Development of Objective Flow Regime Identification Method using Self-Organizing Neural Network

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1. Introduction

Two-phase flow shows various flow patterns according to the amount of the void and its relative velocity to the liquid flow. This variation directly affect the interfacial transfer which is the key factor for the design or analysis of the phase change systems. Especially the safety analysis of the nuclear power plant has been performed based on the numerical code furnished with the proper constitutive relations depending highly upon the flow regimes. Heavy efforts have been focused to identify the flow regime and at this moment we stand on relative very stable engineering background compare to the other research field. However, the issues related to objectiveness and transient flow regime are still open to study. Lee et al.[1] and Ishii[2]developed the method for the objective and instantaneous flow regime identification based on the neural network and new index of probability distribution of the flow regime which allows just one second observation for the flow regime identification. In the present paper, we developed the self-organized neural network for more objective approach to this problem.

Kohonen's self-organizing map (SOM) has been used for clustering, visualization, and abstraction. The SOM is trained through unsupervised competitive learning using a 'winner takes it all' policy. Therefore, its unsupervised training character delete the possible interference of the regime developer to the neural network training. After developing the computer code, we evaluate the performance of the code with the vertically upward two-phase flow in the pipes of 25.4 and 50.4 cmm I.D. Also, the sensitivity of the number of the clusters to the flow regime identification was made.

2. Methods and Results

2.1 Kohonen's Self-Organizing Map (SOM)

The basic concept behind the SOM is preservation of topology, in other word the relation among data. A SOM is a one active layer neural network consisting of a multidimensional array of neurons (usually two dimensional). Each neuron in the grid is also an output neuron. The neurons are connected only with their closed neighbors in the array according to a prescribed topological scheme.

All neurons in the active layer obtain the same multidimensional input, and at the same time. That winner has its weights updated using the current learning rate, while the learning rate for the neighbors is scaled down proportional to the distance to the winner. Consequently, the knowledge of that pattern will be localized in the area of the winner. Any number of inputs may be used as long as the number of inputs is greater than the dimensionality of grid space. Each training cycle involves one pass through the data and the training is stopped when changes to the network's weight become insignificant. The present code has two stages: the preprocessing of the data and the cognitive reasoning. In the preprocessing, we change the impedance signals in the way of the probability distribution function, which empower the neural network to distinguish different flow patterns. The preprocessed data are directly input to the input layers of the neural net and SOM classify the data to the certain cluster.

2.2 Flow Regime Map in 25.4mm ID pipe flow

Figure 1 showed the flow regime map determined by the present SOM network. As shown in Figure 1(a), the bubbly-to-slug transition is well identified by the three clusters SOM. However, a wide range of slug flow were identified as the churn flow. It means that the topological distance of the unstable slug and churn flow is shorter than stable slug flow. Rather, the stable slug is more close to the bubbly flow regime. However, the four-cluster-SOM makes some difference as shown in Figure 1(b). It is interesting that this increase of cluster number just divides the bubbly flow regime into two: discrete bubble and cap bubble. It can be identified by comparing with the result of the supervised flow regime identifier as well as the character of raw signals. However, still large area of the slug bubble is occupied by the churn flow regime. Therefore, four clusters is sensitive in bubbly flow regime but in sensitive in churn flow regime. The five clusters, Figure 1(c), finally produce almost same level of identification as the supervised method. The bubbly flow regime of Mishima-Ishii is classified as two regimes: dispersed bubbly flow regime and cap bubbly flow regime. Also, the slug flow regime is divided into two: stable slug flow regime and unstable slug flow regime as noted by Whale et al. Therefore, the slug-to-churn transition is very close to Mishima-Ishii criteria[3].

