Clustering Study on Constitutive Equations for using Integral Effect Test Data to Improve Accuracy of a Reactor Safety Analysis Code

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1. Introduction

It is necessary to satisfy safety requirements in the nuclear power plant. Among the safety requirements, the safety system should respond and meet safety goals under design basis accidents. However, it is not easy to confirm this with the full-scale experiment. Thus, reactor safety analysis code is used for simulating hypothetical reactor accidents. The accuracy of the reactor safety analysis code has a profound effect on the accident analysis, and the endeavor of increasing safety analysis codes' accuracy has been going on for decades. Most of the reactor safety analysis codes are composed of governing equations and constitutive equations (i.e. wall heat transfer, wall friction, interfacial heat transfer, interfacial friction). The constitutive equation is a fitting correlation of the separate effect test results. Separate effect test is an experiment focusing only on specific local phenomenon.

In recent years, integral effect test (IET) is being conducted. The test facility is a scale down facility of a nuclear power plant including most of the important nuclear reactor's safety system component. There are some cases which the experiment results and code simulation results are different. In this case, constitutive equations are preferentially modified to increase the code accuracy. However, it is difficult to use the IET data directly in this process, and especially not easy to know which constitutive relation is responsible. Therefore, it takes tremendous effort and time to improve the constitutive equations.

In this study, following methods are proposed to improve accuracy of the reactor safety analysis code with the IET data directly. First, the constitutive equations are grouped with clustering method. In this process, 'big' data that can cover the whole design basis accident scenarios is necessary. Second, the optimal multiplier coefficient for each group is obtained. Various optimization techniques can be used to calculate the multiplier coefficient. In this paper, data generation and data clustering are first conducted and presented.

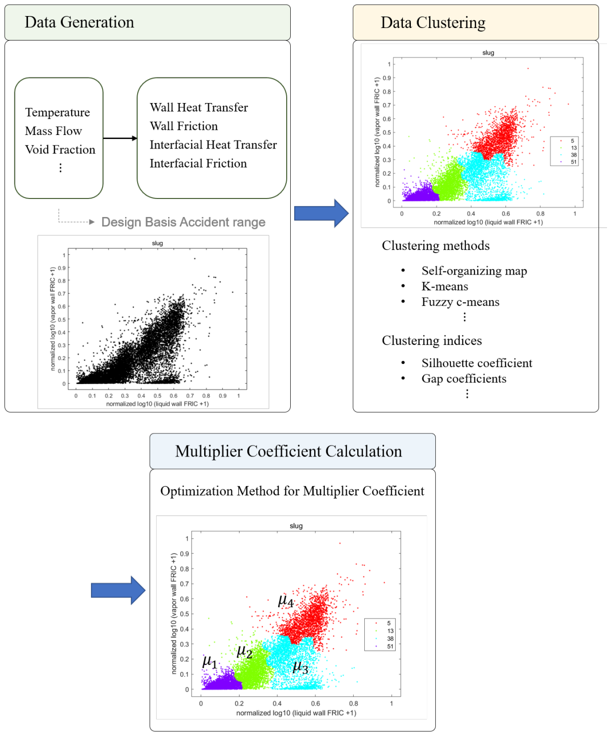


Fig. 1. Proposed method for increasing code accuracy

2. Data Generation

For dividing the range of constitutive equations, it is necessary to generate data that can cover all possible ranges. The data generated in the previous study are used [1]. It is composed of thermal hydraulic variables, and it can cover whole range of design basis accidents. Values of the constitutive equations of MARS-KS for the corresponding thermal hydraulic variables are calculated. The thermal hydraulic variables are selected uniformly random in given range. Geometry information, temperature of wall, vapor, and liquid are not selected randomly. In the cases of temperature, most of the two-phase flow is occurred near the saturation temperature, and the heat transfer regime is sensitive to the wall temperature close to the saturation temperature. Therefore, temperature is selected having more weight near the saturation point. Table 1 represents the range of thermal hydraulic variables and geometry variables. Figure 2 shows the methods to select the temperatures. Figure 3 shows the generated data for the clustering process [1].

