Prediction of Helicopter Rotor Loads and Fatigue Damage Evaluation with Neural Networks

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ABSTRACT

Machine learning algorithms have undergone rapid growth in recent years thanks to the ever-increasing amount of data and the parallel growth of computational power. Among the machine learning algorithms, one of the most famous and most effective classes for performance and flexibility are artificial neural networks, algorithms capable of learning relations between the data. In this work, neural networks are exploited to infer the relation between flight mechanics parameters and resulting loads of an articulated rotor configuration. The accuracy of these algorithms is closely related to the quality of the dataset used for their training. Since rotor loads are time-periodic signals with a precise harmonic content, a dedicated neural network is trained to predict each harmonic separately. The load time history is then reconstructed *a-posteriori* by combining all the predictions given by every single network. Different types of network architectures are tested, and a sensitivity analysis is conducted on hyper-parameters to determine the optimal configuration for the specific application. Furthermore, such predictions are then used to feed a fatigue damage calculation algorithm.

NOTATION

A_0	Static component of a signal
A/C	Aircraft
ANNs	Artificial Neural Networks
BB	Beam Bending
CB	Chord Bending
C_n	Cosine component of the *n-th* harmonic of a signal
FFNN	Feed Forward Neural Networks
HTH	Harmonic Time History
HUMS	Health and Usage Monitoring System
LSTM	Long-Short Term Memory
MSE	Mean Squared Error
RNN	Recurrent Neural Network
TDNN	Time Delay Neural Networks
S_n	Sine component of the n-*th* harmonic of a signal
*X*P	*X*-th harmonic

INTRODUCTION

The development and certification of a new aircraft requires the execution of several experimental flight tests aimed mainly at verifying the aircraft actual capabilities (in terms of performance, handling qualities, aeroelastic stability, ...) which can highlight potential design problems not foreseen in the preliminary phase. Notwithstanding the high-fidelity simulation tools nowadays available, experimental tests are still necessary to assess the behavior of the aircraft when analyses are only an approximation of the reality.

Even with the computational power now available, aeroelastic simulations of a complete rotor, coupling both aerodynamics loads and structural deformations, are very demanding when high fidelity tools are exploited. On the contrary, neural networks algorithms are more flexible and faster, so they can be an ideal candidate for predicting loads in real-time with a fair level of accuracy. Indeed, they require only some matrix multiplications and some evaluations of simple nonlinear algebraic functions. On the other hand, the main drawback of using neural networks is that existent flight-data databases, with large amounts of high-quality data, are needed in order to obtain reliable predictive models that work well throughout the whole flight envelope.

In this work, we demonstrate the effectiveness of using neural networks for predicting loads on a conventional articulated rotor. In particular, we focused our attention on the flap-wise beam bending at the root section of the rotor blade. Furthermore, using the load estimated from the prediction of the artificial neural network, the fatigue damage of the blade specimen can be calculated.

The helicopters of the production fleet are not equipped with sensors for monitoring blade loads because of high maintenance costs, but blades are critical components for the safety of flight. For this reason, current maintenance standards must be very conservative and, consequently, blades can be prematurely withdraw even if they could be used for more flight hours. Better computation of the actual blade damage can open up a new maintenance scenario: extending or reducing the component residual life in relation to the way the aircraft is flown.

The neural networks approach for rotor loads estimation has been already investigated by Ref. 1 and Ref. 2. However, the focus was limited to the prediction of conventional helicopter rotor loads during particular maneuvers. Also, Ref. 3 used neural networks to estimate hub-center loads in real time to design an envelope protection system. Ref. 6 introduces a new methodology for pre-processing the data to predict rotor loads on a tiltrotor application. The present work extends this approach to blade loads of a common articulated rotor.

DATA SOURCE

Among all the flights in the database, a load survey campaign is chosen as training set. A definition of what is the goal of a load survey is summarized as:

"Loads, stresses and strains are measured for ground and flight conditions and used to establish a comprehensive database, that is used to evaluate the fatigue life and/or inspection intervals for the aircraft parts in agreement with the operational usage spectrum".

This set of flights is chosen because, as its objective suggests, it comprehensively explores the flight envelope. In addition, a proper subset of data must be selected for testing and for validating the developed algorithms. These datasets are composed by data never "seen" by the neural network during the training phase. Figure 1 and Figure 2 show a comparison between the training dataset with respect to the test dataset in terms of rotor commands (i.e. collective and longitudinal blade pitch) and in terms of altitude vs TAS envelope.

