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LPPF PREDICTION IN A BWR FUEL LATTICE USING ARTIFICIAL NEURAL NETWORKS

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ABSTRACT

The amount of CPU time required for a typical fuel lattice calculation is considerable; even more if this type of calculations is attempted for carrying out an exhaustive exploration of a search space in a combinatorial optimization problem. This situation has motivated to look at the possibility of replacing the best estimate HELIOS code by an Artificial Neural Network (ANN), in order to predict the major Boiling Water Reactor (BWR) fuel lattice parameters. In this paper the development of an Artificial Neural Network and some results obtained during the training process and application of the ANN are presented. The obtained ANN is used to predict the maximum local power peaking factor (LPPF) in a typical 10x10 BWR fuel lattice. The LPPF is predicted at beginning of life (0.0 MWD/T), at 40% voids moderator density, fuel temperature of 793 ºK, and moderator temperature of 560 ºK. The axial location of the fuel lattice is just above the natural uranium zone, called the power lattice, at the bottom of the reactor core. Finally the trained Artificial Neural Network is applied in order to predict the LPPF of some BWR fuel lattices, which have been used in the real operation of the Laguna Verde Nuclear Power Plant (LVNNP) in Mexico.

Key Words: BWR, Fuel Lattice Design, Artificial Neural Networks

1. INTRODUCTION

The main motivation to deal with Artificial Neural Networks (ANN) is due to its capacity to effectively reduce the computation time needed to perform high CPU time consuming calculations. Some authors, e.g. A.Yamamoto [1] deals with the loading pattern screening using neural networks, and he found that effectively they improve the optimization results; since the computation time for a cycle depletion calculation with the neural network is quite short. There

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are also some other ANN applications, Gonzalves et al. [2] show a neural network to predict the radial power density distribution in the core and the soluble boron concentration at the end of the cycle, in order to optimize fuel load with a genetic algorithm. Ortiz and Requena [3] used a neural network to predict the thermal limits and the effective neutron multiplication factor at the end of the cycle in boiling water reactors (BWRs). Roh et al. [4] used a neural network to predict power levels in a reactor core using real power measures. Jang et al. [5] trained neural networks to predict the power in each fuel channel of an eighth core, and then they used simulated annealing to optimize the fuel loading in PWRs. Generally speaking it can be seen, according to these results, that the use of ANN can broad the scope of a search algorithm in combinatorial problems; as in the case of the optimization of the fissile and the burnable poison materials location in a BWR fuel lattice. This is our next goal and this is why we are currently training an appropriate ANN.

On the other side, this way of proceed is not the only promising one to success facing this kind of optimization problems, an alternative can be seen, for example, in G..F. Cuevas et al. [6] who successfully applied the simplex method to the MOX enrichment distribution optimization in typical LWR assemblies. J. Zheng et.al. [7] showed an application of the Linear Superposition Model (LSM) for estimating lattice-physics parameters. This method also permits substantially decreasing the computation time; they showed that the run-time requirements can be reduced by at least an order of magnitude relative to performing direct lattice-physics evaluations with the CPM-2 or CASMO-3 code. François et al.[8] successfully applied the tabu heuristic technique in order to minimize the enrichment content using a multi-objective function. Finally, R. Perusquia [9] showed that taking into account an appropriate set of boundary conditions in order to know the lattice parameters at the beginning of the lattice life, it is enough to successfully predict a good behavior throughout the lattice life.

In this paper we are dealing with the training of an ANN in order to predict the LPPF (Local Power Peaking Factor) for a given BWR fuel lattice.

2. A MULTI-LAYER ARTIFICIAL NEURAL NETWORK

In order to fulfill our goal of predicting the LPPF in a fuel lattice, a multi-layer artificial neural network was used. To establish the structure of this kind of ANN's, both, the number of layers and the number of neurons inside the ANN must be specified. It is also necessary to know the respective set of weights (w_{ij}) which are associated with the neuron connections. All of these ANN features are known through the process called ANN training. In other words, the ANN training consists in obtaining the optimal weight set associated with the neural connections, in such a way that the error between the predicted ANN values and the target values is minimized. In our case, the training of the ANN is based on a Back-propagation Algorithm (BP). In the following, a brief description of this algorithm is presented.

