Preliminary study of reconstructing MARS-KS constitutive relations with ANN

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1. Introduction

Nuclear reactor safety analyses are usually performed with computer codes such as MARS-KS, RELAP5. Most of the nuclear system analysis codes solve 1-D transient two phase flow governing equations. 1-D approach always necessitates the use of constitutive relations based on empiricism. Therefore, the code development requires experimental data to validate the code results. The code validation is typically performed by comparing the code results with experimental data from SET (Separate Effect Test) and IET (Integral Effect Test). The code constitutive relations to complete the governing equations can be developed from SET data with existing method but utilizing IET data to improve constitutive relations is still limited.

In this paper, a method to utilize IET data to further improve the code accuracy is proposed. Mathematically the constitutive relations are derived from large experimental data obtained from many SETs. Thus, the original constitutive relations are the product of regression analysis of these large SET data. In theory, utilizing artificial neural network (ANN) to represent big data to substitute the original constitutive relation is also possible. Furthermore, since ANN can handle much wider class of data, IET data can be also used for training ANN. This means that by substituting function based constitutive relations with ANN based constitutive relations, it may be also possible to utilize IET data to improve constitutive relations which was not possible previously. However, the feasibility to use ANN for predicting constitutive relations has to be first evaluated before further applying ANN to this field.

Since the data for ANN training cannot be generated from all possible thermal hydraulic (TH) conditions, the TH conditions relevant to Edward pipe problem is arbitrarily chosen [1].

Thus, in this paper, as the first demonstration of the proposed method, wall heat transfer coefficient (HTC) and interfacial friction of the original constitutive relations are reconstructed with ANN. ANN reconstructed wall heat transfer gas but ANN for wall heat transfer liquid and interfacial friction needs to improved.

2. Methods and Results

2.1 Artificial Neural Network

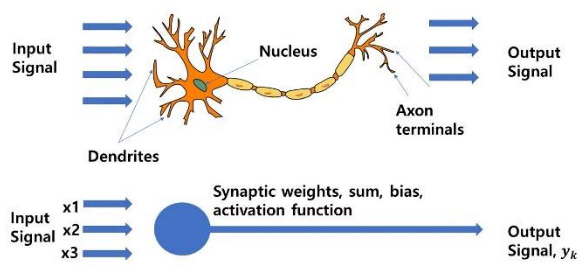

Figure 1 Artificial Neural Network

ANN (Artificial neural network) simulates how a brain analyzes information and solves problems. It solves problems that is simple and needs many calculations. A feed forward neural network is one of ANNs that calculation proceeds in one direction. It is consisted of input nodes, hidden nodes and output nodes. In this research, the results are obtained from single-layer perceptron [2]. This structure is the simplest structure of ANN.

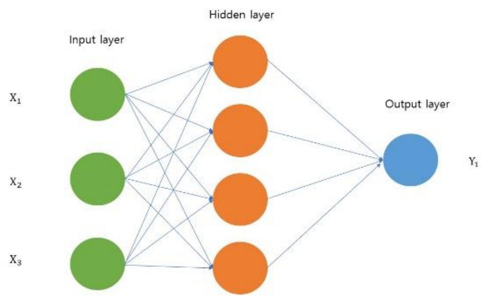

Figure 2 Feed forward neural network

2.2 Edward pipe

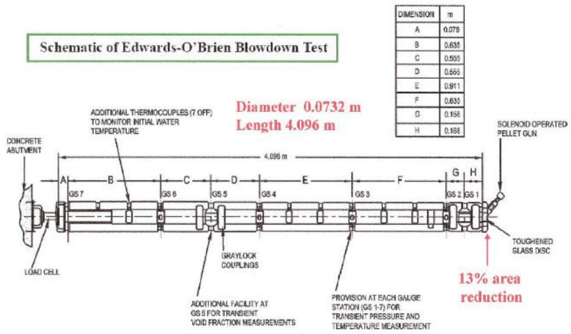

Figure 3 Schematic diagram of Edward Pipe

In the Edward pipe experiment, pressurized super cooled liquid goes under rapid decompression and expansion. Water becomes vaporized outside of the tube in the form of flashing. A critical flow phenomenon occurs and limits the flowrate [3]. Many processes in the Edward pipe are relevant to the pressurized water reactor loss of coolant accident phenomena.

Table 1 Edward Pipe input parameters range

Input parameters	*Range*	*Unit*
Pressure	$\mathbf{9x10^4 \sim 8x10^6}$	*Pa*
Temperature of liquid	*300~600*	℃
Temperature of gas	*360~570*	℃
Temperature of wall	*310~690*	℃
Velocity of liquid	*0~136*	*m/s*
Velocity of gas	*0~136*	*m/s*
Mass flux of liquid	*0~124500*	$kg/m^2\ s$
Mass flux of gas	*0~4350*	$kg/m^2\ s$
Void fraction	*0~1*	*None*
Density of_liquid	*645~996*	kg/m^3
Density of_gas	*0~43*	kg/m^3

Table 2 Edward Pipe output parameters range

Output parameters	*Range*	*Unit*
Wall HTC_liquid	*0~457000*	W/m^2
Wall HTC_gas	*0~17800*	W/m^2
Interfacial friction coefficient	$0 \sim 2.6x10^7$	*None*

2.3 Hyper parameter optimization

There are many parameters to be determined via training with data when using multi-layer perceptron (MLP). For example, number of hidden layer, hidden layer nodes, epoch, optimizer, learning rate, batch size are all parameters that can affect the accuracy of MLP. To achieve high accuracy, tuning these hyper parameters are very important.

