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

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Peer Review Information	Abstract
<p><i>Submission: 10 Feb 2026</i></p> <p><i>Revision: 26 Feb 2026</i></p> <p><i>Acceptance: 11 March 2026</i></p>	<p>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.</p>
<p>Keywords</p> <p><i>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</i></p>	

Introduction

The food supply chain has become increasingly complex due to the involvement of multiple stakeholders and the influence of various dynamic factors such as seasonal variations, promotional

activities, pricing changes, and weather conditions. These factors make demand highly unpredictable, especially for perishable goods where even small forecasting errors can lead to significant financial loss or waste. Maintaining a

balance between product availability and minimal wastage is therefore a critical challenge in this domain.[12]

Traditional demand forecasting methods are often based on simple statistical techniques or manual planning approaches. While these methods are useful for stable environments, they are not capable of capturing nonlinear patterns and dependencies that exist in real-world data. As a result, organizations frequently face problems such as overstocking, which leads to spoilage, or stockouts, which result in missed sales opportunities and reduced customer satisfaction.[6]

To overcome these limitations, modern systems are increasingly adopting Artificial Intelligence and Machine Learning techniques. These approaches enable systems to learn patterns from historical data and adapt to changing demand conditions. When combined with optimization models, forecasting systems can go beyond prediction and provide actionable recommendations for inventory management.[18]

The system presented in this work focuses on building an integrated framework that connects forecasting, optimization, and visualization into a single workflow. It processes multi-source data such as sales, weather, and promotions to generate demand predictions using models like ARIMA, XGBoost, LSTM, and Temporal Fusion Transformer. These predictions are then used to derive optimized inventory decisions, ensuring efficient resource utilization.[2]

An important aspect of the system is its interactive user interface, which allows users to upload data, monitor forecasting performance, and analyze model outputs through visual dashboards. This improves transparency and helps decision-makers understand the system's behavior before applying recommendations in real operations.[9]

Overall, the need for a unified, intelligent, and user-friendly system drives the development of this framework. By combining predictive modeling with decision support and visualization, the system aims to improve operational efficiency, reduce wastage, and support better planning in food supply chain environments. [5]

Objectives Of the System

The primary objective of the system is to develop an integrated and intelligent platform that connects demand forecasting, inventory optimization, and decision support into a single workflow. The system is designed to improve accuracy, reduce wastage, and support better

planning in food supply chain operations.

The key objectives are outlined as follows:

- To collect and integrate multi-source data such as historical sales, weather conditions, and promotional information into a unified dataset for analysis.
- To design and implement forecasting models including ARIMA, XGBoost, LSTM, and Temporal Fusion Transformer for capturing different demand patterns and generating multi-horizon predictions.
- To process and enhance raw data through preprocessing techniques such as cleaning, outlier detection, and feature engineering to improve model performance.
- To develop optimization mechanisms that convert forecasted demand into efficient inventory decisions using approaches such as Economic Order Quantity (EOQ), Newsvendor models, and other optimization strategies.
- To build an interactive dashboard that enables users to upload datasets, visualize demand trends, and analyze forecasting insights in real time.
- To provide model comparison and performance visualization features that allow users to evaluate different forecasting approaches and select the most suitable one.
- To support decision-making through clear visualization of outputs, including forecasting graphs and performance metrics, ensuring transparency and usability.
- To create a scalable and modular system architecture that can adapt to different supply chain scenarios and datasets.

These objectives collectively ensure that the system not only predicts demand accurately but also provides practical, user-friendly tools for managing inventory and improving overall supply chain efficiency.

System Overview

The developed system is designed as an integrated decision-support platform that combines data processing, demand forecasting, and visualization into a unified workflow. It focuses on providing a practical and user-friendly environment where users can interact with data, generate forecasts, and analyze results through an intuitive interface.[11]

At a high level, the system operates in three major layers: data handling, forecasting, and decision support. The process begins with the data handling layer, where users upload datasets containing sales records along with related

influencing factors such as weather conditions and promotional details. The system processes this input data by performing cleaning, transformation, and feature extraction to prepare it for modeling.

