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A TIME ENCODED SIGNAL PROCESSING/NEURAL NETWORK APPROACH TO FAULT CLASSIFICATION OF AN ELECTROHYDRAULIC CONTROL SYSTEM

John Watton[1] and Nick Freebody[2]

[1] Cardiff School of Engineering, Cardiff University, Wales, UK
[2] Expert Monitoring Ltd, Cardiff, Wales, UK
WattonJ@cardiff.ac.uk, n.freebody@dial.pipex.com

Abstract

A fault classification approach is presented which considers the advantages of Time Encoded Signal Processing (TESP) of dynamic signals combined with the ability of Artificial Neural Networks (ANNs) to classify changes in TESP codes. This is demonstrated using a new TESP code approach applied to a pressure control system exhibiting both leakage at the actuator and a servovalve fault. It was found that the use of both pressure transducer voltage and servovalve drive voltage, when entered into the ANN in a parallel data structure manner, resulted in an excellent fault classification capability. In addition the inherent classification approach gave very good leakage discrimination for arbitrarily-set, and low, levels of 0, 2, 4, 6 l/min. A range of 16 different ANNs were investigated and the classification results indicate a preferred topology for this application.

Keywords: fault diagnosis, fluid power systems, time encoded signal processing, artificial neural networks

Introduction

ANNs are now well established in many disciplines including engineering topics such as control, modelling, and fault classification. They are now merely software tools that require no more description than CAD/hydraulic simulation packages. In this fluid power context, there has been some initiatives related to condition monitoring and fault diagnosis. The process is conceptually simple in the sense that the ANN outputs represent the fault states, as close as possible, and the ANN inputs are representative condition signals from the hydraulic control system. There are some specific practical desires such as the use of a minimum number of sensors, the use of non-specialist sensors, low sensor cost, the ability to fault diagnose while the hydraulic system is in operation, and the ability to determine the level of the fault. These issues are being addressed and with an emphasis on the use of dynamic signals. This leads to a decision whether to use time domain signals or frequency domain signals, the latter perhaps more suited to fault-type classification, particularly on pumps and motors, rather than fault-level classification.

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Early work on hydraulic systems monitoring naturally considered techniques such as Fault Tree analysis, Failure Modes and Effects Analysis (FMEA), Expert Systems shells, with an initial emphasis on steady state behaviour combined with frequency domain analysis, Atkinson et al (1992). Work in the last decade of the 20th Century then moved on to the application of ANNs using dynamic signals. For example, work reported by Darling and Tilley (1993) considered 3 pressures and 1 displacement set of transient signals from a valve actuator sequential circuit. A single hidden layer ANN with 60 neurons and 10 output neurons was shown to indicate the existence of different fault types, with a suggestion of long training times. The additional complication of multiple faults, and the desire to predict the fault level, has been considered by Stewart and Watton (1994, 1996). They adopted an Expert System Shell using a novel approach to leakage detection combined with an ANN to give added confidence, particularly for the multiple fault condition. Edge et al (1995) considered qualitative data based on steady state information obtained from an FMEA approach, and by defining discrete levels of operation such as High, Normal, Low or Zero. They then used a single-layer ANN with 4 input neurons, 12 neurons in the hidden layer, and 13 output neurons, and good results were demonstrated even in the presence of data uncertainty. Further work by Crowther et al (1998) used a single layer ANN having 3 input neurons, 10 hidden layer neurons, and 3 output neurons to classify faults in a cylinder control system. Ramden, Weddfelt, and Palmberg (1993, 1995) naturally considered a frequency domain approach for fault diagnosis of a pump and showed a preference for frequency backstrum, rather than spectrum or cepstrum, to train an ANN to classify the new condition and 4 fault conditions. Again the ANN had 1 hidden layer containing 10 neurons. Work by Le, Watton and Pham (1997) considered the transient signals from a cylinder position control system to identify three leakage faults together with the fault levels. They used a 6-50-21 ANN topology to investigate four additional multiple fault conditions although the approach does require the use of fast-acting flow meters. Further work by the same research group (1998), and using the same position control system, then used a Linear Predicting Coding (LPC) method to determine both the coefficients and the LPC cepstra for the transient signals. The multiple fault conditions were again investigated, an additional feature being the use of just the two pressure signals to detect flow leakage type and level. The number of input neurons depends upon the number of LPC coefficients used, but in all cases a single hidden layer contained 50 neurons was used. Both approaches gave excellent results, the LPC cepstra method giving slightly better predictions using 10 LPC coefficients for each pressure.

