European Rotorcraft Forum

HELICOPTER LOADS SYNTHESIS USING HARMONIC REGRESSION

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Abstract

Accurate monitoring of helicopter flight-loads can lead to reductions in maintenance costs and improvements in safety; however, directly monitoring these loads using existing approaches can be both complex and costly. Increased efforts are being devoted to investigating alternative approaches, such as load synthesis, which can be used to indirectly monitor loads on helicopter rotating components. This paper details preliminary investigations of a novel load synthesis approach which exploits the periodic nature of helicopter loading by using synthesized harmonic features of a target load signal to reconstruct the entire signal. A case study demonstrates the potential of this technique by using a single predictive model to accurately synthesize Black Hawk pitch-link load magnitudes at key harmonic frequencies for 160 independent level flight tests at various speeds. These synthesized load magnitudes are synthesized using a combination of airframe strain gauges, and flight state and control parameters, and later combined with known phase information to reconstruct the target signal. Preliminary results show high predictive accuracy of the main-rotor pitch link load magnitudes.

NOMENCLATURE

β	individual regression coefficient
$\hat{\boldsymbol{\beta}}$	vector containing regression coefficients for all predictors within a model
ε	individual residual error of prediction
$\boldsymbol{\varepsilon}$	vector of residual errors
ϕ	phase of either an extracted or predicted sinusoid, in radian
DC	the mean (0 Hz) component of a signal
N	number of events or measurements within a sequence to be transformed
NR	ratio between measured and nominal main rotor frequency, in percentage
RSS	residual sum of squares
t	elapsed time at measurement recording, in seconds
$\hat{t}$	modified elapsed time simulating 100% NR, in seconds
f_{MR}	nominal main rotor frequency
j	index of events or measurements
k	index of harmonic frequencies
n	number of events or measurements
p	number of predictors
x	predictor variable used within regression models
y	individual observation of target variable
z	complex number containing sinusoidal amplitude and phase representing harmonic content of a signal at a specific frequency and time
$\mathbf{y}$	vector of target terms used within regression models
$\mathbf{X}$	matrix of predictor variable terms used within regression models
TR	subscript denoting training data

1. INTRODUCTION

Shifting operational requirements are continually altering how military helicopters are used [1]. Some of these changes are slight, such as small increases in the frequency of specific missions. Other changes are more significant, such as deployment of platforms to exotic operational environments. These changes in usage alter the loading experienced by the helicopter, resulting in the actual component loading differing from the design loading used to derive component safe-lives [2]. The goal of this study is to investigate and develop techniques which can be used to monitor the actual loading components experience, in order to better understand and manage any resultant changes in component fatigue lives.

A thorough understanding of helicopter component loading is vital to proper management of helicopter structural integrity. Helicopter components experience high frequency loading that is both dynamic and highly vibratory, caused by forces generated within their rotor systems [2]. This type of low-amplitude, high-cycle loading means even small changes in flight load values can significantly affect component fatigue lives. A study conducted on the sensitivity of fatigue lives to changes in usage found that a 10% change in helicopter flight load values could result in fatigue life changing by a factor of two or more [1]. By monitoring component loading, operational loads can be assessed to ensure they are less severe than load spectrums used to life components. If the loading is significantly less severe, its accurate monitoring can help justify the removal of conservatism within the component lifing, leading to potential extensions of component lives, and reductions in maintenance costs.

Monitoring helicopter component loads, especially rotating component loads, is not an easy task. Major difficulties arise from the need to maintain physical connections with rotating sensors for data and power transfer. While slip-rings and other mechanical assemblies are often used in flight tests, these methods are ill-suited for fleet-wide implementation due to their complexity, cost, and lack of reliability. In an effort to avoid the problems associated with traditional systems, increased efforts have been made to investigate and develop indirect monitoring techniques which are able to model loading remotely.

Load synthesis, or load prediction, is the name given to indirect monitoring approaches which aim to model loads in one location using measurements made in another. These approaches are well suited for application on helicopters as they allow monitoring of traditionally hard-to-measure locations, such as rotating components, without requiring physical connections to the locations. These approaches to-date are generally based on machine learning methods [3-6], or regression techniques [7-10] and although they have not yet reached a level of accuracy and input parsimony acceptable for implementation; many have shown considerable promise. An investigation into a number of these previous load synthesis attempts [11] identified a promising technique [7] which used linear models within the frequency domain to predict rotating component loads from fixed component loads. It is hoped that by incorporating key aspects of this and other techniques within a new harmonic regression based approach, advancements in the field of load synthesis will be made.

The harmonic regression approach detailed within this paper exploits the periodic nature of helicopter loading to improve the accuracy and robustness of prediction models. It achieves this by using a modified Discrete-Time Short Time Fourier Transform (STFT) to decompose the target component load time-history into a sequence of time-varying sinusoids at key frequencies. By using these sinusoids as targets for the prediction model rather than the original time-history, the problem can be broken up, simplified, and an improved solution found. In this study, the amplitudes of these sinusoids are modelled using multiple linear regression based models, and the phases of the sinusoids are taken from measurements. Once modelled, the amplitude and phase information for each sinusoid is combined, and used to construct the target time-history. The predictive capability of this technique is demonstrated by synthesizing main-rotor pitch-link loads for 160 runs of Black Hawk level flight at various speeds, and comparing these to measured loads.

2. EXPERIMENTAL DATA

2.1. Characteristics of Helicopter Flight Data

During operation, helicopter components experience high frequency cyclic loading dominated by the main and tail rotor frequencies, and harmonics thereof. This loading is predominantly low-amplitude high-cycle loading, for which as previously stated, even small changes in loading have a significant impact on fatigue life. An example load time-history of a main-rotor pitch-link, highlighting its cyclic nature, is shown in Figure 1a. As previously stated, this load time-history is driven by a few key frequencies which are identified within Figure 1b as harmonics of the main-rotor frequency, f_{MR}.

