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MONITORING OF VIBRATING MACHINERY USING ARTIFICIAL NEURAL NETWORKS

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INTRODUCTION

The primary source of vibration in complex engineering systems is rotating machinery. Vibration signatures collected from these components render valuable information about the operational state of the system and may be used to perform diagnostics. For example, the low frequency domain contains information about unbalance, misalignment, instability in journal bearing and mechanical looseness; analysis of the medium frequency range can render information about faults in meshing gear teeth; while the high frequency domain will contain information about incipient faults in rolling-element bearings. There is a large body of literature available that describes the type of vibration signals to be expected for faults in typical systems and the analysis techniques that can be used for early detection of faults, references 1 and 2 present a discussion on actual phenomena and their individual characteristics. In addition, trend analysis may be performed by comparing the vibration spectrum for each machine with a reference spectrum and evaluating the vibration magnitude changes at different frequencies. Standards, such as the ISO 2372 and 3945, may be used to determine the severity of the changes.

This form of analysis for diagnostics is often performed by maintenance personnel monitoring and recording transducer signals and analyzing the signals to identify the operating condition of the machine. This method has proven to be effective in identifying potential failures before they occur. With the advent of portable fast Fourier transform (FFT) analyzers and "laptop" computers, it is possible to collect and analyze vibration data on site and detect incipient failures several weeks or months before repair is necessary. Indeed, it is often possible to estimate the remaining life of certain systems once a fault has been detected. Hence, there is considerable motivation to design systems to automatically perform this analysis on a real-time basis in a reproducible manner.

RMS velocity, acceleration, displacements, peak value, and crest factor readings can be collected from vibration sensors. To exploit all the information embedded in these signals, a robust and advanced analysis technique is required. Our goal is to design a diagnostic system using neural network technology, a system such as this would automate the interpretation of vibration data coming from plant-wide machinery and permit efficient on-line monitoring of these components.

NEURAL NETWORKS FOR THE ANALYSIS OF SPECTRAL SIGNATURES

A network of artificial neurons (usually called a neural network) is a data processing system consisting of a number of simple, highly interconnected processing elements in an architecture inspired by the structure of the cerebral cortex portion of the brain. As a result, neural networks are often capable of doing things which humans or animals do well but which conventional computers often do poorly. Perhaps the most important characteristic of neural networks is the ability to model processes and systems from actual data. The neural network is supplied with data and then "trained" to mimic the input-output relationship of the process or system. Neural networks are also able to recognize patterns, even when the information comprising these patterns is noisy, sparse, or incomplete.

To perform spectral monitoring of components in an operating engineering system, signatures are collected from plant components and analyzed to detect features which reflect the operational state of the machinery. For the analysis of vibration data, neural networks may be used as classifiers. To perform classification it is necessary to attach to each spectral signature a label which describes the operational state of the machine at the time of collecting the signature. The input to the network is a spectrum (or a compressed version) and the output is the class label. The network is trained to identify an arbitrary pattern as a member of a state among a set of possible states.

METHODOLOGY

We have secured vibration data from a steel sheet manufacturing mill consisting of measurements of "laminar flow" table rolls in the facility. There is a total of 246 rolling elements monitored, 39 of which were faulty. Among the faulty signatures 26 reflected single faults in the rollers and 13 were collected from rollers with more than one fault. Data were collected at 9 different locations on each machine and spectra generated using FFT techniques. Each spectrum contains 150 points in the range 1 Hz to 500 Hz and only one data set per machine was used to perform the diagnostics. The general problem areas are misalignment, improper lubrication, looseness, wear in motor brushes and damage to inboard and outboard bearings. The low frequency spectra was used because these faults can usually be identified by detecting specific features in this range of the spectrum.

The readings collected by the nine sensors on a roller at time t are correlated but not identical in amplitude (Figure 1). There are three reasons for the difference : first, the vibration levels are different throughout the machine; second, the effect of neighboring vibrations is not uniform; and finally, faults which are particular to a bearing located near a sensor are not always recorded by other sensors. To compensate for these differences, we produced a single signature per machine by averaging the spectra from the nine sensors (Figure 2). The range of the spectral data was (0.0, 1.0), these values were not normalized or enhanced by any method.

We are addressing the problem of classifying vibration signatures in two phases. Phase I includes compression of the spectral signatures using Recirculation networks. Phase II comprises the classification of the compressed patterns using the Backpropagation algorithm. Compression is an important issue in the context of this analysis because we deal with a very large data set and reducing the dimensionality of the patterns decreases the training time. The Recirculation network acts also as a feature detector by emphasizing the features of the spectrum which are particular to each fault (Figure 3). The organization the system is depicted in Figure 4.

