Approximation of the criticality margin of WWR-c reactor using artificial neuron networks

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Abstract. Two artificial neural networks approximating the criticality margin of the WWR-c reactor (based on model and calculated data) were created and trained. The resulting neural networks realize the correct approximation, have high accuracy, and also high speed of operation. Using the obtained artificial neural networks can be applied to accelerate the preliminary calculations of the state of the reactor.

1. Formulation of the problem
There is an experimental nuclear facility WWR-c in the Karpov Institute of Physical Chemistry in the city of Obninsk. The nuclear facility was commissioned into operation in 1964. WWR-c is a heterogeneous water-water research reactor, specialized for conducting a wide range of experiments in the field of radiation chemistry, structural and material research, activation analysis, neutron doping of semiconductors, etc. [1]

Since 1980, the productions of radionuclides for medical purpose and radiopharmaceuticals based on them have been developing on the reactor. In connection with the success of the development of the production and the convenient geographical location in 1986, it was decided to improve the reactor. [1]

To improve reactor parameters and the efficiency of radionuclide production (⁹⁹Mo, ¹³¹I etc.) the precision neutron-physical model for active zones, reflectors and control systems was created in 2011. A geometry of all fuel elements (fuel, shell, water gap, temperature of each component), a change of isotopic composition as a function of burn-up, control systems, reflectors, experimental channels and structures were taken to account during the simulation. The precise model were verified for calculation of the criticality margin of WWR-c reactor. [2]

The precision model is based on the Monte Carlo method, which makes it possible to achieve great accuracy in the modeling of extremely complex physical processes in the active zone of the reactor. However, for carrying out a correct calculation, a large number of computational experiments are required, and, consequently, a large amount of computer time. Calculation of one state of the active zone takes about 8 hours.

Obviously, with short reactor campaigns (100 hours), the research personnel of the reactor have little time for calculating the modernized state of the reactor. Thus, our task is to create an approximation of the precision model for preliminary calculations of the criticality margin of reactor. Approximation should satisfy the following requirements: high speed of operation and sufficient accuracy.
Let consider parameters of the precise model which are changing from campaign to campaign. This is the percentage of fuel burn-out in each fuel assembly and the position of the control systems. Other model parameters from campaign to campaign remain unchanged. In this case, the task is reduced to approximating the criticality margin of the reactor, depending on the fuel burn-out and the position of the control system.

2. Experiment #1: Model Data Approximation

To construct the approximation, a generalized approximation theorem was applied. According to this theorem it is possible to obtain an arbitrarily exact approximation of any continuous function of several variables, using the operations of addition and multiplication by a number, a superposition of functions, linear functions, and also one arbitrary continuous nonlinear function of one variable. [3] Since these operations are fully implemented by an artificial neural network with one nonlinear formal neuron, an artificial neural network can be used to construct the desired approximation.

To build the approximation based on an artificial neural network, we used the TensorFlow library. The TensorFlow library is the most popular library for machine learning. The computational model of TensorFlow is based on a computational graph that can be executed on both the CPU and the GPU. [4] DNNRegressor, primitive of TensorFlow, was used as a basis to construct a required neural network.

Using TensorFlow, a three-layered neural network was created. An input layer consists of 50 formal neurons with a ReLu activation function:

\[ f(x) = \begin{cases} 
0, & x < 0; \\
x, & x \geq 1.
\end{cases} \]

A hidden layer consists of 10 formal neurons with the ReLu activation function. An output layer consists of 1 formal neuron with a logistic activation function:

\[ f(x) = \frac{1}{1 + e^{-x}} \]

To train the neural network, a dataset was built. Using the precise model computational experiments were performed with 34 different reactor configurations (burn-out of fuel, positions of the control system) and for each configuration, the criticality margin was obtained. From the obtained dataset, a training dataset (25 configurations) and a test dataset (9 configurations) were formed. For the final validation, all 34 configurations were used.

50,000 training epochs were performed for training artificial neural network. The training was made by the method of back propagation of the mean square error on the training dataset. Every 100 epochs, the mean square error was estimated on the test dataset. During the training process, the error was converging to zero without divergence.

Let’s consider the results of validating the training of the artificial neural network: the average absolute approximation error is 0.0405; the maximum absolute approximation error is 0.1029; the average relative approximation error is 1.21%; the maximum relative approximation error is 3.13%.

The average time to calculate the criticality margin using an artificial neural network is 100 ms. The fig. 1 shows the calculated and approximated criticality margin.

Based on the results of the experiment, we can conclude: the construction of the approximation of the precision model was successful.
3. Experiment #2: Measured Data Approximation

From the description of the experiment #1 it is clear that for the training of the artificial neural network only the data on the burning out of fuel assemblies, the position of the control systems, as well as data on the criticality margin of the reactor were used. Such data can be obtained not only from the precision model, but from the direct measurements that are made at the beginning of each campaign. Therefore, it is possible to construct an approximation based on the measured data.

For experiment #2, an artificial neural network was created using the TensorFlow library. The architecture of the neural network is completely identical to the network architecture described in experiment #1.

As a data set for training, the measured data of 24 reactor campaigns were taken. The data set was divided into 2 data sets: training data set (18 campaigns) and test data set (6 campaigns). To validate the trained neural network, data from all 24 campaigns were used.

50,000 training epochs were performed for training artificial neural network. The training was made by the method of back propagation of the mean square error on the training dataset. Every 100 epochs, the mean square error was estimated on the test dataset. During the training process, the error was converging to zero without divergence.

Let’s consider the results of validating the training of the artificial neural network: the average absolute approximation error is 0.0412; the maximum absolute approximation error is 0.1159; the average relative approximation error is 1.26%; the maximum relative approximation error is 3.56%.

The average time to calculate the criticality margin using an artificial neural network is 100 ms. The fig. 2 shows the measured and approximated criticality margin.

Based on the results of the experiment, we can conclude: the construction of the approximation of the measured data was successful.

4. Conclusions and prospects

In this work, two artificial neural networks were created and trained to approximate the criticality margin of the WWR-c reactor (based on model and measured data). The resulting neural networks realize the correct approximation, have high accuracy, and also high speed of operation. The obtained artificial neural networks can be used to accelerate the preliminary calculations of the state of the reactor.
Figure 2. The measured and approximated criticality margin charts

In the future, the transfer of trained neural networks to the Karpov Institute of Physical Chemistry for use, improvement of the quality of approximation due to new data for training, application of the neural network approach for evaluating other complex processes of nuclear installations, development of an artificial intellectual helper for reactor technological processes.

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