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STUDY FOR ON-LINE SYSTEM TO IDENTIFY INADVERTENT CONTROL ROD DROPS IN PWR REACTORS USING EX-CORE DETECTOR AND THERMOCOUPLE MEASURES

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ABSTRACT

Accidental control rod drops event in PWR reactors leads to an unsafe operating condition. It is important to quickly identify the rod to minimize undesirable effects in such a scenario. In this event, there is a distortion in the power distribution and temperature in the reactor core. The goal of this study is to develop an on-line model to identify the inadvertent control rod dropped in PWR reactor. The proposed model is based on physical correlations and pattern recognition of ex-core detector responses and thermocouples measures. The results of the study demonstrated the feasibility of an on-line system, contributing to safer operation conditions and preventing undesirable effects, as its shutdown.

1. INTRODUCTION

The inadvertent control rod drop in core reactor could lead to an unsafe operating condition. This event can be caused by failure or malfunction of the control rod drive mechanism. According to the Final Analysis Report for Angra I (FSAR) [1] this event is a fault of moderate frequency. In this event there is a variation in the power and temperature distribution in the reactor core and could lead to compromise the physical structure of the fuel rods or until the reactor shutdown. Therefore, it is important to quickly identify the dropped control rod to minimize undesirable effects. Operating instructions are require in a set time sequence in this kind of event that characterizes an inability to identify in real-time the control rod dropped.

Souza et al. (2014) [2] proposed recognizing patterns in the neutrons ex-core detector responses using an expert system to identify control rod drops in PWR reactors. Sousa et al. (2015) [3] proposed an identification model using profiles thermocouples measures. However, the both models are limited. The first due the dependence of expert system rules with the reactor condition and the second was necessary used previously established tolerance limits in temperature variations.

The aim of this study is to develop an on-line method to identify a control rod dropped of PWR reactors core based on the reading of ex-core detector responses and thermocouples measures. In this paper a RBF (Radial Base Function) neural network [4] is applied to develop a system of identification.

2. CORE DESCRIPTION

The core considered in this work is similar to that of the Angra-1 PWR, a Westinghouse reactor, with 121 fuel assemblies and 33 control rods, shown in Figure 1. PWR reactors operate with the aid of neutron ex-core detectors that have the purpose of monitoring the neutron flux, providing signals to indicate the state of operation, control and protection of the reactor. The ex-core neutron detectors NE-41, NE-42, NE-43, and NE-44 are located outside the reactor core and are placed in four radial positions in the concrete protection that surrounds the reactor vessel. The reactor has 39 thermocouples which measure the moderator temperatures at top output of the fuel assemblies at selected locations in the core as shown in Figure 2.

