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HEAT TRANSFER CORRELATION FOR TWO PHASE FLOW IN VERTICAL PIPES USING ARTIFICIAL NEURAL NETWORK

A. J. Ghajar, School of Mechanical and Aerospace Engineering , Oklahoma State University, Stillwater, Oklahoma, 74048, USA. Phone: (405) 744-5900, Email: ghajar@ceat.okstate.edu

L. M. Tam, Department of Electromechanical Engineering, Faculty of Science and Technology, University of Macau, Macau. P. O. Box 3001, Taipa, Macau, China

H. K. Tam, Department of Electromechanical Engineering, Faculty of Science and Technology, University of Macau, Macau. P. O. Box 3001, Taipa, Macau, China

ABSTRACT

In many industrial applications, such as the flow of natural gas and oil in flowlines and wellbores, the knowledge of nonboiling two-phase, two-component (liquid and permanent gas) heat transfer is required. Several heat transfer correlations for forced convective heat transfer during gas-liquid two-phase flow in vertical pipes have been published over the past 40 years. These correlations were developed based on limited experimental data and are only applicable to certain flow patterns and fluid combinations. Kim et al. (2000) proposed a heat transfer correlation for turbulent gas-liquid flow in vertical pipes with different flow patterns and fluid combinations. Their correlation was developed using four sets of experimental data (a total of 255 data points) for vertical pipes. The form of their correlation was based on the major nondimensional parameters affecting two-phase heat transfer. The coefficients of their correlation were found by using the traditional least squares regression. Their correlation predicted the experimental data with a deviation range of -64.71% and 39.55%. Majority of the experimental data (245 data points or 96% of the data) were predicted within the ±30% range. The purpose of this study is to apply the method of artificial neural network (ANN) to develop a more accurate correlation. It has been shown that ANN has excellent capability of handling complicated flows. The same sets of experimental data used by Kim et al. (2000) were used in this study. The ANN method employed in this study was a three-layer feedforward network, which is a high dimensional nonlinear regression. To avoid over or under-fitting, the data were separated into two sets. One set was used for the network training and the other set was used for testing. The new correlation outperforms the traditional least squares correlation and predicts the experimental data within the ±15% range. Since the ANN correlation is like a black box, the knowledge extraction from ANN correlation is also discussed in this study.

INTRODUCTION

Numerous heat transfer correlations for forced convective heat transfer during gas-liquid two-phase flow in vertical and horizontal pipes have been published over the past 40 years. However, these correlations for two-phase flow convective heat transfer were developed based on specific experimental data and are only applicable to certain flow patterns. Based on the tabulated and graphical results of the comparisons between the 20 correlations identified in Kim et al. (1999a, 1999b) and the experimental data available, appropriate correlations for different fluid combinations, flow patterns, and tube orientations were recommended by Kim et al. (1999a). Moreover, no single correlation, which is capable of predicting heat transfer for different fluid combinations, flow patterns, and tube orientations, was found in the literature. Hence, Kim et al. (2000) developed a two-phase correlation for turbulent flow (Re_{SL} > 4000) in vertical pipes. The correlation was curve fitted using four fluid combinations (water-air, silicone-air, water-helium, and water-freon 12) in vertical pipes. The four sets of experimental data (a total of 255 data points) were obtained from the three available experimental studies of Aggour (1978), Vijay (1978), and Rezkallah (1986). Using the new correlation for the four data sets, the range of deviation is between -64.71% and 39.55%. The mean deviation for the correlation is 2.54% and the majority of the experimental data (245 data points or 96% of the data) were predicted within the ±30% range. Since the traditional least-squares method did not provide the desired accuracy for all the data points with different fluid combinations, an alternative method is sought. Some recent studies, such as the works done by Ghajar et al. (2002) and Pacheco-Vega et al. (2001) have shown that artificial neural network (ANN) can handle complicated flow phenomena such as mixed convective heat transfer in the transition region and two-phase flow heat transfer in heat exchangers. Therefore, ANN will be used in this study to develop a matrix form correlation using the same data sets from Kim et al. (2000).

