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# DEVELOPMENT OF AN ARTIFICIAL NEURAL NETWORK FOR MONITORING AND DIAGNOSIS OF SENSOR FAULT AND DETECTION IN THE IEA-R1 RESEARCH REACTOR AT IPEN

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## ABSTRACT

The increasing demand on quality in production processes has encouraged the development of several studies on Monitoring and Diagnosis Systems in industrial plant, where 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.

In this work a Monitoring and Diagnosis Systems was developed based on the Artificial Neural Networks methodology. This methodology was applied to the IEA-R1 research reactor at IPEN. The development of this system was divided in three stages: the first was dedicated to monitoring, the second to the detection and the third to diagnosis of failures. In the first stage, several Artificial Neural Networks were trained to monitor the temperature variables, nuclear power and dose rate. Two databases were used: one with data generated by a theoretical model and another one with data to a typical week of operation of the IEA-R1 reactor. In the second stage, the neural networks used to monitor the variables were tested with a fault database. The faults were inserted artificially in the sensors signals. As the value of the maximum calibration error for special thermocouples is $\pm 0,5^{o}C$, it had been inserted faults of $\pm 1^{o}C$ in the sensor for the reading of the variables T3 and T4. In the third stage was developed a Fuzzy System to carry out the faults diagnosis, where were considered three conditions: a normal condition, a fault of $-1^{o}C$, and a fault of $+1^{o}C$. This system will indicate which thermocouple is faulty.

## 1. INTRODUCTION

The increasing demand on quality, reliability and safety in production processes has encouraged the development of studies on fault detection and identification in nuclear and industrial plants. The term "fault" can be defined as an unexpected change of the system functionality that can be associated to a malfunction in a physical component or in a system sensor or actuator.

A fault diagnosis system should perform two tasks: the first refer to the fault detection and the second to the fault isolation. The purpose of the first is to determine that a fault has occurred in the system, so it is necessary to collect and process all the available system information to detect any departure from nominal behavior of the process. The second task is devoted to locate the fault source. In the case of a nuclear reactor, it is necessary to develop reliability and fault tolerant control systems to guarantee the safety and availability of the reactor [1].

The solution of many problems in engineering through Artificial Neural Networks is sufficiently interesting, as much for the form as these problems are represented internally by the network, as also to the generated results. In Artificial Neural Networks, the usual procedure in the solution of problems passes initially by a learning phase, where a set of examples is presented to the networks, which automatically extracts from them the necessary characteristics to represent the supplied information. These characteristics are used later to generate answers to the problems with similar characteristics to the examples. The possibility to learn through examples and to generalize the learned information is the main attractive in the problems solution through Artificial Neural Networks. The generalization, which is associated with the ability of the network to learn through a reduced set of examples and later to give coherent answers to data not known, is a demonstration that the ability of Artificial Neural Networks goes very beyond of simply map relations of inputs and outputs. Neural Networks are capable to extract information not presented in explicit form by the use of examples. The purpose of this works is to present a Monitoring and Diagnosis Systems methodology, which was applied to the IEA-R1 research reactor at IPEN. In this works, two databases were used: one with data generated by a theoretical model of the IEA-R1 research reactor and another one with data to a typical week of operation of the IEA-R1 reactor.

## 2. NEURAL NETWORKS

A neural network 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 [2].

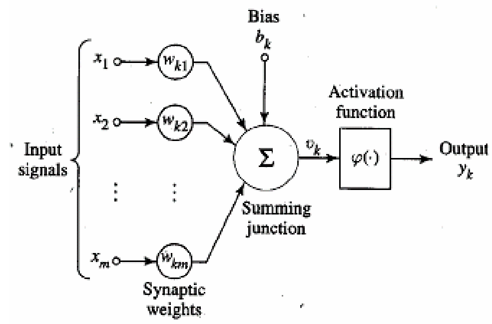



**Figure 1. Neuron Model**

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 an input layer to an output layer. Every neuron in a layer receives its inputs from the neurons in its adjacent lower layer and sends its output to the neurons in its adjacent upper layer. The training is performed using an error backpropagation scheme, 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).

$$E(av) = \frac{1}{N}\sum_{n=1}^{N}\sum_{j\in C}(dj(n) - yj(n))^2 \qquad (1)$$

where: E(av) – mean squared error, C – neurons in the output layer, j – neuron, $y_j(n)$ – target output, N – number of patterns (examples), n – number of interactions, $d_j(n)$ – actual output