2.1. Training of a Multi-Layer Artificial Neural Network (MLANN)

If we consider the i neuron into the input layer and the j neuron into the intermediate layer, in a typical three-layer artificial neural network (Fig. 1), we can denote as ok the k neuron calculated

value in the output layer ok=f(netk), where f is identified as neuron activation function. In this case, f is of sigmoid type; then we have the following:

$\text{net}_k = \sum_{i=1,n} w_{ik} o_i$, is the net input into the k output layer, $o_j = \frac{1}{1+e^{-\text{net}_j}}$, is the explicit form of the f function. The expected error function that we want to minimize takes the following form:

$$E = \frac{1}{2}\sum_p \left\{ \sum_k \left(t_{pk} - o_{pk} \right)^2 \right\} \quad (1)$$

Where:
p represents the p training pattern,
k represents the k neuron in the output layer,
t_{pk} represents the target value for the k neuron and for the p training pattern,
o_{pk} represents the value calculated by the ANN for the k neuron and for the p training pattern,

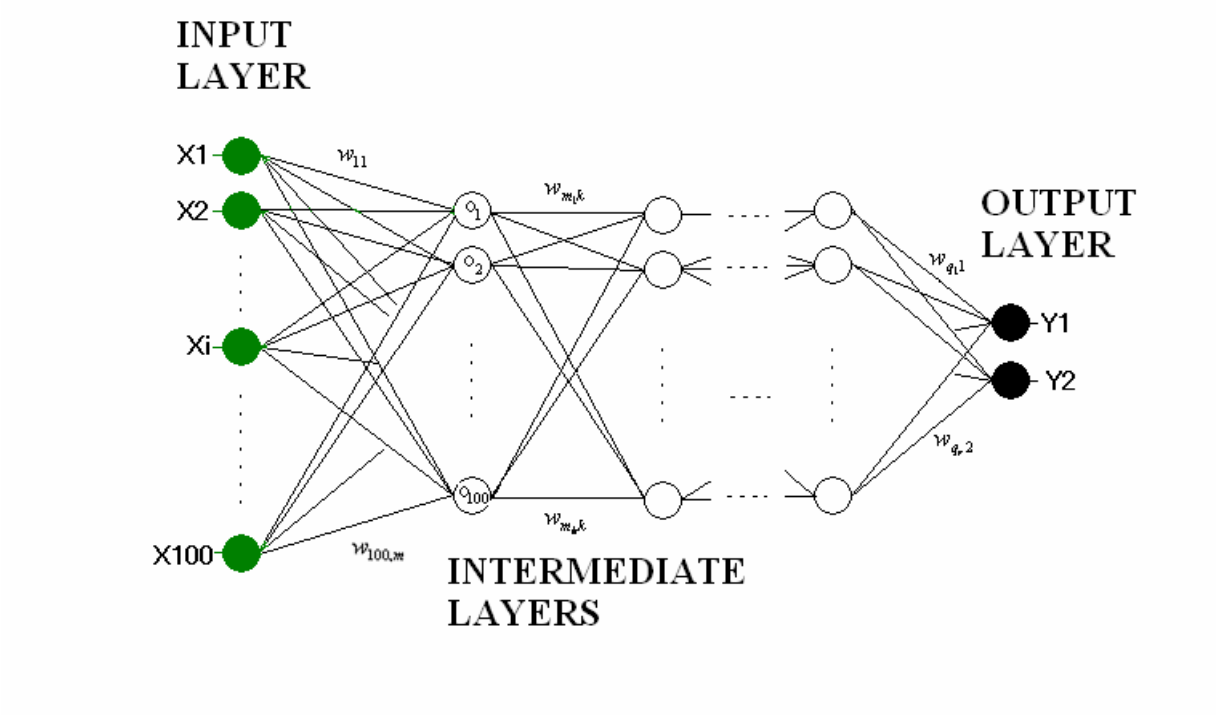

Figure 1. A typical ANN scheme.

