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Helicopter Hydraulic Pump Condition Monitoring Using Neural Net Analysis of the Vibration signature

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ABSTRACT

We apply artificial neural networks to helicopter hydraulic pump condition monitoring. Several neural net models are used to perform pattern classification on the vibration measurements. Various pump conditions are examined using data from accelerometers in different places on the pump. The fundamental pump frequencies and its harmonics are used as input features to two neural net models: (1) a multi-layer neural net using back-propagation and (2) a Kohonen's feature map. Both neural net models have the ability to distinguish between pumps with different flow rates and mechanical conditions. A fundamental result is that the vibration signature can be used to classify pump condition.

INTRODUCTION

Unexpected breakdowns of aircraft's hydraulic pump systems can lead to lost of power, expensive repair work, and reduced personnel safety. Traditional strategies to avoid pump failures involve (1) scheduling repairs at predetermined intervals, (2) letting pumps run to breakdown, or (3) monitoring existing flow and temperature measurements. The first approach entails the risk that pumps in perfect working order may be unnecessarily taken out of service, or that pumps on the verge of failure may be unwittingly left in operation. The second approach requires duplicated pumps as a backup system if loss of pumps cannot be tolerated. The third approach, although it provides some monitoring capabilities, generally does not give early indication of incipient faults.

A preferred approach is to monitor the condition of the hydraulic pump systems in-flight with advanced sensor technology and signal processing techniques, and carry out repairs only when the condition monitoring system indicates the necessity. Furthermore, the condition monitoring system provides another layer of aircraft and aircrew safety by signaling an alert when a fault is detected.

Early work in aircraft hydraulic systems used the rate of leakage of the hydraulic fluid past the pistons as a wear indicator. This fluid leakage is used to lubricate the pump bearings. Too much leakage is a sign of failure of the piston seals. In modern helicopter pumps, the sump which collects the fluid is integrated with the pump, which makes this type of detection impractical. Additionally, the filter (often as fine as 3 microns) used to strain the pump fluid, is integrated with the pump, at the high pressure outlet. This configuration made it impossible to detect pump failure modes via particle debris monitoring without changing the location of the filter. These constraints left us with vibration as the only possible signal.

Machine diagnostics based on vibration analysis has been quite successful in the recent years. The vibration generated by a faulty component is a very early indicator of machine degradation. Moreover, the vibration signal can be used to identify the source of failures by relating the vibration signatures back to various machine components. In general, the vibration signal measured by external accelerometers needs to be processed such that various fault signatures can be extracted and enhanced. Basic vibration signal processing techniques include statistical analysis to look at parameters such as the kurtosis value of the signal, and spectrum analysis to look at the periodic features associated with the rotational frequencies of various machine components[1].

Advanced signal processing techniques such as Wavelet Transform and Hyper-Spectrum Analysis have been applied to mechanical systems fault detection with high degree of confidence. However, these techniques usually require a long processing time and careful interpretation of the results. As such, they are usually not suitable for in-flight application [2][3].

Recently, techniques based on pattern classification have been applied to fault detection and diagnosis. Among the various pattern classifiers used for detection, artificial neural networks are the most notable due to their ability to generate complex decision regions and to perform non-linear interpolation.

