2013 International Nuclear Atlantic Conference - INAC 2013
Recife, PE, Brazil, November 24-29, 2013
ASSOCIAÇÃO BRASILEIRA DE ENERGIA NUCLEAR - ABEN
ISBN: 978-85-99141-05-2

A STUDY OF NEURAL NETWORKS INPUT VARIABLES APPLIED IN SENSORS MONITORING

Elaine Inacio Bueno[1], Iraci Martinez Pereira[2]

[1] Instituto Federal de Educação, Ciência e Tecnologia – Campus Guarulhos
Av. Salgado Filho, 3501 – Vila Rio de Janeiro
07115-000 Guarulhos, SP
bueno_elaine@yahoo.com.br

[2] Instituto de Pesquisas Energéticas e Nucleares (IPEN / CNEN - SP)
Av. Professor Lineu Prestes 2242
05508-000 São Paulo, SP
iraci.martinez.pereira@gmail.com

ABSTRACT

With the continuously growing demand for models of complex systems associated with nonlinearity, high-order dynamics, time-varying behavior and imprecise measurements, there is a need for a relevant modeling environment. Efficient modeling techniques should allow an appropriate selection of pertinent variables and a formation of highly representative datasets. These kinds of techniques are important in a Monitoring and Fault Detection System, because of the complexity, efficiency and reliability in modern industrial systems. In this work was developed a study about the best set of variables to be used in the Artificial Neural Networks (ANNs). This study will be applied in the development of a Monitoring and Fault Detection system of IEA-R1 research reactor. This study was developed and tested using one model which was composed by different sets of reactor variables. The results obtained through the present methodology shows the viability of using ANN in the study of the best input variables to a Monitoring and Fault Detection System.

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 [1] [4] [6] [9] [10] with the purpose to help the nuclear power plants operators, including the Fuzzy Logic [7], Artificial Neural Networks (ANNs) [12] [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 purpose of this work is to develop a study of neural networks input variables applied in sensors monitoring. This study will allow obtaining a set of input variables for the ANNs training; furthermore, it is possible to study the sensitivity of the model. The monitoring model was implemented through many computational simulations in offline form using a database generated by a theoretical reactor model [5].

2. IPEN RESEARCH REACTOR IEA-R1 THEORETICAL MODEL

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. Figure 1 shows a flowchart diagram of the Ipen nuclear research reactor IEA-R1.