Taking the mathematical analytical expressions into account in the minimization process for the equation (1), it is possible to derive two of the most important parameters used in the ANN training process. These parameters are the learning rate (η), that is a relatively small constant that can be related to the error function slope as a function of certain ANN weight, and the other is

the momentum which permits to orient the gradient descent direction in the error function minimization process.

2.1.1. The input data for the MLANN

In general, one of the most important aspects in the ANN training process is to establish the correct encoding for the input data. For instance, in some cases is not necessary to normalize them, in our case it was necessary to do so. Since our intention is to obtain an ANN in order to predict the LPPF for a given BWR fuel lattice, at the beginning of the process we deal with the problem of encoding the combination of U^{235} w/o and Gd_2O_3 data for some lattice's pins. Therefore, we decided to try the following three cases:

a) Encoding the combination of $e(U^{235})$ and $g(Gd_2O_3)$ in terms of the value given by the difference between both data.
b) Encoding the combination of $e(U^{235})$ and $g(Gd_2O_3)$ in terms of the value given by the addition of both data
c) Encoding the combination of $e(U^{235})$ and $g(Gd_2O_3)$ in terms of an equivalent value of $e'(U^{235})$ for the $e(U^{235}) + g(Gd_2O_3)$.

As an example, next we are showing a typical training pattern and its three different ways to encode.

In the first of the next four figures, the training pattern in terms of different U^{235} w/o enrichment values, and Gd_2O_3 concentrations is shown. Afterwards, the three different ways of encoding this training pattern are shown. The normalization was made in such a way that the values close to the boundaries of the data used in the training of the ANN can be correctly predicted, during the utilization of the trained ANN, by adding and reducing 10% to the boundary values. The 10% is taken from the difference between the maximum and the minimum value of the LPPF used during the training of the ANN.

2	2.8	3.95	3.95	2.8	3.95	4.4	3.95	3.95	2
2.8	3.95	3.95	4.9	3.6	3.95	3.95	4.4+4	4.4+5	2.8
3.95	3.95	4.4	4.4+4	3.95	4.4	3.6	4.4+2	3.95+5	4.9
3.95	4.9	4.4+4	3.95+5	3.95	0	0	2.8	4.9	4.9
2.8	3.6	3.95	3.95	3.95+5	0	0	4.4	4.9	3.95
3.95	3.95	4.4	0	0	3.6	3.95+5	3.95	2.8	4.9
4.4	3.95	3.6	0	0	3.95+5	3.95+5	2.8	4.9	2.8
3.95	4.4+4	4.4+2	2.8	4.4	3.95	2.8	4.4	4.4+5	3.6
3.95	4.4+5	3.95+5	4.9	4.9	2.8	4.9	4.4+5	2.8	3.95
2	2.8	4.9	4.9	3.95	4.9	2.8	3.6	3.95	2
1.5824									

Figure 2. A typical training pattern.

0.0833	0.1734	0.3029	0.3029	0.1734	0.3029	0.3536	0.3029	0.3029	0.0833
0.1734	0.3029	0.3029	0.4099	0.2635	0.3029	0.3029	0.8041	0.9167	0.1734
0.3029	0.3029	0.3536	0.8041	0.3029	0.3536	0.2635	0.5788	0.866	0.4099
0.3029	0.4099	0.8041	0.866	0.3029	0	0	0.1734	0.4099	0.4099
0.1734	0.2635	0.3029	0.3029	0.866	0	0	0.3536	0.4099	0.3029
0.3029	0.3029	0.3536	0	0	0.2635	0.866	0.3029	0.1734	0.4099
0.3536	0.3029	0.2635	0	0	0.866	0.866	0.1734	0.4099	0.1734
0.3029	0.8041	0.5788	0.1734	0.3536	0.3029	0.1734	0.3536	0.9167	0.2635
0.3029	0.9167	0.866	0.4099	0.4099	0.1734	0.4099	0.9167	0.1734	0.3029
0.0833	0.1734	0.4099	0.4099	0.3029	0.4099	0.1734	0.2635	0.3029	0.0833
0.8437									