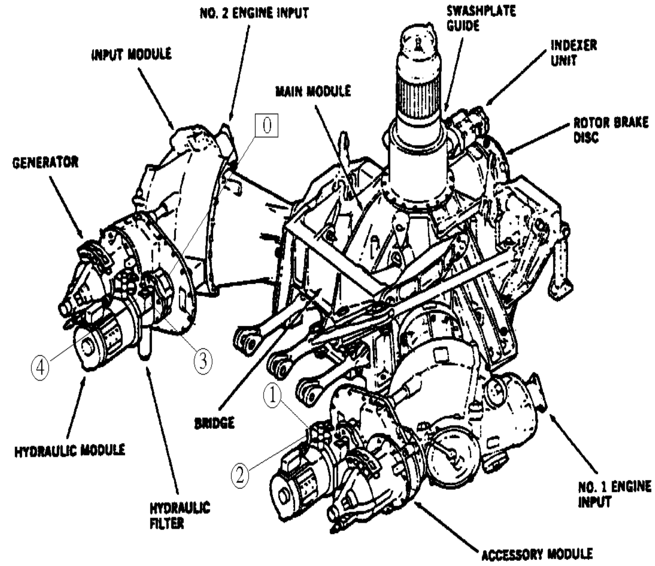

Figure 1 Sensor location on the SH-60B test stand

In general, artificial neural networks can be grouped into three types according to their learning algorithms; namely, supervised, unsupervised, and reinforcement learning. In supervised learning, a set of input-target data is required for training the net to perform classification. The training data should contain the full range of input-output data for accurate classification. In unsupervised learning, the neural net is used to perform clustering on a set of input data without any intervention (i.e., self-learning). Various clusters are formed based on the similarity of input vectors (patterns). In reinforcement learning, the neural net learns various cases using a reinforcement signal generated based on the performance of the classification process (i.e., good or bad). The reinforcement signal is used to guide the net's learning process instead of explicit training.

In this study, various artificial neural net models were investigated in conjunction with vibration signal processing to determine the most effective strategy for pump condition monitoring. For this purpose, vibration data were collected on several hydraulic pumps of an SH-60B drive train system at NAWC Trenton, NJ. The vibration signal generated from each pump was measured by two piezoelectric accelerometers mounted on both the axial and radial directions of the pump module. The four channels of vibration signals (two for each pump) along with one channel of tachometer signal were digitized and stored with Technology Integration's KT-3 system. In the experiment, the SH-60B drive train system was run under a constant load and speed, but with various flow settings for the pumps.

The first stage of experiment involved running one pump with a fixed flow rate at 2 gpm (nominal) and the other with variable flow rates at 0, 1, 2, 3, or 4 gpm. The second stage of experiment repeated the steps of the first stage after the two pumps were intentionally interchanged. These tests showed that we could identify the pump operating condition, and, in certain instances, distinguish one good pump from another. We used supervised nets with backpropogation for these data.

As a first step, a multi-layer net was used to perform condition monitoring on the vibration data. For this purpose, the vibration data measured from the four accelerometers was synchronously averaged with the tachometer data to produce a clean signal average coherent to the pump drive shaft. Vibration energies associated with the piston frequency (nine times the shaft frequency) and its harmonics were used to train and test the multi-layer net so as to classify various pumps and flow rates.

The second set of tests used damaged pumps that were recovered from working helicopters. The type of damage was characterized by the mechanic as "Rachety", "Hot", or "Low pressure". For these tests the pump signature sometimes differed at harmonics of the shaft as well as the piton rate. For this reason , we used all 256 shaft harmonics as data input. We used unsupervised learning to distinguish the pumps. We could use Kohonen's feature maps to characterize a good pump from any single bad pump. For this type of learning to work, you need to have the both good and bad pump data. In a second test we used the adaptive feature map. For this test you need only good pump data to characterize a pump. Deviations from this good data were observed for the bad pumps. In all cases the amount of difference depended on the flow rate. Zero flow rate always showed greater differences than finite flow rates.

EXPERIMENTS AND SIGNAL PROCESSING

To test the applicability of artificial neural networks in hydraulic pump condition monitoring, experiments were performed at NAWC Trenton, NJ on an SH-60B transmission test stand. The collected raw vibration data were then sent to Technology Integration, Inc. (TII) for further processing and analysis.

EXPERIMENTAL SETUP-The SH-60B transmission system has two hydraulic pump modules, one at the port side and one at the starboard side. Vibration signals were measured by four piezoelectric accelerometers placed on the pump modules (two on the port and two on the starboard). They are mounted on

