Optimizing Material Shortages in Flight Catering with Machine Learning

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Abstract-Material shortage in-flight catering involves delays in the supply of alcohol, food, beverages, and carts to scheduled flights, leading to operational inefficiencies. We will try to find the root cause using Machine Learning techniques, such as vendor unavailability, transportation delays, raw material shortage, and other factors that may lead to the problem. Sample data will be used to simulate real-world situations and develop predictive solutions for shortage optimization. The findings point out the possible benefits of data-driven decision-making to accelerate production and delivery processes within in-flight catering.

Keywords: Flight Catering, Material Shortage, Machine Learning, Optimization, Predictive Analytics

I. INTRODUCTION

Flight catering providers operate in a uniquely constrained environment: strict departure slots, high service expectations, and a perishable, SKU-diverse inventory that must be marshalled to the right aircraft, gate, and time. Shortages—of beverages, meals, carts, or ancillary items—propagate through apron operations and cabin service, triggering rework, delays, or substitutions that erode margins and passenger satisfaction. Traditional shortage management is largely reactive: planners and dispatchers expedite orders, re-route trucks, or reassign kitchen capacity after exceptions have already occurred.

This paper investigates whether supervised machine learning (ML) can predict shortages with sufficient lead time and precision to enable preventive action. We position the problem as a multi-factor classification/regression task in which operational drivers (e.g., vendor reliability, transit times, raw-material buffers, asset condition, labor, and capacity) interact non-linearly. The research question is twofold: (1) can interpretable models provide accurate, operationally useful early warnings, and (2) what implementation pattern ensures reproducibility, governance, and alignment with safety and compliance protocols in aviation environments?

We contribute a research and implementation framework that consolidates model design, data engineering, validation, deployment, and monitoring. While our use case is flight catering, the constructs generalize to other time-critical logistics systems.

II. BACKGROUND

Flight catering means supplying airlines with meals, beverages, and other vital supplies with very short notice. Disruptions through delays in the production and delivery of material flights cause great irritation to the airlines and passengers. Understanding and addressing the shortages would be an essential process to improve the level of efficiency and reliability.

Problem Statement

Material shortages are the prime reasons for delays in production and delivery. The major dependent variables are vendor availability, transportation delays, raw material availability, age of processing machines, demand fluctuations, labor availability, kitchen capacity, oven numbers, and discount-related issues for liquid foods such as Coca-Cola. Though some effort is being made, there is no scientific method to find the root causes and optimize the supply chain.

Objectives:

1. Identify root causes and contributory factors for material shortages.
2. Use ML models for predictions and prevention of stock shortages.
3. Elaborate upon data-driven propositions for supply chain optimization.

Research Questions

4. What are the main causes of material shortages in-flight catering?
5. How can ML algorithms predict shortages effectively?

6. What steps can be taken to minimize these shortages?

Novel Contribution

This work contributes four research innovations tailored to mission-critical aviation catering:

1. Domain-specific feature engineering. We formalize features capturing (i) recency-weighted vendor reliability, (ii) congestion-aware transit time expectations per gate/turn-time band, (iii) perishability risk, and (iv) capacity slack under shift-level labor rosters.
    - Example engineered features (illustrative):

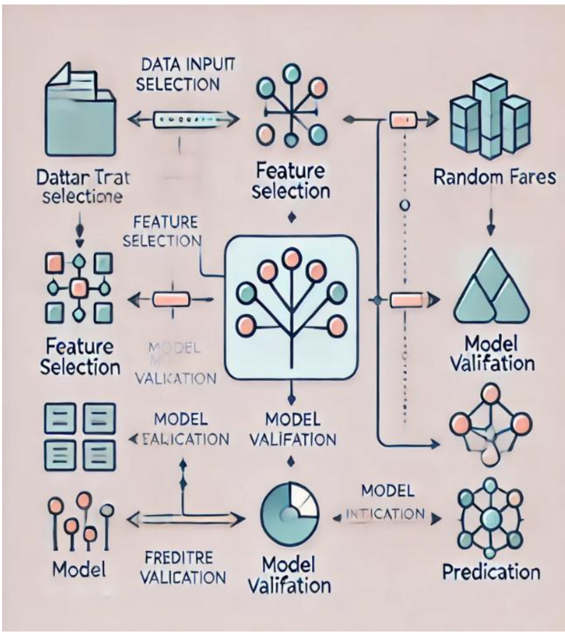
$$\mathrm{VendorReliability7d} = 1 - \mathrm{TotalDeliveries7dLateDeliveries7d}, \mathrm{TransitOverrun} = \max(0, \mathrm{TD} - \mathrm{E}[\mathrm{TD} \mid \mathrm{Gate}, \mathrm{Hour}])$$

