V. B. Jammu*
Graduate Research Assistant.
Mem. ASME

K. Danai
Associate Professor.
Mem. ASME

Department of Mechanical Engineering,
University of Massachusetts,
Amherst, MA

D. G. Lewicki
Mem. ASME
Vehicle Technology Center,
U.S. Army Research Laboratory,
NASA Lewis Research Center,
Cleveland, OH

Structure-Based Connectionist Network for Fault Diagnosis of Helicopter Gearboxes

A new method of diagnosis is introduced for helicopter gearboxes that relies on the knowledge of the gearbox "structure" and characteristics of the "features" of vibration for component fault isolation. Both the structural knowledge and featural knowledge in this method are defined as the fuzzy weights of a connectionist network that maps each sampled set of vibration features, obtained from a signal analyzer, into fault possibility values associated with individual gearbox components. The structural weights in this network are defined to represent the influence of gearbox component faults on the overall vibration sensed by each accelerometer, and the featural weights are defined to denote the influence of components faults on individual vibration features. Given the extremely complex structure of helicopter gearboxes which prohibits accurate modeling of the effect of faults on their vibration, the structural weights in this method are defined based on the root mean square value of the frequency response of a simplified lumped-mass model of the gearbox. The experimental evaluation of the method based on vibration data from two different gearboxes is included in a separate paper.

1 Introduction

Present helicopter gearboxes are significant contributors to both flight safety incidents and maintenance costs. For example, for large/medium civil transport helicopters in the period 1956–86, gearboxes were the principal cause of 22 percent of the accidents which often resulted in loss of life and the aircraft (Astridge, 1989). To prevent such incidents, routine maintenance is scheduled at the cost of 30 percent of the total maintenance cost for the helicopter (Pratt, 1986). Rapid and reliable fault diagnosis of helicopter gearboxes is therefore necessary to prevent major breakdowns due to progression of undetected faults, and for enhancing personnel safety by preventing catastrophic failures. Fault diagnosis is also necessary for reducing maintenance costs by eliminating the need for routine disassembly of the gearbox, and for saving time during inspection.

Fault diagnosis of helicopter gearboxes, like most rotating machinery, is based upon vibration monitoring. Under normal operating conditions, each component in the gearbox produces vibrations at specific frequencies related to the component's rotational frequency. In case of a component fault, the vibration generated by the faulty component is expected to be different from the normal vibration, and will be reflected at the component's rotational frequency and its harmonics. As such, monitoring the changes in vibration should theoretically give an indication of the fault. In practice, however, changes in the measured vibration as a result of component faults are not always distinct. Vibration is attenuated by the housing and other components in its travel path as well as being contaminated by noise.

In order to enhance identification of changes in vibration due to component faults, the raw vibration signal is processed to obtain "features" that characterize the vibration at the frequencies associated with the gearbox components. Accordingly, considerable effort has been directed towards identification of individual features that would consistently reflect specific gearbox faults (Zakrajsek et al., 1995; Mertaugh, 1986; McFadden and Smith, 1985). Examples of such features are Envelope Band and Tone Energies, Cepstrum, and various Figures of Merit (FM).

The traditional approach to fault diagnosis has relied on human expertise to relate vibration features to faults. In this approach, a diagnostician first identifies abnormalities in vibration features, then relates them to component faults considering the proximity of the accelerometer producing the feature to various components as well as the type of component fault characterized by the feature. Using this information, the diagnostician hypothesizes faults in specific components and then verifies or discards the hypothesis by examining features from other accelerometers in the proximity of the suspect component. The advantage of this approach is that it utilizes the gearbox structure to isolate faults. However, it is disadvantaged by (1) the difficulty in identifying abnormality in features which are contaminated with noise, and (2) the tediousness of examining the multitude of features from various accelerometers. Due to the large number of features and accelerometers associated with a gearbox, the diagnostician often cannot pay equal attention to all the features and is likely to ignore information that contradicts the hypothesis.

