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STUDY FOR IDENTIFICATION OF CONTROL ROD DROPS IN PWR REACTORS AT ANY BURNUP STEP

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ABSTRACT

The control rod drop event in PWR reactors induces an unsafe operating condition. Therefore, in a scenario of a control rod drop is important to quickly identify the rod to minimize undesirable effects. The objective of this work is to develop an on-line method for identification of control rod drop in PWR reactors. The method consists on the construction of a tool that is based on the ex-core detector responses. Therefore, it is proposed to recognize patterns in the neutron ex-core detectors responses and thus to identify on-line a control rod drop in the core during the reactor operation. The results of the study, as well as the behavior of the detector responses, demonstrated the feasibility of this method.

1. INTRODUCTION

In a normally operating reactor, the control rod drop accident leads to an unsafe operating condition. According to the Safety Analysis Report of Angra I (FSAR) [1], this type of event in an operating reactor is an accident with moderate failure. This accident can be caused by failure or malfunction of the control rod drive mechanism. As it is an event not directly observable, this accident is characterized by its inability to real-time identification of the control rod dropped by operational procedures.

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. In a control rod drop event, there is a variation in the power distribution in the reactor core. The ex-core detectors respond to the distortion in power distribution in the core, since they are sensitive to these variations. Consequently, the external detector responses, that were very similar, change considerably.

In this work, the ex-core detectors responses are used in the investigation and identification of the control rod drop on the PWR reactor core. A mathematical model for determine ex-core detector response in PWR reactor was presented [2]. This model relates detector response to core power distribution for a given reactor configuration. A methodology to determinate the ex-core detector response is proposed in this work based in previous study [3].

The aim of this study is to develop a method for real-time identification of the control rod dropped at the core of PWR type reactors. The method is presented based on the readings of the responses of the detectors and has as output the identification of control rod at any burnup step of a particular cycle of a PWR reactor.

2. CORE DESCRIPTION

The core considered in this work is similar to PWR Angra-1 reactor (Westinghouse / Eletronuclear reactor) with 121 fuel assemblies. There are 33 control rods at this reactor and they are at the blue positions in Figure 1. The ex-core detectors of neutrons NE-41, NE-42, NE-43 and NE-44 are located outside the reactor core and they are placed in four radial positions in the concrete protection that surrounds the reactor vessel.

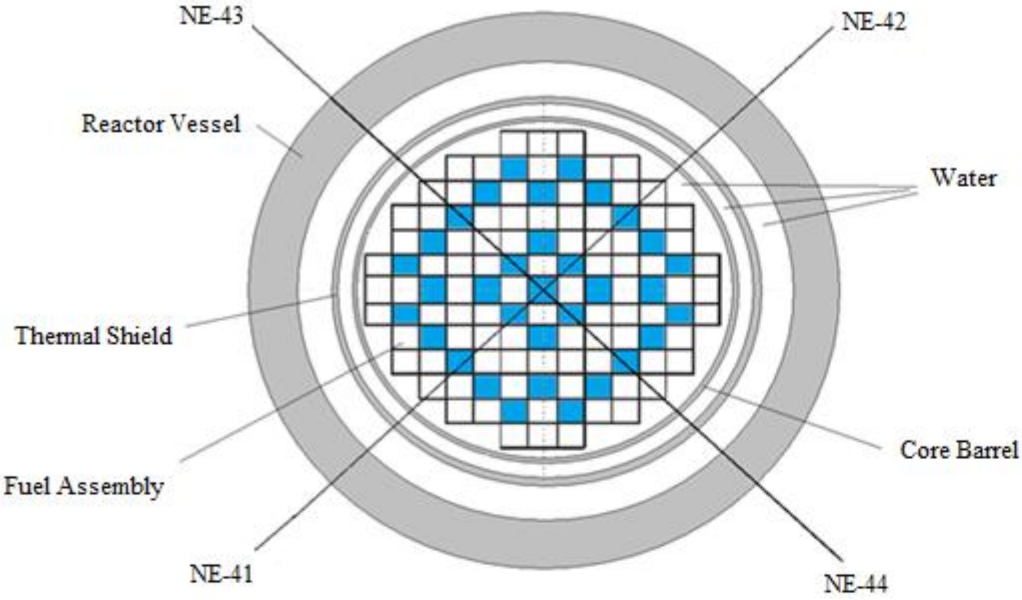

Figure 1: Layout of Reactor

3. CALCULATION OF THE EX-CORE RESPONSES

3.1. CNFR Code Description

The distribution of power in the core was generated using the Código Nacional de Física de Reatores, CNFR code [4]. The CNFR code is able to simulate the behavior of this reactor in steady state, solving neutronic phenomena models, thermal hydraulic and isotopic decay characteristic of these types of reactors.

