NEURAL NETWORK BASED FAULT DETECTION FOR FAULT TOLERANT CONTROL OF SYSTEMS WITH MULTIPLE MAGNETIC ACTUATORS AND SENSORS*

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SUMMARY

There is considerable interest in the improvement of fault tolerance in the design of active position and vibration control systems. In the creation of many magnetic actuator position or vibration control systems there exists potential for the inclusion of redundancy in the number of actuators and sensors used for control. This redundancy can provide improved tolerance to actuator or sensor related faults if, when a fault occurs, control of the system can be rapidly reconfigured to bypass control from a faulty component to the remaining healthy ones. To do this requires a system for the detection and identification of faults as and when they occur. The performance of modern computerised control hardware is now sufficient to allow such a system to run in real-time, in parallel to any digital control algorithm.

In this paper the development of a method for the detection and isolation of faults relating to control sensors and actuators is presented as a basis for the implementation of a fault tolerant control scheme. The method is based on the use of a neural network, operating in real time, for the detection of signal errors occurring in the plant inputs or outputs. The neural network is trained off-line using identification data taken from the plant and therefore does not require an accurate model of the plant dynamics.

Results are presented for the application of this method to an active magnetic bearing/rotor system, both in simulation and experiment. The issues of sensitivity to faults, speed of response and the effect of external disturbances on the reliability of the fault detection system are investigated and discussed. It is demonstrated that, through the implementation of a reconfigurable control scheme with a fault detection system, improved tolerance to sensor and actuator related faults can be achieved.

NOTATION

$\mathbf{A}$, $\mathbf{B}_\alpha$, $\mathbf{C}_\beta$, $\mathbf{D}_\alpha$	system state space matrices (subscripts α/β relate to inputs/outputs)
$\mathbf{b}$	neural network bias vector
$\mathbf{d}$, $\mathbf{D}$	vector of direct rotor forces (time domain, Laplace domain)

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$\mathbf{e}$	neural network output error vector
$\mathbf{f}$, $\mathbf{F}$	system fault signal (time domain, Laplace domain)
$\mathbf{G}_{r\beta}$	fault signal transfer function matrix from β to $\mathbf{r}$
$\mathbf{I}$	identity matrix
J	performance index for network training
j	$\sqrt{-1}$
$\mathbf{n}$	plant identification signal vector
$\mathbf{q}$	sensor noise signal vector
$\mathbf{p}$, $\overline{\mathbf{p}}$	vector of neural network fault detector inputs (with and without fault component)
$\mathbf{r}$, $\mathbf{R}$	fault detector residual (time domain, Laplace domain)
t	time variable
$\mathbf{u}$, $\mathbf{U}$	magnetic bearing control forces vectors (time domain, Laplace domain)
$\mathbf{v}$, $\overline{\mathbf{v}}$	vector of concurrent plant input and outputs (with and without fault component)
$\mathbf{w}$	fault signal vector used for fault detector training
$\mathbf{W}$	neural network weighting matrix
$\mathbf{x}$	system state vector
$\mathbf{y}$	vector of plant outputs
Ω	rotational frequency
Φ	set of detectable fault conditions
ω	angular frequency

INTRODUCTION

Fault detection and diagnosis have been recognised as issues of primary importance in modern process automation as they provide the prerequisites for fault tolerance, reliability, and security. For this reason there has been considerable development in the design of fault detection systems for various purposes and using a wide range of methods. Moreover, the fault detection system is a principal component of a reconfigurable control strategy and it is with this purpose that development of a fault detection scheme will be made. State estimation techniques have been widely studied in this field (ref. 1) and have proved to be successful in numerous cases where linear system theory can be applied to the dynamic modelling of the plant. Alternatively, parameter estimation is also a powerful method for the detection of faults in dynamic systems by on-line estimation of physical system parameters (ref. 2). This is a particularly important method for process plants (chemical processes, nuclear reactors, etc) where the plants often have slow dynamic behaviour, but process faults can cause sudden parameter variations that need to be estimated quickly. The important consideration in common with these methods is that they require a system model on which to base the fault detector design and as such are sensitive to the accuracy of the model. Also, they are applicable only to systems that can be represented by a linear model.

The main requirements for a fault detection and isolation scheme can be classified as either performance or robustness related. Performance criteria can include speed of detection, sensitivity to incipient faults, sensitivity to false alarms, missed fault detections and incorrect fault detections.

Robustness requirements can be defined with respect to unmodelled non-linearities or uncertain system dynamics, unknown disturbance and noise.

In this paper the approach of using fault detection observers will be briefly reviewed, outlining recent work on frequency domain design methods. Although this approach will not be implemented in this study, it serves as a useful comparison to the previously undeveloped approach of using neural network architectures for the parameterisation of fault detectors. The main reason for using the neural network approach to fault detection is that the available system model is unlikely to be sufficiently accurate for the design of a reliable fault detection observer, whereas the neural network approach is model free if training is performed using experimental measurements.

FAULT DETECTION OBSERVERS - BACKGROUND

The use of state estimation techniques for the generation of fault detection signals, or residuals, has been considered for systems with unknown inputs, where the objective is not only to decouple the effects of different faults on the observer output, but also minimise the effect of the unknown plant inputs, that might otherwise cause false fault detection.

Consider a general system model with the discrete time state space structure applicable to a linear system having multiple control actuators and measurement signals:

$$\begin{aligned} \mathbf{x}_{k+1} &= \mathbf{A}\mathbf{x}_k + \mathbf{B}_u\mathbf{u}_k + \mathbf{B}_d\mathbf{d}_k + \mathbf{B}_f\mathbf{f} \\ \mathbf{y}_k &= \mathbf{C}_y\mathbf{x}_k + \mathbf{D}_d\mathbf{d} + \mathbf{D}_u\mathbf{u} + \mathbf{D}_f\mathbf{f} \end{aligned} \tag{1}$$

where $\mathbf{u}$ is the control force applied by the control actuators and $\mathbf{d}$ is the system disturbance. The system input $\mathbf{f}$ represent the effects of faults.

