ESTABLISHMENT OF A NEURAL NETWORK MODEL FOR DETECTING A PARTIAL FLOW BLOCKAGE IN AN ASSEMBLY OF A LIQUID METAL REACTOR

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Received May 12, 2006
Accepted for Publication July 22, 2006

A partial flow blockage in an assembly of a liquid metal reactor could result in a cooling deficiency of the core. To develop a partial blockage detection system, we have studied the changes of the temperature fluctuation characteristics in the upper plenum according to changes of the flow blockage conditions in an assembly. We analyzed the temperature fluctuation in the upper plenum with the Large Eddy Simulation (LES) turbulence model in the CFX code and evaluated its statistical parameters. Based on the results of the statistical analyses, we developed a neural network model for detecting a partial flow blockage in an assembly. The neural network model can retrieve the size and the location of a flow blockage in an assembly from a change of the root mean square, the standard deviation, and the skewness in the temperature fluctuation data. The neural network model was found to be a possible alternative by which to identify a flow blockage in an assembly of a liquid metal reactor through learning and validating various flow blockage conditions.

KEYWORDS : Flow Blockage Detection System, Neural Network, Temperature Fluctuation, Statistical Parameters, Liquid Metal Reactor

1. INTRODUCTION

If a flow blockage in an assembly of a liquid metal reactor occurs, then it will probably affect the integrity of the fuel assembly at the initiating stage and could eventually result in a cooling deficiency of the core. It is difficult to directly detect a flow blockage in an assembly, because a flow blockage occurs in the fuel assembly. Therefore, in this work, we have studied the temperature fluctuations in the upper plenum of a liquid metal reactor in order to develop a partial blockage detection system. From a review of previous studies, no significant temperature increase in the upper plenum is expected at an early stage of an event. However, the characteristics of temperature fluctuations in the upper plenum will be changed by a change of the temperature profile at the exit of the assembly. Hence, the characteristics of the temperature fluctuations in the upper plenum could provide information about a partial blockage of an assembly in a liquid metal reactor [1-3].

To develop a detection algorithm for a partial blockage in a reactor core assembly, an experiment or analysis for temperature fluctuation in the upper plenum of an entire core is required. Previous studies of this subject have been performed only in small facilities, due to the difficulty in performing such experiments. To investigate the characteristics of the temperature fluctuations in the upper plenum of an entire 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 Large Eddy Simulation (LES) turbulence model is known to be suitable for analyzing the time dependent variables of a flow, we adopted the Smagorinsky LES model in the commercial flow solver CFX-5.7 to analyze the temperature fluctuation in the upper plenum [3-4]. Particularly, regarding the computational work involved , the LES model is known to be more suitable than the Direct Numerical Simulation DNS model for handling high Reynolds number cases. Since the Reynolds number in the upper plenum is about 10^7, we used the LES turbulence model in the CFX-5.7 code to analyze the temperature fluctuations in the upper plenum caused by a partial flow blockage in an assembly.

To analyze the temperature fluctuation in the upper plenum, the profiles of the exit temperature and the exit velocity of the assemblies in an entire core are required to establish the initial boundary conditions. These conditions can be obtained from the results of a thermal hydraulic analysis of an entire core and a sub-channel analysis of a partially blocked assembly.

After analyzing the temperature fluctuations in the upper plenum under 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 developed 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 number of LES meshes, we propose that the developed 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. ANALYSIS MODEL

2.1 Calculation Domain

We have been developing a pool-type liquid metal reactor, the Korea Advanced Liquid Metal Reactor (KALIMER), to achieve better performance and safety. Figure 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. In addition, Figure 1 shows the horizontal location of an assembly which is assumed to be partially blocked for analyzing the temperature fluctuations in the upper plenum. We assumed that the assembly (3, 2) was partially blocked, as shown in Fig. 1. Figure 2 shows, in centimeters, a simplified cross-sectional shape of the KALIMER upper plenum beyond the exit of the core and the calculation domain for analyzing the temperature fluctuations in the upper plenum. In KALIMER, there exist several internal structures, such as the Upper Internal Structure (UIS), primary pump, and the Intermediate Heat Exchanger (IHX). The height of the calculation domain is 1 m and its equivalent radius is 1.82 m. By considering similar analyses with sufficient accuracy, the calculation domain was selected as shown in Fig. 2 [4-5].

