# Intelligent Monitoring of Small Transients in a Complex non-linear system using Artificial Neural Networks

By

Llewellyn Joseph D'Souza

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# Abstract


This project uses Artificial Neural Networks (ANNs) to develop a prototype computer based Operator's Advisory System for the early detection and diagnosis of plant transients.

Three transient monitors were developed two of which are ANN based. Each of the independently developed ANN classifiers was then integrated into a multi-level operator advisory system OAS. The first level of diagnosis provides information to the plant operator of the presence of a major transient. Should a transient be detected a corresponding module provides more detailed information on the size of the transient. To validate the diagnosis two methods are used in the OAS: User confirmation and a comparison with simulated plant data. The diagnosis is reproduced in an independently developed PWR simulator and the plant parameters compared. If in agreement, a high level of confidence was attached to the diagnoses, a poor match would suggest that the transient is not one that the diagnostic module had been trained on. The OAS was evaluated on a wide range of scenarios. The results of the tests were encouraging with the OAS successfully identifying a range of standard transients. However, tests on the robustness of the OAS proved inconclusive.

The project concludes with suggestions for future work.

## Acknowledgements

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Most of all, I must acknowledge the love, care and support of my wife Francine, who, while not exactly making this all possible, did make it more bearable. Thanks for your patience.

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## Declaration



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# Chapter 1

# Introduction

## 1.1 Background to Thesis

Many natural and increasingly artificial systems are characterised by complex non-linear behaviour. Examples of such systems include the weather, the stock market and power generation. Each of these systems may be considered to be collections of simple units which evolve as a result of interaction, both between the components, and the components and their environment. Such complex behaviour manifests itself as chaotic, seemingly unpredictable dynamics. A detailed understanding of any one of the components, does not necessarily prescribe knowledge of the behaviour of the full system.

As a result, researchers in a large number of unrelated areas (including, cognitive science, computer science, mathematics, control systems, biology, neuroscience, engineering, etc.) have begun to address, through a combination of basic, applied, theoretical and experimental research, the analysis and modelling of complex systems. One such method that has been successfully applied to the modelling of complex non-linear systems in recent years are Artificial Neural Networks (ANNs), which are a simplified attempt to mimic the brains ability to recognise complex patterns.

The work reported in this document investigates the application of ANNs to the monitoring of a complex non-linear system (Weller 1997) as typified by a Nuclear Power Plant (NPP), although the methods developed are applicable to other domains. The diversity of the control system required for its safe and efficient operation is reflected in the broad range of temporal observed behaviour in the operation of the plant. Over the past few decades there have been major advances in the general understanding of the mechanisms governing the behaviour of the system and to the early detection and management of plant transients.

Plant operators have an important role for the effective functioning of a NPP. A typical control room in a NPP is a data rich environment. The types of data encountered in a control room include temperature, pressure, flow rates and status of valves with the data being presented to the control room operator in the form of analogue and digital readouts. Some pre-processing of the data before presentation to the operator may take place, and is often in the form of alarms, though the amount of pre-processing is limited.

Increasingly many of the analogue instrumentation and control systems are being replaced with digital alternatives which have benefits of greater stability, higher data and storage handling capabilities; and an improved performance in accuracy, reliability and computational capabilities (NRC SECY-01-0155).

However the sheer weight of information presented to the plant operator can affect their decision making process. The human error that can occur during the decision making process when analysing plant data can be exaggerated by factors such as stress and fatigue (Swain, 1983). The result of a failure in the correct diagnosis of a fault can lead to poor management of the fault. At best, this can result in a drop in the efficiency of the NPP as typified by small leaks in a PWR (Hessel 1999) or it may lead to more catastrophic failure of a system within the NPP (Kemeny 1979).

This richness in the amount of information available to the plant operator together with increase in automation technology requires progressively more complex decisions to manage abnormal plant behaviour, for example during the start up of a reactor, or a transition change between operating states. The decision-making process could be improved if the operator's skill and experience were further supplemented by a robust decision support system.

The work reported in this thesis was performed during a four year project. The program is part of an ongoing collaboration between the Centre for Health Informatics, City University, London and the Nuclear Department HMS Sultan, Gosport.

## 1.2 Aims and objectives

The aim of this study was to investigate the use of ANNs in the intelligent monitoring of small transients in a complex system as typified by a nuclear reactor, and to develop a proposal by Weller (1997) of an Operators Advisory System (OAS) based on ANNs.

Specifically the objectives of this thesis are to:

- Present an overview of the current understanding of relevant research

- To extend and validate an existing model of transient classification in the primary circuit of a Pressurised Water Reactor (PWR).

- To investigate the use of ANNs in the monitoring of small transients in a PWR

- Develop a prototype ANN based OAS

## 1.3 Thesis Structure

The remainder of this thesis is described by chapter as follows:

Chapter 2 provides an overview of relevant research in the experimental applications and issues in the use of soft computing methods in the monitoring of transients in Nuclear Power Plants, with an emphasis in the use of ANNs.

Chapter 3 describes the basis of the problem reported on in this thesis.

Chapter 4 reports on the development of a diagnostic ANN based module for the early identification of a major fault in the primary circuit of a PWR, including tests on its robustness.

Chapter 5 investigates the use of techniques used in chapter 4 for the analysis of small transients as typified by a small loss of coolant from the primary circuit of a PWR.

Chapter 6 considers the classification of a small leak from the secondary circuit of a PWR. Two approaches are investigated. The first method looks at the use of data obtained from a simulation of small steam leaks to train an ANN to classify the leak size. The second method investigates the use of acoustic data obtained by real world measurements of a steam raising plant to supplement the data obtained by simulation.

Chapter 7 reports on the integration of work described in chapters 4-6, and the development of a prototype OAS. An iterative approach is used in the testing and refining of the system.

Chapter 8 presents the conclusions, meeting of the objectives, and the recommendation for future work.

# Chapter 2

# Literature Review

## 2.1 Introduction

This chapter outlines research in the application of Artificial Neural Networks (ANNs) in the nuclear power industry, especially those associated with the classification of fault transients. Other soft computing techniques are also included in this review for completeness. Finally, a discussion on the research and the implementation of soft computing techniques in the nuclear industry in particular the use of ANNs is reported on.

ANNs are computational models which, from a numerical modelling point of view, are a general framework for representing non-linear mappings between multi-dimensional spaces in which the form of the mapping is governed by a number of adjustable parameters. By modifying of the adjustable parameters the ANN model 'learns' or identifies the mapping.

The growth of ANNs also has parallels with other non-linear modelling techniques for example, Fuzzy Logic and evolutionary computation. In 1992, Lotfi Zadeh coined the term soft computing which combined the three techniques, and for the first time in 1994, the IEEE had a combined meeting in the three areas of Artificial Neural Networks, Genetic Algorithms and Fuzzy Logic in Orlando, USA.

Amongst the many Artificial Neural Network (ANN) methodologies described in nuclear power research literature, the most widely used is the multi-layer feed-forward (back propagation) ANN that is capable of representing non-linear functional mappings between inputs and outputs. These networks can be trained with a powerful and computationally efficient gradient descent method called the error back-propagation. An introduction to ANNs can be found in Appendix A.

## 2.2 Review of Artificial Neural Network Applications in the Nuclear Power Plants

### 2.2.1 Introduction

Many complex processes as typified by a Nuclear Power Plant (NPP) are difficult to model mathematically as these processes may be; -

"

- To complex to understand or represent simply.
- The models are difficult or too expensive to evaluate.
- The process is subject to large unpredictable environmental disturbances.
- The processes may be distributed, non linear, incomplete, stochastic and temporal therefore not amenable to linear time and variant modelling."

(Harris, 1994)

A typical control room in a nuclear power plant is a data rich environment (Swain 1983). The type of data encountered in a control room includes raw data obtained from transducers found in different systems in and around the NPP. Examples of the measurements made include temperatures, pressure, valve status, flow rates and radio chemical measurements.

The control room of a NPP often contains many gauges and dials displaying the status of the plant and is presented to the control room operator in the form of analogue and digital readouts. In some cases, the data may be digitally pre-processed prior to presentation to the control room operator and is often in the form of alarms or trending, though the amount of pre-processing is limited. The introduction of digital technology for instrumentation and control is now vital to the safe operation of many plant processes; however an examination of the Licensee Event Reports (LERS) database by the US office of Nuclear Regulatory Research found that between 1994 and 1999 approximately 8% of all LERS contained digital, instrumentation and control failures. (Brill 2000).

The large amount of data combined with differing levels of information presented to the operator can affect their decision making process. The human error in this process can be exaggerated by factors such as stress and fatigue (Swain, 1983). The operator often associates a change in state of the reactor plant with an associated pattern change. However, subtle changes in the pattern may well go unnoticed. In the case of a nuclear reactor, if a problem does arise, the plant can go from a normal operating/transient state to a severe accident in a matter of minutes, as was the case in the Chernobyl (Mosey, 1990) and the Three Mile Island (Kemeny, 1979) incidents.

The power plant at Three Mile Island was of a PWR type and was operating at 98% full power when the loss of primary coolant led to an uncovering of the core resulting in an increase in radiation levels within the building. Serious core damage had been sustained during the accident; however there was only a minor release of radioactive isotope into the environment. The immediate cause of the accident was a combination of human and physical errors. Blocked valves and the feed water system were left closed after routine maintenance combined with the failure of valves to close in the condensate polisher and pressuriser. The plant operators also failed to correctly diagnose the fault condition in the plant. The primary method for diagnosing the stuck valve was inadequate. In addition to this, the numerous audible and visible alarms associated with secondary indicators triggered an alarm "shower" diverting the operators attention.

This incident highlighted the need for better signal validation, earlier diagnosis, a change in transient identification and better procedures for turning the data into knowledge that can be presented to the operator to help in the decision making process and also to give advice or predict what will be the consequence in the plant dynamics if a corrective procedure was implemented to deal with an accident.

The **IAEA** (1999) suggests that the number of human operator errors is likely to increase due to the greater need of maintenance of older NPP, and the replacement of experienced control room staff, who were there since the commissioning of many of the NPP.

The development of intelligent support systems is one means by which data can be changed to knowledge in order to better support the control room operator during decision- making.

### 2.2.2 Research in Artificial Neural Networks in Engineering

An insight into the popularity of research into ANNs can be gauged by a search of the British Libraries database of journals published internationally, which lists over 200 titles on the subject. Figure 2.1 is a graph showing the number of publications on ANNs in Engineering and Physics between 1990 and 2001 (taken from INSPEC). The number of publications with the keywords Neural Networks or Artificial Neural Networks in the title peaked in the mid nineties, and although the number of publications seems to be in decline there still remains over 5000 articles published on this subject per year.

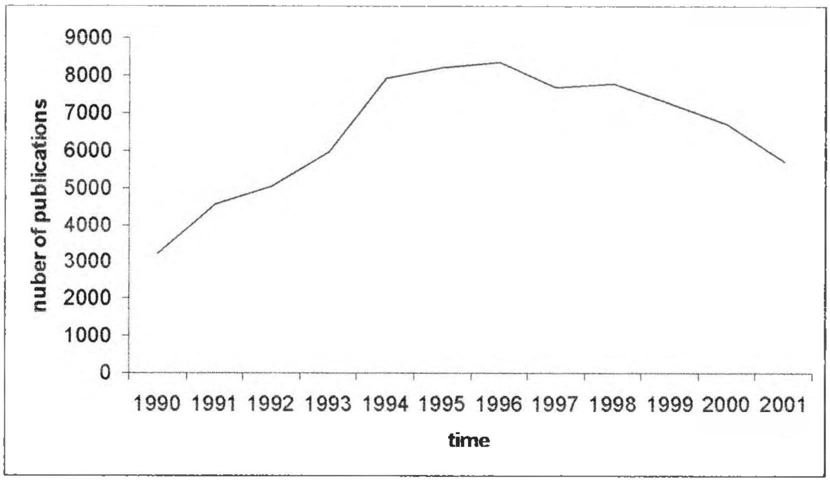



**Figure 2.1 Publications of ANN in Engineering and Physics (Taken from INSPEC)**

There may be several reasons for the apparent decline in the number of ANN publications in engineering and physics as indicated in figure 2.1. One explanation may be the combination of ANNs with other soft computing techniques for example, Neuro-Fuzzy system (combination of ANNs with Fuzzy Logic) and therefore would not appear in the main title. It could also reflect the discipline reaching a level of maturity where it is not explicitly mentioned in the title.

Another possible explanation is that ANNs are often viewed as a "black box" approach to problem solving. Unlike other modelling techniques for example expert systems, ANNs cannot fully explain the decision path of the underlying knowledge base. In a safety critical system, as typified by many plant processes, this is a major obstacle when trying to obtain a safety justification certificate.

However, on searching the US Patents Database (figure 2.2) it is apparent that there has been a steady increase in the number of patents of ANN applications applied for in the US, and this gives some indication as to their increase use and commercial potential.

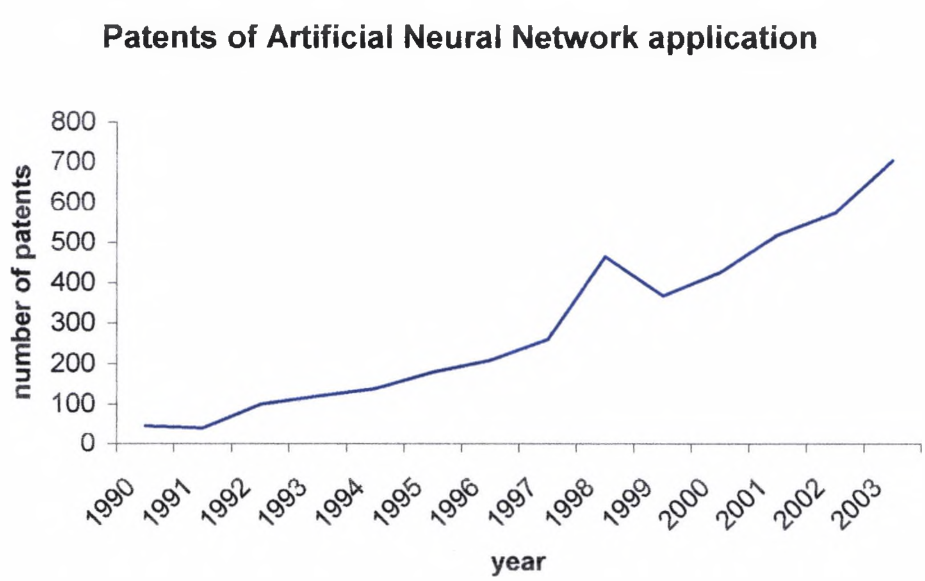



**Figure 2.2 Patent Applications for ANNs in the US**

### 2.2.3 Diagnosing plant condition

One of the essential tasks in the operation of a NPP is the detection, via monitoring of process changes and faults during normal or abnormal operating conditions. To enhance the monitoring activities, the early diagnosis of a fault is required to either eliminate, or better manage the transient. Early diagnostic systems were limited to alarm handling and protection but in recent years computer based systems have been put forward as a means to further improve plant diagnostics. These range from systems that make use of the Fast Fourier Transform (FFT) techniques used in time series analysis (Wach, 1991) through to the use of soft computing techniques such as ANNs (Weller, 1997).

Uhrig (1991) describes one of the earliest solutions to transient identification in a NPP using ANNs. In this landmark paper, Uhrig reviews the potential application of ANNs at several operational levels from major transients ( e.g. a loss of coolant accident), changes of state during normal operating conditions (e.g. reactor start up) and at transducer level (e.g. sensor validation).

Uhrig together with Bartlett (1991) go on to describe the difficulty in diagnosing the state of the plant when the system under surveillance gives noisy, incomplete or intermittent data. A dynamic node architecture scheme was used to optimise the architecture of the ANN. The data to train the neural network were generated from a NPP simulator, which provided a three bit training code as an output. The inputs to the neural network were from twenty-seven plant variables, and the simulator was used to generate seven faults and one normal operating condition. A self-optimising stochastic learning algorithm was used to develop the architecture of the network. The training process began with one perceptron in the hidden layer and the ANN was trained until an optimum performance had been acquired. A further perceptron was then added until a new optimum level was reached, the process continued until a specified level was attained. At this point the least important perceptron was removed until the network structure oscillated about a fixed architecture.

The results of this work were extremely promising with all the fault conditions being correctly diagnosed. Also noted from the results of the experiment was that the ANN exhibited a graceful degradation in performance with the addition of gaussian noise to the input signals. The success of this work led to further research by Basu and Bartlett (1994), in exploring the feasibility of ANNs being used for fault diagnosis, using the dynamic node architecture scheme. This time a simulator generated twenty-seven faults, with ninety-seven plant variables being used as inputs to the ANN. The large size of this network led to an increase in the complexity of the diagnostic ANN. A hierarchical approach was used to solve the problem with individual ANNs being trained independently using sub sets of the original data. Two networks were developed; the first to diagnose if the plant was operating correctly, the second to diagnose the type of fault. Once again the advisor performed well even when the data were corrupted by noise. They also highlighted the advantages of a modular approach to solving this problem. This original work by Basu and Bartlett led the way for subsequent applications of ANNs in nuclear power plants.

Weller (1997) developed the use of ANNs for transient classification and the prediction in a PWR. The concept of modular ANNs as methods of classification was developed further.

In this work it was suggested that a hierarchy of diagnostic ANNs could be developed to provide information to the control room operator on: -

- Plant status
- Area of fault
- Site of fault
- Faulty device

The second concept developed was the training of several ANNs independently on the same data, where the outputs of each of these are fed into a decision maker for a final diagnosis. The data used in the ANN developed for the diagnostic system consisted of sixty -seven PWR variables generated by a generic PWR simulator.

Six transients were used for classification, five fault conditions and one 'no fault' condition.

Weller and Thompson (1999) continued the previous work, by testing a diagnostic ANN with a wider set of unknown transients. As before, the data set for training, testing and validation of the networks was obtained using a generic PWR simulator of the primary circuit. The results from these experiments demonstrated that all of the diagnostic ANNs developed gave acceptable outputs for the unknown transients, but showed difficulty in classification when confronted with similar transients; they concluded that further tests were required.

Roverso (2000) compared several alternatives to the feedforward backpropagation neural network algorithms and models for performing transient classification. The success of each approach was judged upon a series of tests that checked the accuracy, robustness, reliability and real time performance of the ANN. The final design was used to develop of the prototype system ALADDIN, an approach for classifying transients in dynamic processes. This is part of the on going research into nuclear technology, safety and reliability at the Organisation for Economic Cooperation and Development (OECD) Halden Reactor Project. The ALADDIN project was derived from the problem of alarm structuring/suppression in a Nuclear Power Plant alarm system. The four main ANN approaches evaluated were: -

- Radial basis function neural networks (RBF)
- Cascade – RBF neural networks combined with fuzzy clustering
- Self organising map neural network
- Recurrent neural networks.

To compare the four methods a nuclear power plant simulator was used to generate a set of five transients at four separate power levels. The recurrent neural network was the only model to classify all the transients correctly. The second ALADDIN prototype looked at the difficulties of training a neural network when transients occur over a long period of time, as most information used for classifying comes early in the transient. Various training runs (using the same data) produced several networks which all performed differently. In the ALADDIN project an ensemble of independently trained networks were each presented with the data, the outputs of the networks were averaged to produce the final classification. If an unknown output from the ensemble were to be presented to the final classifier, an unknown signal would be generated. Much of the research is still ongoing. The next phase of the project is for the integration of ALADDIN with other systems developed at the OECD Halden Reactor Project (http://www.external.hrp.no/ ).

### 2.2.3 Signal validation

An inquiry into the Three Mile Island accident in 1979 highlighted the need for an independent signal validation system. Fantoni (2001) describes results achieved using the signal validation toolbox PEANO that is based on neuro-fuzzy techniques. The aim of PEANO is to confirm sensors that monitor the functioning of an industrial plant are operating effectively. During the operation of a plant, faulty or mis-calibrated instrumentation channels may lead to erroneous identification and diagnosis of abnormal events, which can result in errors by the operators in a control room. These errors can lead to:

- Process uncontrollability and instability, when sensors are connected to control and automation
- Systems resulting in emergency shutdown of the entire process
- Reduced plant performance and efficiency.

The PEANO signal validation system is now in operation at the Halden Boiling Water research reactor, and has been tested on plant processes outside the nuclear industry.

### 2.2.4 Calculation of Reactor Axial Power Distribution

Yu Seon et al (2002) describes a methodology to calculate the reactor axial power distribution using excore detector signals based on an ANN. In this work an ANN consisting of a single hidden layer with twenty five neurons is trained using a back propagation algorithm to provide a mapping between three level excore detector signals and a 20-node axial power distribution. The training set for the neural network is obtained using a simulator. The results of the experiment demonstrated that the axial power distribution can be deduced from a simulation of the excore detector via the use of an ANN. When compared with existing methods for predicting axial power at the Yonggang nuclear power plant unit 3, the performance of the ANN was found to be superior.

## 2.3 Small Leak Detection

### 2.3.1 Introduction

This section briefly examines the detection and monitoring of small leaks in nuclear power plants (NPPs) and concentrates on techniques relevant to the research in this thesis. The detection of small leaks in a NPP is important for its safe and efficient operation. Often the detection of a small leak may not be sufficient to warrant the shutdown of power plant, but will require accurate monitoring to ensure proper management of the transient. The data used for the development of detection and monitoring systems make use of a much wider range of plant monitoring transducers, both internal and external to the plant process.

### 2.3.2 Leakage detection Expert System

One approach commonly used for solving complex problems are expert systems, which acquire and represent domain specific knowledge. When the expert system is presented with a pattern, the encounter triggers the relevant rule; and the system takes appropriate action. A key distinction between ANN and expert systems is the separating of knowledge from control. In expert systems, knowledge is stored in a knowledge base whilst rules reside in a separate inference engine. In ANN the rules are implicit to its design. The benefits to be gained from using an ANN in the development of a decision support system are:

- The amount of expert domain specific knowledge which is required to develop an ANN is considerably less than that which is required for a rule based system.
- Unlike expert/rule based systems, ANN generate their own rules by learning from example.
- The ability of ANN to generalise allows the ANN to give a recognisable response to incomplete or noisy data unlike expert systems.

Nagasawa (1998) describes leakage detection based on an expert system, which diagnoses a leakage and its source in a Primary Containment Vessel (PCV) of a boiling water reactor (BWR). It achieves this by using chemical and radiochemical data. Changes in the following instruments and monitors were used:

- The PCV atmosphere dew point
- The PCV sump rate flow
- The PCV Air coolant condensate rate flow
- The PCV Radiation monitor
- The PCV Atmosphere temperature
- Valve leakage detection system temperature
- Primary Recirculation Pump (PLR) pump mechanical seal pressure

The evaluation of hydrogen and nuclides in the PCV atmosphere is combined with the evaluation of nuclides in the PCV sump. This expert system is now under planning for use as a plant support tool in a BWR plant.

### 2.3.3 Acoustic Surveillance

Developments in signal processing and microphones over the last two decades now allow for the use of acoustic information for plant diagnostics in real time. Thomas (1991) describes the development of an Acoustic Boiling Noise Detection (ABND) system for the surveillance of fast reactor primary circuits. In this system a series of acoustic waveguides are positioned over the reactor core to transmit acoustic signals to attached accelerometers. The signals were recorded in both a digital and analogue format, for real time and long-term analysis respectively. Initial investigations revealed two components in the background noise recordings; a continuous broadband signal, and impulsive activity, both of which contributed in reducing the signal to noise ratio for the transient signal under investigation. Pattern recognition and source location analysis was used to isolate impulsive acoustic sources.

Shimanansky (2003) also used acoustic methods, this time specifically for the detection of leaks in a NPP. The system is based on the use of high temperature resistant microphones, which are resistant to temperatures up to 300 degrees Celsius and up to 20R/h. The microphone system detects acoustic signals generated by the leak by monitoring the increase in sound pressure level around the piping. A correlation was the observed between artificially generated leak discharge and frequency spectrum. The study noted that for small leaks, high-frequency analysis was preferable for detection purposes.

### 2.3.4 Detection of Small Leaks Using ANNs

Hessel et al (1999) developed a neural network combined with acoustic methods for estimating the leak rate in a pressure vessel head. A combination of structure borne accelerometers (50-500 KHz) and microphones (0.2 – 70 KHz) were placed on or around the pressure vessel. The leaks were simulated by a sound source driven by compressed air jet, a piezo-electric transmitter or a thin metal blade excited by compressed air. The piezo-electric transmitter was used because of its linearity. An array of twelve acoustic emissions sensors and three microphones were used to measure the sound pattern. The pre -processing of this data gave rise to root mean square values (RMS), components of power spectra and coherence values, which were used as inputs to the neural network. The results of the leak localisation with structure bound sound using the twelve acoustic emissions sensors showed that a neural network out-performed the fuzzy pattern classifier. Simulated steam leak sounds ranging from 2-65kg/hr were generated. It was found that leaks of 5kg/hr and above could be reliably classified.

## 2.4 Other soft computing techniques used in Nuclear Power Plants

### 2.4.1 Introduction

This section is a brief review of other soft computing methods used in research of NPP diagnostics. Its inclusion in this report is to highlight that often several techniques may be employed in finding a solution to a problem.

### 2.4.2 Genetic Algorithms

Mukherjee (2002) has applied a Genetic Algorithm (GA), (Mitchell 1994) to the unfolding of neutron energy spectra produced by particle accelerators, in order to accurately evaluate dose equivalent, and the efficient design of neutron shielding. The GA was chosen because of its ability to finding the optimum function of multiple variables. An inter-comparison with other deterministic spectra unfolding was then carried out. The results showed good agreement with the other methods.

### 2.4.3 Fuzzy Logic

Erbay (1996) uses a Fuzzy Logic fault tree as means to interpreting signal validation results in a nuclear power plant. By mapping signal results into fuzzy sets of truthfulness of sensor failure, a fault tree methodology is used to make a decision about the failure of the sensor. The decision-making algorithm consists of three steps: 1) construction of fuzzy sets from primary sets, 2) propagation of fuzzy sets through the fault tree, 3) comparison of the resultant fuzzy set with prototype fuzzy sets using dissemble index calculations. Icons were used to highlight degrees of fault, from safe to severe.

### 2.4.4 Multi Level Flow Models

Many human errors are partly caused by shortcomings in the design of the control and presentation systems. Many plants are equipped with a large number of alarms and in a large accident many alarms become activated which can overwhelm the operator's ability to isolate key faults. An example given is that of the Three Mile Island incident where more than one hundred audio alarms were simultaneously activated, (Lees 1983).

To improve instrumentation and control management, Larson (2000) proposes several methods. These include:

- Sensor fault detection
- Alarm analysis
- Fault diagnosis
- Failure mode and effects analysis

In the case of alarm analysis, Larson presents a Multi Level Flow Model (MLFM), which provides a graphical representation of:

- Goals – which describe the purpose of a system or sub system
- Functions – describes the capability of the system in terms of flows of mass, energy and information.

MLFM are often compared to expert systems and fuzzy logic, and is a representation of human knowledge using natural language.

## 2.5 Current Issues of the use of ANNs in the nuclear industry

### 2.5.1 Introduction

Bartlett and Urhig's (1991), initial seminal work on ANNs stimulated a great deal of interest in the use of ANNs in a variety of fields in the nuclear industry primarily in the early identification of fault transients. A search of peer reviewed publications on artificial neural networks in nuclear technology since 1990 up to 2001(taken from INIS database) is shown in figure 2.3.

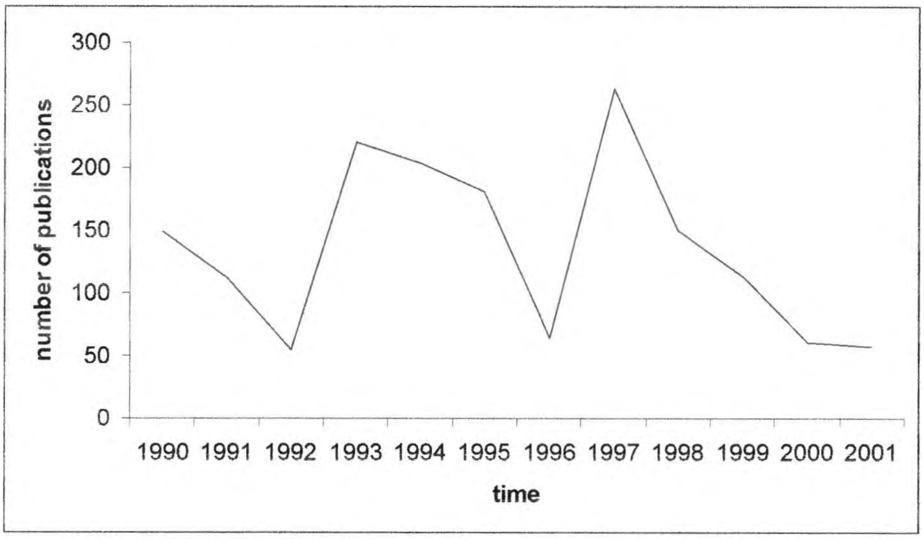



**Figure 2.3 Publications of ANN in Nuclear Technology**

Figure 2.3 shows that the amount of publications in this field peaked in 1994 and again in 1997. Since the early nineties the range in the application of ANNs in nuclear technology has expanded for example from the prediction of critical heat flux (Guaanghui et al, 2003), to loading pattern optimisation in gas-cooled reactors (Ziver et al, 2002).

However, since 1998 the number of publications has dwindled (a similar trend is observed for other soft computing techniques). With the exception of the PEANO project, there have been no reported commercial applications of neural networks within the nuclear power industry (however the lack of reported applications may be due to security or commercial purposes). As previously mentioned this may in part be due to the reluctance to use a 'black box' approach in a safety critical system. However within the general field of engineering, the number of publications of the use of ANN has remained high as shown in Fig 2.1.

What follows are several reviews that have looked at the use of soft computing within the nuclear industry.

Uhrig (1999) reviewed the use of soft computing technologies, particularly neural networks, fuzzy logic and genetic algorithms in the surveillance, diagnostics and operation of nuclear power plants. He comments that virtually all the techniques described have operated only as an advisor to a human operator without any feedback. He highlights at that at the time of the review, there were very few of these systems implemented in a nuclear power plant, even though the financial and performance benefits have been demonstrated. He attributes the lack of implementation of these techniques with the concerns about regulatory issues with the use of soft computing technology in the nuclear power industry. However he notes that the approval of the US Nuclear Regulatory Commission of Digital Instrumentation and Safety Systems bodes well for the eventual acceptance of soft technologies in nuclear power plants.

Many organisations such as the United States Nuclear Regulatory Commission (USNRC), International Atomic Energy Agency (IAEA) and the OECD have stressed the importance of the man-machine interface to safety. In an IAEA Safety Report (IAEA, 1997) it is stated in the introduction:

"The human-machine interaction problems are complex. In many applications, the role of the human operator is often neglected in design and the human functions are defined by default, governed by the limitations and gaps of hardware and software.

It is questioned if the role defined by implication for the operator can be effectively and reliably performed"

The Nuclear Energy Agency (NEA Draft, 1995): "Nuclear Safety Research in OECD countries, Areas of Agreement, Areas for Further Action, Increasing Need for Collaboration" report identifies the following major themes for further research:

- Characterising and assessing the performance of individuals, teams and organisations.
- Man-machine interfaces (MMIs) and communications in the control room and other plant areas
- Selection and training of staff.
- Signal validation and condition monitoring methods for severe accident situations
- Development of operator support systems using advanced data processing and MMIs.

### 2.5.2 Tension between Views

Owre (2001) discusses the changing role of an operator in a NPP. In the non-nuclear industry he observes that the role of a plant operator is more 'operation management', whilst that of the nuclear operator is more manual operation and monitoring. He goes on to describe accident management, and the strategies needed to manage an accident. Also described is the need for comprehensive computer-based support systems for accident management, and how these systems can be used to 'monitor the current status of the plant, and project the progression of key phenomenological events'. The PEANO validation system is introduced as an example of the use of artificial intelligence techniques (in this case a neuro-fuzzy approach). A special feature of this approach is the ability of the system to recognise an 'unknown' scenario. Owre concludes that computers are better at identifying small variations in data during an accident situation, but that humans are better at handling the unexpected.

Reifman (1997) also conducted a survey of artificial intelligence methods for detection and identification of component faults in nuclear power. The review emphasises the limitations of ANNs: -

"

1. *The training process is time consuming and needs large amount of training data, the quality of which strongly affects the success of the approach.*

2. *Neural networks are difficult to train when many categories of transients are to be identified.*

3. *As the number of variables m in the problem increases, the complexity increases faster than a polynomial of order m*

4. *Difficulties in differentiating some transients that exhibit similar behaviour in almost all the process variables have been reported.*

5. *Scale up is more difficult in expert system and involves extending the input and output nodes, reconstructing the ANN architecture and re-training the entire system from scratch.*

6. *When new transient data are made available, incremental learning does not seem to be possible with most types of ANN.*

7. *Unlike expert systems, ANN lack explanation facilities and cannot explain the decision path of the underlying knowledge base.*

8. *The advantage of the ANN to generalize from trained examples and perform inferences when the input data are beyond the scope of their knowledge has negative consequences. For example, a feed forward network might incorrectly give a classification answer with high confidence for a new type of transient on which it has never been trained.*

9. *The necessity to anticipate all possible transient scenarios and use them for training is another limitation of the use of ANNs as transient classification tools*"

(Reifman, 1997)

He concludes that the above difficulties especially to verify and validate an ANN and the diagnostic approach, requires that every component failure in the process be anticipated and explicitly represented. Reifman recommends that future research should focus on developing a knowledge base on fundamental physical properties.

### 2.5.3 In Defence of Artificial Neural Networks

It is a major contention of this thesis that the relegation in the use of ANNs to a mundane level of academic interest, fails to take account of advancements in soft computing methodologies, and, computing power. Consider in the first instance, the increase in time taken for the training of an ANN, especially for ANNs with a large number of input variables:

"The pace of microchip technology change is such that the amount of data storage that a microchip can hold doubles every year."
(Moore 1965)

In general, Moore's prediction has remained pertinent for the last 40 years, albeit at a slower rate of progress (typically 18 months). This increase in computing power has reduced in many circumstances the time required for the training of an ANN. If Moore's prediction holds true, (and it seems that it will for the foreseeable future), the issue of long training times will become negligible.

The difficulty in training an ANN when there are many categories of transients can be overcome by training several ANNs (figure 2.4.), to cover a set number of classifications (Bartlett 1994, Weller 1997). The ANNs can then work in parallel each ANN extracting different features from the same data. In some circumstances there may be some overlap in the classification of a transient category.

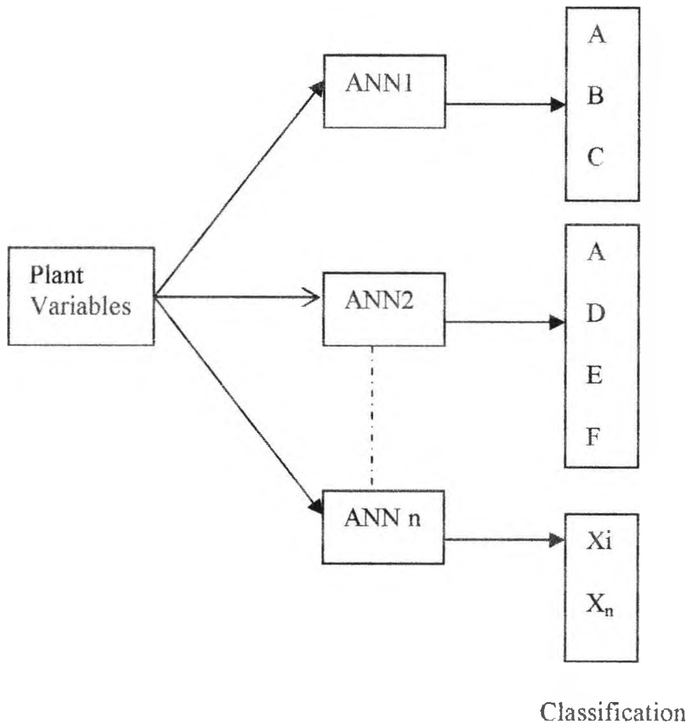



**Figure 2.4 Parallel ANN model**

The limitation of ANNs in differentiating transients that exhibit similar behaviour can in some instances be overcome by using alternative ANN training algorithms, for example the use of recurrent neural networks in time series analysis.

Boger (1998) also suggests several solutions to problems in implementing soft computing techniques described by Reifman; in particular the ANNs lack of an explanation facility and an inability to explain the decision path of the underlying knowledge base. Boger suggests the use of the Causal Index (CI) method as a knowledge extraction technique. The CI looks at the relationship between the input and output of the ANN and provides an indication of the magnitude and sign of the global relationship. He concludes that most of the negative aspects of the ANN modelling may be overcome by using advance techniques of ANN design and recommends that the International Atomic Energy Agency (IAEA) create a database of simulated transient data produced by NPP, so that networks can be trained and tested on new data.

Another approach to validating the classification of an ANN is reported by Marseguerra (1996). Marseguerra describes the early detection of failures in the pressuriser of a Nuclear Power Plant using ANNs. Two multi-layered feed forward ANNs were trained to simulate a non-faulty pressuriser. The trained ANN received process variables at discreet time intervals from a simulated pressuriser and then predicted the system pressure one step ahead. If an accident had occurred a divergence between the pressuriser signal and the predicted signal from the ANN is used to diagnose a fault condition. Two ANNs were used instead of a single network as this was found to be more reliable. The ANNs were only trained on a normal pressuriser response as they argued that system faults are of an unforeseeable kind. Roverso (2000) extends this method via ensembles of ANNs. The predicted output from each of the classifiers is combined to produce an output from the ensemble. The outputs of the classifiers are then averaged to produce a final classification which is subject to a validation test. If in agreement, an output is produced. If not in agreement, an 'unknown' transient is flagged.

## 2.6 Summary

Some of the major uses of ANNs and other techniques used in plant diagnostics have been reviewed. Invariably there is a bias to work relevant to the research conducted in this thesis

As a result of the literature review several observations become apparent. Advances in transducers and the modernisation of plant control rooms to include new digital instrumentation and control systems will lead to an even greater amount of information available to the plant operator. An example of this can be seen with advances in microphone and signal processing technology. The use of ANNs can speed up the development and integration of new technologies into plant diagnostic systems.

The research in the use of ANNs has been applied to a diverse range of activities within the nuclear industry and has reached a level of maturity; as in the case of the PEANO project, where it can be run in parallel with existing plant safety systems.

However, to date there has been no full-scale applications in the use of ANNs. One of the major drawbacks in the implementation of ANNs, is that a nuclear power plant is a safety critical system and the requirement for the licensing of any software based safety system is an ability to follow its decision making process. It is felt that these issues can be resolved by a combination of validation techniques with a rigorous testing regime.

These observations are only the reported results, as there maybe several applications of interest which may have a basis in soft computing, but for commercial and security reasons, their reporting is withheld.

# Chapter 3

# Problem Definition

## 3.0 Introduction

In chapter 2 it was seen that the plant safety and efficiency could be enhanced via the use of appropriate computer-based monitoring and diagnostic systems. The structure of this chapter is that first the specific problem to be addressed in this thesis is introduced followed by a discussion on the analytical and experimental method developed for the research.

## 3.1 Problem definition

A nuclear reactor produces heat through nuclear fission in which atomic nuclei break apart releasing large amounts of energy. In the core of the reactor a self - sustaining nuclear chain reaction takes place. Control rods are raised or lowered to increase and decrease the absorption of neutrons and control the reaction and amount of heat produced. The most common type of nuclear reactor is the pressurised water reactor, it is known as a double loop system because it uses two circuits of water. The first loop or primary circuit pumps water heated by the reactor core through a heat exchanger. The water remains liquid even at 300 degrees Celsius because it is pressurised to high pressures of up to 150 atmospheres. In the second isolated loop, water is converted to steam in the heat exchanger and is fed under pressure to turn turbine generators; the steam is then cooled by water drawn from a large reservoir. It is condensed to water and then pumped back to the heat exchanger, completing the loop. A diagram of a PWR is shown in figure 3.1.

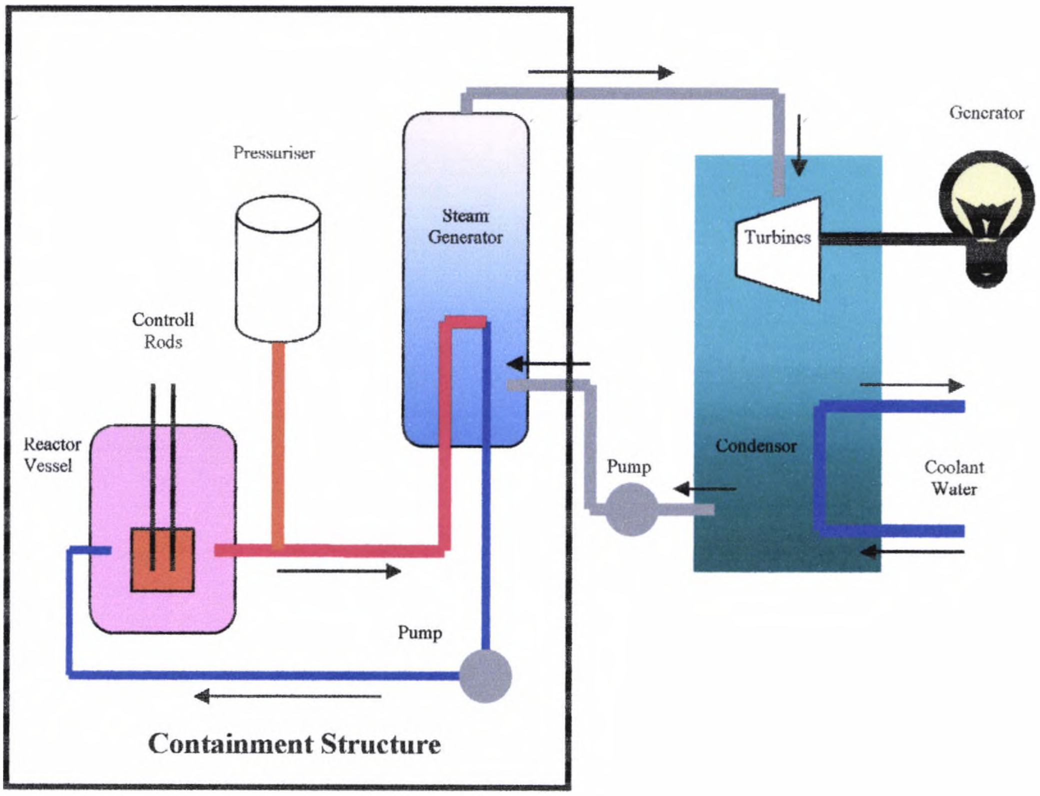



**Figure 3.1 Schematic of a PWR**

The control room of a nuclear power plant (NPP) is a daunting environment. The plant operator is confronted with a variety of information extracted from the plant and then presented in various forms, from raw data through to procedural and advanced alarm systems. The sheer quantity of information presented to the operator can affect their decision making process. A study conducted by the Central Electricity Generating Board (CEGB) (Pope 1992), examined the loss-of-generation events on a NPP between 1976 and 1982. Their findings were that human errors could be categorised as follows: -

- Operating errors – 10%
- Design errors – 20%
- Maintenance /testing errors – 70%

Swain & Guttmann (1983) studied the cause and effect of human error from an applied science prospective. They identified that stress on the plant operator was a key factor in causing human error, an increase in high levels of stress resulting in an increase in human error as shown in figure 3.2.

