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NEURAL NETWORKS FOR THE IDENTIFICATION OF GAS CYLINDER FAULTS

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ABSTRACT
The safety of gas cylinders in domestic applications is of utmost importance. A crucial stage in the appraisal of the risk for failures and possible faults is occurring during the filling process. In Cyprus, this task is currently done by specialized workers who monitor the cylinders during filling. In order to explore the possibility for an automated risk appraisal and consequent screening, a system of fault identification using vibrational time series and neural network classification has been used. Two systems have been attempted. One using a multi-slab feedforward neural structure employing backpropagation-type learning, and a Kohonen self-organizing map. The results were also compared with different simple statistical methods. The feedforward net, proved to be slightly better responding than the Kohonen map for this particular problem.

KEY WORDS
Feedforward neural networks, Kohonen network, gas cylinder safety.

1. Introduction

The monitoring and appraisal of gas cylinder condition in Cyprus, is currently done by dedicated workers who visually observe the moving cylinders in a filling process line. This approach is costly, and sometimes unreliable, especially when it comes to identifying the general corrosion on the underside of the highly corroded cylinders. The cylinders are pressure tested during manufacture and major maintenance, but during the filling process they need to go through a systematic and thorough inspection for any serious faults.

The present study involves the examination of vibrational signatures of individual cylinders in order to appraise their general condition and thus classify them as acceptable or not. The unacceptable ones are properly maintained, provided that this is economically feasible.

The paradigm of neural networks has been used in different attempts for applications in fault classification of different machinery and systems ([1], [2], [3], [4], [5], [6], [7], [8]) Lee et al., 2004). Since, though, in many times, the identification of faults has to do with crucial safety issues, there is a need for a highly reliable identifier system.

For the analysis of the signals, both statistical and non-parametric neural techniques have been used. For the neural network classification, two major systems have been attempted. In each of the two major paradigms a number of special cases involving different architectures and learning procedures have been explored.

The most successful structure found, is that of a multi-slab feedforward neural network employing backpropagation type learning. A Kohonen self-organizing map has also been tried but it was slightly less successful compared to the feedforward structure.

Such systems could also be used as support mechanisms to a larger fault identification system that possibly employs human observers. The system studied and presented in this paper is of such a type

2. Instrumentation and data collection

2.1. Instrumentation set-up

A total of 63 empty gas cylinders that had their relief valves removed, were excited by a suitable hammer and the response was recorded via a Bruel and Kjaer (B+K) set of instruments as will be explained further on. The experimental set-up is shown in Figure 1.

Figure 1. The gas cylinder experimental set-up.

The cylinders were provided by the INTERGAZ FILLING Co in Cyprus. They were manufactured as per the BS5045 Part 2.2A specification, being of 24 liter capacity. They were pressure tested at 30 bar and the working pressure is limited to 20 bars. The tare weight varied between 13.1 kgf to 13.4 kgf.

51 of the tested cylinders were brand new, while 5 had a small artificially produced horizontal dent. 3 more cylinders were given a small, artificially produced, vertical dent. Finally, 4 more cylinders were selected to have a general severe corrosion at the bottom.

The instrumentation used was based on the B+K multichannel analyzer type 3550. The analyzer had many capabilities for signal processing, such as for spectrum averaging, 1/n octave spectrum averaging, zero pad, time capturing, time history, amplitude probability. The associated units that were used in the measurements were a charge amplifier type 2635, a noise generator type 1405, a power amplifier type 2706, an accelerometer type 4370, a vibration exciter type 4809, and an impact hammer type 8202, all from the B+K group.

Table 1. Set-up parameters

PARAMETERS	SET-UP
Mode of measurement	Frequency response
Estimator of measurement	H2
Averaging of measurements	Every Peak 10
Trigger	Signal X1
Frequency span (kHz)	6.4 kHz
Δf (Hz)	8 Hz
T (ms)	125 ms
Δt (us)	61.0
Weighting of signal Y1	Rectangular

A typical measurement and the associated settings are shown in Figure 2, while the values for the different parameters of the set-up are shown in Table 1.

2.2 Collected data

For each cylinder a frequency response has been obtained. A total of 676 discrete values of frequencies have been collected and processed for each cylinder. Thus the data matrix had a size of 676x63. A typical plot of the measured data, showing the difference in response between "GOOD" and "BAD" cylinders of vertical dent is shown in Figure 3.