Figure 3. Encoding typical training pattern case a)

0.5105	0.6225	0.7836	0.7836	0.6225	0.7836	0.8466	0.7836	0.7836	0.5105
0.6225	0.7836	0.7836	0.9167	0.7346	0.7836	0.7836	0.2864	0.1464	0.6225
0.7836	0.7836	0.8466	0.2864	0.7836	0.8466	0.7346	0.5665	0.0833	0.9167
0.7836	0.9167	0.2864	0.0833	0.7836	0	0	0.6225	0.9167	0.9167
0.6225	0.7346	0.7836	0.7836	0.0833	0	0	0.8466	0.9167	0.7836
0.7836	0.7836	0.8466	0	0	0.7346	0.0833	0.7836	0.6225	0.9167
0.8466	0.7836	0.7346	0	0	0.0833	0.0833	0.6225	0.9167	0.6225
0.7836	0.2864	0.5665	0.6225	0.8466	0.7836	0.6225	0.8466	0.1464	0.7346
0.7836	0.1464	0.0833	0.9167	0.9167	0.6225	0.9167	0.1464	0.6225	0.7836
0.5105	0.6225	0.9167	0.9167	0.7836	0.9167	0.6225	0.7346	0.7836	0.5105
0.8437									

Figure 4. Encoding typical training pattern case b)

0.3243	0.4877	0.7226	0.7226	0.4877	0.7226	0.8145	0.7226	0.7226	0.3243
0.4877	0.7226	0.7226	0.9167	0.6511	0.7226	0.7226	0.1467	0.1181	0.4877
0.7226	0.7226	0.8145	0.1752	0.7226	0.8145	0.6511	0.2365	0.0976	0.9167
0.7226	0.9167	0.1752	0.1201	0.7226	0	0	0.4877	0.9167	0.9167
0.4877	0.6511	0.7226	0.7226	0.0915	0	0	0.8145	0.9167	0.7226
0.7226	0.7226	0.8145	0	0	0.6511	0.114	0.7226	0.4877	0.9167
0.8145	0.7226	0.6511	0	0	0.114	0.1201	0.4877	0.9167	0.4877
0.7226	0.1467	0.2365	0.4877	0.8145	0.7226	0.4877	0.8145	0.1303	0.6511
0.7226	0.1181	0.0976	0.9167	0.9167	0.4877	0.9167	0.1303	0.4877	0.7226
0.3243	0.4877	0.9167	0.9167	0.7226	0.9167	0.4877	0.6511	0.7226	0.3243
0.8437									

Figure 5. Encoding typical training pattern case c)

The last value in the previous three figures corresponds to the target normalized LPPF of the fuel lattice. For the c) case it was necessary to carry out a series of HELIOS [10] calculations in order

to establish a relationship between LPPF vs. $U^{235}/U^{235}+Gd_2O_3$ in the range of interest of the variable. The obtained curves are presented in Fig. 6. It can be seen that the values are into a range of small LPPF values, which we expect as a consequence of the Gd_2O_3 presence.

2.1.2. The training space of the MLANN

Essentially, what an ANN makes is to extract the knowledge which is present in a given training set. In our case, the initial training set was formed by 3497 training patterns; such patterns were obtained by means of HELIOS calculations. During the training process, 20% of the training patterns were selected in order to verify the trained ANN behavior. In Fig. 7 the training space is shown.

According to above premise, if we have a broader training space, in terms of its diversity, then we will have the probability of obtaining a bigger scope in the prediction of the desirable parameters, trough the trained ANN. That is the reason because we decided to increase de quantity of training patterns in the training space. We were able to increase it up to 8400 training patterns. All of them were obtained by means of HELIOS calculations. In a certain sense, a cycle can be conveniently established in order to permanently improve the quality of the training space.