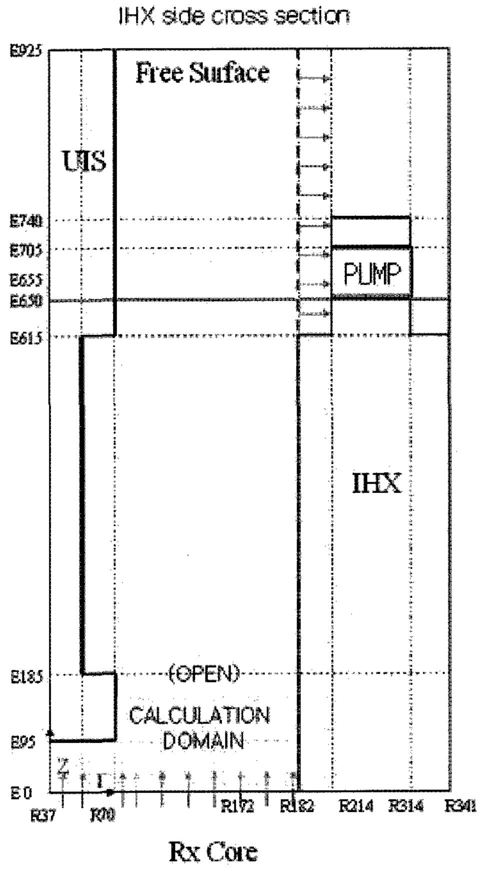

Fig. 2. Simplified Shape of Upper Plenum

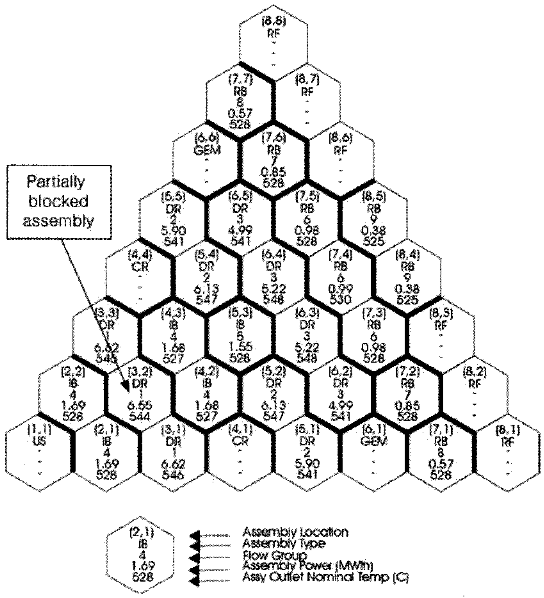

Fig. 1. Symmetric (1/6) Breakeven Core

To analyze the temperature fluctuation in the upper plenum, approximately 50,000 unstructured tetrahedral meshes and 4000 prism meshes were used. Near the wall, we used pyramid meshes 0.01 m in size. The time step was 0.002 seconds for a 4 sec transient calculation. Limited by computer resources, our numerical grids, time step, and calculation domain used in the present study for the LES might not be sufficient to achieve the exact analyses. However, we assumed that they would be sufficient for a feasibility study for designing a flow blockage detection system.

The rotational symmetry condition was used for the boundary conditions at the symmetry plane (1/6 divided wall) along the axial direction. The adiabatic and the no slip conditions were used for the wall boundary conditions in contact with the UIS and IHX. We used the open condition in the CFX at the upper boundary condition [6].

