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Predictive Maintenance Planning for Safety in Civil Aviation

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Abstract. *In recent years the aviation sector has seen growing interest in predictive planning for servicing aircraft, where improper planning and unplanned service events have serious consequences because of the requirements for high availability of the aircraft. Predictive maintenance planning of aircraft allows scheduling line maintenance and positioning needed parts in advance; planning flights with consideration for equipment availability; reducing wear resulting from degraded performance of components in a complex system; and protecting the reputation of the airline. Mathematical algorithms for machine learning and regressive modeling are often used for facilitating predictive maintenance planning. However, one of the most important roles in the analytic system is played by the quality and completeness of the input and training data, as well as the corresponding models. We propose a cost model for planning and discuss factors that limit the speed of adoption of such technologies.*

Index Terms: *Predictive maintenance, service planning, big data.*

I. INTRODUCTION

THE subject of maintenance planning is relevant for many industries, from manufacturing to transport. Such planning is particularly critical for civil transport, where considerations include requirements for high availability of equipment and maximum safety for passengers, as well as high cost of replacements parts that discourages pre-positioning too many replacements parts at all possible service points. In civil aviation the problem of Maintenance, Repair, and Overhaul (MRO) is particularly notable, since the distances between potential service points (airports) may be large, prohibitive costs are associated with out-of-service aircraft, and the cost of safety events is very high, including reputational damage to the airline.

Ideally, predictive maintenance planning will address MRO for specific components and aircraft, as well as for an entire fleet. The economic scale of MRO is significant: according to [1], the global market for MRO is expected to reach 96 billion USD by 2025, of which 22% is components and 40% is engines. New technologies in aircraft, including support of predictive maintenance planning, could reduce heavy maintenance labor hours by 65%, leading to an estimated savings of about 3.5 million USD over a 12-year maintenance schedule for an aircraft.

Recent solutions for predictive maintenance planning in civil aviation are offered by equipment manufacturers, such as those from Boeing [2] and Airbus [3]. In addition to partnering with equipment manufacturers for airline-specific solutions, some airlines, such as Lufthansa [4] have developed platform solutions for themselves and others, and others, such as S7 [5], have begun to develop internal solutions in addition to purchasing third-party solutions [6], for reasons that are discussed in the sequel.

II. Data Sources for Predictive Maintenance

Catastrophic accidents in civil aviation are rare and often attributed to a range of interrelated causes, this making it difficult to model existing and potential risks. But building and maintaining a risk model is essential for civil aviation as well as for other critical modes of transport (e.g. railways).

Of the numerous categories of information about aircraft exploitation that could be used as input to algorithms for predictive maintenance, we propose the following categories to facilitate concise discussion:

1. Wear models for aircraft components from the manufacturer;
2. Historical maintenance records from the airline;
3. Event logs from health monitoring systems;
4. Seasonality of flights;
5. Flight path data, including planned and actual;
6. Historical and predictive weather conditions during flights.

Each of these, including complexities and risks, is detailed below.

A. Component Wear Models

The equipment manufacturer is likely the best-positioned to create component and subsystem wear models for aircraft, since he can instrument components and subsystems across an entire line of aircraft and collect exploitation data from many airlines and geographies. We use the word “component” in the sequel to indicate both individual components and subsystems, since a complex subsystem (such as a pump or part of an engine) may be serviced as a unit.

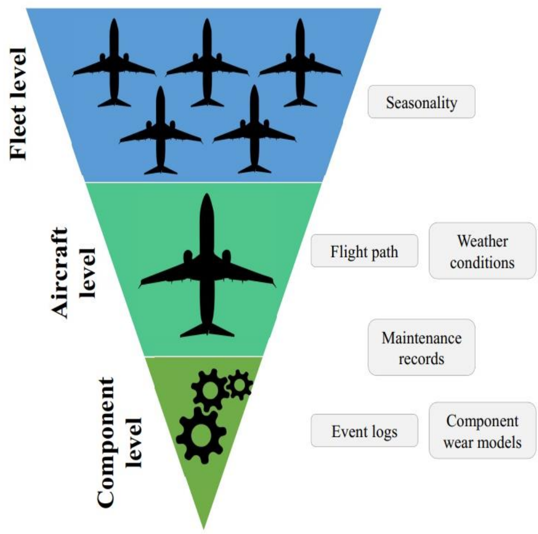

Fig. 1. Inputs to the predictive MRO planning system, shown at approximate level of relationship to the aircraft systems.

