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VIBRATION MONITORING WITH ARTIFICIAL NEURAL NETWORKS

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ABSTRACT

Vibration monitoring of components in nuclear power plants has been used for a number of years. This technique involves the analysis of vibration data coming from vital components of the plant to detect features which reflect the operational state of machinery. The analysis leads to the identification of potential failures and their causes, and makes it possible to perform efficient preventive maintenance. Early detection is important because it can decrease the probability of catastrophic failures, reduce forced outgage, maximize utilization of available assets, increase the life of the plant, and reduce maintenance costs.

This paper documents our work on the design of a vibration monitoring methodology based on neural network technology. This technology provides an attractive complement to traditional vibration analysis because of the potential of neural networks to operate in real-time mode and to handle data which may be distorted or noisy. Our efforts have been concentrated on the analysis and classification of vibration signatures collected from operating machinery. Two neural networks algorithms were used in our project: the Recirculation algorithm for data compression and the Backpropagation algorithm to perform the actual classification of the patterns. Although this project is in the early stages of development it indicates that neural networks may provide a viable methodology for monitoring and diagnostics of vibrating components. Our results to date are very encouraging.

BACKGROUND

A power plant (nuclear or fossil) is fundamentally a thermodynamic system that includes a heat source (fission or combustion), flowing fluids, valves, control systems, and rotating machinery (pumps, fans, motors, gear boxes, turbines and a generator.) Although the flow of fluids (water and steam) can induce vibrations and shock, the primary source of vibrations is rotating machinery. Vibration per se is not necessarily bad if its amplitude and the associated forces are within acceptable limits. Indeed, vibration in machinery can be the source of much information about the various systems involved.

There is a great deal 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. Angelo[1] presents a discussion on actual phenomena and their individual characteristics. 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. 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.

METHODOLOGY

Vibration data are usually collected with accelerometers attached to plant machinery. The sensors are placed at locations where the signals are expected to be reliable, and the data is recorded for an interval of time. From these data, spectra are generated using FFT techniques and the coefficients stored in a database to be analyzed later by expert personnel in an effort to identify faults.

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

Neural Networks

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. Neural networks exhibit capabilities difficult to achieve using other technologies. Neural networks have the ability to recognize patterns, even when the information comprising these patterns is noisy, sparse, or incomplete.

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 have the ability to respond in real-time to the changing system state descriptions provided by continuous sensor inputs. For complex systems involving many sensors and possible fault types, real-time response is a difficult challenge to human operators; neural network technology may provide a viable alternative to the solution of this problem.

Neural Networks for Vibration Analysis

For the analysis of spectral signatures, neural networks may be used both as classifying and clustering systems. 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 (a set of FFT coefficients) 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. Clustering involves the grouping of patterns according to their internal similarity and requires no labels. The aim is to separate the set of patterns into classes such that the patterns in each class have similar statistical and geometrical properties.

We are addressing the problem of identifying and classifying vibration signatures in two phases. Phase I includes compression of the spectral signatures using Recirculation networks. Phase II of the project 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 significantly the training time and computer resources needed.

The vibration levels recorded at each sensor for each machine differ depending on the fault. The vibration levels may differ also because of sensor positioning and overall neighboring vibration. These divergences among sensor readings for each machine make it difficult to produce a "typical" vibration signature for a particular fault and type of machine. We have decided to address this problem by designing a multiple-network system that performs classification on readings collected at each sensor/location separately. Each network is trained on data collected from a single sensor and a solution (class or malfunction) is generated by taking a majority vote among network responses. This approach has proven robust for problems in a number of other areas[2] and may prove very useful in cases of drastic sensor failures since the failure of one sensor is only reflected in one network of the system. Figure 1 illustrates the architecture of the multi-network system.

Recirculation Networks

The Recirculation Network algorithm was developed by Geoffrey Hinton and James McClelland.[3] The network is autoassociative in nature and in its simplest version has only two trainable layers, a visible layer and a hidden layer. The input and output layers act simply as buffers for input and output (Figure 2.)