2.2 Initial Boundary Conditions

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 of SLTHEN developed at KAERI [7]. From the viewpoint of an engineering problem, the assembly-wise distribution of the exit velocity and the exit temperature seemed to be reasonable initial boundary conditions by which to analyze 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 any change of the temperature fluctuation characteristics due to a partial flow blockage in an assembly. We performed some sub-channel analyses of a partially blocked assembly to calculate the profile of the exit temperature at the outlet of the assembly, and the profile was used for the initial boundary conditions. The sub-channel analysis was performed by using a sub-channel analysis code of MATRA-LMR, which was developed at KAERI [7-9]. The sub-channel analysis code has some limitations in that it cannot calculate the outlet temperature of an assembly exactly, because it is not based on the full 3-D model. However, we supposed that its results would be suitable for studying the characteristics of the outlet temperature distribution of an assembly.

2.3 Assumption of the Blockage Conditions

We analyzed various blockage conditions for calculating a temperature fluctuation in the upper plenum due to a partial blockage in an assembly. Figure 3 shows the assumed blockage conditions in the assembly for this study. We performed analyses of the temperature fluctuation according to size changes of the partial blockage, 1.1%, 4.4%, 10% and 17.8%, as well as location changes of the partial blockage, center, middle, and edge, in the assembly. Of 540 channels in an assembly, the number of blocked channels for each blockage size was 6 channels, 24 channels, 54 channels, and 96 channels respectively. The center, middle, and edge locations indicate that the center of the blockage channels was located at the center, middle, or edge in an assembly, as shown in Fig. 3. Furthermore, we analyzed the profile of the exit temperature according to changes of the channel height where a blockage occurred. The exit profile of the temperature was dependent on the distance from the blockage location in the axial direction to the exit of the assembly due to the internal thermo-hydraulic dynamics, such as an internal cross flow, conduction, and convection in the assembly. Therefore, we analyzed two representative heights of 2/4 and 1/4 along the axial direction. The height of most blockage conditions was assumed to be half (2/4) of the assembly height, while the height of the remaining blockages were assumed to be 1/4 of the assembly height. However, we did not analyze the 3/4 height, because it seemed to show a clearer difference in the profile of the exit temperature.

In addition, we evaluated the characteristics of a temperature fluctuation according to a change of the flow rate due to a partial blockage in an assembly. We analyzed each blockage condition with an unchanged flow rate and a reduced flow rate in an assembly, respectively. We refer to those cases with a reduced flow rate as non-isovelocity cases and those without a reduction of the flow rate as isovelocity cases.

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 a friction analysis of the area of the blockage channels in an assembly. The reduced ratio of the flow rate in an assembly was calculated as 4% under the 1.1% blockage conditions, 6% under the 4.4% blockage conditions, 11% under the 10% blockage conditions, and 18% under the 17.8% blockage conditions. We have not determined an exact value for flow reduction in the case of a partial blockage, as yet. Hence, we considered isovelocity cases where the flow rate was not reduced and non-isovelocity cases where the flow rate was reduced according to a change of the friction ratio due to a blockage size. Table 1 shows all the cases of the assumed partial

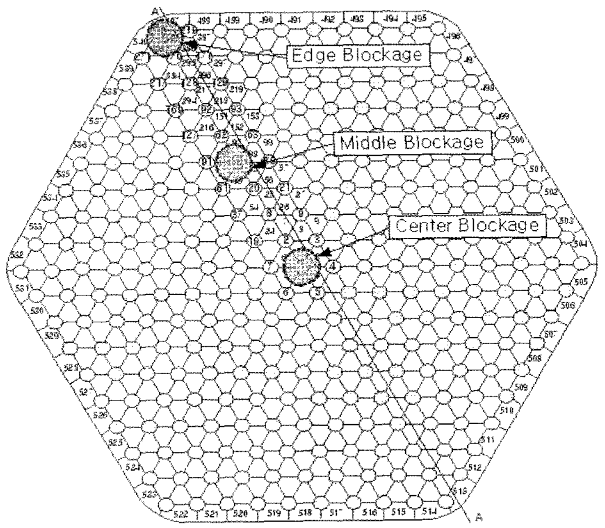

Fig. 3. Blockage Locations of Assembly

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 refers to the various blockage cases analyzed in this paper.

Figure 4 shows the representative exit temperature profile of each partially blocked assembly from the sub-channel analysis along the diagonal direction (A-A') in Fig. 3. The exit profile refers to the profile of the exit temperature at the outlet of the partially blocked assembly.

