Maintenance Oriented Corrosion Severity for Aircraft Predictive Maintenance Tool "CorroVision"

Nabil Humphrey
33 Franklin Street
Adelaide SA 5000
AUSTRALIA

nabil.humphrey@priorianalytica.com

Darren Roles
PO Box 13036, University of Adelaide
Adelaide SA 5000
AUSTRALIA

droles@ascentps.com.au

ABSTRACT

Successful predictive maintenance programmes require the integration of both physical analytical models and input from data gathered from a rigorous history of usage, inspections, repairs, and treatment application effectiveness. Priori Analytica and Ascent Professional Services have built CorroVision, which uses 'credible data' physics-based machine learning models to combine aircraft usage and maintenance data to calculate component-level corrosion severity. Based on the calculated corrosion severity, CorroVision is able to predict and optimise fleet-level maintenance requirements to largely eliminate unscheduled corrosion related maintenance. Through a data fusion approach, we are able to give an independent assessment of the effect of aircraft usage, corrosion treatment application, and maintenance practices on the effect of key performance indicators such as cost and availability.

1.0 THE PROBLEM

Corrosion maintenance activities can broadly be divided into regulatory (e.g. OEM inspection and maintenance requirements) and non-regulatory (e.g. post-flight 'bird-baths'). Regulatory maintenance must be both plenary and a function of Life-of-Type assumptions that are widely aggregated. Non-regulatory maintenance activities are directed by a variety of decision-making processes, often lacking in substantiated quantitative definition, being based on legacy platform established practices, and often contributing to corrosion impost. The key problem attempting to be solved through our R&D programme is to optimise the application of non-regulatory maintenance via a 'credible data' driven process to optimise the cost of maintenance activities. Successful optimisation of non-regulatory maintenance will then contribute to regulatory maintenance requirements definition via a formal assessment process. The initial sub-problem in achieving this goal is the forecasting of the corrosion level of accessible structures, so that credible data can be provided to enable authorised decision makers to make more informed decisions about the relative corrosion severity of a platform. The rationale being that in a well-managed program the level of corrosion found outside of scheduled corrosion maintenance rectifications should have little to no appreciable effect on airworthiness or safety of flight; these events still require the appropriate level of due diligence and engineering input to ensure this.

Established corrosion forecasting approaches do not integrate human maintenance factors such as maintenance record-keeping inconsistencies, accurate record-keeping of actual usage history, and accurate record-keeping of actual corrosion treatments applied. Integrating the learned effect of these human factors on corrosion alongside established forecasting techniques can be utilised to enhance the overall accuracy of corrosion forecasting.

An additional human effect for accurate corrosion forecasting is the fact that many countries are suffering from long-term workforce shortage trends, thereby creating a workforce with lower experience and capability. This effect is further amplified when individuals with long term acquired knowledge are 'retired' without proper knowledge and capability transfer to the remaining workforce.

Once an accurate prediction method based on historical aircraft usage, maintenance, and human factor effects has been developed, a more effective corrosion maintenance strategy can be defined that takes into account real world, practical information.

2.0 METHODOLOGY

The primary variable modelled and predicted by CorroVision is component corrosion severity, which is calculated from corrosion maintenance log entries x_i via "model anchor points". The model anchor points, $a_-(x_i)$ and $a_+(x_i)$, describe the pre-maintenance and post-maintenance state of a particular component, respectively. An aircraft "component" is chosen from an assembly parts hierarchy with the granularity level defined by the level of granularity of the maintenance records. In the current work, the model anchor points are calculated as the output of a chain of physically motivated machine learning models where the loss function is a function of a consistency metric over the full dataset. Once the model-conditional historical anchor points have been calculated, we consider the intervention-independent quantity (see equation below) for each component:

$$c_k = \sum_{i<k} a_-(x_i) - a_+(x_{i-1}),$$

Using a generalised Piecewise-Deterministic Markov Model (PDMM), we "correlate" c_k with exogeneous data such as base locations, flight profiles, and procedures. The trained PDMM then allows us to forecast c_k , based on planned operational data, with confidence intervals that enable predictive corrosion maintenance.

By aggregating the predictions of components, we form aircraft corrosion severity predictions, as well as fleet corrosion severity predictions. The information of the effects of the operational settings on the aircrafts' corrosion severity may be used to detail the operational scenario planning of the aircraft in the fleet. In order to work within the confines of data security sensitivities, we apply a blinding dereference layer such that the internal models aren't exposed to sensitive data.

3.0 RESULTS

Verification and validation have been approached using corrosion severity temporal cross-validation, whereby first a dataset is amputated at a fixed date, then the PDMM forecast bands are calculated, and finally the remaining corrosion severity data is overlaid over the forecast bands to ensure valid predictions through self-consistency. Such a test was conducted against the Australian AP-3C Orion fleet, with successful results shown in Figure 1. In Figure 1 the solid lines represent the actual corrosion severity data, while the predictions are shown as shaded areas at the right hand side of the graph. It can be seen that the actual corrosion severity is within the range of predicted corrosion severity.

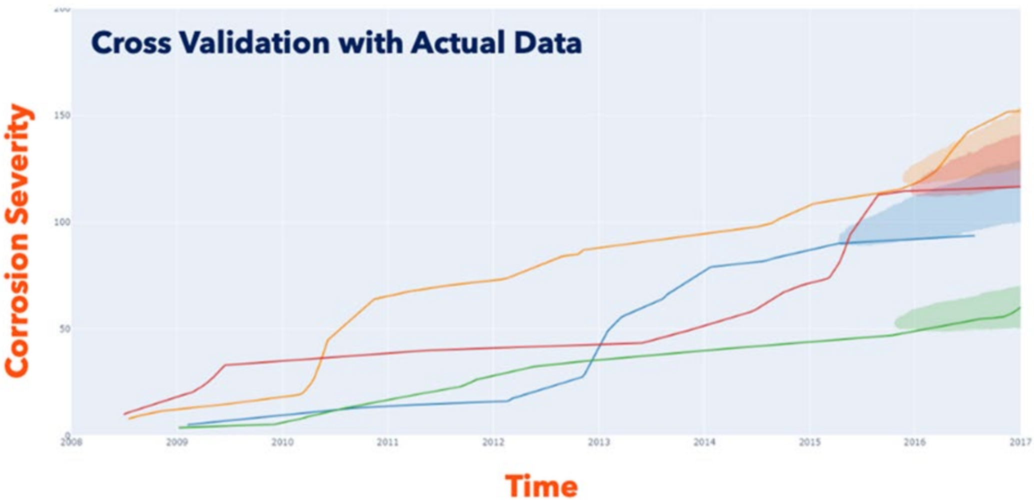

Figure 1: Corrosion Severity Temporal Cross-Validation using AP-3C fleet subset.

4.0 FUTURE WORK

The principal future path is to gain access to a greater number of varied datasets to optimise the data fusion mechanics. The aim is to produce a platform agnostic system that may be applied widely without fundamental re-design, so successful progress will require data from several platforms. Stakeholder engagement will also be a critical component of technology maturation, particularly to shape the requirements for the fleet management sub-system. Ultimately, successful implementation will require continuous co-improvement of maintenance culture and data fusion mechanics.