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# The Analysis of Airborne Acoustics of S.A.W. Using Neural Networks

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## SUMMARY

The analysis of acoustic emissions for machine health monitoring has made rapid advances in the last five years due to a revival of interest in the application of Artificial Neural Networks (ANNs). Complex signal analysis, which has often thwarted conventional statistical methods and expert systems, is now more possible with the introduction of 'neural' based computing methods.

Acoustic emissions from welding processes are well documented. In particular, it has been established that a manual welder is capable of making intrinsic decisions concerning electrode position based on process noise.

The analysis of time / amplitude signals and Fast Fourier Transforms (FFTs), within salient frequency bandwidths of the weld acoustic, has yielded erratic, unpredictable and noise polluted data. Extracting a meaningful interpretation from this data is computationally intensive when utilising standard statistical methods and leads to data explosions, especially when an 'on-line' corrective control signal is required.

An Artificial Neural Network is 'trained' on examples from acquired data and performs a robust signal recognition task rather than relying on a programmed set of data samples as in the case of an expert system. This technique enables the network to generalise and, as a consequence, allows the input data to be erratic, erroneous and even incomplete.

This research defines the development of a hybrid system, utilising high speed date capture and FFT computation for the signal pre-processing and a 'self organising' network paradigm to establish weld stability and real time corrective control of the process parameters.

The paper describes a successful application of a Neural Network hybrid system to determine weld stability in submerged arc welding (S.A.W) through the interpretation of airborne acoustics.

## INTRODUCTION

The Neural Applications Group, within the Department of Design at Brunel University, UK, Directs its' research at the application of Artificial Neural Networks to 'real' industrial problems. The major focus is towards the welding industry, developing process control and NDT techniques. One area in particular has been the application of ANNs to a fully integrated control system for Submerged Arc Welding.

ANNs were principally developed as an attempt to replicate the topology and operation of biological neural systems. Advances have yielded models which 'train' or 'learn' output responses from given data. The consequences of this technique is an emulated biological system capable of dealing with erratic or even incomplete input data.

Observations of skilled manual welders has shown a subconscious tendency to change the angle of the electrode and length of arc by listening to adverse fluctuations in the process noise. This has resulted in much research into the analysis of airborne acoustic emissions (AEs) of welding processes.

Attempts have been made to interpret AEs utilising statistical and rule based techniques (1). The inflexibility of these techniques in dealing with noise polluted data, together with speed limitations, provided little success. Acoustic emissions from SAW requires the classification of large quantities of erratic data samples for any meaningful interpretation to be made (2). Many references can be found to the successful application of ANNs in signal processing (3) and condition monitoring (4,5,6).

In SAW, Logical Neural Networks (7) have been successfully employed to window and interpret noisy ultrasonic echoes from the weld head for seam tracking and weld penetration measurement in real time (8).

Although AEs from welding processes are potentially information rich, to limit the feasibility study into the ANN approach to signal classification, this research has focused on the detection of instabilities caused by non optimum voltage settings. Further studies are to be made into the identification of wayward variables during the welding process.

## EXPERIMENTATION

The parameter setting for an optimum weld were chosen by weld profile dimensions obtained from bead on plate post weld cross sectional inspection. Mild Steel plate, 25mm thick, was used with a root penetration of 15mm. The travel speed, current (determined by the rate of feed of the sacrificial electrode) and voltage were then considered optimum.

A transducer element consisting of three omni-directional electret condenser microphones (ECMs) were mounted 300mm from the welding head. Each ECM exhibited suitable gains and frequency responses for infra, audible and ultra sound ranges up to 40 kHz. Suitably pre-amplified, signals obtained were subjected to 8 active bandpass and appropriate anti-aliasing filters before being analysed by standard DSP methods.

Previous investigation, utilising a TMS320C30 system board hosting Hypersignal Workstation software revealed salient frequencies during welding of between 15Hz and 10kHz (2). Frequency 'signatures' of ambient conditions and ancillary equipment such as the mains transformer, fume extractor, kinetic control system and wire feed motor etc., were identified from a 1024 point FFT analysis as shown in Fig 1.

