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Heat Transfer Correlation for Two-Phase Flow in Vertical Pipes Using Support Vector Machines

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It has been shown by Tam and his coworkers [7] that the support vector machines (SVM) have excellent capability of handling complicated single-phase heat transfer problems. Therefore, it would be logical to extend the investigation to other flow situations, such as two-phase flow or flow in microtubes. In this study, SVM is used to correlate the two-phase, two-component flow data. Four sets of experimental data (a total of 255 data points) for vertical pipes used in this study were from Kim et al. [3]. They proposed a heat transfer correlation for turbulent gas–liquid flow in vertical pipes with different flow patterns and fluid combinations. Their correlation predicted the experimental data with a deviation range of –64.7% and 39.6%. Majority of the experimental data (245 data points or 96% of the data) were predicted within the ±30% range. A new correlation using SVM is developed in this study. The new correlation outperforms the traditional least-squares correlation and predicts the experimental data within the ±15% range.

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 50 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. [1, 2] and the experimental data available, appropriate correlations for different fluid combinations, flow patterns, and tube orientations were recommended by Kim et al. [1]. Moreover, no single correlation that is capable of predicting heat transfer for different fluid combinations, flow patterns, and tube orientations was found in the literature. Hence, Kim et al. [3] developed a two-phase correlation for turbulent flow ($Re_{SL} > 4000$) in vertical pipes. The correlation was curve fitted using four fluid combinations

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(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 [4], Vijay [5], and Rezkallah [6]. Using the new correlation for the four data sets, the range of deviation is between –64.7% and 39.6%. The mean deviation for the correlation is 2.5% 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. The recent studies, such as the works done by Tam et al. [7] have shown that the support vector machines (SVM) can handle complicated flow phenomena such as mixed convective heat transfer in the transition region and the single-phase flow heat transfer in heat exchangers. Therefore, SVM are used in this study to develop a new correlation using the same data sets from Kim et al. [3].

DEVELOPMENT OF CORRELATION

For the traditional regression, a correlation form (prior knowledge) should be defined by the empirical or semi-empirical methods. For 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. [2] have presented descriptions of these concepts and identified the correlations that were developed based on each concept. In Kim et al. [3], the total gas–liquid two-phase heat transfer was assumed to be the sum of the individual single-phase heat transfers of the gas and liquid, weighted by the volume of each phase. In their analysis, they chose the Sieder and Tate [8] equation 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 was expressed as

$$h_{TP} = (1-\alpha)h_L\left[1 + C\left(\frac{\varphi}{1-\varphi}\right)^m\left(\frac{\alpha}{1-\alpha}\right)^n\left(\frac{Pr_G}{Pr_L}\right)^P\left(\frac{\mu_G}{\mu_L}\right)^q\right] \quad (1)$$

where h_L comes from the sub-correlation [8]:

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

After the determination of the correlation form, Kim et al. [3] 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 Eq. (1) if the correlation was curve-fitted to each of the four different fluid combination experimental data sets. The ranges of the independent variables used in Eq. (1) are shown in Table 2.

The reported experimental uncertainties of the two-phase heat transfer coefficients used in their study were ±4 to16% for Aggour [4] water–helium and water–Freon 12 data points, ±4.5 to 14% for Vijay [5] water–air data points, and ±6.9 to 21.1% for Rezkallah [6] silicone–air data points. Equation (1) is applicable to the two-phase flow in a 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–iquid experimental data. About 83% of the data (212
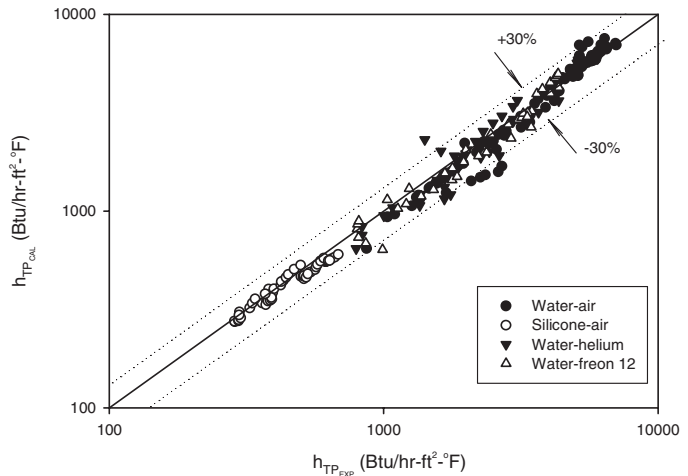
Figure 1 Comparison of Eq. (1) with all of the two-phase heat transfer experimental data (255 data points).

