JUNE 1992

ECN-RX -92-033

NL92C0492

ECN

energy innovation

ON-LINE PLANT-WIDE MONITORING USING NEURAL NETWORKS

E. TÜRKCAN
Ö. ÇIFTÇIOGLU
E. ERYÜREK
BELLE R. UPADHYAYA

ON-LINE PLANT-WIDE MONITORING USING NEURAL NETWORKS

E. TÜRKCAN
Ö. ÇIFTÇIOGLU*
E. ERYÜREK**
BELLE R. UPADHYAYA**

*ISTANBUL TECHNICAL UNIVERSITY, ELECTRICAL ENGINEERING FACULTY,
80191 TEKNIK UNIVERSITE, ISTANBUL, TURKEY
**UNIVERSITY OF TENNESSEE, KNOXVILLE, DEPARTMENT OF NUCLEAR ENGINEERING,
KNOXVILLE, TENNESSEE 37996-2300, USA

PAPER SUBMITTED TO 8TH POWER PLANT DYNAMICS, CONTROL & TESTING SYMPOSIUM,
MAY 27-29, 1992, KNOXVILLE, TENNESSEE, USA

The Netherlands Energy Research Foundation ECN is the leading institute in the Netherlands for energy research. ECN carries out pure and applied research in the fields of nuclear energy, fossil fuels, renewable energy sources, environmental aspects of energy supply, computer science and the development and application of new materials. Energy studies are also a part of the research programme.

ECN employs more than 900 staff. Contracts are obtained from the government and from national and foreign organizations and industries.

ECN's research results are published in a number of report series, each series serving a different public from contractors to the international scientific world.

This RX-series is used for publishing pre-prints: the preliminary versions of articles that will appear in a journal, or conference or symposium proceedings. Please do not refer to this report but use the reference provided on the title page: 'To appear in ...' or 'Submitted for publication to ...'.

The Netherlands Energy Research Foundation ECN
Service Unit General Services
P.O. Box 1
NL-1755 ZG Petten
The Netherlands
Telephone: +31 2246 43 23
Fax : +31 2246 34 83

This report is available on remittance of Dfl. 20 to:
ECN, SU General Services, Petten,
The Netherlands.
Giro account (postal account) No. 3977703.
Please quote the report number.

1/2/

ON-LINE PLANT-WIDE MONITORING USING NEURAL NETWORKS

Erdinç Türkcan,
Netherlands Energy Research Foundation ECN,
P.O. Box 1, 1755 ZG Petten, The Netherlands

Özer Çiftçioglu,
Istanbul Technical University, Electrical Engineering Faculty,
80191 Teknik Universite, Istanbul, Turkey

Evren Eryürek and Belle R. Upadhyaya,
University of Tennessee, Knoxville, Department of Nuclear
Engineering, Knoxville, Tennessee 37996-2300, U.S.A.

ABSTRACT

The on-line signal analysis system designed for a multi-level mode operation using neural networks is described. The system is capable of monitoring the plant states by tracking different number of signals up to 32 simultaneously. The data used for this study were acquired from the Borssele Nuclear Power Plant (NPP) (PWR type), and using the on-line monitoring system. An on-line plant-wide monitoring study using a multilayer neural network model is discussed in this paper. The backpropagation neural network algorithm (BPN) is used for training the network. The technique assumes that each physical state of the power plant can be represented by a unique pattern of instrument readings which can be related to the condition of the plant. When a disturbance occurs, the sensor readings undergo a transient, and form a different set of patterns which represent the new operational status [1]. Diagnosing these patterns can be helpful in identifying this new state of the power plant. To this end, plant-wide monitoring with neural networks is one of the new techniques in real-time applications.

Plant-wide monitoring requires essential sensory signals which indicate the exact operational status of an NPP. Providing this requirement is fulfilled, several advantages of the plant-wide monitoring can be exercised using the neural network paradigms. Entire patterns of the signals are tracked and the deviation from the patterns identified in normal operational conditions are considered to be probable malfunctions in the operation. In case an anomaly occurs then one or more signals will deviate from their normal operational behaviour so that different patterns will follow.