In our case, the complete dataset consists of approximately 100 flight hours and is split into 80% for the training set, 10% for the validation set and 10% for the test set.

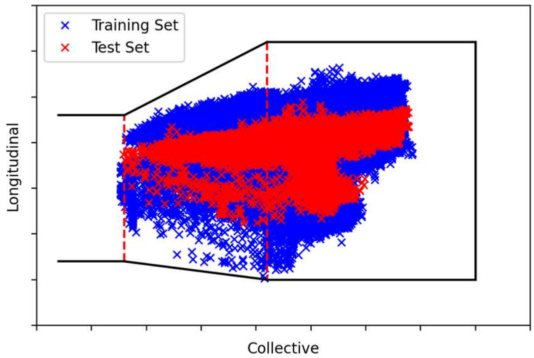

Figure 1: Rotor Commands, Training Set VS Test Set

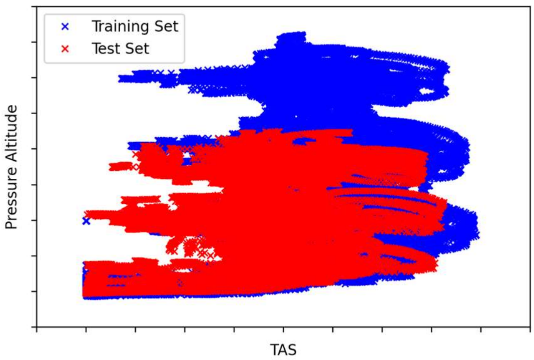

Figure 2: Altitude Envelope, Training Set VS Test Set

After defining those datasets, an appropriate set of inputs must be defined to predict the flap-wise bending moment at the blade root section. These inputs feed the neural network algorithm as pictured in Figure 3.

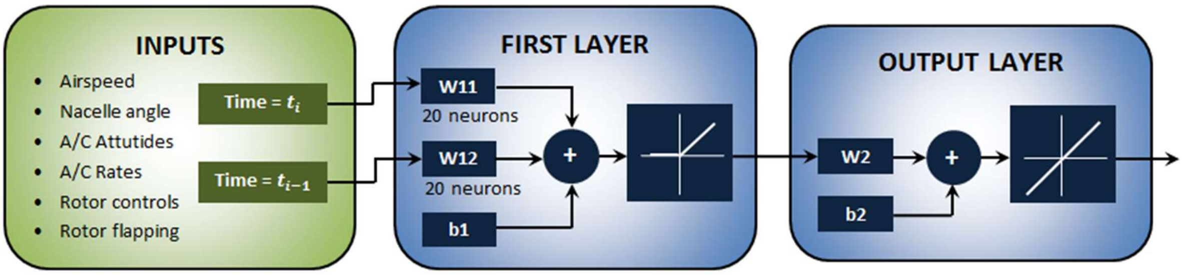

Figure 3: FFNN architecture

Choosing the correct set of inputs that drive the output, i.e. flap-wise bending moment, is not trivial and an explorative data analysis can help in finding the best set. In this branch of Machine Learning, there are many techniques that deduce the correlation between a dataset with a brute force approach (e.g. PCA, Pearson correlation index, …) which would not consider the physics behind the strain gauge sensor.

Our approach choses a different strategy and a domain specialist, who knows the physics of the sensor itself and the driver parameters of that load component, is consulted to determine which parameters are most relevant for predicting the flap-wise bending moment. Without carrying out any reduction of the dimensionality of the dataset, the flight mechanics parameters are initially selected (see Table 1). They can be collected into two groups which separately describes the flight physics of the aircraft and of the rotor.

Aircraft	Pressure altitude & Outside air temperature
	Airspeed
	Load factor
	Pitch / Roll angles
	Body pitch / yaw / roll rates
Rotor	Main / Tail rotor mast torque
	Main Rotor RPM
	Main rotor commands & Pedal

Table 1: NN inputs

DATA PREPROCESSING

The approach presented in this work makes use of an harmonic decomposition of the signal which enable the neural network to separately predict the harmonic components. The time history of the load is reconstructed *a-posteriori* by re-combining the harmonic components predicted by each neural network. This can be accomplished by a technique, proved to be effective in Ref.6, used in the preprocessing of quasi-periodic time series, *i.e.* the harmonic time history (HTH).

