Diametral Creep Prediction of the Pressure Tubes in CANDU Reactors Using Fuzzy Neural Networks

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1. Introduction

Pressure tube (PT) creep is one of the principal aging mechanisms governing the heat transfer and hydraulic degradation of the heat transport system (HTS) in CANada Deuterium Uranium (CANDU) reactors. PT diametral creep affects the thermal hydraulic characteristics of coolant channels and the critical heat flux (CHF). CHF is a key parameter in determining the critical channel power (CCP), which is used in the trip setpoint calculations of regional overpower protection (ROP) systems. Therefore, it is important to predict the PT diametral creep in CANDU reactors. PT diametral creep is mainly caused by fast neutron irradiation, applied stress and temperature.

The objective of this paper is to predict the PT diametral creep using the measured signals of the HTS by applying fuzzy-neural networks (FNNs) according to operating conditions.

2. Fuzzy Neural Networks

2.1 Subtractive Clustering-Based Fuzzy Model

The fuzzy model is constructed from a collection of fuzzy if-then rules. A Takagi-Sugeno type of fuzzy inference system [1] is used where the i -th fuzzy rule for k -th time instant data is described as follows:

$$\begin{aligned}&\text{If } x_1(k) \text{ is } A_1^i(k) \;\; AND \cdots AND \;\; x_m(k) \text{ is } A_m^i(k), \\ &\text{then } \hat{y}^i(k) \text{ is } f^i\left(x_1(k), \cdots, x_m(k)\right)\end{aligned} \tag{1}$$

The fuzzy model can be designed through clustering of numerical data. A subtractive clustering (SC) method is used to identify a fuzzy model and assumes the availability of N input/output training data $\left(\mathbf{x}^T(k), y(k)\right)$ where $\mathbf{x}^T(k) = \left(x_1(k), x_2(k), \cdots, x_m(k)\right)$, $k = 1, 2, ..., N$. When the clustering method is applied to the collection of input/output data, each cluster center is in essence a prototypical data point that exemplifies the characteristic behavior of the system, and each cluster center can be used as the basis of a fuzzy rule that describes the system behavior.

The method starts by generating a number of clusters in the $m \times N$ dimensional input space. The SC method considers each data point as a potential cluster center and uses a measure of the potential of each data point, which is defined as a function of the Euclidean distances to all other input data points. It is assumed that the data points are normalized in each dimension.

The membership function $A^i(\mathbf{x}(k))$ of an input data vector $\mathbf{x}(k)$ to a cluster center $\mathbf{x}^*(i)$ can be defined as follows:

$$A^i\left(\mathbf{x}(k)\right) = e^{-4\left\|\mathbf{x}(k)-\mathbf{x}^*(i)\right\|^2 / r_\alpha^2} \tag{2}$$

The fuzzy model output $\hat{y}(k)$ is calculated by the weighted average of the consequent parts of the fuzzy rules as follows:

$$\hat{y}(k) = \sum_{i=1}^{n} A^i\left(\mathbf{x}(k)\right) f^i\left(\mathbf{x}(k)\right) \Big/ \sum_{i=1}^{n} A^i\left(\mathbf{x}(k)\right) \tag{3}$$

The function $f^i\left(\mathbf{x}(k)\right)$ is a polynomial in the input variables. When the fuzzy the output is of the form

$$f^i\left(\mathbf{x}(k)\right) = \sum_{j=1}^{m} q_{ij} x_j(k) + r_i \tag{4}$$

Therefore, the output of the fuzzy model given by Eq. (3) can be rewritten as

$$\hat{y}(k) = \sum_{i=1}^{n} \bar{w}^i(k) f^i\left(\mathbf{x}(k)\right) = \mathbf{w}^T(k)\mathbf{q} \tag{5}$$

2.2 Training the Fuzzy Model

The optimization of the fuzzy model is accomplished by a genetic algorithm combined with a least-squares method. The genetic algorithm is used to optimize the membership functions to be determined from the cluster radii, r_α and r_β , for the subtractive clustering of numerical data, and the least squares algorithm is used to calculate the consequent parameters, q_{ij} and r_i .

Genetic algorithms require a fitness function that assigns a score to each chromosome in the current population, maximizing the fitness function value. The fitness function evaluates the extent to which each candidate solution is suitable for specified objectives.

3. Uncertainty Analysis of the FNN Model

3.1 Statistical Method

The statistical uncertainty analysis works by generating many bootstrap samples of the training data set and retraining the FNN model parameters on each bootstrap sample. After repetitive sampling and training, the resulting predictions provide a distribution for the output value. This distribution can be used to calculate prediction intervals. In this study, the bootstrap pairs sampling algorithm which is one of statistical methods is used. The available data is divided into development data and test data [2].