The purpose of the training phase 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 and if the network is trained successfully, the hidden representation may be considered as a compressed implementation of the visible representation. For this project we built a network with a hidden layer containing half the nodes of the input layer in order to reduce the dimensionality of the input vector set by a factor of two.

The aim of training is to reduce the error between the original input vector and the reconstructed vector. The reconstructed vector is built by running the compressed representation through the set of weights. This error is an accurate indicator of performance because it is calculated as the sum of the squared error at each node. The algorithm calls for a minimization of this error using a gradient descent strategy. A description of the algorithm and the derivation of the weight adjustment equations may be found in reference.[4]

Backpropagation Network

The Backpropagation network (BPN) is a multilayer fully connected, heteroassociative network. The BPN algorithm 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-squares sense. The generalized delta rule is used for calculating the error between the actual output and the desired output and for generating the weight adjustment coefficients. The basic algorithm is discussed by Rumelhart and McClelland.[5]

It has been established that three-layer networks are capable of representing arbitrarily complex decision surfaces.[6] Figure 3 shows the architecture of a typical three-layer network. The first layer receives the input, modifies it using the set of weights, and passes it to the hidden layer; the hidden layer in turn propagates the modified inputs to the output layer where the overall error is calculated. The hidden layer is used to represent the non-linear characteristics of the data and its size is determined by the complexity of the problem. Although the determination of the size of the hidden layer remains an art, several studies have been conducted which suggest empirical formulas for calculating the dimensions of the hidden layer.[7] Approaches have also been proposed for improving the performance of the algorithm.[7,8]

The BPN is a fully connected network in which every neuron is connected to all neurons in adjacent layers with no lateral connections. During training the information flows forward from the input layer to the output layer and the error is propagated backwards through the weights to calculate the weight adjustments. Training involves the modification of the weights until the error is reduced to an acceptable limit.

SPECTRAL SIGNATURES

To perform spectral monitoring of components in an operating engineering system, signatures are collected from plant machinery and analyzed to detect features which reflect the operational state of the machinery. 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. Data were collected at 9 different locations on each machine. From these data, spectra are generated using FFT techniques and the coefficients stored in a database. Each spectrum contains 100 points and only one data set per machine was collected to perform the diagnostics. The general problem areas are misalignment, improper lubrication, looseness, wear in motor brushes and damage to inboard and outboard bearings. Although the raw data correspond to rollers in a steel sheet manufacturing mill, the behavior of these components is comparable to vibrating equipment in power plants. These techniques should be applicable to a power plant setting without major redesign.

The range of the spectral data was (0.0, 1.0). The input vectors were not normalized or enhanced by any method, and neither were the compressed versions collected from the Recirculation network after training. Figure 4 depicts a typical spectrum with 100 points and its compressed 50-point representation. The Recirculation network had as its input the 100-point spectra and produced a compressed version of the signatures containing only 50 points. The 50-point compressed pattern was then fed to the Backpropagation network to perform the classification.

The 50-point signature produced by the Recirculation network has a different geometrical shape than the original pattern (Figure 4.) However, the patterns retain their statistical characteristics after training. We tested the effectiveness of the compression by clustering both the original patterns and the compressed patterns using standard clustering techniques. These results are included in the Results section of the report.

The data was separated into 9 sets, each set corresponding to readings collected at each location/sensor. The readings collected at different locations for a roller at a particular time **t** are correlated but not identical (Figure 5) because the vibration levels are different throughout the machine, and because the effect of neighboring vibration levels is not uniform. In addition, faults which are particular to a bearing located near a sensor are not necessarily recorded by other sensors. Other factors such as sensor mounting position and roller location on the table may affect the level of vibration detected by each sensor.[9] Each one of the 9 sets constitutes a training set for a different network.

RESULTS

For this project, we used the version of the Recirculation network included in the NeuralWorks™ development package which runs on a Zenith 386 machine. Each vector representing a spectrum was an input to the network. The resulting compressed vectors had 50 inputs, thus achieving a 2/1 compression ratio.