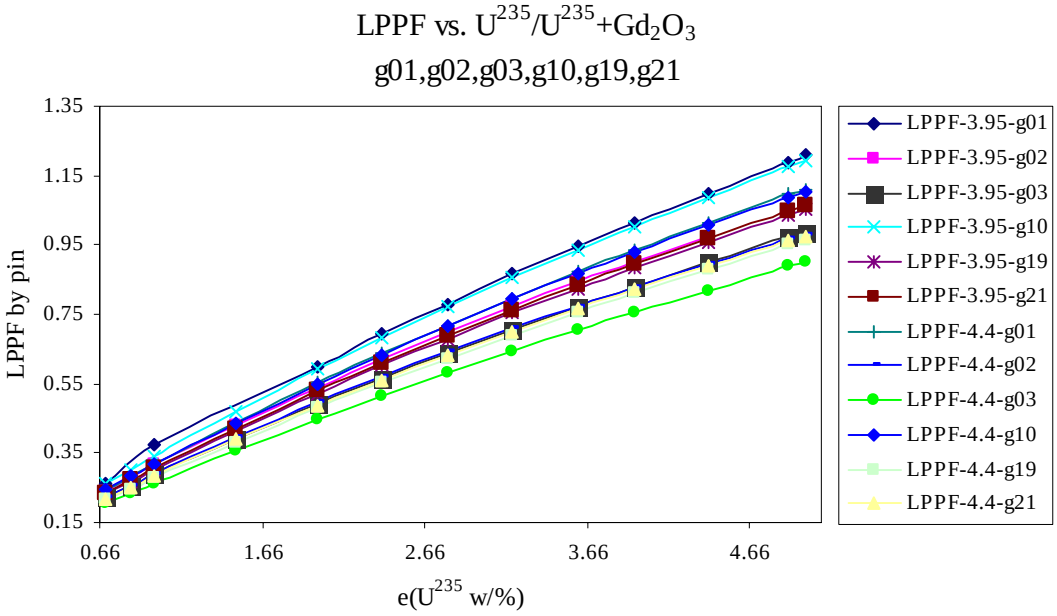

Figure 6. LPPF behavior used to obtain equivalent U^{235} enrichment.