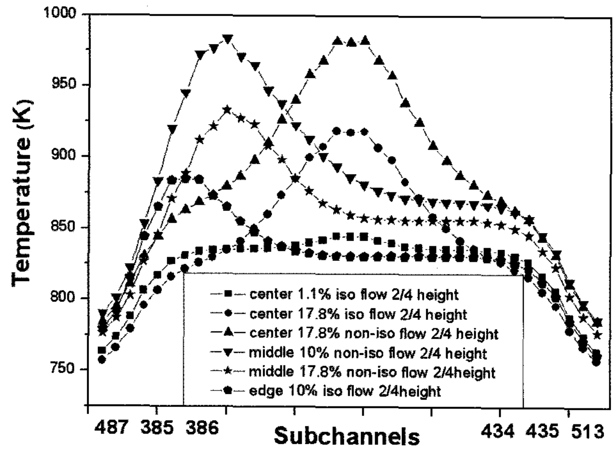

Fig. 4. Representative Results of Sub-channel Analyses

As previously mentioned, we assumed 3 blockage locations (center, middle, and edge) in the assembly. The exit profiles of the temperature of the partially blocked assembly showed different shapes from those of the assumed blockage channels, because the exit temperature was affected by not only the inner blockage channels but also the thermal-hydraulic dynamics and the distance from the blocked area to the exit of the assembly. To represent 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 an analogy of the exit temperature profile calculated by sub-channel analyses according to the blockage conditions. We assigned the averaged temperatures to 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, templ in each blockage case was assigned to the blocked region, and temp2 was assigned to the non-blocked region. This method may reduce 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 analyzing the temperature fluctuation in the 1/6 upper plenum.

Table 1. Assumed Blockage Conditions

Size (%)	Loc. (c,m,e)	height	Vel. (m/sec)	templ1 (K)	templ2 (K)	Case ID
0%	N/A	N/A	6.55	817	817	0
1.1%	Center	2/4	6.55	844	833	1
1.1%	Middle	2/4	6.55	844	833	2
1.1%	Edge	2/4	6.55	833	833	3
4.4%	Center	2/4	6.55	868	833	4
4.4%	Middle	2/4	6.55	853	833	5
4.4%	Edge	2/4	6.55	898	833	6
10%	Center	2/4	6.55	898	833	7
10%	Middle	2/4	6.55	883	833	8
10%	Edge	2/4	6.55	918	833	9
17.8%	Center	2/4	6.55	918	833	10
17.8%	Middle	2/4	6.55	918	833	11
1.1%	Middle	1/4	6.55	836	836	12
4.4%	Middle	1/4	6.55	841	836	13
10%	Middle	1/4	6.55	844	836	14
17.8%	Middle	1/4	6.55	848	836	15
1.1%	Center	2/4	6.29	853	843	16
1.1%	Middle	2/4	6.29	853	843	17
4.4%	Center	2/4	6.16	882	848	18
4.4%	Middle	2/4	6.16	882	848	19
10%	Center	2/4	5.83	928	856	20
10%	Middle	2/4	5.83	928	856	21
17.8%	Center	2/4	5.37	973	873	22
17.8%	Middle	2/4	5.37	973	873	23
1.1%	Middle	1/4	6.23	845	845	24
4.4%	Middle	1/4	6.16	854	849	25
10%	Middle	1/4	5.83	868	860	26
17.8%	Middle	1/4	5.37	893	878	27

We used 3.7%, with the auto-computed length scale, for the value of the turbulence intensity at the initial boundary condition for the LES analysis at the inlet boundary condition, because it is known to be sufficient for a nominal turbulence and it is recommended as a general estimate in the absence of experiment data by the CFX code.

