Surrogate models for helicopter loads problems

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Abstract

One of the activities of the EUROCOPTER flight test department is to measure loads for different components (through load gauges) and flight configurations. In this paper, a flight configuration includes both the manoeuvre and general information about the helicopter itself (helicopter weights, longitudinal/lateral centre of gravity locations, altitudes) and the air characteristics in which the helicopter is flying (Outside Air Temperature). A flight configuration is described by the Flight Configuration Parameters (FCP). Information, obtained from this activity, is stored in a specific database.

In the scope of CHAMALO (acronym of Calculation of Helicopter Approximated MAcros LOads) project, EUROCOPTER is interested in building surrogate models from the existing load database to estimate missing loads from FCP.

Both the objective and challenge is to automatically build accurate and robust surrogate models from the load database, which explain the relations between the input FCP and the output static and dynamic loads.

MACROS tool (developed by DATADVANCE) is used for surrogate modelling. This tool includes a wide range of well-known techniques (e.g., Splines, Linear Regression, Gaussian Process Regression), original techniques (e.g., HDA - High Dimensional Approximation), an automatic selection of the appropriate approximation type based on built-in decision tree and data properties, and a flexible support for accelerated training, smoothing, handling multiple output components, etc.

Once the best surrogate models for each load gauge (66 in total) and manoeuvre family (32 in total) were constructed, CHAMALO software was developed by DATADVANCE for automatic prediction of helicopter static and dynamic loads as a function of FCP.

It is concluded that EUROCOPTER considers this approach to be very promising. In fact, about 50% of missing loads, which need to be estimated, may be calculated by CHAMALO with a sufficient accuracy, drastically reducing the time and manpower needed for such analysis. Further studies are planned to increase this percentage.

1. Introduction and motivation

In the helicopter industry, for each PSE[1] appropriate inspections and retirement time[2] must be established according to airworthiness requirement CS or FAR 29.571 (cf. [1] and [2]).

Both these regulations require:
   a) In-flight measurements to determine the fatigue loads or stresses in all critical conditions throughout the range of design limitations required in CS/FAR 29.309 (including altitude effects), except that manoeuvring load factors need not exceed the maximum values expected in operations.
   b) Loading spectra as severe as those expected in operations, including external load operations, if applicable, and other high frequency power cycle operations.
   c) A determination of the fatigue tolerance characteristics that supports the inspections and retirement times, or other approved equivalent means.

Once the helicopter type is certified, the flight envelope enhancement and more specifically the increase of Weight-longitudinal/lateral Centre of Gravity diagram may be requested for customer satisfaction.
In the short term, preliminary studies are performed to estimate the influence on inspections and retirement time for each PSE, and to list PSEs which need to be re-designed to cope with this new flight envelope.
At the end of this process, in-flight measurements are performed for the certification to comply with CS/FAR29.571.

During these preliminary studies, in-flight measurements for the critical conditions of this new flight envelope are not yet performed. To date, analyses are carried out through models based on Physics (combining aerodynamic and mechanical laws) to estimate the missing loads.

In the scope of CHAMALO[3] project, EUROCOPTER is interested in building surrogate models from the existing load database to estimate missing loads from the Flight Configuration Parameters.
These surrogate models are obtained by MACROS (software developed by DATADVANCE[4]).

The objective of this paper is to present and evaluate this new methodology.

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[1] PSE = Principal Structural Element, the failure of which could have catastrophic effects for the helicopter.

[2] Also named safe-life or replacement time.

[3] CHAMALO is the acronym of **C**alculation of **H**elicopter **A**pproximated **MA**cros **Lo**ads.

[4] DATADVANCE llc is an EADS Company (for more information please visit www.datadvance.net).

2. Method and Tools

2.1. Load database

One of the activities of the EUROCOPTER flight test department is to measure loads for different components (through load gauges) and flight configurations. In this paper, a flight configuration includes both the manoeuvre and general information about the helicopter itself (helicopter weights, longitudinal/lateral centre of gravity locations, altitudes) and the air characteristics in which the helicopter is flying (Outside Air Temperature). A flight configuration is described by the Flight Configuration Parameters (FCP).

