# Monitoring and fault detection: a comparative study using computational intelligence techniques

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***Abstract*— In this work, two different computational intelligence techniques - Neural Networks and Neuro-fuzzy - were used in the development of a Monitoring and Fault Detection system applied to the IEA-R1 experimental nuclear reactor. The monitoring is made by comparing an estimative of the variable generated by the computational intelligence techniques with the actual value. Both techniques have been successfully applied to the Monitoring System and were effective in estimate a monitored variable. The Neuro-Fuzzy technique showed strongly better performance compared with Neural Network.**

***Keywords—neural networks; fuzzy logic; neuro-fuzzy, ANFIS; modeling***

## I. INTRODUCTION

The interest in research and development of more robust methods on Monitoring and Fault Diagnosis have been encouraged because of the increasing demand on quality, reliability and safety in production processes. This interesting is justified due to complexity of some industrial processes, as chemical industries, power plants, and so on. In these processes, the interruption of the production due to some unexpected change can bring risk to the operator's security besides provoking economic losses, increasing the costs to repair some damaged equipment. Because of these two points, the economic losses and the operator's security, it becomes necessary to implement Monitoring and Diagnosis Systems [16] [12] [14] [6].

Nuclear power plants are complex system. There are a lot of variable numbers to be continuously observed in a nuclear power plant; moreover it is necessary to guarantee performance and safeness. During a fault the operators receive a lot of information through the instruments reading. Due to a lot of information in a short period of time, the operators are forced to take some decisions in stress conditions, so in some cases the fault diagnosis became difficult. Many techniques using Artificial Intelligence have been used in Monitoring and Fault Diagnosis with the purpose to help the nuclear power plants operators, including the Fuzzy Logic [13], Artificial Neural Networks (ANNs) [5] [1], the Group Method of Data Handling (GMDH) [3], Genetic Algorithms (AGs) [11] [5]. The uses of these techniques are justified because it is possible to model the process without using algebraic equations [8], by using only a database which contains the plant information.

The use of ANN is interesting because it can perform the correct input-output relationship for the given problem; This shortcoming prevents the ANN from providing expert knowledge about Monitoring and Fault Detection in heuristic terms which human prefer.

The problem of Monitoring and Fault Detection can be solved by incorporating the use of fuzzy logic and neural network (neurofuzzy). Fuzzy logic has the capability of transforming heuristic and linguistic terms into numerical values for use in complex machine computations by using fuzzy rules and membership functions [7]. For these reasons, fuzzy logic can be used to provide a general heuristic solution to a specific problem by using general heuristic knowledge about it.

The purpose of this work is to provide a comparative study by using Neural Networks and Neurofuzzy applied in Monitoring and Fault Detection in sensor of an experimental reactor.

## II. ARTIFICIAL NEURAL NETWORK

An ANN is a massively parallel distributed processor made up of simple processing units, which has a natural propensity for storing experiential knowledge and making it available for use. The knowledge is acquired by the networks from its environment through a learning process which is basically responsible to adapt the synaptic weights to the stimulus received by the environment. The fundamental element of a neural network is a neuron, which has multiple inputs and a single output, as we can see in Figure 1. It is possible to identify three basic elements in a neuron: a set of synapses where a signal $x_j$ at the input of synapse $j$ connected to the neuron $k$ is multiplied by the synaptic weight $w_{kj}$, an adder for summing the input signals, weighted by the respective synapses of the neuron; and an activation function for limiting the amplitude of the output of a neuron.

The neuron also includes an externally applied *bias*, denoted by $b_k$, which has the effect of increasing or lowering the net input of the activation function, depending on whether it is positive or negative, respectively [15].

