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Data-Driven Evaluation of Ground Operations for Enhancing Turnaround Efficiency

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Abstract: In the context of airport logistics, "turnaround time" refers to the interval between an aircraft's landing and its subsequent takeoff. Unfortunately, inefficiencies within these turnaround operations are a major factor behind flight delays. To achieve optimal profitability, airlines must strive to minimize the duration an aircraft remains grounded. Nevertheless, this objective is hindered by the necessity to comply with manufacturer-mandated maintenance procedures, which are vital to ensuring aircraft safety. These activities, outlined in detailed checklists and scheduled by the manufacturer, owner, or operator—under the oversight of certified airworthiness authorities—create significant constraints in reducing on-ground time.

Consequently, streamlining turnaround procedures remains the only controllable aspect through which airlines can improve efficiency and profitability. As air travel serves as a cornerstone of global connectivity, maintaining strict standards for safety and security is indispensable. However, the COVID-19 pandemic has deeply impacted ground handling protocols, prompting the urgent need to revise traditional practices to align with enhanced hygiene and health regulations.

One prominent challenge lies in the passenger embarkation process, which now requires strict physical distancing and thorough disinfection of the cabin after each flight. In response, this study explores potential revisions to in-cabin procedures by comparing them to pre-pandemic turnaround operations. Through a detailed, process-level examination, we identify individual touchpoints and suggest strategic adjustments aimed at improving operational efficiency.
Our findings indicate that boarding durations have increased significantly—more than twice the usual time—due to social distancing mandates. Despite introducing various procedural changes, sustaining previous turnaround benchmarks while maintaining full passenger capacity remains problematic. Nevertheless, adopting alternative strategies—such as maintaining vacant middle seats (reducing capacity to approximately 67%) and boarding from apron stands using both front and rear doors—can help mitigate delays and support smoother aircraft turnaround operations.

Keywords: Aircraft, Turnaround Operations, Air Travel, Turnaround times, Cabin, Post-Pandemic World

I. INTRODUCTION

To remain profitable, airlines must prioritize maximizing the duration aircraft spend in the air. However, a significant portion of an aircraft's operational cycle is spent on the ground, especially during routine maintenance and turnaround activities. Therefore, to improve overall efficiency and profitability, reducing ground time becomes essential. Nonetheless, several safety-critical maintenance checks—such as A-checks and C-checks—are mandatory as per manufacturer guidelines and cannot be shortened, posing limitations on minimizing ground time.

As a result, airlines need to concentrate on shortening turnaround time, the only variable within their operational influence. Turnaround includes a series of tasks that must be completed before the aircraft can depart again—such as refueling, loading and unloading luggage, onboarding and offboarding passengers, catering services, and performing line maintenance inspections.

Delays during this period can trigger a cascade of disruptions, often termed as "reactionary" or "knock-on delays", which significantly affect both airline operations and passenger schedules—especially at major hubs. These disruptions are exacerbated when air traffic control (ATC) must reschedule flights and allocate new time slots, a process that can take up to an hour. Financially, such delays are costly—amounting to approximately £650 million annually, with each minute of delay incurring around £50 in losses.

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Minimizing turnaround durations can help curb these financial losses and improve airline profitability. Therefore, tackling the variables that impact turnaround efficiency remains a pressing concern for the aviation industry. In response to this, the present study investigates strategic solutions for minimizing delays and optimizing the aircraft turnaround process. With profitability hinging on operational efficiency, most airlines are now focusing on shortening turnaround intervals and extending airborne time to gain a competitive edge.

II. AIR TRANSPORT TURNAROUND PROCESS

The duration required to offload an aircraft at the gate and ready it for its next departure is referred to as the aircraft's turnaround time. Since aircraft turnaround protocols vary across airports, each turnaround process is unique. At Fly Airways, the turnaround workflow is primarily categorized into three major segments: ramp services, cabin activities, and fueling procedures. These tasks are executed simultaneously, as depicted in Figure 1. The diagram illustrates the specific time allocation designated for each task within these three segments.

The process begins with the positioning of the aerobridge or air-stair at the aircraft's front left door. Once connected, a flight attendant opens the door and instructs passengers to disembark with their carry-on belongings. After all arriving passengers have exited, the cabin crew alerts the cleaning personnel to board and initiate the cleaning operations. Following this, the flight crew also disembarks, enabling the cleaning team to commence sanitation procedures. During this process, they also perform a safety inspection, which involves thoroughly checking lavatories and all seats for prohibited items or potential threats.