The number of the hidden layer nodes are determined by a statistical methodology. The network inputs are provided with the corresponding live sensory signals to produce outputs for on-line monitoring. Since the set of output signals form a pattern, any deviation in one of the sensory information from normal results in change in pattern in real-time.

The study revealed that neural network approach is rather satisfactory

for surveillance, the technique being another aid replacing model-based approaches. In the paper the detection of purposely designed mismatching operational conditions are demonstrated and network performance is thoroughly verified.

INTRODUCTION

Surveillance having reliable accurate information has always been recognized as a prime need in nuclear power plant operation. This is essentially because in nuclear power plants, it is important to identify the failures in early stage and diagnose before significant degradation in performance takes place. The importance of surveillance for early failure detection is quite obvious from the operational safety as well as from the view point of operation and maintenance costs. With the advance of computer technology the novel surveillance techniques are included in the existing methods. A general survey of such methods occasionally takes place in literature [2]. In a surveillance process, real-time based algorithms are of primary concern. Real-time based applications mainly use model-based system estimation approach, a particular form of which is the Kalman estimator. Such an estimator is optimal in the least-mean-square sense and can be used in adaptive form following the system dynamics. Majority of these methodes identify a system failure by means of pattern recognition techniques. One of the important measures used for this purpose is the Mahalanobis distance. Such a distance measure formed by lattice filter estimation in real-time is described earlier [3].

However, one drawback of the method using real-time estimation methodology is the computational burden for the cost of its excellent performance. In recent years, neural networks have been receiving a great deal of interest worldwide, because of their novel approach to pattern recognition problems in various areas. In this respect it is natural to conceive a neural network structure to be applied for surveillance of a system like a nuclear power plant as a redundant system or substitute for the existing implemented techniques.

As the neural networks consist of highly interconnected processing elements each of which contributes to transform an input pattern to an output pattern for easy recognition of a certain feature of interest. Among these features mention may be made of signal estimation, for example, which can be used for signal monitoring applications, as this is described in the section which follows.

PLANT-WIDE MONITORING THROUGH PATTERN CLASSIFICATION

Plant-wide monitoring by neural networks can be carried out as a signal estimation using the available information presented at the input. Each form of the input information is termed a pattern and the collective input information provides the neural network's ouput with the estimation. To achieve this, initially the input patterns (the characteristics of which are known) are introduced to the neural network to shape the network's structure in such a way that the known input characteristics are reflected at the output in a desired form. Since this procedure is essentially performed under supervision directed by the desired form required at the network's output, the execution of the task is termed as supervised training.

In the present research, the sensory information from an operating plant described in the following section, is used to form the patterns. It is aimed that the patterns are classified through the neural network and certain features are identified. Namely, a collection of date x^1, f^1 R_N are given. Then a function is sought that replicates the given data as accurate as possible. The function of concern which is from a class of functions, interpolates and desirably extrapolates the given data. If we denote the function as $f(x)$, then the trained neural network provides that $f(x^1)=f^1$. Here the problem is similar to classical interpolation and estimation problems. Conventionally, the classification can be accomplished by means of a multilinear classifier given by

$$\sum_{j=1}^{N} w_j x_j \leq \theta \tag{1}$$

where w_j and θ are constants subject to determination; N is a constant.

In place of a multilinear classifier, interconnected perceptron structure forming a neural network, can be used for classification. A perceptron is a basic computational element which is provided with some number of real quantities as input and it performs an affine linear transformation of those inputs of the form

$$\sum_{j=1}^{N} w_j x_j + \theta \tag{2}$$

Using the transformation in a sigmoidal function of the form

$$O(x) = \frac{1}{1+\exp(-\sum_{j=1}^{N} w_j x_j + \theta)} \tag{3}$$

we obtain a procedure which is similar to the case described by the inequality (1). As one notices, in the neural structure a perceptron together with a sigmoidal function performs, in a way, a continuous classification in contrast to the hard limitation in the multilinear case. The interconnected perceptrons in the form of layers collectively constitute a neural classifier so that particular features are subject to selection. Considering the perceptrons arranged in form of layers, the output of one layer is taken as the input for the following. The outputs of the last layer are weighted and summed together to produce the output of the network. A network may have multiple outputs providing different weightings and summations at the last layer. In the formation of the perceptron layers in a neural structure, Cybenko's theorem [4] provides an important result of concern. This implies that a two-layered neural structure of perceptrons can form any, possibly unbounded, convex region in the multidimensional space spanned by the inputs. Here the first layer following the input is termed as hidden layer and the second layer is