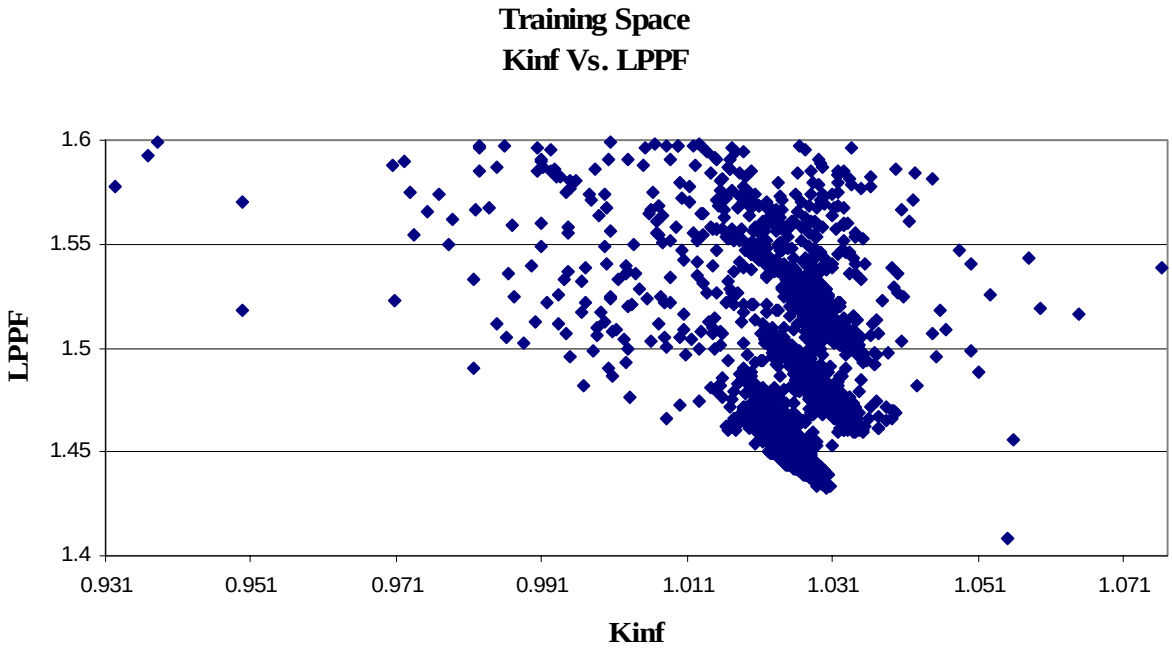

Figure 7. Training space for the MLANN.

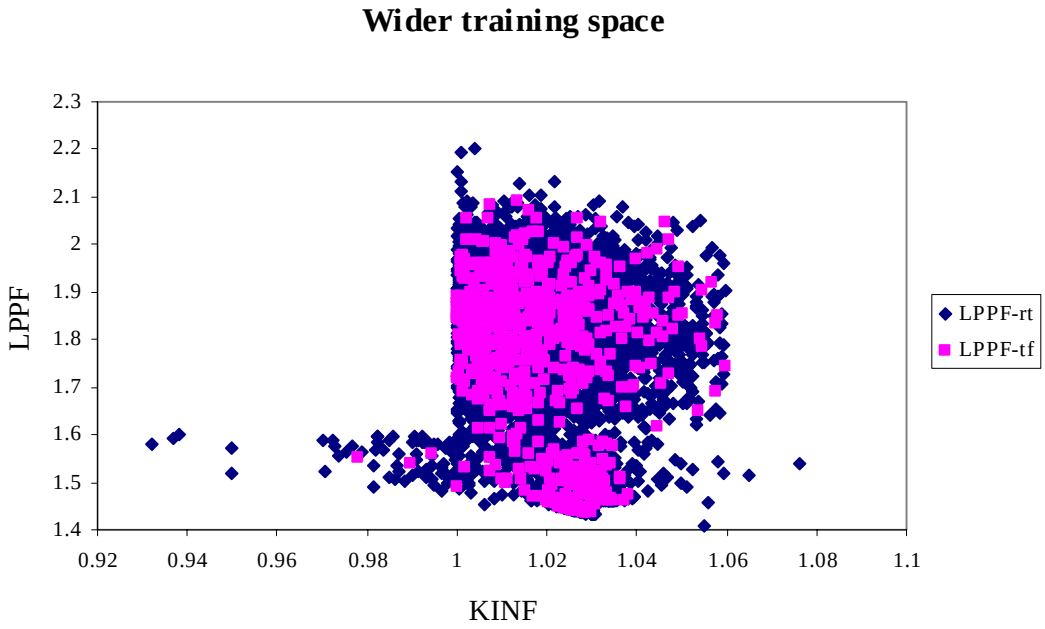

Figure 8. Broader training space for the MLANN.

In the previous figure, label “rt” refers to the training patterns used to run the BP algorithm, and “tf” refers to the training patterns selected to test its performance. The summary of the results obtained after we increased the training space are shown in the next figure.

