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Prediction of Pressure Gradient during Condensation in Inclined Heat Exchanger Using Machine Learning Techniques

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ABSTRACT

This study employs machine learning techniques – random forest and extra trees - to predict the frictional pressure gradient during convective condensation in an inclined in-tube heat exchanger. The experimental data matrix (663) includes conditions for saturation temperatures of 30, 40, and 50°C, mass velocity 100-400 kgm^{-2}s, quality 10-90%, and thirteen inclination angles between -90° and +90° for a smooth tube of an internal diameter of 8.38 mm. Based on statistical analysis, the extra trees outperforms the random forest. The average deviation (AD) and mean average deviation (MAD) are 2.88% and 6.72%, respectively, for random forest (RF) and 0.25% and 2.97%, respectively, for extra trees (ET).

Keywords: Frictional pressure gradient, inclination angle, inclined smooth tube, condensation, machine learning

NOMENCLATURE

Abbreviations	
d	diameter (m)
Fr	Froude number
g	gravitational acceleration (ms^{-2})
G	mass velocity (kgm^{-2}s^{-1})
$\frac{dP}{dz}$	pressure gradient (Pam^{-1})
T	temperature (°C)
x	quality (-)
X	input vector (-)
Symbols	
β	inclination angle (°)
ρ	density (kgm^{-3})
Subscripts	
l	liquid
sat	saturation
v	vapour

1. INTRODUCTION

The study of the pressure gradient is imperative in the heat exchange devices used in the process, chemical and thermal industries, heating, ventilation, and air conditioning (HVAC) systems, nuclear, and the oil and gas industries due to its implication for the systems' power requirements. A high pressure gradient is undesirable because it increases the required power, size, and weight of the heat exchange system. Today, an efficient system design focuses on improving efficiency and decreasing size and weight.

The study of the thermal-hydraulic characteristics of two-phase flow in inclined smooth and enhanced tubes has increased considerably in the past two decades due to their applications in industrial V- and A-frame heat exchangers; automobiles moving downhill and uphill; during take-offs, landing, and banking of air transport vessels [1-3].

Several studies have attempted to predict pressure gradients in horizontal and vertical flows using empirical models [4-6]. Only very few studies considered inclined flows [7,8]. Liu et al. [7] developed flow pattern-based correlations to predict the frictional pressure gradient in tilted smooth tubes. Shaahid et al. [8] experimentally investigated the frictional pressure drop of oil-water flow at different inclination angles. Furthermore, Adelaja et al. [2,9] experimentally studied the frictional pressure drop of HFC134a in inclined smooth and enhanced tubes but did not develop predictive models.

Soft computing techniques such as machine learning have been proposed as predictive and optimization tools for the future. Machine learning has the advantage of rapid computation and accuracy over other modeling and optimization tools. Studies showed that these tools had been deployed to predict the heat transfer coefficient more often than the pressure drop [10]. Furthermore, the literature has shown few studies on pressure drops in inclined tubes. A brief review of the application of machine learning tools for pressure gradient prediction is presented here. Cebi et al. [11] used an artificial neural network (ANN) to predict friction factors in smooth and microfin tubes subjected to cooling, heating, and isothermal conditions. Noori Rahim Abadi et al. [12] employed an adaptive neuro-fuzzy inference system to predict and optimize the pressure drop and heat transfer coefficient in smooth inclined tubes. It was concluded that the numerical model by the same authors performed better than the ANFIS. Hughes et al. [13] compared several flow pattern-based models with three machine learning models (support vector regression, random forest regression, and artificial neural network) to predict heat transfer coefficient and pressure drop. They concluded that the random forest algorithm gave the best prediction. However, the dataset comprised mostly horizontal tube flows. Cepeda-Vega et al. [14] employed the generalized additive model (GAM) to predict the pressure drop in two-phase flow for different inclination angles. However, the inclination angles were scattered and depended on the data sets of various works. The R^2 and mean relative errors obtained were 99.1% and 12.93%, respectively. The performances of four machine learning algorithms - Bayesian Neural Network (BNN), random forest (RF), artificial neural network (ANN), and support vector machines (SVM) - were evaluated based on their abilities to predict the pressure drop of Herschel-Bulkley fluid flowing through the annulus. RF and BNN gave the least mean absolute errors of 2.57% and 3.2%, respectively [15].

