# THE APPLICATION OF MATH-DYNAMIC MODELS TO CHARACTERISE A RANGE OF HELICOPTER ROTOR SYSTEM FAULTS

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**Abstract**

Patterns in low frequency airframe vibration (< 100 Hz) can indicate the health of a large number of helicopter mechanical components. Unfortunately, helicopter operating conditions can also have a dramatic affect on such vibrations which may lead to a false interpretation.

By utilising a comprehensive helicopter math model and recent advances in unsupervised machine learning techniques, a diagnostic methodology is proposed which mitigates operational effects whilst maintaining a good visibility of the helicopter mechanical condition.

## Introduction

A significant proportion of helicopter maintenance relies on the interpretation of sensor measurements or aircrew observations. In many cases sensor measurement interpretation is simply based on periodically checking a measurement amplitude against a predefined threshold. Alternatively, aircrew observations are subjective and variable, and often dependent on contemporary experience.

Integrated Health and Usage monitoring Systems (IHUMS, Ref 1) will provide measurements on a flight by flight basis. Examining such data sets, particularly associated with low frequency (< 100 Hz) airframe vibration measurements, has identified serious shortcomings with the traditional threshold exceedance criteria. The major difficulty is that an aircraft may move in and out of a serviceability state purely as a result of the prevailing operating conditions and not because of any mechanical deterioration (Ref 2).

The above scenario, if left unaddressed, will lead to frequent false alarms. This paper sets out some recent developments in math-dynamic models in order to better understand both operational and mechanical fault affects on IHUMS measurements. The subsequent data processing methodology is also described, covering principal measurement selection and data grouping using machine learning techniques.

## Application of math-dynamic models (1) helicopter operational effects

The comprehensive math-dynamic model used in this study has been described in detail elsewhere (Ref 3). A fairly unique feature is that the model is based on an individual blade concept.

Figures 1 and 2 present actual (not predicted) flight by flight, airframe vibration measurements at main rotor blade pass frequencies (bR). All measurements were taken at "typical" cruise conditions for both the AS332L and S61 helicopters. Tagged with these measurements were various operational parameters such as all-up-weight, indicated air speed, outside air temperature and altitude.

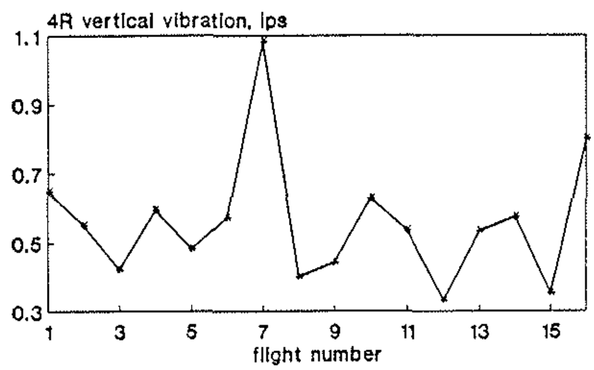


FIG.1 MEASURED 4R AIRFRAME VIBRATION (SPS SENSOR LOCATION), AS332L IN THE CRUISE

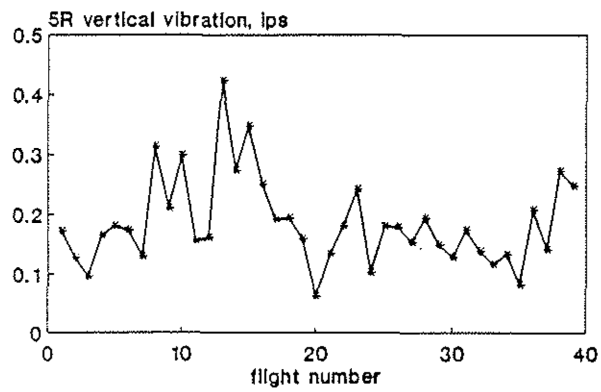


FIG.2 MEASURED 5R AIRFRAME VIBRATION (SPP SENSOR LOCATION), S61 IN THE CRUISE

## Linear regression and correlation

It is readily apparent from figures 1 and 2 that significant flight to flight variations in bR vibration measurements may be anticipated. Since this high degree of variability occurred between flights where no maintenance actions had taken place, it was postulated that the changes were largely attributable to operating conditions.