An alternative to the traditional approach is pattern classification based on neural networks to integrate various vibration features for diagnosis (Kazlas et al., 1993; Chin et al., 1993; Huang and Solorzano, 1991). This approach has particularly become attractive with the recent advances in supervised learning methods which allow training of the network weights to represent the relation between features and faults. Neural network-based diagnosis has several advantages: (1) neural networks can represent complex nonlinear relations between features and faults, (2) they are less affected by noise, and (3) the vibration features are processed in parallel, so diagnosis is not hindered by the large number of features. The main disadvantage of supervised neural networks, however, is their "black box" characteristic which requires their connection weights to be trained *a priori* based on a sample set of feature-fault data. Since such data are generally not available for gearboxes and are very expensive to generate, the utility of supervised neural networks is limited in fault diagnosis of helicopter gearboxes.

Expert systems, although not yet developed for helicopter gearbox fault diagnosis, offer another alternative to the tradi-

* Presently with GE Corporate Research & Development, Schenectady, New York.

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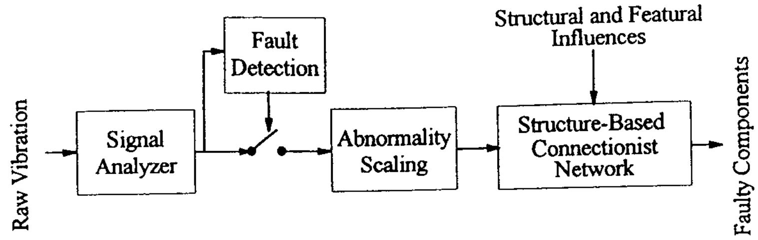

Fig. 1 Schematic of fault detection and diagnosis in the proposed structure-based diagnostic system for helicopter gearboxes

tional approach (Pau, 1986; Milne, 1987; Gilmore and Gingher, 1987). These systems are developed at two different levels: at one level, "shallow expert systems" represent compiled human diagnostician's knowledge relating measurements to faults as "if . . . then" rules; at another level, "deep expert systems" derive the diagnostic rules from the physics of the process (Davis, 1984; Reiter, 1987; Scarl et al., 1987; Yaram and Rosenberg, 1990; Yamada and Motoda, 1983). Shallow expert systems have been used extensively in the industry (Agogino et al., 1988; Karel and Kenner, 1988; McKeever and Blundell, 1986; Cantone et al., 1983), but since they require human expertise and lack generality, they have not been developed for helicopter gearbox diagnosis. Deep expert systems, on the other hand, have the potential to be generic. For example, Davis et al. (1984) have developed a deep expert system for diagnosis of electronic circuits by simplifying the circuits into their basic elements (adders, multipliers, etc.) and defining rules to represent the element connections. The faulty component is then isolated by searching through the elements that are structurally connected to the sensor producing abnormal readings.

The purpose of this paper is to present a deep expert diagnostic system for helicopter gearboxes. In order to cope with the inherent complexity of vibration-based diagnosis, this diagnostic system is developed in the framework of a connectionist network. Using such a framework, this system takes advantage of the integration capability of neural networks, but avoids the need for supervised training. It defines the weights of the network according to the "structural" knowledge of the gearbox and the type of fault represented by various vibration features. In this "Structure-Based Connectionist Network" (SBCN), the structural influences, which represent the proximity effect of faults on accelerometers, are determined based on the root mean square value of the frequency response of a simplified lumped-mass model of the gearbox.

2 System Overview

The schematic of the proposed diagnostic system is shown in Fig. 1. In this system, the vibration features obtained from processed vibration measurements will first be fed into an unsupervised fault detection network to identify the presence of faults in the gearbox. When the presence of a fault is prompted, fault diagnosis will be performed by the Structure-Based Connectionist Network (SBCN). Since SBCN uses abnormal features as inputs, the vibration features need to be scaled for abnormality before diagnosis can be performed. Abnormality-scaling will be performed by an unsupervised pattern classifier referred to as the Single Category-Based Classifier (SCBC) (Jammu and Danai, 1996) that is designed to identify the degree of abnormality in individual features. The SCBC defines a nominal vector based on the normal values of the features to be used as the basis for scaling the abnormality of vibration features between 0 and 1. The abnormality-scaled vibration features will then be propagated through the weights of SBCN (consisting of structural and featural influences) to yield as outputs fault possibility values between 0 and 1 for the individual components of the gearbox.