The CNFR generates the distribution of the average flux of neutrons in the nucleus of PWR reactors solving the neutron diffusion equation in three-dimensional Cartesian geometry for two energy groups, using the nodal expansion method (NEM) [5].

The simulations to obtain the power distribution in the core for a criticality condition were made for 18 burnup steps for a fresh cycle of the reactor. The reactor was maintained at full power and all control rods withdrawn until the boron reached 10 ppm. Table 1 shows the simulated burnup steps. Subsequently, simulations were made for all the cases of control rod drop in such burnup steps.

Table 1: Simulated burnup steps

Burnup Steps	Equivalent in days
1º	0
2º	3
3º	20
4º	60
5º	80
6º	120
7º	140
8º	180
9º	200
10º	240
11º	260
12º	280
13º	320
14º	340
15º	363
16º	368
17º	273
18º	380

3.2. Calculation of Ex-core Detectors Responses

For the construction of the proposed method it was used a methodology for calculating the response of the detectors. This methodology relates the detector responses to a given power setting of the reactor core. This methodology is based on previous work [3]. From these studies, it can be concluded that the responses of the ex-core detectors are basically determined by the average power of the five fuel assemblies more peripheral and near the detectors. The responses were thus calculated by making a ratio of average powers of these five fuel assemblies in each quadrant.

Figure 2 shows the five fuel assemblies used for the calculation highlighted. Moreover, it is possible to observe in Figure 2 the fuel assemblies that have control rods numbered from 1 to 33.

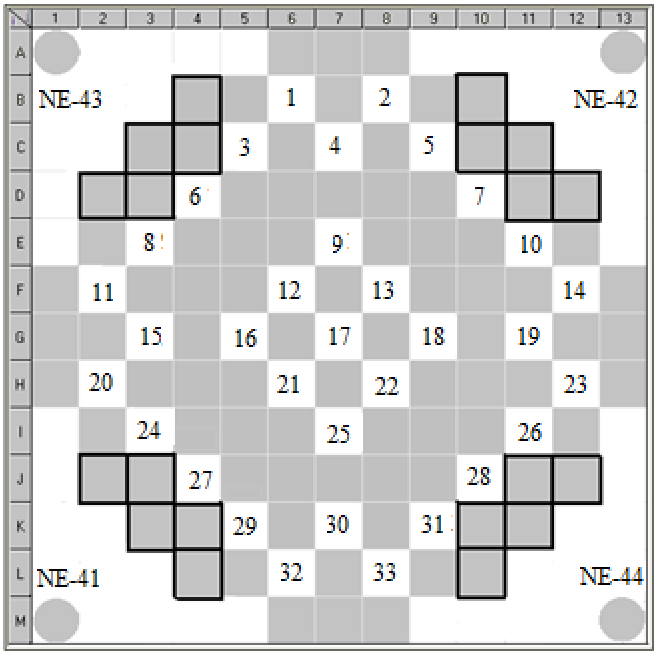

Figure 2: Core map

The calculation made for the ex-core detectors responses with a control rod drop in the nucleus in a burnup step of the reactor is as follows:

$$NE-41=\frac{\left(\bar{P}_{J2}+\bar{P}_{J3}+\bar{P}_{K3}+\bar{P}_{K4}+\bar{P}_{L4}\right)}{5} \tag{1}$$

$$NE-42=\frac{\left(\bar{P}_{D11}+\bar{P}_{D12}+\bar{P}_{C11}+\bar{P}_{C10}+\bar{P}_{B10}\right)}{5} \tag{2}$$

$$NE-43=\frac{\left(\bar{P}_{D2}+\bar{P}_{D3}+\bar{P}_{C3}+\bar{P}_{C4}+\bar{P}_{B4}\right)}{5} \tag{3}$$

$$NE-44=\frac{\left(\bar{P}_{J11}+\bar{P}_{J12}+\bar{P}_{K11}+\bar{P}_{K10}+\bar{P}_{L10}\right)}{5} \tag{4}$$

Where $\bar{P}_{ij}$ is defined as:

$$\bar{P}_{ij}=\frac{P_{ij}^{BC}}{P_{ij}} \tag{5}$$

P_{ij}^{BC} and P_{ij} are respectively the average power of the fuel assembly (i, j) in the case of a drop rod and average power of the fuel assembly (i, j) to a reference case without the control rod inserted into the core. The values i and j indicate the position of the fuel elements, as can be seen on the core map in Figure 2.