From the literature above, it has been shown that the application of machine learning techniques compared with flow pattern-based models has proven to be better tools for the prediction of two-phase flow processes in inclined tubes. Though RF has been applied to predict frictional pressure drop in horizontal and slightly inclined tubes, to the best of the authors' knowledge, the two techniques have not been used for tubes tilted at the inclination angles of ±90°, ±60°, ±30°, ±15°, ±10°, ±5° and 0°. Therefore, this paper aims to apply and evaluate RF and ET when predicting the pressure gradient during convective condensation in inclined flows for all ranges of inclination angles.

2. EXPERIMENTAL SETUP AND PROCESS

2.1 Test facility described

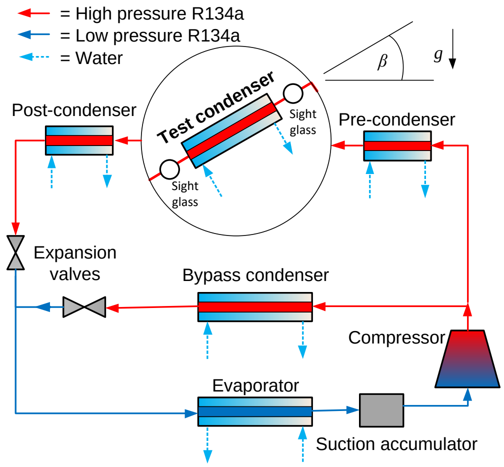


Fig. 1 The sketch of the experimental test setup

A detailed description of the test facility can be found in earlier publications of the authors [1-3,9,16]. In this section, a brief explanation of the test rig is done—the test facility comprised a vapour compression cycle with the compressor's high-pressure line separated into two. One consisted of the pre-condenser, test section, and post-condenser, while the second led to the bypass line. The bypass line helped regulate the amount of refrigerant hence the mass flow rate through the test section. The test condenser was connected to two flexible pressure hoses, which enabled it to tilt between horizontal and vertically upward or downward to change the direction of the flow accordingly. Two sight glasses were situated at the tube inlet and outlet of the test condenser to view the flow distribution. A high-speed camera was positioned at the outlet sight glass through which the flow pattern was captured. The pre-condenser allowed the refrigerant vapour quality to be altered before entering the test condenser. The post-condenser enabled the two-phase flow to be fully liquid and subcooled before entering the electronic expansion valve. Other components were as can be found in a typical refrigeration cycle. A computerized data acquisition (DAQ) system collected and stored data from measuring equipment such as pressure transducers, thermocouples, and Coriolis flow meters.

2.2 Experimental test matrix

The experimental data comprises condensation frictional pressure gradient data for mass velocities of 100 to 400 kgm^{-2}s^{-1}, mean vapour qualities of 10 to 90%, saturation temperatures of 30 – 50 °C, and 13 inclination angles (±90°, ±60°, ±30°, ±15°, ±10°, ±5° and 0°).

3. MACHINE LEARNING TECHNIQUES

Numerous machine learning techniques have proven to considerably minimize the high variance obtainable when using the regression techniques; however, RF and ET are used for this study. The two techniques work on the same principle, and the significant differences between them are:

(i) RF uses bootstrap replicas, i.e., subsets of the training data with replacement. In contrast, ET uses the whole original sample, i.e., takes a random subset of data without replacement.

(ii) RF chooses the optimum split in selecting cut points to split nodes, while ET chooses it randomly**.**

(iii) ET is a relatively recent machine learning technique with a faster execution time.

