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ARTIFICIAL NEURAL NETWORKS FOR SPATIAL DISTRIBUTION OF FUEL ASSEMBLIES IN RELOAD OF PWR REACTORS

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ABSTRACT

An artificial neural network methodology is being developed in order to find an optimum spatial distribution of the fuel assemblies in a nuclear reactor core during reload. The main bounding parameter of the modelling was the neutron multiplication factor, k_{eff}. The characteristics of the network are defined by the nuclear parameters: cycle, burnup, enrichment, fuel type, and average power peak of each element. These parameters were obtained by the ORNL nuclear code package SCALE6.0. As for the artificial neural network, the ANN Feedforward Multi_Layer_Perceptron with various layers and neurons were constructed. Three algorithms were used and tested: LM (Levenberg-Marquardt), SCG (Scaled Conjugate Gradient) and BayR (Bayesian Regularization). Artificial neural network have implemented using MATLAB 2015a version. As preliminary results, the spatial distribution of the fuel assemblies in the core using a neural network was slightly better than the standard core.

1. INTRODUCTION

The fuel reload of a nuclear reactor includes operational and safety restrictions. It is a process involving the insertion of fuel elements with varied enrichment. Some assemblies already contain partially irradiated fuel, while others contain fresh fuel, besides those that have a mixture of burnable poisons. For these reasons, the spatial distribution of the fuel elements in the core influences the behavior of the reactor. The fuel elements with higher burnup have fewer reactivity than another new element, for example. In view of this, when inserting two or more elements with high-level of burnup, together there may be a power outage in that core region. Whereas two or more new elements inserted together tend to increase power in a certain region, which is not adequate [3, 5, 7].

In addition, there is still a concern in the optimization of the fuel elements in the core. It is safe to say that, by reducing the costs of the reactor operation, the cost in electricity production is also reduced [3].

This work goal is to identify an acceptable reload standard to a PWR (Pressurized Water Reactor) core so that minimizes the fuel burnup, thus extending the burbup. There are several published works where the authors conducted tests using modern algorithms such as the evolutionary, heuristic and artificial neural networks (ANN). However, by the time, due to the expensive computational resources, no solution was implemented that could present a reload pattern with the characteristics desired above for any reload set.

Artificial neural networks are used to receive a set of fuel elements composed by ¼ of the PWR core out of the standard and, after processing, they are able to generate a dataset with a satisfactory spatial distribution. This means that the output proposed by the ANN model will be tested by a nuclear code system to calculate and obtain nuclear data to serve as parameters to validate the ANN output.

The choice of this technology was due to the success achieved in difficult-solving problems. Currently, artificial neural networks have been used for some time to predict, extract, classify, and group data [11]. In recent years, work with artificial neural networks has gone beyond, being widely used in electronic games, identification of images, texts and voice, to name just a few.

On the next section some correlated work are presented. Next, artificial neural networks are briefly descripted. Then the methodology adopted will be detailed, as well as the results of the experiments. And finally, considerations will be made on the proposed solution.

2. CORRELATED WORKS

Among the projects identified in the literature, one of the most important is dated in 1972. It's the PhD thesis of Stout [28]. The work was developed using a methodology where statistical, algorithms and mathematics was applied. A computer system has been implemented to receive the dataset and separate the fresh fuels due to the higher neutron flux compared to the fuels that have been irradiated. Stout system had an accurate logic and the developed algorithm has produced great results. The problem is the same that persists to today: the amount of possibilities. Computationally, the algorithm is extremely costly.

In the following decades, several authors have proposed work using modern resources in the search for an acceptable solution. It was used by [6] entire programming. Also, they have been tested for social organization-based algorithms, such as [2, 24]. In this work, the authors used the particle swarm optimization (PSO) in order to find a better solution in the search space. The PSO algorithm is based on the social community of birds, where taken into account the knowledge of a single bird as well as the flock. By adjusting information, the algorithm converges in search space, finding an optimal solution. The algorithm was seeking to find better spatial distribution through the PSO.

Still in the same line, there are variations of the PSO [17]. The artificial bees colony was used with Random Keys, a modified algorithm to solve problems like optimization of fuel management in the core. The authors based on the actual behavior of the bees when producing honey. The results were compared with the genetic and traditional PSO algorithm.

