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IMPROVING THE PERFORMANCE OF THE STRUCTURE-BASED CONNECTIONIST NETWORK FOR DIAGNOSIS OF HELICOPTER GEARBOXES

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ABSTRACT

A diagnostic method is introduced for helicopter gearboxes that uses knowledge of the gearbox structure and characteristics of the 'features' of vibration to define the influences of faults on features. The 'structural influences' in this method are defined based on the root mean square value of vibration obtained from a simplified lumped-mass model of the gearbox. The structural influences are then converted to fuzzy variables, to account for the approximate nature of the lumped-mass model, and used as the weights of a connectionist network. Diagnosis in this Structure-Based Connectionist Network (SBCN) is performed by propagating the abnormal vibration features through the weights of SBCN to obtain fault possibility values for each component in the gearbox. Upon occurrence of misdiagnoses, the SBCN also has the ability to improve its diagnostic performance. For this, a supervised training method is presented which adapts the weights of SBCN to minimize the number of misdiagnoses. For experimental evaluation of the SBCN, vibration data from a OH-58A helicopter gearbox collected at NASA Lewis Research Center is used. Diagnostic results indicate that the SBCN is able to diagnose about 80% of the faults without training, and is able to improve its performance to nearly 100% after training.

INTRODUCTION

Present helicopter power trains are significant contributors to both flight safety incidents and maintenance costs. Power trains comprise almost 30% of maintenance costs and 22% of mechanically related malfunctions that often result in loss of life and the aircraft (Astridge, 1989). Future helicopters such as the LH and fixed wing aircraft like the ATF require increased levels of mission capability which cannot be met without advancing the state of the art in fault diagnosis.

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Fault diagnostic systems are necessary to detect failures in the power train reliably and rapidly, so as to allow scheduling of maintenance before a catastrophic failure occurs.

Fault diagnosis of helicopter gearboxes (like most rotating machinery) is based upon the detection of abnormalities in features of vibration such as the Root Mean Square (RMS), Kurtosis, Skewness, etc. A considerable effort has been directed towards identification of individual features that would be affected by specific faults in the gearbox (Zakrajset et al, 1995, Mertaugh, 1986, Mcfadden and Smith, 1985, Dyer and Stewart, 1978) The traditional approach to diagnosis has relied on human expertise to identify the abnormal features and to relate them to component faults. In this approach, a diagnostician would relate the abnormal features to component faults based on the component's proximity to the sensor producing the feature. Using the proximity information, along with the information about the specific fault that the abnormal feature represents, the diagnostician would hypothesize faults in various components. The hypothesis is then verified or discarded by examining the features from other sensors in the proximity of the suspect component. The advantage of the traditional approach is that it utilizes the structure of the gearbox to isolate faults. Its disadvantages stem from the difficulty associated with identifying abnormality in features that are contaminated with noise, in addition to processing the overwhelming number of features that are obtained from the sensors. Due to the large number of features and sensors associated with a gearbox, the diagnostician cannot pay equal attention to all the features and is likely to ignore information that contradicts the hypothesis.

In order to cope with noise as well as the multiplicity of information in the features, pattern classification through connectionist networks has been proposed as a means to integrate the features for diagnosis (Chin et al, 1993). In these networks, the connection weights which represent the decision regions for various faults are usually formed through supervised training. Therefore, these networks require a sample set of measurement-fault data for training. Since such data is usually not available and is very expensive to generate, the applicability of supervised networks is limited in practice.

Although they have not been extensively developed for helicopter gearbox diagnosis so far, expert systems offer another alternative to the traditional approach (Pau, 1986, Milne, 1987). Expert systems are developed at two different levels. At one level, *shallow expert systems* are developed to compile human diagnostician's knowledge relating measurements to faults into *if ... then* rules. At another level, *deep expert systems* are developed where the diagnostic knowledge is derived from the physics of the process instead of pre-compiling it (Davis, 1984, Reiter, 1987). Shallow expert systems have been used extensively in the industry, but since they require human expertise and lack generality, they have not been considered feasible for helicopter gearbox diagnosis. In deep expert systems, on the other hand, measurements are related to component faults by modeling the energy flow via the structural connections between components and sensors. Although deep expert systems use the knowledge of structure and function for diagnosis, their inherent assumption that faults interrupt the flow of energy to the sensors is a limitation. While this assumption is valid for faults that were considered (e.g., lead breakages in electronic circuits), it is not suitable for gearboxes where a fault does not necessarily result in breakage of energy flow. A gear tooth chip, for example, would invariably increase the level of vibration, but may not break transfer of power from the driver to the driven gear.