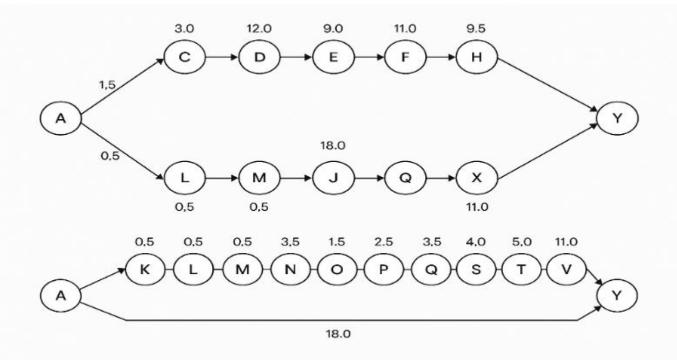

Figure 1 Air Transport turnaround operations (in minutes)

Afterward, the flight attendant closes the left front door of the aircraft, withdraws the aerobridge or air-stair, and shuts any remaining open overhead bins. The fueling process is handled by a third-party contractor contracted for this task. Fly Airways follows a specific set of operational protocols for fueling its aircraft. Fuel is loaded onto the aircraft using a large hose according to these procedures, and the hose is removed once the fueling is completed.

The process of ramp operations (shown in Figure 4a, b) starts with the transfer of vans used for carrying baggage and a belt loader to the aircraft's rear bin. To begin unloading bags, the belt loader is positioned at the bin and the bags move down the belt loader. An operator carefully stacks each piece of luggage onto the baggage van at the bottom of the loader. When the van is filled, it moves the arriving luggage to the airport's assigned conveyor belt, where travelers can pick it up.

Figure 2 Ramp operations. a Movement of baggage carry van and belt loader. b Baggage transported to the airport from baggage bins in aircraft

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Once the bags in the rear bin are completely unloaded, the same procedure is carried out for the front bin. When both bins have been emptied, the luggage retrieval process for arriving passengers is finished. The following step involves organizing the luggage based on the destinations of departing passengers.

III. AI-DRIVEN SOLUTIONS TO REDUCE AIRCRAFT TURNAROUND TIME

To maintain profitability, both airports and airlines must ensure efficient aircraft turnaround operations. As the demand for faster service grows, ground support teams face mounting pressure to minimize delays while upholding rigorous safety standards to avoid preventable accidents. Given the complexity of these operations, identifying opportunities for improved efficiency can be challenging.
Artificial intelligence (AI) offers valuable tools to enhance operational insight, improve safety, and enable real-time monitoring and staff training. Here are key ways AI can help optimize turnaround times:

Key Strategies for AI Integration:

- Conduct thorough audits and detailed operational analyses.
- Enhance safety protocols for ground handling crews.
- Leverage training content to deepen operational understanding.
- Implement real-time monitoring of turnaround procedures.

Operational Assessment and Optimization

Delays in turnaround often result from risky or inefficient actions by ground support teams. AI platforms like Synaptic Aviation provide continuous monitoring throughout the turnaround cycle, enabling early identification and resolution of bottlenecks. Through video analysis and full-process audits, AI can assess team interactions and operational effectiveness.

Improving Ground Crew Safety

Approximately 80% of incidents occur on the gate and apron, frequently resulting in delays. To improve turnaround time, strict safety measures must be enforced. AI systems enhance proactive safety management by instantly flagging unsafe behaviors—such as reckless driving near aircraft—allowing immediate intervention to prevent accidents.

Enhancing Training with Real-World Insights

AI can also serve as a powerful training tool. Synaptic Aviation’s platform audits video footage and alerts, providing meaningful examples for educating ground crews. These recordings allow managers to demonstrate best practices—and what to avoid—during onboarding or refresher sessions.

Real-Time Turnaround Monitoring

Effective communication and coordination are critical during turnaround. AI facilitates this by enabling real-time data collection and alerting, helping teams promptly address any operational disruptions, unsafe behaviors, or equipment issues. This not only enhances safety but also supports faster and more consistent aircraft turnaround.

IV. DATASET DESCRIPTION

For this research, we utilized a comprehensive dataset comprising over 7 million records related to flight arrival delays across 18 Indian airlines. Each record provides monthly summaries of delays experienced by specific airlines at particular airports.
Spanning from August 2013 to August 2023, the dataset offers insights into airline performance across different Indian airports, with a primary focus on arrival delays. It includes metrics such as total arriving flights, delays exceeding 15 minutes, cancellations, and diversions. Contributing factors such as National Airspace System (NAS) issues, weather disruptions, airline-related delays, security problems, and late-arriving aircraft are also captured.
This dataset serves as a rich resource for researchers, data scientists, and aviation professionals seeking to uncover trends, identify delay causes, and develop predictive models for operational improvements.