3. Statistical fault classification

Different attempts were made to identify simple statistical ways to screen the good cylinders from the bad ones. In one attempt, the measured frequency response signal for each gas cylinder was cut above 4 kHz. The remaining values were then divided into four frequency ranges, namely, 0 – 1 kHz, 1 – 2 kHz, 2 – 3 kHz, 3 – 4 kHz. For each one of these ranges, the peak values were identified.

Following that, the ratio of peaks and the differences of minimum values were plotted in order to try to identify significant differences between the "GOOD" and "BAD" cylinders. Graphs of these results are shown in Figure 4 and Figure 5.

As it can be easily seen, the ratio of peak values was unable to distinguish between the "GOOD' and the "BAD" classes of cylinders. The differences of minimum values method, however, gave some reasonably good results as indicated in Figure 5, but definitely not acceptable for reliable fault identification.

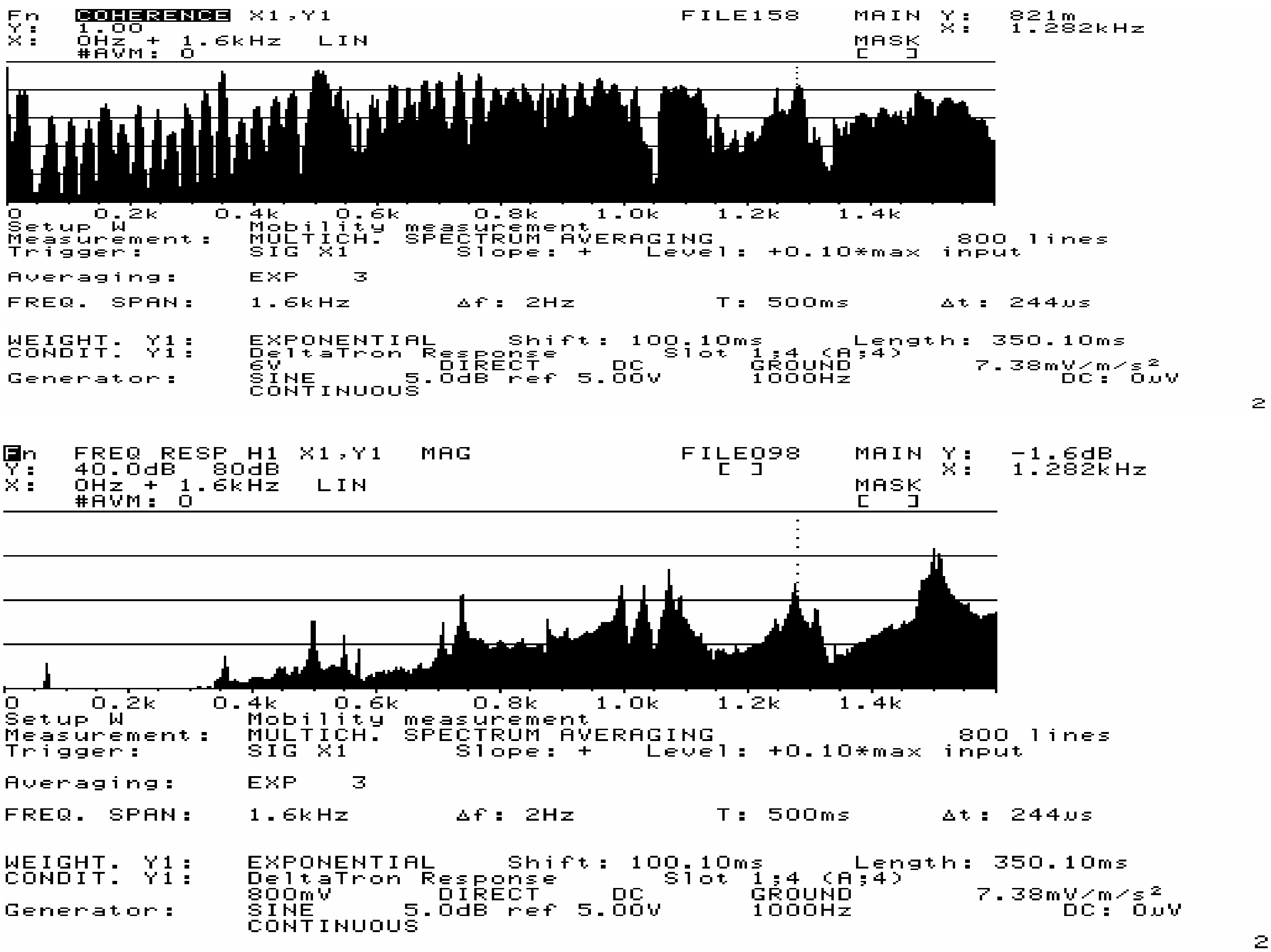

Figure 2. Typical frequency response of an excited gas cylinder.