NOMENCLATURE

A= cross-sectional area
c_p = specific heat at constant pressure
D = inside diameter of the tube
h = heat transfer coefficient
k = thermal conductivity
$\dot{m}$ = mass-flow rate
M= total number of data points
M_a= number of data points used for training
M_b= number of data points used for testing
Pr = Prandtl number, $\mu c_p/k$
Q = volumetric flow rate
Re = Reynolds number, $\rho VD/\mu_B$
Re_{SL}= superficial Reynolds number, $\rho V_{SL} D/(\mu_B)_L$
V = average velocity in the test section
V_{SL} = superficial gas velocity, $Q_L/(A_G + A_L)$
x = flow quality, $\dot{m}_G/(\dot{m}_G + \dot{m}_L)$
α = void fraction, $A_G/(A_G+A_L)$
ρ = density
μ = absolute or dynamic viscosity

Subscripts
B = bulk
CAL = calculated
EXP = experimental
G = gas
L = liquid
SL = superficial liquid
TP = two phase
W = wall

DEVELOPMENT OF CORRELATION

For the traditional regression, a correlation form (prior knowledge) should be defined by the empirical or semi-empirical methods. For the two-phase flow, some of these forms were derived empirically based on experimental data; others were based on concepts such as the liquid acceleration model, the pressure drop model, and the separated flow model. Kim et al. (1999b) have presented descriptions of these concepts and identified the correlations that were developed based on each concept. In Kim et al. (2000), the total gas-liquid two-phase heat transfer is assumed to be the sum of the individual single-phase heat transfers of the gas and liquid, weighted by the volume of each phase. And the Sieder and Tate (1936) equation was chosen as the fundamental single-phase heat transfer correlation because of its practical simplicity and proven applicability. Assuming that two-phase heat transfer coefficient can be expressed using a power-law relationship on the individual parameters. The correlation form can be expressed as

$$h_{TP} = (1-\alpha)h_L[1 + C(\frac{x}{1-x})^m (\frac{\alpha}{1-\alpha})^n (\frac{Pr_G}{Pr_L})^p (\frac{\mu_G}{\mu_L})^q] \qquad (1)$$

where h_L comes from the sub-correlation (Sieder and Tate, 1936):

$$h_L = 0.027 Re_{SL}^{0.8} Pr_L^{0.33} (\frac{k_L}{D})(\frac{\mu_B}{\mu_W})^{0.14} \qquad (2)$$

After the determination of the correlation form, Kim et al. (2000) developed the correlation coefficients based on the four different cases (fluid combinations) using the traditional least-squares method. The leading coefficient (C) and exponents (m, n, p, q) are summarized in Table 1. This table also lists the appropriate coefficients to be used in Equation (1) if the correlation was curve-fitted to each of the four different fluid combination experimental data sets.

Table 1 Constants for Equation (1)

Fluid Combinations	C	m	n	p	q
All of the data points (255 data points)	0.27	-0.04	1.21	0.66	-0.72
Water-air (105 data points)	16.69	-0.32	1.65	1.23	0.40
Silicone-air (56 data points)	2.19	0.40	0.21	0.87	-0.96
Water-helium (50 data points)	61.16	-0.29	1.58	0.24	1.47
Water-freon12 (44 data points)	599.9	-0.30	1.64	5.27	-0.85

The ranges of the independent variables used in Equation (1) are shown in Table 2.

Table 2 Parametric Ranges for Equation (1)

Fluid Combinations	$\frac{x}{1-x}$	$\frac{\alpha}{1-\alpha}$	$\frac{Pr_G}{Pr_L}$	$\frac{\mu_G}{\mu_L}$	Re_{SL}
All of the Data points	8.4×10^{-6} ~ 0.77	0.01 ~ 18.61	1.18×10^{-3} ~ 0.14	3.64×10^{-3} ~ 0.023	4000 ~ 1.26×10^5
Water-air Vijay (1978)	4.7×10^{-5} ~ 0.36	0.03 ~ 17.03	0.10 ~ 0.13	0.016 ~ 0.022	4000 ~ 1.26×10^5
Silicone-air Rezcallah (1986)	1.8×10^{-5} ~ 0.014	0.01 ~ 2.13	1.18×10^{-3} ~ 0.01	3.64×10^{-3} ~ 4×10^{-3}	8350 ~ 0.21×10^5
Water-helium Aggour (1978)	8.4×10^{-6} ~ 0.071	0.04 ~ 18.61	0.10 ~ 0.12	0.02 ~ 0.023	4010 ~ 1.26×10^5
Water-freon12 Aggour (1978)	2.3×10^{-4} ~ 0.77	0.036 ~ 14.15	0.12 ~ 0.14	0.011 ~ 0.013	4190 ~ 0.55×10^5

The reported experimental uncertainties of the two-phase heat transfer coefficients used in this study are ±4 to16% for Aggour

(1978) water-helium and water-freon 12 data points, ±4.5 to 14% for Vijay (1978) water-air data points, and ±6.9 to 21.1% for Rezkallah (1986) silicone-air data points.