Simple linear regression was applied to the raw data sets assuming

$$bR_p = k_1 * \text{variable} + k_2$$

where the variable options considered were all-up-weight (AUW), indicated airspeed (IAS) and altitude (ALT). Both $k_1$ and $k_2$ are constants derived from the linear regression process. The "goodness" of fit was assessed by calculating the correlation coefficient between the raw bR and predicted $bR_p$ data sets. From 12 monitoring locations in an AS332L airframe, 10 locations returned a correlation coefficient (c) > 0.5 when the variable was IAS. The mean c value from the 10 locations was 0.71. For AUW and ALT, 7 and 5 locations respectively returned a coefficient value greater than 0.5 (absolute), with mean values of -0.55 and -0.68.

The conclusion drawn from the AS332L correlation analysis is that bR levels increase with increasing air speed ( as expected) but decrease with increasing all-up-weight and increasing altitude.

In contrast, linear regression analysis of S61 bR data concluded with relatively poor correlation with any of the above variables. In an attempt to improve correlation a simple parameter normalisation study was performed. This lead to effective variables. For example the normalised AUW became:

$$W_n = 1.2256W/(\rho\Omega^2)$$

where $\rho$ is the density at the flying altitude and $\Omega$ is the rotor angular velocity.

Repeating the linear regression analysis with normalised variables generally improved the values of the correlation coefficients. In particular, 6 out of the 12 measurement locations returned a positive correlation coefficient of greater than 0.5 for normalised AUW.

## Simple model approximations

The previous section ignored any knowledge of the form of the vibration which may be expected from fundamental physical considerations. A simplified theoretical approach based on aerodynamic considerations revealed that the hub vibratory loads may be characterised by

[1]. vertical shear, pitching and rolling moments:

$$nR = D_{nR}(A_{1,nR}\mu_n^2 + A_{2,nR}\mu_n + A_{3,nR})W_n\Omega_n^2$$

[2]. lateral shear and torque:

$$nR = E_{nR}(B_{1,nR}\mu_n^2 + B_{2,nR}\mu_n + B_{3,nR})(B_{4,nR}W_n^2 + B_{5,nR}W_n + B_{6,nR})\Omega_n^2$$

where,

| | |
|---|---|
| $W_n$ | effective all up weight |
| $\mu_n$ | effective advance ratio |
| $\Omega_n$ | effective angular speed of rotor |

Coefficients $D_{nR}$ and $E_{nR}$ are Mach number and Reynolds number dependent. The $A_{i,nR}$ and $B_{i,nR}$ coefficients vary slightly with wind direction. However, it is reasonable to assume that all these coefficients are constant, particularly for the relatively narrow band of operating conditions.

Based on these equations, a least squares approach produced much improved results over the simple linear regression analysis. Correlation coefficients throughout were now generally greater than 0.5.

## Alternative approach

By combining an understanding of the underlying physical principles with a procedure known as Principal Component Analysis (PCA), an awareness of the dimensionality of the problem may be realised.

## Data modelling (1)

As indicated in reference 2, IHUMS will produce in excess of 1 MByte of data per flight. From this data, a suite of parameters (nR vibrations, blade track and lag etc) will be extracted along with operational measurements such as rotor torque, outside air temperature, altitude, indicated air speed and helicopter trim state. Whilst all these features may be considered as individual observations, it is prudent to elicit from the math-dynamic model how, it at all, the discrete features should be manipulated in order to mitigate helicopter operational effects. If this can be achieved, variations in the data can be more readily attributed to the mechanical state of the aircraft.

From simple aerodynamic considerations equations [1] and [2] above were derived. Expanding these equations on the basis that a linear combination of equations [1] and [2] is valid for rigid body motion and simple elastic deflections, a maximum of 9 individual terms (observations) may be identified - an example of which would be

$$\Omega_n^2W_n^2\mu_n^2$$

Without further processing, it may be concluded that 9 dimensions are required in order to establish the operational affects on the bR measurements. The following analysis, however, can directly identify the actual dimensionality of the problem.

