DIRECT LOAD RECOGNITION TO ESTIMATE THE DAMPER LOAD ON THE H175 FLEET

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Abstract

This paper presents an application of the Direct Load Recognition (DLR) methodology to estimate the main rotor damper load on customer flights. The DLR producing good results on the prototype flight test data, this paper elaborates the steps to develop a virtual sensor for estimating the loads using the customer data. The DLR methodology is based on the combination of a harmonic decomposition and the use of Machine Learning algorithms. First of all, the approach consists in building and evaluating the DLR methodology on prototype flight test data to estimate the main rotor damper loads from a set of recorded flight parameters. This development phase shows the feasibility of the DLR to estimate the damper load. Then, this paper focuses on the application of the constructed model with DLR on customer flights. From the damper load estimation, a damage is derived and summed up for each aircraft of the H175 fleet, showing that the customer flights are well below the Design Usage Spectrum. Finally, the results of the study indicate that the aircraft maintenance could be adapted on the helicopter usage.

1. NOTATION[1]

Acronyms:

DLR	Direct Load Recognition
ML	Machine Learning
HUMS	Health and Usage Monitoring System
MLP	Multi-Layer Perceptron
MR	Main rotor
ReLU	Rectified Linear Unit
MAE	Mean Absolute Error

2. INTRODUCTION

Big data and predictive analytics applications have been more and more studied in the helicopter industry during the last years. Available data contain valuable information that can be extracted and transformed enabling the helicopter companies and operators to reduce their costs. Within this context, Condition (Usage) Based Maintenance services are rapidly evolving with one objective to adapt the maintenance cycles to the aircraft usage as described in Ref.1. One key point of this process is the use of loads to evaluate the damage of mechanical components during flights (Ref. 2). However the direct monitoring of loads is not possible in operation regarding the difficulty to collect such a large amount of data and to equip serial aircraft with sensors necessary to measure the loads, as strain gauges. To bypass this problem, the loads can be estimated, thanks to virtual sensors (DLR methodology). It consists in using the measurements of flight parameters describing the context of the flight (also available from helicopter operators), harmonic decomposition and Machine Learning (ML) algorithms. Thus, a load estimation can be obtained in operation. The approach to have a load estimation on operational flights relies on, first, the construction of the estimator on prototype flight test data (having both flight parameters and load measurements). And then, the application on customer flights (having only flight parameter measurements). Nevertheless, the DLR methodology, presented in Ref. 3 and 4, has, for now, only been applied on dedicated development flight test campaigns. The generalization from flight test data to customer flight data brings some constraints. In previous studies (Refs. 5, 6, 7) the load estimation has been performed by maneuver, however, this information is not directly available during operational flights. It could be estimated by flight regime recognition techniques as in Ref. 8, but DLR methods have demonstrated promising performance on flight test data, as they include all the transitional phases' loads estimation, contrary to alternative methods (Ref. 3).

However, the DLR application on customer flights raises some key questions,

1. Is it possible to adapt the DLR methodology constructed on flight test data to estimate customer flight loads?
2. Are the customer flights evolving in known flight envelope?
3. Is it possible to adapt the maintenance cycles to the aircraft usage, by estimating customer flight loads?

This paper reproduces the methodology described in Ref. 4 to construct the estimator on another part of the main rotor (MR), the lead-lag damper of the H175 helicopter.

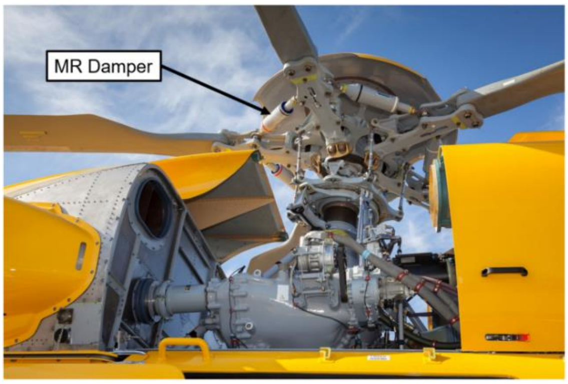

Figure 1: Illustration of the H175 main rotor. The damper is shown at the top of the picture.

By studying the MR damper part of the H175 helicopter, we can take advantage of the availability of both prototype flight test and a large set of operational flight data. This paper focuses on the estimation of the MR damper load. The MR damper displacement has also been studied and will be detailed in another study.