3. RESULTS OF THE TEMPERATURE FLUCTUATION ANALYSIS

3.1 Analysis Results

To compare the analysis results of each case, we used a monitoring point that could represent the temperature at every time step at a point in the numerical grid. Figure 5 shows the representative temperature fluctuations of each case at a selected monitoring point during 4 sec interval. We selected a monitoring point at 10 cm 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. In the isovelocity cases, we did not find an abrupt change of the temperature fluctuation characteristics in the upper plenum even though the temperature profiles at the exit of the blocked assembly were different according to the blockage conditions. However, an abrupt change of the temperature fluctuation characteristics appeared in the non-isovelocity cases.

From the analyses of the results, we found the characteristics of the temperature fluctuation caused by a partial blockage in an assembly. The flow rate (exit velocity) in a partially blocked assembly was one of the major parameters affecting the temperature fluctuations. In addition, the differences of the temperature fluctuation characteristics in the non-isovelocity cases were more apparent than those in the isovelocity cases; these differences were caused by the increased exit temperatures in all the regions of the blocked assembly as well as by the effects of the turbulence mixing, which were maximized by a change of the velocity. Figure 5 shows some results of the fluctuation analysis at the selected monitoring point in the upper plenum, and "normal" in the figure means that the assembly was not blocked.

3.2 Statistical Analysis

To develop a partial blockage detection algorithm, we studied some statistical characteristics of the temperature fluctuation data in the upper plenum taken from the blockage cases. To clearly represent the statistical characteristics of the temperature fluctuation of each case, we introduced the root mean square, the standard deviation, the skewness,

