2011 International Nuclear Atlantic Conference - INAC 2011
Belo Horizonte,MG, Brazil, October 24-28, 2011
ASSOCIAÇÃO BRASILEIRA DE ENERGIA NUCLEAR - ABEN
ISBN: **978-85-99141-04-5**

GMDH AND NEURAL NETWORKS APPLIED IN MONITORING AND FAULT DETECTION IN SENSORS IN NUCLEAR POWER PLANTS

Elaine Inácio Bueno[1], Iraci Martinez Pereira[2] and Antonio Teixeira e Silva[2]

[1] Instituto Federal de Educação, Ciência e Tecnologia – Campus Guarulhos
Av. Salgado Filho, 3501
07115-000 Guarulhos, SP
elainebueno@gmail.com

[2] Instituto de Pesquisas Energéticas e Nucleares, IPEN - CNEN/SP
Av. Professor Lineu Prestes 2242
05508-000 São Paulo, SP
martinez@ipen.br, teixeira@ipen.br

ABSTRACT

In this work a new Monitoring and Fault Detection methodology was developed using GMDH (Group Method of Data Handling) algorithm and Artificial Neural Networks (ANNs) which was applied in the IEA-R1 research reactor at IPEN. The Monitoring and Fault Detection system was developed in two parts: the first was dedicated to preprocess information, using GMDH algorithm; and the second to the process information using ANNs. The preprocess information was divided in two parts. In the first part, the GMDH algorithm was used to generate a better database estimate, called matrix z, which was used to train the ANNs. In the second part the GMDH was used to study the best set of variables to be used to train the ANNs, resulting in a best monitoring variable estimative. The methodology was developed and tested using five different models: 1 Theoretical Model and 4 Models using different sets of reactor variables. After an exhausting study dedicated to the sensors Monitoring, the Fault Detection in sensors was developed by simulating faults in the sensors database using values of +5%, +10%, +15% and +20% in these sensors database. The good results obtained through the present methodology shows the viability of using GMDH algorithm in the study of the best input variables to the ANNs, thus making possible the use of these methods in the implementation of a new Monitoring and Fault Detection methodology applied in sensors.

1. INTRODUCTION

The studies 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 [11] [16] [2] [3].

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 [7], Artificial Neural Networks (ANNs) [14] [15], the Group Method of Data Handling (GMDH) [15], Genetic Algorithms (AGs) [13] [14]. The uses of these techniques are justified because it is possible to model the process without using algebraic equations [18], by using only a database which contains the plant information.

There are a lot of concerns in applications using ANNs due to the appropriate variable input selection to them. There are hundreds of monitored variables in a control room, which indicates the plant status operation. Thus, the correct variables selection is important to choose the lesser possible variable numbers that contain the necessary information to the plant monitoring using ANN. Sometimes, it is necessary to use specialist knowledge to do the appropriate variables input selection, or perform so many tests with different combinations of previously variables until an excellent result will be reached. Because of this, it will be very interesting to have an input automatic selection method which will be used in ANN without using the specialist knowledge. The results obtained will be the use of ANN with a less number of input variables, a faster training time and to discard the use of specialist knowledge to do this work [17].

The GMDH algorithm can be used in automatic input variables selection. The GMDH is a self-organization algorithm of inductive propagation which allows the attainment of a system mathematical model from the database [4].

The purpose of this work is to combine the GMDH and ANN techniques in temperature sensors monitoring of an experimental reactor. The GMDH will be used to do the automatic variables selection and the Neural Networks to model the system. The monitoring model was implemented through many computational simulations in offline form using a database generated by a theoretical reactor model [5]. Both techniques already mentioned had been used separately [1] [6] demonstrating its application viability.

2. GROUP METHOD OF DATA HANDLING - GMDH

The GMDH method is composed by an algorithm proposed by Ivaknenko. It consists of an algebraic method to estimate the systems' states, controllers outputs and actuators functions [9] [10]. The methodology can be considered as a self-organizing algorithm of inductive propagation applied at the solution of many complex practical problems. Moreover, it is possible to get a mathematical model of the process from observation of data samples, which will be used in identification and pattern recognition or even though to describe the process itself.

