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Low-Cost Mechatronic Systems for Teaching Condition Monitoring*

A. AL-HABAIBEH AND R. M. PARKIN
Mechatronics Research Centre, Wolfson School of Mechanical and Manufacturing Engineering, Loughborough University, LE11 3TU, UK. E-mail: a.al-habaibeh@lboro.ac.uk

One of the biggest problems facing the mechatronics field is the high cost of sensors and systems, which makes it difficult for educational institutions to experimentally teach a large number of students the principles of mechatronics. This is particularly the case in developing countries. This paper reports a simple system to teach students the basics of mechatronics by experimentally implementing a condition monitoring system for bearings using sound waves. The experimental work is performed in a cost-effective way. The extracted signals are analysed using a variety of techniques, including time and frequency domain signal processing methods and neural networks, in order to recognise faulty and normal conditions. The experimental work described in this paper has been found to be a crucial stage for the students in developing the necessary knowledge of mechatronics and the concepts behind embedded monitoring and control systems using a low-cost approach.

INTRODUCTION

MECHATRONICS is the synergistic integration of mechanics, electronics, embedded control and IT in the design and realisation of intelligent products, processes and systems. 'Hands-on' engineering experiments are needed in order to provide mechatronic students with the technical and research skills they will need as professional engineers. Many mechatronic experiments and laboratories available for students in most universities would require expensive equipment such as data acquisition systems, sensors, pre-amplifiers and control systems. This does not allow mechatronics to expand rapidly, due to financial restrictions, particularly in the developing countries.

A generic condition monitoring system is described in Fig. 1. A condition monitoring system normally includes a sensor, or a group of sensors, to extract the information about the system which is to be monitored. In most cases, the signals cannot be utilised directly, as signal processing and simplification methods are needed to retrieve the necessary information about the process. A decision-making stage is then implemented to categorise the normal state of the monitored system and identify any deviations from the norm. This is an important stage for classifying the extracted information by the sensors and taking a decision regarding the state of the process. The decision-making strategy alters, according to the application, from a simple threshold value to more complex strategies such as using neural networks. In a modern mechatronic condition monitoring system, the information is extracted using an appropriate sensor(s) and the signals are then amplified to a suitable level so that they may be digitised and read by a data acquisition system. The data is passed to a computer system for analysis and in order for the data to be categorised as being from a 'faulty' or 'healthy' source. In order to teach aspects of condition monitoring systems to mechatronic students, the experiment would require at least a single sensor with its amplifier, a data acquisition card and a computer system to store the data for analysis. Sound-wave signals have been reported for successful condition monitoring of a variety of systems such as machining operations [1], rolling element bearings [2], machinery in noisy environments [3] and fluid dynamics [4]. They have also been used for modelling the dynamics of a simple impact problem [5]. This paper presents an approach to develop a low-cost condition monitoring system for teaching mechatronics students the principles of condition monitoring based on low-cost experiments that utilise sound waves as the main sensory signals.

EXPERIMENTAL WORK

The experimental arrangement is shown in Fig. 2. A low-cost microphone is used as the sensor to extract information about the monitored system. The system to be monitored is a simple mechanical system which consists of a DC motor, a belt and a simple replaceable roller that has two bearings. The tension on the belt can be adjusted to change the loading on the monitored bearing. The experimental procedure consists of two stages, comparing a new roller and an old roller (which contains two worn bearings). The mechanical

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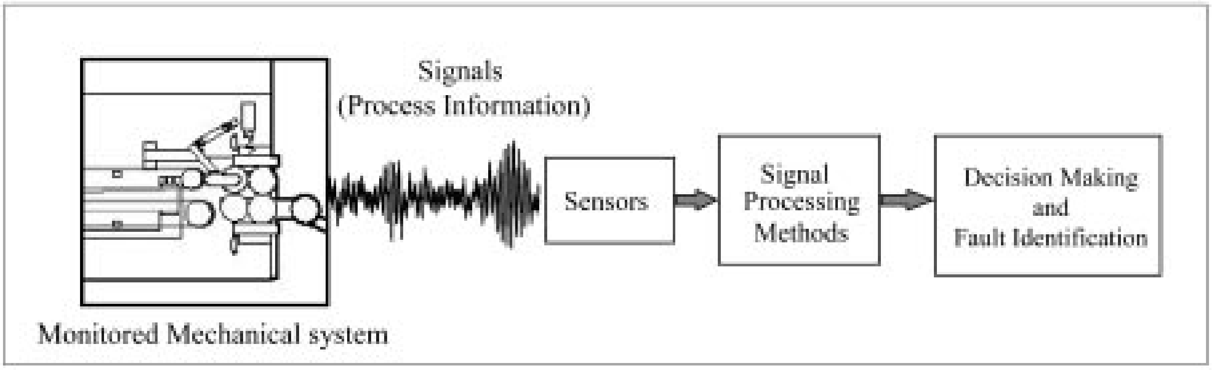

Fig. 1. A general structure of a condition monitoring system.

system is simple and can be built by every student. It should not cost more than $12 for it to be built in reasonable quantities. The students are expected to assemble their own mechanical system before conducting the experiment, as this aids the development of manual skills. The microphones cost $3 each. The reported experimental work utilises the stereo sound card, available in almost every modern PC computer system, as a data acquisition system.