## Principal Component Analysis (PCA)

The 9 terms described above define the observations which are assumed to be related to the outcome - a bR amplitude derived from a given sensor signature. Over a number of flights both the observations and the outcomes vary. PCA simply multiplies the matrix of the observations by its own transpose in order to produce the co-variance matrix. This matrix may be further conditioned (i.e. mean centring the data and normalising by the variance) before establishing its eigenvectors and eigenvalues. In this case each eigenvector defines an axis and its associated eigenvalue the variance of the observations along it.

The usefulness of each eigenvector, which now represents one dimension, is assessed by the magnitude of its eigenvalue - the larger the value the greater its usefulness.

## Data modelling (2)

PCA can be taken one step further by adding a least squares approach to the analysis. The resultant process is often called Principal Component Regression (PCR). From PCA the major axes (eigenvectors) of the operational parameter combinations have been established. PCR may now be applied in order to establish the link between the eigenvectors (observations) and the bR measurements (outcomes). The link assumes constant coefficients, which are determined by applying a least squares approach to a statistical sample of observations and outcomes.

## Corrected bR amplitudes

From the PCR analysis, bR amplitudes may now be predicted. Furthermore, if all predictions are referenced to a "typical" operating state, a serviceability assessment of the helicopter becomes a straight forward matter. In equation form the corrected $bR_c$ vibration amplitude would be

$$bR_c = (bR_m - bR_p) + bR_{pn}$$

where subscripts c, m, p and pn refer to corrected, measured, predicted and predicted "normal" respectively. The latter would be determined by using the prediction formulation with "typical" operating conditions. For example, the measured bR amplitude may be 0.9 inches per second (ips), whereas the predicted normal amplitude may only be 0.5 ips. If the large measurement amplitude was solely due to the operating conditions and assuming the predictive model is correct, $bR_p$ should tend to $bR_m$. Accordingly, the corrected amplitude would be around an acceptable 0.5 ips.

## Worked example (1) - PCR

Figures 3 and 4 detail measured ($bR_m$) and corrected ($bR_c$) 5R amplitudes for an S61 helicopter. The accelerometer locations were adjacent to the port (SPP) and starboard (SPS) sponsons, mounted internal to the airframe and aligned in the vertical plane. In both cases the dynamic range of the corrected amplitudes is less than the raw measurements.

Figure 5 is a re-plot and scaled up presentation of the corrected amplitude trends in figure 4. From inspecting the eigenvalues, two eigenvectors (dimensions) were removed from the prediction model without loss of engineering accuracy.

The prediction model does not, however, offer any fault discrimination capability - addressing mechanical deterioration is pursued in the following sections.