The unknown input fault detection observer (UIFDO) is based on the state space observer (or state estimator) techniques of Luenberger (ref. 3) and has the same basic structure. The observer inputs are the plant control inputs and plant outputs. The observer state space matrices are chosen so that a fault in the system produces a known residual output. However, the effects of different faults must be uncoupled so that individual faults can be isolated. A design method for producing an observer with these qualities from the plant equations given (1) was developed by Frank and Wunnenberg (ref. 1), who used the Kronecker canonical form of the system equations to produce a UIFDO. Other methods have been developed (ref. 4) for the design of optimal state space UIFDOs, but for most systems it is impossible to completely decouple the observer output from the effects of plant disturbances. Recent research has therefore considered a different approach to the UIFDO design, where the design objectives are specified in the frequency domain as performance and robustness bounds on the observer transfer functions. The frequency domain design of fault observers having the structure given by equation (2) has been proposed by Frank and Ding (ref. 5) using an H_∞ design specification. An enhancement of this technique (ref. 6) uses a mixed H_2/H_∞ specification for which a linear matrix inequality (LMI) formulation can be used to obtain a solution.

NEURAL NETWORK FAULT DETECTION

Artificial neural networks (ANNs) have been shown to have enormous potential in application to both system modelling and identification. Recent progression has naturally led to them being employed for control and fault detection purposes (ref. 7). The key properties of ANNs, making them attractive for application to fault detection problems, include:

- The ability to approximate non-linear functions over a finite interval using multi-layer neural networks.
- They can be trained directly from plant data without requiring any predefined model of the plant. On-line adaptation is also possible.
- They have an in-built ability for pattern recognition, whether from static data using feed-forward networks or from time series data using recurrent networks.
- They naturally have multiple inputs and outputs and therefore lend themselves to the modelling of multivariable systems.

Methodology

Although a variety of network architectures (both feedforward and recurrent) could be employed for the fault detection problem, probably the simplest feasible network architecture for a rotor/magnetic bearing system has a form corresponding to a series-parallel model:

$$\mathbf{r}_k = \mathbf{W}\mathbf{p}_k + \mathbf{b} \tag{2}$$

where $\mathbf{p}_k = \left[\mathbf{y}_{k-n}^{\mathrm{T}}, \mathbf{u}_{k-n}^{\mathrm{T}}, \ldots, \mathbf{y}_k^{\mathrm{T}}, \mathbf{u}_k^{\mathrm{T}}\right]^{\mathrm{T}}$. The addition of the bias vector $\mathbf{b}$ allows the model to be linear about a non-zero operating point caused by, for example, an unknown static disturbance. The output $\mathbf{r}_k$ is the fault detection signal, often required to be an estimate of the fault signal $\mathbf{f}$. This detection system has the form of a single linear feed-forward network. This model can be extended to the non-linear case, using a 2-layer network having overall transfer function

$$\mathbf{r}_k = \mathbf{W}_2 \tanh(\mathbf{W}_1 \mathbf{p}_k + \mathbf{b}_1) + \mathbf{b}_2 \tag{3}$$

Here the input layer is a pure linear neuron layer and the output layer neurons have a hyperbolic sigmoid transfer function, allowing the incorporation of some plant non-linearities into the model.

To overcome practical problems associated with training and speed of implementation, the network employed in this study was a single layer linear network. The computational complexity of this type of network is comparable with a linear state space observer algorithm of the same order. A schematic of the network is shown in figure 1. Function computation time is important when implementing the fault detector in real time and the size of the network employed has a direct influence on the maximum sample frequency that can be used for the fault detection algorithm.

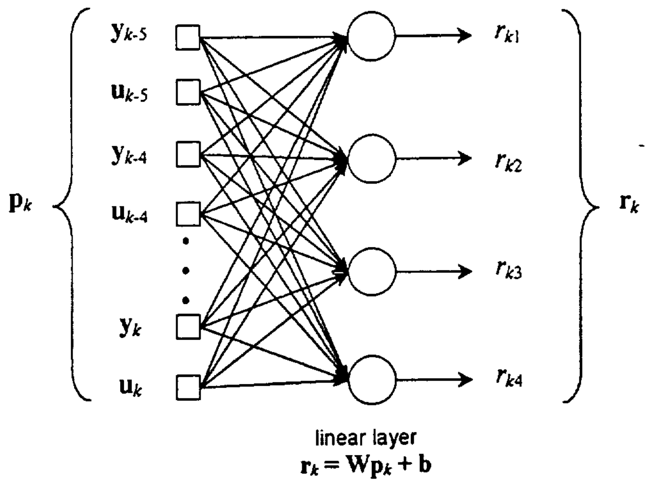

Figure 1 Network architecture for fault detection problem

Combined Plant/Fault Detector Dynamics

The dynamics of the neural network fault detector and plant can be described in state space form and combined to give an overall dynamic model of the system that includes the effects of faults, system disturbances and control inputs. The frequency response of the fault detection signal to these signals can then be written using transfer function matrix notation as:

$$\mathbf{R}(j\omega) = \mathbf{G}_{rf}(j\omega)\mathbf{F}(j\omega) + \mathbf{G}_{rd}(j\omega)\mathbf{D}(j\omega) + \mathbf{G}_{ru}(j\omega)\mathbf{U}(j\omega) \tag{4}$$

where $\mathbf{G}_{ab}$ are the relevant transfer function matrices from b to a and can be derived from equations (1) and (2) as given in Cole *et al.* (ref. 8).

