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Developing a computational tool for predicting physical parameters of a typical VVER-1000 core based on artificial neural network

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ABSTRACT

The main goal of the present article is to design a computational tool to predict physical parameters of the VVER-1000 nuclear reactor core based on artificial neural network (ANN), taking into account a detailed physical model of the fuel rods and coolant channels in a fuel assembly. Predictions of thermal characteristics of fuel, clad and coolant are performed using cascade feed forward ANN based on linear fission power distribution and power peaking factors of FAs and hot channels factors (which are found based on our previous neutronic calculations). A software package has been developed to prepare the required data for ANN training which applies a modified COBRA-EN code for sub-channel analysis and links the codes using the MATLAB software. Based on the current estimation system, five main core TH parameters are predicted, which include the average and maximum temperatures of fuel and clad as well as the minimum departure from nucleate boiling ratio (MDNBR) for each FA. To get the best conditions for the considered ANNs training, a comprehensive sensitivity study has been performed to examine the effects of variation of hidden neurons, hidden layers, transfer functions, and the learning algorithms on the training and simulation results. Performance evaluation results show that the developed ANN can be trained to estimate the core TH parameters of a typical VVER-1000 reactor quickly without loss of accuracy.

1. Introduction

An accurate prediction of thermal–hydraulics (THs) performance of a nuclear reactor is a major concept in its design for both economic and safety reasons. Development of economically advantageous and safe operating conditions requires methods of more accurate and detailed analysis of the TH processes. Moreover, many safety margins are initially related to neutronics behavior of a reactor (e.g., reactivity feedbacks, MDNBR). Therefore, a deeply understanding and calculations of both neutronics and TH make a nuclear reactor analysis. For instance, the main objective in a PWR reactor core TH design is determination of maximum capability of heat removal in most powered channel named hottest channel. The imposed restriction of DNB requires accurate TH analysis based on computations of flow and enthalpy distribution using a detailed physical model. In individual hottest channel, pertinent nuclear and engineering affects are considered. This single channel in a fuel assembly that is established with four adjacent fuel rods in a square lattice (in the Western square design core) or with three neighboring rods in a triangular lattice (in the Russian hexagonal core, e.g., VVER type) is often referred to sub-channel. The TH design based on sub-channel analysis has been taking into account for some advantages; for instance, local variations in dimensions, power generation, flow redistribution, and flow mixing (Chelemer et al., 1972). Also based on this approach, local TH conditions of the hot sub-channel and hottest fuel rod can be determined.

The main goal of a sub-channel analysis is to determine critical heat flux in terms of DNBR, maximum fuel and clad temperatures, and coolant TH conditions during normal and/or hypothetical accidents conditions. This precious analysis of a reactor core requires a detailed map of thermal fission power distribution in the FAs and fuel rods. The power density distribution cannot be directly measured and is usually described in terms of power peak factors, axial and quadrant power differences. The current real time simulation tools, to predict power density distribution and the DNBR, have uncertainties as high as 20% (Souza and Moreira, 2006), and it is important to find alternatives to improve their accuracy.

ANN allows modeling complex systems without requiring an explicit knowledge of formulations that exist among the variables, and constitute an alternative to structure models or empirical correlations (Haykin, 1999; Tsoukalas and Uhrig, 1997).

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Nomenclature

h	heat transfer coefficient (W/m^2 K)	G	coolant mass flux (kg/s m^2)
Pr	Prandtl number at average coolant temperature	X_{in}	inlet flowing vapor quality
h_{in}	inlet enthalpy (J/kg)	q''	local heat flux (W/m^2)
h_{fg}	vaporization enthalpy (J/kg)		

Literatures surveys indicate a wide variety of applications of ANNs to nuclear engineering such as for plant control (Boroushaki et al., 2004), in-core fuel management optimization (Sadighi et al., 2002), non-linear dynamics and transient diagnosing (Khalafi and Terman, 2009), core parameter prediction (Mazrou, 2009), and signal validation (Ikonomopoulos and Van Der Hagen, 1997). Specifically to our case, there are applications for establishing a correlation among primary system variables to obtain information about the power density distribution for improving estimation of the MDNBR (Lee and Chang, 2003; Na et al., 2004; Kim and Chang, 1997). They developed neural networks to estimate the DNBR using input core TH variables and power distribution information in the form of radial peaking factor and axial power density. The results of these researches show that, for constant and known axial power density distribution, the DNBR was predicted with 3.5% accuracy (Kim and Chang, 1997) while for those cases in which the power density distribution was unknown and could change, they predicted DNBR with at least 10% accuracy (Lee and Chang, 2003; Na et al., 2004). In these articles, the common considered approach was to use one neural network to bear all the knowledge involved in the problem; such as how to determine the power density distribution and how to estimate the critical heat flux. In most of the applications, they considered one hidden layer sufficient to solve the problem and its number of neurons are varied according to the considered number of input and output.

