



# Prediction and optimization of condensation heat transfer coefficients and pressure drops of R134a inside an inclined smooth tube

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## ABSTRACT

In this study, an adaptive neuro-fuzzy inference system (ANFIS) is proposed for the prediction and optimization of condensation heat transfer coefficient and pressure drops along an inclined smooth tube. The performance of three ANFIS structure identification methods, grid partitioning (GP), a subtractive clustering method (SCM), and fuzzy C-means (FCM) clustering, were examined. For training the proposed ANFIS model, an in-house experimental database was utilised. Three statistical criteria, the mean absolute error (MAE), mean relative error and root mean square error were used to evaluate the accuracy of each method. The results indicate that the GP structure identification method has the lowest number of training errors for both the pressure drop, i.e., MAE = 6.4%, and condensation heat transfer coefficient, i.e., MAE = 2.3%, models. In addition to the ANFIS model, numerical simulations were also conducted to assess the accuracy and capability of the proposed model. The comparison shows that the CFD simulation results have better accuracy for the specified operating conditions. However, the errors of both the CFD and ANFIS methods were within the uncertainties of the experimental data. It was therefore concluded that the ANFIS model is useful in obtaining faster and reliable results. Finally, the optimization results showed a possible optimum point at a mass flux of 100 kg/m<sup>2</sup>s, saturation temperature of 36.2 °C, downward inclination angle of −15° and a vapour quality of 0.48. At this condition the pressure drop is almost zero.

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## 1. Introduction

The applications of soft computing methods in the modelling and analysis of engineering problems have increased significantly during the last decade. Fuzzy logic, neural networks, and genetic algorithms are among the most frequently used components of soft computing methods. Because soft computing methods can recognise the existing knowledge and patterns behind empirical data, they have received significant attention within a wide range of mechanical engineering applications during the last few years [1–4].

Using experimental data, Gill and Singh [5] suggested the application of prediction models based on a dimensional analysis and the Adaptive Neuro-Fuzzy Inference System (ANFIS) method for an R134a/LPG mass flow in an adiabatic tube. Their results indicated that although both the dimensional analysis and ANFIS method, achieve good statistical performance, the accuracy of the ANFIS model is slightly better.

For better monitoring of wind turbine farms, Morshedizadeh et al. [6] introduced a new methodology based on a combination of an adaptive neuro-fuzzy inference system (ANFIS), an imputation algorithm, and a feature selection method to predict the performance of commercial wind turbines. To show the predictive capability of the suggested methodology, power curves of 2.3 MW pitch-regulated wind turbines were investigated. The results indicate that the proposed ANFIS model performs better than the existing models.

Using an experimental dataset, ANFIS, and an artificial neural network (ANN), Seijo et al. [7] suggested the application of prediction models for 12 different systems within an actual combined heat and power (CHP) power plant. Their results indicated the capability of both approaches to model cogeneration power plant systems with high accuracy. After modelling, a multi-objective optimisation technique was applied to maximise the electric production and amount of heat used in the slurry process, and to minimise the fuel consumption.

An ANFIS and an ANN were utilised by Şahin [8] to predict the coefficient of performance (COP) of a single-stage vapour compression refrigeration system. Three environmental friendly refrigerants, R134a, R404a, and R407c, were used in this system. The

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## Nomenclature

|           |                                                                              |
|-----------|------------------------------------------------------------------------------|
| $A$       | membership function in ANFIS structure [–]                                   |
| $a_{ij}$  | consequent parameter matrix                                                  |
| $B$       | membership function ANFIS structure [–]                                      |
| $b_{ij}$  | consequent parameter matrix                                                  |
| $E$       | internal energy [J]                                                          |
| $f$       | firing strength in ANFIS structure [–]                                       |
| $F$       | source term in the momentum equation [N/m <sup>3</sup> ]                     |
| $g$       | gravitational acceleration [m/s <sup>2</sup> ]                               |
| $G$       | mass flux [kg/m <sup>2</sup> s]                                              |
| $G_b$     | generation of turbulence kinetic energy due to buoyancy, [m <sup>4</sup> /s] |
| $h$       | heat transfer coefficient [W/m <sup>2</sup> K]                               |
| $k$       | turbulent kinetic energy [m <sup>2</sup> /s <sup>2</sup> ]                   |
| $M$       | node label in layer 2 in ANFIS structure [–]                                 |
| $N$       | node label in layer 3 in ANFIS structure [–]                                 |
| $P$       | pressure [Pa]                                                                |
| $q''$     | heat flux [W/m <sup>2</sup> ]                                                |
| $S$       | summation of all signals in ANFIS structure [–]                              |
| $S_E$     | energy source term [J/m <sup>3</sup> s]                                      |
| $S_l$     | condensation mass source term [kg /m <sup>3</sup> s]                         |
| $S_v$     | vaporization mass source term [kg/m <sup>3</sup> s]                          |
| $t$       | time [s]                                                                     |
| $T$       | TEMPERATURE [K]                                                              |
| $T_{sat}$ | saturation temperature [K]                                                   |
| $u$       | velocity [m/s]                                                               |
| $\bar{w}$ | normalized firing strength in ANFIS structure [–]                            |
| $x$       | input parameter in ANFIS structure [–]                                       |
| $X_a$     | predicted value [–]                                                          |
| $X_p$     | actual (experimental) data [–]                                               |
| $y$       | input parameter in ANFIS structure [–]                                       |