The recirculation network was trained for 10,000 iterations until it reached the pre-established error threshold (0.001.) On the average, the training speed was 100 epochs/minute, so the training time was roughly 100 minutes. The effectiveness of the compression was tested by clustering the original and compressed patterns using the K-means algorithm.[10] The results were consistent except in 5 cases out of 31. The agreement translates to a degree of consistency of almost

84% which was beyond our expectations. Given the sensitivity of the K-means algorithm (or its instability), we feel that these results could be improved by using other clustering or self-organizing algorithms. Additional training may help improve the performance of K-means by further tuning the compressed representation.

For the classification of the patterns we used the version of Backpropagation included in PLEXI™[11] which runs on a SUN SPARC IPC workstation. The entire system is comprised of a series of 9 networks trained independently on data from each sensor. A solution is generated by taking a majority vote among network responses (Figure 1.) The potential advantage of this approach is that it could aid in cases of drastic sensor failures or in cases where a machine may be experiencing more than one fault that could not be detected at all locations.

Each network has as input the 50-point compressed spectrum and five output units corresponding to each possible fault. The responses of the individual networks do not always agree for a particular testing case. This is due possibly to the fact that all faults are not always detected at all locations, and also because the neighboring vibrations contaminate the signatures differently at every location. For these reasons, we feel confident that the classification by majority counts is a reasonable and sensible technique.

To train the networks we are exploring a variety of techniques for preprocessing the spectral values. Since the aim of preprocessing is to enhance the individual features of the signatures to reflect clearly the state of the machine, we are using not only the raw coefficients but also their first, second and third derivatives as training data. The set of derivatives is a better training set in some cases but our results are not conclusive at this stage. Our results appear to indicate that in cases where patterns are very similar but belong to different classes, using the raw data for training requires longer training sessions. In some cases convergence was not achieved at all. Using the derivatives forces the network to focus on the severity of the changes and not on the absolute values of the vibration levels. The changes in magnitude are a more unique feature relating to each fault.

CONCLUSIONS

We are working on the implementation of a methodology for interpreting vibration measurements based on neural networks. The anticipated advantage of developing such a system is the possibility of automating the monitoring and diagnostic processes for vibrating components, and building diagnostic systems which complement traditional PSD analysis by dealing with the non-linear characteristics of the signals.

We have studied the performance of neural networks for monitoring applications in other areas.[12,13,14] Our experience leads us to believe that to implement reliable monitoring systems using neural networks, it is best to utilize multiple independent networks to address several phases of the problem, than to design a large network capable of performing all analysis. The major consideration is training time. Training time increases according to the complexity of the network and affects directly the accuracy of the results.

The feasibility of using Recirculation networks for compression of spectral data has been established. Under this study we have achieved compression ratios of 2/1 while maintaining the statistical properties of the original patterns. The original and compressed patterns were clustered using the K-means algorithm and the results obtained are consistent in 84% of the test cases. The Recirculation network used to compress the data had 100 input units and 50 hidden units. The network was trained for 10,000 cycles taking approximately 100 minutes on a Zenith 386 microcomputer. The results of the compression surpass our original expectations and we believe that additional training may improve the representation.

Our results indicate that the multi-network architecture for classification is a robust and viable approach. Using derivatives of the spectral coefficients as the training set enhances the unique characteristics of the data for each class. Derivatives seem to force the network to concentrate on the changes in magnitude of the vibration levels instead of their absolute values. We are not able to assert at this stage how many derivatives are necessary in the preprocessing or to evaluate exactly how much each higher derivative is able to contribute to the enhancement of the data.

Although our project is in the preliminary state of development we feel that neural networks can provide a methodology for improving the analysis of spectra, and may provide a viable alternative to PSD analysis for monitoring and diagnostics of vibrating components. Our results to date are very encouraging.