The data input approach under discussion here takes a new form in relation to previous ANN practice regarding fault diagnosis of hydraulic systems. It is based upon the TESP approach to characterise transient data utilising inherent shape parameters that embrace a combination of dynamic properties as described by Holbeche, Hughes, and King (1986) and also by Rodwell and King (1996). An independent commercial package, TESPAR developed by Domain Dynamics Ltd UK, utilises similar fundamental principles but produces a special numerical alphabet code for classification purposes. The alternative approach being used here, CARCODE, requires a number of processing steps as follows :

- The transient signal of consistent length must be zero-based, and the zero crossings are classified into epochs of appropriate sampling intervals. Each epoch duration is given the descriptor (D).
- Within each zero crossing epoch, the peak value, (A), the number of turning points, (T), and the ab

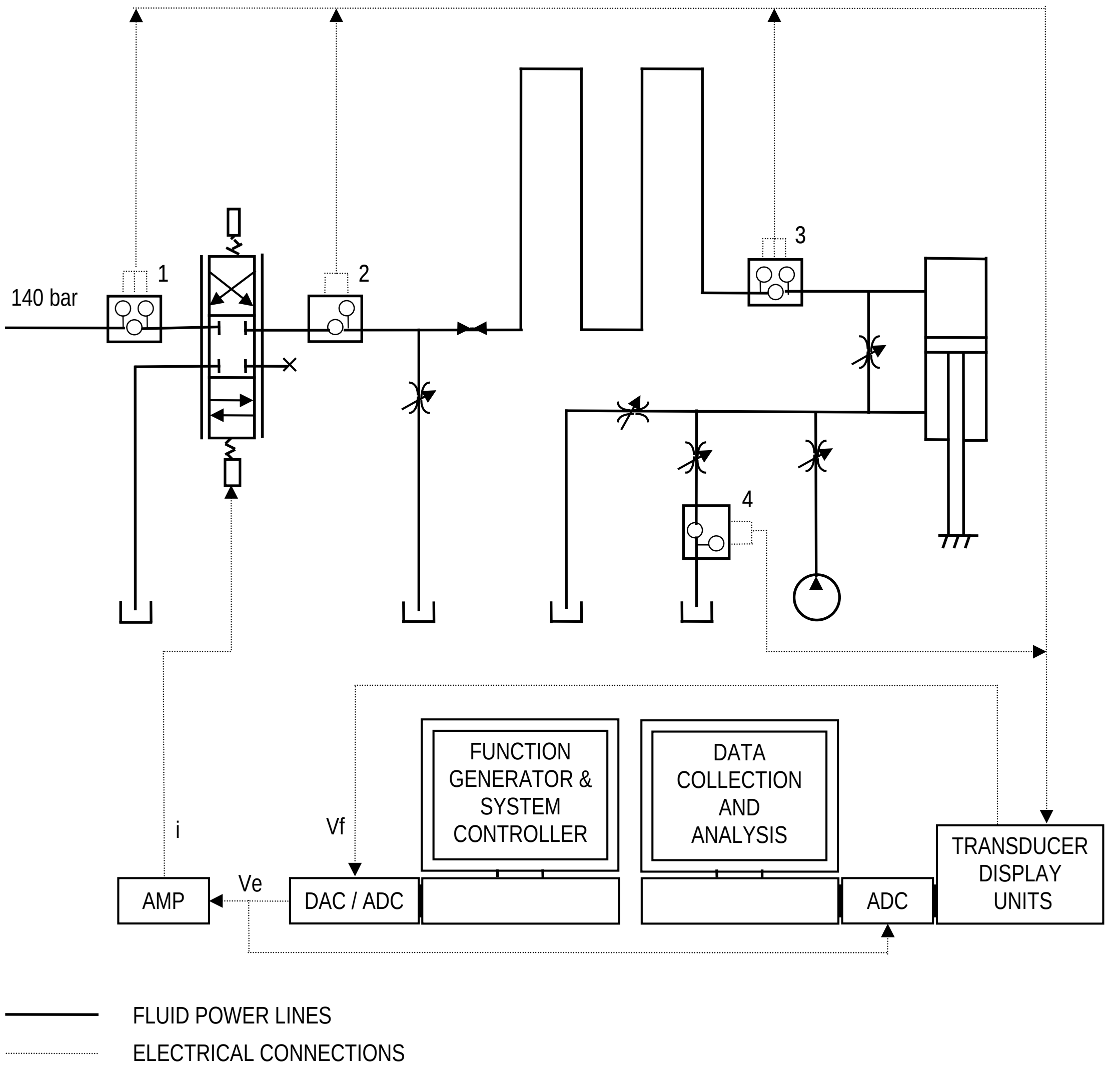


Fig. 1: *The electrohydraulic pressure control system*

solute area, (I), are also recorded resulting in a distribution of each parameter.

- Each distribution is considered to be normal and experience has shown that using data within ± 1 standard deviation from the mean is sufficient for fault classification. Hence the modified data are then divided into 10 equally spaced classes, and this is known as the DATI string
- This DATI string of 40 numbers, and representing the fault identifier from just one transducer, then forms one input block, with 40 associated neurons, to the ANN.

This application considers a rigidly-restrained cylinder pressure control system exhibiting both cylinder leakage and a servovalve fault. The fault diagnosis approach uses just the two possible transient signals, namely pressure and servovalve drive voltage, which are fed in parallel to the ANN following the TESP processing procedure. The pressure signal is first differentiated to produce the zero-based data and the servovalve signal is used directly but with the removal of any steady state bias term. This self-selects an ANN with 80 input neurons, and a suitably selected internal topology is established as discussed later. More details of the CARCODE approach, including examples without the use of ANNs, may be found in Freebody and Watton (1999).