The initial analysis provided the sampling frequency and resolution necessary to isolate salient bandwidths suitable for input to an ANN model. The TMS320C30 was set up to perform a 128 point Radix 2 FFT (yielding 64 real data points), sampling frequency of

20kHz with a 16 bit resolution.

Three welding runs were the initiated over a 1 metre length. Ten recordings were taken from each and monitored to gauge signal consistency. The wire feed rate (current) and travel speed were held constant while the voltage, primarily at optimum level, was changed to a low unstable level followed by a high unstable level as recorded in Table 1.

Further transient noise was removed from the FFT analysis by a statistical method, taking the r.m.s over 25 acquired FFT frames. The 64 real data points of each resulting FFT was treated as a 64 component vector and used as input to the ANN classifying model.

TABLE 1. Voltage, Current and Travel Speed Settings

|  | V | I | S |
|---|---|---|---|
| WELD 1 (optimum) | 41.1 V | 820 A | 6.5mm/S |
| WELD 2 (low voltage unstable) | 29.7 V | 820 A | 6.5mm/S |
| WELD 3 (high voltage unstable) | 61.2 V | 820 A | 6.5mm/S |

## NEURAL NETWORK APPLICATION

Studies of biological neural systems have revealed that differing neuronal topologies as well as individual neurons perform different functions (9). The various characteristics of recognition and abilities in learning are replicated by ANN architectures and learning algorithms. The learning categories are generally of two types, Supervised or Unsupervised. Both these methods are utilised by two ANN paradigms which have emerged to become the most widely adopted methods in applications.

### Back Propagation Networks (BPN)

BPNs provide a method of supervised learning . In essence the input data is given with a desired output, and the learning technique is one of re-inforcement also known as Hebbian learning (10). The architecture is generally a 3 layer network consisting of an input layer, a middle or 'hidden' layer and an output layer. Each layer is fully interconnected to the proceeding layer. The number of neurons in the input and output layers depends on the input pattern organisation and the intended output classification. The number of neurons in the hidden layer is still the subject of much debate, but the optimum number is dependent upon the complexity of the classification problem.

For this experimentation the input layer consists of 64 neurons, one for each component of the input vector, and an output layer of 3 neurons for the classification of each weld run voltage level. The number of hidden layer neurons was initially set at 12, as shown in Fig 2.

In the training stages, the input vector components are transferred through the connected neuronal transfer functions via the synaptic weights (Fig. 3). The resulting values given at the output layer are compared with the desired output. A function of the error is used to adjust the value of the synaptic weights thereby making a subsequently similar input generate an output closer to the desired value.

The success of the BPN model is dependent upon the distribution or the degree of correlation of the input data. Although ANNs have the inherent ability to deal with highly correlated data, the BPN model uses a gradient descent method (11) in its learning algorithm to establish an optimum boundary between similar data patterns. If the separation is complex, it can often lead the network to converge on a local rather than a global minimum resulting in a failure to train or an unreliable output response.

## Self Organising Feature Map (SOM)

The SOM model utilises an unsupervised or competitive learning technique. This method replicates 'learning by experience' rather than by taught responses. The SOM consists of two layers, an input layer consisting of a number of neurons, suitable for the input data, fully interconnected to an output matrix or 'slab' of neurons. The number of neurons in the output slab depends on the required resolution of the desired output classification. (Fig. 4).

During the training phase, the input vector is compared with the randomly initiated synaptic values of each output neuron. The output neuron possessing the least error in vector or Euclidean space is considered the winner and its synapses are updated proportionally to the error as dictated by the learning algorithm. Furthermore, each winning neuron has neighbours within the output slab. These neighbouring neurons are also updated in such a way as to encourage or inhibit its chances of winning when a subsequently similar vector is compared. This training continues until an acceptable state of equilibrium is reached.