A briefly explanation of the technique is here reported. The signal to be analyzed is divided in chunks determined by the rotor turning frequency. In particular, a chunk starts when the reference blade passes through the zero azimuth position and ends exactly one (or more) turn(s) later. Within every chunk, a harmonic fitting is exploited, approximating the signal as

$$y_i(t) \cong A_0^i + \sum_{n=1}^{N} [C_n^i \cos(n\Omega\, t) + \mathrm{S}_\mathrm{n}^i \sin(n\Omega\, t)], \qquad (1)$$

where $y_i(t)$ is the time history of the load within the *i-th* rotor revolution and A_0^i, C_n^i and S_n^i are the values of the harmonic components. So, the different neural networks are trained to predict $A_0(t)$, $C_n(t)$ and $S_n(t)$ during whole flights, knowing that

$$A_0^i = A_0(t_i),$$
$$C_n^i = C_n(t_i),$$
$$S_n^i = S_n(t_i),$$

where t_i is the mid-point time of the *i-th* rotor revolution. Then, the time history of the load can be reconstructed as:

$$y_i^{rec}(t) = A_0^i + \sum_{n=1}^{N} [C_n^i \cos(n\Omega\, t) + \mathrm{S}_\mathrm{n}^i \sin(n\Omega\, t)]. \qquad (2)$$

It might be worth highlighting that $y_i^{rec}(t)$ is just an approximation of $y_i(t)$, particularly when its harmonic components change very fast from a complete revolution to another or when a limited number of harmonics are used.

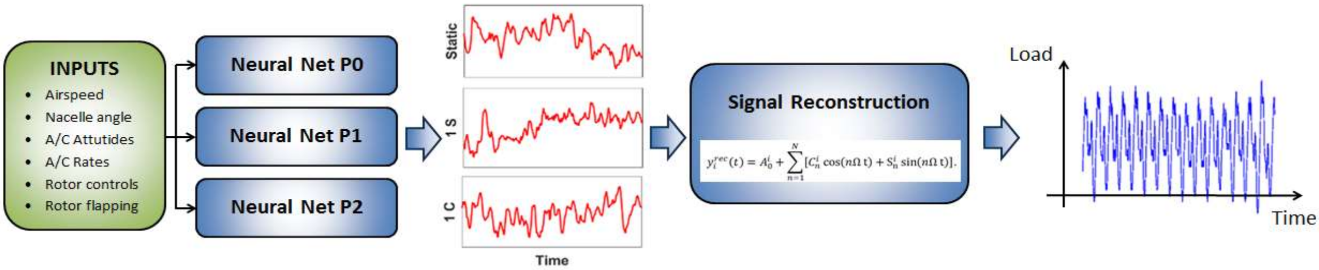

Figure 4: Integration of neural networks in the data processing workflow

Therefore, instead of focusing on the highly demanding task of predicting the complete time history of the signal at a very high sample rate, the approach makes use of neural networks to predict its harmonic components which are related to the slow dynamics of the flight mechanics parameters and then the complete time history of the load is reconstructed by means of Eq. (2).

Besides, one neural network for each harmonic component of the output signal is synthesized, *i.e.* one for the static component, one for the 1st harmonic, one for the 2nd harmonic, *ect*. In this way, the NN architecture can be very simple and the optimization of all the NN hyper-parameters converges relatively easily. The whole process is schematized in Figure 4.

NEURAL NETWORK ARCHITECTURE

The design of a neural network involves the selection of some parameters called hyper-parameters that are not trained by the algorithm but are set by the data scientist himself. Optimizing hyper-parameters is necessary to achieve rapid convergence during the training phase and good metrics performances but there are no general rules for doing this.
Some of these hyper-parameters are investigated, such as: learning rate, activation functions, regularization coefficients, epochs, number of neurons and layers.
Furthermore, different architectures of the network are tested, i.e.: Feed Forward neural networks (FFNN), Time Delay neural networks (TDNN), Recurrent neural networks [4] (RNN) and Long-Short term memory networks [5] (LSTM). In the end, a FFNN proved to be effective to the scope of the present work.
The choice of the simplest architecture of the neural network leads to numerous advantages ranging from lower computational power required in the training phase to shorter time required in the testing/validation phase.
Network architectures which can process temporal information, i.e. time delay networks (TDNNs), recurrent neural networks (RNNs), and long-short term memory networks (LSTM) do not improve the metrics performances obtained with FFNNs. In particular, RNNs and especially LSTM, as well as not improving the predictions, require longer training times with respect to FFNNs and TDNNs. So, for the problem under investigation and with the data preprocess methodology used in this work, the simplest FFNN with a single layer and with the right amount of neurons is sufficient to learn properly the non-linear relation that binds the flight mechanics inputs to the flap-wise beam bending moment at the blade root.

