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Effects of Atmospheric Excitation on Vibration Based Condition Monitoring Methods for Hybrid-Electric Aircraft Propulsion Systems

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Abstract

The advent of electric propulsion systems for aeronautical applications allows the possibility of detecting faults in the propulsion chain before they become critical. This has the potential of further improving the reliability of those systems. Vibration-based condition monitoring is one promising technology in this field, as well as an enabling technology for condition-based maintenance. Therefore, it has the potential to improve overall aircraft economic performance by reducing maintenance cost. However, it is inherently affected by manoeuvring loads and atmospheric excitation such as gusts or turbulence.

Data-driven machine learning is a promising methodology for failure detection and classification. A mixed simulation and experimental data training approach is proposed, and basic simulations models are presented. Moreover, a Stemme S10-VTX research aircraft operated by FH Aachen was equipped with inertial, air-data and acceleration measurement equipment to gather real-world data to further improve the classifiers. Initial results of the flight experiments are also presented.

Keywords: Hybrid Electric Propulsion, Condition Monitoring, Atmospheric Excitation, Flight Experiments

Introduction

Electric and hybrid-electric aircraft propulsion will soon become a necessity for general and commercial aviation to allow the ambitious objectives with respect to a reduction of emissions in air traffic [1] to be achieved. Furthermore, this technology is crucial to facilitate the introduction of new aircraft concepts such as eVTOL for personal air mobility or distributed electric propulsion (DEP) [2]. The low inherent vibration excitation of the electrical propulsion system compared to a reciprocating engine opens new opportunities for vibration-based fault identification and classification. Studies on a generic hybrid-electric propulsion system (HEPS) in Ref. 3 showed the safety potential for the combined motor/propeller bearing of such a system. One main challenge when developing vibration-based condition monitoring methods or adopting approaches typically used in stationary applications is the non-steady environment on board an aircraft due to manoeuvring loads, airframe vibrations, atmospheric influences, and propulsion system induced interactions to measured data which provide the basis for condition-monitoring or health-monitoring strategies. In a robust condition-monitoring system, unsusceptible to these effects, a deep knowledge of the occurring acceleration and vibration signature, transfer paths, and their sources is crucial when developing condition monitoring algorithms.

Framework

Machine learning algorithms have shown in the past that they can overcome this problem and perform well for remaining useful life (RUL) predictions [4]. However, they come with the need for big representative data-sets for training. Sobie et al. [5] suggests high resolution simulations as a source for signal generation to train classifiers and compared several different machine learning algorithms with and without the need for feature extraction and validated them with experimental datasets.

Fig. 1 shows the approach based on [4] that is implemented here: A high resolution bearing simulation with faults (see Fig. 2), implemented in Simcenter Amesim™ based on a bearing fault model described in [6] is used to generate a time series vibration signal that is than further used to train different classifiers. The bearing simulation is fed by a propeller model accounting for the shaft loads generated by aerodynamic forces and gyroscopic moments. The input needed here can be calculated from a mission profile or also from experimental data recorded by an inertial measurement unit (IMU). The second input for the bearing simulation is the external excitation conveyed through the airframe caused by the manoeuvring loads, fluid structure interaction and the atmospheric excitation via the transfer path of the A/C structure itself.