In order to cope with the complications arising from accurate modelling of gearboxes, yet take advantage of the pattern classification capability of artificial neural nets, the authors have recently proposed a connectionist diagnostic network that incorporates structural and featural influences as its weights (Jammu et al, 1995). This method, which is a hybrid between connectionist networks and deep expert systems, determines the weights of the network through incorporation of *structural* and *featural influences*. In this *Structure-Based Connectionist Network* (SBCN), the structural influences represent the proximity effect of component faults on various accelerometers, and featural influences the type of fault characterized by each feature. Ideally, in order to accurately account for the proximity effect, the strength of the vibration signal from the components at the frequencies represented by the features needs to be modeled. This requires modeling the attenuation of vibration at these frequencies as the vibration travels from the components to the accelerometers. However, such a modeling task is difficult to perform, because: (1) the correct values of the stiffness and damping coefficients in the path cannot be accurately determined due to their time-varying and non-linear nature (Lin et al, 1988, While, 1979), and (2) it is not possible to evaluate the attenuation of vibration for the multitude of paths between components and sensors (Singh and Lim, 1990, Hollins, 1986).

As a compromise to accurate attenuation levels for individual vibration features, in the proposed method the average attenuation of vibration across all frequencies is used to represent the overall proximity effect of gearbox components. In order to obtain the average attenuation, the gearbox is represented by a simplified lumped mass model, and the Root Mean Square (RMS) value of the vibration from this model is used to characterize the average attenuation. These RMS values are then used to assign structural influences representing the proximity effect of the components on the sensors. In order to account for the approximate nature of the simplified gearbox model, in the proposed method the structural influences are represented by fuzzy variables.

The structural influences only constitute the knowledge of the gearbox structure. So, there is a need to represent the relation between component faults and vibration features separately. Since vibration features are usually obtained at specific frequencies that are associated with the rotational frequency of individual components (Stewart Hughes, 1986), their relation to various components is readily available. This relation is used to assign the featural influences representing the effect of component faults on features. The structural influences and featural influences are incorporated as weights of a SBCN for diagnosis, which propagates abnormal features through its fuzzy influence weights to calculate fault possibility values for each component in the gearbox. For more details on structural and featural influences, please refer to (Jammu, 1996).

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. Misclassifications in pattern classifying diagnostic systems 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 mechanisms (Hertz et al, 1991) to improve diagnostic performance after misdiagnoses. For this purpose, an error minimizing algorithm, (a least mean square training algorithm customized to SBCN), is developed for adapting the fuzzy influence weights of SBCN so as to avoid re-occurrence of misdiagnosis.

The proposed SBCN is experimentally evaluated in application to a OH-58A helicopter gearbox. Experimental vibration data for the OH-58A gearbox were collected at the NASA Lewis Research Center. The proposed method is evaluated in diagnosis of eleven OH-58A gearbox faults that occurred during 57 days of testing. The diagnostic results indicate that the SBCN is able to correctly diagnose about 80% of the OH-58A gearbox faults without any training and is able to improve its performance to nearly 100% after training.

STRUCTURE-BASED CONNECTIONIST NETWORK

The overview of the proposed diagnostic system is presented in Fig. 1. The inputs to this system are the vibration features which are first utilized by an unsupervised Fault Detection Network (FDN) to identify the presence of faults in the gearbox. When the presence of a fault is prompted by the FDN, fault diagnosis is 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. In this research, abnormality-scaling is performed by an unsupervised pattern classifier, referred to as the *Single Category-Based Classifier* (SCBC) (Jammu and Danai, 1995), which is designed to identify the degree of abnormality in individual features.

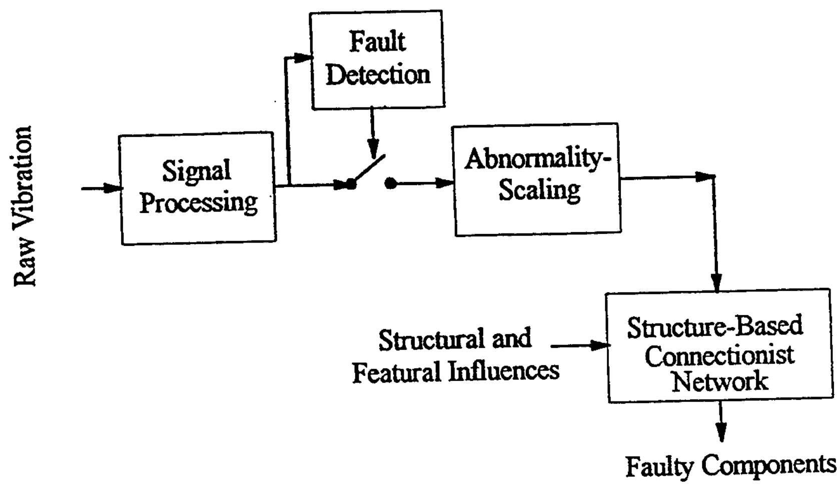

Figure 1: Overview of fault detection and diagnosis in the proposed structure-based diagnostic system for helicopter gearboxes.