This paper starts by discussing about the load estimation methodology in Section 3. Then, Section 4 describes the H175 data used in this study. Section 5 focuses on the model construction on the flight test data, and its evaluation by comparing the estimated load to the measurement. And finally, Section 6 applies the model on customer flights and analyzes the obtained estimations, followed by a conclusion in Section 7.

3. LOAD ESTIMATION METHODOLOGY

The loads have a very dynamic behavior compared to the flight parameters. Therefore, a point to point prediction is not efficient. However, signal components extracted from the load values can be predicted from the flight parameter values. These signal components can be derived from the load by applying a signal decomposition of the loads over each rotor revolution. Different types of decomposition can be applied extracting different coefficients, first, a load can be decomposed in mean (static) and oscillatory (dynamic) components, or in minimum and maximum values. In addition, mathematical decompositions representing the signal on an orthogonal basis can be applied. The principal component analysis, the singular value decomposition, or else the harmonic decomposition are part of this type of decompositions. Signal components are also extracted from these decompositions. Several studies focus on the first type of decompositions as in the old review of studies in Ref. 5 and more recently in Ref. 6. Others, prefer to apply the second type of decomposition to be able to reconstruct the temporal load (Refs 3, 4, 7, 9, 10, 11).

In this paper, the choice is also to have a temporal estimation of the load. A harmonic decomposition is chosen, rather than a principal components analysis or a singular value decomposition, to exploit the known frequency content of the signal. For the harmonic decomposition, the extracted signal components are the pairs amplitude, phase or real, imaginary parts. Thus, the load estimation methodology applied in this study, called DLR, consist in combining a harmonic decomposition/reconstruction and ML algorithms. This process enables to build a direct link between contextual flight parameters and a flight load. The efficiency of the DLR methodology on flight test data has already been shown whether with temporal/recurrent networks (Ref. 11) or with conventional Multi-Layer Perceptron (MLP) (Ref. 3) defining the ML model. Different types of MR and tail rotor loads have already been studied, as the mast bending moment, the MR pitch-link load or the tail rotor torque load (Refs. 3, 6, 9, 10, 11).

The approach developed in this paper relies on several steps, including the models construction and evaluation on the flight test data, and the estimation on customer data.

To sum up, the study steps are the following:

1. Model building on a data training set composed of prototype flight tests,
2. Evaluation of the models on a data test set composed of prototype flight tests not part of the training set,
3. Application on operational flights,
4. Analysis of the load estimated on the customer flights and computation of the damage.

4. DATA USED IN THIS STUDY

The H175 data used in this study is of two types: the prototype flight test data and the customer flight data. These two are described below.

4.1. Prototype flight test data

The flight test data corresponds to prototype flight tests performed during the helicopter development. During these flight campaigns the helicopter is equipped with sensors and strain gauges recording a large variety of parameters. These records include flight parameters describing the aircraft behavior (such as acceleration and control parameters) and external characteristics (such as speed and temperature) during a flight. Moreover, the strain gauges allow the measurement of the flight loads, as for the MR damper load and also the MR damper displacement.

The information of when a MR revolution begins, called rotor top, is also recorded (one top being recorded every rotor revolution). These 3 types of recorded parameters is used in this study.

For this paper, 31 prototype flight tests have been used. These flights consist in a wide variety of maneuvers as level flight, turns, climb, descent, hover and low speed conditions. Moreover, they include transitional phases which are predominant.

Under-represented data

During the first experiments, it has been noticed an underestimation of the high values of dynamic load compared to the other values. The study of these underestimated cases highlights that these values are under-represented (less than 1% of data). In other words, the dataset is imbalanced. Given this low representation, these cases are poorly considered by the model, having a low weight on the error, optimized during the ML model building. However, these high loaded values have more impact on the fatigue computation, so they have to be well estimated.

In order to take more into account the high dynamic load values, a resampling strategy of the data set, is performed. The method consists in the duplication of these values, as applied in Ref. 12. Thus, their weight is increased. This strategy significantly improves the performance on the loads higher values. The distribution of the dynamic values of the damper load before and after duplication are visualized in Figure 2 and Figure 3.