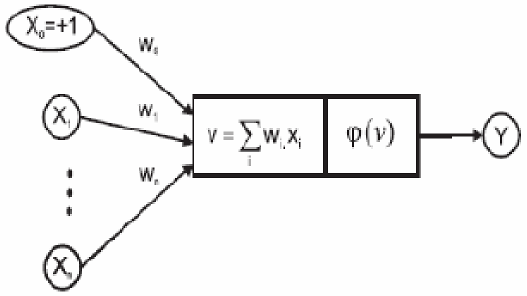


Figure 1. Neuron model

In this work, it was used the Multilayer Perceptron (MLP) neural network. In this kind of architecture, all neural signals propagate in the forward direction through each network layer from the input to the output layer. Every neuron in a layer receives its inputs from the neurons in its precedent layer and sends its output to the neurons in its subsequent layer. The training is performed using an error backpropagation algorithm, which involves a set of connecting weights, which are modified on the basis of a gradient descent method to minimize the difference between the desired output values and the output signals produced by the network, as shown in equation (XX):

$$E = \frac{1}{2}\sum_{m=1}^{m}\left(y_{dj}(n) - y_j(n)\right)^2 \qquad (1)$$

where $E$: mean squared error; $m$: number of neurons in the output layer; $y_{dj}$: target output; $y_j$: actual output; $n$: number of interactions.

## III. NEURO-FUZZY SYSTEMS

Neuro-fuzzy is a combination of artificial neural networks and fuzzy logic. A neuro-fuzzy system is a fuzzy system that uses a learning algorithm derived from or inspired by neural network theory to determine its parameters (fuzzy sets and fuzzy rules) by processing data samples.

Fuzzy logic is a form of many-valued logic or probabilistic logic; it deals with reasoning that is approximate rather than fixed and exact. Compared to traditional binary sets (where variables may take on true or false values) fuzzy logic variables may have a truth value that ranges in degree between 0 and 1. Fuzzy logic has been extended to handle the concept of partial truth, where the truth value may range between completely true and completely false [9]. Furthermore, when linguistic variables are used, these degrees may be managed by specific functions.

The term "fuzzy logic" was introduced with the 1965 proposal of fuzzy set theory by Lotfi A. Zadeh [10][4]. Fuzzy logic has been applied to many fields, from control theory to artificial intelligence. Fuzzy logics however had been studied since the 1920s as infinite-valued logics notably by Łukasiewicz and Tarski [4].

Neuro-fuzzy was proposed by J. S. R. Jang. Neuro-fuzzy hybridization results in a hybrid intelligent system that synergizes these two techniques by combining the human-like reasoning style of fuzzy systems with the learning and connectionist structure of neural networks. Neuro-fuzzy hybridization is widely termed as Fuzzy Neural Network (FNN) or Neuro-Fuzzy System (NFS) in the literature. Neuro-fuzzy system (the more popular term is used henceforth) incorporates the human-like reasoning style of fuzzy systems through the use of fuzzy sets and a linguistic model consisting of a set of IF-THEN fuzzy rules. The main strength of neuro-fuzzy systems is that they are universal approximators with the ability to solicit interpretable IF-THEN rules.

## IV. IPEN IEA-R1 RESEARCH REACTOR

The Ipen nuclear research reactor IEA-R1 is a pool type reactor using water for the cooling and moderation functions and graphite and beryllium as reflector. Its first criticality was in September 16th, 1957. Since then, its nominal operation power was 2 MW. In 1997 a modernization process was performed to increase the power to 5 MW, in a full cycle operation time of 120 hours, in order to improve its radioisotope production capacity. Figure 2 shows a flowchart diagram of the Ipen nuclear research reactor IEA-R1.