Table I: Range of training data generation

Input parameters	Range
Pressure	0.09 – 19 MPa
Fluid Temperature	25 – (Tsat+ 50) K
Wall Temperature	25 – 1184 K
Void Fraction	0 – 1
Mass Flux	3 – 150%
Slip Ratio	1 – 3
Hydraulic Diameter	8E-4 – 12 m
Volume Length	0.01 – 550 m
Angle	0 or 90
Roughness	0 – 2.0E-4

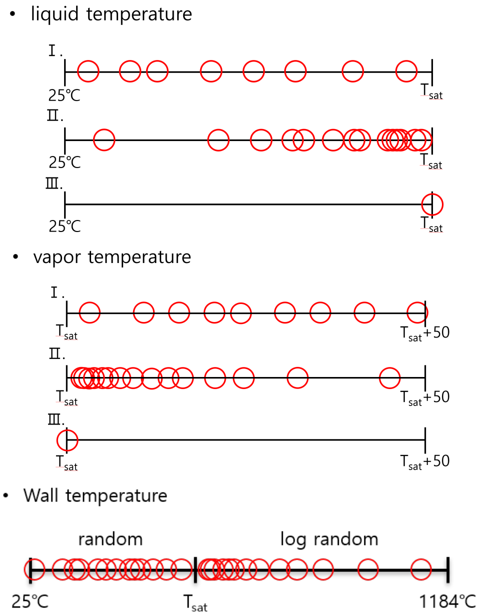
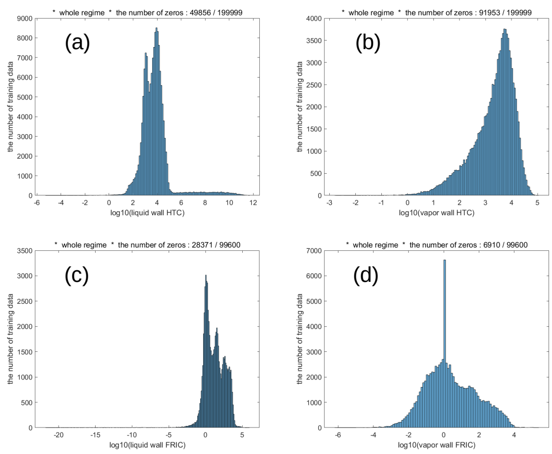


Fig. 2. Fluid, wall temperatures sampling method



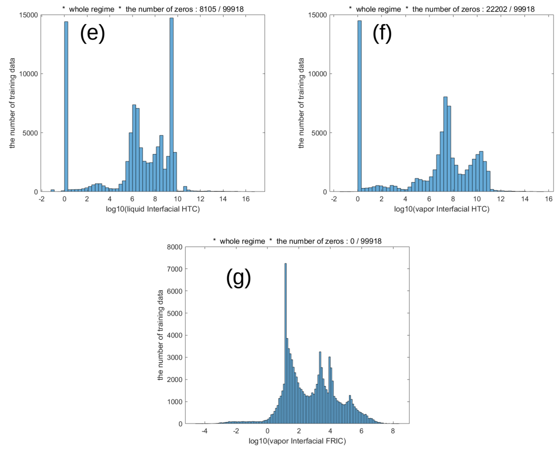


Fig. 3. Training data (a~g: coefficient of liquid wall HTC, vapor wall HTC, liquid wall FRIC, vapor wall FRIC, liquid interfacial HTC, vapor interfacial HTC, interfacial FRIC) [1]

3. Data Clustering

Data for clustering is three-dimensional, and the number of data is more than 100K. The clustering data is consisted of regime number, values of constitutive equations for each phase. For clustering, self-organizing map (SOM) is used. It is a type of artificial neural network, and often used for dimension reduction, and data clustering [2, 3]. It has advantage that can reduce the calculation on large data [4]. After clustering the data with SOM method, the performance of clustering is calculated. Two clustering indices are used, and optimal clustering number is proposed.

3.1 Self-organizing map

Self-organizing map is an artificial neural network that performs both dimension reduction and clustering with simple structure. This method allocates the given data to the map of the size which is pre-determined by the user. Weights exist for each point of the map, and the weight of each point approaches the given data as training is performed. Figure 4 shows the training algorithm.

