DEFECT DETECTION AND TRACING ON HELICOPTER ROTORS BY ARTIFICIAL NEURAL NETWORKS

Hervé Morel*, Mustapha Ouladsine Tomasz Krysinski* and Daniel Brun-Picard****
*** Dynamics Department Eurocopter**
Marignane, France
**** LSIS UMR CNRS 6168 Université d'Aix-Marseille III**
Av Escadrille Normandie Niémen 13397 Marseille France

herve.morel@eurocopter.com
Tel: + 33 4 91 05 60 62 Fax: + 33 4 91 05 60 33

Abstract: This paper describes a method that employs neural networks to detect and trace defects on helicopter rotors. The method analyzes signals of vibration measurements on the helicopter airframe to perform a diagnosis of the rotor before the rotor-tuning phase. The experimental phase – the basis of this paper – focuses on the behavioral analysis of the neural network with the aim of classifying the vibration signatures generated by a parametric model of the helicopter.

Keywords: defect, tracing, detection, rotor, helicopter, vibration signatures, neural networks, classification.

1. INTRODUCTION

In the last decade, the helicopter has experienced the developments taking place in the information technology sector. The number of on-board systems has been increased to handle the vital tasks, such as piloting, navigation, and then maintenance and the comfort aboard. Attenuating the vibration level by active or passive means entails installing temporary or permanent systems on board. The vibration signal acquisition and processing functions can thus be partly or completely performed on the helicopter.

For instance, defect monitoring and diagnosis systems are usually mixed, with acquisition and processing performed on board, and analysis and diagnosis on the ground.

In the case of the helicopter, the defect monitoring and detection systems are applied to the dynamic components, such as the drive shafts, bearings, engines, and gearboxes (Giurgiuttu V., 2001). Often the methods are based on frequency analysis, time-frequency analysis, and threshold-based diagnosis (as with Health and Usage Monitoring Systems [HUMS]). New methods, such as wavelets or Artificial Neural Networks (ANN) based on Kohonen's Self Organizing Maps (SOM), are being proposed for studying these types of applications. Their aim is to extract the signatures of the defective components from the helicopter's dynamics (Giurgiuttu V., 2001).

This paper describes a method for detecting and tracing defects on helicopter rotors. The method employs competitive learning neural networks to discriminate between the signatures or images of the rotor defects.

2. OVERVIEW OF THE PROBLEM

The problem concerns the failure of the mechanical and/or hydraulic components used in the various types of helicopter rotors. The defects in this study are on the main rotor, which generates the helicopter's lift.

No scientific or automatic method available today can replace the expertise of the specialists, i.e. the pilots, design engineers and flight engineers. Moreover, this expertise is specific to each type of helicopter and to each type of dynamic component (rotor, etc.)

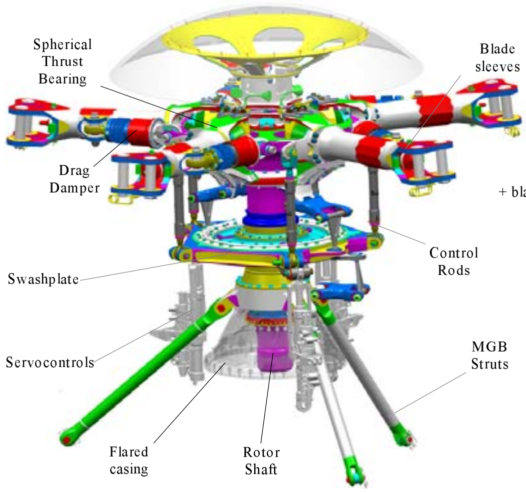

Fig. 1: Schematic of a Helicopter Rotor

Figures 1 shows the main components of a rotor, as well as certain components that often cause vibration problems.

2.1 Defects Specific to Helicopter Rotors

The defects on helicopter rotors occur on components whose mechanical characteristics are no longer within the specified operating tolerances. The defects are caused by timewise degradation (fatigue, drift), corrosive operating environments (e.g. salt mist), impacts, vibration, etc.

Currently the defects are assessed by experience (how the physical phenomena are felt during the flight) and by the vibratory expertise of the flight engineers and pilots. Though advanced systems are used to measure the vibration levels, the systems are not specifically designed for this type of complex characterization. The identification of the defects is thus tricky as the method is neither direct nor scientific.

