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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 and discusses American Airlines’ use of descriptive, predictive, and prescriptive analytics to limit engine caused out-of-service (OTS) issues and meet target engine service levels. One extreme for these metrics would be either leaving an engine on an aircraft too long where it would fail a post-flight inspection, or perhaps fail during a flight, requiring the engine to be repaired or swapped with a spare before flying again. This creates an OTS issue as the aircraft is grounded and out of service. Also, having an engine fail a post-flight inspection can be compounded by not having a working engine replacement on hand, which leads to very expensive problems for any airline. An engine caused OTS means delayed or cancelled flights, and as the replacement or repair of an engine can take many hours this often leads to numerous delayed flights throughout a single day or multiple days. The other extreme would be minimize OTS issues by systematically removing engines well before reaching their suggested service life. However, such removals are highly inefficient from engine service time and cost perspectives as the airline expects a certain life out of the engine in order to reduce costs. To help American Airlines combat engine caused OTS and yet meet engine service goals, analytics models were built to focus on whole engines as well as the repairable engine subcomponents. These models allow the airline to make smart decisions on the cost of inventory versus the benefit of meeting targeted service goals. Airlines typically overhaul most of their engines in house and thus have direct access to the supply lines and inventory data needed to make these detailed models.

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 components 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 components into items that will be successfully refurbished and those that won’t. 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 by using the component

specific data up to that point as the factors. One model could be used on the components in the backlog in order to classify the component based on the number of flight hours since its last overhaul, takeoffs/landings since its last overhaul, hard landings, area of the country (e.g. desert sand at certain airports can create more wear), and other service-life type factors. Another model could be created to classify a component after has started the repair process and gone through the cleaning and initial inspection. Initial inspections usually consist of a series of measurements or check to make sure minimum criteria are met before the component is inducted into overhaul. Even though the component passed the initial individual measurement inspections, can a SVM model look at combinations of these measurements, as well as the data used in the previous model, to classify the component? This type of model creation would then be repeated at various steps in the overhaul process to obtain a detailed understanding of the number and quality of components in the supply line. A summary of these models in the “Given, Use, To” format is shown in Table 1.

Table 1. Descriptive Analytics Model Summary

Given:	Part specific data collected up to the model’s point in time: - If the part is still waiting to be overhauled, it would include: number of flight hours since its last overhaul, takeoffs/landings since its last overhaul, hard landings, area of the country, and other service-life type factors. - If it is after its initial cleaning and inspection, data would include: the above information plus measurements/checks from initial inspection - And so on for other points during the overhaul process.
Use:	A soft classification Support Vector Machine
To:	Classify the parts into items that will be successfully refurbished and those that won’t

By combining these successive classification models with the usual repair times, a model of that components supply chain can be created. For example, if the subcomponent usually takes 4 weeks to repair then the models can predict that 17 successfully overhauled components 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. The SVM models should be soft classifiers as the tradeoff between classification error and margin would need to be tuned based on the costs of indicating too many or too few components in the supply line. Since the overall goal is to limit OTS issues, overestimating the number of components that will be rejected will lead to fewer times that the component is needed and not on hand, but would need to be weighed against the cost of inventorying too many successfully repaired components.

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 demand, as well as engine component demand, could be modeled to understand the future inventory needs. Engines are typically removed at specific intervals for inspections and repairs and if the engine does not pass inspections it is sent for maintenance or overhaul. Failures during these regular inspections as well as in between the inspection intervals (usually meaning that the engine is an aircraft, leading to delays and large costs) need to be understood so that they can be predicted and avoided as much as possible. Since engines with more flight hours tend to fail more often the failures can be modeled using the Weibull distribution with $k > 1$, with k and λ being tuned using historical engine service life data. In conjunction, Holt-Winters Exponential smoothing could model an engine's future flight hours, considering seasonal cyclic and trend effects such as changes due to holiday weekends, historical weather trends, common air delays at certain airports, etc. The α , β , and γ for the Holt-Winter's Model would be found using optimization models which take in historical flight hours, flight paths, airport information, region specific data, etc. to minimize the forecasted error over the training set. In both models the data is again found from records within the company (flight history and times) or easily accessible from open airport records (weather data). However, arguments could be made for more advanced weather models to more accurately predict the future. This would require either creating these models in house or working with an outside company who focuses on weather models.