The estimate with a 95% confidence interval for an arbitrary test input $\mathbf{x}_0$ is

$$\hat{y}_0 \pm 2\sqrt{Var(\hat{y}_0) + bias^2} = \hat{y}_0 \pm \delta . \quad (6)$$

3.2 Analytic Method

The variance of the predicted output can be estimated as follows [2]:

$$Var(y_0 - \hat{y}_0) \approx \sigma^2 + \mathbf{f}_0^T \mathbf{S} \mathbf{f}_0 \approx s^2 + s^2 \mathbf{f}_0^T (\mathbf{F}^T \mathbf{F})^{-1} \mathbf{f}_0 \quad (7)$$

The matrix $\mathbf{F}$ is called the Jacobian matrix of first order partial derivatives with respect to the parameters determined from the least squares. The estimate with a 95% confidence interval is

$$\hat{y}_0 \pm 2s\sqrt{1 + \mathbf{f}_0^T (\mathbf{F}^T \mathbf{F})^{-1} \mathbf{f}_0} = \hat{y}_0 \pm \delta \quad (8)$$

4. Application

The used data consist of a total of 240 input-output data pairs $(x_1, \cdots, x_4, y_r)$ which were taken from the Wolsung nuclear power plants. These data were acquired at 1501, 1944, and 3256 effective full power days (EFPDs). The acquired data was divided into two types of data at first; development data and test data. The test data set was determined first before the training data sets were selected. The 30 test data were selected among the acquired data. Also, the training data was selected using the SC scheme among the pool of development data after the test data was removed from all acquired data. The verification data consists of all the remaining data after removal of the test data. In this paper, the verification data was used to prevent overfitting and also to calculate the prediction interval. Actually the verification data is the development data.

Table 1 summaries the estimation results of the PT diametral creep by the FNN and Table 2 shows RMS errors according to operation time of which magnitudes do not depend on the operation time.

Figure 1 shows the predicted errors for the test data and their prediction intervals. The prediction intervals by the analytical uncertainty method are a little wider than those of the statistical uncertainty method.

5. Conclusions

In this paper, an FNN was developed to estimate the PT diametral creep in CANDU reactors. The developed FNN was applied to the Wolsung nuclear power plants in Korea. The FNNs were trained using a data set prepared for training and verification and were tested using another data set (test data) that differed from the training data and the verification data. The RMS errors of the PT diameter are 0.0576mm for the verification data and 0.0462mm for the test data, which indicates that the proposed FNN method is very accurate. Also, through the uncertainty analysis of the FNN model, estimates with a 95% confidence level were obtained for test data points by performing the analytic and statistical uncertainty analyses.

REFERENCES

[1] T. Takagi and M. Sugeno, "Fuzzy identification of systems and its applications to modeling and control," IEEE Trans. Systems, Man, Cybern., vol. SMC-1, pp. 116-132, 1985.

[2] R. Tibshirani, "A comparison of some error estimates for neural network models," Neural Computation, vol. 8, pp. 152-163, 1996.

Table 1. Performance of the FNN model

Data type	RMS error (mm)	Maximum error (mm)	Number of data points
Training data	0.0562	0.1437	150
Verification data	0.0576	0.1437	210
Test data	0.0462	0.0904	30

Table 2. RMS errors and average diameters according to operation time

Operation time (EFPD)	RMS error (mm)		Average diameter (mm)	
	Verification data	Test data	Verification data	Test data
1501.04	0.0590	0.0474	104.4369	104.3980
1943.71	0.0526	0.0460	104.6152	104.5655
3255.53	0.0599	0.0386	105.0689	104.9180

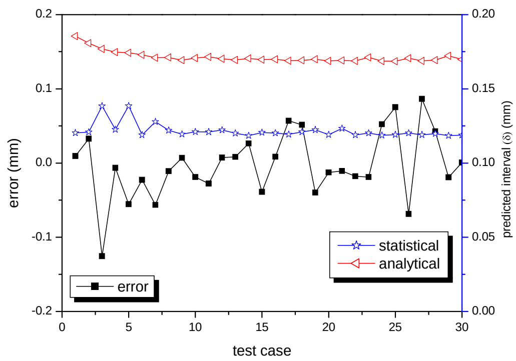

Fig. 1. Predicted errors and intervals by the statistical and analytical methods