The next layer is the forecasting engine, where multiple models are applied to generate demand predictions. Instead of relying on a single approach, the system supports models such as ARIMA, XGBoost, LSTM, and Temporal Fusion Transformer. Each model captures different characteristics of demand behavior, allowing the system to provide more reliable and flexible forecasting outputs. The results from these models are then evaluated and compared to help identify the most suitable approach for the given dataset.[13]

The final layer is the decision-support and visualization component. This part of the system provides an interactive dashboard where users can view forecasting results, analyze trends, and compare model outputs. Visual elements such as graphs and charts make it easier to understand demand patterns and model performance. Users can explore the data, interpret predictions, and make informed decisions based on system outputs.[7]

A key strength of the system lies in its modular design. Each component—data processing, forecasting, and visualization—functions independently but remains connected within a single pipeline. This structure ensures flexibility, scalability, and ease of maintenance. It also allows the system to be extended or modified without affecting the overall workflow.[15]

Overall, the system overview highlights a complete and practical solution that moves beyond standalone forecasting. By integrating multiple functionalities into one platform, it provides a seamless experience for users and supports effective decision-making in food supply chain management.

System Architecture

The system architecture is designed as a modular and layered structure that integrates data processing, forecasting models, optimization logic, and user interaction into a unified framework.[10] The architecture ensures smooth data flow between components while maintaining flexibility and scalability.

AI FORECASTING • OPTIMIZATION • DECISION SUPPORT

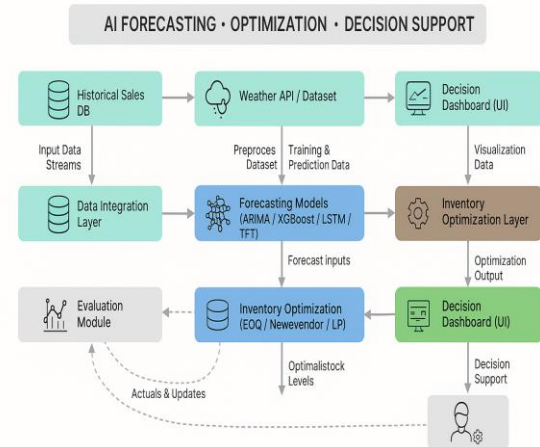


FIGURE 1

Figure 1: System Architecture (AI Forecasting • Optimization • Decision Support)

At the highest level, the system can be divided into three core modules: Data Layer, Processing & Forecasting Layer, and Decision Support Layer.

Data Layer

The data layer is responsible for handling all input data required by the system. It accepts multi-source datasets that include:

- Historical sales data
- Weather-related information
- Promotional and pricing data

This data is collected and stored in a structured format. The system ensures that all inputs are aligned based on time to maintain consistency across different variables. This layer acts as the foundation for all subsequent processing.

Processing and Forecasting Layer

This is the core computational component of the system. It consists of two main sub-modules:

a) Data Preprocessing Module

- Cleans raw data by handling missing values and inconsistencies
- Transforms data into a suitable format for modeling
- Generates features such as lag variables, seasonal indicators, and external regressors

b) Forecasting Module

- Applies multiple forecasting models including ARIMA, XGBoost, LSTM, and Temporal Fusion Transformer
- Each model processes the input data

differently to capture various demand patterns

- Generates multi-horizon demand predictions

The output of this layer is a set of forecasted demand values, which represent expected future consumption trends.

Optimization and Decision Layer

Once forecasts are generated, they are passed to the decision-making component of the system.

a) Optimization Module

- Uses forecasting outputs as input
- Applies inventory models such as EOQ, Newsvendor, and Linear Programming
- Produces optimal ordering and replenishment strategies

b) Decision Support Module

- Presents results through an interactive dashboard
- Displays graphs, trends, and model comparisons
- Allows users to analyze and interpret outputs

This layer ensures that predictions are not just generated but are also converted into meaningful and actionable decisions.

Interaction Flow Between Modules

The system follows a structured flow:

1. Data is collected and stored in the Data Layer
2. Preprocessing prepares the data for modeling
3. Forecasting models generate demand predictions
4. Optimization models convert predictions into decisions
5. Results are displayed through the dashboard for user interaction

This continuous flow ensures that each module contributes to the final output without redundancy.

Architectural Advantages

- Modularity: Each component can be updated independently
- Scalability: Supports large datasets and multiple models
- Flexibility: Allows integration of additional models or data sources
- User-centric Design: Provides clear visualization and interaction

In summary, the system architecture provides a well-structured pipeline that connects raw data to

final decision-making. By integrating forecasting, optimization, and visualization into a single framework, the system ensures efficient and practical operation for food supply chain management.

Methodology

The system follows a structured workflow that transforms raw input data into meaningful forecasting insights and decision-support outputs. The methodology is designed to ensure smooth execution across all modules, from data ingestion to visualization, while maintaining accuracy and usability.

