A study of classifying flow regimes of MARS-KS wall heat transfer coefficient data using unsupervised learning

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1. Introduction

In the reactor safety analysis, the application of system codes is important.

Nuclear system analysis code has been developed to perform realistic multi-dimensional thermal hydraulic system analysis. More specifically, the MARS-KS code is used as widely accepted multi-dimensional thermal hydraulic tool. Code simulations are based on governing equations and constitutive equations. The constitutive equations are based on empiricism.

Since, Nukiyama conducted a study on heat transfer with respect to temperature, steady research has continued. In wall heat transfer models, Nukiyama divided them into 4 regimes [1], RELAP code into 5 regimes [2], and MARS-KS into 6regimes [3]. Each regime has different constitutive equations. In MARS-KS, input variables of wall heat transfer (WHT) coefficients are 10, but regimes are divided by the logic of 5 variables. They are based on experiments but at the boundary, they are not continuous.

There is little knowledge of how to divide flow regimes and transition regimes. In this paper, the method of NEO-K-Means is applied to help to divide the flow regimes and transition regime.

2. Methods

2.1 K-Means

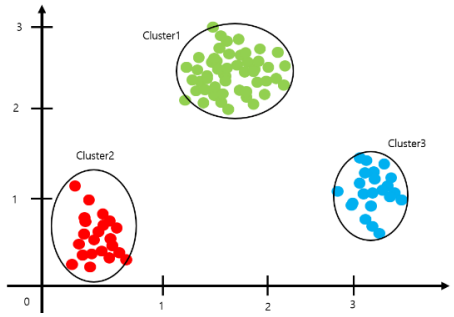

Fig. 1. K-Means clustering

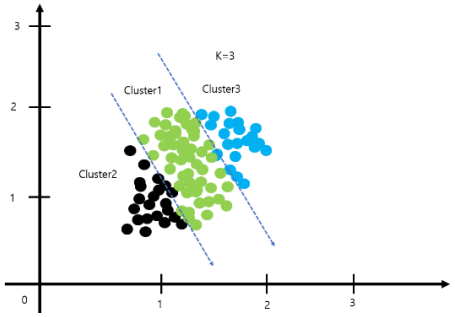

Fig. 2. K-Means clustering

K-means algorithm is a typical clustering algorithm. It aims to cluster N data into k clusters. It assigns label into data and clustering based on labels. It assign the data to K clusters S = {s1, s2, s3,…sK} so that the difference in distance between the center of the cluster to which the data belongs is minimal. It is fast and distinguishes well for specific data.

2.2 NEO-K-Means algorithm

In real world data, there are some data sets that are not clustered clearly, and others include noise. In the flow regimes, there are many ambiguous points between the regimes. People cannot experiment with all the detailed conditions. For these reasons, there are many ways to divide flow regimes.

On the other hand, non-exhaustive, overlapping K-Means algorithms(NEO-K-Means) can divide over-lapping cluster and outlier[4].

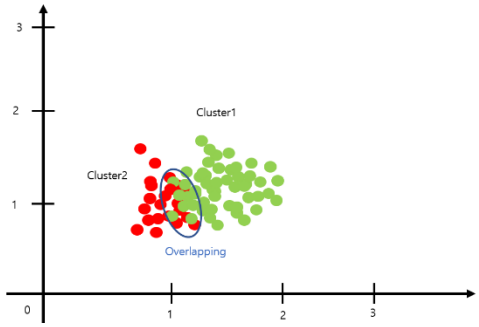

Fig. 3. Clustering overlapping regime

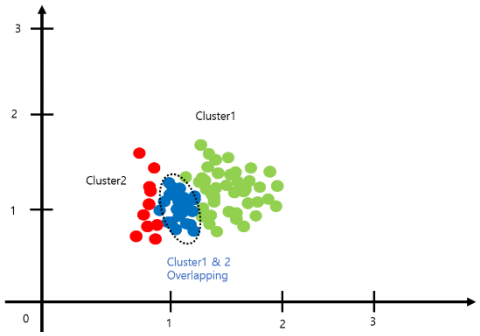

Fig. 4. NEO-K-Means clustering

2.3 Data

Data is selected to include the Design Basis Accident of the APR 1400 as much as possible. DBA accidents include LOCA, SGTR, and LOOP. They are interpreted through hydrothermal safety analysis codes.

Table I: WHT coefficient input parameters and range

Input Parameters	Range
Pressure	0.09~19MPa
Fluid Temperature	25 ~ (Tsat+50)K
Wall Temperature	25~1184K
Void fraction	0~1
Mass flux	3~150kg/m^2s
Slip Ratio	1~3
Hydraulic diameter	8E-4~12m
Volume length	0.01~550m
Angle	0 or 90
Roughness	0~ 2.0e-4

3. Results

The distribution of WHT using flow chart of MARS-KS is as follow.