3.1 Data preparation

This study has 663 original data rows with ten features (i.e., nine input features with one output feature) for training an RF. From this, bootstrapped sample sets were drawn. Each bootstrapped sample was further employed to grow an unpruned regression tree. Segregating the data into training and testing datasets was avoided, but the train-test-split method was adopted. Following the train-test-split step, only a minute number of randomly sampled M predictors were chosen as split candidates. The above procedure was repeated until N number of trees were grown. Aggregating the prediction of the N trees gave rise to the prediction of the new data defined as:

$$\hat{f}_{RF}^{N}(\boldsymbol{X}) = \frac{1}{N}\sum_{j=1}^{N} T_j(\boldsymbol{X}) \quad (1)$$

where ***X*** depicts the vectored input parameter, N is the number of trees, and $T_j(\boldsymbol{X})$ is a single regression tree formed based on a subset of input parameters and the bootstrapped samples. Fig. 2 depicts the Random forest regression procedural tree. The input parameters are the saturation temperature T_{sat} (°C), mass velocity G ($kgm^{-2}s^{-1}$), mean quality x_m (-), inclination angle β (°), acceleration due to gravity g (ms^{-2}), tube inner diameter, d (m), superficial gas Froude number Fr_{sv} (-), liquid density ρ_l (kgm^{-3}) and vapour density ρ_v (kgm^{-3}). The output is the pressure gradient (Pam^{-1})

4. RESULTS AND DISCUSSION

The results present the application of the RF and ET to predict the pressure gradient obtained from the condensation experiment described in section 2. Statistical tools, average deviation (AD) and mean average deviation (MAD), are employed to evaluate their accuracies.

4.1 Prediction using random forest

Fig. 3 compares the experiment with the prediction of the RF for the pressure gradient against the inclination angle for the saturation temperature of 50°C. It reveals that for all the vapour qualities, the downward flows, β < 0° were not well predicted. As the inclination angle decreases, the worse the prediction; however, the quality of 50% shows the worst deviation.

4.2 Prediction using extra trees

Fig. 4 reveals the prediction of the pressure gradient using the ET for the same saturation temperature of 50°C. The ET gives a better prediction than the RF as both upward and downward flows are well predicted except for the quality of 50%, which has the worst deviation during the downward flow.

4.3 Statistical evaluation of the machine learning techniques

The RF and ET are evaluated using AD and MAD (Eqs. 2 and 3, respectively). The predictions are plotted against the experimental data, as indicated in Fig. 5. The ET presents the AD and MAD of 0.25% and 2.97%, respectively, while the RF is 2.88% and 6.72%, respectively. This clearly shows that the ET performs better than the RF for the set of data studied.

$$AD = \frac{1}{M}\sum_{1}^{M}\left[\frac{(\alpha_{pred}-\alpha_{exp})\times 100\%}{\alpha_{exp}}\right] \quad (2)$$

$$MAD = \frac{1}{M}\sum_{1}^{M} ABS\left[\frac{(\alpha_{pred}-\alpha_{exp})\times 100\%}{\alpha_{exp}}\right] \quad (3)$$

Where M is the number of data points, α_{pred} and α_{exp} are the experimental and predicted pressure gradients, respectively. The regression plots for the two techniques are presented in Fig. 6. The R^2 value of the test data for RF is 0.9423, and for ET, it is 0.9833, meaning that the extra trees is better than the RF.

5. CONCLUSIONS

In this study, two machine learning techniques (random forest and extra trees) are employed to predict the frictional pressure gradient during the convective condensation of refrigerant inside an inclined tube-in-tube heat exchanger. The extra trees performs better than the Random forest in that it can predict the upward and downward flows reasonably well, except for the downward flow at 50% vapour quality. However, the random forest fails to fairly predict the downward flow for all qualities. With an average deviation of 0.25% and a mean average deviation of 2.97%, the extra trees outperforms the random forest, which has an average