2 The Hydraulic Circuit and Data Acquisition Approach

The pressure control system is the same as described by Freebody and Watton (1999) and consists of a servovalve connected to a cylinder via a 17.3 m long transmission line in the laboratory set-up. This forms part of a more comprehensive fault diagnostic R&D programme using on-line data from 28 similar controls systems on the Hot Steel Strip Rolling Mill at Corus plc (formerly British Steel) Port Talbot, UK. Long transmission lines are common in such applications. The initial work has concentrated on the Work Roll Bending pressure control circuits, and during the rolling process under extremely large restraining forces within the Automatic Gap Control circuit. Hence the parallel laboratory work used a rigidly-restrained cylinder, with a negligible back pressure, to allow a concentrated effort on the technique in the absence of load dynamics. Fig. 1 shows the system schematic illustrating a comprehensive computer control and computer data acquisition system. It should be noted that although transient flow rate was measured, using sensors having a frequency response of typically 350 Hz, the results of much work showed the data to be of limited use for fault diagnostic purposes. All signals were sampled at a frequency of 2 kHz. Individual pressure, flow, and temperature measurements were taken using manifold blocks at points 1, 2, 3, 4 as shown in Fig. 1.

The test data were obtained by applying step inputs to the system and the corresponding transient servovalve voltage and pressure signals were then preprocessed as described earlier before being used for ANN training, validation, and testing. The servovalve voltage signals will also probably contain a bias voltage in the presence of leakage and/or other faults, hence the need for zero-biasing in practice. Leakage levels were set at 0, 2, 4, 6 l/min and a new servovalve was used followed by the same servovalve but with two further levels of flapper/nozzle erosion typical of the condition occurring at the Steel Mill. Only the first, and low level of damage, was used for this study.

