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Artificial Neural Network Techniques for the Determination of Condensation Nusselt Number in Horizontal Smooth Tubes

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Condensation,
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Abstract: In this study, using readily available experimental data in the literature, artificial neural networks (ANN) method is adopted to specify condensation Nusselt number in horizontal smooth tubes. Condensation heat transfer of R22, R134a and 50/50 and 60/40 of the R32/ R125 azeotropic refrigerant mixtures were examined with four different ANN methods. The experimental data is taken from the study of Dobson et al. [1]. The input parameters are mass flux, quality, hydraulic diameter, Soliman's modified Froude number, density of fluid phase and dynamic viscosity of liquid phase where the output parameter is the condensation Nusselt number. In this study the interval for tube diameters is between 3.14-7.04 mm, and the interval for mass flux is between 50-800 kg/m^{2}s. The training algorithms are tested using different neuron numbers and the best algorithm was found as Bayesian regularization having 8 neurons. It is observed that the Nu number evaluated using ANN is ± 15% error margin compared to experimental results. Furthermore, for increasing mass flux rates the error margin is around ± 5%.

Yatay Pürüzsüz Borularda Yoğuşmadaki Nusselt Sayısının Belirlenmesi için Yapay Sinir Ağ Teknikleri

Anahtar Kelimeler
Yoğuşma,
Yapay sinir ağları,
Soğutucu akışkan,
Nusselt sayısı,
Yatay pürüzsüz boru

Özet: Bu çalışmada, literatürdeki hazır deneysel veriler kullanılarak, yatay pürüzsüz borularda yoğuşmadaki Nusselt sayısını belirlemek için yapay sinir ağları (ANN) yöntemi kullanılmıştır. R32, R134a ve %50/%50 ve %60/%40 R32/R125 azeotropik soğutucu karışımlarının yoğuşma ısı transferi dört farklı ANN yöntemi ile incelendi; Levenberg-Marquardt, Bayes düzenlenmesi, ölçeklenmiş eşlenik değişim ve esnek geri yayılımı. Deneysel veriler Dobson ve ark.[1]'nın çalışmalarından alınmıştır. Giriş parametreleri kütle akısı, kalite, hidrolik çap, Soliman'ın değiştirilmiş Froude sayısı, akışkan faz yoğunluğu ve çıkış parametresinin yoğuşmadaki Nusselt sayısının olduğu sıvı fazın dinamik viskozitesidir. Bu çalışmada, boru çapları aralığı 3,14-7,04 mm arasında ve kütle akı aralığı 50-800 kg/m^2 arasındadır. Eğitim algoritmaları farklı nöron sayıları kullanılarak test edildi ve en iyi algoritma 8 nörona sahip Bayes düzenlenmesi olarak bulundu. ANN kullanılarak değerlendirilen Nu sayısının deney sonuçlarına göre ±%15 hata payı olduğu gözlenmiştir. Ayrıca, artan kütle akı oranları için hata payı ±%5 civarındadır.

1. Introduction

Condensation is observed in systems like power plant, chemical, heating and cooling applications. The condensation energy is considerably high compared to the energy transfer during a single-phase process. Using the lethal energy of condensation, it is possible to design smaller heat exchangers.

The condensation can take place in a number of ways depending on the application. In cooling systems and power plants condensation occurs in horizontal tubes. During a condensation process, different flow regimes are observed such as ring, annular, bullets etc. Each flow regime has its own heat transfer behavior thus condensation turns into a complex

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process. As a result of these the complexities it is difficult to predict accurately the Heat Transfer Coefficient (HTC) and pressure losses for the condensation in smooth tubes [2].

In the literature there are significant amount of study present that focused on condensation in horizontal tubes. Based on the experimental observations the correlations are introduced by Boyko and Kruzhilin [3], Shah [4], Dobson and Chato [5], Kim and Ghajar [6], Jung et al. [7], Thome et al. [8], Cavallini et al. [9] and Huang et al. [10]. These correlations are well accepted in the heat transfer society.

Condensation introduces constantly changing parameters to the process which makes it impossible to postulate a mathematical model. For systems where the output estimation depends on complex processes and many parameters, artificial neural network (ANN) applications have been frequently used. ANN is a powerful tool in making realistic estimates for the outputs of nonlinear, complex problems without explaining the physical mechanism.

