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OPERATOR SUPPORT SYSTEM USING COMPUTATIONAL INTELLIGENCE TECHNIQUES

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ABSTRACT

Computational Intelligence Systems have been widely applied in Monitoring and Fault Detection Systems in several processes and in different kinds of applications. These systems use interdependent components ordered in modules. It is a typical behavior of such systems to ensure early detection and diagnosis of faults. Monitoring and Fault Detection Techniques can be divided into two categories: estimative and pattern recognition methods. The estimative methods use a mathematical model, which describes the process behavior. The pattern recognition methods use a database to describe the process. In this work, an operator support system using Computational Intelligence Techniques was developed. This system will show the information obtained by different CI techniques in order to help operators to take decision in real time and guide them in the fault diagnosis before the normal alarm limits are reached.

1. INTRODUCTION

Computational Intelligent Techniques have been widely used in Monitoring and Fault Detection Systems in a great variety of industrial process. These systems consist in independent module components, which is a typical behavior to guarantee early fault anomaly detection, 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 resulting in economic losses and increasing the costs to repair some damaged equipment [1] [2][3][4][5].

Nuclear power plants are complex systems due to the large number of variables to be continuously monitored. In addition, it is necessary to guarantee performance, reliability and safety. During a fault, operators receive a large volume of information from data acquisition systems in a very short period of time. Because of this, operators are required to make some decisions in stressful conditions, raising difficulties to obtain the fault diagnosis. In order to help nuclear power plant operators many techniques Computational Intelligence Techniques have been used, including Fuzzy Logic [6], Artificial Neural Networks (ANN) [7] [8] [9], GMDH (Group Method of Data Handling) [10] and Genetic Algorithms (GA's) [11] [12]. The use of these methods is justified because they allow process modeling without the use of algebraic equations that mathematically describe the phenomenon [13] [14] [15]. This modeling is performed using a database containing the time history of plant operation.

The main objective of this work is to develop an Operator Support System using a Computational Intelligence Technique (CI): Artificial Neural Networks (ANN). The major expected benefit is associated with providing the information obtained by the CI technique to the operator in real time. The fault detection is performed by calculating the residual value, which is the difference between the measured value and that obtained by the developed ANN model. The residuals patterns obtained are used for identifying the anomaly. The System was developed using IEA-R1 Ipen experimental reactor operational data.

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.

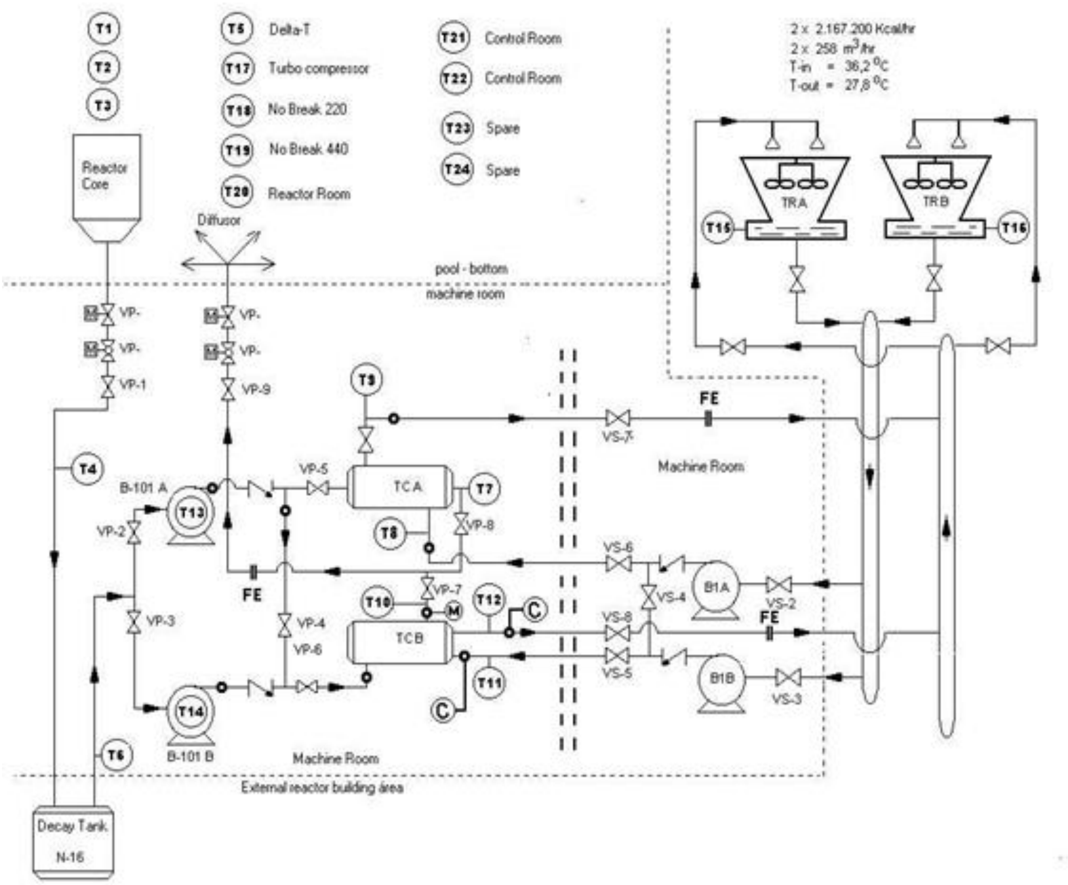

Figure 1: Flowchart diagram of the Ipen nuclear research reactor IEA-R1.

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 [16] [17].

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 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 networks from its environment through a learning process, which is responsible to adapt the synaptic weights to the stimulus received, by the environment acquire the knowledge. The fundamental element of a neural network is a neuron, which has multiple inputs and a single output, as we can see 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 [18].