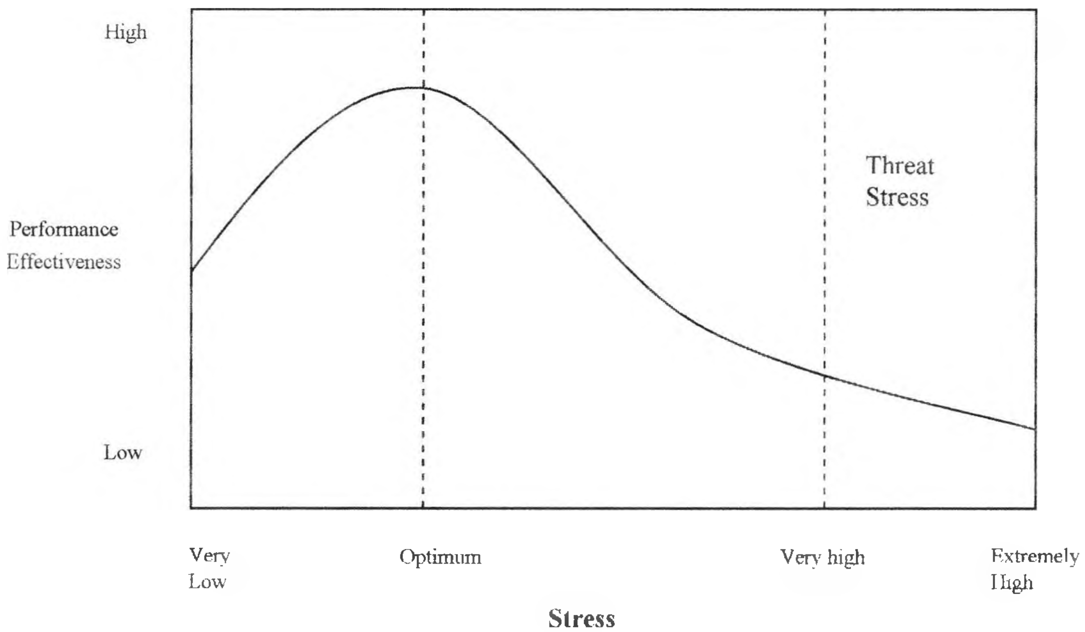



**Figure 3.2 the effect of stress on performance of plant operators**

They described how the robustness of a plant design impacts on how quickly a plant operator is able to diagnose and correct the cause of an abnormal situation before the plant moves into an unsafe state. The operator is much more likely to correctly diagnose the problem if they have more time as shown in Table 3.1

| Available Response Time (Minutes) | Probability of Incorrect Diagnosis |
|---|---|
| 1 | ~1 |
| 10 | 0.5 |
| 20 | 0.1 |
| 30 | 0.01 |
| 60 | 0.001 |

**Table 3.1 Diagnosis of a problem as a function of response time**

The efficiency of an operator is determined by how they perform in different situations. The Technique for Human Error Rate Prediction (THERP) states that human error is a causal effect of stress and available response time. Therefore, the operator's ability to detect plant changes especially those associated with the failure of instrumentation or plant components will be determined by both the time available for detection and the action and quality of available information. The human error in this decision making process can be further exaggerated by factors such as stress and fatigue (Swain, 1983). The result of a failure in the correct diagnosis of a fault can lead to poor management of the fault. At best, this can result in a drop in the efficiency of the NPP, or, it may lead to more catastrophic failure of a system within the NPP as seen at the accident at Three Mile Island where faulty instrumentation and human error led to a small release of radioactive isotopes to the environment.

## 3.2 A Control Systems Approach

The plant operator can be seen as an integral part of a control system, which is a core requirement in plant operations. Transducers placed around the plant constantly relay information to the plant operator in the form of digital and analogue readouts. The plant operator in turn acts upon this information by operating the control mechanisms as shown in figure 3.3

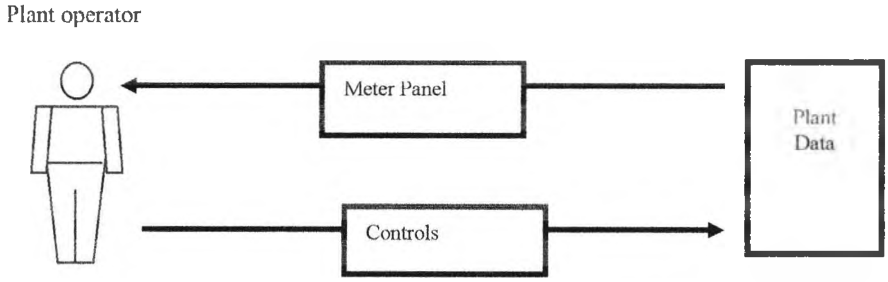



**Figure 3.3 Plant Operations**

However, as plant machinery operates at ever-greater levels of sophistication and at greater speeds of operations the required response can exceed human capabilities leading to a decrease in operator reliability. Also the speed at which some of the transients develop requires a faster response from the plant operator.

Typically the control of a Pressurised water reactor (PWR) is a combination of two control strategies; an automatic control system for example fire control, or a supervised control system, as found in the typical day to day running of a PWR. (figure 3.4). The proposed Operators Advisory System (OAS) is intended for use in decision support role for the plant operator.

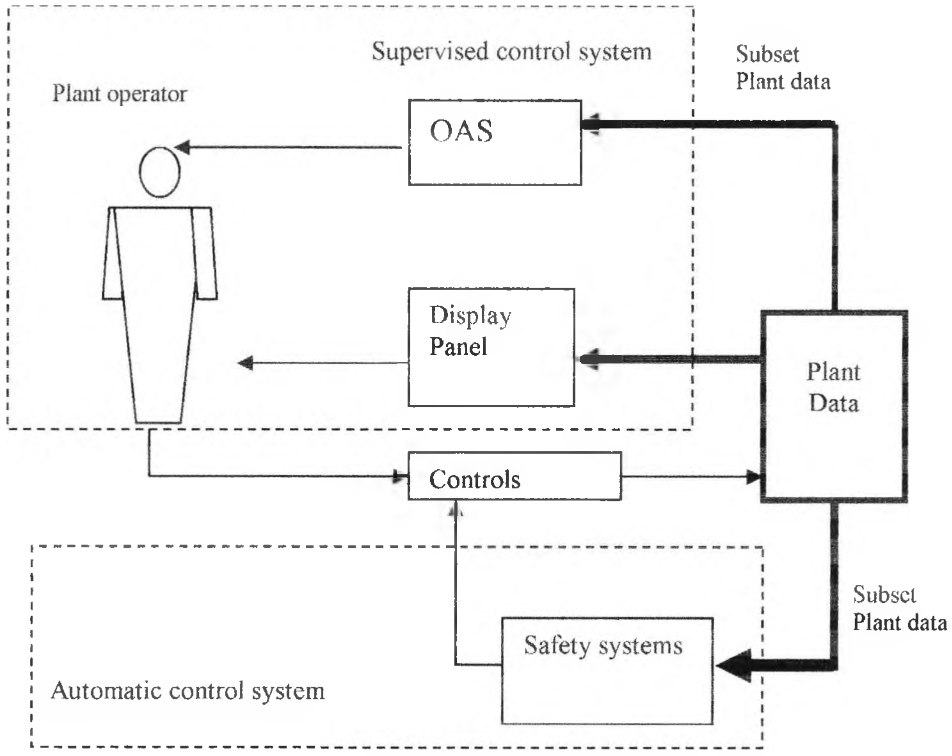



**Figure 3.4 Plant Operation sub-systems**

## 3.3 Automatic Control Systems

A control system involves the feedback of information, which gives the system a degree of sophistication by means of effecting the transmission of an output signal to affect the input. The system is driven by two signals: the normal input signal derived from the plant data and the feedback signal derived from sensors or actions taken by the plant operator. The system is provided information concerning its performance so that it can correct its subsequent performance on the basis of that information. Automatic control performs at least three major functions (Fu 1971):

- Problem solving and planning to select alternative actions
- Modelling of the environment to simulate the effect of its own actions
- Perception to record changes to the real environment

The primary purpose of the control system is to drive the PWR plant to attain specific goals (figure 3.5). To do this the (plant) controller must:

- Remove errors in the output by adjusting the input
- Prevent the output exceeding certain limits
- Produce smooth actions

The control of a PWR implies having to describe the process to effectively attain a given target. Feedback control involves the actual output of the system being compared with the desired output with the difference being used as feedback to drive the system.

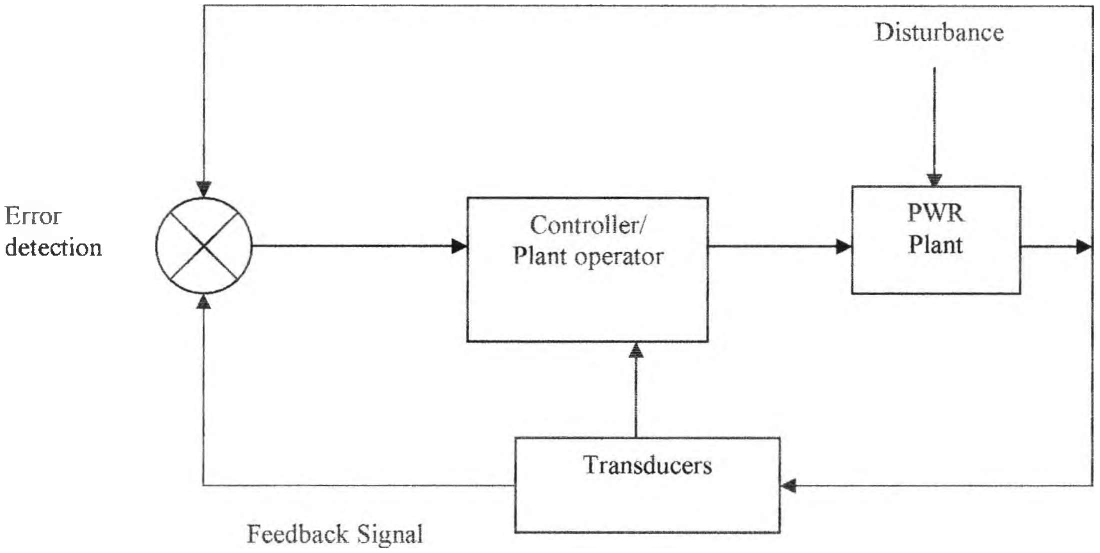



**Figure 3.5 Block Diagram of a control system**

The state of the PWR is the minimal amount of past information required to completely describe its future behaviour, i.e. outputs of a system when the inputs to the system for all present and future times are known.

## 3.4 Supervised Control Systems

In a supervised control system the plant operator provides the feedback control required for the correct operation of the PWR. Information gained from the PWR plant will enable the plant operator to decide as to whether an intervention is required or not. These decisions will be either a reflex or conscious act, following standard or emergency operating procedures. A computer based Operator Advisory System (OAS) can enhance this decision making process by constantly monitoring the control processes of a PWR (figure 3.6) and providing diagnostic advise as to the current and future status of the PWR in a more timely and efficient manner.

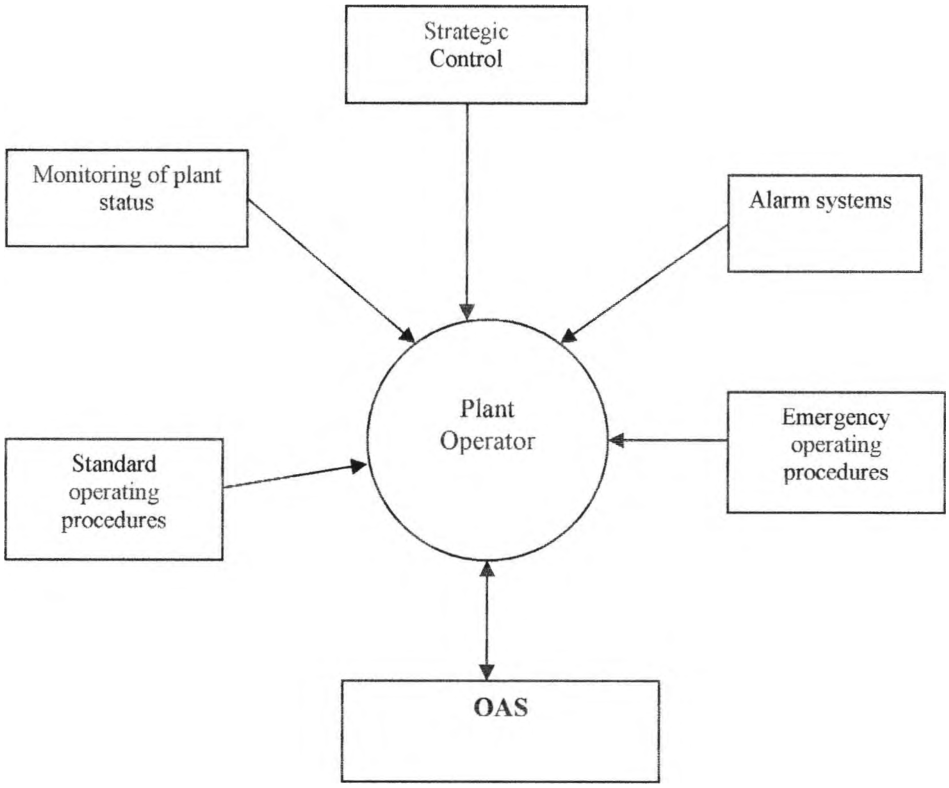



**Figure 3.6 supervised control system with operator advisor**

Examples of information that may be provided to the plant operator by the OAS could be the monitoring of the PWR status for example the monitoring of normal or planned changes in plant status such as a throttle opening transient or, the OAS may provide early warning of an unplanned change in plant status, for example a primary coolant leak.

The advisory system described would have the following advantages:

"

The system would be permanently on duty and not tire or become bored or distracted during operation. It would not require briefing at every duty change.

The same advisory system would be applicable to all models of the plant for which it was developed. This would provide both transferability and portability of the technology.

The system would be easy to upgrade or replace. A computer-based advisory system could be constructed from commercially available hardware and avoid the vast use of expensive bespoke equipment.

The proposed advisory system would not be required to attend extensive training courses nor gain a wealth of experience to operate fully.

A record of reactor history could be stored and so provide a built in audit trail."

(Weller 97)

## 3.5 Classification methods

There have been several approaches to classifying complex non-linear systems as typified by the plant dynamics of a PWR (Erbay 1996, Mukherjee 2002). One of the most popular of these in the last decade being the use of Artificial Neural Networks (ANNs), which meets the requirements of the proposed advisory system stated above. They can be considered as complex adaptive systems in that the model 'learns' by adjusting a number of parameters and provide a framework for representing non-linear mappings between multi-dimensional spaces where the form of the mappings is governed by number of adjustable parameters. An introduction to a Feedforward Back Propagation ANN can be found in Appendix A.

Artificial neural networks fall into two broad categories: supervised and unsupervised learning. In supervised learning, the ANN is trained by providing it with inputs and desired target outputs. The difference between the outputs from the ANN and the desired outputs are for each input set used to adapt the model to reduce the error. In unsupervised learning there is no feedback from the environment to indicate if the outputs from the network are correct and therefore the ANN must discover correlations in the input data automatically.

There are several advantages to using ANN in the development of the proposed OAS.

- They can be used to model complex non-linear systems as found in the operating dynamics of a pressurised water reactor.

- The distributed knowledge representation means the system response degrades gradually in response to errors in data. This may be of concern if a transducer fails to operate correctly or if interference leads to high levels of background noise.

- The short development time for an ANN solution allows for frequent updates of the model (could be online), to allow for intra variability between PWR plants and changes in plant dynamics due to ageing processes within the PWR.

- The ANN will attempt solutions for unknown fault conditions, however the probability of a correct diagnosis will be reduced.

- The parallel processing of an ANN leads to shorter computational time and therefore allows for real time analysis of data.

- Domain expert not required during the initial stages of development

Nevertheless, unlike some modelling techniques, for example expert systems, ANNs lack explanation facilities. They cannot fully explain the decision path of the underlying knowledge base; they are very much a 'black box' approach. This makes the use of ANNs as an operators advisory system difficult to pass a safety justification process. In addition, the development of an ANN requires a large amount of training data that strongly affects the success of the approach.

However, there have been several methods proposed to better explain the decision making process of the ANN (Dybowski 97), (Boger 98) which will help to overcome problems in implementing computer based advisory systems because of safety justification regulations. In this report, the ANN training used is the feedforward back propagation algorithm, a brief introduction to which can be found in appendix A.

## 3.6 Proposed Development Method

The method proposed for the development of the advisory system is a multi-layer system of ANNs (Basu & Bartlett, 1994), (Weller 97) and is shown below in fig 3.7

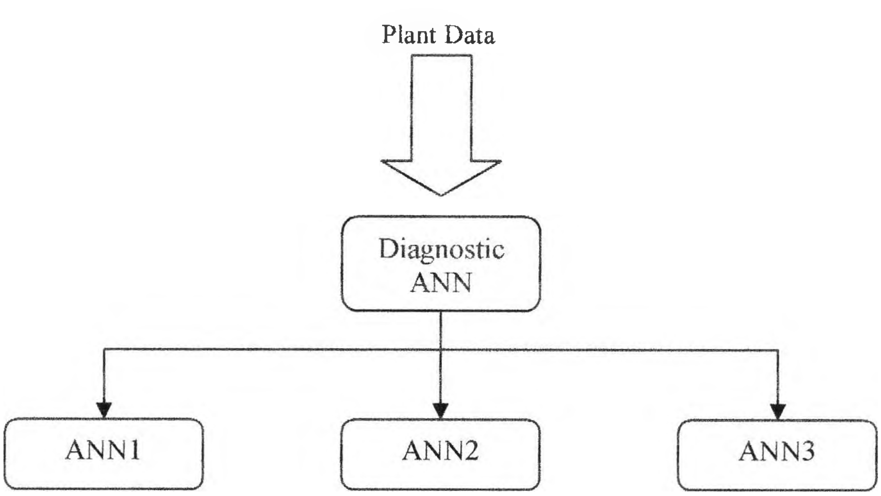



**Figure 3.7 Multi-layer System (Weller 97)**

The multi-layer system consists of functionally similar modules, loosely concatenating one module to another. In the proposed advisory system the top layer of the system will be a diagnostic ANN module reporting on the current status of the PWR. Should a fault transient be identified the output from this layer would initiate the appropriate module in the next level to give the size or possibly the location of the fault. In order to confirm the accuracy of the result a simulator and a comparator could be added to the advisory system. Once a transient has been identified, the simulator would reproduce the plant data for that transient. The comparator would look for differences between the predicted state of the plant and the actual plant variables as shown in figure 3.8. Where any difference was observed an error in the diagnosis or an "unknown diagnosis" would be reported to the plant operator.

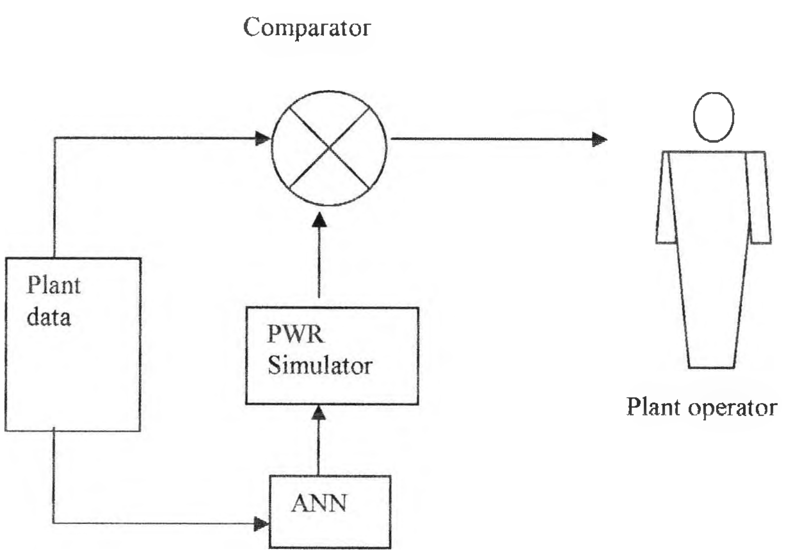



**Figure 3.8 Diagnostic ANN with Comparator**

The system described above will provide information to the plant operator for the early diagnosis of a fault transient, and also information on the success of the management of that transient.

There are several advantages of this modelling method compared to using a single large ANN. The training of a smaller ANN typically requires a smaller dataset to converge to an acceptable level. The reduction in the complexity of the ANN leads to a decrease in training times, and a higher probability of the ANN converging to an optimum solution. A system made up of smaller modules will operate at faster speeds, and has the potential to, if implemented in hardware for several modules to operate in parallel, leading to an even further increase in performance. Another key advantage of this system is that it is much easier to update and modify individual modules. This is of particular importance to allow for changes in the plant dynamics due to ageing, or the addition of new sensors/systems to the PWR. Finally, a hierarchical approach to the system modelling allows easier integration on a non-ANN module, as shown by the example in chapter 5.

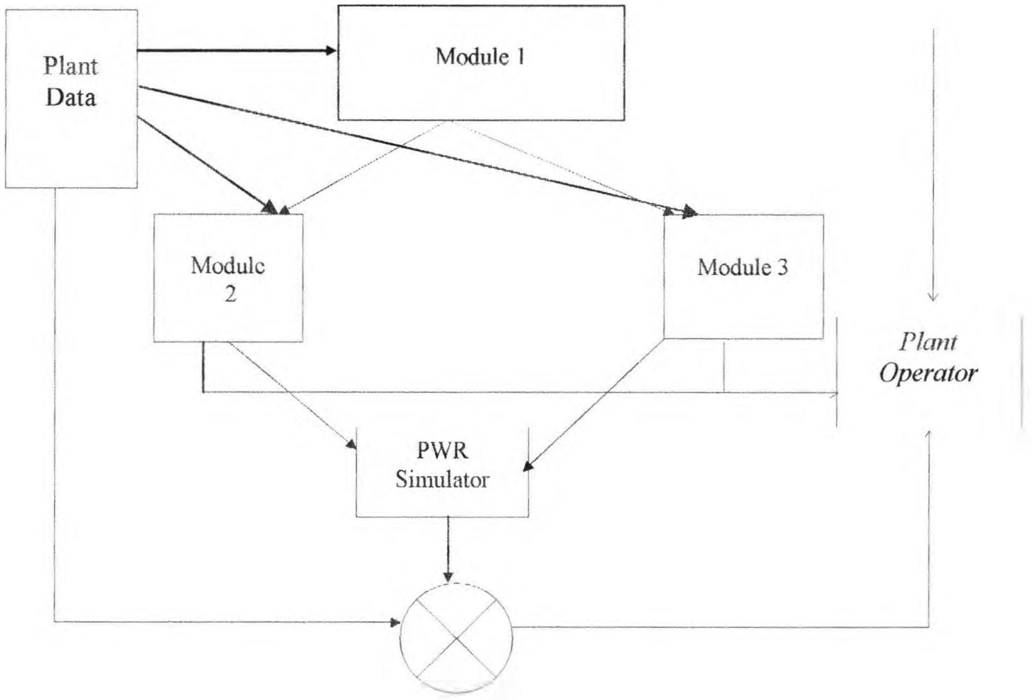



**Figure 3.9 Proposed Operators Advisory System**

Figure 3.9 shows a block diagram of the proposed Operators Advisory System (OAS). Module 1 (major fault classifier) is intended as a controller for data flow to other modules in the OAS. E.g. leak rate classifiers. Output from the modules can be made available at all stages to the plant operator. The diagnosis may be confirmed by the use of a comparator which runs a simulation of the diagnosed transient and compares this with plant data or by the plant operator by accepting or rejecting the diagnosis.

## 3.7 Data Characteristics

In this thesis, the majority of the data used for modelling several of the components in the OAS uses a generic simulator of a Pressurised Water Reactor. It is difficult to obtain actual data from a PWR fault due to safety considerations. The creation of synthetic data sets allows for a much wider range of transients than would normally be available to the developer, and allows for better evaluation of the performance of models. However, during the development of the OAS it was necessary to obtain 'real world' data by experimentation.

## 3.8 Study Scope

The primary aim of this study, the investigation of the development of an neural network based OAS with an emphasis on small transient analysis, is clearly an ambitious one. In order to offset the potential analytical complexity, the scope of the study was constrained in the following way:

1. The domain of interest was limited to the development of three modules to demonstrate the feasibility of an OAS.
2. Limited use of 'real world data'

## 3.9 Summary

This chapter has reported on the multi-layer method that will support the development of an Operators Advisory System to monitor the status of a Pressurised Water Reactor (PWR). The OAS will provide early warning of a fault transient, and information on the management of the fault. This research builds on previous work (Weller 1997). It is essential that the human operator of the PWR remains an integral part of the control system.

The next four chapters explore the components of the system in greater detail.

# Chapter 4

# Fault Analysis

## 4.0 Introduction

This chapter reports on work carried out to investigate the use of Artificial Neural Networks (ANNs) in the task of transient classification of a Pressurised Water Reactor (PWR), exploiting their documented abilities in pattern recognition. The fault classifier module developed in this study is used as the top layer in the Operator Advisory System described in chapter 7. The transient classifier discussed in this chapter builds on work first described by Weller (1997).

The experiments reported on in this chapter were carried out with the following objectives:

- To train an ANN to classify transients found in a Pressurised Water Reactor (PWR).

- To test the trained ANNs ability to generalise and to use the results from the experiments to enhance the ANN classifier.

The structure of this chapter is that first, a brief outline is given of some practical considerations relevant to the investigations reported in this chapter. The initial investigations on the ANN fault classifier are then reported. The performance of the developed ANN is then examined and the information gained is used to train a new ANN fault classifier. The development platform used for the training and analysis of ANNs was NeuralWorks Professional. Finally, a summary is given in section 4.7.

## 4.1 Background

In chapter three and following the Three Mile Island report, the concept of an Operators Advisory System (OAS) was proposed as a novel method for the effective monitoring of a PWR. The information obtained from the OAS would be presented to the plant operator to better enhance the decision-making process during both normal and abnormal plant operations. The low level data obtained from the plant would be mapped to several re-occurring generic transients. Figure 4.1 shows how plant data obtained from transducers placed around the primary circuit of a PWR can be fed directly to an ANN for classification. ANNs are ideally suited to address this problem because of their ability to approximate non-linear functions (Bartlett 1994), and in their ability to generalise (Lawrence 1997).

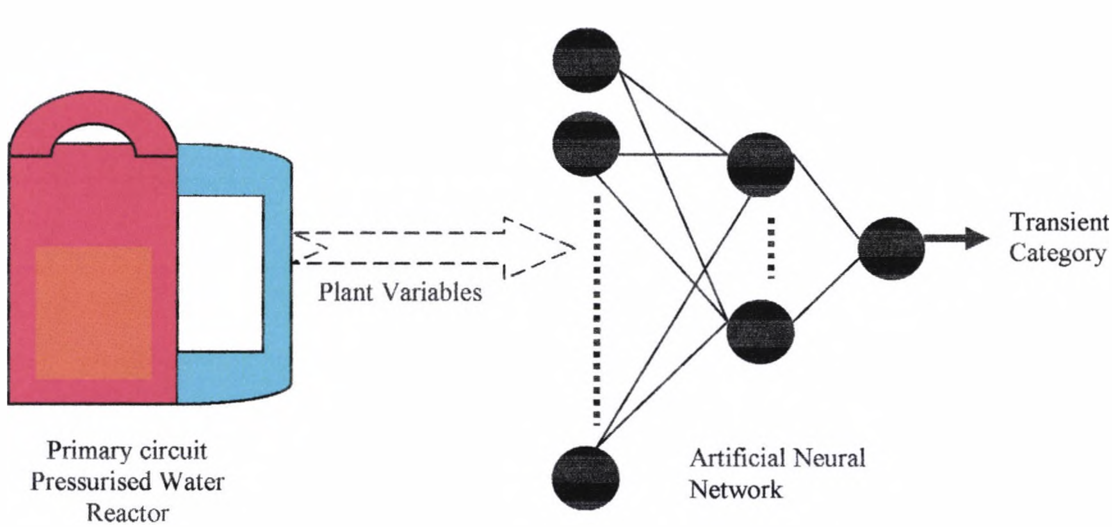



**Figure 4.1 Classification of a transient based on feature set from a PWR**

In a complex system as typified by the primary circuit of a PWR, it is possible for a large range of different transients to occur. This would require a correspondingly large amount of data (potentially limitless) for the training & evaluation of the ANN. The resulting increase in complexity may cause the ANN to either fail to converge to a solution or incorrectly classify or possibly both. Therefore it is essential that a smaller set of important generic transients should be considered.

During the development of an ANN certain considerations need to be observed. It is important that the dataset consisted of measurable plant parameters found in a PWR. Secondly, it is important that when the data is partitioned into training and test sub sets, they are not chronologically dependent (the samples are independent). The random selection for each of the sub sets should not show bias, within the data set either for a single transient or between transients. For example, many of the major fault transients developed in a PWR are rare occurrences; therefore the data collected from a plant would show a bias towards "normal operating conditions" transient. Finally, at some stage during the training and testing of an ANN, it is possible that the optimised network may overfit the training sample space. This can occur if an ANN is overly complex, so that the ANN fit data noise, not just the signal. The effect of this is to reduce the ability of the trained ANN to generalise on unseen data, which may be from a different region of feature space than that covered by the training/testing data set. The optimal model fits the training sample points well but can oscillate wildly between these points. This is analogous to fitting a high order polynomial to a lesser number of data points.

Several methods have been developed to improve the ability of an ANN to generalise and produce an output. These include network pruning and early stopping whilst training the ANN. Once the ANN has been developed, tests on the ability of the ANN to generalise would need to be conducted, as part of the validation process.

Finally, the ANN would need to be embedded into the Operators Advisory System (OAS). An important consideration in the development of the fault classifier is that the structure of the data used for the training and implementation of the ANN module is common to all modules used in the OAS. It may also be the case that an output from the Fault classification ANN can be used as input for another module in the system.

Figure 4.2 shows the proposed implementation of the Fault classifier ANN in the OAS. Plant data were presented to the Fault classifier ANN. The output from the ANN is then presented to the plant operator. The detection of a transient by the classifier may also be used to initiate the use of other diagnostic modules within the OAS to quantify the size or location of the transient. Depending upon the transient, validation of the diagnosis may be left to the plant operator, or confirmed via the use of a comparator (refer chapter 3).

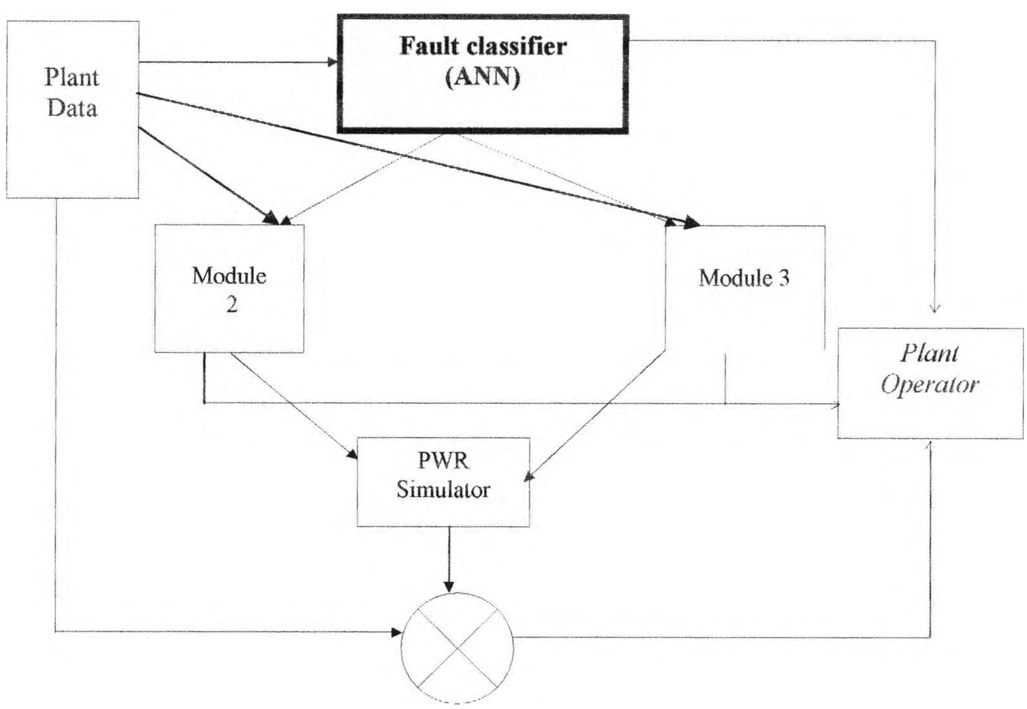



**Figure 4.2 Embedded Fault classifier in proposed OAS**

## 4.2 Implementation

This section outlines the steps involved in the implementation of an ANN classifier.

Due to safety considerations, real time data from an operational PWR for the transients described earlier was not available for the development of the fault classifier. As a result a generic simulator of the primary circuit of a PWR was used to generate a range of fault conditions. For each of the fault scenarios, the simulator generated data for 67 plant variables in real time. The data generated from these simulations were tagged with the labels (a binary value) of the transient categories to which they belonged. Table 4.1 shows the plant variables generated by the simulator.

| **Neural network input parameters (number of inputs)** | **Neural network output parameters** |
|---|---|
| Nodal Temperature (25)<br>Throttle Setting (4)<br>Rod Position (4)<br>Flow Rate Settings (12)<br>Valve Settings (11)<br>Temperature average (1)<br>Neutron Population (1)<br>Pressuriser Pressure (1)<br>Pressuriser Level (1)<br>Power Levels (6)<br>Start Up Rate (1) | *This consists of one output for each of the six positions. A binary coding of '1' signifying the presence of a transient, a '0' for the absence.* |

**Table 4.1: Details of Input Data Set**

The plant variables were either a categorical variable, and the presence or absence of which were represented by a binary value for example a valve that is either open (0) or closed (1) or alternatively the data were a continuous variable such as pressuriser level.

Weller and Thompson carried out the first phase of work in 1997. They used a Feedforward Back-Propagation training algorithm to develop ANN fault classifier. However since that time there had been several refinements to the computer simulator used in their initial investigations. There was a need therefore to retrain a new diagnostic ANN. A computer simulation of the PWR was used to generate data for the following range of six generic transients:

**Primary coolant leak:** the water in the primary circuit is at such high pressures that any small leak can lead to a large loss of coolant from the primary circuit, which can have major safety implications. This is known as a loss of coolant accident (LOCA). These are classified as either a large break (LBLOCA) or small break LOCA (SBLOCA).

**Throttle opening:** when extra power is required, the throttles are opened to draw additional steam through the turbine, this causes transient temperature and reactivity transients, resulting in higher reactor power matching the increased steam power.

**Steam leak:** this occurs when a leak occurs in the secondary loop, which includes the piping to and from the steam generator, turbines, and condenser. The resulting transient is similar to that found in throttle opening.

**Group Drop:** a number or group of control rods may be inserted into the reactor, either deliberate or accidental producing a large reduction in reactivity. Power falls rapidly to very low levels but the reactor may restart if the temperature drops sufficiently.

**Rod Drop:** a rod may accidentally be released, and inserted into the reactor core, resulting in a small drop in reactivity. The power dips but recovers.

**Normal operating conditions:** this category is a special case, the classification identifies a "no fault" Or "unknown fault" situation. This separate category for the normal operation of a PWR allows for its definite classification. Should a transient exist but not be detected by any of the other categories this would indicate that a transient exists

### 4.2.1 Initial investigations using full data set

This section outlines the steps involved in the implementation of a feed forward neural network model. A PWR simulator of the primary circuit was used to generate the five faults and one normal operating transient at four power levels giving 24 transients. The 67 parameters were used as inputs to the ANN, the output was represented by six binary values, a '1' indicating the presence of a transient, a '0' value indicating an absence. The feedforward backpropagation network was chosen, as this had given consistently good results in previous work (Weller 97).

Figures 4.3 and 4.4 show examples of pressure and temperature outputs from the simulator for a rod drop transient at 30% full power:

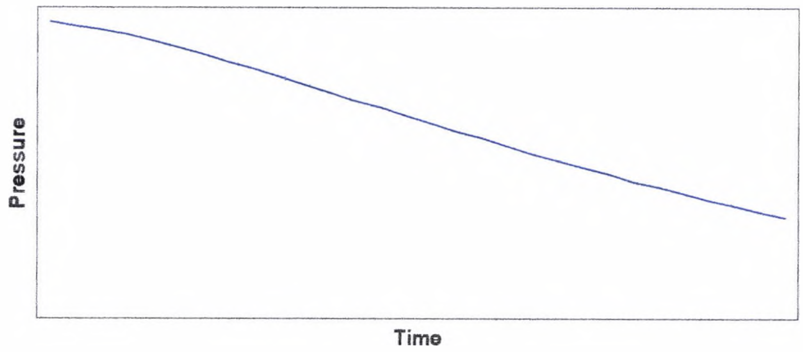



**Figure 4.3 Pressuriser change for rod drop at 30 % power**

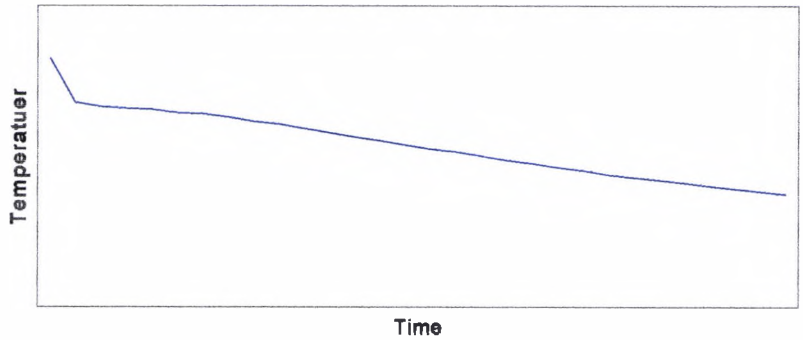



**Figure 4.4 Temperature change of coolant for rod drop at 30%full power**

The simulator was run at a steady state for 50 seconds to allow the simulator variables to reach a steady state condition, before the transient was initiated. Each data set generated consisted of 730 cases. Each case is a snapshot in time, and contains the output of 67 plant variables.

A key factor in the training paradigm in the training of an ANN is that balanced data sets were used regarding the number and transients investigated. If the proportion of transient to non transients in the training dataset is set to reflect the proportion found in the transients generated in the PWR simulation, then a bias in classification would reflect the a priori probability of the classification being a transient or not.

It is also assumed that during the training of an ANN that each of the samples are independent and that there are no chronological influences present in the data set. If these criteria are true, and the data set is sufficiently large, the best approach to this is to build up both data sets by picking samples at random from the original data set.

Three balanced data sets were prepared and randomly assigned for the training, test and validation of the ANN model. Approximately 350 cases would be used as training set for the ANN, 100 cases as a test set, and 230 cases used as an independent validation set. Each case was assigned randomly to either a training, test or validation data set. The development process consisted of training a series of ANNs with one or two hidden layers. Each ANN was trained for 120,000 iterations with testing every 100 iterations, the best network being saved. The RMS error between the expected and the actual output from the ANN was used as a measure of the best performing network.

The best ANN developed had a RMS error of 0.016, and consisted of two hidden layers consisting of 30 and 15 nodes respectively. The full data set was then presented to this ANN to explore the accuracy and distribution of error. Figure 4.5 shows an example output from the ANN for a downstream steam leak at 60% full power.

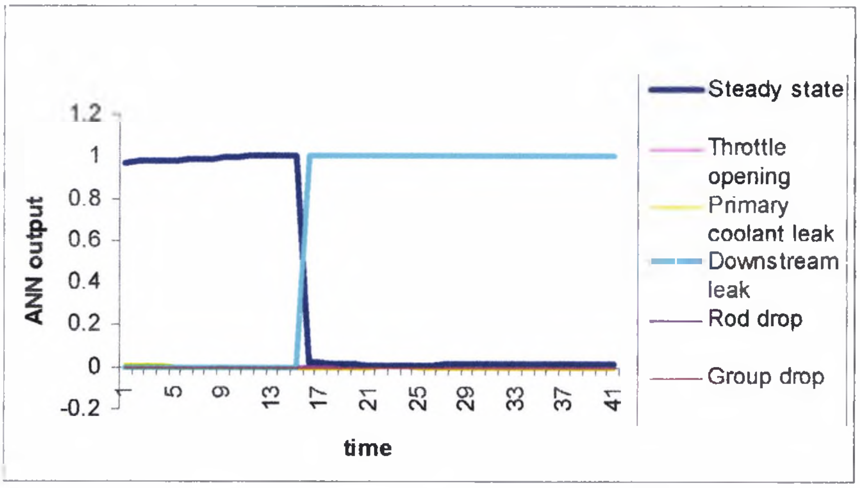



**Figure 4.5 downstream leak at 60% full power**

In this example, using a detection threshold of >0.95 indicating the presence of a transient, the ANN reports a normal operating condition for 15 time steps. Once the transient is initiated, (at 15 time steps), the steady state condition falls to zero, and a downstream leak is detected after 2 time periods.

Analysis of the validation data set showed that all transients were correctly diagnosed within four time steps, and remained above the 0.95 threshold for the duration of the recording. A summary of time steps taken for a transient to be correctly classified is shown in table 4.2.

| Transient | 20% full power | 40% full power | 60% full power | 80% full power |
|---|---|---|---|---|
| Throttle opening | 4 | 3 | 2 | 1 |
| Primary coolant leak | 3 | 4 | 3 | 3 |
| Steam leak | 1 | 1 | 2 | 1 |
| Rod drop | 3 | 3 | 4 | 3 |
| Group drop | 4 | 3 | 2 | 1 |

**Table 4.2 Transient Classification Times (number of time steps)**

### 4.2.2 The Effect of Noise on Classification

There has been much interest in the application of noise to feedforward neural networks in order to observe their effect on network performance. How a trained neural network performs with respect to seen (training data) and unseen data (validation data sets) is known as generalisation, the performance of the network being evaluated on the validation data set.

It was decided to test the fault transient classifier by adding Gaussian noise to the validation data set in order to reflect the noise that may be found in instrumentation, for example a poorly calibrated temperature transducer or a faulty connection. The results from these tests would provide some measure of the 'operational limits' of the neural network.

As an initial investigation, 2% Gaussian noise (Bartlett, 1991) was added to the validation data set (except those parameters which consisted of a binary output, for example valve status), this data set was then presented to the trained ANN described above. The results from this experiment are shown in table 4.3.

| Transient | 20% full power | 40% full power | 60% full power | 80% full power |
|---|---|---|---|---|
| **Throttle opening** | Failed to classify | 12 | 1 | 1 |
| **Primary coolant leak** | 3 | 3 | 4 | 2 |
| **Downstream leak** | 1 | 1 | 1 | 1 |
| **Rod drop** | 2 | 3 | 7 | 1 |
| **Group drop** | 2 | 2 | 2 | 1 |

**Table 4.3 number of time steps taken for classification**

The performance of the trained ANN fault transient classifier when presented with gaussian noise added to the validation data set was poor; the RMS error recorded when 2% Gaussian noise was added to the validation data set led to an increase in the RMS error from 0.016 to an RMS error value of 0.2421. Many of the transients presented to the neural network took much longer to be diagnosed, or in the case of a throttle opening transient at 20% full power, failed to classify as shown in table 4.3. It was also observed in some cases that were correctly diagnosed, several misclassifications or 'false alarms' were indicated prior to the fault being correctly classified. An example of this can be seen in figure 4.6. In this example 2% Gaussian noise is added to the validation set, and the output of the ANN recorded for a steady state condition. A steady output indicating a normal condition is observed after 13 time steps; however, a spike at 11 seconds falsely indicates a primary coolant leak.