Equation (1) is applicable to the two-phase flow in turbulent region (Re_{SL} > 4000) in vertical pipes and should be used with an appropriate set of constants for each fluid combination. Figure 1 shows how well the general correlation predicted the four different sets of gas-liquid experimental data. About 83% of the data (212 data points) were predicted with less than ±15% deviation, and about 96% of the data (245 data points) were predicted with less than ±30% deviation. Table 3 shows the prediction results of the general correlation and the fluid-dependent correlations. Even when specific coefficient and exponents are developed according to different fluid combinations, the accuracy in most cases (except for the silicone-air case) is still not significantly improved. From a practical point of view, a single correlation applicable to all fluid combinations with good accuracy would be very desirable. Because of that, a single matrix correlation is developed based on ANN.

Table 3 Prediction Results for Equation (1)

Fluid Combinations	Number of Data within ±30%	Range of Dev. (%) Mean Dev. (%)
All of the Data points (255 data points)	245	-64.71 and 39.55 2.54
Water-air (105 data points)	105	-18.25 and 27.0 3.22
Silicone-air (56 data points)	56	-5.37 and 10.34 0.55
Water-helium (50 data points)	49	-28.05 and 34.92 3.03
Water-freon12 (44 data points)	44	-25.04 and 28.42 1.67

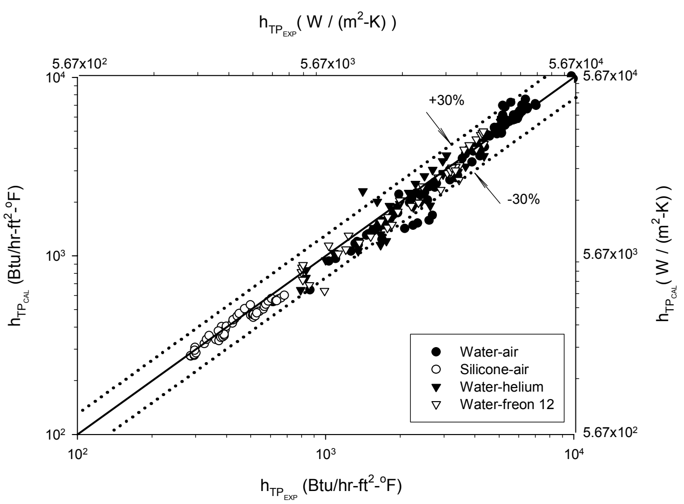

Figure 1 Comparison of the new correlation [Equation (1)] with all of the two-phase heat transfer experimental data (255 data points).

First of all, the architecture of the ANN should be defined. The ANN employed in this study is called a three-layer feedforward neural network with fully weighted connection. Its typical graphical representation is shown in Figure 2. In the input layer, the independent variables $p_1, p_2, \ldots, p_R$ are taken and the s^{th} net input, which is defined as:

$$s^{th} \text{ net input} = \sum_{r=1}^{R} w^1_{sr} p_r + b^1_s$$

is fed to the s^{th} neuron of the hidden layer where s=1,2,..,S Then the neuron converts the net input to a neuron output by utilizing a log-sigmoid transfer function $f(s) = [1+\exp(-s)]^{-1}$. In the output layer, the s^{th} neuron output is weighted by w^2_{1s}. Finally the unique neuron in the output layer sums all the weighted neuron outputs from the hidden layer and the bias b^2_1 and transforms this sum linearly to produce a number, which is the output. This type of ANN can be used as a high dimensional nonlinear regression. Precisely, Hornik (1991) has shown that a smooth function defined on any closed and bounded domain of R^n can be smoothly approximated by the type of neural network within a given error bound if we are allowed to increase the number of hidden neurons of the network. Practically, the number of hidden neurons is fixed and using a supervised learning algorithm called backpropagation identifies the other parameters. Basically, backpropagation proposed by Rumelhart et al. (1986) is an algorithm to find the gradient of the square sums of the difference between the network output and the corresponding experimental reading. So the optimum values of parameters w and b can be reached by using a classical gradient based method like the steepest descent method. In fact, the steepest descent gradient method is very slow and causes the convergence to stick in a shallow local minimum. Because there are not many free parameters used in the network, a faster gradient method, Levenberg-Marquardt, explained in Hagan and Menhaj (1994) is used in this study. Matlab (R.12.1) is used to implement the three-layer feedforward neural network.

