ROTOR LOADS PREDICTION VIA VIRTUAL SENSORS BLENDING PHYSICS AND AI

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Abstract

The paper focuses on the prediction of the load generated by a helicopter lead-lag damper, which is not directly measured in production helicopters but is a valuable parameter for rotor health monitoring and maintenance scheduling. The approach blends the prediction obtained from an artificial intelligence model, called the black box, with the prediction made by a physical model, called the white box. The black box is used to predict the blade motions from the aeromechanical parameters of the helicopter measured in flight. Given the complexity of helicopter aeromechanics and the large data set acquired on helicopter prototypes, an artificial intelligence modelling approach is well suited for this task. The damper force is finally predicted using a white box model describing the core physical behaviour of the damper, which takes as inputs the blade motions predicted by the black box. In this case, the damper dynamics can be described by a relatively simple physical model, yet giving an acceptable level of accuracy. A comparison between the predicted and measured damper loads on a helicopter prototype demonstrates the approach's effectiveness.

1. NOTATION

f	Force exerted by the damper on the damper-link
k	Damper stiffness coefficient
N	Number of harmonics
P	Z-score window length
x	Equivalent linear damper displacement
z	Z-score
A_0	Static Fourier Series coefficient
A_p	Damper equivalent piston area
C_n	Cosine Fourier Series coefficient
L_{link}	Link length
S_n	Sine Fourier Series coefficient
$X_{W\,in}$, $X_{Y\,out}$	Distance of the inboard and outboard points
y_i	Approximated time signal
AI	Artificial Intelligence
HTH	Harmonic Time History
HUMS	Health & Usage Monitoring System
MAE	Mean Absolute Error
MSE	Mean Squared Error
NN	Neural Network
NRMSE	normalized root mean squared error
ReLU	Rectified Linear Unit
WoW	weight-on-wheel
β	Lag blade angle
δ	Damper differential pressure
θ	Pitch blade angle
μ	average
ξ	Flap blade angle
σ	Standard deviation
*	Undeformed case configuration
$\dot{}$	Time derivative

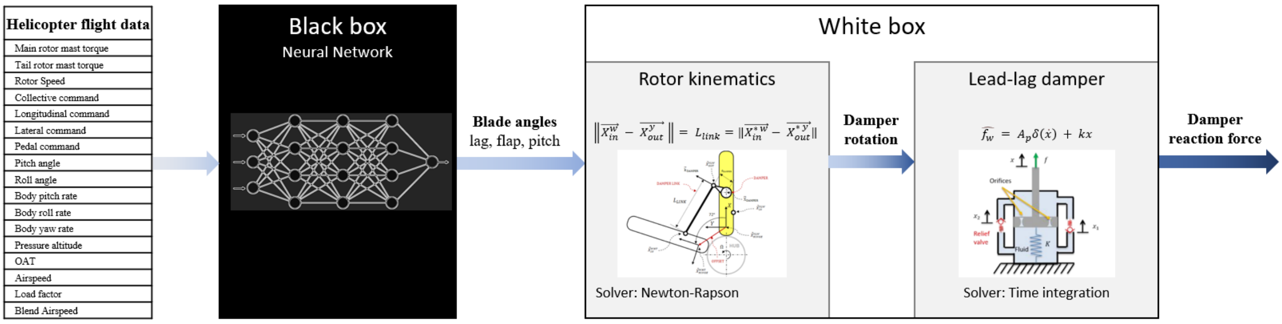

Figure 1 Workflow of the damper force prediction model

2. INTRODUCTION

An accurate knowledge of the rotor loads is necessary for the design of new helicopters and to support the certification process. Moreover, the rotor loads are necessary to assess the fatigue damage of critical components throughout the lifetime of a production helicopter, which strongly depends on the types of manoeuvres flown. In the design phase, the helicopter prototypes are highly instrumented, and the rotor loads can be directly measured using sensors installed on the rotating system. The same data are unavailable on production helicopters, which are typically instrumented with the sensors needed by the flight control system, HUMS, and other systems usually installed in the non-rotating system, i.e. fuselage and characterised by a relatively low sampling frequency.

The availability of large data sets acquired on helicopter prototypes compared to the lack of data on production helicopters suggests that machine learning approaches can be used to train regression models on the prototype data, which can then be used to predict the rotor loads on production aircraft.