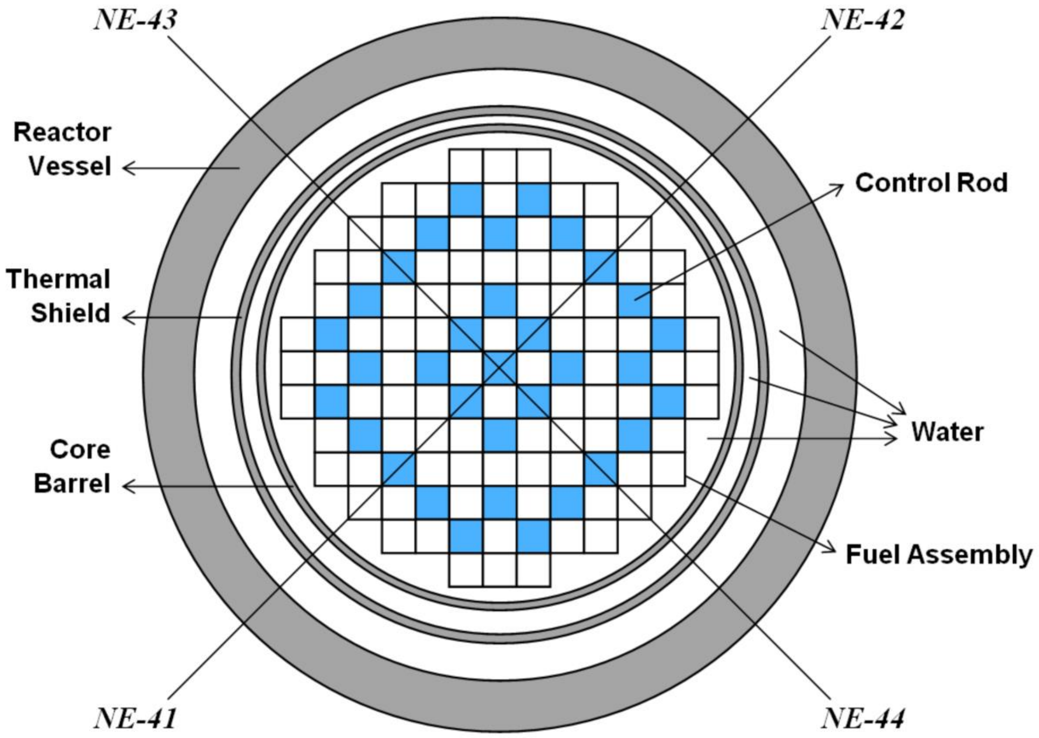

Figure 1: Reactor layout

3. CNFR CODE DESCRIPTION

The power distributions in the reactor core were generated using the CNFR – Código Nacional de Física de Reatores - [5]. The CNFR code can simulate the behaviour of PWR reactors Angra-1 and Angra-2 in a steady state, solving neutronic phenomena models, thermal hydraulic and isotopic decay that characteristic to these types of reactors.

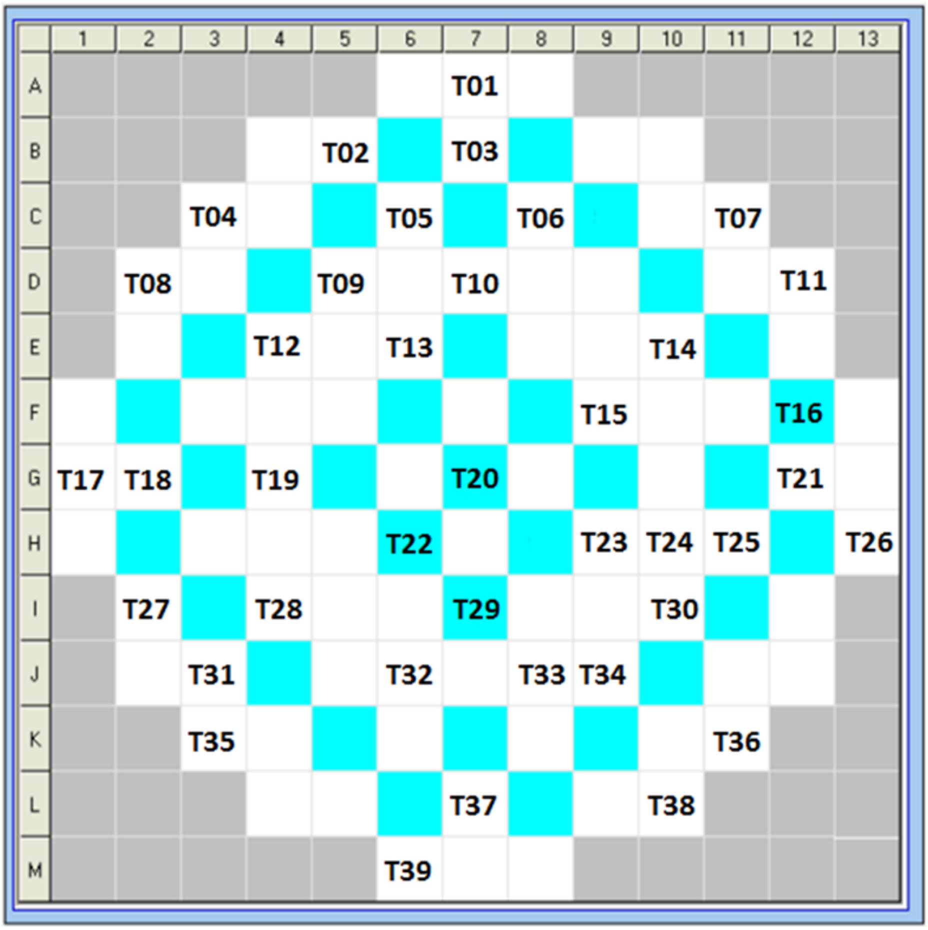

Figure 2: Thermocouples positions

The CNFR generates the distribution of the average neutron flux in the core of PWR reactors by solving the neutron diffusion equation in three-dimensional Cartesian Geometry for two energy groups, using a nodal expansion method (NEM) [6]. With the CNFR code it is possible to simulate different configurations for control rod drop and obtain the core power and temperature distribution for these cases.