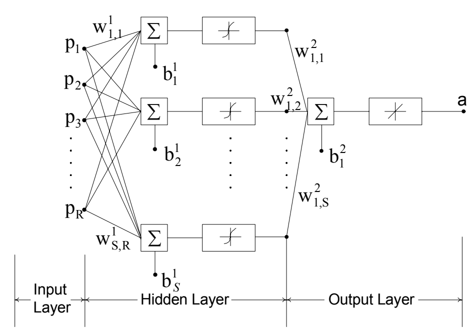

Figure 2 A three-layer network with s neurons in its hidden layer.

After the selection of the gradient method, the number of input variables and neurons are still needed to be determined. The independent variables for the new ANN correlation are based on the work by Kim et al. (2000) with some modifications. The terms α and x will directly be used as the input variables. The number of neurons is determined experimentally. According to the comparison of the absolute deviation among the neurons, eight hidden neurons are used and the initial value of the free parameters (weights and bias) is randomly chosen within ±1. After the backpropagation has been completed and the post-processing of the network output has been performed, the resulted neural network, which is the proposed new correlation, is given in a simple matrix form. The proposed new correlation is as follows.

$$h_{TP} = u^3\{(u^2)^T f(u^1\Phi + v^1) + v^2\} + v^3 \tag{3}$$

where

$$f(s) = [1+\exp(-s)]^{-1} \tag{4}$$

The entries of the vector Φ represent the normalized flow quality, void fraction, Prandtl number ratio, two kinds of μ ratio, and Reynolds number corresponding to superficial liquid, respectively.

$$\Phi = \begin{bmatrix} x_{normal} \\ \alpha_{normal} \\ \left(\dfrac{Pr_G}{Pr_L}\right)_{normal} \\ \left(\dfrac{\mu_G}{\mu_L}\right)_{normal} \\ \left(\dfrac{\mu_B}{\mu_W}\right)_{normal} \\ Re_{SL\,normal} \end{bmatrix} = \begin{bmatrix} 2\cdot[x - x_{min}]/[x_{max} - x_{min}] - 1 \\ 2\cdot[\alpha - \alpha_{min}]/[\alpha_{max} - \alpha_{min}] - 1 \\ 2\cdot\left[\left(\dfrac{Pr_G}{Pr_L}\right) - \left(\dfrac{Pr_G}{Pr_L}\right)_{min}\right] \Big/ \left[\left(\dfrac{Pr_G}{Pr_L}\right)_{max} - \left(\dfrac{Pr_G}{Pr_L}\right)_{min}\right] - 1 \\ 2\cdot\left[\left(\dfrac{\mu_G}{\mu_L}\right) - \left(\dfrac{\mu_G}{\mu_L}\right)_{min}\right] \Big/ \left[\left(\dfrac{\mu_G}{\mu_L}\right)_{max} - \left(\dfrac{\mu_G}{\mu_L}\right)_{min}\right] - 1 \\ 2\cdot\left[\left(\dfrac{\mu_B}{\mu_W}\right) - \left(\dfrac{\mu_B}{\mu_W}\right)_{min}\right] \Big/ \left[\left(\dfrac{\mu_B}{\mu_W}\right)_{max} - \left(\dfrac{\mu_B}{\mu_W}\right)_{min}\right] - 1 \\ 2\cdot[Re_{SL} - Re_{SL\,min}]/[Re_{SL\,max} - Re_{SL\,min}] - 1 \end{bmatrix}$$

The u^1, u^2, u^3, v^1, v^2, v^3 terms used in Equation (3) are constant matrices or scalars. Their numerical values are shown in the following matrices.