Structure:

The dataset is structured as a tabular format with rows representing unique combinations of year, month, carrier, and airport. Each row contains information on various metrics, including flight counts, delay counts, cancellation and diversion counts, and delay breakdowns by different factors. The columns provide specific details such as carrier codes and names, airport codes and names, and counts of delays attributed to carrier, weather, NAS, security, and late aircraft

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arrivals. The structured format ensures that users can easily query, analyze, and visualize the data to derive meaningful insights.

Metadata
FL_DATE = Date of the Flight
OP_CARRIER = Airline Identifier
OP_CARRIER_FL_NUM = Flight Number
ORIGIN = Starting Airport Code
DEST = Destination Airport Code
CRS_DEP_TIME = Planned Departure Time
DEP_TIME = Actual Departure Time
DEP_DELAY = Total Delay on Departure in minutes
TAXI_OUT = The time duration elapsed between departure from the origin airport gate and wheels off
WHEELS_OFF = The time point that the aircraft's wheels leave the ground
WHEELS_ON = The time point that the aircraft'ss wheels touch on the ground
TAXI_IN = The time duration elapsed between wheels-on and gate arrival at the destination airport
CRS_ARR_TIME = Planned arrival time
ARR_TIME = Actual Arrival Time = ARRIVAL_TIME - SCHEDULED_ARRIVAL
ARR_DELAY = Total Delay on Arrival in minutes
CANCELLED = Flight Cancelled (1 = cancelled)
CANCELLATION_CODE = Reason for Cancellation of flight: A - Airline/Carrier; B - Weather; C - National Air System; D – Security
DIVERTED = Aircraft landed on different airport that the one scheduled
CRS_ELAPSED_TIME = Planned time amount needed for the flight trip
ACTUAL_ELAPSED_TIME = AIR_TIME+TAXI_IN+TAXI_OUT
AIR_TIME = The time duration between wheels_off and wheels_on time
DISTANCE = Distance between two airports
CARRIER_DELAY = Delay caused by the airline in minutes
WEATHER_DELAY = Delay caused by weather
NAS_DELAY = Delay caused by air system
SECURITY_DELAY = caused by security reasons
LATE_AIRCRAFT_DELAY = Delay caused by security

V. ARCHITECTURE

Our proposed interactive ‘Turnaround Airlines’ system architecture is designed to streamline and enhance the aircraft turnaround process using data-driven intelligence. This architecture is structured into three core phases, as illustrated in Figure 5 (referenced in the original text). Each phase plays a crucial role in ensuring accurate delay prediction, better reporting, and improved operational efficiency.

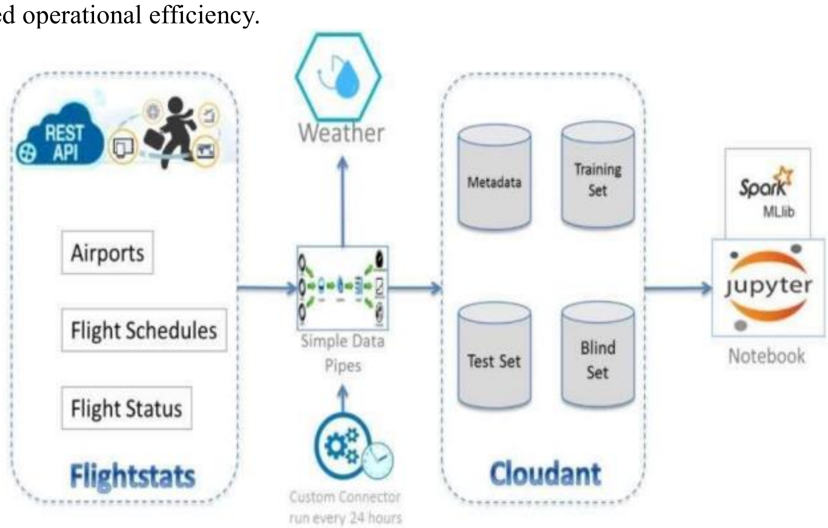

Figure 3 Architecture of Airlines Turnaround Time Estimation

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Phase 1: Data Collection Layer

The first layer of the system focuses on comprehensive **data acquisition**. This involves collecting real-time and historical operational data from **multiple airports** across the country. The types of data include:

- Flight schedules and statuses (arrival, departure, gate time)
- Delay incidents and causes
- Weather conditions
- Ground crew activity logs
- Air Traffic Control (ATC) updates
- Resource allocation (e.g., gate assignments, equipment usage)

Additionally, data from the **National Airspace System (NAS)** is integrated. NAS provides high-level information about airspace usage, traffic flows, and systemic delay sources (e.g., congestion or rerouting due to weather).