4. METHODOLOGY

In simulations the reactor was kept at full power and all control rods withdrawn until the boron reached 10 ppm. The simulations to obtain the power distribution for a criticality condition were made for 18 burnup steps for a fresh cycle of the reactor. A reference case was simulated without a control rod drop and in all successive cases of control rod drops. In brief, apart from the reference case, 33 simulations were run for each of the 18 burnup steps, generating different configurations of the core, one for each control rod dropped. Table 1 shows the simulated burnup steps and equivalent in days.

The ex-core detectors responses are determined using a mathematical model that relates detector response to core power distribution for a given reactor configuration. A methodology

Table 1: Simulated burnup steps

Burnup Steps	Equivalent in days
1	0
2	3
3	20
4	60
5	80
6	120
7	140
8	180
9	200
10	240
11	260
12	280
13	320
14	340
15	363
16	368
17	373
18	380

to determinate the ex-core detector response proposed in this work was based in previous works [2]. In order to simulate the readings of the thermocouples was used the output moderator temperature in thermocouples positions calculated by CNFR code.

For the implementation was necessary to relate a core configuration to a control rod dropped via on-line variables measures, in this case ex-core detector and thermocouples. The identification model is possible through the recognition of patters of these readings. Therefore, in this study was used a RBF network.

4.1. Radial Basis Function Networks

Neural Network is a nonlinear function approximation system. One of the main characteristics of neural networks is its ability to learn from a finite data set [4]. Therefore, networks are able to generalize the knowledge acquired, being able to respond appropriately based on the mapping done. Neural networks have potential in modeling complex nonlinear systems as showed in many previous works. The artificial neuron is a fundamental unit of a neural network and that is where the signals are processed. This mathematical neuron receives input signals and returns an output signal which can be the output signal from the network or the input to another neuron. Neural networks are formed by a set of artificial neurons interconnected by synapses and structured in layers in order to allow the communication between layers of neurons.

The radial basis networks constitute three-layer architecture [4] with an input layer, a hidden layer and an output layer. The input layer consists of nodes that connect the input vectors to the network environment. The hidden layer is responsible for the nonlinear transformation of the input space to the hidden space, in other words it maps the vectors of the input space into a new space. Finally, the output layer of the network provides a response to the given vector through a linear mapping.

A schematic of the RBF network with n input vector and a scalar output is shown in Figure 3. The network implements mapping$f: R^n \to R$.

$$f(x) = w_0 + \sum_{j=1}^{N} \left(w_j \, \varphi_j (\| x - x_j \|) \right) \tag{1}$$

The hidden layer neurons have a set of activation functions $\varphi(\| x - x_j \|)$ which constitute bases to the input vectors, which are then expanded in space by these radial basis functions. The variable $x \in R^n$ is the input vector, $x_j \in R^n$ is the center of N radial basis functions $\varphi(\| x - x_j \|)$ and $\| x - x_j \|$ represents the Euclidean norm. The activation functions of the hidden layer neurons used in the radial basis networks are usually Gaussian:

$$\varphi_j(\| x - x_j \|) = e^{-\left(\frac{\| x - x_j \|^2}{2\sigma^2} \right)} \tag{2}$$

where σ represents the Gaussian width.