3 Fault Detection

In the proposed system (Fig. 1), the presence of faults is prompted by a fault detection network which is a hybrid between the two unsupervised pattern classifiers Kohonen's Feature Mapping (KFM) (Kohonen, 1989) and Adaptive Resonance Theory (ART2) (Carpenter and Grossberg, 1987). For fault detection, KFM would need to form two decision regions from feature vectors during an off-line training phase to represent normal and abnormal categories. Classification would be performed based on the closeness (measured by the Euclidean distance) of the measured feature vector to centers of normal and abnormal regions. The advantage of using KFM for fault detection is that it forms the boundaries of the decision regions wide enough to cope with variations due to noise. Its main disadvantage, however, is that it requires 'a priori' feature values associated with both categories to form the associated decision regions. The other method of unsupervised pattern classification, Adaptive Resonance Theory (ART2), classifies a feature vector as normal unless it is "sufficiently different" (defined by vigilance) from its nominal value. The advantage of ART2, in comparison to KFM, is that it does not require any sample features associated with the fault category. Its disadvantage, however, is that it classifies features that are multiples of a category's weights within the same category, thus producing misclassifications.

The proposed fault detection network uses the positive aspects of both KFM and ART2. In this network, as in ART2, a single weight vector $W = [w_1, w_2, \ldots, w_n]$ is used to represent the normal decision region, thereby avoiding the need for fault-related features otherwise required for prior training. In this network, the closeness of each feature vector $S(t) = [s_1(t), s_2(t), \ldots, s_n(t)]$ to the weight vector W is obtained by using closeness measure of KFM as:

$$\Delta(t) = \sum_{i=1}^{n} (s_i(t) - w_i)^2 \tag{1}$$

where n represents the number of features obtained from each accelerometer. If the similarity measure $\Delta(t)$ exceeds a threshold that is based on the maximum Euclidean distance of a set of feature vectors obtained from the normal gearbox, then the presence of a fault is prompted.

Noise and small variations in the gearbox operating conditions cause gradual changes in the normal values of the vibration features. Therefore, the weight vector W is updated periodically to adapt to these changes. For this, an adaptation mechanism is incorporated with the form:

$$w_i = \begin{cases} w_i + \eta_1[s_i(t) - w_i] & \text{if } S(t) \text{ classified as Normal} \\ w_i & \text{otherwise} \end{cases} \tag{2}$$

where η_1 denotes the learning rate. Adaptation in this network is carried out for k iterations based on a window of m previous feature vectors, and the learning rate η_t is set equal to the inverse of the iteration number.

4 Abnormality-Scaling of Features

In the proposed method, fault diagnosis is performed only when the presence of a fault is detected. Since the SBCN uses abnormality-scaled vibration features as inputs to perform diagnosis, the abnormality of features needs to be identified and scaled before diagnosis can be performed. An unsupervised pattern classifier is designed for abnormality-scaling of vibration features. This classifier is described in detail in (Jammu and Danai, 1996), and it is only described here briefly for completeness. The inputs to this classifier, referred to as the Single Category-Based Classifier (SCBC), are the vibration features $s_i(t)$, $i = 1, \ldots, n$ obtained by processing the vibration signals from each accelerometer, and its outputs are abnormality-scaled features $f_i(t)$ with values between 0 and 1. The value of 0 indicates normality and the other extreme of 1 denotes severe abnormality. The weights w_i of the SCBC represent the normal values of the features, which are initially set equal to the first feature values supplied to the SCBC. Classification in SCBC is performed by measuring the Euclidean distance of each feature $s_i(t)$ from its weight value w_i, and normalizing it into the range [0, 1] using a matching factor ϕ_i of the form:

$$\phi_i(t) = 1 - \exp\frac{-(s_i(t) - w_i)^2}{w_i^2} \tag{3}$$

Since during normal operation of the gearbox, noise causes feature values to deviate from their normal values, a threshold θ is considered in SCBC to account for deviations within the noise level. The threshold θ, which is obtained based on the mean and variance of a set of vibration features recorded during normal operation of the gearbox, is used to hard-limit $\phi_i(t)$ as:

$$\phi_i(t) = \begin{cases} 0 & \text{if} \quad \phi_i(t) < \theta \\ \phi_i(t) & \text{otherwise.} \end{cases} \tag{4}$$