Written in terms of these transfer functions, the fault detector design objectives can be specified as:

- Approximate $\mathbf{G}_{rf}$ to the identity matrix (**I**) over a frequency range for which fault signals need to be detected so that **r** is an approximation of **f** over the bandwidth of detectable faults.
- Minimise a suitable norm of $\mathbf{G}_{rd}(j\omega)$ over the frequency range of expected disturbances.
- Minimise a suitable norm of $\mathbf{G}_{ru}(j\omega)$ over the frequency range of expected control signals.

The network can be trained using time series data taken from the real plant with a sum-squared error criteria to optimise the weighting and bias matrices. Plant data is obtained by applying test signals to the appropriate plant inputs and outputs. The choice of test signal,i.e. magnitude and spectral content will indirectly influence the level of optimisation with respect to the above design criteria.

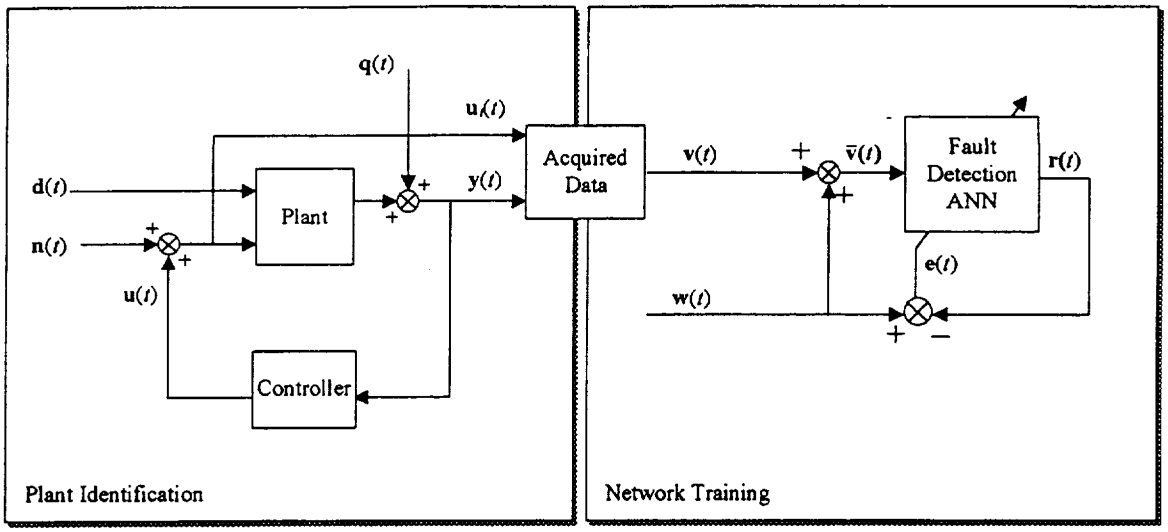

Figure 2 Plant identification and network training with simulated fault

NETWORK TRAINING

The training of the fault detector (FD) network is undertaken using the following strategy:

(i) Obtain plant identification data by applying a (discrete time) input signal **n**(*t*) to the plant input and acquiring corresponding output data.

(ii) The plant data obtained from (i) is used for the training of the fault detector. A simulated fault signal is added to the plant data and the neural network is trained to produce an estimate of this fault signal.

Plant Identification

The system structure for plant identification is shown in figure 2. The form of the discrete input signal **n**(*t*) used for the identification of the plant has an important influence on the design optimisation for the fault detector. Although the optimisation takes place in the time domain the frequency content of the identification signal should also be considered in terms of its design influence.

The choice of identification signal will depend on the nature of the faults being considered for detection. If the fault signal (**f**) is likely to be a band limited noise signal then, in order to minimise the effect of the control signal on the fault detector, a similar identification signal should be employed. If the desire is to produce a fault detector that is optimised for sudden fault occurrence, characterised by step changes in **f**, then a fixed step input signal is probably more suitable. In either case consideration should be made to the steady state accuracy of the fault detector, as all fault signals are likely to have a DC component that needs to be accurately estimated for detection and diagnosis.

Fault Simulation

Acquired plant identification data can subsequently be used for the off-line training of the fault detection network. Defining a set of plant data with sample period T, $\mathbf{V} = [\mathbf{v}_0, \mathbf{v}_1, \ldots, \mathbf{v}_k, \ldots, \mathbf{v}_s]$, where $\mathbf{v}_k = \mathbf{v}(kT)$, and a fault condition, as characterised by $\mathbf{f}_k \in \Phi$, where Φ is the set of fault signals that are required to be detectable/identifiable. Φ should also include the no fault condition ($\mathbf{f}_k=[\mathbf{0}]$). An error signal $\mathbf{w}_k$ is generated that will embody the effect of these faults on the plant input-output pairs ($\mathbf{v}_k$). This error signal $\mathbf{w}$ is added to the plant data $\mathbf{v}$ (figure 2) and the total signal $\overline{\mathbf{v}}$ used as the network input data set. The network is trained using the error signal $\mathbf{w}$ as the set of target vectors, which must be estimated by the network output vector, as defined by the equation:

$$\mathbf{r}_k = \mathbf{W}\overline{\mathbf{p}}_k + \mathbf{b} \tag{5}$$

where

$$\overline{\mathbf{p}}_k = \left[\overline{\mathbf{v}}_{k-n}^{\mathrm{T}}, \overline{\mathbf{v}}_{k-n+1}^{\mathrm{T}}, \ldots, \overline{\mathbf{v}}_k^{\mathrm{T}}\right]^{\mathrm{T}} \quad \text{and} \quad \overline{\mathbf{v}}_k = \mathbf{v}_k + \mathbf{w}_k \tag{6}$$

The network output error is given by

$$\mathbf{e}_k = \mathbf{r}_k - \mathbf{w}_k \tag{7}$$

and the network is optimised using a least squares criterion:

$$\min\left(J(\mathbf{W}, \mathbf{b}) = \sum_k \|\mathbf{e}_k\|^2 \right) \tag{8}$$

Network training can be achieved using a standard back propagation method for the case of non-linear layers, or solved directly in the linear case. The ideal solution would completely filter out both the effects of plant disturbance and plant control input on the fault estimate. In general, however, the solution will be a compromise between minimising the effect of the plant disturbance and plant control input and maximising the accuracy of the fault estimate. The dependency on control input is important because it is desirable for the fault detector to be effective with any control algorithm (and therefore it should be decoupled from the control input). Also, a plant fault will obviously have an effect on the control input through the control feedback loop and therefore, for accurate estimation, the fault estimate must be independent of this signal.