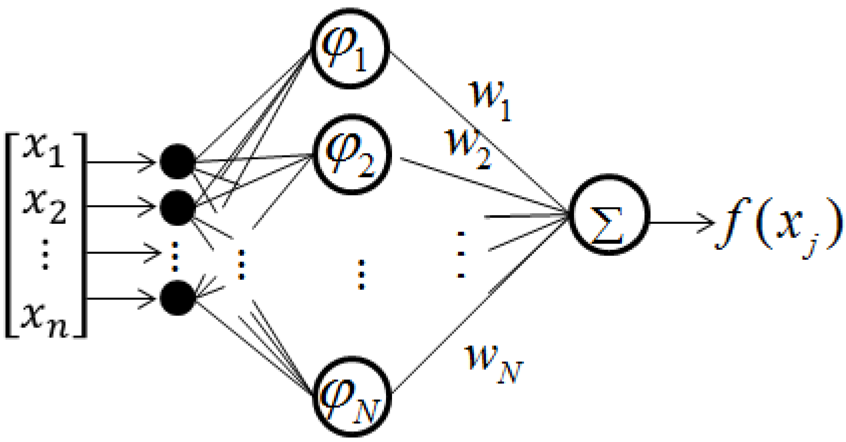

Figure 3: The structure of the RBF Network

The learning process consists of finding the best fit of the set of training data, in other words, making the network closer to the maximum extent possible to the mapping of inputs and outputs of the training data set. Therefore, the weights w_j are determinate according to:

$$\mathbf{\Phi w} = \mathbf{d} \tag{3}$$

$$\mathbf{w} = \mathbf{\Phi^{-1} d} \tag{4}$$

Where $\mathbf{\Phi}$ is:

$$\mathbf{\Phi} = \begin{pmatrix} \varphi_{11} & \varphi_{12} & \cdots & \varphi_{1N} \\ \varphi_{21} & \varphi_{22} & \cdots & \varphi_{2N} \\ \vdots & \vdots & & \vdots \\ \varphi_{N1} & \varphi_{N2} & \cdots & \varphi_{NN} \end{pmatrix} \tag{5}$$

And

$$\mathbf{d} = [\mathrm{d}_1, \mathrm{d}_2, \ldots, \mathrm{d}_N]^T \tag{6}$$

$$\mathbf{w} = [\mathrm{w}_1, \mathrm{w}_2, \ldots, \mathrm{w}_N]^{\boldsymbol{T}}. \tag{7}$$

The vectors **d** and **w** are respectively desired output and weights and *N* the size of data set training.

5. RESULTS AND DISCUSSIONS

5.1. Simulation Results

The dataset of this study is composed by 4 ex-core detector responses and 39 thermocouples measures in 18 burnup steps for all 33 cases of control rod drop, consisting in 43x33x18. Figure 4 and figure 5 shows the ex-core detector responses and thermocouples measures for one of these cases of control rod drop events. The figures show subtle variations in measurements that contributed to the identification by the system. Considering the symmetry of the core and using a set of IF-THEN rules is always possible to recognize patterns in the ex-core detector responses and identify the quadrant where the control rod dropped. Therefore, were implemented 4 RBF networks one for each quadrant and was considered the thermocouples measures for each quadrant.

5.2. Method Result

The data training input of the networks is composed by ex-core detectors responses and thermocouples measures in respective quadrant for 3 selected burnup steps and the output consist of the respective numeric representation of control rod. To enhance the best performance the choice of the burrnup steps training set was made in order to cover the problem domain and wide operation condition possible to get the best generalization.

In the test process all data set was used except the ones used in training stage. The input vector of system should be 4 ex-core detector responses and the thermocouples measures. After identified the quadrant and considering the characteristics of the core, only the quadrant thermocouples measure was used as RBF input. The output is a number corresponding to the control rod identifier. Figure 6 shows the scheme for identification method.