The hard-limited $\phi_i(t)$ are then scaled to yield abnormality-scaled feature values $f_i(t)$ as:

$$f_i(t) = f_{\min} + \exp(\alpha * \phi_i(t)) \tag{5}$$

where $f_{\min}$ represents the minimum abnormality value assigned to any feature that violates the threshold θ, and α controls the slope of the exponential curve. Since $f_i(t)$ is defined to have a value between 0 and 1, it is set to 1 when $f_i(t)$ in Eq. (5) exceeds the value of 1.

After each round of classification of the vibration features, the weight values in the SCBC are updated so as to cope with noise and small variations in the operating conditions. Adaptation is carried out in two stages. In the first stage: "primary adaptation", a network weight is adapted if the feature associated with it is classified as normal. In the second stage, referred to as 'contrast enhancement' (CE) (Carpenter and Grossberg, 1987), the rest of the weights are adapted to achieve homogeneity in the abnormality-scaled values so as to increase the likelihood of all of them being classified as normal or abnormal. Achieving this homogeneity, however, needs to be carried out with respect to specific feature groups, because gearbox faults do not necessarily cause abnormality in all the features. For example, a gear fault will affect the features related to the gear and is not expected to cause abnormality in bearing features.

5 Fault Diagnosis

Fault Diagnosis is performed by propagating the abnormality-scaled vibration features from SCBC through the Structure-Based Connectionist Network (SBCN) (see Fig. 2). The outputs of SBCN which represent the fault possibility values for each gearbox component are obtained as:

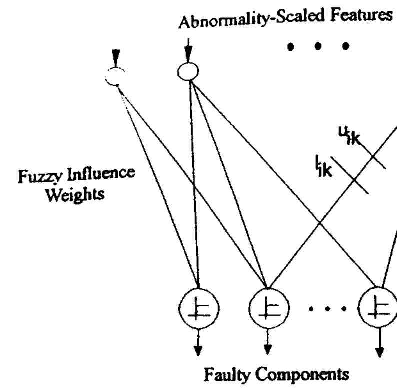

Fig. 2 The Structure-Based Connectionist Network (SBCN) with its fuzzy weights for isolating faulty components

$$p_k(t) = \sum_{i=1}^{n} f_i(t)v_{ik} \tag{6}$$

where $p_k(t)$ represents the fault possibility value for the kth component of the gearbox, $f_i(t)$ denotes the abnormality-scaled value of a feature and v_{ik} represents the weighting factor determined based on the lower and upper bounds of fuzzy influence weights (l_{ik}, u_{ik}) as:

$$v_{ik} = l_{ik} + (u_{ik} - l_{ik})f_i(t). \tag{7}$$

Note that Eq. (6) represents propagation of inputs through the weights of the SBCN, similar to a regular connectionist network with v_{ik} as weights (Hertz et al., 1991). The difference, however, is that the weights of the SBCN vary within the range (l_{ik}, u_{ik}) according to the magnitude of the corresponding input $f_i(t)$. According to Eq. (7), a higher abnormality-scaled value results in a higher weight value v_{ik}, emulating the reasoning by the human expert who pays more attention to the features that exhibit higher abnormality values. In SBCN, in order to make uniform interpretation of the fault possibility values $p_k(t)$, they are normalized to have values between 0 and 1 as:

$$c_k(t) = \frac{p_k(t)}{\sum_{i=1}^{n} u_{ik}} \tag{8}$$

Accordingly, a $c_k(t)$ equal to 1 denotes a definite fault, whereas a value of 0 represents normality. In this system, fault diagnosis is performed hierarchically. First, the faulty subsystem within the gearbox is identified by using the structural influences as v_{ik}. Then, the faulty components within the suspect subsystem(s) are isolated using the product of structural and featural influences as v_{ik}.