In order to illustrate these data, the detector responses calculated on the 14th burning instant for the scenarios of control rod drop are shown in Table 2. The responses of detectors in scenarios of control rod drop simulated compose the set data.

4. IDENTIFICATION METHOD OF CONTROL ROD DROPS

For the implementation of the method it was necessary to relate the variation in the distribution of power in the core with the control rod dropped. This relationship can be established through the ex-core detectors. Therefore, a relationship was established unequivocally of the detectors responses with the control rod dropped. These relationships were established via a set of variable inputs and outputs. The input variables are the ex-core detectors responses in scenarios of control rod drop and the output variable is the identifier of this rod.

In a scenario of a control rod drop, the degree of uncertainty regarding the behavior of the responses of the ex-core detectors increases. So the ability of a model to describe and recognize patterns of responses decreases. However, this method proposes the use of tools that enable the recognition of these patterns of detectors responses for their implementation. In this work we chose to use an artificial neural network, more specifically a radial basis function neural network, for the construction of the method.

One of the main characteristics of neural networks is its ability to learn from a finite set of data [6]. Therefore, networks are able to generalize the knowledge acquired, being able to respond appropriately based on the mapping done. 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 a three-layer architecture [6] 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.

The hidden layer neurons have a set of activation functions $\varphi(\|x_i - x_j\|)$ which constitute bases to the input vectors, which are then expanded in space by these radial basis functions.

Table 2: Detectors responses for the 14ª burnup step

Control rod	NE-41	NE-43	NE-44	NE-42
01	1.1042	0.9529	0.8446	1.1220
02	1.1212	0.8449	0.9524	1.1037
03	1.1018	1.0032	0.6701	1.1613
04	1.1589	0.8728	0.8728	1.1590
05	1.1614	0.6706	1.0032	1.1017
06	1.0627	1.0633	0.5807	1.1761
07	1.1767	0.5817	1.0626	1.0626
08	1.0030	1.1024	0.6703	1.1610
09	1.1507	0.9195	0.9193	1.1508
10	1.1614	0.6707	1.1020	1.0029
11	0.9525	1.1044	0.8447	1.1220
12	1.0539	1.0547	0.8983	1.1529
13	1.1525	0.8989	1.0538	1.0540
14	1.1212	0.8454	1.1044	0.9525
31	0.8723	1.1594	0.8725	1.1586
16	0.9193	1.1516	0.9195	1.1508
17	1.0463	1.0468	1.0465	1.0461
18	1.1507	0.9198	1.1509	0.9192
19	1.1587	0.8736	1.1589	0.8730
20	0.8445	1.1227	0.9524	1.1037
21	0.8981	1.1537	1.0541	1.0540
22	1.0536	1.0547	1.1527	0.8983
23	1.1042	0.9532	1.1214	0.8448
24	0.6702	1.1618	1.0032	1.1017
25	0.9193	1.1516	1.1508	0.9188
26	1.1018	1.0034	1.1616	0.6702
27	0.5811	1.1769	1.0629	1.0629
28	1.0624	1.0633	1.1769	0.5813
29	0.6701	1.1621	1.1021	1.0027
30	0.8726	1.1597	1.1586	0.8722
31	1.0030	1.1024	1.1616	0.6698
32	0.8445	1.1227	1.1044	0.9525
33	0.9522	1.1044	1.1214	0.8443

The variable $x_i \in R^n$ are the input vectors, $x_j \in R^n$ are the centers of N radial basis functions $\varphi(\|x_i - x_j\|)$ and $\|x_i - x_j\|$ represents the Euclidean norm. The activation functions of the hidden layer used in the radial basis networks are usually Gaussian:

$$\varphi_m(\|x_j - x_i\|) = e^{-\left(\frac{\|x_j - x_i\|^2}{2\sigma^2}\right)} \tag{6}$$

where σ represents the function width.

The network structured in this paper has four entries in the first layer, which are characterized by signals from the ex-core detectors. The output layer has only one neuron that generates as network response to the problem the rod identifier. Figure 3 shows a scheme of the neural network used. The activation functions in the hidden layer neurons are Gaussian functions as commonly used and the output layer is a linear function.