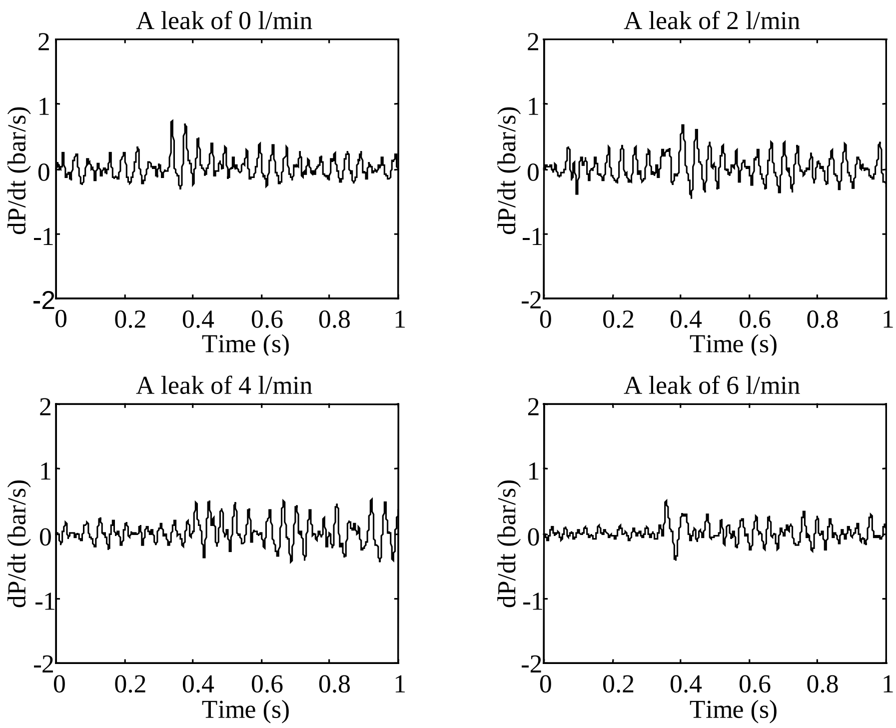
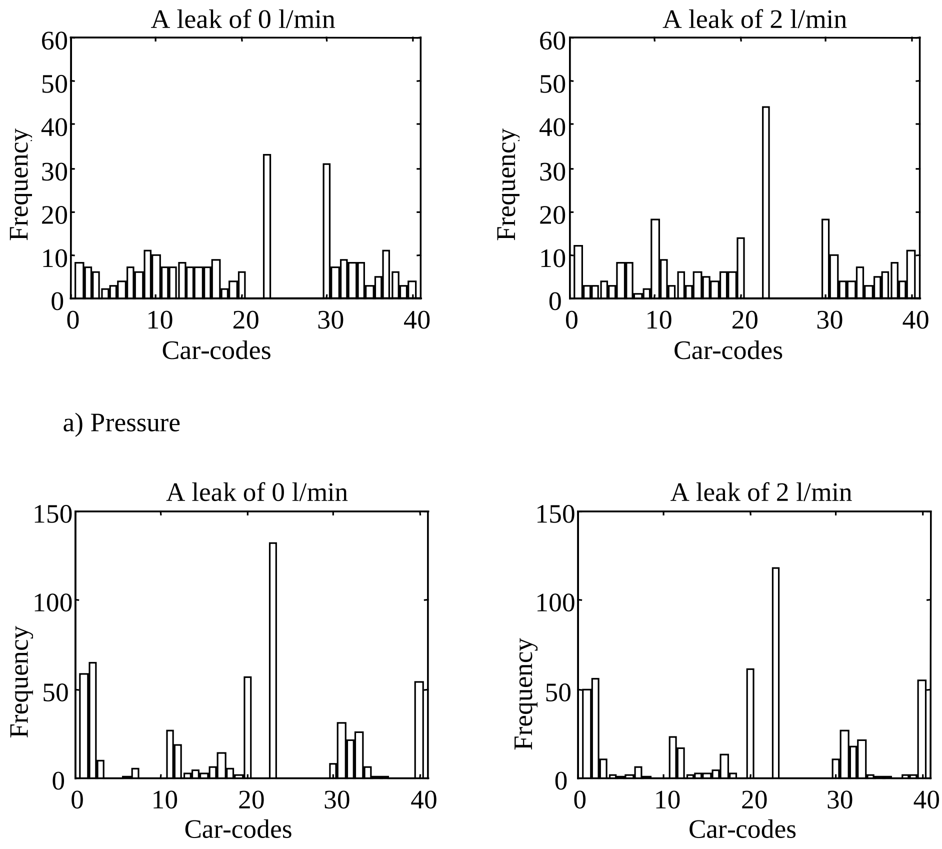


