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Thermal Performance Prediction of Heat Pipe with artificial neural network.

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1. Introduction

The interest in passive safety systems for nuclear power plants has increased since severe accidents including the Fukushima accident. Among the proposed concepts of the passive safety system, which include passive containment cooling systems (PCCS), passive auxiliary feedwater systems (PAFS), hybrid safety injection tanks (Hybrid SIT), etc., the application of heat pipe has been paid attention due to the simplicity. The heat pipe is an effective heat removal device using boiling and condensation. The application of heat pipes for heat removal systems and safety systems has increased for nuclear power plants. However, the accurate prediction for thermal performance of heat pipe is required for application to the nuclear power plant, considering that safety is considered the top priority in nuclear power plants. Furthermore, accurate prediction for the thermal performance of heat pipes could reduce the amount of heat pipe applied to nuclear power plants.

However, the prediction of thermal performance for heat pipes is difficult because the thermal performance of heat pipes is affected by various factors. The heat pipes are operated by capillary force that enhances the heat transfer performance with wick structures, compared with thermosyphon. The application of wick structures has been more difficult to interpret for thermal performance prediction of heat pipe before experiment validation. Furthermore, the thermal performance prediction of the heat pipe based on the correlation has been almost impossible since the studies for performance enhancement of the heat pipe with nanoparticles. The performance of heat transfer on heat pipe could be deteriorated or improved based on the type of wick, the geometrical information, operating condition, and the presence of nanoparticles. Therefore, the prediction and evaluation of the heat transfer performance of heat pipes are conducted based on experimental verification, considering chemical and physical conditions. The experimental validation for the heat transfer performance of heat pipes requires a significant cost. Considering all operating conditions, manufacturing for validation of the performance is cost inefficient because heat pipes applied to nuclear power plants have large-scale. Furthermore, accurate prediction of heat pipes could reduce the number of applied heat pipes.

Because the performance of heat pipe is affected by several factors, the interest in the deep learning application has increased with performance enhancement of prediction compared to correlation. The heat transfer performance prediction with ANN has demonstrated outstanding performance. However, the previous prediction was evaluated within the range of training data. Although heat pipe is affected by wick type, geometrical information, etc. the factor used for deep learning application was not considered sufficiently. Furthermore, previous studies were carried out based on the thermosyphon and pulsating heat pipe.

Therefore, this study suggests the heat transfer performance prediction technique for a cylindrical heat pipe with deep learning application, considering the type of wick, geometrical and chemical information. Datasets used for deep learning application were obtained from the literature. Based on the type of wick, geometrical and chemical information, the thermal resistance of a heat pipe was predicted. The prediction result was compared with the experimental validation. The prediction of the heat transfer performance of the heat pipe is considered to contribute to the improvement of nuclear power plant safety and reduce both time and cost before experimental validation.

2. Modeling and Methodology

2.1. Configuration of dataset

The dataset was obtained to enhance the prediction performance of thermal resistance, considering the published literature for training and evaluation depending on the geometrical and chemical information with various operating conditions [1-14]. The range of datasets used for deep learning applications is shown in Table 1

Table I: The range of dataset for this study

Parameter	Range
Heat load (W)	5-600
Resistance (K/W)	0.05325 - 1.35574
Wick type	Thermosyphon, Groove, Screen mesh, Sintered
Nanoparticle	Al_2O_3, CuO, Cu, SiC, TiO
Concentration (%)	0.0005 - 3.0
Inclination angle (°)	0 - 90
Length of evaporation (Le) / Length	0.2-0.45
Length of adiabatic (La) / Length	0.1-0.6
Length of condenser (Lc) / Length	0.2-0.5
Length (m)	0.2 - 1.0

Diameter (mm)	6.35 – 22
Thickness (mm)	0.5 – 2
Pressure (kPa)	0 - 19.97
Filling ratio (%)	30 – 100
Material	Copper, Stainless 316, Carbon steel
Cooling condition (°C)	24 ± 1