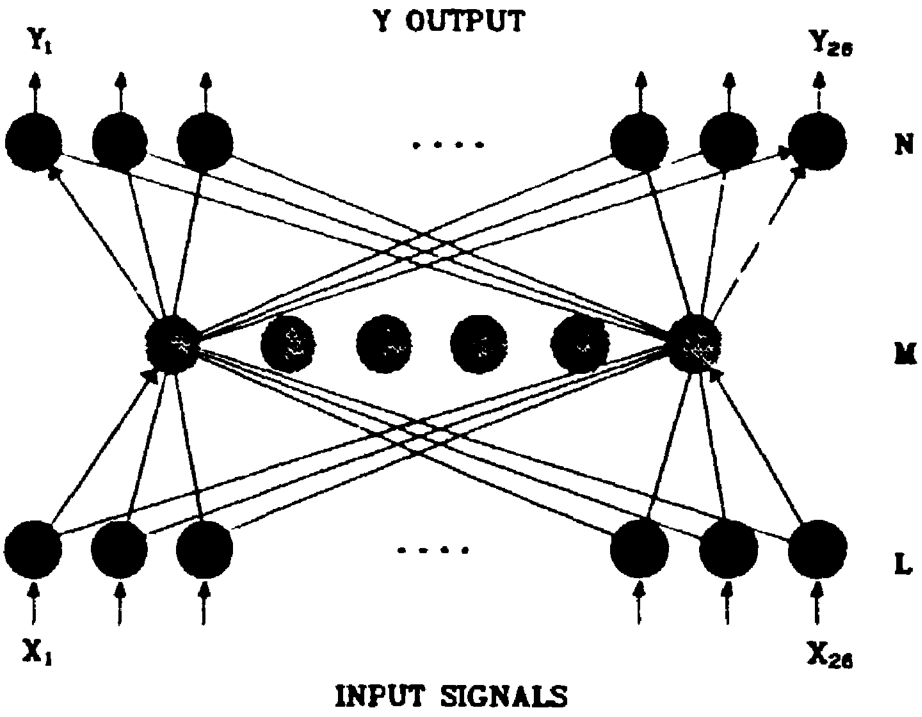


Fig 1 Autoassociative network topology L is the number of input layer nodes, M is the number of hidden layer nodes, N is the number of output layer nodes

