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

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ABSTRACT

The purpose of this paper is to develop a system to monitor the nuclear power of a reactor using Artificial Neural Networks. The database used in this work was developed using a theoretical model of IEA-R1 Research Reactor. The IEA-R1 is a pool type reactor of 5 MW, cooled and moderated by light water, and uses graphite and beryllium as reflector. To monitor the nuclear power the following variables were chosen: T3 – temperature above the reactor core, T4 – outlet core temperature, FE01 – primary loop flow rate and the nuclear power. The inputs are T3, T4 and FE01 and the output is the nuclear power. It was used several networks using the backpropagation algorithm. The conclusion is that the multiplayer perceptrons networks (MLPs), training by the backpropagation algorithm, can be used to solve this problem. The results obtained with the MLPs networks are satisfactory and the mean square error was in the order of 10^{-4} during the network training and in the order of 10^{-2} during the network testing. We intend to monitor the other variables of this model using the same methodology, and after this we will use the real database from the system to compare the results obtained with the model. The monitoring of the reactor variables is part of the development of a fault detection and isolation system which is underway and which is, by its turn, part of a comprehensive ageing management program.

1. INTRODUCTION

The increasing demand on quality, reliability and safety in production processes has encouraged the development of studies and methods 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 refers 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 behaviour 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 network, 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 abitity 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 work is to develop a system to monitor the nuclear power of a reactor using Artificial Neural Networks. A theoretical model of the IEA-R1 research reactor, developed in the platform Matlab, generated the database used in this work.

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 network from its environment through a learning process which is basically responsible to adapt the synaptic weights to the stimulus received by the enviroment [2]. The fundamental element of a neural network is a neuron, which has multiple inputs and a single output, as we can see in Fig. 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.

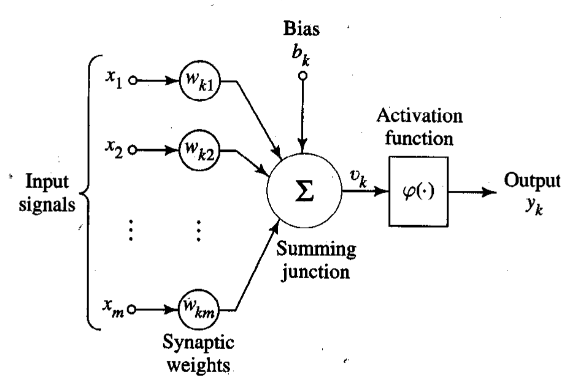

Figure 1. Neuron Model

In this work, it was used the multilayer 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. The connecting weights 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).

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

E(av) = mean squared error	N = number of patterns (examples)
C = neurons in the output layer	n = number of interations
j = neuron	dj(n) = actual output
yj(n) = target 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 Data Acquisition System (DAS) monitors 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 Fault Diagnosis system [3,4].

4. MONITORING THE NUCLEAR POWER REACTOR

A system to monitor the nuclear power reactor was developed using Artificial Neural Networks. The variables chosen were: T3 – coolant temperature above the reactor core, T4 –outlet core temperature, FE01 – primary loop flow rate and the nuclear power, where the inputs are T3, T4 and FE01 and the output is the nuclear power. A theoretical model of the IEA-R1 Research Reactor was used, which was developed using the MATLAB toolbox GUIDE, generating the database used in this work. The system process equations are based in the IEA-R1 mass and energy inventory balance and the physical and operational aspects such as length, pipe diameter, flow rate, temperature and pressure drop, are taken into consideration. Using the model, data were generated for different operational conditions, both under normal and faulty conditions with different noise levels added to the input variables. Data generated by the theoretical model were compared with real reactor data showing a good agreement.

4.1. NETWORK TRAINING DATA

The database was generated varying the variable nuclear power Pot from 0 through 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 and a 1% noise was added in the variable FE01, as described earlier. 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 calculate the gradient and to bring up to date the weights and bias of the network; the validation set is used to monitor the error during the training process, and the testing set is used to compare different models. It was used a Multilayer Perceptron Network with three layers: one input layer, one hidden layer and one 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 numbers of neurons to find the ideal numbers of neurons. The activation function is the hyperbolic tangent; the output layer is composed by a neuron that represents the output of the network.

4.2. NETWORK TRAINING

The networks were trained varying the number of neurons in the hidden layer from 1 up to 10. Two limitors to the learning process had been established: the maximum number of epochs (1000) and a tolerance for the maximum error (0,0001). These limitors have been established to prevent that the energy error function to have points of local minimums, and in this way not obtaining an adequate solution. All the trained networks presented a good performance, as this can be seen in Fig. 2, which presents the networks mean squared errors.