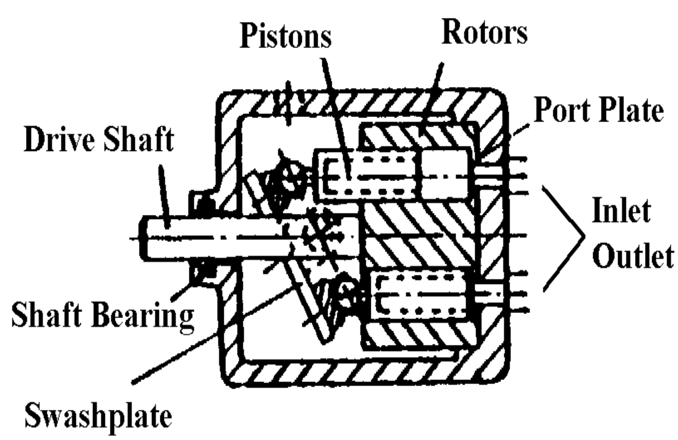

Figure 2 Schematic of a piston pump

Table 1 Sensors used for the Hydraulic Pump experiment

Type	Sensitivity (mv/g)	Location
Tach (0)	n/a	stbd hydraulic spur gear
Accel. (1)	10	stbd pump axial
Accel (2)	10	stbd pump radial
Accel (3)	10	port pump axial
Accel. (4)	10	port pump radial

the flat surface just above the hydraulic filter on the output line of the pump as shown in Fig. 1. In addition to the four accelerometers, one tachometer was used to measure the rotational speed of the hydraulic pump drive shaft. The tachometer was mounted on the starboard hydraulic pump drive shaft's 92-tooth spur gear to measure the pulses generated by the tooth passage. All experiments were performed at a nominal pump shaft speed of approximately 119.8 Hz. Table 1 describes the sensors used for this study.

The vibration data from these accelerometers were collected and digitized with TII's KT-3 system at a sample rate of 100 kHz which gives an effective bandwidth of 50 kHz. The system is capable of performing multi-channel real-time data acquisition and analysis. In this study, the raw vibration data were stored on the hard disk and later transferred to 8 mm tapes for further analysis.

Several test runs were conducted to produce a wide spectrum of pump conditions. A typical pump experiment consisted of 20 tests based on various combination of flow rates . The flow rate of the starboard pump was first fixed at the nominal value 2 gpm and that of the port pump was varied from 0 to 4 gpm with an increment of 1 gpm (tests 1 to 5). The port pump flow rate was then fixed at 2 gpm, and the starboard pump flow rate was varied (tests 6 to 10). The two pumps were then interchanged and the tests described above were repeated (tests 11 to 20). Five second worth of data were acquired for each test, containing approximately 600 rotations of the pump drive shaft.

SIGNAL PROCESSING **-**To extract vibration features that are useful for hydraulic pump condition monitoring, the raw vibration data was processed and analyzed. Each SH-60B hydraulic pump module incorporate one piston (or swash) pump (9 pistons each) that produces 9 pulses per shaft rotation similar to gear meshing signatures produced by a 9-tooth gear. This pump design in general does not require any valves to control (or direct) the flow, instead, it uses a plate with two kidney-shaped slots to direct the flow by changing the angle of the swash plate as shown in Fig.2.

Several signal processing techniques were investigated in this study such that the most enhanced pump signatures were produced. The signal processing techniques used in this study were: *power spectrum* and *signal averaging* analysis[6][8].

Spectrum Analysis-This is perhaps the most widely used technique in vibration signal processing, as failures such as imbalance, misalignment, wear, and roller bearing spalling usually produce a clear change in the spectrum. However, in complex machinery such as a helicopter drive train system where the background noise masks the vibration signatures of interest, changes in the spectra cannot be easily distinguished.

Table 2 Pump experiments

Test	Port (gpm)	Stbd (gpm)	Remarks
1	0	2	
2	1	2	
3	2	2	
4	3	2	
5	4	2	
6	2	0	
7	2	1	
8	2	2	
9	2	3	
10	2	4	
11	0	2	pumps interchanged
12	1	2	
13	2	2	
14	3	2	
15	4	2	
16	2	0	
17	2	1	
18	2	2	
19	2	3	
20	2	4	

Signal Averaging Analysis- The vibration signals generated from a gearbox usually contains signatures from shafts, gears, bearings, and noise. The signal averaging technique uses digitized raw vibration data over a large number of revolutions synchronous with the running speed of a particular shaft. The obtained signal average which has a much improved signal-to-noise ratio, reveals signatures of gears, gear meshes, and other vibration elements associated with the shaft of interest[8].

In this study, the signal averaging technique was used as the primary source of signal processing due to the advantages mentioned above. The raw vibration data were first resampled at a rate synchronous with the pump drive shaft speed (approximately 119.8 Hz) measured by the tachometer. The individual resampled data records were averaged to produce the signal average that represents the vibrations generated by components associated with the pump shaft. In this case, the periodic impulses generated by the hydraulic pump's pistons.