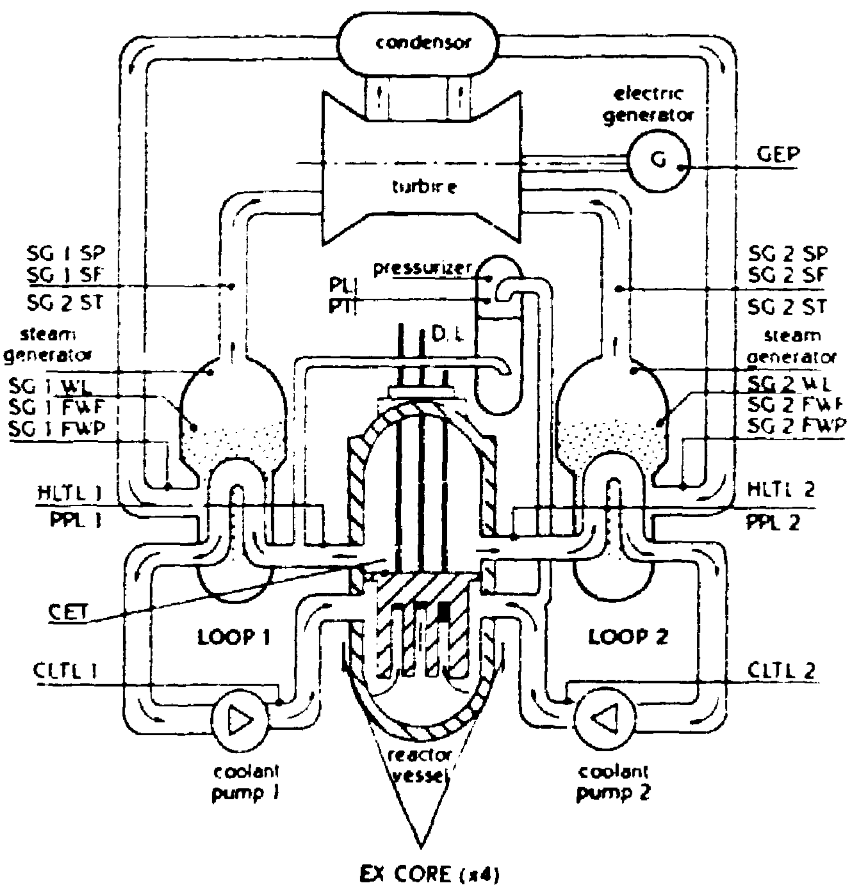


Fig 2 Schematic representation of Borselle nuclear power plant and measured signals

termed as the ouput layer. The convex regions are formed from intersections of the half-plane regions formed by each node in the first layer of the multi-layer perceptron. Therefore, the convex regions have at the most as many sides as there are nodes in the first layer and they are in form of convex poligons.

Cybenko's theorem provides one with an essential clue that one hidden layer is enough to form any convex region subject to selection, so that given an arbitrary collection of input/output data and by using a network with appropriate number of hidden layer nodes, the network can be trained to achieve any error criterion. However the theorem reveals no clue about the number of hidden layer nodes required. In this case different number of nodes corresponds to different classification of input information with the result that one may overlook the features of concern during feature selection. The extreme case of this takes place if an excessive number of hidden layer nodes is used. In this case correspondingly excessive number of classes are defined in the space spanned by the inputs where common features of concern are missing. In the network's learning such a case can be termed as memorizing rather than training. In some particular application , memorizing may be desirable [4]. However, in applications such as plant surveillance the training rather than memorizing is of particular concern since the common features defining normal operational conditions are required for signal estimation. Therefore, selection of the number of hidden layer nodes is considered to be an essential network parameter and a method of statistical test [5] is used for the parameter determination. The test involves a hypothesis testing using a random variable of F_{v_1,v_2} of degrees of freedom v_1 and v_2 formed as result of of a non-linear minimization procedure. For the application of F-test a decision level ℓ is defined in advance, corresponding to type I error probability in the hypothesis testing, such that the null hypothesis is accepted if $F \le \ell$ and rejected if $F > \ell$.

In view of the pattern classification considerations, autoassociative network topology is used for estimation following the training. The network is schematically shown in Fig. 1 where input signals are used for supervision, namely comparison at the output during the training. By the end of the training, each class formed in the multidimensional space represents the corresponding output signal in the training phase and the estimation is performed in form of the selection of the class. In this respect, selection of the signal ranges are important to define the class boundries. Neural network extrapolations beyond the signal ranges of training need to be carefully considered as the class boundries might be violated in this case.

REAL-TIME APPLICATIONS

In relation to present plant surveillance studies using neural networks, extensive off-line signal estimation has been performed [7,8]. Progressively the present work involves real-time application for wide range plant wide monitoring. The on-line plant data are obtained from the Borssele Nuclear Power Plant in the Netherlands [8]. The Borssele power plant is a two-loop pressurized water reactor with nominal electrical power output of 477 MWe. The on-line signal analysis system designed for the multi-level mode operation is capable of monitoring the plant state by tracking 32 DC and 32 AC signals simultaneously. In this application only the DC signals are used as input to neural networks.

The first test involves the data from normal operation with power dip on August 28/29, 1990. In this operation a special test was carried out upon the request of the reactor safety authority of the Netherlands. The schematic representation of the reactor with available signals is given in Fig. 2. 26 signals were used out of 32 available signals. The signals used in the analysis are indicated also in Fig. 2.