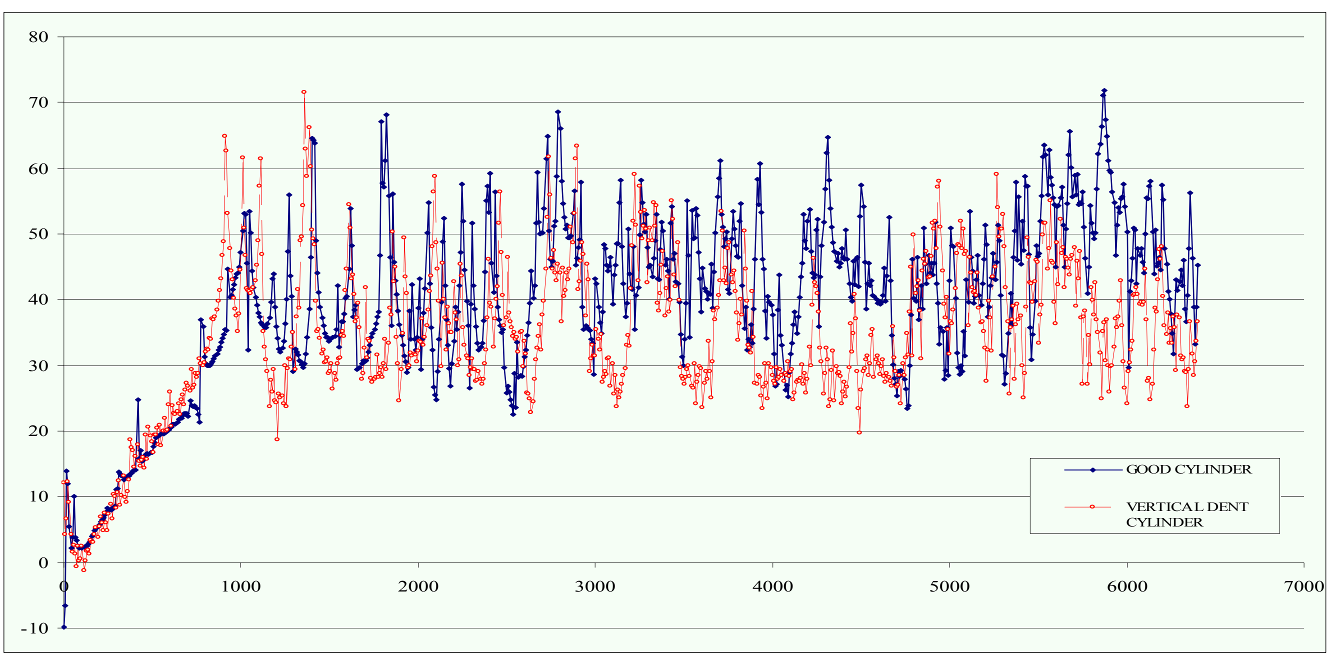

Figure 3. Frequency response of a typical “GOOD” and a typical “BAD” cylinder.

