address this issue, a system is developed that focuses on predictive analysis, visualization, and integrated control through an interactive dashboard environment. The proposed system combines ensemble-based delay prediction with dynamic fare adjustment and real-time visualization in a unified platform. It processes multi-source aviation data, generates delay predictions, and presents insights through a user-friendly dashboard. The system also includes control modules for model training, prediction execution, and operational monitoring, allowing users to interact directly with the analytics pipeline. A key feature of the system is its dashboard-driven design, which provides live system metrics, delay breakdown analysis, and real-time alerts. Users can monitor flight activity, analyze delay patterns, and make informed decisions using a centralized interface. The system also supports offline functionality using local storage, ensuring continuous operation even when connectivity is limited. Through the integration of predictive modeling, control mechanisms, and visual analytics, the system demonstrates a practical approach to improving airline decision-making. It highlights the importance of combining system design and implementation with user interaction to create an effective decision-support platform.

Introduction

Airline operations involve continuous coordination between multiple factors such as flight schedules, weather conditions, airport congestion, and resource availability. Because these elements are interconnected, even a small disruption can quickly affect multiple flights and lead to large-scale delays. In many existing systems, such disruptions are identified only after they occur, which makes decision-making reactive rather than proactive.[1]

A major challenge in current aviation systems is the lack of integrated tools that combine prediction, monitoring, and control in a single platform. Operational teams, revenue teams, and management often rely on separate systems, leading to fragmented decision-making. As a result, important insights such as delay risks are not effectively communicated across departments, and actions such as fare adjustments or resource allocation are not aligned with real-time conditions.[8]

With the increasing availability of aviation data, there is a strong need for systems that can transform raw data into meaningful insights. Machine learning techniques provide the ability to analyze patterns in historical data and predict future events such as flight delays. However, prediction alone is not sufficient. The results must be presented clearly and made actionable through an interactive system that supports real-time decision-making.[13]

The system presented in this work addresses this need by focusing on a dashboard-driven approach. It combines predictive analytics with visualization and control features, allowing users to interact directly with the system. Instead of only generating predictions in the background, the system provides a live interface where users can monitor system metrics, analyze delay patterns, and manage model training and prediction processes.

The platform includes multiple components such as live system metrics, delay analysis dashboards, control center for model execution, and real-time alerts. These components are designed to work together, providing a unified view of the system. By integrating these elements, the system reduces dependency on multiple tools and improves operational efficiency.[2]

Another important aspect of the system is its ability to function in real-world conditions. The design supports offline operation using local storage, ensuring that predictions and analytics remain available even when network connectivity is unstable. This makes the system more reliable and practical for deployment in different environments.[10]

Overall, the need for a unified, interactive, and predictive system forms the foundation of this work. The approach focuses on combining system design, implementation, and visualization to create a solution that is both technically effective and easy to use.[15]

Objectives Of the System

The system is designed with clearly defined objectives that guide its development, functionality, and evaluation. These objectives focus on integrating prediction, control, and visualization into a single interactive platform.

The primary objective is to develop a unified dashboard-based system that can predict flight delays, support decision-making, and provide real-time insights through an interactive interface.

To achieve this, the following specific objectives are defined:

- To design a data processing pipeline that collects and prepares multi-source aviation data, including flight schedules, historical delays, weather conditions, and operational parameters.
- To implement ensemble-based machine learning models (Random Forest, XGBoost, and Neural Network) for predicting delay probability and delay duration.
- To create a control center that allows users to manage model training, configure parameters, and execute predictions through an interactive interface.
- To develop a real-time dashboard that displays live system metrics such as total flights, delay rate, number of airlines, and airport coverage.
- To provide detailed delay analysis through categorized breakdowns such as weather delays, technical issues, air traffic control delays, and crew-related problems.
- To integrate visualization components such as charts, indicators, and maps to represent flight activity, delay patterns, and system performance.
- To enable dynamic decision support by linking predictive insights with operational monitoring and control features.
- To ensure offline functionality using local storage so that the system remains operational even without internet connectivity.
- To maintain system reliability, fast response time, and ease of use for multiple stakeholders including operations teams, analysts, and management.

These objectives ensure that the system is not limited to prediction alone but also focuses on usability, control, and real-time interaction, making it suitable for practical deployment scenarios.