2.2. Flight Strain Survey and Selected Data

The flight data used in this present study was selected from a Black Hawk Flight Strain Survey (FSS) conducted in 2000 by the United States Air Force (USAF) and Australian Defence Force (ADF). During the survey, an instrumented Australian Black Hawk performed 3759 runs of 98 unique manoeuvres to produce 65 hours of useful flight test data. The manoeuvres were performed for varying aircraft configurations, gross-weights, altitudes, and centre of gravity locations.

The recorded data included; 217 channels of airframe strain data; 20 channels of dynamic component data; 18 channels of airframe accelerations; and, the 28 standard flight state and control system parameters.

This study was based on a subset of the FSS data, consisting of 160 unique runs of level flight, evenly drawn from 8 manoeuvre groups corresponding to level flight at speeds from 0.3Vh to 1.0Vh. These 160 runs were representative of all configuration, gross-weight, centre of gravity, and altitude points tested during the flight test program.

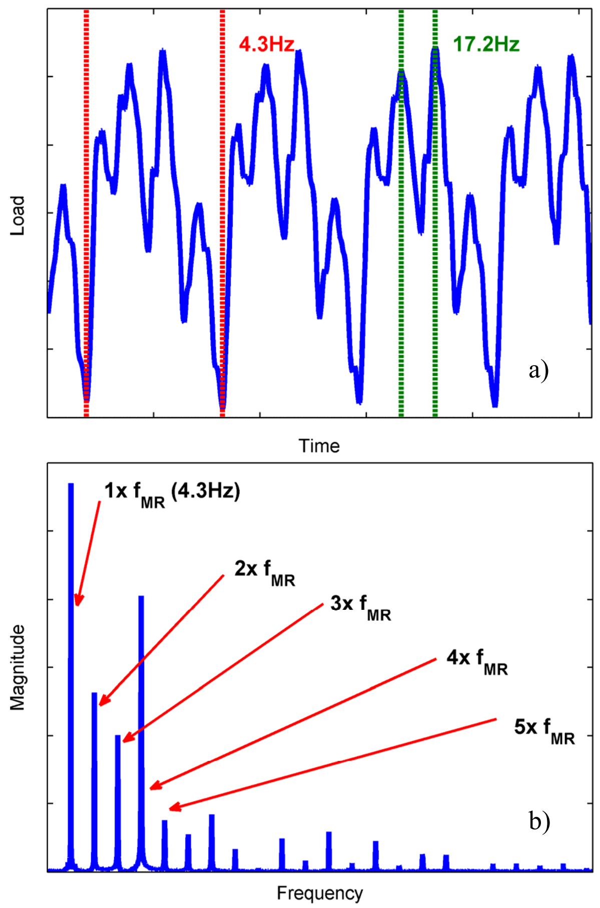

Figure 1 Example helicopter loading in time and frequency domain. a) Sample of main-rotor pitch-link loading during level flight. b) Analysis of frequency content of main-rotor pitch-link loading during level flight, determined using discrete Fourier transform.

This specific subset was chosen for a number of reasons; these included: (i) restricting runs to level flight manoeuvres, to limit variability in load relationships and simplify model development; (ii) including runs conducted at various flight speeds, to aid development of generalized models; (iii) the even distribution of selected runs (20 runs from each speed regime) to prevent bias; and (iv) including a range of gross-weight, configuration and centre of gravity test points to aid development of generalized models.

The main rotor pitch-link axial load was selected as the target for prediction for two main reasons. Firstly, pitch-link loads form a basis for the fatigue substantiation of numerous dynamic components [12], and therefore refinements in their prediction have a wide impact. Secondly, pitch-link loads are complicated load signals, which ensured the prediction problem simulated real-world difficulties.

2.3. Cross-Validation and Data Partitioning

A 10-fold cross validation was adapted and used in this study to make the most of available data. The generic cross-validation process involves partitioning the data into 10 folds; with one fold reserved for evaluating the model, and the remaining nine used for training. The training process is repeated 10 times with each fold reserved once for evaluation.

To realistically assess the predictive ability of a model produced by a regression process, testing data must not be seen by the model during training. However, as Figure 1a highlights, helicopter flight data is periodic in nature meaning data recorded at different times within a run may be nearly identical. To ensure the folds reserved for evaluation were not influenced by training data; the generic cross-validation data partitioning process was modified to force each run of flight data to be contained wholly within one of the ten folds. This prevents identical data being used for both training and evaluating, thereby maintaining the integrity of the predictive accuracy evaluation.

The construction of the 10-folds data sets used within this study is illustrated in Figure 2 where the tabulated numbers are indexes of level flight runs. Each fold contained 16 level flight runs, 2 for each speed regime, with the 2 runs randomly allocated from a pool of 20 runs at each speed.

20 level flight files at each flight speed

2 files from each speed randomly selected for each fold

	0.3 Vh	0.4 Vh	0.5 Vh	0.6 Vh	0.7 Vh	0.8 Vh	0.9 Vh	1.0 Vh
Fold 1	6	12	15	8	19	19	13	12
	3	20	14	9	12	12	7	6
Fold 2	16	2	5	17	11	15	1	20
	11	14	20	14	16	1	16	8
Fold 3	7	15	11	18	6	5	20	9
	17	10	18	12	20	13	15	7
Fold 4	14	13	2	2	1	7	13	10
	8	18	1	10	9	3	9	17
Fold 5	5	8	7	16	18	20	14	3
	19	9	6	20	13	11	8	19
Fold 6	15	1	16	3	4	4	11	5
	1	5	19	7	10	17	19	11
Fold 7	2	17	8	19	17	6	18	16
	4	11	13	4	3	8	4	15
Fold 8	18	7	12	1	8	9	10	4
	13	6	9	13	7	10	5	2
Fold 9	9	16	10	11	14	12	6	1
	20	3	4	5	2	16	17	18
Fold 10	10	4	4	15	5	14	12	13
	12	19	17	6	15	18	2	14

Figure 2 Illustration of 10-fold Cross-Validation data partitioning process [13]

3. HARMONIC REGRESSION APPROACH

3.1. Key Features

The harmonic regression approach uses a minimal amount of airframe mounted strain gauges and flight state and control parameters in combination with regression techniques to model main-rotor pitch-link loads in the harmonic domain.

