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NASA Technical Memorandum 107667

APPLICATION OF A NEURAL NETWORK AS A POTENTIAL AID IN PREDICTING NTF PUMP FAILURE

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January 1993

NASA

National Aeronautics and
Space Administration

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INTRODUCTION

The National Transonic Facility (NTF) has three centrifugal multi-stage pumps to supply liquid nitrogen to the wind tunnel. Reliability of these pumps is critical to the facility operation and test capability. Therefore, a highly desirable goal is to be able to detect a pump rotating component problem (associated with excessive vibration of the pump) as early as possible during normal operation and avoid serious damage to other pump rotating components. If a problem can be detected before serious damage occurs, the repair cost and the downtime could be reduced significantly.

Currently, the tunnel operator monitors only the pump frequency amplitude. If this amplitude exceeds a predetermined value, the pump is immediately shut down without knowing the true cause of the problem. One potential method for the early detection of a pump rotating component problem is through real-time monitoring of the performance of the pump. Changes in the amplitudes at certain critical frequencies could be used as a means of detecting a pump rotating component problem, and allow for the pump to be stopped before a failure occurs. Data containing these amplitudes are available from frequency scans generated by accelerometers attached to the pumps, but there are currently no techniques available to use this data in predicting a pump failure.

The purpose of this research project is to investigate an approach for developing a neural network-based tool for monitoring pump performance and aid in predicting pump failure. Once trained with known inputs and known outputs, neural networks can process many combinations of input values other than those used for training very rapidly to approximate previously unknown output values. Therefore, the neural network can be applied to establish relationships among the critical frequencies and serve as an aid in predicting pump failures.

This paper presents the initial results from this research project. Data from frequency scans taken from typical tunnel operations were used to develop training pairs for training a back-propagation neural network. After training, various combinations of critical pump frequencies were propagated through the neural network. The approximated output was used to create a contour plot depicting the relationships of the input frequencies to the output pump frequency. This plot would enable a tunnel operator to visually monitor the pump performance based on the operational frequencies and potentially predict a failure.

FORMULATION OF FREQUENCY RELATIONSHIPS

The three NTF centrifugal multi-stage pumps (designated P1, P2, and P3) are shown in figure 1.