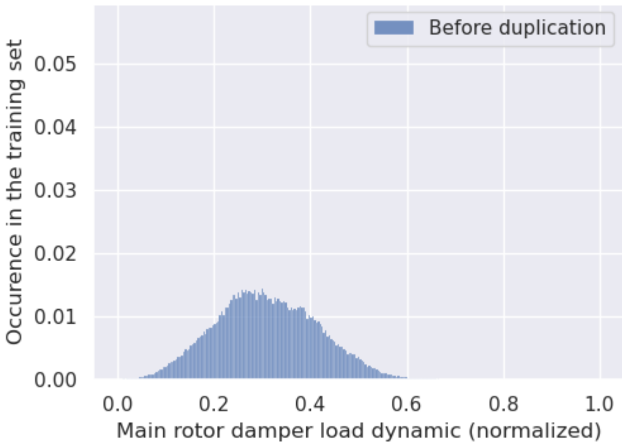

Figure 2: Distribution of the damper load dynamic values.

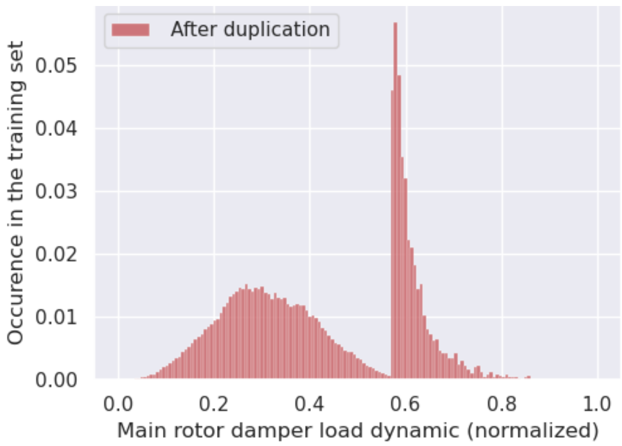

Figure 3: Distribution of the damper load dynamic values after duplication of the higher values.

The percentage of duplication has been set by experiment. Other techniques of optimization of the training set could have been applied, as other resampling methods or other distribution for the duplication of data points. In the future, this method has to be adapted. It could be done specifically depending on the customer needs. There is still ongoing research on this topic.

4.2. Customer flight data

The second type of data, used in this study, is the customer operational flights. For this type of data, the flight parameters are measured thanks to the HUMS embedded monitoring system.

In this paper, around 70.000 sessions of customer flights have been used.

4.3. Discussion

In this study, 16 flight parameters are used. These parameters have been selected by engineering experience making sure they have a good description of the context and behavior of the helicopter flight.

5. MODEL CONSTRUCTION ON FLIGHT TEST DATA

This section details the methodology applied in the 1st and 2nd steps of the study.

5.1. Description of the approach

The flight parameters have quasi-static evolution, meaning that they are assumed to be invariant over a rotor revolution. In the contrary, during the same moment, the loads have large evolutions. Indeed, the loads have dynamic evolutions synchronous of the rotor revolutions. Therefore to be able to perform a linkage between the flight parameters and the flight loads, they have to be preprocessed.

Preprocessing

The same preprocessing is performed as in Ref. 4. More precisely, for the flight parameters a mean value is computed over each rotor revolution, defining the input parameters. Before using a ML model the input parameters are normalized to standardize the scale of each input (except if the ML model is part of tree algorithms), using a Z-score normalization (Ref. 13). Concerning the flight loads, a harmonic decomposition is computed over each rotor revolution. The static and the real and imaginary parts of the K selected harmonics are extracted, defining $2K + 1$ output parameters to be estimated.

Model construction

During the first step of the study, the model type and configuration have to be defined. Since we have a high number of output parameters, this is a multi-output problem. ML algorithms are usually constructed to predict one output, however, two approaches can be implemented to handle multi-output problems. First, it can be transformed in multiple 1-output problems, called the binary relevance method. Then, some ML algorithms have been developed to be able to tackle the multi-output problem. Depending on the K, the number of output can be higher than the number of input, therefore, in this study, it is preferred to use the first method.

Concerning its definition, in Ref. 4, DLR methodology has been applied using different algorithms performing linear or non-linear regression. The MLP ReLU model gave the best results by having the most consistent deviation. In this paper, the same model configuration is used for the damper load estimation. MLP models are fully-connected neural network; in our case, it has one input layer of 16 neurons (corresponding to the flight parameters), one hidden layer of 100 neurons and one output layer of one neuron. A ReLU activation function is applied on the hidden layer enabling to have sparse weights of neurons and a quick implementation.