This work employed ANNs to predict safety TH parameters of the Bushehr VVER-1000 reactor core include maximum and average temperature of the fuel and clad and MDNBR for the hottest fuel rod in each fuel assembly of the core. A very fast estimation system has been developed using a cascade feed forward type of ANNs on the basis of linear fission power distribution and power peaking factors of each fuel assembly and its corresponding rod.

Preparing the input for the TH codes such as COBRA and also running the code and obtaining results are time consuming. In addition human error in preparing the input files can cause some difficulties. If the power distribution changes, it is necessary to regenerate the input and run the code again. While by using the ANN model developed in this article, one has the capability to calculate the safety TH parameters by knowing just the power peaking factors. These factors are computed by the core designer for each core configuration and different FAs burn-up or they are measured from ex-core and in-core detectors. This tool can be used for TH analysis of the VVER-1000 type reactor core that have same specifications as well as for coupling of neutronic and thermal–hydraulic computations.

The DNBR is a very important safety parameter of the core which must be monitored continuously and in real time by the rector protection system (RPS) in nuclear power reactors (Souza and Moreira, 2006). Therefore the proposed computational tool can be used as a part of the RPS system to predict the safety parameters very fast. However, in this stage we are able to predict TH safety parameters just by using the measured PPF. Therefore, this model can be applied as a part of a general fast predicting tool to compute DNBR parameter for RPS and in the future study we are going to design a comprehensive tool which is applied in transient conditions by considering changes in other reactor parameters such as pressure, flow, inlet temperature and critical boron concentration.

This model has the capability of computing TH core parameters very fast and accurate with high degree of reliability in different core burn up and configurations and can also be applied for problems of optimization of the core configuration design, because in this case one needs a fast method to calculate the values of fitness functions during optimization process. This ANN method is effectively faster than iterative numerical methods.

In the current research, sub-channel TH analysis has been performed using an accurate physical model for the Bushehr NPP, a Russian VVER-1000 fuel assembly at hot full power (HFP) and steady-state condition. Neutronics calculations and reactivity coefficients were found previously using WIMS and CITATION codes (Faghihi et al., 2007). Also, a full Monte-Carlo core simulation for shut down margin estimations of both current solid fuel and annular pins (a proposal for the next generation VVER reactor) were carried out (Farshad Faghihi and Mirvakili, 2011). Moreover, herein, the COBRA-EN code (Basile et al., 1999) is used as the main TH analysis code that we previously have modified it for TH behavior of the VVER-1000 core (Safaei Arshi et al., 2010). This code has capability of sub-channel analysis of LWR core to predict distribution of flow, temperature, density and pressure for both single and two phase flow conditions.

2. Artificial neural network

Artificial neural networks can be defined as a parallel distributed processor consisting of a great number of processing elements, neurons, connected to each other with different connection strengths. The strength of a connection between neurons is called weight. In the beginning of the neural development process, these weights are initialized randomly and are adjusted in a model calibration phase called training so that to minimize the error between calculated outputs and the corresponding target output values for the particular training data set, whereas the testing subset is used to check the performance of the developed network. The types of ANNs are different and associated with its applications.

2.1. Cascade feed forward neural network

In this paper a very fast estimation system of the core TH parameters has been introduced and developed using cascade feed forward type of ANNs. A feed forward multilayered network consists of a layer of input, a layer of output neurons, and one or more hidden layers of neurons. Fig. 1 shows a general type of a three layers feed-forward ANN. This type of ANNs has wide applications in parameter prediction and data approximation problems. A cascade type of feed forward ANNs is similar to a general type of feed-forward ANNs; the first layer has weight coming from the input. But each subsequent layer has weight coming from the input and all previous layers so that all layers have biases, and the last layer is the network output. Each layer weights and biases must