**Short communication**

# A Toy Model for Nuclear Reactor Core Simulation with Artificial Neural Network

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**Abstract**

Nuclear reactor core configuration search is a standard optimization procedure. To avoid the time consuming reactor core characteristic evaluation for different core configurations we have investigated the training of artificial neural network (ANN) with a simple core neutronics simulator model. To find an optimum structure of the network is a matter of trial and error. Further the computationally expensive neutronics calculation steps makes it more difficult. It is found that ANN can learn the assumed property of our simple model. This simulator model has been demonstrated as a screening tool to find the optimum ANN structure for the core neutronics simulation. Besides, the optimum structure of the neural network is expected to predict the characteristics of a reactor core of equivalent dimension of that of the simulator model. Future direction of work has been identified.

***Keywords:*** Neutronics simulator, in-core fuel management, artificial neural network

## 1. Introduction

For reactor core design, optimum core configuration search is an important issue. In-core fuel management of a nuclear reactor includes multiple steps of fuel reshuffling and calculating neutronics parameters recurrently. Optimum core configuration evaluation and selection is a standard optimization procedure, but the neutronics calculation is time consuming. Usually for core management study simple neutronics models are used [1]. Now-a-days with the increase of computer performance detailed model computer codes are in practice [2]. The application of artificial neural network for nuclear core characterization is already reported [3-7]; here we have investigated the training of an artificial neural network (ANN) with a simple core neutronics simulator model.

## 2. Materials and Methods

To grasp the inherent feature of in-core fuel management and to perform preliminary selection of core configurations we attempted artificial intelligence technique. Particularly, we concentrated on neural network approach. Here we investigated the feasibility of training an artificial neural network for neutronics simulation of a nuclear reactor core. Again it is a daunting task to train the network with hundreds of neutronics simulation data. So for the feasibility study of training a neural network for core neutronics simulation we have prepared a simple model coded in QBASIC. We consider this simple model as toy model. Power peaking factor and reactivity of the core is considered very frequently to define the objective function for the core management problem [8]. Both these parameters depend on neutron flux and fuel distribution in the core. The relative neutron flux at any location inside the reactor core depends on the number of neighboring fuel elements [9]. In this toy model we have made assumption that the worth of individual fuel element depend on the nearest neighbor fuel loadings and on the fuel loading itself on that location. Hence we can multiply the individual fuel loading with the nearest neighbor fuel loadings to get the fuel element worth; this worth distribution is equivalent to power distribution. Next we can sum up the individual fuel worth values to obtain the power peaking by dividing with the total number of the loaded fuels. This power peaking factor may be used for power flattening of the core. Now with this model we have another opportunity to define the core life considering the zero reactivity at the end of cycle. As we measure the reactivity of a control rod free core in terms of the total fuel element worth and vice-versa, hence the total worth of our model will represent the cycle length. Different core configuration with same fuel element set gives different core reactivity and hence longer cycle length configuration ensures efficient fuel consumption. Finally we get the interpretation of power peaking factor and core cycle length in terms of our modeled fuel element worth. In this article, to serve our purpose we shall focus on power distribution only.

ANN mimics our brain. In many cases, the issue is approximating a static nonlinear, mapping with a neural network. It consists of a large class of different architectures. The most useful neural networks in function approximation are Multi-layer Layer Perceptron (MLP) and Radial Basis Function (RBF) networks [5]. Here we concentrate on MLP networks. A MLP consists of an input layer, several hidden layers, and an output layer. In a MLP network each node, also called a neuron, includes a summer and a nonlinear activation function. Detail is available elsewhere [10]. We used MATLAB (Matrix Laboratory) Neural Network Toolbox to simulate our network. MATLAB is a product of Mathworks, a scientific software package designed to provide integrated numeric computation and graphics visualization. The network model studied was chosen as multilayer perceptron with a feed-forward back propagation algorithm. We have used linear output function and tangent hyperbolic function as input activation function. The back propagation learning algorithm uses gradient method.