The network constructed using the GMDH algorithm is an adaptive, supervised learning model. The architecture of a polynomial network is formed during the training process. The node activation function is based on elementary polynomials of arbitrary order. This kind of networks is shown in Figure 1.

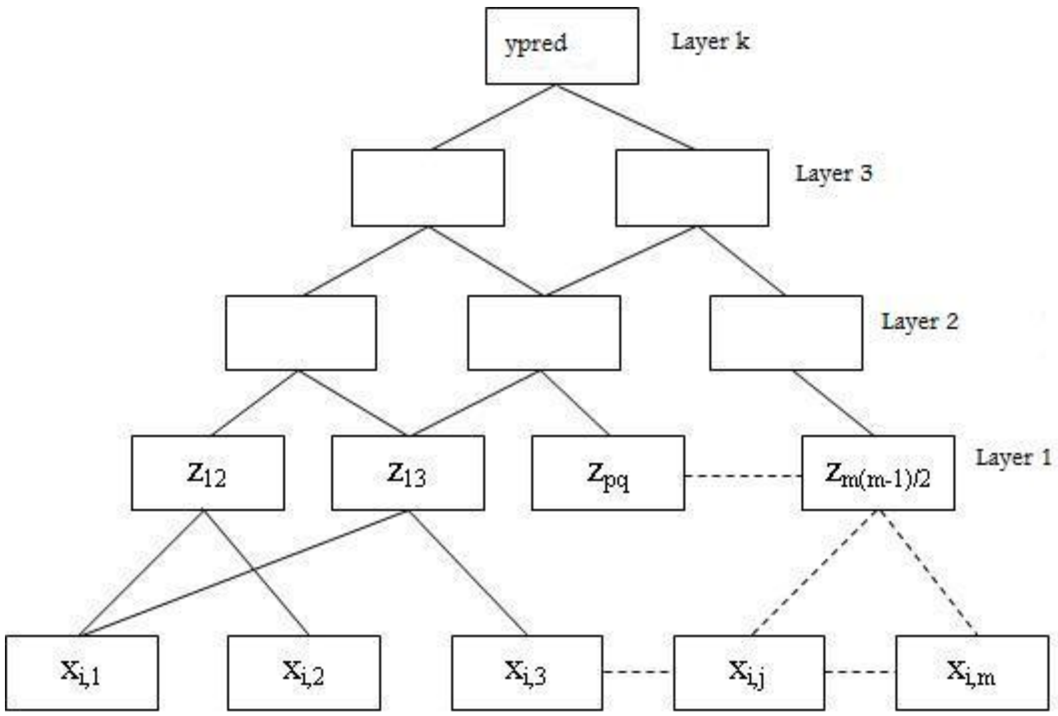

Figure 1. Self-organizing GMDH structure with m inputs and k layers

This method solves the multidimensional problem of model improvement by the choice procedure and selection of models chosen from a set of candidate models in accordance with a supplied criterion. The majority GMDH algorithms use reference polynomial functions. A generic connection between inputs and outputs can be expressed by the series functions of Volterra which is the discrete analogous of the polynomial of Kolmogorov-Gabor, as we can see in equation (1):

$$y = a + \sum_{i=1}^{m} b_i x_i + \sum_{i=1}^{m}\sum_{j=1}^{m} c_{ij} x_i x_j + \sum_{i=1}^{m}\sum_{j=1}^{m}\sum_{k=1}^{m} d_{ijk} x_i x_j x_k + \cdots \qquad (1)$$

Where:

$\{x_1, x_2, x_3 ...\}$: inputs
$\{a, b, c...\}$: polynomials coefficients
y: the node output

The components of input matrix can be changeable independent, functional forms or terms of finite differences, moreover, can be used other nonlinear reference functions. The methods still allow, simultaneously finding the model structure and the output system dependence as a function of the most important inputs system values.

2.1. General description of the GMDH algorithm

In this section, the basic GMDH algorithm implementation will be described. The following procedure is used for a given set of ***n*** observations of the ***m*** independent variables $\{x_1, x_2, \ldots, x_m\}$ and their associated matrix of dependent values $\{y_1, y_2, \ldots y_n\}$ [4] .