The obtained signal averages were then transformed to frequency domain via the Fast Fourier Transform (FFT) such that the energies of various frequency contributors can be extracted. The FFT of a signal average (usually refer to as signal average spectrum) contains frequency elements in terms of shaft orders (SO). The periodicity of a 9-piston hydraulic pump can be characterized by the vibration amplitude at the 9th shaft order and its integer multiples (i.e., 18th, 27th,...) and are referred to as harmonics. These harmonics were used as features or input patterns to train and test several neural net models which will be discussed in the next section.

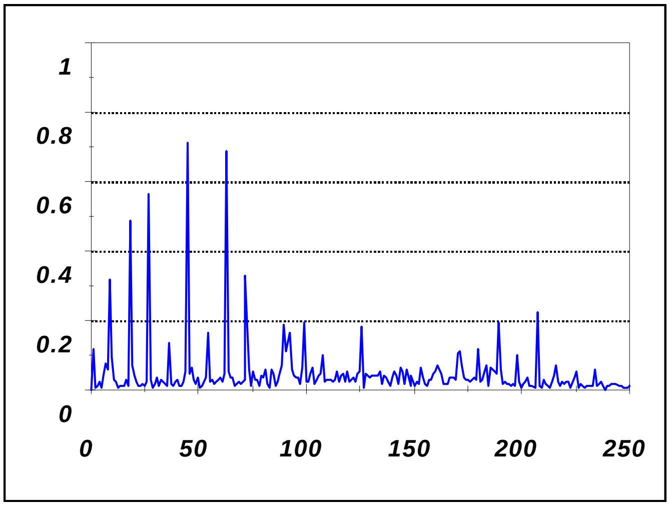

Figure 3 Good pump spectra 0 gpm

EFFECT OF FLOW RATE ON THE VIBRATION SIGNATURE-Here we show acceleration spectra for a good pump using a radially oriented sensor. The vertical axis is acceleration (in G's) the horizontal axis is shaft order. All data are synchronously averaged before the FFT is taken. Notice that most of the energy is in harmonics of the piston rate (9 times shaft rate). Most of the energy occurs in the first 10 harmonics of the piston rate. The differences in the distribution of this energy allows us to distinguish flow rates (Fig 3 and 4) .

EFFECT OF PUMP CONDITION ON THE VIBRATION SIGNATURE- Here we show the effect of condition on the vibration signature. All data are taken at 0 gpm. The vertical axis is acceleration (in G's). the horizontal axis is shaft order. We show the data at zero flow rate because the neural net tests show that the distinction between pumps is greatest here. The major characteristic that distinguishes bad pumps from the good ones is the appearance of energy at shaft orders from 100 to 200(Fig. 5,6 and 7). Notice that this energy occurs between the piston harmonics. The low pressure pump is distinguished in that the vibration energy peaks at 3.5 G's as opposed to a more normal level of 1 G.