The objective of the fault detector design is to produce a system that generates a set of signals that are an estimate of the predicted faults, as represented by the error signal $\mathbf{w}(t)$. However, this signal must then be monitored for any significant excursion from zero and on occurrence of a fault give an interpretation upon which a suitable action can be made e.g. give an alarm or reconfigure the control to bypass the fault.

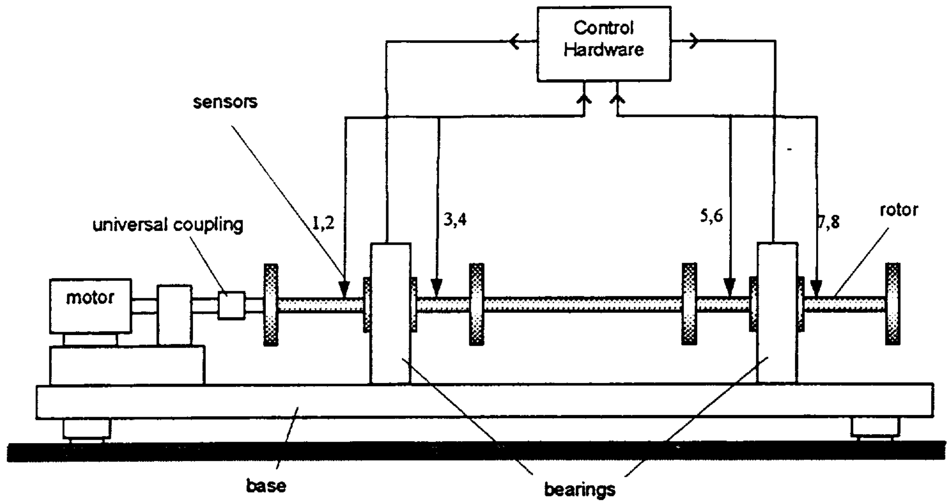

Figure 3 Schematic diagram of magnetic bearing/flexible rotor system
(rotor length 2 m, rotor mass 100 kg, shaft diameter 0.05 m)

The form that this signal post-processing takes will be dependent on the nature of the faults that need to be detected. However, it will generally embody some method for the comparison of signal magnitudes with a threshold signal, which indicates a fault when exceeded. The dynamics of the fault will also be an important consideration. For example, an additional detection criterion may be necessary for rapid detection of sudden faults which, by this fact, cannot be identified instantly, but still require some immediate corrective action.

SIMULATION RESULTS

The procedure for plant identification and fault detector design was investigated in a simulation study, in order to assess parameter choice in the fault detector design and various performance related effects. System models were created in Matlab (ref. 9), based on the experimental flexible rotor/ magnetic bearing rig shown schematically in figure 3, and the simulations carried out in the Simulink dynamic modelling environment. The rig itself consists of a two metre long rotor supported by two radial magnetic bearings. Eight displacement transducers measure the rotor displacement in four planes.

The simulation used a linear two-dimensional state space half model of the plant at zero rotational speed, incorporating translatory motion in one plane only (i.e. the y plane), including the first four rotor flexural modes. The model incorporated four displacement sensors (indexed 1, 3, 5 and 7), located inboard and outboard each of the two bearings with the two inner sensors (3 and 5) used to stabilise the plant with control feedback. Figure 4 shows the two singular values of the rotors transfer function matrix from control inputs to sensor measurements as a function of frequency. The first four natural frequencies of the rotors flexural modes are evident at 171 rad/s, 423 rad/s, 1075 rad/s and 1588 rad/s.

Typically, plant data was acquired over a ten second period, where the identification signal magnitude was selected to produce rotor displacement signals over the range ±1 mm. Initially, the running speed of the plant was chosen to be 100 rad/s with sinusoidal forcing representing a single unbalance mass at one end of the rotor. Plant input-output data was acquired at a sample frequency of 100 Hz, giving a total data set of 1000 sample points. A signal to represent sensor noise **q** was added to the plant output, having a low frequency cut-off of 100 rad/s.

The fault signal **w** is added to the plant input-output data. This represents the effect of an error occurring in one of the plant measurement transducers or actuators. The fault detector is then trained to reproduce this signal given the original set of plant input-output data only.