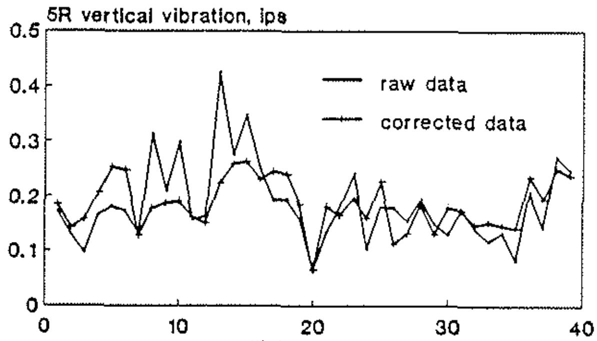


FIG.3 MEASURED AND CORRECTED 5R AIRFRAME VIBRATION (SPP SENSOR LOCATION), S61 IN THE CRUISE

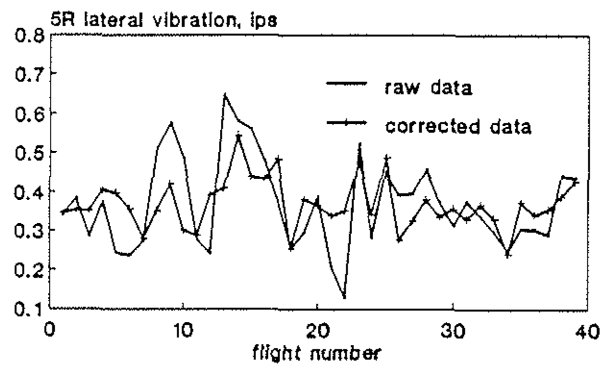


FIG.4 MEASURED AND CORRECTED 5R AIRFRAME VIBRATION (SPS SENSOR LOCATION), S61 IN THE CRUISE

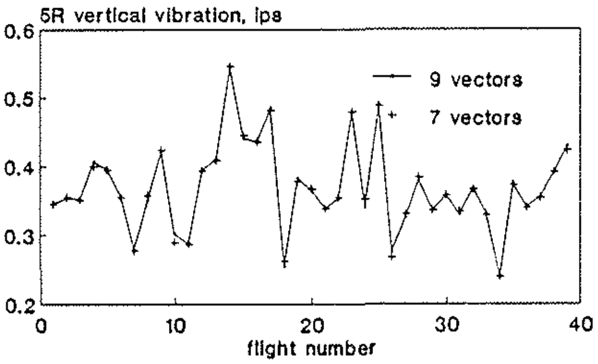


FIG.5 CORRECTED VIBRATION USING 7 AND 9 EIGEN VECTORS IN THE PREDICTION MODEL, S61 IN THE CRUISE

**Application of math-dynamic models (2)**
**mechanical fault effects**

In order to establish the applicability of computer based, automated pattern separation strategies, a database of simulated fault observations was generated by the MJAD helicopter math model (Ref 3). These observations were limited to vibration components measured by two fuselage mounted tri-axial accelerometers.

Five fault classes were considered, namely pitch link, tab and mass maladjustments along with a damper fault and a blade flapwise crack. The intensity of the fault within each class was varied such that low to severe vibrations were produced.

**Data Clustering**

The aim of data clustering is to establish unambiguous fault classes. Data clustering concludes with a set of data groupings, each with defined boundaries. Ideally each data grouping will be associated will one fault class.

**Worked example (2) - fault classification**

Figure 6 presents a first attempt at separating the aforementioned five fault classes. The axes of the three dimensional plot represent; vertical: number of cases in a group (cluster); horizontal: various fault classes, pitch link (HP), mass (HM), tab (HT), lag damper (HD) and blade crack (HC); oblique: group identifier. The observations selected from the database were 1R to 5R vibration components in the vertical plane, measured by one accelerometer. Clearly, the fault classes were not separated.

Figure 7 presents a second attempt with more observations - 1R to 5R inclusive, in 3 orthogonal planes from one measurement location. Fault separation was still not realised.

By adopting a different tack, and using only two observations (see Figure 8), significant progress was made. In this case the observations were composed of complex (vector) ratios - the vibration components from the first accelerometer were normalised by the respective vibration components from the second.

