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Thermal Hydraulic Design Parameters Study for Severe Accidents Using Neural Networks

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Abstract

To provide the information on severe accident progression is very important for advanced or new type of nuclear power plant (NPP) design. A parametric study, therefore, was performed to investigate the effect of thermal hydraulic design parameters on severe accident progression of pressurized water reactors (PWRs). Nine parameters, which are considered important in NPP design or severe accident progression, were selected among the various thermal hydraulic design parameters. The backpropagation neural network (BPN) was used to determine parameters, which might more strongly affect the severe accident progression, among nine parameters. For training, different input patterns were generated by the latin hypercube sampling (LHS) technique and then different target patterns that contain core uncovery time and vessel failure time were obtained for Young Gwang Nuclear (YGN) Units 3&4 using modular accident analysis program (MAAP) 3.0B code. Three different severe accident scenarios, such as two loss of coolant accidents (LOCAs) and station blackout (SBO), were considered in this analysis. Results indicated that design parameters related to refueling water storage tank (RWST), accumulator and steam generator (S/G) have more dominant effects on the progression of severe accidents investigated, compared to the other six parameters.

I. Introduction

The most important design objective of advanced or new type of nuclear power plants (NPPs) is to enhance plant safety, even if the design objectives of them emphasize plant reliability and availability as well as cost reduction in construction, operation and maintenance. There are various desirable approaches for plant safety and for further reduction of residual risk for nuclear power plant accidents, mainly for core melt accidents and for radioactive release to the environment. One approach among them is to increase safety design margins so that the primary system may have a longer response time and be less sensitive to plant abnormal initiative events, transients and severe accidents[1].

If so, it should be determined whether NPP has good safety design margins for severe accidents or not. It can be verified by core uncovery time and vessel failure time which are very important factors associated with severe accident management[2]. These two parameters could be affected by how to determine the thermal hydraulic design parameters. However, it is difficult to find which design parameters are the most effective and how much effective they are with a view to mitigating severe accidents. There have been few related works but MELCOR sensitivity studies which Juan J. Carbajo[3] performed for a low-pressure, short-term station blackout at the Peach Bottom plant in 1994.

The objectives of this study are 1) to investigate the effect of thermal hydraulic design parameters on severe accident progression, 2) to determine parameters which affect the severe accident progression more strongly and 3) to propose the PWR design guidelines for severe accident mitigation.

Nine parameters, which are considered important in NPP design or severe accident progression, were selected among the various thermal hydraulic design parameters. The parametric study for design parameters selected was accomplished using backpropagation neural network (BPN). For training, different input patterns were generated by the latin-hypercube sampling (LHS) technique[4] and then different target patterns that contain core-uncovery time and vessel failure time were obtained for Young Gwang Nuclear (YGN) Uints 3&4 using modular accident analysis program (MAAP) 3.0B code. Three different severe accident scenarios, such as two loss of coolant accidents (LOCAs) and station blackout (SBO), were considered in this analysis.

II. Backpropagation Neural Network as a Parameter Estimator

An artificial neural network (ANN), such as BPN, is composed of elements that are analogous to the elementary functions of biological neurons. ANNs have the capability to learn complex relationships from a set of associated input-output. The ANNs also have the characteristic of tolerance against code error, such as noise, owing to the massive internal structure of the network[5]. They have been applied to many areas involving NPPs, such as plant malfunction diagnosis[6], signal prediction and validation[7], vessel failure identification[8], etc.