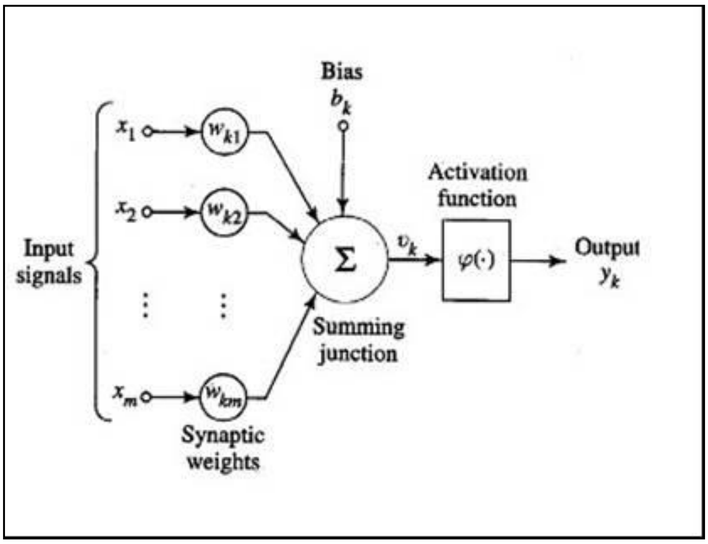

Figure 2. Neuron Model

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. OPERATOR SUPPORT SYSTEM USING COMPUTATIONAL INTELLIGENCE TECHNIQUES

An Operator Support System using Computational Intelligence Techniques was developed using ANNs methodology.

The methodology was developed and tested using a model, which contains 38 variables including: temperature, flow rate, nuclear radiation and control rod position (see Table 1 –DAS IEA-R1 variables). In this work, it will be shown the results obtained monitoring the following variables: N1 and N2 (nuclear power – [%]), Z1 (control rod position [mm]), Z2-Z4 (safety rod position [mm]) and T1, T2, T3, T4, T7, T8 and T9 (temperature [ºC]).

In future works, it will be used all the DAS IEA-R1 variables. Another Computational Intelligence Techniques will be applied and compared. Figure 3 shows the steps for the Operator Support System methodology development.

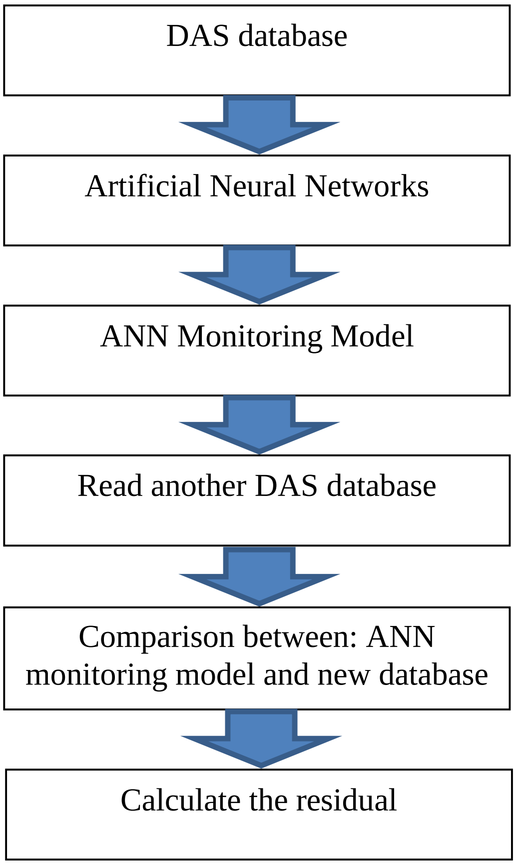

Figure 3: Operator Support System using Artificial Neural Networks.

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 thirty-eight 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 to study the sensors behavior in monitoring, as shown the equation (2):

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

Table 2 shows the results obtained during sensors monitoring using DAS IEA-R1 data from 4 different operation cycles.

Table 2: Sensors Monitoring using different DAS IEA-R1 data

	MEAN RESIDUAL (%)				
	ANN training	**1st**	**2nd**	**3rd**	**4th**
Z1	2,1809	0,0331	0,0086	0,0072	0,0049
Z2	7,0133	0,0046	0,0083	0,0049	8,7894e-5
Z3	4,6215	0,0055	0,0014	0,0100	1,7833e-4
Z4	3,8799	0,0127	0,0131	0,0060	0,0035
N1	2,1983	0,0020	0,0089	0,0084	0,0042
N2	2,2630	0,0094	4,8280e-4	0,0054	0,0012
T1	1,5053	0,9730	0,0021	0,0219	3,3565E-4
T2	3,2072	0,0165	0,0312	0,0224	0,0448
T3	1,5897	0,2791	0,0149	0,0159	0,0200
T4	2,8940	0,0019	0,0057	0,0042	0,0075
T7	2,1110	0,0015	0,0051	0,0152	0,0497
T8	0,7667	0,0611	0,0017	0,0284	3,1515e-4
T9	4,2433	0,0041	0,0034	0,2076	0,0050

The main thing that can be observed in Table 2 is that the mean residual values are below 7%.

6. Conclusion and Future Work

It was presented a study using the ANN methodology to sensors monitoring using different data given of IEA-R1 research reactor. The following variables were monitored using the developed methodology: Z1, Z2, Z3, Z4, N1, N2, T1, T2, T3, T4, T7, T8 and T9. The preliminary results showed that the mean residuals obtained are below 7% stimulating the development of an Operator Support System using another Computational Intelligence Techniques and different databases to study the model sensibility and robustness.

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