Application of data driven modeling for MARS-KS code to improve performance

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1. Introduction

The safety analysis of a reactor accident scenario is dependent on the accuracy of the safety analysis code and how the code is utilized. Among many factors affecting the accuracy of the code, the user effect and the physical model of the constitutive equations are dominant. Therefore, to improve the accuracy of the system code from the code developer's point of view, it is necessary to develop more accurate constitutive equation from a large database. In addition, in order to improve the physical model of safety analysis codes, various institutes around the world are continuously conducting integral effect test (IET) and separate effect test (SET). However, due to the complexity of two phase flow and the difficulty of modeling, there are still cases which the experiments and code calculated results do not exactly match.

In this study, a methodology for using IET experimental data and SET experimental data to improve the system code constitutive equation is proposed. Heat transfer regimes and flow regimes of MARS-KS code were further divided by using the self-organizing map (SOM) clustering method. This method further divides the existing heat transfer and flow regimes into sub-regimes. For each sub-regime divided by SOM clustering, multipliers were applied to the constitutive equation, and how similar the modified code results correspond to the experimental results were evaluated. The methodology was applied to the MIT pressurizer transient SET experiment in this study.

2. Methods and Results

2.1 SOM clustering

SOM clustering is a method of clustering by simulating original data using a self-organizing map, a type of artificial neural network. Self-organizing map is a unsupervised learning method, and has a feature that it becomes topology preservation using the neighborhood function. It is useful to visualize high-dimensional data through dimension reduction, and has the advantage of taking less computation time compared with other clustering methods as the number of data increases.

In this study, SOM clustering was used for each regime of wall heat transfer, interfacial hear transfer, wall friction, and interfacial friction used in MARS-KS code. Accordingly, it was confirmed that each regime of the constitutive equation was divided into at least 2 to 26 sub-regimes. The numbers 6, 14, 27, and 34 in the legend shown in Fig.2. represent the numbers corresponding to the regime number of mist area when the entire wall friction regime is divided by the new regime number.

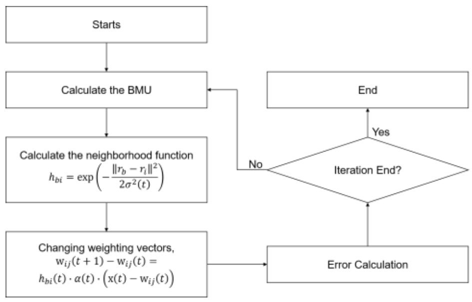

Fig. 1. SOM calculation algorithm

Table I: SOM hyper parameters

MAP size	30 x 30
Initial topology	Hexagonal Layer
The number of iterations	10000
Learning restraint	1 – t/t(end)

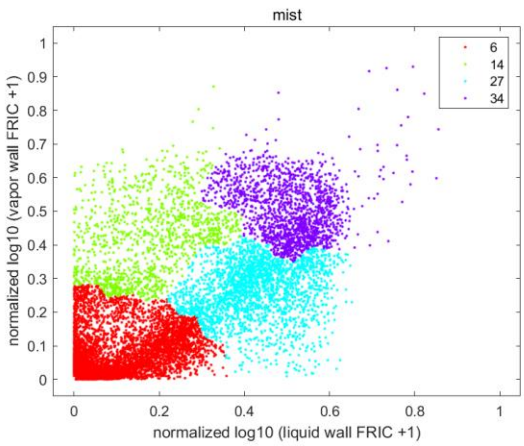

Fig. 2. Wall friction SOM clustering result

2.2 Modified MARS-KS

MARS-KS code has been modified to use SOM clustering inside the source code. During the MARS-KS code calculation process, each sub-regime was calculated, and then clustering related calculations were additionally performed to get newly defined regime number. In addition, MARS-KS code has been modified to read the multiplier value from an input file.

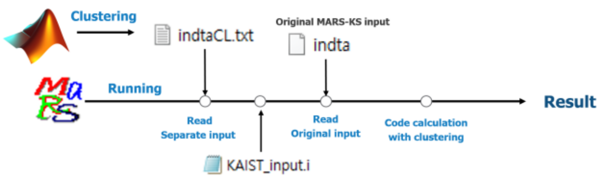

Fig. 3. Code progress of Modified MARS-KS code

Therefore, in the process of calculating MARS-KS every time step, the newly defined regime number is calculated, and the constitutive equation is multiplied by a coefficient for the corresponding regime number which is prescribed to the code via input.

2.3 Error measurement method for transient experiment

In the case of a steady state experiment, the similarity was measured by comparing the measured value of the experiment with the calculation result of the MARS-KS code, and mean square errors can be measured. However, in the case of most IET and SET, it is impossible to compare them at the same time because the nature of experiment is time dependent. Therefore, a newly defined error evaluation and similarity measurement function are required. In this study, to compare the experimental measurement value and the code calculation result, a new error measurement function was defined by applying a dynamic time warping method suitable for comparison between time series data. Original dynamic time warping methods transform time series data to compare time series with different lengths. However, in the case of safety analysis code data, it is possible to set the running time of the code calculation to be the same as the experiment time series data. The error measurement method for comparing time series data is defined through the following equation.

$$\text{Error} = \frac{\sum_{i=1}^{n} \overrightarrow{Vi,min}}{n * (X\_\max - X\_\min) * (Y\_\max - Y\_\min)}$$

The average distance difference is calculated by normalizing the shortest distance from each measurement value of the experiment to the calculated value of the safety analysis code.