## 3. IEA-R1 REACTOR

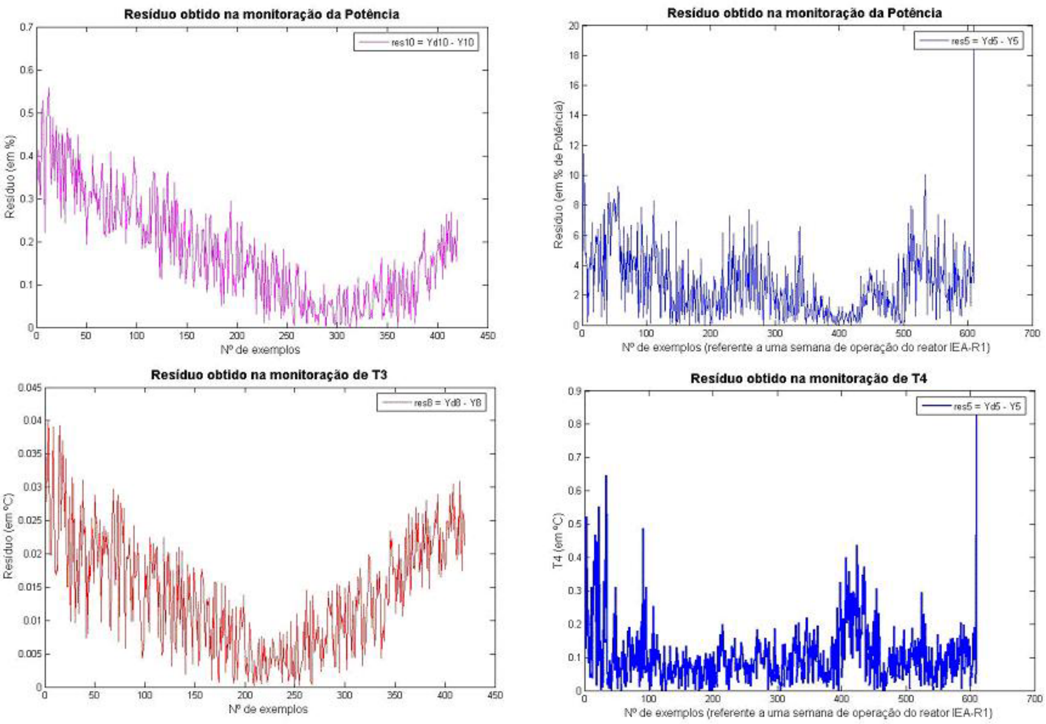
The IEA-R1 is a pool type reactor of 5 MW, cooled and moderated by light water that uses graphite and beryllium as reflector. In this work, it was used a database from a theoretical model of IEA-R1 reactor by the developed system; later it will be use an actual database from the IEA-R1 DAS (Data Acquisition System). The purpose of DAS is to monitor and register the main operational parameters of the reactor. Processing modules and signals conditioning composes the DAS, and a man-machine interface installed in a microcomputer. The DAS monitor 58 operational variables, including temperature, flow rate, level, pressure, nuclear radiation, nuclear power, safety and control rod position. The DAS allows storing the temporal history of all the process variables monitored, thus supplying the data that will be used in the Monitoring and Diagnosis System [3,4].

## 4. MONITORING AND DIAGNOSIS SYSTEM

A Monitoring and Diagnosis System was developed using Artificial Neural Networks. The methodology was divided in three stages: the first was dedicated to monitor the temperature variables, nuclear power and dose rate. In the second stage, the neural networks used to monitor the variables were tested with a fault database, which were inserted artificially in the sensor signals. Finally, in the third stage a Fuzzy System was developed to carry out the fault diagnosis, where were considered three conditions: a normal condition, a fault of -1ºC and a fault of +1ºC. It was used two databases: one with data generated by a theoretical model and another with data to a typical week of operation of the IEA-R1 reactor.

## 5. MONITORING MODEL

It was trained neural networks to monitor the temperature variables, nuclear power and dose rate. First, the neural networks were trained using data generated by a theoretical model, where the variables Nuclear Power (Pot) was varied from 0% to 100%, in 5% steps, where 20 patterns were taken for every condition in the power range considered, totalizing 420 patterns. A 0,4% noise was added to the variable T3 (coolant temperature above the reactor core) and a 1% noise was added to the variables FE01 (primary loop flow rate). After this, it was used data to a typical week of operation of the IEA-R1 reactor. This database was so large, then it was used a program which reads the database in 8 to 8 seconds and saves it to train the networks. To prevent overfitting, the method of Early Stopping was used, which suggests a database division in three subsets: training (50%), validation (25%) and testing (25%). 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. The Figure 2 shows the results obtained during the monitoring stage using the database generated by a theoretical model Fig. 2(a) and the data to a typical week of operation of the IEA-R1 reactor.