In references [1-4], neural networks (NNs) have successfully been used to forecast helicopter rotor loads. In reference [1], the pitch link loads are predicted by the neural network from information measured by the flight control system (e.g. roll, pitch, yaw rates, airspeed, etc.). In reference [2] and [3], in addition to the pitch link loads, the neural network has been trained to predict the blade bending moments and main rotor damper loads again, starting from the information acquired in the non-rotating system. In ref. [4], NNs were used to evaluate rotor hub loads to create an envelope protection system.

Regression models, such as NNs, are pure numerical models whose parameters are learnt directly from data and usually do not have a physical meaning. Therefore, any available physical knowledge of the system cannot be embedded in the model to help with the prediction [5]. On the other hand, pure physical models describe the underlying physics by equations. One drawback in this case is that their derivation may become complicated when dealing with complex phenomena.

This paper describes the implementation of a hybrid model to predict the in-flight loads produced by a lead-lag damper of an inter-blade articulated helicopter rotor.

The proposed approach takes advantage of a hybrid formulation, blending a black box, consisting of a general regression numerical model, with a white box, consisting of equations describing the system's underlying physics. Figure 1 shows a scheme of the framework used. The basic idea is to decouple the damper load prediction into two steps: i) the inference of the rotor motion via a black box model and ii) the evaluation of the damper load via a white box model. The first step is achieved via a neural network that takes as inputs a selection of helicopter flight data (e.g. pilot command, airspeed, rotor RPM, etc.) and outputs the time histories of the lag, flap, and pitch blade angles. In this case, a regression model is well suited for this scope, given the availability of the large amount of data acquired on the helicopter prototype and the complex aeromechanical phenomena to be described. The second step takes as inputs the predicted blade angles and, by solving a set of kinematic equations, predicts the lead-lag damper rotation. A time domain model of the lead-lag damper is finally used to predict the reaction damper force. In this second case, a simplified physical model can describe the dynamics of the lead-lag damper with a satisfactory accuracy level, given the component's relatively low complexity. The physical model also has the advantage of providing a more straightforward interpretation of the results.

The paper is divided into five sections. Section 3 briefly describes the flight data used to train the NN and predict the blade angles. Section 4 describes the black box model details and the training and validation approach. Section 5 focuses on the description of the white box model. Finally, results are presented in Section 6 and conclusions are drawn in Section 7.

3. FLIGHT DATA

A well-structured and organized data set and thorough data cleaning are crucial for achieving reliable and consistent results in data-intensive projects. In machine learning applications, in particular, the quality of the data provided significantly impacts the model's performance.

The complete list of the input and output data of the black and white box models for this application is provided in Table 1. The data encompassing approximately 100 h of experimental flights have been collected during the AW169 developmental flight test campaign.

The data have been preliminary filtered by considering only the actual in-flight conditions. These are selected considering the available weight-on-wheel (WoW) parameter, which detects the ground contact.

Figure 2 shows the time history of the blade pitch angle (top plot) and the WoW parameter (bottom plot).

Table 1 Input/Output data

Input Data	**Output Data**	
	Black box	**White box**
Main rotor mast torque	White blade lag angle	Damper rotation
Tail rotor mast torque	White blade flap angle	Damper reaction force
Rotor Speed	White blade pitch angle	
Collective command	Yellow blade lag angle	
Longitudinal command	Yellow blade flap angle	
Lateral command	Yellow blade pitch angle	
Pedal command	Damper link axial load	
Pitch angle		
Roll angle		
Body pitch rate		
Body roll rate		
Body yaw rate		
Pressure altitude		
Outside air temperature		
Airspeed		
Load factor		
Blend Airspeed		

The orange portion of the signal is the selected time history corresponding to a flight condition where the WoW parameter is zero. As shown in Figure 2, the inflight condition is characterised by high oscillatory dynamics, and thus it is also expected to produce higher damper loads.

Figure 2: In-flight condition filter. Top axes shows the (—) raw pitch angle data, and the (—) filtered one. The lower axes shows the WoW sensor data.

The input data have been further filtered to avoid inconsistent data (e.g. degraded sensors or acquisition errors), which may impact the training phase of the NN and lead to inaccurate predictions.

Since corrupted data usually presents spikes due to signal saturation, the method chosen in this work to detect spikes uses the Z-score index over a moving window. The Z-score for each sample is calculated as:

$$z_i = \frac{(x_i - \mu_i)}{\sigma_i} \tag{1}$$

Where x_i is the i^{th} sample, and μ_i and σ_i are the mean and standard deviation calculated over a window which includes P previous samples where P is the window length.