ARTIFICIAL NEURAL NETS

This section presents the background of the two neural net

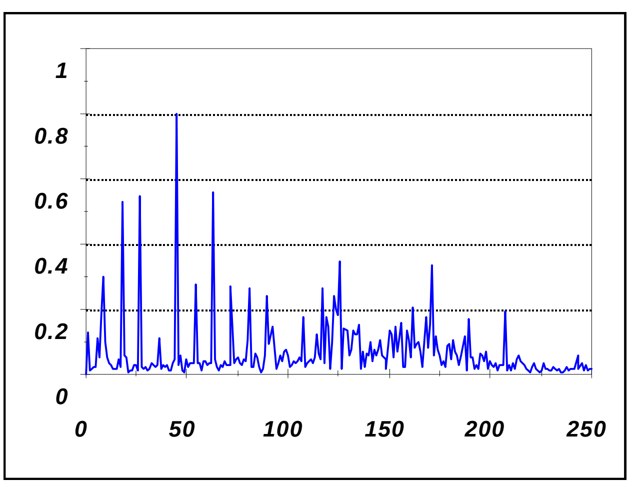

Figure 4 Good pump 4 gpm

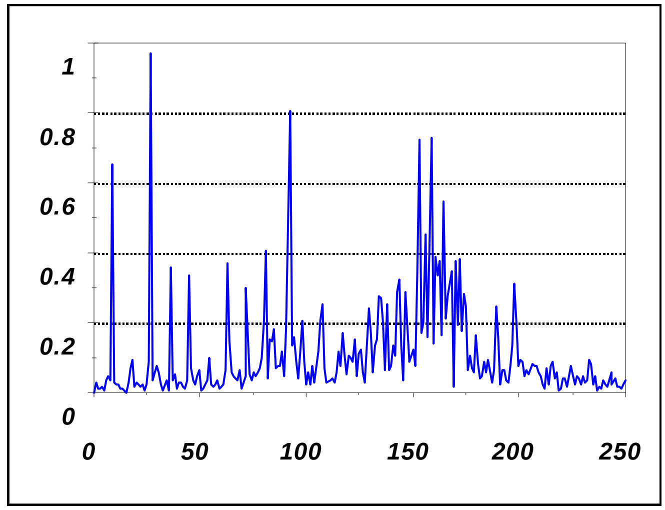

Figure 5 Rachety pump 0 gpm

models used in this study. The multi-layer neural net model is discussed first, followed by the Kohonen's feature maps.

MULTI-LAYER NEURAL NETS-Multi-layer neural nets are trainable feed-forward nets with one or more layers of *hidden units* between the input and output nodes. Multi-layer neural networks are composed of many nonlinear computational elements which operate in parallel in order to mimic the arrangements of neurons found in biological neural networks. The hidden units serve as an internal representation of the input patterns which can be viewed simply as an intermediate representation which increases the systems ability to learn nonlinear mappings. It has been proven that a multi-layer neural net with one layer of hidden units can represent any continuous function[4][7].

KOHONEN'S FEATURE MAP-In order to capture the exact time of fault occurrences, *Kohonen's feature mapping* algorithm which performs unsupervised competitive learning was used. Kohonen's algorithm utilizes continuous-valued input vectors which are then presented sequentially to a feature map without specifying the desired outputs. After enough input vectors have been presented, the weight vectors of the feature map will become the centers of these input vectors (clusters). As such, the point density function of these clusters approximates the probability density function of the input vectors. In addition, the weights will be organized in such a

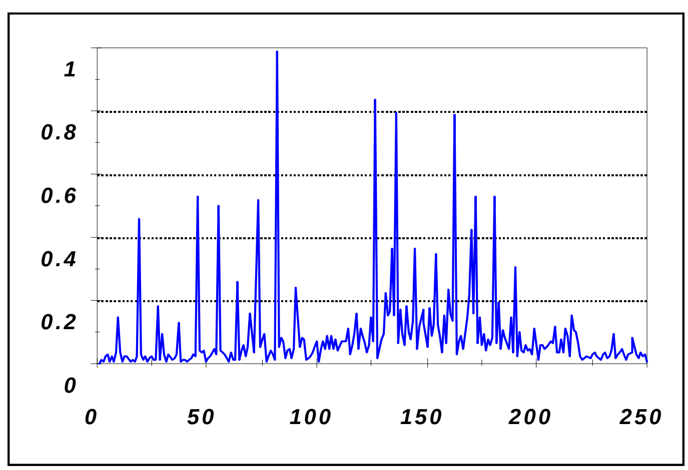

Figure 6 Hot pump 0 gpm

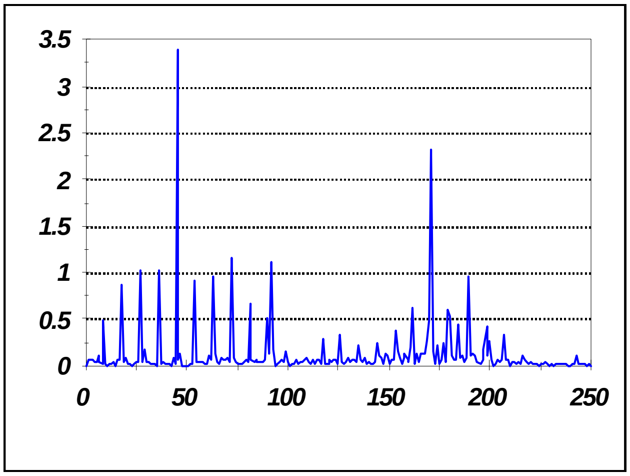

Figure 7 Low pressure pump 0 gpm

way that nodes which are close together in the feature map are sensitive to input vectors that are physically similar. Outputs will thus be ordered in a natural manner based on the weights[4][5].