There are plenty of studies in the literature on HTC of two-phase flows using ANN. While M.H. Hosoz et al. [11] have examined the cooling performances of the cascade cooling systems with ANN; similarly E. Arcaklıoğlu et al. [12] investigated the performance of different refrigerant mixtures in heat pump applications. Y. İslamoğlu [13] analyzed the thermal performances of the wire condensers using ANN methods. Sencan et al. [14] have used ANN to determine the thermophysical properties of different fluid mixtures.

Demir et al. [15] investigated the condensation HTCs of the R600a fluids in the horizontal tubes. It is shown that the results are 20% accurate with experiments using the correlations in the literature however with ANN the results are 5% accurate with the experimental observations.

Balcılar et al. [16] estimated the HTC and pressure drop of the R134a flow in a vertical tube MLP, RBFN, GRNN and ANFIS. It was determined that the best results are in the range of 5% error with MLP and RBFN. S. Azizi and E. Ahmadloo [2] investigated coagulation HTC with the ANN and compared their results with the experimental data for the R134a inclined tubes in the literature. Estimates were made with an error margin of 2-5%.

In this study, the results of experimental work by Dobson et al. [1] are used. Dobson et al. studied condensation in smooth tubes ranging from 3.14 mm to 7.04 mm in diameter for R22, R134a and 50% / 50% and 60% / 40% of the R32/ R125 azeotropic mixture refrigerants. In the study of Dobson the heat transfer characteristics and flow regime behaviors of the related fluids are tabulated and different flow regimes are considered. It is shown that heat transfer behavior varies considerably depending on the flow regime. With large number of input parameters, the error range of the correlations at the estimated point of the result increases significantly. In this study, the Nu number for condensation in the smooth tubes is estimated using four different ANN methods. Therefore, the main aim of the study is to establish an artificial network to predict the Nu number accurately for different refrigerants under different flow conditions such as mass flux, quality, tube diameter, Soliman's modified Froude number and density and dynamic viscosity of liquid phase."

2. Material and Method

2.1. Numerical Model

Artificial neural networks are reliable and precise predictor models for various engineering applications. The aim of ANN is to ensure solution algorithm for complex problems like pattern association, projecting the future values, classification, clustering, data compression, control applications, function approximation or optimization.

ANN is used in prediction of HTC and pressure drop in heat transfer problems [14, 15, 16, 17]. Although there have been a huge number of studies in the literature for fluids and heat transfer problems using ANN, there is still a necessity for better networks that have more robust and general prediction ability. To achieve that, various network properties should be adjusted to find the network with the most successful and the best generalized version. The neural networks that fail to form a proper network would result in poor generalization or over fitting. The method of artificial neural networks is very attractive to handle problems with multiple-input however without optimizing the structure of the procedure the result may lose its prediction ability for intermediate values and lose its overall prediction ability. Therefore, performance of neural network during training phase should be carefully monitored.

In this study, a neural network with acceptable prediction capability for condensation Nu number is developed. Output of the neural network is Nu number while inputs are fluid density (ρ_L), fluid dynamic viscosity (μ_L), hydraulic diameter (D), mass flux (G), quality (x) and Soliman's modified Froude number (Fr_{SO}). Schematic diagram of a neural network with n neurons in hidden layer with described inputs is shown in Figure 1.

Only one hidden layer is considered for this study since more hidden layers would complicate the solution without additional improvement. 70% of the experimental data is used for training set while test and validation sets percentages were both 15%. It should also be noted that the division of the experimental data between sets is made in a random manner.