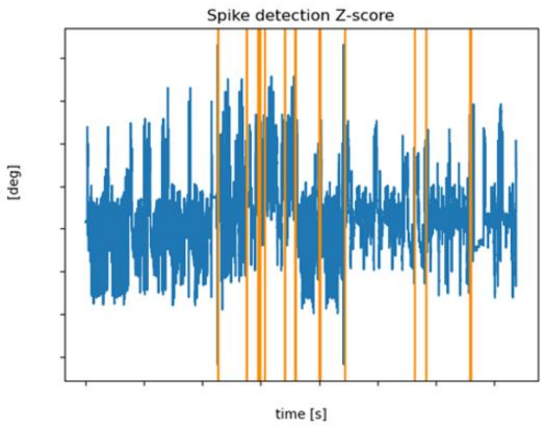

Figure 3: Z-score spike detection algorithm applied to the cyclic lateral command

An example of the outcome of the proposed method is shown in Figure 3 for an input parameter time series data. Samples with a high Z-score have been categorised as spikes and discarded from the data set.

4. BLACK BOX MODEL

In this section the black box model architecture is first defined. The training and validation process using the flight data is finally discussed.

4.1. Harmonic time history

When training a regression model, it is crucial to select and, in some cases, engineer new input features from the available data set to improve the prediction accuracy and the computational effort. In this case, the blade angle time histories are harmonic signals of the rotor fundamental frequency, Ω, kept constant in nominal flight conditions.

Harmonic Time History (HTH) efficiently decomposes the time series. The HTH algorithm: i) divides the time series into windows containing a single period, $T = 1/\Omega$ of the fundamental frequency and ii) applies a harmonic Fourier decomposition. The i-th portion of the generic signal, y^i, can be written as the sum of N harmonic components, as follows:

$$y^i(t) \approx A_0^i + \sum_{n=1}^{N} C_n^i \, cos(n\Omega t) + S_n^i(n\Omega t) \qquad (2)$$

Where the coefficients A_0^i, C_n^i, S_n^i are the static, sine, and cosine coefficients respectively of the n-th harmonic. As one would expect, the accuracy of the HTH algorithm improves as the number of harmonics, N, in equation (2) increases.

The signals were processed with the HTH algorithm and reconstructed back to the time domain for comparison. The accuracy of the reconstruction was evaluated using the normalized root mean squared error (NRMSE), which indicates how well the estimated signal matches the original one.

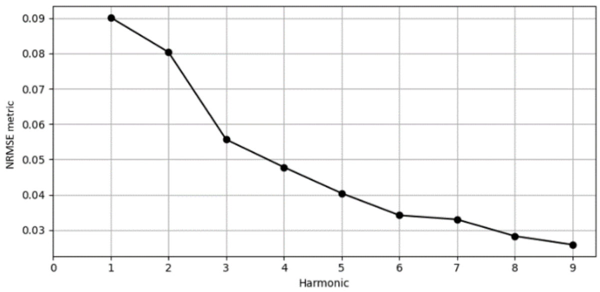

Figure 4: Lag angle HTH reconstruction error, as function of the number of harmonics.

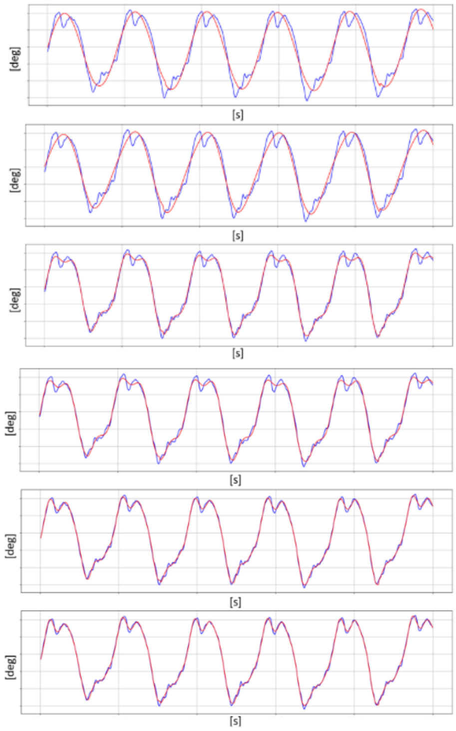

Figure 5: Lag time reconstruction after HTH algorithm, from 1st to 6th harmonics. (—) original, (—) HTH fitting

Figure 4 shows the HTH reconstruction error for the blade lag angle data as a function of the number of harmonics, N. Figure 4 confirms that the error decreases as the number of harmonic increases.