## 3. Results and Discussion

We have considered a 5 by 5 core matrix fueled with either numerical values from 1 to 3, and our computer program

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computed the total number of neighboring fuel element values around each element and their worth values as defined above. Hence the simulator output represents the power distribution. Our concern is of 3 by 3 core matrix model, thus the outermost ring of the 5 by 5 matrix is a dummy ring loaded with the value zero, added for the sake of network training. Next we define the input vector for neural network having elements first with central fuel element of the matrix, then from the next ring in clock wise direction, starting with the 2×2 element, and so on. Similarly we defined the output vector to train the network with the computed worth value matrix distributed in the same manner as the input vector, but this time we have excluded the outermost ring. We have trained the network with fifty different data sets obtained from the neutronics simulator and finally tested with another sets of data. Results for sample data sets are shown in Table 1. The main hurdle is to find the appropriate neural network architecture for the problem in hand. There is no standard rule for doing this leaving trial and error. The ANN corresponding to our model simulator includes 25 inputs and 9 output units. We

**Table 1:** Neural network sample test data

| Input | Simulator output | ANN output | RMSE (Normalized Error) |
|---|---|---|---|
| 0 0 0 0 0<br>0 1 1 2 0<br>0 2 3 3 0<br>0 1 1 3 0<br>0 0 0 0 0 | 6 11 14<br>14 42 30<br>6 12 21 | 6.621 11.290 13.720<br>12.950 41.821 28.761<br>6.913 12.548 20.262 | 0.738<br>(4.26%) |
| 0 0 0 0 0<br>0 1 2 1 0<br>0 3 1 3 0<br>0 1 2 1 0<br>0 0 0 0 0 | 6 18 6<br>21 14 21<br>6 18 6 | 5.669 17.474 7.013<br>19.926 13.131 21.706<br>5.487 18.642 8.431 | 1.075<br>(8.34%) |
| 0 0 0 0 0<br>0 1 1 1 0<br>0 1 1 1 0<br>0 1 1 1 0<br>0 0 0 0 0 | 3 5 3<br>5 8 5<br>3 5 3 | 2.708 4.811 2.994<br>5.051 8.239 4.723<br>3.218 4.938 2.849 | 0.192<br>(4.32%) |

varied the number of layers and number of neurons per layer. The optimum network has been settled with single hidden layer of 100 neurons. The training performance of the network obtained from MATLAB is demonstrated in Fig. 1. To evaluate the network prediction we used the root mean square error (RMSE) value, which is normalized by normalizing the average of the expected (computed) output values to 100. This compares the ANN simulation result with the desired output values (Table 1). Normalized error values are within 20% for this optimum network. It means ANN can learn the assumed property of nuclear reactor core to a reasonable extent. We can expect to predict the characteristics of a reactor core of equivalent dimension of that of the simulator model with this optimum network structure. Alternately we hope to apply this neutronics simulator model as a screening tool to find the optimum ANN structure for the real core neutronics simulation. The neutronics model simulation can be extended to study with the variants of neural network architecture. Also investigation of the simulator for higher dimensional core is remaining.

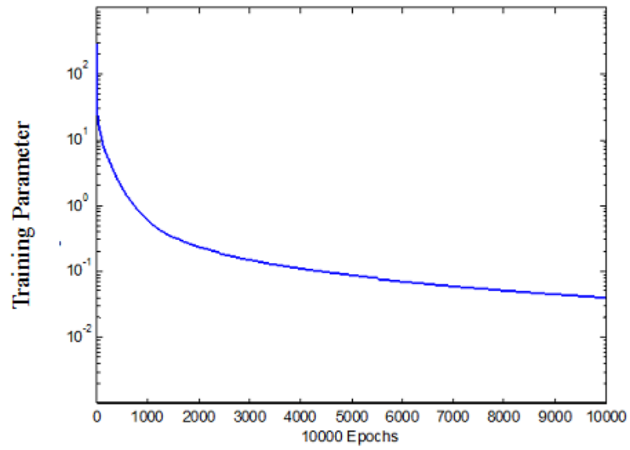


**Fig. 1:** Neural network training performance

## 4. Conclusion

From the economic and safety point of view in-core fuel management has to be done carefully. For such fuel management, reactor core neutronics characterization is the first step. We have studied the application of artificial intelligence to perform this job. For a real reactor system it will be difficult to perform neotronics calculation recurrently to supply sufficient training data for a neural network; whereas, it is expected that our simple model study will aid to find the optimum structure of the network quickly that will characterize the reactor core reasonably. In the future work, the netronics simulator model will be ornamented with real reactor parameter values and can be used for preliminary study for in-core fuel management. This handy equipment is expected to help core characterization and the search of optimum core configuration as well as for the assessment of application of artificial intelligence for nuclear reactor core design and safety.

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