Following this same paradigm, some authors performed another work; however, foundation was in the community of another animal, the firefly [20]. According to the authors, the algorithm, similar to the PSO, uses the light intensity information of the fireflies that clump together where problem is positioned. They organize themselves to resolve it by exploring the search space. In addition to this approach, another work performed was the authors [19] who used multipurpose programming in order to optimize the core PWR. According to the authors, the method could not only save fuel consumption, but also reduce the radial power point.

PSO was also used by the authors [1] and in this approach probabilistic methods were used to choose which particle to communicate and update in each iteration cycle. This is a variation of the traditional PSO.

The work of [26] presented a tool, which adds quantum concepts to the biological metaphor of the collective learning of the ants. The authors [16] used the quantum evolution algorithm to optimize the core of the Brazilian PWR reactor. The results obtained were compared with the genetic algorithm.

Also, another method proposed by the authors [25] based on the optimization of a self-learning mechanism of parameters. Used in association with the basic structure of the Quantum named Auto-adaptive Quantum.

The use of artificial neural network has come as soon as it has begun to disseminate the fact that it is a robust tool. Artificial neural networks were employed with various architectures and training algorithms. Even in some cases, the training algorithm was evolutionary type generating a hybrid artificial neural network. Still with this approach, the literature presents the authors [8, 10, 13] that have developed a Multi_Layer_Perceptron using Backpropagation algorithm for training. The authors obtained satisfactory results with the model, since they found several sets of acceptable set core. Also, there can be cited, the authors [27] who used an artificial neural network of type RBF (radial-based function network). According to the authors of the article, was possible to decrease the safety margin of the peak power factor by up to 5%.

Still in the approach of artificial neural networks, the authors [16] used a recurring ANN. In this article, authors made different from others in order not to use any nuclear code to validate or even generate a dataset. ANN generated all work, even the initial recharging set.

In order to obtain satisfactory results, authors of two articles [4, 18] have carried out work using artificial neural network and genetic algorithms. According to these references, use of genetic algorithms had function to generate a set of acceptable initial patterns of fuel elements and ANN as a leading role to refine the model.

There are other works that have the same goal, which is to get a reload with acceptable values of k_{eff}. Due to amount of possibilities of spatial distributions in core, the problem becomes complex. Computationally impossible to accomplish all the possibilities, because the reactors core possesses large amounts of fuels elements, such as Angra I, that has 121 positions. This generates millions of attempts, and if it were to analyze the distribution of neutrons as the exchange occurred, the time would be considerably greater. Therefore, it is still necessary for surveys to be carried out until the objective is achieved.

Artificial neural network tend to be a tool that can achieve this purpose, because they have parallel processing which makes them powerful and fast. They are robust tools based on the human brain and therefore have the ability of generalize. The next topic covers artificial neural network.

3. ARTIFICIAL NEURAL NETWORK

Artificial neural networks (ANNs) process information differently than traditional computer. ANN has fitness to them, making them able to solve complex problems such as pattern recognition [21].

A traditional computer system cannot resolve simple tasks like some that are performed by animals, such as recognition of a familiar face in an unknown scenario. The brain has a learning capability and, in humans, this phase happens with greater intensity in the first two years of life. However, the process goes well beyond, practically in the entire life of the individual [14]. Artificial neural networks have similar traits, so they can learn from experience, as well as the biological brain. Next sections will presente neural, feedforward architecture and backpropagation training algorithm.

3.1. Artificial Neuron

The first model of ANN (Artificial Neural Network) arose around 1946 with McCuloch and Pitts[22]. Scientists proposed the first artificial neuron as can be verified in Figure 1.

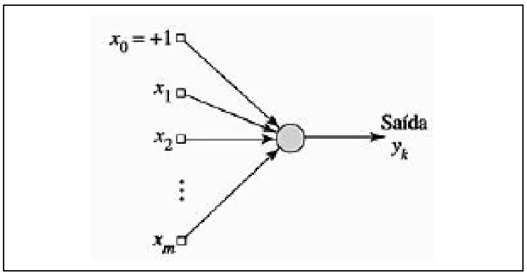

Figure 1: Model of Artificial Neuron

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The model was composed of a processor unit represented in Figure 1 by the filled or colored circle. The entries or data to be processed are characterized by squares starting with X_1, X_2... x_m. The output is represented only by Y_K. The first square $x_0 = +1$ corresponds to the bias, for instance, it is an entry that always receives value 1. The purpose of this differentiated entry assist in processing the data.

ANN is formed by several brain cells and layers. The quantity is defined according to the complexity of the problem [14]. Figure 2 shows an ANN model.