Step-by-Step Workflow

The complete workflow of the system is organized into the following sequential steps:

Step 1: Data Upload and Input Handling

The process begins with the user uploading the dataset through the system interface. The dataset typically contains historical sales data along with additional attributes such as weather conditions and promotional indicators. The system accepts this data and prepares it for further processing.

Step 2: Data Preprocessing

Once the data is uploaded, preprocessing is performed to ensure quality and consistency. This includes:

- Handling missing or inconsistent values
- Normalizing and formatting data
- Converting raw inputs into structured formats
- Generating useful features such as time-based indicators and lag variables

This step is critical because the quality of input data directly affects model performance.

Step 3: Feature Engineering

In this stage, the system enhances the dataset by extracting meaningful patterns. Features such as seasonal trends, promotional effects, and environmental influences are derived. These features help models better understand demand behavior.

Step 4: Model Selection and Forecasting

The system applies multiple forecasting models to the processed dataset. These include:

- ARIMA for capturing linear trends
- XGBoost for handling nonlinear relationships
- LSTM for sequential and time-dependent patterns
- Temporal Fusion Transformer for multi-horizon forecasting

Each model generates its own prediction output.

This multi-model approach improves robustness and ensures adaptability across different demand scenarios.

Step 5: Model Evaluation and Comparison

The outputs from all models are evaluated using standard performance metrics. The system compares models to identify the most suitable one for the given dataset. This step ensures that only reliable predictions are used for further analysis.

Step 6: Forecast Visualization

The selected forecasting results are presented in graphical form through the dashboard. Users can visualize demand trends, observe predicted values, and analyze patterns over time. This makes the system easy to interpret even for non-technical users.

Step 7: Decision Support and Analysis

The final stage involves presenting insights through an interactive interface. Users can:

- Analyze forecasting results
- Compare different models
- Understand demand behavior
- Make informed decisions based on system outputs

This stage ensures that the system is not limited to prediction but also supports practical decision-making.

Workflow Characteristics

- Sequential yet flexible: Each step follows a logical order but allows updates and iterations
- Data-driven: Every stage depends on processed and validated data
- User-interactive: Users are involved in data upload, visualization, and analysis
- Modular execution: Each component operates independently but contributes to the overall system

End-to-End Flow Summary

The workflow can be summarized as:

Data Upload → Preprocessing → Feature Engineering → Forecasting → Evaluation → Visualization → Decision Support

In summary, the methodology ensures that the system operates as a complete pipeline, transforming raw data into actionable insights. By integrating multiple stages into a single workflow, the system provides a practical and efficient approach for managing demand forecasting and decision-making in food supply chain environments.

System Implementation

The system implementation focuses on providing a practical and interactive interface where users can perform forecasting tasks, analyze results, and understand system behavior through visual components. The implementation is designed to be user-friendly, allowing even non-technical users to interact with the system efficiently.

User Interface and Data Upload

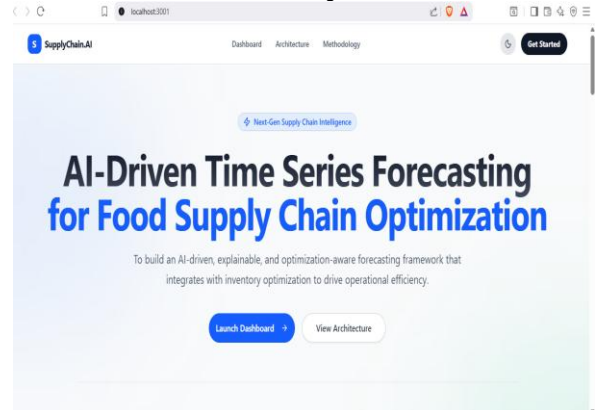


Figure 2: Data Upload Interface

This screen shows the initial interface where users can upload their dataset. It allows selection of input files containing sales and related data. This step is important because it serves as the entry point of the system, enabling users to provide real-world data for analysis.