Fig. 2: *Pre-processed pressure signals for different leakage conditions and with an undamaged servovalve*



a) Pressure

b) Servovalve voltage

Fig. 3: *Typical CARCODE histograms of DATI data for pressure and servovalve drive voltage*

Tests were carried out with individual faults and all combination of faults and some typical pre-processed signals are shown in Fig. 2, the pressure being measured at sample point 3 in Fig. 1.

The developed software program automatically generates the DATI histograms by considering the statistical distribution of each parameter derived from the ensemble of pressure recordings of equal time length. Some typical processed data are shown in Fig. 3 for both the pressure transducer and servovalve signals, for the ideal condition and for the condition with a leakage flow of 2 l/min. The particular results shown in Fig. 3 illustrates that in practice not all components of the DATI string necessarily produce obvious fault diagnostic information, and it is therefore more fruitful to work with the most significant components. It has been found that further processing by biasing dominant elements of the DATI string does help the fault diagnostic process although this is not rigorously essential. In the data shown, the D and T parameters would be reduced in favour of the A and I parameters via a software routine within CARCODE.

3 ANN Selection and Training

The selection of an appropriate ANN topology still remains somewhat of a matter of experience, although previous work discussed earlier does seem to converge to a topology having a single hidden layer. However using the CARCODE method requires the input parallel data to be entered in blocks of 40 numbers per transducer signal used. The present application only utilises two signals but clearly the input neuron count can become large in other multi-sensor applications. Since earlier work at Cardiff showed good success at fault classification using the multilayer perceptron network, the same training technique was used, although there are other networks that may well be equally efficient. The networks were trained using standard error back propagation with conjugate gradient and batch update algorithms. The cross-validation method was used to terminate the learning process to limit the possibility of overtraining. Note, however, little success was achieved using a single hidden layer and was attributed to the large number of input neurons required.

For this study a range of 16 topologies were selected and tested from a large number of trials, and are shown in Table 1, and for each of the three fault conditions as follows :

- leakage faults (*LK*) only and having levels of 0, 2, 4, 6 l/min.

Hence the ANN will have 80 inputs and 4 outputs.

- servovalve faults (*SV*) only and having levels of new and "as found" low level flapper/nozzle erosion

Hence the ANN will have 80 inputs and 2 outputs.

- combined leakage and servovalve faults (*LS*) composed of all elements from (*LK*) and (*SV*).

Hence the ANN will have 80 inputs and 8 outputs. Output neurons 1-4 represent no servovalve fault for the four leakages, and neuron outputs 5-8 represent a servovalve fault for the four leakages.

The fault conditions are indicated in the output neurons in the usual way, that is, the appropriate fault is indicated as an ideal "1" with all other neuron outputs indicated as an ideal "0". To avoid over-training, unseen data was introduced after every 20 iterations to