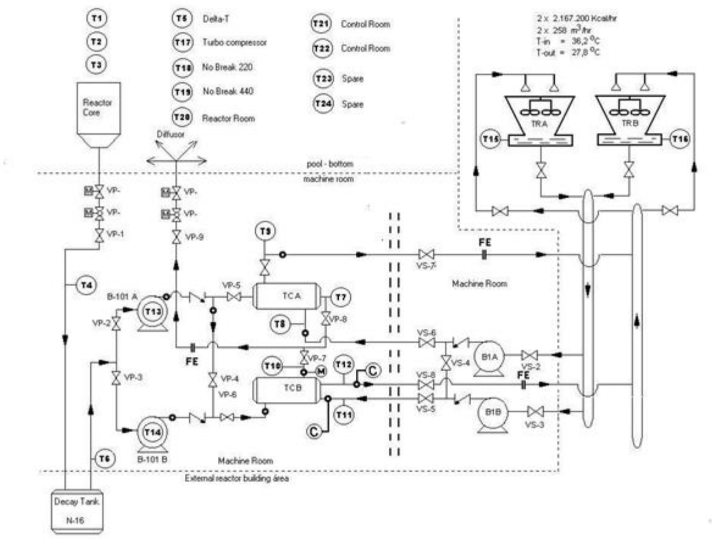


Figure 2. IEA-R1 experimental reactor schematic diagram

## V. IEA-R1 DATA ACQUISITION SYSTEM (DAS)

The Ipen reactor Data Acquisition System monitors 58 operational variables, including temperature, flow, level, pressure, nuclear radiation, nuclear power and rod position (Table 1). The DAS performs the storage the temporal history of all process variables monitored and does not interfere with the reactor control.

Table I. IEA-R1 DAS variables.

| | |
|---|---|
| Z1 | Control rod position [0 a 1000 mm] |
| Z2-Z4 | Safety rod position 1, 2 and 3[0 a 999 mm] |
| N2-N4 | % power (safety channel 1, 2 and 3) [%] |
| N5 | Logarithm Power (log channel) [%] |
| N6-N8 | % power [%] |
| F1M3 | Primary loop flowrate [gpm] |
| F2M3 | Secondary loop flowrate [gpm] |
| C1-C2 | Pool water conductivity [μmho] |
| L1 | Pool water level [%] |
| R1M3-R14M3 | Nuclear dose rate [mR/h] |
| T1-T3 | Pool water temperature [º C] |
| T4 and T6 | Decay tank inlet and outlet temperature [º C] |
| T5 | (T4-T3) [º C] |
| T7 | Primary loop outlet temperature (heat exchanger A) [º C] |
| T8-T9 | Secondary loop inlet and outlet temperature (heat exchanger A) [º C] |
| T10 | Primary loop outlet temperature (heat exchanger B) [º C] |
| T11-T12 | Secondary loop inlet and outlet temperature (heat exchanger B) [º C] |
| T13-T14 | Housing pump B101-A and B102-A temperature [º C] |
| T15-T16 | Cooling tower A and B temperature [º C] |
| T17 | Housing turbo compressor temperature [º C] |
| T18-T19 | NO-BREAK temperature –220V and 440V [º C] |
| T20-T24 | Room temperature [º C] |

## VI. MONITORING AND FAULT DETECTION SYSTEM

A Monitoring and Fault Detection system was developed using two different intelligent computational techniques: Neural Networks and Neuro-fuzzy.

These methodologies was developed and tested using a model composed by 9 variables: N2, T3, T4, T7, T8, T9, F1M3, F2M3 and R1M3, which were described in section V. This model was used previously in a Monitoring System [2].

Data from the 1st week experimental reactor IEA-R1 operation from October 2012 was used to perform both Monitoring Systems. The DAS performs the acquisitions at an interval of 30 seconds.

Database was divided in subsets in a following way: 60% for training, 20% for test and 20% for validation. This division was used in both Monitoring Systems.

The Monitoring and Fault Detection Systems use Neural Networks and Neuro-Fuzzy techniques to calculate each of one of the 9 variables estimative. These values are then compared with the actual variable value. For each one of the monitored variables it was calculated the percent error called residual.

The Neural Network used a Multilayer Perceptron Network (MLP) as architecture of neuron model. The MLP was composed by three layers: one input layer, one hidden layer and on output layer. The input layer is composed by 8 neurons and its activation function is linear; the hidden layer is composed by 10 neurons and its activation function is the hyperbolic tangents. The output layer is composed by a neuron that represents the output of the network.