The schematic of the SBCN is shown in Figure 2. Diagnosis in SBCN is performed by propagating the n abnormality-scaled values of the vibration features $f_i(t)$ through the SBCN, and obtaining as outputs the fault possibility values associated with individual gearbox components as:

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

where the w_{ik} represents the weighting factors determined based on the lower and upper bounds of the fuzzy influences (l_{ik} and u_{ik}) between the ith accelerometer and kth component as:

$$w_{ik} = l_{ik} + (u_{ik} - l_{ik}) f_i(t). \tag{2}$$

In SBCN, in order to make uniform interpretation of the fault possibility values $p_k(t)$, they are normalized to have values between 0 an 1 as:

$$c_k(t) = \frac{p_k}{\sum_{i=1}^{n} u_{ik}} \tag{3}$$

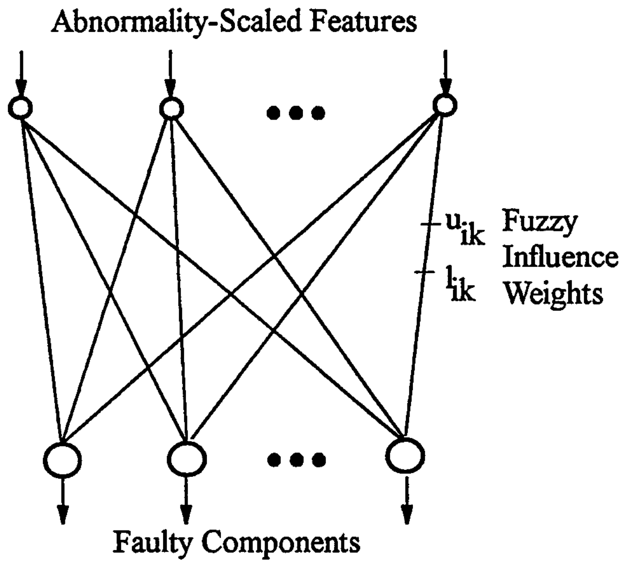

Figure 2: Schematic of the *Structure-Based Connectionist Network* (SBCN).

An important feature of SBCN is the ability to improve its performance after occurrence of misdiagnoses. It is assumed that upon detection of a fault by FDN, the hypothesis of SBCN indicating possible faulty components is verified by a physical inspection of the gearbox. If the hypothesis is found to be incorrect, then a misdiagnosis is assumed to have occurred. To ensure that this misdiagnosis does not re-occur, an adaptation mechanism is proposed for SBCN which uses the correct information about the faulty component from physical inspection to adjust the weights of the SBCN. The adaptation algorithm for SBCN is a generic error minimizing least mean square training algorithm (Hertz et al, 1991) customized to SBCN. This algorithm reduces the error between the outputs of the SBCN $c_k(t)$ and the binary target $T_k(t)$ obtained from physical inspection. The binary target takes the value of 0 for all the normal components and 1 for the faulty component. Sequential update rules for adapting the fuzzy influences in SBCN have the form:

$$l_{ik} = \begin{cases} l_{ik} + \eta(T_k(t) - c_k(t))(1 - f_i(t))f_i(t) & \text{if } 0 < l_{ik} < 1 \\ l_{ik} & \text{otherwise} \end{cases} \tag{4}$$

$$u_{ik} = \begin{cases} u_{ik} + \eta(T_k(t) - c_k(t)(f_i(t))^2 & \text{if } 0 < u_{ik} < 1 \\ u_{ik} & \text{otherwise} \end{cases} \tag{5}$$

where η represents the learning rate which can have values between 0 and 1. 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.

EXPERIMENTAL

The effectiveness of the SBCN was demonstrated using vibration data from an OH-58A helicopter main rotor gearbox (see Fig. 3). Vibration data was collected at the NASA Lewis Research

Center as part of a joint NASA/Navy/Army Advanced Lubricants Program. Various component failures in an OH-58A main rotor transmission were produced during accelerated fatigue tests(Lewicki et al, 1992). The vibration signals were recorded from eight piezoelectric accelerometers (see Fig. 4) with frequency range of up to 10 KHz using an FM tape recorder. The signals were recorded once every hour, for about one to two minutes per recording (using a bandwidth of 20 KHz). Two magnetic chip detectors were also used to detect the debris caused by component failures.