The key features of the approach include: i) use of advanced pre-processing techniques to decompose complicated signals into simpler elements, ii) use of novel variable selection techniques to select an optimal subset of predictors from a large candidate set; and iii) use of regression techniques to train models to predict these simpler elements.

3.2. Pre-Processing Training Data

3.2.1. Frequency Synchronization

As previously discussed and shown in Figure 1, helicopter component loads are vibratory loads, driven at the frequency and harmonic frequencies of the rotor system. Although the nominal values for these frequencies are known, their actual value fluctuates during operation due to changes in main-rotor RPM. This shifting RPM must be accounted for when attempting to isolate harmonic features at specific frequencies, as performed by the harmonic regression approach.

Equation (1) is used to modify the elapsed time, t, associated with each sampling point, j, to the value it would have been, $\hat{t}$, had the RPM been at its nominal value. Where NR is measured RPM as a percentage of its nominal value.

$$\hat{t}_j = \sum_{i=2}^{j} \left(t_i - t_{i-1}\right) \frac{NR_i + NR_{i-1}}{2} \quad (1)$$

This modification of elapsed time values varies the effective sampling rate in order to simulate a constant RPM. As a constant sampling rate is required for the harmonic regression approach, the second step of the synchronization is to interpolate and resample the modified signals at that constant rate. A sampling rate of 550.4 Hz was chosen so that rotor revolutions would fit exactly within a whole number of sample points that was also a factor of 2. This improved the ability to window data based on rotor revolutions and also improved the computational efficiency of future Fourier transforms. The steps of the time-modifying and resample process are illustrated in Figure 3 using a generic load signal, with a 10x exaggeration in NR fluctuations.

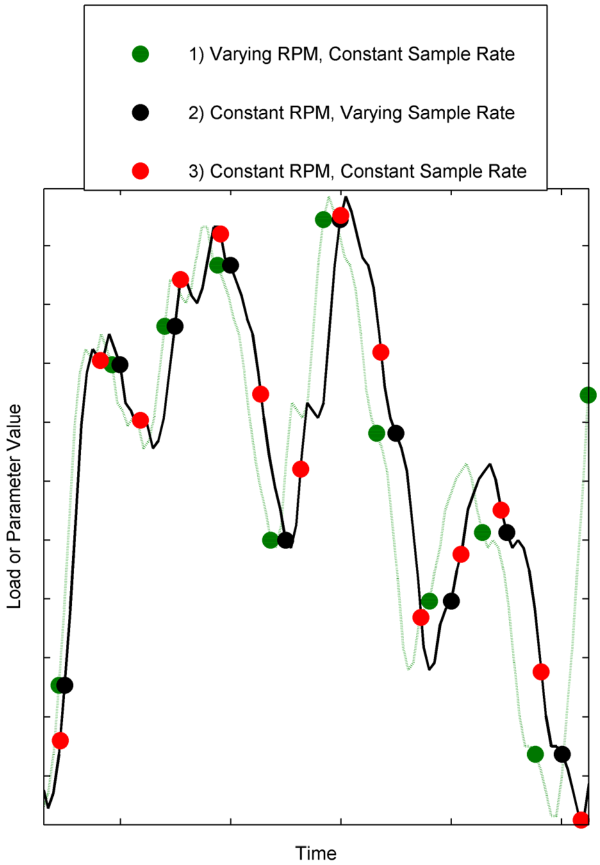

Figure 3 Synchronization of Main Rotor RPM for a generic signal with 10x exaggeration in NR fluctuations. Note: Markers represent every 1 in 10 samples

3.2.2. Signal Decomposition

One of the key aspects of this harmonic regression approach is the decomposition of all flight data signals into their time-varying harmonic components. These harmonic components take the form of sinusoids at key frequencies and are used within the predictive models in place of the original flight data signals. As shown in Figure 4, a small number of these harmonic components can be used to accurately represent the original complicated signal. Increasing the number of harmonic components used, allows for more accurate representations. For this study, the DC and 7 harmonic components were selected for use as this balanced model accuracy and simplicity. This decomposition process was performed for all flight data used within the approach. For non-cyclic data such as some flight state parameters, only the DC components proved useful, with higher harmonics comprising uninformative noise. Figure 5 displays a comparison of a sample main rotor pitch-link load time-history with its recreation using the DC and 7 harmonic components previously shown in Figure 4.