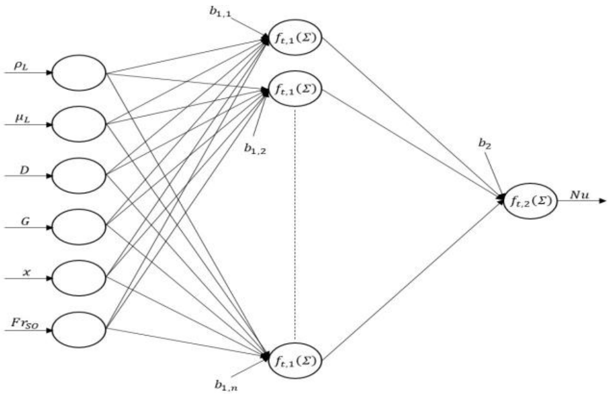


Figure 1. Schematic representation of the proposed neural network structure with n neurons in hidden layer

Inputs and outputs are processed with normalization functions to improve the success of the network. All parameters are normalized between -1 and 1 and then forwarded to the network for training phase. Weights and biases of the networks are initialized by Nguyen-Widrow procedure in order to reduce the computation time. Transfer function for input and output layers are selected as tangent-sigmoid and pure-linear respectively. Input layer transfer function is decided by trying both log-sigmoid and tangent-sigmoid function, latter is selected after overall performance observations. Four different training functions with different number of neurons for hidden layer is applied and the related worst, best and 15 neuron results are shown in Table 1. The hidden layer neuron number is varied 1 to 15. In order to prevent over fitting, necessary settings are employed and performance of the network is monitored during training phase. Performance criteria for the tested networks are mean square error (MSE) and coefficient of determination (R^2) which are defined as

$$MSE = \frac{1}{n}\sum_{i}(f_i - y_i)^2 \tag{1}$$

Table 1. Selected results for the trained neural network structures

Training algorithm	Neuron number	MSE	R^2
Levenberg-Marquardt	1	0.01619	0.84025
	10	0.00112	0.98860
	15	0.00134	0.98640
Bayesian regularization	1	0.01619	0.84133
	8	0.00091	0.99077
	15	0.00104	0.98940
Scaled conjugate gradient	1	0.01648	0.83739
	12	0.00277	0.97189
	15	0.00876	0.91279
Resilient backpropagation	1	0.01998	0.80118
	11	0.00331	0.96654
	15	0.00624	0.93775

$$R^2 = 1 - \frac{SS_{res}}{SS_{tot}} \tag{2}$$

SS_{res} and SS_{tot} are defined as residual sum of squares and total sum of squares and can be defined as

$$SS_{res} = \sum_{i}(y_i - f_i)^2 \tag{3}$$

$$SS_{tot} = \sum_{i}(y_i - \bar{y})^2 \tag{4}$$

where f_i, y_i, n and $\bar{y}$ are defined as predicted value, experimental value, pattern number and the mean value of experimental values respectively.

The ANN study is investigated by considering four different artificial neural network structures, as shown in Table 1. It is determined that Bayesian regularization structure gave the most consistent results amongst four network structures, and ANN calculations presented in this study are evaluated using this structure. In the Bayesian regularization method, calculation is made based on the number of 1, 8 and 15 neurons, and the most compatible results are determined to be related to the number of 8 neurons. Thus, the best-performed network is observed to be the Bayesian Regularization method with 8 neurons.

A correlation analysis is performed to determine the most influential input parameters. The best performed network structure is selected for base network for the analysis. All inputs and their different combinations are formed and fed into the neural network and their respective performance results are obtained. Due to large amount of combinations only the results that show significant improvement in the estimation of condensation Nu number are tabulated in Table 2. The measure of success is chosen as MSE value. As shown in Table 2 the Fr_{SO} number had the major improvement in reduction of MSE. The combination of ρ_L and D with Fr_{SO} showed further reduction in MSE. The use of more parameters reduced the error even further, as expected. Therefore, it can be concluded that the Fr_{SO} has the major contribution to the results compared to the other parameters used in this network.

Table 2. Results of dependency analysis

Input parameters						MSE
ρ_L	μ_L	D	G	X	Fr_{SO}	
X						0.1321
	X					0.3968
		X				0.4054
			X			0.3224
				X		0.3883
					X	0.0695
X					X	0.0621
	X				X	0.0593
X		X			X	0.0098
		X		X	X	0.0063
X		X		X	X	0.0042
X	X	X	X	X		0.0013

3. Results and Discussion

Condensation Nu number is compared with the experimental results from the study of Dobson et al. [1] and the estimated results obtained using the artificial neural network models. Four different training algorithms were used, Bayesian regularization, Levenberg-Marquardt, resilient back propagation and scaled conjugant gradient with three different neuron numbers. The MSE analysis showed that the best estimation training algorithm is the Bayesian regularization method with 8 neurons, which is consistent with the results in the literature [15,16]. The order of the training algorithms and the neuron numbers (NN) according to the best performance can be given with this sequence: Bayesian regularization (MSE=0.00091, NN=8), Levenberg-Marquardt (MSE=0.00112, NN=10), scaled conjugate gradient (MSE= 0.00277, NN=12) and resilient back propagation (MSE=0.00331, NN=11).