To be able to evaluate the predictions, the available data is separated in two different datasets: the training set, used to build the models, and the test set, used to evaluate the models and its generalization capabilities. Usually the training set represents from 60% to 80% of the available data. In this study, the choice is to keep the flight sequences, with 75% of the available flights selected to define the training set. The training and test sets are defined ensuring the variety of their maneuvers.

Signal reconstruction

The models described above allow to have a prediction of the harmonics parts of the load signal, however the aim of this study is to have a temporal load estimation. The reconstruction of the load is carried out by applying the same method than in Ref. 4.

Once the signal is reconstructed, the rainflow cycle counting algorithm (Ref. 14) is applied, enabling to have the information of the number of cycles by dynamic load range, and produces the damage of the component.

Evaluation

To evaluate the performance of the load estimation produced by the model, the Mean Absolute Error (MAE) criterion is computed. It is defined as follows,

$$MAE(y_i, \hat{y}_i) = \frac{1}{m \times n} \sum_i |y_i - \hat{y}_i|, \quad \in [0, +\infty[$$

With,

- y_i and $\hat{y}_i \in \mathbb{R}$ being respectively the measured and estimated values for $i \in \{1, \dots, n\}$ and $n \in \mathbb{N}$ their length,
- $m \in [0, +\infty[$ being the maximum measured value in the training set,

The objective value of this criterion is 0, meaning that lower is the MAE value, better is the estimation. The MAE computation expresses the mean absolute error depending on the maximum measured value in the training set. For example if MAE=0.03, that means that the absolute error is 3% of the maximum measured value in the training set.

Other mathematical criteria have been computed to check the consistency of the results. As for example, the median absolute error, being more robust to error outliers, or the normalized root square error, giving more weight to high errors.

In addition, a loads criterion is computed from the rainflow output, i.e. the number of cycles associated to the dynamic load levels, to assess the performance of the loads prediction. This criterion is defined as follows,

$$LC = \sum_i nc_i \times l_i^3,$$

With, nc_i being the number of cycles corresponding to l_i the dynamic load level at the ith index.

The loads criterion is defined in such a way that the higher the dynamic load value, the greater the impact on the load criterion value. This behavior is due to the cubic power on the dynamic load. The cubic power has been defined knowing that, for a damage computation, the higher load values have more effect on the fatigue.

This criterion is computed over the measured and the estimated values to compute a ratio between estimation and measurement,

$$LC_{ratio} = \frac{LC_{estimated}}{LC_{measured}}.$$

The ratio objective value is 1, meaning that the load criterion on estimated values is equal to the one on the measured values.

Moreover, visualizations, as the dispersion between estimated and measured values, are displayed to help to understand how the models behave locally.

5.2. Results obtained with this approach

An example of signal estimation for the damper load and displacement is visualized on Figure 4 for a flight included in the test set.

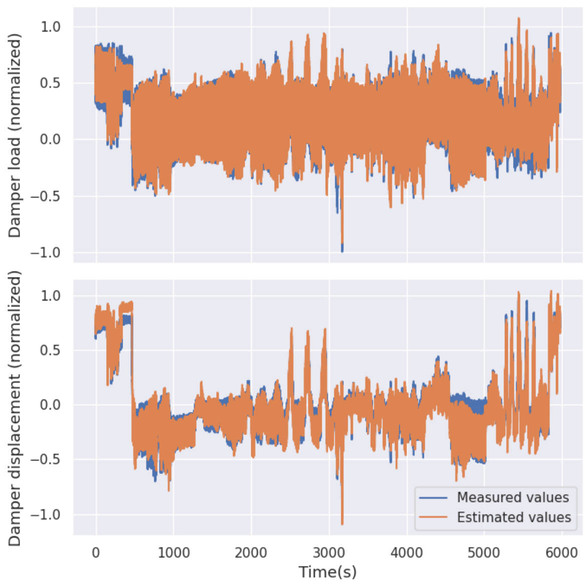

Figure 4: Example of MR damper load (upper graph) and displacement (lower graph) estimation in orange, compared to the measured values in blue, normalized for a flight of the test set.