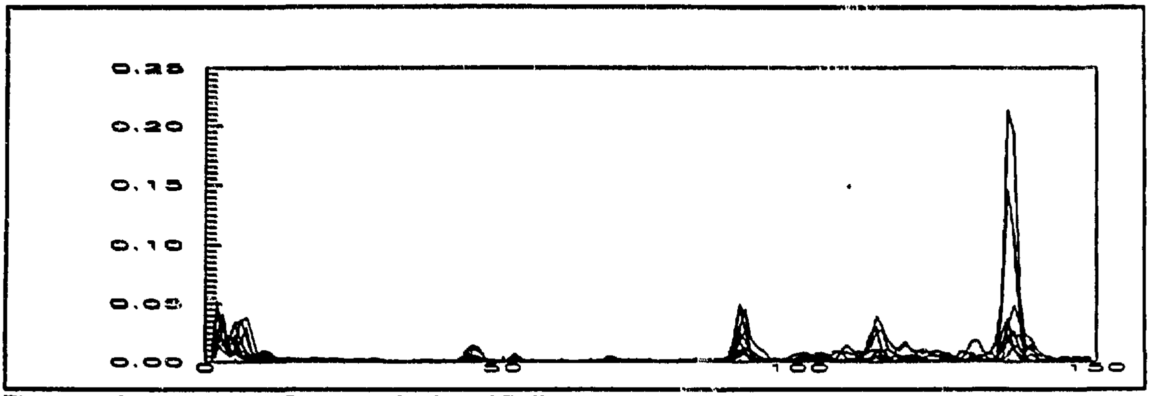

Figure 1. Spectra from 9 Sensors (Misaligned Roller)

