ESTABLISHMENT OF NEURAL NETWORK MODEL FOR FLOW BLOCKAGE DETECTION SYSTEM IN A LIQUID METAL REACTOR

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1. Introduction

If a flow blockage in an assembly of a liquid metal reactor has occurred, then it will probably affect the integrity of the fuel assembly at the initiating stage and finally it could result in a cooling deficiency of the core. It is difficult to directly detect a flow blockage in an assembly, because it occurs in the fuel assembly. So, we have studied the change of the temperature in the upper plenum of a liquid metal reactor in order to develop a partial blockage detection system. No significant temperature increase in the upper plenum is expected at an early stage of the event from a review of previous studies. However, the characteristics of the temperature fluctuations in the upper plenum will be changed by the change of a temperature profile at the exit of the assembly. So, the characteristics of the temperature fluctuations in the upper plenum could provide information about a partial blockage of an assembly in liquid metal reactors.1,2)

For developing a detection algorithm for a partial blockage of an assembly in a reactor core, an experiment or analysis for a temperature fluctuation in the upper plenum of a whole core is required. The previous studies were only performed in small facilities due to a difficulty in performing such experiments. For investigating the characteristics of the temperature fluctuations in the upper plenum of a whole core, we have numerically analyzed the fluctuating temperature field in the upper plenum beyond the exit of the assemblies in a reactor core by using a computational fluid dynamics code. Since the LES (Large Eddy Simulation) turbulence model is known to be suitable for analyzing the time dependent variables of a flow, we adopted the Smagorinsky LES model in CFX-5.7 for analyzing the temperature fluctuation in the upper plenum.3-5)

After analyzing the temperature fluctuations in the upper plenum with various blockage conditions, we studied their statistical characteristics such as the root mean square, the standard deviation, the skewness and the kurtosis of the fluctuation data. Then, we established a detection algorithm based on the feed-forward neural network model with the changes of the root mean square, the standard deviation and the skewness of the fluctuation data as inputs and the size and the location of the blockage conditions as outputs. Although the results of the analyses had some limitations such as the accuracy of the sub-channel analyses and the LES meshes, we supposed that the neural network model with the fluctuation data in the upper plenum could be a possible alternative for detecting a flow blockage through learning and validating some blockage cases of an assembly.

2. Numerical Computation Model

We have been developing a pool-typed liquid metal reactor with a better performance and safety. Fig. 1 shows the simplified shape of the 1/6 symmetric breakeven core and the distributions of the flow velocity and temperature at the exit of the assemblies. Also, Fig. 1 shows the horizontal location of an assembly which is assumed to be partially blocked for analysing the temperature fluctuations in the upper plenum. We assumed that the assembly (3,2) was partially blocked as shown in Fig. 1. Fig. 2 shows a simplified cross-sectional shape of the upper plenum beyond the exit of the core and the calculation domain for analysing the temperature fluctuations in the upper plenum. In the upper plenum, there exist several internal structures such as the Upper Internal Structure (UIS), primary pump and the Intermediate Heat Exchanger (IHX). The numbers in the figure show the dimensions in cm unit.
The profile of the exit temperature and the exit velocity of each assembly in the core were used for the initial boundary conditions in the analysis domain. The distributions of the flow velocity and the temperature at the exit of the assemblies in the 1/6 symmetric breakeven core were obtained from the thermal hydraulic analysis code, SLTHEN, developed at KAERI. From the viewpoint of an engineering problem, the assembly-wised distribution of the exit velocity and the exit temperature seemed to be reasonable for the initial boundary conditions for analyzing the temperature fluctuation in the upper plenum. Otherwise, we assumed a homogeneous profile of the exit velocity and the exit temperature at the outlet of each assembly, respectively, except for the assumed partially blocked assembly in the core.

In addition, the profile of the exit temperature of the partially blocked assembly was required as an initial boundary condition for evaluating a change of the characteristics of the temperature fluctuation due to a partial flow blockage in an assembly. We performed the sub-channel analysis of a partially blocked assembly for calculating the profile of the exit temperature at the outlet of the assembly, and it was used for the initial boundary conditions. The sub-channel analysis was performed by using a sub-channel analysis code, MATRA-LMR, which was developed at KAERI. The sub-channel analysis code had some limitations in that it could not calculate the outlet temperature of an assembly exactly because it was not based on a full 3-D model. However, we supposed that its results would be suitable for studying the generic characteristics of the outlet temperature distribution of an assembly.

We analysed the various blockage conditions for calculating the temperature fluctuation in the upper plenum due to a partial blockage in an assembly. Fig. 3 shows the assumed blockage conditions in the assembly in this paper. We performed analyses of the temperature fluctuation according to a change of the size of the partial blockage with 1.1%, 4.4%, 10% and 17.8% as well as a change of the location of the partial blockage with the center, middle and edge in the assembly. The number of blocked channels in each blockage size was 6 channels, 24 channels, 54 channels and 96 channels from among a total of 540 channels in an assembly as shown Fig. 3 (a). The center, middle and edge location means that the center of the blockage channels was located at the center, middle and edge in an assembly as shown in Fig. 3 (a). Fig. 3 (b) shows the location of the assumed blockage conditions along the axial direction.

