# HYBRID DIGITAL SIGNAL PROCESSING
# AND
# NEURAL NETWORK APPLICATIONS IN PWRS

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## ABSTRACT

Signal validation and plant subsystem tracking in power and process industries require the prediction of one or more state variables. Both heteroassociative and auotassociative neural networks were applied for characterizing relationships among sets of signals. A multi-layer neural network paradigm was applied for sensor and process monitoring in a Pressurized Water Reactor (PWR). This nonlinear interpolation technique was found to be very effective for these applications.

## INTRODUCTION

In recent years, the neural network approach has emerged as a powerful tool for achieving high computational effectiveness in mapping one set of information to another. The hybrid technique of digital signal processing and parallel distributed processing has been shown to overcome problems related to physical or empirical modeling. Other applications include parameter estimation, chemometric data analysis, speech recognition, pattern classification, and process control. Often it is necessary to pre-process network input information in order to achieve the greatest sensitivity in the relationship between the input and the desired output. Digital signal processing techniques such as spectral-domain estimation, signal smoothing, and other data-dependent transformation are routinely applied.

Signal validation and plant-wide monitoring are two of the industrial applications of multi-layer neural network techniques. Signal validation can improve the effectiveness of control and protection systems. "Signal validation is used to check the consistency of redundant measurements of selected process variables, estimate their expected values from measurements, and detect, isolate and characterize the type of anomaly in the instrument channel outputs [1]." The routine validation of critical signals in a reactor system, especially in a nuclear power plant, plays a vital role in monitoring incipient changes in sensor behavior [2] [3]. In plant-wide monitoring, several signals from different parts of a plant are simultaneously tracked and deviations of one or more signals from their expected values are monitored. If any deviation is detected by the monitoring system,

it will be easier for the operator to identify an incipient problem.

Traditionally model-based techniques are used for estimating process variables in validation techniques. Model-based techniques assume a fixed structure for characterizing steady-state or transient relationships among process variables. The accuracy of the model depends highly on the assumed structure (or the degree of the polynomial relationship). Neural network (distributed parallel processing) paradigms offer a number of advantages when compared to model-based techniques. Most importantly it is not necessary to define a functional form relating a set of process variables. The functional form as defined by an Artificial Neural System (ANS) is implicitly nonlinear. Neural networks do not require the detailed system specifications. Finally, neural network models are more fault-tolerant in the presence of noise and with an incomplete information than the traditional techniques [2].

An adaptive backpropagation network (BPN) [4] was used to create models for estimating one or more signals. The algorithm was developed and implemented on a VAX workstation. Several significant improvements were made to the basic algorithm and had resulted in accelerated training and improved accuracy. Normally neural network parameters which appear in the weight updating and thresholding equations are kept constant during the learning period. Studies have shown that changing these parameters during the learning phase accelerates convergence and improves accuracy. We have concluded that progressively adjusting the threshold shaping parameter (thus leading to the terminology adaptive backpropagation neural network) is the most important part of accelerating the convergence and improving the accuracy. Another important parameter in the BPN, the so called *momentum term*, was also employed in this study. An important point during network training is that increasing the learning coefficient may trap the error function at a local minimum. The momentum term can be used to overcome this problem [5]. The momentum term coefficient provides a form of rate-of-change in weight space that effectively filters out high-frequency variations of the weights [2].

The most important part of a multi-layer neural network topology is the hidden layer(s). These layers are introduced to handle the nonlinear relationship in the data. These layers do not have direct connections to the outside world, and they make it possible to improve the nonlinear interpolation of input-output relationships. Recent studies have shown that one hidden layer is enough to solve most of the nonlinear problems [6]. One of the most important issues is the size of the hidden layer. An empirical formula was developed based on Shannon's information theory [7]. This formula was derived from the following observations:

1. A three-layer neural network is sufficient to solve estimation problems.

2. The minimum number of required hidden units is $log_2 N$ ([5] Chapter 8) where $N$ is the number of training patterns.

Depending on these facts, the empirical formula for estimating the optimum hidden layer size, especially for signal validation and plant-wide monitoring applications, is given by

$$H = I \times log_2 N \pm I \qquad (1)$$

where $I$ is the size of the input vector and $N$ is the number of training patterns [2].