System Overview

The system is designed as an interactive, dashboard-driven platform that integrates prediction, monitoring, and control into a single environment. Instead of operating as a backend-only analytical model, it provides a complete user-facing system where data processing, model execution, and visualization are tightly connected.[7]

At a high level, the system works as a continuous flow where aviation data is processed, analyzed, and presented through an interface that allows users to interact with the system in real time. The platform is structured to support both analytical operations and decision-making activities within the same environment.[9]

The system consists of the following core components:

- Data Processing Module:

This module handles the ingestion and preparation of aviation data. It ensures that raw data from different sources is cleaned, formatted, and transformed into a structured format suitable for analysis and prediction.

- Prediction Module:

The system uses ensemble machine learning models to generate delay predictions. These models analyze historical patterns and current conditions to estimate delay probability and expected delay duration. The predictions are generated quickly to support real-time usage.

- Control Center Module:

A dedicated control interface allows users to manage system operations. Users can trigger model training, run prediction processes, and monitor system activity. This module acts as the operational core of the system, providing flexibility and control.

- Visualization Dashboard

The dashboard presents system outputs in a clear and interactive format. It displays live metrics such as total flights, delay rates, number of airports, and airline distribution. It also includes visual components such as charts and graphs for delay analysis and system monitoring.

- Alert and Monitoring Module:

The system provides real-time alerts for significant events such as high delay probability or system issues. This helps users take immediate action and improves operational responsiveness.

- Offline Storage Module:

To ensure reliability, the system uses local storage to maintain data, predictions, and logs. This enables the system to function even when internet connectivity is unavailable, ensuring uninterrupted operation.

Working Flow of the System

The overall system flow can be described as follows:

Data Input → Preprocessing → Prediction → Visualization → User Interaction → Logging

Each stage is interconnected, allowing smooth transition from raw data to actionable insights. Users can observe system behavior through the dashboard and interact with the control center to execute specific operations.

Key Characteristics of the System

- Integrated platform combining prediction, control, and visualization
- Real-time data processing and interactive dashboard
- User-driven control over model execution and monitoring
- Offline capability for uninterrupted system operation
- Multi-user usability with role-based understanding of data

The system overview highlights how different modules work together to create a unified environment. By combining backend analytics with frontend interaction, the platform provides both technical capability and practical usability, making it suitable for real-world aviation scenarios.

System Architecture

The system architecture is designed to support a smooth interaction between data processing, predictive modeling, control operations, and visualization.[20] It follows a modular structure where each component performs a specific function while remaining connected to the overall workflow. This modular approach ensures flexibility, scalability, and ease of maintenance.

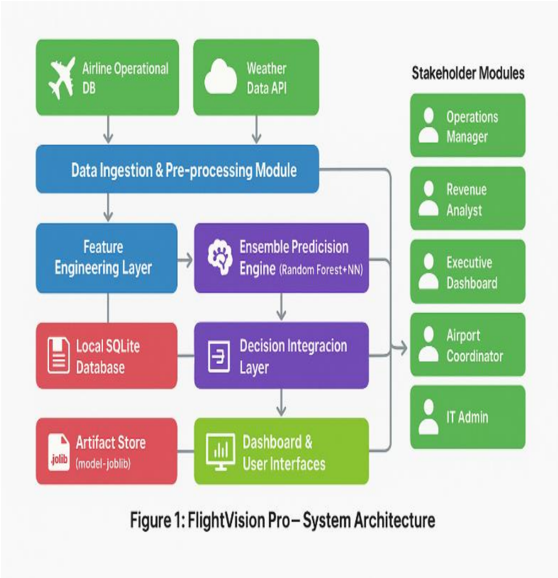

Figure 1: System Architecture

Architectural Structure

The architecture can be divided into four main layers:

- Data Layer
- Processing and Prediction Layer
- Control Layer
- Visualization Layer

Each layer communicates with the others through a structured data flow, ensuring that information is processed efficiently and presented in real time.

Data Layer

The data layer is responsible for storing and managing all system data. It includes:

- Flight schedule data
- Historical delay records
- Weather and operational data
- System logs and predictions

A local SQLite database is used to store this information. This allows the system to operate even without internet connectivity and ensures that all data remains available for analysis and auditing.

Processing and Prediction Layer

This layer handles all analytical operations. It includes:

- Data preprocessing module
- Feature engineering module
- Machine learning models (Random Forest, XGBoost, Neural Network)

The data is first cleaned and transformed into a structured format. Then, features are generated to capture important patterns. Finally, the ensemble models process these features to generate delay predictions.

The output of this layer includes:

- Delay probability
- Expected delay duration

These outputs are passed to the next layers for further processing and visualization.

Control Layer

The control layer acts as the operational core of the system. It provides an interface through which users can interact with the backend processes.