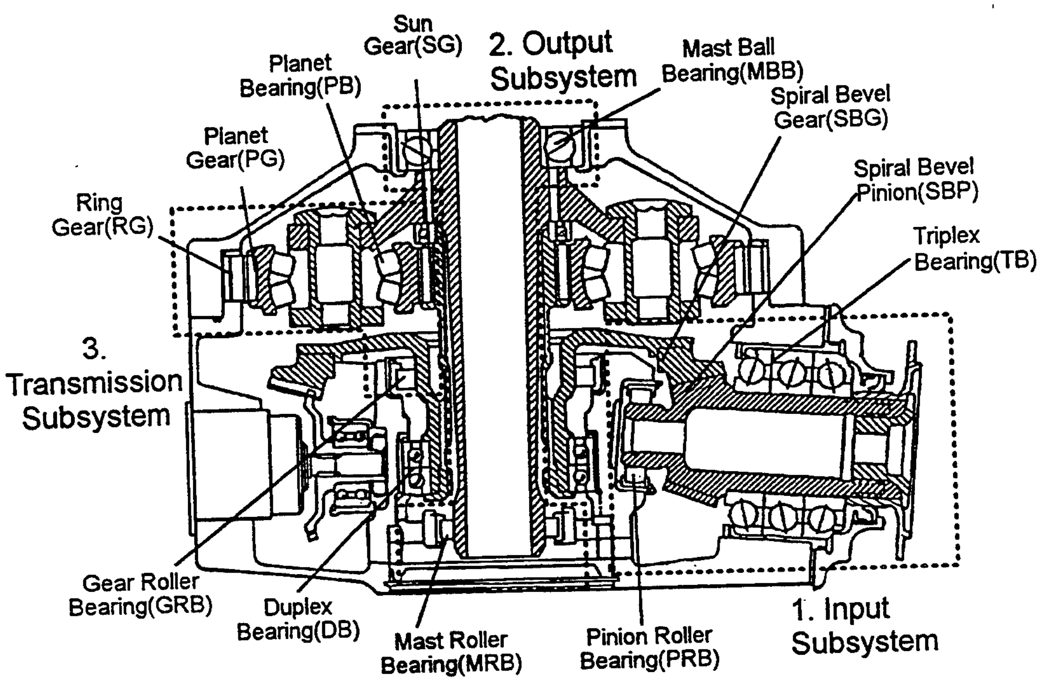

Figure 3: Layout of the various components in the OH-58A gearbox. The figure also shows division of the gearbox into subsystems for diagnosis.

In these experiments the gearbox was run under a constant load and was disassembled and inspected periodically, or when one of the chip detectors indicated a failure. A total of five tests were performed, where each test was run between nine and fifteen days for approximately four to eight hours a day. Among the eleven failures which occurred during these tests, there were three cases of planet bearing pitting fatigue, three cases of sun gear pitting fatigue, two cases of top housing cover cracking, and one case each of spiral bevel pinion pitting fatigue, mast bearing micropitting, and planet gear pitting fatigue. Insofar as fault detection during these tests, the chip detectors were reliable in detecting failures in which a significant amount of debris was generated, such as the planet bearing failures and one sun gear failure. The remaining failures were detected during routine disassembly and inspection.

In order to identify the effect of faults on the vibration data, the vibration signals obtained from the five tests were digitized and processed by a commercially available diagnostic analyzer (Stewart Hughes, 1986). For analysis purposes, only one data record per day was used for each test. Overall, fifty four vibration features were extracted for each accelerometer. Out of these, nineteen features were indicators of general faults, whereas the other thirty five features were synchronous time averaged signals which related to specific gears in the gearbox. The detailed