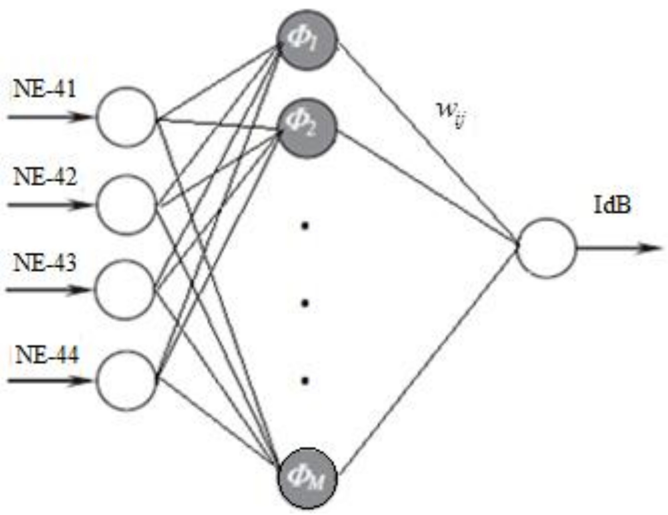

Figure 3: The structure of the Artificial Neural Network

The network mapping is done by a data set used for training. 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.

With this construction, it is aimed that the network generalize the data set, enabling the same detector response values to vary, and the method be able respond satisfactorily. This is done in order to identify a pattern in the responses of the detectors and hence the control rod dropped.

5. RESULTS AND DISCUSSIONS

Figure 4 shows the behavior of the ex-core detectors in the scenarios of control rod drops and the behavior of the detectors responses rehearses certain symmetry. This symmetry is justified because the control rods are in symmetrical positions in the core.

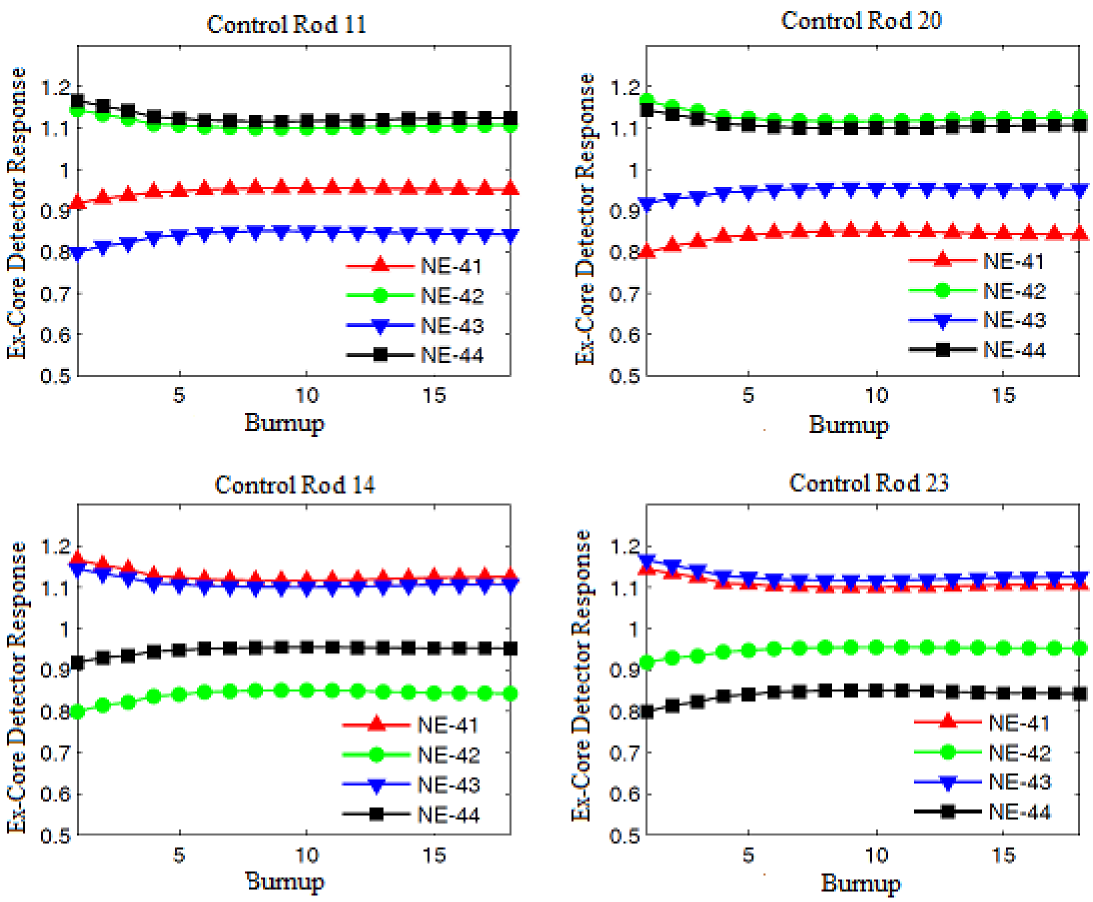

Figure 4: Behavior of the detectors at the burnup steps simulated for the control rods 11, 20, 14 and 23.