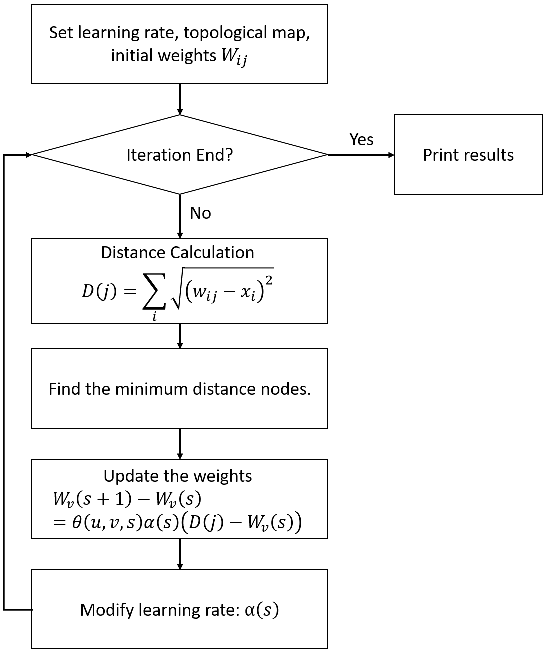


Fig. 4. Training algorithm of self-organizing map

Clustering is performed using the points of map, and then the existing data is matched to each point. K-means algorithm [5] is used for clustering the map points.

3.2 Clustering Results

The optimal clustering number can be calculated from the clustering indices. The least number of clusters for each regime is set to two. Clustering proceeds by increasing the number of clusters.

Silhouette coefficient [6] and gap coefficient [7] is used for evaluating the clustering number in this paper. Both of them can determine the optimal clustering number. A large value of the silhouette coefficient is the preferred number of clusters. In terms of the gap coefficient, smaller k that satisfies the equation 1 is preferred.

$$\mathrm{Gap}(k) \geq \mathrm{Gap}(k+1) - s_{k+1} \qquad (1)$$

Figures 5 and 6 show the silhouette coefficient and gap coefficient with respect to the number of clustering in case of wall friction. In Figure 5, the five dots in the order of the highest values are marked in orange color. In these values, the smallest number of clusters that satisfies the equation 1 is marked on thick dot. In wall friction, the optimal clustering number is 55 according to the silhouette coefficient and the gap coefficient. Table II shows the number of clusters which the minimum group number for each regime is more than two, and the optimal number of clusters.

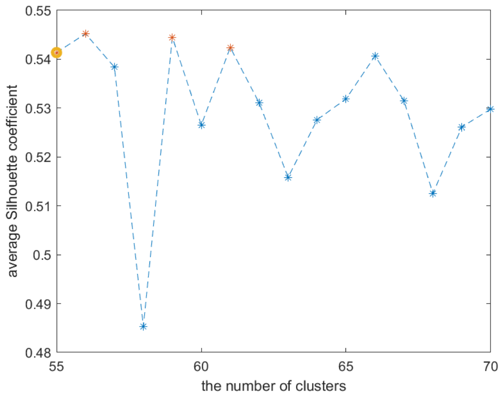


Fig. 5. Silhouette coefficient according to the number of clusters.

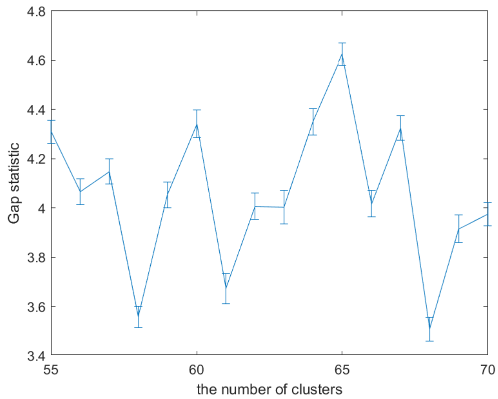


Fig. 6. Gap coefficient according to the number of clusters

Table II: Minimum group number of clusters

	Minimum clustering number	Optimum clustering number
Wall Heat Transfer	71	109
Wall Friction	55	55
Interfacial Heat Transfer	49	83
Interfacial Friction	51	60

Some examples of the clustering results are shown in Figure 7. Figure 7 shows the clustering results of the wall friction coefficient according to the flow regime. It is the result of the clustering algorithm at optimum clustering number.