ROTOR LOAD PREDICTION

As already explained, different neural networks are trained to predict a single harmonic component of the load and then the complete signal is reconstructed with Eq.(2).

Figure 5 shows the comparison of the true signal (black line) with the FFNN prediction (red dots) for a complete flight.

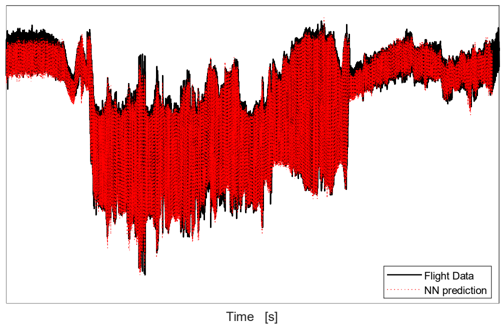

Figure 5: Comparison for a complete flight

Blade beam bending

The blade beam bending near the blade root, estimated during a whole flight of the *test se*t is represented in Figure 5. Figure 6 shows the correlation coefficient computed on the whole *test se*t and is equal to R=0.989.

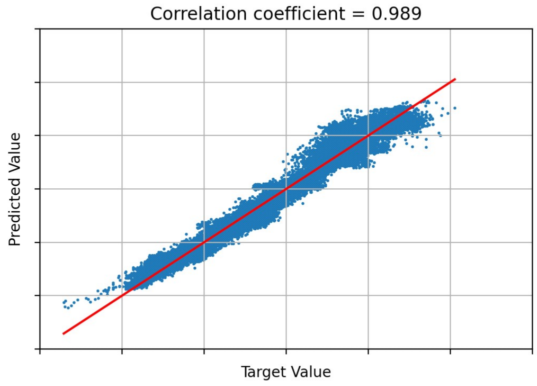

Figure 6: Correlation between Predicted and Real Signal

Moving to the prediction of a harmonic, the black line represents the data actually measured during the flight. The red line represents the prediction of the neural network. Figure 7 shows the prediction of the 1st harmonic, both sine and cosine component.

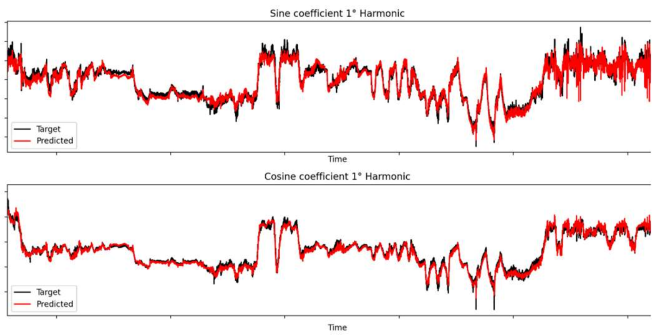

Figure 7: Blade BB Prediction of the 1st Harmonic

Figure 8, Figure 9 and Figure 10 show how the neural network behaves in different maneuvers. The black line represents the data actually measured during the flight. The blue line represents the reconstruction of the real signal with only a certain amount of harmonics. The blue line represents the prediction of the neural network.