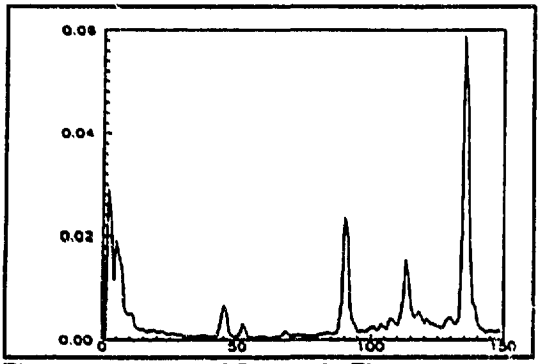

Figure 2. Average of Spectra in Figure 1

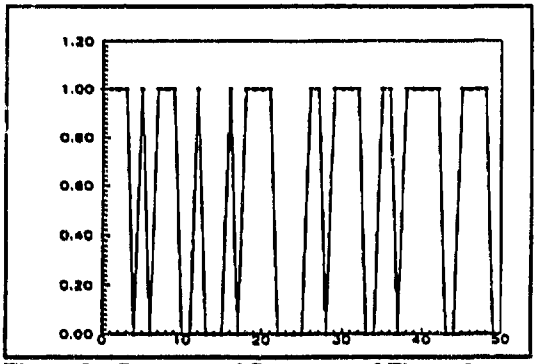

Figure 3. Compressed Spectrum of Figure 2

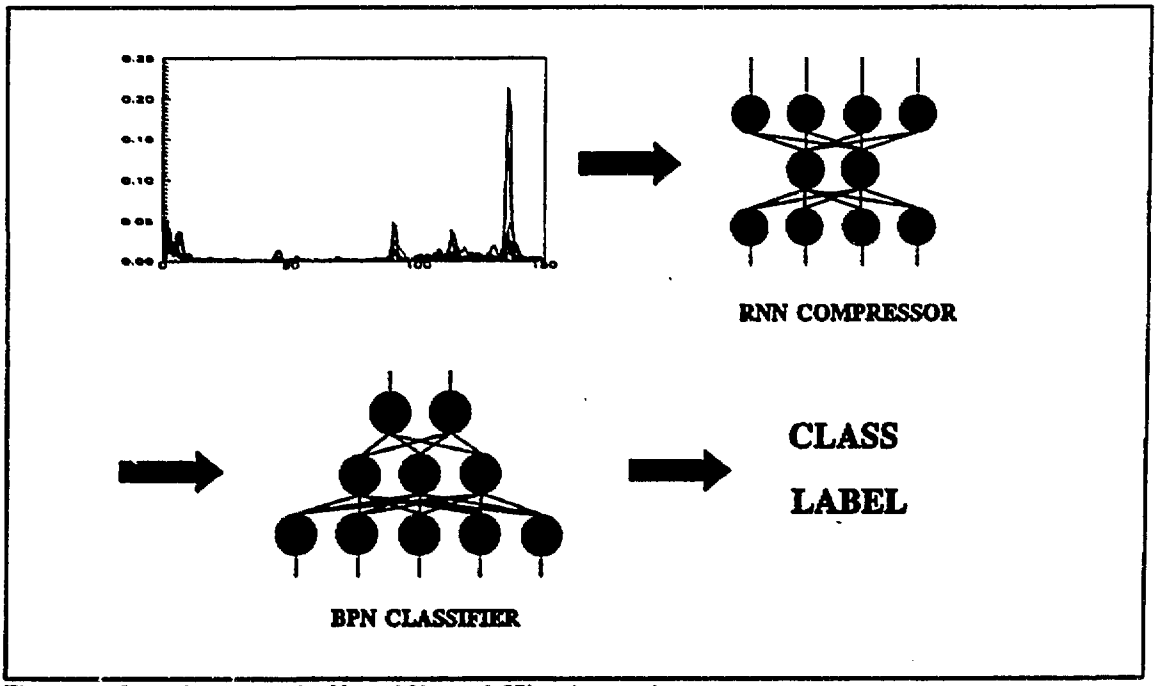

Figure 4. Organization of the Neural Network Vibration Analyzer

The Recirculation network (RNN) algorithm [3] is autoassociative in nature and in its simple version has only two trainable layers: a visible layer and a hidden layer. The purpose of training is to construct in the hidden layer a representation of the data presented at the visible layer (the input vector). If the number of hidden units is less than the number of visible units, the hidden representation is a compressed version of the input vector. Using the Recirculation network a compression ratio of 3/1 was achieved. The network takes as input a 150-point spectrum and produces as output a 50-point signature. This signature becomes the input to the Backpropagation network which performs the classification.

Backpropagation (BPN) is a multi-layer, fully connected heteroassociative network. The BPN algorithm [4] computes the weights between pairs of processing elements such that the difference between the actual output and the desired output is minimized in a least squared sense. The Backpropagation network used in our system has a 50-neuron input layer, a 26-neuron hidden layer and an output layer with one neuron corresponding to each identifiable fault. For multiple faults, more than one neuron is activated corresponding to the appropriate combination of faults.

RESULTS

For this project we used the version of the Recirculation network included in the NeuralWorks Professional(TM) running on a Zenith 386SX machine. The network was trained for 12,000 epochs until the error was reduced to 0.02. The network's output was a set of compressed 50-point signatures, these signatures were later used without normalization to train the classifier. The classifier network was trained on single-fault signatures describing misalignment, bearing problems, wear in motor brushes, inadequate lubrication and looseness. The network learned for 12,000 epochs on a SUN SPARC workstation using the Backpropagation version of PLEXI(TM). Each of the nodes in the output layer of the classifier had a linear threshold function centered around 0.5. The function reports a '1' if the output of the node is greater than 0.5 and reports a '0' if the output of the node is less than or equal to 0.5. A '1' indicates the presence of a fault in the roller while a '0' indicates absence of a particular fault.

The classifier network was trained with 75% of the single-fault patterns in the original set, the remaining patters (25%) were used exclusively for testing. Recalling of the set of single faults was 100% accurate. The data from rollers with multiple faults (13 patterns) were not used for training because we wanted to use these patterns as special cases for recall. If we recall using these data we are able to identify only the most prominent fault in the roller.

CONCLUSIONS

We are working on the implementation of a methodology for interpreting vibration measurements based on neural networks. We feel that neural networks can provide a methodology for improving the analysis of spectral data, and a viable alternative to PSD analysis for monitoring and diagnostics of vibrating components; the anticipated advantage of developing such a system is the possibility of automating the monitoring and diagnostic processes.

The averages of signatures coming from different sensors on a machine is a good indicator of vibration behavior. Since the vibration increases due to different faults is not detected by all sensors, the average provides an overall estimate of the vibration levels at each frequency. For example if a peak is detected by only one sensor, the reading at that sensor when averaged with the remaining signatures will tend to raise the vibration levels at the appropriate frequencies. If the sensor locations and the effect of neighboring vibration are known in detail, a multi-network approach may be used in which each sensor is monitored through a different network [5].

Traditionally, diagnosis of components based on vibration analysis has been made by looking at specific regions of the spectra which depict features related to each fault. However, vibration analysis in general is imprecise because the behavior of components under certain operating conditions is not always predictable, especially when the behavior is induced by more than one fault. We believe that the compressed signature is a more efficient descriptor of the component behavior because it provides complete information about the spectrum and allows the analysis to be made on a broader base. Under this study we have achieved compression ratios of 3/1 while maintaining the statistical properties of the data. The Recirculation network provides an excellent mechanism for this compression.

This project deals exclusively with the analysis and classification of signatures coming from roller elements in a steel sheet manufacturing plant. However, the behavior of these components is comparable to vibrating equipment in other engineering systems. We have extended this concept to the analysis of data from rolling element bearings [6], and to components in operating nuclear power stations.

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