Functions of this layer include:

- Triggering model training
- Running prediction processes
- Monitoring system execution
- Managing configurations

This layer ensures that users are not passive observers but active participants in the system workflow.

Visualization Layer

The visualization layer is responsible for presenting system outputs in an interactive and user-friendly format. It is implemented using a dashboard interface.

This layer displays:

- Live system metrics (flights, delay rates, airlines)
- Delay analysis charts
- Prediction outputs
- Alerts and notifications

The goal of this layer is to simplify complex analytical results and make them easily understandable for users.

Data Flow Interaction

The interaction between layers follows a sequential flow:

Data Layer → Processing Layer → Prediction Output → Control Layer → Visualization Layer

At the same time, the control layer can trigger actions in the processing layer, creating a bidirectional interaction. This makes the system dynamic rather than static.

Architectural Characteristics

The architecture is designed with the following key characteristics:

- Modular design for easy maintenance
- Real-time data flow for fast decision-making
- User-driven control for flexibility
- Offline capability through local storage
- Integrated visualization for better understanding

Overall Architectural Insight

The system architecture ensures that all components work together as a unified system. Data is not only processed but also made accessible and actionable through user interaction. The integration of prediction, control, and visualization within a single architecture makes the system practical for real-world usage.

Methodology

The methodology defines how the system operates internally from data input to final visualization and user interaction. It is designed as a structured workflow where each stage performs a specific function, ensuring smooth data transformation and real-time usability. The focus is on practical execution rather than complex theoretical modeling.

Overall Workflow

The system follows a step-by-step execution pipeline:

Data Input → Preprocessing → Feature Engineering → Model Execution → Prediction Output → Dashboard Visualization → User Interaction → Logging

Each stage is interconnected, allowing continuous flow of data and results.

Step 1: Data Input

The workflow begins with collecting aviation-related data such as:

- Flight schedules
- Historical delay records
- Weather conditions
- Operational parameters

This data forms the foundation for prediction and analysis.

Step 2: Data Preprocessing

The collected data is cleaned and standardized before use:

- Missing values are handled
- Data is normalized for consistency
- Categorical values are encoded into numerical form

This step ensures that the dataset is reliable and suitable for machine learning models.

Step 3: Feature Engineering

Additional features are generated to improve prediction quality:

- Delay patterns based on historical data
- Time-based features (hour, day, season)
- Weather impact indicators
- Airport congestion indicators

These features help the models capture real-world patterns more effectively.

Step 4: Model Execution

The processed data is passed to multiple machine learning models:

- Random Forest
- XGBoost
- Neural Network

Each model independently analyzes the data and produces predictions.

Step 5: Ensemble Prediction

The outputs from all models are combined to generate a final prediction:

- Individual model outputs are aggregated
- A balanced prediction is generated
- Final output includes delay probability and duration

This improves stability and reduces dependency on a single model.

Step 6: Dashboard Visualization

The prediction results are displayed through an interactive dashboard:

- Live metrics such as total flights and delay rate
- Visual charts for delay analysis
- Indicators for quick understanding

This step converts technical outputs into user-friendly insights.

Step 7: User Interaction

Users interact with the system through the control center:

- Trigger model training
- Run prediction processes
- Monitor system status

This allows users to actively control system operations.

Step 8: Logging and Storage

All system activities are stored locally:

- Prediction results
- User actions
- System logs

This ensures traceability and supports offline functionality.

Key Workflow Characteristics

- Continuous data flow from input to output
- Integration of prediction and visualization
- Real-time interaction with system components
- Offline-capable execution
- User-driven control mechanism

Summary of Workflow

The methodology ensures that the system is not only predictive but also interactive and practical. By connecting data processing, model execution, and visualization in a single workflow, the system enables efficient and real-time decision support.

System Implementation

The system implementation focuses on the practical realization of the dashboard-driven platform. It integrates prediction, visualization, and control into a working interface where users can directly interact with the system. The implementation is modular, with each component contributing to the overall functionality of the platform.