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

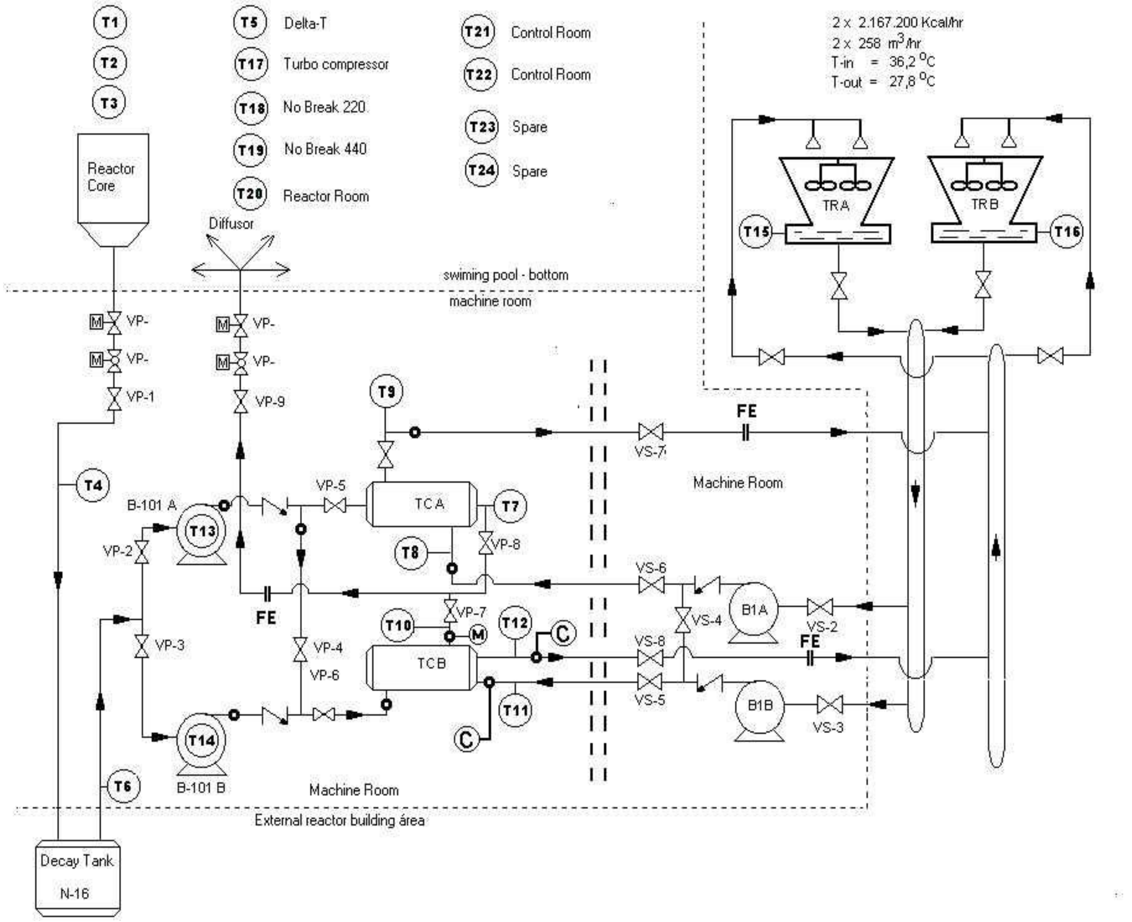

Figure 1. Flowchart diagram of the Ipen nuclear research reactor IEA-R1

3. 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 1. 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]

4. ARTIFICIAL NEURAL NETWORRKS

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 xj at the input of sinapse j connected to the neuron k is multiplied by the synaptic weight wkj, 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 bk, 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].

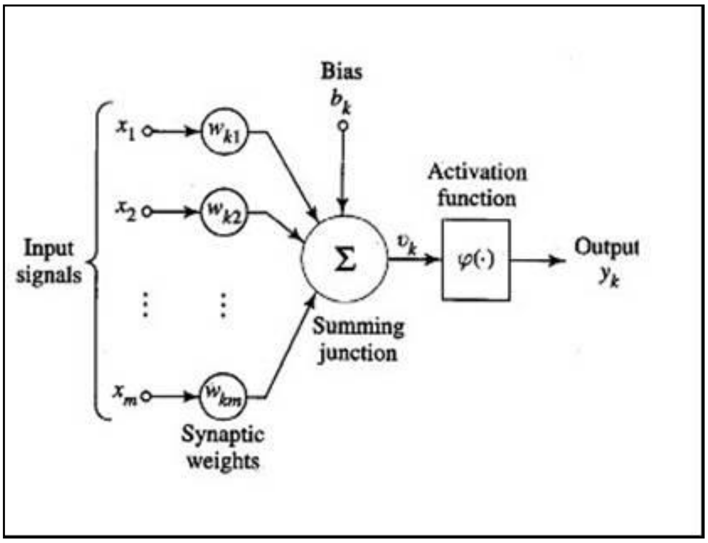

Figure 2. Neuron Model

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 (1):

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

Where:

E: mean squared error
m: number of neurons in the output layer
ydj: target output
yj: actual output
n: number of interactions

5. MONITORING MODEL

A Monitoring model was developed by using ANNs methodology. The ANNs was used to study the best set of variables to the mode.

The methodology was developed and tested using a model which contains 12 variables, including temperature (T3, T4, T7, T8 and T9), flow rate (F1M3 and F2M3), nuclear radiation (R1M3 and R2M3), nuclear power (N2), and control rod position (Z1, Z2 and Z3).

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 twelve neurons and its activation function is linear; the hidden layer is composed by ten neurons and its activation function is the hyperbolic tangents. The output layer is composed by a neuron that represents the output of the network.

It was calculated the residuals obtained in the ANNs for the choice of the best model, as shown the equation (2):

$$residual = \frac{|y_{dj}(n) - y_j(n)|}{|y_{dj}(n)|} * 100 \qquad (2)$$

Figures 3, 4 and 5 shows the study of the best input variable to train an artificial neural network. This study was made for all variables previously described, but it will be shown only the results obtained in the T3, T4 and N2 monitoring.