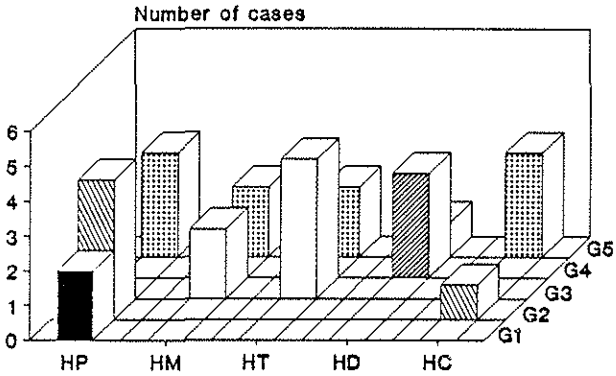


FIG.6 FAULT CLASSIFICATION BASED ON FIVE VERTICAL VIBRATION COMPONENTS

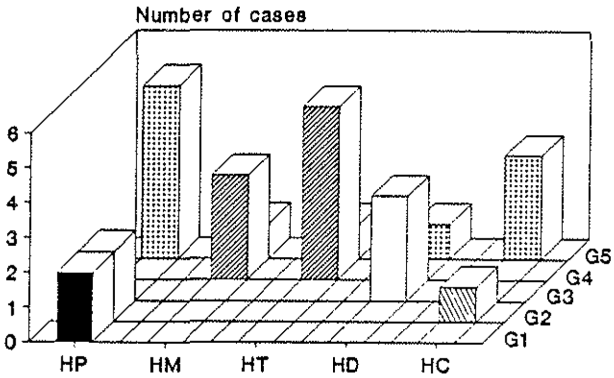


FIG.7 FAULT CLASSIFICATION BASED ON 15 VIBRATION COMPONENTS

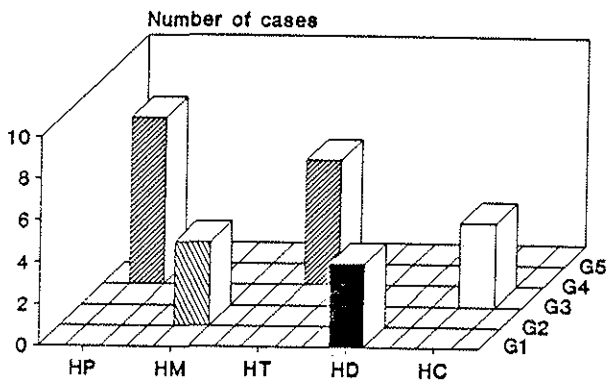


FIG.8 FAULT CLASSIFICATION BASED ON TWO NORMALIZED VIBRATION COMPONENTS

As can be seen in Figure 9, full recognition of each fault class was realised by using only 3 complex ratio observations.

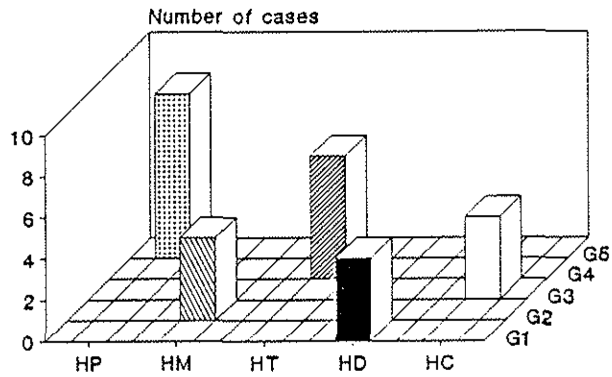


FIG.9 FAULT CLASSIFICATION BASED ON THREE NORMALIZED VIBRATION COMPONENTS

## Discussion

Alternative approaches to understanding low frequency, airframe vibration measurement variability have been described. It has been proposed that this variability may be predominantly attributed to two causes - changes in helicopter operating conditions and mechanical deterioration. In order to avoid false alarms when considering the health of the helicopter, the influence of operational conditions must be nullified.

### Simple correlation

By applying simple correlation techniques to bR airframe vibration measurements a first impression of operational influences was anticipated. Measurement sets from two aircraft were considered, namely the AS332L and S61 helicopters. Whilst an increase in airspeed was generally associated with an increase in bR vibration amplitudes, the influence of all-up-weight (AUW) was inconsistent - the AS332L measurements indicated a decreasing bR amplitude trend with increasing AUW in the cruise, and conversely for the S61 (the expected trend).

The apparent inconsistency with the AS332L may be explained when the cruise settings are considered. Instead of aiming for a predefined indicated air speed (IAS), the pilot trims the aircraft with 15.5 degrees of collective pitch set. The resulting air speed can vary by more than 25 knots. A high AUW will result in a lower IAS which will tend to effect a lower bR amplitude. Accordingly, whilst simple correlation techniques may yield some insight into the nature of operational effects, these examples also draw attention to their shortcomings - a number of operational parameters must be considered simultaneously.

### Problem dimensionality

The simple aerodynamic model revealed that 9 observations (dimensions) are required to account for helicopter operational effects. Principal Component Analysis indicated that the observations could be reduced to 7 without loss of engineering accuracy (see figure 5). Such pre-processing may become paramount if the number of observations are too large to manage efficiently.