Main Dashboard Interface

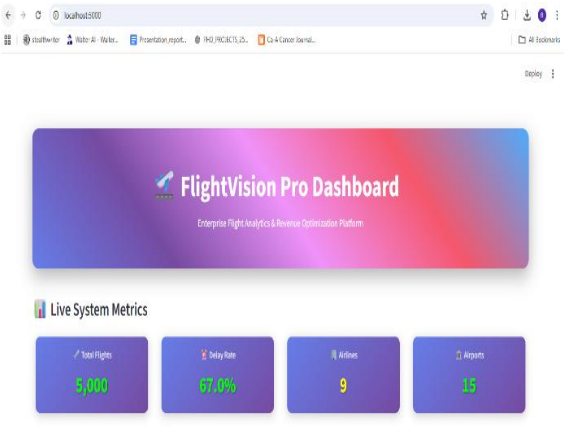

Figure 2: Main Dashboard Overview

This screen presents the central interface of the system, displaying key metrics such as total flights, delay rate, number of airlines, and airports. It provides a quick summary of system status and allows users to understand overall operational conditions at a glance. This is important for decision-makers who require immediate insights without deep analysis.

Live System Metrics Panel

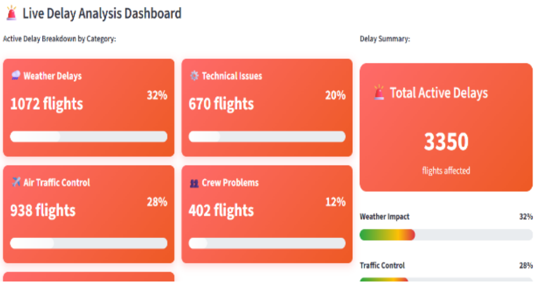

Figure 3: Live Metrics Display

This section shows real-time system indicators such as active flights, delay percentage, and system activity. The metrics are updated dynamically, enabling users to monitor ongoing operations continuously. It helps in identifying sudden changes in delay patterns and system behavior

Delay Analysis Dashboard

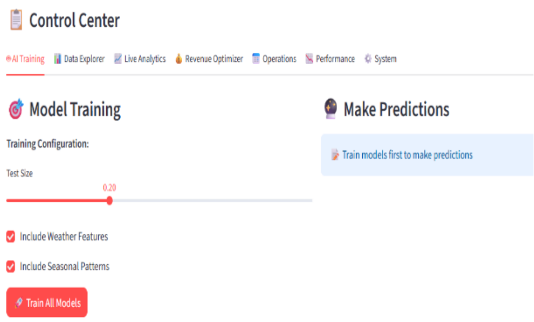

Figure 4: Delay Distribution Analysis

This screen provides a breakdown of delays based on different categories such as weather, technical issues, air traffic control, and crew-related factors. The visual representation helps users understand the primary causes of delays. This is useful for identifying trends and planning corrective actions.

Control Center Interface

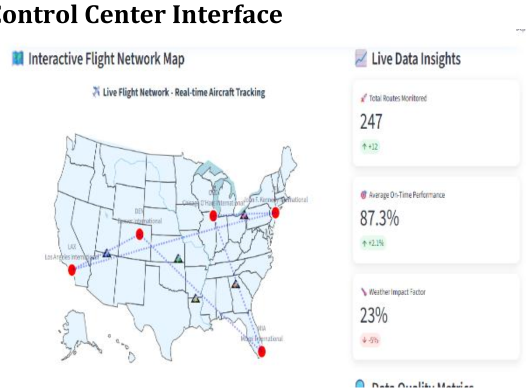

Figure 5: Model Control Center

The control center allows users to manage backend operations such as training models and running predictions. It includes interactive controls that enable users to initiate processes and monitor their execution. This module ensures that users have direct control over system functionality.

Prediction Output Panel

Figure 6: Prediction Results Display

This section displays the output of the machine learning models, including delay probability and expected delay duration. The results are presented clearly so that users can quickly interpret them. This helps in making timely operational decisions.

Visualization Charts and Graphs

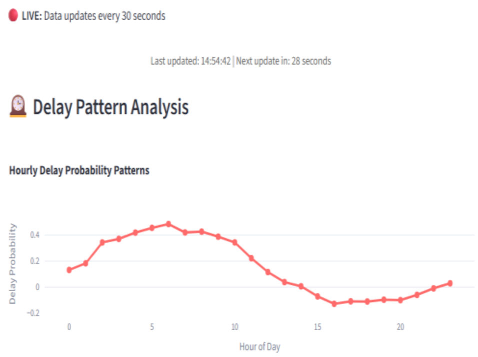

Figure 7: Graphical Visualization of Delays

This part of the interface shows charts and graphs representing delay trends and patterns. Visual tools such as bar charts and line graphs make it easier to analyze historical and current data. These visualizations improve understanding and support data-driven decision-making.