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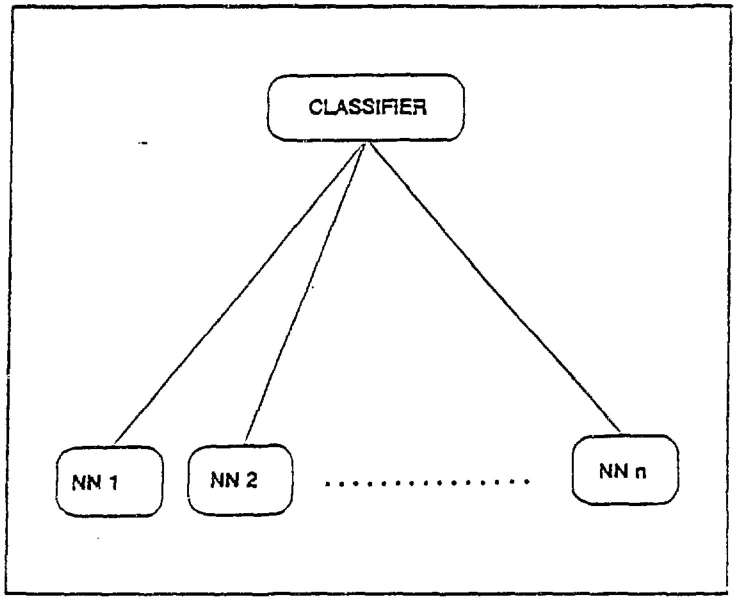

Figure 1. Multi-Network System for Classification.

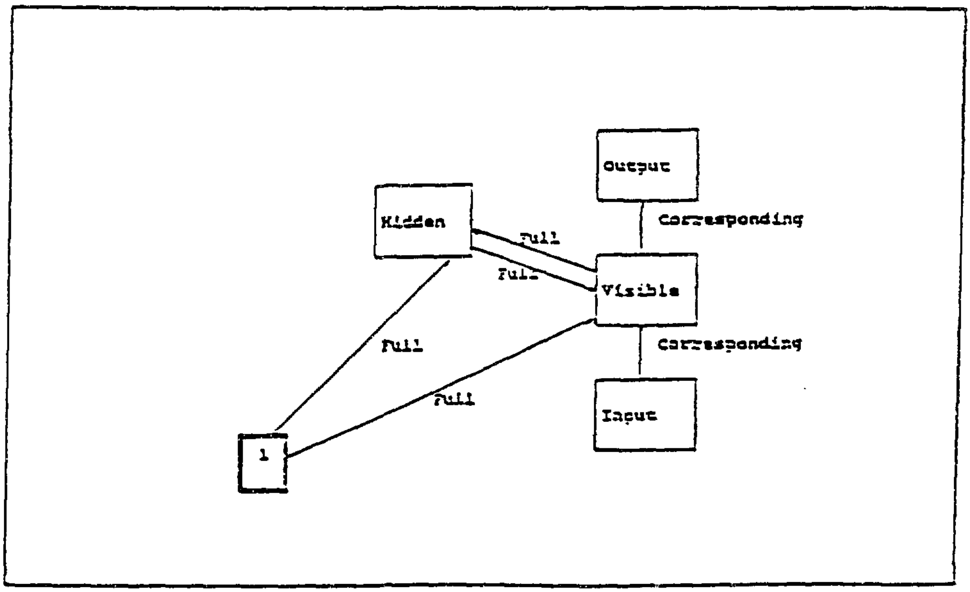

Figure 2. Recirculation Network Architecture.

Note: Connections marked "Full" indicate fully connected layers. Connections marked "Corresponding" have one-to-one connections.