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 were 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 new correlation is developed based on the SVM.

The SVM method was first developed for pattern recognition based on the statistical learning theory [9]. The method was later on used for regression estimation when Vapnik [9] devised the so-called ε-insensitive loss function,

$$|y - f(\mathbf{x})|_\varepsilon = \max\{0, |y - f(\mathbf{x})| - \varepsilon\}, \quad (3)$$

which does not penalize errors below some $\varepsilon \geq 0$, chosen a priori. According to Schölkopf and Smola [10], the algorithm was called ε-SVR and seeks to estimate linear functions,

$$f(\mathbf{x}) = \langle \mathbf{w}, \mathbf{x} \rangle + b, \quad \mathbf{w}, \mathbf{x} \in \mathbf{R}^N, b \in \mathbf{R}, \quad (4)$$

where $<\mathbf{w}, \mathbf{x}>$ is the dot product in Euclidean space and the function is based on independent and identically distributed data,

$$(\mathbf{x}_1, y_1), \ldots, (\mathbf{x}_l, y_l) \in \mathbf{R}^N \times \mathbf{R}. \quad (5)$$

where $\mathbf{R}^N$ is the dot product of the space in which the (mapped) input patterns live (i.e., the feature space induced by a kernel). The goal of the learning process is to find a function f with a small risk (or test error). It was tried to get the small risk by minimizing the regularized risk functional,

$$\frac{1}{2}\|\mathbf{w}\|^2 + C \cdot R_{emp}^\varepsilon[f]. \quad (6)$$

Table 1 Constants for Eq. (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) [5]	16.69	−0.32	1.65	1.23	0.40
Silicone–air (56 data points) [6]	2.19	0.40	0.21	0.87	−0.96
Water–helium (50 data points) [4]	61.16	−0.29	1.58	0.24	1.47
Water–Freon 12 (44 data points) [4]	599.9	−0.30	1.64	5.27	−0.85

Table 2 Parametric ranges for Eq. (1)

Fluid combinations	$\frac{x}{1-x}$	$\frac{\varphi}{1-\varphi}$	$\frac{Pr_G}{Pr_L}$	$\frac{\mu_G}{\mu_L}$	Re_{SL}
All of the data points	$8.4 \times 10^{-6} - 0.77$	$0.01 - 18.61$	$1.18 \times 10^{-3} - 0.14$	$3.64 \times 10^{-3} - 0.023$	$4000 - 1.26 \times 10^5$
Water–air, Vijay [5]	$4.7 \times 10^{-5} - 0.36$	$0.03 - 17.03$	$0.10 - 0.13$	$0.016 - 0.022$	$4000 - 1.26 \times 10^5$
Silicone–air, Rezcallah [6]	$1.8 \times 10^{-5} - 0.014$	$0.01 - 2.13$	$1.18 \times 10^{-3} - 0.01$	$3.64 \times 10^{-3} - 4x10^{-3}$	$8350 - 0.21 \times 10^5$
Water–helium, Aggour [4]	$8.4 \times 10^{-6} - 0.071$	$0.04 - 18.61$	$0.10 - 0.12$	$0.02 - 0.023$	$4010 - 1.26 \times 10^5$
Water–Freon 12, Aggour [4]	$2.3 \times 10^{-4} - 0.77$	$0.036 - 14.15$	$0.12 - 0.14$	$0.011 - 0.013$	$4190 - 0.55 \times 10^5$