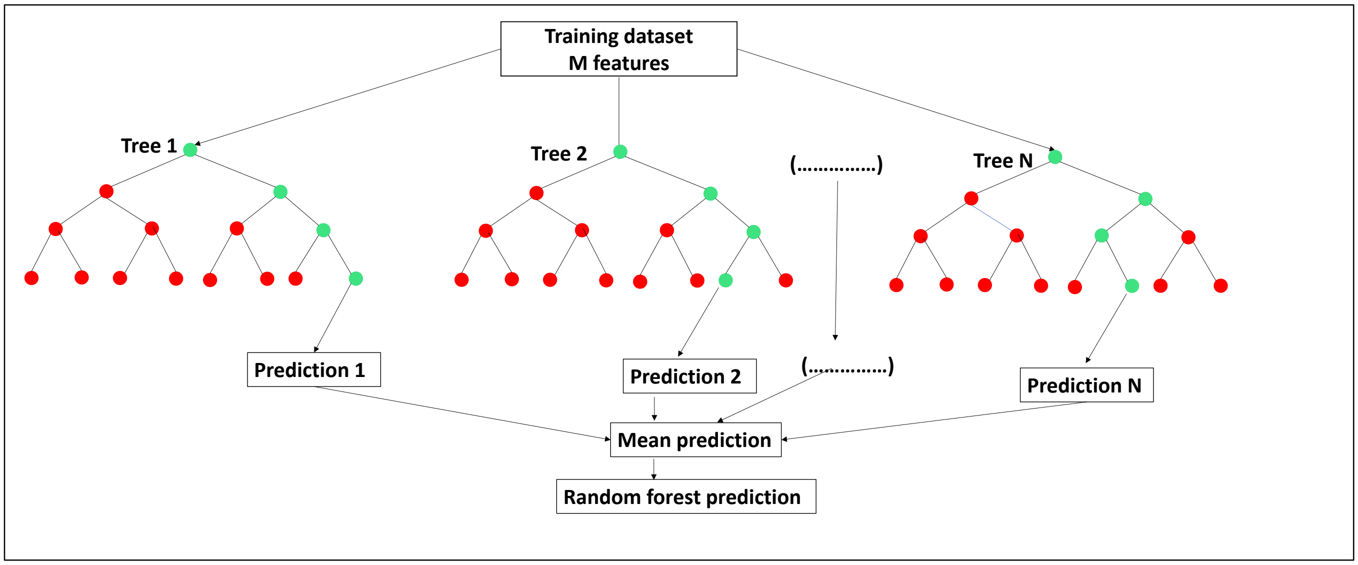


Fig. 2 *A Random forest regressor with N number of trees and M sampled data*

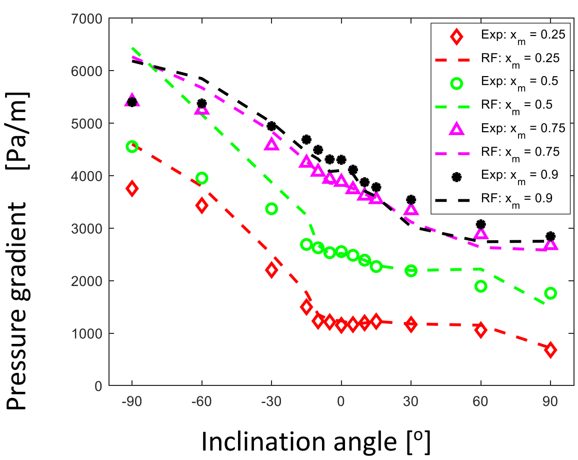


Fig. 3 Variation of frictional pressure gradient with inclination angle for saturation temperature of 50 °C using RF