Numerous factors should be considered for the enlargement of the prediction range because the thermal resistance of heat pipe significantly depends on the factors. Therefore, the database was carried out based on numerous consideration that includes pressure, filling ratio, thickness, length, diameter, length ratio, material, the concentration of nanoparticle, cooling condition, and type of wicks. Furthermore, interpolation was carried out to increase the amount of dataset about each literature, because each literature represents a small amount of dataset. The total amount of data was 97204. 20% of data were used for evaluation and 80% was classified as a training and validation dataset.

2.2. Configuration of ANN

ANN has been developed based on the nervous system by a generalization of mathematical models. The structure of ANN is composed of three types of layers: input layer, hidden layer, and output layer. In the case of this study, the input layer represents the information of heat pipe and output layer represents the thermal resistance of heat pipe. The weights and biases of ANN are constructed in the hidden layer for the prediction. The function of ANN for weights and biases is shown below

$$y_i = f\left(\sum (x_i \times w_{ij} + bias)\right) \tag{1}$$

The performance of regression has been improved with the development of ANN. This study was carried out based on the optimal deep learning model. The optimal deep learning model was derived with a comparison of ANN architecture and Deep neural network (DNN) architecture, which has several hidden layers. The number of nodes for hidden layers of ANN and DNN was compared for the selection of the optimal model. The architecture of ANN and DNN is shown in Fig.1 with the input layer, hidden layer, and output layer. The batch size for deep learning training was 64 and the activation function for the hidden layer was the rectified linear unit (ReLU) function. The optimization function for deep learning applications was the adaptive momentum estimation (Adam) algorithm with a 0.001 learning rate.

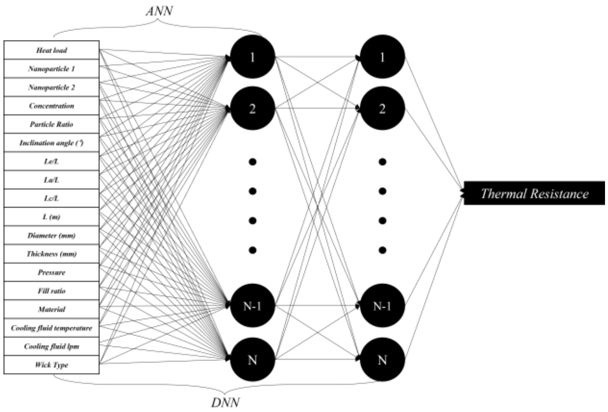

Fig. 1. Architecture of ANN and DNN

The loss of deep learning means the error between the reference value and the output resulting from the deep learning model based on the criterion. The weights and biases are adjusted to optimize the loss, as training proceeds. Therefore, proper application of the loss function is considered critical in the output of the model. The type of loss functions used for deep learning regression is related to the performance evaluation of the regression method. Based on the performance evaluation method for the regression technique, mean absolute error (MAE), mean square error (MSE), mean absolute percentage error (MAPE), percentage error (PE), and coefficient of determination (R2) are used for the performance evaluation of this study. Equations for each performance evaluation are shown in the following:

$$Mean\ Absolute\ Error\ (MAE) = \frac{\sum_{i=1}^{n} |y_i - \hat{y}_i|}{n} \tag{2}$$

$$Mean\ Square\ Error\ (MSE) = \frac{\sum_{i=1}^{n} (y_i - \hat{y}_i)^2}{n} \tag{3}$$

$$Mean\ Absolute\ Percentage\ Error\ (MAPE) = \frac{\sum_{i=1}^{n} \frac{|\hat{y}_i - y_i|}{y_i}}{n} \tag{4}$$

$$Percentage\ Error\ (PE) = \frac{|\hat{y}_i - y_i|}{y_i} \tag{5}$$

$$Coefficient\ of\ determination\ (R^2) = 1 - \frac{\sum_{i=1}^{n} |y_i - \hat{y}_i|^2}{\sum_{i=1}^{n} |y_i - \bar{y}_i|^2} \tag{6}$$