For both MR damper load and displacement, the estimation is accurate compared to the measured values.

To illustrate how the estimation behaves on all the flights of the training and the test sets, the dispersion between the estimated values and the measured values is illustrated for the static part in Figure 5 and Figure 6 and for the dynamic part of the load in Figure 7 and Figure 8. For each graph, the color corresponds to the density of points, darker means higher density of points, while lighter means lower density of points.

The static dispersion shows that the majority of the estimated data points are close to the measured values. This result is specifically highlighted by the density coloring of the dispersion points. Some points have lower performance of estimation. However, it is interesting to notice that the error has a constant interval around the identity (objective) line $f(x) = x$. In addition, the dispersion is similar between the training and the test sets.

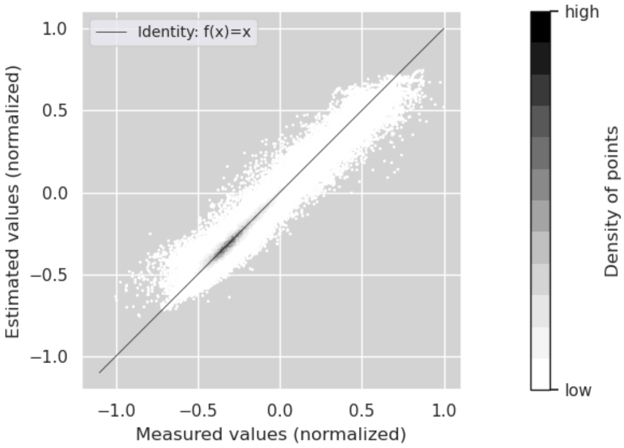

Figure 5: Dispersion between the estimated and the measured values of the static of the MR damper load on all the flights of the training set.

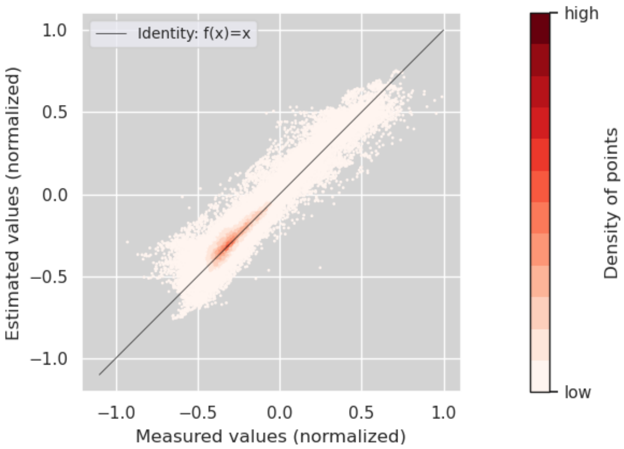

Figure 6: Dispersion between the estimated and the measured values of the static of the MR damper load on all the flights of the test set.

Concerning the dynamic dispersion, there are two behaviors. Some low dynamic values, corresponding to low speeds conditions, are underestimated. Nevertheless, this low dynamic values have no impact on the fatigue computation since they are remaining below the fatigue limit. In addition, as for the static dispersion, there is a higher density of points close to the identity line. This result means that the majority of the estimated data points are close to the measure values, especially for the high values having a big impact on the damage computation. In addition, the global dispersion evolution is similar between the training and test sets.

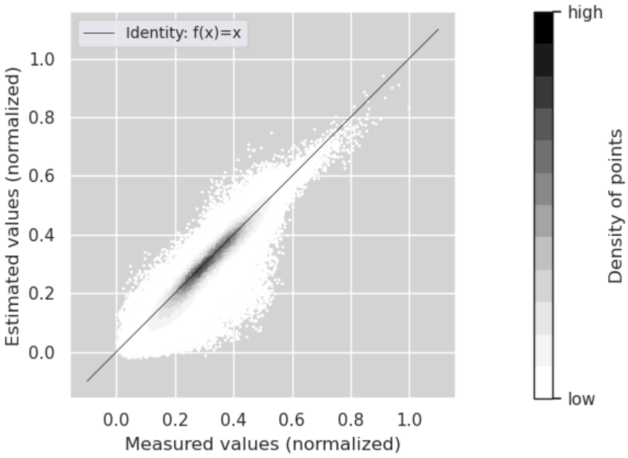

Figure 7: Dispersion between the estimated and the measured values of the dynamic of the MR damper load on all the flights of the training set.

