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Neural networks applications in condition monitoring

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Abstract

Condition monitoring is the term used to describe a combination of techniques for implementing a condition-based maintenance strategy on industrial machinery. Data such as vibration levels (both overall and in terms of frequency spectra), temperature, oil analysis etc, are acquired from plant, and analysed to determine the condition of that plant at the time of measurement.

Software packages provide a graphical display of the data, and most provide some form of diagnostic tools to assist engineers in performing data analysis. Rule-based expert systems are available to perform machinery defect diagnosis, with varying degrees of automation and human interaction. However, such systems have inherent problems, such as their ability to deal successfully only with clearly defined problems within a narrow band of parameters, and their inability to cope with contradictory, incomplete, or "noisy" data - just the type of data found in many real-world applications.

This paper describes the implementation of an off-line condition monitoring system at Blyth Power Station, one of the stations owned by National Power in the United Kingdom. It explains the application area and the type of data acquired. The paper then goes on to describe the neural network models which have been developed to analyse condition monitoring data, both at Blyth Power Station, and by the Neural Applications Group at Brunel University.

1 Introduction

Blyth Power Station is part of National Power, the major electricity generating company in the United Kingdom. The Station occupies a 241 acre site on the North East coast of England, approximately 15 miles north of Newcastle-upon-Tyne. The site comprises two stations, Blyth 'A' and Blyth 'B', with a combined generating capacity of 1,180 megawatts. Blyth 'A' was commissioned in June, 1960, and Blyth 'B' in September, 1966. Blyth 'A' consists of four 120MW generating units, and Blyth 'B' two 350MW units.

The age of the plant, on-going reductions in maintenance resources, and increased commercial pressures as a result of privatisation, have combined to create a requirement within the Station to move away from the traditional, manpower-intensive strategies of Planned or Breakdown Maintenance, towards a Condition Based Maintenance policy for critical areas of auxiliary plant [1]. The Station management recognised this requirement, and in September, 1992, entered into a collaborative agreement with the University of Sunderland to establish a SERC (Science and Engineering Research Council) funded project whose aim would be to develop and implement an intelligent condition monitoring system for use within the Station.

2 Condition Monitoring

Blyth Power Station began implementation of an off-line condition monitoring system on various items of critical auxiliary plant in January, 1993. The system involves the capture of various types of data from items of plant which can be analysed to give a diagnosis of the operating condition of the machine. Typically, data captured include vibration levels, temperatures, oil samples, and various process parameters such as pressures and load currents. This data is collected off-line, using a portable data collection instrument - the PL31b-01, manufactured by Diagnostic Instruments Ltd., in Scotland - for the vibration, temperatures etc, and a simple syringe kit for oil samples. Data collected with the portable instrument is then automatically uploaded into a specialised predictive maintenance database package from Entek Scientific Corporation, who are based in Cincinnati, which allows graphical plotting and trending of the data, and provides various analysis aids such as spectral alarm levels and frequency identification techniques. Oil samples are sent to a specialist laboratory and specific values from the resulting reports are manually entered into the database. Previous papers [2,3] describe in detail the operation of the condition monitoring system at Blyth, and Figure 1 below shows the basic outline of how the system has been developed and implemented.

However, it is the analysis of the collected data and subsequent diagnosis of the condition of each machine being monitored, with the objective of either performing maintenance before the machine fails or deferring planned maintenance which is deemed to be unnecessary, which is the most difficult task. This function essentially relies on the experience and expertise of a

