The Fourteenth International Conference on
Computational Structures Technology
23–25 August, 2022 | Montpellier, France

Proceedings of the Fourteenth International Conference on
Computational Structures Technology
Edited by B.H.V. Topping and J. Kruis
Civil-Comp Conferences, Volume 3, Paper 22.4
Civil-Comp Press, Edinburgh, United Kingdom, 2022, doi: 10.4203/ccc.3.22.4

Learning virtual sensors of structural stress from on-board instrumentation of a commercial aircraft

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Abstract

The prediction of actual loads on aircraft structures in service phase is an on-going challenge of particular interest for aircraft manufacturers and operators as it directly impacts the optimization of the aircraft design or the optimization of maintenance scheduling in service phase. The variability of mission history, pilot actions or environmental perturbations, for instance, makes accurate prediction particularly challenging. As part of the IA2021 plan, the french Île-de-France region and Dassault Aviation have organised the challenge "AI Challenge for Industry 2020" whose objective was to develop virtual sensors through learning techniques that estimate the mechanical stress of various structural parts of a Falcon business jet using only the aircraft's onboard instruments. The work presented here is based on the response to this challenge provided by the consortium Aquila Data Enabler and ISAE-Supméca. It introduces the approach implemented to predict the mechanical stress of the structure of a business jet in service phase from flight instruments solely.

Keywords: virtual sensor, structural stress prediction, machine learning

1 Introduction

The prediction of actual loads on aircraft structures in service phase is an on-going challenge of particular interest for aircraft manufacturers and operators as it directly impacts the optimization of the aircraft design or the optimization of maintenance scheduling in service phase. The variability of mission history, pilot actions or environmental perturbations, for instance, makes accurate prediction particularly challenging. As part of the IA2021 plan, the french Île-de-France region and Dassault Aviation have organised the challenge "AI Challenge for Industry 2020" whose objective was to develop virtual sensors through learning techniques that estimate the mechanical stress of various structural parts of a Falcon business jet using only the aircraft's onboard instruments. The work presented here is based on the response to this challenge provided by the consortium Aquila Data Enabler and ISAE-Supméca. It introduces the approach implemented to predict the mechanical stress of the structure of a business jet in service phase from flight instruments solely.

Aircraft manufacturers have large databases of test flights necessary for the development and validation of new aircraft models. In addition to the on-board instrumentation of conventional aircraft, the test aircraft are equipped with numerous additional sensors . In particular, strain gauges, glued on different structural parts of the tested aircraft, allow to validate the mechanical stress of the aircraft in different flight phases for certification purposes and enable the validation of numerical models used in conception and design phases. Commercial aircraft are not equipped with strain gauges, the mechanical state of the structure throughout its service phase is thus unknown and only regular maintenance operations check the structural health of the aircraft. As part of the challenge, Dassault Aviation has provided a significant database of test flights of their Falcon business jets. The signals from 130 on-board instruments and 67 strain gauges were recorded during nearly 300 test flights. This database was used to train Machine Learning models to predict the mechanical stress state of the aircraft structure in service. Once trained, these models could be used as a virtual sensor of mechanical stress. This virtual sensor would provide meaningful data to feed a digital twin of the aircraft and could be used as an input of an aircraft predictive maintenance plan. The proposed approach addresses the issue of time series forecasting with heterogeneous data and extreme events.

2 Methods

2.1 Challenge rules description:

The whole dataset was hosted on Université Paris-Saclay's server and was available through the CodaLab plateform of Chalearn http://www.chalearn.org/. It is worth noting that the whole dataset was not directly available to the candidates for confidentiality reasons. A reduced set of three flights, referred to as *Starting Kit*, was however available for data exploration and algorithm prototyping. The dataset satisfies the following assumption: the sampling frequency of each sensor is constant over each flight but sensors are not synchronised and can have different sampling rates; data are heterogeneous as sensors can return real, integer or boolean values. Models developed by the candidate have to be submitted on the CodaLab platform and only one metric and the computation time were returned by the platform to evaluate the model performance. The metric considered was the Mean Absolute Error (MAE) defined by

$$MAE = \sum_{i}^{n_{val}} \frac{|f(X_i) - Y_i|}{n_{val}} \quad (1)$$

where X_i is the input time series (on-board instrument signals), Y_i the output time series (strain gauges signals) and f the trained model.