For each flight configuration, the measured loads versus time are post-treated to derive static and dynamic loads per revolution versus time, and then, to calculate maximum/mean/minimum static loads, rainflow matrixes and maximum dynamic load per configuration.
All these values are stored in a huge load database.

In the scope of CHAMALO project, medium class twin-engine helicopter EC225 (see fig 1) was selected.

Figure 1: EC225 (Photo EUROCOPTER – Patrick Penna)

EC225 database contains 66 loads (Main Rotor shaft bending, Main Rotor pitch rod load, …) with 2 available outputs (Maximum signed static and dynamic loads), and many flight configurations regrouped into 32 manoeuvre families (Forward flight, turn, spot turn, climb, descent,….).

In total there are 66 X 2 X 32 = 4 224 cases for which the possibility to build surrogate models from training samples[5] should be investigated.

2.2. Split of load database

For DATADVANCE, both the objective and challenge is to automatically build the models with the highest predictive power for each of the 4 224 cases. However in case if the sample size is low compared to complexity of the function we want to approximate, it can happen that the constructed surrogate model will be not enough accurate and robust.

Screening the EC225 load data base, it appears that:
- 72 cases have a training sample size equals to zero (no data at all), so obviously no models could be constructed.
- 196 cases have a training sample size equals to one, meaning that only model with constant model can be provided, based on the single value from the corresponding sample.
- 1 608 cases have a training sample size less than the number of parameters describing the flight configuration; so at best only highly penalized linear model could be created. If the accuracy is not good enough, a constant model is provided, based on the average of data from the corresponding sample.

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[5] The training sample is a matrix. One column is the output (load), and the other columns are the inputs (Flight Configuration Parameters).

- 1 354 cases have a training sample size still quite small, however, non-trivial surrogate models may be built but the accuracy may be an issue. If the accuracy is not good enough, either constant or linear model is provided.
- 994 cases have an appropriate training sample size; so non-trivial surrogate models may be built with expected good accuracy. However, if the accuracy is not good enough, either constant or linear model is provided.

Consequently, the selection of the best models should be performed for each of 3 956 cases.

2.3. Surrogate model building

All of the 3 956 best models were built using the "Generic Tool for Approximation (GT Approx)" module of the MACROS software, developed by DATADVANCE. "GT Approx" is used for construction, evaluation and analysis of approximation and interpolation response surfaces. Among the features of the tool are a wide range of well-known techniques (e.g., Splines in Tension, Linear Regression, Gaussian Process Regression) and original techniques (e.g., HDA – High Dimensional Approximation), an automatic selection of the appropriate approximation type based on built-in decision tree and data properties, a flexible support for accelerated training, smoothing, handling multiple output components, etc.

Another challenge in model building was the selection of the best model for each case. As the training sample size may be very limited to check the ability of the model to predict outputs in the new input points, cross validation error fit check was performed using "GT Approx" built in Internal Validation functionality.

Cross validation is a common approach to estimate model predictive power: one object (data point) is removed from the sample, model is built with all other objects and fit quality is checked on the removed object, the procedure is repeated for all the objects in the sample thus giving the average model prediction accuracy on the training sample. This approach is preferred over computing residuals for the data points the model were fit to directly because cross validation approach allows to avoid over fitting to the training data [3].

The requirements for the models were to be accurate and robust, and in cases it's not possible to achieve, (for example, due to very small sample size) constant models were selected, and a report that no trustworthy results are available is generated, avoiding misleading predictions (CHAMALO program warns the user that the constant model is used).

The following main types of models were considered (if not constant).

2.3.1. Response Surface Models (RSM)

RSM is the simplest model available in "GT Approx", suited for the cases when dependency is not too complex or only small sample is available. It is assumed that the training data set is generated by the linear model.

$$Y = X\alpha + \varepsilon \tag{1}$$

where α is a vector of unknown model parameters, ε is a vector generated by white noise process, modeling the real noise in the data. Here X is an extended design matrix containing input features x_i and their cross terms $x_i x_j$. Procedure, realized in "GT Approx", estimates coefficients α using ridge regression approach [3]. After the coefficients $\widehat{\alpha}$ are estimated, output prediction for the new input X is calculated by the formula:

$$Y = X\widehat{\alpha} \tag{2}$$

Also a number of stepwise techniques are implemented in "GT Approx" that allow selecting only subset of input features with the highest predictive power, thus potentially increasing models quality especially in case when sample size is small.