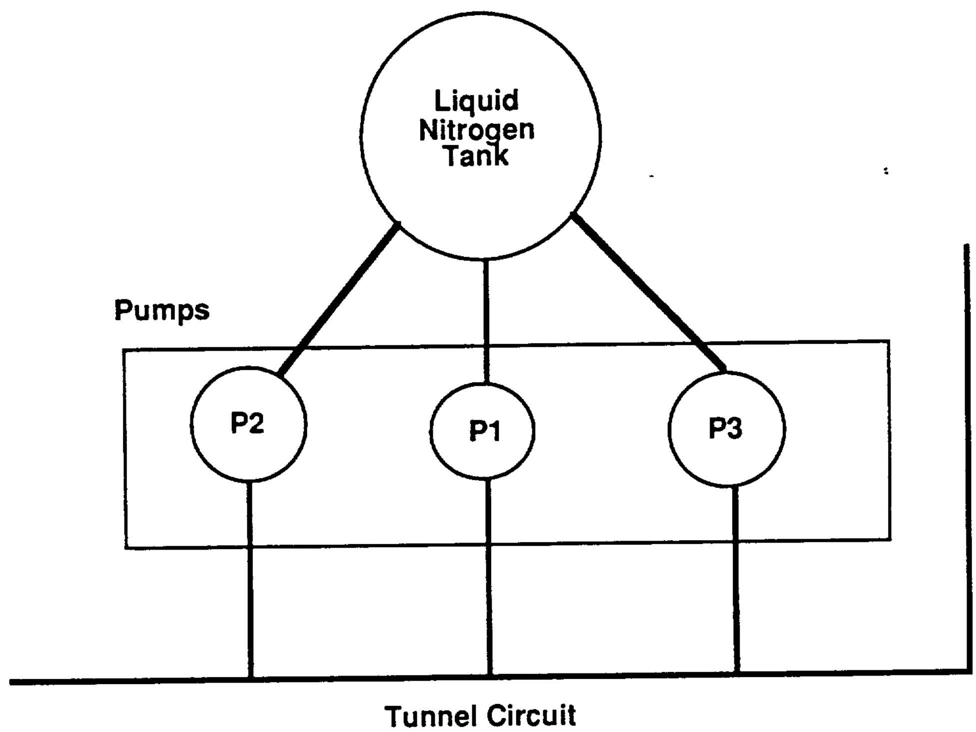

Figure 1 - NTF liquid nitrogen supply pumps.

To establish a viable method for predicting a pump failure, the critical frequency ranges must be determined. Experience has shown that responses in the neighborhood of five frequencies are the most critical in detecting a pump rotating component problem (ref. 1). They are:

(1) the fundamental train frequency - FTF
(2) the ball pass frequency of the inner race - BPFI
(3) the ball pass frequency of the outer race - BPFO
(4) the ball spin frequency - BSF
(5) the pump frequency - PF

FTF is the frequency with which the balls revolve as a set. The ball pass frequency is the frequency with which a single ball passes a given point. The race is the channel where the balls rotate. Thus, BPFI and BPFO are the respective ball pass frequencies for the inner and outer races. BSF is the angular velocity of an individual ball. The neighborhoods for these four frequencies are around 8Hz, 13Hz, 58Hz, and 72Hz, respectively. The amplitude (eq. 1) of the response at the pump frequency (about 29Hz) is related to the amplitudes at the first four frequencies defined above, but the exact relationship is unknown at this time.

$$\text{Amplitude at PF} = a^*(\text{amp. at FTF}) + b^*(\text{amp. at BPFI}) + c^*(\text{amp. at BPFO}) + d^*(\text{amp. at BSF}) \quad (1)$$

where a,b,c, and d are unknown coefficients

Currently, when the tunnel is in operation, the tunnel operators are able to obtain real-time log charts from frequency scans, such as the one shown in figure 2.

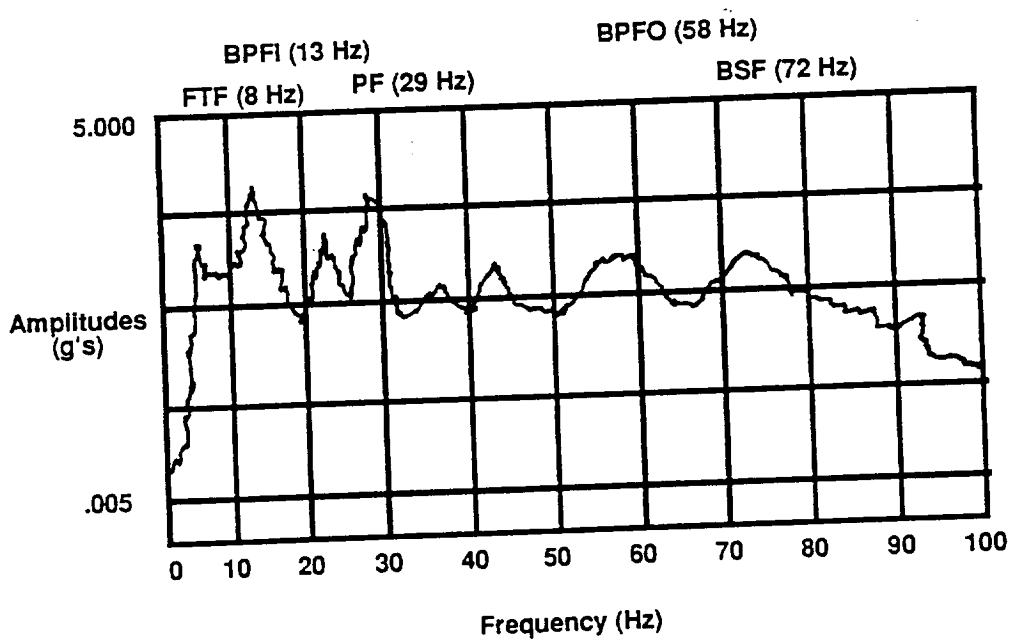

Figure 2 - Sample frequency scan.

