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Identifying Maintenance, Repair and Overhaul Events based on ADS-B Data

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Abstract
Maintenance, Repair and Overhaul (MRO) plays a big role in aviation schedules and operational costs. In this work service difficulty reports are combined with aircraft ADS-B data to identify MRO activity based on an aircraft's layover information. The "Inspection/Maintenance" stage of operation and date of service difficulty reports allow to label layovers from ADS-B with the presence of MRO activity. Using a support vector machine this work classifies layovers based on their duration and time of day, achieving an 86% overall accuracy and 78% balanced accuracy. These results reflect the difficulty of working with this sparse and incomplete dataset, however, they allow to study MRO schedules. The combination of these data sources offers new opportunities to find relations between aircraft trajectory information and MRO, which will be further investigated in future work.

Keywords: Maintenance, Repair and Overhaul; ADS-B; OpenSky; Service Difficulty Reports

Abbreviations: ADS-B: Automatic Dependent Surveillance - Broadcast MRO: Maintenance Repair and Overhaul, FAA: Federal Aviation Administration, SDR: Service Difficulty Report

1. Introduction

Maintenance, Repair and Overhaul (MRO) has a large impact on an aircraft's operational costs and schedule. While each operator has information regarding MRO of their own fleet and each MRO service provider has information regarding all the services they performed on an aircraft, the MRO service provider does not always have the information of MRO services performed at different providers, as this has to be delivered by the operator. Aircraft manufacturers define intervals for maintenance events and checks; however, an operator might choose to perform tasks in advance if they need the aircraft around the time of the deadline. Furthermore, during aircraft operations, unscheduled maintenance events may occur. As such, maintenance events cannot reliably be identified based on a manufacturer-defined timeline. In this work, we propose a solution to identify MRO activities based on an aircraft's whereabouts. This allows us to study actual MRO schedules and find patterns in aircraft trajectories that indicate the need for maintenance. For this purpose, the following two large public data sources are combined: the OpenSky Network[1] for Automatic Dependent Surveillance-Broadcast (ADS-B) and aircraft data and Service Difficulty Reports (SDRs)[2] to identify MRO activity.

2. Service Difficulty Reports

Aviation regulatory bodies define specific conditions in which a certificate holder is obliged to file a report of operational and structural difficulties[2][3]. The Federal Aviation Administration (FAA) publishes these reports in their Service Difficulty Reports database[1]. This is a structured database where a range of information is provided together with the report itself, which is in free-text form. Among the information provided in these reports are:

- during what stage of operation the difficulty occurred or was found
- identification of the aircraft
- date of difficulty
- number of flight hours and flight cycles flown before difficulty was found

For the purpose of this work, 59 656 reports of the Airbus A320 family were considered in the time frame between January 2016 and June 2023.

70% of the reports state the difficulty was identified during the "Inspection / Maintenance" stage of operation, however, this can range from a daily check to heavy maintenance visits. These reports were used to label a layover as MRO activity and will be further referred to as "inspection reports".

3. ADS-B Data and Layover Information

Through the OpenSky Network[1] information is obtained regarding the location of the aircraft, the duration of the layover at the time of the difficulty. Using the pyopensky[2] library all flights involving the 1 674 aircraft of which at least one inspection report has been filed were downloaded. For each aircraft, the estimated arrival airport and estimated departure airport of two consecutive flights are compared. If both airports are defined and coincide, or if only one of the airports is defined a layover is identified. For each layover, the following parameters are extracted:

- The aircraft which the layover concerns
- The Airport in which the layover took place
- The start of the layover ("lastseen" value of the first flight)
- The end of the layover ("firstseen" value of the consecutive flight)
- The duration of the layover (by subtracting the start of the layover from the end of the layover)

If the difficulty date lies within the timeframe between the start (rounded down to the day) and end (rounded up to the day) of a layover, this layover is marked as having an inspection and the layover details are linked to the SDR entry. Out of 9 543 009 flights, 6 998 227 layovers were found, 93% of reports could be mapped to a corresponding layover.

4. Identification of layovers with MRO activity

Several layover features were considered for the identification of MRO activity, however, some proved to be inapplicable. Flight cycles are a commonly used metric for MRO scheduling[4]. As the reports state the aircraft flight cycles, this number can be compared to the number of flights that have been identified in the ADS-B data up to the layover related to the inspection report. However, comparing the offset between the number of flights in ADS-B data and the flight cycles in reports, the average standard deviation per aircraft is of 400 flight cycles. While the age of the aircraft can be an important feature, the manufacturing year, as provided by the OpenSky[1] aircraft database. However, for inspections, the age of the aircraft in months is considered[4]. This means that the

[1] https://sdrs.faa.gov/ accessed on 25/10/2023
[2] https://github.com/open-aviation/pyopensky

aircraft age would have an error of up to 11 months. The presence of MRO sites was also considered since the FAA publishes a list of certified repair stations[3]. However, each certificate is related to a single address, whereas certificate holders might perform repairs at several sites and subcontract non-approved workshops at their own approval. As such the features used for classification are layover duration and time of day. Their distribution can be seen in Figure 1.

