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GMDH AND ARTIFICIAL NEURAL NETWORK APPLIED IN AN EXPERIMENTAL REACTOR SENSORS MONITORING

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Abstract- In this work a Monitoring System was developed using GMDH (Group Method of Data Handling) algorithm and Artificial Neural Networks (ANN) which was applied in the IEA-R1 research reactor at IPEN. GMDH is used in two different ways to perform an input data preprocessing to the ANN. The system perform the monitoring by comparing the estimative calculated values with the measured ones. Each Monitoring System was developed and tested for five different sets of input data, ancluding data from a Reactor Teoretical Model and for four different sets of reactor variables. The results for the most of cases show an improvement when GMDH is combined with ANN algorithm in the Monitoring Systems. The good results obtained in the present work show the viability of using GMDH algorithm in the study of the best input variables to the ANN, thus making possible the use of these methods in the implementation of a new Monitoring Methodology applied in sensors of a nuclear power plant.

Keywords – ANN, GMDH, experimental reactor, input selection, monitoring system.

1 Introduction

Nowadays, with the advent of computer-controlled processes, there is a lot of process data information to be observed by the operator. This information is rarely presented in a manner which reflects the important underlying trends and events in the process. Because of the real-time noisy database, it is difficult to extract significant trends in the process. In other words, it might be difficult to differentiate between normal and abnormal condition or when a perturbation will cause a new steady-state condition just by looking at the raw sensor database. When the plant is operating under tight quality and control requirements and strict economic objectives it is extremely important to identify an abnormal condition. The operators need to identify important disturbances quickly and take corrective actions to control the situation. Because of the economic losses and the operator's security, it becomes necessary to implement Monitoring and Diagnosis Systems (Maki and Loparo, 1997; Sydenham and Thorn, 1993; Clark, 1978; Echendu and Zhu, 1994). 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 (Goode, 1995), Artificial Neural Networks –ANN (Rovithakis et al., 2004; Samanta, 2004; Bueno, 2006; Bueno et al., 2010), the Group Method of Data Handling -GMDH (Bueno et al., 2011; Gonçalves et al., 2005; Gonçalves, 2006), Genetic Algorithms -AG (Raymer et al., 2000; Rovithakis et al, 2004). The use of these techniques are justified because it is possible to model the process without using algebraic equations (Zupan et al., 1997), by using only a database which contains the plant information.

There are a lot of concerns in applications using ANN due to the appropriate variable input selection to them. In a control room, there are a lot of variables to be monitored, which indicates the plant status operation. Thus, the correct variables selection is important to choose the smallest possible variable numbers which 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 is interesting to have an input automatic selection method to 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 (Uhrig and Guo, 1992).

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 (Farlow, 1984). This work shows the results of a Monitoring and Diagnosis System based on GMDH and ANN algorithms, applied to the Ipen research Reactor IEA-R1. The GMDH was used to study the best set of variables to be used as input parameter to train an ANN, resulting in a best monitoring variable estimative. The system performs the monitoring by comparing these estimative values with measured ones. Different sets of input variables were used, including data generated by a research reactor theoretical model, and data obtained from the reactor Data Acquisition System.

2 GMDH –Group Method of Data Handling

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 (Ivakhnenko, 1969; Ivakhnenko and Yarachkovskiy, 1981). 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 network is shown in Figure 1.

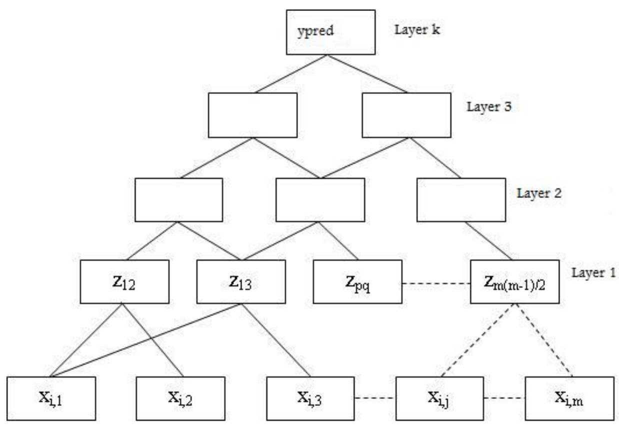

Figure 1: Self-organizing GMDH structure with m inputs and k layers.