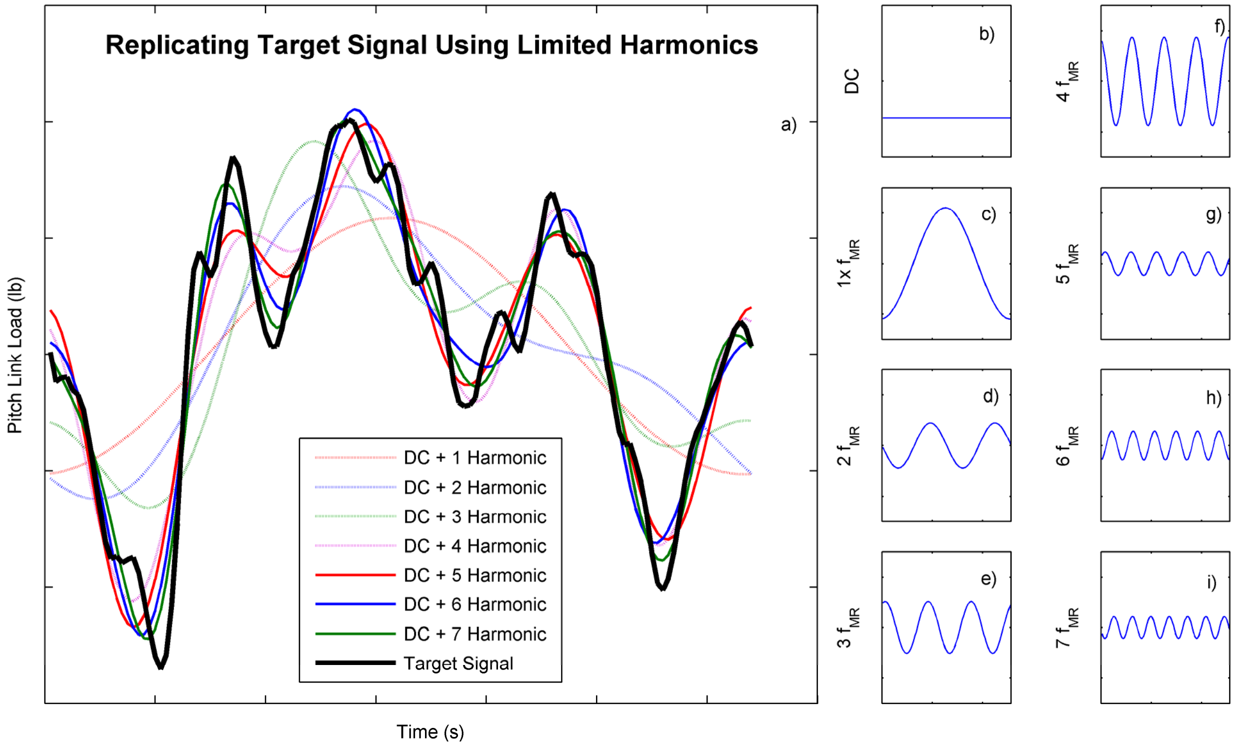

Figure 4 Representing main-rotor pitch-link load signals, using varying numbers of sinusoids at harmonic frequencies of the main-rotor a) signals replicated with various components b) DC component (0Hz) c) f_{MR} component (4.3Hz) d) 2x f_{MR} component e) 3x f_{MR} component f) 4x f_{MR} component g) 5x f_{MR} component h) 6x f_{MR} component i) 7x f_{MR} component

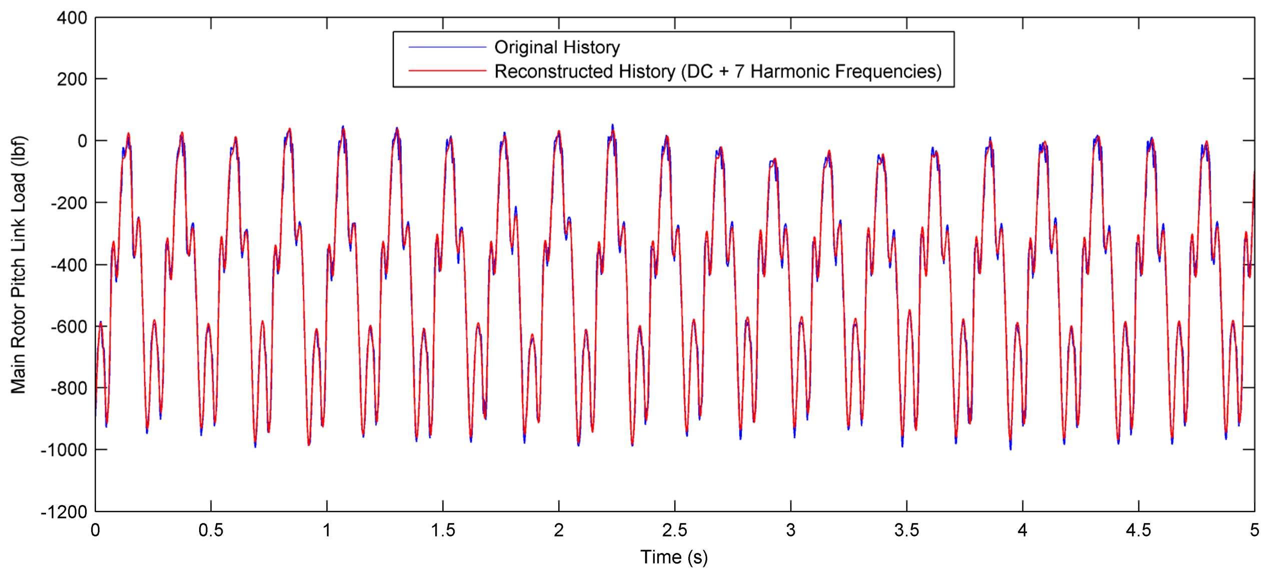

Figure 5 Comparison of original load time-history and its recreation using DC + 7 harmonic components

STFT is a Fourier related transform, which makes use of a sliding Discrete Fourier Transform (DFT) to extract these sinusoids and capture their amplitude and phase content as they change over time. Using Equation (2), DFTs transform complicated signals into a sequence of sinusoids at different frequencies, $\frac{k}{N}$.

(2) $$z_k = \sum_{j=0}^{N-1} x_j \cdot e^{-i2\pi\frac{k}{N}j}$$

Where $k = 0,...,N-1$; $x_0,...,x_{N-1}$ is a sequence to be transformed; and, z_k is a complex number encoding both the amplitude, $|z|$, and phase, $\phi(z)$, of a sinusoidal, which can be calculated using Equations (3) and (4).