The x-axis of the scan represents frequencies from 0 Hz to 100 Hz. The y-axis indicates the amplitude at each frequency. The largest amplitude at each of the above frequency neighborhoods is measured, however the tunnel operator monitors only the PF amplitude. If this amplitude exceeds a predetermined value, the pump is immediately shut down without knowing the true cause of the problem. The cause is not discovered until the pump is repaired and a scan is made of the data tapes to indicate the relationship of the pump frequency to the four frequencies defined above. No techniques are currently available to monitor or predict pump failure.

NEURAL NETWORK

A neural network was developed as an aid in understanding the relationship among the five different frequencies. Once this relationship is better understood, it could be used in predicting pump failure. NETS (ref. 2), a back propagation neural network (ref. 3,4) developed at NASA Johnson Space Center, was chosen as the software package. NETS uses a sigmoid function as the activation function, therefore all data must be scaled between 0.1 and 0.9.

Configuration

The configuration of the neural network is shown in figure 3. There are four nodes on the input layer corresponding to the amplitudes for the FTF, BPFI, BPFO, and BSF frequencies. Ten nodes (arbitrarily chosen) are on the hidden layer to allow for the non-linearity of the problem. The output layer has one node corresponding to the amplitude for PF. The lines between the nodes represent unknown weights corresponding to the unknown coefficients from eq. 1. NETS initially generates random numbers for these weights. After training, the weights will represent a relationship among the four input nodes and the output node.

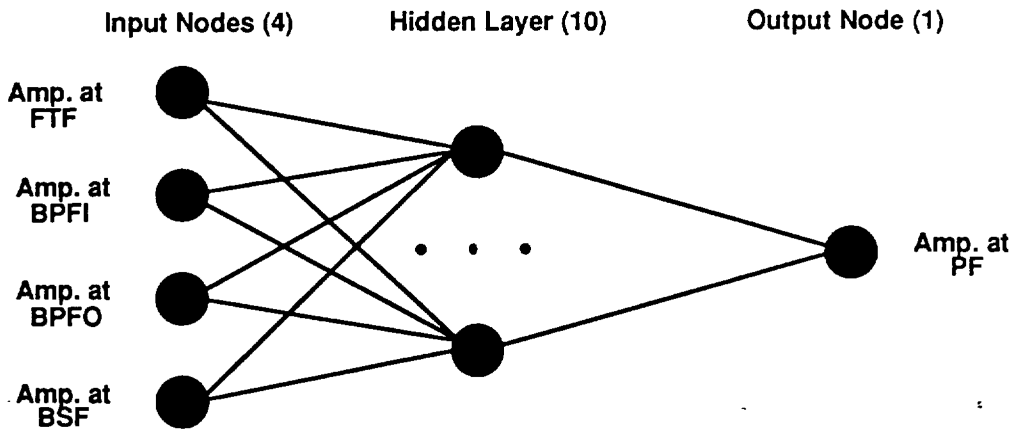

Figure 3 - Neural network for NTF pump frequency responses.

Training the Neural Network

Training pairs must be selected for training the neural network. For this network, a training pair is a set of four known input values and their corresponding known output value. To train the network, an output value is computed from the known input values and the random weights. This computed output is then compared to the known output. A change in the weights is computed and propagated back through the neural network. The modified weights are then used with the known inputs to compute another output value. This process continues until the root mean square (RMS) difference between the known output and the computed output converges to some given tolerance, arbitrarily chosen to be .001 for this problem.