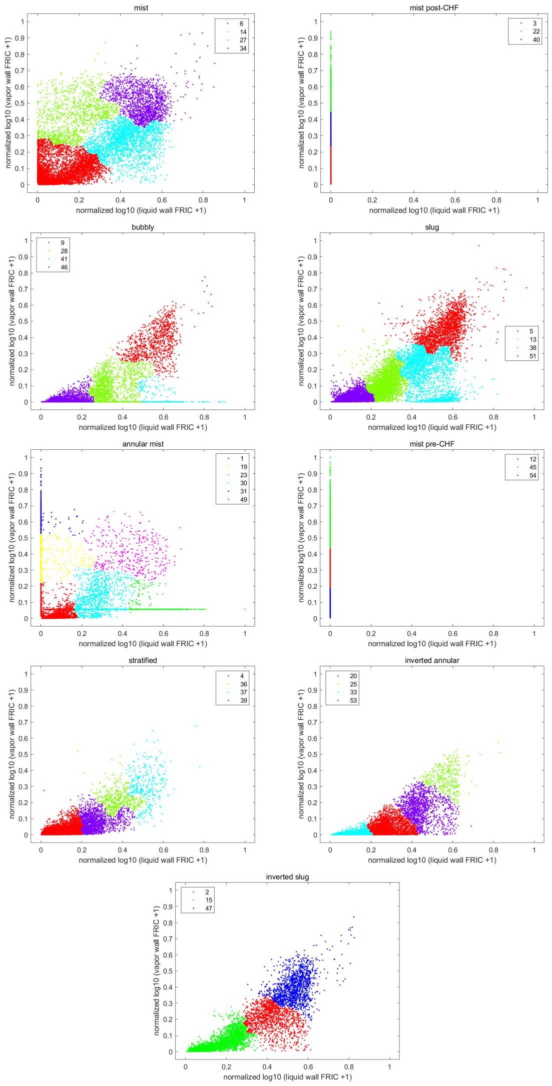


Fig. 7. Wall friction clustering results according to the flow regime

4. Summary and Further Works

In this study, a new method is being developed to directly utilize IET data to improve accuracy of the reactor safety analysis code: clustering the constitutive equations, and calculating the multiplier coefficient for each group. In this paper, data for clustering is first introduced, and optimal clustering number is obtained. Data for clustering is generated from the MARS-KS constitutive equations, and SOM method is used for clustering. In future works, multiplier coefficient should be calculated for each group. Various optimization methods can be used for multiplier coefficient calculation. After this process, the accuracy of a reactor safety analysis code can be improved that can simulate the integral effect test.

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REFERENCES

[1] ChoHwan Oh et al., Development of constitutive equations in reactor safety analysis code with data-based modeling using artificial neural network, Transactions of the Korean Nuclear Society Spring Meeting, Jeju, Korea, July 9-10, 2020.
[2] Kate A Smith, Alan Ng, Web page clustering using a self-organizing map of user navigation patterns, Decision Support Systems, Vol.35, pp.245-256, 2003.
[3] Wen-Ping Tsai et al., A data-mining framework for exploring the multi-relation between fish species and water quality through self-organizing map, Science of The Total Environment, Vol.579, pp.474-483, 2017.
[4] Juha Vesanto, Esa Alhoniemi, Clustering of the Self-Organizing Map, IEEE TRANSACTIONS ON NEURAL NETWORKS, Vol.11, No.3, pp.586-600, 2000.
[5] J. MacQueen, Some methods for classification and analysis of multivariate observations, Proc. Fifth Berkeley Symp. On Math. Statist. And Prob., Vol.1, pp.281-297, 1967.
[6] Peter J. Rousseeuw, Silhouette: a graphical aid to the interpretation and avlidation of cluster analysis, Journal of Computational and Applied Mathematics, Vol.20, pp.53-65, 1987.
[7] Robert Tibshirani et al., Estimating the number of clusters in a data set via the gap statistic, J. R. Statist. Soc. B, Vol.63, Part 2, pp.411-423, 2001.