

# US Commercial Aviation Fleet Audit (2024)

7.09M Records | \$4.6 Billion Liability | Python to  
Power BI

# Executive Summary: Fleet Reliability Audit

## SCALE

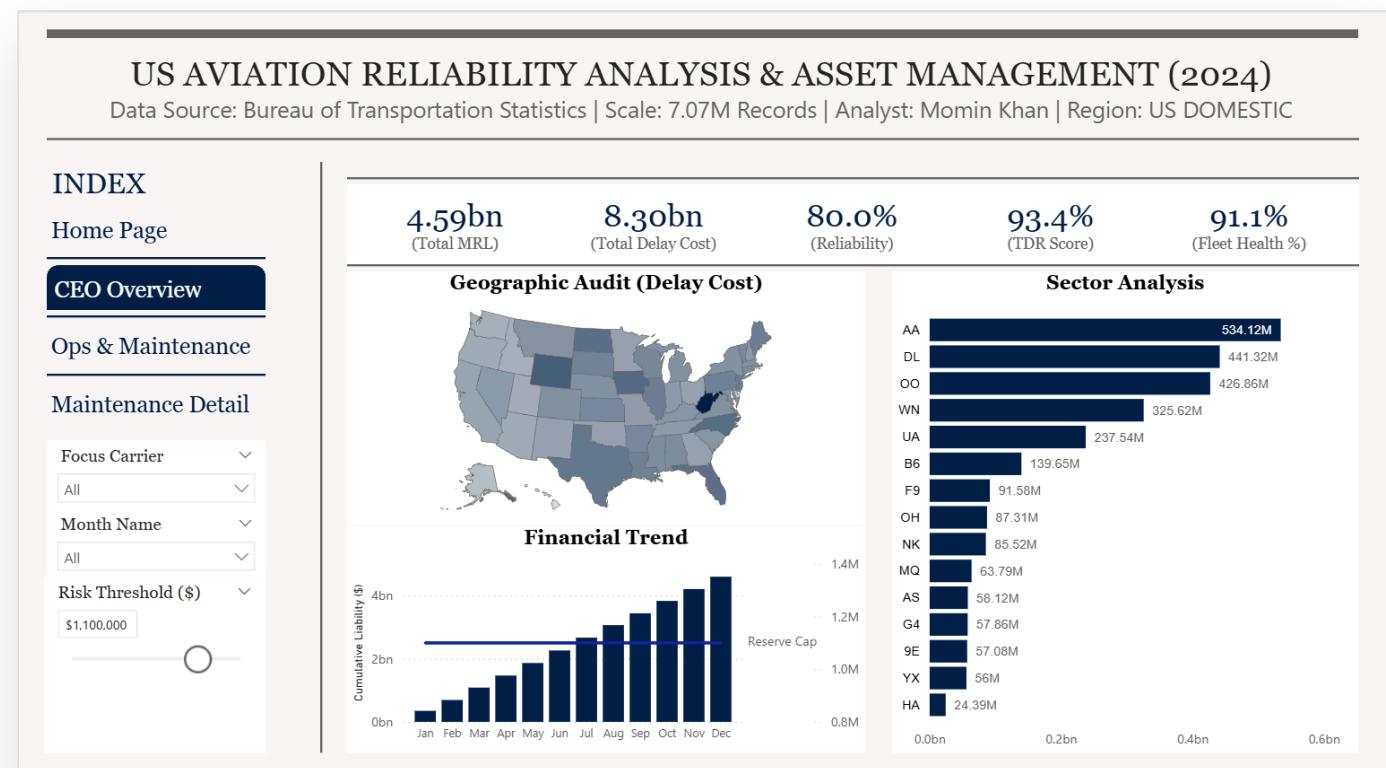
Ingested 7.09M flight records (BTS & FAA) to construct a comprehensive US domestic fleet baseline.

## KPI ENGINEERING

Modeled real-time Technical Dispatch Reliability (TDR) to identify **\$4.6B in delay liabilities**.

## BUSINESS IMPACT

Deprecated legacy Excel workflows, reducing reporting latency from Monthly to Sub-Second.



# Risk Segmentation: Isolating \$150M Exposure

## THE CHALLENGE

Fleet averages hide outliers. We need to find aircraft burning cash faster than they generate revenue.

