An investigation of accuracy enhancement by reconstructing MARS-KS constitutive relations with ANN using data augmentation

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1. Introduction

A computer code is an important tool in nuclear reactor safety analysis. Almost all nuclear analysis codes solve two phase, 1-D governing equations. However, the equations used by computer codes are based on empiricism. They have continued to develop to better reflect the results of experimental data from SET (Separate Effect Test) and IET (Integral Effect Test). It is possible to improve the constitutive relations through SET data, but it is difficult to improve using IET data.

To solve this problem, ANN(artificial neural network) is applied in the research. Mathematically the constitutive relations come from numerous sets of SET experimental data. Therefore, the original constitutive relations are the result of regression analysis of these large SET data sets. Theoretically, artificial neural network trained by big data can substitute the original constitutive relations. ANN can handle not only SET data but also IET data. Because of this, there is significant potential to enhance the existing system codes with this method. However, before ANN can replace the existing constitutive relations, it needs to be verified and numerically evaluated before application.

In the past, research has been conducted to verify and evaluate the ANN methodology. The data for ANN training can't reflect all the possible thermal hydraulic (TH) conditions, and thus the Edward pipe problem has been chosen arbitrarily. In many variables, wall heat transfer coefficient was used because it is more related with safety.

It is relatively easy to simulate for single-phase flow, but it is difficult to simulate for two-phase flow. This is because the simulation results fit well for single-phase flow, but it does not fit well for two-phase flow.

There is little knowledge of how to increase the accuracy of ANN for this application. In this paper, it is demonstrated that data perturbation helps to improve ANN accuracy.

2. Methods

2.1. Artificial Neural Network(ANN)

ANN is a training algorithms based on the human neuron network. It has the advantage of performing large number of computations. In this paper, single-layer neural network among the feed forward neural network methods is adopted.

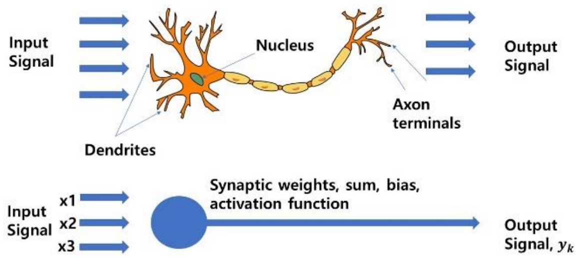

Figure 1 Artificial Neural Network

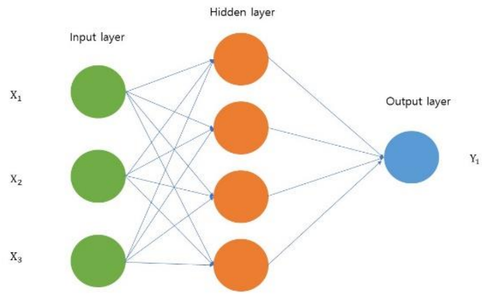

Figure 2 Feed forward neural network

2.2. Edward pipe

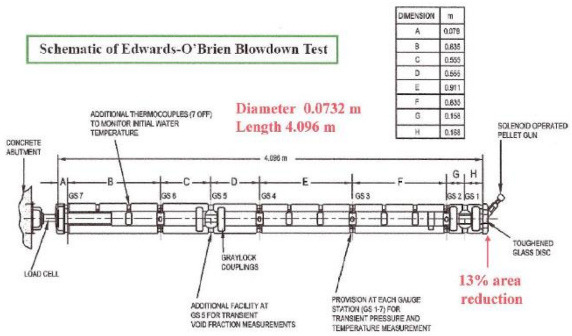

Figure 3 Schematic diagram of Edward Pipe

Edward pipe problem was used because to narrow down the thermal hydraulic conditions for ANN training. It is a good example because of strong implication for a pressurized water reactor loss of coolant accident.

Table 1 Input and output parameter ranges adopted for the simulation

Input parameters	Range	Unit
Pressure	$9\mathrm{x}10^4$ ~$8\mathrm{x}10^6$	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

Output parameters	Range	Unit
Wall HTC_liquid	0~457000	W/m^2K
Wall HTC_gas	0~17800	W/m^2K
Interfacial friction coefficient	$0\text{~}2.6\mathrm{x}10^7$	None

2.3. Hyper parameter optimization

When training ANN, there are many parameters to tune to achieve high accuracy. The tuned parameters are hidden layer nodes, epoch, learning rate, and batch size. .