6 Deriving Diagnostic Knowledge

The connection weights of the Structure-Based Connectionist Network (SBCN) are defined based on the influences between the component faults and vibration features. Ideally, the structural influences should represent the strength of component vibration at the particular frequency (frequencies) represented by the feature. For this, the attenuation property of the 'travel path' between each component and accelerometer needs to be modeled as a function of the moment of inertia, stiffness, and damping of the components in the path (Lyon, 1995; Smith, 1983; Badgley and Hartman, 1974). In order to appreciate the difficulties associated with vibration modeling of gearboxes, the vibration model of a simple gearbox is considered (Choy and Qian, 1993):

$$[M][\ddot{X}] + [\dot{G}_v][\dot{X}] + [G_A][X] + [C_b][\dot{X} - \dot{X}_c] + [K_b][X - X_c] + [K_s][X - X_r] = [F(t)] + [F_G(t)] \quad (9)$$

where X represents the generalized displacement vectors in the lateral x, y, and z, and rotational θ_x, θ_y, and θ_z directions, M denotes the inertia matrix, G_v represents gyroscopic forces, G_A denotes the rotor angular acceleration, C_b and K_b represent the damping and stiffness matrices of bearings, respectively, $[X - X_c]$ denotes the casing vibration, $[X - X_r]$ represents the shaft residual bow, and K_s denotes the shaft bow stiffness matrix. The excitation force $[F(t)]$ is due to mass-imbalance, and $[F_G(t)]$ represents the nonlinear gear mesh force, which in the x direction has the form (Choy and Qian, 1993):

$$F_{Gxk} = \sum_{i=1, i\neq k}^{n} K_{tki}[-R_{ci}\Theta_{ci} - R_{ck}\Theta_{ck} + (X_{ci} - X_{ck})\cos(\alpha_{ki}) + (Y_{ci} - Y_{ck})\sin(\alpha_{ki})][\cos(\alpha_{ki}) + SIGN(\mu)\sin(\alpha_{ki})] \quad (10)$$

where F_{Gxk} denotes the gear mesh force in the x direction on the kth gear due to its mesh with $(n - 1)$ other gears, K_{tki} represents the nonlinear gear mesh stiffness between the kth gear and ith gear, R_{ci} denotes the radius of the ith gear, α_{ki} represents the orientation angle between the kth and ith gears, and μ denotes the coefficient of friction. Equations similar to Eq. (10) can be defined to represent the force in y direction as well as torsional gear mesh forces. Furthermore, the vibration of the casing due to the vibration of the gear-shaft system needs to be represented by a separate set of coupled equations of motion similar to Eq. (9). The above equations need to be integrated numerically in order to estimate the vibration signal recorded on the housing. However, there are some difficulties: (1) the values of stiffness and damping coefficients for the components are not readily available, (2) the cross-coupling terms in the stiffness matrices in the x, y, and z directions cannot be easily defined (Choy and Qian, 1993; Mitchell and Davis, 1985), and (3) it is difficult to take into account the multitude of travel paths and the associated models of attenuation for the many component-accelerometer pairs in the gearbox. For example, K_{tki}, the gear mesh stiffness, which is obtained by considering the gear tooth as a non-uniform cantilever beam (Lin et al., 1988; Boyd and Pike, 1989), is a function of the cross-section of the tooth at the point of loading as well as load variation due to changes in the direction of load application (Lin et al., 1988; Choy and Qian, 1993; Mark, 1987), friction between the meshing teeth (Rebbechi et al., 1991), contact ratio (Cornell and Westervelt, 1978), the type of gears (spur, helical, etc.) (Lin et al., 1988; Boyd and Pike, 1989; Mark, 1987), and gear errors such as profile, transmission and manufacturing errors (Smith, 1983; Mark, 1987). Similarly, the stiffness of bearings is a time-varying, nonlinear function of bearing displacement and the number of rolling elements in the load zone, as well as the bearing type (roller, ball, etc.), axial preload, clearance, and race waviness (While, 1979; Harris, 1966; Walford and Stone, 1983). All these factors make it very difficult to obtain an accurate and computationally inexpensive vibration attenuation model for gearboxes.