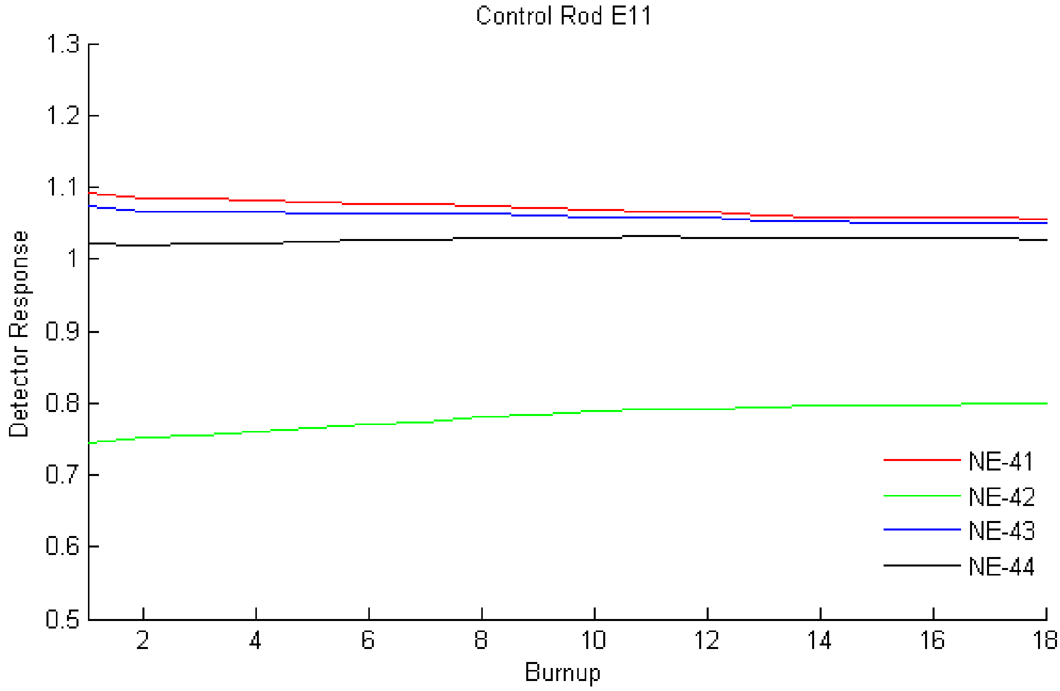

Figure 4: Detector behaviors

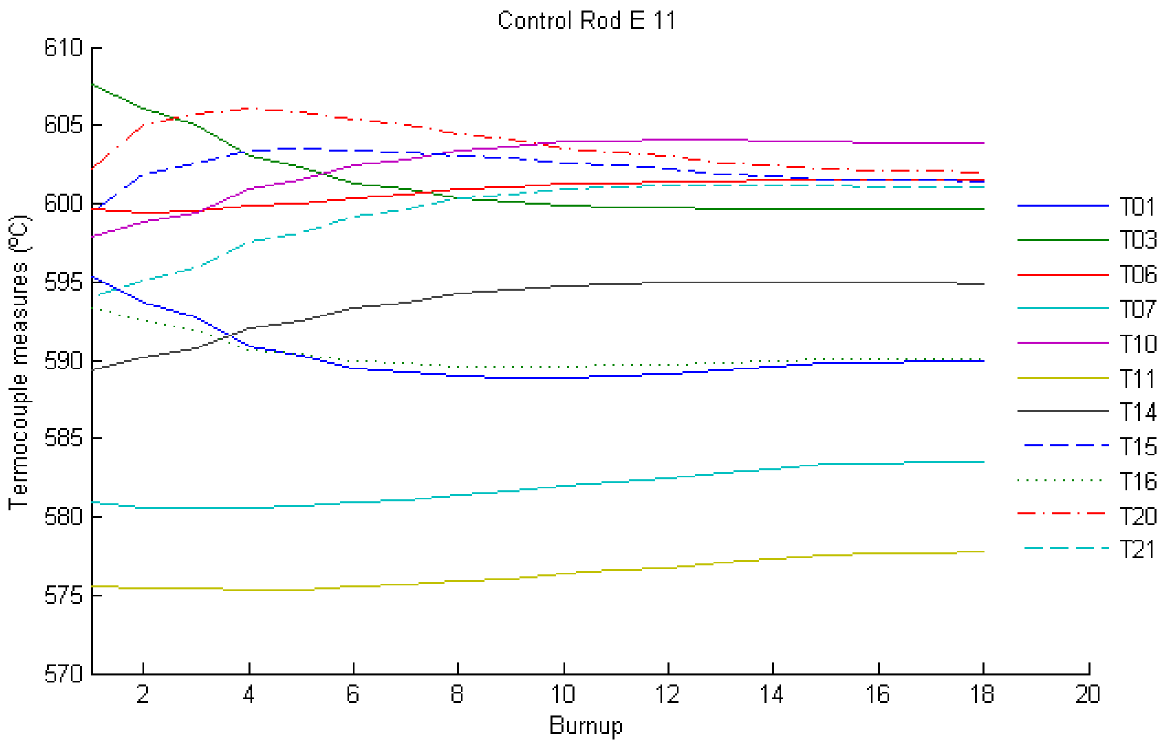

Figure 5: Thermocouple behaviors

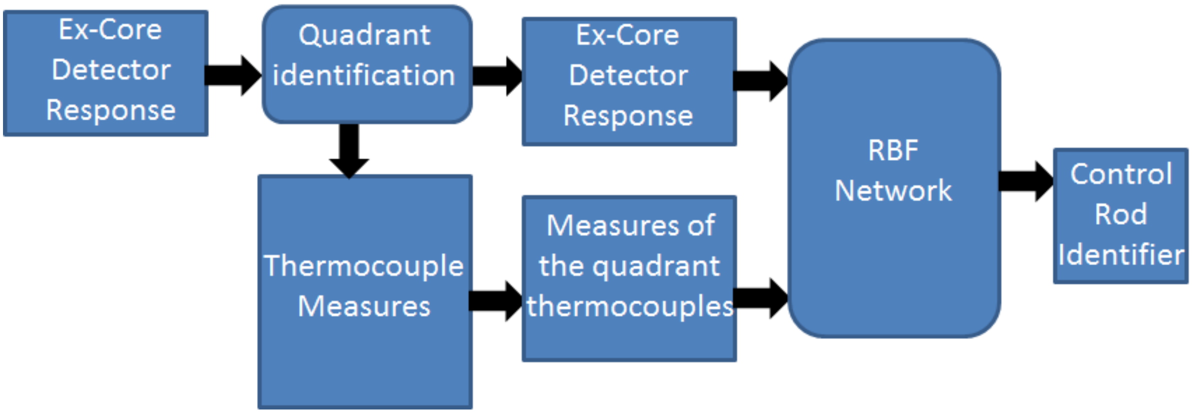

Figure 6: Scheme for the expert system

The error verification was made by comparing the response of the RBF with the correct response from the dropped control rod. Figure 7 shows the sensibility of RBF network with the width of the Gaussian function where is possible to see a range of values that network is optimized. The results showed that the system is able to correctly identify all of patterns of control rod dropped at any time in a determinate range of Gaussian width.

Further to the study of the sensitivity of Gaussian width, the good result presented by the methodology can also be attributed to some choices when compared with previous works [7]. One of these choices was the use of thermocouples measures which was a kind of knowledge that contributed considerably to the pattern recognition. Another important contribution was the use of four smaller networks one for each quadrant, different of previous works [7] when was used one network for the whole core.

5.2. Sensitivity Analysis and Parameters of The Network

Another important discussion that can be done is about the condition number [8] of interpolation matrix **Φ** calculated in the training process. The condition number is defined by:

$$\mathrm{cond}(\boldsymbol{\Phi}) = \|\boldsymbol{\Phi}\|\left\|\boldsymbol{\Phi}^{-1}\right\| \tag{8}$$

Where norm is represented by:

$$\left\|\boldsymbol{\Phi}\right\|_{\infty} = \max_{1<j<m} \sum_{j=1}^{M} \left|\varphi_{ij}\right| \tag{9}$$

The figure 8 shows the variation in the condition number of interpolating matrix **Φ** with Gaussian width. Each curve represents one of four core networks.