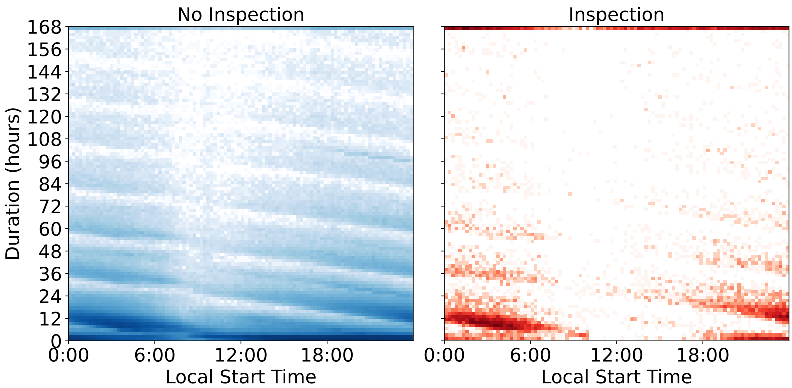

Figure 1. 2-dimensional histogram of the density distribution of layover duration and time of day at which the layover started.

The layover duration was clipped at 1 weak and both features were normalised to fit the range between 0 and 1, this produces a 2-dimensional input dataset for binary classification, whether the layover had at least one inspection report or not.

The dataset, however, presents several difficulties, including a large class imbalance, as only 0.2% of layovers were identified as inspection. While inspections occur in the minority of layovers, the imbalance is partially due to the fact that not every inspection leads to the filing of a report. To address the class imbalance the dataset is resampled to increase the inspection rate. After which they were given to a support vector machine with radial basis function kernel and C-support, implemented using scikit-learn[5].

hyper-parameter	value
C regularisation parameter	25
gamma regularisation parameter	0.1
resampling inspection rate	0.1
maximum iterations	7 000
single class c regularisation	“balanced”

Table 1. Optimal hyper-parameter configuration

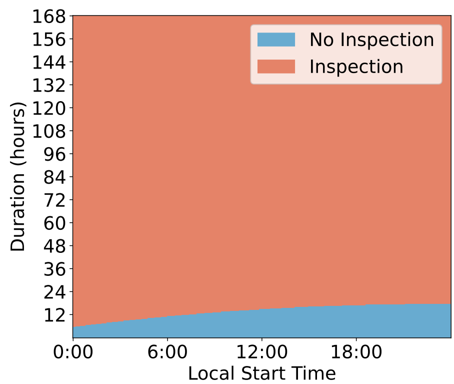

Figure 2. Decision boundaries

After a hyper-parameter grid search the optimal set of hyper-parameters was found and is shown in Table 1. The results obtained with this model are an overall accuracy of 86% and 78% balanced

[3] https://av-info.faa.gov/RepairStation.asp accessed 09/08/2023

accuracy, averaged per class. The decision boundaries obtained by the support vector machine can be seen in Figure 2.

5. Conclusion

The dataset in question presents several difficulties which are reflected in the results.

- "Inspection/Maintenance" can be anything ranging from a daily check to a heavy maintenance visit (although the chances of a report being filed during longer checks is higher)
- many inspections do not lead to a report being filed
- class imbalance

To address the first two and to further verify the performance of this model, and improve it, it is necessary to obtain an exhaustive list of MRO activity for several aircraft, which can only be provided by an operator. Nonetheless, these results allow us to analyse maintenance schedules and show that using layover duration alone, the most intuitive approach, is not sufficient. The main result of this work, however, is the combination of these two data sources, which will allow us to study the impact of an aircraft's whereabouts on its degradation and MRO activity from different perspectives in future work.

Author contributions

- Emy Arts: Conceptualization, Methodology, Data curation, Software, Writing–Original draft
- Hendrik Meyer: Conceptualization, Writing–Review & Editing
- Florian Raddatz: Resources, Writing–Review & Editing
- Gerko Wende: Resources

Open data statement

The data used for this publication can be downloaded from https://sdrs.faa.gov/, https://opensky-network.org/ and https://ourairports.com/.

Reproducibility statement

All source code necessary to reproduce this research and the figures in this work, as well as instructions on how to access the databases, can be found at https://github.com/DLR-MO/OSN-SDR [6]

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