Nonetheless, it is possible to give a short list of the transmission components generating the most frequent defects that cause problems in helicopter vibration tuning.

- *Inter-Blade or Drag Dampers*: Of hydraulic or viscoelastic design, the dampers can cause ground and air resonance problems (coupling of helicopter roll and blade drag modes). These divergent phenomena appear in certain flight phases due to insufficient damping, and give rise to unstable unbalance problems, which vary with the power and are caused by insufficient static stiffness.
- *Attachments of Inter-Blade or Drag Dampers*: Backlash in the balljoints attaching the dampers augments the vibration level at all the rotor harmonic frequencies.
- *Frequency Adapters*: Made of laminated rubber parts and located at the end of the blade sleeves, the adapters cause unbalance problems (modulus and phases) that vary with the power level and are caused by insufficient static stiffness,
- *Blades*: The vibration level at all the rotor harmonic frequencies is increased by cracks, and differences between the blades (fatigue-induced timewise drift): defects imprecisely identified.
- *Spherical Thrust Bearings (*on Starflex rotors): defects imprecisely identified.
- *Rotor Shaft Bearing Stack*: Usually indicated by an increase in the vibration level of harmonic 1.
- *Concentricity of Flared Casing*: This defect is not precisely identified but is frequently identified by an increase in the vibration level of harmonic 1.

2.2 Impact of the Defects on Rotor Tuning

Today no helicopter rotor tuning method is capable of allowing for any defects on the rotors: the tuning operations are made under the assumption that the rotor is healthy and isotropic. When components are defective, the existing methods do not converge, and the optical sighting methods and manual methods (plotting points on charts) lose their effectiveness.

In such cases, the experts have no choice but to apply their proven experience and "tweak" the rotor components until the vibration level is satisfactory – after numerous validation flights.

2.3 Impact of Vibration on Human Health

Four physical parameters are fundamental in determining how human beings react to vibration: its intensity, frequency, direction, and the duration of exposure. There are three physiological criteria:

- Not to impair the level of comfort,
- To maintain the ability to work,
- To guarantee health and safety.

These criteria form the basis of the international standards ISO 2631 and BS 6841, applied to analyze the discomfort level in ground vehicles and aircraft, and to determine the maximum exposure time to measured vibration that the human body can withstand (Teodosiu C., 2001).

Both past (1940) and recent research work looking into the effects of vibration on the human body has fixed the vibration perception threshold at about $0.01 m/s^2$ for frequencies below 8 Hz (Griffin M.J., 1990). Since a helicopter main rotor has a frequency between 4.4Hz and 6.6 Hz (harmonic 1), the frequency is critical in that it is close to the resonant frequency of the human body (Griffin M.J., 1990). Any defects generating the first rotor harmonic will therefore significantly affect the amount of discomfort in the vehicle. What is needed therefore is a method for detecting and tracing the rotor defects so that the comfort in the helicopter can be improved.

3. PROPOSED METHODOLOGY

The methodology applied in this paper to detect and trace rotor defects is based on having representations of each of the system's states (normal operation and operation with defects), then on discriminating between these states in a manner similar to pattern recognition methods. However, such a situation is ideal and is very unlikely to be encountered in practice. The systems to be monitored are too expensive and/or too critical, so that any thought of injecting the defects into them has to be dismissed (Basseville M., 1996).

The methods for classifying data by neural networks ("black box" modeling) appear suitable for the discrimination of vibration signatures representing the states of the system (Oukellou L. & Aknin P., 1998; Fessant F. & Aknin P., 2000; Dujardin A.S., 2001).

Write at least one sentence on the simulator which provided us with the data for the learning process (apprenticeship).

3.1 Preliminary Simulations

Signatures computed by simulation with parametric models were employed for the preliminary tests. This initial approach allowed the accelerations at different points on the helicopter airframe to be computed, and the ANN, adapted to the classification, to be evaluated in terms of the topologies and learning processes in comparison to the vibration signatures. Each signature is defined by the equation:

$$S = f(\gamma_{k,p,h})^T \qquad (1)$$

where γ represents the complex accelerations output by the sensors k, in a stable flight phase p at the frequency of harmonic h. Each signature representative of a defect or out-of-tolerance parameter is a residue computed with respect to the baseline signature (rotor tuned and with no defects).