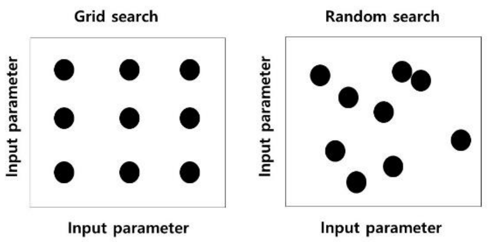

Figure 4 Grid search and Random search

There are several methods to optimize the hyper parameters. Grid search method checks regular intervals, and random search checks points randomly. These are potential ways to find high accuracy point. However, Bayesian optimization method finds the high accuracy point more efficiently because it performs with Bayesian inference. Therefore, Bayesian optimization is adopted to optimize hyper parameters.

2.4. Data augmentation

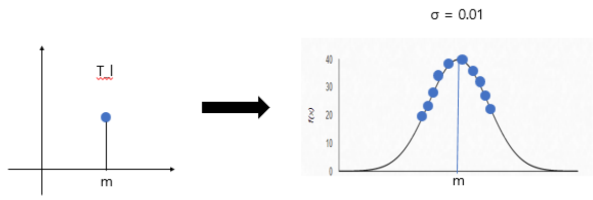

Figure 5 Data perturbation

As the number of data increases, the accuracy of ANN increases. Creating similar data by introducing artificial noise is a way of implementing data augmentation. In the case of perturbed training data in ANN, the noise can be generated via expansion, contraction and rotation. In our study, input variables are perturbed with assuming normal distribution having standard deviation = 0.01, Multiple = 10.

3. Results & Discussions

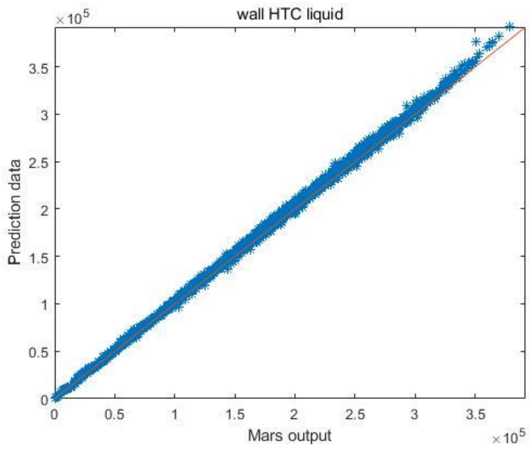

Figure 6 Wall heat transfer coefficient single regime

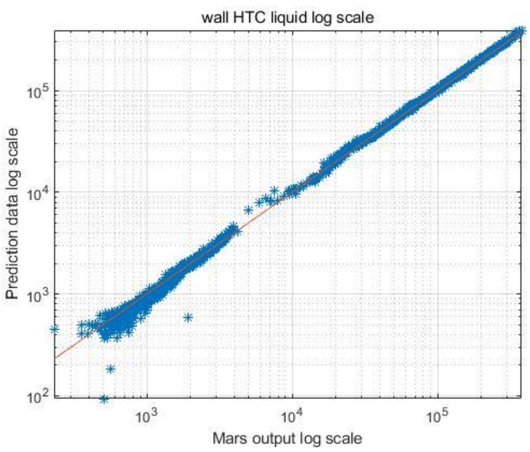

Figure 7 Wall heat transfer coefficient single regime log scale

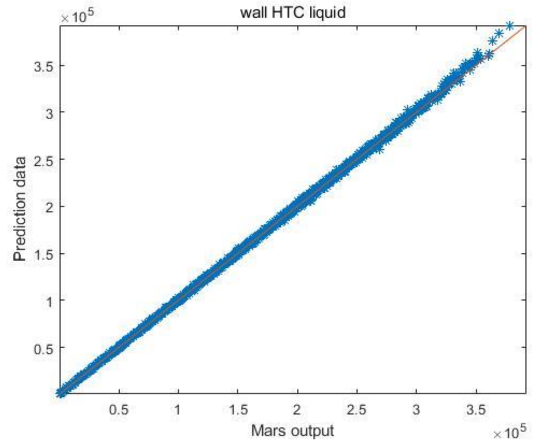

Figure 8 Wall heat transfer coefficient single regime with data augmentation

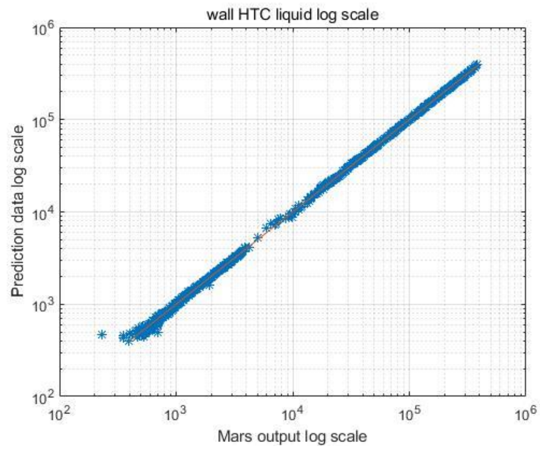

Figure 9 Wall heat transfer coefficient single regime log scale with data augmentation