The advantage of using a standard sound card is that it allows the monitoring of two channels at a rate of up to 44 k sample/second in 16 bits resolution. Figure 3 shows the application of a standard sound recorder to acquire the sound waves of faulty and healthy bearing using a PC sound card.

Another advantage of using sound waves to monitor bearings is that students could play the files and listen to the noise produced in order to attempt to manually differentiate between the two types of bearings before using mathematical analysis. This makes it easier for students to understand the need for signal processing and analysis. The experimental set-up described is also used to teach students the A/D concepts as an important aspect of modern data acquisition and condition monitoring, including the effect of sampling rate and resolution on the acquired signals. This gives the students the possibility not only to draw the signals but also to listen to them and to differentiate between them and investigate how sampling rate and resolution would influence the final results. A brief example of some typical results found during a test at a roller speed of 100 rpm is presented. This is only an example of the type of experimental work and analysis that can be performed on the system; the range of experiments can easily be extended to provide a laboratory exercise of two or three hours duration.

DATA ANALYSIS TECHNIQUES

The sound waves are captured in .wav format. Once the .wav files are saved on the computer, students utilise the capability of MATLAB® software to retrieve the signals using the 'wavread' command, draw them on the screen and write their

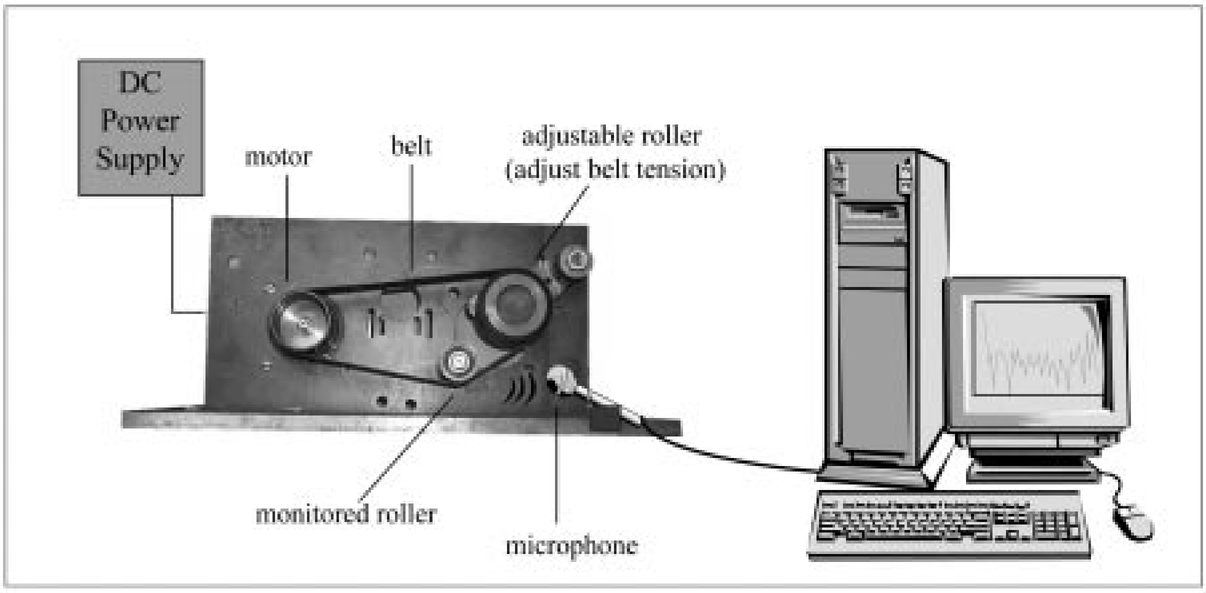

Fig. 2. The low-cost condition monitoring system.