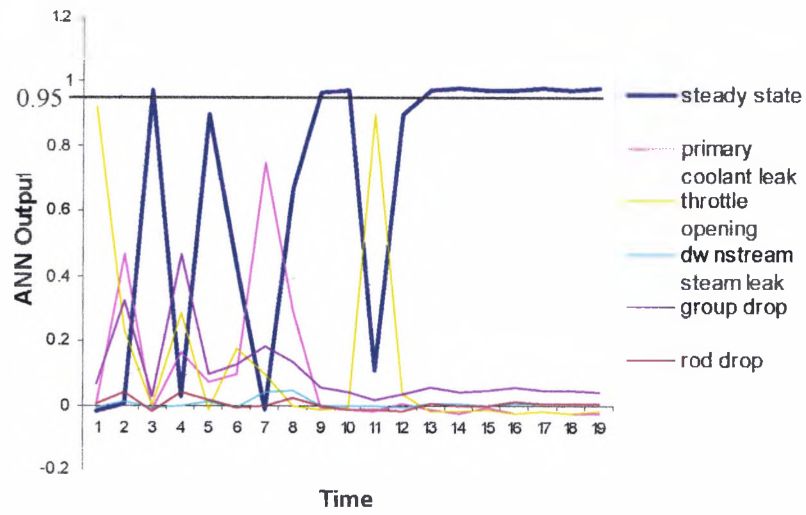



**Figure 4.6 ANN Output for a steady state condition with 2% Gaussian noise in validation set**

One possible explanation for the dramatic drop in performance of the ANN is that even though an optimised network may have been achieved for the training and testing data set, it is possible that this model may have overfit the training sample space resulting in poor generalisation capabilities on unseen data. This is because the unseen data may be from a different region of parameter space than that covered by the training/testing data. A further explanation may be that some transients may be very similar, resulting in a complex decision boundary (Bishop 1996), a 2% change in a parameter value, may result in a change in output.

## 4.3 Generalisation

### 4.3.1 Introduction

The aim during the training of an ANN is to minimise the RMS error between the actual ANN output and a target value in the training set. It is important that in a safety critical system, the successful ability of an ANN to deal with unseen or noisy data known as generalisation be demonstrated.

One method for improving the ability of the ANN to generalise is to add noise to the data used for the training of the ANN. Lawrence (1997) demonstrates that the addition of noise to the training data set can result in lower training and generalisation error. The effect of this would be to reduce the absolute accuracy of the classification (a reduced RMS error), but increase the overall classification of unseen transients.

Another method used to improve the generalisation capabilities of the ANN is a process known as early stopping (Masters 1993). In this process, training on a given data set is stopped prematurely before an optimal solution is obtained. The idea behind this is that if training is continued the generalisation capabilities of the model will diminish, as at some point the additional 'Knowledge' of the system will not be gained but characteristics of the data considered. By monitoring the cross validation performance during learning, the learning process is stopped when there is no more improvement.

Finally the large size of the ANN (67 input parameters, and 45 parameters in two hidden layers), leads to an increase in complexity of the ANN, which can cause the ANN during its training phase, to learn solutions that are consistent with the training data, but poor approximations of the problem under consideration. The excessive number nodes may cause a problem called overfitting (Masters 1993).

The next stage of work was to train a series of ANNs, incorporating the strategies described above, and to see if improvements could be made to the ANN fault classifier in its ability to correctly diagnose unseen/noisy transients.

### 4.3.2 Addition of noise during the training of an ANN

Several authors (Bishop 1996, Lawrence 1997) have observed that the addition of noise to the input vectors during the training of an ANN can improve the ability of an ANN to generalise.

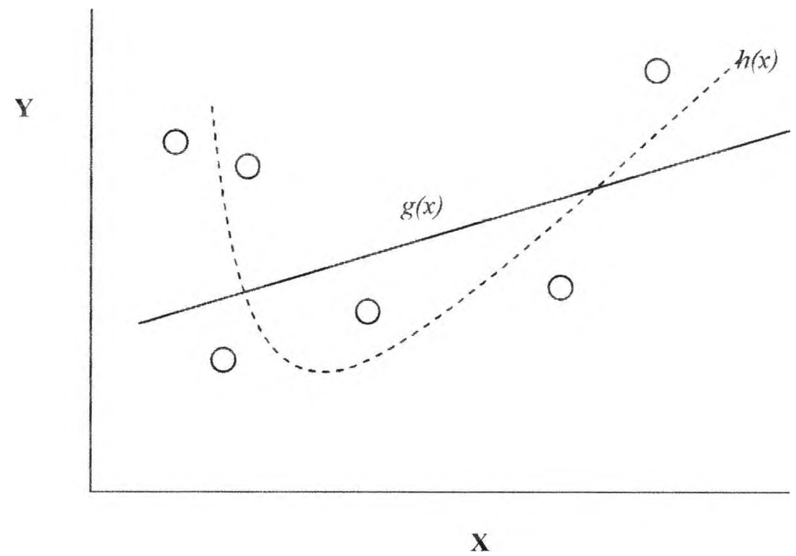



**Figure 4.7 fixed function approximation of a function with noise**

In figure 4.7 the circles denote the data points about the underlying function *h(x)*, with the addition of noise. For a fixed function *g(x)*, the bias will be high, whilst the variance will be zero, however, should the function *g(x)* model exactly the data points as in figure 4.8, the bias is low but the variance is high.

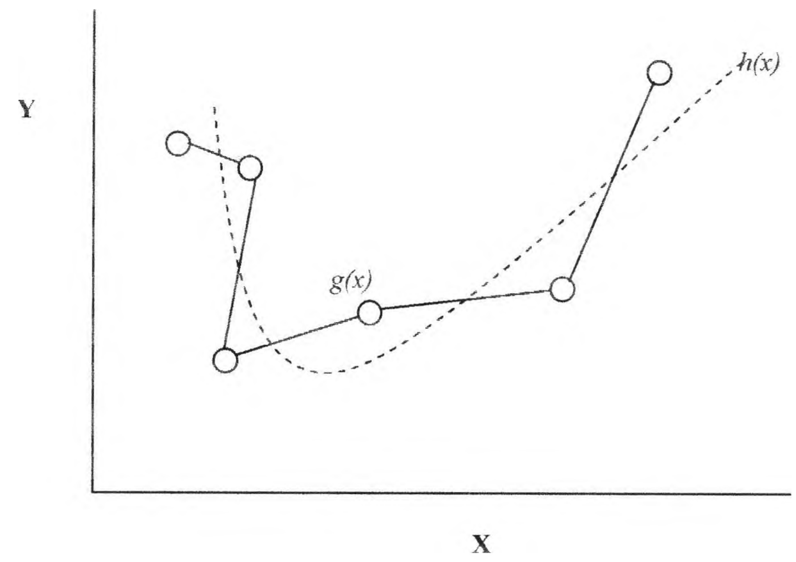



**Figure 4.8 exact interpolation of a function with noise**

Bishop describes the effect of adding noise to the input vectors is to 'smear out' each data point, thereby making it difficult the training algorithm to fit every point, and therefore reducing the chances of the ANN of over-fitting the data.

### 4.3.3 Implementation

Keeping the same ANN architecture and data sets used in the previous work, a new ANN was trained. However, this time 2% Gaussian noise was added to real numbers in the training set, with 0 to 2 % noise added to the validation data set for use in testing the performance of the ANN.

Figure 4.9 shows the reduction in RMS error when training the ANN with (network f8), and without noise present in the training data (network f9). During the training of the ANN, a test data set was presented every 100 iterations, the best ANN (lowest RMS error) saved automatically.

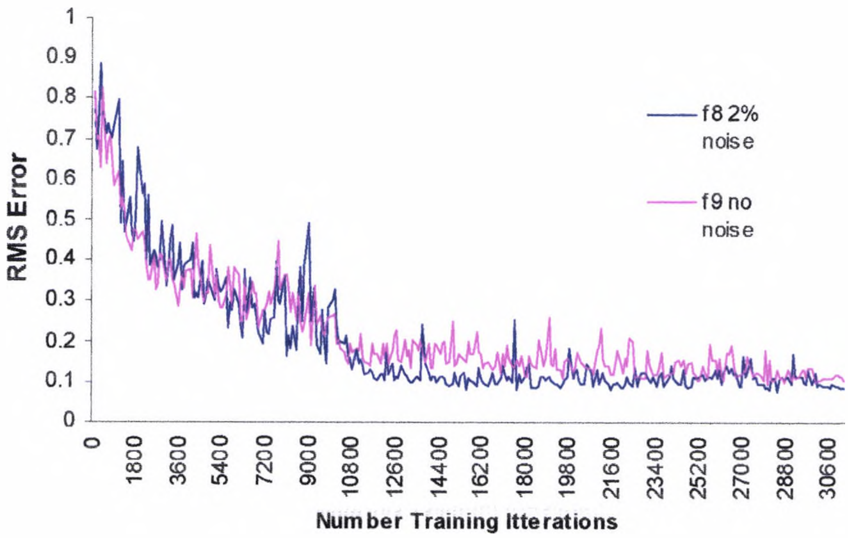



**Figure 4.9 ANN network training with and without noise**

The minimum recorded RMS error is reached at approximately 17000 iterations. The results indicate that training with noise, not only reduces the time taken to achieve a minimum error, but also produces an ANN with a lower RMS error.

During the training process, the test set used for cross verification and for identifying the early stopping of training (training is stopped when no improvement in the RMS observed when test data is presented to the ANN over several iterations set by the user), in effect becomes part of the training set; therefore a validation set is used to independently test the ANN. To test the generalisation abilities of the ANN, between 0-2% Gaussian noise was added to the validation data set. Each validation data set was then presented to the fault classification ANNs trained with and without noise. The results are shown in table 4.13.

| ANN trained without noise | | ANN trained with noise (2%) | |
|---|---|---|---|
| Validation data set (% noise) | RMS error | Validation data set (% noise) | RMS error |
| 0.0 % | 0.1264 | 0.0 % | 0.1229 |
| 0.5 % | 0.1314 | 0.5 % | 0.1238 |
| 1.0 % | 0.1625 | 1.0 % | 0.1393 |
| 1.5 % | 0.1982 | 1.5 % | 0.1639 |
| 2.0 % | 0.2421 | 2.0 % | 0.1879 |
| Average RMS error | **0.172** | Average RMS error | **0.14756** |

**Table 4.4 RMS error for ANN trained with/without noise**

The average RMS error provides an overall measure of the performance of the system. The lower average RMS value of the neural network trained with noise may suggest a better performing network than one trained without noise, and inspection of the results finds this to be the case. Figure 4.10 shows the results for a network trained with noise presented with data for a steady state at 30% full power with 2% Gaussian noise added. When compared to fig 4.6 it can be seen that there is an improvement in the ability of the ANN to generalise, with a corresponding reduction in the potential for misclassification.

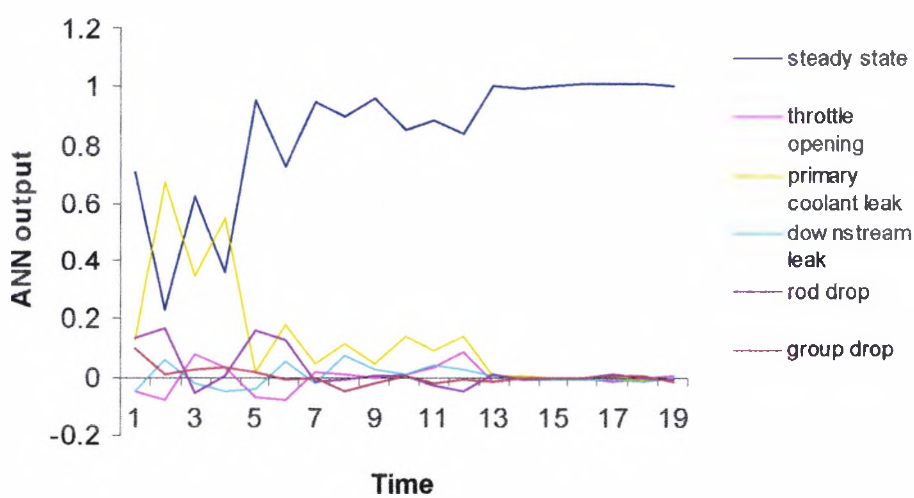



**Figure 4.10 ANN output for a steady state condition with Gaussian noise added to training data set**

The results of this investigation would suggest that the addition of noise to the training set would improve the overall performance of the ANN by representing the underlying systematic aspects of the data, rather than capturing the specific details,

## 4.4 ANN fault Classifier Training

### 4.4.1 Introduction

The series of experiments that follow incorporate the three methods, early stopping of training, the addition of noise to the input data, and a reduction in complexity of an ANN, in trying to improve the ability of the ANN fault classifier in correctly diagnosing unseen transients in a PWR.

When developing an ANN, many problems require its architecture to follow a geometric pyramid rule (Masters 1993). A large number of input nodes would increase the complexity of the ANN, but generalisation favours simpler structures (Bishop 1996).

In the initial ANN fault classifier, there were 67 input parameters. Discussions with plant operators on the results of the experiment highlighted that several of the parameters used in the ANN may not be measurable despite initial investigations. Analysis of the input data during training revealed that several of the plant parameters did not vary. Taking these considerations into account, the number of input parameters was reduced from 67 to 32 input parameters.

The experiment highlighted the need for the addition of the noise to the training set to improve classification, but the amount of noise to be added is unknown.

### 4.4.2 Implementation

In order to investigate the effect of noise on the training of the ANN fault classifier, the number of hidden layers, and the number of nodes, would need to be fixed.

For a four-layer network with $n$ input neurons and $m$ output neurons, Masters (1993) gives a good starting point for the computation of hidden-layer neurons:

$$r = \sqrt[3]{\frac{n}{m}} \tag{4.1}$$

Number of neurons in hidden layer 1 NHID1= $mr^2$ (4.2)

Number of neurons in hidden layer 2 NHID2= $mr$ (4.3)

The number of plant parameters to be used as inputs (n) was 32, with 6 outputs

Therefore:
Number of neurons in hidden layer 1 = 18
Number of neurons in hidden layer 2 = 11

The ANN topology defined by Masters was used to investigate the effect of adding gaussian noise to the input vectors. Gaussian noise was added to the training data in 0.2% increments. Unlike the previous experiment, the topology of the ANN was fixed during training.

A series of ANN were trained three times with randomly assigned weights to ensure that the ANN during training had not been trapped in a local minima. The eleven best ANNs developed for each increment of noise added to the training data were then tested against validation sets that had between 0-2% Gaussian noise added to them. The full results obtained from these experiments are given in Appendix B. Figure 4.11 illustrates the RMS error profile from the experiments.

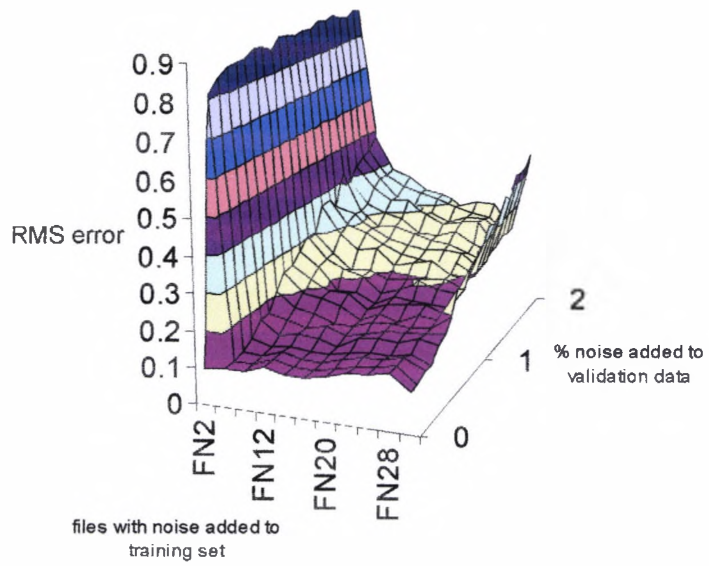



**Figure 4.11 RMS error profile**

The results of the experiment show that initially a small addition of noise (0.2%) to the training data results in an increase in performance of the ANN. However when the amount of noise added to the training data (2%) is increased, the performance of the ANN deteriorates. It can also be seen that overall, the performance of all the ANNs deteriorates as noise in the validation data sets is increased.

### 4.4.3 Noise in training, experimental results

The results in the previous work had indicated that the addition of noise in the training data could dramatically improve the robustness of the ANN. The next stage in development was to investigate whether the performance of the fault classifier could be further improved by examining a new ANN topology and the effect of adding noise to the input parameters.

Finding the optimum ANN using Masters method for defining ANN topology as a starting point the ANN were varied by node increments. In total 147 ANNs were trained using a hyperbolic transfer function, with testing every 100 iterations using an independent test set. The training was stopped when no further improvement in the RMS error was observed. The results of training can be found in Appendix B.

From the above the four best performing ANNs were chosen (table 4.5), using the RMS error:

| File name | Hidden layer 1 | Hidden layer2 | RMS error |
|---|---|---|---|
| X84 | 16 | 5 | 0.0783 |
| X42 | 14 | 5 | 0.082 |
| X62 | 22 | 7 | 0.0826 |
| X132 | 16 | 7 | 0.0845 |

**Table 4.5 Best ANNs from training**

The four ANNs were then tested against the validation data sets containing increasing amounts of Gaussian noise to a maximum of 2%. The results are summarised in table 4.6.

| Noise in validation data set | File name X84 | X42 | X62 | X132 |
|---|---|---|---|---|
| 0 | 0.1271 | 0.1192 | 0.1203 | 0.1116 |
| 0.1 | 0.1293 | 0.1229 | 0.1214 | 0.1131 |
| 0.2 | 0.126 | 0.1207 | 0.125 | 0.1164 |
| 0.3 | 0.1186 | 0.1183 | 0.1181 | 0.113 |
| 0.4 | 0.133 | 0.1362 | 0.1296 | 0.1419 |
| 0.5 | 0.1526 | 0.1742 | 0.1569 | 0.1561 |
| 0.6 | 0.1683 | 0.1654 | 0.1685 | 0.1595 |
| 0.7 | 0.1921 | 0.1863 | 0.1693 | 0.2033 |
| 0.8 | 0.1947 | 0.2174 | 0.1981 | 0.2051 |
| 0.9 | 0.2117 | 0.2096 | 0.2012 | 0.2269 |
| 1 | 0.2256 | 0.2552 | 0.2409 | 0.242 |
| 1.1 | 0.2409 | 0.2623 | 0.2298 | 0.2552 |
| 1.2 | 0.2848 | 0.2821 | 0.2798 | 0.2761 |
| 1.3 | 0.2836 | 0.285 | 0.2785 | 0.3191 |
| 1.4 | 0.2726 | 0.3018 | 0.2834 | 0.2899 |
| 1.5 | 0.3056 | 0.2992 | 0.3034 | 0.3209 |
| 1.6 | 0.3111 | 0.3513 | 0.3285 | 0.3442 |
| 1.7 | 0.3598 | 0.2761 | 0.3605 | 0.3775 |
| 1.8 | 0.3639 | 0.3704 | 0.3748 | 0.3863 |
| 1.9 | 0.3353 | 0.3572 | 0.3383 | 0.3691 |
| 2 | 0.3857 | 0.4006 | 0.3861 | 0.3944 |
| Average RMS | 0.234395 | 0.238638 | 0.233924 | 0.243886 |
| Standard deviation | 0.088318 | 0.090656 | 0.091863 | 0.099514 |

**Table 4.6 validation of ANNs trained without noise**

The best ANN (file X62) developed had an average RMS error of 0.233924, and consisted of 2 hidden layers of 22 and 7 nodes respectively. This ANN topology was then used for further testing. With the ANN topology fixed, a further series of ANNs were trained with increasing (0.2 % increments) amounts of Gaussian noise added to the training data set. The best performing ANN trained for each increment of noise was saved. These ANN were then tested against increasing levels of Gaussian noise in the validation set. The results of the experiment are shown in figure 4.12. Full results of the experiments are given in appendix B.

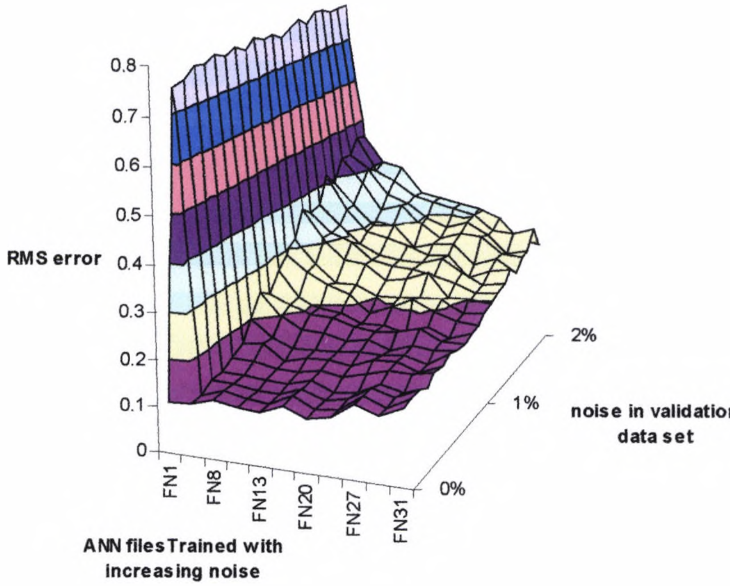



**Figure 4.12 RMS error profile**

### 4.4.4 Discussion

A key attribute of ANNs is their ability to generalise. The relationship between the amount of data available for training and ANN complexity can lead to the ANN overfitting of the data during training. Should the ANN overfit the training data then its ability to generalise may be reduced. The complexity of an ANN is governed by the number of adaptable parameters that exist, e.g. the number of weights in an ANN model. However as the relationship between the number of weights in an ANN model and the minimum amount of training data needed to prevent overfitting is not explicitly known, the generalisation ability of an ANN is often monitored during its training. Another method to improve the ability of an ANN to generalise is to add artificial noise to the training set.

The results of the previous experiment (figure 4.12) suggest that the addition of levels of noise required to dramatically improve the ability of the ANN are small, typically 1% Gaussian noise. When comparing ANNs trained with variable architectures and the fixed architecture (figure 4.13) described by Masters (1993), there is only a marginal improvement, in the average RMS error.

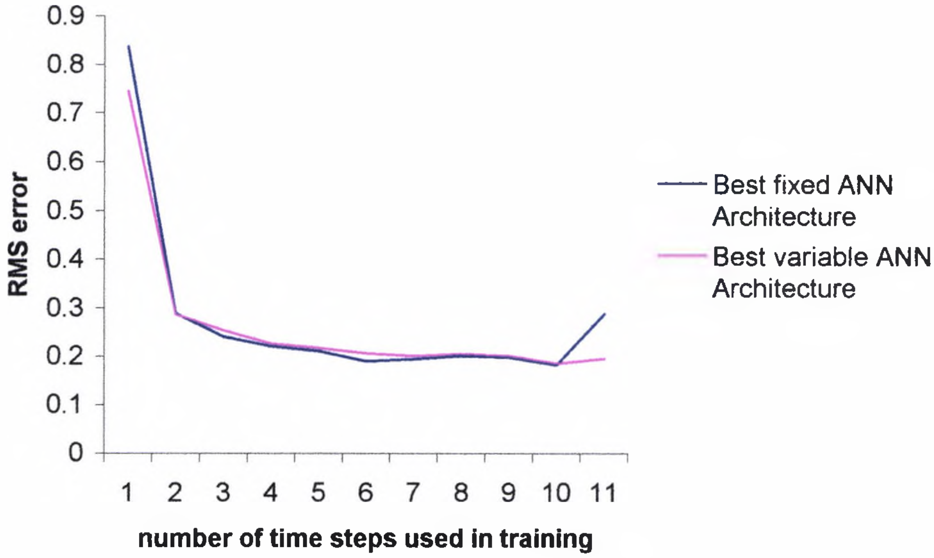



**Figure 4.13 comparisons of fixed and variable ANN architectures**

An improvement in the ability of the ANN to generalise would be reflected in increased robustness of the fault ANN to noise that may present in plant parameters for example calibration drift or core ageing, but at the expense of classification accuracy.

### 4.4.5 Final validation fault classifier

After inspecting the results of the previous experiments, the ANN (FN20) with an RMS error of 0.1815 was chosen as the ANN to be implemented in the Operators Advisory System. This ANN with 1.2 % Gaussian noise added to the training data performed better when presented with validation data containing 0-1% gaussian noise.

A summary of the number of time steps taken to identify a transient is shown in table 4.7. In general, there has been an overall increase in the number of time steps to classify a transient when compared to the initial experiments (table 4.2), with the maximum number of time steps to diagnose a transient increasing from 4 to 15. The time steps taken to classify a throttle opening transient at 60% and 80% full power is higher then at 20% and 40% full power, the reverse trend found in the initial experiment.

| Transient | 20% full power | 40% full power | 60% full power | 80% full power |
|---|---|---|---|---|
| Throttle opening | 8 | 7 | 15 | 10 |
| Primary coolant leak | 6 | 3 | 2 | 4 |
| Steam leak | 2 | 3 | 6 | 4 |
| Rod drop | 2 | 3 | 2 | 6 |
| Group drop | 7 | 2 | 7 | 3 |

**Table 4.7 number of time steps taken to identify transient**

Further tests on FN20 were conducted with a new set of six transients generated by the PWR simulator. Gaussian noise (0.5%) was added to the data and presented to the ANN FN20. The results are shown in figures 4.14 - 4.19.

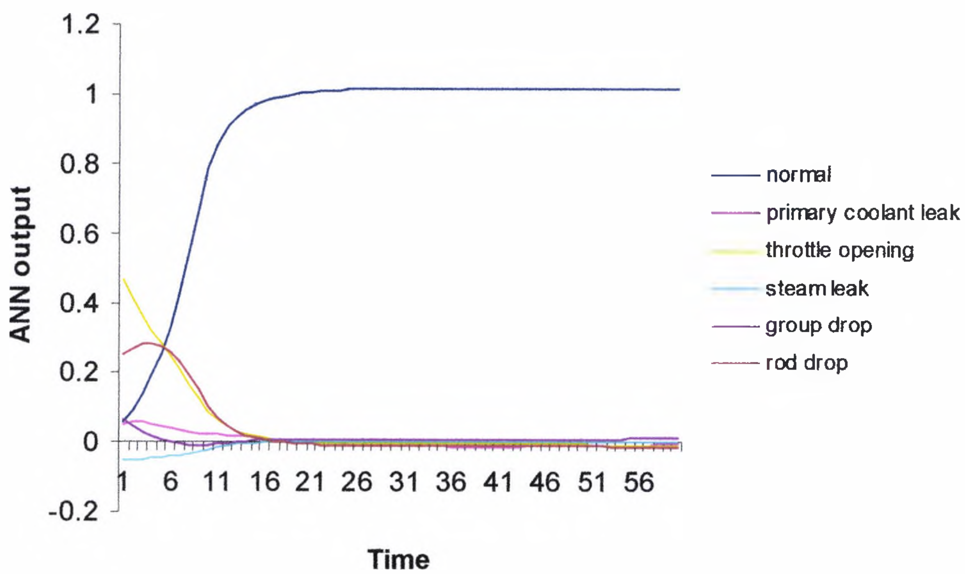



**Figure 4.14 Normal Operating Conditions**

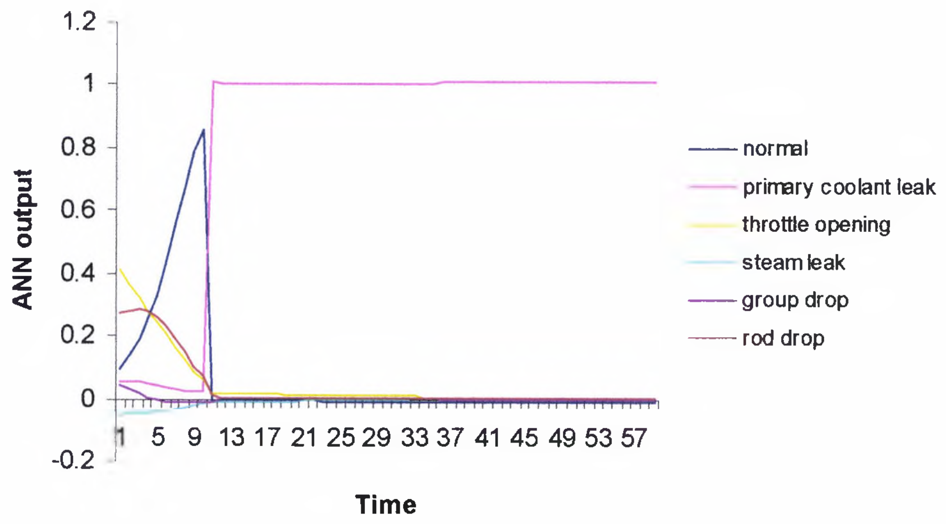



**Figure 4.15 Primary Coolant Leak Transient**

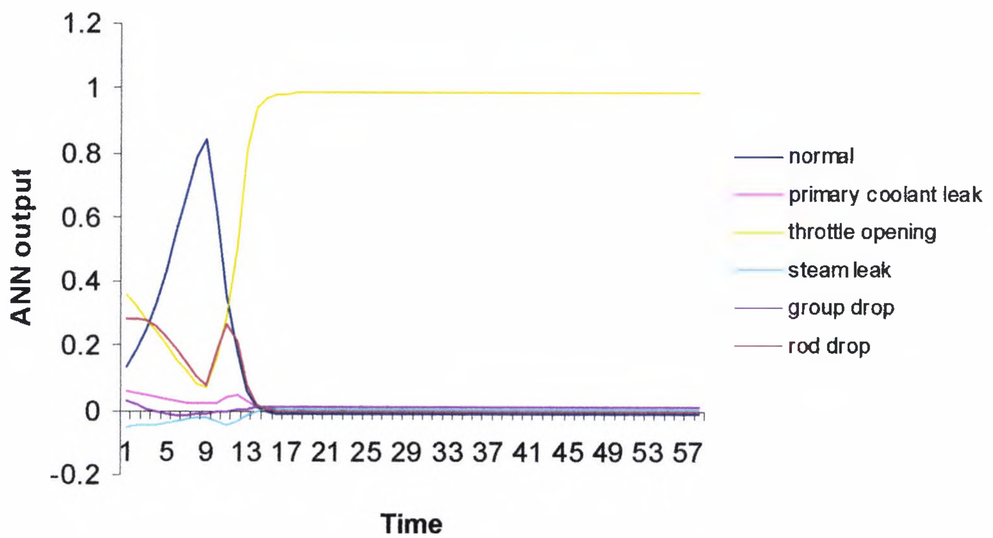



**Figure 4.16 Throttle Opening Transient**

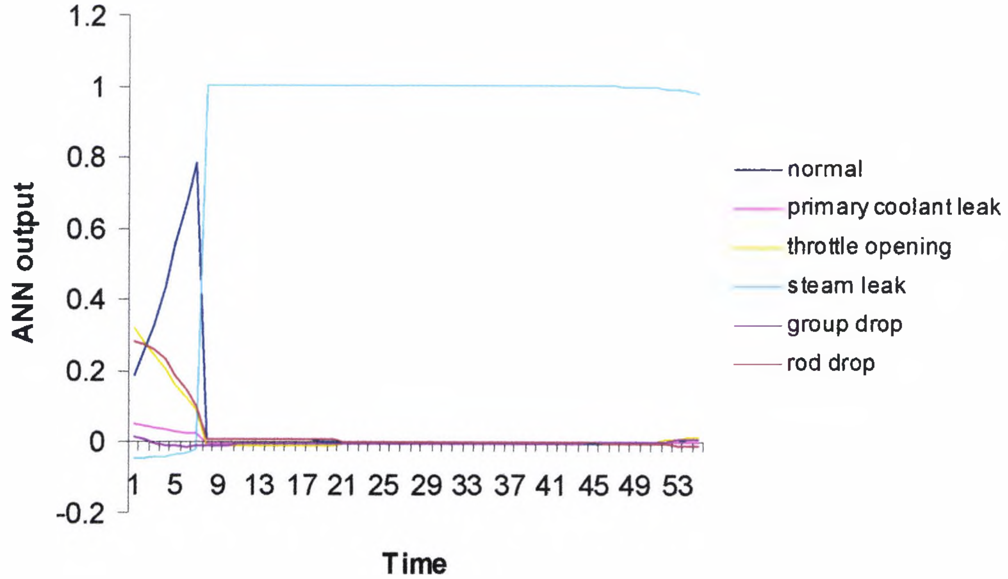



**Figure 4.17 Steam Leak Transient**

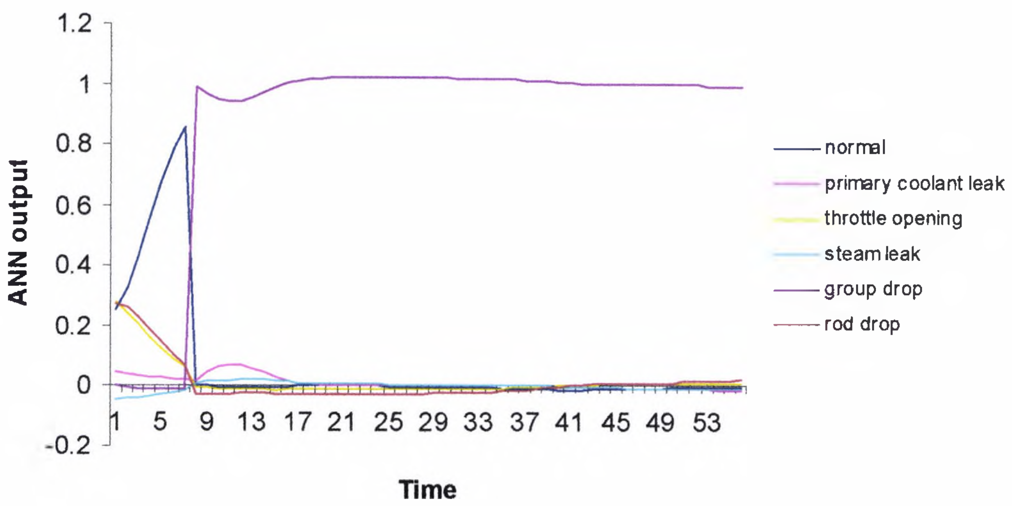



**Figure 4.18 Group Drop Transient**

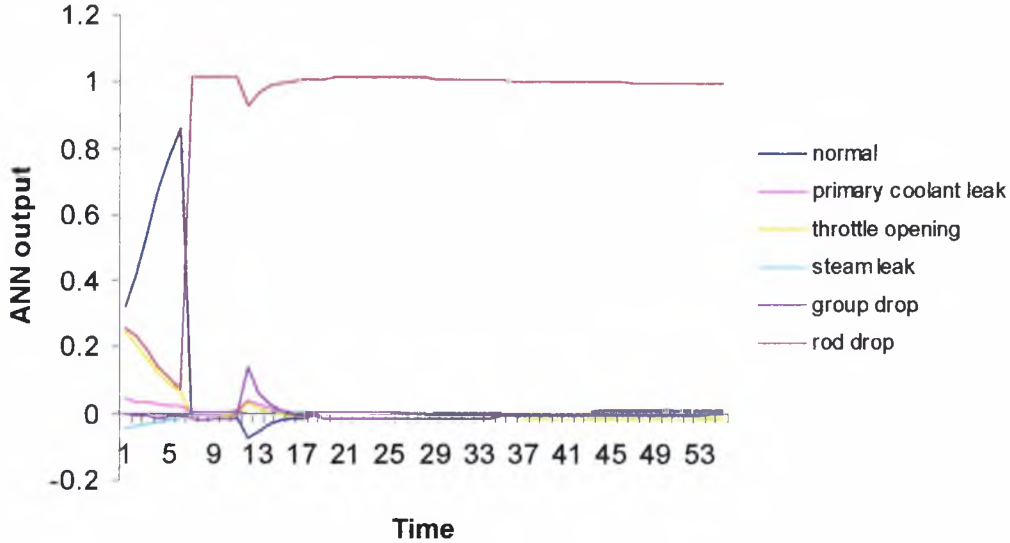



**Figure 4.19 Single Rod Drop Transient**

Generally the results from the further testing of the ANN with a new set of transients were very encouraging. All the transients were correctly diagnosed. The trained ANN is sufficiently robust to deal with levels of noise that may occur within a transducer or in signal processing during the measurement of plant parameters within the primary circuit of a PWR. The transients were quickly diagnosed with the exception of the single and group rod drop (figures 4.18 and 4.19), where there is a short hesitation in the correct diagnosis of the transient. This may be due to the simulator not being allowed to settle into a steady state condition, prior to the initiation of the transient.

Difficulties have been reported in the training of ANNs in the diagnosis of transients over long periods of time (Bengio et al 1994); however as can be seen in figures 4.14 to 4.19, this is not the case in the above trained ANN transient classifier. Once the correct diagnosis has been achieved, the ANN output remains stable for the remainder of the recording.

### 4.4.6 Discussion

The results of the experiment show an overall enhancement in the performance of the ANN. The accuracy of classification and stability of the ANN output over time are better then the ANN trained without noise added to the training data however, the amount of time taken to correctly identify the transient is longer. The time taken for the identification of a fault is comparable and often faster than a plant operator. All of the transients were quickly diagnosed,

## 4.5 Conclusion

This chapter has presented work undertaken to investigate the use of an ANN for the early identification of a fault transient. The experiments conducted in this chapter confirm that feedforward ANNs are an ideal tool in diagnosing transients in a pressurised water reactor, with all transients quickly and accurately classified. These were pre-defined as an ANN output value greater than 0.95 to classified as a 1 (transient present), 0 (transient absent).

The initial ANN model failed to correctly classify transients when presented with noisy data. However, when noise was added during training stages of an ANN, the performance and sensitivity of the ANN was dramatically improved. The choice of network topology suggested by Masters were very close to finding the optimum solution for the problem, even when the addition of noise to the training data. The final ANN reported on will be used in the development of the proposed Operators Advisory System described in chapter 8.

# Chapter 5

# Small Loss of Coolant Leak Monitor

## 5.1 Introduction

In chapter four, an Artificial Neural Network (ANN) was used in the development of a pressurised water reactor (PWR) fault classifier. However, the information relayed to the plant operator did not quantify the size of the fault. The small loss of coolant leak monitor module developed in this chapter is used in the quantifier layer in the Operator Advisory System (OAS) described in chapter seven. The inputs to the monitor would be a recordable subset of the plant data available for analysis.

The structure of this chapter is as follows; a brief outline is given of some practical considerations relevant to the investigations reported in this chapter. The initial investigations on the ANN small loss of coolant leak monitor are then reported. The performance of the developed ANN is then examined and the information gained is used to train a new ANN monitor. Finally, a summary is given in section 5.7.

In the proposed OAS, its top layer performs a diagnostic function. The next layer in the OAS contains modules that pertain to the size or location of the fault diagnosed. The problem under consideration here is the monitoring of a small loss of coolant accident (LOCA). The data used for the monitor, would is a sub set of data obtained from the primary circuit of a pressurised water reactor. The criteria for its implementation in the OAS could be one of two methods:

- A LOCA is detected in the fault classifier
- The monitor is on all the time

If a leak were present, this information together with the fault diagnosis would be presented to the plant operator (refer to chapter 3). The proposed implementation of the small loss of coolant monitor in the OAS is shown in figure 5.1.

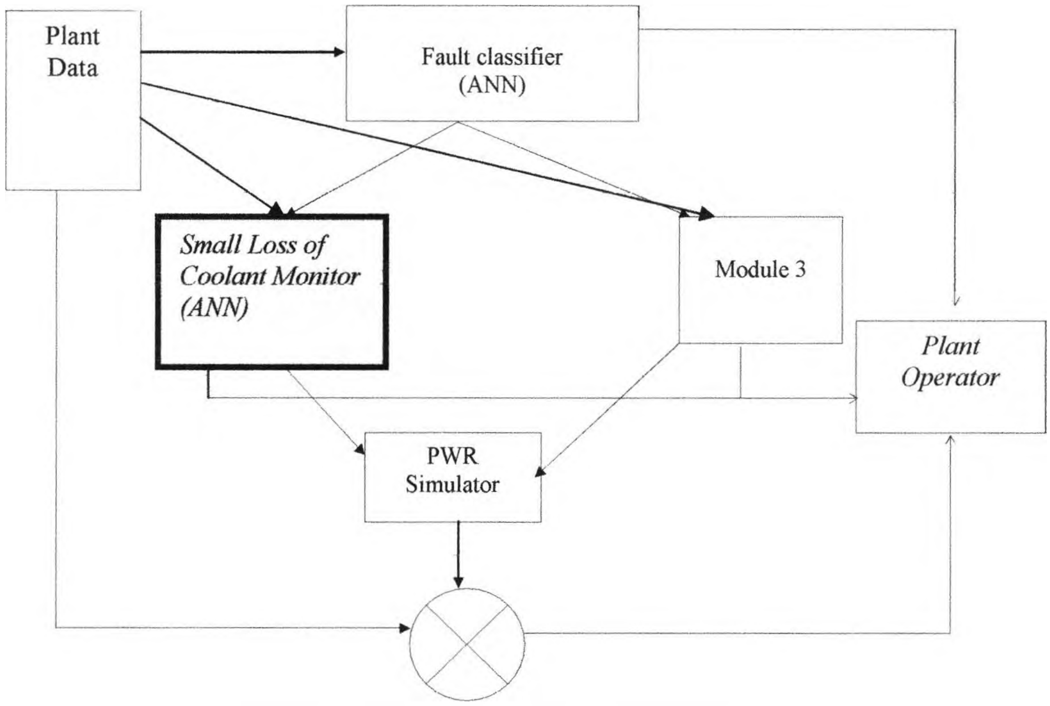



**Figure 5.1 Embedded Small Loss of Coolant Monitor in OAS**

## 5.2 Background

The reactor compartment of a Pressurised Water Reactor' is often referred to as a 'hostile environment' with high temperatures and humidity. Because of the harsh conditions, the transducers used for the monitoring of plant parameters are designed to withstand the tough conditions and provide a stable output over long periods. However, during an accident the readings from the transducers in this environment may become unreliable. Over the last few years, new leakage detectors have become available for the early identification of leaks. The requirement of small leakage monitoring (IAEAC 1999) is to meet international standards and regulations and has become an important part of a planned maintenance. Small leaks can often provide early warning of a major break pipe break or ageing of pump or valve seals.

The main effects of a loss of coolant leak occurring in a confined space can be defined as:

- Radiation/chemical
- System Response
- Heat
- Noise

The two most common methods for determining primary-to-secondary leak rates are the sampling of the secondary side of the steam generator for iodine and sampling feedwater for tritium. This chapter investigates the use of recordable plant parameters in the primary circuit of a PWR to estimate the leak rate of a small primary-to-secondary leak.

## 5.3 Implementation

This section outlines the steps involved in the development of an ANN to monitor small losses of coolant from the primary to the secondary circuit of a PWR

The management of small leaks from the primary circuit relies on observations of the effects on the loss of primary coolant from the PWR and the environment within the containment vessel, the primary observations being radiation/chemical monitoring, the rate of fall of water height within the pressuriser, and acoustic noise. However these are only approximate indicators, as these observations take no account of the dynamic changes in the volume of coolant in the primary circuit during differing operating conditions, for example changes in power demands, rod positions etc.