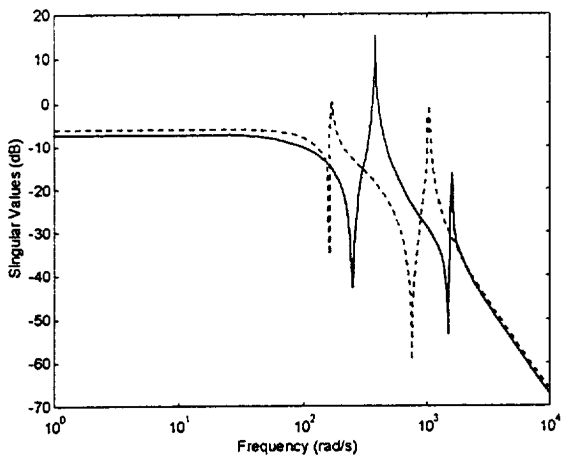

Figure 4 Singular values of (open loop) plant model transfer function at zero running speed

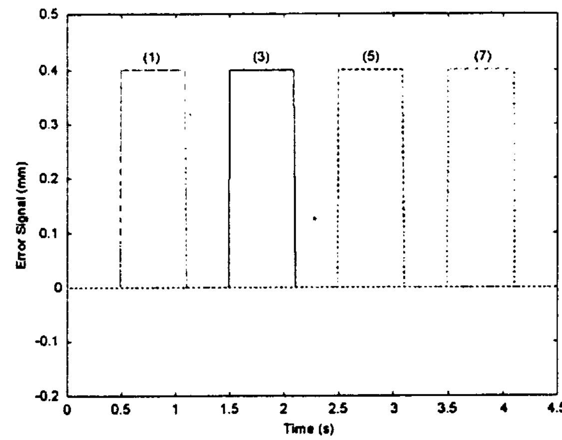

Figure 5 Sensor error signal for training/simulation. This signal is added to the actual sensor signal to simulate occurrence of a fault

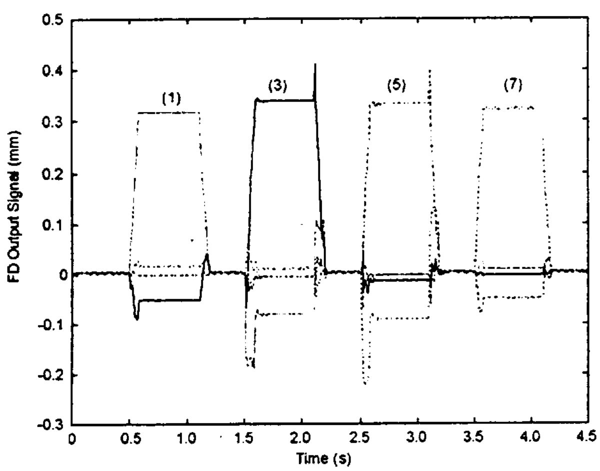

Figure 6 FD output signals for fault detector 1

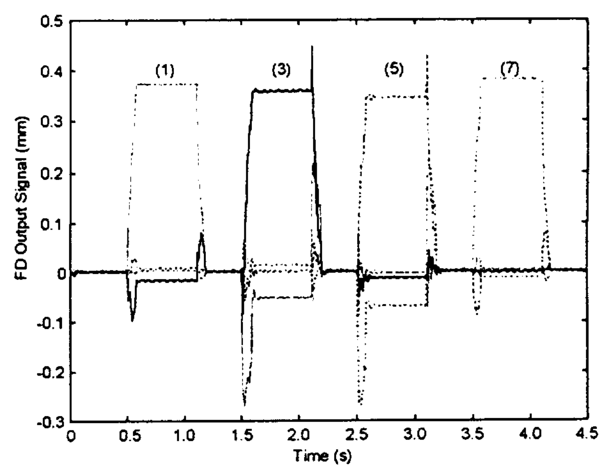

Figure 7 FD output signals for fault detector 2

Fault Detector Performance

In this simulation study, four different neural network fault detectors were generated using different identification and training data, summarised as follows:

Fault detector 1	Band limited white noise plant identification signal. Fault amplitude during training = 0.1 mm.
Fault detector 2	Band limited white noise plant identification signal. Fault amplitude during training = 0.2 mm.
Fault detector 3	Random step plant identification signal. RMS sensor noise = 0.05 mm. Fault amplitude during training = 0.2 mm.
Fault detector 4	Random step plant identification signal. RMS sensor noise = 0.01 mm. Fault amplitude during training = 0.2 mm.

The resulting network weighting and bias matrices can be implemented in simulation and the performance tested using a simulated fault error signal similar to that used in the training. The influence of training parameters, on the resulting network performance can be assessed from the time responses of the fault detector output $\mathbf{r}(t)$ to various fault types. The results in figures 6, 7, 8 and 9 show the fault detector responses to an offset error occurring on each of the four sensors in turn over a four second period. The amplitude of the error is 0.4mm, as seen from figure 5.

Comparison of figures 6 and 7 shows a number of important characteristic features of the simulated outputs in which they differ from the desired responses. Firstly, there is the steady state performance of the network. This includes, not only the steady state accuracy of the error estimate for a particular sensor, but also the degree of spillover that effects the network outputs corresponding to the other three sensors. Accuracy during the no fault condition is also important for avoiding false alarms, during which the outputs should be close to zero. The transient response of the network to the step change in error should also be assessed, in terms of response time, overshoot and, again, the degree of spillover. Unlike in network training, the response for sensors 3 and 5 will differ to those for 1 and 7, as sensor 3 and 5 are used as control inputs while 1 and 4 are for fault monitoring only. Therefore, a fault acting on sensors 3 and 5 acts as a disturbance on the plant via the control feedback. One other consideration is the amplitude of the ripple on the FD signal due to synchronous disturbance.

Figures 6 and 7 show the response of two networks to the fault conditions. Both networks have been generated using plant identification signals consisting of band limited white noise. However the amplitude of error signal $\mathbf{w}$ used in the training differs. The results show that increasing the amplitude of the error signal improves the steady state performance, i.e. the mean deviation in the non-faulty sensor signals is reduced slightly. However, it has a detrimental effect on the transient response, i.e. large signal spikes now occur when the fault is activated.

Figures 8 and 9 show the results of network training from data generated with a random step signal at the controller input. Comparison with the results from the random noise signal generally show better performance, attributable to the fact that the training signal is specifically for a step type disturbance (as caused by the step error signal). Comparison of figures 8 and 9 show how decreasing the noise level on the sensor signal has the same effect as increasing the error signal amplitude i.e. it improves the steady state performance, but degrades the peak transient response.