# NEURAL NETWORKS APPLICATIONS IN THE NUCLEAR INDUSTRY

Neural networks are intrinsically parallel and non-algorithmic methods; these features of neural networks make real-time processing of data and information feasible. Some of the applications of neural networks include nuclear fuel management, multi-sensor information fusion, sensor validation, control problems, plant-wide monitoring, and pattern recognition for diagnostics of plant malfunctions [8].

Neural networks have been traditionally used for pattern classification and similar problems. Such networks perform reliably even when used with noisy and incomplete data [8] [9]. Neural networks may also be used to adaptively control a system by optimizing control parameters. Another useful feature of neural networks is the ability to respond in real-time to changing system states whose descriptions are provided by the process sensors. For complex systems involving many sensors and possible fault types, estimating real-time response is a challenging problem in nuclear industry [2]. Once the networks are trained they can be implemented for fast recall. Unlike most other computer programs, neural networks can give high performance even when there is a failure in the network structure, such as a missing processing element.

## SUMMARY OF SIGNIFICANT RESULTS

The feasibility of using neural networks for signal validation and plant-wide monitoring problems was studied. Neural networks or parallel distributed processing was found to be highly suitable for the development of relationships among various parameters. Signal validation and plant-wide monitoring applications were completed using startup and steady-state data from operating Pressurized Water Reactors (PWRs). A *dynamic network* approach was developed for signal validation problems. The objective of this approach was to take into account any delay between the responses of the input and output variables used in training the networks. The inclusion of several previous samples and using them as inputs to the network improves the accuracy of network models [3]. The use of recurrent networks is another approach for characterizing transient responses [10]. The complexity of network training increases with the number of regression terms. Neural networks were also applied to detect venturi fouling by estimating feedwater flow rate and to estimate turbine first stage impulse pressure. Finally, neural networks were used to identify the mismatch between thermal power and generator power in a four-loop operating PWR.

## BACKPROPAGATION NETWORK (BPN) ALGORITHM

This section briefly discusses one of the most commonly used neural network training algorithms, namely the Backpropagation Network (BPN). BPN is applied to a multi-layer and fully connected network [5]. Figure 1 shows a typical topology for a three-layer perceptron. The first layer receives the information, and feeds it to the inner layers, the second layer which is commonly known as a hidden layer receives information from the input layer and propagates this forward through the connection weights. Hidden layer size and number of hidden layers are one of the important issues in the development of a network architecture. The hidden layers are used to

characterize the nonlinear properties of the system to be analyzed. Cybenko [11] has shown that nonlinear interpolation of the form $y = f(x)$ is possible through weighted summation of the outputs of processing elements which are, for example, characterized by a sigmoidal function (Equation 2). The last layer is the output layer where the desired output values received from the outside world and the calculated values are presented to the environment. The output layer consists of multiple processing elements. If the goal is to predict one variable as a function of $(x_1, x_2, \ldots, x_n)$, then the output will be a single processing element. If the purpose of using the BPN is plant-wide monitoring, then there will be many processing elements in the output layer; each processing element corresponding to one of the signals. The generalized delta rule is employed in calculating the error between the desired output and the calculated output [5].

The backpropagation algorithm has several limitations. One of them is that it cannot reach its extremities [0,1], therefore normalization of the training data is very important in BPN applications. The algorithm developed on the VAX workstation has the feature of automatic normalization between 0.1 and 0.9 which enables the network to reach the extremities. This type of normalization gives the advantage of interpolating and especially extrapolating the data.

The backpropagation network algorithm uses the generalized delta rule for training. Figure 1 shows the topology of the network. The algorithm as presented in [5] is outlined below.

1. Assign a random number $r$ (uniformly distributed) in the range $[+1,-1]$ to all the connection weights $w_{ij}^l$, and bias $\theta_j^l$ of all PE's.

2. Present the normalized input vector, between 0.1 and 0.9, to the first layer and propagate it to the output layer as

$$x_{jp}^l = \frac{1}{1 + e^{-\beta(\sum_i x_{ip}^{l-1} w_{ij}^l + \theta_j^l)}} \tag{2}$$

after which each PE in every layer of the network will have an associated value $x_{jp}^l$.

3. For each PE compute the local error at the output layer between the desired value and the calculated value using the generalized delta rule

$$\delta_{jp}^l = x_{jp}^l (1 - x_{jp}^l)(t_{jp}^l - x_{jp}^l) \tag{3}$$

where, $t_{jp}^l$ is the target value.