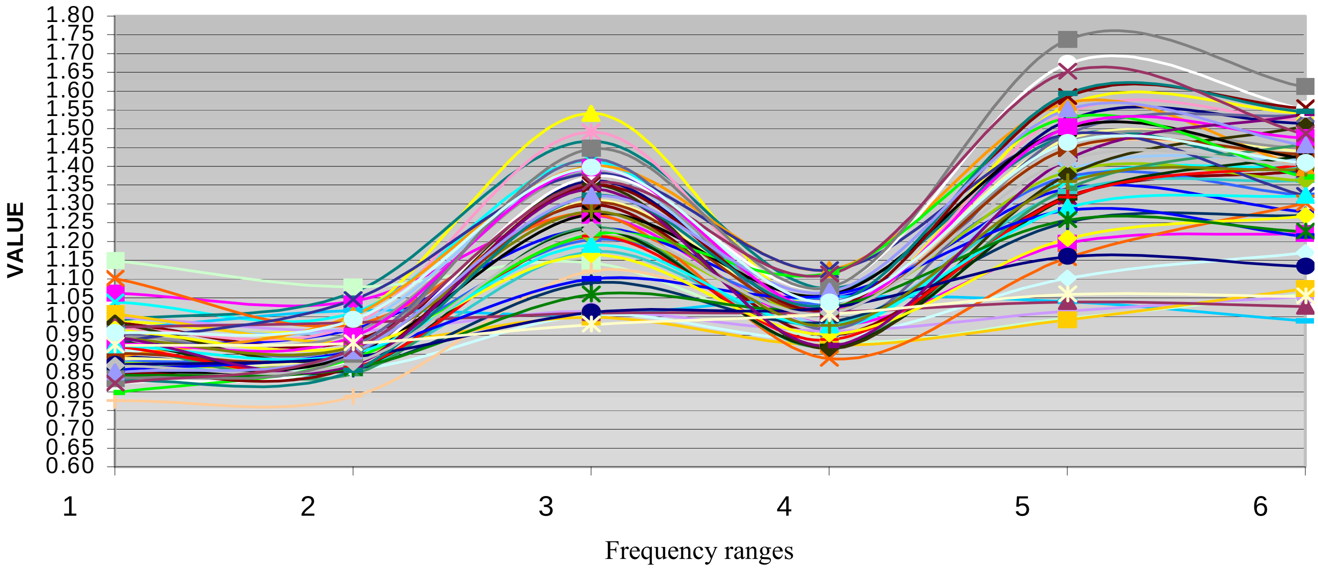

Figure 4. Ratio of peak values for the different frequency ranges.

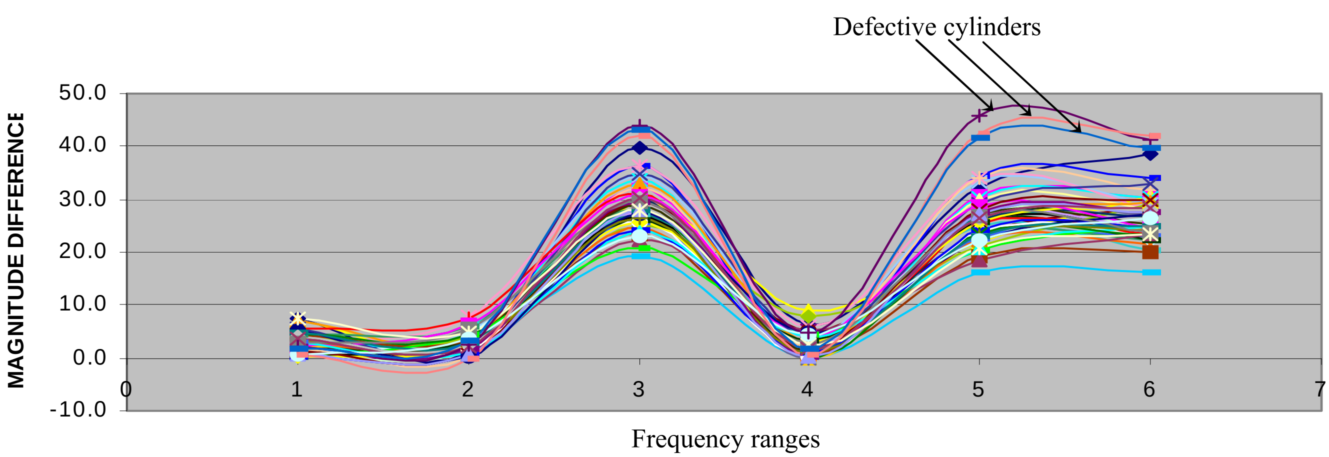

Figure 5. Differences of minimum values for the different frequency ranges.

4. Neural network fault classification

Two systems of neural structures have been attempted. A Kohonen self-organizing map and a multi-slab feedforward architecture using backpropagation-type learning.

4.1 The Kohonen self-organizing map

Standard Kohonen self-organizing maps of different structures and characteristics have been used to help in classifying the "GOOD" and the "BAD" cylinders. The parameters of the best responding network, that was finally used, are given below.