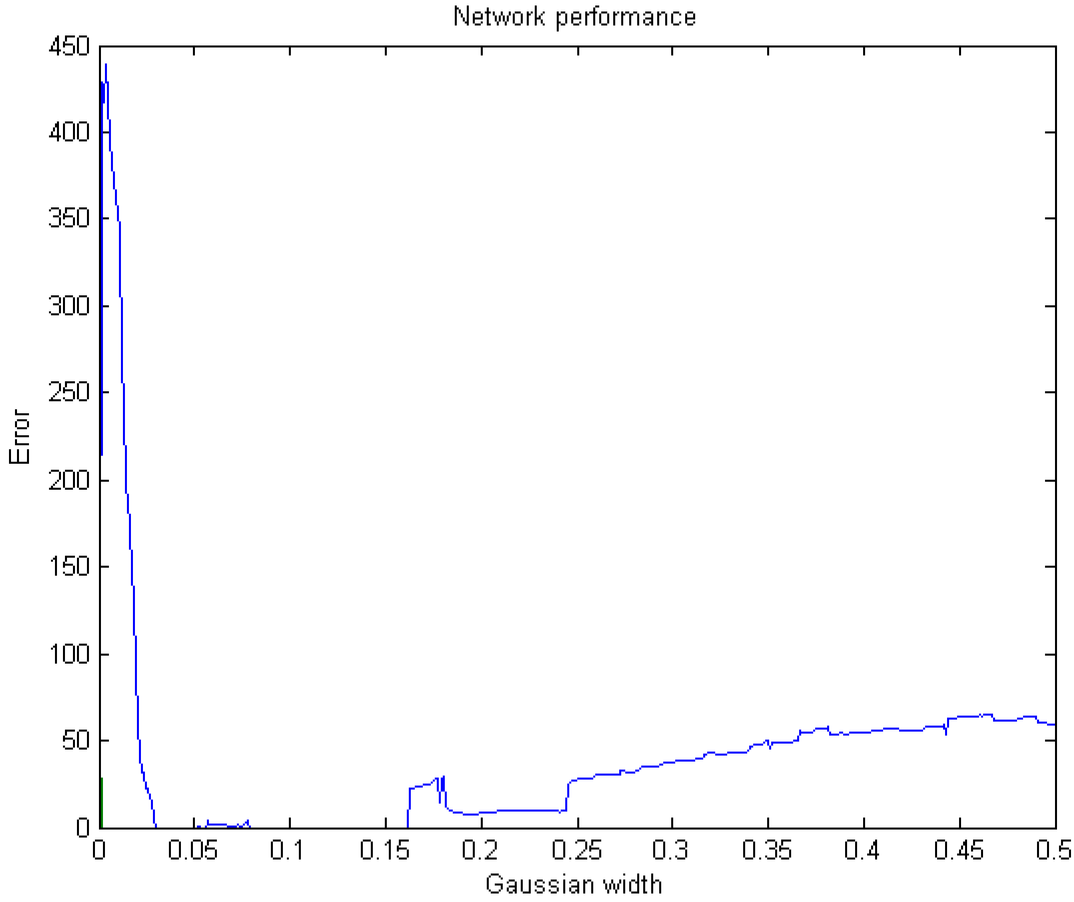

Figure 7: Network Error

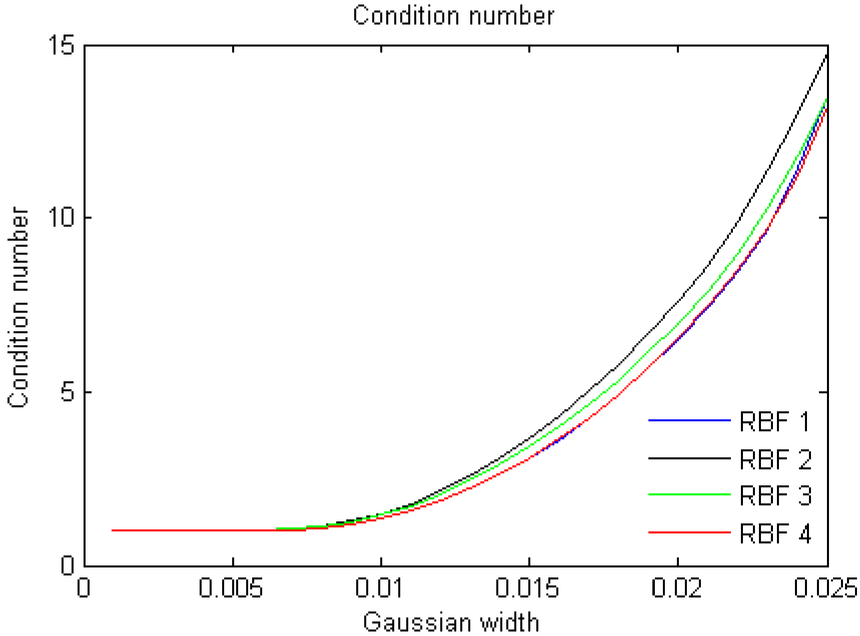

Figure 8: Condition Number

Considering the system representing the RBF network:

$$\mathbf{y}' = \mathbf{\Phi}'\mathbf{w} \tag{10}$$

Where $\mathbf{y}'$represent the identifier of control rod response by RBF and $\mathbf{\Phi}'$ the matrix modified by perturbation in the system due different input measures. They are defined as:

$$\mathbf{\Phi}' = \mathbf{\Phi} + \Delta\,\mathbf{\Phi} \tag{11}$$

$$\mathbf{y}' = \mathbf{d} + \Delta\,\mathbf{y} \tag{12}$$

.