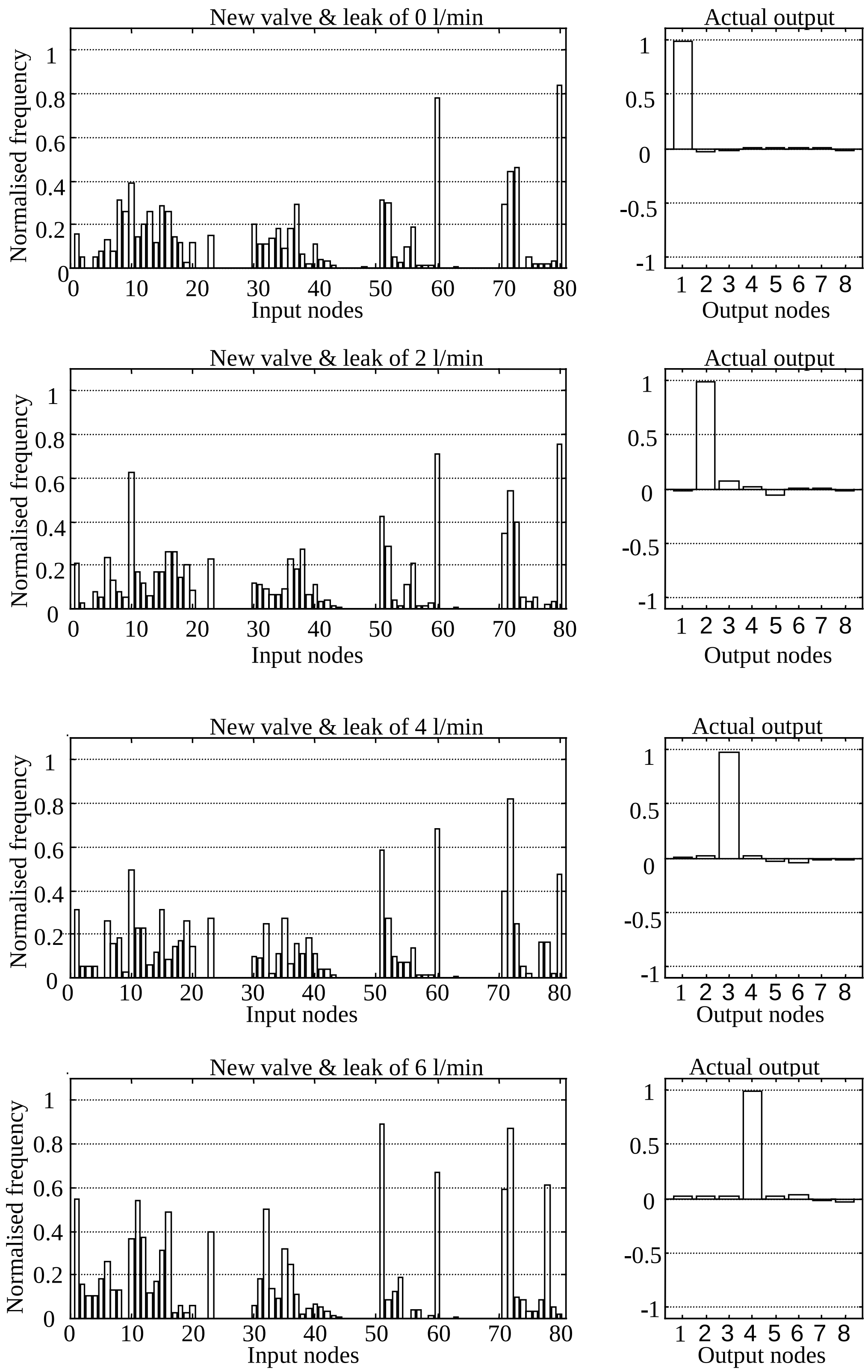


Fig. 4: *ANN outputs for the testing data condition--no servovalve fault and four leakage conditions of 0, 2, 4, 6 l/min*

