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

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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/m²s. 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 N number evaluated using ANN is ± 15% error margin compared to experimental results. Furthermore, for increasing mass flux rates the error margin is around ± 5%

Keywords: Condensation, Artificial neural networks, Refrigerant, Nusselt number, Horizontal smooth tube

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
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 Gharaj
[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 azotrope
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 (ρf), fluid
dynamic viscosity (μf), hydraulic diameter (D), mass
flux (G), quality (x) and Soliman’s modified Froude
number (Fr50). 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.
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

$$MSE = \frac{1}{n} \sum_i (f_i - y_i)^2$$  \hspace{1cm} (1)$$

$$R^2 = 1 - \frac{SS_{res}}{SS_{tot}}$$  \hspace{1cm} (2)$$

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

$$SS_{res} = \sum_i (y_i - f_i)^2$$ \hspace{1cm} (3)$$

$$SS_{tot} = \sum_i (y_i - \bar{y})^2$$ \hspace{1cm} (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$_{50}$ number had the major improvement in reduction of MSE. The combination of $\rho_t$ and D with Fr$_{50}$ 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$_{50}$ has the major contribution to the results compared to the other parameters used in this network.

### 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| 0.97199|
|                            | 15            | 0.00876| 0.91279|
| Resilient backpropagation  | 1             | 0.01990| 0.80118|
|                            | 11            | 0.00331| 0.96654|
|                            | 15            | 0.00624| 0.93775|

### Table 2. Results of dependency analysis

| Input parameters | MSE  |
|------------------|------|
| $p_t$            | X    |
| $\mu_t$          | X    |
| D                | X    |
| G                | X    |
| X                | X    |
| Fr$_{50}$        |      |

| X    | X    | X    | 0.01321|
| X    | X    | 0.3968|
| X    | 0.4054|
| X    | 0.3224|
| X    | 0.3803|
| X    | 0.0695|
| X    | 0.0621|
| X    | 0.0593|
| X    | X    | 0.0098|
| X    | X    | X    | 0.0063|
| X    | X    | X    | 0.0042|
| 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 conjugate 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%.

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.

| 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 |
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.

Figure 4. 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.
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, FrSO 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 flux and quality is shown and this pattern has also been reported by Wang et al [18].

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