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 (Nelles, 2001), as we can see in equation (1):

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

Where:
$\{x_1, x_2, x_3 \ldots x_m\}$: inputs
{a, b, c...}: polynomial coefficients
y: node output

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 $\{y_1, y_2, \ldots y_n\}$ (Farlow, 1984).

- Take the input variables, two by two, for all the possible combinations; as the number of input variables is m, then the total number of combinations is equal to m(m-1)/2;

- Compute the regression polynomial using 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 using the previous calculated polynomial coefficients (equation 3). 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 $x_1, x_2, \ldots, x_m$;

$$z_{ij} = a + bx_i + cx_j + dx_i^2 + ex_j^2 + fx_i x_j \tag{3}$$

- Screening out the least 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 (j=1 to m(m-1)/2). The regularity criterion is given by the equation (4);

$$r_j^2 = \frac{\sum_{i=1}^{n} (y_i - z_{ij})^2}{\sum_{i=1}^{n} y_i^2} \tag{4}$$

- 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 the input matrix 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 (Haykin, 1999).

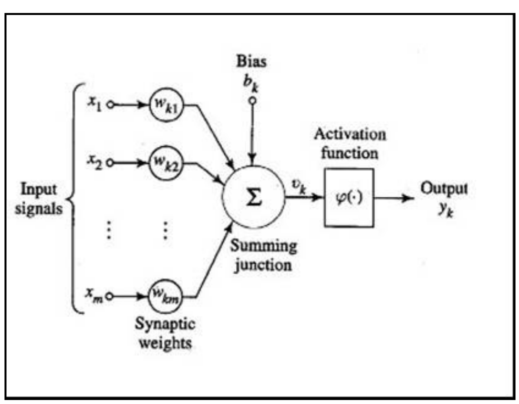

Figure 2: Neuron Model.

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 shown in equation (5):

$$E = \frac{1}{2}\sum_{m=1}^{m}\left(y_{dj}(n) - y_j(n)\right)^2 \tag{5}$$

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

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%). 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 number of input layer depends on the number of input variables (as will be explained in section 5) 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.