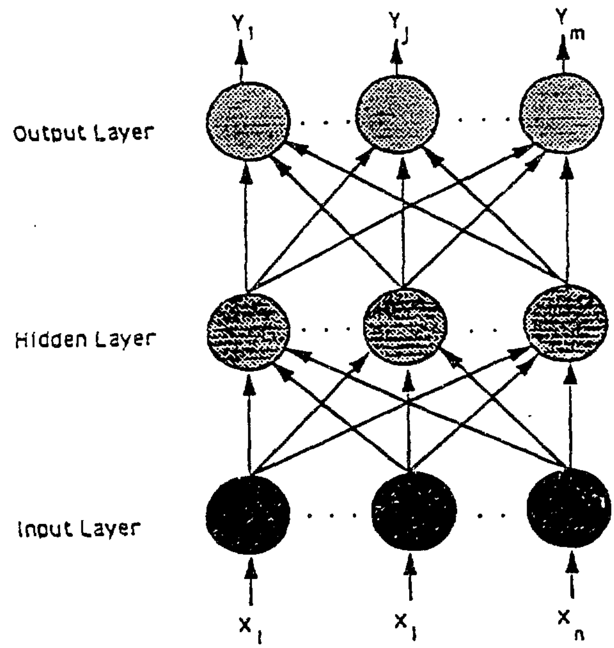

Figure 3. Three-layer Neural Network Architecture.

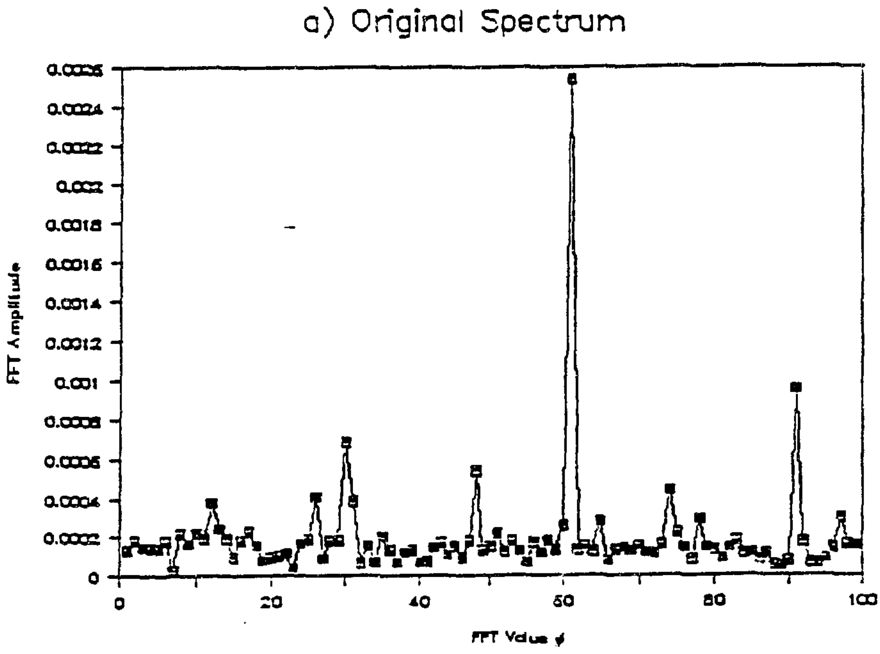

Figure 4a. Original Spectral Signature.