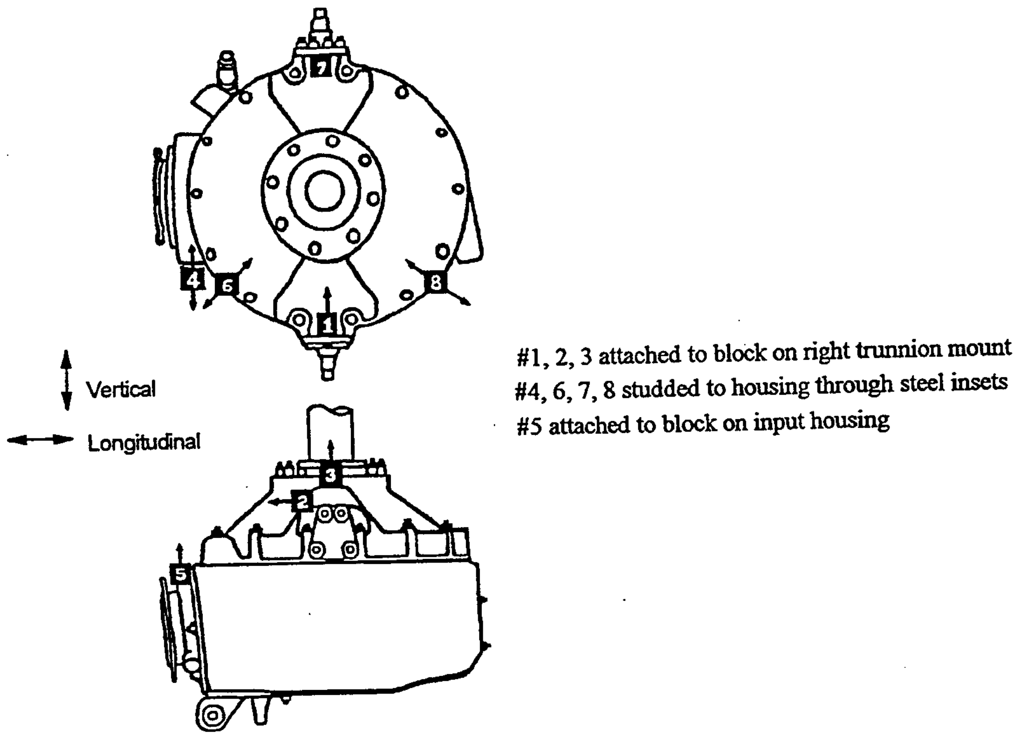

Figure 4: Location of the accelerometers on the test stand for OH-58A.

description of these parameters is included in (Chin 1992).

RESULTS

For fault diagnosis of the OH-58A gearbox, the influences between the gearbox components and the eight accelerometers were obtained. For this purpose, five primary vibration travel paths in the gearbox were modeled using lumped mass modeling. These paths consisted of: (1) Duplex Bearing to Triplex Bearing through Spiral Bevel mesh, (2) Duplex Bearing to Ring Gear through the Sun-Planet mesh, (3) Mast Roller Bearing to Mast Ball Bearing through the Main Shaft, (4) Ring Gear to Mast Ball Bearing through Planet Bearing, and (5) Duplex Bearing to Mast Ball Bearing through the Sun-Planet mesh. The first travel path was in connection to Accelerometers 4, 5, and 6, whereas all the other paths were connected to Accelerometer 1, 2, 3, 6, 7, and 8. Based on the lumped mass model of these paths, the RMS values of vibration are computed and used to assign the fuzzy influences between each of the components and the accelerometers.

Fault diagnosis of the OH-58A is performed in two hierarchies. In the top hierarchy, the gearbox is divided into three subsystems (see Fig. 3) and faults in each subsystem are isolated. The weights of the top SBCN sub-section are set equal to the average of the structural influences of the components within each subsystem (see Table 1). The inputs to this sub-section consist of the averaged values of abnormality-scaled features from the eight accelerometers, and its outputs denote the fault possibility values for the three subsystems. In the second hierarchy, the faulty components within each subsystem are isolated. The inputs to the SBCN in this hierarchy were eleven of the nineteen features which were indicators of gear and bearing faults, and the thirty five synchronous time averaged features associated with the OH-58A gears. Due to the unavailability of synchronous time averaged features associated with bearings for the OH-58A gearbox, faults in individual bearings could not be isolated, and only bearing groups were considered. For this level of diagnosis, the featural influences (see Table 2) were multiplied by the subsystem influences so as to reflect both the proximity and frequency-specific information, and were used as the weights of the second SBCN sub-section.

Table 1: Influences of the three OH-58A subsystem on the eight accelerometers. The influences shown are: '-' Nil, L Low, M Medium, and H High.

Accelerometer	Subsystems		
	1. Input	2. Output	3. Transmission
1	-	M	H
2	-	M	H
3	-	M	H
4	H	-	L
5	H	-	M
6	M	M	H
7	-	M	H
8	-	M	H

Table 2: Influences of the gear G and bearing B families on the features. The influences shown are: '-' Nil, 'L' Low, 'M' Medium, 'H' High, 'D' Definite. The characters shown in parenthesis indicate the association of each feature to the fault: (G) Gear faults, (B) Bearing faults, (R) Rotating element faults (both gears and bearings).

Feature	Subsystem					
	1		2		3	
	G	B	G	B	G	B
TEO-G(R)	M	M	-	M	M	M
TEO-P(R)	M	M	-	M	M	M
TM1-G(R)	M	M	-	M	M	M
TM1-P(R)	M	M	-	M	M	M
Cepstrum1911(G)	D	-	-	-	L	-
Cepstrum572(B)	-	L	-	L	-	D
Tone1911(G)	D	-	-	-	L	-
Tone572(B)	-	L	-	L	-	D
Env. Kurtosis(B)	-	H	-	H	-	H
Env. Base Energy(B)	-	H	-	H	-	H
Env. Tone Energy(B)	-	H	-	H	-	H