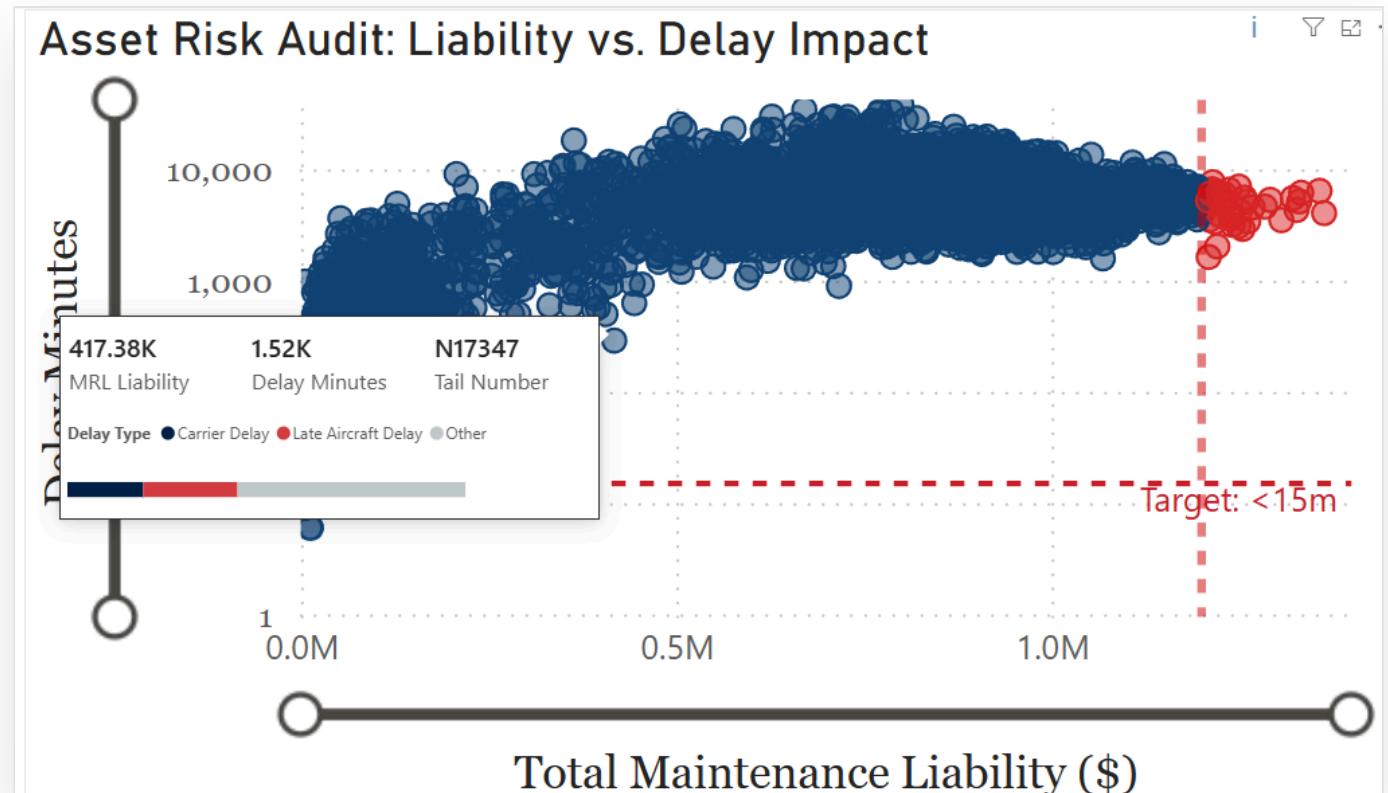
## THE MODEL

A bottom-up "Burn Rate" algorithm calculated for every individual flight leg:

$$\text{Liability} = (\text{Hours} \times \$250) + (\text{Cycles} \times \$180)$$

## PARETO INSIGHT

The Scatter Plot reveals that **5% of the fleet** (top-right quadrant) drives **80% of maintenance risk**.