- Subdivide the data into two subsets: one for training and other for testing;
- Compute the regression polynomial using the equation (2), for each pair of input variables x_i and x_j and the associated output y of the training set which best fits the dependent observations y in the training set. From the observations, m(m-1)/2 regression polynomials will be computed from the observations;

$$y = A + Bx_i + Cx_j + Dx_i^2 + Ex_j^2 + Fx_i x_j \tag{2}$$

- Evaluate the polynomial for all ***n*** observations for each regression. Store these ***n*** new observations into a new matrix Z. The other columns of Z are computed in a similar manner. The Z matrix can be interpreted as new improved variables that have better predictability than those of the original generation $x_1, x_2, \ldots, x_m$;
- Screening out the last effective variables. The algorithm computes the root mean-square value (regularity criterion – r_j) over the test data set for each column of Z matrix. The regularity criterion is given by the equation (3);

$$r_j^2 = \frac{\sum_{i=1}^{nt} \left(y_i - z_{ij}\right)^2}{\sum_{i=1}^{nt} y_i^2} \tag{3}$$

- Order the columns of Z according to increasing r_j, and then pick those columns of Z satisfying $r_j < R$ (R is some prescribed value chosen by the user) to replace the original columns of X;
- The above process is repeated and new generations are obtained until the method starts overfitting the data set. One can plot the smallest of the r_j's computed in each generation and compare it with the smallest r_j's of the most recent generation start to have an increasing trend.

3. ARTIFICIAL NEURAL NETWORKS

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 se in Figure 2. It is possible to identify three basic elements in a neuron: a set of synapses, where a signal x_j at the input of sinapse 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 [8].

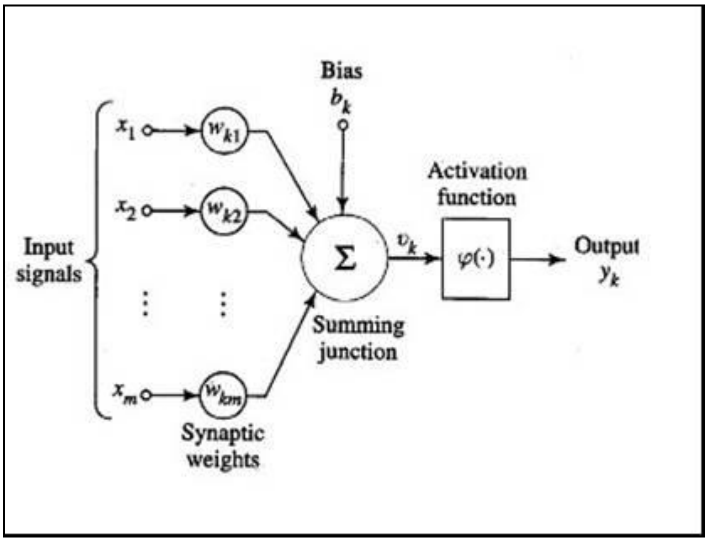

Figure 2. Neuron Model

In this work, it was used the MLP (Multilayer Perceptron 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 show the equation (4):

$$E = \frac{1}{2}\sum_{m=1}^{m}\left(y_{dj}(n) - y_j(n)\right)^2 \qquad (4)$$

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

4. MONITORING AND FAULT DETECTION MODEL

A Monitoring and Fault Detection model was developed in two parts: the first was dedicated to preprocess information using GMDH algorithm; and the second to the process information using ANNs. The preprocess information was divided in two parts. In the first part, the GMDH algorithm was used to get a mathematical model of the process from observation of data samples, in other words, it was used the *z matrix* because it contains a better estimative of data samples, which will be used to train the ANNs (Figure 3). In this way, it was not necessary to use the knowledge specialist because of the z matrix. In the second part the GMDH was used to study the best set of variables to be used to train the ANNs, resulting in a best monitoring variable estimative (Figure 4). After an exhausting study dedicated to sensors monitoring, it was developed the Fault Detection in sensors by simulating faults in the sensor database using values above of 5%, 10%, 15% and 20% in the sensors measurements.