The results obtained can be observed in Table II.

TABLE II. Results obtained by using Neural Network

| Monitored variable | Residual (%) |
|---|---|
| N2 | 1,8624 |
| T3 | 0,4136 |
| T4 | 0,4836 |
| T7 | 0,6154 |
| T8 | 1,4659 |
| T9 | 0,6967 |
| F1M3 | 16,9914 |
| F2M3 | 0,0760 |
| R1M3 | 4,8926 |

Figure 3 shows the monitoring results in T3 variable (coolant temperature above the reactor core) using neural network.

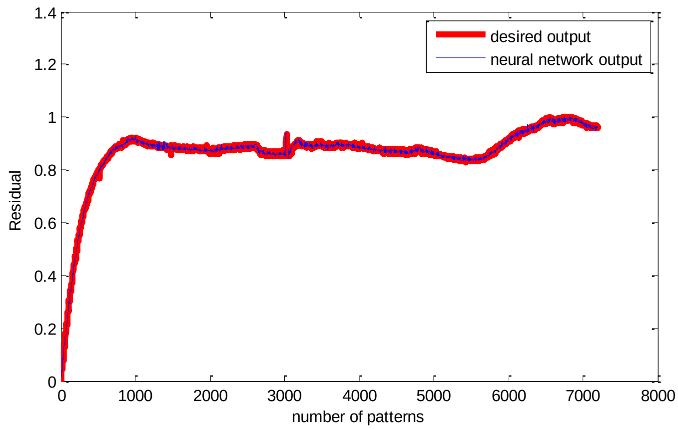


Figure 3: Neural network result for Temperature T3 monitoring.

The monitoring result for F1M3 variable is showed in Figure 4. Although the residual has a value of almost 17%, this is caused more because this particular variable presents a great value of noise.

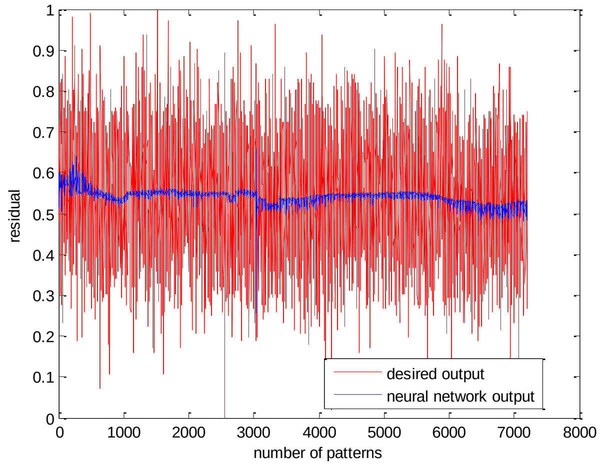


Figure 4: Neural network result for F1M3 monitoring.

The Neuro-fuzzy System was built using the ANFIS Matlab which was found in Fuzzy Logic Toolbox [11]. Using a given input/output data set, the toolbox function anfis constructs a fuzzy inference system (FIS) whose membership function parameters are tuned (adjusted) using either a backpropagation algorithm alone, or in combination with a least squares type of method. This allows your fuzzy systems to learn from the data they are modeling. The algorithm creates a fuzzy decision tree to classify the data into one of 2n (or pn) linear regression models to minimize the sum of squared errors (SSE):

$$\boldsymbol{SSE = \sum_{j} e_j^{\,2}} \qquad (2)$$

where:

- ➢ ej is the error between the desired and the actual output

This technique provides a method for the fuzzy modeling procedure to learn information about a data set, in order to compute the membership function parameters that best allow the associated fuzzy inference system to track the given input/output data.

Using this ANFIS Editor GUI we can:

- Load the data ( training, tests and validate);
- Generate an initial FIS model;
- Choose the number of training epochs and the training error tolerance.
- Choose the FIS model parameter optimization method: backpropagation or a mixture of backpropagation and least squares (hybrid method).
- Train the FIS model by clicking the Train Now button. This training adjusts the membership function parameters
- Plot the training (and/or checking data) error plot(s) in the plot region.
- View the FIS model output versus the training, checking, or testing data output by clicking the Test Now button.