The topology was of a 4x4 network (total of 16 neurons) and the learning of standard Kohonen type. The initial neighborhood size was 2.5 and the initial learning rate 0.1. A total of 30,000 training presentations of 39 (out of 64) representative selections of cylinders were done. Of the 39 cylinders, 30 were of the "GOOD" class and 9 were of the "BAD" class. The "GOOD" and "BAD" samples had an equal exposure of 15,000 presentations each. The remaining 25 cylinders (19 "GOOD" and 6 "BAD") were used only as a test set for verification.

The best results obtained for the unknown test sample were 24 correctly classed (out of 25). Thus a success rate of 90% on the verification set was obtained.

4.2 Multi-slab feedforward architecture

The frequency response at 676 frequency values for the 63 cylinders was first reduced to a smaller size matrix of 67x63 in order to keep the size manageable by the Ward

System architecture. This was done by averaging the response for every 10 raw measurements. With such modified data, a WARD 2 multi-slab feedforward neural network structure as shown in Figure 6 was implemented. The selected architecture was based on extensive experience we had on using similar structures [9], and being able to identify the "best" for the problem at hand.

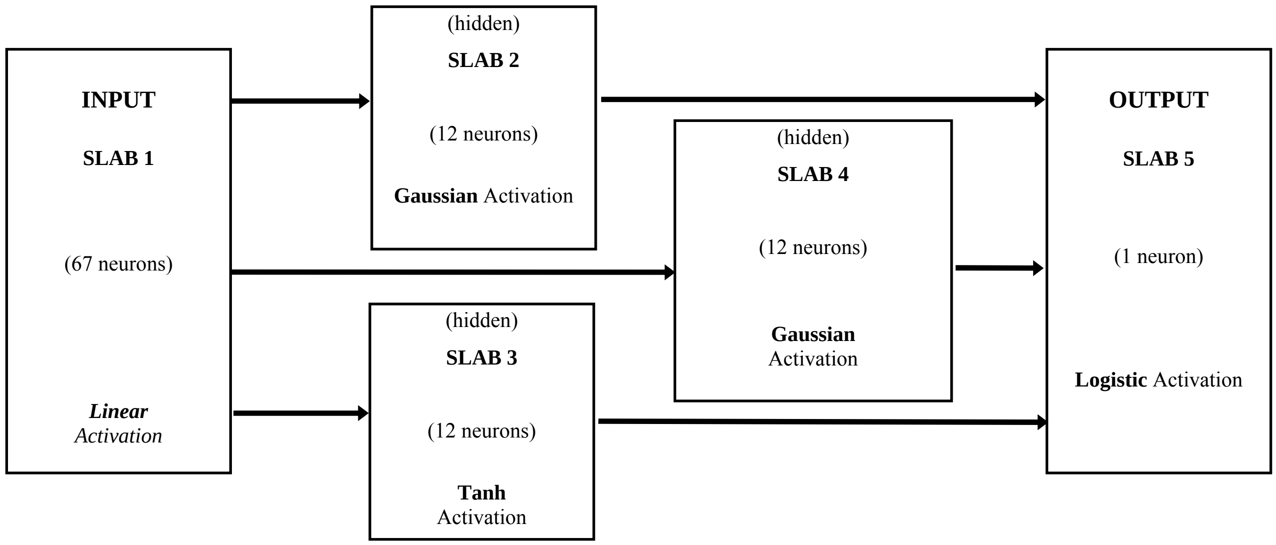

Figure 6. The specific WARD 2 multi-slab feedforward neural architecture used for the simulations.

The learning rate used was 0.1 for all the slabs, while the momentum rate was 0.1. All neurons were initialized at a value of 0.3. During the training of the architecture, 11 representative cylinders (of a mixture of "GOOD" and "BAD" classes) were left out of the training sample to be used for verification. The best results obtained for this structure were 98% correct classifications based on all the cylinder samples and 91% based on the unknown sample of the 11 cylinders.

5. Comparisons and discussion; Conclusion

From the three methodologies used, the multi-slab feedforward structure proved to be slightly better than the Kohonen net. The statistical approaches, as used, were unable to yield a satisfactory screening of the two distinct classes of gas cylinders. Once the method is established and tested in a greater sample, it may also be feasible to test cylinders so that different individual faults may be discriminated.

The research team is presently also examining the possibility of using acoustic signals for fault identification through the use of suitable neural structures. Such an approach will be more economical in implementation. Results will be presented in a future article.

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