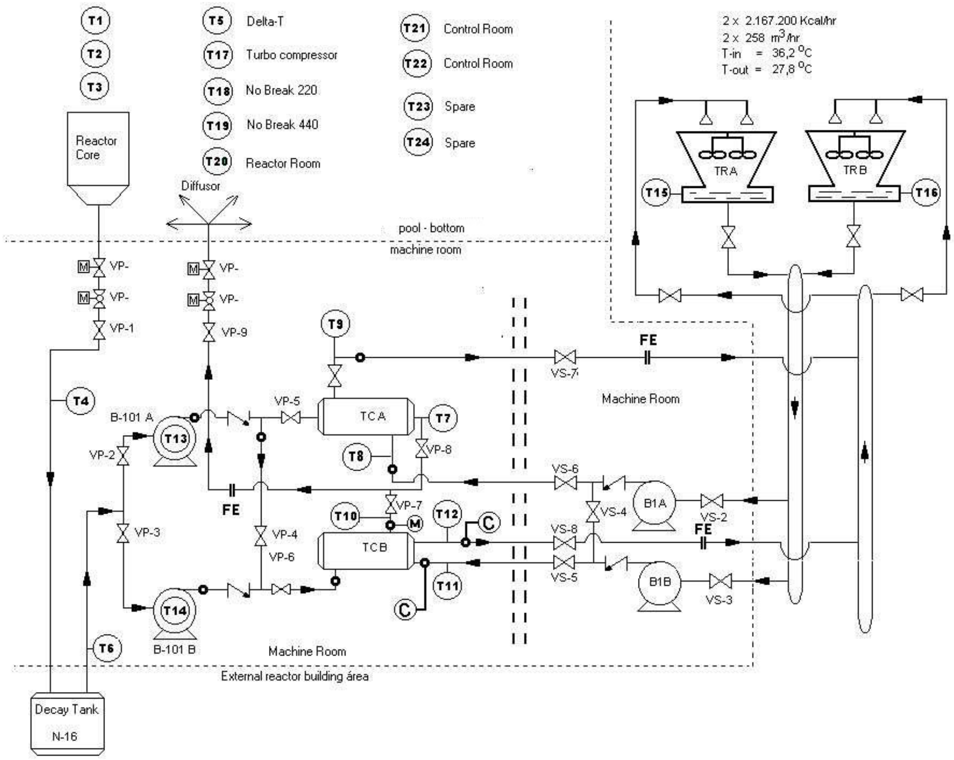

Figure 3: Flowchart diagram of the Ipen nuclear research reactor IEA-R1.

4 IPEN Research Reactor IEA-R1

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 is 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.

The research reactor main purposes are:

- Radioisotope production for medicine, industry and agriculture;
- Source of neutrons for experimental research;
- Training for nuclear researchers and nuclear power plant operators.

The nuclear reactor core is immersed in a 272 m^3 water pool, internally revested of stainless steel. The reactor has two redundant cooling water loops, each one with, secondary loop pump, valves and pipes, heat exchanger, and cooling tower. The fuel element is of MTR (Material Testing Reactor) type, and is composed for 18 plates of 20% enriched Uranium. The reactivity control is made by 3 safety rods and one control rod. The thermohidraulic variables are measured by flow rate and temperature sensors. Nuclear radiation detectors send the dose rate measurements to the Data Acquisition System in the control room. Figure 3 shows a flowchart diagram of the Ipen nuclear research reactor IEA-R1.

A total of 57 operational variables are monitored by the Data Acquition System (DAS), including temperature, flow, pressure, radiation, nuclear power, and rod position. The variables monitored are listed in Table 1. This system allows the recording of data containing the time history of all monitored process variables. All variables are acquired at 1-min intervals during one cycle operation, from startup to shutdown. The IEA-R1 reactor cycle is one-week long.

Table 1: Data Acquisition System Variables

Variable	Variable description
Z1-Z4	Control and safety rod position
N2-N6	% power
N7	% demand
N8	N16 power
C1-C2	Water conductivity
R1M3-R14M3	Nuclear dose rate
T1-T24	Water temperature
F1M3- F2M3	Primary and secondary loop flow rate
DP	Delta P do núcleo [V]
L1	Pool water level

4.1 IPEN Research Reactor IEA-R1 Theoretical Model

A Ipen research reactor theoretical model was built in order to generate data in different reactor operation conditions, allowing flexibility in situations where it is not possible to obtain data experimentally because of restrictions due to the nature of a nuclear reactor operation. Using the model, data was generated both under normal and faulty conditions. The IEA-R1 theoretical model performs the following tasks:

- Generation of data in different reactor operation conditions
- Setting the input variable values in an easy and fast way using a graphic interface
- Setting the noise level for the input variables
- Selecting a faulty variable from a list
- Visualization of the results in a dynamical way

The model represents the basic relationships among the different process variables. The system process equations are based on the IEA-R1 mass and energy inventory balance (Bassel, 1996) and (Kern, 1950), and the physical and operational parameters, such as pipe length and diameter, relationships among the flow rate, temperatures and pressure drop are taken into consideration.

The Ipen research reactor model was built using the Matlab GUIDE toolbox. The GUIDE (Graphical User Interface Development Environment) toolbox is a set of functions designed to develop interfaces in an easy and fast way. One can add plots, sliders, frames, editable texts and push buttons that are related to other Matlab functions.