The location of the leak can also prove problematic, as often the actual site of the coolant leak may be several metres from the observed leak. This can occur when the thermal lagging material surrounding the piping masks the leak, the coolant travelling through the boundary layer between the pipe and the lagging emerges elsewhere. Condensation runoff and radiochemical observation, though measurable, can be difficult to quantify. For example, a radiation detector may provide a warning when the amount of radiation present, is greater than a pre-determined threshold. Small leaks in the primary coolant system are therefore difficult to not only detect, but also to monitor.

A constant loss of pressure can equate to a small or large loss of coolant (figure 5.2);

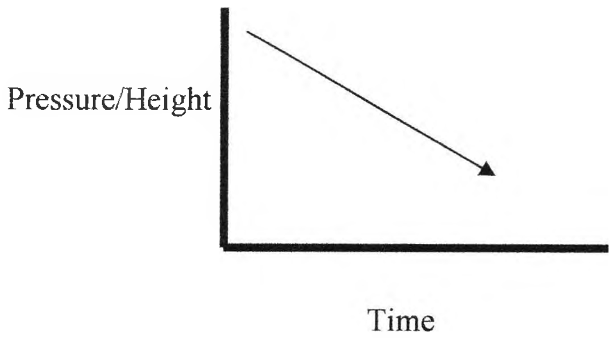



**Figure 5.2 Embedded Small Loss of Coolant Monitor in OAS**

A constant pressure with a loss of pressuriser height together with an increase of reactor compartment temperature can also indicate a loss of coolant accident (LOCA); this may also be combined with a high water level recorded in the reactor compartment. It is often the case that a radiation detector will be the first to provide a warning if a leak has occurred.

### 5.3.1 Initial investigations with full data set

The next stage of work was to investigate whether the technique used to diagnose PWR transients, could be used to develop a small leak monitor for a loss of coolant from the primary circuit of a PWR. A primary circuit simulator was used to generate 6 small coolant leaks, at 4 power levels. The simulator was run for 50 time steps before a LOCA was initiated, and an output file for the transient was generated. The data for 32 plant variables were randomly divided into training and test data sets in the approximate ratio of 2:1. A series of ANNs were trained with the data. In each case the training data was presented for 120,000 cycles with testing every 100 cycles with the best ANN being saved. The number of nodes was chosen heuristically.

### 5.3.2 Results

The best ANN developed with an RMS error 0.178 consisted of 2 hidden layers with 26 and 10 nodes respectively. The trained ANN was then presented with an independent validation data set of 6 simulated leak rates at 4 power levels. Table 5.1 shows the number of time steps taken for the trained ANN to correctly identify the presence of a correct leak size.

| Size of leak | 10%full power | 30% full power | 50% full power | 70% full power |
|---|---|---|---|---|
| **0.2 Kg/s** | 20 | 45 | 22 | 20 |
| **0.4 Kg/s** | 81 | 17 | 11 | 12 |
| **0.6 Kg/s** | 64 | 21 | 14 | 16 |
| **0.8 Kg/s** | 51 | 17 | 13 | 55 |
| **1 Kg/s** | 61 | 18 | 13 | 19 |
| **1.2 Kg/s** | 70 | 8 | 5 | 8 |

**Table 5.1 Times to Detection**

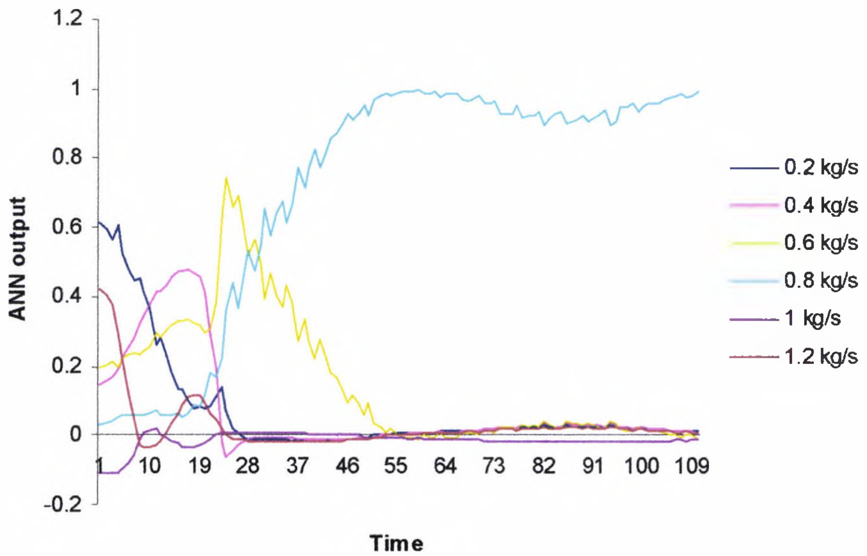



**Figure 5.3 ANN output for a 0.8kg/s loss of coolant accident at 10% full power**

All leaks were correctly diagnosed within 81 time periods when an acceptance threshold was set at 0.95 (table 5.1). An example of the ANN output for the trained network is shown in figure 5.3, which indicates correctly the presence of a 0.8 kg/s loss of coolant from the primary to secondary circuit, in 51 seconds. The lowest RMS level was chosen as an indicator of the best ANN, no attempt at this stage was made to see if any of the inputs from the data sets were redundant.

### 5.3.3 Discussion

The results for transient identification demonstrated that an ANN could quickly diagnose a transient condition. The time taken to diagnose a transient compared favourably with earlier work. A general observation is that the greater the power level, the more accurate and faster the classification time (table 5.1). The initial results for small leak monitoring showed that the ANN was able to correctly classify all leaks within 81 time steps. However, the performance of the network was poor when classifying leak rates at low power levels for example at 10% full power, and this was reflected in an increase in classification time. For a 0.4 kg/s and 0.6kg/s leak rates, the network correctly diagnosis the LOCA but not before indicating the presence of much larger LOCA first.

One possible explanation may be the change in the plant dynamics caused by the initial starting conditions of the PWR simulator. An example for a potential misclassification (false positive) can be seen in figure 5.4.

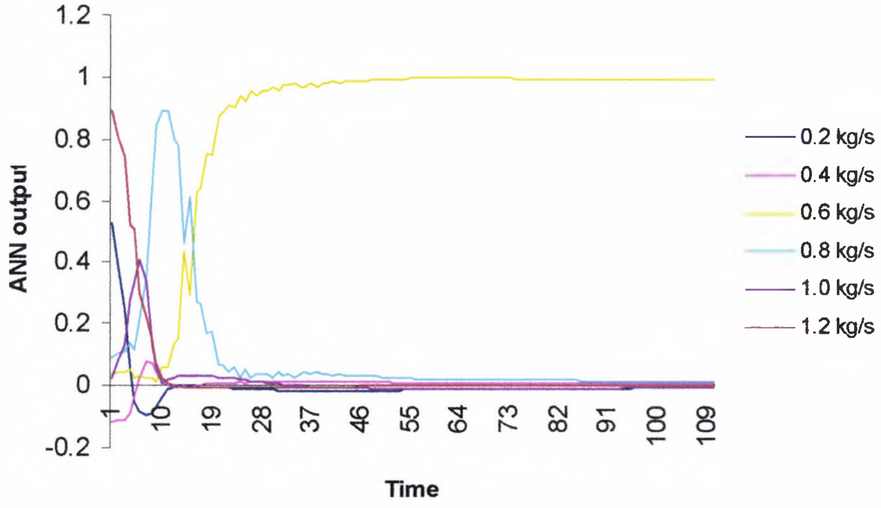



**Figure 5.4: ANN output for a 0.6kg/s**

If the acceptance threshold were lowered to 0.85, the 0.6kg/s LOCA at 10% full power would have been misclassified. The ANN would have incorrectly indicated a 1.2kg/s and 0.8 kg/s leak rate before providing a correct diagnosis. The results at higher power levels resulted in faster classification times, and a larger difference between the correct size LOCA, and others. The 'jagged' output for 0.6, 0.4 and

0.2 kg/s in fig 5.3, seems to occur at lower power levels, this may be due to the leak rates sharing a similar solution space. Once again this noise has the potential to miss-classify a leak rate.

The results for a no leak or normal transient are also of interest. The ANN classifies the normal transient to be the smallest transient, i.e. the 0.2 kg/s, and this result was consistent at all four power levels as shown in figure 5.5.

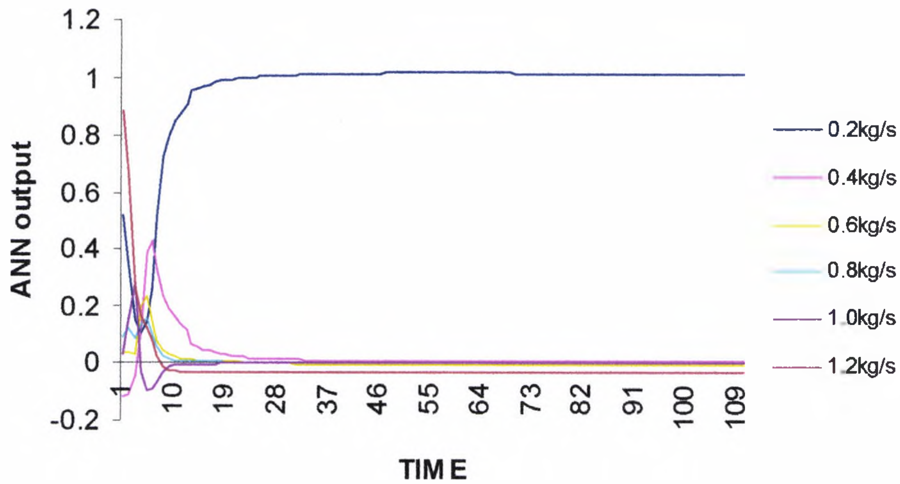



**Figure 5.5 No Leak at 30% full power**

The results from the initial investigation of the use of ANN as a small leak monitor were encouraging. The ability of the ANN to find the very small changes in plant parameters and then correctly classify them had been demonstrated.

The simulator code was then modified to provide a double fault, a background transient of a throttle closing during a 0.2 kg/s loss of coolant. The data from the simulation were presented to the ANN the results of which are shown in figures 5.6.

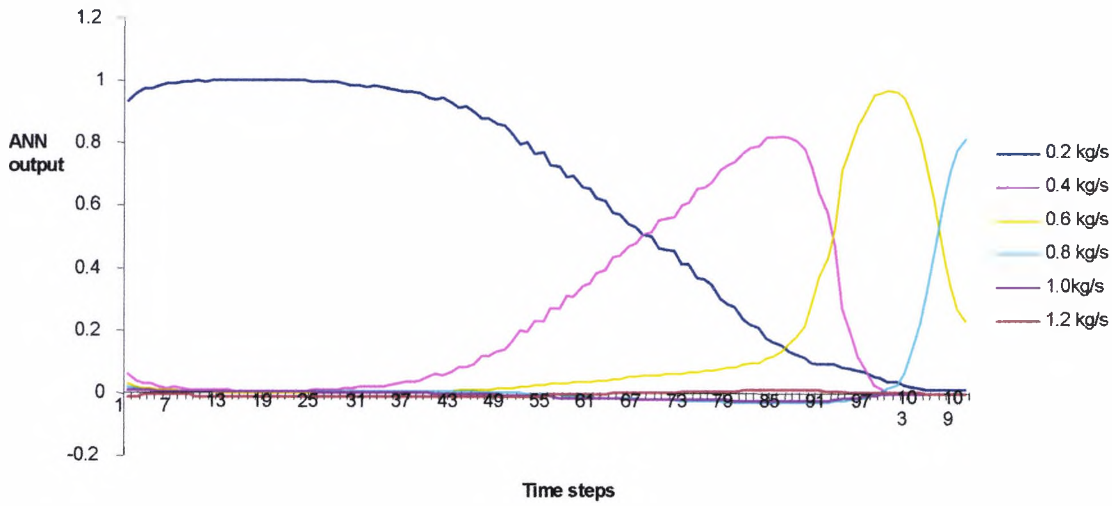



**Figure 5.6 0.2kg/s LOCA with a throttle closing transient**

The output of the ANN initially indicate a leak rate of 0.2 kg/s, but as the throttle closing transient begins to take effect in the primary circuit of the PWR, larger leak rates (0.6 kg/s when an ANN output level of 0.85 is used) are indicated.

The results for these preliminary experiments were promising; however the limits of the feedforward back propagation method for classifying plant parameters for small leaks within the primary circuit had been reached. Analysis of the simulated plant data for small leak rates, revealed only small changes in plant parameter values, and in the real world many of the changes would be so small as to be un-measurable.

## 5.4 Artificial Neural Network, Time-delay

### 5.4.1 Introduction

The results from the initial investigation of the use of ANN as a small leak monitor were encouraging and warranted further investigation. After speaking to plant operators, it was proposed that a more realistic range of small leaks would be between 0.1 and 0.6 kg/s. but as observed in the previous work the accuracy needed to be improved at these small leak sizes.

To help improve the accuracy of the classification, temporal patterns within the data needed to be taken into account. One way of converting a time varying signal into a static vector is to accumulate several time steps of data and then present them as a single vector (Swingler 1996, p43) thus creating a time delay neural network. By delaying the signal at various lengths, more complicated ANNs can be created.

If the input contains *n* parameters and is delayed by *d* time periods, there will be *nd* inputs to the network. As new data becomes available, they are placed in nodes at one end, and old information shifted down a series of nodes. An example of a time delay ANN is shown in figure 5.7, where a plant parameter *p* is delayed by *nd* time steps.

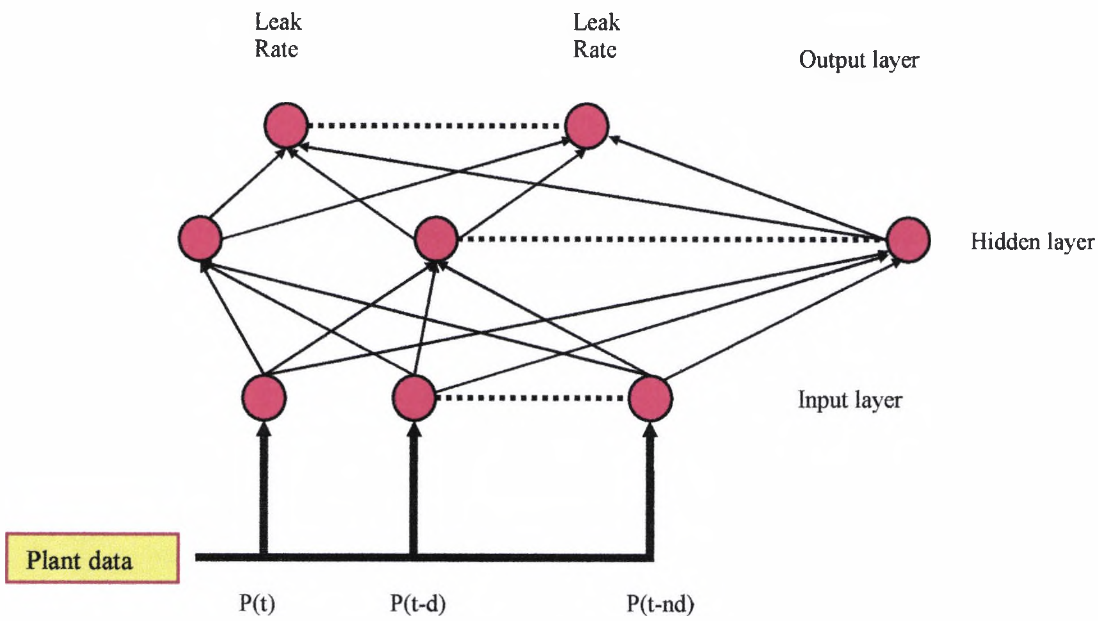



**Figure 5.7 Time-Delay ANN**

However, it can be seen that as the number of time steps is increased, there is a corresponding increase in the complexity of the ANN, which is governed by the amount of adaptable parameters i.e. the weights. An increase in the number of variables in a problem to *n*, the associated complexity increases faster than a polynomial of order *n* (Basu, 1994).

Relationship exists between the complexity of an ANN and the amount of training data. An increase in the complexity of an ANN requires an increase in the amount of data required for the training to prevent the ANN from overfitting the data, and hence in a reduction in the ability of the ANN to generalise. In addition, the result of the increased complexity can lead to an increase in training times, and a higher probability of the ANN failing to correctly classify leak rates. In order to investigate the effect of number of time steps and classification, it was necessary to reduce the number of input parameters, in order to reduce ANN complexity.

### 5.4.2 Sensitivity Analysis

Sensitivity analysis is a method for examining the cause and effect relationship between the inputs and outputs of the network. The network learning is disabled during this operation such that the network weights are not affected. The sensitivity about the mean test provides feedback as to which input parameters are the least significant. Once completed, the results of the test allow pruning the input parameters by removing the insignificant channels. This will reduce the size of the network, which in turn reduces the complexity and the training times.

Figure 5.8 shows a sensitivity about the mean analysis for the 67 input parameters. During the training of the ANN, the input parameters to the ANN are shifted slightly (by 1 standard deviation), and the corresponding change in the output is reported.

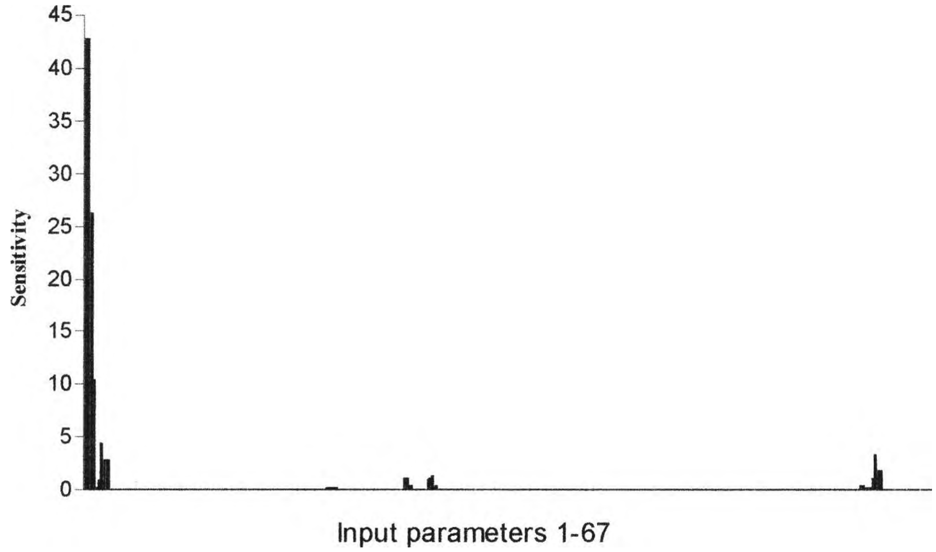



**Figure 5.8 Sensitivity about the Mean Analysis**

From the sensitivity analysis and consultations with plant operators, the most significant plant parameters chosen for use in the training of an ANN to monitor a small loss of coolant were:

- Temperature average (Tavg)
- Pressuriser pressure
- Pressuriser water level
- Start up rate
- Rod position
- Temperature cold leg

The plant variables chosen for use in the development of a loss of coolant leak rate monitor are all measurable and routinely monitored in a PWR control room by plant operators.

## 5.5 Optimum Time Steps

### 5.5.1 Introduction

A PWR simulator was used to generate a new set of small loss of coolant leaks for the training and evaluation of a leak rate monitor. For it to be used in the proposed Operators Advisory System, it was important that this time a 'no leak' diagnosis was included in the classification. The sizes of the leaks were between 0-0.5 kg/s. and using the results from the experiment above, 6 plant parameters were chosen (5.4.2).

### 5.5.2 Implementation

As in the previous experiment, the method described by Masters for the selection of the network architecture was used as a starting point; a series of ANNs were trained, with the number of nodes altered heuristically. Unlike the previous experiment, Gaussian noise was added to the training, and validation data sets. As before the hyperbolic tangent transfer function was used and each ANN was trained for 120,000 cycles with testing every 100 cycles with the test set, the best network being saved. The optimum network for each time step was found using the RMS error as a guide to performance. The results of the test are summarised in table 5.2. Full results are given in appendix C.

| Number of time steps | Number of inputs | Hidden layer 1 | Hidden layer 2 | RMS error |
|---|---|---|---|---|
| 1 | 6 | 20 | 10 | 0.4489 |
| 2 | 12 | 40 | 20 | 0.3833 |
| 3 | 18 | 30 | 15 | 0.2883 |
| 4 | 24 | 40 | 20 | 0.3098 |
| 5 | 30 | 30 | 15 | 0.2418 |
| **10** | **60** | **30** | **15** | **0.1657** |
| 15 | 90 | 36 | 15 | 0.1682 |

**Table 5.2 number of time steps**

The ANN trained using ten time steps was chosen for further testing as this network had a marginally lower RMS error (0.1657) than for fifteen time steps (0.1682). An ANN trained with ten time steps gives rise to an input vector consisting of 60 inputs. It was thought that this should be the maximum number of time step used as the larger the number of inputs leads to an increase in complexity and associated problems also. The increase in the number of time steps leads also to an increase in the time taken for a diagnosis to be made. The results of the presentation of the validation data set to the ten time step ANN are given in table 5.3.

| Size of leak | 40 %full power | 60 % full power | 80 % full power | 100 % full power |
|---|---|---|---|---|
| **0.0 Kg/s** | 3 | 10 | 8 | 9 |
| **0.1 Kg/s** | 13 | 7 | 7 | 8 |
| **0.2 Kg/s** | 8 | 12 | 9 | 14 |
| **0.3 Kg/s** | 7 | 5 | 7 | 9 |
| **0.4 Kg/s** | 10 | 3 | 5 | 7 |
| **0.5 Kg/s** | 12 | 6 | 11 | 4 |

**Table 5.3 number of time steps**

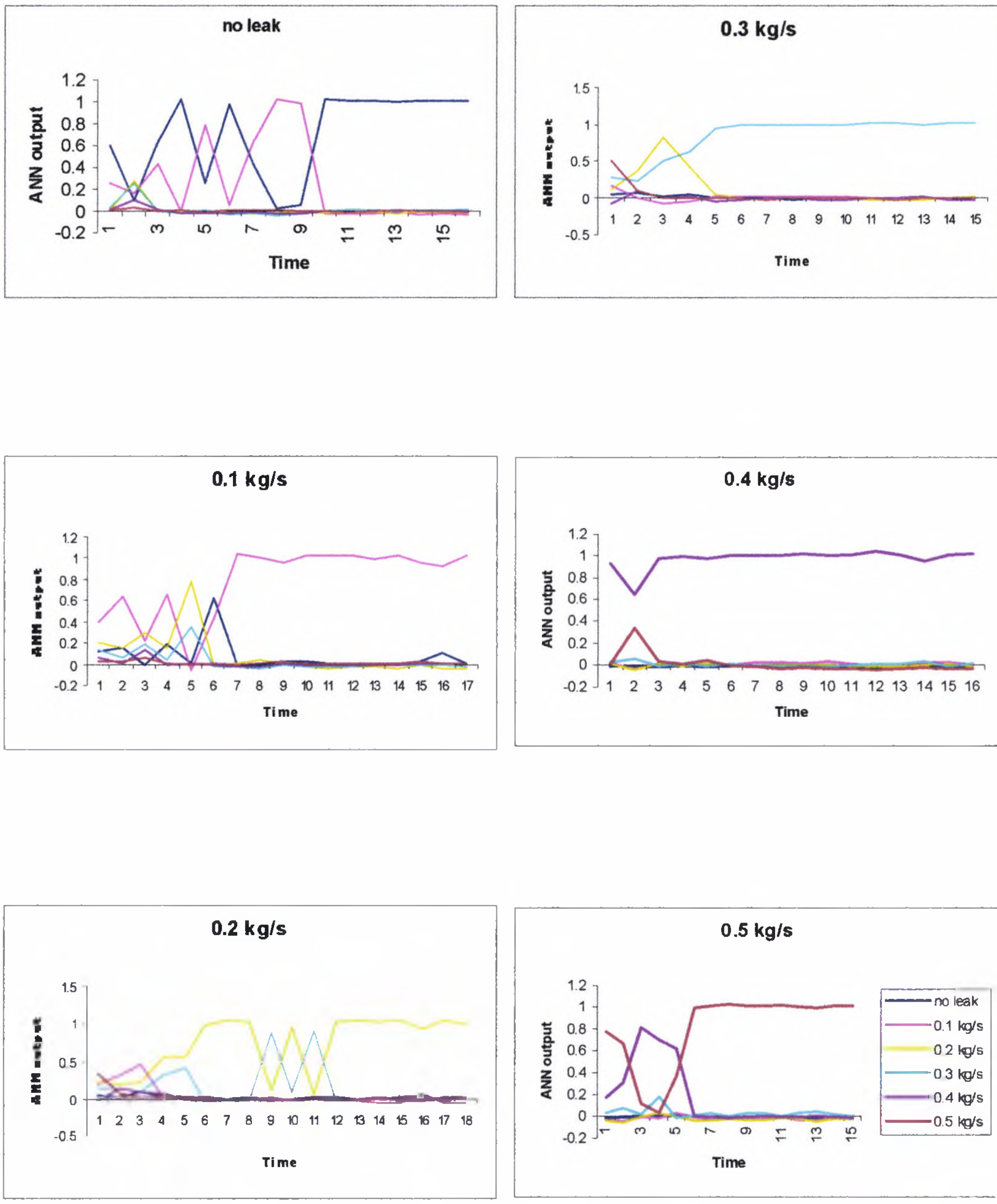



**Figure 5.9 ANN results for LOCA 0-0.5 kg/s**

The ANN classification of loss of coolant leak rates trained using the 6 plant parameters that were derived from the sensitivity analysis and were routinely monitored by plant operators, produced results that are acceptable. The oscillations in ANN output shown for a no leak, and 0.2kg/s classification leads to a false classification of 0.1 and 0.3 kg/s respectively (see table 5.3). This leads to an increase in the time taken to correctly classify the leak rate.

### 5.5.3 Intermediate values

Another data set was generated, this time to explore the effect of leak rates, which were intermediate to leak rates used for the training of the ANN. The leak sizes simulated were 0, 0.15, 0.25, 0.35, 0.45 and 0.55 Kg/s. The full data set was then presented to the ANN to investigate the accuracy and performance of the ANN.

The best RMS error from the ANN when presented with the test data was 0.4685. When 1% gaussian noise was added to the data set, the RMS error increased to 0.5345. The results are given in figure 5.10.

Closer inspection of the results for intermediate leak rates show that for leak rates 1.5, 2.5, 3.5 and 4.5kg/s the ANN output oscillates between the two closest values. For example for a leak rate of 1.5 kg/s the ANN output oscillates between 0.1 and 0.2 kg/s. for a leak rate of 0.55 kg/s, the ANN output settles on the largest leak rate classification, 0.5 kg/s.

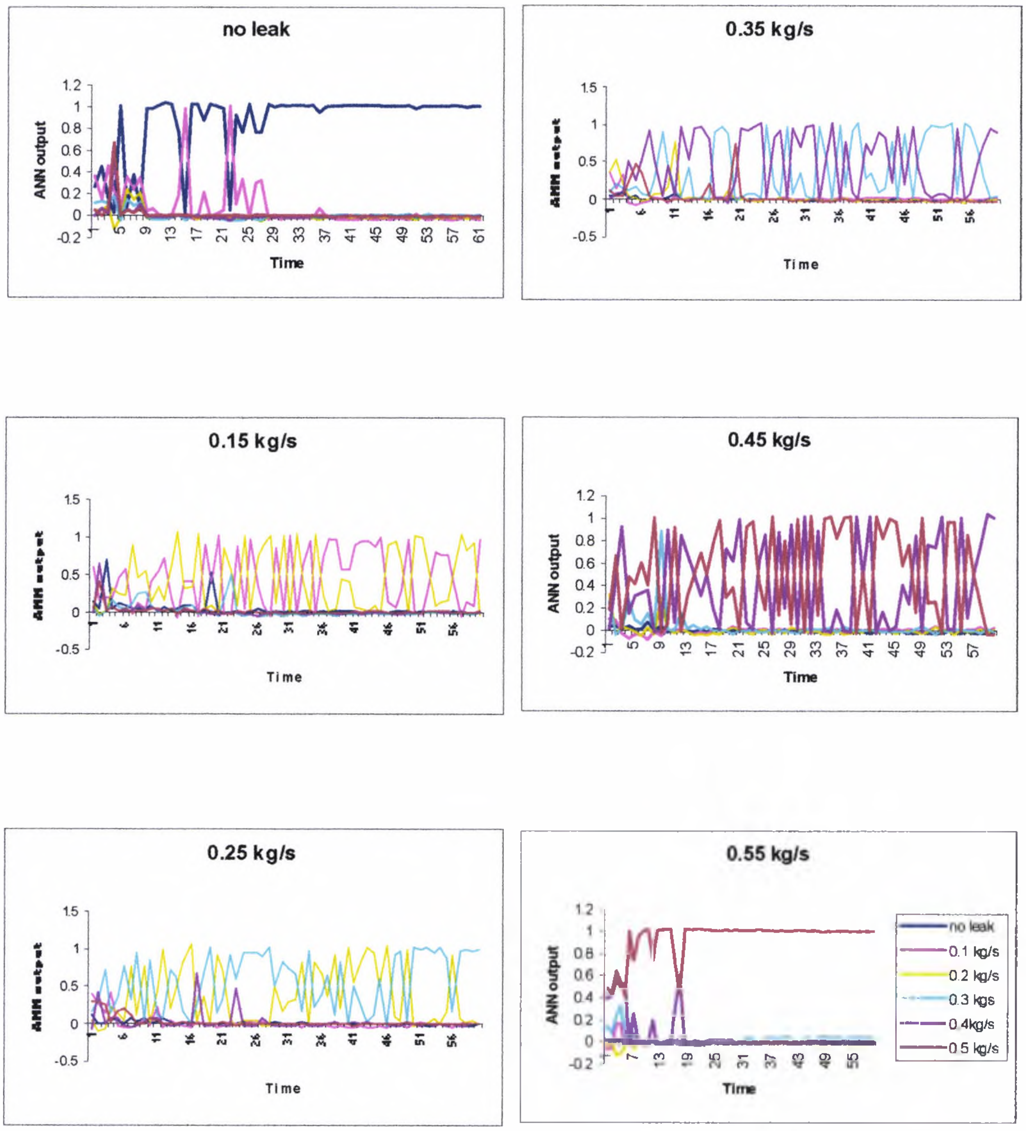



**Figure 5.10 ANN results for intermediate LOCA**

## 5.5.4 Discussion

Generally these results were encouraging; the ANN correctly classified leak sizes it was trained on. The leak rates that were used for training were those that were useful to diagnose and classify quickly. The maximum time taken for the correct estimation of a leak rate was less than 15 time steps (table 5.3). However, for intermediate values the ANN cannot choose between the two nearest classification values as the ANN output was in a binary format. To obtain the correct leak rate it may be necessary to train another ANN on intermediate values and then compare ANN outputs.

## 5.6 Classification of Actual Leak on a Continuous Scale

### 5.6.1 Introduction

So far, two schemes for estimating leak rate of primary coolant have been investigated. Though adequate for operational purposes, (only discrete intervals are required), they did not satisfactorily quantify intermediate leak rates for example a leak rate of 0.25 Kg/s. The extra ANN modules required for finding a solution would lead to an extra processing step, leading to an increase in complexity and time taken for the OAS to provide an estimate in leak rate.

The previous experiment confirmed the use of a time delay ANN did increase the accuracy of the classifier to estimate the actual primary coolant leak rate. A further method of improving the performance of the ANN would be to investigate this method to estimate the leak rate on a continuous scale rather than discrete values. To investigate this concept further two ANN models were investigated using five and ten time-steps.

### 5.6.2 Prediction of leak rate using 5 time steps

A series of ANNs were trained using the same data as the previous experiment. However, this time the target value during training was the leak rate value (real number) provided by the PWR simulator. The training data with 1% Gaussian noise were presented for 120,000 cycles, with testing every 100 cycles, the best network being saved. The results are given in table 5.4.

| File name | Layer1 | Layer2 | RMS error |
|---|---|---|---|
| **L37** | **35** | **15** | **0.2966** |
| L38 | 40 | 10 | 0.3015 |
| L39 | 20 | 10 | 0.3062 |
| L40 | 25 | 10 | 0.2977 |

**Table 5.4 Leak rate using five time steps**

The best ANN (file L37) had an RMS error of 0.2966. When presented with the validation data set, the RMS error increased to 0.3015, and when 5% Gaussian noise was added to the validation data set the RMS error increased to 0.4521.

Figure 5.11 shows the output of ANN (estimated leak rate) for a range of primary coolant leaks.

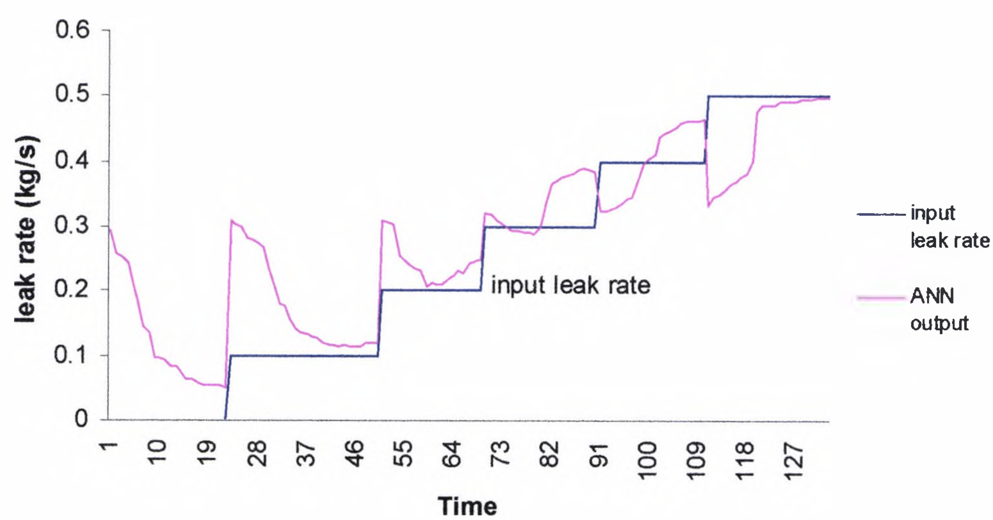



**Figure 5.11 ANN results for classification of leak rate (5 times step)**

The above results show that for the normal operating condition, and smaller leak rates (0.1 and 0.2 kg/s) the estimation is poor. The ANN overestimates the leak rate at the beginning of the transient, and then tends towards the actual leak rate. However, for the larger leak rates the ANN underestimates the leak rate though it is closer to the actual leak rate. A possible reason for the over/under estimation in leak rate may be the time taken for the transient to settle during the simulation. This could be eliminated by having the simulator run for a longer start-up period.

### 5.6.3 Estimation of leak rate using 10 time steps

The above experiment was carried out this time with ten time steps, using the same data sets for training, testing and validation. As before, 1% Gaussian noise was added to the training set and each network was trained for 120,000 cycles with testing every 100 cycles, the ANN with the lowest RMS value being saved.

The two networks with the lowest RMS error were chosen for further testing. A series validation data set containing no noise, one and five percent were presented to the ANNs, with the corresponding RMS errors noted. The results are summarised in table 5.5.

| File name | Layer1 | Layer2 | RMS error | Validation | Validation (1% noise) | Validation (5% noise) |
|---|---|---|---|---|---|---|
| L45 | 35 | 15 | 0.0456 | 0.0727 | 0.154 | 0.4968 |
| L46 | 40 | 10 | 0.0534 | | | |
| L47 | 30 | 10 | 0.0491 | | | |
| **L49DR** | **20** | **14** | **0.0413** | **0.0629** | **0.1545** | **0.4788** |

**Table 5.5 Leak rate using ten time steps**

The leak rate estimation by the best performing ANN (file L49 DR) using the three validation sets is shown in Figures 5.12-5.14.

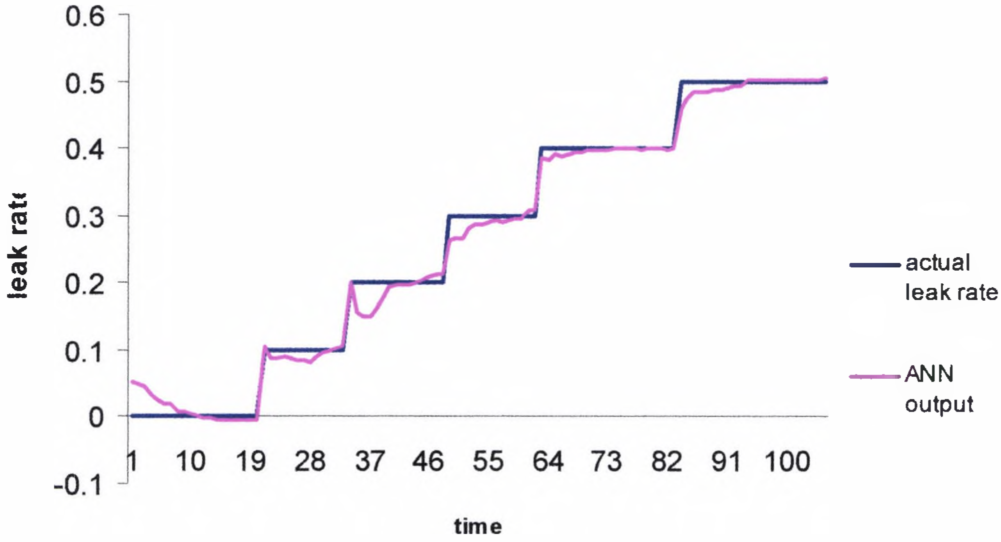



**Figure 5.12 ANN results for classification of leak rate (10 times step) no noise**

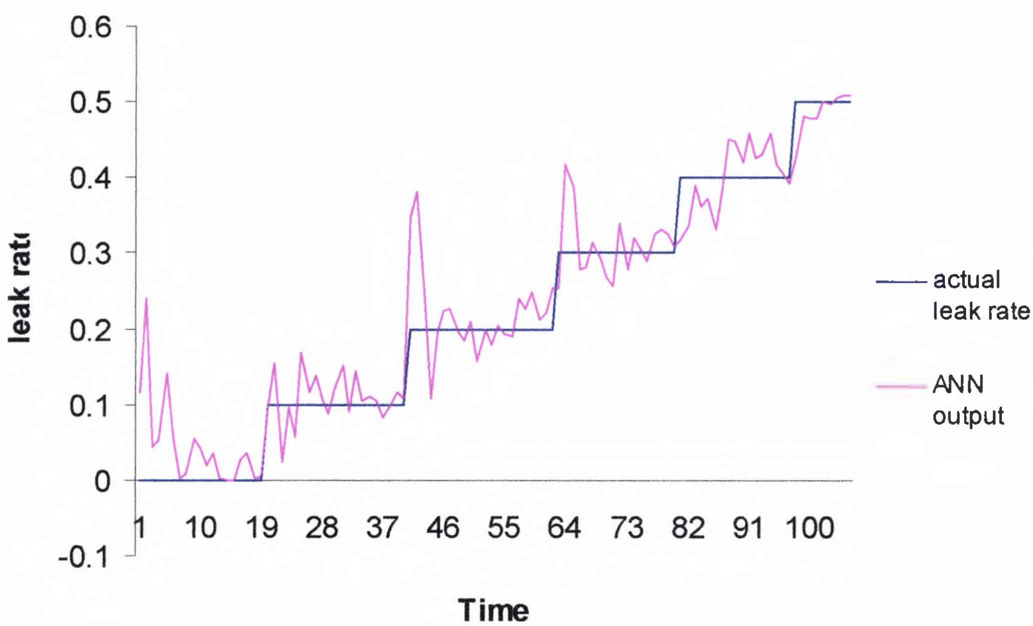



**Figure 5.13 ANN results for classification of leak rate (10 times step, 1% noise)**

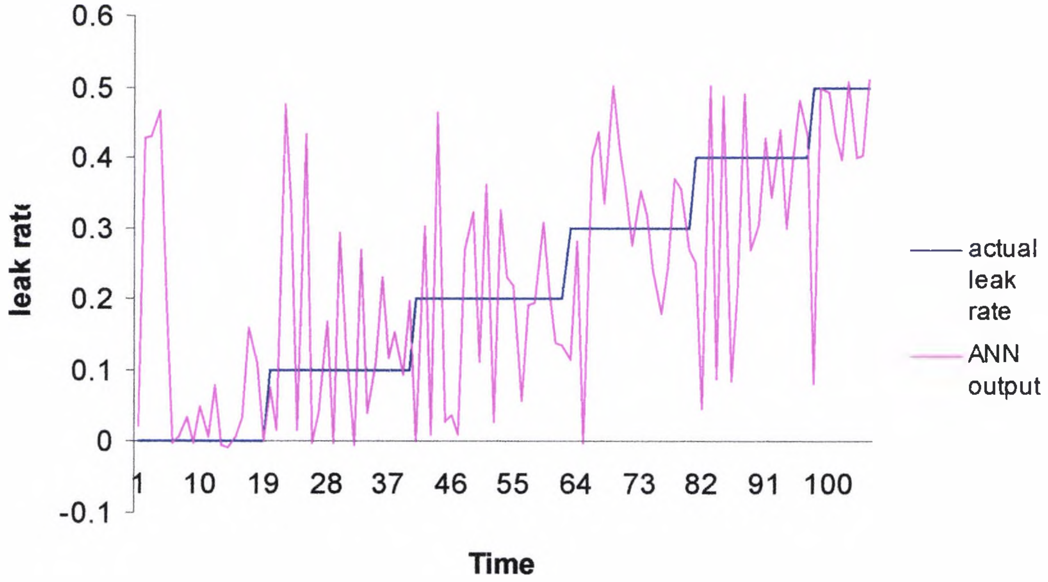



**Figure 5.14 ANN results for classification of leak rate (10 times step, 5% noise)**

The simulated data for intermediate leak rates from the previous experiment were then presented the ANN; the results are shown in figure 5.15.

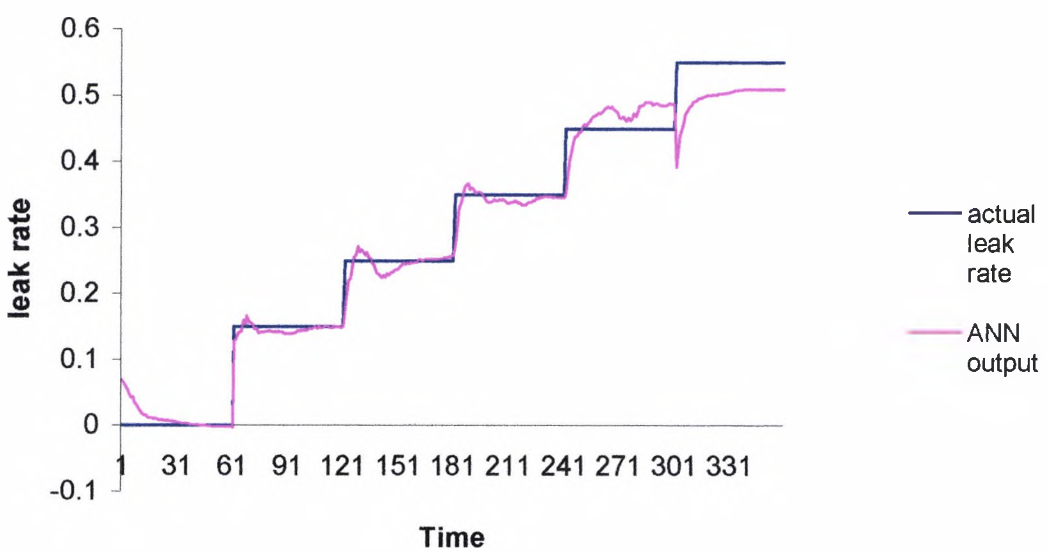



**Figure 5.15 ANN results for classification for intermediate leak rate**

### 5.6.4 Analysis of results

From this investigation it can be seen that in general the results for estimation of primary coolant leak rate using ten time steps were good. When 1% noise was added to the validation data set, the degradation in performance was predictable. However when 5% noise was added to the validation data, the RMS error had increased to 0.4788, with a corresponding failure in the ANN to provide a meaningful output. The actual tolerances stated for many of the transducers used for measuring plant parameters are quoted as better than 0.1%, well within the capabilities of the ANN leak rate estimator.