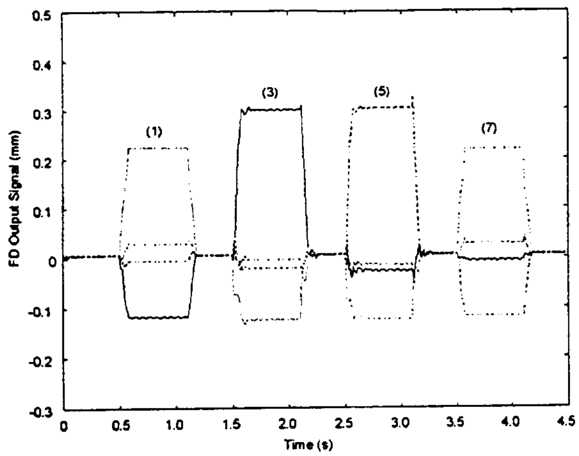

Figure 8 FD output signals for fault detector 3

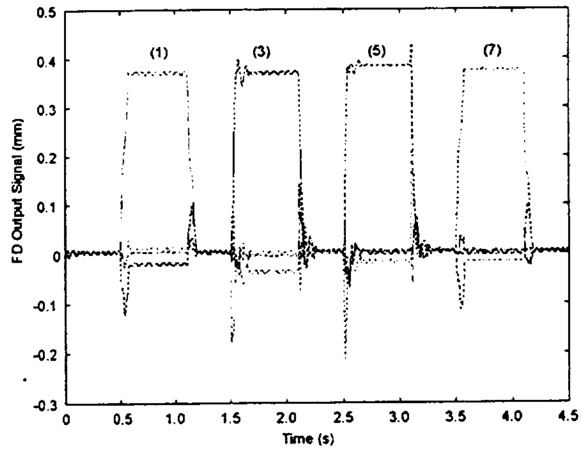

Figure 9 FD output signals for fault detector 4

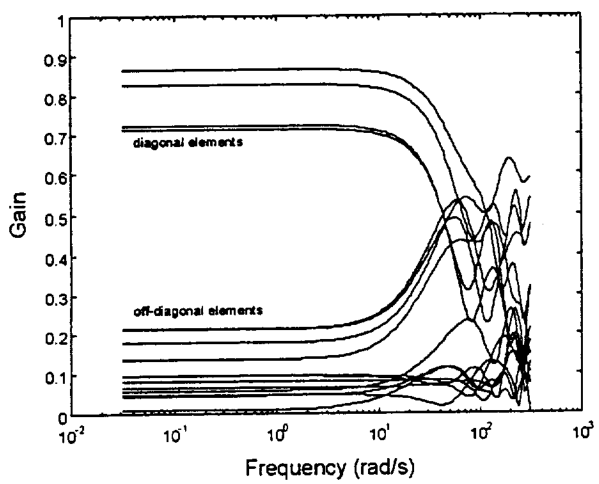

Figure 10 Magnitude of matrix elements of $\mathbf{G}_{rf}(j\omega)$ for fault detector 1 showing diagonal dominance up to the cross over frequency at 40 rad/s

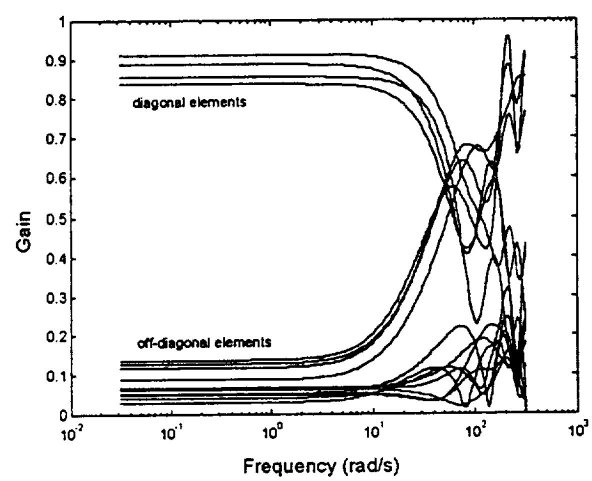

Figure 11 Magnitude of matrix elements of $\mathbf{G}_{rf}(j\omega)$ for fault detector 4 showing diagonal dominance up to the cross over frequency at 50 rad/s

It can be concluded from these results that the network solution is a trade-off between the transient response and state steady accuracy of the fault detection signal. The ability to influence these factors is provided through the choice of error signal (amplitude) used as the target set and the frequency spectrum of the plant identification signal used to generate the input set. Sensor noise also has an important influence on the resulting network performance, but is an intrinsic property of the real system and cannot easily be changed in practice. The exact nature of this behaviour can be seen through comparison of the frequency response matrices for the system $\mathbf{G}_{rf}(j\omega)$ and $\mathbf{G}_{ru}(j\omega)$ (defined by equations (4)). Figures 10 and 11 show magnitudes of the elements of the frequency response matrix for $G_{rf}(j\omega)$ for two different fault detectors. At low frequencies the four diagonal elements are close to unity and the remaining elements are small, so the fault detector will give a good estimate of the error signal. However, above the cross over frequency (approximately 50 rad/s) the transfer function matrix is no longer diagonally dominant, and spillover occurs.

Plant Disturbance Changes

The effect of variations in plant disturbance on the FD network output, from either changing rotor speed, changes in unbalance, or possibly some other direct forcing disturbance such as rotor impact or mass loss, can be assessed through inspection of the frequency response matrix $G_{rd}(j\omega)$. Plots of the frequency dependent matrix elements amplitudes of $G_{rd}(j\omega)$ are shown in figure 12 and 13 corresponding to fault detectors 1 and 4. It is evident from the plots that the responses have been minimised close to the synchronous frequency of 100 rad/s.