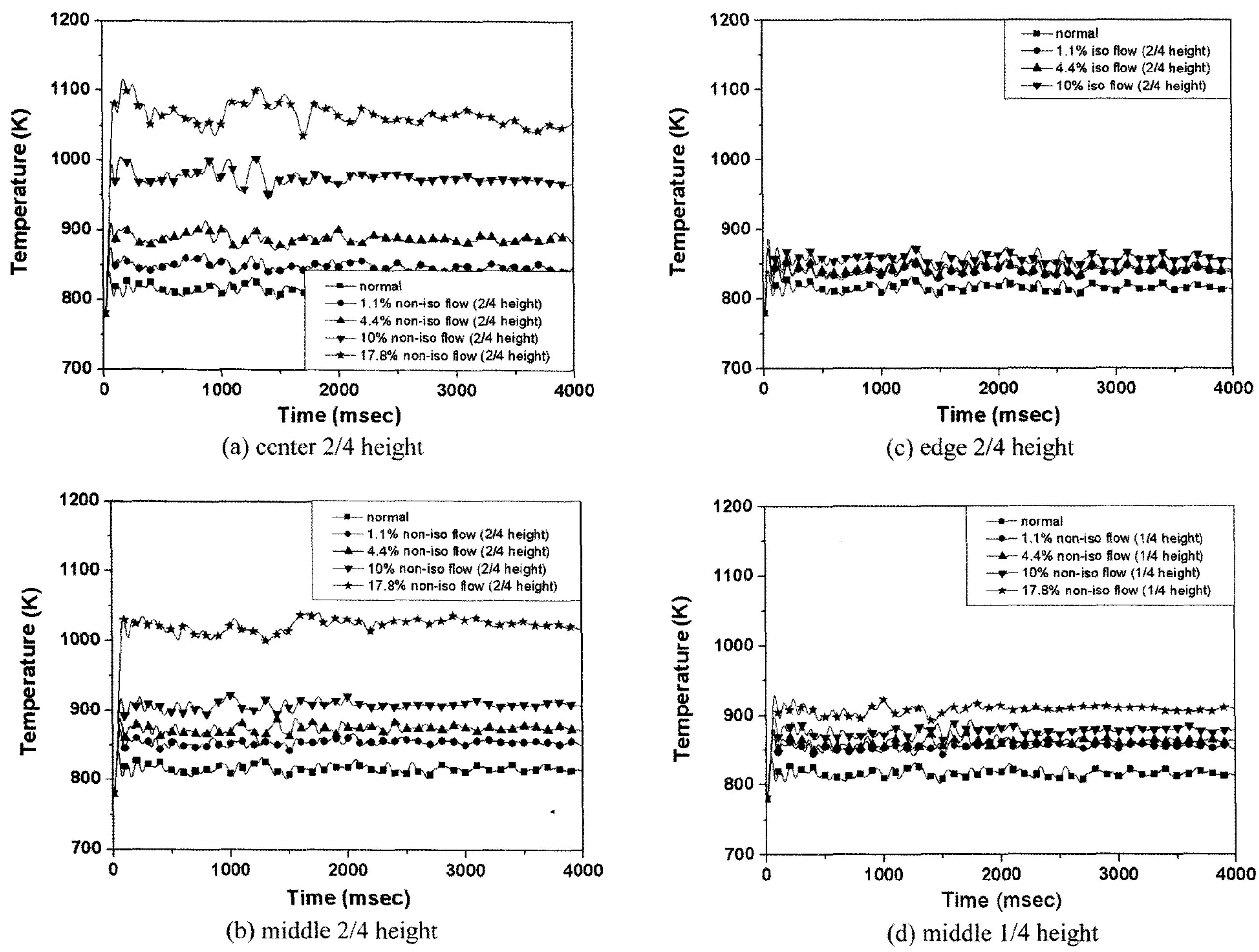

Fig. 5. Representative Temperature Fluctuation Data

and the kurtosis of the temperature fluctuation data. To evaluate the characteristics of the fluctuation data, we analyzed the fluctuation data during the second half (2 sec) of the total 4 sec transient by considering the exit velocity of the sodium in the core, because we assumed that the initial temperature field in the upper plenum was constant for the LES analyses.

By evaluating the statistical parameters of the fluctuation data, we investigated the relationships between the size and the location of each blockage condition and the changes of the root mean square, standard deviation, skewness, and the kurtosis of the temperature fluctuation data. The root mean square, the standard deviation, and the skewness were found to have certain relationships with the blockage conditions. However, the kurtosis was nearly independent of the blockage conditions. The statistical parameters of the non-isovelocity cases abruptly changed and showed complex nonlinear relationships between the analysis cases with the blockage conditions and the normal condition. These relationships originated from an abrupt change of the exit temperature profile and from a change of the flow rate at the exit of the assembly. Additionally, we found that the temperature fluctuation was originally slightly skewed in the upper plenum under the normal condition and that the skewness in the upper plenum had a weak relationship with the location of a blockage due to the effects of the neighboring assemblies in the isovelocity cases. This result was somewhat different from those of the previous studies. Some previous studies have easily found a change of the skewness of the temperature fluctuations beyond the exit of an assembly without considering the effects of the neighboring assemblies in a whole core, because most of the previous studies that found a change of the skewness were based on an experiment or an analysis for a single assembly or a small-scaled facility [1-2,10].

To establish the response time of the measuring device, we performed a fast Fourier transform (FFT) analysis using the temperature fluctuation data. We found that the maximum frequency of the temperature fluctuation was about 15 Hz and that it was independent of the position of the monitoring points and the blocked conditions of the isovelocity and non-isovelocity cases. Accordingly, we determined that the response time should be shorter than 13 msec. The response time was calculated from the inverse of the maximum frequency divided by 5, which meant a ratio for a sufficient resolution to represent the frequency of the signal characteristics in general. We think that a fast-response thermocouple would satisfy the above mentioned criteria [11].

4. NEURAL NETWORK MODEL FOR DETECTING A FLOW BLOCKAGE

4.1 Developed 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. We did not find a clearly linear relationship between the statistical parameters of the fluctuation data in the blockage conditions and those of the normal condition. Therefore, we introduced a neural network model that could identify the nonlinear relationships between various parameters. We designed a two hidden-layered neural network model of a learning algorithm with a scaled conjugate gradient [12]. The inputs of the neural model were a 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 and edge) and the sizes of the various blockage conditions. The two hidden layers consisted of 7 neurons and one bias neuron in each layer. The hyperbolic tangent function was used as an activation function for each neuron. The neural models using the isovelocity cases and the non-isovelocity cases were learned twice, because the characteristics of the two cases showed a large difference. Finally,