Dataset Preview and Processing

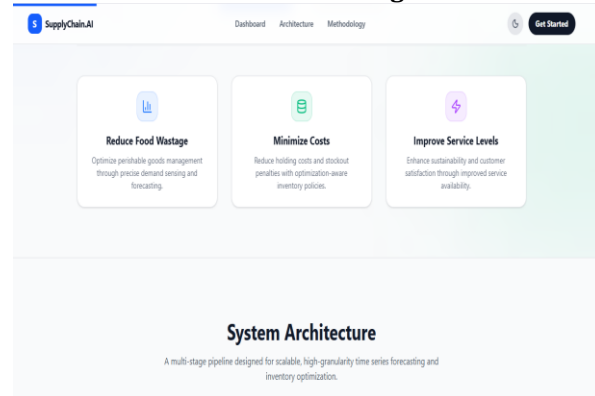


Figure 3: Dataset Preview Screen

After uploading, the system displays a preview of the dataset. Users can verify the structure, columns, and data quality before processing. This helps ensure that the input data is correct and suitable for forecasting.

Model Selection and Execution

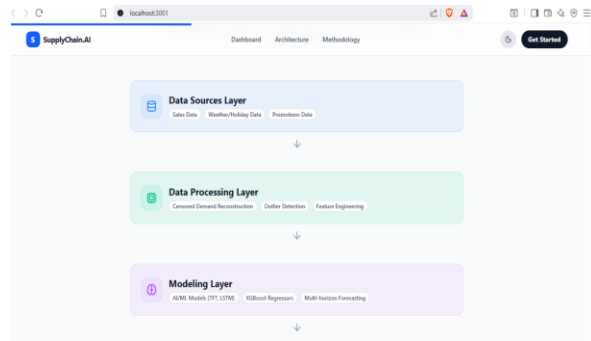


Figure 4: Model Selection Interface

This screen allows users to select forecasting models such as ARIMA, XGBoost, LSTM, and Temporal Fusion Transformer. The system provides flexibility to choose one or multiple models for comparison. This step is essential for analyzing how different models perform on the same dataset.

Forecast Visualization

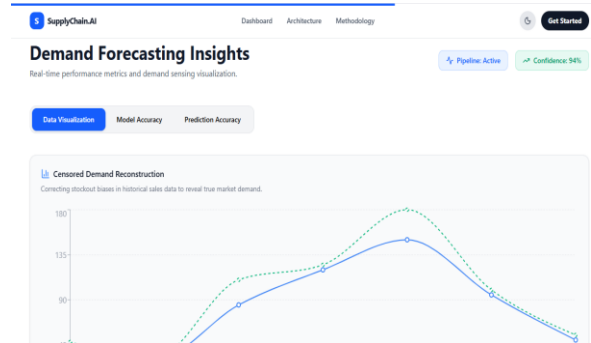


Figure 5: Forecast Graph Output

The system generates graphical representations of demand predictions. These graphs display trends over time, making it easier to understand how demand is expected to change. Visualization plays a key role in interpreting model outputs.

Model Comparison Dashboard

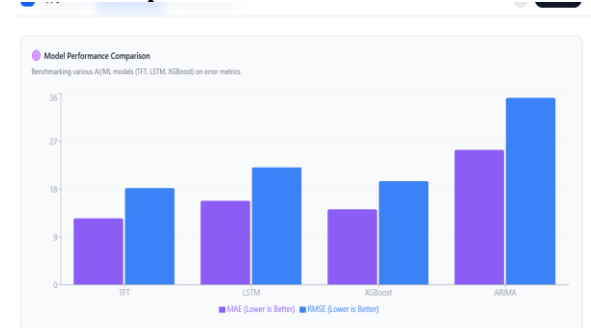


Figure 6: Model Comparison Results

This screen presents a comparison of different forecasting models. Users can observe performance differences and identify which model provides better results. This supports informed model selection.

Performance Metrics Display

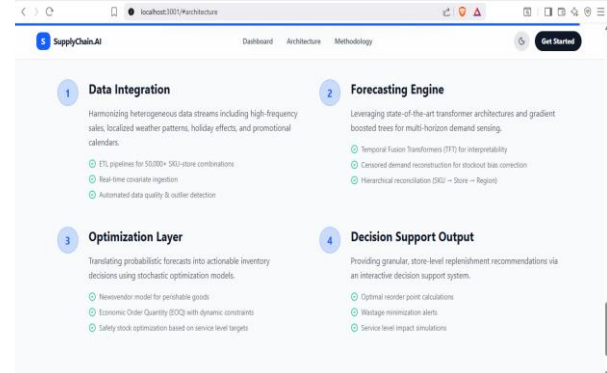


Figure 7: Performance Metrics Panel

The system displays evaluation metrics such as MAPE, RMSE, and Bias. These metrics help users assess prediction accuracy and reliability. This step ensures transparency in model performance.