Figure 5 shows that this symmetry extends to other control rods which are in symmetrical positions. This symmetry contributes significantly in identifying the control rods.

During the training of the neural network, it was selected a data set for the implementation of the training. This training data set consists of the responses of the detectors in the following burnup steps: 1st, 4th, 9th and 16th.

Figure 6 shows the results of the training phase to the entire training data set. The choice of the four burnup steps for the training was made in order to cover the problem domain and to enable the best network possible. It can be seen in the graphics of the training phase that at the end of the learning process the network make the better adjustment and the difference between the network response and the correct answer is zero for all training data set.

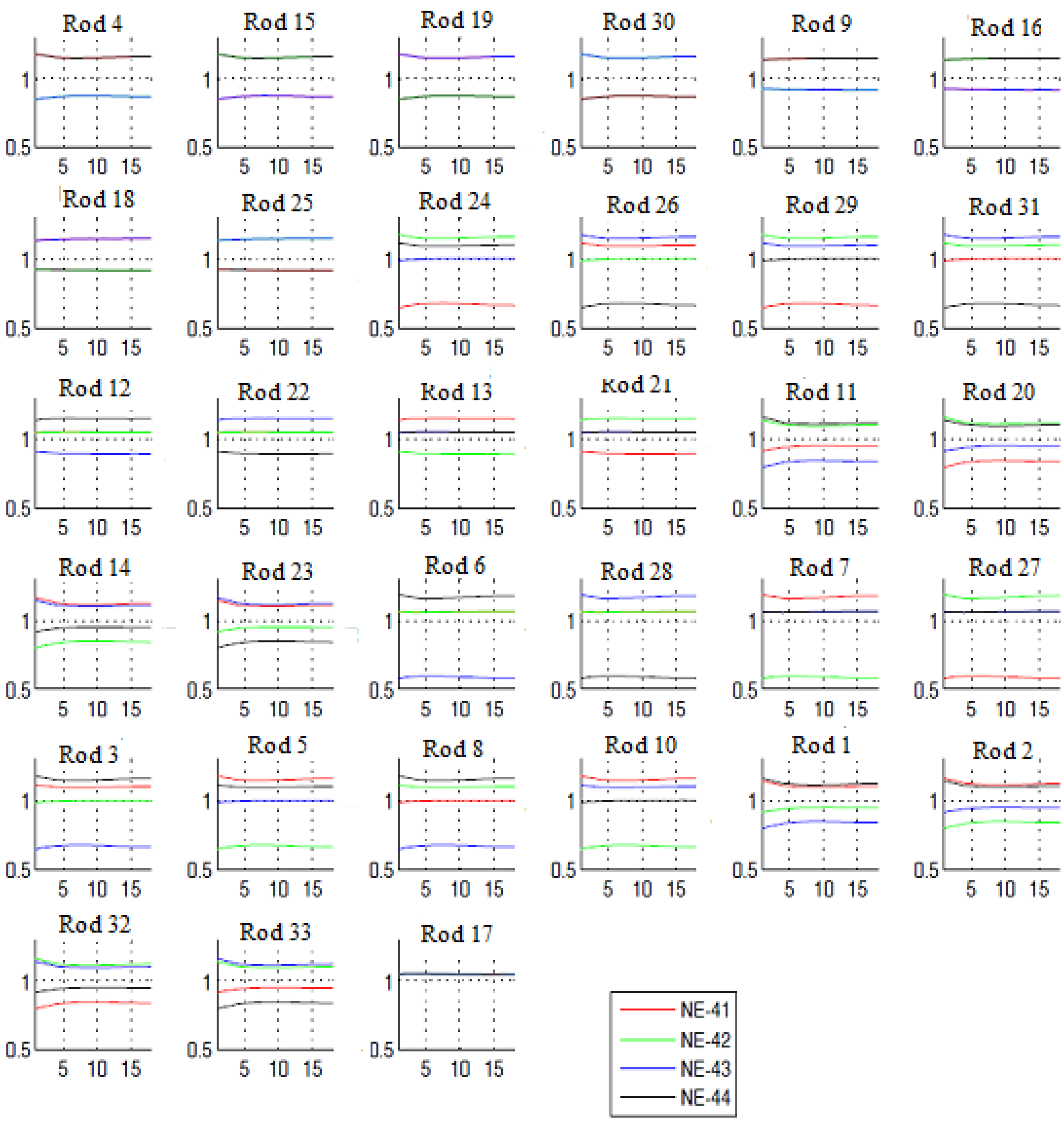

Figure 5: Behavior of the detectors for the burnup steps simulated.

