**A Data-Driven Flight Difficulty Score to Enhance Operational Efficiency at ORD**

**Project Submission for the SkyHack 3.0 Challenge October 5, 2025**

**1. Executive Summary**

**This report presents a solution to the United Airlines SkyHack 3.0 challenge, which tasked participants with developing a data-driven framework to identify high-complexity flights. Our analysis of two weeks of departure data from Chicago O’Hare (ORD) reveals that nearly 50% of flights depart late, with an average delay of over 21 minutes.**

**The primary drivers of this difficulty are not simply high passenger loads, but rather pre-existing operational constraints, most notably insufficient ground time and complex baggage transfers. By creating a Flight Difficulty Score based on these factors, our model successfully identifies at-risk flights and routes, with flights to St. Louis (STL) consistently ranking as the most difficult. We recommend a shift from a reactive to a proactive model by using this score to deploy targeted resources, beginning with a pilot program on the ORD-STL route.**

**2. Exploratory Data Analysis: Key Operational Questions Answered**

**Our initial analysis focused on answering the core questions posed in the problem statement to establish an operational baseline.**

**Question 1: What is the average delay and what percentage of flights depart later than scheduled?**

* **Answer: The average departure delay across all flights from ORD in the dataset is 21.19 minutes, with 49.65% of flights departing after their scheduled time.**
* **Significance: This establishes the scale of the challenge. With nearly half of all flights facing delays, the issue is systemic. Reducing this average delay can have a significant positive impact on the entire network.**

**Question 2: How many flights have scheduled ground time close to or below the minimum turn minutes?**

* **Answer: A total of 621 flights (7.7% of all flights) had a scheduled ground time *below* the minimum required for their aircraft type.**
* **Significance: This is a critical finding. It reveals that a meaningful portion of delays are a result of an overly optimistic schedule, setting frontline teams up for failure and validating ground\_time\_pressure as a crucial feature for our difficulty score.**

**Question 3: What is the average ratio of transfer bags vs. checked bags across flights?**

* **Answer: The average flight handles 3.05 transfer bags for every one checked (origin) bag.**
* **Significance: This highlights that baggage complexity at a hub like ORD is driven more by connection logistics than by local passengers.**

**Question 4: How do passenger loads compare, and do higher loads correlate with operational difficulty?**

* **Answer: There is a weak negative correlation (-0.16) between passenger\_load\_factor and departure\_delay.**
* **Significance & Graph Analysis: This counter-intuitive insight proves that the simple assumption "fuller flights equal more delays" is incorrect. The scatter plot below shows no clear positive trend; in fact, the densest clusters of high-delay flights occur across all load factors, not just at the highest levels. This suggests that the airline may already allocate more resources to its fullest flights, confirming that passenger load alone is not a sufficient predictor of difficulty.**

***Figure 1: Scatter plot of Passenger Load Factor vs. Departure Delay, showing no strong positive correlation.***

**Question 5: Are high special service request (SSR) flights also high-delay after controlling for load?**

* **Answer: Yes, decisively.**
* **Significance & Graph Analysis: As the bar chart below clearly demonstrates, at every level of passenger capacity (Medium, High, and Very High), flights with a greater number of Special Service Requests (SSRs) have a significantly higher average delay. This isolates ssr\_count as an independent driver of complexity. It’s not just that full flights have more SSRs; an aircraft with many special assistance requests is statistically more likely to be delayed, regardless of how many seats are filled.**

***Figure* 2: Bar chart showing average delay by SSR *category, controlled for passenger load. High SSR flights consistently have higher delays.***

**3. Production-Ready Architecture: A Database-Centric Approach**

**To move this analysis from a one-time script to a scalable operational tool, we designed a robust PostgreSQL database architecture. This approach replaces flat CSV files with a centralized database, offering significant improvements in performance, scalability, and data integrity.**

**The Workflow:**

1. **Storage: Raw data (flights, PNRs, bags) is loaded into structured tables in the database.**
2. **Processing: A Python script queries these tables to load the data into pandas DataFrames.**
3. **Analysis: All data aggregation, feature engineering, and scoring logic is executed within pandas, leveraging its powerful analytical capabilities.**
4. **Persistence: The final flight\_difficulty\_scores are written back into a dedicated table in the database, making the results easily accessible for dashboards, alerts, or further analysis without re-running the entire process.**

***Figure 3: PostgreSQL database schema for storing raw data and final analysis results.***

**4. Methodology: Developing the Flight Difficulty Score**

**Based on our findings, we constructed the difficulty score by assigning weights to the most impactful features. The rationale for this weighting is central to the model's accuracy.**

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| **Feature** | **Weight** | **Why This Weight Was Chosen** |
| **ground\_time\_pressure** | **30%** | **The single strongest predictor. It represents a built-in, non-negotiable risk to on-time performance.** |
| **transfer\_bag\_ratio** | **20%** | **Directly measures baggage complexity, a key operational strain identified in the EDA.** |
| **ssr\_count** | **15%** | **Our analysis proved this is a major, independent driver of delays that reflects service complexity.** |
| **passenger\_load\_factor** | **15%** | **While not the top factor, a fuller plane increases general operational load (e.g., boarding time).** |
| **hot\_transfer** | **10%** | **Represents time-critical baggage transfers that add an extra layer of acute pressure.** |
| **Other Factors** | **10%** | **Minor weights assigned to child\_count and lap\_child\_count to account for gate-side complexity.** |

**5. Flight Difficulty Score Development**

**Question: Build a systematic daily-level scoring approach that resets every day with ranking and classification.**

* **Answer: Our model produces two key outputs daily:**
  1. **Ranking (daily\_difficulty\_rank): Within each day, flights are ordered by their difficulty score in descending order. Rank 1.0 represents the most difficult flight to manage for that day.**
  2. **Classification (difficulty\_class): Flights are grouped into three categories based on their rank distribution: Difficult (top 30%), Medium (next 50%), and Easy (bottom 20%).**

**Data Snapshot**

**The final output is stored in the flight\_difficulty\_scores database table. This table serves as the single source of truth for daily operational planning, providing a ranked and classified list of all departures. It contains the core flight identifiers, the calculated difficulty score and its components, and the final rank and classification.**

**6. Post-Analysis & Operational Insights**

**Question: Summarize which destinations consistently show more difficulty.**

* **Answer: Our analysis shows that operational difficulty is not evenly distributed; it is concentrated on specific routes. Flights to St. Louis (STL) appear as the most consistently challenging destination from ORD, followed by DTW, GRR, and DSM.**

**Question: What are the common drivers for those flights?**

* **Answer: A deep dive into the top difficult route (STL) reveals two primary drivers:**
  1. **Ground Time Pressure: Difficult flights to STL have approximately 41% less ground time buffer than the airport average.**
  2. **Baggage Complexity: These flights handle a 61% higher ratio of transfer bags, indicating intense pressure on the baggage handling system.**

**Question: What specific actions would you recommend based on the findings for better operational efficiency?**

* **Answer: We recommend a shift from a reactive to a proactive operational model with these targeted actions:**
  1. **Proactive Resource Allocation: Use the daily "Difficult" flight list to pre-assign an extra ramp lead or operations coordinator to the top 5 most at-risk flights.**
  2. **Implement a "Priority Transfer Bag" Protocol: For flights with a high transfer\_bag\_ratio score, flag their baggage in the system to be prioritized during unloading from connecting flights.**
  3. **Launch an ORD-STL Pilot Program: Implement the above recommendations as a one-month pilot focused exclusively on the St. Louis route to provide a quantifiable business case for expanding this data-driven methodology across**