Initial experiments on using larger levels of noise during the training of the network resulted in a failure of the ANN weight values to converge to a useful value. The maximum level of noise that could be added during the training of the network and still give acceptable performance was 1% and this is reflected in the ability of the ANN to give an adequate estimate of leak rate when 1% noise was added to the validation data set.

Unlike the initial investigations, the output from the ANN was not binary; instead, the output was an estimation of the actual leak rate. Figures 5.15 and 5.16 highlight the inability of the ANN to produce a linear output, by either over or under estimating the initial stages of the transient. A possible reason for this behaviour could be that the PWR simulator had not reached a steady state condition prior to the start of the transient.

## 5.7 Summary

This chapter has reported on work undertaken to devise an ANN based small loss of coolant monitor for use in the operators advisory system described in chapter 7. In the first part of the chapter, a general description for leak monitoring is described. A PWR simulator was then used to simulate a range of primary-to-secondary leaks. The data was used to train an ANN to map plant vectors to their respective leak rate category.

In the second half of the chapter, the use of a time delay ANN for classifying leak rates is investigated. Practical considerations required a reduction in the maximum leak rate to be classified from 1.2 kg/s to 0.5 kg/s. The increase in the number of input parameters when using a time delay ANN results in an increase in the number of plant parameters and therefore an increase in network complexity. Practical considerations and a sensitivity analysis reduced the number of plant parameters to be used in the investigation from 67 to 6. A time delay ANN was then trained for a leak rate on a continuous scale. The best ANN (10 time steps) was then tested on a wide range of untrained leak rates. The results show good generality of diagnosis and early diagnosis. The ANN leak rate monitor was felt to be suitably robust to be used in proposed Operators Advisory System described in chapter 7.

# Chapter 6

# Steam Leak Monitor

## 6.1 Introduction

In chapters 4 and 5, ANNs were used to develop transient classification modules for use in the proposed OAS. The small loss of steam leak monitor discussed in this study is to be used in the quantifier layer in the OAS described in chapter 7. The development of the module uses information gained from experiments gained in chapter 4 and 5 in development of the ANNs.

This chapter reports on a field study carried out to develop a monitor to estimate a small loss of steam from the secondary circuit of a Pressurised Water Reactor (PWR). The field study acted as a dual-purpose research vehicle to satisfy two objectives.

1. To supplement the PWR simulated primary circuit plant variables, with 'real world' external plant parameters.
2. To investigate the potential of using acoustic information for small leak rate monitoring using artificial neural networks (ANNs).

To achieve these objectives, acoustic sensors were used to detect and quantify the loss of steam from the secondary circuit of a PWR passively. The results from this experiment would be used in the development of the Operators Advisory System (OAS)

The study goes on to investigate the use of ANNs for differentiating between features extracted from the acoustic signatures of small steam leaks generated in a steam generator test rig. Analysis of the steam leaks was carried out using a sound level meter equipped with a third octave band filter to separate the different frequency elements of the noise produced by the different leak rates. Simultaneously, a real time digital sound recording of the noise produced by the steam leaks was also carried out. The sound recording was transformed into the frequency domain for additional processing using a Fast Fourier Transform (FFT). The frequency spectrum was then divided into set frequency bands, which were then used as inputs into a feedforward backpropagation ANN.

## 6.2 Background

In chapter 3, the proposed OAS top layer performs a diagnostic function. The next layer in the OAS contains modules that pertain to the size or location of the fault diagnosed. The problem under consideration here is the monitoring of a small loss of steam from the primary circuit of a PWR. It was envisaged that the data used in the monitor, would be a sub set of data obtained from the primary circuit of a pressurised water reactor. The implementation of the small steam leak monitor could be in one of two ways, either once a steam leak is detected in the fault classifier, the small steam leak monitor is initiated, or, the monitor remains on constantly.

If a leak were present, this information together with the fault diagnosis would be presented to the plant operator. The proposed implementation is shown in figure 6.1.

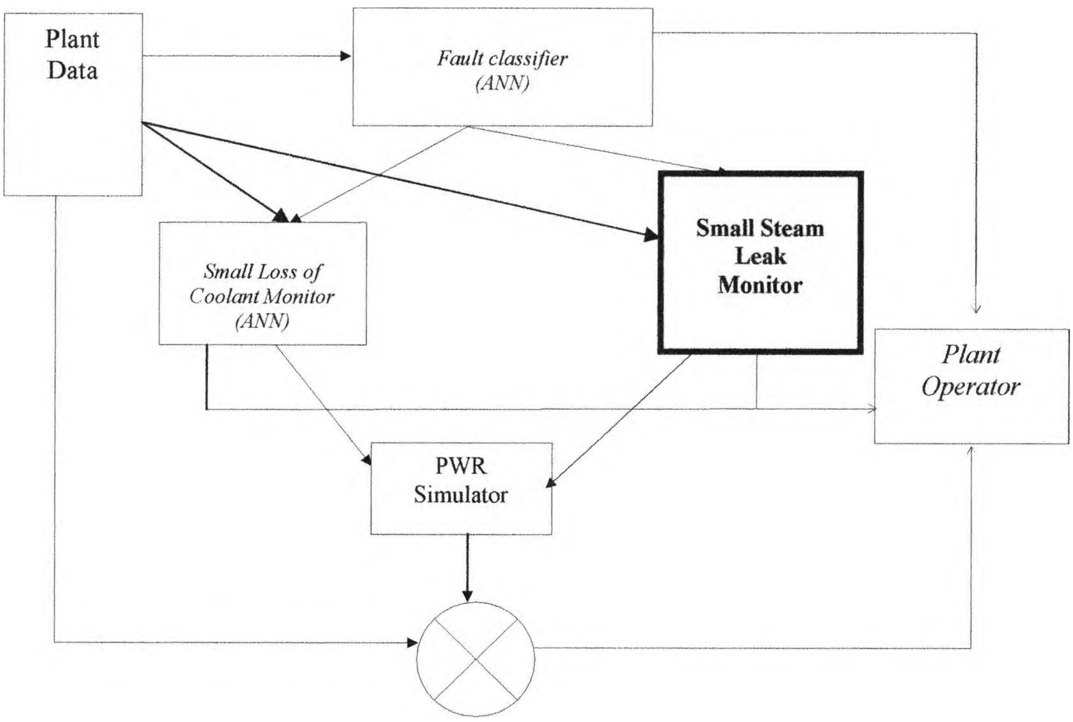



**Figure 6.1 Embedded Steam Leak Monitor in OAS**

### 6.2.1 Steam Leaks

The energy developed in a PWR is used to produce steam in heat exchangers called steam generators. Dried steam is generated in the secondary circuit of a PWR, which is then used to drive turbines, which generate power. A small loss of steam due to a break in the secondary circuit can lead to cooling of the steam causing it to change state back to liquid; a consequence of this is a drop in efficiency in power generation and may lead to damage of the turbines. The main effects of a steam leak to the environment are:

- Noise
- Heat
- Water
- System response

By observing the above effects either by monitoring the indirect effects of a leak or via the use of instrumentation, the plant operator is able to identify the occurrence of a steam leak. However if the leak rate is small (typically less than 0.5 kg/s), many of the physical effects may not be in evidence. At best, this would result in a long delay in its diagnosis, or the leak may go unnoticed. The aim of this chapter is therefore the early identification and estimation of a small loss of steam in the secondary circuit of a PWR by observing a system response in the primary circuit.

## 6.3 Initial Investigation

### 6.3.1 System response to a steam leak

Using the existing simulator of a PWR, a series of five small steam leaks ranging from zero to 0.6 kg/s were generated. Initial analysis of the data produced by the simulations showed that for this range of steam leaks it was observed that there was very little change in the system response of the primary circuit of a PWR. Figure 6.2 shows the progression of simulated temperature changes in the hot leg of the primary circuit of a PWR at a leak rate of 0.3 kg/s. The temperature variations for these small leak rates for many of the plant parameters in the primary circuit of a PWR are typically less than 0.2 °C and in a real world scenario are approaching the limits of which transducers can accurately record the changes.

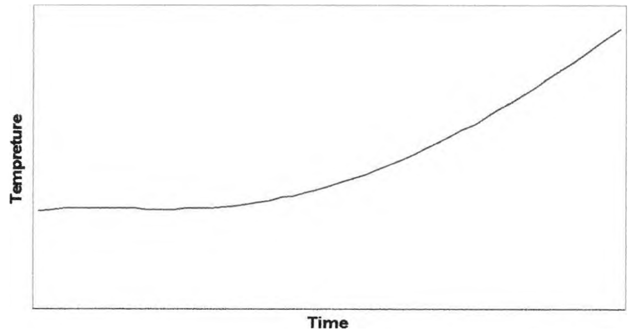



**Figure 6.2 Temperature change for secondary circuit steam leak of 0.3 kg/s**

Using techniques outlined in chapter 5, attempts were made to train a feedforward ANN. However, the ANN failed to converge to an acceptable level when presented with both a full data and a reduced data set using a time delay ANN. A range of ANN learning parameters and topologies were used with no reasonable indication of learning in any case. The best network consisting of two hidden layers (31 and 14 nodes respectively) and at 10-time steps and had an RMS error 0.5823. This compares unfavourably with results achieved for the loss of coolant monitor where an RMS error of 0.0413 was achieved.

### 6.3.2 Results

The inability to train an ANN prompted further analysis of the simulated plant data. By plotting a graph of the plant data in a suitable format the recognition of distinguishing features such as clustering, which characterise the data, may become apparent.

However, when the dimensionality of the data is high as is the case from the PWR simulations (up to 68 plant variables), a dimension reduction technique is required in order to visualise the data set. Techniques allowing the visualisation of high-dimensional data in a low-dimensional space are called projection methods, which looks to the preservation of interpoint distances in the mapping. One such projection is Sammon Mapping (Lerner 2000).

Figure 6.3 shows a Sammon mapping for three small steam leaks (0.1-0.3 kg/s). The mapping highlights the difficulties encountered during the development of a leak rate monitor. The projection shows no difference in the data during the initial stages of the transient. As the transient progresses, only a marginal separation of the data sets is observed.

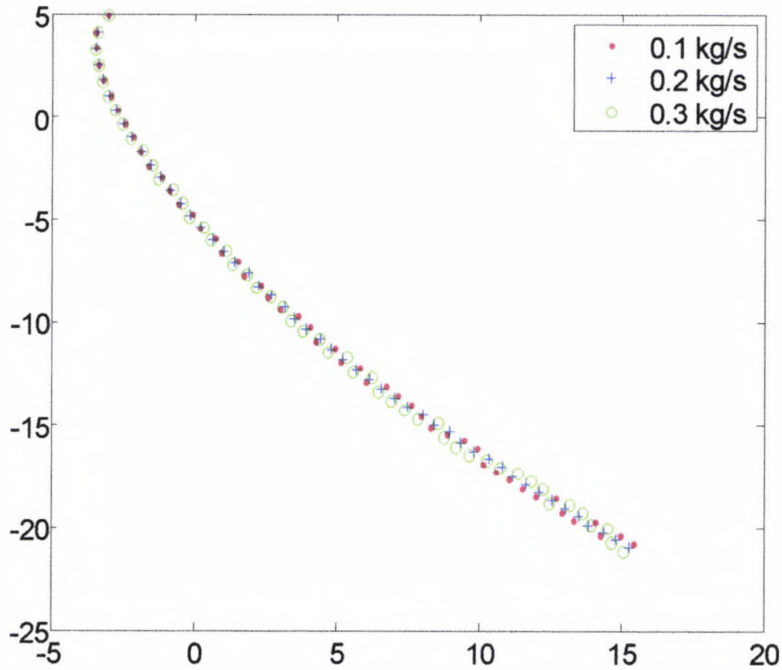



**Figure 6.3 Sammon map three small steam leaks**

The results of this investigation suggested that effects of a small loss of steam in the secondary circuit of the PWR had only a minor impact on the primary circuit. The small changes that do occur are probably not measurable as indicated in figure 6.2. It was therefore necessary to examine other possible sources of data, external to the primary and secondary circuit of a PWR that could be used to estimate rate of a small steam loss each of which provides a signal, which can be used in an ANN for transient analysis.

### 6.3.3 Alternative methods for estimating leak rates

There are several alternative methods for steam leak monitoring that have been developed over the last few years, mainly due to advances in instrumentation. These techniques are briefly outlined below.

### 6.3.4 Acoustic monitoring

The environment surrounding the a PWR can be systematically checked for leaks by using acoustic equipment, which detects the sound or vibration (or more recently ultra sound) induced by the steam as it escapes from pipes under pressure (Thomas 1991). The transducers (both vibration and acoustic) used for acoustic detection often include built in signal processors to help in difficult environments.

### 6.3.5 Infrared Thermography

Infrared (IR) Thermography is a non-intrusive method of analysing diagnostic information about the thermal pattern of a piece of equipment. All objects radiate energy in the IR spectrum. As a steam leak develops, IR detectors can be used to “sense" infrared radiant energy and produce electrical signals proportional to the temperature of above the pipe. (Lanius 2000).

### 6.3.6 Tracer Gas

In the tracer gas method, helium or another lighter than air non-toxic gas is introduced into the pipe system under pressure. Should a break in the pipe system exist, the gas leaks into the environment, above the piping system. A highly sensitive gas monitor, is used to detect the tracer gas, the amount of tracer gas detected is proportional to its leak rate and therefore to the size of the leak (Gassonic 2004).

### 6.3.7 Ultrasonic Gas Leak Detection

This new method of leak detection uses ultrasonic gas sensors to detect gas leaks by sensing the airborne ultrasound emitted from leaking gas at high pressure. The intensity of the sound will vary proportionally to the distance of the source, therefore aiding in the location of the leak site. The advantage of the ultrasonic detection is that there is no interference with any other background acoustic noise, which in most generators can be exceptionally noisy (CTRL Systems 2003).

### 6.3.8 Discussion

Any of the above methods for the detection of leaks could be used in the development for the monitoring of a small steam leak. However, due to practical considerations, only the acoustic method could be investigated. The aim of the experiments was firstly to derive a simple relationship between the levels of noise generated by steam leak from a pipe that could be used in the proposed Operators Advisory System. Secondly, a more detailed noise measurement to provide data explored the use of an ANNs in estimating steam leak rates.

## 6.4 Acoustic Monitoring of a steam leak

### 6.4.1 Introduction

Sound is an aural sensation caused by pressure variations in the air, which are always produced by some sort of vibration. They may be from a solid object or from turbulence in a liquid or gas. These pressure variations may take place very slowly, such as those caused by atmospheric changes, or very rapidly and be in the ultrasonic frequency range. The velocity of sound is independent of the rate at which these pressure changes take place and depends solely on the properties of the air in which the sound wave is travelling. The velocity (c) of sound is therefore dependent on the frequency ($f$), which is the number of vibrations or pressure changes per second measured in Hertz and the wavelength ($\lambda$) which is the distance travelled by the sound during one complete vibration.

$$C = f\lambda \qquad (6.1)$$

Where $C$ = velocity of sound, $f$ is frequency and $\lambda$ is Wavelength.

The wave produced is longitudinal, where the vibrations are in the direction of the motion. Sound energy is transmitted through air by vibration of air molecules, which in turn set the neighbouring air molecules in motion and begins a chain of movement. This movement causes areas where the air molecules are close or widely separated and are known as compression and rarefaction. Sound does not travel in a straight line it radiates from a source like ripples on a pond radiating from a stone splash. Reflection of sound takes place when there is a change of medium.

### 6.4.2 Measurement of Sound

The average displacement and pressure fluctuations of the air molecules are zero due to equal positive and negative changes. To overcome this problem measurements are made of the root mean square pressure changes (RMS value). The most commonly used aspects of sound are particle displacement, particle velocity, particle acceleration and sound pressure. As the ear is a pressure sensitive mechanism, pressure is used as the measure of sound magnitude. The sound intensity is the sound power per unit area in a sound wave and is related directly to the square of the sound pressure. The size of sound pressure affecting the ear varies from $2x10^{-5}$ Pa at the threshold, up to 200 Pa in the region of damage and pain. This may be compared to normal atmospheric pressure of $10^5$ Pa. Because of the large values involved, and also that the ears response is not directly proportional to pressure a logarithmic scale is used.

$$\text{Sound Pressure Level (SPL)} = 20 \log_{10}(P_1/P_0) \qquad (6.2)$$

The above is a comparative scale relating two pressures were $P_0$ = pressure at the average threshold of hearing at 1000Hz of $2x10^{-5}$Pa.

Most sound investigations begin with measurements using a sound level meter. The sound level meter used for the measurement of RMS sound pressure levels consists of a microphone, amplifier and a meter. The microphone converts the sound pressure waves into electrical voltage fluctuations, which are amplified and operate the meter. Because the meter is unable to indicate accurately over a large range of 30-120dB the amplification is altered as required in steps of 10dB and the meter reads the difference between the amplifier setting and the sound pressure level. Most meters have connections to which filters can be added were the response varies with frequency. The most common measurement of noise is the dB(A) level. It can be measured with a sound level meter having an A-weighting filter to simulate the subjective response of the human ear as shown in figure 6.4. When simple direct readings are needed the dB(A) scale is the best one to use. The sound level meter is calibrated by means of a source of known noise level, such as a pistonphone, which helps to verify that the chain of sound measuring instrumentation is measuring properly and accurately.

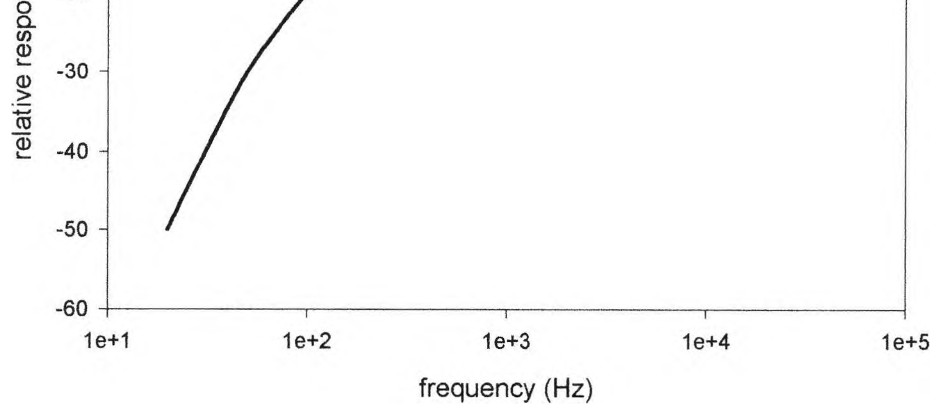



**Figure 6.4 A Weighting Frequency Curve**

### 6.4.3 Initial Investigation

The objective of this experiment was to investigate whether a simple relationship existed between sound pressure level and the size of a steam leak. The experiments were conducted at a steam raising plant shown in figure 6.5. A large boiler plant was used to simulate a steam leak by venting steam through a valve in controlled amounts.

**Figure 6.5 A Steam raising plant**

A KAMPLEX SLM3 sound level meter was mounted on a tripod at a height of 1 meter, and at a distance of 2 and 4 meters from the leak source. The distance of 2 meters from the source of the sound was chosen primarily for safety reasons. The first measurements made were for ambient noise, with the sound level meter set to 'fast' mode. Several measurements were made for both average and maximum dB(A) levels. The valve was then opened at measured intervals, to provide a known leak rate given by:

$Ws = KvA\Delta P$

Where $Ws$ is the mass flow rate of steam, $A$ is the effective area of the valve, $\Delta P$ is differential pressure across the valve and $Kv$ is a valve constant (type of valve).

At each opening of the valve, three measurements were made. The valve was then closed as before, again recording the noise levels.

### 6.4.4 Discussion

The results for dB(A) measurements at 2 and 4 meters are given in figure 6.6.

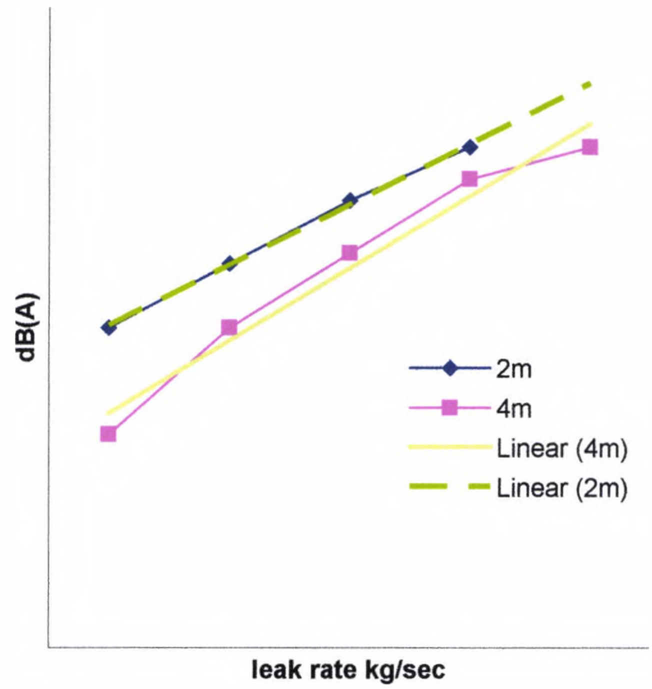



**Figure 6.6 results of sound measurements**

The results of the experiment although not conclusive indicate that a linear relationship exists between sound intensity (I) and leak rate (R):

$$I = MR + C$$

The results from the experiment do not accurately model the noise generated by a small steam leak in a real plant environment (a complex sound field), however the intensities of noise recorded are feasible, and the assumption of a linear relationship is used for the remainder of this work.

The derived model for estimating the leak rate at 2 meters for sound levels above ambient noise is later used in the development of the Operators Advisory System described in chapter 7.

## 6.5 Further Investigation

### 6.5.1 Introduction

The results from the experiment provided a simple linear regression model that could be used in Operators Advisory System however, the linear regression model is dependent on the distance of the microphone to the sound source. If a leak were to occur closer or further away from the microphone, a new set of relationships would need to be found.

Further investigation of an audio recording conducted at the same time as the sound level measurements indicated a slight change in frequency as the leak rate was increased. Shimanansky (2003) has also reported this observation in similar investigations. If a frequency change were observed, this would be independent of microphone position and therefore a more accurate gauge of the steam leak size. It was therefore decided to repeat the experiment but this time doing a third octave spectral analysis of the steam leak, together with an audio recording.

Sound does not consist of single frequency notes, but a highly complex combination of tones and is best represented by finding out what bands of frequency are represented, and at what magnitude. This is performed using a sound level meter fitted with a set of Octave Band Filters. The use of electrical filters helps to separate the appropriate band of frequencies from the remainder, thus measuring the magnitude of that one group. One octave band consists of all sounds from any frequency to twice that same frequency. In most cases it is convenient to refer to the centre frequency within each band. An octave analysis is needed in order to calculate loudness. To measure the level in each octave band a sound level meter is set to the linear scale using a set of octave band filters. The noise is recorded with a suitable attenuation on the sound level meter. The recording is played back through an audio-frequency analyser or spectrogram and the levels recorded on paper.

### 6.5.2 Measurement Procedure

Using the same test rig as the previous experiment, a third octave analysis of the noise generated for each of the valve positions generated, was conducted using a B& K 2260 modular sound level meter together with a third octave filter (fig 6.7).

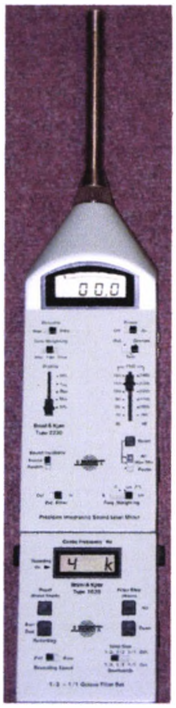



**Figure 6.7 B&K 2260 with 1/3 octave filter**

The microphone on the sound level meter has a flat frequency response between 20 Hz to 20 KHz. As before several reading for each of the valve positions was taken, for both opening and closing of the valve.

Simultaneously a SURE 849 professional microphone together with a personal computer was used to record digitally the noise generated by the steam leak for the duration of the above experiment for further analysis. A schematic of the experimental set up is shown in figure 6.8

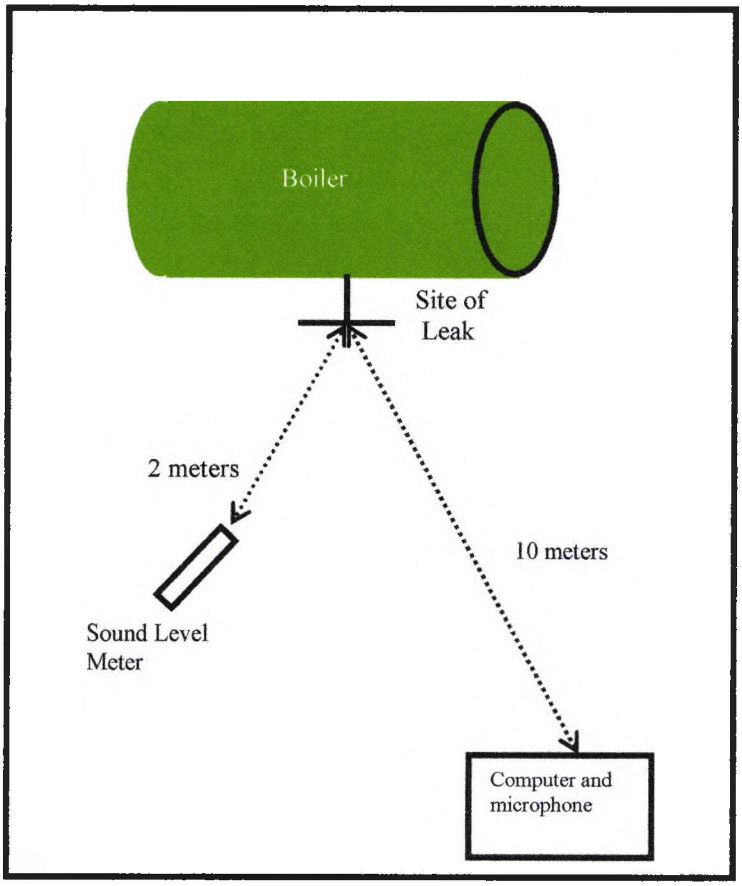



**Figure 6.8 Experimental set up**

A distance of 2 meters from the source of the steam leak was chosen to measure the noise generated from the steam leak, once again for safety reasons. The audio recorder was positioned 10 meters away to avoid microphone saturation.

As in the previous experiment several reading at each of the valve positions was taken, for both opening and closing of the valve but this time a full third octave (from 50Hz-20Khz) frequency analysis was carried out at each position. At valve position seven, only frequencies between 3150 Hz and 20 KHz were recorded

### 6.5.3 Results

The results for the third octave analysis are shown in figure 6.9.

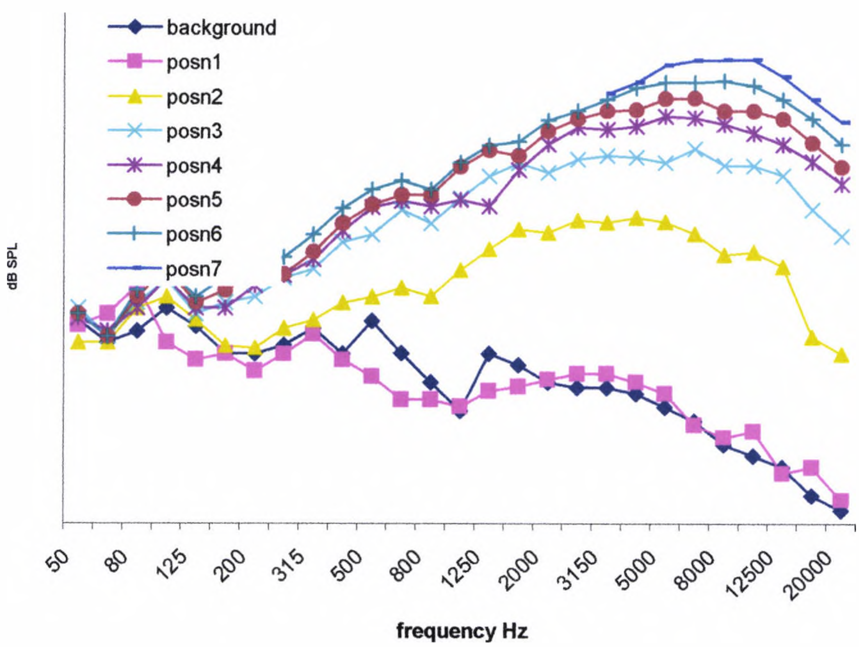



**Figure 6.9 Third Octave Frequency Analysis**

The difference between the background reading and position one were similar, suggesting that the valve may have already been partly open. Most of the background noise observed was below 1000 hz, most of the changes observed occurring above

3000 Hz. It can be seen that not only is there an increase in intensity at the frequencies above 3000 Hz but the pattern changes with a peak occurring between 6-12 KHz. The results from this spectral analysis suggested that it might be possible to train an ANN to recognise the different frequency response for each of the valve positions.

## 6.6 Frequency Analysis

### 6.6.1 Introduction

This section outlines the steps involved in the implementation of an ANN. As described earlier, most noise is complex and has a continuous frequency spectrum. One way of abstracting this information is to perform a Fast Fourier Transformation (FFT). A FFT analyser uses digital signal processing techniques to produce very rapid narrowband frequency analysis of acoustic signals, and allows the conversion of an acoustic signal in the time domain into the frequency domain (fig 6.10). A full explanation of the FFT can be found in (Smith 1996).

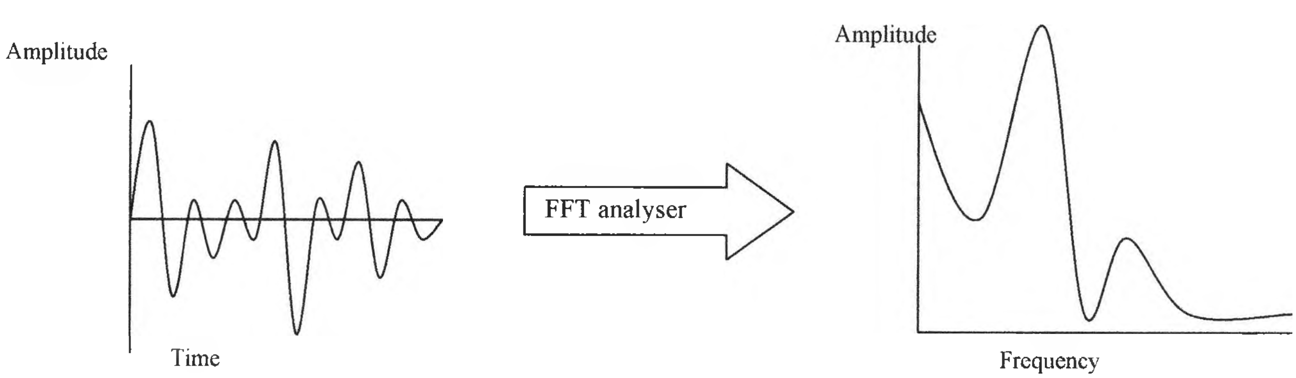



**Figure 6.10 FFT analyser**

### 6.6.2 Frequency Analysis of Field Results

Figure 6.11 is a sample (3 seconds) of the audio recording of the transition from valve position 4 to valve position 5 (after 1 second), and shows a plot of amplitude in the time domain. As expected, as the valve is opened, the amplitude increases.

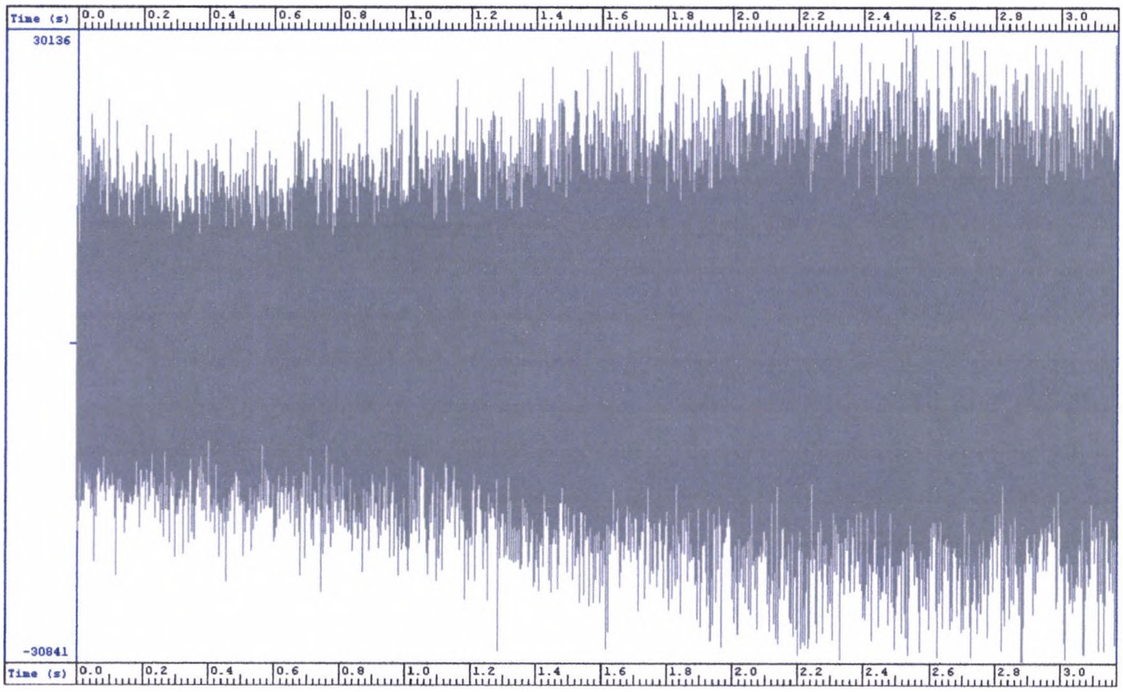



**Figure 6.11 Transition between valve positions 4 and 5**

Figure 6.12 shows the results of an FFT analysis (spectrogram) of the audio recording of the generated steam leaks. A spectrogram is a display of the frequency content of a signal drawn so that the energy content in each frequency region and time is displayed as a grey scale. The horizontal axis of the spectrogram is time, and the picture shows how the signal develops and changes over time. The vertical axis of the spectrogram is frequency and it provides an analysis of the signal into different frequency regions.

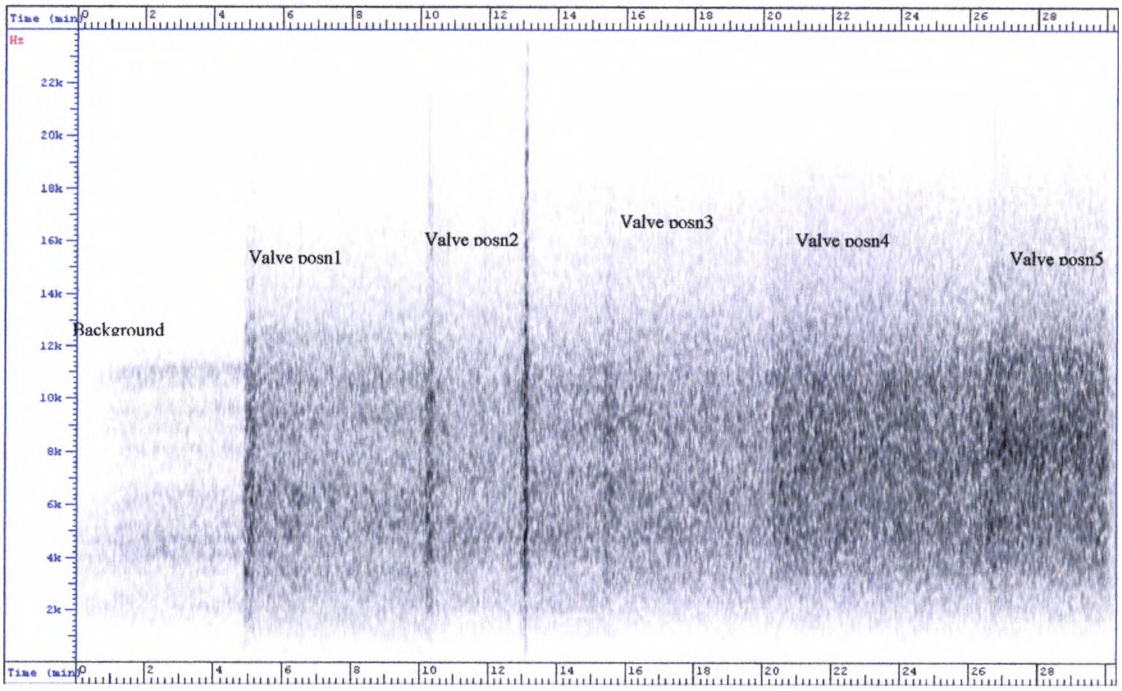



**Figure 6.12 Spectrogram of steam leak recording**

The spectrogram reveals that most of the energy found in the steam leak is between 4 to 12 KHz. From this analysis, it can be seen that changes were occurring in frequency during the transition from one valve position to the next and warranted further investigation. The dark bands that occur at each of the valve positions may be due a sudden release in pressure during the initial stages in the opening of the valve.

### 6.6.3 Data pre-processing

For many applications, an ANN can be used to map the raw input data directly to a required output. However there are some circumstances where it is necessary to pre-process the input data prior to presentation to an ANN (Masters 1993). The pre-processing of the data can vary from simple filtering through to the use of complex algorithms for feature extraction. From the data analysis of the sound recording, it was observed that each change in leak size resulted in a new frequency spectrum.

A data file of the acoustic recording was generated which divided the spectrum into frequency bands of 200Hz, from 0-20KHz, thus giving 11 frequency bands which would provide the input parameters for an ANN. An output was generated every second. An example output for the third valve position is shown in figure 6.13. This highlights the prevalence of low frequencies to be found in the generated steam leak.

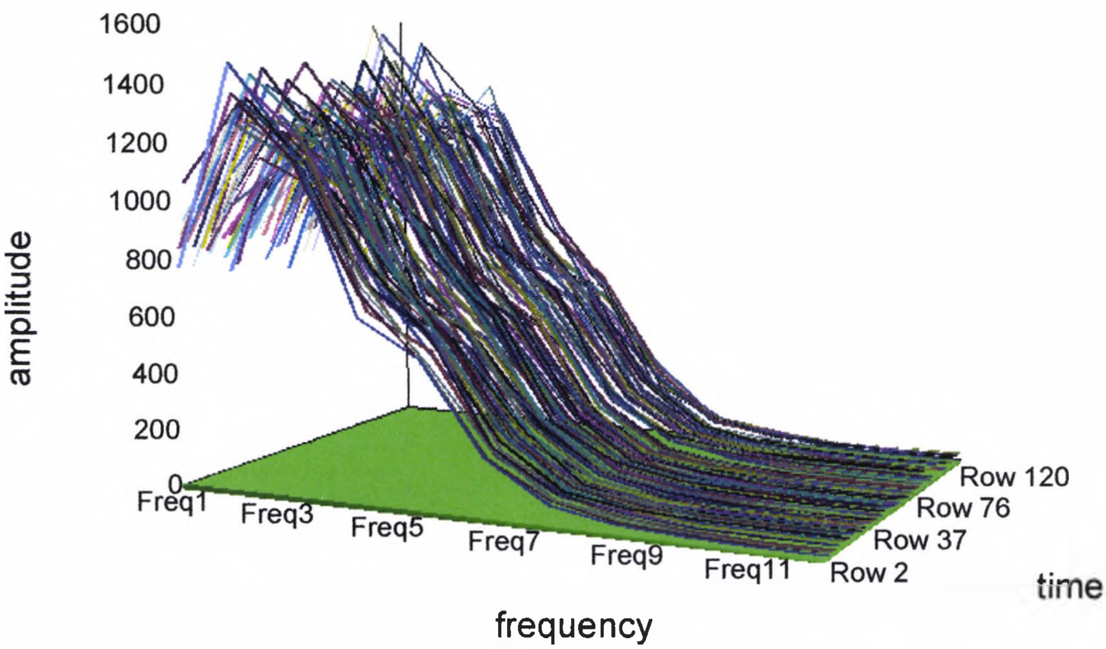



**Figure 6.13 Frequency versus Time plot of valve position 3**

### 6.6.4 Implementation of an Artificial Neural Network (ANN)

Before the data from the FFT could be used for the training of an ANN only the most relevant data is selected for training purposes. The careful selection of relevant data makes the development of an ANN easier and can improve their performance on noisy data.

The data generated from the frequency analysis were first checked for any anomalies, and these removed. During the frequency analysis of the data, it was observed that at each opening of the valve, there was a momentary increase in the intensity of the noise, for approximately 20 seconds, seen as solid lines in figure 6.12 before resuming a steady state. Figure 6.14 shows a more detailed examination of the anomaly after pre-processing of the data. It is thought that this is a specific response to the test rather than a generic occurrence. The data were then checked that an equivalent number of data points were in each of the six output categories (background noise and 5-valve positions).this was done to avoid bias during the training of the ANNs.

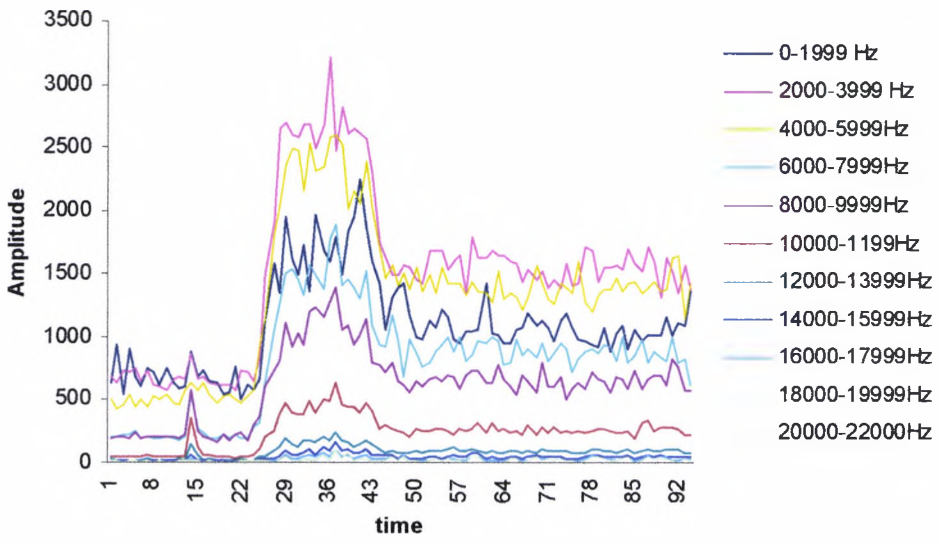



**Figure 6.14 Transition from first to second valve position**

The data (1704 vectors) of 11 frequency bands consisting of real numbers was randomly divided into a training test and validation data sets (60, 10, and 30% respectively). The number of layers and nodes in the hidden layer were chosen heuristically, with previously stated equation from Masters (1993) used as a starting point. The Root Mean Square Error (RMS) was used as the criterion for choosing the best ANN.