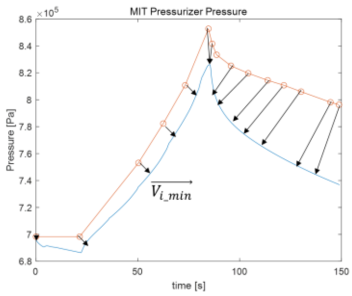

Fig. 4. Newly defined error measurement method

2.4 Multiplier coefficient optimization

Using the modified MARS-KS code, the multiplier coefficient is optimized so that the constitutive equation of the MARS-KS code predicts close to the experimental value. Modified MARS-KS input file modification, execution, and error calculation through output file are all automated and executed in MATLAB code. Through the Latin Hypercube sampling method, the distribution of the multiplier coefficient is determined within the range of 0.8-1.2, which is the uncertainty of the correlation, and a combination of the multiplier coefficient that minimizes the defined error function was found.

2.5 Target experiment: MIT Pressurizer

The Massachusetts Institute of Technology (MIT) Pressurizer Test involved a small scale, low pressure pressurizer that was initially partially filled with saturated water. The test was initiated by opening two quick-opening valves, which resulted in the insurge of subcooled water into the bottom of the pressurizer. The pressurizer pressure of experimental measurement value is selected as the time series value for calculating the defined error function.

2.6 Results

It was confirmed that the result of multiplier coefficient optimization within the constitutive equation uncertainty range (0.8-1.2) was not significantly different between the original MARS-KS and the modified MARS-KS.

Original MARS-KS error: 0.1318
Modified MARS-KS error: 0.1300 (0.8-1.2)
In order to see the limit that the code improves as the constitutive equation is multiplied by the multiplier coefficient, it was confirmed that the calculated error function became smaller when the multiplier coefficient was set to 0.1-10.0.

Original MARS-KS error: 0.1318
Modified MARS-KS error: 0.1193 (0.1 – 10.0)

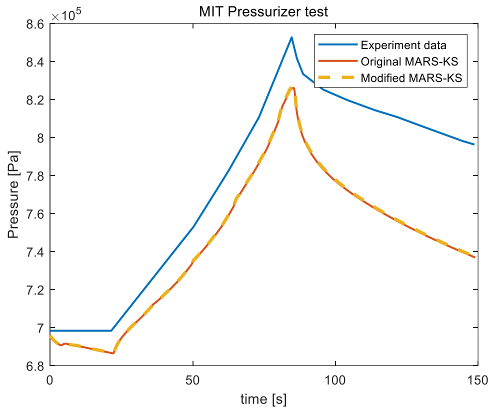

Fig. 5. Pressure calculation result by multiplier coefficient (0.8-1.2)

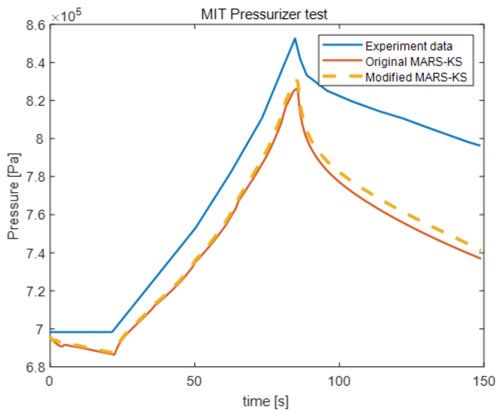

Fig. 6. Pressure calculation result by multiplier coefficient (0.1-10.0)

3. Summary and Further Works

As a result of applying the developed methodology to the MIT pressurizer experiment, it was confirmed that the calculation result did not improve significantly within the range of the correlation uncertainty, but the code calculation results improved when the range for searching optimal coefficient value was widened. Also, in both cases, it was confirmed that the regimes used in the actual experiment, the condensation wall heat transfer and the stratified interfacial heat transfer regions, were modified. However, in the case of the MIT pressurizer experiment, there is a problem that the code calculation results change substantially when the heat loss model changes. This is a good example when user effect dominates the prediction of the safety analysis code. Through this study, a sub-regime of the constitutive equation was newly defined, the code calculation result was marginally improved, and the regime mainly used in the experiment could be found by the developed methodology. However, it seems that the methodology needs to be applied to the transient SET experiment after the user effect is minimized.

Acknowledgments

This work was supported by the Nuclear Safety Research Program through the Korea Foundation Of Nuclear Safety(KoFONS) using the financial resource granted by the Nuclear Safety and Security Commission(NSSC) of the Republic of Korea. (No. 1903002)

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