ADAPTIVE FEATURE MAP - The AFM method uses a hybrid learning algorithm that takes the advantage of both Kohonen's feature mapping algorithm and Adaptive Resonance Theory (ART). Similar to these two unsupervised learning algorithms, the AFM method utilizes continuous-valued input patterns (vectors) which are presented sequentially to a feature map without specifying the desired outputs.

In the AFM method, it is assumed that the first input vector represents the normal (no-fault) case and the weight vector in AFM is an exact copy of the first input vector. Note that initially there is only one weight vector in the AFM representing the prototype vector of the normal case. The subsequent input vectors are then presented to AFM and compared to the weight vector by computing the Euclidean distance between the two vectors. If the computed Euclidean distance exceeds a vigilance factor (sensitivity coefficient), then a new category (e.g., faulty case) is formed, with the current input vector as the prototype vector (weight vector) of the new category. If the computed distance does not exceed the vigilance factor, then the first weight vector is adjusted so as to account for the current input vector. All the weight vectors are constantly being updated to cope with the variability.

METHODS USED- The supervised training methods to determine flow rate and pump identity were done with good pumps only. On inspection of the good pump data, that we had, we did notice that the Fourier amplitude of the synchronously averaged data varied with flow rate. In particular we noticed that this signature varied at harmonics of the piston rate (9 times shaft frequency) . We were able to classify the pump flow rate based on harmonics of this data using back propogation.

The unsupervised learning to determine pump health was done with both good and bad pumps .The bad pump spectra differed at harmonics other than the those of the piston rate. To include the effect we used all 256 shaft harmonics. These data were used as the inputs to the Kohonen/Adaptive feature map classification of the bad pumps.

NAVY HYDRAULIC PUMP RESULTS

This section contains the analysis results based on the vibration data collected from several SH-60B helicopter hydraulic pumps at NAWC Trenton transmission test stand. The vibration signals generated by helicopter transmission systems are generally very complex, consisting of the vibrations of several components, as well as signals due to nonlinear effects and noise. In order to enhance the hydraulic pump vibrations, signal averaging was performed on the vibration data to reveal the vibration signatures produced by the hydraulic pumps.

The products of this signal averaging process, which are usually referred to as "signal averages", were then FFTed to produce the amplitude spectra of the signal averages. These spectra were then used as input vectors to train and test the performance of several neural net models.

CLASSIFICATION OF PUMPS AND FLOW-**A** multi-layer neural net was designed and used to differentiate between two healthy pumps under various operating conditions (i.e., flow rates). The effectiveness of the multi-layer neural net was evaluated with two training sets and two test sets (one for the Axial and one for the Radial sensor set). For this purpose, the two training sets were formed based on all the 28 pump harmonics from both the Axial and Radial sensor sets using tests 1 to 10 in Table 2 (a total of 20 training cases for each sensor set for both pumps). The multi-layer net was tested based on the 28 harmonics from tests 11 to 20 in Table 2 (a total of 20 training cases for each sensor set for both pumps). Note that the spectra of individual signal averages contained 256 vibration elements, and we concluded that by using the 28 pump harmonics was suitable for the purpose of classification; adding or removing any frequency components produced worse results.

The multi-layer net which contained 45 hidden units was trained with the back-propagation learning algorithm. For training the net, the learning rate and momentum coefficient were set at 0.2 and 0.8, respectively. The number of hidden units and training parameters were carefully selected such that the performance of the neural net was optimized with respect to both generalization and speed.

The multi-layer neural net also requires a set of training targets to adapt its weights. As such, two target sets were formed according to the pump identification and flow rate, using binary numbers. Each target vector consisted of 7 elements with the first 2 elements representing the pump identification, and the last 5 the flow rates. For examples, the target vector [1 0 1 0 0 0 0] was associated with the Port side pump running at 0 gpm, and [0 1 0 0 1 0 0] the Stbd side pump at 2 gpm.

