Preliminary Study of replacing the constitutive equations in the MARS-KS code to data-based modeling using the Artificial Neural Network

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1. Introduction

For large nuclear power plants, it is hard to experiment on whole scale nuclear power plant accident. Most of the reactor accident analysis of whole nuclear power plant scale is performed with safety analysis codes. An accurate safety analysis is based on the accuracy of the safety analysis code. Constitutive equation is one of the factors that greatly affects the safety analysis code accuracy. In the constitutive equations, defining the flow regimes, and calculating the coefficients are included. Regulators in various countries endeavor to improve the accuracy of the safety analysis code, and experiments on separate effect tests and integral effect tests [1-3]. As a result, accuracy of the safety analysis code is improving steadily [4]. However, there are still many uncertainties and errors in the reactor accident modeling. The complexity and non-linearity of two phase flow makes it hard to improve accuracy. Also, the constitutive relations are limited in mathematical functional forms, which makes it hard to include the whole range of data. These problems can limit the accuracy of the safety analysis.

To resolve these limitations, the final object of this study is developing a data driven modelling that can replace all the constitutive equations in a safety analysis code. An artificial neural network (ANN) can represent non-linear equations better than the previous mathematical functions often used in a NPP safety analysis code, which can be a solution to the constrained mathematical form. The ANN has shown high performance in data regression and predictions [5]. Also, there is an advantage in that the performance of the model can be increased through continuous learning by adding new training data (i.e. experimental data).

ANN that predicts the constitutive equation for wall heat transfer coefficient was studied in the previous paper [6]. In this paper, the study of ANN that can predict the wall friction factors has been conducted. The wall friction coefficients are calculated from the constitutive equations in MARS-KS code which is the safety analysis code used by Korean regulatory body. An ANN is trained from these MARS-KS constitutive equations. In this study, more wide-ranging conditions are considered to include various accident situations than the previous study.

2. Model description

2.1. Data Generation

A lot of wall friction data sets are necessary to train and test the ANN. In the previous study [6], thermal hydraulic conditions of LOOP, SGTR and SLOCA for APR1400 were considered when generating the heat transfer coefficient data. APR1400 is a pressurized light water reactor with 1400 MW electric power generating capacity. In this study, based on these hypothetical design basis accidents, wider range of thermal hydraulic and geometry conditions are considered to cover more situations. In the pressure conditions, it has been modified to include the atmospheric pressure in data generation. It has been also modified to include the room temperature in training data sets. When LOCA occurs at the nuclear power plant, boundary of the break pipe is atmospheric pressure and room temperature, and the temperature of safety injection water is much lower than that of the primary loop water at normal operating condition. Also, various size of pipe diameters are considered to cover the primary side of APR1400 and ATLAS. ATLAS is a thermal-hydraulic test loop, developed by the Korea Advanced Energy Research Institute (KAERI). The reference plant of ATLAS is APR1400. ATLAS was designed with 1/288-volume scale of APR1400 [7].

More specific information for training conditions is summarized in Table I. Wall friction factor is calculated in the condition which is randomly selected in the given range. The number of data for training is 100,000. A quarter of the training data is used for validating the artificial neural network. 25,000 data sets different from the training data were used to test the trained ANN. Wall friction factors of training data are described in figure 1 and figure 2.

Table I. Defined conditions for training

Thermal Hydraulic Conditions	
Pressure	0.09 – 19.0 MPa
Fluid Temperature	25 – (T_{sat}+50) K
Wall Temperature	0 – 350 K
Mass Flux	7 – 120 %
Slip Ratio	1 – 3
Geometry Information	
Hydraulic Diameter	9.5E-4 – 11.28 m
Heated Length	20.0 m
Angle	0° or 90°
Material Property	

Roughness	0 – 2.0E-4 m

Table II. The number of training data according to the heat transfer mode

Heat Transfer Mode	
Single Phase	34566
Subcooled Nucleate Boiling	54661
Subcooled Transition Boiling	5869
Subcooled Film Boiling	4904