4. For each PE in the hidden layers, starting at the layer below the output layer and ending above the input layer, compute the local error by using

$$\delta_{jp}^l = x_{jp}^l (1 - x_{jp}^l) \sum_i \delta_{ip}^{l+1} w_{ij}^{l+1}. \tag{4}$$

5. Compute all the connection weight corrections by using

$$\Delta_p w_{ij}^l (n + 1) = \alpha(\delta_{jp}^l x_{ip}^{l-1}) + \mu \Delta_p w_{ij}^l (n). \tag{5}$$

where n indexes the presentation number, and the bias corrections are given by

$$\Delta \theta_j^l = \alpha \delta_j^l \tag{6}$$

6. Update all the connection weights by adding the weight corrections to the old weights as

$$w_{ij}^l(n+1) = w_{ij}^l(n) + \Delta_p w_{ij}^l(n+1) \qquad (7)$$

7. Update all the PE bias values by adding the bias corrections to the previous bias values as

$$\theta_j^l(n+1) = \theta_j^l(n) + \Delta\theta_j^l \qquad (8)$$

8. Present the next pattern, $p$, to the network until all the patterns are presented.

9. Repeat (step 2) until the error between the desired and the calculated values of the output is sufficiently small.

# SIGNAL VALIDATION APPLICATIONS USING PWR STARTUP DATA

The prediction of various process variables during the startup of a four-loop Westinghouse Pressurized Water Reactor (PWR) is considered first. The predicted values may be used for sensor validation, process monitoring. and diagnostics applications [2] [4].

Separate networks were developed for hot leg temperature, pressurizer level, steam generator main feedwater flow, and steam generator steam pressure. Many configurations with different inputs may be used for modeling each of these signals. It may be necessary to have redundant network models with different input combinations for the same output signal. If one of the sensors fails, then the other network will be responsible for estimating that signal.

Details of the networks and their results for several signals will be presented in tables and figures. For the case studies discussed. the networks were trained over the entire operational range. Different intervals were used for training and recalling data sets so that the interpolation and extrapolation capabilities of the BPN algorithm can be exploited. The software, developed on a VAX workstation, has the feature of normalizing the inputs and outputs in the range (0.1, 0.9). After training the networks, the output was denormalized and the variable was plotted showing both the measured and estimated values.

During these case studies, the number of processing elements in the hidden layer was determined by the formula developed under this project and is given by

$$H = I \times log_2 N \pm I$$

where I is the size of the input vector, N is the number of training patterns, and $\pm I$ is adjusted between 0 and $I$.

## Reactor Coolant System Hot Leg Temperature

Hot leg temperature signatures are very important in reactivity control using $T_{average}$ strategy. It is important to validate the sensor readings at each state of the plant. Several networks with

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different input combinations were developed for the hot leg temperature signal using startup data. Figure 2 shows the prediction of the hot leg temperature using the trained network (test data). The standard deviations for training and recalling are given in Table 1.

Table 1: Network Performance for Hot Leg Temperature in a PWR

| Input Signals | Reactor Power Pressurizer level RCS Cold Leg Temperature |
|---|---|
| Number of Training Patterns | 150 |
| Number of Hidden Nodes | 21 |
| Training Standard Deviation | 0.536 $^0F$ |
| Recalling Standard Deviation | 0.593 $^0F$ |

Table 2: Network Performance for Pressurizer Level in a PWR

| Input Signals | Reactor Power RCS Hot Leg Temperature Steam Generator Main feedwater Flow |
|---|---|
| Number of Training Patterns | 100 |
| Number of Hidden Nodes | 19 |
| Training Standard Deviation | 0.710 % |
| Recalling Standard Deviation | 0.818 % |

## Pressurizer Level

Several networks with different sets of input combinations were created for the pressurizer level signal. It should be noted that during the pressurizer analysis the charging pump flow was not included. It is necessary to include this signal, if available, as an input signal. One of the input sets included sensor readings of reactor power, hot leg temperature, and steam generator main feedwater flow. The other set included reactor power and hot leg temperature. Table 2 shows the standard deviation of estimation for training and recalling data sets of the network. Figure 3 compares the test data and interpolation using the network. A high degree of accuracy was observed in the performance of the above two networks.