Training inputs and targets were randomly presented to the multi-layer net with equal probability for each case so as to ensure the efficiency of the training process. Training was continued until perfect classification was achieved in the training set (i.e., correct identification for both pump and flow rate for all training cases). The net converged after 1674 iterations (83.7 epochs) for the Axial sensor set and 2006 iterations (100.3 epochs) for the Radial sensor set, respectively. The performance of the trained multi-layer net was then tested with the test sets. Classification results for all the test cases for both Axial and Radial sensor sets, were obtained. The results suggest that the radial sensor is more accurate in distinguishing flow rat and pump.

In table 3 we show the effectiveness in distinguishing flow rate. The ideal result has the form of the identity matrix. Although there are some misclassifications, the trained net is very good at identifying pump flow rate. (In table 3 we omit output nodes associated with pump identification.)

In table 4 we show how well the net can identify a given pump. The ideal result has the identity (1,0) for tests 1 through 5 and tests 16 to 20. The result is (0,1) for tests 6 to 10 and tests 11 to 15. Notice that the pumps are accurately identified even though we switch them around after tests 10. (In table 4 we omit the output nodes associated with pump flow rate.)

HYDRAULIC PUMP CONDITION MONITORING-In the previous section , a multi-layer neural net was used to perform classification of two healthy pumps with different flow rates. Perhaps a more important issue is to determine the condition of a pump, that is, whether the pump of interest is in perfectly healthy condition, or the pump has a developed mechanical fault. For this purpose, three fleet rejected pumps which were supplied from the US Coast Guard were tested at NAWC - Trenton to collect vibration data. The three pumps were rejected for three different reasons: (1) Low Pressure (180 psi), (2) Ratchety (clicking sound), and (3) Hot (50% above normal operating temperature). The initial assessment of the three pumps at Trenton based on the basic parameters such as the oil and pump skin temperature was inconclusive, except the third pump which has a high temperature reading. That is, these non-vibration parameters indicated normality for both the "Low Pressure" and the "Ratchety" pumps.

Five sets of data were taken from each rejected pump which was mounted on the Stbd side, as well as from the healthy pump mounted on the Port side. The test condition was identical to the healthy pump test described above. Both the sensor sets (Axial and Radial) were used in this test

Spectra of individual signal averages were obtained for all the rejected and healthy pumps, based on 100 revolutions of vibration data. Note that the two major differences in this test were: (1) all the vibration elements (256 frequency components) in the spectrum of a signal average were used since the faults may be reflected on the locations other than the pump harmonics, and (2) the frequency components were normalized such that they are independent of the flow rates. The individual normalized frequency components were then used as input vectors to a Kohonen's Feature Map (KFM) to perform classification. For comparison, the same input vectors were used by an Adaptive Feature Map (AFM), an enhanced version of KFM.

Table 3 Flow Results with the radial sensor.

Test gpm:	0	1	2	3	4
1	0.7	0.6	0.0	0.0	0.1
2	0.0	0.3	0.3	0.0	0.0
3	0.0	0.1	0.9	0.6	0.0
4	0.0	0.0	0.9	0.6	0.0
5	0.0	0.0	0.0	0.0	1.0

Table 4 Pump Identification with the radial sensor

Test	Port	Stbd	Test	Stbd	Port
1	0.8	0.3	11	0.0	1.0
2	0.9	0.1	12	0.0	1.0
3	1.0	0.1	13	0.0	1.0
4	1.0	0.0	14	0.0	1.0
5	0.2	0.8	15	0.0	1.0
6	0.0	1.0	16	1.0	0.1
7	0.0	1.0	17	0.9	0.1
8	0.0	1.0	18	1.0	0.0
9	0.1	1.0	19	0.9	0.1
10	0.3	0.7	20	1.0	0.1

The main difference between the multi-layer neural net and the feature maps is the learning process. Unlike the multi-layer net, the feature map does not require training targets to adjust its weights. Instead, the feature map performs adaptation and classification based solely on the input vectors. This is usually referred to as "unsupervised learning" or "clustering". Note that the classification or clustering performed by the feature maps is similar to Principle Component Analysis or Singular Value Decomposition which extracts the singular values (or eigen values) and eigen vectors from the input vectors and determines the importance of each eigen vector. For detection, the first two eigen values and their eigen vectors can be used as the templates (or prototype vectors) for the normal and abnormal cases, respectively. Classification of vectors then becomes a matter of computing the projections onto the two eigen vectors. Note that the eigen vectors form the orthogonal basis of the space. The weight vectors formed by the feature maps, however, are not necessarily orthogonal.