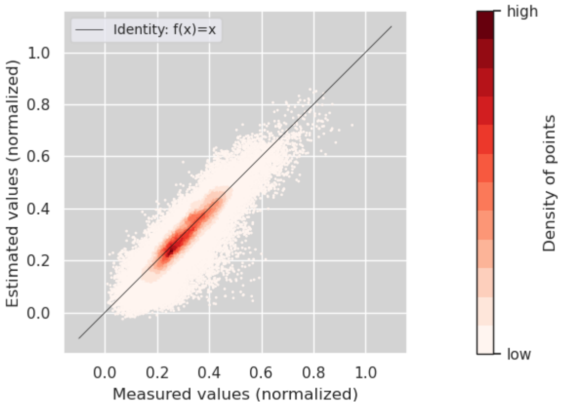

Figure 8: Dispersion between the estimated and the measured values of the dynamic of the MR damper load on all the flights of the test set.

The criteria described in the previous subsection are computed for the general analysis of the training and test set. First, the MAE mathematical criterion is computed to evaluate the performance on the load estimation and on the estimation of its static and dynamic parts. Its distribution is visualized as a boxplot in Figure 9 which consist of a box and two whiskers. The bound lines of the box represent the 1st ($Q1$) and 3rd quartile ($Q3$) of the MAE values, i.e. the values for which 25% and 75% of flights have a criterion value lower. While the internal line represents the median value. The minimum and maximum limits of the whiskers are respectively defined as the first datum greater than $Q1 - 1.5 \times (Q3 - Q1)$ and the last lower than $Q3 + 1.5 \times (Q3 - Q1)$. All values that fall outside the minimum-maximum intervals are considered as outliers, illustrated as a rhombus point in the figure.

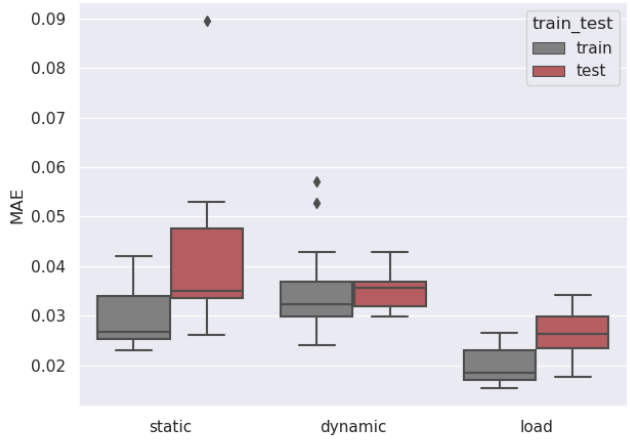

Figure 9: Boxplots of the MAE values obtained on the MR damper load estimation and its static and dynamic part for all the flights.

Figure 9 shows that the MAE results are good compared to the maximum value. Indeed, the majority of flights have a MAE lower than 4% of the maximum value for the static and dynamic parts and especially for the load. Some outliers can be noticed, corresponding essentially to low speeds conditions, already highlighted before in the dispersion visualizations.

The other mathematical criteria, cited above in Section 5.1, are consistent with the MAE result.

After the computation of the MAE, the load criterion ratio, LC_{ratio}, is computed. The results are displayed in Figure 10.

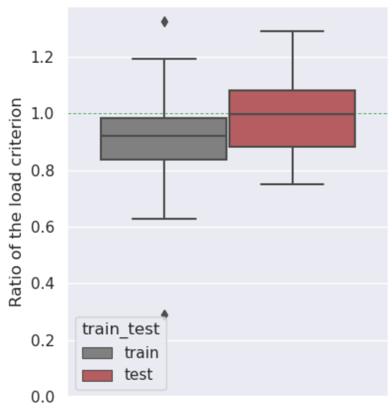

Figure 10: Boxplots of the ratio between the load criterion computed on the estimated values and the one computed on the measured values of the MR damper load for all the flights.

The ratio values obtained are good, with a majority of flights within 0.8 and 1.2, so close to 1, especially for the test set having very good performance. In addition, the results are in consistency with the MAE values. Indeed, the outliers, corresponding to low speed conditions having no impact on the fatigue computation, are detected by both criteria as having lower estimation performance.