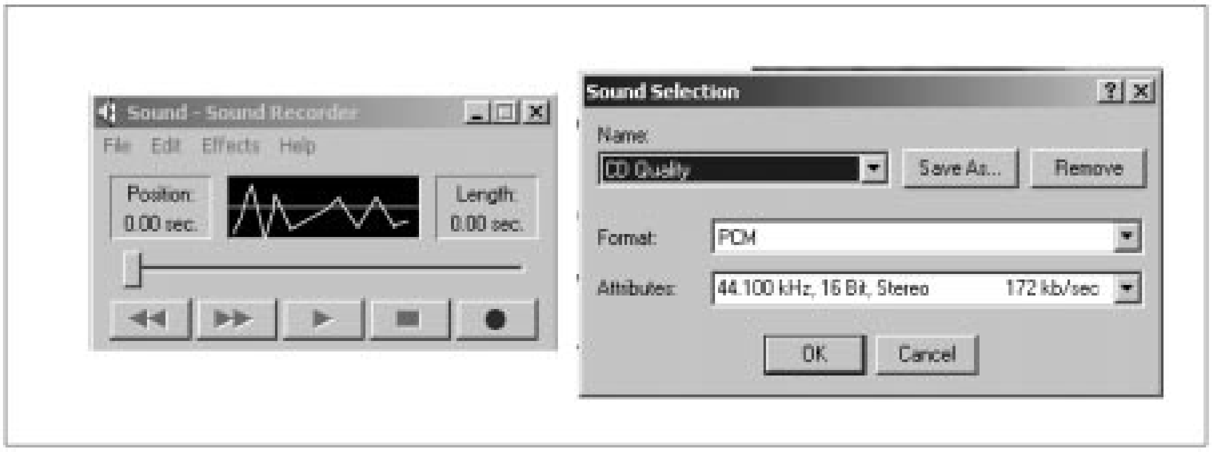

Fig. 3. Using a standard sound recorder to record the data.

own code to perform different types of analysis. Students need to perform the basic analysis as described below. Every student is then expected to perform a separate investigation to find the optimum results for his/her own experiment. However, this paper describes typical examples of the implemented signal processing and decision-making methods and their results.

SIGNAL PROCESSING METHODS

It is desirable that every student should be able to use several signal processing and pattern recognition techniques. Students are encouraged, in the laboratory session, to use several signal processing techniques in order to compare between them. Some of the suggested signal processing methods in the laboratory, in the time domain, are: the average (μ); standard deviation (σ); power [6]; kurtosis value (K) [7]; skew value [8]; and range. Frequency domain methods such as fast Fourier transformation (FFT) are also used [9]. Clearly more techniques may also be used (see [10]), and the analysis is not limited to the methods described.

The mathematical descriptions of the implemented signal processing methods are described below for a sample of length N:

$$\text{average: } \mu = \frac{\sum_{i=1}^{N} x_i}{N} \quad \text{where } x \text{ is the sensory signals} \tag{1}$$

$$\text{standard deviation: } \sigma = \sqrt{\frac{\sum_{i=1}^{N} (x_i - \mu)^2}{N-1}} \tag{2}$$

$$power \approx \frac{\sum_{i=1}^{N} x_i^2}{N} \tag{3}$$

$$\text{Kurtosis value } Kr = \frac{1}{N} \sum_{i=1}^{N} \frac{(x_i - \mu)^4}{\sigma^4} \tag{4}$$

$$Skew = \frac{1}{N} \frac{\sum_{i=1}^{N} (x_i - \mu)^3}{\sigma^3} \tag{5}$$

$$\text{Range R} = \text{maximum value} - \text{minimum value} \tag{6}$$

The FFT algorithm is used to convert a digital signal (x) with length (N) from the time domain into a signal in the frequency domain (X).

$$X[h] = \sum_{i=0}^{N-1} x[i] W_N^{ih} \quad \text{Where} \quad W_N = e^{-J2\pi/N}. \tag{7}$$

for $h = 0, 1, 2, \ldots, N-1$ and where $J = \sqrt{-1}$.

NEURAL NETWORKS

Back propagation neural networks are used as a methodology to explain artificial intelligence. Neural networks are an expanding field of interest in the area of condition monitoring, which is important in teaching students mechatronics. In theory, neural networks are able to learn complex relationships between inputs and outputs without a previous knowledge of the system or any of its mathematical models [11]. This gives the students the capability to design an automated system that learns from experience without the need to preview the signals to look for the information. If the number of classes or categories is known, then neural networks could allocate the input data into these classes. The main advantage of using neural networks is the full automation of the learning and classification process. MATLAB® software and its standard Neural Networks Toolbox are used to perform the neural networks analysis [11]. A back propagation neural network (BPNN) is selected to explain the neural networks concept. The back propagation neural network is a