In this way similar vector patterns are clustered within a multi-dimensional vector space or hyperspace. Depending upon the density function and the correlation of the input data, natural separations can occur. The degree of separation is measured in terms of error distances within hyperspace. Consequently this method requires a comprehensive understanding of the nature of the input data and necessitates the re-analysis of the clustered vector patterns.

In general, the problems associated with pattern recognition by means of ANNs is greatly relieved by careful signal pre-processing. Training data should be of a standard which highlights salient features. This not only reduces training times but increases the chances of achieving a fully optimised network (12).

Depending upon the number of training data sets and the size of the network, training can be a time consuming phase. The benefits are yielded from the network's inherent ability to generalise on previously unseen data patterns together with fast response times. The main limitation of this technique is memory allocation for computed vector analysis.

## Network Implementation

The ANN models used for this research were software emulated. Commercially available software, in the form of the NT5000 from Neural Technologies was used for the BPN and custom compiled software for the SOM model. Although the networks are operated on a von Neumann derived computer architecture in which data is actually processed serially, the speed of operation of a trained system enables viable real time application (11). This is due to the simulated parallel processing of the input vectors.

## RESULTS

Typical FFT frames introduced to the network models are shown in Figures 5, 6 and 7. Five hundred rms frames, sampled from a weld length of approximately 0.1 meters or 15 seconds, from each weld run was used as training data. Although pre-processed the FFTs are still erratic and certain characteristics are apparently similar in all three weld runs. This was evident from the results of the attempts to train the BPN model.

The primary training session of the BPN model yielded negative convergence after 15 minutes. The high correlation of the input data proved too complex for the initial system architecture to reach a satisfactory conclusion.

The architecture was subsequently amended by increasing the hidden layer neurons up to 24. Further training eventually provided a convergence after 25 minutes. The gradient descent method was assisted by the frequent injection of noise known as weight joggling. This technique is designed to assist the prevention of local rather than global minima detection.

Testing the network entailed the input of previously unseen data vectors in an attempt to correctly classify the three levels of weld stability. The success rate was gauged on a percentage correct basis. Results proved inconclusive with all three test sets yielding between 42% and 51% correct classification.

Further investigation is in progress for the application of optimisation techniques for BPNs.

The self organisation of the SOM model negates the need for a global convergence. The input data vectors are automatically clustered within the 64 dimensional hyperspace. The clusters are of similar input patterns and subsequent test vectors are associated to or within the trained cluster by means of a calculated error distance.

The network was initially trained on the signals obtained from the optimum weld run and data from the unstable welds used as test vectors. The high dimensionality of the data compounds the graphical representation of the clusters which necessitates the re-analysis of the patterns and calculated error distances. Analysis of the resulting errors showed that the high voltage unstable weld was regarded as a sub-set of the optimum weld cluster, whilst the low voltage unstable data was clearly segregated as shown in Fig. 8.

The second training run was initiated with the high voltage weld data and the subsequent errors from the optimum and low voltage test patterns assessed. Almost full separation was achieved with a minor union evident between the optimum and high voltage data

clusters as shown in Fig. 9.

The training times for the SOM amounted to approximately 15 minutes on a 486 / 66MHz PC machine. Response times to individual input vector classification was approximately 0.02 microseconds with total cluster comparison in 3.5 milliseconds.

The pattern separation is achieved with data representing the extremes of voltage level instability. If an appropriate corrective control signal is to be generated, a vector signal needs to be quantified from the individual or clustered test pattern errors. The classification of AEs with respect to intermediate discrete voltage settings requires a calibration technique capable of providing such a signal. As the voltage is adjusted from unstable to stable the generated data clusters will converge reducing the computed errors, however, data separation also reduces and cluster boundaries become unclear. Consequently, the detection of the *onset* of weld instability becomes more complex.

Solutions to this problem are currently under investigation.. Fuzzy logic and control (13) and further ANN models which exhibit predictive capabilities, such as Probablistic Networks and Spation Temporal Networks (14), are invisaged as providing possible remedies. Thes systems yield outputs relating to successively occurring data patterns and consequently emphasise cluster density functions.