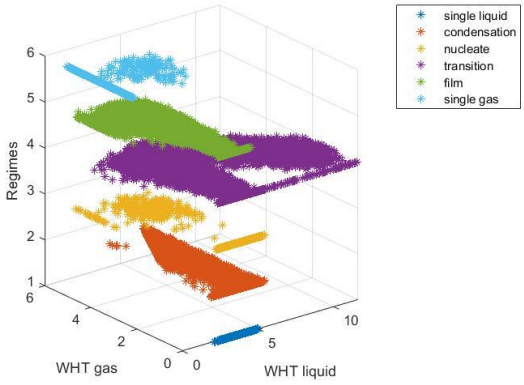

Fig. 5. Distribution of WHT coefficient

The WHT value was preprocessed as log(value+1).

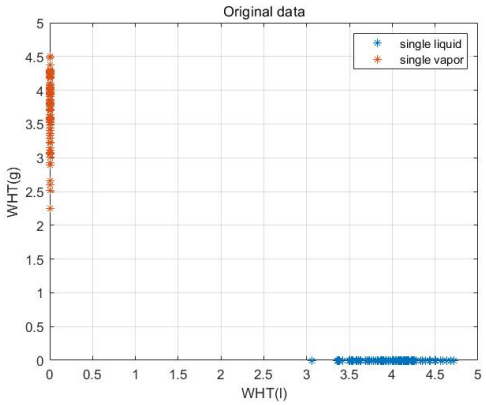

Fig. 6. Distribution of MARS-KS data, two regime

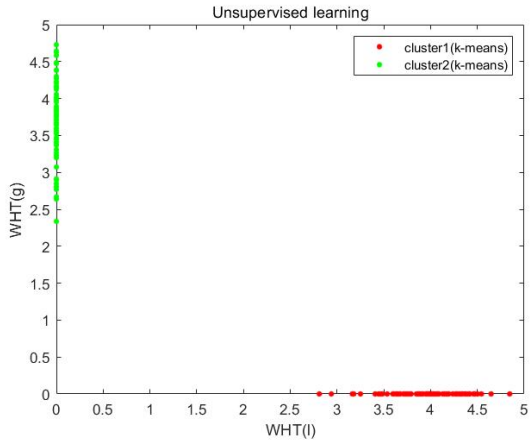

Fig. 7. Distribution of unsupervised learning data, two regimes

Classifying regimes between single phase gas and single phase liquid using unsupervised learning is straightforward. This is because WHT of single phase liquid and WHT of single phase gas are mutually exclusive.

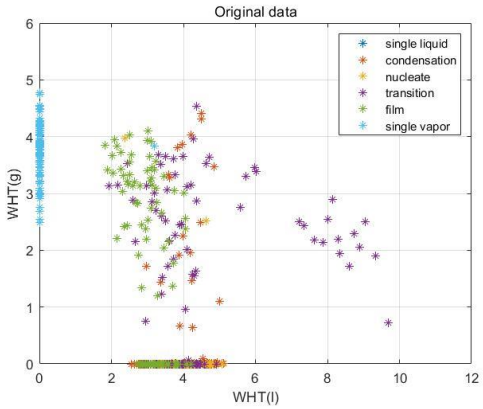

Fig. 8. Distribution of MARS-KS data, 6regime

However, classifying 6 regimes using unsupervised learning requires further research because WHT coefficient of 6 regimes are not mutually exclusive. There are several reasons. First of all, the calculation of

WHT in the code sometimes involve arbitrarily determined interpolation and extrapolation. Especially some data is located in transition regime of two regimes and classifying regime of this data is not clear. Another reason is that WHT values can be similar even for the different regimes. Moreover, since the code developer determined the heat transfer regime logic from indirect observation, this process involves a certain arbitrariness in this decision. Thus, there is always a possibility that the regime classification may not agree with the observation of complete set of data.

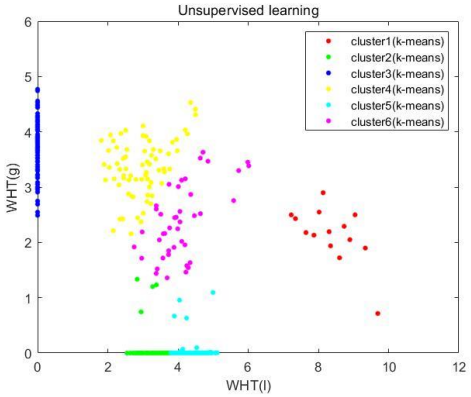

Figure 9. Distribution of unsupervised learning data, 6 regime

4. Future works

In the future, the range of the experiment of finding WHT correlation will be first checked. This will be followed by generating a data set that satisfies the direct experimental observation that corresponds to the valid range of the correlation. In the case of overlapping regime, Neo-K-means will be used to classify the regimes. Finally, the regime classification derived from unsupervised learning will be compared to the regime determined from algorithm implemented in the MARS code.

This research is motivated by a simple curiosity that whether the programmer determined heat transfer regime selection logic truly corresponds with the experimental observation. Since recent advancement in machine learning technique makes possible to investigate dataset with higher dimension better, the classification learning algorithm is used to test the hypothesis that the simple regime determination logic is sufficient to represent the directly observed experimental data.

5. Acknowledgement

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