Since the validation of the good results on a test set, the application on customer flights is considered.

6. MODEL APPLICATION ON CUSTOMER FLIGHT DATA

This section details the methodology applied in the 3rd and 4th steps of the study.

6.1. Description of the approach

The application process is similar between the flight tests and the customer flights. The same preprocessing is applied on the flight parameters, being then used as input parameters of the models built on the training set to produce the harmonics predictions. Finally, the estimated load is obtained by the harmonics reconstruction.

In addition, as for the flight test data, the rainflow cycle counting algorithm is computed on the estimated damper load. As explained at the beginning of this paper, the aim of a load estimation is to derive the damage of the component. By using fatigue properties on the obtained rainflow, a damage estimation of the metallic part can be computed. The fatigue properties consist in linking the load and the number of cycles before rupture at a given probability. It can be represented as a fatigue curve having an infinite lifespan for low loads values. The infinite lifespan corresponds to a load limit, the fatigue limit.

Input parameters verification

As a precaution the input parameters envelope is verified. The process consists in verifying that for each input parameter, i.e. each preprocessed flight parameter, the training set bounds are not exceeded. Indeed, if the studied sessions of flights are not covered by the training set, the model estimation cannot be guaranteed, in fact the MLP model cannot extrapolate.

The developed method on customer flights adapt the DLR methodology to estimate the customer flight loads.

6.2. Results obtained with this approach

The analysis of the load factor (NZ) and the true airspeed (TAS) parameters, impacting the damper load, shows that the customers evolve in a known flight envelope, as illustrated in Figure 11.

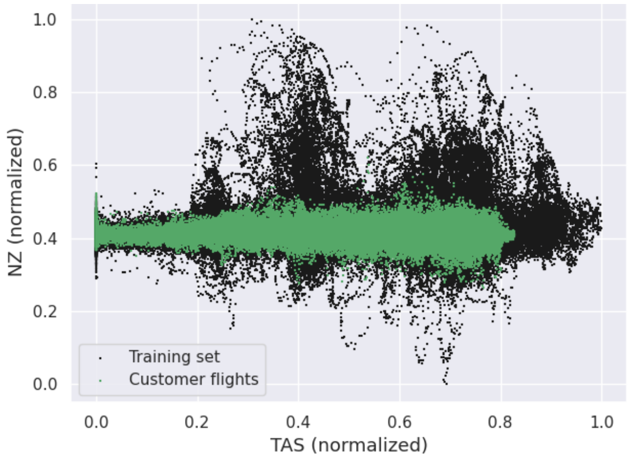

Figure 11: Load factor (NZ) plotted against the True Airspeed (TAS). Comparison between the training set and the studied customer flights.

Example of results

Two examples of estimated dynamic are visualized for two different flights in Figure 12. The first example corresponds to a flight having load factor values close to 1, while the second is a flight with higher values of load factor. In addition, the flight control positions are lower for the first flight. For Figure 12, the y-axis is normalized compared to all the flight tests as in Figure 7 and Figure 8

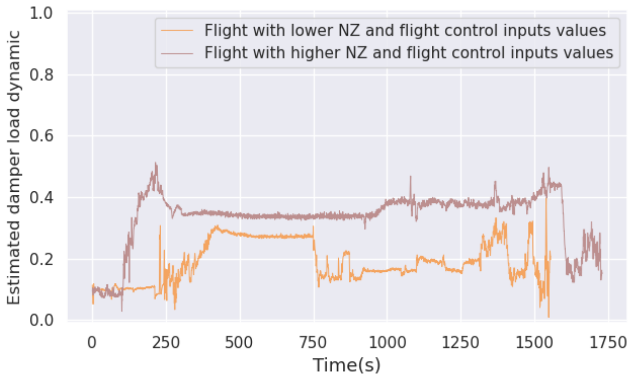

Figure 12: Estimated dynamic of the MR damper load for two customer flights having different values of NZ and flight control inputs.

The impact of the NZ and the flight control inputs is noticeable, with higher estimated values for the case with higher parameter values.

Damage computation

To complete the study, the damage is computed from the obtained rainflow for each customer flight. For better interpretation, the computed damage is converted into virtual flight hour compared to the real flight hour of the flight. More precisely, the virtual flight hour corresponds to the damaging flight hour.