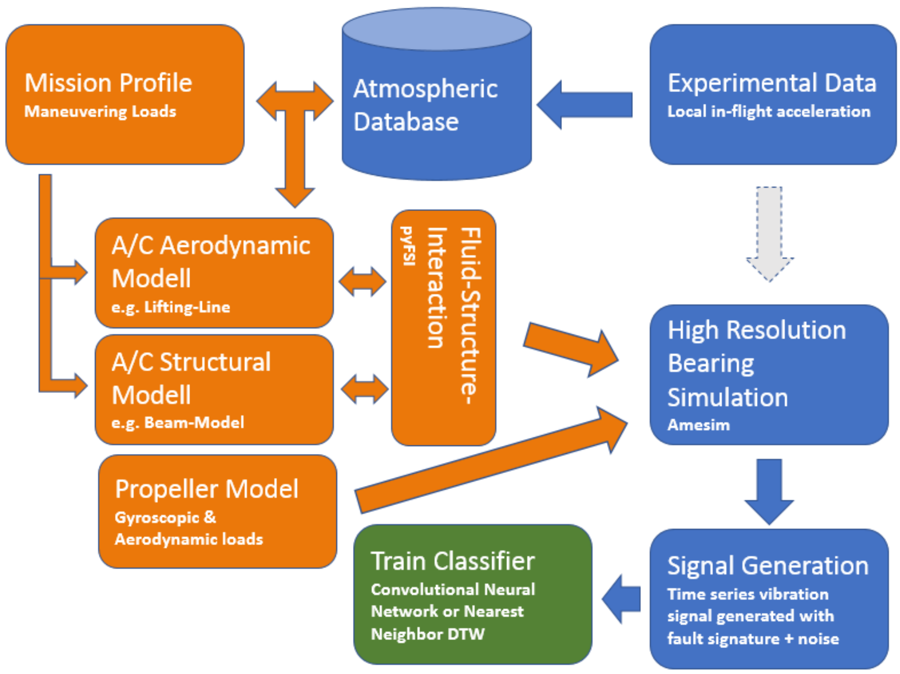

Fig. 1: Schematic Approach for Simulation-Driven Machine Learning (based on [6])

For initial set-up and benchmarking of the aircraft model (orange) the experimental data can also be used directly as an input for the bearing model (dashed arrow). A database with time-based atmospheric disturbances is used to feed real-world data into the models. This approach comes with the advantage, that the classifiers of a condition monitoring system can be trained before or without having experimental data of the specific system with a high representativeness. Furthermore, the use of convolutional neural networks (CNN) [7] or nearest neighbour dynamic time warping (DTW) [8] for the classifications have the advantage, that they are not based on detecting differences from an expected behaviour but recognizing the characteristic fault signature, making them more robust against external disturbances.

The bearing simulation model used here is shown in *Fig. 2*. It basically consists of a mass-spring-damper combination for the inner- and outer ring. The fluid-film is modelled with the elastic-stop elements (centre). The defect is modelled as a Dirac-impulse acting as a force to the outer ring. The accelerations coming from experimental or model data act directly to the housing spring-damper model. Inner ring forces can also be feed into the model via a propeller model or by experimental data or combinations thereof (right side). Even though Fig. 2 shows no connection between outer- and inner ring forces / accelerations, they are of course coupled via the structural-, aerodynamic- and propeller model as shown in *Fig. 1*. The outer right mass has a mass of zero needed to ensure causality. Furthermore, the transfer-path from the outer-ring to the vibration transducer and the sampler are modelled before storing the data.

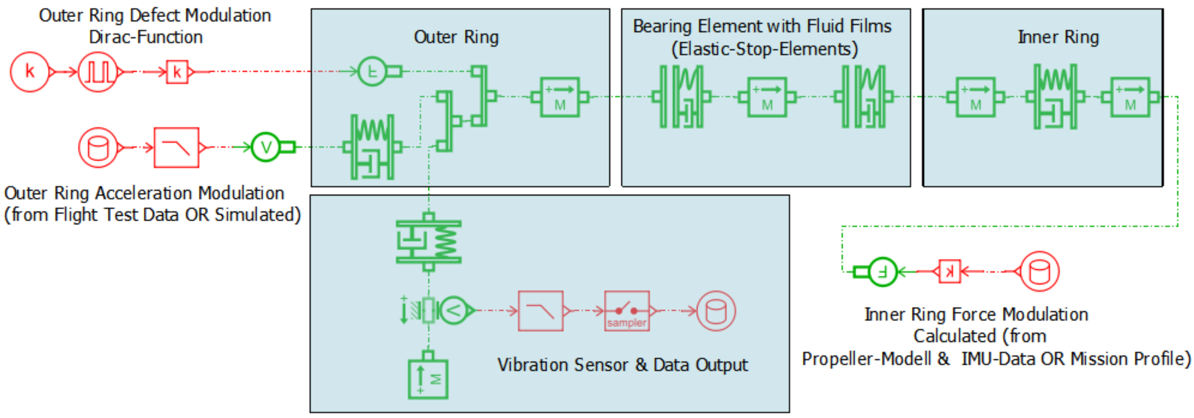

Fig. 2: High Resolution Simcenter Amesim Bearing Model including Sensor Model [based on 4]

Airborne Research Platform

To gather real-world atmospheric data a Stemme S10-VTX aircraft *(Fig. 3)* was equipped with inertial, air-data and acceleration-measurement equipment for three objectives:

1. Gather experimental data to be used directly for the bearing model in order to generate time-based signals for training.
2. Set-up a structural and aerodynamic-response-model based on in-flight operational modal analysis (OMA), transfer-path analysis (TPA) and flight dynamics characterization.
3. Build-up a database with time-based atmospheric data corrected for the A/C disturbances which can be used as an input for the simulation-driven machine learning.