A model may have aspects based on the physics of the component, as it was designed. However, the complexity of systems themselves, including interdependencies among components, and of the conditions under which they are utilized suggests a benefit to including heuristic considerations in the model. Interdependencies may include wear resulting from the degradation of a "neighboring" component; e.g., increased wear on engine parts as the performance of an oil pump slowly degrades with time.

One aspect of vendor-created component models has motivated airlines to develop their own, complementary models: the vendor has an implied financial and reputational interest in frequent component replacement. More specifically, in addition to the financial reward to the vendor for selling more replacement components, his reputation depends on avoiding failures in the field, since such unplanned problems can appear in the press. However, the sheer number of equipment instances manufactured by the vendor and the breadth of exploitation conditions, as compared to the same for one specific airline, suggest that the manufacturer's models comprise at least an important part of any solution model.

B. *Maintenance Records*

International documentation standards for aircraft resales require very detailed records to be kept on MRO, down to the component level. Because of the value of the resale market, airlines are motivated to maintain detailed records of MRO. Aircraft valuation for a particular sale may be done in a number of ways, including online or by an expert valuator, using maintenance records. Market values even in 2009 ranged up to 120 million USD for a Boeing 777-200, but devalue on the resale market with age as 2^{nd}-order polynomials [7]. As well, the resale market includes pooling (among airlines) of components scavenged from retired aircraft, which is expected to reach 45-50% of the financial volume of component programs by 2024 [1].

The advantage of using maintenance records as input to predictive modeling is the actuality of the data: unlike the manufacturer's theoretical model, the maintenance records include effects from the historical exploitation of the component in the aircraft system. Depending on a number of factors, some of which are addressed in the following subsections, actual wear trajectories may significantly differ from those simulated by the manufacturer.

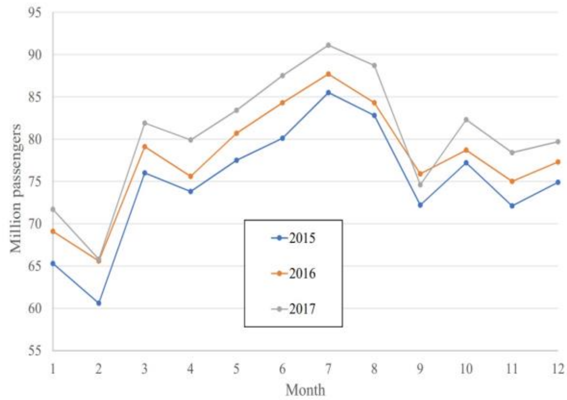

Fig. 2. Civil aviation passengers per month, USA flights, sourced from https://www.bts.gov/newsroom/2017-traffic-data-us-airlines-and-foreign-airlines-us-flights

A complication with the historical data is that maintenance engineers may make interventions in the components based on recommended maintenance procedures or based on preliminary symptoms of wear. These interventions may change the wear trajectory of the component and any interdependent components. As such, designers of a predictive system based on such data should consider the tradeoffs of incorporating intervention factors into the models.

C. *Health Monitoring Systems*

Event logs from aircraft health monitoring systems are electronic records automatically generated by components in the aircraft. These are time-ordered records from various sensors in the aircraft. Records do not necessarily indicate failure events but can be used to track trajectories in performance with time.

D. *Seasonality*

Civil aviation is strongly subject to seasonality in flights, which has a direct effect on the exploitation of aircraft. For example, an airline in a popular vacation destination will likely see a notable increase in the frequency of flights and/or in the type of equipment used for flights during the vacation season. Including this information in the model is important for capturing higher-order effects in component wear.

Fig. 2 shows actual seasonality data for USA flights over three years, where the impact of summer vacations and winter holiday travel are clearly shown.