where $\|\mathbf{w}\|^2$ is a term that characterizes the model complexity,

$$R_{emp}^{\varepsilon}[f] := \frac{1}{m} \sum_{i=1}^{m} |y_i - f(\mathbf{x}_i)|_{\varepsilon}, \qquad (7)$$

which is the measure of the ε-insensitive training error, and C is a constant determining the trade-off. Minimizing Eq. (6) captures the main insight of statistical learning theory, stating that in order to obtain a small risk, the training error and model complexity need to be controlled. As shown in Figure 2, the minimization of Eq. (6) is equivalent to the following constrained optimization problem:

$$\underset{w \in \mathbf{R}^N, \xi^{(*)} \in \mathbf{R}^m, b \in \mathbf{R}}{\text{minimize}} \tau(w, \xi^{(*)}) = \frac{1}{2} \|\mathbf{w}\|^2 + C\frac{1}{m} \sum_{i=1}^{m} (\xi_i + \xi_i^*), \quad (8)$$

$$\text{subject to } (\langle \mathbf{w}, \mathbf{x}_i \rangle + b) - y_i \leq \varepsilon + \xi_i \qquad (9)$$

$$y_i - (\langle \mathbf{w}, \mathbf{x}_i \rangle + b) \leq \varepsilon + \xi_i^* \qquad (10)$$

$$\xi_i^{(*)} \geq 0. \qquad (11)$$

where i = 1, ..., m, and the boldface Greek letter ξ denotes m-dimensional vectors of the corresponding variable; (*) is a shorthand notation implying the variables both with and without asterisks, ξ_i, ξ_i^*.

In Eqs. (9) and (10), the value of the parameter ε is used to adjust the desired level of accuracy of the approximation. It has to be determined prior to the training. Sometimes the desired level of accuracy is not indicated a priori and the function approximation is required to be as accurate as possible. Thus, the

Table 3 Prediction results for Eq. (1)

Fluid combinations	Number of data points within ±30%	Range of deviation (%), mean deviation (%)
All of the data points (255 data points)	245	−64.71 and 39.55, 2.54
Water–air (105 data points) [5]	105	−18.25 and 27.0, 3.22
Silicone–air (56 data points) [6]	56	−5.37 and 10.34, 0.55
Water–helium (50 data points) [4]	49	−28.05 and 34.92, 3.03
Water–Freon 12 (44 data points) [4]	44	−25.04 and 28.42, 1.67

υ-SVR algorithm (proposed by Schölkopf et al. [11]), which is a modification of the ε-SVR, is suggested to be used. The algorithm can compute the parameter ε automatically to a minimum level. In this study, the υ-SVR algorithm is used instead of Eq. (8). The functional form of the υ-SVR algorithm is shown here:

$$\underset{w \in \mathbf{R}^N, \xi^{(*)} \in \mathbf{R}^m, \varepsilon, b \in \mathbf{R}}{\text{minimize}} \tau(\mathbf{w}, \xi^{(*)}, \varepsilon)$$

$$= \frac{1}{2} \|\mathbf{w}\|^2 + C \cdot \left(\upsilon\varepsilon + \frac{1}{m} \sum_{i=1}^{m} (\xi_i + \xi_i^*) \right), \quad (12)$$

$$\text{subject to } (\langle \mathbf{w}, \mathbf{x}_i \rangle + b) - y_i \leq \varepsilon + \xi_i \qquad (13)$$

$$y_i - (\langle \mathbf{w}, \mathbf{x}_i \rangle + b) \leq \varepsilon + \xi_i^* \qquad (14)$$

$$\xi_i^{(*)} \geq 0, \varepsilon \geq 0 \qquad (15)$$

Then, the preceding problem can be solved by the convex optimization method [12]. By solving the primal–dual problems, the functional form of Eq. (4) for regression can be written as:

$$f(x) = \sum_{i=1}^{m} (\alpha_i^* - \alpha_i)k(x_i, x) + b, \qquad (16)$$

where $k(x_i, x)$ is the kernel that transforms the low-dimensional nonlinear input data space into the high-dimensional linear feature space through a nonlinear mapping. Hence, Eq. (16) is capable of handling nonlinear problems.