## CONCLUSIONS

The airborne acoustic emissions from submerged arc welding yields highly correlated erratic data which requires specific pre-processing to emphasise salient features.

Conventional DSP methods including FFT and averaging techniques are capable of revealing features, in real time, which are compatible with certain Artificial Neural Network models.

A Back Propagation Network proved inconclusive when attempting to classify data patterns derived from acoustic emissions associated with the voltage stability of submerged arc welding.

A Self Organising Feature Map successfully separated and classified low, high and optimum voltage settings from the acoustic emissions of submerged arc welding.

Complex and erratic signal interpretation often requires both conventional statistical and neural network techniques.

Research continues into neural network optimisation, corrective control signal generation and the development of a fully integrated welding control system.
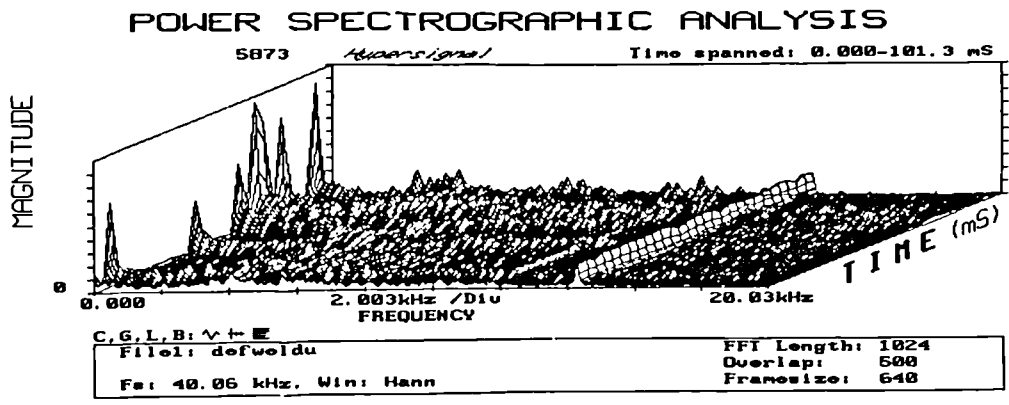
POWER SPECTROGRAPHIC ANALYSIS

**Figure 1.**
1024 Point FFT of Typical optimum weld run.

Input Layer

Hidden Layer

Output Layer

—Optimum

—High

—Low
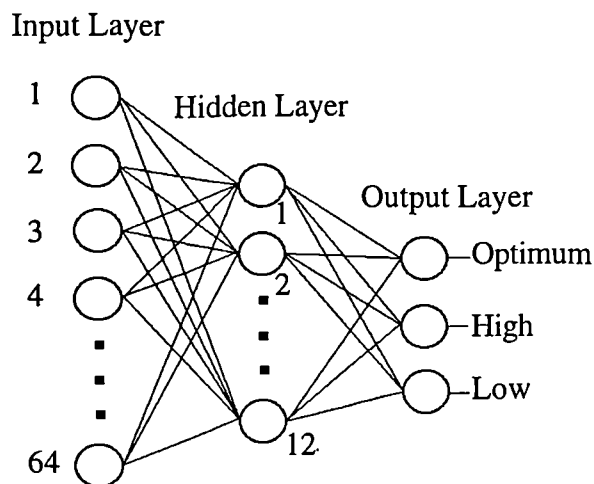
**Figure 2.**
Typical Back Propogation architecture