The fault possibility values for the three subsystems of the OH-58A gearbox obtained from the top sub-section of SBCN are shown in Table 3. The results in this table represent the hard-limited fault possibility values (threshold of 0.5) and include, for comparison, the actual condition of the gearbox reported from routine inspection inside parentheses. The results in Table 3 indicate that in Test 1, faults in Subsystems 1 and 3 were correctly identified on Days 5, 7, and 8. In Test 3, the fault in Subsystem 3 on Days 3 and 4 was correctly identified, along with a possible fault in Subsystem 1. The housing crack on Day 9 of this test was left unidentified because it was never prompted by the Fault Detection Network. Nevertheless, this particular fault (housing crack) could not be isolated by the current SBCN due to the absence of features that would be effected by this fault. Also for this test, faults in Subsystems 2 and 3 were correctly identified on Days 11 and 12. In Test 4, the fault in Subsystem 3 was correctly diagnosed on Days 10, 11, 12, 14 and 15. Moreover, on Day 13 of Test 4, even though the gearbox was supposed to be normal, the SBCN indicated faults in Subsystem 3. This was due to the replacement of the three-planet assembly with a four-planet assembly, which changed the vibration characteristic of Subsystem 3. In Test 5, the fault in Subsystem 3 was correctly identified on Day 9. There was also a misdiagnosis in Subsystem 1.

Table 3: Results from the faulty subsystem isolation by the first subsection of the SBCN for OH-58A gearbox. Inside parenthesis the actual faults are included with '*' indicating the observed faults.

Faulty Subsystems Isolation for OH-58A										
Day	Test 1		Test 2		Test 3		Test 4		Test 5	
1	-	(-)	-	(-)	-	(-)	-	(-)	-	(-)
2	-	(-)	-	(-)	-	(-)	-	(-)	-	(-)
3	-	(-)	-	(-)	1, 3	(3)	-	(-)	-	(-)
4	-	(-)	-	(-)	1, 3	(3*)	-	(-)	-	(-)
5	1, 3	(1, 3)	-	(-)	-	(-)	-	(-)	-	(-)
6	-	(1, 3)	-	(-)	-	(-)	-	(-)	-	(-)
7	1, 3	(1, 3)	-	(-)	-	(-)	-	(-)	-	(-)
8	1, 3	(1, 3)	-	(-)	-	(-)	-	(-)	-	(3)
9	-	(1*, 3*)	-	(-)	-	(3)	-	(-)	1, 3	(3)
10					-	(-)	3	(3)	-	(3)
11					2, 3	(2, 3)	3	(3)	-	(3*)
12					2, 3	(2, 3)	3	(3*)		
13					-	(2*, 3*)	3	(-)		
14							3	(3)		
15							3	(3*)		

Table 4 presents faulty component isolation results from the second sub-section of SBCN. For Test 1, the Spiral Bevel Pinion (SBP) failure in Subsystem 1 was correctly identified (with a possibility value of 0.9) on Day 5. However, the possibility value decreased on Days 7 and 8, probably due to increased noise levels immediately after the occurrence of faults that mask the affect of faults on vibration features. Also, the sun gear failure in Subsystem 3 was correctly identified only on Day 8. The SBCN also misdiagnosed faults in bearings of Subsystems 1 and 3 (BRG1 and BRG3, respectively) on Days 5 and 7 of Test 1. This misdiagnosis is due to the presence of strong cross-correlation between gear and bearing features. This point is better reflected by the maximum correlation values between features and faults for the OH-58A gearbox.

The results indicate reasonable correlation values of 0.49 between gear features and gear faults, and 0.44 between bearing features and bearing faults. These numbers, however, are not as impressive when they are compared with the cross-correlation values of 0.57 between gear features and bearing faults, and 0.38 between bearing features and gear faults. Such similar levels of correlation values indicate that these features do not provide the resolution necessary for faulty component isolation.

In Test 3, the bearing fault (BRG3) was correctly identified on Day 4, but a carry-over misdiagnosis from the top sub-section of SBCN occurred in Subsystem 1. In Test 3, the two bearing faults in Subsystems 2 and 3 (BRG2 and BRG3, respectively) were correctly identified on Day 12, however, they were misdiagnosed as gear faults on Day 11. In Test 4, the bearing fault (BRG3) in Subsystem 3 was correctly identified only on Day 10, while it was misdiagnosed on the next 2 days due to the masking of the fault by noise. Also, the Sun Gear (SG) failure on Days 14 and 15 was not assigned the highest fault possibility values. It should be noted that the fault possibility values for Sun gear (SG), Planet Gear (PG) and Ring Gear (RG) have very similar values. This misdiagnosis is due to the new four-planet assembly installed on Day 13 of this test, which changed the vibration associated with these gears. In Test 5, the Sun Gear (SG) fault in Subsystem 3 was correctly identified, however, the planet gear failure did not have a high fault possibility value. There was also one carry-over misdiagnosis in Subsystem 1 on Day 9 of this test.