The effect of quality during the condensation on the error margins of the estimated condensation Nu number for the refrigerants, R22, R134a refrigerant, %50R32/ %50R125, 60%R32/ 40%R125 azeotropic mixtures, are summarized in Figure 2. It is observed that the error margin changes mainly in the range of 5% and 15% with the quality during the condensation. However, it is observed that the most deviation between experimental results and ANN model occurred during when quality values between 0 and 0.3. It is determined that even at this region the error range do not exceed 20%.

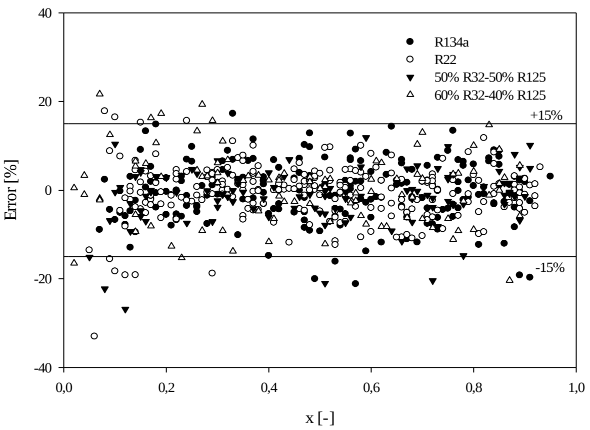


Figure 2. Error margin in the most predictive artificial neural network method (trained by Bayesian regularization technique with 8 neurons) due to change of quality of refrigerant during condensation

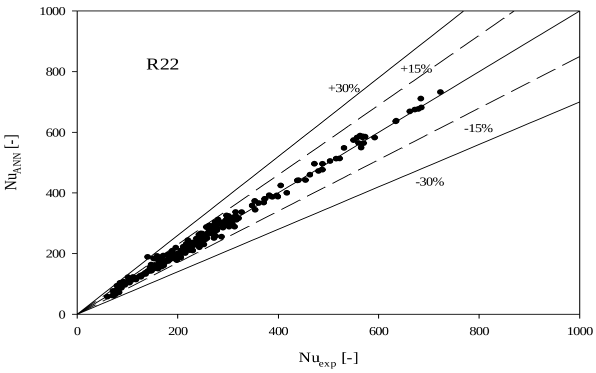
The Figure 3 demonstrates comparisons of experimental Nu number and the Nu number obtained by ANN for different refrigerants considered in this study. It is noticed that low Nu number values (Nu~200) R22, R134a and 50% R32 / 50% R125 refrigerants showed significant error (around 30%), however for higher Nu numbers the error dropped as low as 2%. Although similar trend is observed for the refrigerant azeotropic mixture 60% R32 / 40% R125, for low Nu numbers the error is observed to be better than other refrigerants.

The error is around 15% for Nu number as small as 100. The experimental results and ANN predictions for Nu number for different refrigerants are summarized in Table 3. It is observed that refrigerant R22 showed the lowest deviation where 60% R32/ 40% R125 showed the highest deviation. Additionally, 99% of the refrigerant R22 resulted within ±10 (%) error and 83.42% of the refrigerant R134a resulted within the same error margin. It can be concluded that the proposed ANN method introduces considerable accuracy in estimation of condensation Nu number. Particularly because of the increase in mass flux, the results obtained are very reasonable under ± 5% error.