$$I = \sum_{j=0}^{n} WjXj$$
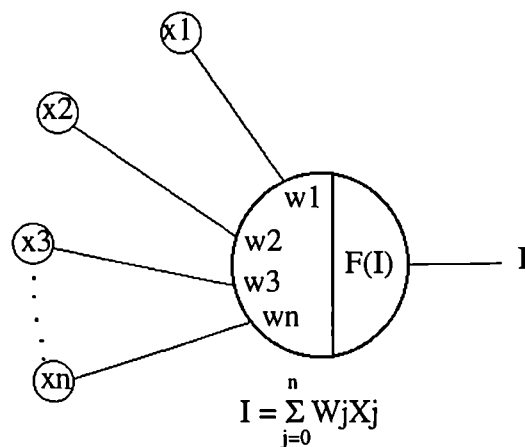
**Figure 3.**
Typical artificial neuron showing
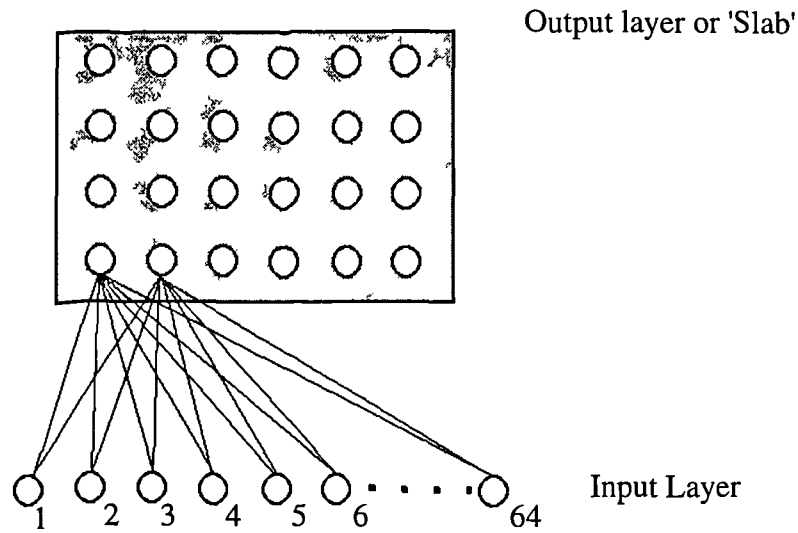transfer function.

Output layer or 'Slab'

