PhD Open Days

An Integrated Methodology for Aircraft Maintenance Planning and **Scheduling Under Uncertainty**

MIT Portugal EDAM, Leaders for Technical Industries Doctoral Program

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Introduction

Aircraft maintenance comprises scheduled and unscheduled maintenance. Scheduled maintenance refers mainly to prespecified inspections carried out at predetermined intervals, being the workload essentially deterministic. Unscheduled maintenance, which results from scheduled maintenance and depends on the probabilistic nature of failures, presents a workload inherently stochastic. This fact results in a high degree of uncertainty when planning the maintenance work. On the one hand, this may originate capacity problems, in which the planned resources are insufficient, or otherwise excessive, to perform the actual work. On the other hand, scheduling problems may also occur, in which potential constraints in the execution of the work are not taken into account. Based on real data from a Portuguese Maintenance, Repair and Overhaul (MRO) company, this work addresses these problems by proposing an integrated methodology comprised by: (1) a framework for maintenance work characterization; (2) Bayesian networks (BNs) for capacity planning; and (3) an extension to BN for estimation of future and unprecedented maintenance events.

A Framework for Maintenance Planning and Scheduling

The developed framework, entitled FRamework for Aircraft Maintenance Estimation (FRAME), comprises a set of requirements for the treatment and recording of maintenance data, and a method for data analysis. The established requirements address shortcomings found in literature and in collected data. The data analysis method, entitled 3-Dimensional Maintenance Data Analysis (3D-MDA), consists in a space-time-skill coordinate system intended to be used for the qualitative and quantitative characterization of the expected maintenance work, including risk assessment regarding workload impact, as presented in Figure 1.

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Figure 2 – BN for aircraft maintenance capacity planning

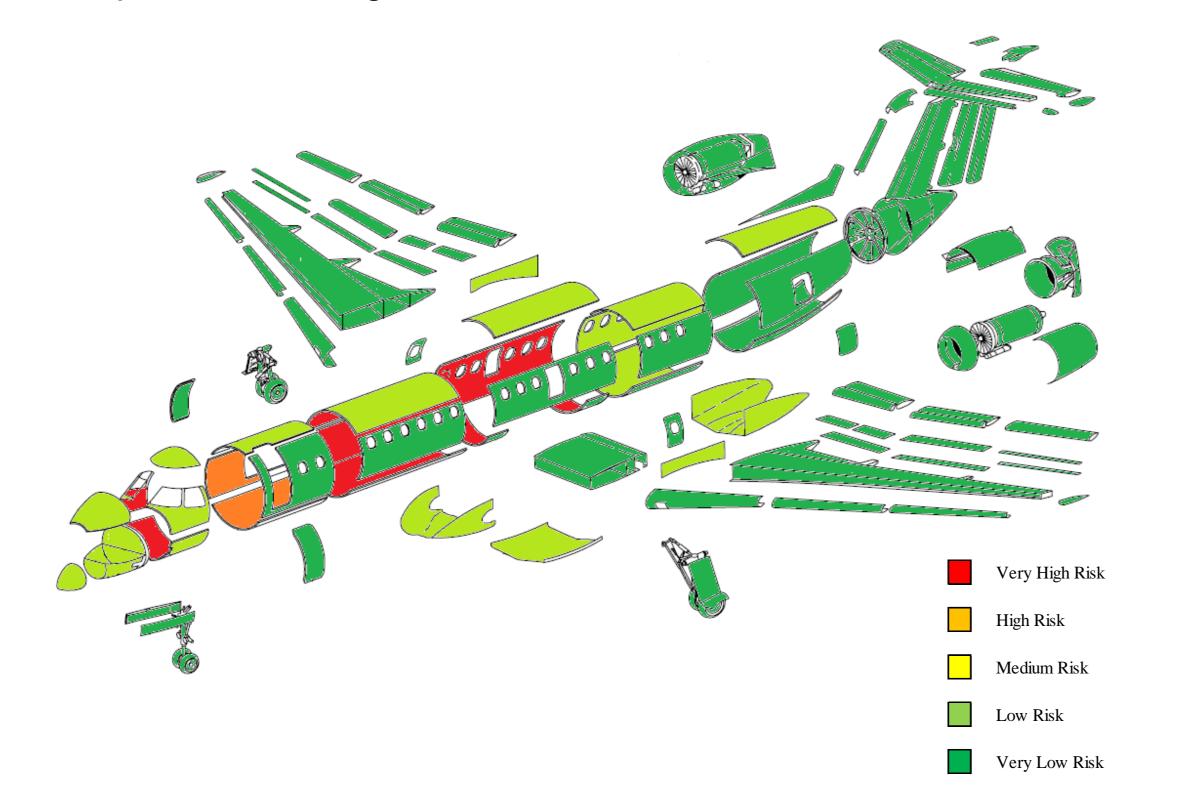


Figure 1 – Risk assessment performed with the 3D-MDA

Extending BNs through Forecasting and MC Simulation

By only using data generated and stored during the maintenance planning process, BNs are limited to the probabilistic inference of maintenance events that have already occurred, not allowing workload estimations of future and unprecedented events. In order to overcome such limitation, forecasting models and Monte Carlo (MC) simulation have been explored in this work as means to predict the workload of future events. Accurate results have been obtained with state space formulations of exponential smoothing forecasting models, which allow complete probability distributions of workloads to be estimated. Then, MC simulation models generate simulated maintenance events according to the forecasted distributions with the goal of uploading such simulated events in BNs for capacity planning, as the one presented in Figure 2.

Conclusion

Capacity planning and tasks scheduling are important problems faced by aircraft MROs. However, current maintenance management tools and processes prove to be inadequate to deal with the complexity and stochasticity involved. Contributing factors to this include the lack of reliable forecasts, the uncertainty about maintenance workloads, the types of contracts and clauses, and the constraints on the allocation of resources. This work addresses these problems by allowing MROs to gain a detailed picture about the content and scope of maintenance interventions early in the planning process. First, FRAME enables the qualitative and quantitative characterization of the expected maintenance work with an adequate level of detail and tractability. Second, BNs allows MROs to cope with the uncertainty of maintenance workloads and improve the planning decision-making process based on incomplete information. Finally, forecasting models and MC simulation greatly extend the capabilities of BNs by allowing unprecedented maintenance events to be estimated. With the proposed methodology, MROs are expected to make better and more coherent decisions throughout the maintenance planning process, and, as a result, to improve their overall efficiency and to promote the on-time completion of maintenance projects.

Bayesian Networks as a Big Data Tool

Despite the considerable amount of data generated and stored during the planning process, these have yet to provide a decisive competitive advantage to aircraft MROs. BNs have been explored in this work as a big data and predictive analytics (BDPA) tool to improve the MROs maintenance planning process based on incomplete information. The developed BNs consider input variables such as the aircraft operator, the maintenance event, the aircraft version, and the aircraft utilization. Evidences are provided to these variables in order to infer a given set of output variables such as total workload and workload per maintenance work phase, as presented in Figure 2.

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