The methodology was developed and tested using five different models: 1 theoretical model and 4 models using different sets of reactor variables. In this work it will be shown the results obtained through the fifth model which contains 38 variables, the most important variables to the Monitoring and Fault Detection model. It was used the DAS (Data Acquisition System) database which monitors 58 operational variables, includ including temperature, flow rate, level, pressure, nuclear radiation, nuclear power, safety and control rod position.

To prevent overfitting during ANNs training, the method of Early Stopping was used, which suggests a database division in three subsets: training (60%), validation (20%) and testing (20%). The training set is used to compare different models. It was used a Multilayer Perceptron Network with three layers: one input layer, one hidden layer and on output layer, because this kind of network has shown the best results. The input layer is composed by three neurons and its activation function is linear; in the hidden layer, 10 cases was studied and tested with different number of neurons to find the ideal number of neurons, its activation function is the hyperbolic tangents. The output layer is composed by a neuron that represents the output of the network.

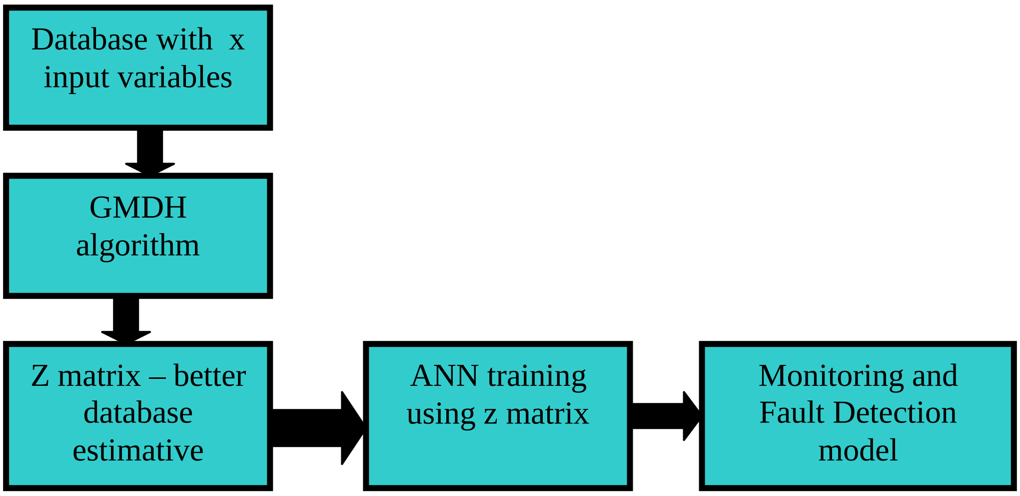

Figure 3. The first preprocess information

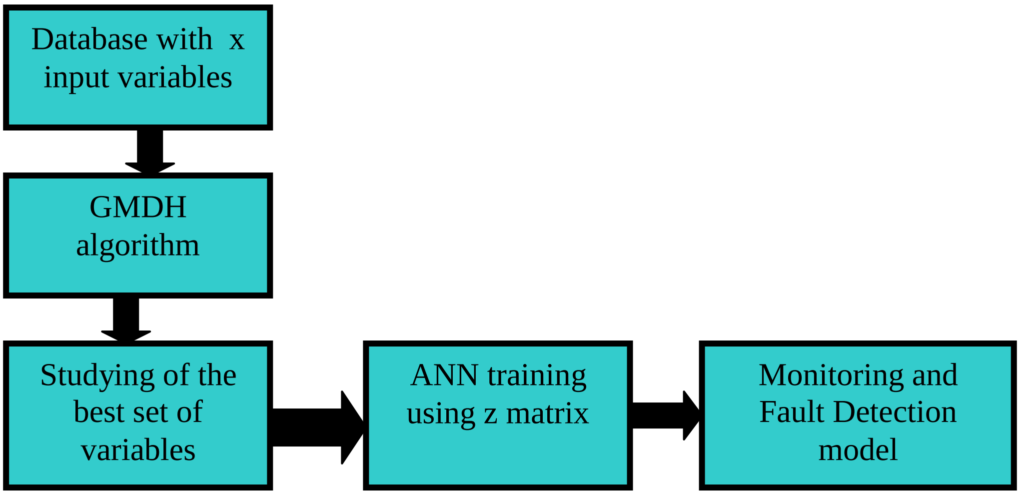

Figure 4. The second preprocess information

It was calculated the residuals obtained in the ANNs for the choice of the best model, as shown the equation (5):

$$residual = |y_{dj}(n) - y_j(n)| \qquad (5)$$

Figures 5 show the monitoring results in T3 variable (coolant temperature above the reactor core). In the figure was shown the results obtained using only the ANN with the purpose to study the improvements obtained when the GMDH algorithm was used in two different preprocess information.