Based on Eq. (16) with Gaussian kernel function used, the functional form of the SVM-based correlation form can be written as

$$h_{TP}(\mathbf{x}) = \sum_{i=1}^{l} (\alpha_i^* - \alpha_i) \exp(-\gamma \|\mathbf{x}_i - \mathbf{x}\|^2) + b, \qquad (17)$$

where h_{TP} is the two-phase heat transfer coefficient, l is the number of sample points, γ is the kernel parameter defined a priori, $\alpha_i, \alpha_i^{(*)}$ are the constant coefficients, b is the bias, and $\mathbf{x}_i$ are the support vectors. The entries of the vector $\mathbf{x}$ represent the normalized flow quality, void fraction, Prandtl number at gas phase, Prandtl number at liquid phase, two kinds of μ ratio, and Reynolds number corresponding to superficial liquid,
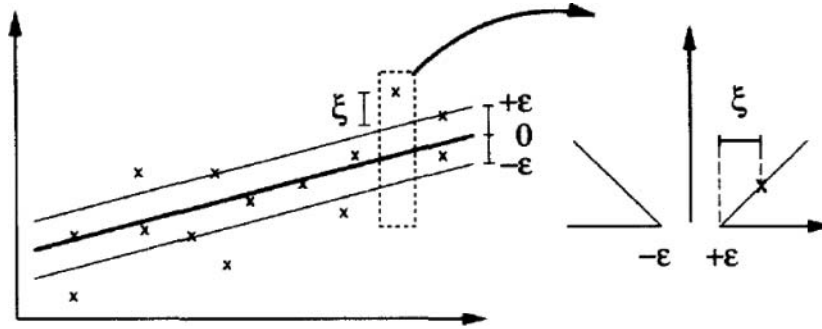
Figure 2 Schematic diagram represents the constrained optimization problem, Eqs. (8)–(11). Taken from Schölkopf et al. [11].

respectively.

$$\mathbf{x} = \begin{bmatrix} \varphi_{normal} \\ \alpha_{normal} \\ \mathrm{Pr}_{G,normal} \\ \mathrm{Pr}_{L,normal} \\ \left(\frac{\mu_G}{\mu_L}\right)^{0.14}_{normal} \\ \left(\frac{\mu_B}{\mu_W}\right)^{0.14}_{normal} \\ \mathrm{Re}_{SL,normal} \end{bmatrix}$$

$$= \begin{bmatrix} 2(\varphi - \varphi_{min})/(\varphi_{max} - \varphi_{min}) - 1 \\ 2(\alpha - \alpha_{min})/(\alpha_{max} - \alpha_{min}) - 1 \\ 2(\mathrm{Pr}_G - \mathrm{Pr}_{G,min})/(\mathrm{Pr}_{G,max} - \mathrm{Pr}_{G,min}) - 1 \\ 2(\mathrm{Pr}_L - \mathrm{Pr}_{L,min})/(\mathrm{Pr}_{L,max} - \mathrm{Pr}_{L,min}) - 1 \\ 2\left[\left(\frac{\mu_G}{\mu_L}\right)^{0.14} - \left(\frac{\mu_G}{\mu_L}\right)^{0.14}_{min}\right] \Big/ \left[\left(\frac{\mu_G}{\mu_L}\right)^{0.14}_{max} - \left(\frac{\mu_G}{\mu_L}\right)^{0.14}_{min}\right] - 1 \\ 2\left[\left(\frac{\mu_B}{\mu_W}\right)^{0.14} - \left(\frac{\mu_B}{\mu_W}\right)^{0.14}_{min}\right] \Big/ \left[\left(\frac{\mu_B}{\mu_W}\right)^{0.14}_{max} - \left(\frac{\mu_B}{\mu_W}\right)^{0.14}_{min}\right] - 1 \\ 2(\mathrm{Re}_{SL} - \mathrm{Re}_{SL,min})/(\mathrm{Re}_{SL,max} - \mathrm{Re}_{SL,min}) - 1 \end{bmatrix}$$