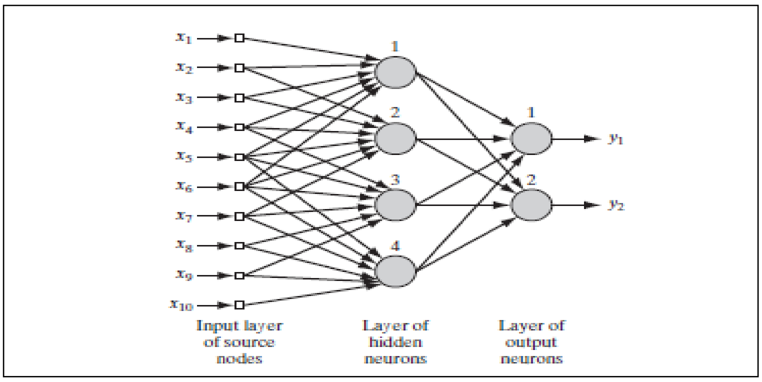

Figure 2: Artificial Neural Network Model

Figure 2 shows an artificial neural network with an input layer, a layer hidden, and a layer output. The choice of architecture besides depending on the complexity of the problem should also take into account also learning algorithm. There are several algorithms that can be used, the more traditional being backpropagation [21].

3.2. Learning Algorithm

Learning algorithms are structured programs that aim to assist in the learning of ANN. They have two main features, namely, learning algorithms can be or not supervised.

A supervised algorithm is the one that receives input and output data for processing. With this, ANN during a stage called training knows the input and output [14].

Unsupervised algorithms do not receive output, only the input. Therefore, they do not know the nature of data. Generally, these algorithms are used for grouping, for instance, they receive multiple data and organize them according to the identified characteristics [21].

Backpropagation algorithm is supervised, thereby, receives a vector with data in input to be computed and another vector with the corresponding responses. When arriving in the ANN output layer, the Backpropagation compares output computed by ANN with corresponding response that it received. If the results are different, for example, if ANN computed wrong, he stores the error and returns to beginning of the ANN architecture, restarting processing.

For all commonly supervised algorithms, initial dataset is separated into three sets. The first of them is for training, usually 80% of the total. The second and third sets are divided into 10% each, the second for validation and third for testing [14]. This procedure appropriate because with 80% of total data, ANN will train, for instance, will receive the input, compute the output and compare to the answer. This is the training phase. However, necessary to perform tests to verify the learning, so the 10% separated previously has this purpose and last set is used for validation that is a parameter used by the ANN programmer to stop processing if ANN not learning [22]. Thus, while improvements are occurring, while ANN is computed as the input compared to the output, the process continues. In this case, stop parameter will be the amount of processing stipulated by the programmer. Otherwise, if ANN reaches the stipulated quantity for validation without improving the learning, the ANN stops processing. This parameter will prevent the ANN from performing all tests without reaching the goal. In some cases, the performance can be around 20% or 30% of the training. The ideal in this case is to stop [23].

3.3. Learning Process

ANN of type Multi_Layer_Perceptron can contain N connections to represent the N input variables. An example of input vector could be {x_1, x_2.... x_n}. The corresponding weight vector, w, would be {w_1, w_2, w_3,... w_n}. The response of the processing represented by the letter u in equation 1 below would be [21]:

$$u = w_1 x_1 + w_2 x_2 + \cdots + w_n x_n \tag{1}$$

The threshold function defined in the source produces a y - output, so that:

$$y = \begin{cases} 0, & u < 0 \\ 1, & u \geq 0 \end{cases} \tag{2}$$

If ANN response is correct so that computed values are equal to those received, the weight vector is not adjusted. Otherwise, the individual weights are adjusted using a Perceptron learning algorithm, which is a modified form of Hebbian learning that incorporates the error as follows [22]:

$$Error = E = t - y \tag{3}$$

Where´s T is the expected exit. The weights vector is upgraded to equation 4.

$$w_{new} = w_{old} + \beta \, x \, E \tag{4}$$

Where w_{new} is the new weight value, w_{old} is the value of the old weight, x is the input vector and β is the learning rate. This is a constant between 0 and 1 that aims to adjust the learning speed. When β has a lower value, the adjustment occurs slower and so, the training time will be longer. While using higher values, learning will accelerate.

Accelerating learning does not mean better performance, because it can cause instability. The algorithm jumps in wide steps oscillating around optimal points, without yet reaching them [21].