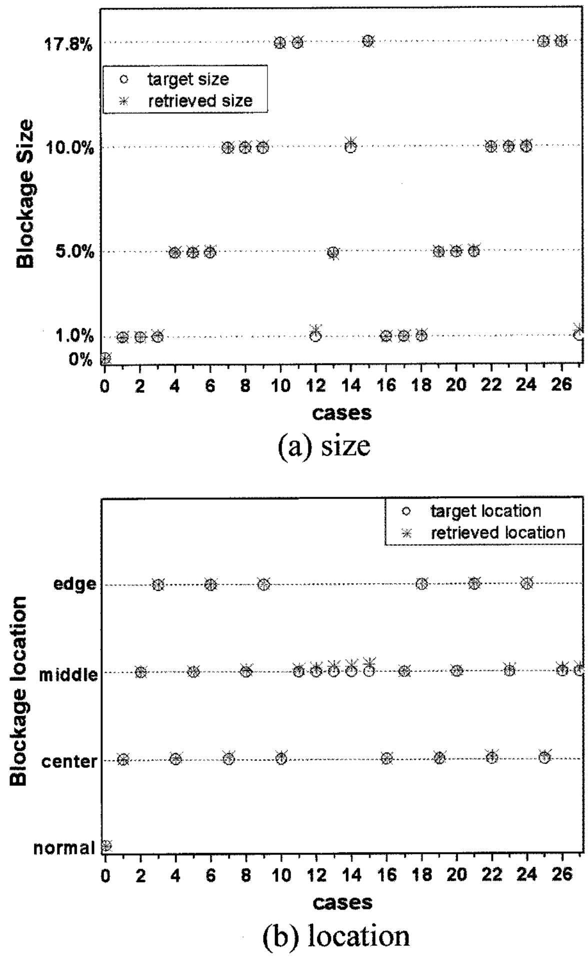

Fig. 6. Results of Learning

the neural model learned the relationships between the inputs and the outputs corresponding to various blockage conditions. Figure 6 shows the results of learning for the neural network model. In the figure, the cases refer to the various blockage conditions, corresponding to the case ID column of Table 1. As shown in the figure, the model had a good capability to retrieve the location and the size of the blockage conditions.

4.2 Validation of Neural Model

To validate the developed neural model, we analyzed new blockage conditions, as shown in Table 2. As shown in the table, we analyzed different middle blockage conditions with a 7.2% (36 channels) blockage and a 13.3% blockage (72 channels) at 2/4 and 1/4 heights, respectively, which had not been used in the earlier learning phase of the developed neural model. Figure 7 shows the results of the sub-channel analyses, and Fig. 8 shows the temperature fluctuation data.

The locations and the sizes of blockage conditions for the validation were retrieved by the neural model. Figure 9 shows the target value and the retrieved values by the

Table 2. Blockage Conditions for Validation

Size (%)	Loc. (c,m,e)	height	Vel. (m/sec)	templ1 (K)	templ2 (K)	Case ID
7.8%	Center	2/4	6.55	883	833	1
13.3%	Middle	2/4	6.55	908	833	2
13.3%	Middle	1/4	6.55	846	836	3
7.8%	edge	2/4	6.55	875	833	4
7.8%	Middle	2/4	5.99	904	853	5
7.8%	Middle	1/4	5.99	861	855	6
13.3%	Center	2/4	5.57	951	860	7