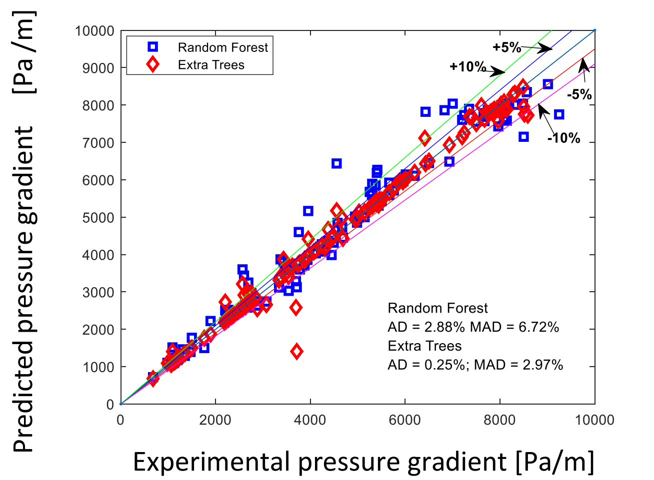


Fig. 5 Experimental data compared with machine learning predictions

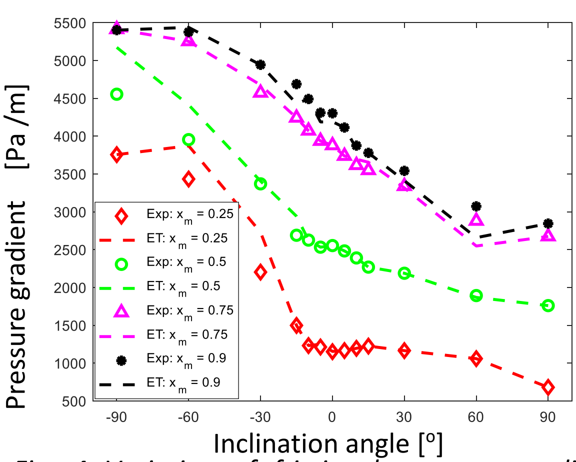
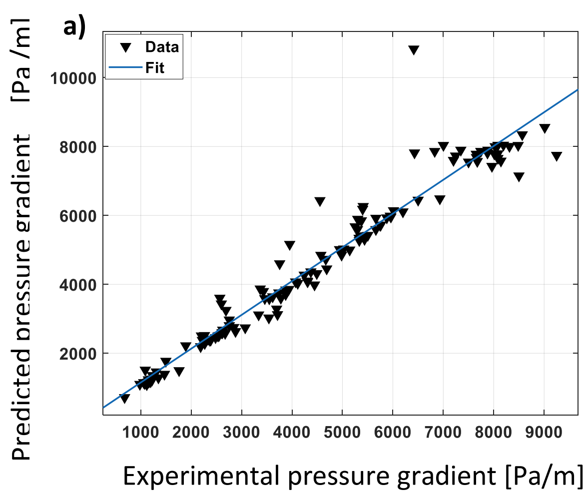


Fig. 4 Variation of frictional pressure gradient with inclination angle for saturation temperature of 50 °C using ET



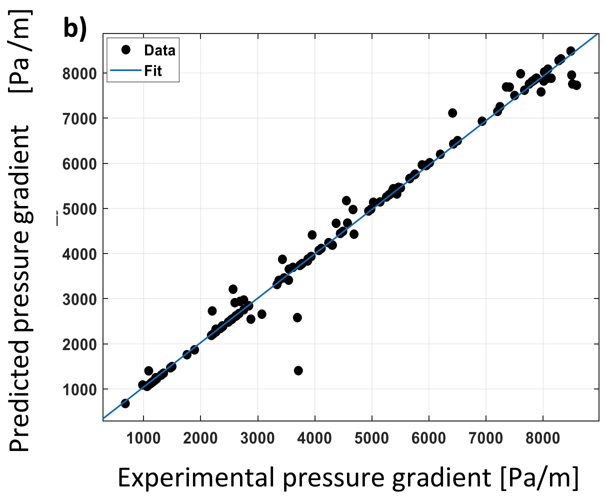


Fig 6. Regression plots for test datasets for a) random forest technique and b) extra trees technique

deviation of 2.88% and a mean average deviation of 6.72%.

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