4. METHODOLOGY

The first task performed was to obtain the data to be processed by ANN. These were obtained by the nuclear code package SCALE6.0[1]. 70 cores were generated with ¼ of fuel elements each. Fuels were composed of fresh materials, as well as others that contained some level of burnup. The fresh ones were referenced as belonging to class 1, the iradiated elements received the value 3 and those who had more time in the reactor and, in consequence had higher level of burnup received the value 2 as a description. Figure 3 shows an example of core ¼ model used as ANN input.

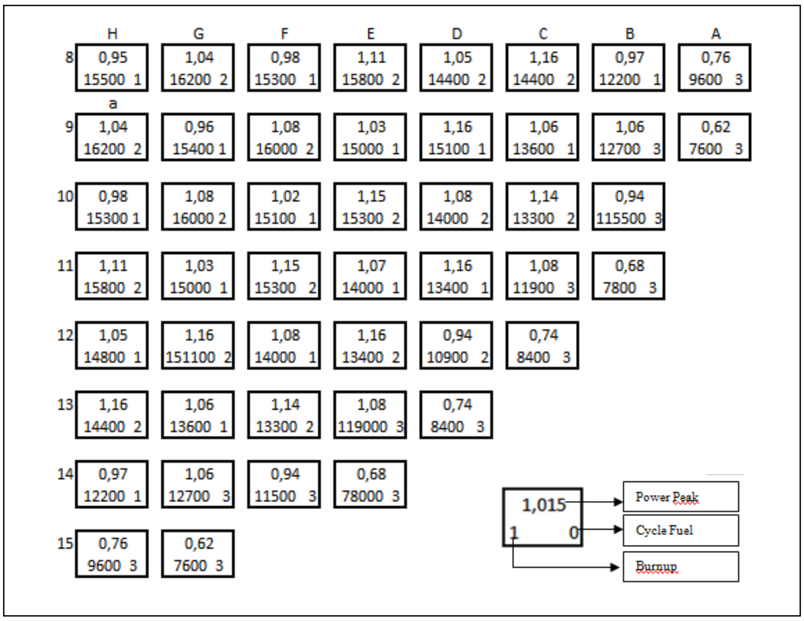

Figure 3: ¼ core with cycle, peak power and burnup

[1] https://www.ornl.gov/scale

The assemblies obtained contained some information that would be used as characteristics for ANN, such as: cycle, burnup, enrichment, fuel type, and average power peak of each element. The input vector was composed of the data above and the output vector was populated with the position of each fuel element.

All input data have been standardized. The type of normalization used was a simple scaling scale. The approach consists of fixing the minimum and maximum values for the variables at 0 (zero) and 1 (one).

Equation 5 shows the normalization used [20].

$$x_{Ti} = \frac{x_i - x_{imin}}{x_{imax} - x_{imin}} \tag{5}$$

Where x_{imin} and x_{imax} are the minimum and maximum values of the x_i variable.
Table 1 shows input sample used:

Table 1: Example of input variables ANN

Type of fuel	Cycle	Burns	Enrichment	Peak Power
1.00	0.20	-0.96	0.92	0.22
0.67	0.00	-0.84	1.00	0.43
0.33	0.00	-0.87	0.46	0.38
1.00	0.20	-0.91	0.92	0.66
1.00	0.20	-0.92	0.92	0.71

The response vector was composed of positions values such as {1, 2, 3, 4... 31}. For this work was used ¼ of the PWR core, so the amount of positions consisted of 31 fuel elements. However, ANN gets better performance with normal and uses of binary numbers. Thus, for response, the decimal values were converted to 0 and 1 binaries. Table 2 shows examples of output or positions of 5 fuel elements.

Table 2: ANN Variable response

Standard output	**Binary output**
1	00001
2	00010
3	00011
4	00100
5	00100
6	00101
7	00110
8	00111
9	01001
10	01010
. .	. .
31	11111

ANN Feedforward Multi_Layer_Perceptron with various layers and neurons were constructed. The algorithms used were: LM (Levenberg-Marquardt), SCG (Scaled Conjugate Gradient) and BayR (Bayesian Regularization). Artificial neural network have implemented using MATLAB 2015a version.

4.1 Experiments Conducted and Results Obtained

Core obtained for conducting the experiments summed up 2.232 rows of data. Of this total, 10% were used by ANN for testing, 10% for validation and 80% for training.

Several models of artificial neural network and training algorithms have been tested. MLP (Multi_Layer_Perceptron) models were generated using LM (Levemberg Marquadt) algorithm, also BayR (Bayesian Regularization), in addition to the model SCG (scaled conjugate Gradient). Language used for configuring the ANN was Matlab. Table 3 shows results achieved.