## PLANT-WIDE MONITORING USING STEADY-STATE PWR DATA

The use of neural networks in diagnosing transient or abnormal conditions in nuclear power plants has been investigated [2] [12]. The technique is based on the fact that each physical state

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of the plant can be represented by a unique pattern of sensor outputs or instrument readings that can be related to the condition of the plant. When a disturbance occurs in a power plant, sensor outputs or instrument readings change, and form a different pattern that represents the new state of the plant. To implement a diagnostic tool based on this principle (which is useful in the operation of nuclear power plants) requires a real time method of pattern recognition. Artificial neural networks are able to provide this capability [8]. Plant-wide monitoring with neural networks is one of the real-time applications. In this particular application, there are many inputs and many outputs. These inputs and outputs may or may not be related to each other.

In the balance of plant (BOP) system, it is necessary to minimiaze the unaccounted heat lossses. This is the difference between the calculated and the measured heat rates. These losses sometimes may result from the measurement errors. Factors such as, low pressure turbine efficiency, changes in environmental conditions, and others would also contribute to this error. Computer programs are used for heat rate calculations based on thermal-hydraulic analysis methods and to determine unaccounted losses quantitatively. Diagnostic techniques are also used to determine, if possible, the corrective actions to be taken. An alternative approach to this problem is to apply plant-wide monitoring by using autoassociative BPN network models.

For this case study, steady-state data from an operating four-loop Westinghouse Pressurized Water Reactor were used. These data consisted of weekly measurements of plant variables and some calculated values based on these measurements. Typical data spanning fourty weeks were used during the neural network analysis. The training data included 14 signals. These signals and their physical units are given in Table 3. The first 32 out of 40 patterns were used to train the network, and the remaining eight patterns together with the first 32 were predicted by the network.

The standard deviation errors of the signals are given in Table 3. It was observed from the network results that most of the signals followed their expected patterns. There was only one signal with an apparent deviation from its expected pattern, namely, the generator output signal. Figure 4 shows the comparison between the actual and the predicted output values for the generator output signal.

# CONCLUSIONS

For effective control strategy development in nuclear power plant systems (without challenging their complex operability), it is necessary to validate plant sensors and to monitor a multitude of variables. Neural networks or parallel distributed proccesing is found to be highly suitable for developing relationships among various parameters. Neural networks are capable of performing arbitrary mapping from inputs to outputs without knowing the complete system specifications (a black-box approach to modeling). The following applications were completed using a multi-layer neural network algorithm, the *Backpropagation Network (BPN)*:

- Multiple-input single-output heteroassociative networks for signal validation of distributed sensor arrays.

- Multiple-input multiple-output autoassociative networks for plant-wide monitoring of a set of process variables for diagnostics.

Table 3: Network Performance of the Plant-wide Monitoring Network

| Input signals | Std. Dev. of Signals |
|---|---|
| Reactor Power, % | 0.051 |
| Ideal Generator Output, MWe | 0.771 |
| Measured Generator Output, MWe | 1.308 |
| Final Feedwater Temperature, $^0F$ | 0.115 |
| Impulse Pressure No. 1, Psig | 0.672 |
| Impulse Pressure No. 2, Psig | 0.911 |
| Feedwater Flow $10^6$ lbm/hr | 0.008 |
| Loop 1 Temperature Difference, $^0F$ | 0.053 |
| Loop 2 Temperature Difference, $^0F$ | 0.063 |
| Loop 3 Temperature Difference, $^0F$ | 0.067 |
| Loop 4 Temperature Difference, $^0F$ | 0.050 |
| Loop Avg. Temp. Difference, $^0F$ | 0.032 |
| Turbine Power Corrected to Design, MWc | 1.188 |
| Impulse Pressure average, Psia | 0.630 |

An enhanced version of the BPN algorithm was implemented on a VAX workstation. Several innovations were made in the original algorithm to accelerate the training and to improve the accuracy of the network models. The most important aspect of implementing neural networks is network training. In the normal use of neural networks, parameters which appear in the weight updating and thresholding (activation) function equations are held constant during the learning phase. The present study has shown that progressively changing these parameters during the learning phase, accelerates the convergence and improves the accuracy.