2.3.2. Gaussian Processes (GP)

Gaussian Processes (GPs) are one of the most convenient ways to define distribution on the space of functions (see [6] for details). GP $f(X)$ is fully determined by its mean function $m(X) = Ef(X)$ and covariance function $cov(f(X), f(X')) = k(X, X') = E[(f(X) - m(X))(f(X') - m(X'))]$.

It is assumed that the training data $S = (X, Y)$ was generated by some GP $f(X)$

$$Y_i = Y(X_i) = f(X_i) + \varepsilon_i, i = 1, 2, \dots, |S| \tag{3}$$

where $|S|$ is a sample size, the noise ε is modeled by gaussian white noise process with zero mean and variance $\tilde{\sigma}^2$. Also, it is assumed that GP $f(X)$ has zero mean function $m(X) = E[f(X)] = 0$ and covariance function $k(X, X')$, belonging to some parametric class of covariance functions $k(X, X'|a)$, where a is a vector of unknown parameters.

Under such assumptions the data sample (X, Y) is modeled by GP with zero mean and covariance function $cov(Y(X), Y(X')) = k(X, X') + \tilde{\sigma}^2 \delta(X - X')$, where $\delta(X)$ is a delta function. Thus, a posteriori (with respect to the given training sample) mean value of the process for some test point X^*, used as a prediction, takes the form

$$\hat{f}(X^*) = k^* (K + \tilde{\sigma}^2 I)^{-1} Y \tag{4}$$

where $I_{|S| \times |S|}$ is an identity matrix, $k^* = k(X^*, X) = [k(X^*, X_j), j = 1, \dots, |S|]$,
and $K = K(X, X) = [k(X_i, X_j), i, j = 1, \dots, |S|]$.

When processing the real data, parameters of covariance function a are not known, so specially developed tuning algorithm, based on maximum likelihood maximization, is used for estimation of a.

2.3.3. High Dimensional Approximation (HDA)

HDA is an original technique implemented inside "GT Approx". HDA approximation $\hat{f}(X)$ (see also [4] for details) consists in several basic approximations $g_i(X), i = 1, 2, \dots$, which are iteratively constructed and integrated into $\hat{f}(X)$ using specially elaborated boosting algorithm, until the error of HDA approximation stop to decrease, see [5] for details.

In turn basic approximations $g_k(X), k = 1, 2, \dots, B$ are represented as some average

$$g_k(X) = \frac{1}{M_k} \sum_{i=1}^{M_k} h_{k,l}(X), k = 1, 2, \dots, B \tag{5}$$

of elementary approximations

$$h_{k,l}(X), l = 1, \dots, M_k, k = 1, 2, \dots, B \tag{6}$$

obtained using multistart on their parameters. The value of M_k is estimated by the training algorithm of HDA.

As elementary approximation model in HDA linear expansion in parametric functions from the dictionary is used, i.e. functions $h_{k,l}(X), l = 1, \dots, M_k, k = 1, 2, \dots, B$ have the following form.

$$h(X) = \sum_{j=1}^{p} \alpha_j \psi_j(X) \tag{7}$$

where $\psi_j(X), j = 1, \dots, p$ are some parametric functions.

Three main types of parametric functions are used (justification of use of such basis functions can be found in [3]), namely:

1. Sigmoid basis functions:

$$\psi_j(X) = \sigma\left(\sum_{i=1}^{dimX} \beta_{ij} x_i + \beta_{0j}\right) \tag{8}$$

where $X = (x_1, \dots, x_{dimX})$, $\sigma(z) = \frac{e^z - 1}{e^z + 1}$

2. Gaussian functions

$$\psi_j(X) = e^{\left(-|X - d_j|_2^2 / \sigma_j^2\right)} \tag{9}$$

3. Linear basis functions

$$\psi_j(X) = x_j \tag{10}$$

where $j = 1, 2, \dots, dimX$, $X = (x_1, \dots, x_{dimX})$.

In order to fit the model $\hat{f}(X)$ to the data, the number of functions p, their type and the values of their parameters should be estimated. This is done by minimizing the mean-square-error on the training data set with penalties on smoothness of the approximation.