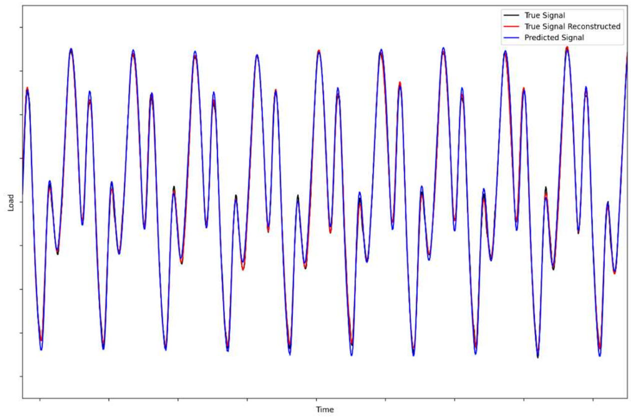

Figure 8: Blade BB in Forward Flight

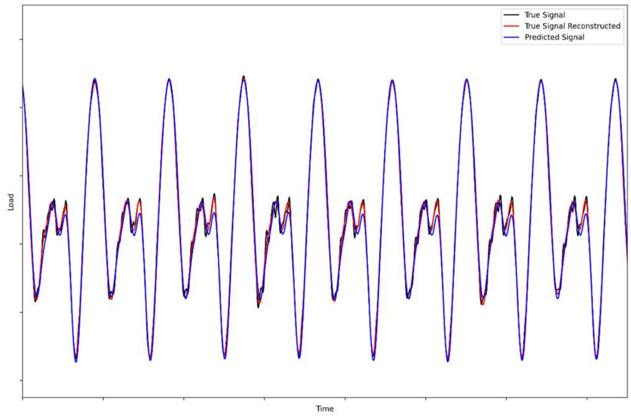

Figure 9: Blade BB in a bank Turn at 20 deg

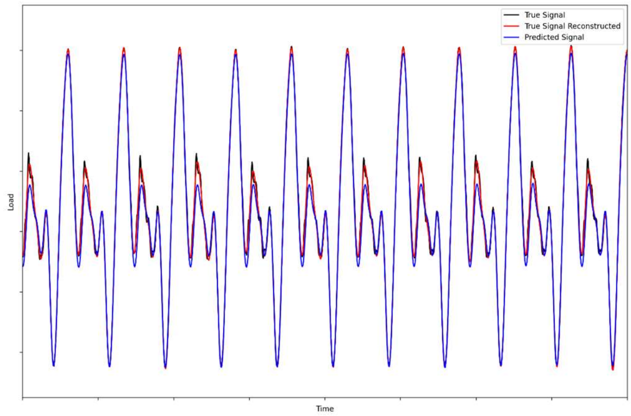

Figure 10: Blade BB in a bank Turn at -15 deg

FATIGUE DAMAGE ESTIMATION

As we have shown that the FFNN load predictions are quite reliable over the most of the flight envelope, the predicted load time histories can be used to evaluate the fatigue damage of the blade root section. Figure 11 shows the comparison in terms of number of cycles for every load bin between the actual signal (black bars), the reconstructed signal with a certain amount of harmonics (red bars) and the predicted signal (blue bars). The computation of the load cycle is performed using the rainflow-counting technique and the Goodman relation accounting for the mean value.

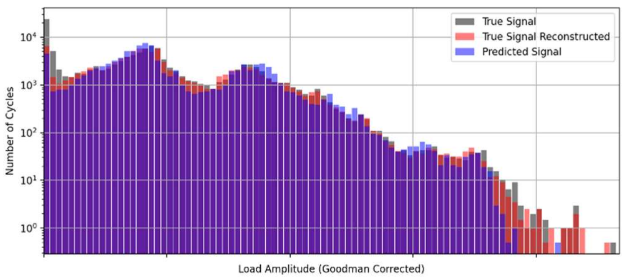

Figure 11: N. Cycles Vs Load Amplitude

It can be noted that the only differences in terms of load cycles are related to the highest load bins which are, unfortunately, the most damaging cycles. So, even if the error between the time histories (see Figure 8, Figure 9 and Figure 10) seems small, there can be a huge difference in terms of the highest load cycles. This fact could lead to a bad prediction of the total damage suffered by the components and other counter actions should be used to prevent inaccuracy in signal prediction.

CONCLUSIONS AND WAY FORWARD

The usage of neural networks to estimate the blade loads of a common helicopter is proven to be feasible. An effective solution for the architecture of a simple FFNN along with the HTH preprocessing is proposed and tested, analyzing briefly the pros and cons of such a network vs. other possible architectures (e.g. RNN and LSTM networks). In the end, the fatigue damage suffered by the component is computed with the predictions of the trained NNs and some issues are highlighted.

Other applications where these predictive tools can be used are here summarized. Firstly, the synthesized neural networks can be used to extract loads by feeding ANNs with inputs coming from a flight simulator. In this way, there can be a reduction of the test flights. Secondly, these neural networks can also be implemented in the telemetry monitoring system, as generators of "*special*" parameters, so that it will be possible to have a real time prediction of the loads that the blades are supposed to experience during flight tests. This significantly helps the flight test crew for enhancing the test safety. Finally, a set of "virtual sensors" can be virtually installed on the production fleet in order to monitor the actual fatigue damage and so the remaining life of different components.

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