Figure 7 shows the network responses to the entire data set used in the tests. The dataset used for the tests is composed of the burnup steps: 2nd, 3rd, 5th, 6th, 7th, 8th, 10th, 11th, 12th, 13th, 14th, 15th, 17th and 18th.

Figure 8 shows the error from the network to the test data in each burnup stages, in order to check whether the network has correctly identified the control rod dropped on the core. Verification was made by comparing the response of the network with the correct answer. Thus, the network error in this phase is defined by:

$$E_2 = idB - iB \tag{7}$$

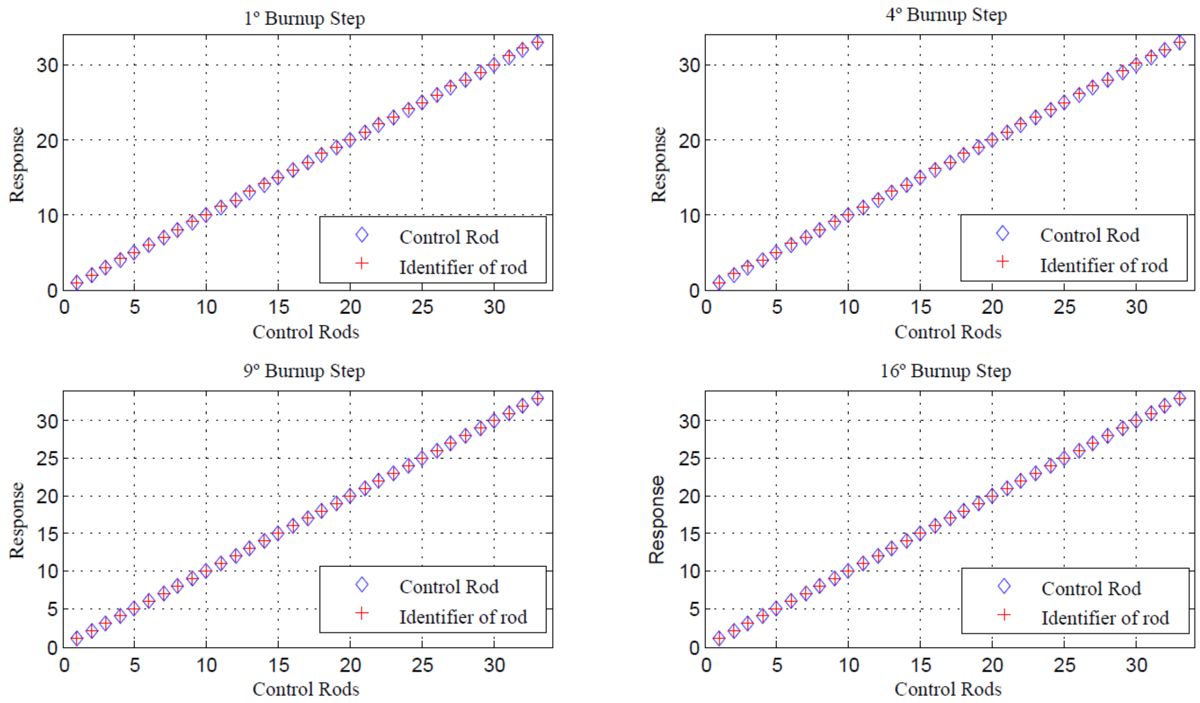

Figure 6: Network response to the training data set.

Where idB is the identifier of the control rod generated as a solution to the problem by the artificial neural network and iB is the correct value of the control rod.

It can be guaranteed that the network correctly identifies the control rod dropped when $\|E_2\| < 0.5$. If the error is less than 0.5, the value of the network response is closer to the correct value of the rod. When the error is greater than 0.5 we can say that the network response is closer to the numerical value of another control rod. In summary, when the magnitude of error is greater or equal than to 0.5 means that the neural network could not correctly identify the control rod that is dropped in the core.

Table 2 shows the points where the control rods were not correctly identified, as well as the error of the network, the type of rod and the simulated step. This means that the network gets the correct answer in 95.3% of the decisions.

One possible explanation for the results presented for the method is the detectors behavior when in a scenario of control rods drops. There is a subtle variation in the behavior of the detectors at burnup steps, which allowed the generalization to be performed reasonably well.