2.3.4. Number of times each model type was selected

Table 1 provides the number of times and percentage each model was selected. It can be seen that for many cases RSM models were selected due to very small size of the training samples.

Model type	Static load	Dynamic load	Percentage (%)
No model	36	36	1.7
Constant model	1 271	1 606	68.1
RSM	514	263	18.4
GP	261	179	10.4
HDA	30	28	1.4

Table 1. Number of times each model type was selected

2.4. CHAMALO Software

Developed by DATADVANCE, CHAMALO software was implemented as Windows executable with user friendly graphical interface. The purpose of this software is to estimate the static and dynamic loads for a given set of FCP using the appropriate models.

The software was designed with a view that new helicopters, load types, maneuvers and/or surrogate models could be easily added or updated.

Excel file of specific format is used as a software input that allows the user to fill input data automatically as well as filling the input data form by hand.

The input may be specified in two ways:
- Directly as FCP values,
- Through a 8 letter Flight Configuration Code for which exact values of the FCP may be extracted through transcription procedure.

Software has a large built-in dictionary to form a code, but also allows the user to add new code words through the user transcription file.

To warn the user if prediction is unreliable, CHAMALO software shows pop up window with warning that results may be unstable and writes detailed warning message in the listing file.

Warnings are given in cases:
- There is no model,
- The model is the constant prediction model,
- The model accuracy is low so the predictions may be unreliable and user should treat predictions with cautious,
- The user wants to compute loads at points laying outside the training sample range.

Since the calculated values may be unreliable for some cases, a filtering mechanism was introduced to allow the user to specify which level of reliability he would like to have. With high filtering the user only has the prediction if the model is accurate, whereas with no filtering, the user always has the prediction (good or bad).

3. Result evaluation

For all static and dynamic loads, predictions were compared[6] by EUROCOPTER to measurements for each manoeuvre family and for all or filtered flight configurations.
Extrapolated loads around existing flight configurations were also investigated.

3.1. Prediction/measurement comparison (per manoeuvre family)

3 cases could be observed:

3.1.1. Model with high accuracy
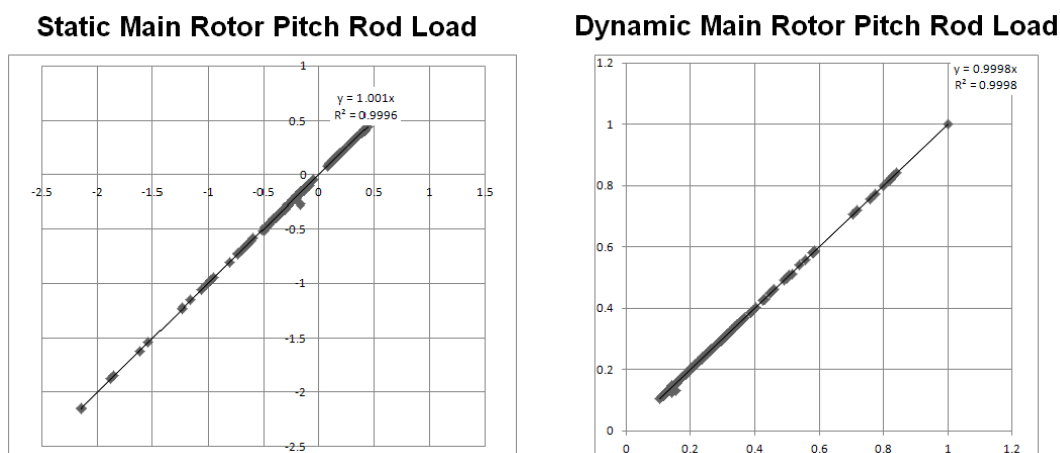
Figure 2 shows an excellent prediction.

Figure 2: Static and dynamic Main Rotor pitch rod loads (Turn)

In this case, the surrogate model was built with high accuracy.

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[6] For helping the reading of plots, the same relative scale is used. 1 corresponds to max measured static (in tension) or dynamic load.
  x-axis is predictive load; y-axis is measured load.