In order to avoid the difficulties associated with accurate modeling of vibration transfer, a simplified method is devised here that accounts separately for the two main aspects of vibration change due to faulty components: (1) the proximity effect of the faulty component on the accelerometer generating the feature (structural influence), and (2) the frequency represented by the feature (featural influence). Structural influences in this research are defined to represent the average strength of the vibration signal across all frequencies measured by an accelerometer due to a component fault. To compute this average vibration, several simplifications have been adopted in this research: (1) a lumped-mass model of the gearbox is used to model vibration; (2) in the absence of accurate values for stiffness coefficients, only the average static values for the stiffness coefficients are used; (3) damping ratios of bearings and shafts are neglected (Lin et al., 1988; Kraus et al., 1987); (4) the damping ratios of gears, estimated between 0.03 and 0.17 (Kasuba and Evans, 1981), are set at 0.1 for all gears; (5) the cross-coupling terms in the stiffness matrix are neglected; and (6) only the shortest vibration travel path between each component-accelerometer pair is considered.

Using the above simplifications, the average vibration registered by an accelerometer due to a faulty ith component can be simulated by applying an excitation source y at the ith component in the lumped-mass model (see Fig. 3). Furthermore, in order to represent all frequencies in the excitation source, y can be selected to consist of unit amplitude sine waves of all frequencies. The displacement of various components in the travel path due to an excitation exerted at the ith component can be obtained for a typical N-mass path as (James et al., 1994):

$$\begin{bmatrix} a_{11} & a_{12} & 0 & \cdots & 0 \\ a_{21} & a_{22} & a_{23} & \cdots & 0 \\ \vdots & \vdots & \vdots & \cdots & \vdots \\ 0 & \cdots & 0 & a_{NN-1} & a_{NN} \end{bmatrix} \begin{bmatrix} x_1 \\ x_2 \\ \vdots \\ x_N \end{bmatrix} = \begin{bmatrix} y \\ 0 \\ \vdots \\ 0 \end{bmatrix} \quad (11)$$

where $[x_1, x_2, \ldots, x_N]^T$ represent the displacements of the N components in the path, y denotes the magnitude of excitation at the first component, and the coefficients a_{ij} are defined as:

$$a_{nn-1} = -jwc_{n-1} - k_{n-1}$$
$$a_{nn} = -m_n w^2 + jw(c_{n-1} + c_n) + (k_{n-1} + k_n)$$
$$a_{nn+1} = -jwc_n - k_n. \quad (12)$$

In the above equation, m_n denotes the mass of the nth component, k_n and c_n represent the stiffness and damping coefficients between the nth and $(n + 1)$th components respectively, and w denotes frequency.

In this research, to represent the overall vibration transferred from the component to the accelerometer, the average vibration from the component is characterized by the root mean square (RMS) value of vibration across all frequencies. RMS values of vibration are readily obtained from Eq. (11) by numerical integration of the square of displacements across all frequencies. In these calculations, to avoid unnecessary numerical problems at the natural frequencies of the components with negligible damping, the integration is carried out by excluding the natural frequencies.

For the purpose of assigning structural influences, the RMS values are scaled so that the component directly adjacent to the accelerometer has the highest influence. Different functions can be used for defining influences. For example, the influences can be defined as:

$$I_i = \frac{\log(r_i)}{\log(r_N)} \quad (13)$$

where r_i represents the RMS value of vibration with the excitation source at the ith component, and r_N denotes the RMS value when the excitation is at the Nth component. In both cases, the accelerometer is considered at the Nth component. The influence for the other components is obtained in a similar fashion by moving the excitation source to them in the travel path.