<u>Low Pressure Pump</u>- The data collected from the Port side sensors) were used as normal cases and the data from the Stbd sensors were marked as low pressure cases. There were a total of 5 normal and 5 low pressure cases for each sensor set. The input vectors were arranged such that the first 5 were the normal cases and the last 5 were the low pressure cases.

The results indicated that the KFM (table 4) successfully identified the data from the normal cases (the first 5 cases represented by the shaded bars) and that from the low pressure cases (the last 5 cases represented by the clear bars). The results also showed that the data from the Radial sensor set provided the best separability in terms of the computed Euclidean distances.

Table 5 Kohonen feature map, Low Pressure pump

Test	GPM	Pump	%Good	%Bad
1	0	Good	.69	.24
2	1	Good	.34	.10
3	2	Good	.40	.10
4	3	Good	.40	.11
5	4	Good	.23	.05
6	0	Bad	.14	.52
7	1	Bad	.20	.52
8	2	Bad	.11	.40
9	3	Bad	.18	.52
10	4	Bad	.27	.65

The results obtained from AFM (table 5) also indicated that the AFM was able to differentiate between the normal and low pressure cases. The two cases were significantly different based on the AFM outputs (Euclidean distances). Note that the first AFM output is always zero because it uses the first input vector as the prototype vector for the normal case. The weights are then adaptively updated for the subsequent cases.

Ratchety Pump **-**The same procedures were applied The data collected from the two Port side sensors were used as normal cases and the data from the two Stbd sensors were marked as low pressure cases. There were a total of 5 normal and 5 low pressure cases for each sensor set. The input vectors were arranged such that the first 5 were the normal cases and the last 5 were the low pressure cases.

The KFM results obtained from the two different sensor sets. The results indicated that the KFM successfully identified the data from the normal cases and that from the low pressure cases. The results also showed that the data from the Radial sensor set provided the best separability in terms of the computed Euclidean distances.

The results obtained from AFM also indicated that the AFM was able to differentiate between the normal and bad cases. The two cases were significantly different based on the AFM outputs (Euclidean distances). The results were similar to those obtained for the Low Pressure pump illustrated in table 5 and 6.

Hot Pump **-**The same procedures were applied to the data collected from both the Port (normal) and Stbd (hot) pumps. The KFM mis-classified the last abnormal case as one of the normal cases with data from the Axial sensor, and the first normal case as one of the abnormal cases with data from the Radial sensor set. It should be noted that for all cases, the separability between the normal and hot pumps was significantly less than the previous two abnormal pumps. This is perhaps that there is little correlation between the temperature and vibration measurements. The results from AFM, however, indicated that the AFM successfully identified the normal and hot pumps with the data from all three sensor sets, although the separability between the two is also less then the other two abnormal pumps.

Table 6 Adaptive feature map, Low Pressure pump

Test	GPM	Pump	L2 Distance %
1	0	Good	0
2	1	Good	3
3	2	Good	3
4	3	Good	1
5	4	Good	5
6	0	Bad	105
7	1	Bad	93
8	2	Bad	68
9	3	Bad	75
10	4	Bad	81

CONCLUSIONS

We have demonstrated the effectiveness of neural networks in condition monitoring of helicopter hydraulic pumps. Several experiments were performed at NAWC - Trenton to collect vibration signals generated from several healthy hydraulic pumps, as well as three fleet rejected pumps. Spectral components of individual signal averages were used as input vectors to train and test several neural net models to verify the applicability of these models.

A multi-layer neural net was designed to perform classification on two different healthy pumps running under 5 different operating conditions. Classification results showed that the multi-layer net provided fairly good results when the Radial sensor set was used and the flow rate was fixed.

Two feature maps (KFM and AFM) were utilized to perform fault detection (condition monitoring) of the fleet rejected pumps. The spectral components were normalized such that they are independent of the pump operating conditions. Detection results indicated that the feature maps were quite effective in differentiating between the healthy pump and the three rejected pumps. In particular, the AFM produced 100% correct classification for all the three rejected pumps.

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