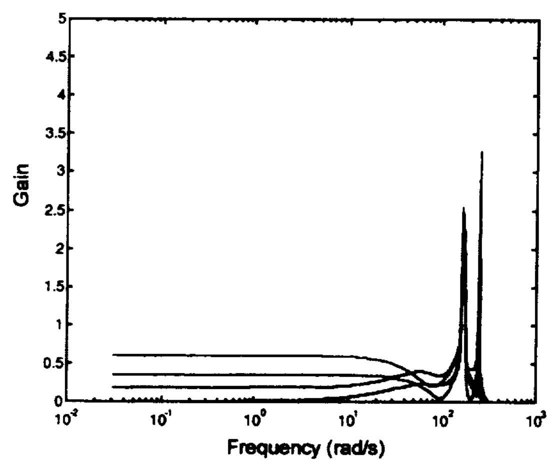

Figure 12 Magnitude of matrix elements of $G_{rd}(j\omega)$ for fault detector 1 showing minima at disturbance frequency (100 rad/s)

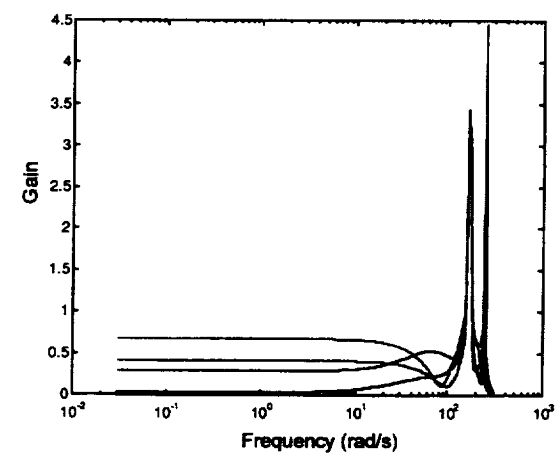

Figure 13 Magnitude of matrix elements of $G_{rd}(j\omega)$ for fault detector 4 showing minima at disturbance frequency (100 rad/s)

EXPERIMENTAL RESULTS

Experimental implementation of the neural network based fault detector has been used to demonstrate the performance capabilities and show how it can be used as a basis for a reconfigurable control system. In the experimental system, the fault detectors were implemented in software to run in real-time on a DSP system, used also for controller implementation. Fault detectors were trained using data taken from the rig during operation. These fault detectors were then tested by simulating a number of fault conditions on the rig. In this example the rotor is under steady operating conditions with a rotational speed of 88 rad/s prior to the onset of the fault. Figures 14 and 15 show the eight fault detector outputs (one corresponding to each sensor) when an offset error occurs on one of the sensors after one second. The responses differ due to the fact that sensor 3 is being used for control feedback at the time whereas sensor 1 is used purely for condition monitoring purposes.

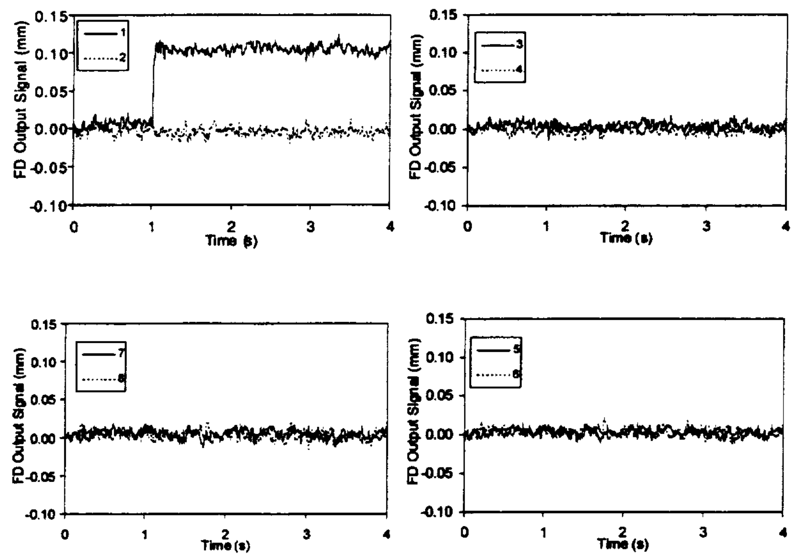

Figure 14 Fault detector output during fault on sensor 1 ($\Omega = 88$ rad/s)

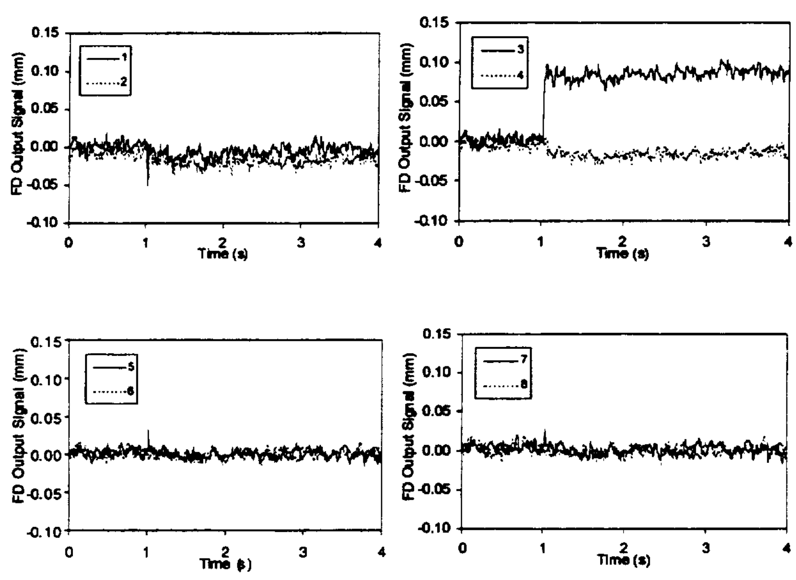

Figure 15 Fault detector output during fault on sensor 3 ($\Omega = 88$ rad/s)

The complete failure of a sensor may produce damaging behaviour, depending on the response of the rotor. Figure 16 shows the response of the rotor to a failure of sensor 3 while it is being used for control feedback. It can be seen that stability is lost and the rotor collides and remains in contact with the retainer bearing. Damage to the retainer bearings and/or rotor could result from prolonged contact at high running speed, or when interaction of the rotor and bearing involves large impact forces.