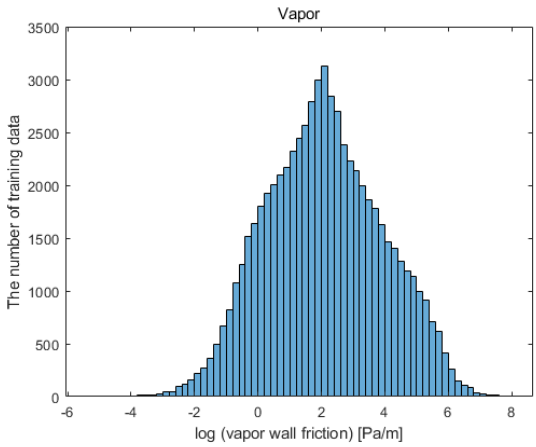

Fig. 1. Vapor wall friction factor training data

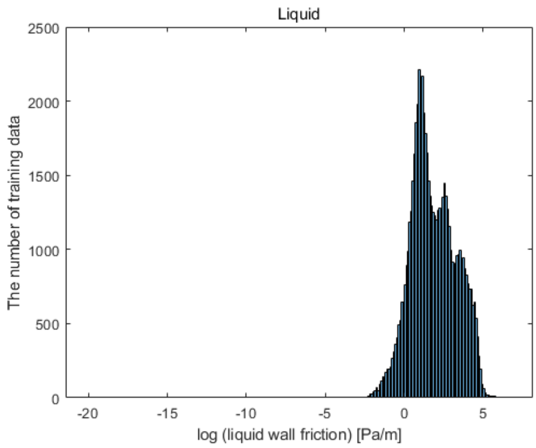

Fig. 2. Liquid wall friction factor training data

2.2. Artificial Neural Network

In this study, multi-layer perceptron is used for the ANN. The number of layer is 2, and the number of node is 20 per layer. Batch size is 5000, and other specific information is summarized in Table III. Total of 11 input parameters are considered: temperature of liquid and vapor, pressure, wall temperature, velocity of vapor and liquid, void fraction, heated diameter, hydraulic diameter, roughness, and angle. Output parameters are wall friction factor of vapor and liquid. As wall friction factors have wide range, these values are normalized with logarithmic scale. Figure 3 shows the mean squared error according to the epoch.

Table III, Specific information of the model

Data	
	Training and Validation : 75% / 25%
	The number of data : 100,000
	Batch size : 5000
Hyper parameters	
	Platform : Pytorch v.3.6 (Python)
	The number of hidden layer : 2
	The number of node : 20 / 20
	The number of Input parameter : 11
	The number of output parameter : 2
Learning	
	Epoch : 500
	Learning rate : 1E-2
	Loss function : Mean Squared Error (MSE)
	Activation function : ReLU function [8]
	Optimizer : Adam optimizer

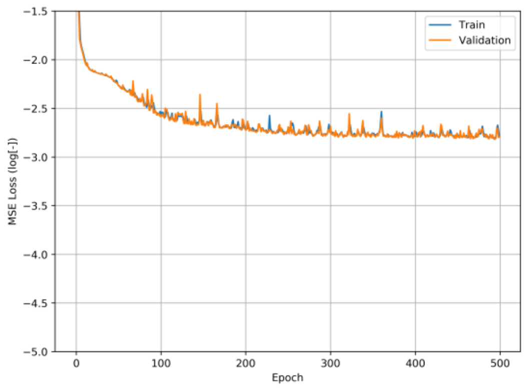

Fig. 3. Mean Squared Error according to the Epoch

3. Results and Discussions

Test results of the ANN model are shown in Table IV. As mentioned above, the number of the test data is 25,000. R-squared is about 0.95 in both phases. MAXE is maximum absolute error of the test data, and MAPE is mean absolute percentage error. Some of the wall friction factors are very low that a slight difference between actual and prediction value can significantly increase the error. "Filtered" is the test data with the lowest 15% of wall friction factor filtered out. In cases of the filtered values, MAPE is about 10% in both phases. However, MAXE is larger than 100% in both phases.

Table IV. Results of the artificial neural network

	vapor wall friction factors	liquid wall friction factors
R-square	0.9791	0.9458
MSE	9.57E-3	2.31E-2
MAPE	31.62 %	1.86E+11
MAPE (filter)	12.3 %	9.97 %
MAXE	26,756 %	2.57E+15
MAXE (filter)	548 %	238 %

4. Conclusions and Further works

The artificial neural network has been developed to replace the constitutive equations in nuclear safety analysis code. The artificial neural network is a data driven modeling, which has advantage on the possibility of reflecting updated experimental data without constraint mathematical form. For the preliminary study, replacing wall friction coefficients in the safety analysis code has been conducted. It is evaluated how well the artificial neural network could predict the data from the constitutive equation in MARS-KS code. MAPE was about 10% in both liquid and vapor phases while excluding very small value of wall friction factor data. However, there were cases in which the wall friction factors predicted by the model were significantly different. Also, the accuracy of the model is considerably low in the low value range of wall friction factors.

In this paper, only simple structure multi-layer perceptron is applied. Other artificial neural networks such as convolution neural network, genetic algorithm-neural network can be utilized in the wall friction factor prediction in near future. Also, changing the hyper parameters of the multi-layer perceptron could increase the prediction accuracy. For example, changing the activation function or the number of the node could be the solutions for increasing the model accuracy.

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