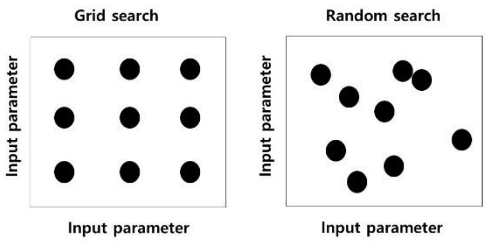

Figure 4 Grid search and Random search

Hyper parameters can be optimized by utilizing various methods. Grid search method can be used to find the optimal hyper parameters. However, this method consumes to much resources. Random search method can improve the resource consumption of the grid search method. Bayesian optimization method can be more efficient than the random search method since it utilizes random search method initially but the sampling becomes more effective since it is performed with Bayesian inference [4]. Thus, in this study, hyper parameters are optimized with Bayesian optimization method.

2.4 Results

The TH conditions summarized in Edward pipe are used for generating data to train ANN. 170,000 data is generated from MARS-KS code to train ANN. The testing of the trained ANN was performed with 30,000 data. The accuracy of ANN is measured with mean absolute percentage error (MAPE) and root mean square error (RMSE). The accuracy is shown for liquid wall HTC, gas wall HTC and interfacial friction. As it can be observed from the results, a simple ANN structure can be used for gas wall HTC prediction, but using the same structure to predict liquid wall HTC and interfacial friction predictions can yield unsatisfactory results.

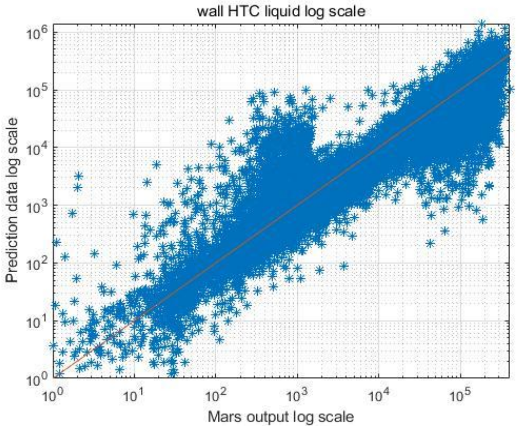

Figure 5 Wall HTC liquid deviation of Mars code & ANN

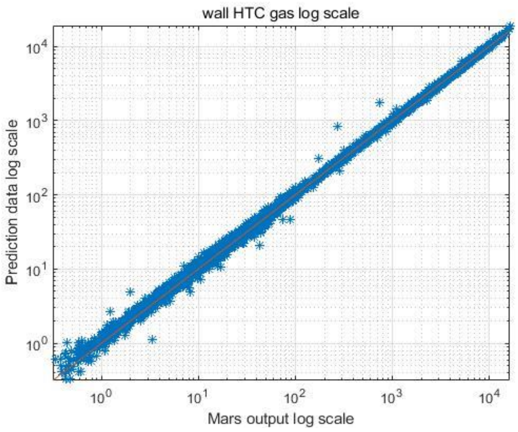

Figure 6 Wall HTC gas deviation of Mars code & ANN

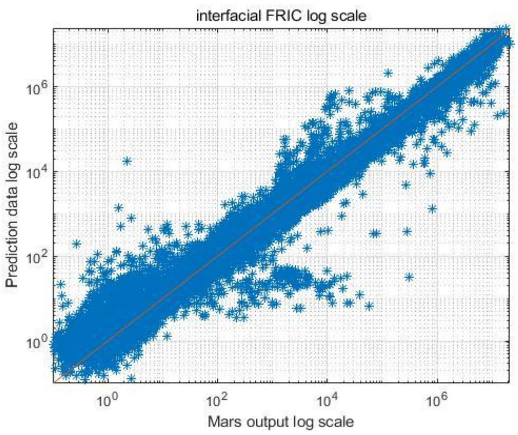

Figure 7 Interfacial friction deviation of Mars code & ANN

Wall HTC liquid	
MAPE	***1.8518x10³***
RMSE	***8.1306x10⁶***
Wall HTC gas	
MAPE	***6.0232***
RMSE	***1.0016x10⁴***
Interfacial Friction	
MAPE	***87.3961***
RMSE	***8.9841x10⁷***

Table 3 Deviation of Mars code & ANN

3. Summary and Future works

In this paper, a preliminary study to reconstruct constitutive relations of MARS-KS code with ANN is performed. This is a part of effort to utilize integral effect test data to improve the predictability of constitutive relations in a 1-D system analysis code with the simplest ANN structure. TH conditions from Edward pipe problem are arbitrarily chosen to test the feasibility of the concept. The initial test shows that heat transfer relations such as gas wall heat transfer can be predicted quite accurately, but more complex liquid wall heat transfer or interfacial friction cannot be predicted accurately with a simple ANN structure or training method. Therefore, more advanced options for training ANN will be searched and tested to further improve the accuracy of the ANN.

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