### 6.6.5 Results

Using Masters (1993) as a starting point, the best performing feedforward backpropagation ANN consisted of an input layer of 11 nodes corresponding to the 11 frequency bands, two hidden layers of 10 nodes each using the hyperbolic transfer function, and 6 binary outputs, corresponding to one background noise level and the 5 valve positions. The ANN was trained for 150,000 iterations. The ANN returned RMS error 0.2052 with presented with the test data set, and an RMS error 0.1541 when presented with an independent validation data set. Table 6.1 shows the percentage correct greater than 0.95 ANN output:

| | |
|---|---|
| Background noise | 96% correct |
| Valve position 1 | 88% correct |
| Valve position 2 | 73% correct |
| Valve position 3 | 82% correct |
| Valve position 4 | 99% correct |
| Valve position 5 | 93% correct |

**Table 6.1 Percentage of correct classification of leak rate**

The results of the estimation of leak rates by the ANN for each of the valve positions are given in figures 6.15 to 6.20.

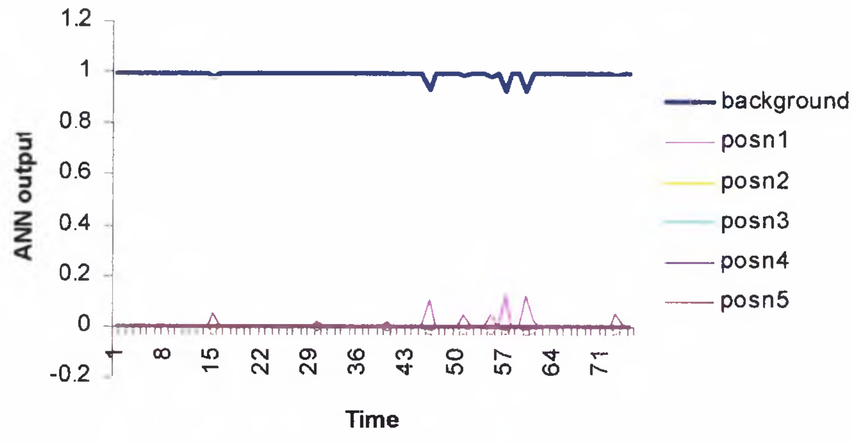



**Figure 6.15 ANN output for Background noise**

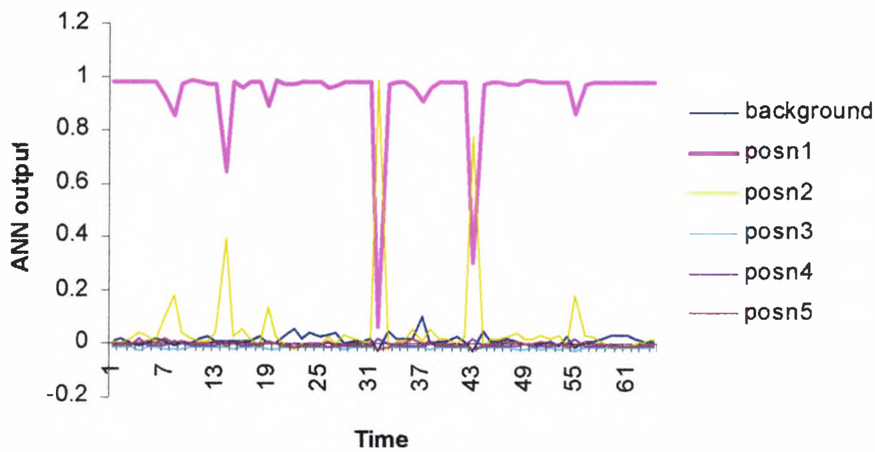



**Figure 6.16 ANN output for Valve position 1**

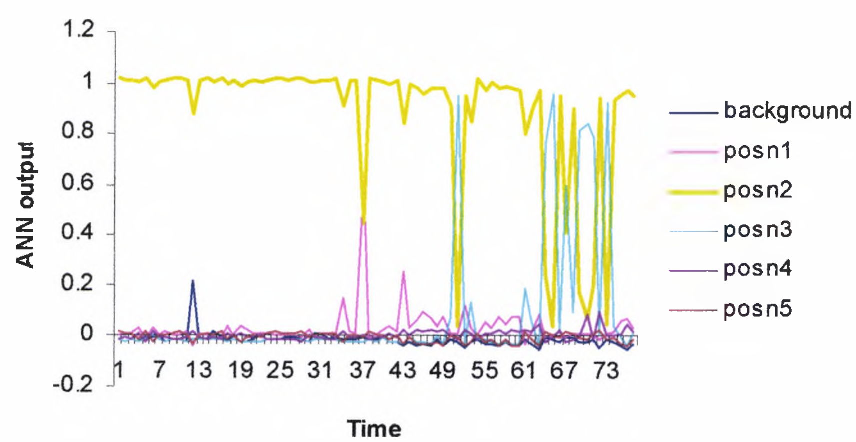



**Figure 6.17 ANN output for Valve position 2**

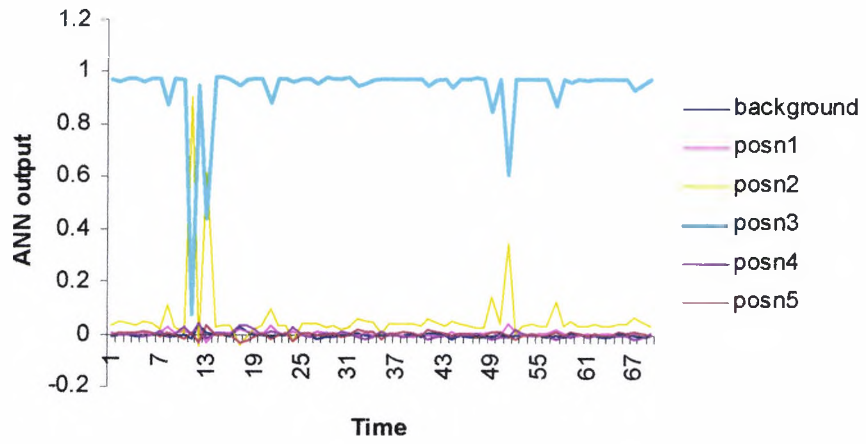



**Figure 6.18 ANN output for Valve position 3**

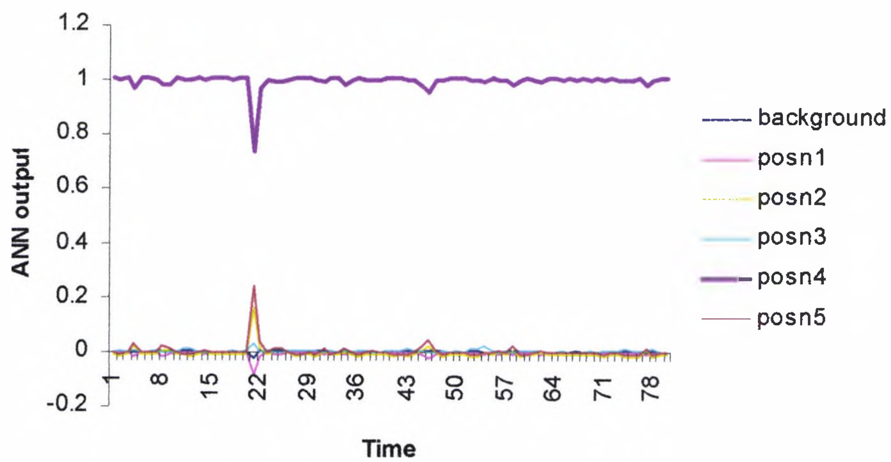



**Figure 6.19 ANN output for valve position 4**

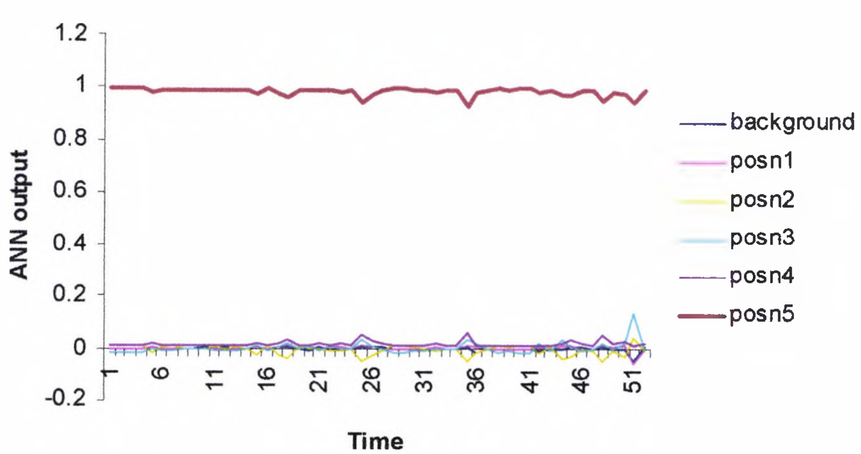



**Figure 6.20 ANN output for valve position 5**

Overall, the results for the training of an ANN to classify steam leak rates were promising. For valve positions, 2 and 3 (figures 6.17, 6.18) a false positive output from the ANN is observed, in each case a larger leak rate is reported. For valve position 2, the accuracy of the estimation starts to diminish after 63 seconds and this is reflected in the lower percentage correctly classified (73%), with the ANN output for a larger leak rate (valve position 3), staring to emerge. Figure 6.21 shows the frequency bands derived from the FFT of the audio recording

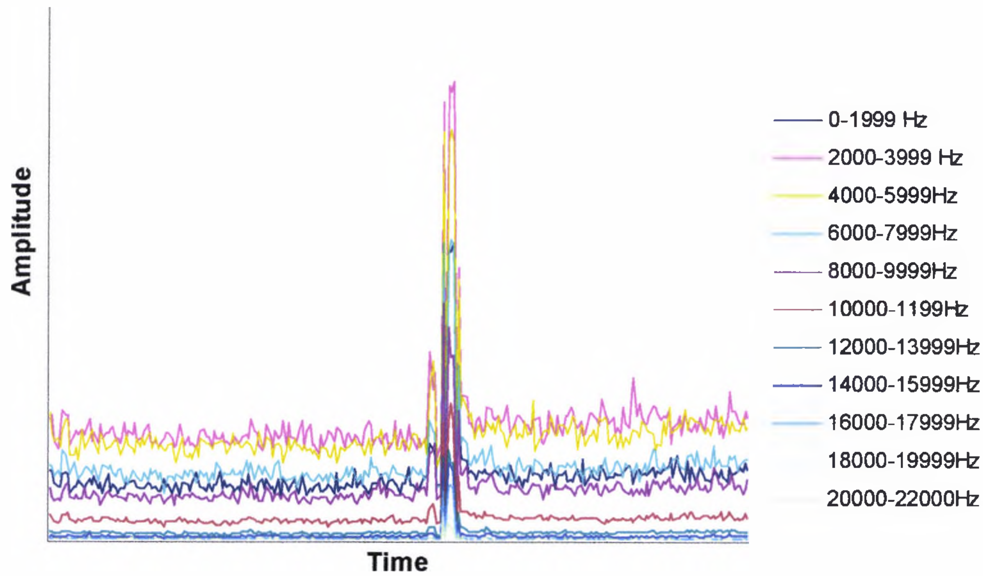



**Figure 6.21 frequency bands for valve position 2**

The artefact in the middle of the recording may be due to a sudden loud noise. In order to examine the relative importance of each feature it was decided to examine which feature the class separability measures using a Sammon map. Figures 6.22 and 6.23 show Sammon mappings both with and without the impulse noise artefact, for valve positions 1 to 3 respectively.

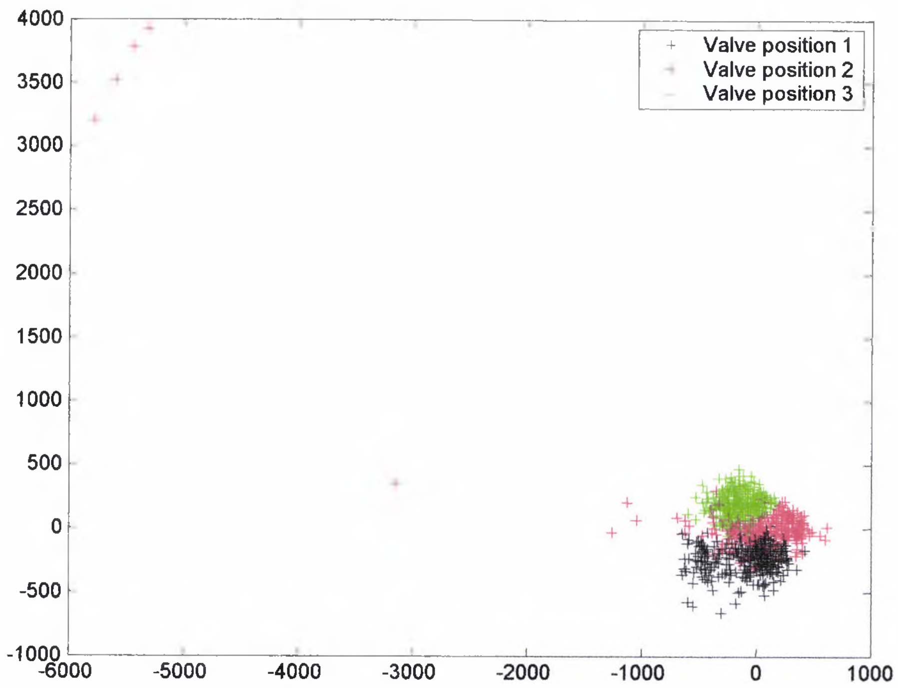



**Figure 6.22 Sammon Mapping for valve positions 1,2 and 3 (With Artefact)**

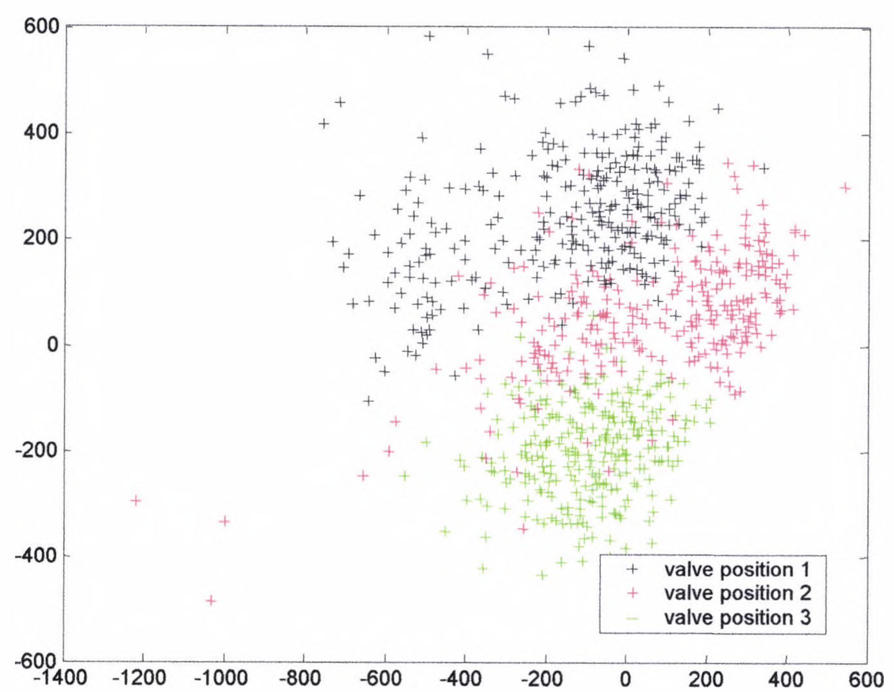



**Figure 6.23 Sammon Mapping for valve positions 1,2 and 3 without artefact**

Visual inspection of the Sammon mappings show that for valve positions 1 and 3, the data points are relatively tightly clustered; however, the data values for valve position 2 are more widely dispersed, even when omitting the impulse noise artefact. The wider dispersion of data values for valve position 2 may explain the poor performance of the ANN for valve position 2.

## 6.7 Discussion

The introduction of new noise measuring sensors together with advances in signal processing, have made the real time estimation and location of small leaks from the primary or secondary circuits of a PWR a reality. The acoustic sensors must cover a wide frequency and dynamic range, enough for the investigation of small steam leaks. As the noise analysis would generally be performed in complex sound fields with both high temperatures and humidity, the transducers must be capable of discriminating between normal background noise generated during normal plant operations, and insensitive to the effects of these environmental conditions.

This initial investigation show that the use of acoustic monitoring combined with the pattern recognition capabilities of an ANN can be used to estimate the leak rate from the primary circuit of a PWR. Acoustic monitoring devices could be used, as an additional input to the monitor. One method to achieve this aim is to use a combination of structure and air based acoustic transducers. Leaks could be simulated at points along the primary circuit. An arrangement of accelerometers and microphones could be placed at several points along the structure and inside the containment vessel, and the output from these recorded. The data obtained would then be put through a band pass filter, to reduce the amount of normal environmental noise, for example pump noise. The data were sampled and analysed, using either RMS or a Fourier transform signal processing package. The output from this stage would provide information on the size, frequency and phase of the noise. This data could then be fed into an ANN classifier system along with the primary circuit data. The noise analysis could also be used to train a separate neural network and used as a check on the neural net primary circuit classifier. A possible system is shown in figure 6.24.

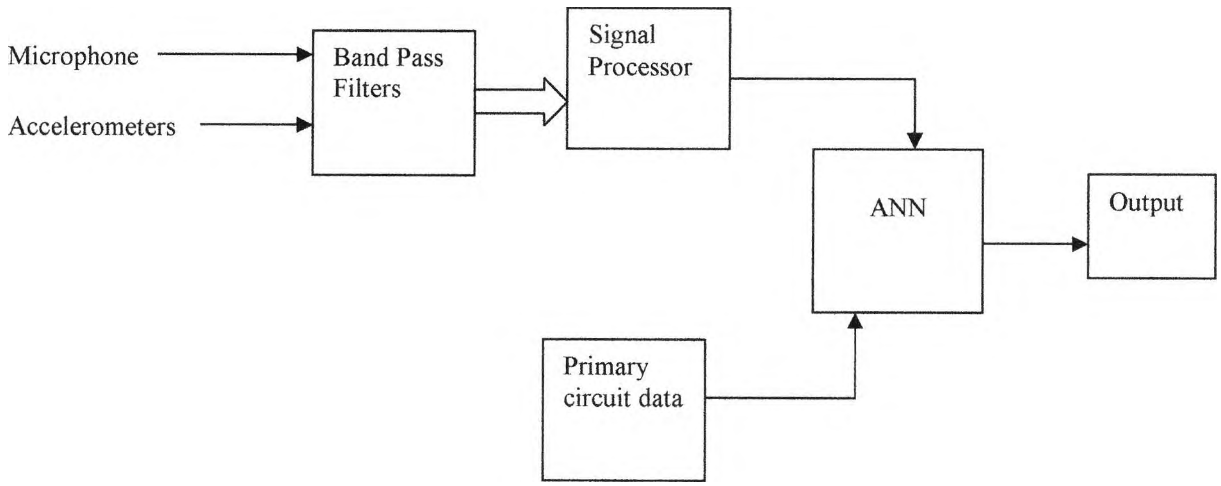



**Figure 6.24 Possible acoustic Neural Net Monitor**

To summarise, the following present a list of the main advantages and disadvantages of ANN based acoustic leak rate monitor.

**Advantages:**

- Capable of dealing with a wide range of sensor inputs by either a single ANN or an array of ANNs.

- Capable of analysing pre processed data, such as a Fourier analysis of the leak.

- Information gained from the acoustic monitoring can also be used for leak location.

- As the main data source is remotely sensed the technique is ideally suited to the hostile environments such as the reactor compartment.

**Disadvantages:**

- A considerable amount of time would be required to calibrate microphones and accelerometers

- Transducer selection, the high temperatures, humidity and radioactivity can affect calibration.

- It is difficult to model a complex sound field, as typified by a power plant.

- The site of a leak may be several meters away from where the steam emerges, for example due to the lagging of pipes.

## 6.8 Summary

This chapter has reported work undertaken to investigate the use of sound for the estimation of a loss of steam due to a small break in the secondary circuit of a Pressurised Water Reactor.

The first half of the chapter described investigations made into the relationship between the leak rates, and noise levels. The derived model from this experiment is then used in the development of the prototype OAS system described in chapter 7.

The second half of the chapter explained a novel approach for using the noise generated by several steam leaks to train an ANN. A Fast Fourier Analysis of the sound converted data in the time domain into frequency domain, which was then used to train an ANN. As a result of the investigations into the use of acoustics and ANNs for estimating leak rates, a scheme is put forward for the development of an ANN based acoustic steam leak monitor.

# Chapter 7

# Development of a Prototype Operator's Advisory System

## 7.1 Introduction

This chapter reports the design, implementation and initial evaluation of a prototype computer based Operators Advisory System (OAS) for monitoring the control processes of a Pressurised Water Reactor (PWR). The OAS would provide diagnostic advice as to the current and future status of the PWR in a more timely and efficient manner.

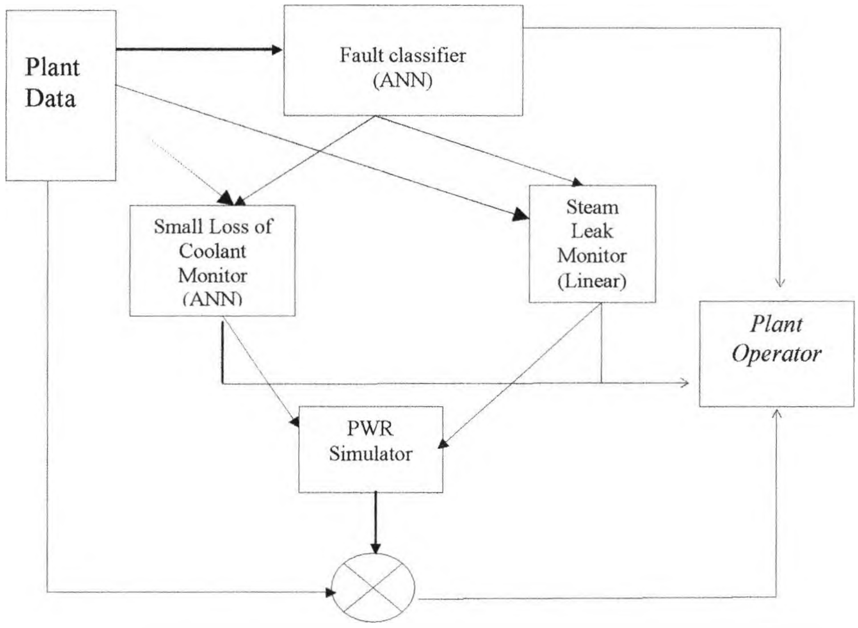



**Figure 7.1 Block diagram of proposed Operators Advisory System**

At this stage of the project, several modules had been developed as described in previous chapters, and as stated in the introduction, it was proposed that each of the independently trained diagnostic classifiers be integrated into a multi-level OAS. A block diagram of the proposed OAS advisory system is shown in figure 7.1

The development of the OAS involved three major stages. The development of a major fault transient classifier as described in chapter four, the loss of coolant leak and steam leak rate monitors as described in chapters five and six respectively. Secondly, the design and development of the OAS using appropriate software development tools. Finally, the testing and modification of the OAS using independently generated test data. It is the design, development and testing of the OAS system that is reported on in this chapter.

The input to the OAS is data generated by a generic simulator of the primary circuit of a pressurised water reactor, simulated environmental noise measurements, and user interventions. In future the data would be derived from real plant data. The advisory system would be expected to correctly identify unseen transients and report the findings to the plant operator

## 7.2 Methodology

The method proposed for the development of the OAS is a multi-layer system of Artificial Neural Networks (ANNs). In the proposed advisory system, the top layer of the system is the diagnostic ANN module as described in chapter 4 and shown in figure 7.1. The requirement of this level of diagnosis is the rapid identification of a major fault transient, which requires an immediate response in order to manage the situation.

Should a fault be identified, the output from this layer would notify the plant operator of the transient. The plant operator may decide to verify the diagnosis, and rectify the situation by following standard operating procedures.

If the classification of the OAS identified a 'normal' operating condition (figure 7.1), it is intended that the next level of classification i.e. a small primary or a secondary circuit break module (described in chapters 5 and 6 respectively) be initiated. This effectively increases the resolution of the OAS in looking for small transients that are below the threshold of detection in the upper layer. The multilayer classification system would only report on the major transient, and not secondary transients that are caused because of a major fault. Once the main fault is dealt with, only then would the minor faults start to be diagnosed. This by default can allay some of the problems associated by 'alarm showers' (Lees 1983).

Due to the smaller changes in the plant dynamics, the time taken for a correct classification of leak rate can be longer. However, the emphasis at this level is on long term monitoring for the successful management of the small transient, the speed of response is of less importance as the transient is unlikely to cause a critical failure of the plant, but will lead to a drop in its efficiency and effectiveness.

During the early design stages of the OAS as shown in figure 7.1, it was envisaged that once a transient has been identified, an independent PWR simulator would reproduce the plant data for that transient. A comparator would then look for differences between the predicted state of the plant and the actual plant variables. Where any difference was observed a measure of confidence in the diagnosis would be reported to the plant operator. It was initially envisaged that a 'traffic light' approach could be adopted;

**Green** - accept system result
**Orange** - accept result, but with caution
**Red** – reject system diagnosis

However, when plant operators were asked whether it was necessary that information regarding the confidence of the OAS output be displayed along with the results, they indicated that if there were a need to 'double-check' the accuracy of the OAS, they would prefer the system output be suppressed.

After due consideration, it was decided that should the difference between the simulated and actual plant parameters deviate by more than a prescribed amount, the diagnosis from the relevant module would be suppressed. If the difference between the simulated and actual plant parameters was small, a high level of confidence could be attached to the diagnoses presented to the plant operator. It was also decided to include the plant operator in the decision making process of the OAS, by drawing the attention of the plant operator to a diagnosed transient, and requiring the plant operator to confirm the OAS diagnosis.

## 7.3 Prototype Operators Advisory System Development

### 7.3.1 Tools

The software tool used in the development of the OAS was MATLAB version 6.5, a high-performance software development package used extensively in academia and industry for all types of research. MATLAB has an inbuilt interpreted language for numeric computation and visualisation. The advantage of using MATLAB was the ease of integrating the developed ANN modules into the OAS system. This also meant should any modules be developed in the future, these could quickly be integrated within the existing system. A sample of the OAS MATLAB code is given in appendix D.

### 7.3.2 Translating

All the ANN modules reported on in this thesis had been developed using NeuralWorks Professional, a neural network development platform. The initial development work concentrated on re-coding the NeuralWorks based ANN modules into MATLAB language. This was a two-stage process. First, the ANN modules needed to be converted from the NeuralWorks development environment into C programming language, an automated process. The generated C code was then manually translated into MATLAB.

### 7.3.3 The Operators Advisory System model

Once the individual ANN modules had successfully been tested in MATLAB using independent validation data sets, the coding of the OAS could then proceed.

The OAS is made up of several functions:

**Fault Analysis** - This first level of diagnosis provides information to the plant operator of the presence of a major transient, for example a downstream steam leak, or a 'single rod drop' transient.

**Size of transient** - If a primary coolant or steam leak were detected, the corresponding diagnostic modules would provide an estimation of the leak rate. The results from this level would be presented to the operator.

**Comparator** - An independent PWR simulator is used to generate the diagnosed transient. The simulator utilised in the comparator was developed in MATLAB, and is based on the generic PWR simulator used to generate the data used extensively in this project and therefore a high degree of correlation exists between the PWR and the simulated transient. Significant plant parameters are then compared with corresponding simulated plant parameters, and any difference between the values used as an indication of accuracy of diagnosis.
The confirmation of the small loss of coolant monitor is used to demonstrate the use of the comparator; however the technique could be extended to confirm the output of other modules used in the OAS. Two plant parameters were chosen to compare with actual plant data, the pressuriser pressure and level as they showed the greatest variation in plant values during a small loss of coolant accident. These plant parameters would also be routinely monitored by a plant operator to help infer leak rate. The technique could be extended to confirm rate of loss for a steam leak in the secondary circuit of a PWR. If the difference were less than 10%, the

results would be displayed to the plant operator. If the difference between the OAS simulation and plant data was greater than or equal to 10% the results from that module, would be suppressed as previously discussed. A threshold of 10% was chosen in the initial design stages for the acceptance of a diagnosis to allow for differences between the two data sources (one a newly developed simulator). However future developments of the system should aim to reduce this figure to 5%.

**Confirmation of Diagnosis** – If a throttle opening, group or single rod drop is identified, plant operator confirms diagnosis. The confirmation of the presence or absence of a transient by a plant operator is an essential component of any decision support system. By asking the plant operator for confirmation, it encourages further inspection of raw plant variables and ensures that the plant operator remains an integral part of the decision process.

**'None of the above' classification** - One of the design decisions that had to be made before implementation was whether to give equal weighting over many transients in the fault layer the ANN was trained on, or to assign a priority role to one particular transient, the 'none of the above' classification. Giving overall priority to this classification has the advantage of considerably simpler control flow and makes the addition of new modules easier.

## 7.4 System Evaluation

### 7.4.1 Introduction

To evaluate the effectiveness of the OAS, a generic PWR simulator was used to generate a series of transients to test the overall performance of the OAS.

The same PWR simulator used in the development of the fault and loss of coolant monitors (consisting of 67 plant parameters, subsets of which are used in various ANNs), was used to generate the data set for the evaluation of the OAS. In addition to the simulated PWR data sets, an extra plant parameter containing acoustic information (dBA noise level) was also simulated and added to the PWR data set, thereby creating a data set of 68 plant variables.

### 7.4.2 Application Testing – Fault Transients

To assess the performance of the OAS for a major fault transient, the following transients the fault ANN was trained on were simulated:

- Throttle opening transient
- Steam leak
- Group drop
- Single rod drop
- Primary coolant leak
- Normal operating

Each transient simulation was run for 50 seconds, in order to allow the reactor to reach a steady state condition. The plant parameters were then recorded every second for 80 seconds.

A Sammon map was generated to aid in the visualisation and analysis of the multi dimensional input vector (plant parameters) for the six transients (figure 7.2). This diagram shows that the largest changes in the plant parameters of the primary circuit occur during a group or single control rod drop, as expected.

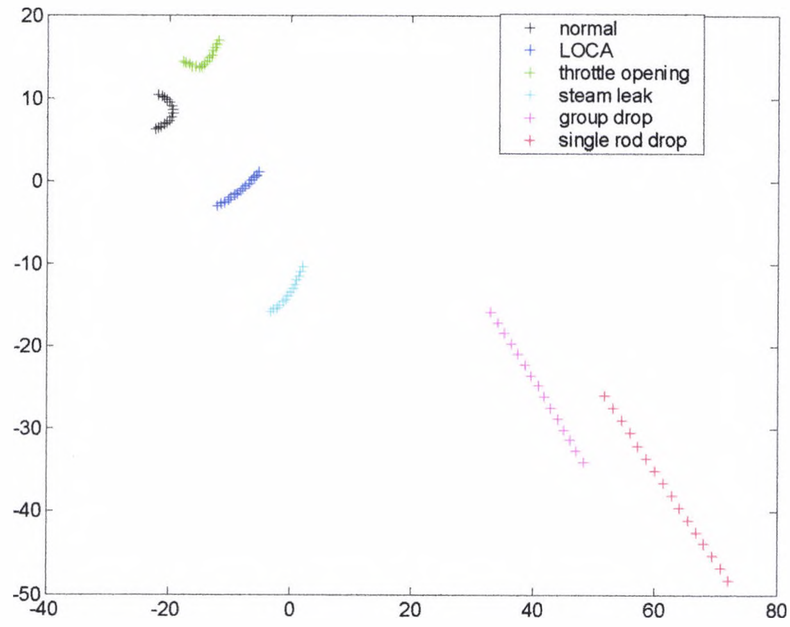



**Figure 7.2 Sammon map of Major Fault Transients**

However there was little variance between normal operating conditions and a small primary coolant, this partly explains the increased difficulty encountered when developing an ANN based LOCA analyser for use in the OAS

In order to test the abilities of the OAS, a 15 second sample of data was randomly chosen for each of the six transients, and then presented to the OAS. Table 7.1 shows a summary of the OAS outputs, for each of the samples.

For both a single and group rod drop, the fault ANN module correctly identified the transients. The plant operator is then prompted to confirm the classification. If confirmed the programme is terminated. If the classification is not accepted by the OAS the plant operator is advised of an unknown transient.

For large primary coolant and steam leaks from the primary and secondary circuit of a PWR respectively, the OAS correctly identified the transients.

| Transient | OAS output |
|---|---|
| Single Rod Drop | *Is the transient a SINGLE ROD DROP Y/N* |
| Group Rod Drop | *Is the transient a GROUP DROP Y/N* |
| Steam Leak | *DOWNSTREAM STEAM LEAK* |
| Throttle transient | *THROTTLE* |
| Primary coolant leak | *Primary coolant leak* |
| Normal | *'None of the above'* |

**Table 7.1 Operators Advisory System output for major fault transients**

The results from the first tests were encouraging. All the major transients were correctly identified. Using a desktop PC, with a 2.2GHz processor with 512 MB of RAM, results were obtained within 3-5 seconds, meeting the objectives for a rapid and accurate diagnosis of a major transient.

### 7.4.3 Application Testing – LOCA

To assess the ability of the OAS to identify a small primary coolant leak, and establish the threshold of detection for a diagnosis of a LOCA in the major fault classifier ANN, the PWR simulator was used to generate a range of coolant leaks, from 0.1-10 kg/s. Figure 7.3 shows a Sammon map for five LOCA's between 1-8 kg/s and for a 'no leak' or normal operating condition.

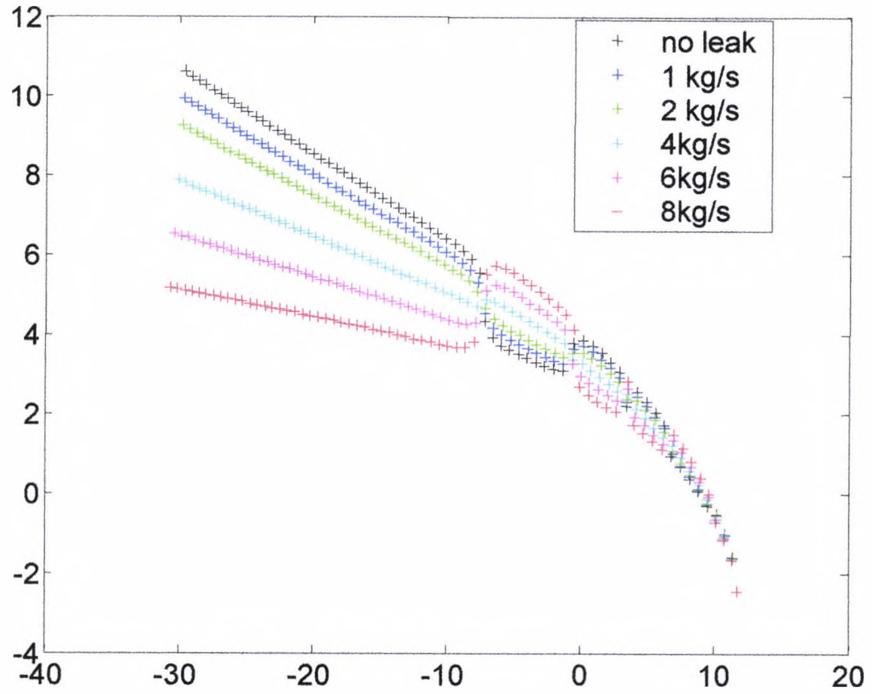



**Figure 7.3 Sammon map for 5 LOCAS**

The mapping indicates that the variability in the plant parameters for each of the leak rates grows larger as they develop. For the higher leak rates (>2kg/s) the separation in the transients is clear and allows for the early classification of the transient. The divergence between leak rates becomes ever greater as the leak develops. The cross over of the leak rates in the Sammon map may arise because the PWR simulator has not yet reached a steady state.

However for leak rates below 1kg/s, this is not the case. Figure 7.4 shows a Sammon map for five leak rates between 0-1kg/s. The map shows a great deal of overlap between the transients, with a difference between leak rates late in the transient's development. Closer inspection of the simulated plant data reveals little difference in plant variables. In the real world, these differences are too small to measure accurately (chapter 6).

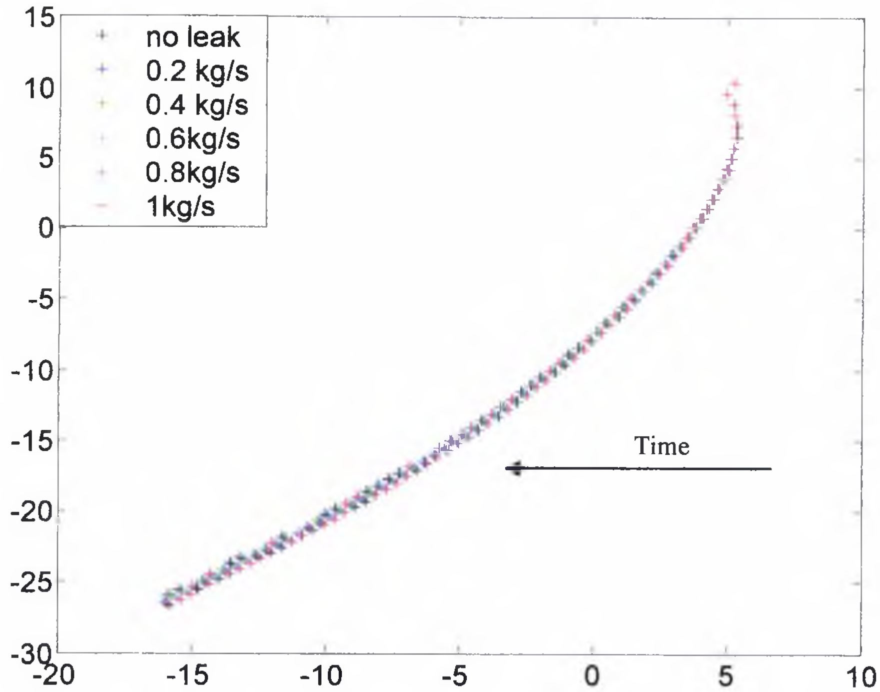



**Figure 7.4 Sammon mapping for five small LOCAS**

### 7.4.4 Application Testing – LOCA results

To test the OAS applications performance for small primary coolant leaks, samples of data (15 continuous time periods) were randomly chosen for a range of leak rates between 0-10kg/s, which were then presented to the OAS. The results from these experiments are summarised in Table 7.2, which shows the outputs from the OAS and the real number outputs from the small loss of coolant and fault ANN modules.

| Actual leak rate kg/s | Fault ANN output NOA | PCL | Throttle | Steam leak | Group Rod Drop | Single rod drop | Recorded Leak rate | % Difference | OAS output to plant operator |
|---|---|---|---|---|---|---|---|---|---|
| 0 | 1.04 | -0.02 | 0.00 | 0.00 | 0.00 | -0.04 | 0.01 | | NOA |
| 0.1 | 1.04 | -0.02 | 0.00 | 0.00 | 0.00 | -0.04 | 0.11 | 6.42 | NOA |
| 0.15 | 1.04 | -0.02 | 0.00 | 0.00 | 0.00 | -0.04 | 0.16 | 3.54 | NOA |
| 0.2 | 1.04 | -0.03 | 0.00 | 0.00 | 0.00 | -0.04 | 0.21 | 5.92 | NOA |
| 0.25 | 1.04 | -0.02 | 0.00 | 0.00 | 0.00 | -0.04 | 0.27 | 7.82 | NOA |
| 0.3 | 1.04 | -0.02 | 0.00 | 0.00 | 0.00 | -0.04 | 0.30 | 0 | NOA |
| 0.35 | 1.04 | -0.02 | 0.00 | 0.00 | 0.00 | -0.04 | 0.36 | 3.05 | NOA |
| 0.4 | 1.04 | -0.02 | 0.00 | 0.00 | 0.00 | -0.04 | 0.40 | 0.26 | NOA |
| 0.45 | 1.04 | -0.03 | 0.00 | 0.00 | 0.00 | -0.04 | 0.47 | 3.93 | NOA |
| 0.5 | 1.04 | -0.02 | 0.00 | 0.00 | 0.00 | -0.04 | 0.51 | 1.61 | NOA |
| 0.55 | 1.04 | -0.03 | 0.00 | 0.00 | 0.00 | -0.04 | 0.51 | | NOA |
| 0.6 | 1.03 | -0.02 | 0.00 | -0.01 | -0.01 | -0.03 | 0.51 | | NOA |
| 0.7 | 1.03 | -0.02 | 0.00 | -0.01 | -0.01 | -0.03 | 0.51 | | NOA |
| 0.8 | 1.03 | -0.02 | 0.00 | -0.01 | -0.01 | -0.02 | 0.51 | | NOA |
| 0.9 | 1.03 | -0.02 | 0.00 | -0.01 | -0.01 | -0.02 | 0.51 | | NOA |
| 1 | 1.03 | -0.02 | 0.00 | -0.01 | -0.01 | -0.02 | 0.51 | | NOA |
| 1.2 | 1.03 | -0.02 | 0.00 | -0.01 | -0.01 | -0.02 | 0.51 | | NOA |
| 1.4 | 1.03 | -0.02 | 0.00 | -0.01 | -0.01 | -0.02 | 0.51 | | NOA |
| 1.6 | 1.03 | -0.01 | 0.00 | -0.01 | -0.01 | -0.02 | 0.51 | | NOA |
| 1.8 | 1.03 | 0.00 | 0.00 | -0.02 | -0.02 | -0.02 | 0.51 | | NOA |
| 2 | 1.04 | -0.01 | 0.00 | -0.01 | -0.02 | -0.02 | 0.51 | | NOA |
| 2.2 | 1.03 | 0.01 | 0.00 | -0.02 | -0.02 | -0.02 | 0.51 | | NOA |
| 3 | 1.03 | 0.03 | 0.01 | -0.02 | -0.03 | -0.01 | 0.51 | | NOA |
| 4 | 1.00 | 0.06 | 0.04 | -0.02 | -0.03 | -0.02 | 0.51 | | NOA |
| 5 | 0.92 | 0.08 | 0.11 | 0.00 | -0.01 | -0.04 | 0.51 | | NO OUTPUT |
| 6 | 0.64 | 0.40 | 0.07 | 0.03 | 0.00 | -0.05 | 0.51 | | NO OUTPUT |
| 7 | 0.17 | 0.91 | 0.02 | 0.03 | -0.03 | -0.04 | 0.51 | | NO OUTPUT |
| 7.5 | 0.10 | 0.96 | 0.01 | 0.03 | -0.03 | -0.03 | 0.51 | | LOCA |
| 8 | 0.07 | 0.98 | 0.01 | 0.03 | -0.03 | -0.03 | 0.51 | | LOCA |
| 8.5 | 0.06 | 0.98 | 0.01 | 0.02 | -0.03 | -0.03 | 0.51 | | LOCA |
| 9 | 0.04 | 0.99 | 0.01 | 0.02 | -0.03 | -0.03 | 0.51 | | LOCA |
| 9.5 | 0.03 | 0.99 | 0.00 | 0.01 | -0.02 | -0.02 | 0.51 | | LOCA |
| 10 | 0.02 | 0.99 | 0.00 | 0.01 | -0.02 | -0.02 | 0.51 | | LOCA |

**Table 7.2 Operator's Advisory System output**

For leak rates between 0-4kg/s, the fault analyser module of the OAS failed to detect a primary coolant leak. The classification 'none of the above' (NOA) is reported to the plant operator. If a NOA classification is observed by the OAS, the OAS then cycles through the small leak monitors developed earlier in the thesis. The OAS correctly classified within 10% all leak rates up to and including 0.5 kg/s, 60% of the classifications were within 5% of the stated value.