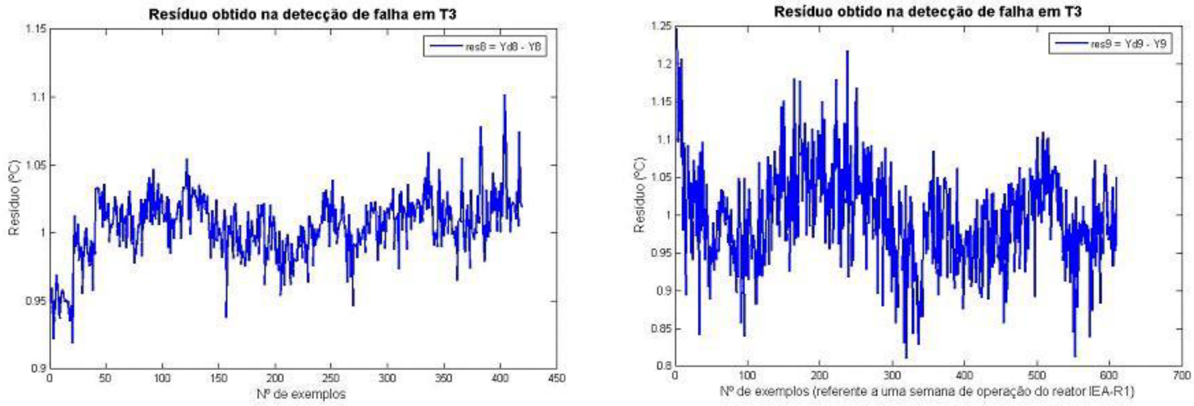

2(a). Data generated by a theoretical model

2(b). Data to a typical week of operation of the IEA-R1 reactor

Figure 2. Results obtained during the monitoring stage

## 6. DETECTION AND DIAGNOSIS MODEL

After the definition of the Monitoring Model, the networks which presented the best ones results had been tested with a database whose faults were inserted to simulate the faulty thermocouples. For in such a way, two databases had been used: a database with faults generated for the theoretical model and another one given of reactor operation. The results were shown in Figure 3. As we can see, the residues obtained were lesser than that allowing for specials thermocouples which is $\pm 0{,}5^{o}C$.




3(a). Theoretical Model Database

3(b). Reactor Operation Database

Figure 3. Results obtained during the detection stage

The Table I summarize the results obtained during the monitoring and fault detection. As we can see, the error energy obtained during fault detection is bigger than the ones obtained during the monitor of the same variables. Moreover, the results obtained during the fault detection was excellent because the networks used during de monitoring show good performance when they were tested using a faulty database.

Table I. The results obtained during the monitoring and fault detection

| Monitoring | Variables | Number of neurons | Error Energy (En) |
|---|---|---|---|
| Theoretical Model | T3 | 8 | $1{,}59947 \cdot 10^{-5}$ |
| | T4 | 10 | $6{,}98342 \cdot 10^{-6}$ |
| Reactor Operation | T3 | 9 | $9{,}21064 \cdot 10^{-3}$ |
| | T4 | 5 | $7{,}26921 \cdot 10^{-3}$ |
| **Fault Detection** | **Variables** | **Number of neurons** | **Error Energy (En)** |
| Theoretical Model | T3 (fault of +1%) | 8 | $6{,}44891 \cdot 10^{-5}$ |
| | T3 (fault of –1%) | 8 | $7{,}48689 \cdot 10^{-5}$ |
| | T4 (fault of +1%) | 10 | $6{,}03138 \cdot 10^{-5}$ |
| | T4 (fault of –1%) | 10 | $6{,}69459 \cdot 10^{-5}$ |
| Reactor Operation | T3 (fault of +1%) | 9 | $6{,}71722 \cdot 10^{-2}$ |
| | T3 (fault of –1%) | 9 | $6{,}81395 \cdot 10^{-2}$ |
| | T4 (fault of +1%) | 5 | $9{,}44376 \cdot 10^{-3}$ |
| | T4 (fault of –1%) | 5 | $9{,}84578 \cdot 10^{-3}$ |

The Figure 4 shows the system developed to diagnosis the thermocouples faulty. The results obtained were excellent.

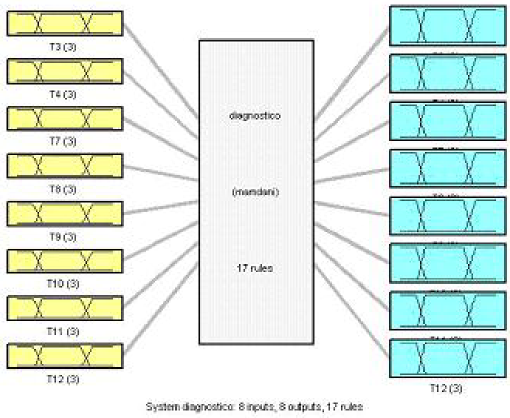



Figure 4. Fault Diagnosis System

## 7. CONCLUSION AND FUTURE WORK

It was concluded that the Monitoring and Diagnosis System was a good methodology to prevent faults to the IEA-R1 reactor. The results obtained were excellent and in the future, it is intended to expand the system to simulate some transients which can occurs during the operation, and in this way, study the time influence in the process and if this methodology will have good results to it.

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