Additionally, Figure 5 shows a qualitative comparison between the original blade angle time history (blue line) and the reconstructed signals (red line) with increasing harmonics.

The number of harmonics necessary to obtain a reasonably low reconstruction error differs for each blade angle signal and is summarised in Table 2. Due to the intrinsic dynamic behaviour of the helicopter rotor, it is evident that some blade degrees of freedom are characterised by higher harmonic content than others. Finally, for the input signals, since their dynamics are relatively slow compared to the fundamental frequency of the rotor, only the static coefficient is required to obtain an acceptable NRMSE reconstruction error. The HTH approximates the signals only using a set of Fourier coefficients for each window, bringing an evident advantage in data size.

Table 2: blade angle HTH setting

Blade motion	No. of harmonics
Lag	3
Flap	2
Pitch	1

As shown in reference [6, 7], a regression model can be built to predict the Fourier series coefficients instead of working directly on the entire time series, reducing the NN's complexity and, consequently, the training process's computational cost. However, this harmonic approach involves training a NN for each harmonic considered. As shown in the scheme of Figure 8, the static coefficients of the input signals are used as inputs of each NN to predict the static coefficient, A_0, and the N sine and cosine coefficients S_n and C_n for each blade angle. The predicted Fourier coefficients are then used to reconstruct the time domain signal using equation (2). As summarised in Table 2, the total number of NNs necessary to predict the motion of a single blade is 9 (3 for the lag, flap and pitch static coefficients and a total of 6 harmonic coefficients, 3 for the lag, 2 for flap and 1 for pitch angles). However, given the inter-blade architecture of the rotor under consideration, the rotation of a single damper is determined by the motion of two adjacent blades. Therefore, a total of 18 NNs is necessary. The same architecture for all 18 NNs was chosen for simplicity, consisting of a feedforward neural network, with fully connected neurons. The Rectified Linear Unit (ReLU) activation function is applied to the hidden layer units, while the output layer uses a linear activation function.

A hyperparameter tuning process has been carried out to determine the optimal number of layers and neurons. Initially, the tuning process focussed on the lag angle. The loss function chosen for the training is Mean Squared Error (MSE), while the evaluation metrics include MSE and Mean Absolute Error (MAE).

The NNs were trained multiple times on the training data set, each time using a different combination of the number of neurons and layers.

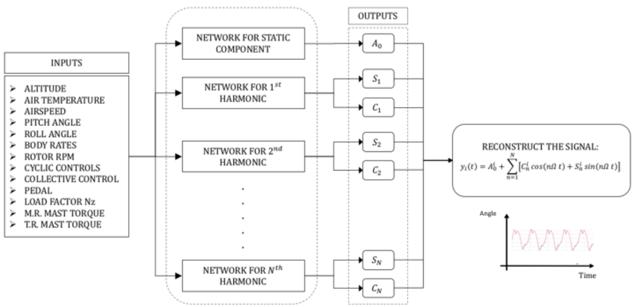

Figure 6: Structure of the black box in the generic case of N harmonics

Table 3 NNs tuning results. The two adjacent blades a labelled as white and yellow

Parameter	Nuber of Neurons	Number of Layers	Blade
Pitch A_0	[50]	[1]	White
Pitch 1^{st} harmonic S & C	[50]	[5]	White
Lag A_0	[50]	[1]	White
Lag 1^{st} harmonic S & C	[50]	[5]	White
Lag 2^{nd} harmonic S & C	[50]	[5]	White
Lag 3^{3d} harmonic S & C	[50]	[5]	White
Flap A_0	[50]	[1]	White
Flap 1^{st} harmonic S & C	[50]	[5]	White
Flap 2^{nd} harmonic S & C	[50]	[5]	White
Pitch A_0	[50]	[1]	Yellow
Pitch 1^{st} harmonic S & C	[50]	[5]	Yellow
Lag A_0	[50]	[1]	Yellow
Lag 1^{st} harmonic S & C	[50]	[5]	Yellow
Lag 2^{nd} harmonic S & C	[50]	[5]	Yellow
Lag 3^{3d} harmonic S & C	[50]	[5]	Yellow
Flap A_0	[50]	[1]	Yellow
Flap 1^{st} harmonic S & C	[50]	[5]	Yellow
Flap 2^{nd} harmonic S & C	[50]	[5]	Yellow

Both the loss and evaluation functions were calculated on the validation data set (to avoid overfitting), and the combination providing the best evaluation metrics was chosen. For the lag angle NNs, the best combination used 1 and 5 layers for the static and harmonic coefficients, respectively, with 50 neurons per layer. For the flap and pitch angle NN hyperparameter tuning, only the number of layers was varied, keeping the number of neurons to 50. Table 3 summarises the NN hyperparameters for each of the 18 NNs.