The interface layout was built to look like the reactor process flowchart. Figure 4 shows the program interface. The reactor core is represented immersed in the water pool. The temperatures T1, T2 and T3 are the temperatures above the core near the pool surface, at mid high and close to the core, respectively. The nuclear power is an input data and a nuclear power of 100% corresponds to the maximum operation power of 5 MW.

The reactor coolant system is also represented in the interface. The primary loop water flows through the reactor fuel elements and leaves the pool through a nozzle under the core. Then, the water passes through the decay tank: T4 which is the reactor core outlet temperature and T6 is the outlet temperature. B101-A is the primary loop pump. The heat exchanger is also represented. T7 is the heat exchanger outlet temperature (primary loop side). FE 01 is the primary loop flowmeter. The primary water loop flows out of the heat exchanger and then returns to the pool. The secondary loop is partially represented by the secondary side of the heat exchanger.

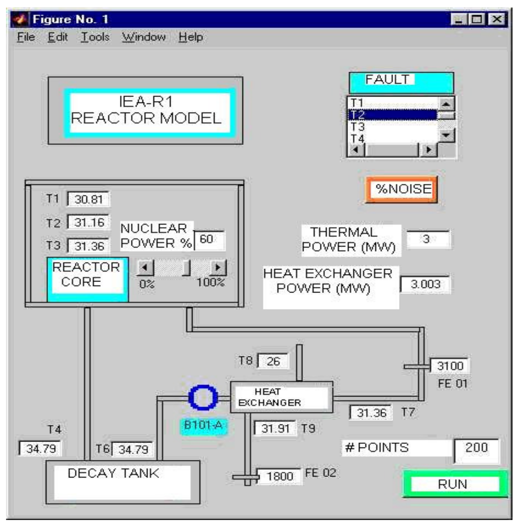

Figure 4: Program interface developed to compute the IEA-R1 nuclear reactor model variables.

The pump in the secondary side and the cooling towers are not represented. T8 is the inlet temperature of the heat exchanger secondary side, and T9 is its outlet temperature. The secondary loop flow is measured by the FE 02 flow meter. The units of temperature and flow are the same used in the reactor data acquisition system that is Celsius degrees and gallons per minute.

The user can define the time interval by defining the total number of points and the time step where the variables are to be calculated by the model for a given operational condition. In this case the program calculates for one point, refreshes the values and restarts the computation for the next point.

The user defines the desired variable values for the temperatures, flow rate or nuclear power directly in the interface editable dialog box. After entering the variable values, the noise level, the fault condition and the number of data points, pressing the button *calculate* initiates the program, which calculates the thermal power according to the mass and energy inventory balance equations.

The IEA-R1 model was used to generate data at the same reactor operation conditions. Figure 5 shows the difference % between model data temperatures and real operation data temperatures. For the others reactor variables, flow rate and power, the results are less than 5%, so the model was validated. (Gonçalves et al, 2005)