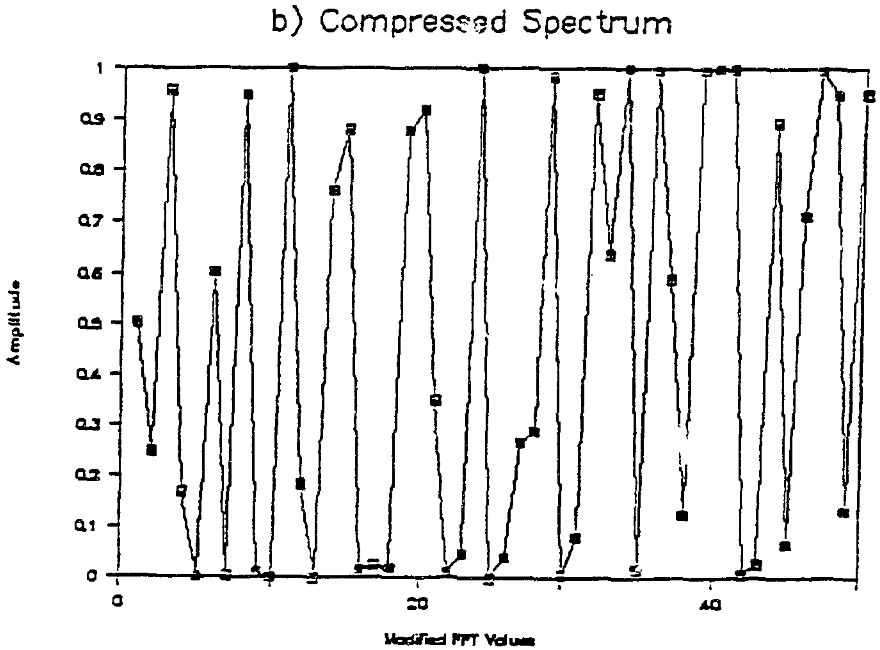

Figure 4b. Compressed Spectral Signature.

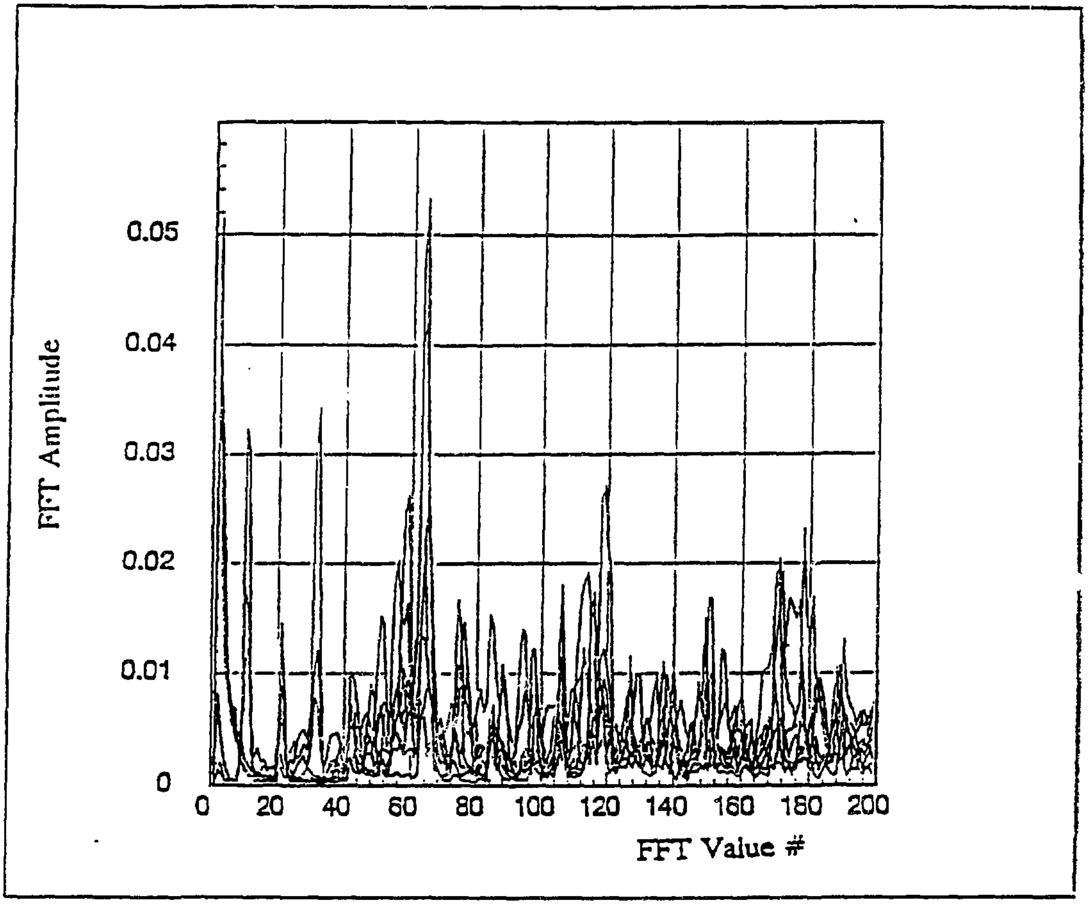

Figure 5. Vibration Levels Recorded by Different Sensors on the Same Machine.