Table 3: Results of Experiments

Algorithm	Neurons	Performance
LM	100	78%
	250	83%
	500	86%
BayR	100	79%
	250	86%
	500	92%
SCG	100	36%
	250	40%
	500	60%

As seen in table 3 the best performance ANN model was the one that used Bayesian algorithm with 500 neurons. During training, the model reached 92% of hits.
¼ data from a core that ANN did not know, for instance, it was not in the training set was used for the test. Figure 4 shows ¼ distribution of the tested core.

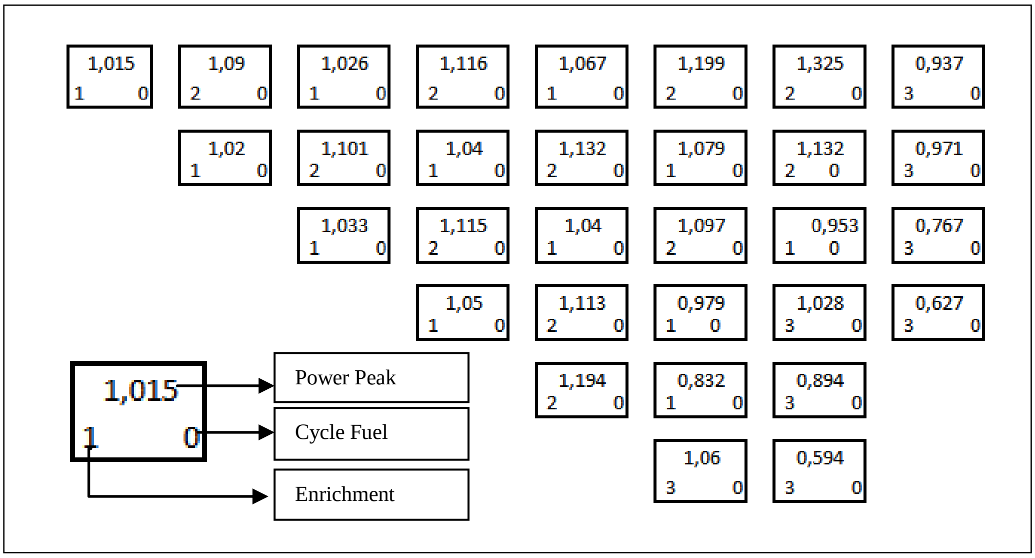

Figure 4: ¼ core representation with cycle, peak power and burnup

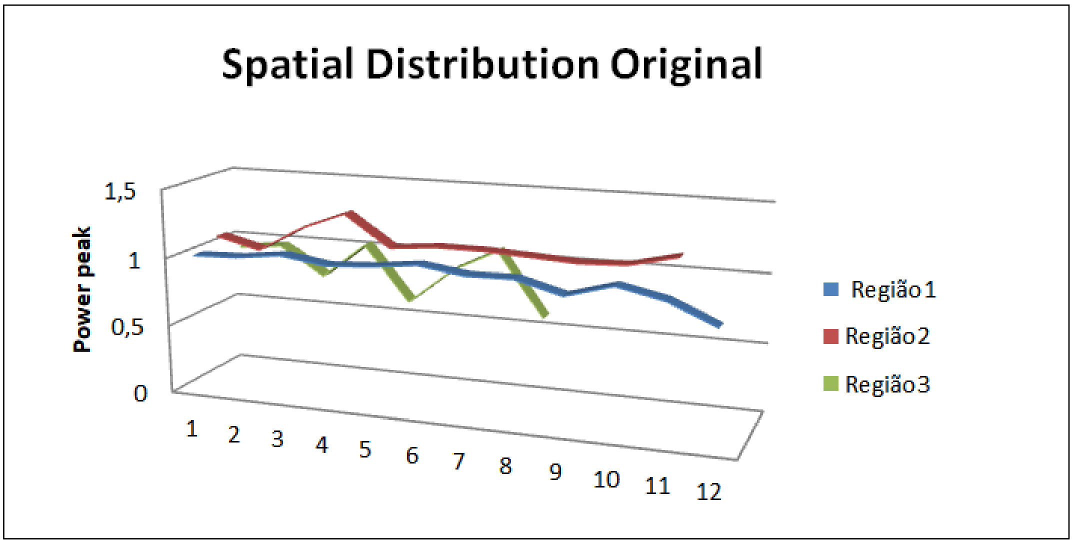

Figure 5: Real Spatial distribution of regions in core of the Figure 4

In Figure 5, there is a noticeable discrepancy between the data in Region 3. In this region, the power peaks are more irregular, but in the ¼ core distribution in Figure 4, the fuel elements belonging to Region 3 were positioned in the periphery of the reactor. With this location, in general, the core obtains leveling in the temperature, because in the periphery, the heat is smaller. All assemblies were fresh.