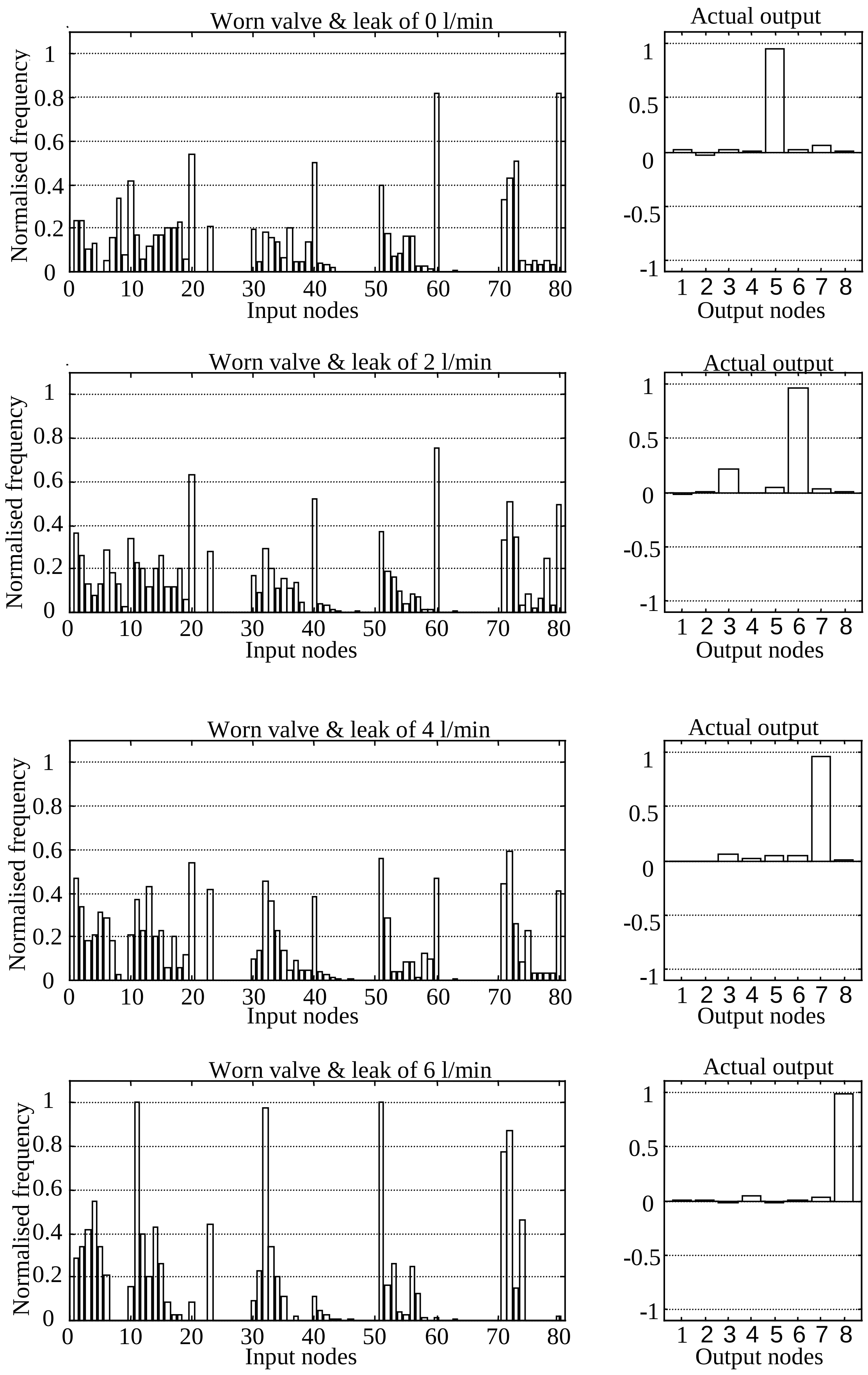


Fig. 5: *ANN outputs for the testing data condition--with a servovalve fault and four leakage conditions of 0, 2, 4, 6 l/min*

validate the training performance, and a maximum number of 500 iterations were found to be adequate in practice. Typical testing results for the multiple-fault condition (*LS*) are shown in Fig. 4, for the good servo-valve condition, and in Fig. 5 for the faulty servovalve condition. It may be seen that the classification performance is excellent for the best topology selected as shown in Fig. 4 and 5. It will be seen later that not all the topologies selected perform equally well.