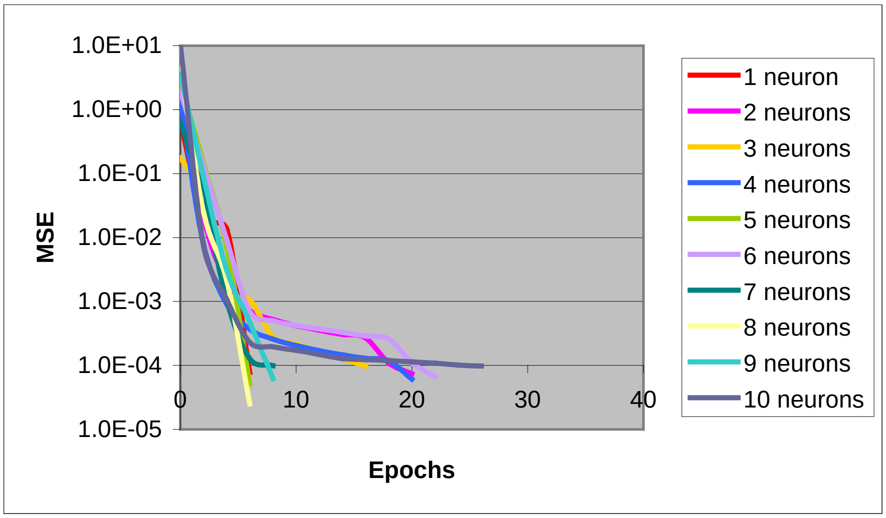

Figure 2. Mean squared error versus epochs for all trained networks

Table 1 shows the values of the mean squared errors for the trained networks. It can be observed that the values obtained to all the networks are of the same order of magnitude.

Table 1. The MSE getting during the networks training

Nº of Neurons	Epochs	MSE
1	6	7.7653E-05
2	19	7.4228E-05
3	16	9.8454E-05
4	19	6.0828E-05
5	6	5.1414E-05
6	21	6.6942E-05
7	7	9.9057E-05
8	6	2.5089E-05
9	7	6.1705E-05
10	25	9.8264E-05

4.3. NETWORK TESTING

After the training, it was initiated a network testing. All the trained networks present satisfactory results, where the power value estimated by the networks trained are similar to the target power (t). Figure 3 shows in detail the estimated powers by the networks, in the interval of 0 to 5%.

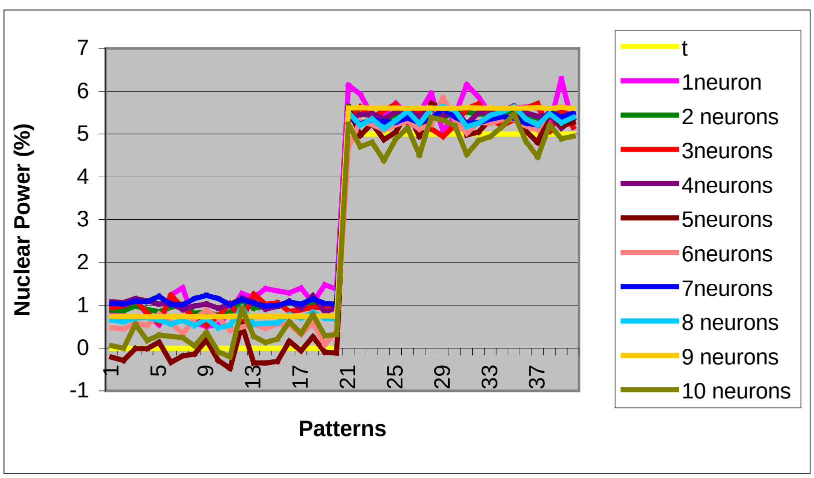

Figure 3. Estimated Power (%) by the networks trained in the interval of 0 to 5%

The mean squared errors obtained during the testing network were shown in Table 2. As we can see, the networks that showed the smallest MSE were the networks with 4 (MSE - 0.07908), 5 (MSE - 0.06933), 8 (MSE - 0.06772) and 9 (MSE - 0.07684) neurons in the hidden layer. To solve this problem, we decided to choose the simplest model with the smallest MSE and number of epochs, in this case the network with 5 neurons was chosen because of its simplicity.

Table2. MSE obtained during the networks testing

Number of Neurons	Epochs	MSE
1	6	0.09312
2	19	0.95931
3	16	0.12111
4	**19**	**0.07908**
5	**6**	**0.06933**
6	21	0.10626
7	7	0.13284
8	**6**	**0.06772**
9	**7**	**0.07684**
10	25	0.14716

5. CONCLUSION AND FUTURE WORK

It was concluded that to the Nuclear Power monitoring using data from the theoretical IEA-R1 reactor model, a Multilayer Perceptron Network could be trained by the backpropagation algorithm. The network configuration chosen to solve this problem was the network with 5 neurons in the hidden layer because of its simplicity and the MSE, which was 0.06933. In the future, it is intended to use operational data from the reactor to establish a comparative study with the results obtained with the theoretical model. After this comparative study, it is intended to expand the system, and in this way, monitor other process variables and simulate some cases of faults in the sensors.

6. REFERENCES

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