(3) $$|z| = \frac{\sqrt{real(z)^2 + imag(z)^2}}{N}$$

(4) $$\phi(z) = 2\arctan\frac{imag(z)}{|z| + real(z)}$$

STFT captures time-varying sinusoidal content by breaking the data to be transformed into a number of overlapping chunks, and transforming each chunk using a DFT. The resulting complex numbers are added to a matrix which records amplitude and phase for each frequency over time. The size of each chunk is kept quite small allowing for high time-resolution of the STFT at the cost of reduced frequency resolution. The reduction in frequency resolution does not negatively affect this approach as the driving frequencies are well defined and known. The extraction of two time-varying harmonic components of an airframe stress time-history is shown in Figure 6. A transient manoeuvre was selected for this example to emphasize how the harmonic features change over time.

The harmonic regression approach exploits this aspect of helicopter loading by modelling this small number of sinusoids and recreating the target time-history out of the predictions, rather than attempting to model the entire load-history.

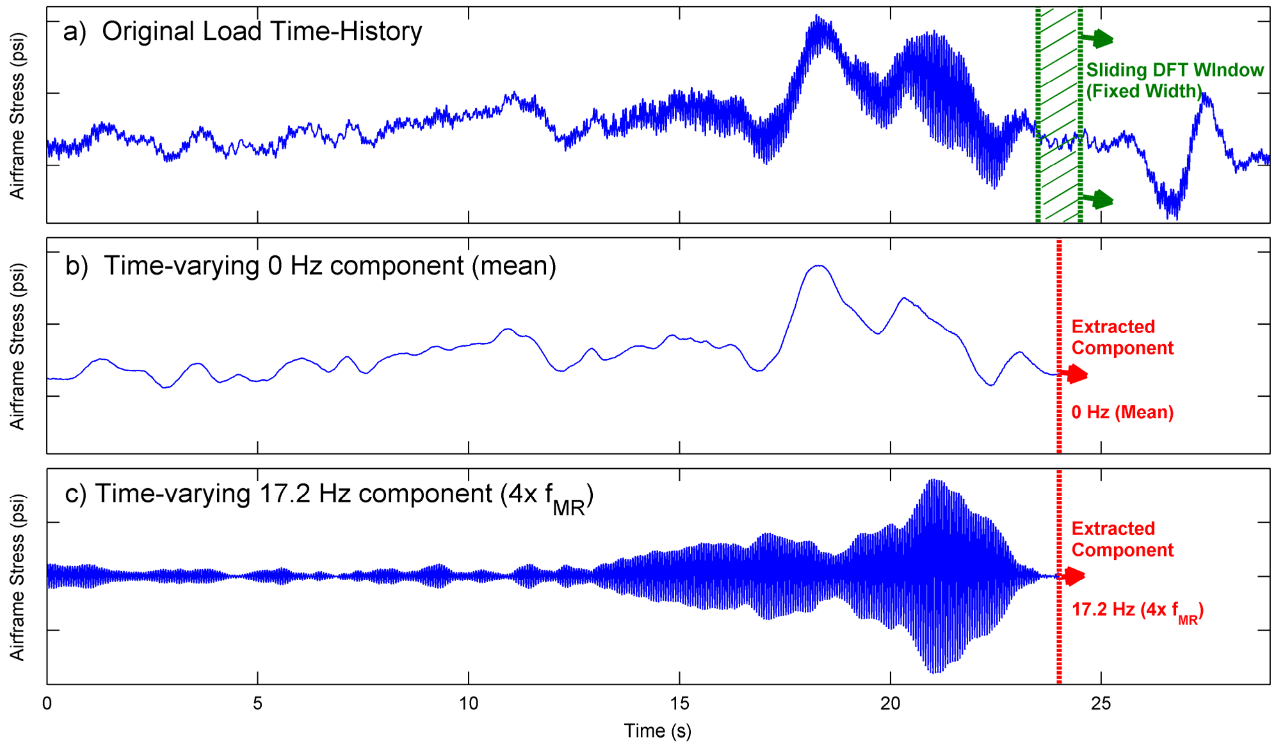

Figure 6 Graphic representation of using a sliding DFT to extract signal components at specific frequencies a) time-history of airframe stress during a dash and quickstop manoeuvre b) the 0 Hz extracted component c) the 4x f_{MR} extracted component

The ability to decompose signals into their harmonic components provides numerous benefits to the load synthesis approach; including: i) simplification of the prediction problem into multiple easier-to-solve problems; ii) extracting useful harmonic components at specific frequencies, from otherwise uninformative training data signals; and, iii) removing noise from the prediction problem, by allowing modelling of an optimized group of target frequencies.

3.3. Variable Selection

Variable selection techniques are an important aspect of load synthesis approaches. They provide a means of discarding redundant and irrelevant predictors, and aid in the selection of optimal predictors. A common goal of variable selection techniques is to minimise the number of inputs required, as this increases both the practicality and robustness of the resultant model.

The variable selection process is especially important within the harmonic regression approach, as decomposing signals into their harmonic content greatly increases the number of candidate predictor variables. As linear regression is used to train the predictive models, the current variable selection technique is a form of stepwise regression which identifies and selects a subset of predictors which minimise the ordinary least squares (OLS) residual sum of squares (RSS) of the model.

The variable selection technique is performed for each target harmonic to be predicted, and operates by iteratively adding predictors to a subset until all predictors are included. At each iterative step, the algorithm adds that predictor whose addition would most decrease the OLS RSS of the model as calculated by Equation (5). This selection process is performed for each set of cross-validation training data, and the current predictor subset is recorded at each iterative step.

(5) $$RSS = \left| \mathbf{y}_{\mathbf{Tr}} - \mathbf{X}_{\mathbf{Tr}}\hat{\boldsymbol{\beta}} \right|^2$$

Where $\mathbf{y}_{\mathbf{Tr}}$ is a vector of target harmonic amplitudes within the training data; and, $\mathbf{X}_{\mathbf{Tr}}$ is the matrix of predictor harmonic amplitudes.