Input Layer

**Figure 4.**
Self Organising Feature Map architecture
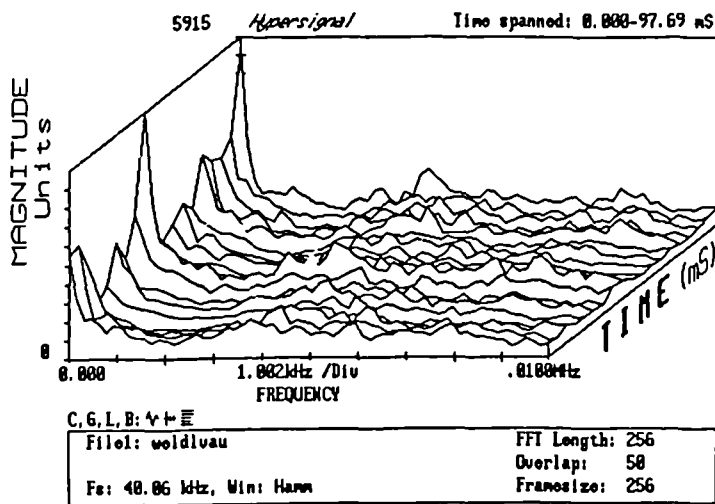


**Figure 5.**
128 Point FFT, low voltage signal
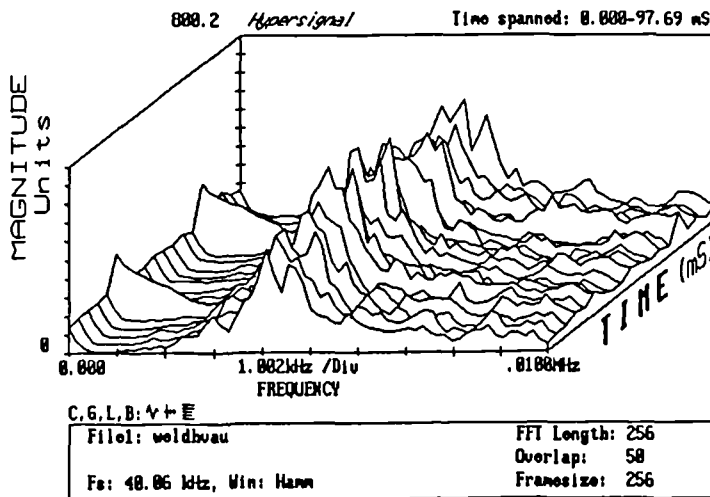
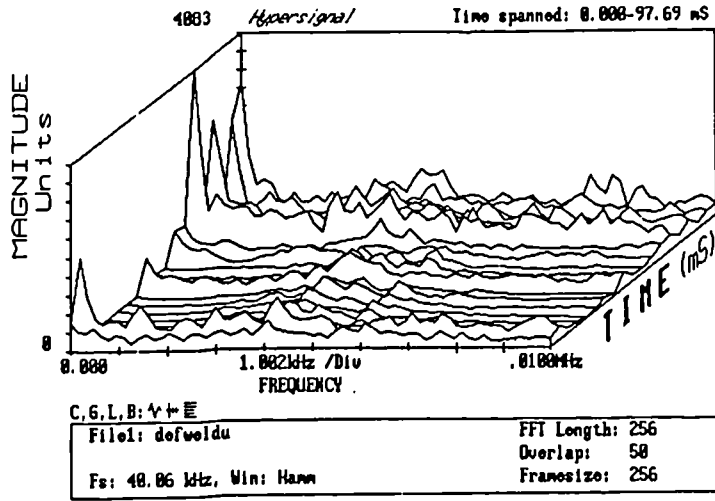

**Figure 6.**
128 Point FFT, high voltage signal

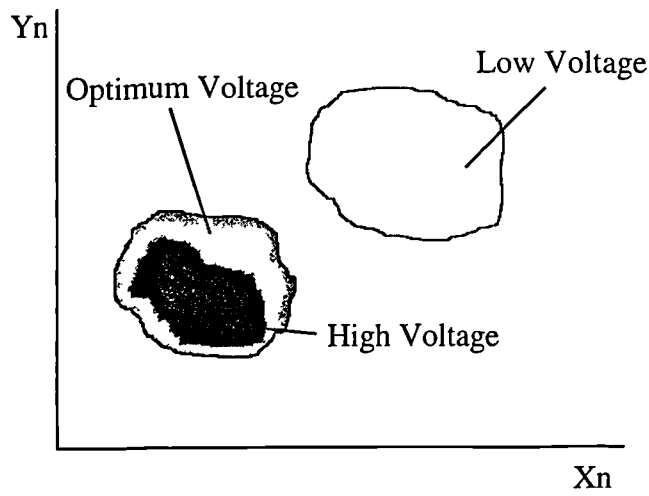**Figure 7.**
128 Point FFT, optimum voltage signal



**Figure 8.**
Data cluster representation with high voltage
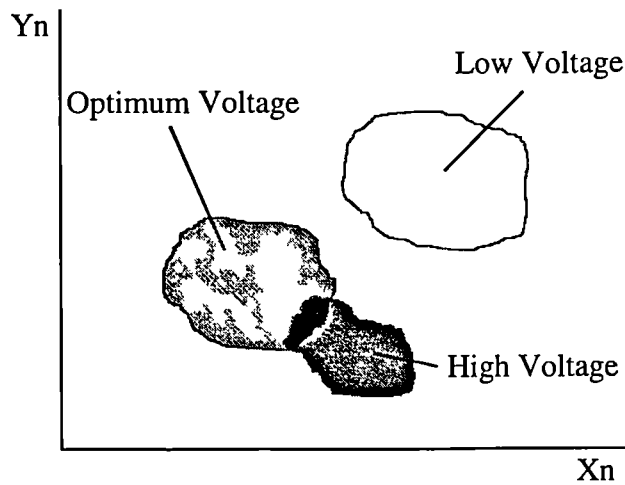a subset of optimum voltage



**Figure 9.**
Retraining with high voltage data causes
further separation with a minor union

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