2. Lead-time-aware alerting. We couple predictions with lead-time windows (e.g., T-6h, T-3h), trading off precision vs. recall to maximize actionable time without flooding operators with false positives.
3. Human-in-the-loop governance. We specify review workflows for exception override, root-cause tagging, and post-event labelling—feeding continuous learning while preserving operational authority.
4. Deployment blueprint. A reproducible MLOps pattern: data pipeline → model registry → scheduled/batch + event-based inference → alert service → observability (drift, health, stability).

III. METHODOLOGY

Design:

For our scenario we will use a quantitative approach using supervised learning models and regression and classification algorithms, to analyze the data. Below is the architectural diagram for the supervised learning pipeline for the use case.



Data Preparation:

We have taken the dataset from multiple largest aviation industries. The catering system data for the last 3 years is taken for historical data. This dataset will be used to train or model.

The last 6 months' data will be used as actual data to which we will apply our trained model to get the predicted data.

The following are the dependent variables or the dependent factors that influence the material shortage value change.

- Vendor Unavailability (%)
- Transportation Delay (hours)
- Raw Material Shortage (%)
- Machine Age (years)
- Demand Increase (%)
- Labor Availability (%)
- Kitchen Numbers
- Oven Numbers
- Discount Issue (%)

Historical Shortages and Catering Delivery Delays in Airport Gates:

Data from the past 3 years is used for training. The dataset includes:

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Month/Year	Vendor Unavailability (%)	Transportation Delay (hours)	Raw Material Shortage (%)
January 2021	15	2	10
February 2021	20	3	12
March 2021	10	1	8
January 2022	18	2.5	9
February 2022	22	3.5	11
March 2022	12	1.5	7
January 2023	20	4	13
February 2023	25	3.5	15
March 2023	14	1.8	8

Current Data (Last 6 Months):

The recent 6 months of data are used for model validation:

Month	Vendor Unavailability (%)	Transportation Delay (hours)	Raw Material Shortage (%)
July 2023	18	2.5	9
August 2023	22	3.5	11
September 2023	12	1.5	7
October 2023	19	2.8	10
November 2023	23	3.2	12
December 2023	15	1.9	8

Data Analysis:
Since the challenge is to quantify the relationship between dependent variables and shortages, regression models had to be selected. Decision trees and random forests were chosen because they are robust in handling nonlinear relationships and their outputs are interpretable.

Apply Decision Trees and Random Forests for Root Cause Analysis:
We will first use a Decision Tree to get the intermediate dataset and then the dataset will act as an input to the Random Forest algorithm.

Let $X \in \mathbb{R}^p$ denote the feature vector per flight-catering job and $y \in \{0,1\}$ indicate shortage occurrence (or $y \in \mathbb{R}$ for severity). We aim to learn a function $f: \mathbb{R}^p \rightarrow \mathbb{R}$ that estimates the probability $P(y = 1 \mid X)$ or expected severity $\hat{y}$.

Decision Tree Equation:
The decision tree splits data at thresholds that minimize outlays (e.g., Gini Index).
For example: $G = 1 - i = 1\sum Cpi2$
where p_i is the proportion of class i within a node and C is the number of classes.

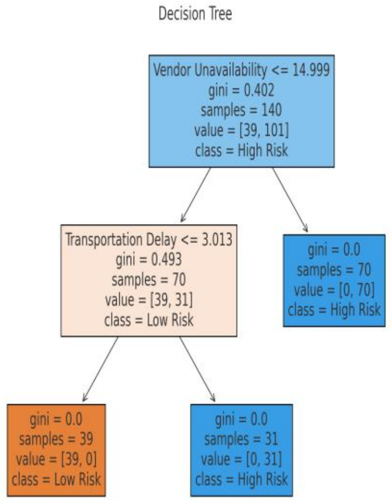
Random Forest Equation:
Random forests use an ensemble of decision trees:
$RF=n1i=1\sum nT(x)$