3.2 Artificial Neural Networks (ANN) for Diagnosis

The following two types of networks were utilized to discriminate between the vibration signatures: MLP (supervised learning with back-propagation of the gradient) and SOM (unsupervised competitive learning) (Morel H., 2003). MLP networks have been found to have the following drawbacks:
- local minimums are present during the learning process (Kohonen T., 2001),
- it is difficult to set the size of the network (hidden neurons, hidden layers, activation functions, algorithm, etc.),
- definition set of the signatures.

In contrast, the unsupervised competitive learning attenuates the problems cited above. The SOM topology is hexagonal or more generally rectangular. The hidden neurons are connected to each other, and then to the neurons of the input layer.

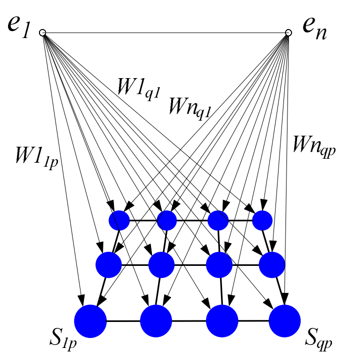

Fig.2 : Topology of SOM

3.3 Learning Algorithm

The learning algorithm (computing the synaptic weights), developed by Teuvo Kohonen in 1984, is derived from Hebb's law (Hebb D.O., 1949 ; Kohonen T., 2001). The weights W_{ij} are initialized randomly. Let E represent each input vector as follows:

$$E = [e_1, e_2, \ldots, e_n]^{\mathrm{T}} \qquad (2)$$

The algorithm computes the Euclidean distance between each of the neurons X_j from the elements e_n:

$$X_j = \sum_{k=1}^{p} \left\| W_{jk} - e_k \right\| \qquad (3)$$

The "elected" neuron is the neuron whose Euclidean distance is minimum:

$$c_{élu} = \min(X) \qquad (4)$$

The change in the weights of the neurons is computed as follows:

$$W^{i+1}_{élu,k} = W^{i}_{élu,k} + \mu\left(e_k - W^{i}_{élu,k}\right) \qquad (5)$$

and then the change in the weights of the neighboring neurons is given by:

$$W^{i+1}_{V_{n,k}} = W^{i}_{V_{n,k}} + \beta\left(e_k - W^{i}_{V_{n,k}}\right) \qquad (6)$$

where μ and β are the synaptic weight change steps, μ for the elected neuron and β for the closest neighboring neurons. The algorithm then iterates this phase until the number specified in the learning process is reached.

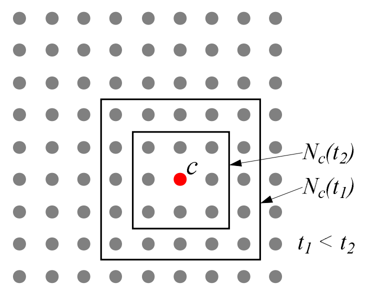

Fig. 3 - Elected Neuron c and its Closest Neighbors $N_c(t_3)$, $N_c(t_2)$ et $N_c(t_1)$

3.4 Classifying the Static Defect of the Drag Damper

3.4.1 Definitions

For a helicopter rotor, it is first necessary to locate the defect in terms of rotor symmetry, and then to detect the type of defect. First, a class per rotor sector and then per type of defect is defined, and finally a baseline class is defined. In our case for a rotor with n blades and a given defect, all the classes to be learned are given by:

$$E_c = \left[C_1, C_2, C_3, \ldots C_n, C_{ref}\right] \qquad (7)$$

and then all the defects belonging to the classes by:

$$C_n = [d_1, d_2, \ldots d_n] \quad (8)$$

3.4.2 Testing

The SOM self-organizes during learning, which separates the signatures of different classes, and positions the signatures of the same class according to the amplitude of the simulated defect. The figure below shows the rotor geometry through the paths formed by the learned signatures.