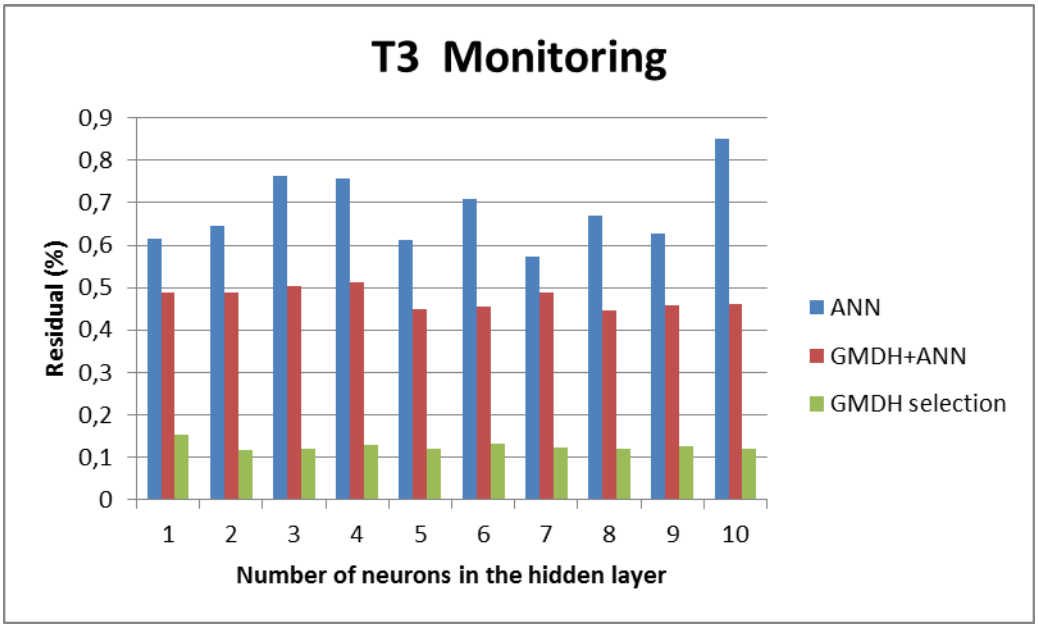

Figure 5. T3 Monitoring using an input selection method

Table 1 show the residuals obtained in T3 and N2 monitoring

Table 1. Residual obtained during sensors monitoring

		RESIDUAL (%)		
	# NEURONS*	**GMDH - selection**	**GMDH + ANN**	**ANN**
T3	1	0.1528	0.0044	1.1740
	2	0.1180	0.0044	1.2182
	3	0.1199	0.0044	1.1799
	4	0.1286	0.0044	1.4334
	5	0.1217	0.0044	1.3691
	6	0.1329	0.0044	0.9963
	7	0.1230	0.0044	0.9527
	8	0.1210	0.0043	1.3291
	9	0.1264	0.0044	0.8081
	10	0.1196	0.0044	0.9459
N2	1	0.1894	0.2831	0.3044
	2	0.1626	0.2451	0.359
	3	0.1561	0.2554	0.3377
	4	0.1517	0.2528	0.4205
	5	0.1470	0.2648	0.3883
	6	0.1429	0.295	0.3861
	7	0.1483	0.2876	0.3187
	8	0.1413	0.2911	0.3601
	9	0.1467	0.2439	0.3663
	10	0.1426	0.2667	0.3983

*** Number of neurons in the hidden layer**

As we can see, the residuals obtained in both cases (T3 and N2 monitoring) were better when it was used the GMDH – selection preprocess when it was studied the most important variables by using the polynomial equation. The most important variables were used to train the ANN and the results were much better than with the other methods.