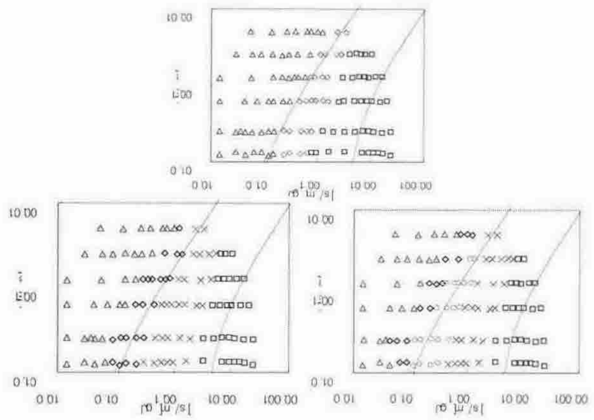

Figure 1. Flow regime identification with Slef-organization neural network and comparison with the works of Mishima-Ishii(1985) in 25.4mm ID pipe (a) three clusrters (b) four clusters (c) five clusters

2.3 Flow Regime Map in 50.8mm ID pipe flow

Figure 2 illustrated the flow regime map determined by the present SOM network. As shown in Figure 2(a), the bubbly-to-slug transition is well identified by the three clusters KSOM. However, a wide range of slug flow was identified as the churn flow. It means that the topological distance of the unstable slug and churn flow is shorter than stable slug flow. Rather, the stable slug is more close to the bubbly flow regime. However, the four-cluster-KSOM makes some difference as shown in Figure 2(b). It is interesting that this increase of cluster number just divides the bubbly flow regime into two: discrete bubble and cap bubble. It can be identified by comparing with the result of the supervised flow regime identifier as well as the character of raw signals. However, still large area of the slug bubble is occupied by the churn flow regime. Therefore, four clusters is sensitive in bubbly flow regime but in sensitive in churn flow regime. The five clusters, Figure 2(c), finally produce almost same level of identification as the supervised method. The bubbly flow regime of Mishima-Ishii is classified as two regimes: dispersed bubbly flow regime and cap bubbly flow regime. Also, the slug flow regime is divided into two: stable slug flow regime and unstable slug flow regime as noted by Whale et al. Therefore, the slug-to-churn transition is very close to Mishima-Ishii criteria.

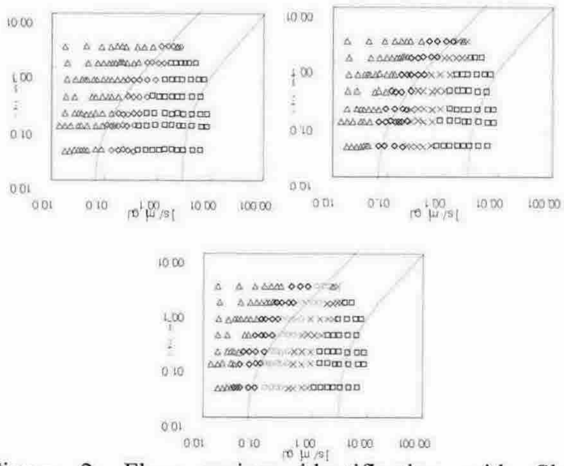

Figure 2. Flow regime identification with Slef-organization neural network and comparison with the works of Mishima-Ishii(1985) in 50.8mm ID pipe (a) three clusrters (b) four clusters (c) five clusters

3. Conclusion

A method of objective and instantaneous flow regime identification was developed here to meet the needs in the practical two-phase flow such as the rapid transition or unstable state under incident or weak gravity field.

On the behalf of the objective nature of the neural network and their relaxed restriction in data handling, the present method was actualized by input the sorted data of short sampling period considerable to be instantaneous to the neural network. This direct input set the too free from the need of sufficiently long sampling time to meet the statistical justification.

The present SOM unsupervised neural networks produced flow regime maps for the flow in the upward flow loop s of 25.4 mm ID and 50.8 mm ID, which proved the capability of the instantaneous identification of the present method.

REFERENCES

[1]J.Y.Lee, N.S.Kim and M.Ishii, An Instantaneous Flow Regime Identification Using Probability Distribution Function and Feed Forward Neural Network, A00309, NURETH-10, Seoul, 2003.

[2]M.Ishii, Objective Characterization of Interfacial Structure in Two-Phase Flow, NURETH-10, Seoul, Keynote Lecture, KL-01, 2003.

[3]K.Mishima and M.Ishii, Flow Regime Transition Criteria for Upward Two-Phase Flow in Vertical Tubes. Int. J. Heat and Mass Transfer, Vol.27, pp.723~737, 1984.