As $\hat{\boldsymbol{\beta}}$ is calculated using the ordinary least squares approach, Equation (5) is transformed into:

(6) $$RSS = \mathbf{y}_{\mathbf{Tr}}^{\mathbf{T}}\mathbf{y}_{\mathbf{Tr}} - \mathbf{y}_{\mathbf{Tr}}^{\mathbf{T}}\mathbf{X}_{\mathbf{Tr}}\left(\mathbf{X}_{\mathbf{Tr}}^{\mathbf{T}}\mathbf{X}_{\mathbf{Tr}}\right)^{-1}\mathbf{X}_{\mathbf{Tr}}^{\mathbf{T}}\mathbf{y}_{\mathbf{Tr}}$$

Once all predictors are included within the subset, the process is reversed with the technique iteratively removing predictors from the subset. Predictors are removed based on how little their removal will affect the model RSS. The order of variable selection is important in stepwise regression techniques, this backward selection step alleviates this somewhat, by providing an alternate path of variable selection.

Finally, the technique calculates how well the subsets selected at each iterative step would perform against the unseen test data. The subset of predictors with the best predictive accuracy for the unseen test data is then selected as the optimal subset of predictors for the model.

3.4. Model Development

3.4.1. Linear Models of Harmonic Data

This harmonic regression approach fits predictive linear models to the selected set of Black Hawk flight data, using a multiple linear regression approach. Assuming that the relationship between the dependent variable, y_i, and the p-vector of predictors, x_i, is linear, β are regression coefficients estimated using a least squares approach. Standard linear models take the form shown in Equation (7), where $j = 1,...,n.$, and ε_i is an error term defining noise.

(7) $$y_j = \beta_1 x_{j1} + \cdots + \beta_p x_{jp} + \varepsilon_j$$

These n equations are often stacked together and written in vector form as

(8) $$\mathbf{y} = \mathbf{X}\hat{\boldsymbol{\beta}} + \boldsymbol{\varepsilon}$$

where

$$\mathbf{y} = \begin{pmatrix} y_1 \\ y_2 \\ \vdots \\ y_n \end{pmatrix}, \qquad \mathbf{X} = \begin{pmatrix} x_{11} & \cdots & x_{1p} \\ x_{21} & \cdots & x_{2p} \\ \vdots & \ddots & \vdots \\ x_{n1} & \cdots & x_{np} \end{pmatrix},$$

$$\hat{\boldsymbol{\beta}} = \begin{pmatrix} \beta_1 \\ \beta_2 \\ \vdots \\ \beta_p \end{pmatrix}, \qquad \boldsymbol{\varepsilon} = \begin{pmatrix} \varepsilon_1 \\ \varepsilon_2 \\ \vdots \\ \varepsilon_n \end{pmatrix}$$

Noting that RSS is equal to $|\boldsymbol{\varepsilon}|^2$

3.4.2. Modelling Harmonic Amplitude

The harmonic regression approach requires the modelling of those complex numbers calculated using Equation (2) which represents changes in the sinusoid over time. To best achieve this, each sinusoidal component is modelled independently.

The process for modelling the sinusoidal amplitude is straight-forward. It involves fitting a linear model similar to Equation (8) using data from each cross-validation training dataset; where $\mathbf{y}$ is a vector of pitch-link amplitudes at a specific frequency; and $\mathbf{X}$ is a matrix of amplitudes for each predictor within the optimal subset. All of these amplitudes are calculated from their respective complex sinusoids using Equation (3).

This approach is simple yet has proven very successful, as demonstrated by the included case study.

3.4.3. Harmonic Phase

As a preliminary study, the present investigation does not incorporate the modelling of harmonic phases. Instead, the phases from the actual measurements were used to reconstruct the load-time history. This allows for the evaluation of the best possible prediction if the phase was modelled perfectly.

3.4.4. Composing Load Time-History

The ability to restructure the target component load time-history from the predicted harmonic content is essential if the approach is to be used for indirect load monitoring. This is achieved by performing a process which is in essence the inverse of the STFT previously detailed.

A sequence of complex numbers $z_{1k,\cdots,}z_{nk}$, which represent sinusoids at specific harmonic frequencies of the target load as they change over time, is constructed, using Equation (9), from the amplitudes and phases modelled by the approach.

(9) $$z_{jk} = \left|z_j\right| \times e^{i\phi(z_j)}$$

Where $|z|$ is the sinusoidal amplitude, and $\phi(z)$ the sinusoidal phase.

A sliding inverse DFT is then used to transform this sequence of complex numbers into a sequence of real numbers equal to the target component load-time history.

As previously stated, the approach is not yet able to model the sinusoidal phase. In order to effectively evaluate the ability of the approach to model sinusoidal amplitude, the measured phase from the testing data is used to reconstruct the signal.

4. DEMONSTRATED CASE STUDY

A linear model was developed using the harmonic regression approach to predict the main-rotor pitch-link loads of a Black Hawk helicopter during level flight manoeuvres. This model was trained using flight data from 160 level flights at various airspeeds, aircraft configurations, gross-weights, altitudes and centre of gravity locations. The model uses a number of fixed strain measurements and flight state and control parameters to predict time-varying sinusoids at 8 frequencies including; 0 Hz (DC); 4.3 Hz (f_{MR}); and the first 6 harmonics of f_{MR}. These time-varying sinusoids, or harmonic components, are defined by amplitude and phase values which are independently modelled by the approach. The predicted sinusoids at each frequency are combined to construct a predicted load time-history.

The harmonic regression approach is capable of modelling the magnitude of these harmonic components to a high-degree of accuracy, as shown in Figure 7 by small values of Root Mean Squared Error (RMSE) which were calculated using test data unseen in training. This level of accuracy is possible largely as a result of the signal decomposition process. By separating the flight load data into its fundamental harmonic components, predictive models of target signals become simpler and more relevant predictive information can be extracted from predictors.