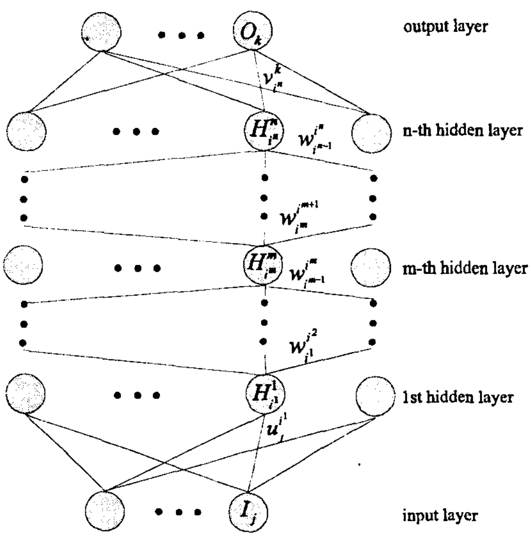

Fig. 1 Backpropagation Neural Network with various hidden layers

A schematic depiction of BPN is illustrated in Fig.1. A successfully trained neural network works essentially as a mapping function, which maps a set of input vectors $\mathbf{I}$ to a set of output vectors $\mathbf{O}$. The network mapping process is that when an input pattern, $\mathbf{I}$, is received by the neurons in the input layer, it first mapped as an output pattern, $\mathbf{H}_1$ of the first hidden layer, and then, $\mathbf{H}_1$ is mapped forward to the second hidden layer. Finally, an output pattern, $\mathbf{O}$, is formed. Mathematically, the mapping process is the following:

$$H^1_{i^1} = f(\sum_{j=1}^{a} u^{i^1}_j I_j + \theta_{i^1}) \qquad i^1 = 1,2,\ldots,l_1 \qquad (1)$$

$$H^m_{i^m} = f(\sum_{i^{m-1}=1}^{l_{m-1}} w^{i^m}_{i^{m-1}} H^{m-1}_{i^{m-1}} + \theta_{i^m}) \qquad i^m = 1,2,\ldots,l_m \qquad (2)$$

$$O_k = f(\sum_{i^n=1}^{l_n} v^k_{i^n} H^n_{i^n} + \beta_k) \qquad k = 1,2,\ldots,b \qquad (3)$$

where $f(x) = 1/(1+e^{-x/\delta})$ is the sigmoid transfer function and δ is the sigmoid slope. θ_{i^m} and β_k are the threshold values of the i^mth neuron in the mth hidden layer and the kth neuron in the output layers, respectively. a, b and l_{mi} is a number of neurons in input layer, output layer and the mth hidden layer, respectively.

This sigmoid function is used many times as the network is trained. To reduce the computing time, the non-linear function by Paul J. Werbos[9] is used the activation function in this paper. This function is as follows:

$$f(x) = \frac{1}{1 - x + 0.5 \times x^2}, \qquad x < 0 \tag{4}$$

$$f(x) = 1 - \frac{1}{1 + x + 0.5 \times x^2}, \qquad x > 0 \tag{5}$$

The partial derivative, $\partial O_k / \partial I_j$, is the rate of change in O_k with respect to a change in I_j. Therefore, $\partial O_k / \partial I_j$ can be used to measure the importance among the input variables, I_j, by ranking to the value of $\left|\partial O_k / \partial I_j\right|$. The partial derivative is expressed by applying chain rule as described in Eq. (6).

$$\frac{\partial O_k}{\partial I_j} = \frac{\partial O_k}{\partial H^n_{i^n}} \cdots \frac{\partial H^m_{i^m}}{\partial H^{m-1}_{i^{m-1}}} \cdots \frac{\partial H^1_{i^1}}{\partial I_j} = \frac{1}{\delta} O_k (1 - O_k) \sum_{i^n=1}^{l_n} F_n \tag{6}$$

where

$$F_1 = \frac{1}{\delta} H^1_{i^1} (1 - H^1_{i^1}) u^{i^1}_j \tag{7}$$

$$F_m = \frac{1}{\delta} H^m_{i^m} (1 - H^m_{i^m}) \sum_{i^{m-1}=1}^{l_{m-1}} w^{i^m}_{i^{m-1}} F_{m-1} \qquad m = 1,2,3,\ldots,n \tag{8}$$

Three layer BPN including one hidden layer is considered in this study, then $\partial O_k / \partial I_j$ is represented by Eq.(9).

$$\frac{\partial O_k}{\partial I_j} = \frac{\partial O_k}{\partial H^1_{i^1}} \frac{\partial H^1_{i^1}}{\partial I_j} = \frac{1}{\delta} O_k (1 - O_k) \sum_{i^1=1}^{l_1} \frac{1}{\delta} H^1_{i^1} (1 - H^1_{i^1}) u^{i^1}_j \tag{9}$$

The equation shows that the partial derivative depends not only on the network connection weighting factors, $u^{i^1}_j$ and $v^k_{i^1}$, which are the memory of the training, but also on the activation of neurons in both hidden layer and output layer.