3.1.2. Model with low accuracy

Figure 3 shows a typical example of scattered predictions for static loads, despite the good sample size.
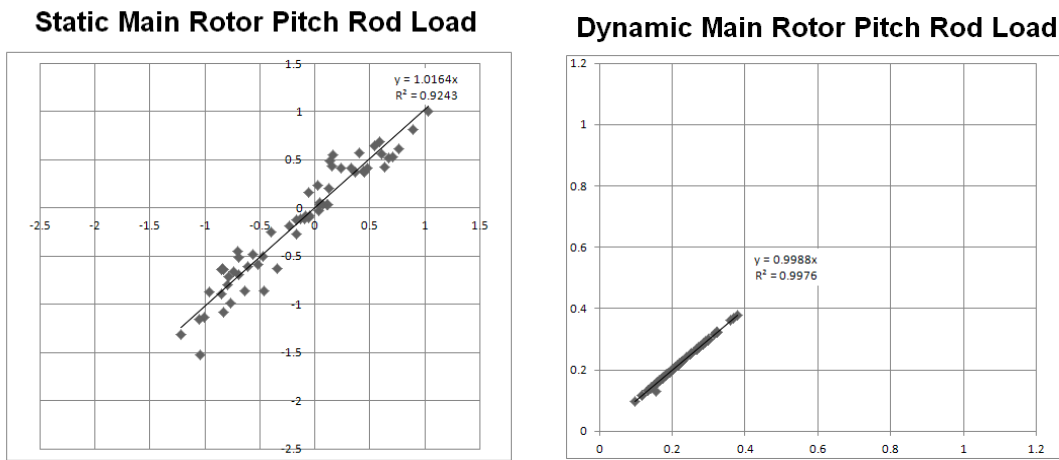

Figure 3: Static and dynamic Main Rotor pitch rod loads (Descent)

For this manoeuvre family, the static loads themselves are rather scattered, and of course, the surrogate model cannot avoid this intrinsic variability. In other words, the model is only as good as the data it is based on.

3.1.3. Constant surrogate model

Figure 4 shows typical results when no surrogate model could have been built. The manoeuver family "Approach" is split into 4 groups. For each group, the mean (constant) value of the training sample is used.
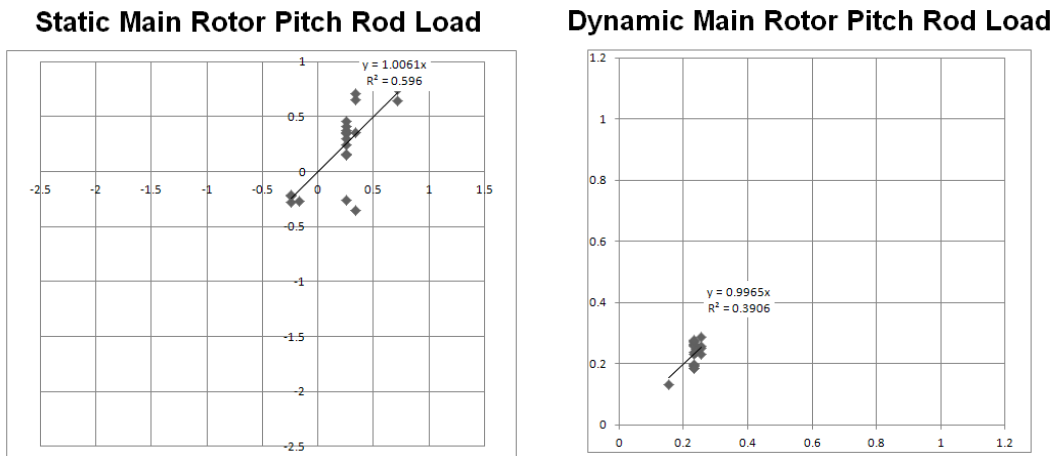
Figure 4: Static and dynamic Main Rotor pitch rod loads (Approach)