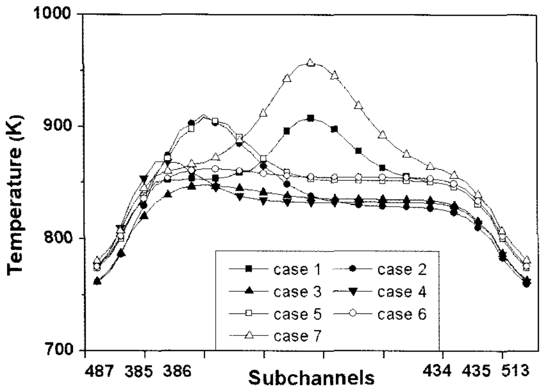

Fig. 7. Results of Sub-channel Analyses for Validation

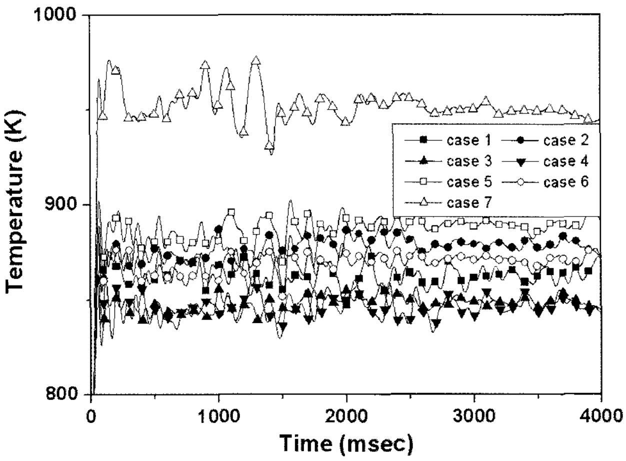

Fig. 8. Temperature Fluctuation Data for Validation

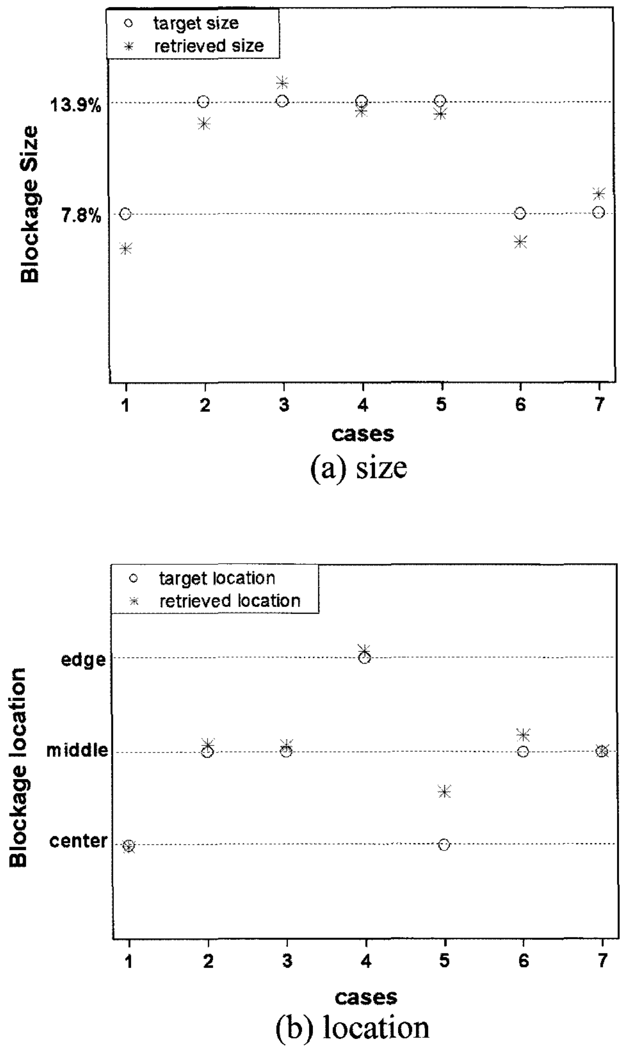

Fig. 9. Results of Validation

model. The results showed a good agreement with all the validation cases. Thus, the developed neural network model has been proven a good alternative for detecting a partial flow blockage in an assembly of a liquid metal reactor.

5. CONCLUSIONS

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 a 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. To analyze the temperature fluctuation in the upper plenum, we performed numerical analyses using 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 using changes of the statistical parameters of the temperature fluctuation data corresponding to the partial flow blockage conditions in an assembly. Although the results of the analyses had some limitations, such as the accuracy of the sub-channel analyses and the LES meshes, we propose that the developed neural network model using the fluctuation data from the upper plenum could be an alternative for detecting a flow blockage. Further experimental research will focus on improving the detection algorithm for a partial flow blockage of an assembly.

ACKNOWLEDGEMENTS

This study has been carried out under the Nuclear R&D Program supported by the Ministry of Science and Technology, Republic of Korea.

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