Final Project

Due: Nov. 27, 2025

After reading through several studies, I landed on a case study from Informs on American Airlines engine maintenance[1]. Engines are expensive and their maintenance is critical for air safety therefore, their maintenance is highly regulated especially for commercial flights[2,3]. However, there are different levels of maintenance from minor to full rebuilds and per the report these might occur in different locations. This complicated environment would benefit from using analytical methods. A possible pipeline is outlined in this report.

1 Determination of repair measurables distributions

- Given:
    - Historical repair metrics (repair times, scrapping rates, repair probabilities) which in addition to being listed in the case study as inputs are also required by FAA regulation[4].
    - Engine model and operating conditions. In modern commercial aircraft, telemetry data is required to be generated and stored in the "black box," so this data is likely already being collected by airlines.
- Use probabilistic programming – I am partial to hierarchical modeling using Bayesian Markov chain Monte Carlo to extract as much common information as possible given data limitations[5].
- To create probability distributions of the observed metrics of the repair process

2 Optimization of repair resources

- Given:
    - Estimated repair times, scrapping rates, repair probabilities determined from the probabilistic repair models and current fleet engine models and operating conditions
    - Cost of maintaining stock and labor at different locations
    - Opportunity cost of aircraft downtime
- Use linear programming
- To estimate schedules and material that should be kept in stock to perform maintenance at minimum lost profit

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[1] https://www.informs.org/Impact/O.R.-Analytics-Success-Stories/Overcoming-the-Challenges-of-Aircraft-Engine-Maintenance-and-Repair
[2] https://www.ecfr.gov/current/title-14/chapter-I/subchapter-C/part-43
[3] https://www.faa.gov/sites/faa.gov/files/12_amtp_ch10_0.pdf
[4] https://www.faa.gov/sites/faa.gov/files/Paper-Maintenance-Logs-SOP_0.pdf
[5] https://www2.stat.duke.edu/courses/Fall21/sta601.001/slides/07-hierarchical-models-handout.pdf

3 New parts or engines evaluation

The team also mentions prescriptive analytics – what-if scenarios to evaluate new parts or engines. After the models from 1 and 2 are validated they can be used for this purpose alongside the ongoing inference from 2.

- Given:
    - Probabilistic models of repair
        - Note: A key benefit of using hierarchical modeling is the ability to use incomplete information to estimate resulting distributions, making it an especially strong candidate for these sorts of what if scenarios.
    - Distribution of fleet telemetry to use as inputs to the model
    - Cost of newly proposed parts
- Use statistical metrics (expectation values and confidence intervals)
- To estimate whole cost of ownership of new engines/parts compared to current fleet.

4 Drawbacks, and additional comments

- Bayesian Markov chain Monte Carlo: a downside of MCMC models is that individual chains must be run sequentially, making these models slow to train.
- Bayesian models can be overconfident depending on the depth of training data. Ensemble "stacking" methods can be used to combat this tendency[6].
- These models should be reevaluated on a reasonable timescale (possibly on the order of a repair cycle, although that is just a guess) to determine if parts of the pipeline need retraining. Automatic drift detection could also be implemented to enable continuous quality monitoring. System disturbances such as significant increases in input costs, introduction of new engines, etc. should also prompt retraining.
- Models must be validated to ensure they don't compromise safety for cost savings.

[6] https://sites.stat.columbia.edu/gelman/research/published/stacking_paper_discussion_rejoinder.pdf