Five accelerometers are used in each pump to measure the amplitudes of vibration and generate frequency scans (figure 2). For this initial investigation, it was decided to try and model the problem with six training pairs. These six pairs to be used in training the neural network were created by interpreting data (arbitrarily chosen) from these frequency scans. The set of scaled training pairs is shown in table 1. The first five pairs were taken from scans when the pump was running normally. The sixth pair was taken after a problem had occurred. All data has been scaled between 0.1 and 0.9.

		Training Pairs					
	Amplitudes at Frequency	1	2	3	4	5	6
Input	FTF	.226	.112	.416	.204	.127	.235
	BPFI	.684	.278	.724	.551	.170	.213
	BPFO	.100	.290	.312	.161	.359	.220
	BSF	.166	.167	.213	.178	.138	.125
Output	Pump	.550	.644	.593	.649	.650	.892

Table 1 - Training pair data from frequency scans.

RESULTS

Once trained, the neural network was applied to create the contour plot for displaying the relationship among the five frequencies. Data for the contour plot were generated by propagating various combinations of the amplitudes of the four input frequencies through the weights of the neural network to compute the output amplitude of the pump frequency. The contours on the plot are divided into three shades to indicate different amplitudes of the pump frequency. White indicates everything is normal, gray indicates a warning zone, and black indicates danger and the pump should be stopped before entering this zone.

Figure 4 is given to explain how to read this type of a contour plot. In this example, only a portion of the frequency ranges are displayed. The two boxes with number represent a unique combination of the four frequencies. The color of one box would represent the amplitude of the pump frequency when the amplitudes at: FTF equals 0.1, BPFI equals 0.7, BPFO equals 0.1, and BSF equals 0.8. The color of the other box would represent the amplitude of the pump frequency when the amplitudes at: FTF equals 0.2, BPFI equals 0.1, BPFO equals 0.2, and BSF equals 0.1.

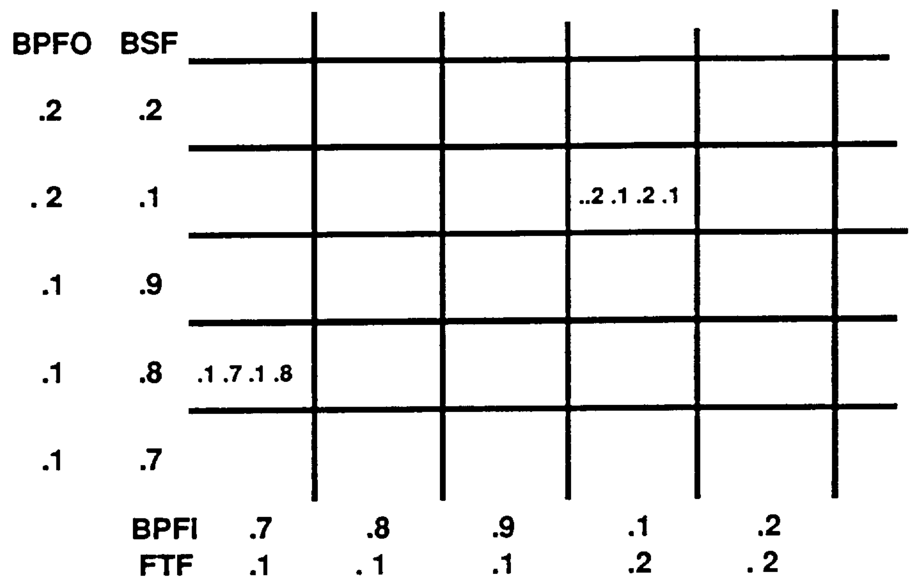

Figure 4 - Explanation of contour plot.