In order to investigate the signal estimation property of the network, the training is performed in the autoassociative mode for a duration of 150 min. The number of hidden layer nodes in the neural structure is M=6 and the number of output layer nodes is equal to the input nodes, L=N=26. The number of patterns used for training is 150. The training results collaborated the statistical tests considerations described in the preceding section so that the network is able to learn the input information with a low number of hidden layer nodes as an overdetermined system. Correspondingly training time takes relatively less time. Upon completion of the training the individual 26 monitoring signals are estimated for a duration of further 183 minutes. Four examplary figures (Figs. 3a, b, c and d) indicating satisfactory signal estimation performance of the network are presented. Concerning this particular data the steam generators' flows and pressures are slightly changed in the opposite directions adjusting a relevant valve where the operational status of the plant remains the same. The extrapolation by the neural network is clearly seen, although above mentioned individual signals i.e. steam-pressure and -flow signals are deliberately varied for a short period. This situation is seen in the relevant figures where a particular event is observed at about 100 minutes.

The second test involves the data of condenser rinsing on September 7, 1990. The signals used are described in Fig. 2. For the investigation of the signal estimation property of the network the training is performed in the autoassociative mode for a duration of 2000 seconds, the number of patterns used is 250. The number of hidden layer nodes in the neural structure is the same as in the first test. The range of the signals in this test is relatively less than the signal range of the first test. Upon completion of the training the 26 monitoring signals concerned are estimated for a duration of further 6000 seconds.

Four examplary figures (Figs. 4a, b, c and d) indicating satisfactory performance of signal estimation of the network are presented. Since the data belong to normal plant operation no particular point of concern is present.

The third test is aimed at investigating the network performance while the data used for training differs from the data used for signal estimation. In this respect the data from a wide range of normal operation (data of October 10, 1990) signals were used. Nineteen signals, excluding PP, PT, PL, SG1WL, SG2WL, D, L (see Fig. 2) from the previous set of signals are used. These data comprise 300 patterns, the duration of which is 300 minutes and all the patterns are used for training. The