One of the open areas of multi-layer network research is the estimation of the size of the hidden layer. The studies completed in this research had shown that it is sufficient to use only one hidden layer for solving the signal validation, plant-wide monitoring, and diagnostics problems. An empirical formula for estimating the optimum size of the hidden layer in the above mentioned applications was developed based on Shannon's information .

The parameter estimation capability of neural networks is currently being investigated for estimating the moderator temperature coefficient of reactivity, $\alpha_c$, in a PWR. Preliminary results indicate the feasibility of this approach [13]. Further research is necessary for extending this technique to estimate performance parameters during a fuel cycle using networks that are trained on-line.
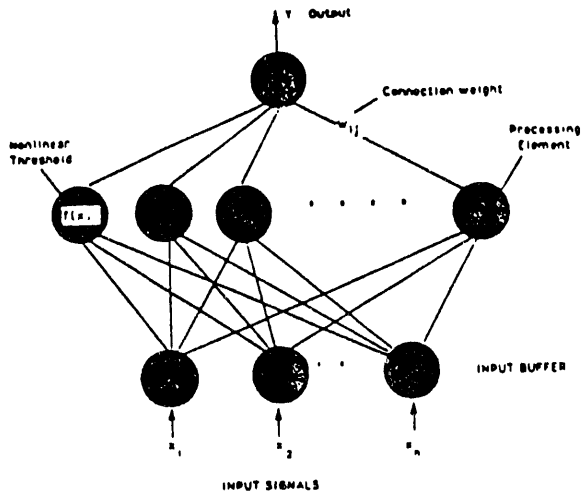
# ACKNOWLEDGMENTS

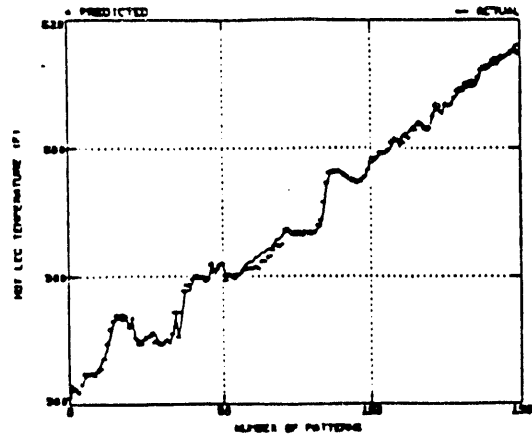Figure 1: Topology of a three-layer perceptron.



Figure 2: Prediction of hot leg temperature (test data) using the trained network.
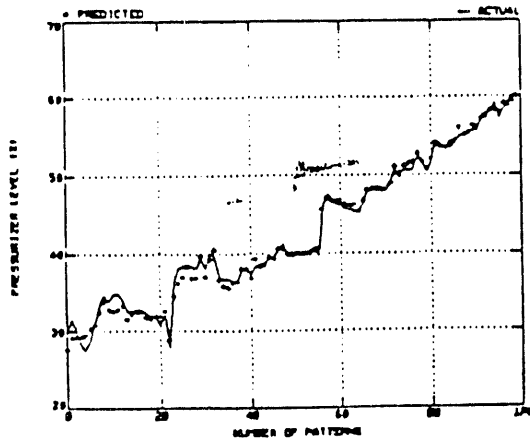


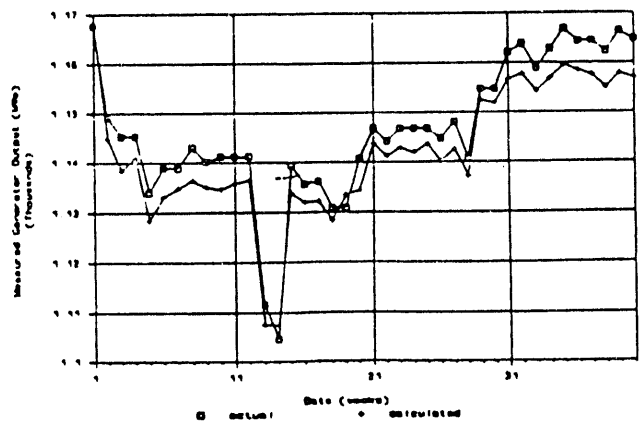Figure 3: Prediction of pressurizer level (test data) using the trained network.



Figure 4: Prediction of generator output signal using the trained network.

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