In addition, we evaluated the characteristics of the temperature fluctuation according to a change of the flow rate due to a partial blockage in an assembly. We analysed each blockage condition with an unchanged flow rate and a reduced flow rate in the assembly, respectively. We assumed that the flow rate was nearly maintained or it was reduced according to the shape and the location of a blockage in an assembly.
We will call the cases with a reduced flow rate as the non-isovelocity cases and those without a reduction of the flow rate as the isovelocity cases from now on. We performed sub-channel analyses with two flow conditions (isovelocity and non-isovelocity) for each blockage condition. The reduced flow rate of each blockage condition could be calculated from the friction analysis of the area of the blockage channels in the assembly. Table 1 shows all the cases of the assumed partial blockage conditions in this study and the initial boundary conditions (temperature and flow) used in the fluctuation analysis for each blockage condition. In the table, the case ID column means the various blockage cases analysed in this paper.

For representing the distribution of the exit temperature of a partially blocked assembly, we divided the exit of the partially blocked assembly into 2 initial boundary regions Sizes of the boundary region and the temperatures of boundary conditions were obtained from the analogy of the exit temperature profile calculated by the sub-channel analyses according to the blockage conditions. We assigned the averaged temperatures for the 2 boundary regions for each blockage condition and we determined the size and the averaged temperature of each region from the results of the sub-channel analyses by an engineering judgment. In table 1, temp1 in each blockage case was assigned to the blocked region and the temp2 was assigned to the non-blocked region. This could reduce the numerical accuracy, but we thought that the effects of the heterogeneous profiles at the exit of the assembly were sufficiently considered by the divided regions of the assembly for analysing the temperature fluctuation in the 1/6 upper plenum.

For comparing the analysis results of each case, we used the monitoring point which could represent the temperature at every time step at a point in the numerical grid. Fig. 4 shows the temperature fluctuations of each case at a selected monitoring point during 4 sec. We selected the monitoring point at 10cm along the z-direction at the center of the blocked assembly in a planar direction beyond the exit of the assembly in the upper plenum.

3. Statistical Analysis

For developing a partial blockage detection algorithm, we investigated some statistical characteristics of the temperature fluctuation data in the upper plenum according to the blockage cases. For clearly representing the statistical characteristics of the temperature fluctuation of each case, we introduced the root mean square, the standard deviation, the skewness and the kurtosis of the temperature fluctuation data. The skewness means a measure of the asymmetry of the data around the sample mean and the
kurtosis is a measure of how much an outlier is prone to a distribution. Fig. 5 shows the statistical analysis results of the temperature fluctuations data during the later 2 sec at the monitoring point which was located at 10cm along the axial direction at the center of the blocked assembly.

Figure 4 Temperature fluctuation data at the monitoring point

Figure 5 Statistical characteristics of temperature fluctuations
We found that the changes of the root mean square of the temperature fluctuation data had relationships with the size and flow rate of each blockage condition as well as the changes of its skewness and standard deviation which were affected by the size and the location of the flow blockage. However, the kurtosis was nearly independent of the blockage conditions. The statistical parameters of the non-isovelocity cases abruptly changed and showed complex relationships between the analysis cases with the blockage conditions and the normal condition. They originated from a change of the exit temperature profile and a change of the flow rate at the exit of the assembly.

4. Neural Network Model

From the analogy in Section 3, we found the possibility of detecting a partial flow blockage in an assembly from the relationships between the partial blockage conditions and the statistical parameters. However, the relationships between the statistical parameters of the fluctuation data in the blockage conditions and those of the normal assembly were not clearly shown, because the temperature fluctuated because of a mixed effect of the exit temperature profile and the neighboring assemblies in the core. So, we introduced a neural network model which could identify the nonlinear relationships between various parameters. We designed the two hidden-layered neural network model of a learning algorithm with the scaled conjugate gradient. The inputs of the neural model were the change of the root mean square, the standard deviation and the skewness between the variously assumed blockage conditions and the normal condition. The outputs of the model were the location (center, middle, edge) and the size of the various blockage conditions. The two hidden layers consisted of 7 neurons and one bias neuron in each layer and the hyperbolic tangent function was used as an activation function of each neuron. The neural models with the isovelocity cases and the non-isovelocity cases were learned twice because the characteristics of the two cases showed a large difference. Finally, the neural model learned the relationships between the inputs and the outputs with various blockage conditions. Fig. 7 shows the results of learning. In the figure, the cases mean the various blockage conditions as shown in the case ID column in Table 1. As shown in the figure, the model had a good capability to retrieve the location and the size of the blockage conditions according to the analyses results.

5. Conclusion

We have developed a neural network model for detecting a partial flow blockage in an assembly of a liquid metal reactor through numerical analyses of the temperature fluctuation in the upper plenum of a liquid metal reactor. The developed neural network model for a partial flow blockage was based on the changes of the statistical characteristics of the temperature fluctuation data. For analyzing the temperature fluctuation in the upper plenum, we performed numerical analyses with the LES turbulence model in the CFX code and evaluated its statistical parameters. We developed a flow blockage detection algorithm based on the neural network model with the changes of the statistical parameters of the temperature fluctuation data according to the partial flow blockage conditions in the assembly. Although
the results of the analyses had some limitations such as the accuracy of the sub-channel analyses and the LES meshes, we suggested that the developed neural network model with the fluctuation data in the upper plenum would be a possible alternative for detecting a flow blockage. After some experiments or more detailed analyses, we will improve the detection algorithm for a partial flow blockage of an assembly.

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8. References