This multi-source data collection creates a **massive, heterogeneous dataset** that represents both localized airport operations and broader, system-wide influences.

Phase 2: Data Analysis and Processing Layer

Once data is gathered, the system moves into the **analysis phase**. In this layer, sophisticated **machine learning and AI algorithms** are applied to process and extract meaningful patterns from the large dataset. Key functions in this phase include:

- **Data cleaning and normalization**: Ensuring the quality and consistency of data across all sources.
- **Feature engineering**: Identifying the most relevant factors (weather, crew delays, equipment unavailability, etc.) that influence turnaround time.
- **Predictive modeling**: Using historical trends and real-time inputs to **forecast future delays** at both individual airports and across the entire network.
- **Anomaly detection**: Flagging unusual behaviors or patterns that could indicate operational inefficiencies or potential safety risks.

This analytical layer transforms raw data into actionable insights that can support decision-making and proactive management.

Phase 3: Insights, Reporting, and Forecasting

The final phase utilizes the processed data and model outputs to generate **future-oriented insights**:

- **Delay prediction**: Identifying flights or airports at high risk of delay in advance.
- **Operational reports**: Producing real-time dashboards and post-operational summaries for airline and airport management.
- **Strategic planning support**: Offering long-term forecasts and recommendations for infrastructure, staffing, and scheduling improvements.

This interactive system enables continuous learning and feedback, allowing stakeholders to not only respond to current issues but also anticipate and mitigate future challenges.

VI. DATA AND RESULT ANALYTICS

As shown in Figure 4 is self-explanatory and easy to interpret. It clearly highlights the top five airlines with the highest number of flights which we have used in our research:

- Southwest Airlines
- Delta Airlines
- American Airlines
- SkyWest Airlines
- United Airlines

At this point, no further analysis is necessary. I will revisit this list after reviewing additional plots to provide more context and insights.

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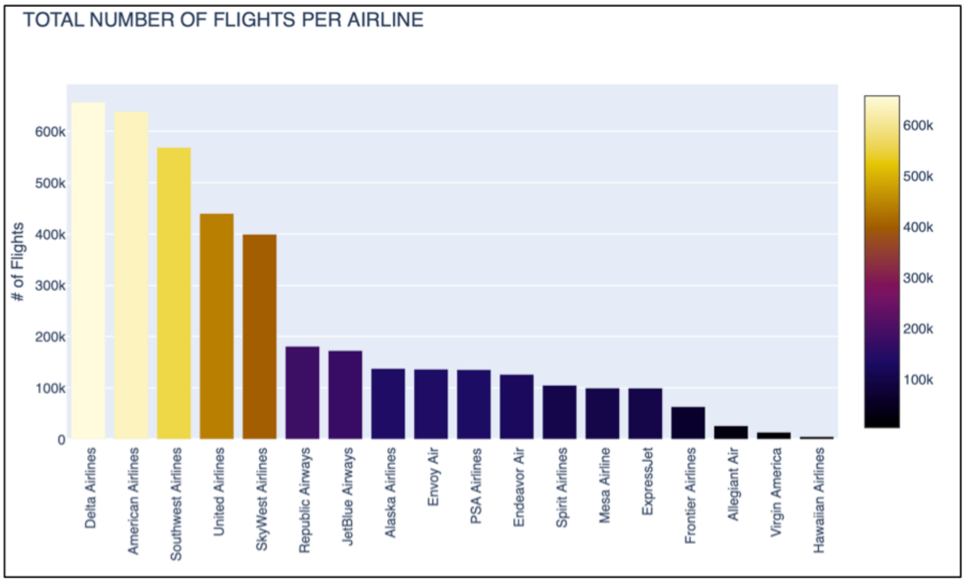

Figure 4 Total number of flights by airline sorted is descending order

The statement refers to a **summary figure** that presents the **performance evaluation results** for a specific machine learning model, identified as **Model_5**, which belongs to the **second set of models** developed during the research or experimentation process.