However, for primary coolant leaks greater than 0.5 kg/s and less than 5 kg/s, the threshold at which the fault ANN detects a LOCA, the OAS indicated normal operating conditions with a small loss of coolant leak of 0.51kg/s. For leak rates greater than 5kg/s but smaller than 7.5kg/s, the OAS only indicated a leak rate of 0.51kg/s, and failed to diagnose a major transient. For leak rates greater than and equal to 7.5kg/s, the fault classifier correctly identified a primary coolant leak- the OAS provides an output stating the presence of a LOCA.

### 7.4.5 Application refining – LOCA

Although the small loss of coolant monitor reported a 0.5 kg/s leak, which could be programmed to indicate the presence of a leak, the plant operator would still need to infer the rate of coolant loss by monitoring another plant process, for example a drop in the water level of the pressuriser.

It was therefore decided that the range of leaks the ANN would report on would need to be extended to cover the absence of information provided to the plant operator (between 0.5 -7.5 kg/s).

Early experiments using a single ANN proved unsuccessful. The weight values within the ANNs failed to converge to any useful value, despite using several backpropagation training algorithms. The Sammon maps shown in figure 7.3 and 7.4 demonstrate the dynamic changes that occur in the primary circuit of the PWR are greater at higher leak rates (>1kg/s). As a result of these experiments, it was decided to divide the range of leaks under investigation into three categories (small, medium, and large), and train a further ANN (medium, large) for each category.

A further series of ANNs were trained on an extended range of leak rates. The medium leak rate monitor was trained on a range of leak rates between 0.4 and 1.9 kg/s. The training data for ten time steps (with 1% Gaussian noise added to the input data) was presented for 120,000 cycles with testing every 100 cycles with the test set, the best network being saved. The best ANN consisted of two hidden layers of 32 and 16 nodes, and an RMS error of 0.0277. Figure 7.5 shows the ANN output for leak rates between 0.55-1.85kg/s

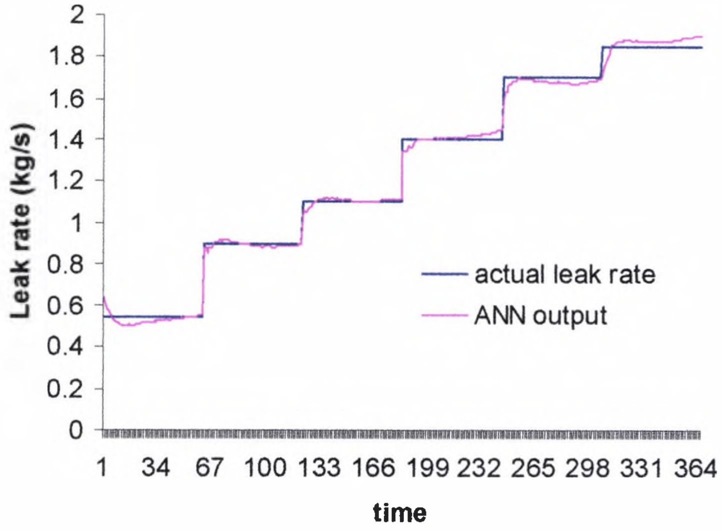



**Figure 7.5 Estimation of medium size leak rates**

Finally, a series of ANNs were trained on the large leak sizes between 1.8 and 8.3 kg/s for 120,000 cycles with testing every 100 cycles to facilitate early stopping, the best network being saved. The best ANN developed had a RMS error of 0.04, and consisted of two hidden layers of 20 and 10 nodes respectively. The results for an independently generated validation data are shown for leak rates between 2-7.9 kg/s in figure 7.6

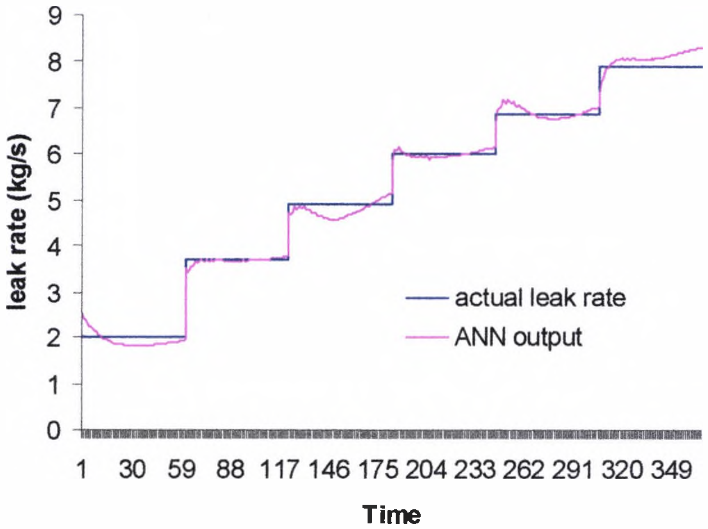



**Figure 7.6 Estimation of large size leak rates**

The RMS error of 0.04 is higher than that observed for the medium leak rate analyser (0.0277). A possible reason for this is the greater range of leak sizes the ANN was trained on (1.8-8.3 kg/s). An example of the drop in performance is reflected in the estimation of a leak rate of 4.9 kg/s as shown in figure 7.7

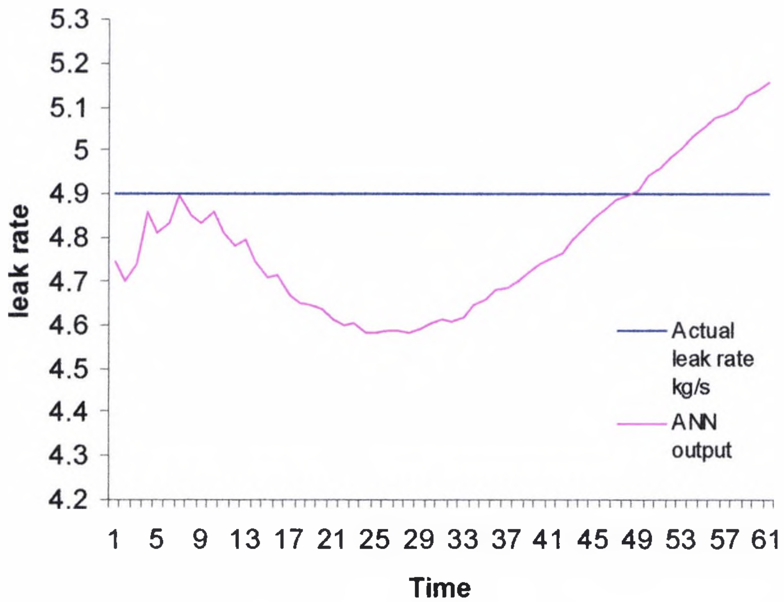



**Figure 7.7 Estimation of a leak rate of 4.9 kg/s**

Although the performance of the ANN classifier for large leak rates was not as accurate as the medium ANN leak rate classifier, the diagnosis is still acceptable (compares well with small leak RMS error of 0.0413), as all the estimates were within 10% of the actual leak rate. The results could be improved by training further ANN on smaller ranges of leak rates.

The data used for training each of the ANNs contained an overlap in leak rate range, to ensure that the output node for each of the three ANNs were not saturated for leak rates at the extremes of each range. The artificial increase in the boundaries for the output node would have the added benefit of improving the tolerance of the ANNs to noise, which may be present on the input parameters.

As before, the ANNs were converted into C code, translated into MATLAB and embedded into the OAS as separate MATLAB files.

Simulated leak rates from the previous experiment (15 continuous time period samples) presented again to the OAS, the results of which are summarised in table 7.4. Values that are highlighted are actual outputs from the OAS. For leak rates of 7 kg/s and below, the OAS reports a ‘none of the above’ classification, as well as the estimated leak rate. For leak rates of 7.5 kg/s and above the OAS reports a ‘primary coolant leak’ classification, the estimated leak rate is suppressed.

| Actual LR | Fault ANN output Primary Coolant Leak | Small | Medium | Large |
|---|---|---|---|---|
| 0 | 0.00 | 0.01 | 0.32 | 1.56 |
| 0.1 | 0.00 | 0.11 | 0.32 | 1.56 |
| 0.15 | 0.00 | 0.16 | 0.33 | 1.56 |
| 0.2 | 0.00 | 0.21 | 0.33 | 1.56 |
| 0.25 | 0.00 | 0.27 | 0.34 | 1.56 |
| 0.3 | 0.00 | 0.30 | 0.33 | 1.56 |
| 0.35 | 0.00 | 0.36 | 0.37 | 1.56 |
| 0.4 | 0.00 | 0.40 | 0.40 | 1.57 |
| 0.45 | 0.00 | 0.47 | 0.42 | 1.56 |
| 0.5 | 0.00 | 0.51 | 0.48 | 1.57 |
| 0.55 | 0.00 | 0.51 | 0.52 | 1.56 |
| 0.6 | 0.00 | 0.51 | 0.56 | 1.57 |
| 0.7 | 0.00 | 0.51 | 0.65 | 1.57 |
| 0.8 | 0.00 | 0.51 | 0.75 | 1.57 |
| 0.9 | 0.00 | 0.51 | 0.84 | 1.58 |
| 1 | 0.00 | 0.51 | 0.94 | 1.59 |
| 1.2 | 0.00 | 0.51 | 1.14 | 1.60 |
| 1.4 | 0.00 | 0.51 | 1.33 | 1.60 |
| 1.6 | 0.00 | 0.51 | 1.58 | 1.64 |
| 1.8 | 0.00 | 0.51 | 1.77 | 1.72 |
| 2 | 0.00 | 0.51 | 1.89 | 1.78 |
| 2.2 | 0.00 | 0.51 | 1.92 | 1.96 |
| 3 | 0.02 | 0.51 | 1.92 | 2.70 |
| 3.5 | 0.03 | 0.51 | 1.93 | 3.22 |
| 4 | 0.04 | 0.51 | 1.93 | 3.81 |
| 5 | 0.11 | 0.51 | 1.93 | 4.80 |
| 6 | 0.40 | 0.51 | 1.93 | 5.85 |
| 7 | 0.91 | 0.51 | 1.93 | 6.75 |
| 7.5 | 0.96 | 0.51 | 1.93 | 7.16 |
| 8 | 0.98 | 0.51 | 1.93 | 7.91 |
| 8.5 | 0.98 | 0.51 | 1.93 | 8.37 |
| 9 | 0.99 | 0.51 | 1.93 | 8.43 |
| 9.5 | 0.99 | 0.51 | 1.93 | 8.44 |
| 10 | 0.99 | 0.51 | 1.93 | 8.44 |

**Table 7.3 Operators Advisory System output (Revised)**

### 7.4.6 Implementation

Figure 7.8 shows the implementation of the three primary coolant leak monitors centred on the regions populated by the training vectors (small, medium and large leak rates), into the OAS.

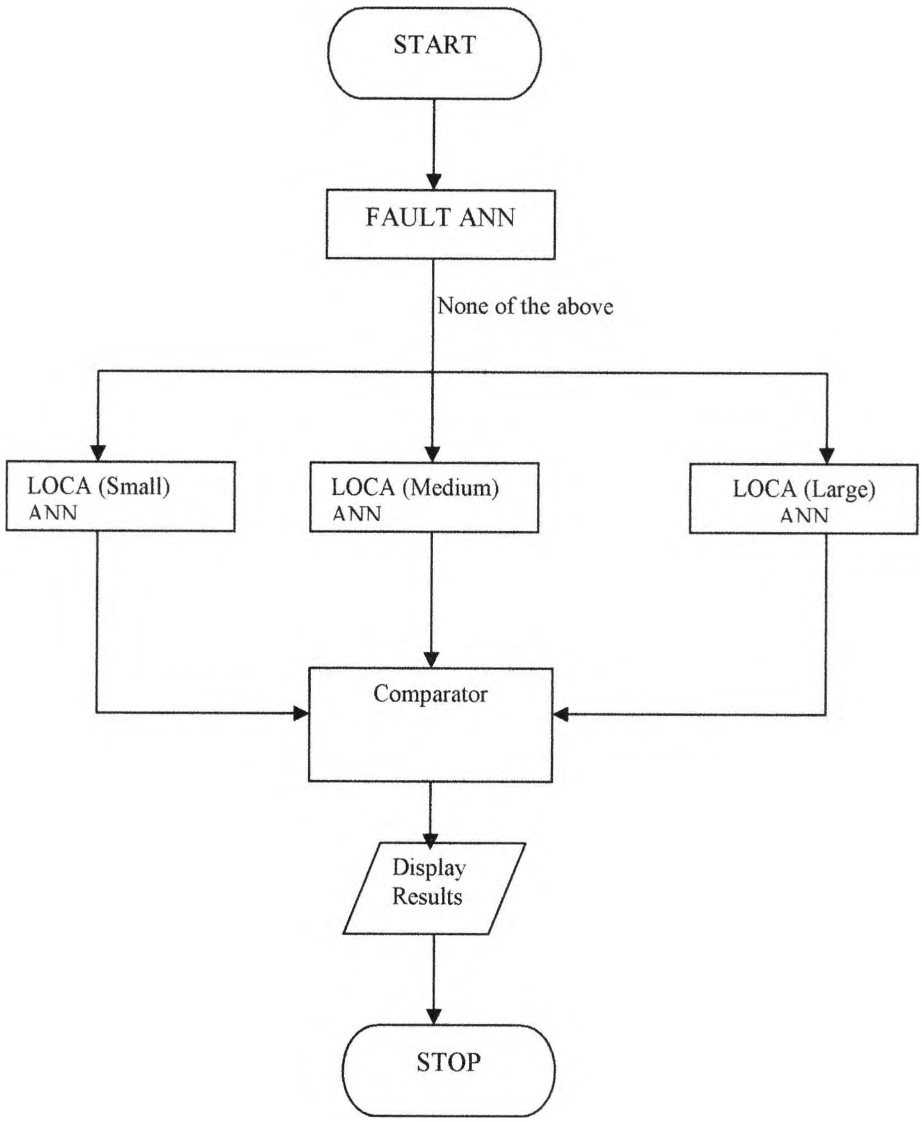



**Figure 7.8 Flow diagram of LOCA Classification**

If the fault classifier makes a 'none of the above' diagnosis, the plant data is then (buffered 10 time steps) presented to each of the primary coolant leak monitors.

If a leak is diagnosed by any of the three classifiers, the output (leak rate) from the corresponding ANN is then used to modify the input data for an independently developed PWR simulator. The simulation then reproduces the diagnosed leak. Figure 7.9 shows a simulation for a leak rate of 0.5 kg/s (diagnosed as 0.482 kg/s) for 6 plant parameters. In this example (the data is normalised for security reasons), the simulator is run for 50 time periods to stabilise prior to the initiation of a 0.5 kg/s LOCA lasting for 70 time periods.

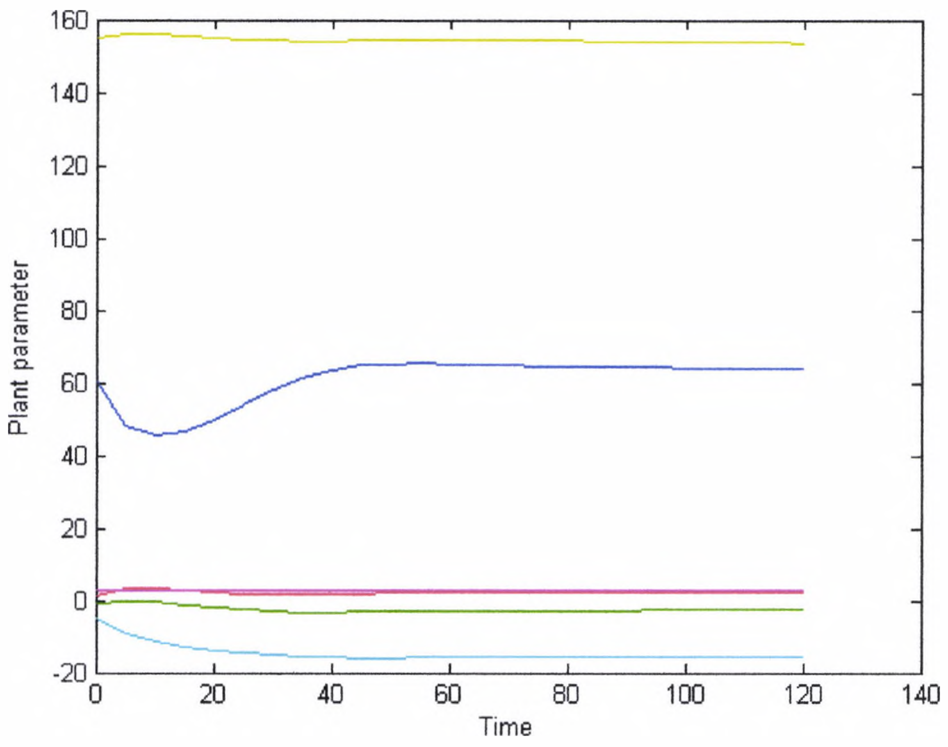



**Figure 7.9 OAS trend data for a small primary coolant leak**

Two of the simulated parameters, the pressuriser level and pressure are then compared with the corresponding plant parameters. If the difference between the two values is less than +/-5%, the confirmed diagnosis is presented to the plant operator. If the difference is greater than +/- 5%, the diagnosis is suppressed and an unknown transient is reported.

### 7.4.7 Discussion- Small LOCA, Initial Findings

Dividing the LOCA into three smaller ranges allowed for the successful estimation of leak rate using ANNs. Figure 7.10 shows a plot of the OAS estimate versus actual leak rate.

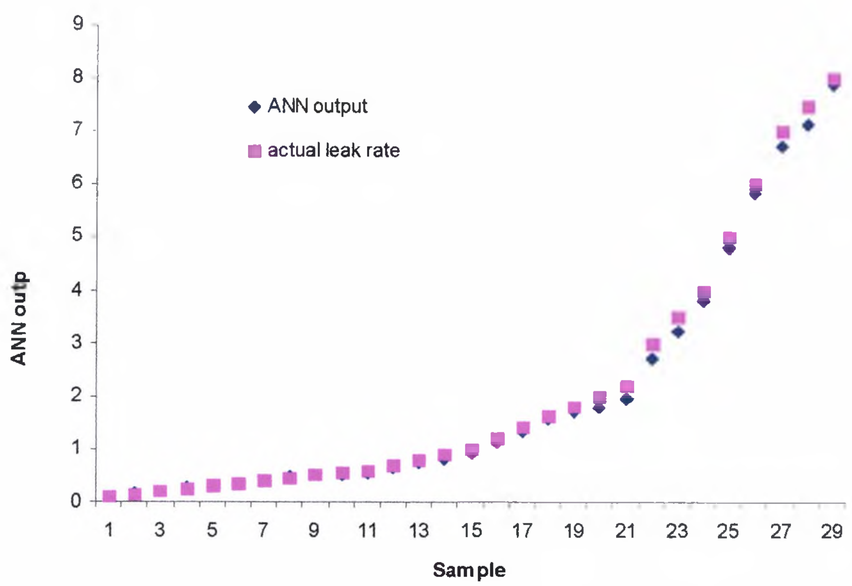



**Figure 7.10 Estimated leak rate (LOCA)**

In general the accuracy of the loss of coolant monitor was very good, 90% of leak rate estimates were within 10% of stated values. The widest deviation was recorded for leak rates of 2.2 and 3kg/s, each of which was at 11% of the stated value. It was also noted that from 2kg/s onwards the estimated leak rates were consistently below the actual leak rate. One explanation for this may be the use of a time-delay ANN used in the development of the small loss of coolant monitor. The time-delay ANN maintains a 'history' of the transient as it develops, which may cause the ANN output to lag behind any transient changes that occur.

The constant limit reached by each of the three ANNs can be explained as follows:

Problems can occur when presenting raw data to the ANN using a hyperbolic transfer function. Very large values for plant parameters can cause the transfer function to saturate presenting. One way to address this problem is to normalise the input/output vectors during the training stages of the ANN by taking the minimum and maximum values of the plant parameters. The process is shown in figure 7.11

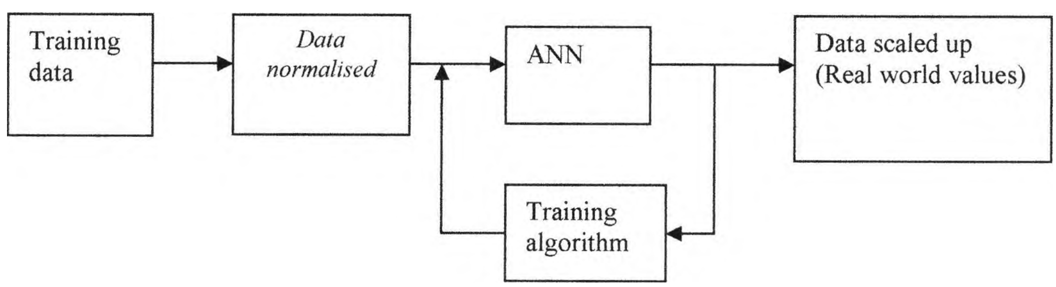



**Figure 7.11 Supervised learning model**

The final node of the ANN figure (7.12) has the following output:

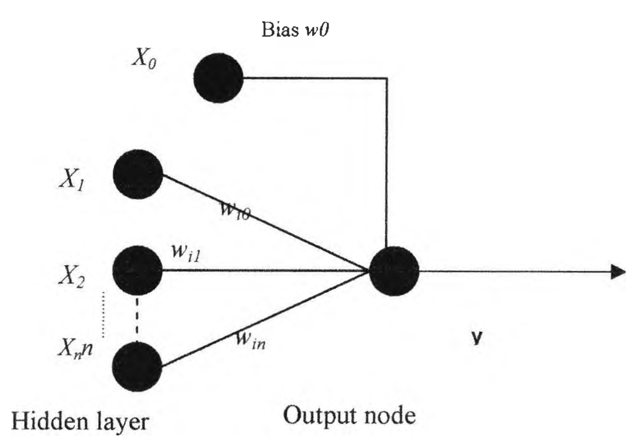



**Figure 7.12 processing unit**

The output node receives data from all the nodes of the hidden layer and outputs computation results equation 7.1. An activation function the hyperbolic tangent given in equation 7.2 and presented graphically in figure 7.13 is then used to calculate the output $y$.

$$y = \frac{\left(1-e^{-net}\right)}{\left(1+e^{-net}\right)} \qquad 7.1$$

Where $$net = w_0 + \sum_i w_i x_i \qquad 7.2$$

And $w_0$ is the bias of each node; each $w_i$ is a weight for the connection from the i-th node of the previous layer

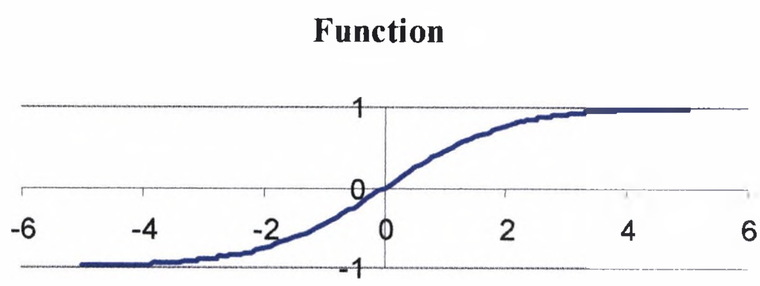



**Figure 7.13 Hyperbolic Tangent Function**

For continuous-valued targets such as leak rates with a bounded range, the hyperbolic tangent functions are useful, provided that either the outputs or the targets to be scaled to the range of the output activation function. This is done automatically in NeuralWorks. A scaling function is then used on the output y, to give real world values.

The effect of the scaling can be observed if for the medium LOCA ANN actual leak rate is compared to the ANN output (figure 7.14).

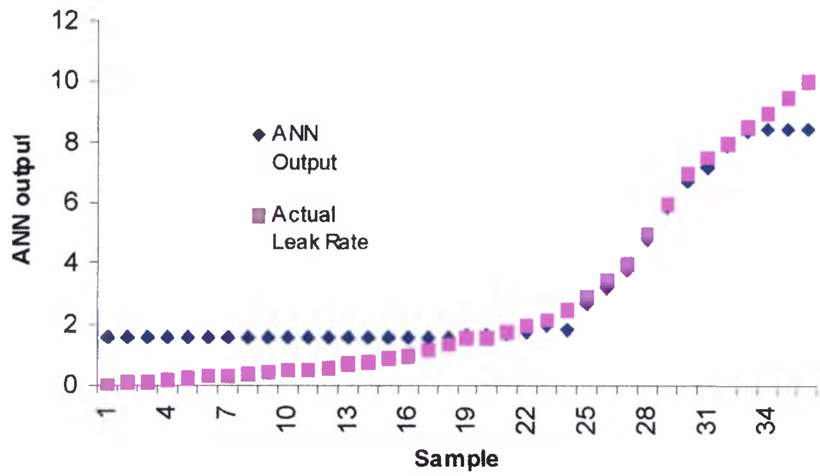



**Figure 7.14 Estimated leak rate**

However, this still compares favourably with established techniques for estimating a small loss of coolant from the primary circuit of a PWR, which usually relies on inferring the leak rate from a secondary source, for example particle detectors (rarely provide quantitive data), or observing the decrease in water level in the pressuriser over a given period, typically several hours.

### 7.4.8 Application Testing – Secondary System Steam Leak

The development of the steam leak monitor for the secondary circuit of a PWR was discussed in chapter 6. Experiments at a steam raising test plant revealed a linear relationship between noise levels and leak rates. Figure 7.15 shows the implantation of the steam leak monitor in the OAS.

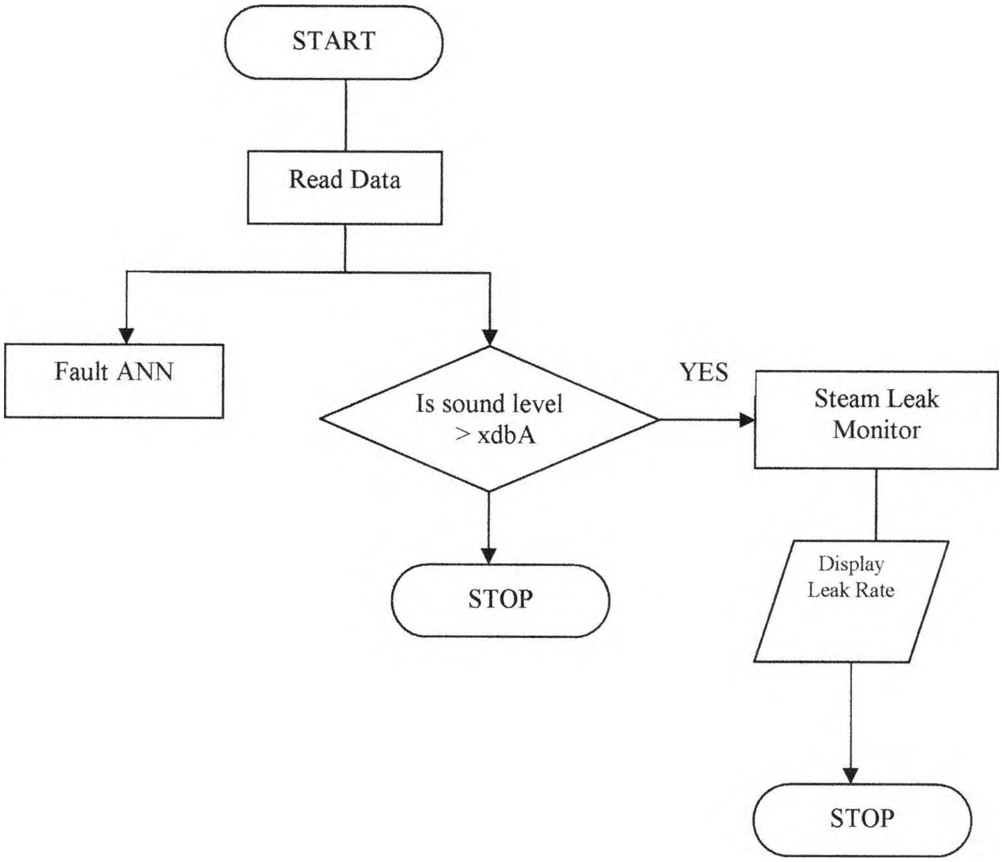



**Figure 7.15 Implementation of Steam leak Monitor**

Unlike the hierarchical implementation of the primary coolant leak classifiers, it was decided the OAS would constantly monitor for a break in the secondary circuit of the PWR. If a sound level measured by a transducer were greater than a pre-determined level, the OAS would calculate and display the estimated leak rate. The minimum (above background noise) and maximum leak rate were defined by experiments described in chapter 6.

### 7.4.9 Results

Using the results of the experiments described in chapter 6, the PWR primary circuit was modified to include an acoustic plant parameter. To assess the ability of the OAS to identify correctly a small break in the secondary circuit of a PWR, a range of steam leaks, from 0.2-0.6 kg/s were simulated.

The threshold of detection for a steam leak in the secondary circuit of the PWR by the Fault ANN was established at 0.52 kg/s. The results of the ANN fault monitor for the simulated leak rates is shown in figure 7.16.

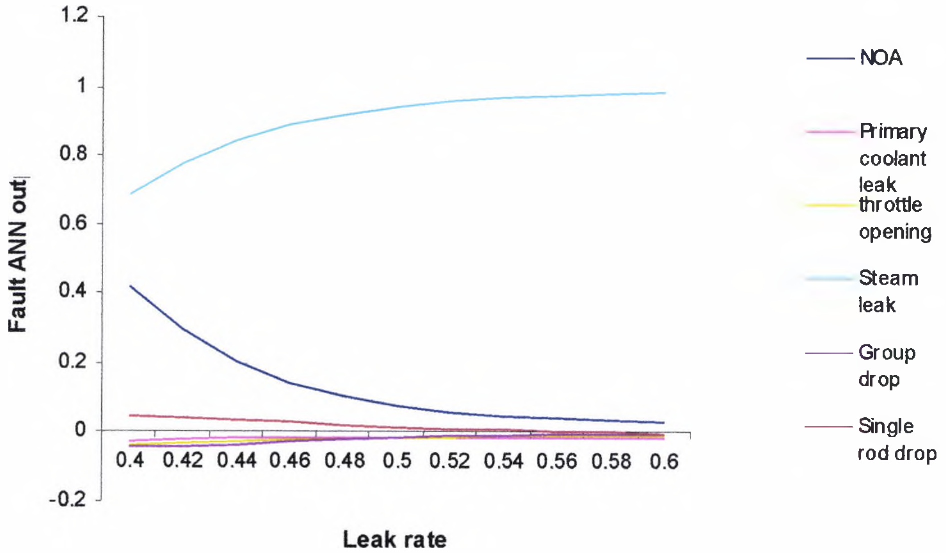



**Figure 7.16 Fault ANN output for a range of downstream steam leaks**

Table 7.6 summarises the results obtained from the OAS for a range of steam leaks in the secondary circuit of the PWR.

| Noise levels Decibels | OAS Output Leak rate |
|---|---|
| F0 | None of the above |
| F1 | 0.11 Kg/s |
| F2 | 0.35 Kg/s |
| F3 | 0.58 Kg/s |
| F4 | 0.8 Kg/s |
| F5 | None of the above |

**Table 7.4 Displayed outputs for small steam leaks**

The results show that the OAS for sound levels between F1 and F5 provides an estimate of leak rate, which is beyond the threshold of detection for the fault classifier ANN. At F0, the OAS returns a 'none of the above' classification. A leak may exist, but the noise levels are similar to background noise, and are therefore below the threshold of the acoustic monitor.

### 7.4.10 Further Application Testing

To investigate the performance OAS further, a double fault was simulated: a small downstream steam leak coupled with throttle opening. The OAS reports the major transient (throttle opening), and not the minor steam leak. This is because a major transient takes precedence over a minor fault. This triage of transient's addresses (by default) problems associated with alarm showers (Lees 1983). The OAS would only provide a leak rate estimate when the power plant returned to a steady state.

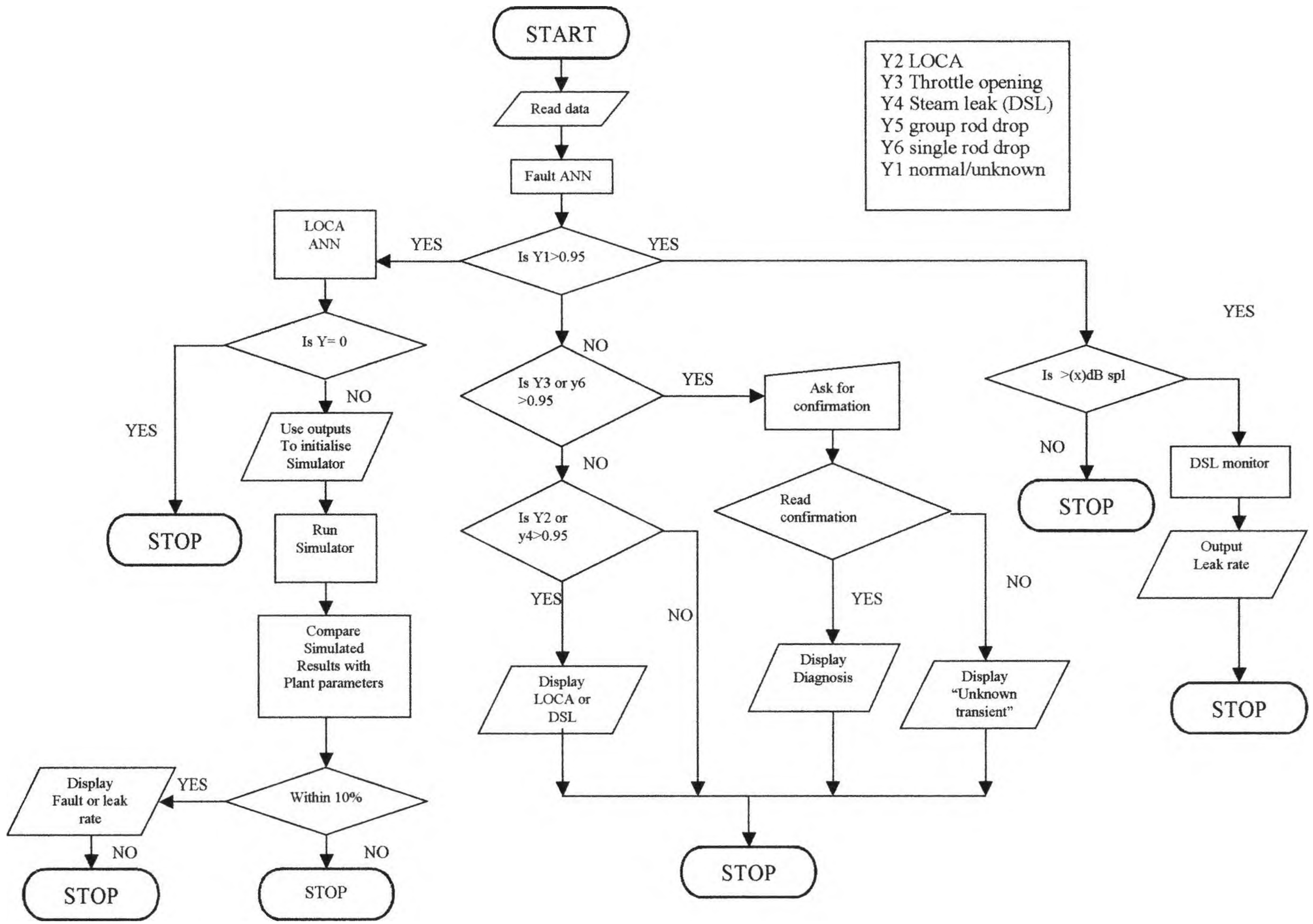
The next stage was to observe the effect of corrupted data on the performance of the OAS. The simulated plant data for a single rod drop was replaced with random numbers. The OAS failed to return an output. Next a single channel of data was replaced with first zero values, and then twice the original value. Once again, in both cases the OAS failed to provide an output or 'fails safe'.

## 7.5 Discussion

### 7.5.1 Results

The results obtained in the previous section are now discussed in more general terms. The motivation for this study was to establish a methodology for the development of an ANN based Operators Advisory System (OAS) for the diagnosis of PWR transients. In particular, the focus was the identification of small transients as typified by small breaks in the primary and secondary circuits. Extensive use was made of PWR simulators, to provide data for the development and validation of the OAS.

Diagnostic modules developed early in this thesis for the classification of major and minor transients were successfully integrated to form the basis of the prototype OAS. Initially the modules were tested individually. The results from these tests were then used to modify the OAS to improve its performance. The study then proceeded to treat the modules as a linked system, particularly for the estimation of a small break in the primary circuit of PWR. The study concluded by investigating the tolerance of the OAS to missing or noisy data. A flow diagram of the prototype OAS is shown in figure 7.17


START
Read data
Fault ANN
Y2 LOCA
Y3 Throttle opening
Y4 Steam leak (DSL)
Y5 group rod drop
Y6 single rod drop
Y1 normal/unknown
LOCA ANN
YES
Is Y1>0.95
YES
YES
Is Y= 0
NO
Is >(x)dB spl
Is Y3 or y6 >0.95
YES
Ask for confirmation
YES
NO
Use outputs To initialise Simulator
NO
DSL monitor
NO
STOP
STOP
Run Simulator
Is Y2 or y4>0.95
Read confirmation
Output Leak rate
NO
YES
YES
NO
Compare Simulated Results with Plant parameters
Display LOCA or DSL
Display Diagnosis
Display "Unknown transient"
STOP
Display Fault or leak rate
YES
Within 10%
NO
NO
STOP
STOP
STOP

The overall performance of the OAS was very good. The prototype OAS was able to identify all major fault transients quickly and accurately (ANN output > 0.95) when tested on an independent data set. Plant operators are required to confirm the diagnosis for two of the transients (single and group rod drop). The inclusion of the plant operator interaction in the decision making process may be beneficial to the successful implementation of the OAS.

When the OAS was presented with a range of small breaks in the primary circuit of the PWR, it failed to provide an output for leak rates that exceeded the limits of the ANN leak rate monitor, and below the threshold of detection of the major transient classifier. Two further ANNs were trained to 'bridge' the gap, and were implemented, in parallel, in the OAS. The fast and successful introduction of the two new ANN classifiers demonstrated the adaptability of the design methodology. An independently developed plant simulator was then used to compare the results of the simulation with plant data. If in agreement, the leak rate estimate was confirmed, and the results presented to the plant operator. The output to the plant operator also included a plot of the predicted progress of the diagnosed plant transient. Further research is required to exploit this information.

It was decided in the design stages of the OAS that the acoustics based leak rate monitor developed in the first part of chapter 6 would constantly monitor for a break in the secondary circuit. This would allow the OAS system to better identify a double fault, for example a major fault and a small break in the secondary circuit.

An alternative implementation of an acoustic leak rate monitor (ANN based or otherwise) is shown in figure 7.18. The use of a hierarchical system for transient diagnosis would by default, only allow major transients to be reported, and in effect suppress spurious or low level alarms.

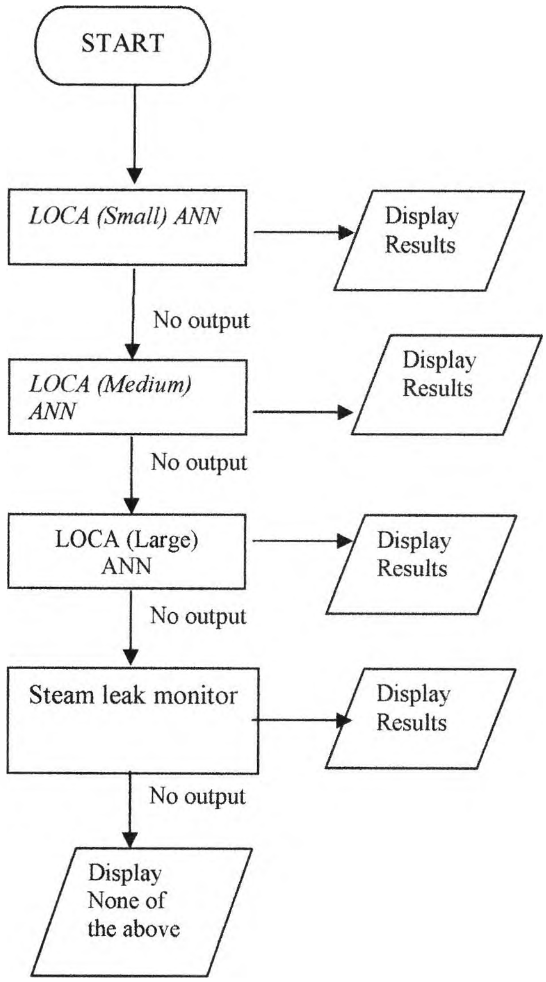



**Figure 7.18 Flow diagram for Steam leak Monitor in OAS**

A further difference between the two approaches is the speed of response, the elapsed time between the occurrence of the transient and its diagnosis. A parallel implantation of diagnostic modules results in a faster diagnosis, but requires an increase in computing power. The sequential selection of alternative modules used in a hierarchical system leads to longer diagnostic times. For example, in the proposed implementation of an acoustic monitor shown in figure 7.17, it may take several time steps for the fault classifier to diagnose a 'none of the above' classification. In addition, the loss of primary coolant monitor uses a minimum of 10 time steps to make a diagnosis (typically 15 time steps). Finally the acoustic monitor is then accessed to estimate the leak rate. The parallel implementation of the acoustic monitor would typically provide a response in a single time step. The speed of response of either method when used in the OAS still compares favourably with that of a human operator.

The response of the OAS to missing or corrupted data was to provide no output or 'fail safe'.

### 7.5.2 OAS Validation

It has been demonstrated that the OAS can provide several advantages to the plant operator in the diagnosis of transients in a PWR. However as the OAS is developed further (for example the addition of further modules), so does the complexity of the system. This increase in complexity has the potential for decreasing the dependability of the overall safety critical system, the failure of which can lead to injury or loss of life and damage to the plant and the environment. Before the implementation of the OAS it is essential that various aspects of the system be assessed for its dependability and any malfunction predicted.

The principle dimensions of a safety critical system are as follows:

- **Availability** – the ability of the system to deliver services when requested
- **Reliability** – the ability of the system to deliver services as requested
- **Safety** – the ability of the system to operate without catastrophic failure
- **Security** – the ability of the system to protect itself against accidental or deliberate intrusion

(Sommerville 2004)

As the levels of dependability required for a safety critical system are increased, so are the costs associated with the systems development – increased testing and system validation, and more expensive development techniques.

The OAS must also follow government regulations or industry standards for safety critical systems and be certified by licensing bodies (Isaksen 1996), (Nuclear Regulatory Working Group 2000).

# Chapter 8

# Conclusion

## 8.1 Introduction

A research aim was proposed in the introduction of this thesis; this chapter draws conclusions on the research, and what contribution has been made and possible areas of further research.

The development of powerful instrumentation for the monitoring of Pressurised Water Reactors (PWR) has resulted in the routine production of data to be analysed. In turn this has prompted much research into approaches to automatic system analysis. Due to the successful track record of artificial neural network models (ANNs) in application to difficult problems, there is considerable interest in the industrial use of safety-related ANNs (Lisboa 2001).

The aim of this thesis was to investigate the use of Artificial Neural Networks in the development of a prototype Operators Advisory System (OAS) for the early identification and management of a fault condition in a Pressurised Water Reactor (PWR). It is intended that the OAS act as an advisor to the PWR plant operator, not as a replacement.