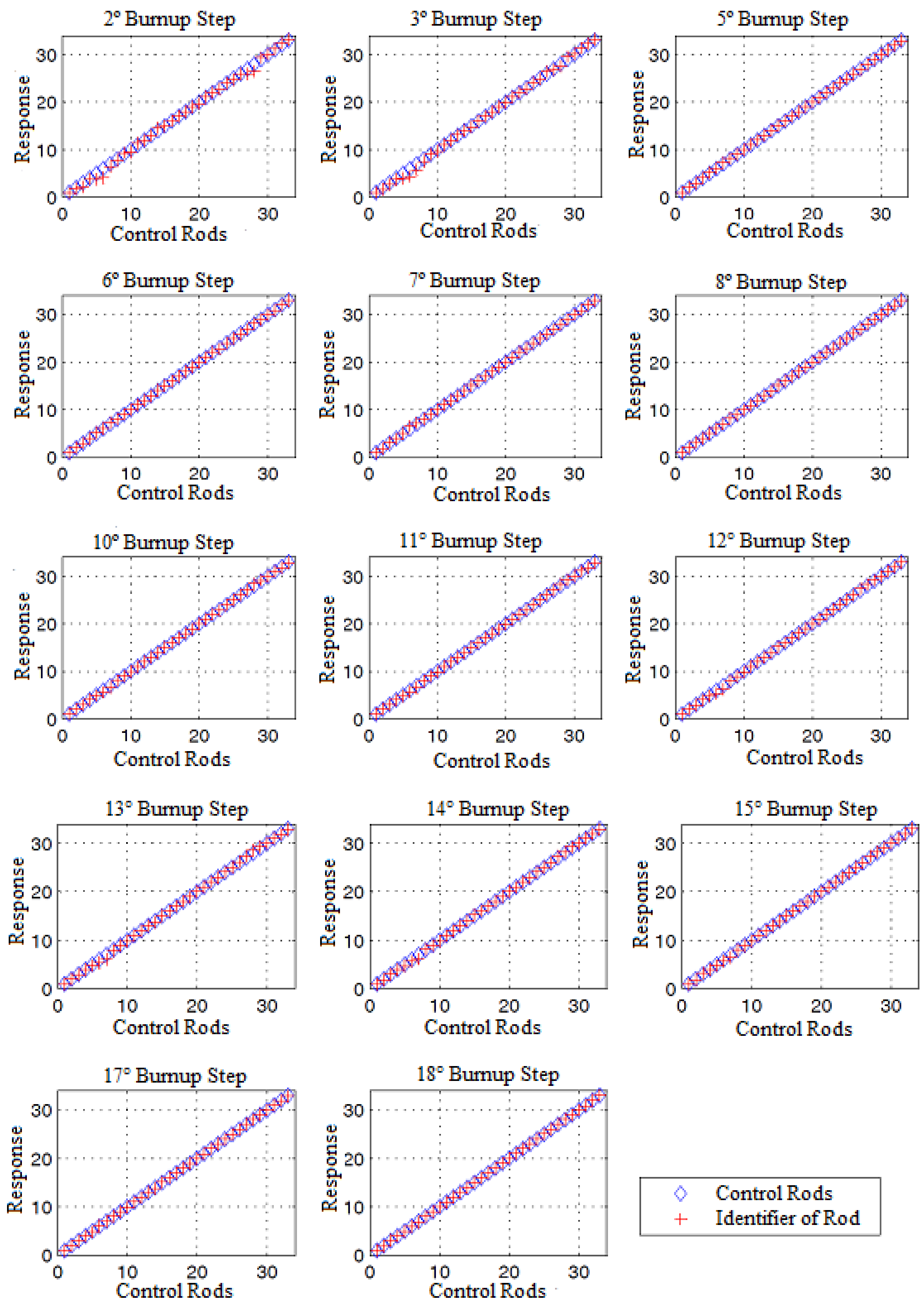

Figure 7: Network response to the test data set.