3.2. Prediction/measurement comparison (all flight configurations)

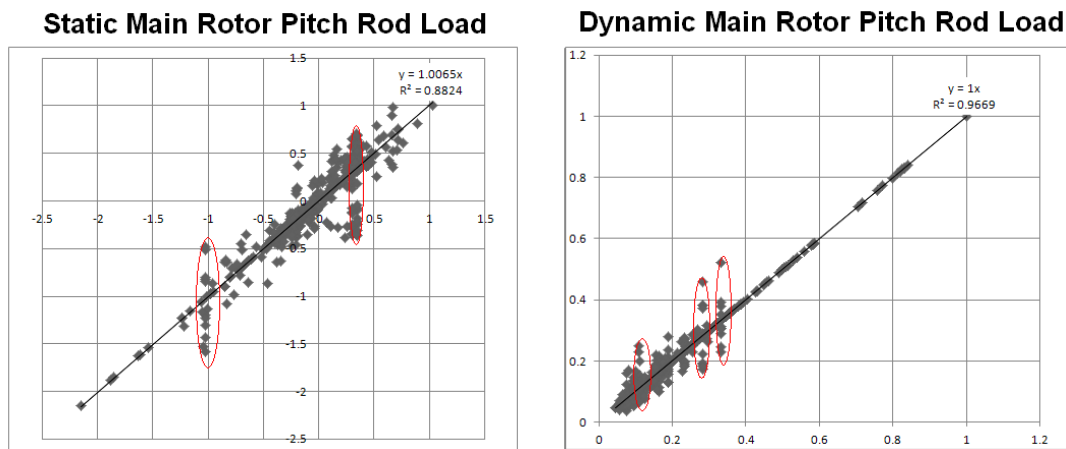Figure 5 shows typical results when all[7] flight configurations are considered.

Figure 5: Static and dynamic Main Rotor pitch rod loads (All flight configurations)

For dynamic loads, respectively 71% and 86% of predictions have a precision better than ±10% and ±20 %.
It is noteworthy to remember that constant surrogate models (see vertical red ellipses) decrease the general accuracy of the prediction.

3.3. Prediction/measurement comparison (filtered flight configurations)

Figure 6 shows typical results when only filtered[8] flight configurations are considered.
Filtered flight configurations represent about 50% of all flight configurations for this load.
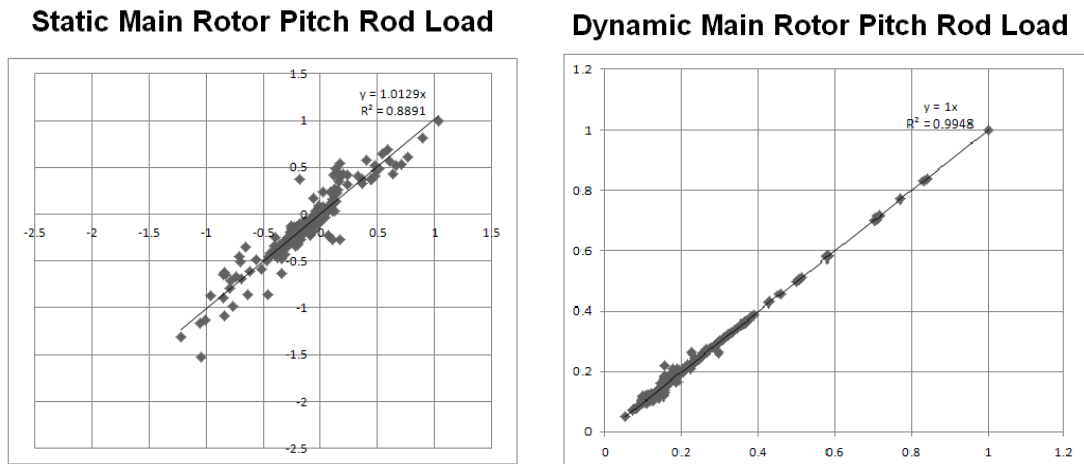

Figure 6: Static and dynamic Main Rotor pitch rod loads (Filtered flight configurations)

For dynamic loads, respectively 89% and 98% of predictions have an accuracy better than ±10% and ±20 %.

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[7] This means that the results of good, scattered and constant surrogate models are plotted.

[8] This means that only the results of good surrogate models are plotted.

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3.4. Extrapolated loads around a flight configuration

The selected flight configuration for which extrapolated static and dynamic loads are calculated by CHAMALO is a level flight at 125 kt, (see Table 2). This flight configuration depends on 9 FCPs.

W1 (%MCP[9])	W2 (%MCP)	NR (RPM[10])	BETAI (deg)	MASS (kg)	CGX (m)	CGY (cm)	ZP (ft)	OAT (°C)
60	60	265	0	10 000	4.67[11]	0	0	15

Table 2: Flight Configuration Parameters[12] for level flight

Depending on the sample, the extrapolated loads may be correct or not, when compared with models based on physical laws (EUROCOPTER HOST software (cf. [7]) used for this analysis).