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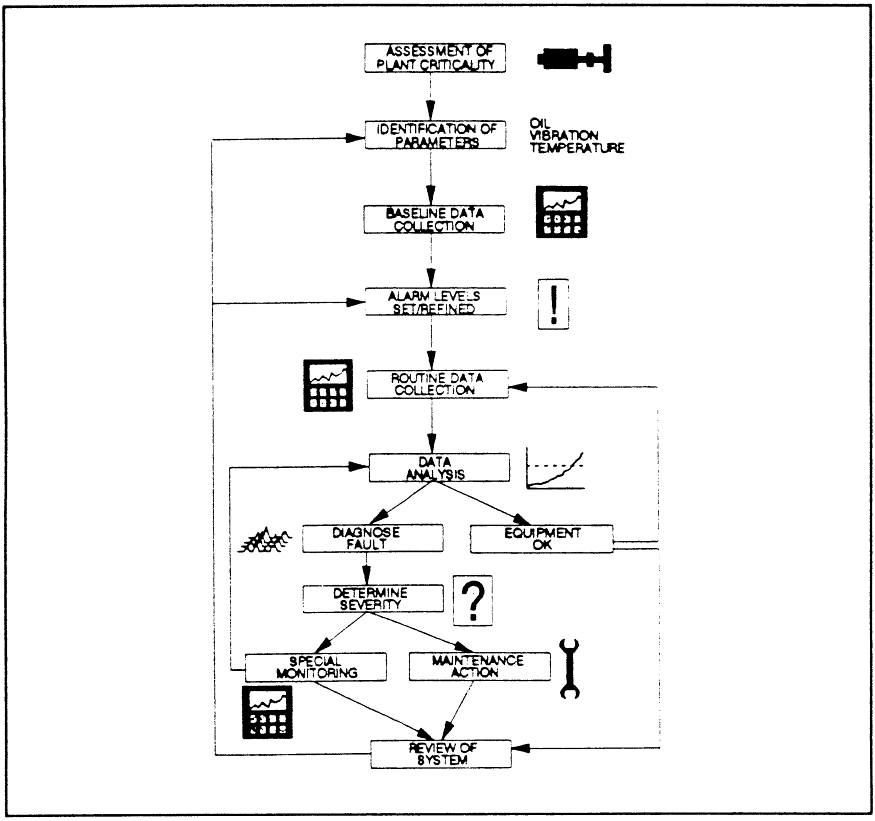

Figure 1 - Schematic of Condition Monitoring System at Blyth

maintenance engineer in interpreting the data, albeit with the aid of some of the diagnostic functions of the software. This introduces into most condition monitoring systems a potential for errors, either through the lack of an appropriately qualified engineer, or through human error. Nevertheless, condition monitoring has been successful in many areas of industry, and the Blyth system has correctly identified defects prior to failure, thus allowing maintenance action to be taken, and identification of areas where planned maintenance actions could be deferred. This has generated significant financial benefit for the Station, with a substantial return on investment in hardware and software.

2.1 Typical Condition Monitoring Data

Figure 2 below shows a vibration spectrum captured from the inboard bearing on a Primary Air Fan. The spectrum is obtained by performing a Fast Fourier Transform (FFT) on the time domain vibration signal, after a band pass filter and envelope filter have been applied to it. The spectrum plots vibration frequencies against amplitudes, in this case in acceleration (g). In this spectrum, a large peak is visible at the frequency specific to an outer race defect (ORD). Inspection of the bearing confirmed that an outer race defect existed, and the bearing was replaced. Figure 3 shows the spectrum after replacement, with no significant outer race peak.

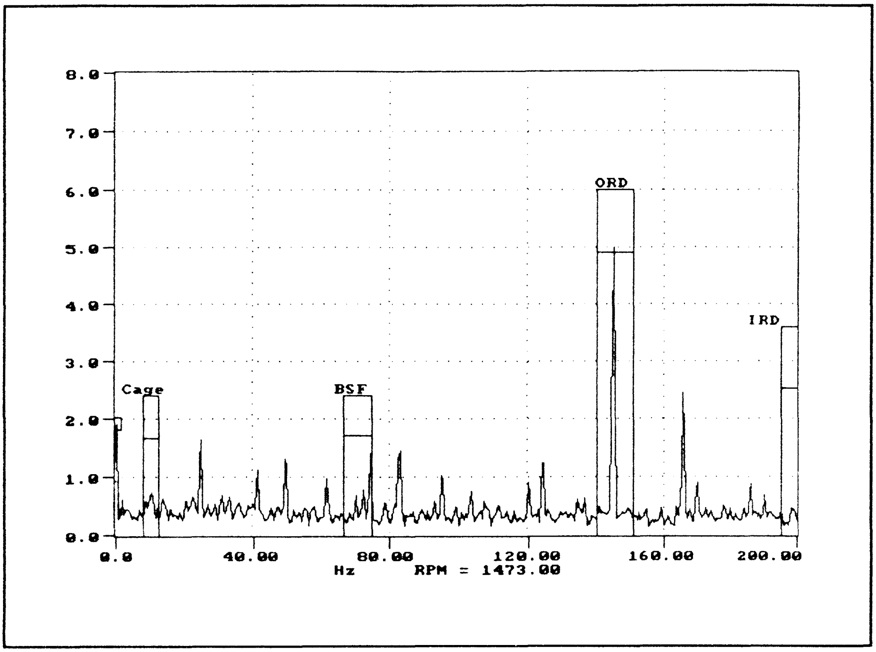

Figure 2 - Vibration spectrum of Primary Air Fan bearing, clearly showing outer race defect