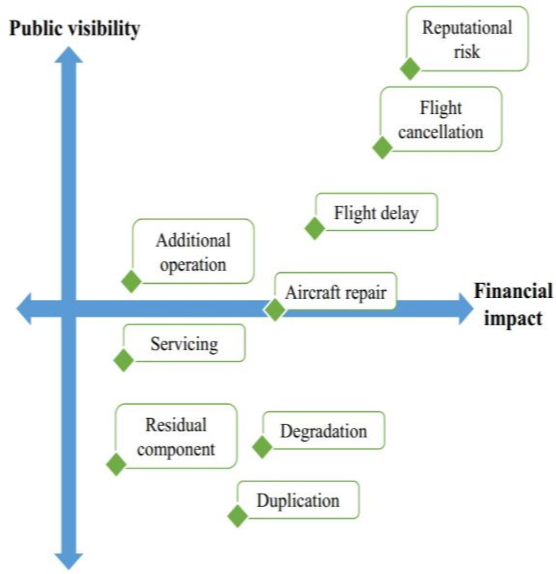

Fig. 3. A subjective comparison of various cost elements with unplanned impact on public visibility and finances of the airline.

E. *Flight paths*

Flight plans are filed with air traffic control (ATC) in advance of flights but may vary in practice for a number of reasons. A common cause of variation is angle of approach to the destination airport or slight deviations made to delay arrival time, based on local traffic conditions, such as Flight NK739 on July 5, 2016, which deviated significantly on approach to Seattle [8]. Such deviations may be suggested by a trajectory management system, which adjusts traffic speeds to avoid future conflicts. The deviation may have only a small effect on the total use data for an aircraft but may still be considered. More significant deviations occur from airport redirection due to weather or equipment problems, which can add additional kilometers and pressurization-depressurization events outside of plan.

Given that standards for recording Air Traffic Control (ATC) data differ between some geographical regions, designers of predictive systems are likely to need preprocessing for normalizing the data, if it is not sourced from a third-party source that performs the normalization.

F. *Weather conditions*

As noted in the previous section, weather conditions can impact the flight path, but they can also change the character of aircraft exploitation. For example, if strong wind at the destination airport requires a "hot" approach and landing, the resulting wear on some of the aircraft elements will differ from more friendly operating conditions. For this reason, weather conditions at the time of exploitation may also be considered.

III. Cost Function

Optimizing MRO planning, as any optimization task, requires a cost function. In this section, we propose factors that may be included in a cost function for effective MRO planning, starting from the model proposed in [9]:

1. Residual component cost, resulting from replacing components with remaining exploitation time;
2. Flight cancellation cost, resulting from unavailability of the aircraft because of problems with personnel or parts availability;
3. Aircraft additional operation cost, when operational tasks are imposed by a degraded component (e.g., operating at a reduced altitude);
4. Flight delay cost, caused by maintenance which takes longer than expected;
5. Degradation cost, when the aircraft is used under degraded conditions (e.g., higher fuel utilization because of a worn component);
6. Aircraft repair cost;
7. Servicing cost, which includes preventative measures such as changing lubricants.

We propose adding to this list the following costs:

1. Reputational risk cost: any unplanned maintenance event, leading to delay or cancellation of the flight, impacts the performance indicators of the airline, as well as the impression of passengers. Furthermore, with social media resources such as Twitter in the hands of many passengers, even the perception of an unplanned event may be exaggerated in the social media before the airline has the chance to respond.
2. Duplication cost: expenditures on developing and maintaining in-house or other nonstandard systems to mitigate real or perceived risks of using the standard systems, or to reduce licensing expenditures for the third-party systems. This cost position also includes additional risks of lower accuracy of the models than the industry-standard models.

An important consideration leading to trade-offs in the cost model is that there is no point at which a component of any system is 100% reliable; i.e., with zero probability of sudden failure. On the other hand, as noted above, events may be exaggerated in the press of social media, so exploiting a component until its failure date carries reputational and other risks.

A subjective matrix of these various costs is shown in Fig. 3 to give the reader a rough picture of the tradeoffs between public and financial positioning of the airline. It is assumed that costs such as servicing are planned, whereas event-related costs are not.