The system is well conditioned [8] when a small variation $\Delta\mathbf{\Phi}$ due to input variables in the system results in small change in the output system $\Delta\mathbf{y}$. The relationship between $\Delta\mathbf{\Phi}$ and $\Delta\mathbf{y}$ is:

$$\frac{\|\Delta\,\mathbf{y}\|}{\|\mathbf{y}\|} \leq \mathrm{cond}(\mathbf{\Phi})\frac{\|\Delta\,\mathbf{\Phi}\|}{\|\mathbf{\Phi}\|} \tag{13}$$

Then the system is well conditioned when the value of the condition number is minimal or very close to 1, then for small values of sigma. This implies that the system can respond satisfactorily despite variations in the responses of the detectors and thermocouples measures, since the magnitude of the variations in measurements is compatible with the system's response, making it more reliable.

6. CONCLUSION

The goal of this study was the development of a system that allows the on-line identification of a control rod dropped in the core of a PWR reactor at any burnup step, with the responses of the ex-core detectors and thermocouple.

The core power and thermocouple measures distribution in all cases of control rod dropped and without any inserted rod were obtained through simulations in CNFR code that provide the data set for the implemented model. The simulations were made for 18 burnup steps, covering 380 operating days at full power.

The study shows that it is possible to recognize patterns in online variables such thermocouples and ex-core detectors in order to identify a control rod drop. The results show that the radial basis function network has excellent performance in a range of Gaussian width, which allows the system answer correctly all decisions.

In summary, it is important to highlight the contribution of thermocouple measures to get the good results when compared to previous work. The insertion of this kind of knowledge contributed significantly to the results. Another significant contribution has been the use of four smaller networks one for each quadrant not only one for the whole core as was done previously.

Additionally, the system is well-conditioned when used small values of the Gaussian width that means the condition number of the training matrix is close to 1. Therefore, the small variation in ex-core detector and thermocouple measures results in a small change in output vector.

As future work we intend to identify control rod through reconstruction of temperature mapping using the thermocouple measure.

REFERENCES

1. Final Safety Analysis Report (FSAR) - Central Almirante Álvaro Alberto - Unit I, Vol.12, Capítulo 15, Item 15.2.3, Furnas Centrais Elétricas S.A., Rio de Janeiro. (1980).
2. T. J. Souza, A.S. Martinez, J.A.C.C. Medeiros, D.A.P. Palma, A.C. Gonçalves, "On-line method to identify control rod drops in Pressurized Water Reactors," *Annals of Nuclear Energy*, **vol. 71**, pp.293-297 (2014).
3. G. R. G. Souza, "Identificação de queda inadvertida de barra de controle utilizando medidas dos termopares", COPPE/UFRJ http://www.con.ufrj.br/MSc%20Dissertacoes/2015/Dissertacao_Gabriel_Sousa.pdf (2015).
4. S. Haykin, *Redes Neurais: Princípios e Práticas*, 2ed, Bookman, Porto Alegre (2001).
5. D.A.P. Palma, A.Z. Mesquita, A.C. Gonçalves, A.C. Martinez, "Evaluation of Thermomechanical Behavior of Nuclear Fuel Using the Codes CNFR and Frapcon", *International Congress of Mechanical Engineering-COBEM*, Ribeirão Preto, SP, Brazil, Dates of Meeting, (2013).
6. A.C.M. Alvim, F.C. Silva, A.S. Martinez, "Improved Neutron Leakage Treatment on Nodal Expansion Method for PWR Reactor", *World Academy of Science, Engineering and Technology*, **vol. 6**, pp. 193-196 (2012).
7. T. J. Souza, A.S. Martinez, J.A.C.C. Medeiros, D.A.P. Palma, A.C. Gonçalves, " Study for Identification of Control rod drops in PWR reactor at any burnup step," *International Nuclear Atlantic Conference-INAC*, Recife, PE, Brazil, November 24-29, (2013).
8. G.H. Golub, C.F. van LOAN, *Matrix Computations*, 3ed, The Johns Hopkins University Press, Baltimore-Maryland (1996).