Performance of CFD and ANN modeling of heat transfer enhancement in a circular tube with artificial roughness

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Abstract. This paper presents a comparison of three different approaches for modeling enhanced heat transfer characteristics of turbulent airflow in a circular tube with artificial roughness of transverse ribs. A number of CFD simulations are carried out forming the first dataset as well as the second dataset extracted from a number of classical works. A deep feed-forward neural network is developed to predict Nusselt number and friction factor for a variety of rib roughness and flow parameters. The ANN is trained by the first dataset (the CFD and ANN approach) and the second dataset (the experiment and ANN approach) independently and by a combination of datasets (the hybrid approach) showing good quality predictions in all the cases. All results are compared with experimental data and CFD modelled values showing the best results of the experiment and ANN approach.

1. Introduction

Application of machine learning methods for a variety of engineering problems has grown in popularity during the last two decades. Numerous works [1-4] report high efficiency and low computational cost of artificial neural networks (ANNs) application for modeling complicated sequences of data. The most important issue of this approach is obtaining a valid dataset for training the ANN with the help of experiment or computational fluid dynamics (CFD).

A relevant engineering problem that occurs in the modern heat exchanger industry is efficient heat transfer enhancement allowing to achieve both demands of high unit power and compactness. As for tubular heat exchangers, a technologically acceptable heat transfer enhancement method is artificial turbulentization of flow [5] by roughness elements: annual diaphragms, wire coils, transverse ribs, etc. An experimental investigation should be performed assuming a wide range of combinations of roughness parameters to obtain the optimal correlation between enhanced heat transfer and pressure drop. CFD simulations can be carried out instead of the experiment to minimize technical difficulties.

The present work shows three different approaches of generalizing data on heat transfer and friction loss characteristics of a tube section equipped with transverse rectangular ribs. Series CFD simulations are carried out forming the first dataset. The second dataset obtained from several experimental works by Zukauskas et. al [6]. A deep feed-forward ANN is developed and trained by different data and compared to CFD results to find the best approach of modeling enhanced heat transfer.
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 velocity inlet; (2) is 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. Schematic of two-dimensional solution domain for CFD analysis.](image)

The rib pitch-to-tube diameter ratio (p/d) is in the range 0.1-1.5; the rib height-to-tube diameter ratio (e/d) is in the range 0.01-0.05; the considered Reynolds number (Re) is in the range $10^4$–$10^6$. The working fluid in all cases is air. The overall number of examined combinations of all conditions is 651.

It is assumed that the problem is described by the two-dimensional RANS equations and energy equation with the following assumptions: steady incompressible fluid flow, physical properties of working fluid is temperature independent. 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 [7-8] on 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.

![Figure 2. Close up view of the two-dimensional uniform mesh.](image)

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 [9] 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

\[ Nu = \frac{hd}{\lambda_f} \]  

where \( h \) is a convective heat transfer co-efficient and \( \lambda_f \) is working fluid thermal conductivity.

The friction factor is computed by pressure drop \( \Delta P \) and can be obtained by

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

Thermal hydraulic performance parameter

\[ \text{Thermal hydraulic performance} = \left( \frac{Nu}{Nu_m} \right)^{1.4} \left( \frac{f}{f_m} \right)^{0.4} \]  

Where \( Nu_m \) and \( f_m \) are Nusselt number and friction factor for a smooth tube respectively which has been taken from additional calculations of a smooth tube model.

2.4. Artificial neural network (ANN) approach

In the present study, 3 independent feed-forward ANNs sharing the same topology of 3 hidden layers are developed to predict Nusselt number and friction factor. A schematic diagram of ANN is shown in Figure 3, the detailed information on inputs and outputs is shown in Table 1. The inputs and outputs are made dimensionless and normalized in the range [0; 1] for better convergence. Learning parameters of the ANNs (optimizer, learning rate, batch size) as well as the number of neurons in hidden layers and their activation functions are varied to achieve the minimum of mean square error (MSE). A number of cases has been added to all datasets for better behavior at extreme points of \( e=0 \), \( p=0 \), and \( p=\infty \). All datasets have been randomly shuffled and divided for training (85% data) and validation (15% data).

![Figure 3. A schematic diagram for the deep feed-forward neural network.](image)

| ID | Input/output data | Normalized data |
|----|-------------------|-----------------|
| x1 | rib height        | \((e_i - \min e_i)/(\max e_i - \min e_i)\) |
| x2 | rib pitch         | \((p_i - \min p_i)/(\max p_i - \min p_i)\) |
| x3 | flow Reynolds number | \((Re_i - \min Re_i)/(\max Re_i - \min Re_i)\) |
| y1 | Nusselt number    | \((Nu_i - \min Nu_i)/(\max Nu_i - \min Nu_i)\) |
| y2 | friction factor   | \((f_i - \min f_i)/(\max f_i - \min f_i)\) |
The first dataset of 192 cases extracted from experimental study [6] is proceeded into the ANN representing the first (experiment and ANN) approach. The same is done with the second dataset of 651 CFD obtained cases (CFD and ANN approach). As long as the both datasets are taken for the same range of input values, some conflicts in the combined dataset are observed. To solve them and minimize prediction error a methodic represented by Ledesma et. al [10] is applied: a learning conflict level $c_{ij}$ is calculated for each pair of cases as follows:

$$ c_{ij} = |y_i - y_j| \exp \left( -\frac{1}{M\sigma^2} \sum_{k=1}^{M} (x_{ik} - x_{jk})^2 \right), \quad (4) $$

where $x$ is a $N \times M$ matrix of input values, $y$ is a $N \times 1$ matrix of target values, and $\sigma = 0.01$. Then all individual conflict values $c_{i1}, c_{i2}, ..., c_{iN}$ are analyzed. The pairs of conflicting cases ($c_{ij} \geq 10^{-5}$) are replaced with the arithmetic average of them. The obtained combined dataset of 687 cases is used for hybrid approach. All results of training and validation for 3 present ANNs are shown in Table 2.

### 3. Results and discussion

The least MSE for all datasets is obtained with deep ANNs of 64, 32 and 16 neurons of sigmoid activation function in the first, second and third hidden layers respectively, trained by Adam optimization algorithm [11] with batch size of 4 cases. From Table 2 it can be seen that the best result is obtained for CFD dataset, one of the largest and the most balanced one. A significant effect of removing learning conflicts is also seen for the combined dataset.

| Dataset                        | Training MSE | Validation MSE | Overall MPE |
|--------------------------------|--------------|----------------|-------------|
| Experiment [6]                 | $2.3 \times 10^{-4}$ | $2.7 \times 10^{-4}$ | $1.26\%$    |
| CFD simulation                 | $4.3 \times 10^{-5}$ | $5.4 \times 10^{-5}$ | $0.60\%$    |
| Combined, with conflicts       | $1.6 \times 10^{-3}$ | $1.7 \times 10^{-3}$ | $3.27\%$    |
| Combined, conflicts removed    | $5.1 \times 10^{-4}$ | $5.2 \times 10^{-4}$ | $1.85\%$    |

Effect of the rib height-to-diameter ratio ($e/d$) on relative Nusselt number and friction factor at the fixed pitch of $p/d=1$ and flow $Re=10^5$ is shown in Figure 4 along with ANNs predictions. It can be seen that results obtained in the experiment and the ANN approach are in good agreement with those in CFD and ANN approach. In this way hybrid approach does not make a difference, however, it provides better results than pure CFD and ANN trained by CFD.

**Figure 4.** Variation of relative (a) Nusselt number (b) with relative roughness height.
Figure 5 shows the variation of relative Nusselt number with rib relative pitch ratio (p/e) and (p/d) at several fixed rib heights and Re=10⁵ obtained with different approaches. An important issue reported by Kalinin et al [5] of global maximum for fixed relative pitch value of p/e=10 (the vertical marker) cannot be observed for experiment and ANN approach (Figure 5a) due to lack of data. However, for CFD and ANN approach (Figure 5b) this feature can be seen. In this case, the hybrid approach (Figure 5c) shows higher accuracy than CFD and also captures the feature.

![Figure 5. Variation of relative Nusselt number with relative rib pitch for fixed rib height and Re for (a) experiment and ANN approach (b) CFD and ANN approach (c) hybrid approach (painted markers stand for experimental dots, blank markers stand for CFD dots).](image)

The influence of the flow Reynolds number on relative Nusselt number and friction factor for fixed rib parameters of e/d=0.05 and p/d=1 is shown in Figure 6 according to all approaches considered. The sizeable difference between experimental and CFD results can be settled out, taking into consideration the effect of rib shape, which is not specified by the authors [6] and is different. For example, the monotone increase of relative friction with Reynolds number obtained from CFD indicates keen rib profiles, while nearly constant relative friction indicates stream-lined rib profiles (Figure 6b).

4. Conclusions
The performance of three different approaches of machine learning methods application to heat transfer enhancement problem is demonstrated. Two datasets have been obtained: the first one from a 2-dimensional CFD analysis of the present study and the second one extracted from experimental study [6]. The following conclusions can be drawn from the present investigation:

- All ANNs considered show accurate predictions, the highest accuracy is achieved for bigger datasets without learning conflicts;
- Despite some defects, experiment and ANN approach shows the best predictions among other methods (pure CFD, CFD and ANN, hybrid ANN);
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Figure 6. Variation of relative (a) Nusselt number (b) friction factor with flow Reynolds number.

- The hybrid approach can be a powerful mean of making accurate predictions with less costly experimental data requirements. However, the best performance is achieved when the combined (experimental and CFD) dataset has no learning conflicts and sizeably differences;
- The trained ANNs of the present study can be used for searching optimal transverse rib roughness parameters for a circular tube based only on considered working fluid and range of Reynolds number with no need of repeating any simulations or experiments and hence has a perspective of industrial application and theory of experiment planning.

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