Automatic Control Reconfiguration

For the purposes of condition monitoring and automatic control configuration the fault detector has been combined with a post processor algorithm (ref. 10) that monitors and interprets the output from the fault detector. This is combined with some simple decision logic that provides the ability to reconfigure control or issue warnings when a fault is recognised. Figure 17 shows the response of the rotor to complete loss of sensor 3 (while being used for control feedback) when the automatic control reconfiguration is in operation. Comparison with figure 13 shows that the fault detector has enabled recognition of the fault and has invoked automatic reconfiguration of the control algorithm to bypass the faulty sensor. Although the speed of recognition is not sufficient to completely avoid collision of the rotor with the retainer bearing, the touchdown is brief and the rotor quickly returns to steady operation when control is switched to a healthy sensor.

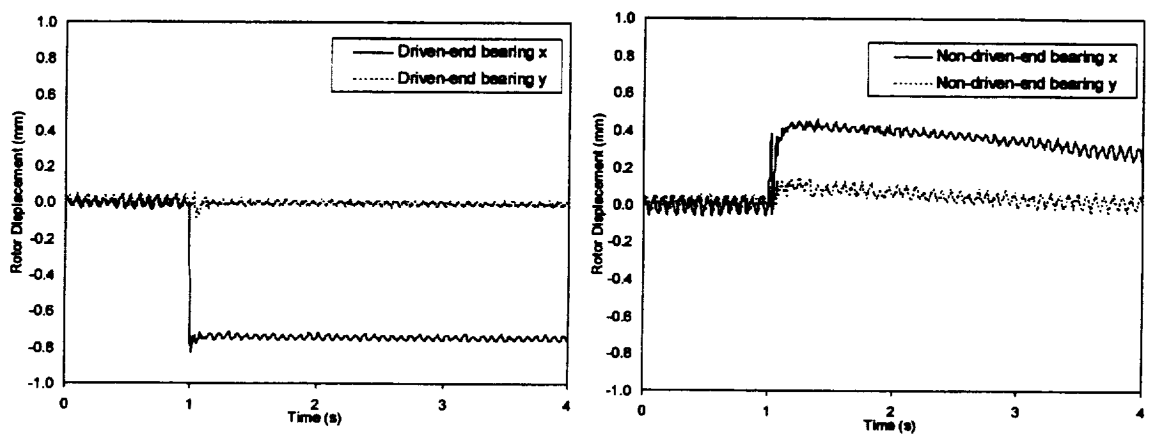

Figure 16 Measured rotor response during sensor 3 failure ($\Omega = 88$ rad/s)

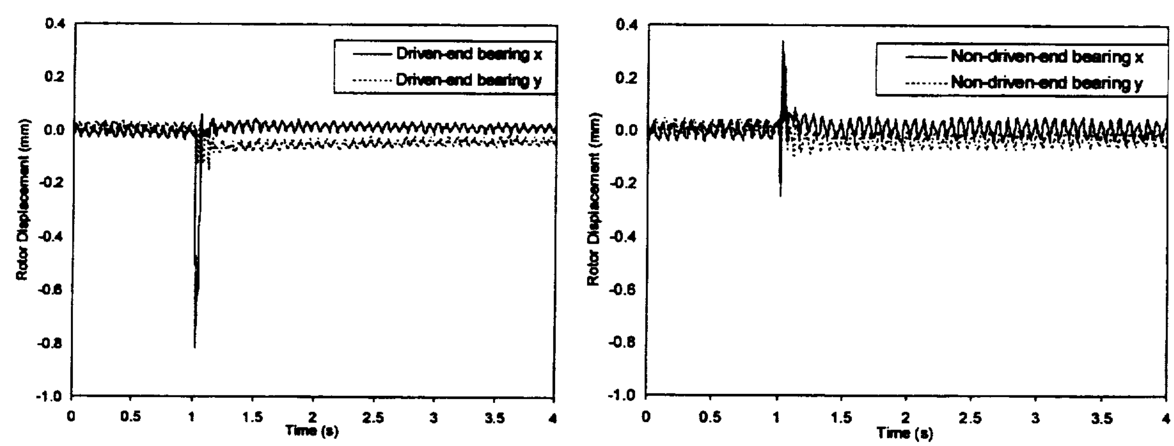

Figure 17 Measured rotor response during sensor 3 failure with automatic control reconfiguration ($\Omega = 88$ rad/s)

CONCLUSIONS

This study has shown how a method for fault detection, based on a neural network type architecture, can be applied to a dynamic system with multiple inputs and outputs. Application of the method to a magnetic bearing/flexible rotor system through simulation has shown that the performance of the fault detector is dependent on the plant input and output signal data used for the training of the network. Application to an experimental system was successful during tests to simulate faults occurring on any of the rotor displacement transducers. Tests demonstrated that it was possible to use the fault detector as the basis for a reconfigurable control system that could switch control algorithms on detection of a fault in order to bypass the failed component. The results indicated that the severity of damaging touchdowns with retainer bearings could be significantly reduced.

The ability of neural networks to give a non-linear mapping property suggest that further investigation would be worthwhile into the application of this method to strongly non-linear systems.

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