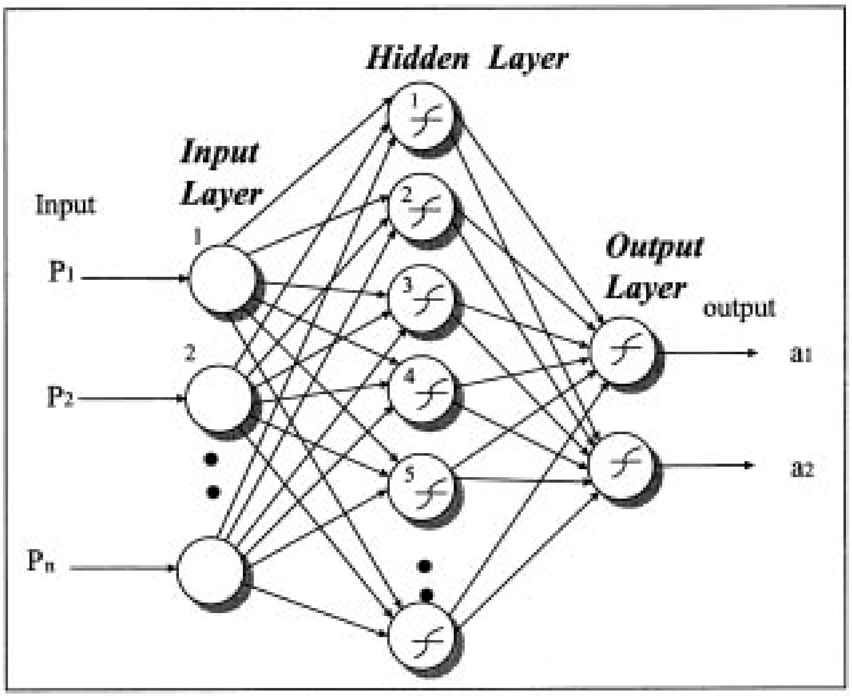

Fig. 4a. Back propagation neural networks.

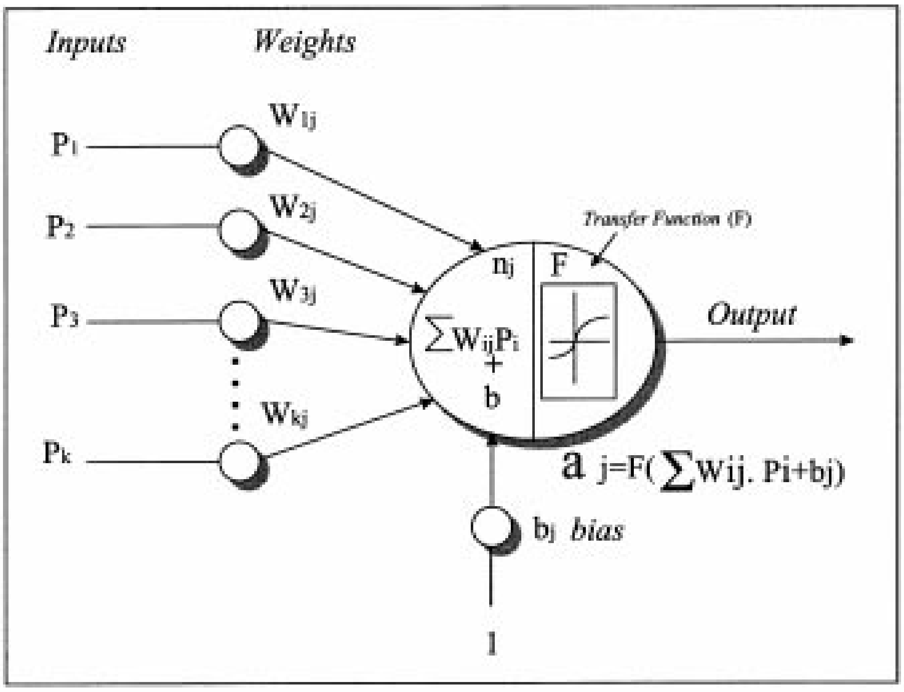

Fig. 4b. A back propagation neuron.

supervised neural network, which consists of n number of neurons connected together to form an input layer, hidden layers and an output layer. A back propagation neural network is shown in Fig. 4a. A basic back propagation computational element is illustrated in Fig. 4b. The node or neuron can have several inputs but only one output.

The BPNN used in this work uses a Sigmoid function in the hidden layer and the output layer which has been found to be the most suitable to use in this application; see equation (8).

$$f(n_j) = \frac{1}{1 + e^{-n_j}} \tag{8}$$

The most important characteristic of neural networks is the ability to learn or to be trained. The training or learning process is performed through the change in the connection weight values that result