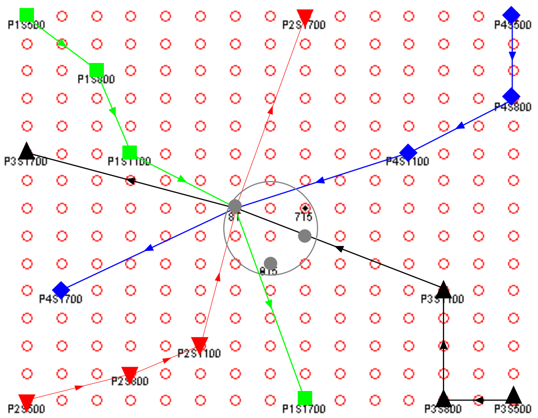

Fig. 4: Positioning of the Learned Signatures

The SOM positions the baseline signature (●) for different helicopter weights in the center of the map. The paths formed by each defect of increasing and decreasing amplitude pass through the center.
The same principle is applied for positioning both unlearned defects, and superposed defects of the same class: unlike the MLP network tested (Morel H., 2003), the SOM correctly identifies the unlearned signatures, where ♦ and • are the values respectively below and above the baseline value (zone 1).

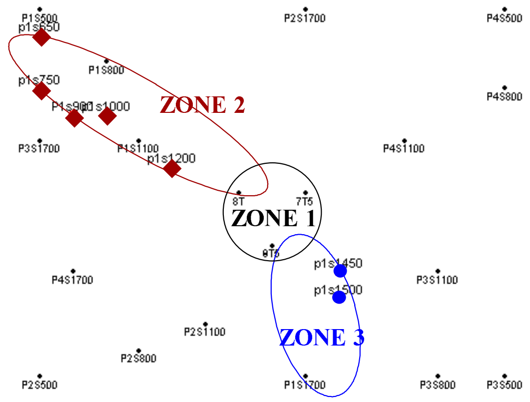

Fig. 5 : Representation of Unlearned Signatures

It is seen, that the SOM is capable of discriminating between the signatures containing different classes. The figure below shows the positioning of signatures with two classes (●) and three classes (▸) superposed, the positioning depending on the defect amplitude. Note that the SOM places an image signature of two defects existing on two opposite blades and having the same amplitude (■) in zone 1 of the baseline signatures.

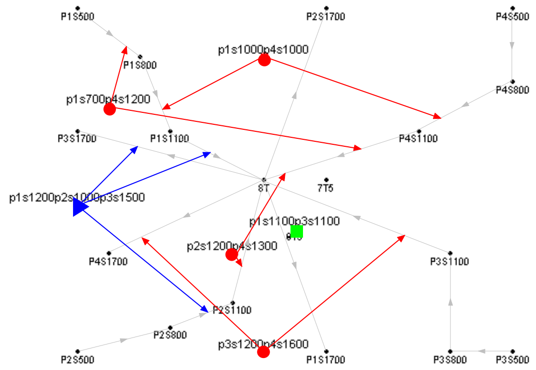

Fig. 6 : Representation of Signatures with Superposed Defects

3.5 Discriminating Between Defects and Out-of-tolerance Parameters

In addition to detecting and tracing the various types of defects, out-of-tolerance rotors must also be treated. Three tuning parameters can be modified in each rotor sector: mass, rod length, and tab incidence. The figure below shows the positions of the 4 classes in a dial on the map. The classes C_2 are C_3 seen to be superposed and separated from classes C_1 and $C_{baseline}$. The superposition is due to the strong correlation between the vibration signatures representing drag damper defects (characterized by harmonics 1 and 2) and out-of-tolerance weights (characterized by harmonic 1). C_2 differs from C_3 by the phase of harmonic 2.

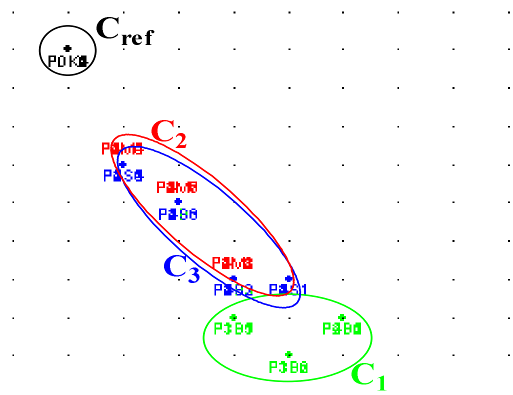

Fig. 7: Classification of 4 Classes without Weighting

It is possible to separate these two classes by weighting harmonic 2 to decrease the correlation coefficient of the signatures of C_2 and C_3. The next figure demonstrates that this separation can be achieved by weighting. Since C_2 (out-of-tolerance weight) is independent of harmonic 2, C_2 stays in the same position on the SOM.