### Principal Component Regression

By adding a least squares approach to PCA a number of model constants were determined, linking observations with bR predictions. It was found that these predictions generally returned more significant correlation coefficients when correlated with raw measurements, than the simple linear regression methods.

However, as indicated in figures 3 and 4, the stability of the corrected bR amplitudes (as opposed to predicted) is not yet capable of supporting a diagnostic methodology. It is postulated that the model can be improved by exploiting other IHUMS monitored parameters. First, AUW could be replaced by measured rotor torque, since the latter is measured at the point of acquisition - AUW is an estimated parameter. Second, bR amplitudes are affected by the elastic deflection of the local structure to which the sensor is attached and the rigid body motion of the complete helicopter about its centre of gravity. The latter may be deduced from the measured cyclic pitch settings, which again will be recorded at the point of data acquisition. These additional terms will be added to the model to see if further improvements can be realised.

The model will also be expanded to consider not only aerodynamic influences ( the forcing) but structural effects (forced response). For example, a number of helicopter types, including the S61, have tuneable devices which operate at a "design" main rotor R.P.M., in order to mitigate the bR vibrations induced in the airframe. Unfortunately, the actual R.P.M. may be more than 2 percent above or below the "tuned" frequency. This can have a dramatic affect on the bR amplitudes.

### Data Clustering

Initial attempts at separating mechanical fault classes by grouping theoretically generated airframe vibration data highlighted a number of apparent difficulties with data clustering techniques. The major problem was that a fault from a given class could migrate from one data group to another, simply because of its intensity. This conclusion remained true even when the number of observations (vibration components) was increased.

By pre-processing the data in order to effectively remove fault intensity, the desired result was realised. The pre-processing was based on complex (vector) ratios of the vibration components using data from two accelerometers in the airframe. The principle is based on assuming linearity between fault intensity and induced vibration amplitudes. It was therefore unexpected that the non-linear, blade crack fault was uniquely separated from the other linear faults. Increasing the number of normalised vibration components to 15 (observations) and clusters to 7, revealed the non-linearity (see figure 10). Whilst each cluster is tagged with only one fault, 3 clusters are now associated with the non-linear blade crack.

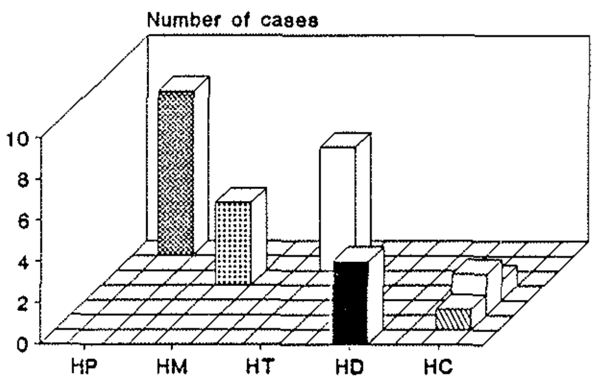


FIG.10 FAULT CLASSIFICATION BASED ON 15 NORMALIZED VIBRATION COMPONENTS

## Conclusions

- Variations in low frequency airframe vibration (< 100 Hz), particular bR, may be attributed to helicopter operational conditions and mechanical deterioration. In order to pin-point causes of mechanical deterioration, the effects of helicopter operating conditions must be known a priori.

- Simple aerodynamic considerations combined with a technique for selecting principal observations (measurements) has culminated in a model for correcting bR vibration amplitudes. Improvements to the model have been proposed which will further nullify helicopter operational effects.

- It is anticipated that the interpretation of pattern changes in the corrected vibration amplitudes will establish the mechanical state of components which can affect low frequency airframe vibration.

- Data clustering techniques have been investigated using a theoretically generated database containing vibration measurements from 5 separate rotor system faults. Using complex ratios of vibration components from two airframe accelerometers, it has been shown that all five fault classes can be unambiguously identified.

## References

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## Acknowledgements

The authors would like to acknowledge the cooperation and support of Bristow Helicopters Limited, the Ministry of Defence and the Civil Aviation Authority.