## Greek symbols

|               |                                                              |
|---------------|--------------------------------------------------------------|
| $\alpha$      | volume fraction [–]                                          |
| $\mu$         | molecular viscosity [Pa s]                                   |
| $\rho$        | density [kg/m <sup>3</sup> ]                                 |
| $k$           | curvatures of liquid and vapour phase [–]                    |
| $\varepsilon$ | turbulent dissipation rate [m <sup>2</sup> /s <sup>3</sup> ] |
| $x$           | vapour mass fraction [–]                                     |
| $\beta$       | inclination angle [°]                                        |
| $\sigma$      | surface tension [N/m]                                        |

## Subscripts

|       |           |
|-------|-----------|
| $ave$ | average   |
| $eff$ | effective |
| $l$   | liquid    |
| $L$   | laminar   |
| $m$   | mean      |
| $v$   | vapour    |

## Abbreviations

|       |                                       |
|-------|---------------------------------------|
| ANFIS | Adaptive Neuro-Fuzzy Inference System |
| FCM   | fuzzy C-means clustering              |
| GP    | grid partitioning                     |
| MAE   | mean absolute error                   |
| MF    | membership function                   |
| MRE   | mean relative error                   |
| RMSE  | root mean squared error               |
| SCM   | subtractive clustering method         |

same datasets were used for both ANFIS and ANN modelling. The results show that the ANN model performs better than ANFIS for R134a, whereas the prediction performance of the ANFIS is better than that of the ANN for R404a and R407c.

The applicability of an ANN for the identification of a two-phase flow regime has been investigated by various researchers [9,10]. Pan et al. [10] developed a fuzzy C-means (FCM) clustering algorithm to create a flow regime identification map for a co-current air-water two-phase flow in the vertical direction. They conducted several experiments to build a suitable database. Their results indicate that the proposed fuzzy method can be applied to the successful identification of the flow regime for both upward and downward flows.

Balcilar et al. [11] used multilayer perceptron (MLP), radial basis networks (RBFN), and generalised regression neural network (GRNN) ANN methods, as well as the adaptive neuro-fuzzy inference system (ANFIS) technique for the prediction of the condensation heat transfer coefficient and pressure drop inside a vertical tube with a diameter of 8.1 mm. They used different refrigerant mass fluxes, saturation temperatures, and wall heat fluxes for training purposes. They examined the performances of above mentioned ANN methods and ANFIS technique in their study. Their results indicate that the ANFIS, radial basis network (RBFN), and multi-layer perceptron (MLP) methods can predict the condensation heat transfer coefficient and pressure with a deviation of less than 20% as compared with the experiment data.

In addition to the development of the ANFIS model, numerical simulations of condensation inside an inclined smooth tube have been conducted. The purpose of the CFD simulation was to conduct an assessment of the accuracy and computational costs of the pro-

posed ANFIS model. Literature reviews have shown that previous numerical studies on the condensation inside different tubes have been limited to horizontal or vertical orientations [12–15]. Numerical simulations have been recently conducted to investigate the effects of the inclination angle on the condensation heat transfer coefficient, pressure drop, and flow regimes inside a smooth tube. The results showed an optimum downward inclination angle of between  $-30^\circ$  and  $-15^\circ$  through which the heat transfer coefficients become maximum. It was also found that the effect of the inclination angle on the pressure drop and void fraction become negligible at a high mass flux and vapour quality [16].

Beside the applications of numerical methods for simulation and predicating purposes, their performance and ability to conduct optimization studies have been proven in the past. Genetic algorithm (GA) is one of the most favorite ones among evolutionary algorithms (EA) due to its simplicity and population-based search methodology. Applying different approaches for fitness assignment, elitism or diversification resulted in various genetic algorithm-based multi-objective optimization methods in literature [17].

In 2002 Deb et al. [18], proposed a modified non-dominated sorting genetic algorithm, called NSGA-II. This method later received significant attention as one of the most efficient genetic algorithm-based multi-objective optimization methods. Detailed information about this method has been given in Section 4. During the last fifteen years, NSGA-II was used in a wide range of mechanical engineering applications to find optimum design Pareto fronts [19–23].

Literature reviews have shown that there have been no studies investigating the potential of a neuro-fuzzy inference system to

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