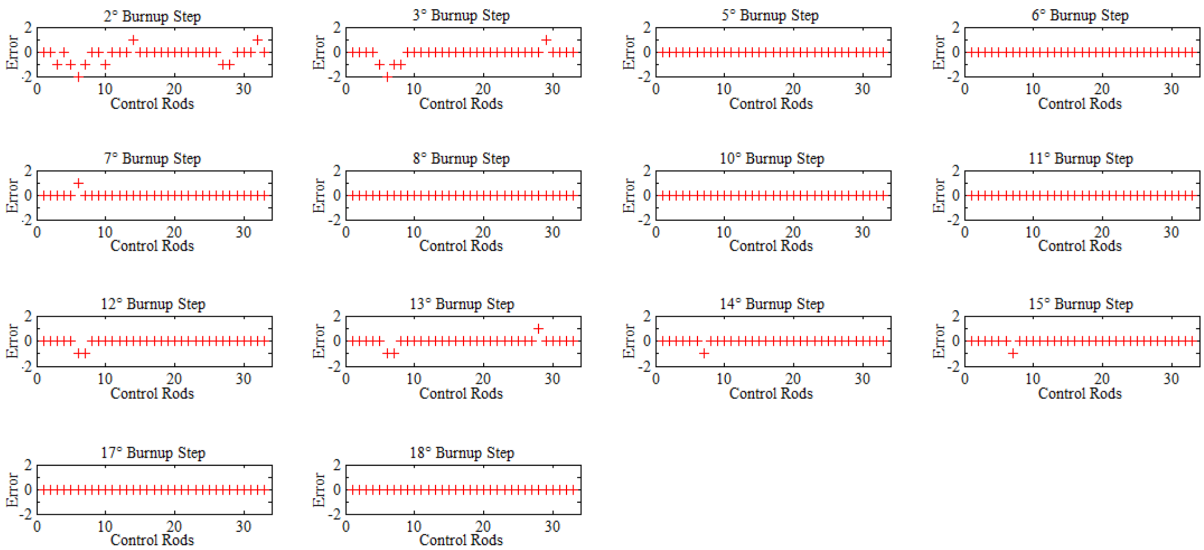

Figure 8: Network Error

Table 2: Non-properly identified control rods

Burnup Steps	Position in the Core	Control Rod type	Correct answer T2	Network answer Y2	Error - $\|E_2\|$
2º	C05	SA	3.0	2.1819	0.8181
2º	C09	SA	5.0	3.7743	1.2257
2º	D05	C	6.0	4.1286	1.8714
2º	D10	C	7.0	6.4002	0.6998
2º	E11	SA	10.0	9.4045	0.5955
2º	F12	A	14.0	14.5652	0.5652
2º	J04	C	27.0	26.0011	0.9989
2º	J10	C	28.0	26.5041	1.4959
2º	L06	A	32.0	32.5082	0.5082
3º	C09	SA	5.0	3.9627	1.0373
3º	D04	C	6.0	4.3685	1.6315
3º	D10	C	7.0	5.7834	1.2166
3º	SA	SA	8.0	7.4596	0.5404
3º	SA	SA	29.0	29.5843	0.5843
7º	D04	C	6.0	6.5946	0.5946
12º	D04	C	6.0	5.3662	0.6338
12º	D10	C	7.0	6.1491	0.8509
13º	D04	C	6.0	5.3433	0.6567
13º	D10	C	7.0	6.0418	0.9582
13º	J10	C	28.0	28.6383	0.6383
14º	D10	C	7.0	6.1498	0.8502
15º	D10	C	7.0	6.3853	0.6147

6 – CONCLUSIONS

The goal of this study was the development of a method that allows the on-line identification of a control rod dropped in the core of a PWR reactor in any burnup step, by means of the responses from the ex-core detectors.

The obtained results from the ex-core detectors responses were calculated by simulations that provided data for the method implementation. The simulations were performed for 18 burnup steps covering 380 operating days at full power.

It was verified that for a given specific cycle of a PWR reactor, it is possible to recognize patterns in the responses of the ex-core detectors in order to identify on-line a control rod drop. The results show that the radial basis function network used in this method had a good performance. However the neural network shows some difficulty in recognizing certain fluctuations responses of the detectors.

It is believed that an improvement of these results is possible with a better choice of the set training network data which allows a better generalization of the problem. Anyway, the behavior of the ex-core detectors responses in relation to the burnup steps as showed contributes satisfactorily to a good response from the network.

These results allow us to conclude that the implementation of an on-line identification method of control rod drop based on the responses of ex-core detectors is possible. Moreover, it can be said that the ex-core detectors respond satisfactorily to the variation in the distribution of power in the core due to the control rod drop. This ensures the effectiveness of systems based on such knowledge.

However, it is not possible to infer about the applicability of this method in other cycles of the reactor, since we cannot say for sure that the behavior of the ex-core detectors responses will be similar to these observed in this work. However, a crucial question to be investigated is whether this type of behavior is valid for other cycles, other power levels or even other cores, to allow a deduction regardless of the specific conditions of the reactor.

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