4.2. Model robustness

Comparing the evaluation metrics between the training and validation sets and evaluating the model's performance on the test set is usually sufficient to assess a model's robustness. However, in this work, additional efforts were made to understand the generalisation properties of the trained models. The data set was split into training, test and validation subsets using random sampling with percentages of 70%, 15% and 15%, respectively, while keeping a constant seed value. The seed ensures results reproducibility however may lead to a model that performs well only with that specific data partition. Training the model with the data partitioned with two different seeds ensured that the prediction was not dependent upon the specific seed value. Results showed that the overall performance of the models remained unvaried with both seeds, highlighting good generalisation properties of the NNs built.

A specific test was conducted using a different approach to assess the model's generalisation capabilities further. The training and validation subsets were created using all flight data except one flight, which was used as the test set. This flight was not used during the model training phase, ensuring an evaluation of its performance on unseen data. The evaluation confirmed the model's ability to generalise to new instances within the overall range of flight data.

5. WHITE BOX MODEL

This section describes the physical model of the rotor kinematics and lead-lag damper used to estimate the reaction damper force. The rotor system of the AW169 helicopter is characterized by an inter-blade architecture that uses a rotative damper. The damper is connected to two adjacent blades through the damper link, as shown Figure 7.

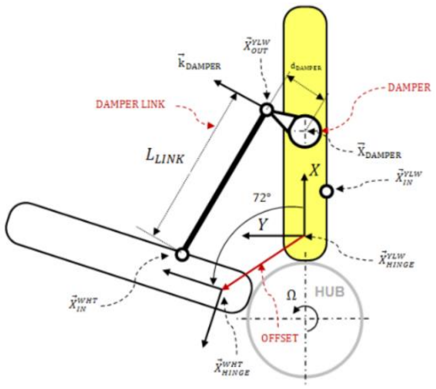

Figure 7: Damper inter-blade architecture. [8]

The main rotor damper rotation depends on the motion of the two adjacent blades. The damper rotation can be obtained by solving a congruence problem, starting from the motion of two adjacent blades to which it is connected. In particular, the damper rotation is obtained by imposing the congruence between the damper link length L_{link} and the distance of the inboard and outboard damper link attachments (X_{in}, X_{out}, see Figure 7) given by:

$$\left\| \overrightarrow{X_{in}^{w}} - \overrightarrow{X_{out}^{y}} \right\| = L_{link} = \left\| \overrightarrow{X_{in}^{*w}} - \overrightarrow{X_{out}^{*y}} \right\| \tag{3}$$

where the superscript * refers to the deformed kinematics while ^{w} and ^{y} refer to the white and yellow blade in Figure 7 respectively. Newton-Raphson method has been used to solve the non-linear equation (3) to find the damper rotation.

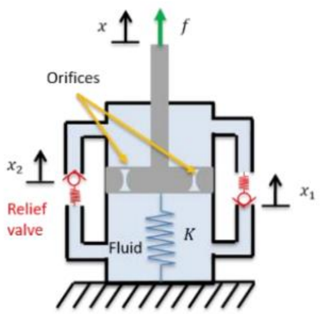

Figure 8: Scheme of the lead-lag damper [9].

Once the damper rotation is calculated, it can be fed to the damper model to give the final force prediction. The lead-lag damper uses the characteristics associated with a high-viscosity fluid's action and an elastomeric material's deformation. Even if the damper is rotative, its dynamic can be described by an equivalent linear damper, as schematically shown in Figure 8. The force f generated by the damper is given by the sum of force generated by the fluid pressure distributed over the piston area, A_p, and a stiffness component [9]:

$$f = A_p \delta(\dot{x}) + kx \tag{4}$$

where x is the equivalent linear damper displacement, k is the stiffness coefficient, and δ is the differential pressure between the upper and lower chamber. The complete formulation of the damper dynamics can be found in reference [9]. The differential equation (4) is integrated in time to predict the damper force time history f.

6. RESULTS

This section describes the damper force prediction obtained with the combined black and white box models.