Figure 6 introduces the distribution indicated by ANN Bayesian.

1	2	3	4	5	6	7	8
1,02	1,097	1,026	1,199	1,067	1,194	1,09	0,937
	9	10	11	12	13	14	15
	1,015	1,101	1,04	1,113	1,079	1,132	0,971
		16	17	18	19	20	21
		1,033	1,115	1,04	1,325	0,953	0,767
			22	23	24	25	26
			1,05	1,132	0,979	1,028	0,627
				27	28	29	
				1,116	0,832	0,894	
					30	31	
					1,06	0,594	

Figure 6: Spatial distribution of regions in core recommended by ANN

As can be seen, trained Bayesian ANN with 500 neurons presented slightly better distribution than original core. In this case, a better spatial distribution means that it had more flat power peaks.

Although a distribution presents $k_{eff} = 1$, large amounts of power peaks indicate higher concentration of energy at certain points in the core. ANN maintained the location of 71% of the original positions. Of the 31 ¼ core outlets, it suggested trading 9 assemblies. Figure 7 shows the distribution graph of the ANN distribution.

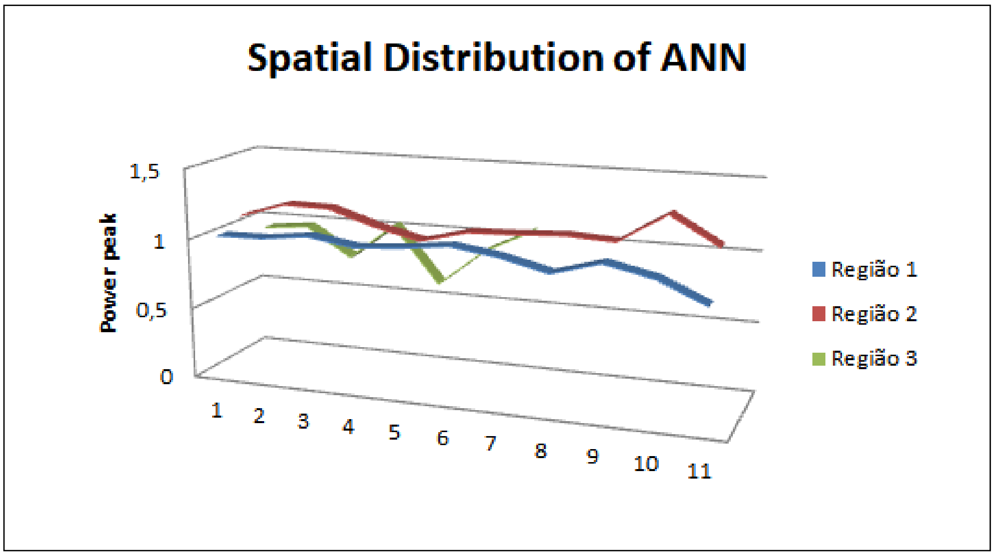

Figure 7: Spatial distribution of regions in core indicate for ANN

5. CONCLUSIONS

The objective of this work was to carry out studies and implement an artificial neural network model for present a spatial distribution of fuel elements in a PWR core.

Spatial distribution of fuel elements in a PWR core is performed following a certain standard. This is a complex problem, because when carrying out an exchange, the peak power of the fuel element itself changes, in addition to those around it.

Several studies have been developed in this area and artificial neural networks have been implemented in search of this solution.

As seen in this article, ANNs learn through examples. Thus, three sets of data were generated: 10% for tests, 10% for validation, and 80% were reserved for training. Then, 3 different configurations were developed and the ANN Bayesian model presented result above 90.
Spatial distribution of fuel elements presented by ANN was slightly better than the original core data. The model generalized to unknown data, which leads to believe in the success of technology. The studies will continue and other models of ANNs will be implemented and the results validated by nuclear codes.

Suggestions are training with greater amount of features. In addition, other technologies are also suggested, such as deep learning. They are modern techniques that have been obtaining satisfactory results in several fields, especially, unknown data.

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