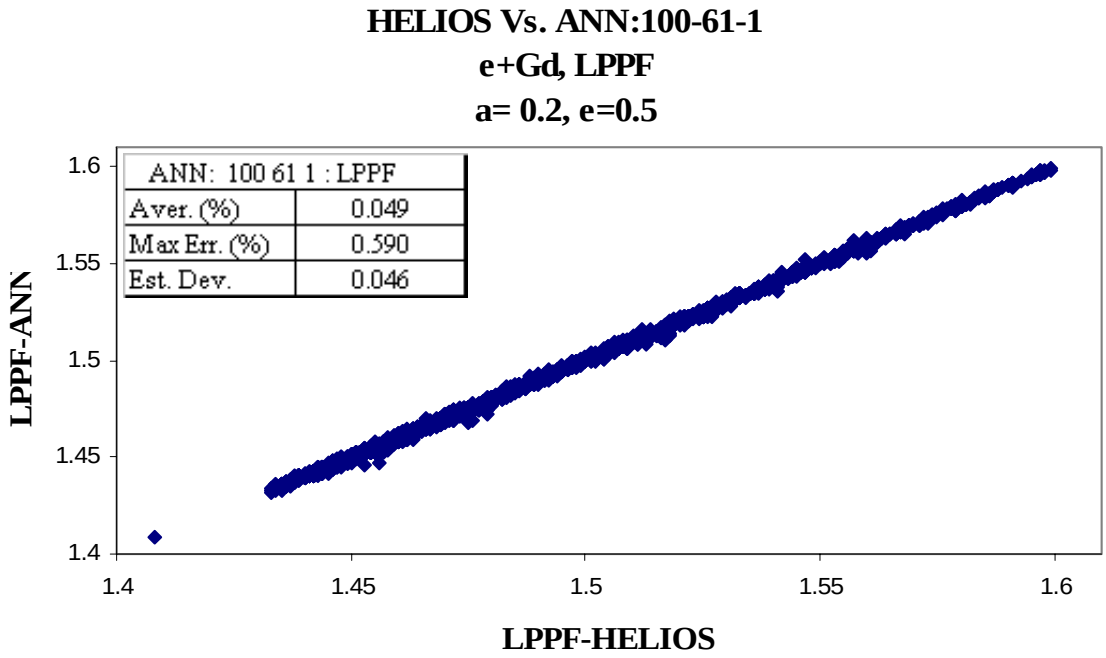

Figure 9. MLANN vs. HELIOS comparison for LPPF.

The structure of the trained ANN has 61 intermediate neurons. This trained ANN has been applied in order to predict the LPPF for several BWR fuel lattices. These fuel lattices have been used in the actual BWR reactor operation of the Laguna Verde Nuclear Power Plant (LVNPP). An error of around 2.0 % was obtained with respect to the reference fuel lattices. These BWR fuel lattices correspond to cycle 10 and 11 of the Unit 1 of LVNNP.

A typical example of the ANN application is shown in the following comparative Table I.

Table I. ANN application example comparison

MLANN Vs. Ref. Real Lattice	
HELIOS (Real Lat.)	1.4471
MLANN	1.4350
Abs. Err. (%):	0.8470

3. CONCLUSIONS

According to the conditions that we specified, several observations can be derived from the present study, related to the prediction of LPPF by means of a Multi-Layer Artificial Neural Network.
First, it can be said that the unique way of encoding, that produced satisfactory results, was that of c) case, which is based on the change of U^{235} + Gd_2O_3 combination, for the value given by the addition of the these two material concentrations.
Second, it is possible to obtain a MLANN that permited to predict the LPPF of some of the BWR fuel lattices, used in the real operation of LVNNP. Furthermore, this ANN is good enough to start the process of developing a search algorithm for solving the U^{235} and Gd_2O_3 optimization distribution problem. When the ANN can be used systematically, the size of the training space can be conveniently increased in order to obtain improved results with the ANN.
Third, with respect to CPU time performance, HELIOS takes 0.14 minutes of CPU time, in an Alpha Station 833 MHz and 256 MB of RAM, for computing one eigenvalue calculation of a BWR fuel lattice, and the ANN takes $3.9x10^{-4}$ minutes of CPU time, to carry out the same calculation, in a PC with a Pentium 4 CPU, 2.80 GHz and 512 MB of RAM. It means that the ANN takes 360 times less time in performing a lattice evaluation. The total CPU time needed to train the ANN was 1.8 CPU days, in the above mentioned PC.
Finally, it can be said that according to the potential application of the results presented here, and those found in the references, the relatively large time needed to train an ANN is after all justifiable; and that it is feasible to successfully apply the artificial neural networks to predict specific BWR fuel lattice parameters, instead of using HELIOS, mainly for the application in combinatorial optimization problems, where thousands of calculations are needed.

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