Below, Figure is the model performance evaluation summary

This indicates that the figure shown directly below this text (possibly in a thesis or report) contains quantitative results used to assess how well the model performs. These results typically include **evaluation metrics** such as:

- Accuracy
- Precision
- Recall
- F1-score
- Root Mean Square Error (RMSE)
- Mean Absolute Error (MAE)
- R^2 Score (for regression models)
- Confusion Matrix or ROC-AUC curve (for classification models)

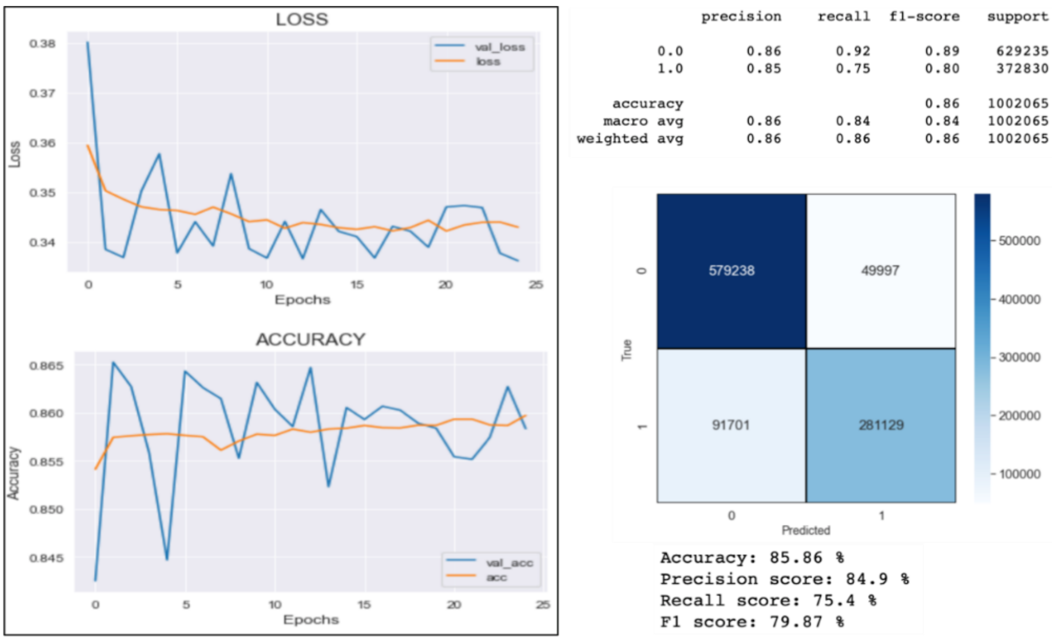

Figure 5.5: Model 5 performance summary

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Selecting the best model based on performance metrics is a **critical step** in any data science or machine learning project. The chosen model (Model_5, in this case) will likely be used for:

- **Making predictions on future data**
- **Generating insights**
- **Informing decision-making processes**
- **Being deployed into a real-time or production environment**

VII. FUTURE SCOPE

While delays may result from Air Traffic Control (ATC) operations, a well-planned flight schedule can greatly improve punctuality. Returned aircraft schedules with enough buffer time increase the dependability of airport flight connections. Using this method helps airlines keep a positive customer reputation for on-time performance while cutting operational costs by optimizing aircraft rotation schedules within their flight networks.

VIII. CONCLUSION

The key conclusions derived from the conducted interviews provide valuable insights into aircraft servicing and maintenance practices. These findings highlight the crucial role that technicians' firsthand experiences and expertise play in shaping more efficient and effective maintenance procedures.
By incorporating the perspectives and recommendations of technicians—those directly involved in day-to-day operations—organizations can enhance the accuracy, responsiveness, and practicality of maintenance protocols. This integration not only improves operational workflows but also contributes to greater safety and reliability in aircraft performance.

The **Results and Discussion** section has been carefully structured to present the interview findings in a clear and logical manner. This format allows for a comprehensive analysis of how these insights can be applied within the aviation maintenance domain. It ensures that the relevance of each conclusion is thoroughly examined, linking qualitative input from professionals to tangible improvements in aircraft servicing strategies.
Various interviews, along with their implications for servicing and maintaining aircraft helped in concluding. The integration of technician insights into maintenance procedures is emphasized as a means of improving efficiency and effectiveness. Clear presentation of the interview results and a thorough analysis of their applicability to the field of aircraft servicing and maintenance are made possible by the Results and Discussion section's structured format.

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