Figures 6 show the detection results in N2 variable (nuclear power). The Fault Detection was done by simulating faults in the sensors database of 5%, 10%, 15% and 20% above the measurements of these instruments. After, the ANNs were tested with this fault database.

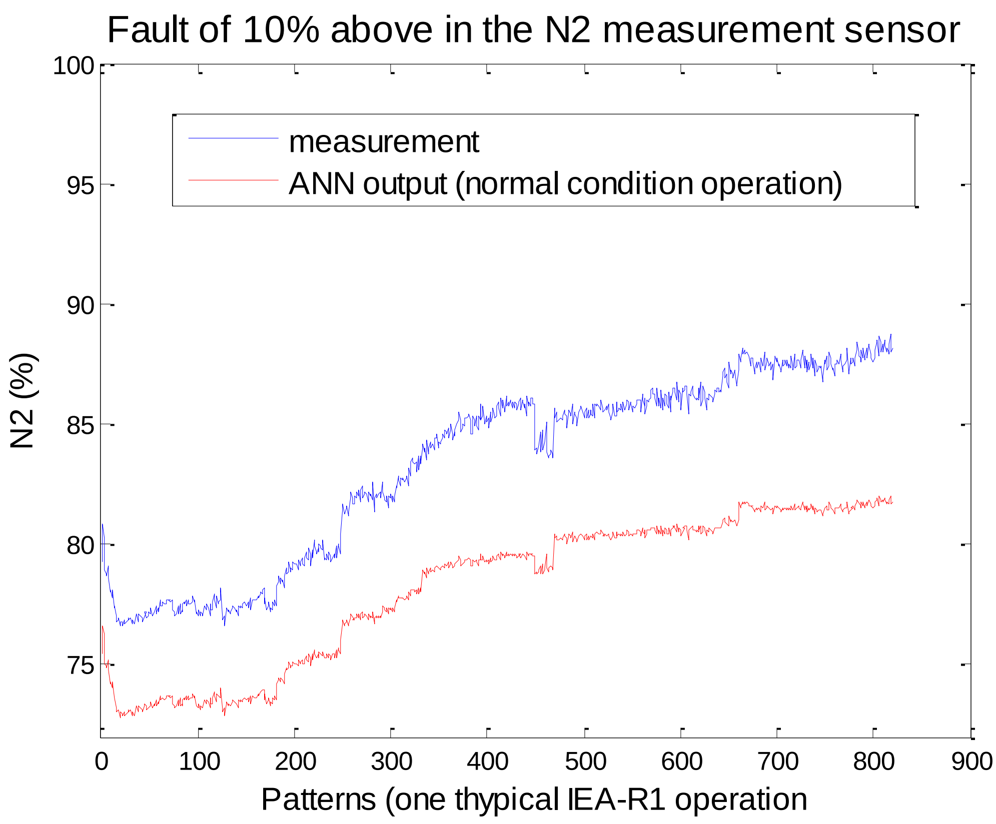

Figure 6. N2 Fault Detection

Table 2 show the residuals obtained in N2 Fault Detection

Table 2. Residual obtained during N2 Fault Detection

Fault	**Residual (%)**
5% above the measurement	6,58
10% above the measurement	9,96
15% above the measurement	12,83
20% above the measurement	15,23

The residuals obtained in N2 Fault Detection were higher than the ones obtained in N2 monitoring. This result shows that the Fault Detection model can identify the simulated sensors anomalies.

5. CONCLUSION AND FUTURE WORK

It was presented a methodology using the GMDH algorithm and ANN applied in Monitoring and Fault Detection in sensors of the IEA-R1 research reactor by using a database given by a nuclear reactor operation. The GMDH algorithm was used during the information preprocessing in two different ways: first it was use a better estimative of the original database (z matrix) as input variables to the ANN; and second it was investigated the most important variables to the GMDH algorithm by using the polynomial equation. The results obtained using the GMDH as an input selection method to the ANN was better than that obtained using only ANN and the specialist knowledge.

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