2.3. Experimental setup

The performance of the deep learning model was further investigated with experimental validation. The experimental verification was conducted in out of range for the dataset to confirm the prediction performance of the heat transfer performance for heat pipe. Stainless steel 316 heat pipe with screen mesh, an outer diameter of 1 in (23 mm inner diameter), and a length of 800 mm was prepared. The temperature distribution was acquired from nine K-type thermocouples (TCs) installed on the evaporator, adiabatic, and condenser sections. Fig. 2 represents the TC locations on the heat pipe with screen mesh. The heat pipe was operated with DI water as a working fluid. The pressure of the heat pipe was set to 4.2 kPa to remove non-condensable gases. DI water was injected into the heat pipe with a 50% of fill ratio. The summary of the test condition is shown in Table 2.

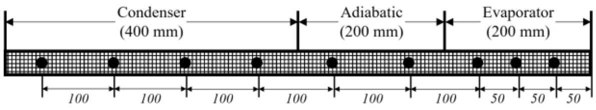

Fig. 2. The location of thermocouples on the heat pipe

Table II: The experimental condition for validation

Parameter	Condition
Heat load (W)	100
Fill ratio (%)	50
Wick type	100-mesh SS screen mesh
Initial pressure [kPa]	4.2
Cooling condition	26 °C, 2.04 lpm
Inclination angle (°)	90
Length ratio (%)	25 : 25 : 50

3. Results and discussions

All performance evaluations of the heat transfer performance prediction model were carried out based on the validation dataset and test dataset, 20% of data, not used for training. The comparison of overall MAE, MSE, MAPE, and coefficient of determination between actual thermal resistance and predicted thermal resistance was carried out to confirm overall prediction performance. The variation of prediction performance in accordance with the number of nodes is shown in Fig. 3. DNN model demonstrated the highest performance for prediction at 256 nodes.

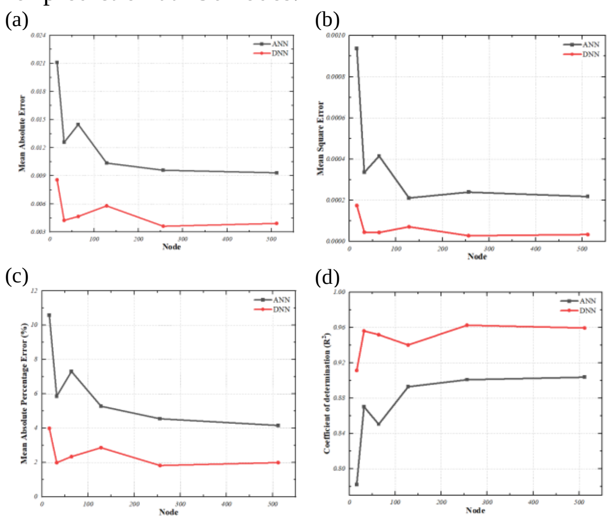

Fig. 3. The variances of errors in accordance with nodes: (a) mean absolute error, (b) mean square error, (c) mean absolute percentage error, and (c) coefficient of determination.

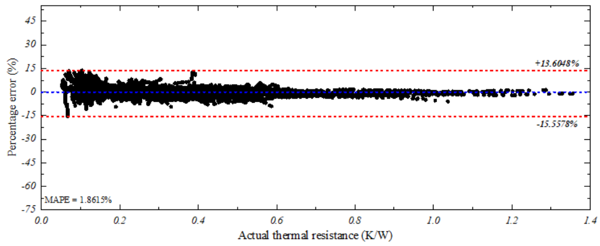

Fig. 4 The PE and MAPE of DNN having 256 nodes.