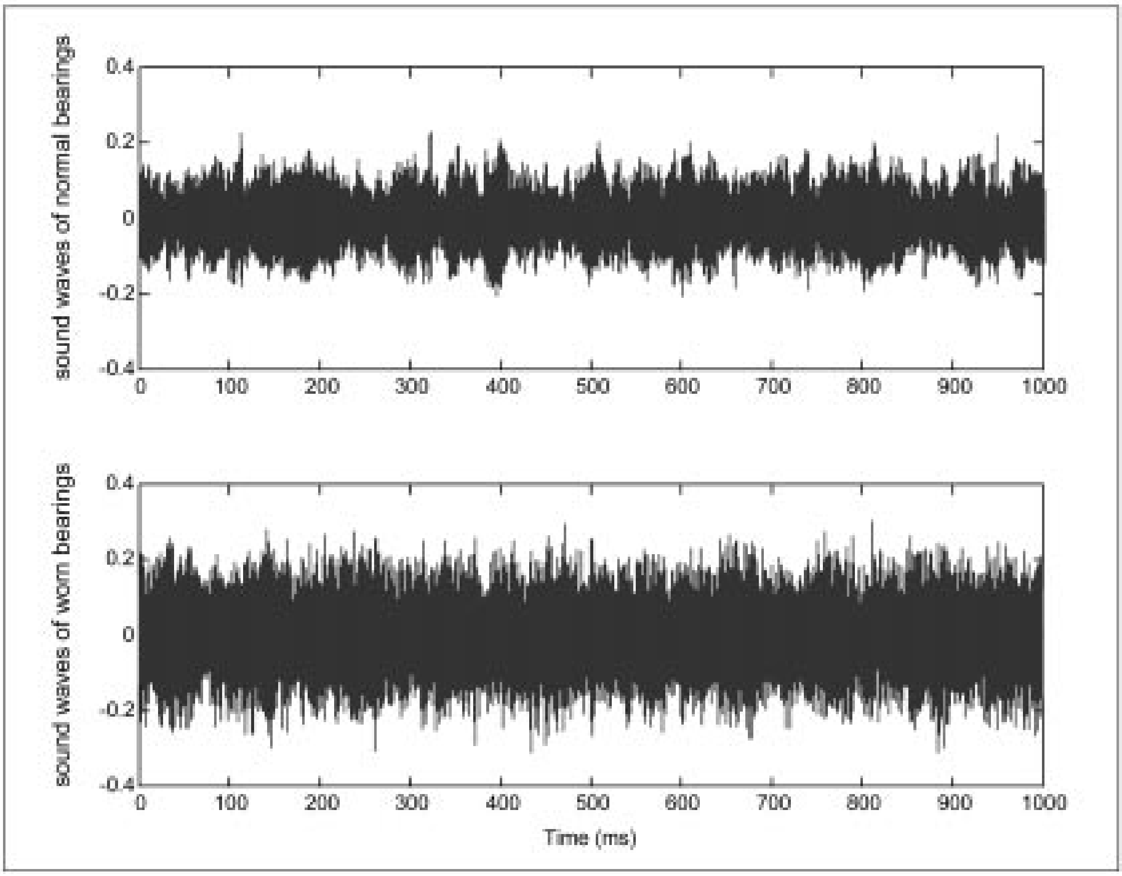

Fig. 5. Sound waves of normal and worn bearings.

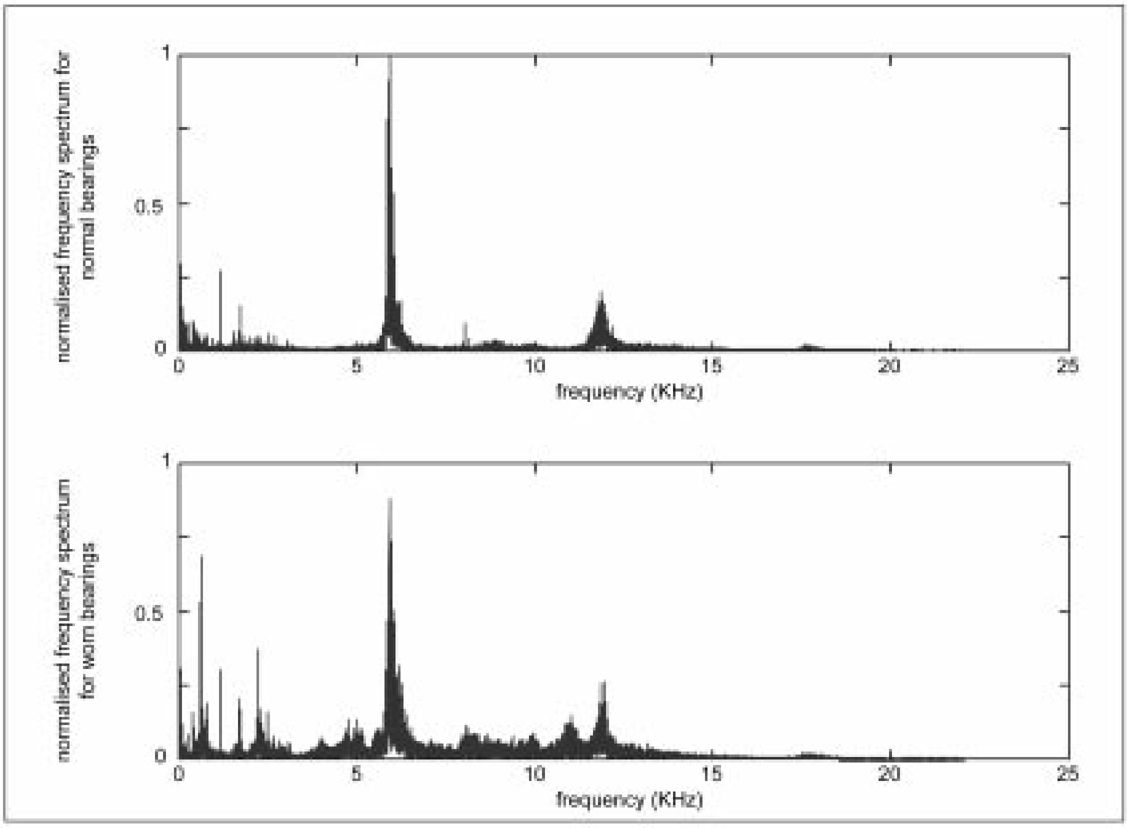

Fig. 6. Comparison between the frequency contents of normal and worn bearings.