As exponential smoothing is best for short term forecasting its predictions would become more accurate and more actionable as that time period approached. As an example, if the year was broken down into bi-weekly segments, the model might forecast 4 time periods, or 8 weeks, out. When combined with the Weibull distribution based failure model, models could predict which engine will not make it to the next scheduled removal for inspection and thus could be sent to overhaul immediately to avoid OTS issues. If the airline views the OTS risk as small and wants the engine to meet its service goals, the airline can leave the engine in service to avoid potentially unnecessary overhaul costs. The model could then combine the forecasted failure with the aircraft's upcoming routes to predict the airport or geographical area the aircraft will be when the engines fail. If multiple engines are predicted to fail inspections at a similar time and place additional spare engines or parts could be sent to that site to avoid depleting the local spare supply and costlier delays. A summary of these models in the “Given, Use, To” format is shown in Tables 2 and 3.

Table 2. Predictive Analytics Model Summaries, Engine Failure Prediction

Given:	An engine's current flight hours and historical engine service life data
Use:	A Weibull distribution with $k > 1$
To:	Predict when engines will fail to determine whether the engine should be removed or not

Table 3. Predictive Analytics Model Summaries, Holt-Winters Flight Hours Forecast

Given:	<ul style="list-style-type: none">- Historical daily flight hours- Events that would impact the number of flight hours such as holiday weekends, historical weather trends, common air delays at certain airports, etc.
Use:	Holt-Winters Exponential Smoothing
To:	Predict the number of flight hours an engine will accrue in the future. Combined with the engine failure prediction to model when/where an engine may fail.

Even though exponential smoothing is best at short term forecasting, where the furthest out time period prediction would be the least accurate, it would allow predicted inventory levels from the descriptive analytics to be compared to forecasted demand to ensure that the proper amount of components were being overhauled, given the repair process lead times. As time progresses, both the forecasted demand and inventory analysis become more accurate leading to better proactive decision making.

Lastly, prescriptive models were “used in what-if scenarios to suggest the spare ownership level based on different targets on service level and OTS performance metrics”. Here it would make sense to use stochastic simulations and optimization to find the proper balance between readiness and cost. Variability can be added to the random airport delays, flight hours, failure rates of engines, component repair times, and component rejection rates within the engine supply and demand forecasts to see if the projected spares will still meet the stated service time and OTS goals. This will allow the airline to make informed choices about increasing or decreasing spares allocation. If simulations show that more engines are needed for any given time period, the component level supply models can then be checked to see if any choke points, such as a shortage of a critical path component, lack of engine test cells due to multiple engine overhauls being completed too close together, etc. are likely. A summary of this simulation in the “Given, Use, To” format is shown in Table 4.

Table 4. Prescriptive Analytics Model Summary

Given:	<ul style="list-style-type: none">- The descriptive and predictive models mentioned above, which forecast engine supply and demand, plus additional variability on those models' inputs- Could also inject random major events like poor quality of work during a certain time period or other large scale random event like extreme weather.
Use:	Stochastic Simulation
To:	<ul style="list-style-type: none">- Balance spares inventory vs. cost by making informed choices about increasing or decreasing spares allocation- Model critical issues or choke points to allow for preemptive corrections/responses- Test the engine supply system's ability to handle major events

This would allow proactive steps to be taken to minimize their impact. These steps could include tentative PO's being cut to vendors to buy new or refurbished components, authorizing overtime for technicians weeks or months before the forecasted shortage, minimizing an aircraft's flight hours, or altering routes of a certain aircraft to ensure it is taking off and landing at airports with the correct level of spares in case of an issue, all while minimizing the overall cost to the airline. Additionally, random major events, like a rash of component failures due to bad work a single repair line during a single week, the recent fire at the Atlanta airport, or a major northeastern snowstorm could be simulated in the upcoming time periods to help determine how these events would impact demand and the system's ability to respond. If enough data is available, these predictive models could be run daily, even hourly, to forecast, understand, and preemptively mitigate any issues that could impact the airlines engines or aircraft.

Using this combination of descriptive, predictive, and prescriptive analytical models creates a map for American Airlines to meet its service time and OTS metric goals. Despite the complexity and scale of the models, they are made from data that is nearly always collected from sources within American Airlines and most of the required data is being collected anyways in the overhaul process, engine logs, or weather data from airports. Therefore, the additional cost of collecting this information is minimal especially when compared to the benefits of meeting service time and OTS goals. By consistently gathering new information, running the models, and making informed decisions American Airlines can get its customers where they need to go when they need to be there, all while ensuring themselves as much profit as possible.