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KEEPING THEM FLYING: PREDICTING SPARE PARTS INVENTORY FOR JET FIGHTERS USING SAS

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ABSTRACT

An effective preventive maintenance practice is expected to maximize asset uptime while minimizing need to hold large amounts of spare parts inventory. The development of such a practice requires advanced analytics capability to accurately predict asset lifetime distributions and use these predictions for optimizing management of spare parts inventory. Challenges of developing a spare parts inventory management solution include the need to work with right-censored event data sets for asset lifetime prediction, the assessment of statistical models created to represent asset lifetime distributions, the need to optimize inventory levels under uncertainty, and the validation of the resulting solution with the available historical data sets. For a real project at a large aircraft manufacturer, we develop a solution that overcomes these challenges of predicting spare parts inventory levels with an integrated use of statistical modeling, simulation, and optimization. Our goal is to share this case study at SAS with WSC community.

1 INTRODUCTION

We consider a scenario where an asset is removed from an aircraft and sent to a repair shop. We track each removal and record the number of hours between the removals. At the repair shop, it is determined whether the asset has really failed. If the diagnostic testing concludes that the asset has not failed, then it is sent to the warehouse inventory of the supply chain network. In the case of an asset failure, however, the asset is scrapped, and a procurement order is placed. The event data set contains records of the history described here for each asset of interest over time. We also assume the availability of information about the assets' unit costs and order lead-times. We further recognize that an aircraft may contain an asset at multiple different locations on its frame and that there may be a budget limitation on how much inventory can be stored at a location at any given time. Our simulation-based prediction tool helps determine how many spare parts inventory to hold to achieve a target availability for each asset by utilizing SAS programming procedures that enable advanced statistical analysis and the SAS data step enabling stochastic simulations.

2 BENEFITS

The primary benefit of our prediction tool is the identification of the optimal inventory levels to minimize inventory investment while attaining the target availability specification. Two important requirements of this solution are "explainability" and "uncertainty quantification." Therefore, the use of a stochastic simulation lies at the heart of the solution development. It provides its users a summary containing mean availability and its 95% confidence interval and average number of backlogs and its 95% confidence interval for each asset at any given level of inventory. Another important benefit of the tool is the accurate estimation of asset lifetime distributions for any number of assets by using the historical but right-censored asset data sets. This is also known as reliability modeling and includes "regression modeling" and "model assessment" as two major steps of asset lifetime prediction. It is critical for this tool building on an integrated use of reliability modeling and simulation optimization to offer data-driven validation to build confidence in the methodology and to replay history. Thus, another benefit of our tool is its offering of procedures to validate both asset lifetime distribution estimation and inventory optimization under uncertainty by using the available historical data sets. Finally, the length of the available historical data sets is often quite long. For example, one of our use cases involves data collected for 50 different parts across 20 different aircrafts from 12K sensors producing 1.4M records per hour (Biller et al. 2023). Any effort involving reliability modeling and spare parts inventory optimization requires descriptive analysis of the historical fleet trends in large data sets. Often, this presents an opportunity in reducing data preprocessing time. In the corresponding use case, it is reported that accuracy of data improves dramatically, data cleanup and ingestion time decreases by 95%, and the customer saves 1,400 hours of downtime over three months.

3 DEVELOPMENT STEPS

There are three key development steps (see Figure 1): (1) event data generation; (2) reliability modeling; and (3) spare parts inventory. At the foundation of our prediction tool lies a stochastic simulation that generates asset failures based on the asset lifetime distributions identified during the reliability modeling step of the development. All the development steps illustrated in Figure 1 are implemented by using SAS software where we use its simulation, optimization, and visual data mining and machine learning capabilities in an integrated manner to support making spare parts inventory management decisions under uncertainty.

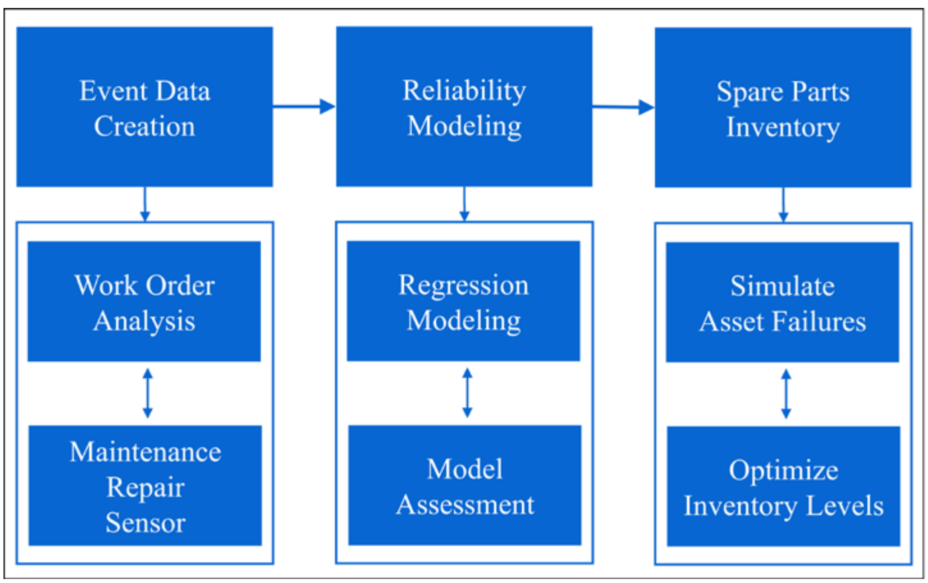

Figure 1: Development steps: Data creation, reliability and optimization.

4 CONCLUSION

Each of the development steps in Figure 1 will be discussed in detail with key implementation challenges that we have overcome. Simulation with its capability of representing uncertainty and offering explainable analytics is a key critical component of this preventive maintenance use case. Synthetically generated input data will be used for the demonstration of the underlying statistical and simulation models.

REFERENCES

Biller, B., J. Yi, and S. R. Biller. 2023. “A Practitioner’s Guide to Digital Twin Development”. In *Tutorials in Operations Research*, edited by E. Bish, H. Balasubramanian, and D. Shier, 198-227. Maryland: INFORMS.