The contour plot developed from the neural network trained with the above set of training pairs is shown in figure 5. The x-axis contains ranges of amplitudes at FTF and BPFI. The amplitude at FTF is set at 0.1 while the amplitude at BPFI increases from 0.1 to 0.9 in 0.1 increments. The amplitude at FTF is then increased to 0.2 and the amplitude at BPFI is again incremented from 0.1 to 0.9. This process continues until all combinations of the FTF and BPFO scaled amplitudes ranging from 0.1 to 0.9 in increments of 0.1 are represented on the x-axis. The y-axis similarly contains the amplitude ranges at BPFO and BSF. Therefore, each box on the contour plot represents a unique combination of amplitudes of the four input frequencies, with the shade of the box representing the computed output value of the amplitude of the pump frequency.

Thus, in a single contour, the operator can visualize the relationships among all five frequencies. For example, the results shown in the figure indicate that when the FTF amplitude is low and the BPFO amplitude is high (upper left corner) there is no problem, regardless of the amplitudes of the other two frequencies. On the other hand, if the FTF amplitude frequency is high and the BPFO amplitude is low (lower right corner) there is a problem, again regardless of the amplitudes of the other two frequencies. The frequency scan would determine the amplitudes of the four input frequencies and place a pointer on the appropriate box of the plot. If the operator notices that the points are drifting towards either a warning or a danger zone, then the pumps can be shut down before a serious problem occurs. By knowing the amplitudes when the problem began, the cause of the problem can be anticipated.

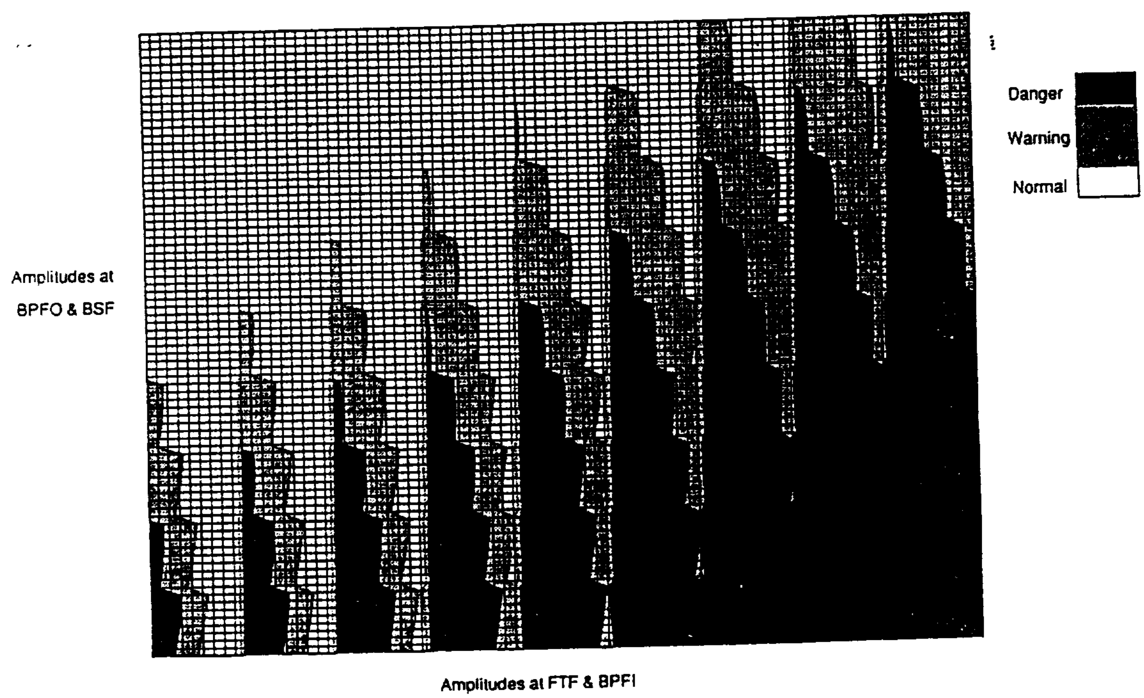

Figure 5 - Contour plot of pump frequency amplitudes.