III. Method

3.1 *Input and Output Preparation for Training*

Nine thermal hydraulic design parameters, which are important in NPP design or severe accident progression, are considered in the training interval as shown in Table 1. They are used as input variables of BPN. Two LOCAs and SBO, which are representative severe accidents, were selected. NPP design parameters can be determined various values by designer. Therefore, independence among nine parameters is assumed in the training interval and the optimized random sampling based on LHS technique is adopted to effectively generate different input patterns in the design space. Different target patterns that contain core uncovery time and vessel failure time were obtained for YGN 3&4 using MAAP 3.0B. Brief descriptions of three severe accidents and MAAP code running results for nominal value of YGN 3&4 are shown in Table 2.

Table 1 Input Parameters and Training Interval for YGN 3&4

Parameters	Nominal value	Training Interval
RCS Pressure (MPa)	15.51	15.20 - 15.82
RCS Avg. Temperature (°C)	311.55	308.43 - 317.78
RCS Mass Flow Rate (kg/s)	55.100e6	52.345e6 - 57.855e6
Vessel Volume (m^3)	102.090	100.048 - 107.195
Pressurizer Volume (m^3)	51.40	48.83 - 53.97
S/G Heat Transfer Area (m^2)	9,522.60	9,046.47 - 9,998.73
S/G Volume (m^3)	67,244.0	63,881.8 - 70,606.2
RWST Water Mass(kg)	1.780e6	1.691e6 - 1.869e6
Accumulator Volume (m^3)	68.130	64.724 - 71.537

Table 2 Description and MAAP code Running Results for Three Severe Accidents

Accident	Description	Core uncovery(sec)	Vessel failure(sec)
LOCA 1	small LOCA (0.00218 m2) in intermediate leg	17681.90	23709.97
LOCA 2	intermediate LOCA (0.02 m2) in cold leg	12529.42	18853.38
SBO	power not available, small seal LOCA	23089.85	47875.52

The overall procedure of this investigation is shown in Fig. 2. The starting point is the selection of input and output parameters. As shown in the figure, different input patterns are generated using LHS technique and different output patterns, which include core uncovery time and vessel failure time, are obtained from MAAP code. Data obtained from LHS and MAAP code running are divided into two sets for BPN training and simulation. The model of the plant behavior is obtained through BPN training. Finally parametric study for nine thermal hydraulic design parameters is established.

3.2 *Neural Modeling*

The training and simulation data listed in Table 3 are prepared from MAAP code. Optimized BPN structure with three layer is obtained by varying the number of neurons in hidden layer. The network is set up with 9 neurons in the input layer (8 neurons for SBO), 20 in hidden layer (18 for SBO), and 2 in the output layer. RWST volume is not considered in analysis of SBO accident because engineered safety feature is not available during SBO. As shown in the table, the network was successfully trained with sufficiently small system error listed in Table 3. Here, error assessment is performed with the simulation data which are not used in the BPN training. The RMS errors of the simulation are 0.031%, 0.047%, and 0.115% for LOCA 1, for LOCA 2, and for SBO, respectively. The small simulation error indicates that the training is successful and the well trained network can be used to analyze the effect of thermal hydraulic design parameters on severe accident progression.