The above are examples of clear and well-defined spectra which show distinct characteristics relating to the bearings. However, in many cases the data is far more difficult to analyse, due to background noise, low frequencies and amplitudes, difficulty of access for measurements etc. Figure 4 shows a vibration spectrum acquired from a Coal Pulveriser Gearbox; the general level of noise, plus the fact the defect frequencies are in the low end of the spectrum and therefore can be masked by the background vibration, make this a much more complex problem for analysis [3,4]. In the case of the Coal Pulveriser Gearbox, samples of the lubricating oil are taken and analysed, and certain values from the resulting data are trended [5]. Figure 5 below shows the trend plot of the ferrous content (parts per million) of the oil from one such gearbox. This information is used to help in diagnosing the condition of the gearbox, with vibration data such as is shown in Figure 4.

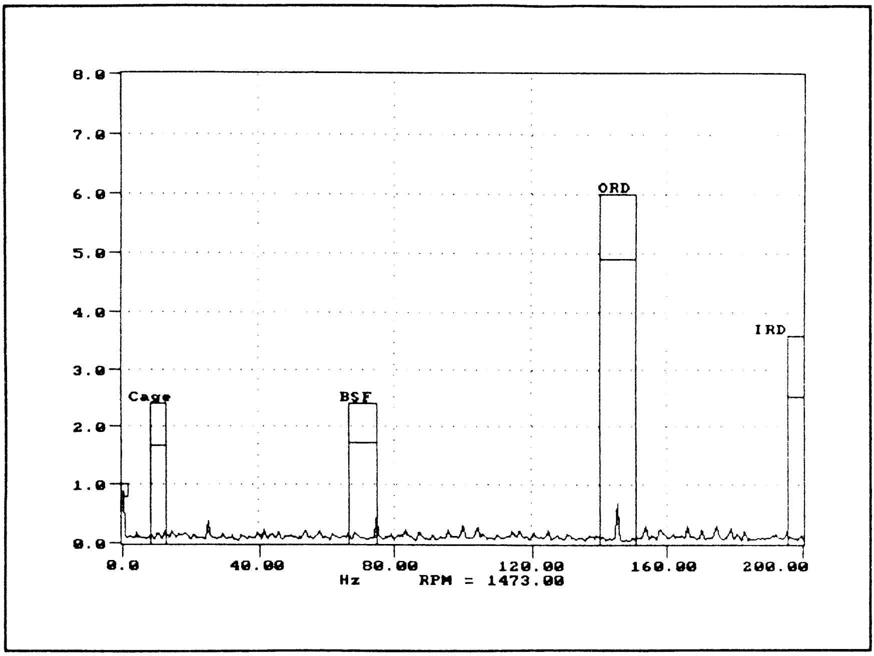

Figure 3 - Vibration spectrum after replacement of fan bearing

3 Neural Networks Applications

The data analysis function in condition monitoring involves diagnostic and decision-making tasks, and it is natural that, as artificial intelligence techniques for automating such tasks have developed, so attempts would be made to apply them to condition monitoring. Furthermore, the evolution of AI techniques has been such that the main area of interest and applications development has been (until recently) that of expert systems. Recently, however, attention has been turning to the potential for neural networks to perform some of the more complex data analysis. Burrows [6] identifies the need for automated systems to improve the decision-making process in plant maintenance; Broomhead and Jones [7] show the difficulty of analysing chaotic signals; Harris [8], and Javed and Littlefair [18] demonstrate that neural networks can be used for data analysis and diagnosis where complex data patterns are experienced.