The research aircraft, a Stemme S10-VTX, is a two-seat touring motor glider (TMG) manufactured by Stemme AG in Strausberg, Germany. Aircraft belonging to the TMG class are characterized by the alternative operating modes of powered flight and gliding flight.

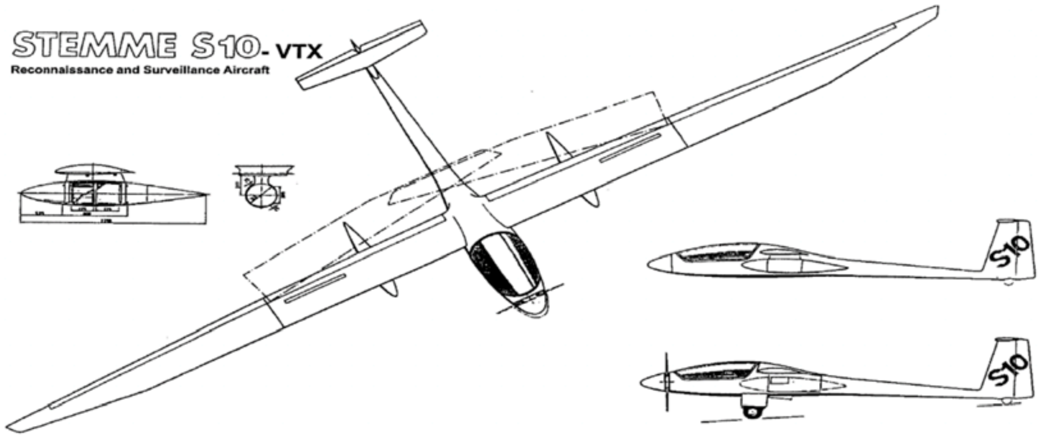

Fig. 3: Drawing Stemme S10-VTX [9]

Compared to the standard S10-VT aircraft, the S10-VTX of the FH Aachen UAS is operated under a "permit to fly" and has several modifications for the integration of measurement equipment. Due to the reinforced wing spar structure, it is possible to attach up to 60 kg of external loads to each wing. In addition. there are hardpoints allowing air-data-probes and sensors to be mounted on the wing, fuselage, and empennage.

The high performance in terms of cruise speed and range of the S10-VTX [9] combined with the initially mentioned operation in gliding mode with a high glide ratio gives the chance to explore different metrological conditions without the disturbances that come from an engine or propeller interfering with the measurements.

To measure airflow vector data an Air Data Probe, type SIMTEC ADP-5.5 is mounted on the right wing at position "ADP" (Fig. 4). The accelerometers, type PCB M353B15 & 352C33 are attached at the positions shown in figure 2. The black dots mark possible sensor positions, the red dots show the positions in use. Additionally, a 3-axis accelerometer type PCB 356B21 is installed at the main spar close to the center of gravity. The inertial measurement data is taken from the avionics integrated inertial measurement unit (IMU). For the data acquisition two Siemens LMS SCADAS XS are installed.