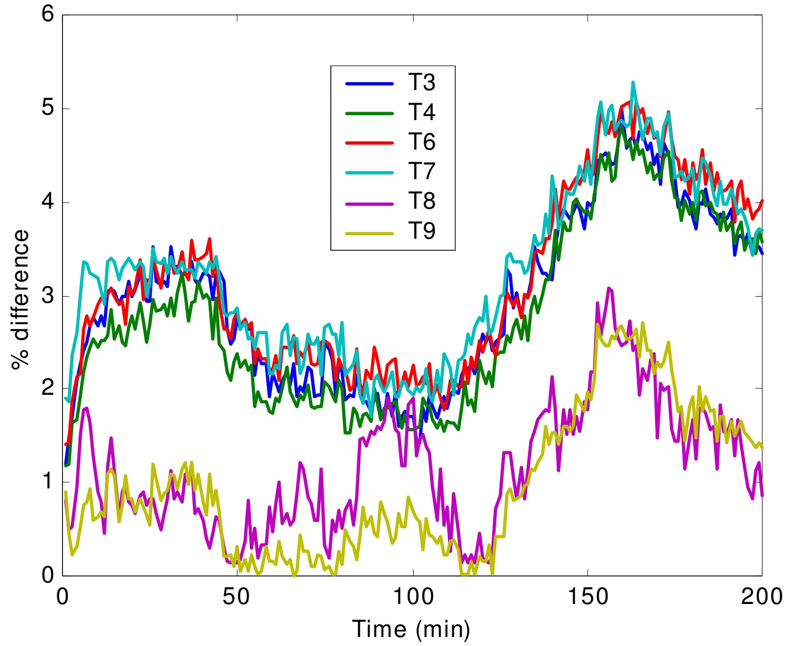

Figure 5: Difference between IEA-R1 reactor model and real reactor operation temperatures.

5 Monitoring System Algorithm

Two Monitoring Systems were developed using GMDH and ANN algorithms to evaluate the variables. The system perform the monitoring by comparing these estimative calculated values with measured ones. The two systems use GMDH to preprocess the input data to be used in a ANN. The results were compared with a previous Monitoring Systems developed using ANN with no preprocessed data (Bueno, 2006).

The first Monitoring System is called **GMDH selection**, and the GMDH algorithm was used to study the best set of variables to be used as input to train an ANN;

The second Monitoring System is called **GMDH+ANN** and the GMDH algorithm was used to get a new input data, based on the Z matrix (see section 2.1).

Each Monitoring System was developed and tested for 5 different sets of input data. The first one uses data from the Reactor Teoretical Model (see section 4.1) and 4 using different sets of reactor variables as shown in Table 2. The choice of these sets of input variables is fully explained in reference Bueno, 2006.

The monitoring is performed by comparing the variable value estimated by the ANN with those measured by the Data Acquisition System (actual value). This comparison is computed calculating the residual, as shown in equation (6) where y_{di} are the desired output (measured value), y_i are the values calculated by the ANN and n is the number of samples.

$$\text{residual} = \sum_{i=1}^{n} \frac{(y_i - y_{di})^2}{y_{di}} * 100 \tag{6}$$

A Monitoring System was developed for each set of variables showed in Table 3. All the variables in each model were monitored and the respective residuals were calculated. Figure 6 shows the monitoring results for coolant temperature above the reactor core T3 of model number 5.

Table 2: Variables used in each Monitoring System

	Variables
1	N2, F1M3, F2M3, T1, T2, T3, T4, T6, T7, T8 and T9 (theoretical values)
2	N2, F1M3, F2M3, T1, T2, T3, T4, T6, T7, T8 and T9
3	Z1, Z2, Z3, N2, F1M3, F2M3, R1M3, R2M3, T3, T4, T7, T8 and T9
4	Z1, Z2, Z3, N2, R1M3, R2M3, T3, T4, T7, T8 and T9
5	Z1, Z2, Z3, Z4, N1, N2, N3, N4, N5, N6, N7, N8, C1, C2, F1M3, F2M3, R1M3, R2M3, R3M3, R4M3, R5M3, R6M3, R7M3, R8M3, R9M3, R10M3, R11M3, R12M3, R13M3, R14M3, T1, T2, T3, T4, T6, T7, T8 and T9