6.1. Black box blade motion predictions

Figure 9 compares the black box predictions (green line) and the measured blade motion (red line). The prediction closely matches the original signal for the blade lag, flap, and pitch angles. Figure 4 reports the NRMSE error metrics calculated for the flight data reported in Figure 9. The NRMSE values demonstrate the good matching between the prediction and the original time series.

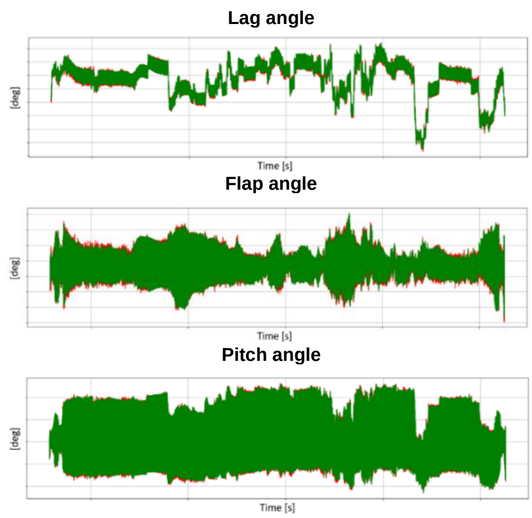

Figure 9: Lag, flap, pitch blade angle prediction. (—) measured data, (—) black box prediction.

Table 4: NRMSE error metrics

Variable	Description	NRMSE error
ξ	Lag	0.057
β	Flap	0.055
θ	Pitch	0.043

6.2. White box damper force prediction

The final step is the damper force prediction using the white box model. The Newton-Raphson method solves the non-linear equation for damper rotation, which is used as input to the Simulink time domain damper model.

A comparison between the simulated and measured damper force time histories is shown in Figure 10. The damper force on the helicopter prototype is measured by a strain gauge measuring the axial deformation of the link. The force is then calculated by multiplying the link deformation by the link axial stiffness.

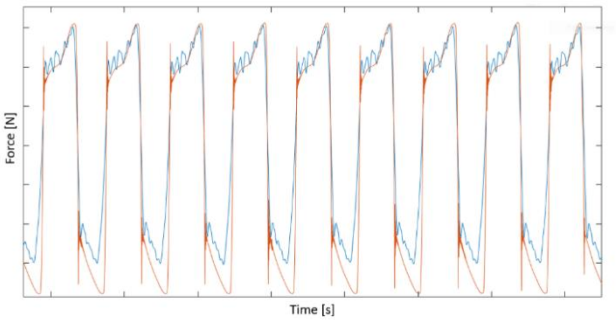

Figure 10: Damper link load comparison. (—) hybrid model prediction vs (—) experimental data

The plot shows the strain gauge's measured axial force in blue and the damper model's simulation output in orange. The two signals exhibit synchronization, with peaks aligning correctly. However, differences are observed in the valleys. The simulated axial force based on predicted inputs indicates an overestimation. To investigate the source of overestimation, a comparison between the axial force obtained from the strain gauge and the simulated axial force using the measured damper rotations as input was made. It can be concluded then that the overestimation in Figure 10 is the result of different reasons:

- The prediction made by the black box does not precisely match the measured blade angles,
- The kinematics used to calculate the damper rotations does not account for any elastic deformation of rotor components
- The simplified damper model overestimates the force in some conditions
- The experimental data used as ground truth are affected by measurement errors themselves.

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7. CONCLUSIONS

In conclusion, this research demonstrates the effectiveness of data-driven virtual sensors for accurate predictions of rotor components in helicopters. Integrating these data-driven approaches with physical modelling proves to be a valuable framework, as virtual sensors provide new data that can be processed by physical models, leading to a clearer understanding of simulation outputs. However, limitations related to the Harmonic Time History (HTH) algorithm and the simplified kinematics approach for the damper rotation reconstruction have been identified. Proposed solutions include exploring alternative real-time usable algorithms, employing advanced data-cleaning techniques, and developing a more accurate physical model considering the damper's actual kinematics.

This research introduces an innovative methodology centred around virtual sensors. The results emphasize virtual sensors' potential to significantly enhance structure monitoring's safety and reliability in various applications. By providing accurate predictions across different flight conditions, virtual sensors could be implemented to enable early detection of potential issues in rotor components, facilitating proactive maintenance and reducing the risk of unexpected failures. By incorporating virtual sensors into existing practices, potential component issues or degradation can be identified, enabling predictive maintenance strategies.

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