Annals of Nuclear Energy 110 (2017) 989–994

Contents lists available at ScienceDirect

Annals of Nuclear Energy

journal homepage: www.elsevier.com/locate/anucene

Prediction and uncertainty analysis of power peaking factor by cascaded fuzzy neural networks

Ju Hyun Back, Kwae Hwan Yoo, Geon Pil Choi, Man Gyun Na *, Dong Yeong Kim

Department of Nuclear Engineering, Chosun University, 309 Pilmun-daero, Dong-gu, Gwangju 61452, Republic of Korea

ARTICLE INFO

Article history:
Received 19 October 2016
Received in revised form 26 July 2017
Accepted 5 August 2017

Keywords:
Cascaded fuzzy neural network (CFNN)
Local power density (LPD)
Power peaking factor
Uncertainty analysis

ABSTRACT

Nuclear reactor cores should be maintained within various safety limits such as the local power density (LPD). Therefore, a detailed three-dimensional core power distribution monitoring is required during reactor operation. In addition, LPD must be predicted to prevent nuclear fuel melting. In this study, the most important parameter related to LPD—the power peaking factor—was predicted. A cascaded fuzzy neural network (CFNN) methodology was utilized to predict the power peaking factor in the reactor core. A CFNN model was developed using the numerical simulation data of the optimized power reactor 1000 and its performance was analyzed. Additionally, its uncertainty analysis was conducted to determine the prediction accuracy of the CFNN model. The prediction intervals were found to be pretty narrow, which confirms that the predicted value is reliable. The accuracy of the proposed CFNN model proves to be able to assist nuclear reactor operators in monitoring the power peaking factor.

1. Introduction

The integrity of nuclear fuel rods during reactor operation should be assured within various safety limits for safe reactor operation such as the local power density (LPD) and departure from nucleate boiling ratio (DNBR). Therefore, a three-dimensional (3D) core power distribution is monitored during nuclear reactor operation.

The LPD and DNBR must be calculated to conduct two key functions of the core protection calculator system (CPCS) and the core operation limit supervisory system (COLSS) installed at the optimized power reactor 1000 (OPR1000).

COLSS provides information about monitoring the limiting conditions for operation to reactor operators. Meanwhile, CPCS conducts nuclear reactor protection functions and calculates the important safety parameters such as LPD and DNBR. If the LPD and DNBR exceed their safety limits, CPCS halts the plant operation by an automatic reactor trip signal. CPCS due to its conservative nature generates higher LPD and lower DNBR values than COLSS. CPCS is adjusted periodically by the accurately calculated COLSS values.

LPD must be predicted to keep nuclear fuel rods from melting. Particularly, LPD at the hottest position of the nuclear reactor core is more important to prevent the fuel melting at that position and is directly related to the power peaking factor (PPF) that is defined as the thermal output of the hottest fuel rod over the average thermal output of fuel rods. PPF is one of the most important factors, which must be continuously monitored from a safety aspect.

PPF was estimated accurately by using artificial intelligence methods such as fuzzy neural networks (FNN) (Na et al., 2004) and a support vector regression (SVR) method (Bae et al., 2008; Bae et al., 2009). It was known that the SVR is superior to the FNN. However, the SVR requires too much computational capability to optimize itself. The aim of the present study is to calculate PPF in a nuclear reactor core by using a cascaded fuzzy neural network (CFNN) model under various operating conditions of the nuclear reactor core. The CFNN model goes through several stages to infer the PPF value by the process of repeatedly adding FNN modules. Since the reasoning outcome in a preceding stage is transferred continuously to the subsequent stage as a fact, the CFNN has a characteristic that advances the inference mechanisms as the reasoning stage proceeds (Duan and Chung, 2001). Therefore, in this paper, the CFNN model is applied to calculate PPF in a nuclear reactor core. The reactor operation condition is expressed by nuclear reactor core power, axial offset (AO) indicating an axial neutron flux shape, reactor core inlet temperature, reactor coolant mass flowrate through a reactor core, pressurizer pressure, and various control rod positions.

The proposed CFNN model, which is a PPF prediction algorithm, is optimized to achieve good monitoring performance on LPD and is verified by using the simulated operating data collected from a number of numerical simulations of OPR1000.

* Corresponding author.
E-mail address: magyna@chosun.ac.kr (M.G. Na).

http://dx.doi.org/10.1016/j.anucene.2017.08.006
0306-4549/

2. Cascaded fuzzy neural networks

2.1. Fuzzy neural network

FNN is referred to as the fuzzy inference system (FIS) combined with a neural network of outstanding learning capability. A fuzzy rule in the FIS can be expressed as the following well-known *if-then* rule:

$$If\ x_1(k)\ is\ A_{i1}(k)\ AND \cdots\ AND\ x_m(k)\ is\ A_{im}(k),\ then\ y^i(k)\ is\ f^i(\mathbf{x}(k)), \tag{1}$$

where

$x_j(k)$: j^{th} input signal values ($j = 1, \cdots, m$) at data point k
m: number of input signals
A_{ij}(k): fuzzy membership functions of the i^{th} fuzzy rule and j^{th} input signal
$y^i(k)$: i^{th} fuzzy rule output

$$f^i(\mathbf{x}(k)) = \sum_{j=1}^{m} a_{ij}x_j(k) + a_{i0} \tag{2}$$

$\mathbf{x}(k) = (x_1(k), x_2(k), \cdots, x_m(k))^T, \quad k = 1, 2, \cdots, N_t$
N_t: number of training data
a_{ij}: weight of the i^{th} fuzzy rule and j^{th} input signal
a_{i0}: bias of the i^{th} fuzzy rule