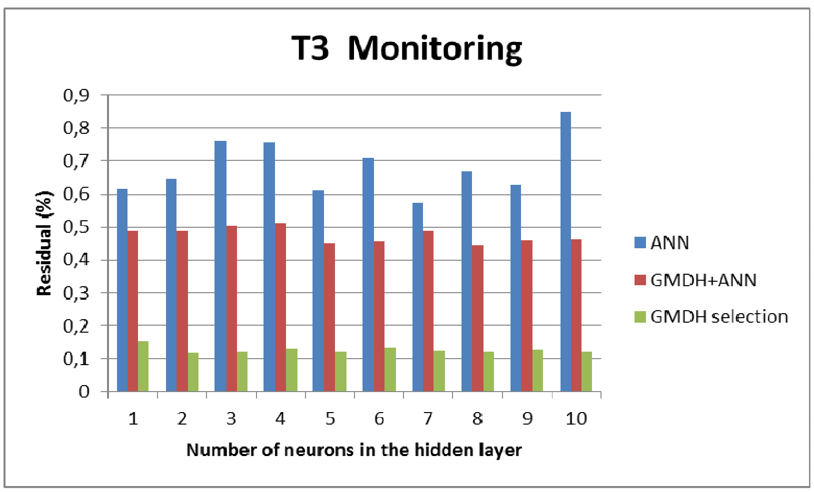

Figure 6: Residuals for T3.

The results for the others variables show a similar behavior, with a reduction of the residual value when GMDH is combined with ANN algorithm in the Monitoring Systems. As we have the number of neurons in the hidden layer variyng from 1 to 10, we choose the best result, that one with the least residual value. Table 3 show the best results obtained in monitoring using the 3 Monitoring Systems for the variables of set number 5.

The ANN developed for the set of variables number 5 did not converge for the variables: N1, N5, R4M3 to R6M3, R13M3, F1M3 and F2M3.

Table 3: System Monitoring Results

	RESIDUAL (%)		
Variable	**GMDH selection**	**GMDH + ANN**	**ANN**
Z1	0.5279	1.3692	**0.3267**
Z2	**0.1053**	0.2362	0.2803
Z3	**0.0019**	0.1916	0.3142
Z4	**0.0036**	0.2122	0.2955
C1	2.0564	**0.1309**	2.0083
C2	0.1030	0.1038	**0.0955**
N2	**0.1413**	0.2439	0.3044
N3	**0.1642**	0.2347	0.2726
N4	**0.1511**	0.2176	0.3041
N6	**0.1342**	0.2457	0.3046
N7	**0.0468**	0.2176	0.3041
N8	**0.4293**	0.5195	0.6101
R1M3	**2.9378**	3.1934	3.2171
R2M3	**2.6268**	2.7846	2.9562
R3M3	**2.8834**	3.0375	4.0342
R7M3	**2.8065**	2.9555	2.8201
R8M3	1.9831	4.0144	**1.7784**
R9M3	**1.6833**	1.6640	1.7832
R10M3	**3.1599**	3.1947	3.2419
R11M3	**2.3390**	2.6222	2.3411
R12M3	**5.0551**	5.0736	5.0919
R14M3	**6.0936**	6.1203	6.1500
T1	**0.1137**	0.4630	0.5015
T2	**0.1049**	0.4250	0.5172
T3	**0.1180**	0.4478	0.5741
T4	**0.0023**	0.3708	0.5271
T6	**0.1041**	0.4390	0.5243
T7	**0.1436**	0.4542	0.5166
T8	**0.2004**	0.9999	1.1297
T9	**0.1229**	0.5781	0.5810

6 Conclusion and Future Work

This paper presents the results of a Monitoring System using ANN and GMDH algorithms. A Monitoring System was developed earlier using ANN and the results were dependent on the choice of the input variables. The Monitoring System is developed and applied to sensors of the IEA-R1 IPEN research reactor. The monitoring is performed by comparing the variable value estimated by the System with those measured by the reactor Data Acquisition System.

GMDH is used in two different ways to perform an input data preprocessing to the ANN. The first Monitoring System is called **GMDH selection**, and the GMDH algorithm was used to study the best set of variables to be used as input to train an ANN; and the second Monitoring System is called **GMDH+ANN** and the GMDH algorithm was used to get a new input data, based on the Z matrix.

The results for the most of cases show an improvement when GMDH is combined with ANN algorithm in the Monitoring Systems. The good results obtained in the present work show the viability of using GMDH algorithm in the study of the best input variables to the ANN, thus making possible the use of these methods in the implementation of a new Monitoring Methodology applied in sensors of a nuclear power plant.

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