System Activity and Alerts Panel

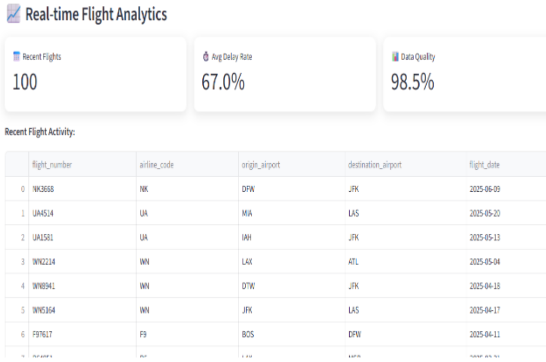

Figure 8: Alerts and System Notifications

This screen displays system alerts and notifications related to high delay risk or operational issues. It helps users respond quickly to critical situations. The alert system ensures that important information is not missed during monitoring.

Implementation Characteristics

The system implementation highlights the following:

- User-friendly interface for easy interaction
- Integration of prediction and visualization in one platform
- Real-time updates for continuous monitoring
- Control features for managing backend processes
- Clear presentation of results for quick understanding

Overall Implementation Insight

The implementation demonstrates how a complex analytical system can be converted into a practical and interactive tool. By combining multiple modules into a single dashboard, the system provides both technical functionality and usability. This makes it suitable for real-world operational environments where quick decisions are essential.

Discussion

The developed system demonstrates how combining predictive analytics with an interactive dashboard can improve usability and decision-making in aviation operations. Instead of relying only on backend models, the system brings prediction results directly to the user through a visual and controllable interface. This shift from a model-centric approach to a system-centric approach makes the solution more practical and easier to adopt.

One of the key strengths of the system is its integration of multiple functionalities into a single platform. Prediction, monitoring, and control are not treated as separate components but are connected through a unified workflow. This reduces dependency on multiple tools and improves coordination between different operational roles. Users can observe system behavior, trigger actions, and analyze results without switching between systems.

The dashboard-driven design significantly enhances user experience. Visual elements such as charts, metrics, and alerts make complex data easier to understand. Instead of interpreting raw numerical outputs, users can quickly identify patterns and risks through graphical representations. This is especially useful in time-sensitive environments where quick decisions are required.

Another important aspect is the control center functionality. By allowing users to initiate model training and prediction processes, the system provides flexibility and transparency. Users are not limited to passive observation; they actively interact with the system, which increases trust and usability. This feature also supports experimentation and iterative improvement of models.

The offline capability adds practical value to the system. In many real-world scenarios, especially in regional or low-connectivity environments, continuous internet access cannot be guaranteed. The use of local storage ensures that the system remains operational even during connectivity issues. This improves reliability and makes the system more suitable for deployment in diverse environments.

From an implementation perspective, the system balances complexity and usability effectively. While it incorporates advanced machine learning models, the interface remains simple and intuitive. This balance is essential for ensuring that the system can be used by different stakeholders, including operations teams, analysts, and management.

However, the system also highlights certain limitations. The performance of the prediction module depends on the quality and completeness of input data. If the data is inconsistent or incomplete, prediction accuracy may be affected. Additionally, while the dashboard provides clear insights, further enhancements such as deeper explainability or automated recommendations could improve usability.

Overall, the discussion shows that the system successfully addresses the gap between prediction and practical implementation. By focusing on system design, visualization, and user interaction, it provides a more complete solution compared to traditional standalone models.

Conclusion

The presented system demonstrates a practical approach to improving airline operations through an integrated, dashboard-driven platform. By combining flight delay prediction, visualization, and system control into a single environment, the solution moves beyond traditional standalone models and focuses on real-world usability.

The system successfully transforms raw aviation data into meaningful insights that can be directly used for decision-making. The use of ensemble machine learning models enables reliable delay prediction, while the interactive dashboard ensures that these predictions are clearly visible and easy to interpret. The inclusion of control features further enhances the system by allowing users to actively manage model execution and monitor system behavior.

A key contribution of the system is its emphasis on visualization and interaction. Instead of presenting outputs in a static format, the platform provides dynamic views of system metrics, delay patterns, and prediction results. This improves situational awareness and allows users to respond quickly to changing conditions.

The offline capability adds an important practical dimension to the system. By using local storage and maintaining system functionality without continuous internet access, the solution becomes more robust and suitable for deployment in various environments.

Overall, the system achieves its objective of creating a unified platform that integrates prediction, monitoring, and control. It highlights the importance of combining analytical models with user-friendly interfaces to create effective decision-support tools. The work demonstrates that a well-designed system can bridge the gap between technical capability and practical application, making it valuable for both academic study and real-world implementation

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