$$u^1 = \begin{bmatrix} 0.16 & -1.15 & 1.66 & 1.59 & 2.61 & 3.03 \\ -0.07 & 0.86 & -1.64 & -1.34 & -2.55 & -3.43 \\ -0.97 & 0.37 & -1.54 & 0.51 & -6.39 & 1.48 \\ -1.88 & 5.35 & -5.67 & -3.14 & 0.65 & 3.23 \\ 1.15 & -0.44 & 1.59 & -0.67 & 7.19 & -1.95 \\ 0.16 & 2.35 & 1.50 & 0.06 & 0.52 & 3.09 \\ 12.96 & 22.65 & -13.20 & 17.92 & 32.22 & 1.60 \\ 5.83 & 2.19 & 4.61 & 1.02 & -2.52 & 0.80 \end{bmatrix}, \quad u^2 = \begin{bmatrix} -14.17 \\ -15.15 \\ 6.91 \\ -0.77 \\ 5.47 \\ 2.29 \\ 0.12 \\ -0.94 \end{bmatrix}, \quad u^3 = 3378.15$$

$$v^1 = \begin{bmatrix} 0.50 \\ -0.93 \\ 3.50 \\ 4.71 \\ -4.03 \\ -0.36 \\ -6.63 \\ 3.64 \end{bmatrix}, \quad v^2 = 9.06, \quad v^3 = 286$$

For reliability purposes, ninety percent of the total of 255 data points were used for training and all the data were tested. As shown in Figure 3 and Table 4, M_a represents the training data (90% of the total data) and M_b represents test data (10% of the total data) for testing and verification. The training and testing data were selected randomly. However, the extreme values for each fluid combination (such as the maximum and minimum points) were definitely selected as the training data. In this study, the random selection of the training and testing data were done in order to generate the coefficient matrices. Even if the same training data set is used to establish the network, the parameters, i.e., the constant matrices will be different if different initial weight and bias are used. The parameters in this study are from the network which gives the minimal absolute average deviation when predicting not only the training data but also the test data. Table 4 shows that all the experimental data is predicted within -13.68% to +14.54%. The absolute deviation of all the predictions is 2.99% and the majority, eighty two percent of all the data (209 data points), is predicted with less than ±5% deviation. About fourteen percent of all the data (36 data points) is predicted within ±5 to ±10% deviation, and only four percent of all the data (10 data points) is predicted within ±10 to ±15% deviation. The prediction of water-freon12 data points has the most accuracy, i.e. all the data points are predicted within ±10% deviation. As compared to the previous correlation, significant improvement is observed. Table 4 also provides information on how the proposed correlation predicted the results of the individual fluid combination test data.

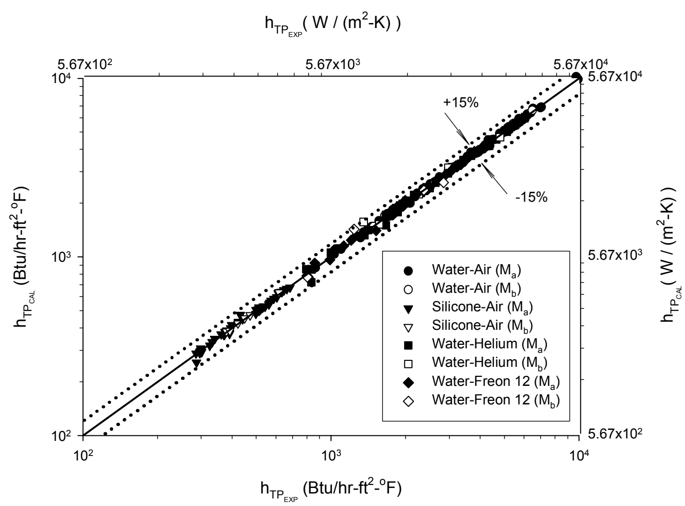

Figure 3 Comparison of the correlation using ANN with all of the two-phase heat transfer experimental data (255 data points).

In general, ANN is treated as a black box in many applications. Although the ANN correlation is a simple matrix form, the knowledge (e.g. input-output relationship) is difficult to be observed from the form. Because of this reason, the extraction of physical meaning (knowledge) from the ANN is an attractive and useful topic. For example, in this study, the heat transfer coefficient for the two-phase vertical pipe flow is correlated by using the ANN. However, the relation between the dependent output and various independent variables cannot be seen in the network. Numerous efforts for knowledge extraction from ANN were suggested and published in the open literature in the last decades. Moreover, some studies (e.g. Tickle et al., 1998) also proposed some taxonomies for categorizing the numerous contributions in the field of knowledge extraction from ANN.