# Root Cause Forensics: Traceability

## THE PROBLEM

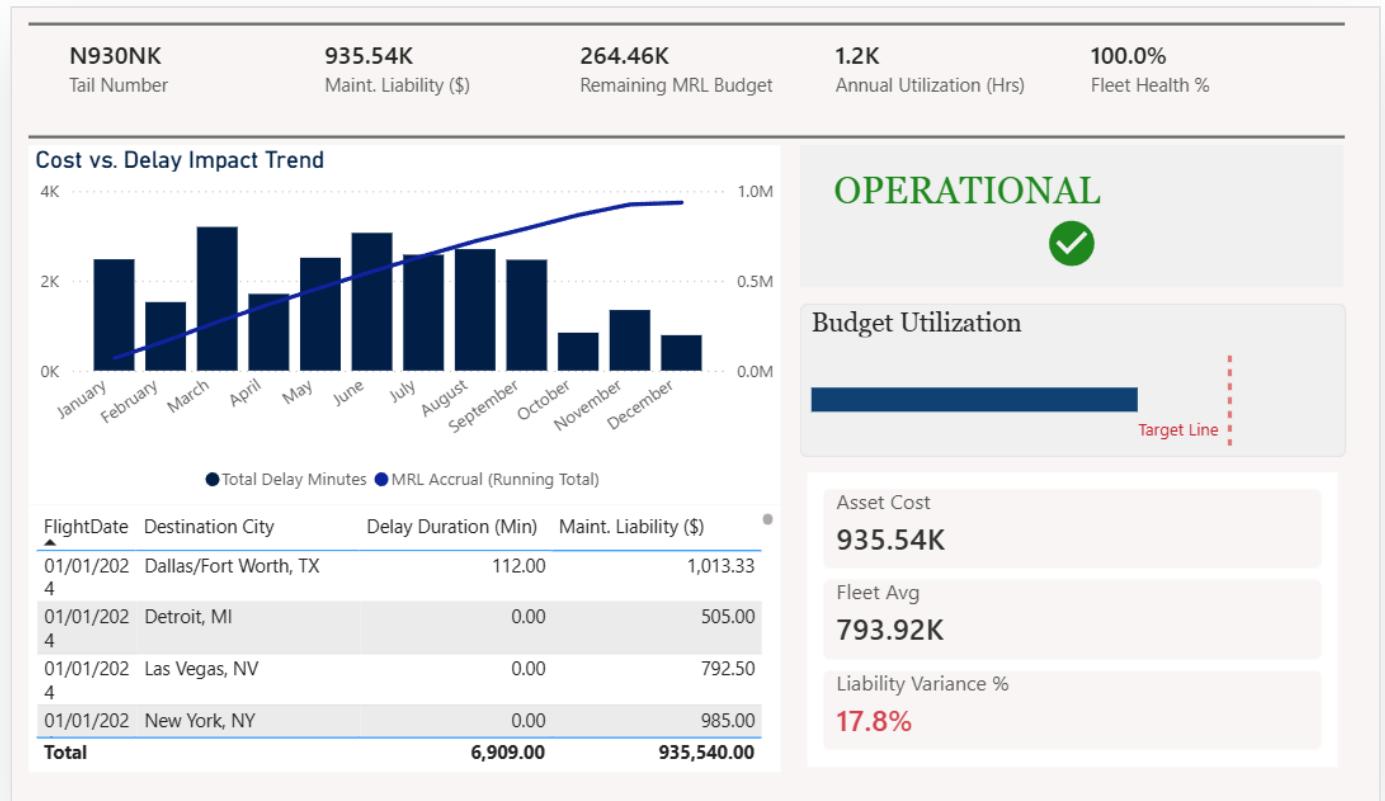
High-level dashboards often fail to explain *why* a metric is red.

## THE SOLUTION

Engineered "Drill-Through" functionality. Right-click any executive metric to jump to the granular flight log.

## DATA INTEGRITY

Validated against "Ghost Aircraft" audits to ensure no flight is attributed to the wrong airframe.



# Engineering Scale: Star Schema Architecture

## THE ARCHITECTURE

Standard Kimball Star Schema.

Optimized for Power BI's VertiPaq engine.

## FACT TABLE

**Fact\_Flights:** Narrow, long table containing integer keys for high-speed aggregation.

## PERFORMANCE RESULT

- Storage: Parquet compression reduced file size by ~85%.
- Speed: Dashboard refresh < 10 seconds.