Table 1: The ANN topologies tested for each of three fault conditions

Network number	Fault *LK*	Fault *SV*	Fault *LS*
1	80-20-2-4	80-20-1-2	80-20-4-8
2	80-20-4-4	80-20-2-2	80-20-8-8
3	80-20-8-4	80-20-4-2	80-20-16-8
4	80-20-16-4	80-20-8-2	80-20-32-8
5	80-40-2-4	80-40-1-2	80-40-4-8
6	80-40-4-4	80-40-2-2	80-40-8-8
7	80-40-8-4	80-40-4-2	80-40-16-8
8	80-40-16-4	80-40-8-2	80-40-32-8
9	80-60-2-4	80-60-1-2	80-60-4-8
10	80-60-4-4	80-60-2-2	80-60-8-8
11	80-60-8-4	80-60-4-2	80-60-16-8
12	80-60-16-4	80-60-8-2	80-60-32-8
13	80-80-2-4	80-80-1-2	80-80-4-8
14	80-80-4-4	80-80-2-2	80-80-8-8
15	80-80-8-4	80-80-4-2	80-80-16-8
16	80-80-16-4	80-80-8-2	80-80-32-8

4 Fault Classification Performance

In excess of 1000 data signals were available following an extensive experimental programme. Classification results were obtained for the 48 ANNs used, and by applying 30 example signals not contained in the population of archetype data used for training and testing. Important aspects of the study are shown in Table 2.

It may be deduced from Table 2 that the classification performance is excellent provided the most appropriate network is selected. All the networks indicated as "Best" required training times of 12-13 minutes, those indicated as "Worst" required training times of 25-38 minutes simply because of the increased number of nodes. Classifying the servovalve fault presented no problems for all the networks used, apart from the variation in training times. It is also evident that there is a clear indication of the preferred topology for all cases considered, this being 20 neurons in the first layer and the number of neurons in the second layer being more-or-less equal to the number of output neurons.

Table 2: ANN classification performance summary

Fault	Network Topology	**%** identified
Leakage *LK*	Best 80-20-4-4 Worst 80-80-2-4	98 70 Average for all tests 90
Servovalve *SV*	Best 80-20-1-2 Worst 80-80-8-2	100 100 Average for all tests 100
Combined *LS*	Best 80-20-8-8 Worst 80-80-4-8	100 63 Average for all tests 90

5 Conclusions

- The TESP method has proved useful in adding yet another tool for condition monitoring and fault diagnosis of hydraulic control systems. In this sense, it can add a further measure of confidence when used in conjunction with other techniques.
- The technique requires sufficient dynamic information in the transient response to give fault discrimination information. In this sense, the presence of transmission line dynamics can be a useful feature.
- The ANN approach complements earlier work by the authors using the same data but analysed using statistical methods, and the results are almost identical. This gives further confidence in the ANN classification technique.
- The TESP approach requires careful consideration of the signal processing used, but results have shown excellent fault classification even with sparse elements of the DATI data string.
- A clear topology emerged from this study, and reasonably consistent for all fault conditions. For two transient signals, the first hidden layer should contain 20 neurons and the second hidden layer should contain typically as many as the output layer.

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JOHN WATTON
Following his BSc and PhD degrees in the 1960's, John Watton has been continually working in the area of fluid power for the past 30 years in both Industrial and Academic environments. He has co-designed mobile machines now in commercial production and is currently Professor of Fluid Power at Cardiff University. He was awarded his DSc degree in 1996 for contributions to fluid power, and also received the 1999 Bramah medal from the Institution of Mechanical Engineers. Prof Watton teaches Fluid Power, Condition Monitoring, and Control to final year undergraduates, has supervised many PhD students, and has published over 120 papers.

NICK FREEBODY
obtained a first class honours MEng degree in Mechanical Engineering at Cardiff University in 1995, followed by a PhD degree on fault diagnostics of steel rolling mill hydraulics using time encoded signal processing, also at Cardiff University. Since early 1999 he has been a Development Engineer with Expert Monitoring Ltd Cardiff, principally concerned with Systems integration in the broad area of condition monitoring and fault diagnosis.