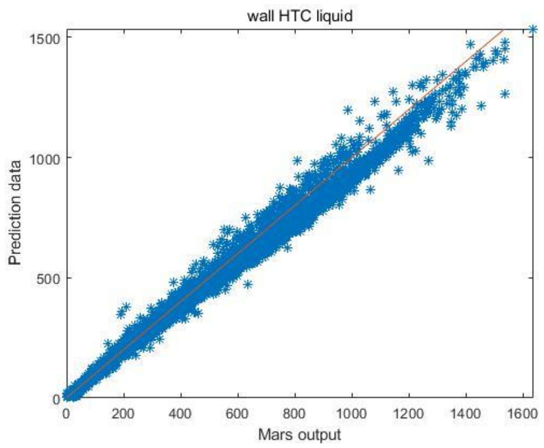

Figure 10 Wall heat transfer coefficient film regime

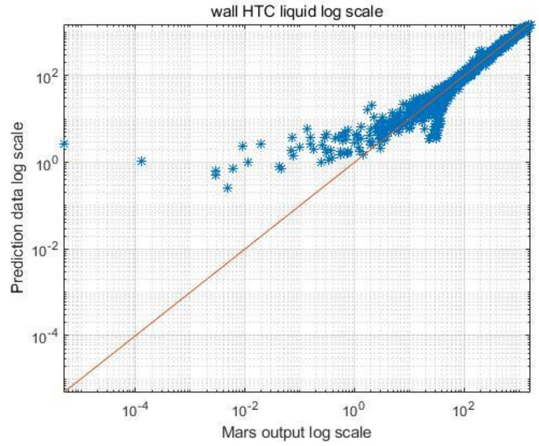

Figure 11 Wall heat transfer coefficient film regime log scale

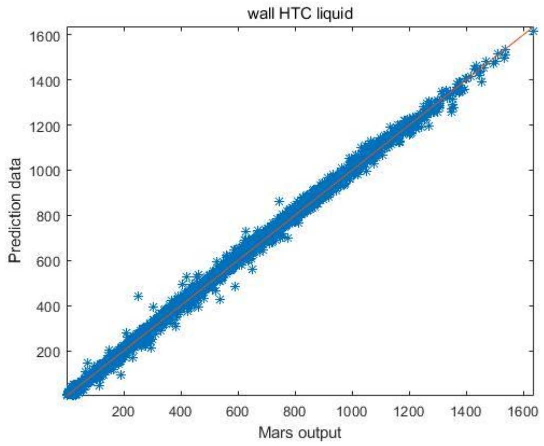

Figure 12 Wall heat transfer coefficient film regime with data augmentation

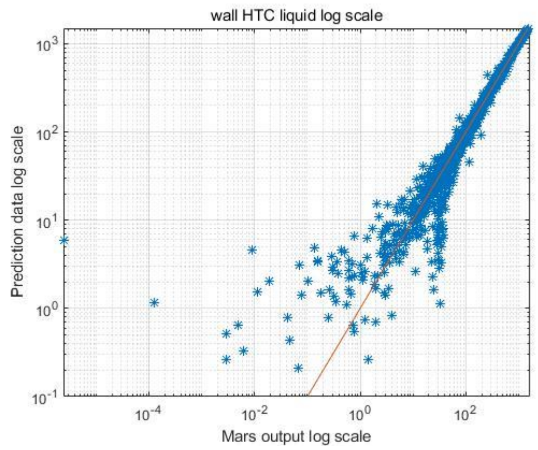

Figure 13 Wall heat transfer coefficient film regime log scale with data augmentation

	Wall heat transfer	**Wall heat transfer with perturbation**
MAPE Single	2.9654	0.9544
RMSE Single	$\mathbf{2.763x10^5}$	$\mathbf{1.15x10^3}$
MAPE Film	1.4492	$\mathbf{3.24x10^4}$
RMSE FIlm	285.711	17.3874

There are two representative way to evaluate effectiveness. The RMSE decreases well with data augmentation, but MAPE does not decrease with data augmentation. However, data augmentation in general seems to be a good way to improve accuracy of ANN.

4. Conclusion

The accuracy of ANN (artificial neural network) has to be improved further to utilize it for modeling complex liquid. A method of increasing number of data artificially to augment data was tested for this purpose. Adding more data from data augmentation for the ANN training showed some potential for improving accuracy of ANN. Further research will be conducted to improve accuracy and efficiency of ANN for the system analysis code application.

Acknowledgement

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