In order to evaluate the effectiveness of the adaptation algorithm for SBCN in improving the diagnostic performance, data from the OH-58A gearbox were used to train the two sub-sections of SBCN. The fuzzy influence weights of both the SBCNs were adapted until the smallest mean square was achieved with a learning rate η set to 0.1. The target faults required for training for each day were determined based on information from the debris sensors, maintenance reports, and analysis of vibration features.

The results from training the two sub-sections of SBCN using data from all the five tests for the OH-58A gearbox are presented in Tables 5 and 6. These results indicate that the training algorithm was able to improve the diagnostic results for both the subsystems and components. At the subsystem level, results after training show improvements with faults in Subsystems 1 and 3 being picked up on Days 6 and 9, and misdiagnoses of faults in Subsystem 1 on Day 4 of Test 3 and Day 9 of Test 5 no longer present. For the second sub-section of SBCN, training results show a considerable improvement. Faults in Spiral Bevel Pinion (SBP) and Sun Gear (SG) in Test 1 and bearing faults (BRG2, and BRG3) in Test 3 are clearly indicated by the trained SBCN. The faults in bearings of Subsystem 3 (BRG3) from Days 9 through 12 and Sun Gear (SG) fault on Days 14 and 15 are indicated as definite faults with a fault possibility value of 1.0. Similarly in Test 5, both Sun Gear (SG) and Planet Gear (PG) faults are clearly indicated as faulty with the high fault possibility values. In summary, the result indicate that before training the SBCN was able to diagnose about 80% of the OH-58A gearbox faults, and after training produced near perfect diagnostic results. These results demonstrate the ability of SBCN to perform diagnosis without any training when training data is unavailable, while being flexible to improve its performance when such data is available.

Table 4: Faulty component isolation by the second sub-section of SBCN. The components listed are - SBP: Spiral Bevel Pinion, SBG: Spiral Bevel Gear, BRG1: Bearings in Subsystem (SS) 1, BRG2: Bearings in Subsystem 2, SG: Sun Gear, PG: Planet Gear, RG: Ring Gear, and BRG3: Bearings in Subsystem 3. A '*' indicates the observed faulty component.

Faulty Component Isolation for OH-58A								
	SS 1			SS 2	SS 3			
Days	SBP	SBG	BRG1	BRG2	SG	PG	RG	BRG3
Test 1								
1 to 4	-	-	-	-	-	-	-	-
5	0.90*	0.62	0.89	-	0.52*	0.73	0.12	0.86
6	-*	-	-	-	-*	-	-	-
7	0.68*	0.43	0.79	-	0.67*	1.00	0.23	0.72
8	0.65*	0.74	0.18	-	0.98*	0.70	0.70	0.33
9	-	-	-	-	-	-	-	-
Test 2								
1 to 9	-	-	-	-	-	-	-	-
Test 3								
1 to 2	-	-	-	-	-	-	-	-
3	0.43	0.77	0.80	-	0.65	0.56	0.71	0.72*
4	0.38	0.60	0.78	-	0.56	0.47	0.04	0.79*
5 to 10	-	-	-	-	-	-	-	-
11	-	-	-	-	0.67	0.79	0.52	-*
12	-	-	-	0.74*	0.67	0.71	0.55	1.00*
13	-	-	-	-*	-	-	-	-*
Test 4								
1 to 9	-	-	-	-	-	-	-	-
10	-	-	-	-	0.34	0.41	0.75	0.79*
11	-	-	-	-	0.54	0.53	0.79	-*
12	-	-	-	-	0.59	0.50	0.91	0.64*
13	-	-	-	-	0.72	0.85	0.83	1.00
14	-	-	-	-	0.81*	0.90	0.88	0.68
15	-	-	-	-	0.79*	0.90	0.93	0.48
Test 5								
1 to 8	-	-	-	-	-	-	-	-
9	0.58	0.24	0.68	-	0.60*	0.54*	0.50	0.58
10 to 11	-	-	-	-	-*	-*	-	-

Table 5: Subsystem isolation results for OH-58A gearbox after training the top sub-section of SBCN. For comparison the actual faults are included inside parenthesis with '*' indicating the observed faults.

