Application of machine learning methods for investigating the heat transfer enhancement performance in a circular tube with artificial roughness

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Abstract. This paper presents a hybrid approach for investigation of heat transfer enhancement performance using computational fluid dynamics and artificial neural network. More than 5,000 CFD simulations are carried out for turbulent flow in pipes provided with artificial roughness of transverse rectangular ribs to analyze heat transfer, pressure drop, and thermal hydraulic performance. The rib height and pitch are widely varied along with the flow Reynolds number, working fluid, and material of roughness elements. To accurately predict major parameters (Nusselt number, friction factor, and thermal hydraulic performance) a deep neural network is developed, trained, and tested by current CFD data. The ANN allowed finding optimal rib roughness parameters for the current problem and opened perspectives of industrial application due to low computational cost and prediction error of less than 1.5%.

1. Introduction
Manufacturers of modern highly efficient tubular heat exchangers are facing continuously increasing industrial demands of unit power and compactness. Both demands can be achieved using heat transfer enhancement methods [1]. One of the most efficient and technologically acceptable heat transfer enhancement methods in tubes is artificial turbulentization of the flow by roughness elements: annual diaphragms, wire coils, transverse ribs, knurling of the outer tube surface, etc. Since the growth of heat transfer involves friction losses the optimal rib roughness parameters are to be found for each specific case which may be costly and technically difficult.

This and other common engineering problems can be examined with the help of machine learning methods providing a powerful, resource-efficient approach for modeling highly complicated nonlinear systems. Artificial neural networks (ANNs) trained and validated on experimental or CFD simulation data are capable of making accurate predictions without the need for any additional experiments.

The present work submits a numerical study on heat transfer, friction loss characteristics, and thermal hydraulic performance of a tube section with transverse rectangular ribs. The optimal rib and flow parameters are to be found with the help of CFD modeling and ANN predictions.
2. Numerical modeling

2.1. Solution domain
The numerical simulations are conducted on a two-dimensional axisymmetric domain which represents a tube of 10 mm diameter and 150 mm length. A schematic view of the solution domain is shown in Figure 1 where (1) is the velocity inlet; (2) is the velocity outlet; (3) is the wall with no-slip and constant temperature conditions; (4) is the axis of the tube with symmetry condition; (5) are the ribs’ sides with no-slip condition.

![Figure 1](image.png)

Figure 1. Schematic of two-dimensional solution domain for CFD analysis.

The rib pitch-to-diameter ratio (p/d) is in the range 0.1-1.5; the rib height-to-diameter ratio (e/d) is in the range 0.01-0.05; and the considered Reynolds number (Re) is in the range $10^4$–$10^6$ and specified by the inlet pressure (up to $10^7$ Pa). The working fluids considered are air, R22 refrigerant, and water. The considered tube and rib materials are steel, aluminum, and copper. The overall number of examined combinations of all conditions is 5,880.

The problem is described by the two-dimensional RANS equations and energy equation with the assumption of steady incompressible fluid flow and temperature independent physical properties of working fluid is. To close RANS equations, an additional component representing the Reynolds stresses is modeled by Renormalization-group k-ε turbulence model as it has shown good performance in numerous investigations [4-6] in flows in rough tubes.

2.2. Grid generation
Computational domains consisting of a uniform quadrilateral mesh layout with approximately 230,000 cells are alike in all considered cases. The grid is concentrated near the wall to provide $y^+$ value between 30 and 60. Grid independence tests have been conducted. An example of computational domain for rib parameters e/d=0.03, p/d=1 is represented in Figure 2.

2.3. Calculation of major parameters
Three parameters of interest of the present study are Nusselt number, friction factor and thermal hydraulic performance parameter developed by Dreitser [1] and representing the ratio of the volumes of the heat exchanger with channels provided with enhancement means compared to the heat exchanger with similar plane channels.

Average Nusselt number is defined as

$$Nu = \frac{hd}{\lambda_f}$$  \hspace{1cm} (1)

where $h$ is the convective heat transfer co-efficient and $\lambda_f$ is the working fluid thermal conductivity.
The friction factor is computed by pressure drop $\Delta P$ and can be obtained by

$$f = \Delta P \cdot \left[ \frac{l}{d} \left( \frac{\rho v^2}{2} \right) \right]^{-1} \quad (2)$$

Thermal hydraulic performance parameter

$$\text{Thermal hydraulic performance } = (Nu/Nu_m)^{1.4} / (f/f_m)^{0.4} \quad (3)$$

where $Nu_m$ and $f_m$ are, respectively, the Nusselt number and friction factor for a smooth tube, taken from additional calculations of a smooth tube model.