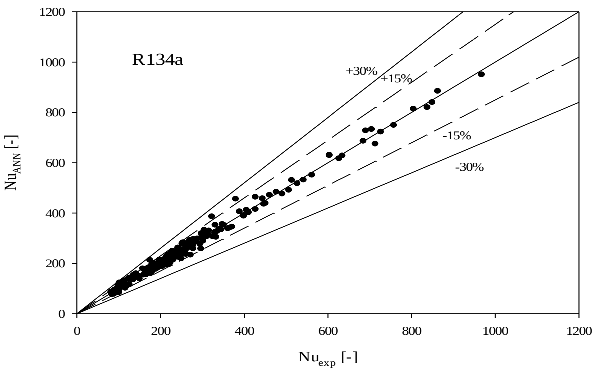
The transferred heat in two-phase flows depends on the general flow regime. Flow and heat transfer characteristics in shear-dominant flow regimes are mainly depend on mass flux and quality of the mixture [4]. The effects of different quality values and different mass fluxes on Nu number is showed in Figure 4. It is observed that for increased quality levels the low mass fluxes do not significantly affect the condensation Nu number, but it is understood that increasing mass fluxes have significantly increased Nu number with increased quality. It is shown that for all refrigerants (Figure 4 a-d) the estimated Nu number is in good agreement with the experimental results within the error range of 10%, in average.

Table 3. The comparison of experimental and ANN results for condensation Nu number estimates for different refrigerants: the compliance rates

Refrigerant	Mean Deviation (%)	% of Points within ±10 (%)	% of Points within ±25 (%)
R134a	6,12	83,42	100,00
R22	4,17	99,00	100,00
60% R32/ 40% R125	6,81	85,42	97,92
50% R32/ 50% R125	4,20	92,38	99,05



(a)



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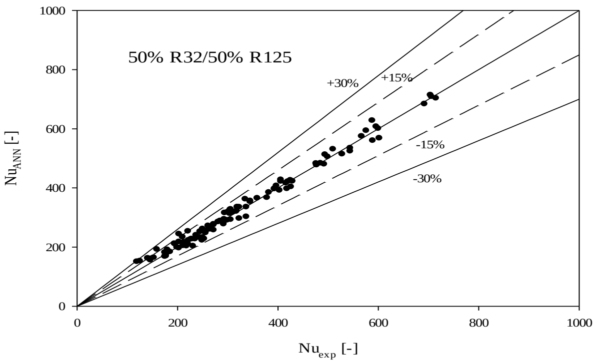
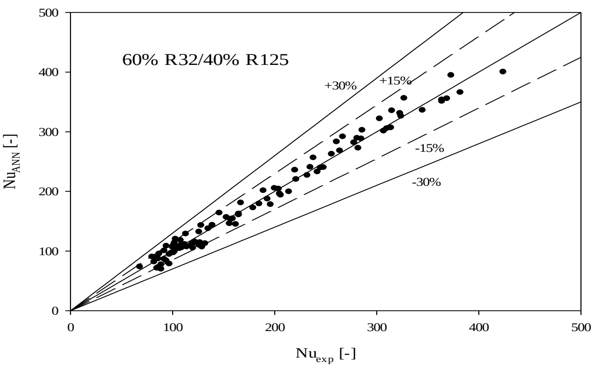
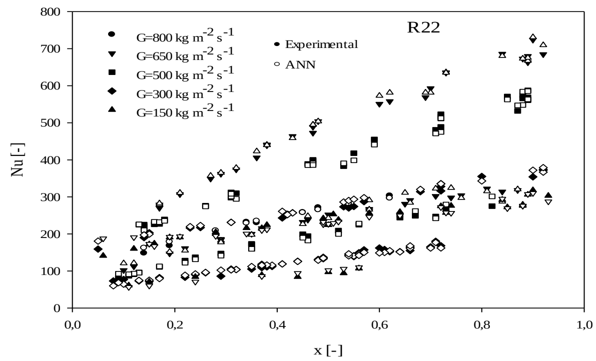


(c)

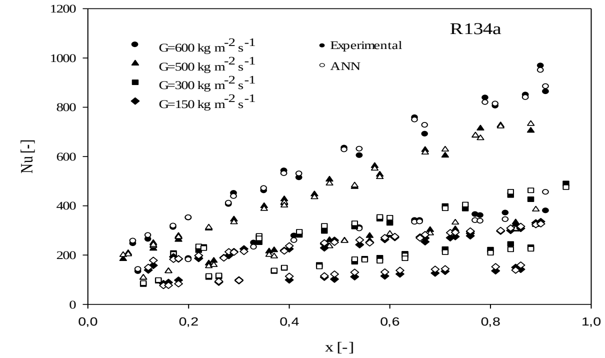


(d)