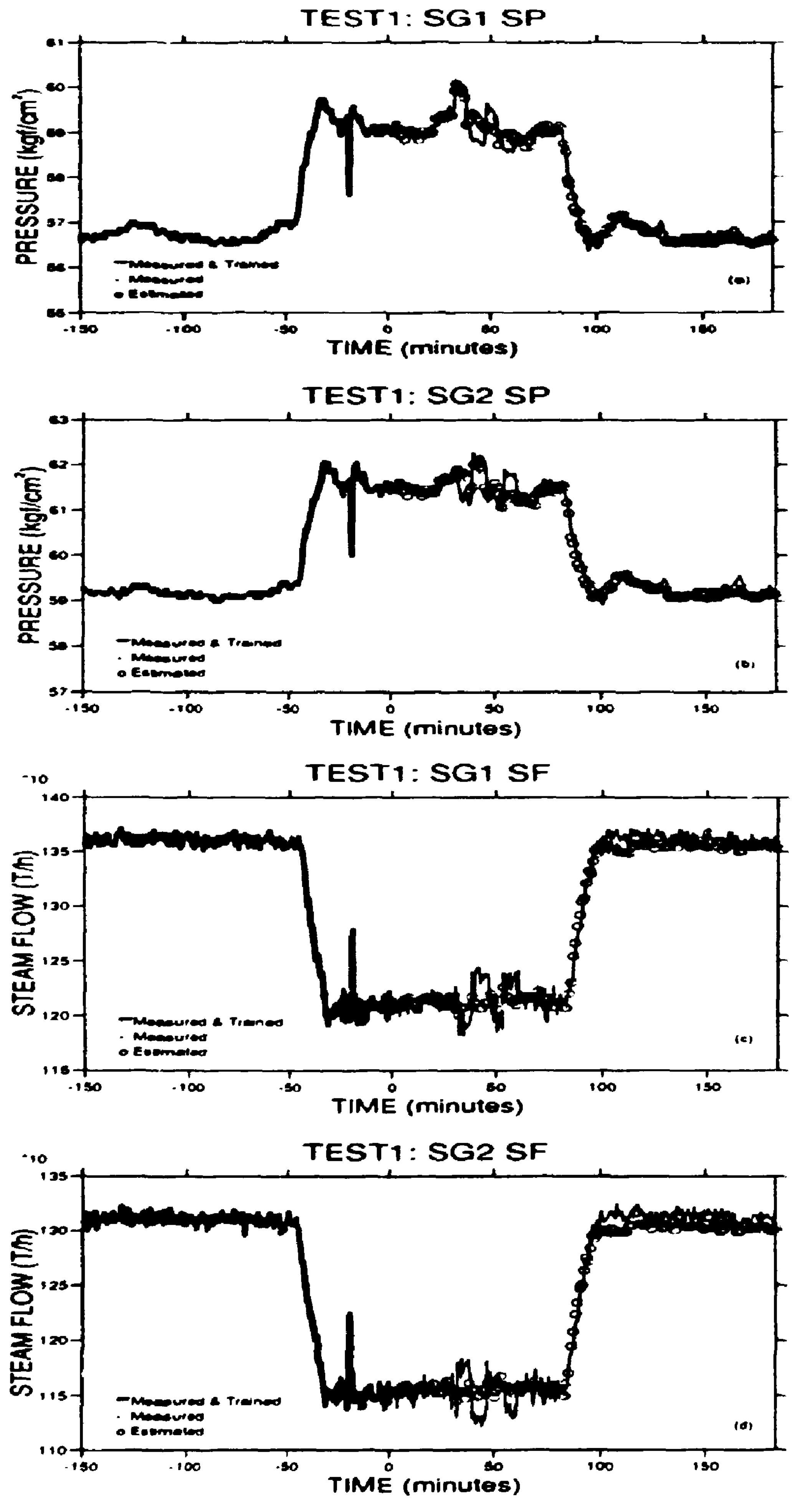


Fig 3 Test1 Neural network estimation for SG1 and SG2, steam pressure (a,b), steam flow(c,d)