Figure 7 gives the static and dynamic Main Rotor pitch rod loads (y-axis) versus side slip angle (BETAI) (x-axis).
It shows good behaviour of static loads (in blue) of CHAMALO model compared to HOST model.
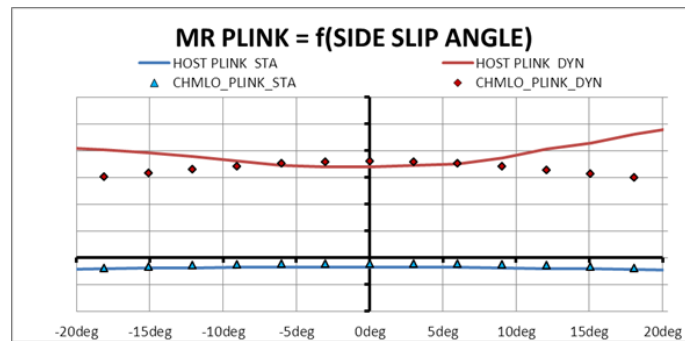Dynamic loads (in red) behaviour is more variable.

Figure 7: Static and dynamic Main Rotor pitch rod loads versus side slip angle (BETAI)

Figure 8 gives the static and dynamic Main Rotor pitch rod loads (y-axis) versus Main Rotor rotation speed (NR) (x-axis). It shows a problem for dynamic load (in red) versus NR variation (x-axis), when prediction is requested out of the training sample range. The static load (in blue) is rather good, but this should be considered as a stroke of luck.
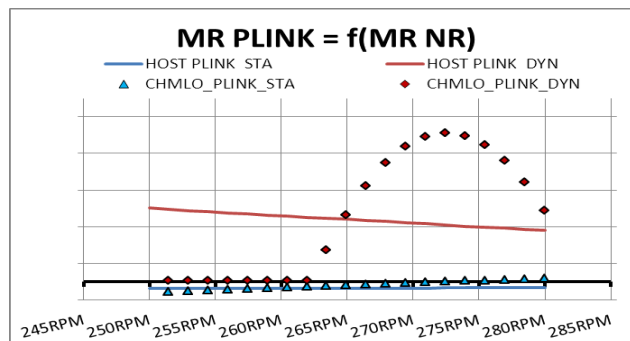

Figure 8: Static and dynamic Main Rotor pitch rod loads versus Main Rotor rotation speed (NR)

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[9] MCP= Maximum Continuous Power

[10] RPM = Rotation Per Minute

[11] CGX=4.67 m corresponds to longitudinal neutral centring.

[12] W1=W2 (engine power in percentage of MCP) - NR (Main Rotor rotation speed in RPM) – BETAI (side slip angle in deg) – MASS (mass of helicopter in kg) – CGX (longitudinal centre of gravity in m) – CGY (lateral centre of gravity in cm) – ZP (altitude in ft)- OAT (Outside Air Temperature in Celsius degree)

In the training samples used to build the static and dynamic surrogate models, NR was nearly constant and equal to 265 RPM. Extrapolations up to 280 RPM or down to 250 RPM cannot be reliable, if no physical laws are implemented.

It can be concluded that extrapolations out of the training sample range have to be carefully analysed by the user. Implementation of physical laws during modelling should drastically improve this situation.

4. Conclusion and future works

In the scope of CHAMALO project, EUROCOPTER was interested in extracting surrogate models from the existing load database to estimate missing loads from the parameters describing the flight configurations.

In general, it is found that surrogate models built by MACROS are consistent across many runs. When the surrogate models cannot be predicted, this is due to either too small sample sizes or to samples with inherent scatter.

EUROCOPTER consider this approach very promising. In fact, about 50% of missing loads (with high filtering), which need to be estimated, may be calculated by CHAMALO with a sufficient accuracy (< ±20 %.), drastically reducing the time and manpower needed for such analysis.

Further investigations are planned to increase the reliability of the surrogate models for some manoeuver families and loads, either by improving the load database (by adding new flight load data) and/or by implementing physical laws.

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