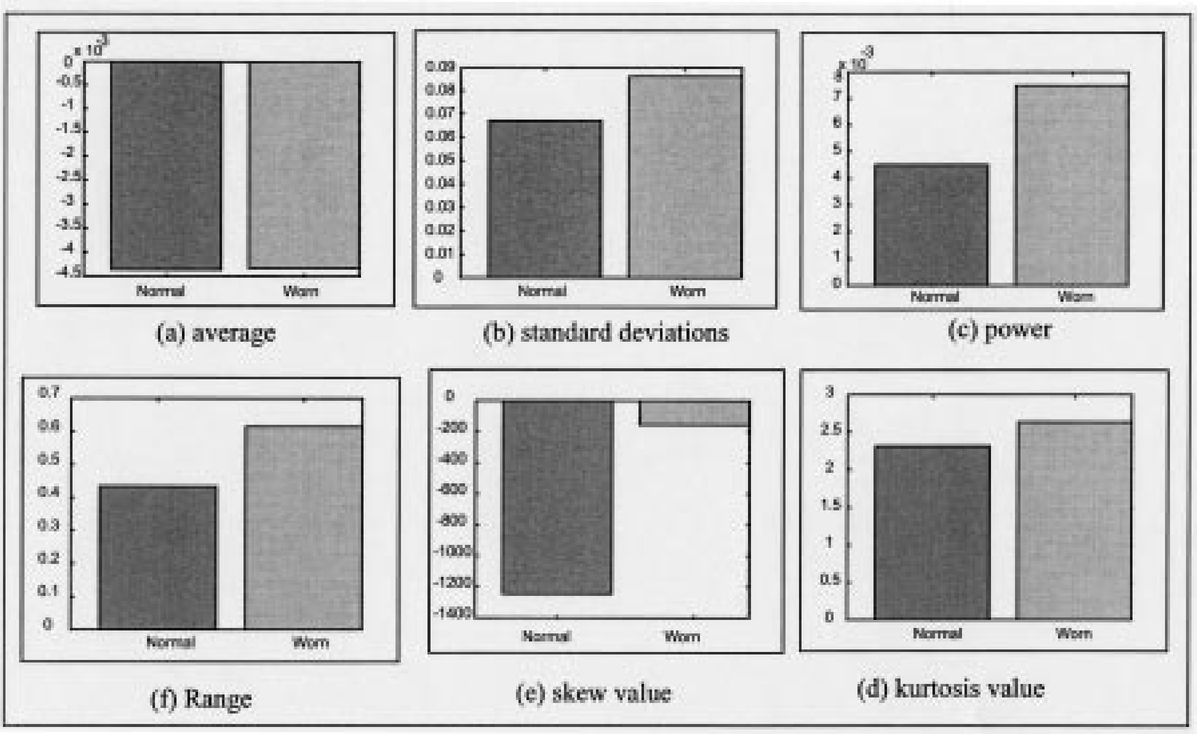

Fig. 7. Comparison between some statistical values of normal and worn bearings.

in the capture of information that can later be called. Supervised training is done by iteratively adjusting the weights to minimise the error between the output and the target. As shown in Figs 4a and 4b, neural networks with three layers are used. The target error and the learning rate used are 0.01 and 0.009 respectively, with a maximum number of iterations of 50,000. More information concerning BP neural networks and their learning algorithms can be found in detail in Haykin, Demuth and Beale, and Pao [11, 12, 13].

RESULTS AND DISCUSSION

Figure 5 shows an example of the acquired sound signals for normal and worn bearings. The students are asked to analyse their graphs and listen to the sound waves before undertaking any signal processing methods, in order to evaluate the use of signal processing techniques.

Following the examination of the acquired signals, programming of different signal processing methods is needed to compare some of the features. Figures 6 and 7 show a comparison