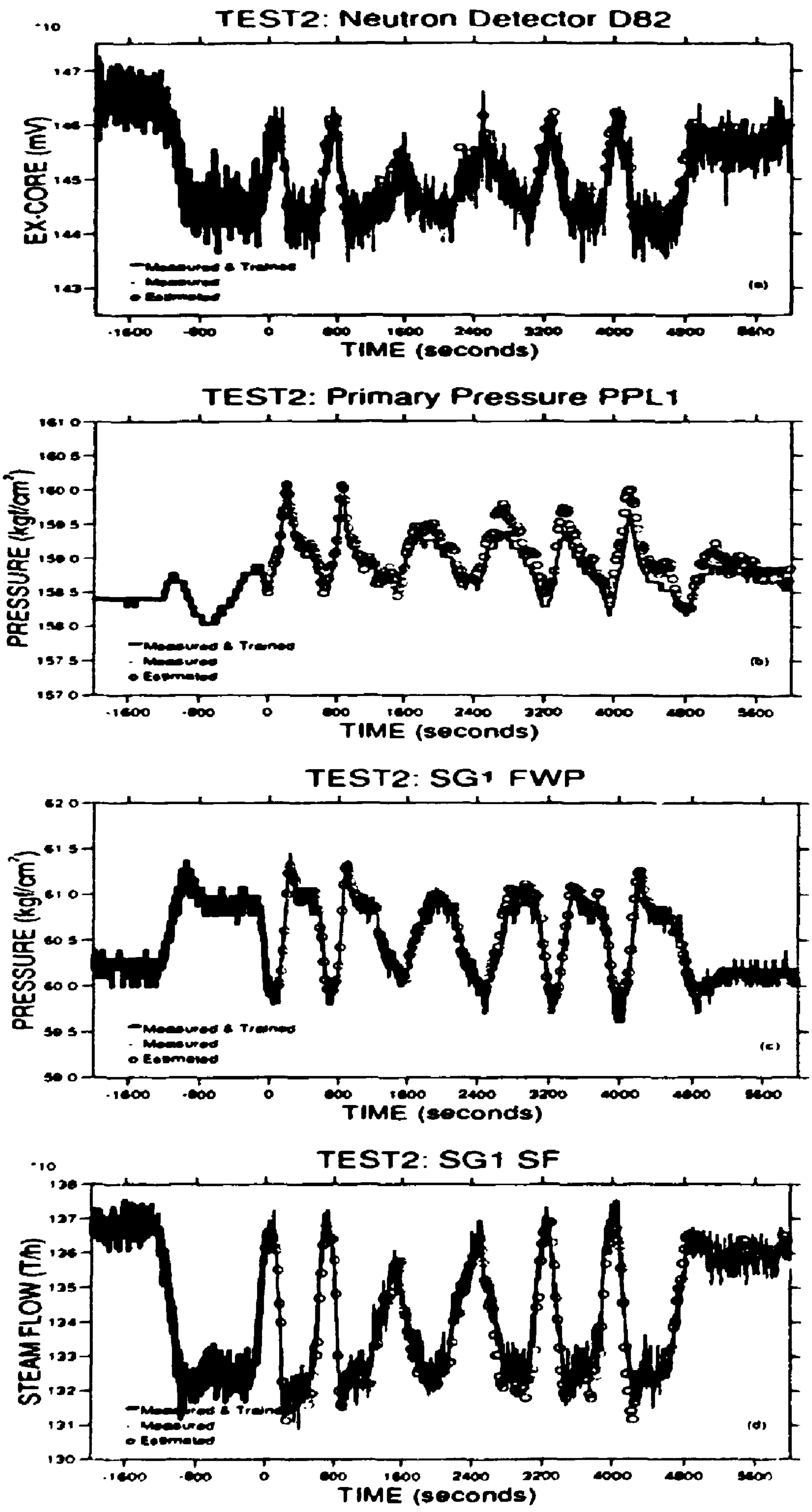
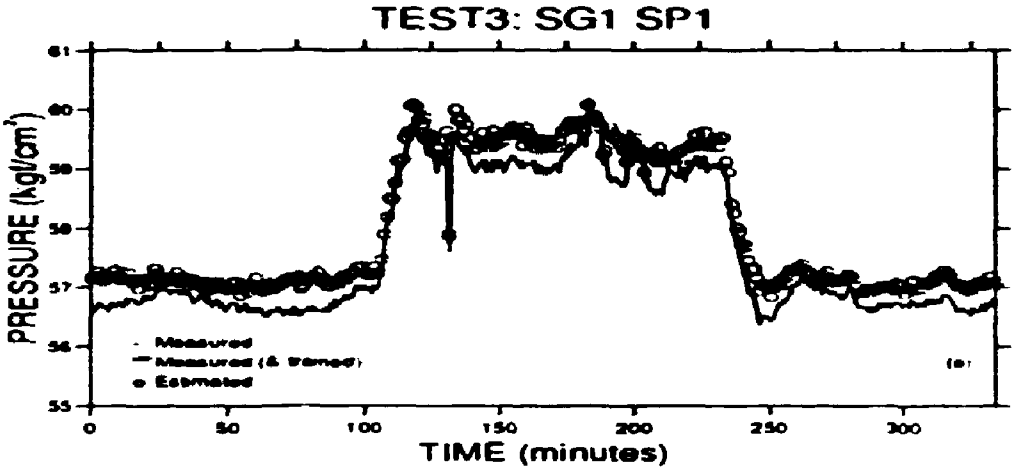


Fig 4 Test2 Neural network estimation for excore neutron detector (a), primary pressure loop1 (b), SG1 feed water pressure (c) and SG1 steam flow (d)