A number of proprietary software systems have been developed using knowledge-based approaches for condition monitoring diagnostics. Some of these rely on a high degree of inter-activity with the user in terms of question-and-answer input, where the user's answers provide the condition statement of an IF {condition} THEN {statement} clause in the rule base. Milne [9], and Armor *et al* [15] give details of a number of such knowledge-based developments.

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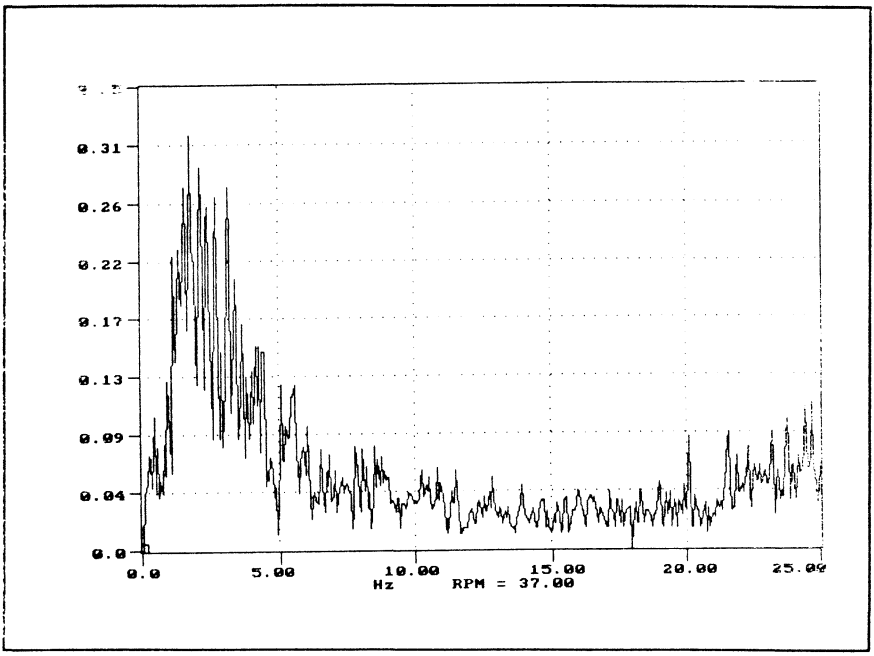

Figure 4 - Vibration spectrum taken from a Coal Pulveriser Gearbox

3.1 Authors' Application of the Multi-Layer Perceptron

At Blyth Power Station, a neural network model has been developed for the analysis of vibration spectra from the Primary Air Fan bearings. This network is based on the Multi-Layer Perceptron (MLP) architecture, using the back propagation training algorithm. The use of back propagation allows the adjustment of weights in the neural connections in multiple layers; this is critical if a network is to solve non-linearly separable problems [10,11]. The MLP architecture using back propagation relies on a technique referred to as "supervised training", in which an input vector (that is, a numerical representation of the input pattern, in vector form) is presented to the neural network along with a target ouput vector (a numerical representation of the desired output for the given input, again in vector form). The actual output is compared to the target output for each input vector, and the root mean squared (RMS) error is calculated. This error is then propagated backwards through the neural connections, and the process is repeated until the RMS error is within an acceptable threshold, typically 0.001 [10,11,12].

The Neural Bearing Analyser (NBA) model was developed initially in two versions; the first took only certain areas of the vibration spectrum as the input vector, and had a relatively large output set, with separate classes for each of the bearing components, and different levels of defect severity. The second version involved presentation of the full vibration spectrum (400 datum points)

