Decontamination Factor Prediction Using Artificial Neural Networks Method

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1. Introduction

Accidents at Nuclear Power Plant (NPP) can lead to leakage of radioactive material outside the NPP site. In the event of a hypothetical severe accident in a light water reactor, gaseous and particulate fission products and aerosols are released from the reactor core and transported through a pipe system network. Therefore, it is necessary to mitigate the release of radioactive materials to the environment outside the NPP site.

Pool scrubbing is one of the methods that reduce the environmental impact of radioactive materials by eliminating and holding fission products in the pool installed in the pipe system. In the pool scrubbing process, Decontamination Factor (DF) is usually known as a measure of how effectively the radioactive materials are removed in the pool scrubbing process.

Many researchers have developed pool scrubbing analysis code, such as BUSCA (Bubble Scrubbing Analysis), to simulate an aerosol removal mechanism. As a code verification process, they compared the DF values of experiments with the results calculated by the BUSCA [1, 2, 3, 4]. However, depending on the experimental conditions, the BUSCA cannot predict DF value accurately with a large difference. The reason is that the BUSCA not only requires parameters that are difficult to obtain from the experiments but also uses many rule-based algorithms to implement the aerosol removal mechanism. Inevitably, thermal hydrodynamic models used in the BUSCA calculate the DF values with many assumptions which could result in poor predictability.

This study introduces the ANN (Artificial Neural Networks) methodology to predict DF value because the ANN overcomes limitations of strictly defined rule-based algorithms by making data-driven training and prediction. Although there were no thermal hydrodynamic models in the neural network, it was sufficient to provide reliable results. This paper describes the method for constructing ANN structure for predicting DF value based on the experimental data of the pool scrubbing.

2. Artificial Neural Network

The ANN used in this study consists mainly of three layers; the input layer receives the input variable and the hidden layers contain the mathematical model, and the output layer that returns the result (Fig. 1). The input data includes 14 features, e.g., steam volume fraction, inlet orifice gas flow rate, pool height, pool temperature, bubble temperature, orifice diameter, aerosol mass mean diameter, inlet pressure, particle density and so on. Each feature can have a small or large effect on the DF. Therefore, the relative importance of each feature should be investigated in further study.

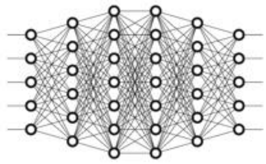

Fig. 1. Typical neural network structure. There are input layer, hidden layers, and output layers. Each layer is composed of interconnected neurons.

Each input feature was standardized by removing the mean and divided by unit variance. This normalization of input data can reduce the calculation errors and time [5].

$$Z_i = \frac{X_i - \bar{X}}{\sigma} \quad (1)$$

where Z_i denotes i-th scaled data of each feature data and $\bar{X}$ is the mean of each feature data, and σ is the standard deviation of each feature data. The neural networks learn through the adaptation of connection weights and bias.

$$H = WZ + b \quad (2)$$

where H is a hypothesis, W is weight vector, Z is a scaled data vector, b is a bias vector. As a neural network learning strategy, Rectified Linear Unit (ReLU), which is the most popular non-linear function, is used as an activation function in 3 hidden layers.

$$F(H) = \begin{cases} (F(H) > 0) & F(H) = H \\ (F(H) \le 0) & F(H) = 0 \end{cases} \quad (3)$$

The ReLU function $F(H)$ returns H when $F(H)$ is greater than zero while it returns zero when H is less than zero. The difference between experimental DF value and calculated value can be reduced by optimizing weight and bias with a gradient descent algorithm.

There are 44 available data set from the four different experiments. In selecting data, 73% of the data set were randomly extracted from each of four experiments, i.e., PECA, LACE-ESPAÑA, ACE, and POSEIDON-II. To avoid overfitting problem, cross-validation procedure was conducted by using the remaining 27% data set as a test data set. The training stopped when the coefficient of determination was no longer improved. As an index of the evaluation for the trained ANN method, Relative Absolute Error (RAE) was used.

3. Result

The study set up and trained the ANN using 73% of pool scrubbing experimental data. The ANN predicted the DF value with the remaining 27% experimental data.

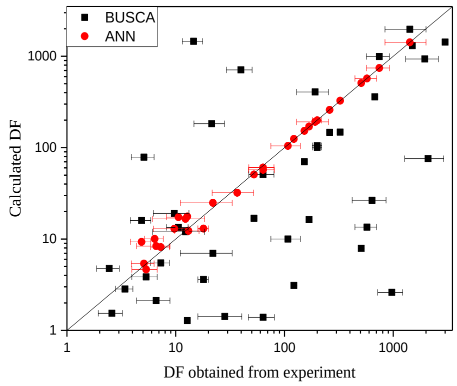

Fig. 2. The DF calculated by ANN, BUSCA, and experiments with the training data set.

Fig. 2 compares the results of ANN and BUSCA with the experimental results. The x and y-axis are represented using a log scale and the x-axis error bar is the experimental error. The RAE for ANN is 32.7% while the BUSCA has 115%. It can be confirmed that the training has been well conducted with the training data set for a wide range of DF from 1 to about 4000.

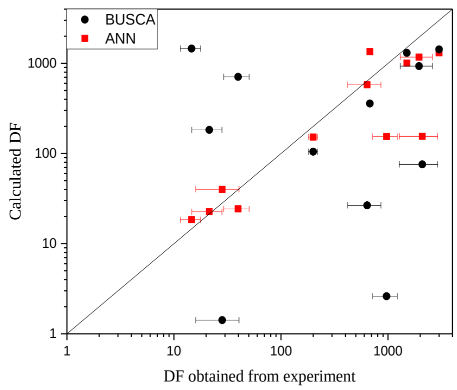

Fig. 3. DF calculated by ANN, BUSCA, and experiments with the test data set.

The ANN calculated DF and RAE with a test data set that the ANN had not encountered during training process. Fig. 3 shows the calculation results from the BUSCA and ANN using the test data set. The ANN has the RAE value of 46% while the RAE of BUSCA is 129%. The reason why there is a huge difference between the BUSCA results and experimental results is that it is difficult to simulate the aerosol removal mechanism. Without the thermal-hydrodynamic theory or equation, the ANN provides more reliable results than the BUSCA in the entire experimental range.

4. Conclusions

In this paper, the construction procedure of ANN was described. The ANN, trained by four different types of experimental data set, calculated a more accurate DF value compared to the BUSCA value in the entire experimental range. In addition to calculating the DF based on a given condition, designing a pool scrubbing system that effectively removes radioactive materials requires an evaluation of the design parameters affecting the DF. Therefore, further study should investigate the interpretable ANN to explain the relation between the main parameters of the pool scrubbing process and the DF.

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