The cumulated damage results are displayed for each aircraft in Figure 13. The y-axis correspond to the virtual flight hour by aircraft, while the x-axis is the realized flight hour by aircraft. The aircraft visualization is compared to the Design Usage Spectrum (DUS), corresponding to the red line $f(x) = x$. The other lines are derived from the DUS by being described as $f(x) = x/a,\ a \in \{2, 4, 8\}$. The points of same color correspond to a same helicopter operator.

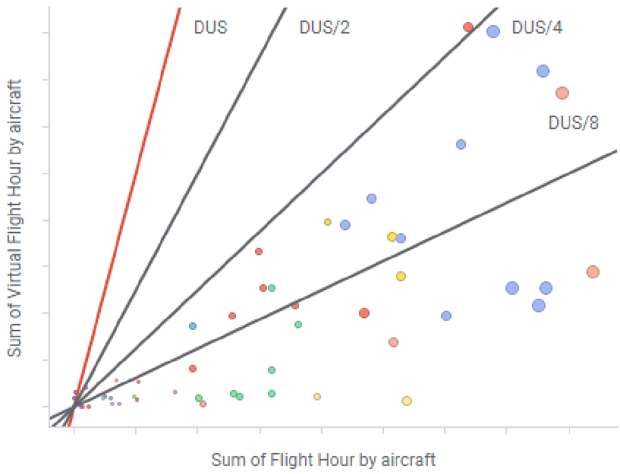

Figure 13: Comparison of the virtual flight hour computed from the load estimations and the real flight hour grouped by customer aircraft.

This visualization shows that,

- The DUS hypothesis is conservative compared to the customer flights. Indeed, for all the aircraft the virtual flight hour is well below the DUS line.
- The majority of the aircraft is lower than DUS/4 and even DUS/8 for more than half. Therefore, the application of the DLR methodology could adapt the maintenance of each aircraft based on its usage.
- A difference can be seen between helicopter operators. In addition, we observe a variety of usage for a same helicopter operator.

To complete the third point, the loads criterion values computed on the estimated damper load are illustrated for two different aircraft in Figure 14. The two compared aircraft belong to the same helicopter operator and have the same number of flight hours (several thousand hours). Nevertheless, the number of virtual flight hours is different, around 20% of the flight hours for the first aircraft and less than 10% for the second.

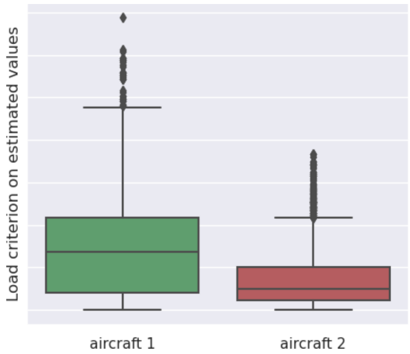

Figure 14: Boxplot of the loads criterion computed on the estimated MR damper load values for two aircraft with different damage behavior.

The obtained criterion values are in consistency with the computed damage. Indeed, the median value of the load criterion is much higher for the first aircraft, which shows that the load criterion values are in majority higher than for the second aircraft.

7. CONCLUSIONS

This paper presents an application of the DLR methodology to the MR damper load and a use case showing the impact of the methodology on the customer flights. The damper loads estimator constructed on prototype flight test data gives good results, which has been shown with several criteria of evaluation. Therefore, the load estimation is generalized on approximatively 70.000 sessions of operational flights lasting more than 80.000 hours.

The study presented in this paper shows that,

1. The DLR methodology can be used to construct an estimator of the MR damper load on flight test data. Since the good performance obtained on the flight tests, the method can be applied on customer flights.
2. The flight envelope, and therefore the flight tests used to build the DLR model, covers the customer flights.
3. The damage estimation computed for the customer aircraft is well below the Design Usage Spectrum. This result shows that this method could help to adapt the maintenance to the aircraft usage.

This study essentially focuses on the high cycle fatigue. In future works, the low cycle fatigue will also be addressed. However, for this analysis, instead of estimating the static value around the entire flight, it would be preferred to target the minimum and maximum values.

Finally, the DLR methodology shall be completed with the determination of results uncertainties, as the method developed in Ref. 12. The adding of confidence interval to the loads estimation would benefit to the certification process of such a method.

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