The RMS values r_i are only approximate estimates, due to the simplifications made for their computation. Such approximate RMS values would, in turn, result in approximate influences. To characterize the approximate nature of influences they are defined as fuzzy variables (Zadeh, 1975) by mapping the

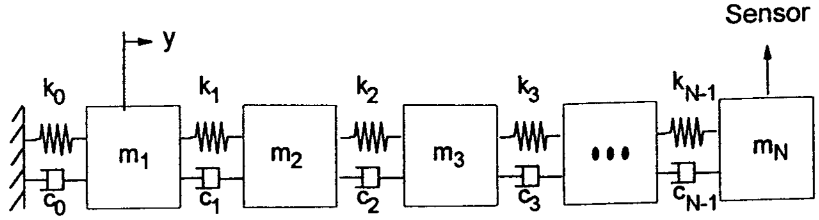

Fig. 3 Illustration of the lumped-mass model of a vibration travel path consisting of *N* masses

influences into the range associated with the following five fuzzy variables: Nil: (0, 0.1), Low: (0.1, 0.4), Medium: (0.4, 0.6), High: (0.6, 0.9) and Definite: (0.9, 1).

Another body of knowledge commonly used by diagnosticians is the type of fault represented by a feature. To incorporate this knowledge, fuzzy featural influences are defined according to the relation between the frequency content of each feature and the rotational frequencies of various components (McFadden and Smith, 1985; Stewart Hughes, 1986). For example, a feature such as Envelope Band Energy (BE) which represents the energy at the bearings rotational frequencies and harmonics is assigned a featural influence of "High" in relation to bearing faults.

The SBCN is designed to provide fault possibility values for gearbox components without any prior training. However, its design does not preclude the possibility of training when confronted with misclassifications which are in the form of undetected faults, false alarms, and misdiagnoses. Among these, undetected faults are safety hazards that should be avoided at all costs, and false alarms and misdiagnoses, although not as crucial as undetected faults, should be minimized so as to improve the reliability of the diagnostic system. One of the features of the SBCN is its ability to benefit from connectionist learning (Hertz et al., 1991) to improve diagnostic performance after each misdiagnosis. For this purpose, an error minimizing adaptation algorithm is developed for adapting the fuzzy influence weights of SBCN so as to avoid re-occurrence of misdiagnosis. This algorithm reduces the error between the outputs of the SBCN $c_k(t)$ and the binary target $T_k(t)$ obtained after inspection. The binary target takes the value of 0 for all the normal components and 1 for the faulty components. Sequential update rules for adapting the fuzzy influences in SBCN have the form:

$$l_{ik} = \begin{cases} l_{ik} + \eta_3(T_k(t) - c_k(t))(1 - f_i(t))f_i(t) & \text{if } 0 < l_{ik} < 1 \\ l_{ik} & \text{otherwise} \end{cases} \tag{14}$$

$$u_{ik} = \begin{cases} u_{ik} + \eta_3(T_k(t) - c_k(t)(f_i(t))^2 & \text{if } 0 < u_{ik} < 1 \\ u_{ik} & \text{otherwise} \end{cases} \tag{15}$$

where η_3 represents the learning rate. In the proposed method, in order to allow uniform interpretation of the trained fuzzy influences with respect to their original values, adaptation is stopped when the weight values reach the bounds: 0 or 1.

7 Conclusion

A diagnostic system for helicopter gearboxes is introduced that uses knowledge of gearbox structure and characteristics of the vibration features to define the influences of features on faults. This system brings together the diverse areas of dynamic modeling, fuzzy systems and connectionist networks. A simplified method for representing the gearbox structure based on lumped mass modeling is presented along with a procedure to obtain diagnostic influences from this model. In this system, the presence of faults in the gearbox is recognized by a fault detection network and abnormality-scaling of features by a Single Category-Based Classifier (SCBC). A Structure-Based Connectionist Network (SBCN) is devised for fault isolation that maps the abnormality-scaled features into fault possibility values for individual gearbox components using the structural and featural influences as its connection weights.

The primary hypothesis of this research is that the approximate structural and featural influences used as the connection weights of SBCN are adequate substitutes for prior training. This hypothesis is tested by applying SBCN to two different helicopter gearboxes in the following article (Jammu et al., 1997).

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