2.4. Artificial neural network (ANN) approach

Using artificial neural networks for predicting data with a non-linear correlation between inputs and outputs is a powerful approach requiring less time and machine resources than CFD and showing good performance in numerous engineering studies [7-8]. In the present study, a deep feed-forward neural network with 3 hidden layers of neurons with hyperbolic tangent activation function is chosen to predict Nusselt number and friction factor. A schematic diagram of ANN is shown in Figure 3, the detailed information about inputs and outputs is represented in Table 1.

Train data of 5,880 CFD simulations are randomly shuffled and divided into two datasets for training (75% data) and validation (25% data). The inputs and outputs (see Table 1) are made dimensionless and normalized in the range [0; 1] for better convergence. Learning parameters of the ANN (optimizer, learning rate, batch size) are varied to find the best solution.

3. Results and discussion

The obtained data of CFD simulations have been normalized and proceeded to deep ANN. The number of neurons in hidden layers is varied along with the batch size and optimization method to obtain the minimum of a quadratic loss function (mean square error or MSE) calculated as follows:

$$\text{MSE} = \frac{1}{n} \sum_{i=1}^{n} (y_i - \hat{y}_i)^2 \quad (4)$$

where $y_i$ is the predicted value, and $\hat{y}_i$ is the CFD modeled value.

Two optimizers are considered in the present study: stochastic gradient descent (SGD) and Adam [9] which has shown better performance. From Figure 4 it can be seen that the decrease in batch size leads to fewer epochs that need convergence but MSE behaves more stochastically.
Reducing the model’s capacity (number of layers and neurons per layer) can result in faster convergence but also leads to underfitting. On the other hand, a too complicated model can reach overfitting: the state when train error rapidly decreases in conjunction with increasing validation error. Underfitting for a small model of 8 neurons and overfitting for a complex model of 2048 neurons are shown in Figure 5.
The least MSE of $5.17 \times 10^{-5}$ on validation dataset is obtained by Adam [9] optimizer after 592 epochs for ANN with 32, 16, and 8 neurons in the first, second, and third hidden layers, respectively, and batch size of 8 data rows. This ANN has been used in the present investigation for making all further predictions.

Individual dots in Figures 6-10 stand for the CFD results, the lines represent the ANN predictions. Validation of CFD and ANN modeling with experimental data reported by Kalinin et. al [3] is shown in Figure 6. It can be seen that both the Nusselt number and friction factor are under-predicted which may be due to assumptions of the two-dimensional model.

Effect of the rib height-to-diameter ratio (e/d) on thermal hydraulic performance at p/d=1 and Re=10$^5$ is shown in Figure 7 along with ANN predictions for steel tubes and all working fluids considered. The maximum of performance is observed at e/d=0.02 for air and at e/d=0.01 for R22 refrigerant and water.

Figure 8 shows the variation of relative friction factor as a function of rib pitch-to-diameter ratio (p/d) along with ANN predictions for R22 refrigerant in an aluminum tube at Re=10$^5$ and fixed rib height of e/d=0.01, 0.03 and 0.05. The maximum of friction is reached nearby the value of relative pitch p/e=10, and the same is observed for the relative Nusselt number. These results are in good agreement with experimental data reported by Kalinin et. al [2-3].

![Figure 6. Comparison of numerical and experimental values of Nusselt number and friction factor.](image)

![Figure 7. Variation of thermal hydraulic performance with relative roughness height.](image)

![Figure 8. Variation of relative friction factor with roughness pitch for R22 and fixed rib height.](image)
Effect of the flow Reynolds number $Re$ on thermal hydraulic performance along with ANN predictions for all working fluids and fixed rib parameters $e/d=0.05$ and $p/d=1$ is shown in Figure 9. The best performance is achieved at $Re=10,000$ for R22 and water and at $Re=20,000$ for air.

Applying materials with high thermal conductivity value for rough tubes leads to greater rib efficiency and hence increasing Nusselt number. This can be seen in Figure 10.

![Figure 9. Variation of thermal hydraulic performance with flow Reynolds number.](image)

![Figure 10. Relative Nusselt number for different tube materials.](image)

**Conclusions**

The performance of machine learning methods is demonstrated for a problem of optimal heat transfer enhancement. A 2-dimensional CFD analysis has been carried out to obtain major characteristics and train the deep ANN. It has been found that cooper tubes with transverse rib roughness and flow parameters $e/d=0.025$, $p/d=0.15$, $Re=20,000$, and water as a working fluid provide the best thermal hydraulic performance of 250% for the studied range of parameters.

The result demonstrates that ANN can offer a powerful approach for modeling enhanced heat transfer characteristics based on CFD simulations with a mean error of less than 1.5%. The trained ANN of the present study can be used for searching optimal rib roughness parameters for a circular tube based only on considered the working fluid and the range of Reynolds number with no need of repeating any simulations or experiments and, hence, has a perspective of industrial application.

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