2.2 Model architecture:

After a step of data exploration and several numerical tests on the CodaLab platform, a workflow has been defined. It includes a first step of data cleaning (interpolation of missing data, data resynchronization, redundancy removal), a step of feature engineering and an ensemble learning strategy which consists of two consecutive regressors layers.

The feature engineering considered aims at taking into account the operating phases of the aircraft. The main working assumption is that the aircraft in-flight physic varies little in a phase of flight. Assuming that the air data system (ADS) sensors and the inertial reference system (IRS) sensors provide sufficient information to describe the in-flight physic, and in particular the loads applied to the structure, signals from ADS and IRD sensors have been clusterized using a k-means algorithm. Phase clusters have then been added to pre-processed sensors data and used as input to train the first regressors layer (one regressor per gauge to be predicted). The LightGBM regressor, an advanced Gradient Boosting Decision Tree model developed by Microsoft in 2017 [1], is used for each regressor of the first layer. In the second layer, a linear ridge model is used for each regressor of the layer. These regressors are trained considering the prediction of the first layer as input and the gauges values as output. The second layer is thus used as a regularization layer to get rid of the outlier predictions.

3 Results

3.1 Model performances:

The proposed pipeline has been trained on the whole training set of 102 flights available on the CodaLab platform and the accuracy of the prediction is evaluated with the MAE metric on a validation set of 178 flights. The proposed pipeline was trained on the training set in 1280 seconds and its score on the validation set was MAE = 0.01402. In order to better assess the MAE score of the proposed approach, it can be noted that data provided by Dassault Aviation were normalized (due to confidentiality), all outputs (gauge signals) considered to train the model were thus in the range of 0 to 1.

The prediction performances have also been evaluated depending on the gauges location on the aircraft. Even though the average MAE remains low in all cases, it can be noticed (Table 1) that the model performance is lower for gauges on fuselage and pitch than for gauges on wings, fin or actuators. The accuracy of the model during specific flight phases associated with heavy loads on the aircraft has also been evaluated. It can be noticed that the average MAE remains lower than 0.015 at any flight phase.

Gauges Location	MAE	Specific flight phases	MAE
Fuselage Wings Pitch Fin Actuator	0.02050 0.01014 0.01467 0.01023 0.01155	MANEUVER GUST TURBULENCE	0.01405 0.01505 0.01229

Table 1: Average MAE obtained on the validation set for different gauge location and different flight phases

During the prototyping phase of the challenge, different regressors have been tested and compared using the MAE and training duration as a criterion for evaluation. LightGBM, Random Forest, Adaboost, Multi-Layer Perceptron, Ridge and LASSO have been trained and tested using the database available on Codalab. The LightGBM provided the best predicion with the lowest training duration.
A comparative analysis of the performance of the proposed approach in comparison with solutions provided by other competitors of the challenge has been proposed by Pavao et al [2].

4 Conclusions and Contributions

The solution developed to address the challenge proposed by the Île-de-France region and Dassault Aviation has lead to a new concept of virtual sensor for the prediction of the structural mechanical stress of an aircraft. This virtual sensor relates the measurement of flight instruments available on any commercial aircraft to the mechanical stress undertaken by the plane. The solution proposed in this work mainly relies on the combination of a clustering algorithm to identify flight phases and a two-stage regressor based on LightGBM and Ridge algorithms.

The performance of the proposed approach in terms of training frugality and prediction accuracy has been demonstrated. The natural interpretability of tree-based algorithm is another advantage of the proposed approach.

Winner of the challenge, the consortium Aquila Data Enabler and ISAE-Supmeca has started a collaborative project of 18 months whose primary objective is to develop an industrial solution of virtual sensor dedicated to the prediction of aircraft structural stress. In order to exceed the performance of the solution developed during the challenge (in only two months and with no direct access to the full dataset), state-of-the-art deep learning architectures are under investigation. In particular, the Variational Auto Encoder (VAE) [3] architecture is studied. The possibility to explicitly structure the VAE latent space to give it desirable properties appears as a good opportunity to hybridise VAEs with physic-based models. This approach aims at taking advantage of the capabilities of deep-learning techniques while providing interpretability to the model thanks to its physics awareness.

Acknowledgements

This action is supported by the french *Ile-de-France Region*

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