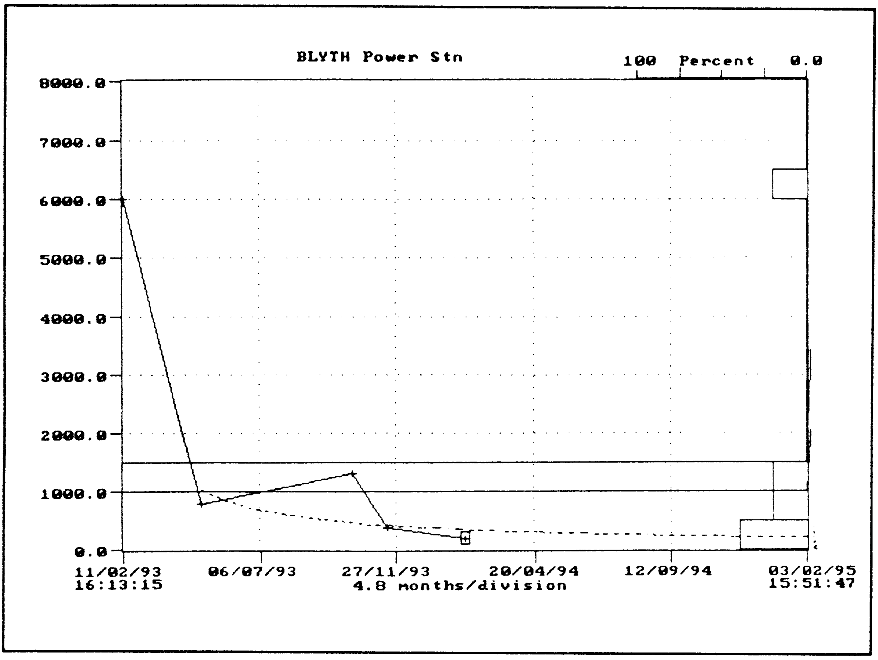

Figure 5 - Trend plot of the ferrous debris (parts per million) in the Coal Pulveriser Gearbox lubricating oil

to the network, and a simplified output set, with condition estimates for the bearing as a whole. In both cases, training data sets were constructed from real data collected from Station machinery, where the target ouput could be confidently generated as a result of known bearing condition due to inspection or replacement of bearings. Figure 6 below shows the input and output sets for both versions of the model. Testing of the model was performed both with real data acquired from the Primary Air Fans, some of which had known conditions from inspection, and also with artificially-generated data to examine the network's performance in identifying particular defect types. The network's classifications were compared with known condition data, and also with the classifications of a consultant condition monitoring engineer.

Version 1 of the model demonstrated the well-documented difficulties of back propagation [10,11] in achieving convergence to within an acceptable RMS error level. To achieve convergence it was necessary to alter the learning parameters in order to avoid the algorithm sticking in local minima. Convergence was eventually achieved, and in testing the network produced 93% agreement with the consultant engineer's classifications.

Version 2 of the model proved much more difficult to train effectively. Convergence was only achieved after raising the RMS threshold to 0.01, and much "tweaking" of the learning parameters. Running on a 33Mhz 486 PC, the

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NEURAL BEARING ANALYSER MODELS			
VERSION 1		VERSION 2	
INPUTS	OUTPUTS	INPUTS	OUTPUTS
Spectrum Carpet Level (g)	Bearing in good condition	Full 400-line vibration spectrum, giving 400-dimensional input vector	Bearing OK
Cage Freq. (g)	inner race - slight wear		Slight damage
Ball Spin Freq. (g)	inner race - moderate damage		Moderate damage
Outer Race Freq. (g)	Inner race - significant damage		Significant damage
Inner Race Freq. (g)	Inner race - serious damage		Serious damage
2x Outer Race (g)	inner race failure		Imminent failure
2 x Inner Race (g)	Outer race - slight wear		
Outer Race Freq. Sidebands (g)	Outer race - moderate damage		
2 x Outer Race Sidebands (g)	Outer race - significant damage		
Inner Race Sidebands (g)	Outer race - serious damage		
	Outer race failure		
	Rolling elements - slight wear		
	Rolling elements - moderate damage		
	Rolling elements - significant damage		
	Rolling elements - serious damage		
	Rolling element failure		

Figure 6 - Table showing inputs and outputs for both versions of the Neural Bearing Analyser at Blyth Power Station

network took almost 1.5 hours to train, using over 100,000 training iterations. In training, this version of the network performed less well than Version 1, with only 81% agreement in classifications.

The same basic training data was used for both versions, and testing has revealed that the mis-classifications were due to a flaw in the training set; one type of defect was missing entirely from the data, and hence the network had not been trained to recognise it. This type of defect rarely occurs and very little of this type of data is available; the authors are examining the possibilities for artificial generation of data to correct this deficiency.

Future work will examine the use of Radial Basis Function (RBF) network models with the same data, and it is expected that significant improvements will be seen in training times; however, there is a need to ensure that the centres of the reduced RBF set are correctly positioned, and that the resultant hyperplane approximates the decision surfaces accurately, but still offer some immunity against noise in the data. Mayes [16] and O'Brien [17] both give details of some work has been done on the use of Radial Basis Function networks in diagnosis.