IV. Prediction Models

As with any predictive system, there is a large body of work that has been done in algorithm design. As a result, software engineers implementing systems for predictive maintenance planning do not need to invent new approaches and can utilize algorithms from standard libraries for machine learning and regression analysis, for example. Some of the standard and logical choices for model design are summarized in this section.

We separate the analysis algorithms into two levels of application: input data and event modeling. Input data is processed to reduce noise in heuristic component models. Event modeling is then supplemented with the component models to enrich interpretation of the performance trajectories in failure prediction.

A. *Smoothing Algorithms for Component Failure Models*

A data-driven approach to component failure modeling requires some degree of smoothing to reduce noise in the prediction curves. Complications in the models include the following:

- Nonuniform data sampling: data points from component sensors may be taken only during operation of the aircraft, which would exclude the time-based degradation occurring during non-use. As well, sampling during exploitation of the equipment may or may not be uniform, based on various factors.
- Nonuniform exploitation wear: some components experience increased wear during take-off and landing (or depressurization and pressurization) events, which introduce non-linear factors into the models.
- Seasonality of equipment exploitation, as discussed in the prequel.

In [9], the authors show that a nonlinear version of the Kalman Filter, integrated with a multiple-model approach, outperforms liner and polynomial models, while allowing optimization according to a complex cost function.

In [10], the authors employ a multiplicative Holt-Winters seasonal model for a type of aircraft, since with aircraft seasonal fluctuations in usage vary, depending on the overall volume of flights. The authors predict failure at the aircraft level, rather than the component level. However, the principles may be applied at the component level for smoothing the time variable of prediction.

B. *Regression Models*

Event logs are used as the source of input to the predictive models in [11], which are solved using the Random Forest Regression (RFR) model. The models are used to correlate events which may indicate a future failure; e.g., performance changes in a component or connected components over time. The authors found that RFR outperformed the popular Support Vector Machine (SVM), since RFR uses a threshold value to minimize false positives.

V. Limits to the Speed of Adoption

As outlined above, there are some factors that limit the speed of adoption of technological solutions for predictive maintenance in civil aviation. These factors are summarized and discussed further in the current section.

A. *Digitization*

Whereas recent records may be in electronic form with some level of online-verification of part numbers and other identifying information, historical records were kept on paper. Paper records may contain small errors in transcribed information, and the handwriting of the maintenance engineer may not be easy to parse. As a result, scanning historical records for electronic use is not a trivial task, often requiring advanced algorithms for character and word recognition, as well as secondary verification.

B. *Non-instrumented components*

Complementary to the challenges of digitization of paper maintenance records, event logs will be available only for instrumented components. Although Vehicle Health Monitoring Systems are present in some commercial aircraft since the 1980s (Airbus 310, Boeing 757 and 767), advanced data buses that support such systems, such as AFDX, became available only in 1999 [12]. As a result, older aircraft may have limited or no component-level instrumentation. For such aircraft, predictive maintenance planning is limited to maintenance and health-check records for historical component data.

C. *Third-Party Solutions for Maintenance Records*

Some manufacturer solutions for predictive maintenance, such as Boeing's Aerdata "Stream", invite the airlines to store maintenance records "in the cloud" to facilitate analysis by machine learning algorithms, global access by MRO crews, and sharing with lessors and banks. An important consideration is that the geographical location of data hosting for these solutions determines the legal framework governing third-party access to data, data privacy concerns, and the rights of various governing bodies to access data. Since civil aviation may be viewed as having importance for national security, national airlines may not wish to participate in such cloud solutions. For example, maintenance records will indicate parts that are potentially close to needing replacement, but which are still safe. As well, maintenance records will also include information about errors made during previous exploitation and maintenance of the aircraft. Such information leaked to the press by a hostile third party or government could damage the reputation of an airline.

VI. Conclusions

We have shown that practical predictive maintenance for civil aviation requires data from a number of sources. These sources span component-level data to fleet-level data on aircraft deployment. As well, there are compelling reasons for airlines and/or national air traffic control bodies to develop their own repositories and algorithms for analysis, rather than depending entirely on a third-party solution. The concepts shown herein, although specific to civil aviation, may be extended to other forms of civil transport, such as rail transport, which have similar challenges in terms of risks, volume, and costs.

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