This high degree of accuracy is also partly due to the variable selection techniques used to determine the models subset of predictors. The current variable selection techniques used are optimized to improve predictive accuracy with no consideration for model parsimony. As a result, the predictor subset selected for the final model was quite large, comprising 466 total harmonic components from 198 unique strain gauges and flight state and control parameters. The improvement of these techniques will most likely see a trade-off between model accuracy, and model parsimony, with accuracy reducing as the subset size shrinks. That being said, previous investigations of similar approaches have found that the accuracy level can be held and even improved while reducing the predictor subset size, by improving the models ability to predict unseen data.

Despite the lack of phase predictive capability, the final load time-history can be constructed using measured phase values; this reconstruction is the best-case model prediction, assuming perfect phase prediction, with current amplitude prediction accuracy. Figure 8a shows a reconstructed pitch-link load time history for 160 level flights at various airspeeds. Figure 8b and Figure 8c enhance 3 seconds of the predicted and measured time-histories to emphasize how well the final prediction matches.

These reconstructed time-histories emphasize how well the predicted amplitudes match the measured. If similar levels of accuracy can be achieved with the phase prediction techniques currently being investigated, then the harmonic regression approach would be an extremely promising indirect load monitoring technique.

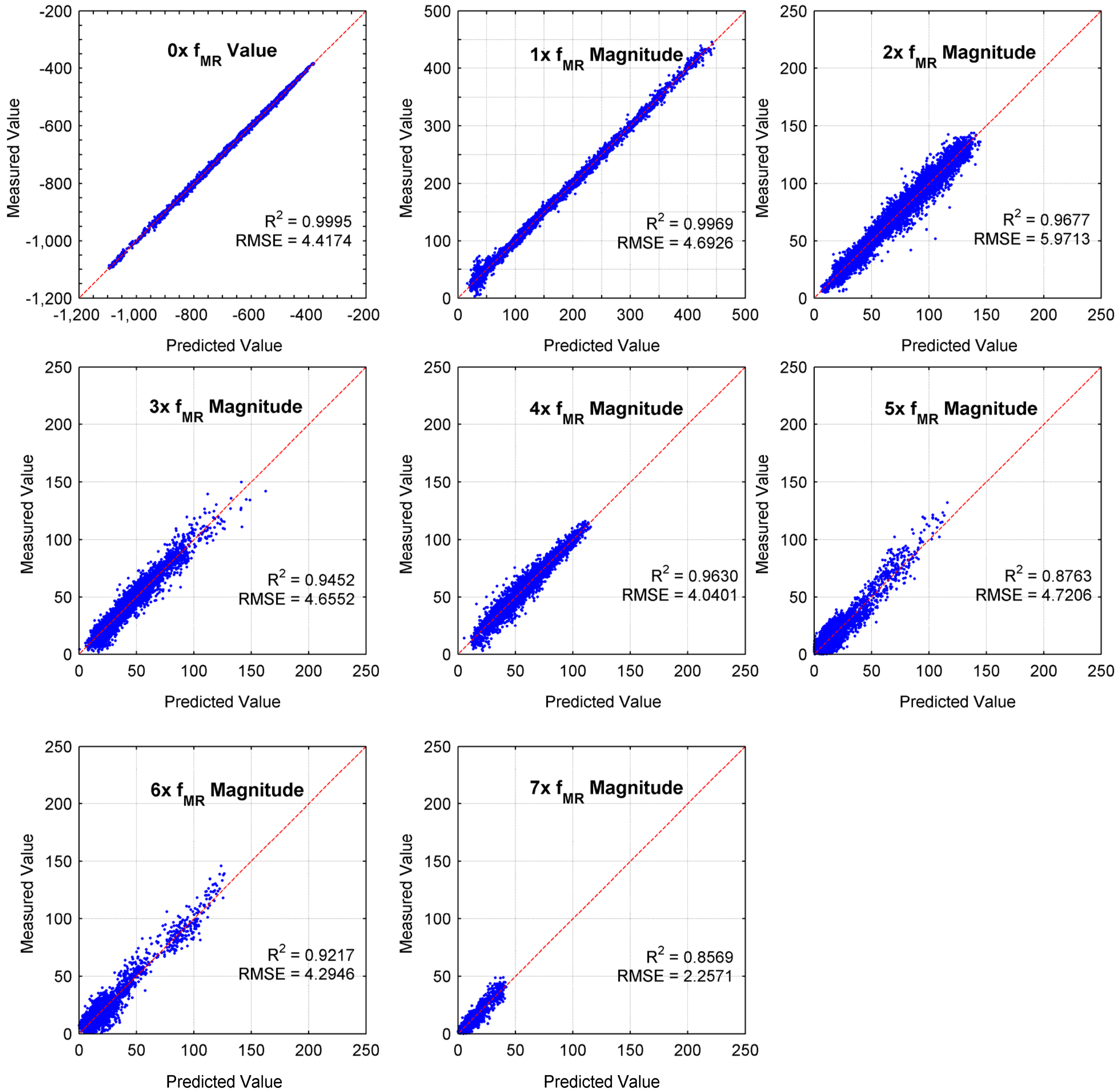

Figure 7 Accuracy for the magnitude predictions of each harmonic component. Note the change in scale between the first 3 harmonic component plots..