In this study, 90% of the 255 data points (denoted by M_a) were used to find the coefficients and bias of Eq. (17). The rest of the data (i.e., 10%, as denoted by M_b) were used for verification. The data points with the maximum and minimum values of each independent variable were arranged into the training data set. Then the remaining data were divided into the training and testing data sets, respectively. The percent of the training and testing data was arbitrarily determined.

Prior to developing the SVM-based correlation, the parameters C and γ should be determined. As shown in Figure 3, different combinations of the parameters were used for the training of the model based on the training data (M_a). Then, all the experimental data (M) were tested by the SVM model to obtain the mean squared error (MSE). The ranges of the C and γ were selected arbitrarily within [10 to 30,000] and [1–12]. When the value of γ equaled 8 and the value of C exceeded 20,000, the mean squared error (MSE) was the smallest among all the combinations of the parameters. Therefore, the values of the parameters C and γ used in this study were 20,000 and 8, respectively.

As shown in Table 4, all the experimental data are predicted within −12.8% to +10.7%. The absolute deviation of all the pre-
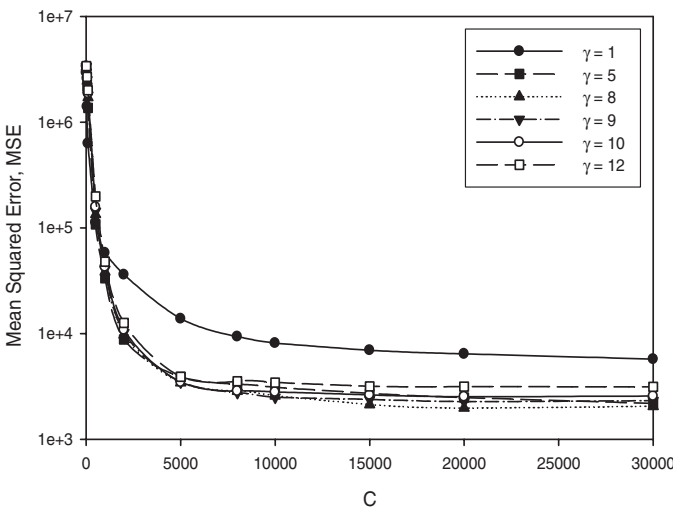

Figure 3 Determination of the desired values of the constants C and γ of the SVM model.
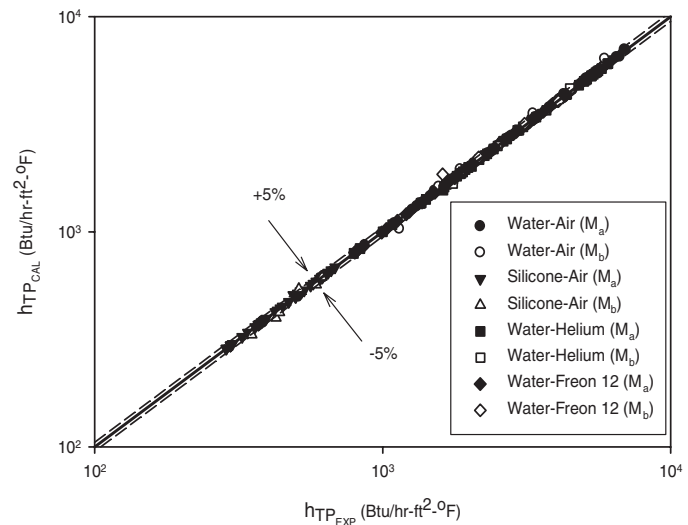

Figure 4 Comparison of the correlation using SVM with all of the two-phase heat transfer experimental data (255 data points).