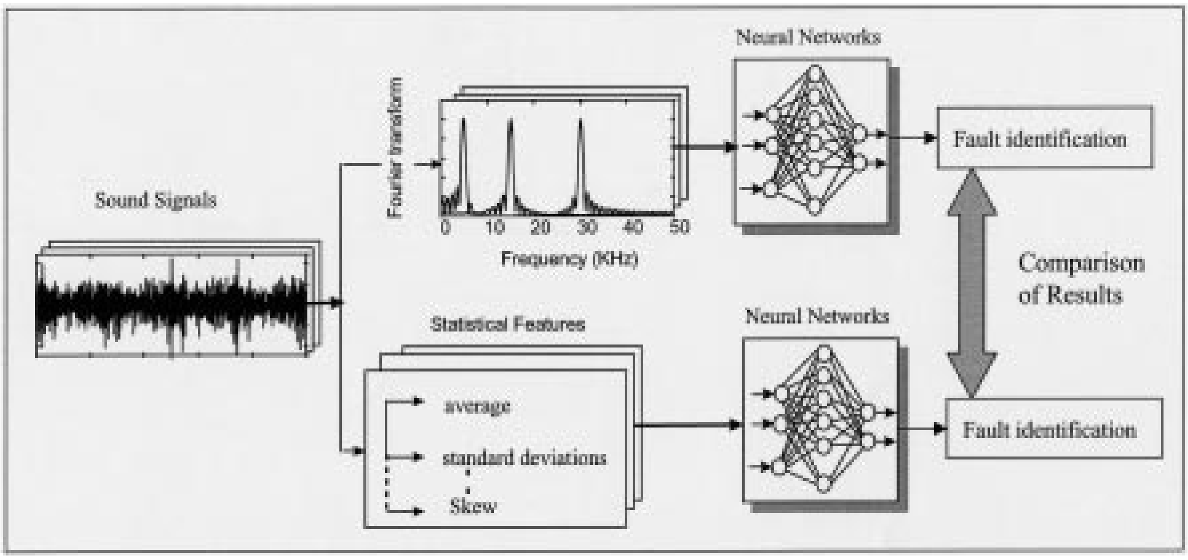

Fig. 8. Comparison between using statistical methods and Fourier transformation.

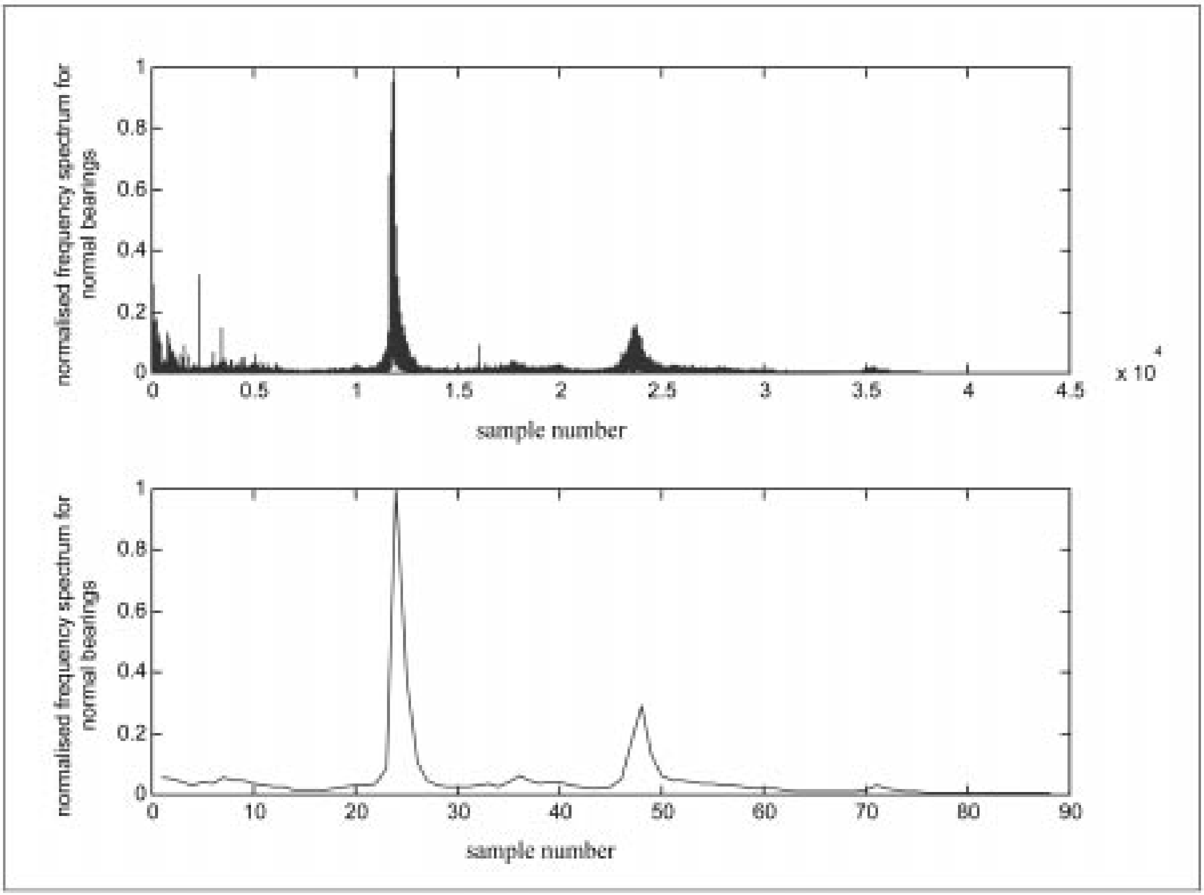

Fig. 9. Averaging FFT spectrum for better neural network response.

between the features of normal and faulty sound signals using Fourier transformation and statistical methods. As shown in Fig. 6, the frequencies between 7 kHz and 11 kHz are much higher for the worn bearing. The same can be said for 1 kHz to 5 kHz. Figure 7 presents the statistical features obtained. It has been found that the skew values and the power of the signals are the most sensitive to bearing faults.