As shown in Fig. 4, the highest PE was confirmed at a thermal resistance of less than 0.2 K/W for DNN with 256 nodes because the loss function was utilized as MSE. Therefore, the thermal resistance was artificially increased to enhance the prediction performance. The artificial increase for predicted data helps the performance of artificial intelligence converge by manipulating the prediction range. The modified thermal resistance was multiplied by 100 to the actual thermal resistance. The heat transfer performance prediction model was trained by the modified thermal resistance based on the DNN with 256 nodes. As a result, the overall performance of prediction increased. Therefore, this model was used for experimental validation. Fig. 5 represents the PE to the actual thermal resistance with MAPE, MAE, MSE, and the coefficient of determination.

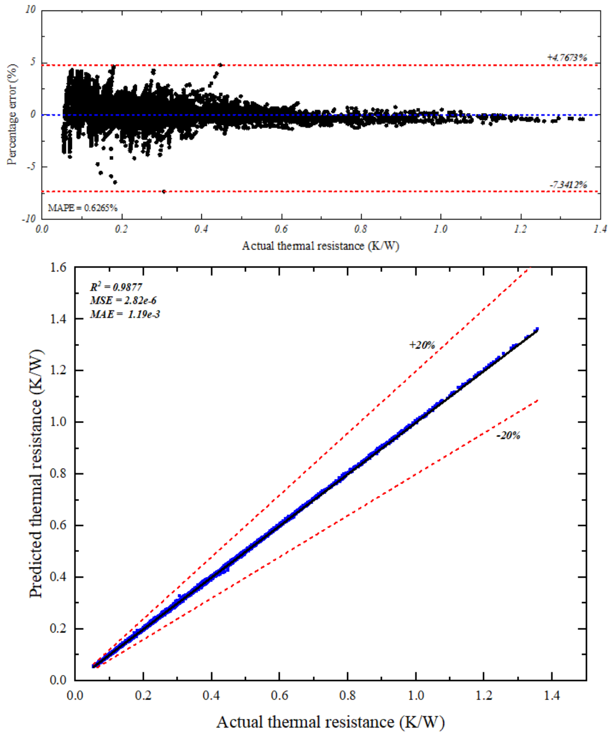

Fig. 5 The MAEs, MSEs, coefficient of determination, and PE actual thermal resistance graph with MAPE.

Table 5 represents the experimental verification results through stainless steel heat pipe with screen mesh at 100W. Considering that the previous literature shows a maximum error of 20% for data within the range, 16.5% is considered appropriate. However, further experimental validation would be required to confirm the prediction performance of the deep learning model.

Table III. Experimental validation

Actual	Prediction	Error
0.3284 K/W	0.3826 K/W	16.5 %

4. Conclusion

Recently the attention to the heat pipe has increased to remove heat for the nuclear power plants. However, the prediction of the heat transfer performance of the heat pipe is considered difficult because the thermal performance of the heat pipe is affected by numerous factors. Furthermore, the prediction of the heat pipe heat transfer has been more difficult with the suggestion of the type of wick type and chemical addition as nanoparticle. Therefore, this study proposes the deep learning-based thermal performance prediction of the heat pipe, considering various operating conditions, and geometrical and chemical information. Database for deep learning application was conducted based on the published literature to enhance the diversity of data. The derivation of the optimal model was conducted with the comparison of ANN and DNN including the number of nodes. Furthermore, the thermal resistance used for training the deep learning model was modified to enhance the prediction performance. As a result, the experimental validation showed a 16.5% of percentage error by the optimal model with modified thermal resistance. However, the experimental validation should be conducted more and the performance Improvement for the prediction of the deep learning model should be considered.

The proposed technique could contribute to reducing the time and cost without experimental validation before application to nuclear power plants with the enhancement of the safety of nuclear power plants. Furthermore, this method would be considered to be utilized in numerous industrial fields as well as nuclear power plants.

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