Faulty Subsystems Isolation for OH-58A After Training										
Day	Test 1		Test 2		Test 3		Test 4		Test 5	
1	-	(-)	-	(-)	-	(-)	-	(-)	-	(-)
2	-	(-)	-	(-)	-	(-)	-	(-)	-	(-)
3	-	(-)	-	(-)	1, 3	(3)	-	(-)	-	(-)
4	-	(-)	-	(-)	3	(3*)	-	(-)	-	(-)
5	1, 3	(1, 3)	-	(-)	-	(-)	-	(-)	-	(-)
6	3	(1, 3)	-	(-)	-	(-)	-	(-)	-	(-)
7	1, 3	(1, 3)	-	(-)	-	(-)	-	(-)	-	(-)
8	1, 3	(1, 3)	-	(-)	-	(-)	-	(-)	3	(3)
9	1, 3	(1*, 3*)	-	(-)	-	(3)	-	(-)	3	(3)
10					-	(-)	3	(3)	3	(3)
11					2, 3	(2, 3)	3	(3)	3	(3*)
12					2, 3	(2, 3)	3	(3*)		
13					2, 3	(2*, 3*)	-	(-)		
14							3	(3)		
15							3	(3*)		

CONCLUSION

A diagnostic method for helicopter gearboxes is introduced that uses knowledge of gearbox structure and characteristics of the vibration features to define the influences between the features and faults. This method brings together the diverse areas of dynamic modeling, fuzzy systems, and neural networks for the purpose of modeling the gearbox structure, representing the diagnostic knowledge and performing diagnosis, respectively. The effectiveness of SBCN has been experimentally evaluated in diagnosis of OH-58A helicopter gearbox faults. Promising diagnostic results have been obtained from SBCN for the OH-58A gearbox at the subsystem level. However, at the component level the results lacked resolution due to the strong cross-correlation among features. The effectiveness of the proposed supervised training algorithm has been tested in improving diagnostic performance for the OH-58A gearbox. The results indicate that the algorithm has been able to improve the diagnostic performance considerably for both the first and second sub-sections of SBCN.

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Table 6: Faulty component results for OH-58A after training the second sub-section of SBCN.

Faulty Component Isolation for OH-58A After Training								
	SS 1			SS 2	SS 3			
Days	SBP	SBG	BRG1	BRG2	SG	PG	RG	BRG3
Test 1								
1 to 4	-	-	-	-	-	-	-	-
5	0.90*	0.01	0.03	-	1.00*	0.41	0.01	0.78
6	0.00*	0.00	-	-	0.00*	-	-	-
7	0.94*	0.00	0.02	-	1.00*	0.41	0.03	0.77
8	0.92*	0.01	0.01	-	1.00*	0.56	0.01	0.69
9	0.86*	0.01	0.02	-	1.00*	0.47	0.01	0.62
Test 2								
1 to 9	-	-	-	-	-	-	-	-
Test 3								
1 to 2	-	-	-	-	-	-	-	-
3	0.48	0.03	0.01	-	0.68	0.31	0.03	1.00*
4	-	-	-	-	0.73	0.40	-	1.00*
5 to 10	-	-	-	-	-	-	-	-
11	-	-	-	0.73*	0.61	0.37	0.04	1.00*
12	-	-	-	0.74*	0.65	0.36	0.05	1.00*
13	-	-	-	0.77*	0.62	0.41	0.02	1.00*
Test 4								
1 to 8	-	-	-	-	-	-	-	-
9	-	-	-	-	0.75	0.35	0.03	1.00*
10	-	-	-	-	0.89	0.37	-	1.00*
11	-	-	-	-	0.88	0.38	0.01	1.00*
12	-	-	-	-	0.94	0.42	-	1.00*
13	-	-	-	-	-	-	-	-
14	-	-	-	-	1.00*	0.35	0.03	0.71
15	-	-	-	-	1.00*	0.38	0.03	0.68
Test 5								
1 to 7	-	-	-	-	-	-	-	-
8	-	-	-	-	1.00*	0.95*	0.01	0.61
9	-	-	-	-	1.00*	0.90*	0.01	0.66
10	-	-	-	-	1.00*	0.95*	-	0.60
11	-	-	-	-	1.00*	0.92*	0.01	0.73

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13. ABSTRACT *(Maximum 200 words)*

A diagnostic method is introduced for helicopter gearboxes that uses knowledge of the gearbox structure and characteristics of the 'features' of vibration to define the influences of faults on features. The 'structural influences' in this method are defined based on the root mean square value of vibration obtained from a simplified lumped-mass model of the gearbox. The structural influences are then converted to fuzzy variables, to account for the approximate nature of the lumped-mass model, and used as the weights of a connectionist network. Diagnosis in this Structure-Based Connectionist Network (SBCN) is performed by propagating the abnormal vibration features through the weights of SBCN to obtain fault possibility values for each component in the gearbox. Upon occurrence of misdiagnoses, the SBCN also has the ability to improve its diagnostic performance. For this, a supervised training method is presented which adapts the weights of SBCN to minimize the number of misdiagnoses. For experimental evaluation of the SBCN, vibration data from a OH–58A helicopter gearbox collected at NASA Lewis Research Center is used. Diagnostic results indicate that the SBCN is able to diagnose about 80% of the faults without training, and is able to improve its performance to nearly 100% after training.

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