Table 4 Accuracy of the Proposed Correlation

	Range of Dev.	Abs. Dev.	Less than ±5% Dev.	Between ±5% and ±10% Dev.	Between ±10% and ±15% Dev.
All of the data, M = 255 pts, M_a = 230 pts, M_b = 25 pts					
M	-13.68% ~ 14.54%	2.99%	209 pts	36 pts	10 pts
M_a	-13.68% ~ 12.39%	2.89%	190 pts	32 pts	8 pts
M_b	-7.44% ~ 14.54%	3.90%	19 pts	4 pts	2 pts
Water-air, M = 105 pts, M_a = 95 pts, M_b = 10 pts					
M	-13.66% ~ 7.79%	1.98%	100 pts	4 pts	1 pts
M_a	-13.66% ~ 7.79%	1.96%	91 pts	3 pts	1 pts
M_b	-6.22% ~ 2.66%	2.20%	9 pts	1 pts	0 pts
Silicone-air, M = 56 pts, M_a = 50 pts, M_b = 6 pts					
M	-13.68% ~ 14.21%	4.67%	35 pts	15 pts	6 pts
M_a	-13.68% ~ 12.39%	4.53%	32 pts	13 pts	5 pts
M_b	-6.64% ~ 14.21%	5.87%	3 pts	2 pts	1 pts
Water-helium, M = 50 pts, M_a = 45 pts, M_b = 5 pts					
M	-10.15% ~ 14.54%	3.66%	37 pts	10 pts	3 pts
M_a	-10.15% ~ 10.89%	3.33%	34 pts	9 pts	2 pts
M_b	-7.44% ~ 14.54%	5.61%	3 pts	1 pts	1 pts
Water-freon 12, M = 44 pts, M_a = 44 pts, M_b = 4 pts					
M	-8.82% ~ 6.32%	2.53%	37 pts	7 pts	0 pts
M_a	-8.82% ~ 6.32%	2.60%	33 pts	7 pts.	0 pts
M_b	-3.77% ~ 0.17%	1.83%	4 pts	0 pts	0 pts

Different extraction methods might be categorized and applicable to the different problems or different types of ANN. One approach is to change the expression form of ANN. For example, Saito and Nakano (1997) discovered a new expression of the correlation form. The weights are expressed as the exponents of the input variables so the relation of the input variables to the output can be observed clearly after training. Another approach is to break down a network into a set of comprehensive rules. For example, Benitez et al. (1997) and Castro et al. (2002) suggested a fuzzy rule based system to setup a set of fuzzy rules to represent the confused ANN form. The fuzzy form is in the IF-THEN rule format. In fact, the fuzzy rule based system is suitable for extracting knowledge from ANN because it is a post processing method and there is no need to concern the training algorithm. The concept is that the activation function in ANN is treated as the membership function in fuzzy logic. Each fuzzy rule is developed according to each hidden neuron. Through the calculation, the generated IF-THEN rules can give clear information regarding how to generate the desired output based on the independent variables. The fuzzy rule based method may give us a direction to extract knowledge in this complicated two-phase flow case since this method may allow us to observe how Pr, Re, flow quality and void fraction, etc. contribute to the heat transfer coefficient based on the IF-THEN rule. Moreover, the input variable, which makes the most or least contribution, may also be observed. Based on the above discussions, it is definitely worthy to conduct an in-depth study to see whether the fuzzy rule based method can extract more information from the ANN correlation.

CONCLUSIONS

In this study, a single ANN correlation for turbulent gas-liquid two-phase flow in vertical pipes with four different fluid combinations is developed. The results based on the new correlation are compared with the correlations developed by Kim et al. (2000). It is observed that the accuracy of the ANN correlation outperforms not only the general correlation for all fluid combinations but also the individual correlations based on different flow combinations. Majority of the data (80%) are predicted with less than ±5% deviation and 96% of the data were predicted with less than ±10% deviation. It is again proven that ANN can be used to correlate complicated flow situations. A direction for knowledge extraction is discussed and more in-depth study should be conducted to discover more useful functions in ANN for solving complex problems.

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