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Categorization of aircraft missions for exploitation by a digital twin

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The use of new recurrent neural models with layers of attentions has proven to be very effective in monitoring the internal state of an aircraft's engines. Our research work has shown the effectiveness of these methods for predicting corrosion or just measuring a deterioration in performance. However, until now, only the data broadcast by the engine has been readily available, but it seems logical that the description of the mission and the way the pilot handles the aircraft seem equally important. We have therefore developed a mathematical method to describe each mission, in this way it becomes possible to import new data helping to monitor engine wear. In the meantime, these new measurements also give us a new methodology to explore the use of our systems. For example, we are now able to categorize flights and it will become possible to adapt our design and our maintenance offer to the real needs of airlines.

Keywords: Aircraft Engines, PHM, Neural Network.

1. Introduction about PHM

Prognosis & Health Monitoring (PHM) of aircraft engines consists in identifying characteristics to assess its condition. These algorithms are generally separated into two parts: an on-board component to build indicators from the measurements collected during each flight and another, on ground computers, which processes these measurements with other contextual elements to estimate trends or drifts in engine behaviour (Fig. 1). These drifts will be analysed by experts or artificial intelligence algorithms to anticipate risks of degradation.

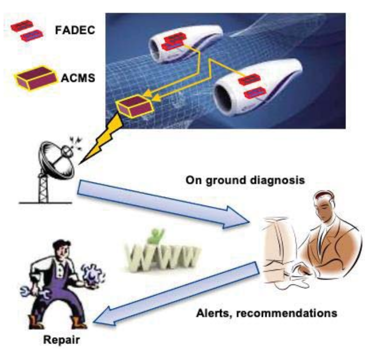

Fig. 1. PHM process.

Initially, PHM directly used summary data produced during each flight in the form of snapshots. This first static analysis made it possible to identify damage present on the engine or a performance drift. By adding contextual data, such as meteorological and pollution data, the damage estimators could be seriously improved (Flandrois et al. 2009).

2. Recurrent neural methods

Finally, very recently, we have started to use recurrent temporal models that evaluate a latent state updated after each flight. The addition of this temporal component, which considers the history of the engine's successive missions, has improved the quality of our predictions (Fig. 2).

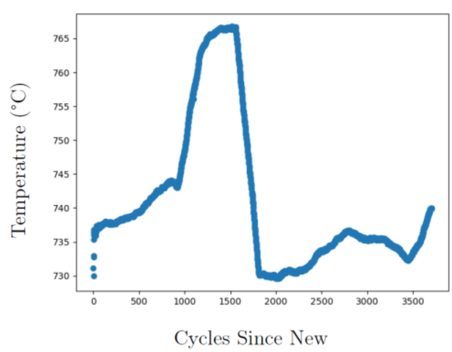

Fig. 2. Observing the wear of an aircraft engine by increasing exhaust temperature and the effectiveness of subsequent repair work. Each point represent the mean value of 10000 simulated flight using the neural network.

The data set corresponds to the entire flight history of 40 aircraft equipped with the new LEAP engine. For each engine of these aircraft, we had information from visual inspections by boroscopy as well as from maintenance operations. The dynamic models seem more efficient than the previous static models even if potential counters which capitalized, for example, the time spent beyond certain load levels, are computed on board the aircraft (Langhendries and Lacaille 2022).

3. Missions categorization

One crucial element was still missing from these models, a description of the missions themselves. Indeed, each flight is different, and we have therefore implemented a detailed method of categorizing flights with a metric allowing them to be compared two by two. This method first performs a decomposition of the rotational speed of the fan, which in our case of turbojets is a relevant indicator of thrust. Once the flight has been segmented from this control signal, each flight segment is categorized. The complete flight can thus be described as a sequence of labels (Cottrell et al. 2019). To build a metric between the flights, we took care to use a topographic categorization procedure using self-organizing maps (SOM) to classify the segments. This type of categorization automatically gives a distance measure between segments, which makes it possible the use of an edit distance as a similarity measure between flights.

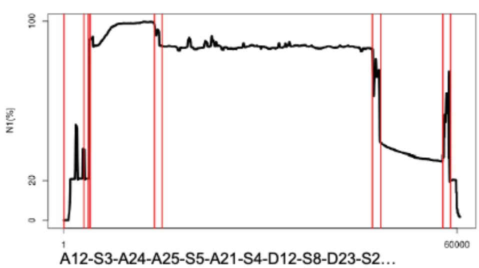

Fig. 3. Automatic division of the flight into transient and stabilized segments. Each segment is then categorized by an unsupervised classification algorithm. The flight is thus transformed into a sequence of labels, as shown below the graph, which represents core rotations speed versus time.

This metric consists of measuring the minimum cost of transforming one flight into another by exchanging, adding, or removing labels. Hence, we categorize the missions and enter the flight class as a new contextual data of the recurrent model.

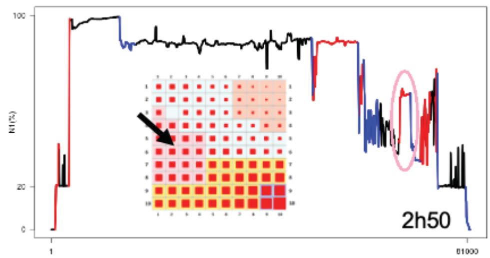

Fig. 4. This chart shows a specific type of flight identified by a category (each box on the self-organizing map) among all flights in a given airline fleet. Here a specific behaviour can be observed by an increase in thrust before landing.

4. Conclusion

An advantage of this method is that it applies to a very large database of past flights automatically and is fast enough. When some missions are original, for example in the case of helicopter or military aircraft tracking, it is not possible to have instant flight summaries easily. Our method makes it possible to identify the categories of the most frequent flight segments and thus to reconstruct such snapshots from temporal data. This allows us to better control the evolution of the state of these engines, much more difficult to follow than for airliners.

References

Cottrell, Marie, Cynthia Faure, Jérôme Lacaille, and Madalina Oltéanu. 2019. “Detection of Abnormal Flights Using Fickle Instances in SOM Maps.” In *WSOM - International Workshop on Self-Organizing Maps*, 1–10. Barcelone.

Flandrois, Xavier, Jérôme Lacaille, Jean-Rémi Massé, and Alexandre Ausloos. 2009. “Expertise Transfer and Automatic Failure Classification for the Engine Start Capability System.” In *AIAA InfoTech*. Seattle (USA, Washington).

Langhendries, Raphaël, and Jérôme Lacaille. 2022. “Turbofan Exhaust Gas Temperature Forecasting and Performance Monitoring with a Neural Network Model.” In *European Conference on Safety and Reliability (ESREL)*. Dublin. https://doi.org/10.3850/981-973-0000-00-0.