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3.2 Authors' Application of the Kohonen Self-Organising Map

The Neural Applications Group at Brunel University have examined the potential of another neural network architecture, namely the Kohonen network, which is an example of a self-organizing map using "unsupervised learning". Here the output layer is a grid of interconnected nodes, all of which are fully connected to the input vector. A competitive learning algorithm is used in which the output neurons compete with each other to present the highest value in the output vector. In this case, frequency spectra values are used as vector inputs and the Kohonen network is trained with vibration data from a machine in good condition. In its monitoring mode, vibration frequencies are presented to the network and the winning node identified. The error distance between the input and the winning node is calculated and used as a measure of the machine's "health". As a fault develops the input vector will move away from the nodes in the network, and thus the error distance will increase giving a warning that a fault is developing. This system, however, can only detect a fault, and the lack of diagnosis represents a significant restriction in its use [19].

An extension of the system described above enables limited diagnosis by training the network with examples of vibration data from a machine with a known fault, as well as normal or "healthy" data. The network is then labelled so that when monitoring, the output indicates that a trained fault type has been detected. It is, however, very difficult to collect sufficient representative data from machines in poor condition. Unless the machine can be set up with faults specifically for data collection purposes, it is practically impossible to get a full training set which is representative of all possible fault data.

Figure 7(a) below shows a graphical representation of a two-dimensional Kohonen network which has identified a fault, although at this stage the fault cannot be diagnosed - the network simply indicates that the input vector has moved outside of the normal "space". Figure 7(b) depicts a similar network with labelled nodes, which can be used to identify the fault by finding the nearest labelled node to the input vector. This type of network has been successfully applied to the detection and diagnosis of a variety of condition monitoring and welding applications [13].

3.3 Further Developments

The authors are currently examining the possibilities for hybrid neural networks systems, in which different neural architectures, and possible expert system components, are combined in an integrated environment which is robust in dealing with data of varying types, and which can address the problems associated with collection of comprehensive training data. A number of neural architectures are being investigated, such as ART, Radial Basis Functions, and logical projection networks.

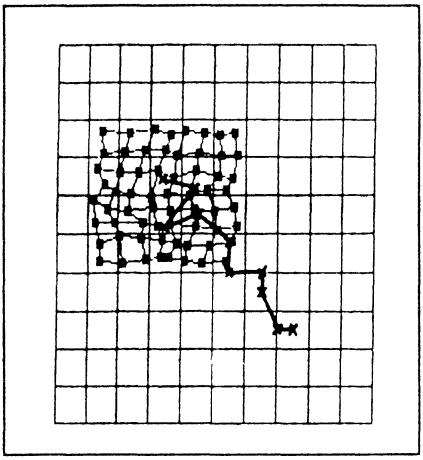

Figure 7(a) - Two-dimensional Kohonen network identifying "abnormal" input vector

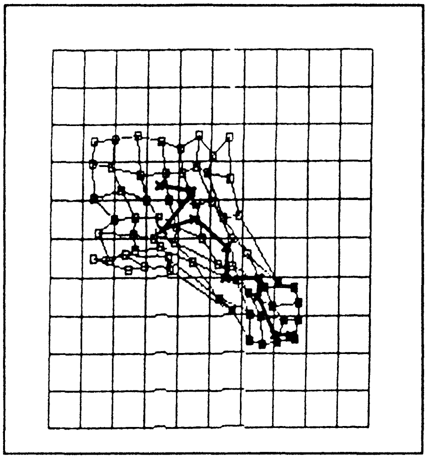

Figure 7(b) - Fault identification using a labelled Kohonen network

4 Conclusions

In practical terms, condition monitoring has been shown in its implementation at Blyth Power Station to be an extremely valuable technique in the area of industrial plant maintenance, and can generate significant financial benefits. The task of analysing condition monitoring data, which is difficult and subjective, offers an application area for neural networks which is both promising and potentially beneficial to engineering and manufacturing industry. Work carried out by the authors to date indicates that this potential can be realised through the correct design and implementation of appropriate neural network architectures, and further work will attempt to enhance the performance of a neural solution to this problem.

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