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Fusing Mode S and Earth observation data for ML-driven engine performance deterioration modeling

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Abstract
In the following, an approach currently being researched, is presented. The objective of this approach is to more precisely model engine performance and condition deterioration with the help of Mode S and Earth observation data. The fusion of Mode S with Earth observation data is described with a focus on the contributions of Mode S data. Also, the Earth observation data contained in Mode S data is pointed to. Research in progress is presented and user needs are highlighted.

From the preliminary findings, one can conclude that the usage of Mode S data is essential to engine performance and condition deterioration modeling in situations in which no aircraft position data can be obtained. ADS-B data provides the means to achieve a mapping of the aircraft location to outputs from aerosol models, such as the Copernicus Atmospheric Modelling Service's global reanalysis, and other ambient condition data from in-situ sources or satellites.

Aero engine condition and hence, engine performance deterioration is a function of the severity of the operational environment. Exposure of aero engines to contaminants leads to fouling, erosion, and corrosion. Additional maintenance, repair, and overhaul costs, and excess emissions result from exposing aircraft engines to harsh operating environments. ADS-B and Enhanced Surveillance (EHS) data bear the opportunity to better determine the exposure to and the impact of contamination on aero engine condition and performance. Subsequent data analysis and generation of decision-critical information will ideally decrease operational costs and the environmental footprint.

Keywords: ADS-B; Earth observation; Aerosols; Engine deterioration

1. Introduction

Aero engine condition and hence engine performance deterioration is a function of the severity of the operational environment, i.e., the ambient conditions during flight and ground operations. Exposure of aero engines to airborne natural and anthropogenic contamination like dust, salt, soot, etc., and exposure to sand, temporarily uplifted into the atmosphere by wind or sucked in by the engine, leads to fouling, erosion, and corrosion. Engines are also stressed by high operating temperatures and altitudes due to increased thrust requirements resulting in higher fuel burn and associated temperatures [1]. Additional maintenance, repair, and overhaul expenditures, and excess emissions result from exposing aircraft engines to harsh operating environments. To manage and decrease operational costs, maintenance costs, and emissions, monitoring, and forecasting of the effects of ambient conditions is necessary. For example, information derived from such exposure analysis can be utilized for the scheduling of maintenance events like, for example, engine washing. In such a case the engine washing is data-driven and based on the analysis of the engine state during past missions [2]. Another use case is cost and risk analysis, for example in power-by-the-hour contracts given an expected route network. Hence, methods that allow for more precise modeling of the engine performance and condition are desirable to decrease operational expenditures, analyze customer risk and the environmental footprint of engine operation, etc.

2. Method

To analyze the impact of ambient conditions on aero engine performance and condition, the following steps are taken during each phase of the engine's/aircraft's flight and life cycle. Firstly, the trajectory of the engine/aircraft is mapped to ambient contamination, weather data etc. Secondly, an estimation of the amount of contamination passing through engine sections is performed to obtain contaminant mass flow estimates and capture the operational severity in an engine penetration model. Thirdly, engine performance and condition parameters are correlated with the contaminant mass flow estimates, etc. Insights are generated by the use of deterioration/fault detection methods. These methods deliver aero engine performance indicators and subsequent forecasting of the expected type and severity of deterioration based on the identified fault signatures. The approach is illustrated in Figure 1. Next to the model components, dashed boxes contain information on the type of Mode S data that can support that particular modeling step. Details on the model components are described in the following paragraphs in more detail.

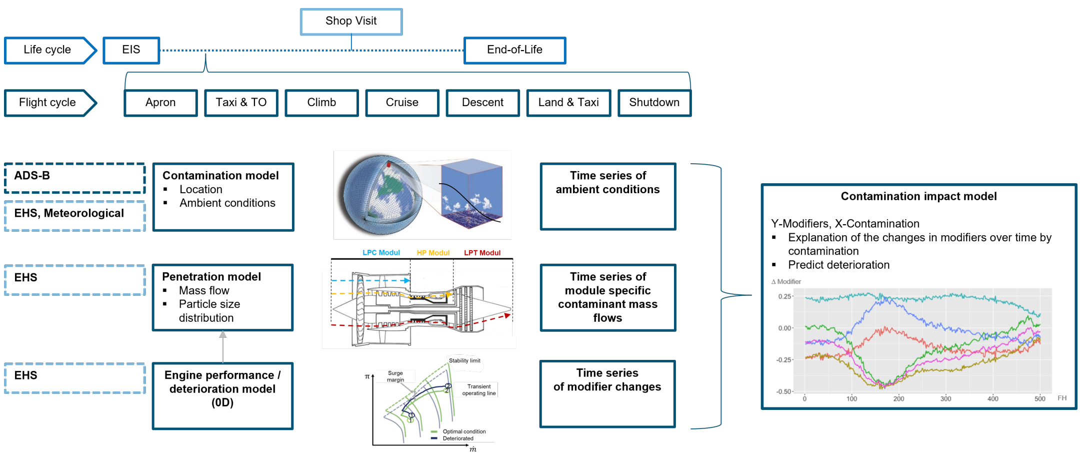

Figure 1. Model components

During the engine life cycle, aero engines are subjected to events like shop visits and line maintenance which can contribute to performance restoration. Every flight cycle generally contributes to performance deterioration to a certain degree. Aircraft repeatedly go through a ground operation segment, perform a taxi out, and take off, followed by a climb, cruise, etc. In the given approach, each of the phases of a flight cycle is modeled such that it captures the ambient conditions of relevance and the associated contaminant mass flows through the engine.