Table 4 Accuracy of the proposed correlation

	Range of deviation	Absolute deviation	Less than ±5% deviation	Between ±5% and ±10% deviation	Between ±10% and ±15% deviation
	All of the data, M = 255 points, M_a = 230 points, M_b = 25 points				
M	−12.81% ∼ 10.72%	0.54%	248 points	5 points	2 points
M_a	−4.01% ∼ 3.70%	0.19%	230 points	0 points	0 points
M_b	−12.81% ∼ 10.72%	3.67%	18 points	5 points	2 points
	Water–air, M = 105 points, M_a = 95 points, M_b = 10 points				
M	−7.54% ∼ 10.72%	0.59%	102 points	2 points	1 points
M_a	−2.49% ∼ 2.14%	0.26%	95 points	0 points	0 points
M_b	−7.54% ∼ 10.72%	3.66%	7 points	2 points	1 points
	Silicone–air, M = 56 points, M_a = 50 points, M_b = 6 points				
M	−5.61% ∼ 7.15%	0.65%	53 points	3 points	0 points
M_a	−4.01% ∼ 0.66%	0.20%	50 points	0 points	0 points
M_b	−5.61% ∼ 7.15%	4.42%	3 points	0 points	0 points
	Water–helium, M = 50 points, M_a = 45 points, M_b = 5 points				
M	−3.58% ∼ 4.92%	0.37	50 points	0 points	0 points
M_a	−0.97% ∼ 3.70%	0.19%	45 points	0 points	0 points
M_b	−3.58% ∼ 4.92%	2.02%	5 points	0 points	0 points
	Water–Freon 12, M = 44 points, M_a = 40 points, M_b = 4 points				
M	−12.81% ∼ 0.55%	0.45%	43 points	0 points	1 points
M_a	−0.50% ∼ 0.13%	0.03%	40 points	0 points	0 points
M_b	−12.81% ∼ 0.55%	4.64%	3 points	0 points	1 points

dictions is 0.54% and the majority, 97% of all the data (248 data points), is predicted with less than ±5% deviation. About 2% of all the data (5 data points) is predicted within ±5 to ±10% deviation, and less than 1% of all the data (2 data points) is predicted within ±10 to ±15% deviation. The prediction of water–helium data points has the most accuracy—i.e., all the data points are predicted within ±5% deviation. As compared to the previous correlation [3], significant improvement is observed. Figure 4 compares the predicted two-phase heat transfer coefficient obtained from the proposed SVM-based correlation for the different kind of fluid combinations with the measurements.

CONCLUSIONS

In this study, a single SVM 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. [3]. It is observed that the accuracy of the SVM correlation outperforms not only the general correlation for all fluid combinations but also the individual correlations based on different flow combinations. Unlike the ANN type correlation by Ghajar et al. [13], the SVM correlation does not depend on the initial conditions and has a consistent form. Majority of the data (97%) are predicted with less that ±5% deviation and nearly 100% of the data were predicted with less than ±10% deviation. It is again proven that SVM can be used to correlate complicated flow situations.

NOMENCLATURE

A   cross-sectional area, m^2

c_p specific heat at constant pressure, kJ/(kg·K)
D   inside diameter of the tube, m
h   heat transfer coefficient, W/(m^2·K)
k   thermal conductivity, W/(m^2·K)
ṁ   mass-flow rate, kg/s
Pr   Prandtl number (= $\mu c_p / k$)
Q   volumetric flow rate, m^3/s
Re   Reynolds number (= $\rho V D / \mu_B$)
Re_{SL} superficial Reynolds number (= $\rho V_{SL} D / (\mu_B)_L$)
V   average velocity in the test section, m/s
V_{SL} superficial gas velocity (= $Q_L / (A_G + A_L)$), m/s
φ   flow quality (= $\dot{m}_G / (\dot{m}_G + \dot{m}_L)$)
α   void fraction (= $A_G / (A_G + A_L)$)
ρ   density, kg/m^3
μ   absolute or dynamic viscosity, Pa·s

Subscripts

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

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