CONCLUDING REMARKS

This project is a first step in developing a neural network-based tool to aid in predicting NTF pump failures. A neural network is developed and trained with data obtained from frequency scans generated by accelerometers placed in the pumps. The neural network, trained with six training pairs, represents the relationship between the pump frequency and four other frequencies that are critical in detecting a pump rotating component problem. A contour plot which graphically displays this relationship was created as an aid in predicting pump failure.

To become operational, a computer with this display and Analog/Digital boards would have to be connected to the current accelerometer data collection system. The accelerometer data would then appear as points on the display and enable the tunnel operators to watch as any combination of frequencies begin moving toward a danger zone and stop the pump before a failure occurs. Also, the data could be used to plot a history of pump performance, thus assisting in the scheduling of preventive maintenance. This technique could potentially be applied to any other facility where frequency monitoring is critical. For example, it could be expanded to other wind tunnels that use pumps, fans, or similar rotating equipment.

Results from this study have contributed to the development of a tool for monitoring pump performance and predicting potential pump failures through the application of neural networks. Further studies of increased complexity, such as the use of additional training pairs, are necessary since the initial training with six training pairs is probably not sufficient to accurately predict a pump failure. The inclusion of training pairs created with currently available data from previous pump failures would be particularly desirable.

ACKNOWLEDGMENTS

This effort was a research project for David E. Bradley, a student at Denbigh High School, working in the Interdisciplinary Research Office under the auspices of the New Horizons Program.

The authors also wish to express their appreciation to Mr. Henry T. Thornton, Jr. of the Sverdrup Corporation for his help in obtaining the frequency scan data.

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REPORT DOCUMENTATION PAGE

Form Approved
OMB No. 0704-0188

1. AGENCY USE ONLY (*Leave blank*)	2. REPORT DATE	3. REPORT TYPE AND DATES COVERED
	January 1993	Technical Memorandum

4. TITLE AND SUBTITLE
Application of a Neural Network as a Potential Aid in Predicting NTF Pump Failure

5. FUNDING NUMBERS
WU 505-63-50-06

6. AUTHOR(S)
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7. PERFORMING ORGANIZATION NAME(S) AND ADDRESS(ES)
NASA Langley Research Center
Hampton, VA 23681-0001

8. PERFORMING ORGANIZATION REPORT NUMBER

9. SPONSORING/MONITORING AGENCY NAME(S) AND ADDRESS(ES)
National Aeronautics and Space Administration
Washington, DC 20546-0001

10. SPONSORING/MONITORING AGENCY REPORT NUMBER
NASA TM-107667

11. SUPPLEMENTARY NOTES
James L. Rogers and Jeffrey S. Hill: Langley Research Center, Hampton, VA.
William J. LaMarsh II: Unisys Corporation, Hampton, VA
David S. Bradley: New Horizons, Hampton, VA.

12a. DISTRIBUTION/AVAILABILITY STATEMENT
Unclassified - Unlimited
Subject Category 61

12b. DISTRIBUTION CODE

13. ABSTRACT (*Maximum 200 words*)

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A neural network-based tool was developed for monitoring pump performance and aiding in predicting pump failure. Once trained, neural networks can rapidly process many combinations of input values other than those used for training to approximate previously unknown output values. This neural network was applied to establish relationships among the critical frequencies and aid in predicting failures. Training pairs were developed from frequency scans from typical tunnel operations. After training, various combinations of critical pump frequencies were propagated through the neural network. The approximated output was used to create a contour plot depicting the relationships of the input frequencies to the output pump frequency.

14. SUBJECT TERMS
Neural Networks, Frequency, Contour Plot

15. NUMBER OF PAGES
11

16. PRICE CODE
A03

17. SECURITY CLASSIFICATION OF REPORT	18. SECURITY CLASSIFICATION OF THIS PAGE	19. SECURITY CLASSIFICATION OF ABSTRACT	20. LIMITATION OF ABSTRACT
Unclassified	Unclassified	Unclassified	