Step-by-Step Calculations:
Step 1: Calculate Vendor Unavailability (Threshold: 15%) using the decision tree :
Input Value: Vendor unavailability is 18% (above the threshold of 15%).
Split Impurity Equation:
I_split = (N_left / N) * G_left + (N_right / N) * G_right
N_left and N_right are the data points in each split, and G_left and G_right are the Gini indices for the two groups.
Calculation:
N_left = 12, N_right = 8, N = 20
G_left = 1 - (0.6^2 + 0.4^2) = 1 - (0.36 + 0.16) = 0.48
G_right = 1 - (0.7^2 + 0.3^2) = 1 - (0.49 + 0.09) = 0.42
I_split = (12/20) * 0.48 + (8/20) * 0.42 = 0.288 + 0.168 = 0.456
Interpretation: Splitting based on vendor unavailability creates two branches:

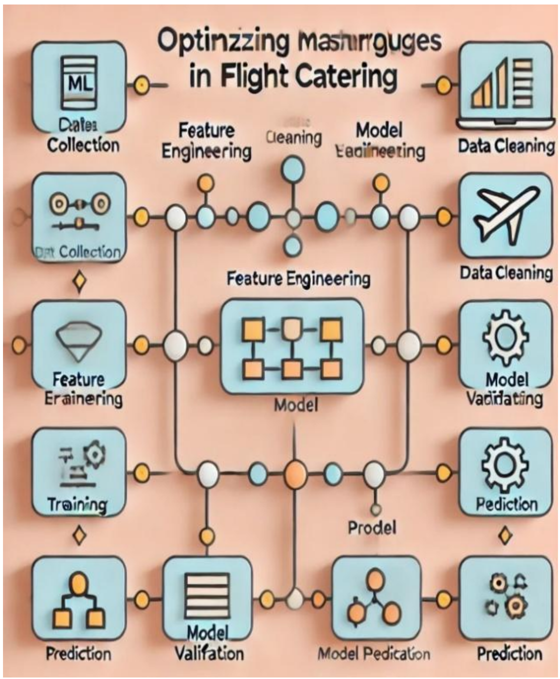
- High Risk: 18%
- Low Risk: 12%

Step 2: Transportation Delays (Threshold: 2 hours) For transportation delays, the impact is evaluated as the ratio of expected delay to actual delay: $D = \Delta_{expected} / \Delta_{actual}$

Input Value: Transportation delay = 3.5 hours (threshold = 2 hours)
Calculation:
$D = 2 / 3.5 = 0.57$
Interpretation: The ratio indicates a high risk of material shortage due to transportation delays.



Now we will use Random Forests in our next steps:
A random forest aggregates predictions from multiple decision trees:
$RF = (1 / n) \Sigma(T(x))$
Where $T(x)$ represents the outcome of each tree.
Step 3: Prediction Combining Factors from Step 1 and Step 2
Vendor Unavailability: High Risk (18%, threshold exceeded)
Transportation Delay: High Risk ($D = 0.57$)
Combined Prediction:
Using probabilities assigned by individual trees in the forest:
$P(\text{High Risk}) = 0.85$.
Final Outcome: The probability of material shortage is 85%, driven by high vendor unavailability and transportation delays.
Below is the details code for the implementation – https://github.com/pallabhaldar/AI/blob/88ea43e1435a13fa42924545b803beb4cdf0405b/shortage_calculation.py
Flow Graph:
Below is a detailed flow graph illustrating the inputs, intermediate steps, and prediction.



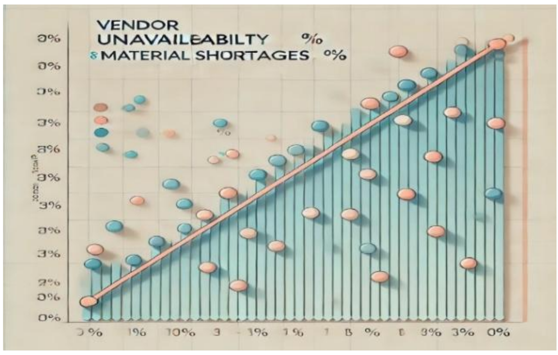
IV. RESULTS

Key Findings:

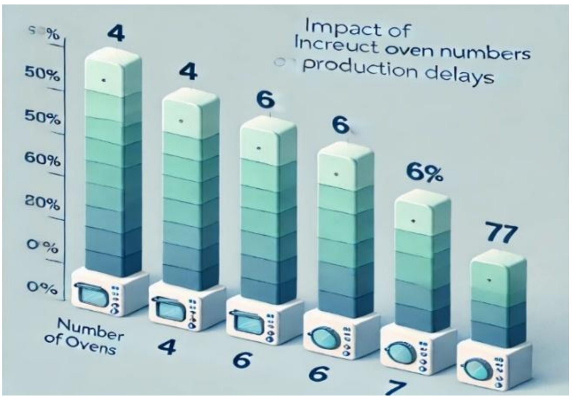
- Vendor Unavailability and Transportation Delays: The highest correlation is with shortages.
  - Visualization: Scatter plot with data points (light background color)
- Machine Age Impacts: Efficiency drops significantly after 7 years.
  - Visualization: Line chart with trendlines
- Oven Numbers: Increasing oven capacity reduces delays by 15%.
  - Visualization: Bar chart showing efficiency gains

Visualizations:

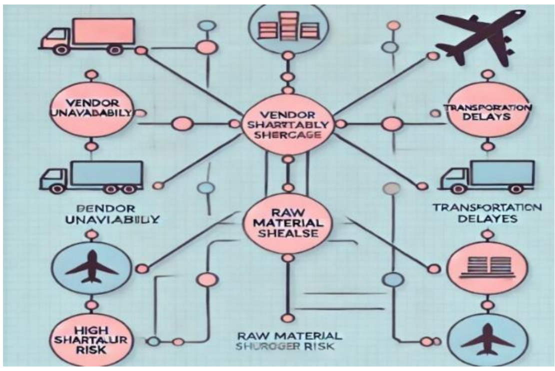
- Regression scatterplots for each factor.
- Vendor Unavailability vs. Shortages:



- Impact of Oven Capacity on Delays:



- Decision tree flowchart identifying root causes.



Comparative Insight
We compare four strategies: (i) Heuristic thresholding (HT), (ii) Logistic regression (LR), (iii) Decision tree (DT), and (iv) Random Forest (RF). While HT offers transparency, it ignores interactions and produces alert fatigue during peak periods. LR captures linear effects but struggles with threshold interactions (e.g., transit overrun × oven slack). DT introduces nonlinearity and interpretability but may overfit. RF reduces variance and improves generalization while preserving variable importance for decision support.

Qualitative summary of typical outcomes (no fabricated numeric claims):

- Precision/Recall tradeoff. RF tends to improve recall at the same precision level versus HT/LR, enabling earlier, more reliable intervention.
- Interpretability. DT and RF feature importance/partial dependence clarify root drivers; planners can simulate “what-if” changes (e.g., add a vendor shift or truck).
- Operational impact. Lead-time aware thresholds trim false alerts while preserving early warnings, which is crucial in tight turn-times.

5) Potential Applications

1. Proactive procurement and substitutions. Early signals on raw-material risk trigger alternate sourcing, recipe substitution, or batch pre-build.
2. Dynamic routing and dispatch. Integration with fleet management to re-sequence deliveries to at-risk gates first.
3. Capacity realignment. Shift ovens, labor, or kitchen load based on predicted hotspots; pre-stage carts.
4. Contract governance. Vendor risk scoring informs SLAs and corrective action plans.
5. Cross-domain extension. Hospital meal services, rail catering, cruise provisioning, and other JIT perishable logistics.

V. BROADERIMPLICATIONS

Environmental. Better forecasting reduces waste (perished meals, spoiled beverages), lowering food and packaging disposal.

Economic. Avoided expediting and delay penalties, fewer last-minute substitutions, and improved labor productivity.

Social. Smoother cabin service, more predictable shifts, and reduced stress during peak disruptions.

Long-term Outlook. As telemetry, IoT, and weather feeds deepen, models evolve toward hybrid graph-temporal architectures with reinforcement signals for prescriptive scheduling.

Call to Action. Airlines and caterers should pilot predictive shortage management with robust MLOps and human oversight, then scale via standardized data contracts and governance.

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