Artificial Neural Networks are a general framework for the mapping of input/output systems and readily lend themselves to the study of complex non-linear systems as typified by a PWR. The main advantage of using ANNs is that they make no apriori assumptions about the system under consideration and are straightforward to implement. A shortfall is their lack of transparency in directly revealing the nature of the system under consideration. The standard back-propagation algorithm for training feed-forward neural networks has proven robust even for difficult problems. However, its high performance results are attained at the expense of a long training time to adjust the network parameters. The extensive use of simulations of a generic PWR was used in this thesis.

## 8.2 Summary

This thesis has provided a synopsis of some aspects of the current state of understanding of the uses of ANN in the nuclear industry and highlights the main challenges facing the research community, namely, the development of benchmark data sets for future development. Intrinsically linked with this goal is the need to continue collecting large-scale real time data sets.

The first investigation undertaken was the use of ANNs for transient classification. The aim of this operation was to further develop a major PWR fault classifier first proposed by Weller 1997. This was a multidimensional classification problem and as such was ideally suited for ANN application.

The focus of the current work has been towards the improvement of the practical applicability of this type of system to real processes as demonstrated by the experiments on the effects of noise on the performance of the trained ANN. The results of the experiments were to improve the robustness of the transient classifier to noisy transducers, and take account of the ageing process within the plant.

The techniques used to develop the fault classifier were then used to develop the next module in the OAS, the estimation of leak rate, for a small primary coolant leak. These small leaks only made small dynamic changes within the primary circuit of the PWR, it was therefore necessary to extend the use of a feed forward ANN to take account of temporal information, to aid in the development of the classifier. The final ANN provided a real number estimate of the leak rate.

During the development of the module for a small loss of steam from the secondary circuit of a PWR, the effects on the primary circuit plant parameters were too small to successfully develop a leak rate estimator using an ANN. In keeping with the aim of this work, practicability, external information was used to supplement the data provided by the PWR simulators. Experiments were conducted in the use of acoustics to aid in the development of the classifier. From these experiments a relationship was derived between the levels of noise generated by a steam leak and the rate of steam leak.

Also investigated was the pre-processing of the sound data, a Fourier transform, which could then be used to develop an ANN leak rate classifier.

Finally the three modules developed were integrated into the prototype OAS. The OAS would provide to the PWR plant operator early warning of a PWR transient. As noted in the synopsis on the use of ANNs in the nuclear industry, much has been made of the lack of transparency and therefore confidence in the results provided. In answer to these concerns, two strategies were adopted in the development of the OAS system. First, the use of a independently developed PWR simulator, the data from which was used to confirm the OAS diagnosis. Secondly, confirmation by the plant operators for major transients for example a 'rod drop' transient. Early tests indicated that the use of a single ANN for the classification of a small primary coolant leak was inadequate; therefore three ANNs were developed to overcome this problem. The rapid development and integration of the new ANNs highlighted the flexibility of the proposed system

## 8.3 Discussion

This section deals with each of the objectives listed in the introduction and describes the extent to which they were met.

**To extend and validate an existing model of transient classification in the primary circuit of a Pressurised Water Reactor (PWR).**

This objective was only partly met. The original fault classifier was extended and applied to data derived from a modified PWR simulator. Unfortunately the lack of real plant data limited the validation of the fault ANN to the effects of noise, calibration drift, and plant ageing on input data.

**To investigate the use of ANNs in the monitoring of small transients in a PWR**

This objective was met in full. ANNs were used to investigate small breaks in the primary and secondary circuits of a PWR.

**Develop a prototype ANN based OAS**

This objective in the development of an ANN based OAS was also met as planned. The successful integration of the fault and small LOCA ANN into a decision support system was established. Unfortunately the investigation into the use of an ANN based acoustic small leak monitor could not be incorporated into the OAS due to a lack of data. However, information gained from the investigation provided valuable data for the development of a non-ANN acoustic leak monitor, which was included in the OAS.

## 8.4 Future Work

This section highlights theoretical and practical aspects, which merit further exploration and development.

### 8.4.1 Further Testing

The development of the OAS system described in this thesis, made extensive use of simulated data. Indeed many of the studies in the use of ANNs for transient analysis report results from qualitative assessments using simulated data. It is very difficult to assess such work and to determine the generalisation capacity of the proposed approaches. The work reported in this thesis was performed in order to investigate and demonstrate the potential of ANNs in application to PWR analysis. Information gained from experimentation in chapter 4 in the development of a major fault classifier, was used to improve the robustness of ANNs developed later on in the thesis. However further research is required into improving the robustness of ANNs to missing/noisy data.

### 8.4.2 New diagnostic modules

Currently, only three modules have been developed for the diagnosis of plant transients. Whilst this approach was necessary to demonstrate the feasibility of an ANN based multi layered support system. The models implemented so far could serve as a benchmark for the development of future modules. The modules developed could be extended to not only detect a transient and the size of the transient but also to include the location.

An example could be the further development of the acoustic ANN monitor. Chapter 6 investigated the use of ANN for the classification of leak rates. Unfortunately, the model validity could not be ascertained due to the limited amount of data, and could not therefore be included in the OAS. Despite the fact, the model was not included in the ANN; the results are of importance and could serve as a benchmark for future development. A more detailed investigation this time including both air and structure borne microphones, together with signal processing could yield information for an ANN to not only detect and estimate a leak, but also its location. The development of a passive leak monitoring system using instrumentation, which has been protected against high temperatures and humidity, would be extremely useful in the hostile environment of a reactor compartment.

The OAS described, by default requires that the output data delivered by instrumentation is in a standardised/common format. This makes for the easier integration of future developed modules.

### 8.4.3 Confidence levels

In chapter 7, two methods were used to improve the level of confidence which could be attached to a diagnosis by the OAS. The inclusion of a comparator to compare the predicted plant parameters by the OAS with actual/real plant parameters the smaller the difference the greater the degree of accuracy, also and as important is user confirmation it is envisaged that both of these methods be included in future development. However, another method to improve the confidence attached to a decision maybe to train several ANNs for the same task, each trained on an independent test data set. A polling strategy (Weller1997) can then be adopted for the acceptance of a diagnosis. For example, if two out of three ANNs agree the diagnosis is confirmed.

### 8.4.4 On-line Calibration

Because of dynamic nature of PWR systems their environment, inherent elements of the domain as well as the type of tasks completed by the systems may change. Initially very well performing ANN may encounter a significant drop of performance after plant characteristics have changed, for example calibration drift in instrumentation or aging processes within the reactor.

Most diagnostic systems described will only report a problem when the diagnosis no longer satisfies expectation. One solution may be the continuous external monitoring of the proposed OAS as well as plant instrumentation to continually 'fine tune' the overall system. This may include re-training ANN modules using the latest available plant data.

### 8.4.5 The Man-Machine Interface

Plant operators where possible were consulted in the development of the OAS. Another area of research could be to investigate the point at which the plant operator interacts with the OAS, the Man-Machine Interface (MMI). A well-designed user interface can reduce human error in process control. Research is required on how much information generated by the OAS is presented to the plant operator. Too much information may well lead to an increase in human error. The manner, in which the information is displayed to the plant operator in either the form of a computer display, dedicated gauges, audible alarms or a combination of all, will also require investigation. The optimising of the MMI may well require the changes in the OAS development, e.g. from a multi-layered system as described in this thesis, to a hierarchical system.

### 8.4.6 Assessment of Safety-Critical Software

Arndt (2004) highlights the following challenges in the introduction of digital systems:

- Increased complexity
- New failure modes (particularly common cause failures)
- Difficulties in demonstrating system safety
- Rapid technology changes
- Cyber security

The assessment of the OAS to meet relevant standards is an important part of the software validation process,

## 8.5 Summary

It is envisaged that the needs of intelligent monitoring systems will increase in the future. New technology has led to an increase in the number and complexity of transducers used in the monitoring of a nuclear power plant, and it is hoped the developed systems will be able to capitalise on the increasingly data rich environment of the control room, and further enhance existing safety systems.

Due to concerns in the use of a 'black box' approach to aid in the decision making process in a safety critical system as typified by the operation of a PWR, it may be the case that individual modules be implemented (in parallel with existing systems) and their reliability proved. This 'bottom up' approach to implementation may be more acceptable.

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# Appendices

## A: An Introduction to Artificial Neural Networks

This appendix is a brief introduction to the principal modelling technique used in this research, the feedforward Artificial Neural Network (ANN). Further information can be obtained from specialist books (Bishop 1996, Masters 1993).

ANNs are a simplified attempt to mimic the brains ability to recognise complex patterns. The building blocks of an ANN are the node. The basic architecture of ANN consists of nodes or neurones, which are highly interconnected. The origins of these networks can be traced back to the "perceptron" introduced by Rosenblatt (1958).

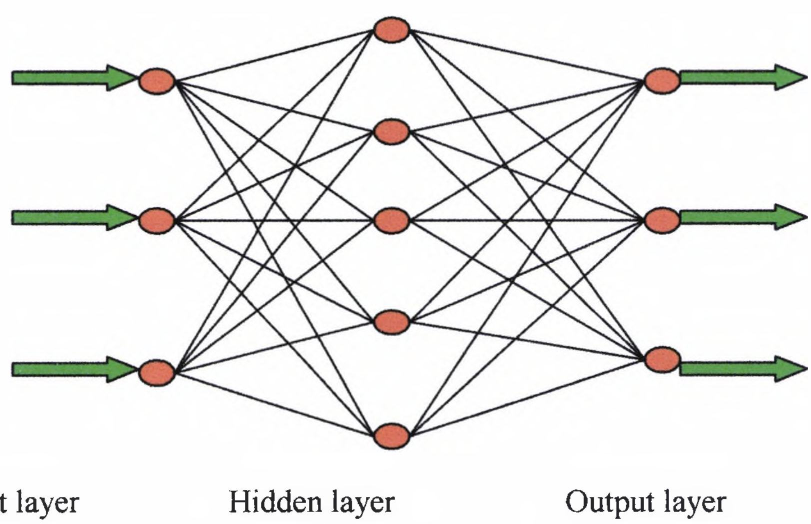


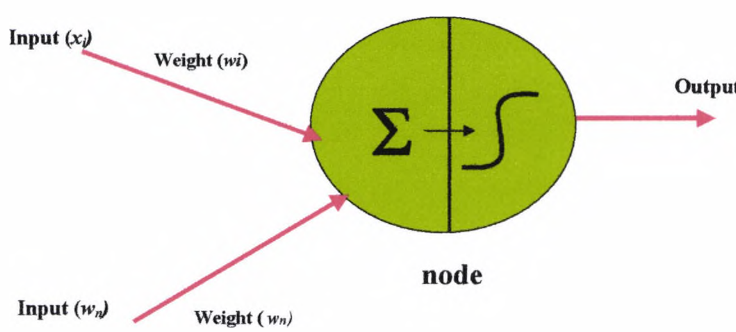

**Figure A.1 Feedforward Artificial Neural Network (ANN)**

Figure A.1 shows a typical architecture for a trained (though could be untrained), feedforward backpropagation ANN. The example above consists of an input layer of three nodes (data from the environment), a hidden layer of five nodes, and an output layer of three nodes. The ANN, once trained, can be used to diagnose unknown cases. In this example each neuron is able to sum many weighted inputs whether plant data or other nodes with each input being modified by an adjustable weight. The sum of these weighted inputs is added to a bias for that neuron and then passed through a modifying function, typically step, sigmoid or hyperbolic tangent, which determines the final output (figure A2).

For n inputs, $\{x_{i,}, i=0, \ldots, n-1\}$, the neurons output is calculated as:

Neuron output = f(net) = f( $\sum x_i w_i + x_n w_n$ )

**Fig A.2 Diagram of an ANN node**




In supervised learning, the ANN the topology is usually held fixed, and the Connection weights are changed during training to minimise error between actual and desired output data.

To train a network and measure how well it performs, a cost function must be defined to provide an unambiguous numerical rating of system performance. A few basic functions are very commonly used. One of them is the sum of squares error function,

$$E = \frac{1}{NP} \sum_{p=1}^{P} \sum_{i=1}^{N} (t_{pi} - y_{pi})^2$$

where $p$ indexes the patterns in the training set, $i$ indexes the output nodes, and $t_{pi}$ and $y_{pi}$ are, respectively, the target and actual network output for the $i$th output unit on the $p$th pattern. In real world applications, it may be necessary to complicate the function with additional terms to control the complexity of the model.

The training method used in this thesis, and the most common is the Back-Propagation training algorithm, which is based on the minimising of the cost function using a gradient descent rule.

## B: Results of effect of noise on training

| Noise added to training | File name | RMS error |
|---|---|---|
| 0 | FN1 | 0.0861 |
| 0 | FN2 | 0.0829 |
| 0 | FN3 | 0.09 |
| 0.2 | FN4 | 0.0896 |
| 0.2 | FN5 | 0.0969 |
| 0.2 | FN6 | 0.0988 |
| 0.4 | FN7 | 0.0975 |
| 0.4 | FN8 | 0.0984 |
| 0.4 | FN9 | 0.0908 |
| 0.6 | FN10 | 0.0916 |
| 0.6 | FN11 | 0.096 |
| 0.6 | FN12 | 0.0895 |
| 0.8 | FN13 | 0.0973 |
| 0.8 | FN14 | 0.0969 |
| 0.8 | FN15 | 0.092 |
| 1 | FN16 | 0.1037 |
| 1 | FN17 | 0.099 |
| 1 | FN18 | 0.0949 |
| 1.2 | FN19 | 0.1066 |
| 1.2 | FN20 | 0.0988 |
| 1.2 | FN21 | 0.121 |
| 1.4 | FN22 | 0.1084 |
| 1.4 | FN23 | 0.1109 |
| 1.4 | FN24 | 0.1277 |
| 1.6 | FN25 | 0.1162 |
| 1.6 | FN26 | 0.1186 |
| 1.6 | FN27 | 0.1001 |
| 1.8 | FN28 | 0.13 |
| 1.8 | FN29 | 0.1477 |
| 1.8 | FN30 | 0.1494 |
| 2 | FN31 | 0.0886 |
| 2 | FN32 | 0.092 |
| 2 | FN33 | 0.0855 |

**Table B1 Effect of Noise on ANN performance**

Best results (lowest RMS error) are highlighted.

| Noise added to validation set | FN2 | FN4 | FN9 | FN12 | FN15 | FN18 | FN20 | FN22 | FN27 | FN28 | FN33 |
|---|---|---|---|---|---|---|---|---|---|---|---|
| 0 | 0.101 | 0.1074 | 0.1043 | 0.1246 | 0.1131 | 0.1124 | 0.1249 | 0.1383 | 0.1422 | 0.155 | 0.1112 |
| 0.1 | 0.8148 | 0.1085 | 0.1076 | 0.1262 | 0.1143 | 0.1111 | 0.1255 | 0.1374 | 0.1431 | 0.1545 | 0.1132 |
| 0.2 | 0.8436 | 0.1163 | 0.1075 | 0.1283 | 0.1155 | 0.1132 | 0.1274 | 0.1405 | 0.1431 | 0.1562 | 0.128 |
| 0.3 | 0.8651 | 0.1281 | 0.1143 | 0.1209 | 0.1164 | 0.1148 | 0.1272 | 0.1329 | 0.1346 | 0.1462 | 0.1215 |
| 0.4 | 0.8674 | 0.1658 | 0.1282 | 0.1375 | 0.1307 | 0.1181 | 0.1451 | 0.1539 | 0.1514 | 0.1657 | 0.158 |
| 0.5 | 0.8646 | 0.1649 | 0.1535 | 0.1393 | 0.147 | 0.1279 | 0.1396 | 0.1572 | 0.1599 | 0.1594 | 0.1684 |
| 0.6 | 0.8871 | 0.2074 | 0.1723 | 0.1602 | 0.1404 | 0.1376 | 0.1552 | 0.1575 | 0.1514 | 0.1614 | 0.1987 |
| 0.7 | 0.8812 | 0.2478 | 0.1925 | 0.1848 | 0.1697 | 0.1376 | 0.1615 | 0.1433 | 0.1678 | 0.1627 | 0.2599 |
| 0.8 | 0.864 | 0.253 | 0.2169 | 0.1896 | 0.1877 | 0.1509 | 0.1678 | 0.1772 | 0.1823 | 0.1621 | 0.241 |
| 0.9 | 0.8899 | 0.2777 | 0.2373 | 0.1745 | 0.1761 | 0.1499 | 0.174 | 0.1666 | 0.1655 | 0.1624 | 0.2851 |
| 1 | 0.8824 | 0.3038 | 0.2422 | 0.2233 | 0.2036 | 0.1578 | 0.1815 | 0.2093 | 0.1917 | 0.1866 | 0.2968 |
| 1.1 | 0.8739 | 0.3011 | 0.2446 | 0.2013 | 0.2058 | 0.1868 | 0.1924 | 0.1972 | 0.2055 | 0.1823 | 0.3205 |
| 1.2 | 0.8803 | 0.3689 | 0.2891 | 0.247 | 0.258 | 0.2082 | 0.2277 | 0.2387 | 0.1998 | 0.196 | 0.3613 |
| 1.3 | 0.8766 | 0.3744 | 0.3066 | 0.2815 | 0.256 | 0.2269 | 0.2185 | 0.2094 | 0.2233 | 0.1831 | 0.3519 |
| 1.4 | 0.8916 | 0.3409 | 0.3209 | 0.2809 | 0.2526 | 0.2401 | 0.233 | 0.2382 | 0.232 | 0.191 | 0.3678 |
| 1.5 | 0.8832 | 0.4288 | 0.3133 | 0.2726 | 0.277 | 0.2596 | 0.2454 | 0.2423 | 0.2159 | 0.1971 | 0.402 |
| 1.6 | 0.8956 | 0.3861 | 0.3255 | 0.2989 | 0.2883 | 0.2466 | 0.243 | 0.2644 | 0.2307 | 0.2094 | 0.3801 |
| 1.7 | 0.8742 | 0.4258 | 0.3617 | 0.3265 | 0.3287 | 0.2901 | 0.2671 | 0.2785 | 0.2813 | 0.2126 | 0.4378 |
| 1.8 | 0.8662 | 0.4349 | 0.3759 | 0.3208 | 0.2988 | 0.2817 | 0.2582 | 0.2785 | 0.28 | 0.2298 | 0.4367 |
| 1.9 | 0.8858 | 0.451 | 0.3746 | 0.3429 | 0.3253 | 0.3133 | 0.2927 | 0.276 | 0.267 | 0.2249 | 0.4418 |
| 2 | 0.8755 | 0.4764 | 0.3813 | 0.3593 | 0.326 | 0.3151 | 0.2846 | 0.2964 | 0.2993 | 0.2256 | 0.4606 |
| Average RMS error | 0.8364 | 0.289 | 0.2414 | 0.221 | 0.211 | 0.1905 | 0.1949 | 0.2016 | 0.1985 | 0.1821 | 0.28773 |
| Standard deviation | 0.1694 | 0.1242 | 0.0985 | 0.0809 | 0.0775 | 0.0721 | 0.0562 | 0.056 | 0.0515 | 0.0265 | 0.12119 |

**Table B2 Effect of noise in the validation data on trained ANN**

| File name | Hidden layer 1 | Hidden layer2 | RMS error |
|---|---|---|---|
| X1 | 24 | 17 | 0.0945 |
| X2 | 24 | 15 | 0.0993 |
| X3 | 24 | 13 | 0.0932 |
| X4 | 24 | 11 | 0.0941 |
| X5 | 24 | 9 | 0.1031 |
| X6 | 24 | 7 | 0.0928 |
| X7 | 24 | 5 | 0.1039 |
| X8 | 22 | 17 | 0.097 |
| X9 | 22 | 15 | 0.0891 |
| X10 | 22 | 13 | 0.1081 |
| X11 | 22 | 11 | 0.091 |
| X12 | 22 | 9 | 0.0935 |
| X13 | 22 | 7 | 0.1085 |
| X14 | 22 | 5 | 0.097 |
| X15 | 20 | 17 | 0.1043 |
| X16 | 20 | 15 | 0.095 |
| X17 | 20 | 13 | 0.0955 |
| X18 | 20 | 11 | 0.0902 |
| X19 | 20 | 9 | 0.0916 |
| X20 | 20 | 7 | 0.0954 |
| X21 | 20 | 5 | 0.0985 |
| X22 | 18 | 17 | 0.0895 |
| X23 | 18 | 15 | 0.0918 |
| X24 | 18 | 13 | 0.0977 |
| X25 | 18 | 11 | 0.0927 |
| X26 | 18 | 9 | 0.0938 |
| X27 | 18 | 7 | 0.0964 |
| X28 | 18 | 5 | 0.0914 |
| X29 | 16 | 17 | 0.1184 |
| X30 | 16 | 15 | 0.0923 |
| X31 | 16 | 13 | 0.0931 |
| X32 | 16 | 11 | 0.1178 |
| X33 | 16 | 9 | 0.0918 |
| X34 | 16 | 7 | 0.0891 |
| X35 | 16 | 5 | 0.0974 |
| X36 | 14 | 17 | 0.1043 |
| X37 | 14 | 15 | 0.0886 |
| X38 | 14 | 13 | 0.1056 |
| X39 | 14 | 11 | 0.0916 |
| X40 | 14 | 9 | 0.0936 |
| X41 | 14 | 7 | 0.0874 |
| **X42** | **14** | **5** | **0.082** |
| X43 | 12 | 17 | 0.0876 |
| X44 | 12 | 15 | 0.0884 |

| | | | |
|---|---|---|---|
| X45 | 12 | 13 | 0.1065 |
| X46 | 12 | 11 | 0.0977 |
| X47 | 12 | 9 | 0.0952 |
| X48 | 12 | 7 | 0.1014 |
| X49 | 12 | 5 | 0.1012 |
| X50 | 24 | 17 | 0.1015 |
| X51 | 24 | 15 | 0.0912 |
| X52 | 24 | 13 | 0.093 |
| X53 | 24 | 11 | 0.1033 |
| X54 | 24 | 9 | 0.0918 |
| X55 | 24 | 7 | 0.089 |
| X56 | 24 | 5 | 0.0891 |
| X57 | 22 | 17 | 0.0938 |
| X58 | 22 | 15 | 0.097 |
| X59 | 22 | 13 | 0.0856 |
| X60 | 22 | 11 | 0.0848 |
| X61 | 22 | 9 | 0.0934 |
| **X62** | **22** | **7** | **0.0826** |
| X63 | 22 | 5 | 0.0932 |
| X64 | 20 | 17 | 0.0904 |
| X65 | 20 | 15 | 0.092 |
| X66 | 20 | 13 | 0.0936 |
| X67 | 20 | 11 | 0.0902 |
| X68 | 20 | 9 | 0.0917 |
| X69 | 20 | 7 | 0.0934 |
| X70 | 20 | 5 | 0.1385 |
| X71 | 18 | 17 | 0.0931 |
| X72 | 18 | 15 | 0.0986 |
| X73 | 18 | 13 | 0.0864 |
| X74 | 18 | 11 | 0.0928 |
| X75 | 18 | 9 | 0.1305 |
| X76 | 18 | 7 | 0.096 |
| X77 | 18 | 5 | 0.093 |
| X78 | 16 | 17 | 0.0912 |
| X79 | 16 | 15 | 0.0974 |
| X80 | 16 | 13 | 0.0994 |
| X81 | 16 | 11 | 0.0924 |
| X82 | 16 | 9 | 0.0893 |
| X83 | 16 | 7 | 0.0906 |
| **X84** | **16** | **5** | **0.0783** |
| X85 | 14 | 17 | 0.1088 |
| X86 | 14 | 15 | 0.0966 |
| X87 | 14 | 13 | 0.0937 |
| X88 | 14 | 11 | 0.0944 |
| X89 | 14 | 9 | 0.0938 |
| X90 | 14 | 7 | 0.1018 |
| X91 | 14 | 5 | 0.0965 |
| X92 | 12 | 17 | 0.0981 |

| | | | |
|---|---|---|---|
| X93 | 12 | 15 | 0.0894 |
| X94 | 12 | 13 | 0.0989 |
| X95 | 12 | 11 | 0.0917 |
| X96 | 12 | 9 | 0.0902 |
| X97 | 12 | 7 | 0.0921 |
| X98 | 12 | 5 | 0.0952 |
| X99 | 24 | 17 | 0.103 |
| X100 | 24 | 15 | 0.0984 |
| X101 | 24 | 13 | 0.0928 |
| X102 | 24 | 11 | 0.0874 |
| X103 | 24 | 9 | 0.0884 |
| X104 | 24 | 7 | 0.0932 |
| X105 | 24 | 5 | 0.0947 |
| X106 | 22 | 17 | 0.1326 |
| X107 | 22 | 15 | 0.0966 |
| X108 | 22 | 13 | 0.0874 |
| X109 | 22 | 11 | 0.1017 |
| X110 | 22 | 9 | 0.0966 |
| X111 | 22 | 7 | 0.0847 |
| X112 | 22 | 5 | 0.1065 |
| X113 | 20 | 17 | 0.0963 |
| X114 | 20 | 15 | 0.0984 |
| X115 | 20 | 13 | 0.0977 |
| X116 | 20 | 11 | 0.1034 |
| X117 | 20 | 9 | 0.1002 |
| X118 | 20 | 7 | 0.0913 |
| X119 | 20 | 5 | 0.0966 |
| X120 | 18 | 17 | 0.0953 |
| X121 | 18 | 15 | 0.0972 |
| X122 | 18 | 13 | 0.0957 |
| X123 | 18 | 11 | 0.0879 |
| X124 | 18 | 9 | 0.1001 |
| X125 | 18 | 7 | 0.0947 |
| X126 | 18 | 5 | 0.0875 |
| X127 | 16 | 17 | 0.0898 |
| X128 | 16 | 15 | 0.0908 |
| X129 | 16 | 13 | 0.099 |
| X130 | 16 | 11 | 0.0921 |
| X131 | 16 | 9 | 0.0985 |
| **X132** | **16** | **7** | **0.0845** |
| X133 | 16 | 5 | 0.0946 |
| X134 | 14 | 17 | 0.1076 |
| X135 | 14 | 15 | 0.0914 |
| X136 | 14 | 13 | 0.1031 |
| X137 | 14 | 11 | 0.0918 |
| X138 | 14 | 9 | 0.0897 |
| X139 | 14 | 7 | 0.1014 |
| X140 | 14 | 5 | 0.0925 |

| | | | |
|---|---|---|---|
| X141 | 12 | 17 | 0.0998 |
| X142 | 12 | 15 | 0.0918 |
| X143 | 12 | 13 | 0.0907 |
| X144 | 12 | 11 | 0.0934 |
| X145 | 12 | 9 | 0.0967 |
| X146 | 12 | 7 | 0.1077 |
| X147 | 12 | 5 | 0.1043 |

**Table B3 Training of fault ANN without noise**

| Noise added to training | File name | RMS error |
|---|---|---|
| 0 | FNA1 | 0.0803 |
| 0 | FNA2 | 0.0997 |
| 0 | FNA3 | 0.0921 |
| 0.2 | FNA4 | 0.0959 |
| 0.2 | FNA5 | 0.0865 |
| 0.2 | FNA6 | 0.0899 |
| 0.4 | FNA7 | 0.0908 |
| 0.4 | FNA8 | 0.081 |
| 0.4 | FNA9 | 0.1051 |
| 0.6 | FNA10 | 0.0924 |
| 0.6 | FNA11 | 0.0906 |
| 0.6 | FNA12 | 0.0968 |
| 0.8 | FNA13 | 0.0884 |
| 0.8 | FNA14 | 0.0957 |
| 0.8 | FNA15 | 0.0893 |
| 1 | FNA16 | 0.092 |
| 1 | FNA17 | 0.0984 |
| 1 | FNA18 | 0.0935 |
| 1.2 | FNA19 | 0.1034 |
| 1.2 | FNA20 | 0.1028 |
| 1.2 | FNA21 | 0.104 |
| 1.4 | FNA22 | 0.1192 |
| 1.4 | FNA23 | 0.1058 |
| 1.4 | FNA24 | 0.1262 |
| 1.6 | FNA25 | 0.1457 |
| 1.6 | FNA26 | 0.1081 |
| 1.6 | FNA27 | 0.0968 |
| 1.8 | FNA28 | 0.1178 |
| 1.8 | FNA29 | 0.1523 |
| 1.8 | FNA30 | 0.1214 |
| 2 | FNA31 | 0.1333 |
| 2 | FNA32 | 0.1336 |
| 2 | FNA33 | 0.1513 |

**Table B4 Training of file X62 with increasing amounts of noise**

| Noise in validation set | FNA1 | FNA5 | FNA8 | FNA11 | FNA13 | FNA16 | FNA20 | FNA23 | FNA27 | FNA28 | FNA31 |
|---|---|---|---|---|---|---|---|---|---|---|---|
| 0 | 0.1111 | 0.1151 | 0.1299 | 0.1204 | 0.1177 | 0.1387 | 0.1164 | 0.1265 | 0.1596 | 0.1424 | 0.1654 |
| 0.1 | 0.7489 | 0.1161 | 0.1322 | 0.1199 | 0.1176 | 0.1412 | 0.118 | 0.1244 | 0.1603 | 0.1415 | 0.1645 |
| 0.2 | 0.7559 | 0.1319 | 0.1298 | 0.122 | 0.1196 | 0.1384 | 0.1175 | 0.1292 | 0.1603 | 0.1442 | 0.1693 |
| 0.3 | 0.7749 | 0.1329 | 0.1324 | 0.1276 | 0.1232 | 0.1371 | 0.1203 | 0.1242 | 0.1493 | 0.1374 | 0.1572 |
| 0.4 | 0.7706 | 0.1461 | 0.1457 | 0.1351 | 0.1342 | 0.1425 | 0.1351 | 0.1473 | 0.1618 | 0.1594 | 0.1721 |
| 0.5 | 0.7834 | 0.1625 | 0.1705 | 0.1351 | 0.147 | 0.1478 | 0.1428 | 0.1616 | 0.1631 | 0.1475 | 0.1699 |
| 0.6 | 0.7731 | 0.2001 | 0.166 | 0.1479 | 0.1512 | 0.15 | 0.1595 | 0.1549 | 0.1608 | 0.1475 | 0.1792 |
| 0.7 | 0.7799 | 0.2463 | 0.1971 | 0.173 | 0.171 | 0.1587 | 0.1682 | 0.1498 | 0.1683 | 0.1624 | 0.1674 |
| 0.8 | 0.7675 | 0.2304 | 0.2123 | 0.1943 | 0.1891 | 0.1752 | 0.173 | 0.1771 | 0.1916 | 0.167 | 0.1683 |
| 0.9 | 0.7872 | 0.2695 | 0.2112 | 0.1943 | 0.1876 | 0.1684 | 0.1705 | 0.1574 | 0.1789 | 0.1583 | 0.1741 |
| 1 | 0.7759 | 0.2915 | 0.257 | 0.235 | 0.2169 | 0.1786 | 0.1987 | 0.2183 | 0.1967 | 0.1812 | 0.1785 |
| 1.1 | 0.7801 | 0.3146 | 0.2637 | 0.2241 | 0.2256 | 0.202 | 0.2018 | 0.2098 | 0.2105 | 0.1836 | 0.1886 |
| 1.2 | 0.7642 | 0.3706 | 0.3082 | 0.2596 | 0.2567 | 0.2233 | 0.2318 | 0.2526 | 0.2009 | 0.201 | 0.1984 |
| 1.3 | 0.7766 | 0.3532 | 0.309 | 0.2925 | 0.2529 | 0.244 | 0.2429 | 0.2326 | 0.2223 | 0.2036 | 0.2077 |
| 1.4 | 0.7919 | 0.3586 | 0.3152 | 0.2751 | 0.2532 | 0.2421 | 0.2469 | 0.2601 | 0.2299 | 0.2093 | 0.2175 |
| 1.5 | 0.7733 | 0.416 | 0.3409 | 0.2913 | 0.2794 | 0.2661 | 0.2494 | 0.2535 | 0.2053 | 0.2244 | 0.2342 |
| 1.6 | 0.7913 | 0.39 | 0.338 | 0.2932 | 0.3017 | 0.2504 | 0.263 | 0.2684 | 0.225 | 0.2403 | 0.2132 |
| 1.7 | 0.7884 | 0.4353 | 0.3832 | 0.3198 | 0.3376 | 0.296 | 0.2628 | 0.2787 | 0.277 | 0.2389 | 0.2368 |
| 1.8 | 0.7779 | 0.4363 | 0.4025 | 0.344 | 0.3304 | 0.2955 | 0.2783 | 0.2964 | 0.2655 | 0.2241 | 0.241 |
| 1.9 | 0.7785 | 0.464 | 0.3909 | 0.3662 | 0.3316 | 0.3246 | 0.3125 | 0.3011 | 0.2661 | 0.264 | 0.2804 |
| 2 | 0.7804 | 0.4602 | 0.3992 | 0.3901 | 0.3315 | 0.3197 | 0.3151 | 0.3041 | 0.2829 | 0.237 | 0.2305 |
| | | | | | | | | | | | |
| Average | 0.7443 | 0.2877 | 0.2540 | 0.2267 | 0.2179 | 0.2067 | 0.2012 | 0.2061 | 0.2017 | 0.1864 | 0.1959 |
| Standard deviation | 0.1455 | 0.1234 | 0.0992 | 0.0885 | 0.0796 | 0.0655 | 0.0656 | 0.0649 | 0.0429 | 0.0399 | 0.0335 |

**Table B5 Effect of noise in the validation data on trained ANN**

# C: Primary Coolant Monitor Results

**Single Time Step**

| FILE NAME | LAYER 1 | LAYER 2 | RMS error |
|---|---|---|---|
| A1 | 16 | 12 | 0.187078 |
| A2 | 16 | 10 | 0.18951 |
| A3 | 16 | 8 | 0.182427 |
| A4 | 16 | 6 | 0.178421 |
| A5 | 16 | 4 | 0.226477 |
| A6 | 14 | 12 | 0.189774 |
| A7 | 14 | 10 | 0.18873 |
| A8 | 14 | 8 | 0.18249 |
| **A9** | **14** | **6** | **0.172226** |
| A10 | 14 | 4 | 0.286537 |
| A11 | 12 | 12 | 0.181359 |
| A12 | 12 | 10 | 0.199172 |
| A13 | 12 | 8 | 0.178152 |
| A14 | 12 | 6 | 0.192903 |
| A15 | 12 | 4 | 0.252449 |
| A16 | 10 | 12 | 0.179889 |
| A17 | 10 | 10 | 0.194358 |
| A18 | 10 | 8 | 0.194806 |
| A19 | 10 | 6 | 0.199407 |
| A20 | 10 | 4 | 0.198946 |
| A21 | 8 | 12 | 0.175807 |
| A22 | 8 | 10 | 0.187086 |
| A23 | 8 | 8 | 0.191555 |
| A24 | 8 | 6 | 0.203062 |
| A25 | 8 | 4 | 0.277354 |
| A26 | 6 | 12 | 0.209713 |
| A27 | 6 | 10 | 0.199976 |
| A28 | 6 | 8 | 0.194458 |
| A29 | 6 | 6 | 0.221167 |
| A30 | 6 | 4 | 0.257711 |

## Two Time Steps

| FILE NAME | LAYER 1 | LAYER 2 | RMS error |
|---|---|---|---|
| B1 | 24 | 16 | 0.129966 |
| B2 | 24 | 14 | 0.13565 |
| B3 | 24 | 12 | 0.125653 |
| B4 | 24 | 10 | 0.128832 |
| B5 | 24 | 8 | 0.127018 |
| **B6** | **24** | **6** | **0.121968** |
| B7 | 22 | 16 | 0.131249 |
| B8 | 22 | 14 | 0.134367 |
| B9 | 22 | 12 | 0.129163 |
| B10 | 22 | 10 | 0.137943 |
| B11 | 22 | 8 | 0.132099 |
| B12 | 22 | 6 | 0.126523 |
| B13 | 20 | 16 | 0.129888 |
| B14 | 20 | 14 | 0.134833 |
| B15 | 20 | 12 | 0.132106 |
| B16 | 20 | 10 | 0.133119 |
| B17 | 20 | 8 | 0.125792 |
| B18 | 20 | 6 | 0.130315 |
| B19 | 18 | 16 | 0.137765 |
| B20 | 18 | 14 | 0.127822 |
| B21 | 18 | 12 | 0.13734 |
| B22 | 18 | 10 | 0.126106 |
| B23 | 18 | 8 | 0.128838 |
| B24 | 18 | 6 | 0.132644 |
| B25 | 16 | 16 | 0.132075 |
| B26 | 16 | 14 | 0.136684 |
| B27 | 16 | 12 | 0.134345 |
| B28 | 16 | 10 | 0.140852 |
| B29 | 16 | 8 | 0.144664 |
| B30 | 16 | 6 | 0.130387 |
| B31 | 14 | 16 | 0.134411 |
| B32 | 14 | 14 | 0.133094 |
| B33 | 14 | 12 | 0.135172 |
| B34 | 14 | 10 | 0.1358 |
| B35 | 14 | 8 | 0.135478 |
| B36 | 14 | 6 | 0.131262 |
| B37 | 12 | 16 | 0.1311 |
| B38 | 12 | 14 | 0.139507 |
| B39 | 12 | 12 | 0.138112 |
| B40 | 12 | 10 | 0.137786 |
| B41 | 12 | 8 | 0.147646 |
| B42 | 12 | 6 | 0.139856 |

**Three time steps**

| FILE NAME | LAYER 1 | LAYER 2 | RMS error |
|---|---|---|---|
| C1 | 27 | 17 | 0.104711 |
| C2 | 27 | 15 | 0.107908 |
| C3 | 27 | 13 | 0.113785 |
| C4 | 27 | 11 | 0.10166 |
| C5 | 27 | 9 | 0.098508 |
| C6 | 27 | 7 | 0.102642 |
| C7 | 25 | 17 | 0.108204 |
| C8 | 25 | 15 | 0.113085 |
| C9 | 25 | 13 | 0.10532 |
| C10 | 25 | 11 | 0.108302 |
| C11 | 25 | 9 | 0.101712 |
| C12 | 25 | 7 | 0.10694 |
| C13 | 23 | 17 | 0.112326 |
| C14 | 23 | 15 | 0.102636 |
| C15 | 23 | 13 | 0.10468 |
| C16 | 23 | 11 | 0.111378 |
| **C17** | **23** | **9** | **0.096972** |
| C18 | 23 | 7 | 0.103358 |
| C19 | 21 | 17 | 0.111007 |
| C20 | 21 | 15 | 0.109732 |
| C21 | 21 | 13 | 0.107229 |
| C22 | 21 | 11 | 0.109089 |
| C23 | 21 | 9 | 0.100004 |
| C24 | 21 | 7 | 0.100972 |
| C25 | 19 | 17 | 0.105291 |
| C26 | 19 | 15 | 0.106962 |
| C27 | 19 | 13 | 0.110128 |
| C28 | 19 | 11 | 0.109667 |
| C29 | 19 | 9 | 0.107145 |
| C30 | 19 | 7 | 0.102466 |
| C31 | 17 | 17 | 0.106548 |
| C32 | 17 | 15 | 0.120648 |
| C33 | 17 | 13 | 0.107123 |
| C34 | 17 | 11 | 0.11834 |
| C35 | 17 | 9 | 0.119336 |
| C36 | 17 | 7 | 0.105957 |

**Four time steps**

| FILE NAME | LAYER 1 | LAYER 2 | RMS error |
|---|---|---|---|
| D1 | 28 | 16 | 0.133147 |
| D2 | 28 | 14 | 0.11837 |
| D3 | 28 | 12 | 0.114552 |
| D4 | 28 | 10 | 0.116557 |
| D5 | 28 | 8 | 0.110502 |
| D6 | 28 | 6 | 0.115617 |
| D7 | 26 | 16 | 0.130143 |
| D8 | 26 | 14 | 0.112685 |
| D9 | 26 | 12 | 0.111579 |
| D10 | 26 | 10 | 0.120447 |
| **D11** | **26** | **8** | **0.104759** |
| D12 | 26 | 6 | 0.111781 |
| D13 | 24 | 16 | 0.125872 |
| D14 | 24 | 14 | 0.125704 |
| D15 | 24 | 12 | 0.119773 |
| D16 | 24 | 10 | 0.115021 |
| D17 | 24 | 8 | 0.124038 |
| D18 | 24 | 6 | 0.105963 |
| D19 | 22 | 16 | 0.133344 |
| D20 | 22 | 14 | 0.120943 |
| D21 | 22 | 12 | 0.116951 |
| D22 | 22 | 10 | 0.123745 |
| D23 | 22 | 8 | 0.123225 |
| D24 | 22 | 6 | 0.135028 |
| D25 | 20 | 16 | 0.113594 |
| D26 | 20 | 14 | 0.121802 |
| D27 | 20 | 12 | 0.131562 |
| D28 | 20 | 10 | 0.119046 |
| D29 | 20 | 8 | 0.125952 |
| D30 | 20 | 6 | 0.139183 |

# D: Sample MATLAB code for Operators Advisory System

```
% m file advisor
% This is a script for the overall PWR operator's advisory system
% It uses jloca.m and faultann1b.m

% returns 6 real valued outputs

%       (c) Peter Weller, Llew D'Souza, Alex Thompson
%           City University
%       12/1/06


clear all
close all

global Yout1 Yout2 Yout3 Yout4 Yout5 Yout6 small medium large leakr

%initialize;

%sim10;


load ('testfile.txt');


faultann1b;
% Yout1 = 1; % Check point for checking outcome of second ANN, toggle on/off for use

if Yout1 > 0.95

  jloca;
  j2loca;
  jloca3;
  if testfile(11, 33) > A & testfile(11, 33) < B
    dsl = (testfile(11, 33)-C)/D;
    break;
  else
  end
```

```
else
   if Yout5 > 0.95
      n = input('Is the transient a GROUP DROP Y/N ' ,'s');
      if n == 'Y'
         disp ('program end')
         break;
      else
         disp ('unknown transient has occured')
      end
   end
   if Yout3 > 0.95
      n = input('Is the transient a throttle opening Y/N ' ,'s');
      if n == 'Y'
         disp ('program end')
         break;
      else
         disp ('unknown transient has occured')
      end
   end
   if Yout6 > 0.95
      n = input('Is the transient a SINGLE ROD DROP  Y/N ' ,'s');
      if n == 'Y'
         disp ('program end')
         break;
      else
         disp ('unknown transient has occured')
      end
   end
   disp ('program end')
end;

leakr=[0 0 7000 7000];
leakt=[0 50 51 300];

if small <= 0.45
   leakr=[0 0 small small]
   disp('Primary coolant leak of ');
   disp(small)
elseif medium > 0.45 & medium <= 1.6
   leakr=[0 0 medium medium];
```

```
   disp('Primary coolant leak of ');
   disp(medium)
elseif large > 1.6
   leakr=[0 0 large large];
   fprintf('Primary coolant leak of %5f kg/s', large)
end

if leakr == [0 0 7000 7000]
   break;
else
   oSim10;
end
%inptime2;

% Comparator between calculated and recorded values

comp = zeros(2, 1);
comp(1,1) = 100 + ((pres(ned, 1) - testfile(10,27)*100)/testfile(10,27));
comp(2,1) = 100 + ((levp(ned, 1) - testfile(10,28)*100)/testfile(10,28));

if comp(1,1) <= 5 & comp(1,1) >= -5 & comp(2,1) <= 5 & comp(2,1) >= -5
   plot(tp,pp,tp,tc,tp,th,tp,ts,tp,levp,tp,pres)
else
   disp('out of limits')
end

x = pres(1);
y = levp(1);



% End of program
```