THE APPLICATION OF NEURAL NETWORKS

As shown in Fig. 8, two basic analysis steps are performed using back propagation neural networks: the application of FFT as an input to the neural networks and the use of the statistical features as another input. Ten signals from every type are acquired for analysis. Two are used for training the neural networks and the other eight for testing them. When using the complete frequency spectrum for the neural networks (i.e. using 44,100 inputs), the neural network training was extremely slow and impractical. Therefore, every 500 samples are averaged to reduce the number of inputs to 88 inputs with 100 neurons in the hidden layer. Figure 9 presents the complete frequency spectrum for one of the samples and its associated input to the neural networks following the sample reduction.

The statistical values are also used to train another neural network with six inputs and 10 nodes in the hidden layer. Every test was repeated 100 times for both neural networks and the average errors of the eight tests are presented in Fig. 10.

As shown in the figure, the frequency spectrum neural networks have a much better response where 92 independent training and testing events of the neural networks have zero error in the classifying of patterns. However, the statistical features have an average error of between 5% and 40% in all the 100 independent training and testing trials.

CONCLUSIONS

The design and realisation of condition monitoring systems is a multi-disciplinary field of mechatronics which requires experience in sensors, amplifiers, signal processing methods and artificial intelligence. Condition monitoring systems often require expensive hardware in order to facilitate experimental or research work. This paper has described using a computer sound card and a low-cost microphone to develop the necessary components of a condition monitoring system for

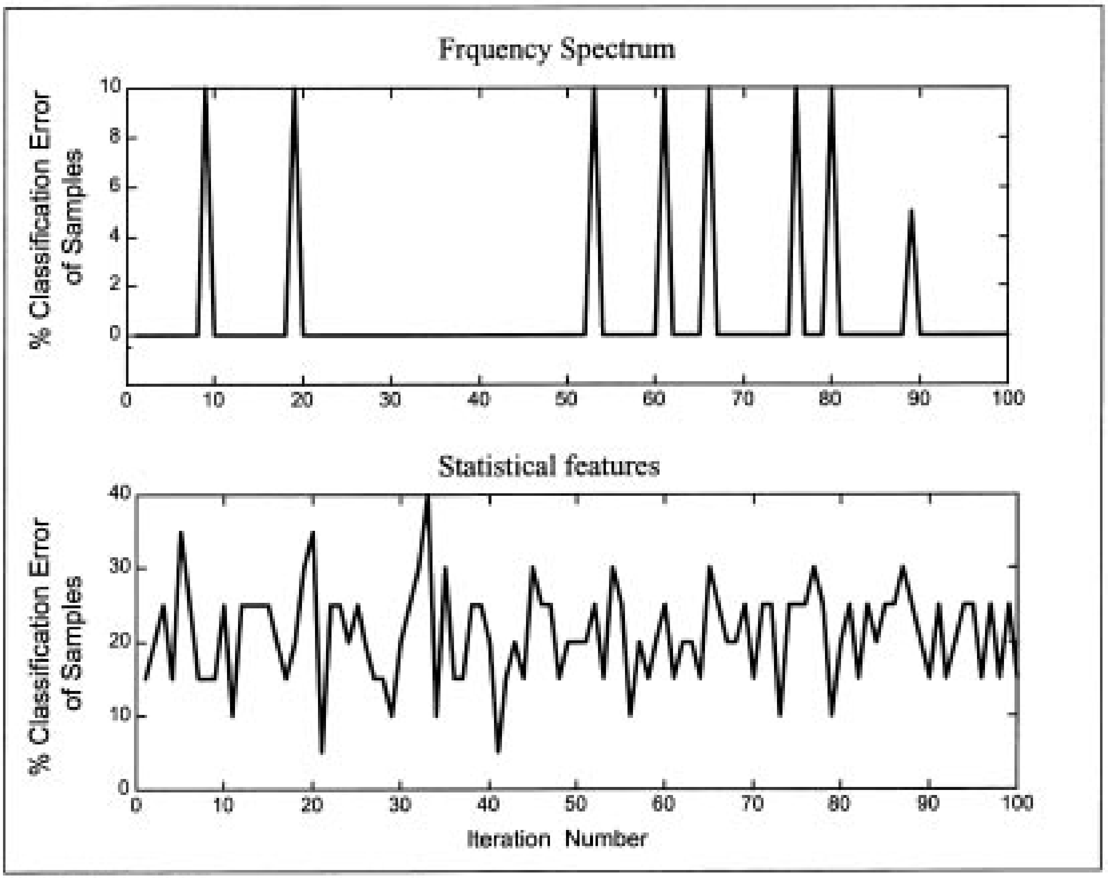

Fig. 10. Neural networks results.

education and training purposes. The paper also reported a low-cost mechanical system which can be used to monitor bearing health, belt tension and speed of rotation using a simple mechanical system. The system can also be used to teach students the principles of sampling and A/D conversion. Several signal processing methods combined with the application of neural networks are suggested to develop a complete suite of analysis and decision-making algorithms. The results show that the suggested system could provide a successful low-cost solution for helping mechatronic institutes to develop comprehensive condition monitoring experiments.

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