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Course Project

My chosen article is titled “Overcoming the Challenges of Aircraft Engine Maintenance and Repair” (<https://www.informs.org/Impact/O.R.-Analytics-Success-Stories/Overcoming-the-Challenges-of-Aircraft-Engine-Maintenance-and-Repair>) from [www.informs.org](http://www.informs.org) and discusses American Airlines’ use of descriptive, predictive, and prescriptive analytics to limit engine caused out-of-service (OTS) issues and meet target service levels. Models were built to focus on engines as a whole, as well as the repairable engine subcomponents.

First, descriptive analytics were developed after processing “large sets of historical data to extract the parameters that represent key aspects of the repair process, e.g. repair times, scrapping rates, repair probabilities.” Given the number of parts in the repair process and the spares in the backlog/storage waiting to be repaired the above data could be used to create various support-vector machine models to classify the parts into items that will be successfully refurbished and those that won’t. SVM’s would work well in this case as the total number of estimated repairable parts available will be used in successive models. Logistic Regression could also be used, however, given that we are not looking for the probability of a successful repair just a binary yes/no, using SVM’s seems simpler.

Models would be created to classify the components at multiple steps along the repair process, taking in the part specific past data up to that point. One model could be used on the parts in the backlog that classify based on the number of flight hours, takeoffs/landings, area of the country (e.g. desert sand at certain airports can create more wear). Another model could be created for after a part has started the repair process and gone through the cleaning and initial inspection. Even though the part passed the initial individual measurement inspections (wall thicknesses, hole clearances, etc. all within certain tolerances), can a SVM model look at combinations of these measurements, as well as the data used in the previous model, to classify the part?

Using these successive models and the usual repair time a prediction of that subcomponents supply chain can be made. That is, if the subcomponent usually takes 4 weeks to repair the models can predict that 17 will be available at the end of this week, 21 next week, 6 the third week, and 15 the fourth week, with 28 out of 40 components in the backlog classified as repairable. These models would not have to be hard classifiers as parts would not be thrown out if classified as not repairable. The tradeoff between error and margin would need to be tuned based on the costs of indicating too many or too few parts in the supply line. Since the overall goal is to limit OTS issues overestimating the number of parts that will be rejected will lead to fewer times that the part is needed and not on hand, but this would need to be offset by the cost of inventorying too many successfully repaired parts.

Secondly, the article says that predictive analytics provide “estimations of the required level spare engines and parts ownership based on forecasted demand of repairs”. Forecasts for engine, and thus subcomponent, demand could be created so that the business can understand the future needs. Failures of engines between regular inspection intervals can be modeled using the Weibull distribution with k > 1, as engines with more flight hours tend to fail more often. When combined with Holt-Winters Exponential smoothing, which would take into account yearly cyclic and seasonal effects such as increased flight hours due to holiday weekends or historical weather trends, a forecast could be made