Final Output and Decision Support

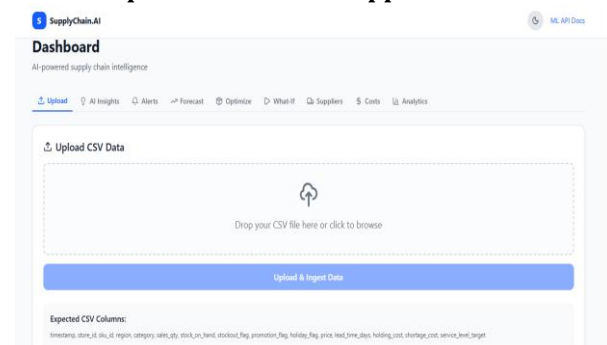


Figure 8: Final Output Dashboard

The final dashboard integrates all outputs, including forecasts, comparisons, and metrics. It provides a complete view of system results, enabling users to make decisions based on analyzed data. This interface connects all system components into a single view.

Implementation Insights

The implementation demonstrates how different modules are connected through a smooth user interface. The system ensures that users can:

- Upload and validate data
- Select and execute forecasting models
- Visualize predictions through graphs
- Compare models using performance

metrics

- Interpret results using an integrated dashboard

The use of interactive screens makes the system practical and easy to use in real-world scenarios.

In summary, the implementation highlights the practical realization of the proposed system. By combining functionality with visualization, the system provides a complete platform for demand forecasting and decision support in the food supply chain.

Discussion

The developed system demonstrates a practical approach to handling demand forecasting and decision support in the food supply chain. By combining multiple components into a single platform, it moves beyond traditional standalone forecasting tools and provides a more comprehensive solution.

One of the key strengths of the system is its ability to integrate different forecasting models within the same workflow. Instead of relying on a single method, the system allows users to compare multiple approaches such as ARIMA, XGBoost, LSTM, and Temporal Fusion Transformer. This flexibility improves reliability, as different models perform better under different demand conditions. The inclusion of model comparison features further enhances decision-making by enabling users to select the most suitable model based on performance.

Another important aspect is the system's interactive design. The use of dashboards and visual outputs makes complex forecasting results easier to understand. Graphical representations of demand trends and performance metrics allow users to quickly interpret results without needing deep technical knowledge. This improves usability and ensures that the system can be effectively used by planners and decision-makers.

The modular structure of the system also contributes to its effectiveness. Each component—data processing, forecasting, and visualization—operates independently while remaining connected within the overall pipeline. This design makes the system scalable and adaptable to different datasets and use cases. It also allows future enhancements without affecting the entire system.

From a practical perspective, the system addresses common challenges in food supply chains such as demand uncertainty and inefficient inventory planning. By providing accurate forecasts and clear visual insights, it supports better planning and

reduces the chances of overstocking or stockouts. The ability to analyze data interactively further strengthens decision-making.

However, the system also highlights certain limitations. Its performance depends heavily on the quality of input data, and incomplete or noisy datasets may affect results. Additionally, advanced models like LSTM and Temporal Fusion Transformer require computational resources and proper tuning, which may limit their use in resource-constrained environments.

Overall, the system demonstrates how combining forecasting, visualization, and user interaction can improve supply chain decision-making. It provides a balanced approach that focuses on both technical capability and practical usability, making it suitable for real-world implementation in food supply chain environments.

Conclusion

The presented system delivers a complete and practical solution for demand forecasting and decision support in the food supply chain. It integrates data processing, multiple forecasting models, and interactive visualization into a unified platform, making the overall workflow efficient and user-friendly.

The system successfully demonstrates how different forecasting techniques such as ARIMA, XGBoost, LSTM, and Temporal Fusion Transformer can be applied within a single environment and compared effectively. By allowing users to visualize predictions and evaluate model performance, it enhances transparency and supports informed decision-making.

A key contribution of this work is the focus on system design and implementation rather than only theoretical modeling. The inclusion of an interactive dashboard enables users to upload data, explore forecasting results, and understand system outputs through clear visual representations. This improves usability and makes the system suitable for real-world applications.

The modular architecture ensures flexibility and scalability, allowing the system to adapt to different datasets and requirements. It also provides a foundation for future enhancements, such as adding new models or extending decision-support capabilities.

In summary, the system bridges the gap between forecasting and practical application by combining predictive analytics with visualization and user interaction. It supports better planning,

reduces uncertainty, and contributes to improved efficiency in food supply chain operations.

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