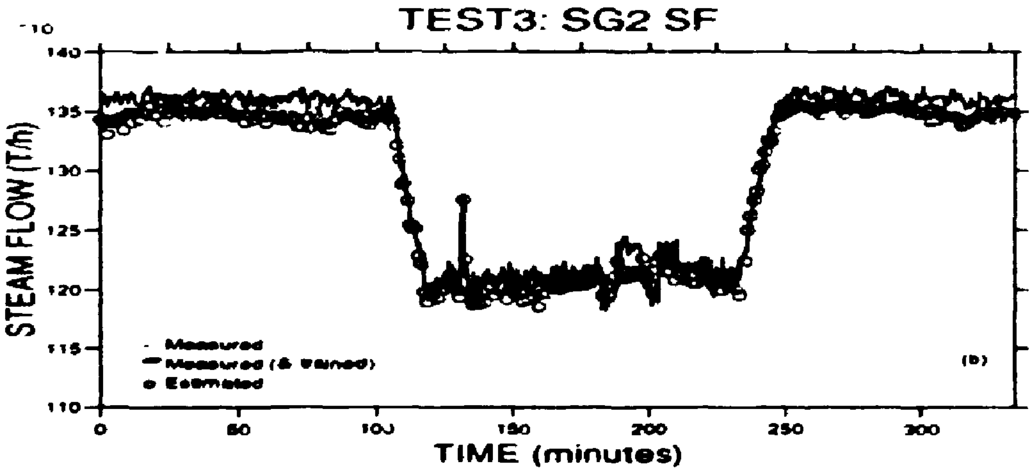


Fig 5 Test3 Investigation of network performance while the data used for training differs from the used for signal estimation (a) is the estimated signal of SG1 steam pressure. (b) is the estimated signal os SG2 steam flow

estimation results from the data of the first test are shown in Fig. 5a and Fig. 5b. The minor deviations in the estimation are due to extrapolations beyond the range.

CONCLUSIONS

This research presents signal estimation performance of artificial neural network in real-time environment. In power plant operation signal estimation has importance from the monitoring view point. It is concluded that the artificial feedforward neural structure can be satisfactorily implemented for this purpose. Important factors contributing to this achievement are the selection of the number of hidden layer nodes and the signal ranges used for training. Signal estimation by neural network is based on the overall reactor operational status so that in normal operation the estimated signals are in align with their nominal counterpart. Therefore minor individual changes in some signals are easily identified as they do not affect overall plant operation.

From the computational viewpoint using less number of hidden layer nodes based on the statistical tests provides the suitability of the neural structure for real-time application A small number of hidden-layer nodes also results in faster training.

Plant-wide monitoring requires important sensory signals which indicate the exact operational status of the plant. These signals having been implemented, several advantages of the plant-wide monitoring can be exercised by tracking the entire estimation of the signals in the form of extrapolation. The deviations of estimations from the nominal operational conditions are considered to probably be malfunctions in the operation. Such information can be also used for signal validation purposes incorporating the method with signal redundancy.

ACKNOWLEDGMENT

The authors gratefully acknowledge the NV EPZ Borssele Nuclear Power Plant Authorities for the permission to release the data in connection with this study.

REFERENCES

[1] E. Eryürek, B.R. Upadhyaya and R.E. Uhrig, "Development and Application of Multi-Layer Neural Networks for Estimation of Power Plant Variables", DOE Report DOE/NE/88ER 12824-01 (April 1991).

[2] Alan S. Willsky, "A Survey of Design Methods for Failure Detection in Dynamic Systems". Automatica, Vol. 12, pp 601 - 611 (1976).

[3] Ö. Ciftcioglu, E. Türkcan, "Failure Detection by Adaptive Lattice Modelling Using Kalman Filtering Methodology": Application to NPP. ECN-RX--91-025 (March 1991).

[4] George Cybenko, "Approximation by Superpositions of a Sigmoidal Function", Mathematics of Control, Signals and Systems, 2, pp 303 - 314 (1989).

[5] K. Doya and S. Yoshizawa, "Memorizing Oscillatory Patterns in the Analog Neural Network", 1989 IEEE, INS International Joint Conference on Neural Networks, Vol. 1, IEEE Catalog Number 89 CH.2765-6.

[6] Ö. Ciftcioglu and E. Türkcan, "Statistical Methodology for Selection of Hidden Layer Nodes". ECN-R-92-001 (1992).

[7] E. Eryürek and E. Türkcan, "Neural Networks for Sensor Validation and Plant-Wide Monitoring". ECN-RX--91-089 (August 1991).

[8] E. Türkcan and Ö, Ciftcioglu, "Pattern Classification Studies by Neural Networks". ECN-RX--91-116 (December 1991).

[9] E. Türkcan, W.H.J. Quaadvliet, T.T.J.M. Peeters and J.P. Verhoef, "Operational Experiences on the Borssele Nuclear Power Plant Using Computer Based Surveillance and Diagnostic System On-line". ECN-RX--91-057 (June 1991).