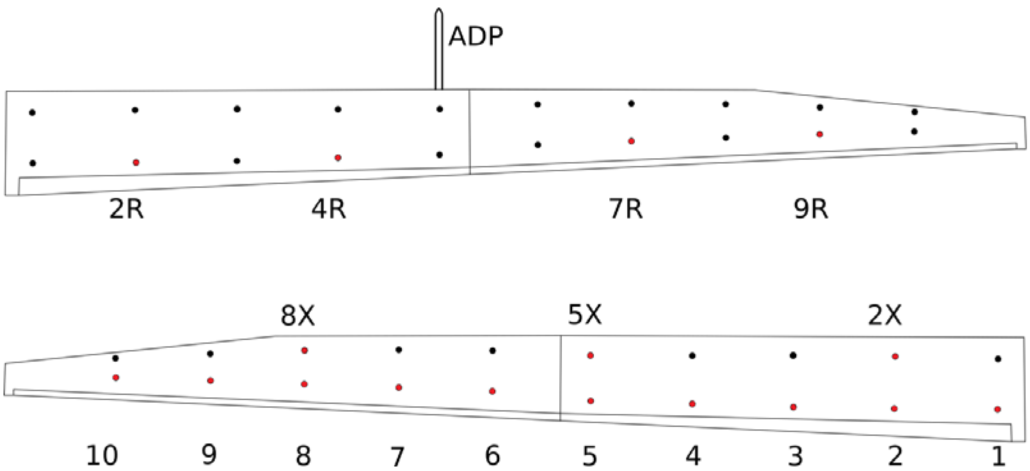

Fig 4.: Sensor and Air Data Probe Positions

Results

Initial flight experiments were performed to validate the integrity of the recorded data. Fig. 5 shows a 10 second segment of the outer ring velocity, which was fed into the model from Fig. 2 directly. This data is calculated by a numerical integration of the acceleration signal recorded by the IMU. The inner ring force is calculated by the gyroscopic moments of the propeller resulting from pitch and yaw movements and fed into the model correspondingly.

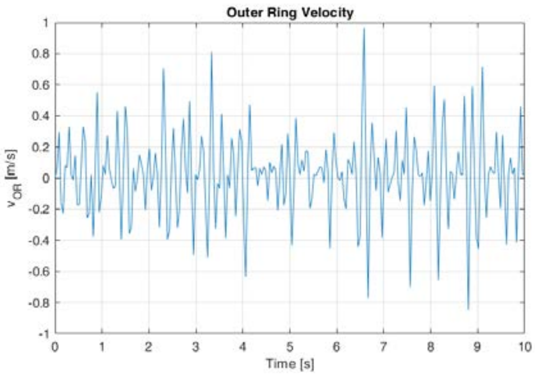

Fig. 5: typical outer ring velocity time-history during steady flight conditions

A synthesized time-series acceleration signal for a SKF 6207 bearing with a fault at the outer ring, running at 2500 rpm and with model parameters adopted from [4] and [6] was calculated to show general functionality of the AMESIM Model from Fig. 2. Acquired flight test data was fed into the model successfully.

As next step, modal parameters were identified using operational modal analysis (OMA) [10] performed in Simcenter TestLab™. Compared to vibration testing which relies on a well-defined excitation, there is no explicit knowledge of the excitation in OMA and thus it cannot be guaranteed, that all relevant modes are well excited. However, it is possible to clearly identify some of the modal parameters repeatable over several analyzed flight segments. There is a good correlation with the ones well-known from [11] computed by a combination of a doublet-lattice-method (DLM) combined with a modified p-k-method [12]. As an example, Fig. 6. shows the resulting mode-shape of the 1st symmetric wing bending mode about the x-axis (S-WI-BX-1 / axis according to ISO 1151) at a frequency of 2.79 Hz.

Fig. 6: S-WI-BX-1 Mode at 2.79 Hz from OMA[1]

The modal parameters identified can be utilized to set up a structural model and in combination with an aerodynamical model of the aircraft as well as with the atmospheric database new time series data as an input to the bearing model (Fig. 2) can be synthesized. **a**

[1] The asymmetry in the shape is caused by the imbalanced sensor distribution over the wings.

Conclusion

A simulation-driven approach for the training of convolutional neural network (CNN) or dynamic time-warp-based (DTW) classifiers was proposed as a vibration-based condition monitoring method for motor bearing fault classification. A model for generating high resolution time-based signals has been adopted and can handle the gathered flight data as well as model-based data. Initial evaluation of the flight test data demonstrated the acquired data's integrity and good performance for the system identification via operational modal analysis. The proposed approach can use experimental as well as computed data for generating training data. This enables a quick adaption to other integration set-ups. In combination with the ongoing data acquisition with the Stemme S10-VTX research aircraft, providing real-world atmospheric data as an input to the generation of training-data, a significant improvement of the robustness of bearing fault detection is expected, contributing to an increased system safety. By empowering condition-based maintenance, it also has the chance to increase aircraft economic performance by reducing both direct and indirect maintenance cost.

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