The Fuzzy Inference System uses Sub. Clustering, the optimization Method was Hybrid and the Neuro-fuzzy System was trained for 30 epochs.

Figure 5 shows the result for the temperature T3 monitoring.

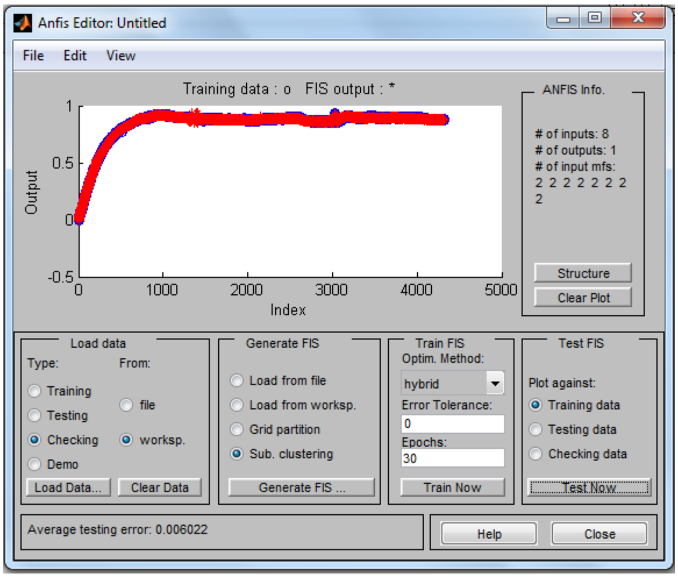


Figure 5. Neuro-Fuzzy result for Temperature T3 monitoring

Table III presents the results for the variable monitoring using Neuro-Fuzzy technique.

TABLE III. Results obtained by using Neuro-fuzzy

| Monitored variable | Residual (%) |
|---|---|
| N2 | 0,044825 |
| T3 | 0,006022 |
| T4 | 0,007657 |
| T7 | 0,007788 |
| T8 | 0,013113 |
| T9 | 0,009898 |
| F1M3 | 0,12445 |
| F2M3 | 0,11858 |
| MA1 | 0,090971 |

Figure 6 shows a comparison between the two techniques, showing a better result for the Neuro-Fuzzy.

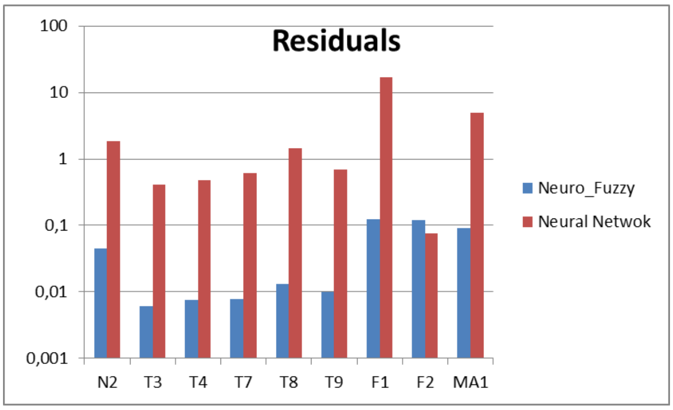


Figure 6. Neuro-Fuzzy and Neural Networks results

## VII. CONCLUSION

In this work two different computational intelligence techniques were used: Neural Networks and Neuro-fuzzy to develop a Monitoring and Fault Detection system. A set of nine variables were used from the IEA-R1 experimental nuclear reactor data acquisition system. We can conclude that both techniques have been successfully applied to the Monitoring System and were effective in estimate a monitored variable. The Neuro-Fuzzy technique showed strongly better performance compared with Neural Network. As a continuation of this work, we are planning to develop a new Monitoring System using all the acquired variables.

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