The contamination model links the location of the aircraft to a source of Earth observation data. To establish this link, a unique identifier for an aircraft, given by the horizontal and vertical coordinates and a timestamp location is necessary [2].

The aircraft's spatiotemporal location and its trajectory can be derived from the latitude, longitude, barometric altitude, and time transmitted in the ADS-B messages [3]. Evaluation of historic routes with ADS-B data considers flown routes and hence also variation in approaches according to given wind conditions, operational procedures, etc. The use of ADS-B data reduces uncertainties compared to route modeling due to capturing variability in flight conditions, for example. When going beyond historic data analysis into the forecasting of ambient conditions and associated exposure to contaminants, trajectory modeling approaches become relevant. See [4] for further references. Furthermore, it is assumed to be necessary to represent the flight trajectory in detail in the planetary boundary layer. Departure and approach are flight phases where exposure to particles is more likely to occur than at higher altitudes. Hence, simplifying trajectories during these flight phases could result in a loss of explanatory information. Gaps in trajectories, resulting from the lack of ground-based ADS-B receiver coverage, are interpolated. Satellite-based ADS-B could fill the currently interpolated gaps [5]. The contaminant species and meteorological data used in the contamination model can be obtained from various sources like atmospheric composition models, weather models, and ground stations. The data is integrated from sources that provide gridded data sets in 3D or 4D, or from in-situ point data. In the given framework the ambient condition data is augmented by data from support models. For example, during operations at the apron, a support model is constructed to forecast the occurrence of anti-ice or de-icing events, based on Earth observation and Mode S data. Where accessible meteorological routine air report (MRAR) data is used. MRARs provide valuable information by describing meteorological conditions at the exact location of the aircraft and the specific time point. METAR data or weather model data, alternative data sources, potentially only provide data points that lie apart from the aircraft in space and time. Furthermore, for example, space-borne Light Detection and Ranging profiles can be used to examine airborne contamination [6]. Data scarcity issues with EHS and MRAR data have to be addressed depending on the application [3],[7]. Widespread accessibility and interrogation will be key to fully exploiting the value of this data.

The penetration model provides estimates of module-specific contaminant mass flows, i.e. it estimates how much contamination is ingested and it estimates where the ambient contamination is transported within the engine. By linking the air mass flow and knowledge of the engine architecture and operating point to the contamination data, the flow paths of the contamination are estimated. The goal behind this is to obtain a component-specific contamination history. EHS data can be used, for example, for ground vortex formation prediction. Together with the track angle and wind direction data, the headwind component can be derived and used in the prediction of ground vortex formation. In case of missing EHS data, for example, the true airspeed can be derived by using wind direction and wind speed data from the MRARs [8].

For the penetration model to provide an estimate of the air mass flow and subsequently, the contaminant mass flow, an engine model is required. A realistic engine model, describing the current condition of the engine and the associated mass flow, requires external inputs, i.e., usually not publicly available, operational aircraft data. A constant mass flow model is used for performance modeling [9]. The engine model hence provides the data for performance and condition deterioration monitoring but also the mass flow as an input to the penetration model. The mass flow estimation requires a thrust estimate which is obtained here with the help of OpenAP, EHS data or weather data [10].

Each of the three model components provides a time series, of the location, ambient conditions, contaminants within the engine modules, and finally performance characteristics. ADS-B, EHS, and meteorological data play a key role in creating these time series. The correlations between and within the time series are used in a contamination impact model to obtain insight into the dynamics of engine deterioration given certain ambient conditions. A detailed explanation of this modeling component goes beyond the scope of this paper but will follow.

3. Discussions and Conclusion

The presentation of the ongoing research project shows how Mode S data from the OpenSky Network can be synthesized with Earth observation data for the analysis of the impact of ambient conditions on the deterioration of engine performance and condition. The benefit of using this Mode S data depends on the specific subset of data used. EHS and MRAR data are desirable but their limited availability limits it's usage in the given approach. For matching the data sources of Earth observation data and the aircraft position, ADS-B data is a valuable data source. Reporting on final results and further modeling aspects is left to later publications.

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- Jan Göing: Writing - Review and Editing
- Jens Friedrichs: Funding Acquisition, Supervision

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Open data statement

There is no underlying data set.

Reproducibility statement

This research is in a conceptual phase.

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