Figure 3. Comparisons of experimental Nu number with the most predictive artificial neural network method (trained by Bayesian regularization technique with 8 neurons) (a) for R22 refrigerant, (b) for R134a refrigerant, (c) for %50 R32/ %50 R125 azeotropic mixtures, (d) for 60% R32/ 40%R125 azeotropic mixture



(a)



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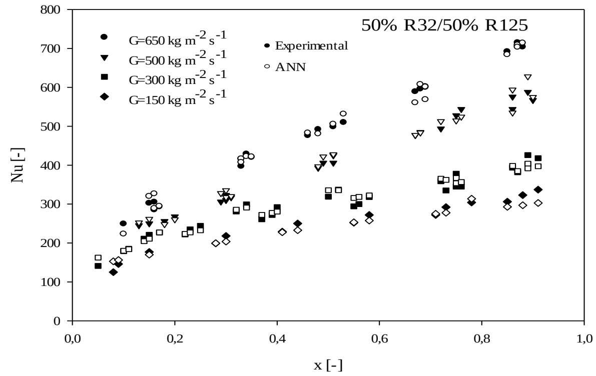

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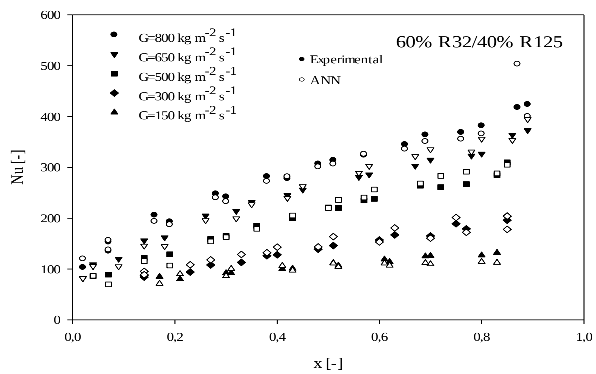

(d)

Figure 4. Comparisons of experimental Nu number with the most predictive artificial neural network method (trained by Bayesian regularization technique with 8

neurons) with increased quality during the condensation of the refrigerants (a) R22, (b) R134a , (c) for %50 R32/ %50 R125 azeotropic mixtures, (d) for 60% R32/ 40%R125 azeotropic mixtures

4. Conclusion

Prediction of heat transfer characteristic of a condensation in horizontal smooth tubes is investigated. The condensation of the R22, R134a refrigerants and 60% R32/ 40% R125, 50% R32/50% R125 azeotropic mixture refrigerants is carried out with ANN. The analysis is carried out using the data supplied by Dobson et al [1]. The parameters are mass flux, quality, hydrodynamic diameter, Fr_{SO} number, density and dynamic viscosity of liquid phase measured in the experimental work are used as input parameters of ANN study. The compatibility of the ANN study based on these parameters is examined. Among the four different network structures, calculations are made according to Bayesian regularization with 8 neurons. While 75% of experimental data is used for training, the rest for testing. The trained network can predict Nu numbers in the range of ±5-15%. It is concluded that ANNs are very effective in predicting Nu number. The concluding remarks can be summarized as:

1- The most effective training algorithm is the Bayesian regularization with 8 neurons.
2- The most important input parameter to lower the overall MSE is FrSO where simultaneous effect of density, hydrodynamic diameter and quality improves the accuracy of the estimated value of condensation Nu number.
3- For the low values of quality (0<X<0.3), the highest error is observed (around 20%). For higher quality values as the condensation continues the error margin is observed to be less than 15%.
4- For higher convection heat transfer regime (Nu>400) the ANN calculations reach the best accuracy to estimate the condensation Nu number (MSE<15%) however when the conduction dominates (Nu<200) the error reaches 30%.
5- It is observed that the heat transfer characteristics are affected by the mass flux and quality [18]. At low mass flux flow regime, the condensation Nu number do not change significantly with increasing quality whereas for higher mass fluxes the condensation Nu number increases significantly with increased quality. Here a strong dependence on mass flus and quality is shown and this pattern has also been reported by Wang et al [18].

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