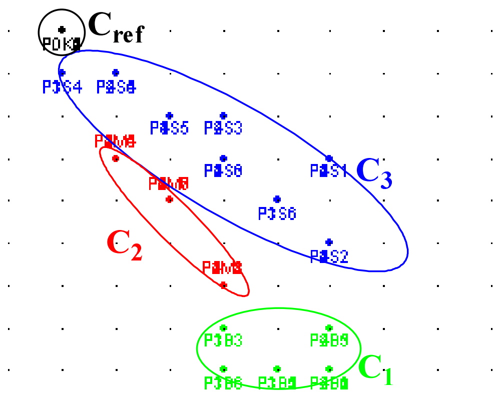

Fig.8 : Classification of 4 Classes with Weighting of the Harmonics

4. CONCLUSIONS AND PROSPECTS

Currently, when simulating an anisotropic rotor, the helicopter model is simplified (blades and airframe assumed rigid, no landing gear), and the behavior of the helicopter on the ground is not integrated in the vibration signatures. The method can only be validated with confidence using the vibration signatures recorded in flight.

By means of simulation, we have shown that the SOMs are capable of classifying the learned and unlearned vibration signatures having various classes of defects. There are several ways of improving class separation, i.e. by weighting the harmonics or by modifying the learning coefficients μ and β of the elected neurons and their nearest neighbors. The coefficients may be constant or decrease linearly during the leaning process (Kohonen T., 2001).

We have observed that the rotor geometry produces symmetry in the formation of the signatures, and that this affects the self-organization of the SOM during learning. It appears feasible to consider a hybrid ANN architecture for classifying the signatures according to the two phases mainly applied in system diagnosis:

- tracing the defect in the rotor sector using an ANN based on supervised learning,
- detecting what type of defect is involved using the SOM that has learned the signatures corresponding to a sector of the rotor acting as a baseline (sector 1 has been selected): $E_{c/SOM}$.

By applying a phase shift equal to the angle between sector 1 and the sector corresponding to the class determined by the ANN during the tracing phase, only the set of C_n. defects can be shown on the SOM. This method optimizes the SOM surface and will cut down the computation of the separation surfaces of the classes.

5. BIBLIOGRAPHY

Basseville M., Cordier M.O. (1996). *Surveillance et diagnostic des systèmes dynamiques: approches complémentaires du traitement de signal et de l'intelligence artificielle (*Monitoring and diagnosis of dynamic systems: complementary methods of signal processing and artificial intelligence*)*. Research Report, topics 3 and 4, No. 2861, April 1996. INRIA.

Dujardin A.S., (2001). *Pertinence d'une approche hybride multi-neuronale dans la résolution de problèmes liés au diagnostic industriel ou medical (*Relevance of a hybrid multi-neuronal approach for solving problems involving industrial and medical diagnosis). Paris XII University Thesis.

Fessant F., Aknin P. (2000). *Classification de défauts de rail à l'aide de cartes auto-organisatrices supervisees* (Classifying rail defects using supervised self-organizing maps*)*. 10th Day of Neurosciences for the Engineer, Dinard.

Giurgiuttu V. (2001). *Helicopter health monitoring and failure prevention through vibration management enhancement program*. International journal of condition monitoring and diagnostics engineering management.

Griffin M.J. (1990). *Handbook of human vibration*. Academic press, London.

Hebb D.O. (1949). *The organization of behavior*. Wiley, New York.

Kohonen T. (2001). *Self-organizing maps*. Spinger, Information sciences, third edition.

Morel H. (2003). *Diagnostic de défauts des rotors d'hélicoptères : approches connexionnistes pour l'analyse vibratoire (*Diagnosis of helicopter rotor defects: connectionist methods for vibration analysis). DEA, LSIS, UMR CNRS Report 6168.

Oukhellou L., Aknin P. (1998). *Optimisation de l'espace de représentation de données dans un problème de classification par réseaux de neurons* (Optimizing the data representation space in a classifying problem by means of neural networks). European Journal of Automated Systems.

Teodosiu C. (2001). *Etude de synthèse sur le confort vibratoire* (Comprehensive study of vibration-related comfort). Internal Eurocopter Report.