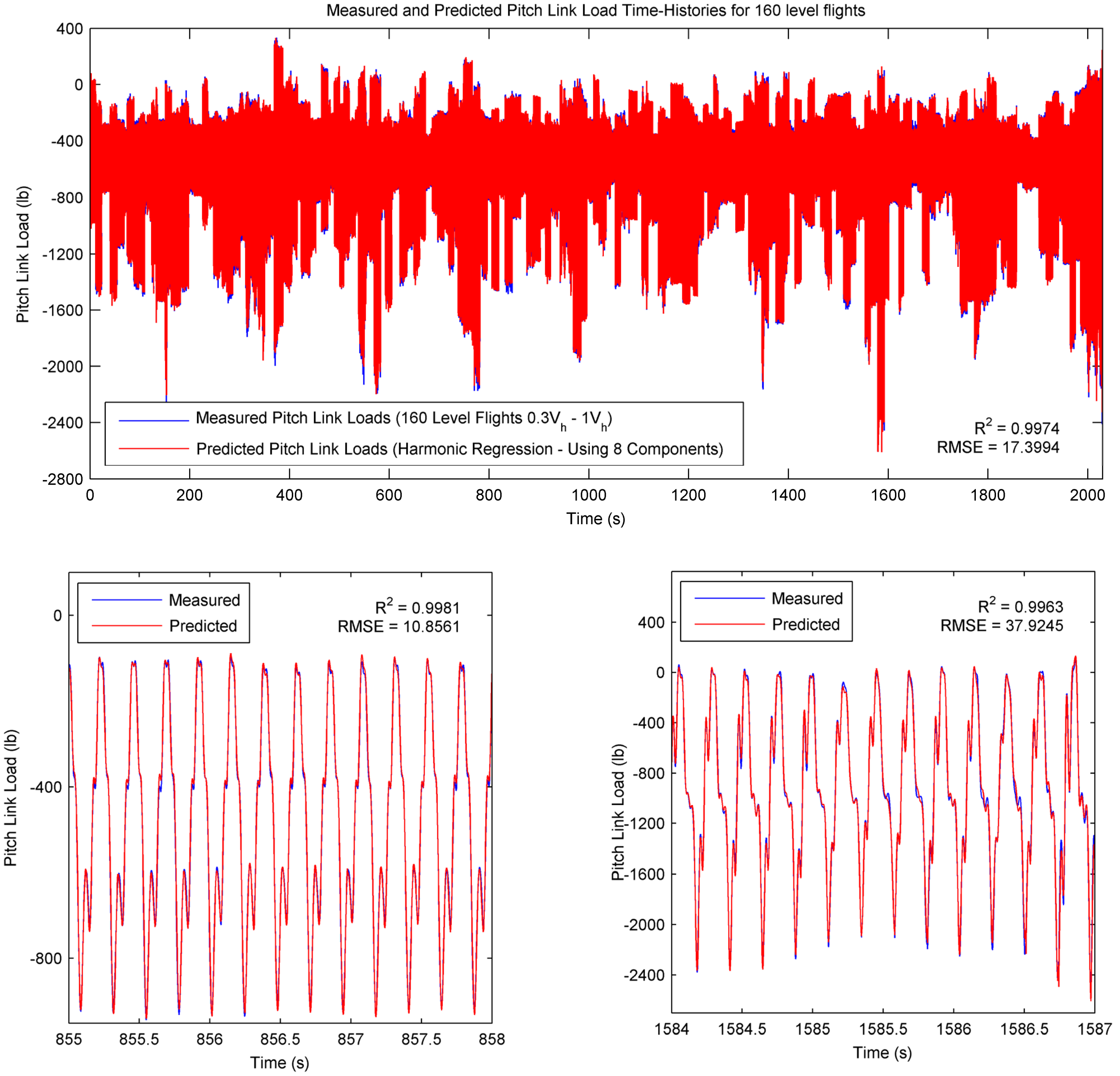

Figure 8 Comparison of measured and predicted main rotor pitch-link load time histories, using measured phase information during the construction of the predicted history. a) time-history predictions for all 160 level flights used during model training and testing. b) 3 second sample of a relatively steady period of flight. c) 3 second sample of a less steady period of flight

5. DISCUSSION OF FUTURE WORK

5.1. Optimising Selection Across Harmonics

The current variable selection technique selects unique predictor subsets which are optimal for each target harmonic. There is currently no emphasis placed on minimising the number of predictors used to model each harmonic, or the total number of predictors required. By incorporating more sophisticated optimisation routines within the variable selection technique, it is hoped that the number of predictors required can be reduced significantly, whilst maintaining acceptable levels of accuracy.

Potential improvements could be made by adapting the current technique to concurrently select predictors across all target harmonics. By selecting predictor subsets concurrently, the technique can be guided to select a common subset of predictors. Although this subset may be inferior for predicting each independent harmonic, it would significantly reduce the total number of predictors required. Previous investigations of concurrent variable selection techniques have shown that due to the increase in robustness of models which use common subsets, overall model accuracy may actually improve using this technique [13].

5.2. Modelling Harmonic Phase

The sinusoidal phase cannot be modelled as simply as the amplitude. This is in large part due to the circular nature of phase data rendering traditional statistical regression approaches inadequate. In order to accurately model phase information for time-varying sinusoids, which is required for the harmonic regression approach, modelling techniques applicable to circular data must be investigated and adopted.

6. CONCLUSION

A load synthesis approach using harmonic regression was investigated as a means to indirectly monitor loads on helicopter dynamic components. The approach uses a synchronization technique to normalize the frequency content of flight data, and advanced signal processing techniques to decompose this data into harmonic components. Once decomposed, an optimal subset of predictor components is selected using advanced variable selection techniques, and predictive models trained using OLS linear regression. A case study demonstrated the predictive accuracy of this approach for main-rotor pitch link loads over 160 level flights at various speeds. The approach produced a general model for pitch-link load harmonics, capable of highly accurate amplitude predictions. Further work is required to i) investigate model performance with reduced number of predictor variables, and ii) investigate and develop phase prediction techniques which can be incorporated within the approach.

7. ACKNOWLEDGEMENTS

The author would like to thank his colleagues Xiaobo Yu, Luther Krake, Domenico Lombardo, and Cedric Rosalie for their advice and support.

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