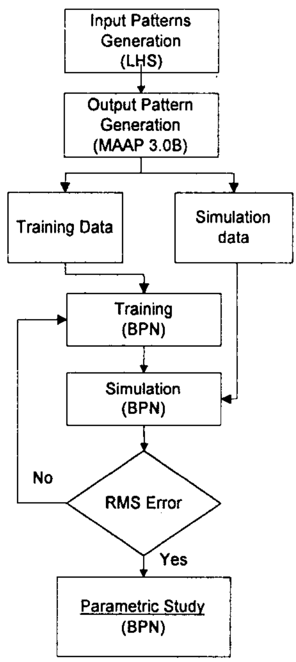

Fig. 2 Overall Procedure

Table 3. Data Classification and Results of Training and Simulation

Accident	No. of training data	No. of simulation data	System error (%)	RMS error (%)
LOCA 1	107	12	0.024	0.031
LOCA 2	100	11	0.01	0.047
SBO	106	12	0.020	0.115

IV. Results and Conclusions

Since the partial derivatives may be different by using different input patterns, the results of this paper were represented by pattern average of the absolute values of the partial derivatives over all input patterns.

Table 4. Results for Core Uncovery Time

Parameter	Importance ranking (avg. of $\left\|\partial O_k / \partial I_j\right\|$)		
	LOCA 1	LOCA 2	SBO
RCS pressure	6 (0.303)	8 (0.135)	7 (0.235)
RCS temperature	7 (0.303)	6 (0.213)	8 (0.228)
RCS mass flow rate	9 (0.275)	9 (0.108)	6 (0.272)
Vessel volume	8 (0.297)	4 (0.324)	5 (0.291)
PRZR volume	4 (0.369)	5 (0.234)	4 (0.293)
S/G Area	5 (0.318)	7 (0.207)	3 (0.393)
S/G volume	2 (0.503)	1 (0.472)	2 (0.418)
RWST volume	1 (0.628)	2 (0.402)	NaN
Accumulator volume	3 (0.476)	3 (0.329)	1 (0.568)

Table 5. Results for Vessel Failure Time

Parameter	Importance ranking (avg. of $\left\|\partial O_k / \partial I_j\right\|$)		
	LOCA 1	LOCA 2	SBO
RCS pressure	8 (0.004)	7 (0.004)	8 (0.004)
RCS temperature	7 (0.005)	8 (0.004)	7 (0.004)
RCS mass flow rate	9 (0.004)	9 (0.003)	6 (0.005)
Vessel volume	5 (0.220)	2 (0.334)	5 (0.203)
PRZR volume	4 (0.288)	6 (0.137)	4 (0.206)
S/G Area	3 (0.290)	4 (0.214)	1 (0.419)
S/G volume	6 (0.212)	1 (0.347)	3 (0.239)
RWST volume	1 (0.360)	5 (0.185)	NaN
Accumulator volume	2 (0.298)	3 (0.222)	2 (0.362)

Table 4 shows the ranking results for core uncovery time according to order of important of nine thermal hydraulic design parameters. As shown in the table, although the initiating accidents are different, the parameters, which have higher importance rank, is very similar. In addition, it shows that RWST, S/G and accumulator volume have more dominant effects, compared to other parameters. This is resulted the RCS water inventory increased due to the water injection of RWST and accumulator, and secondary heat removal capacity enhanced due to the increased S/G water volume during the accidents. PRZR volume is somewhat dominant, although the effectiveness on core uncovery time is not much than above three parameters mentioned. The average value of RWST volume for LOCA 1 is 0.628. It means that for the severe accident investigated, LOCA1, core uncovery time can be delayed till 62.8% of nominal core uncovery time by increasing 100% RWST volume.

Table 5 shows the ranking results for vessel failure time, similar to core uncovery time. The average value of partial derivative for RCS pressure, temperature and mass flow rate is nearly zero. It means that vessel failure can't be delayed by varying design values of these three parameters. Other parameters effect on vessel failure remarkably, compared to these three parameters. However, the effectiveness of dominant parameters on vessel failure is smaller than on core uncovery because the average partial derivative values of all dominant parameters for core uncovery are larger than the largest value of average partial derivative for vessel failure.

To investigate the effect of thermal hydraulic design parameters on severe accident progression of PWR, a parameteric study was performed using BPN. From this study, the following conclusions were drawn.

1) A parametric study model for BPN with various hidden layers was developed by applying chain rule.
2) RWST, accumulator, and S/G volume were most important parameters among nine parameters in severe accident progression investigated. Water capacity in NPP design should be increased to expand response time on severe accidents as much as possible.

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