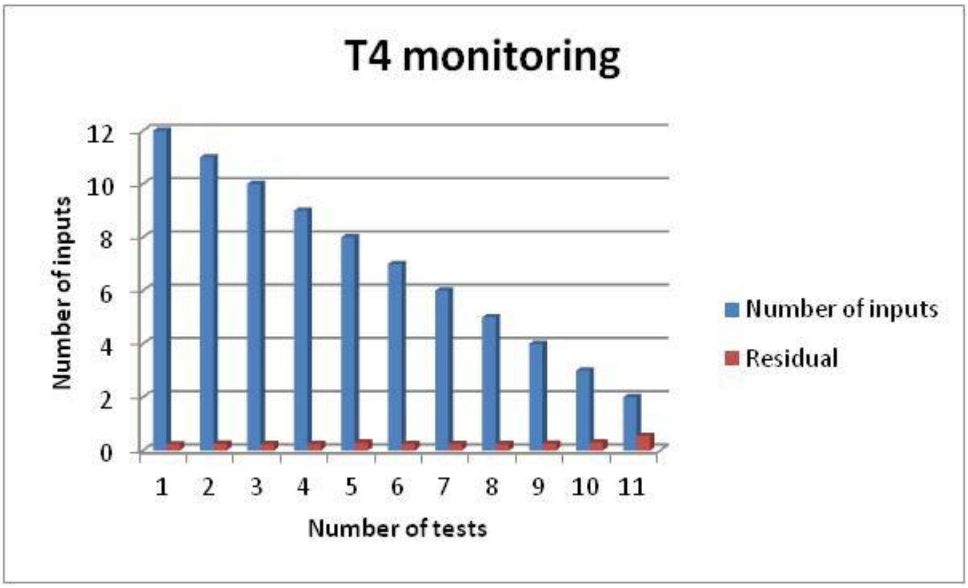

Figure 3. T4 Monitoring – study of the best input variables to train an ANN

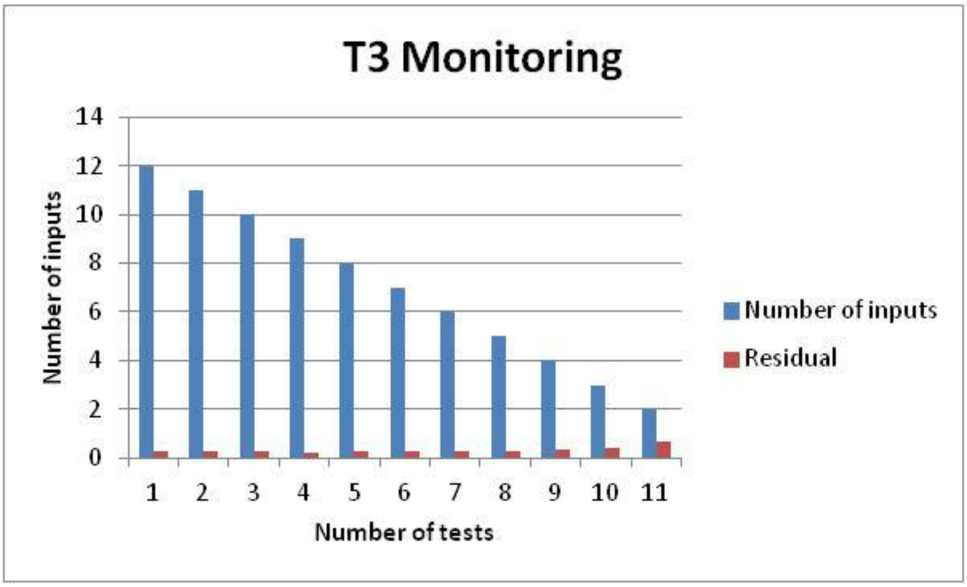

Figure 4. T3 Monitoring – study of the best input variables to train an ANN

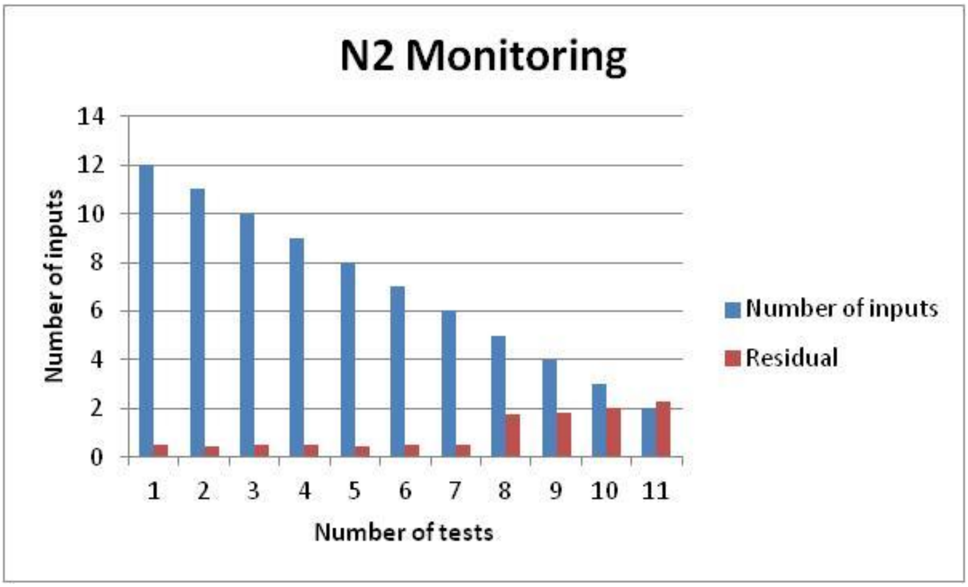

Figure 5. N2 Monitoring – study of the best input variables to train an ANN

As can be seen in the Figures 3, 4 and 5, by reducing the number of input variables, the residual increased.

3. CONCLUSIONS

It was presented a study using the ANN methodology to find the best set of input variables to develop a Monitoring Model by using a database given by IEA-R1 research reactor. The preliminary results showed that by reducing the number of input variables to train an artificial neural network, the residue increased, thus indicating that there is an adequate set of input variables to model the system.

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