The above FIS is the first-order Takagi-Sugeno-type FIS (Takagi and Sugeno, 1985) where the output of a fuzzy rule is described as a first-order polynomial of input signals as shown in Eq. (2). The input and output data are assumed to be normalized. The present study uses the following symmetric Gaussian membership function:

$$A_{ij}(x_j(k)) = e^{-\left(x_j(k)-c_{ij}\right)^2/2s_{ij}^2} \tag{3}$$

where

c_{ij}: center of a membership function A_{ij}
s_{ij}: width of a membership function A_{ij}

The predicted output of the FIS at data point k is computed by weight-averaging all the outputs of fuzzy rules as follows:

$$\hat{y}(k) = \sum_{i=1}^{n} w^{-i}(k)y^i(k) = \sum_{i=1}^{n} \overline{w}^i(k)f^i(\mathbf{x}(k)) = \mathbf{w}^T(k)\,\mathbf{a}, \tag{4}$$

where

$$\overline{w}^i(k) = \frac{w^i(\mathbf{x}(k))}{\sum_{i=1}^{n} w^i(\mathbf{x}(k))} \tag{5}$$

$$w^i(k) = \prod_{j=1}^{m} A_{ij}(x_j(k)) \tag{6}$$

n: number of fuzzy rules
$\mathbf{a} = [a_{11} \cdots a_{n1} \cdots\cdots a_{1m} \cdots a_{nm}\ \ a_{10} \cdots a_{n0}]^T$
$\mathbf{w}(k) = [w^{-1}(k)x_1(k) \cdots w^{-n}(k)x_1(k) \cdots\cdots w^{-1}(k)x_m(k) \cdots w^{-n}(k)x_m(k)\ \ w^{-1}(k) \cdots w^{-n}(k)]^T.$

The predicted output for a data point is calculated from Eq. (4) and the predicted outputs for all data points can be derived from Eq. (4) and is expressed as follows:

$$\hat{\mathbf{y}}_t = \mathbf{W}_t\,\mathbf{a}, \tag{7}$$

where

$$\hat{\mathbf{y}}_t = [\hat{y}(1)\ \hat{y}(2) \cdots\ \hat{y}(N_t)]^T$$
$$\mathbf{W}_t = [\mathbf{w}(1)\ \mathbf{w}(2) \cdots\ \mathbf{w}(N_t)]^T$$

Fig. 1 describes a six-layered FNN (Kim et al., 2016).

The parameters included in the fuzzy membership function and the parameter vector **a** should be optimized to accomplish a good modeling performance. In this study, these parameters were optimized using the two combined methods: the genetic algorithm and the least squares method. The training data were prepared to optimize the proposed FNN model. The test data were prepared to verify the FNN model independently. The genetic algorithm optimizes the parameters included in the fuzzy membership function. If the parameters in the fuzzy membership function are known, the vector $\mathbf{w}(k)$ can be calculated. The genetic algorithm uses the following fitness function that consists of the maximum and root mean square (RMS) errors.

$$Fitness = e^{-\lambda_1 E_1 - \lambda_2 E_2}, \tag{8}$$

where

E_1: RMS error
E_2: maximum error
λ_1, λ_2: their weighting values

After the membership function parameters have been optimized first using a genetic algorithm and the matrix $\mathbf{W}_t$ has been calculated, the resulting parameters **a** can be determined through minimizing an objective function that is expressed as follows, which is called the least squares method:

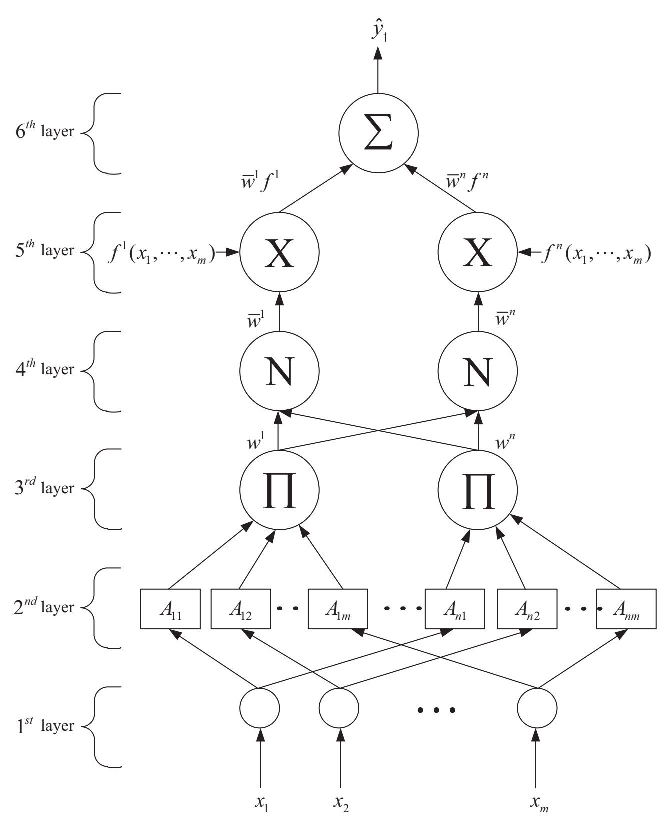

Fig. 1. Fuzzy neural network.