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Adaptive Neuro-Fuzzy Inference System of friction factor and heat transfer nanofluid turbulent flow in a heated tube

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ABSTRACT

In this paper, estimating of hydrodynamics and heat transfer nanofluid flow through heated tube has been conducted by using Adaptive Neuro-Fuzzy Inference System (ANFIS). The CFD data related to three types of nanofluids (Al_2O_3, SiO_2 and TiO_2) flow in horizontal tube with 19 mm diameter and 2000 mm length. Heat flux around tube is fixed at 5000 W/m^2, the range of Reynolds number is (3000–30,000) and volume concentrations are (1% and 2%). ANFIS model has three input data presented by Reynolds number, volume concentration of nanofluids and materials and two output presented predicting friction factor and Nusselt number in the tube. The simulation results of proposed algorithm have been compared with CFD simulator in which the mean relative errors (MRE) are 0.1232% and 0.1123 for friction factor and Nusselt number respectively. Finally, ANFIS models can predict hydrodynamics and heat transfer of the higher accuracy than the developed correlations.

1. Introduction

Large wide of world using tube in engineering applications and is significant in practical applications, such as heat exchangers, steam generators, chemical reactors, membrane separations, and piping systems [1]. Recent research has been focused on practical tube applications based on emerging both soft computing fields like Computational fluid dynamic (CFD), and computational intelligence such as ANN, GA, PSO, and fuzzy logic [2].

The heat transfer enhancement by used aluminum oxide nanofluid with different volume concentration and constant wall temperature studied experimentally by Sundar and Sharma [3]. It was concluded that the friction factor and heat transfer enhancement by 10% and 40% respectively. The single-phase approach may be used for heat transfer and pressure drop prediction of new nanofluids. Numerical study of convection flow of a Al_2O_3-water nanofluid inside the tube under turbulent flow with the wall uniform temperature was presented by Bianco et al. [4]. Their results showed the convective heat transfer coefficient for conventional liquid is lower than nanofluids and friction factor data was agreed with experimental data of Pak and Cho[5].

Many researchers have introduced different forms of neural-fuzzy networks and its applications in bioinformatics, petroleum engineering and pattern recognition [6–7]. Group of Artificial intelligence methods was used to estimate the convective heat transfer coefficient and pressure drop during annular flow numerically such as multilayer perceptron (MLP), generalized regression neural network (GRNN) and radial basis networks (RBFN), likewise, the Adaptive Neuro-Fuzzy Inference System (ANFIS) have been used to decide best approach of heat transfer [8].

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Nomenclature

C	specific heat capacity [J/kg °C]
D	diameter [m]
f	friction factor
h	convection heat transfer coefficient [W/m^2 °C]
k	thermal conductivity [W/m °C]
n	number of runs
Nu	Nusselt Number [$h\,D/k$]
P	Pressure [N/m^2]
Pr	Prandtle Number [$C.\ \mu/k$]
Re	Reynolds Number [$\rho D\ u/k$]
u	Velocity [m/s]
G	Response parameters
μ	Viscosity [N s/m^2]
ρ	Density [kg/m^3]
ϕ	Volume concentration
ANFIS	Adaptive Neuro-Fuzzy Inference System
CFD	computational fluid dynamic
MR%	Maximum Error
MAE%	Mean Average Error

Subscripts

f	liquid phases
p	solid particle
nf	nanofluid
h	hydraulic

Reynolds number, velocity and flow rate have been used as inputs to estimate friction factor of an open channel flow with ANFIS by Samandar [9]. Experimental data from the laboratory have been used to learn algorithm and training with ANFIS model, in addition, the simulation results of friction factor were compared with experimental results. A good correlation was obtained between the experimental data and predicted results of Balcilar et al. [10]. ANFIS is a hybrid scheme based to a combination of neural networks and Fuzzy logic, which is an efficient tool for modeling different kind of uncertainty associated with imprecision and vagueness [6,10–14].

This paper, focus on hydrodynamic and heat transfer under turbulent three types of nanoparticles (Al_2O_3, SiO_2 and TiO_2) suspended in water flow in a heated straight tube for two volume concentration 1% and 2% by ANFIS. Firstly, introduce a brief description of a heated tube and its boundary conditions. Secondly, ANFIS with three input parameters and two output to predict the friction factor and Nusselt number. Finally, the results of proposed algorithm shows it effectiveness compared with CFD simulation for different Reynolds number, volume concentrations and materials of nanofluid flow through the heated tube.

2. Theoretical analysis

2.1. Physical model

Fig. 1 shows the test rig as included straight horizontal tube of 19 mm diameter and 2000 mm length with wire heater around it to fix heat flux at 5000 W/m^2. The nanofluid is flowing inside tube with high velocity and Reynolds number range (3000–30,000) so it will gain heat from input to output that taken in this case.

The simulation results are compared to the equations for the friction factor (1) and Nusselt number (2) that correlated by Blasius and Dittus-Boelter respectively [1]:

$$f = \frac{0.316}{Re^{0.25}} \tag{1}$$

$$Nu = 0.023 \times Re^{0.8} \times Pr^{0.4} \tag{2}$$

These two equations correlated for pure water that used for verification process.

The thermal properties of nanofluid were calculated by using the equations below [15]:

Density (ρ_{nf}) of nanofluid can be calculating by:

$$\rho_{nf} = \varphi\rho_p + (1-\varphi)\rho_f \tag{3}$$

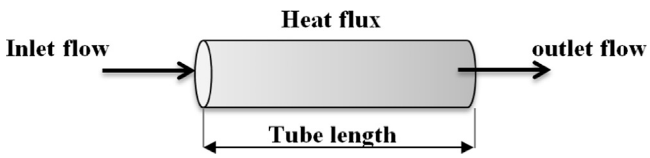


Fig. 1. Schematic of physical model.

Specific heat capacity (C_{eff}) of nanofluid can be calculating by:

$$C_{nf} = \frac{\varphi(\rho C)_p + (1 - \varphi)(\rho C)_f}{\rho_{nf}} \tag{4}$$

Thermal conductivity (k_{nf}) of nanofluid as:

$$\frac{k_{nf}}{k_f} = 1 + \frac{3\left(\frac{k_p}{k_f} - 1\right)\varphi}{\left(\frac{k_p}{k_f} + 2\right) - \left(\frac{k_p}{k_f} - 1\right)\varphi} \tag{5}$$

Viscosity (μ_{eff}) of nanofluid can be calculated by:

$$\frac{\mu_{nf}}{\mu_f} = \left(1 + 2.5\varphi + 6.25\varphi^2\right) \tag{6}$$

where φ is the volume concentration of nanofluid and subscript p, f and nf are referred to solid particles, fluid and nanofluid part respectively. All properties of fluid (water) have taken from [16].

3. Neuro–fuzzy

3.1. Basic of adaptive neuro-fuzzy

The Adaptive Network Based Fuzzy Inference Systems (ANFIS) is a hybrid type of framework, which learns the rules and membership functions from data. The ANFIS is a network of nodes and directional links associated with a learning rule for instance, back propagation learning a relationship between inputs and outputs. Fig. 2 shows the ANFIS configuration in which the circular nodes represent fixed nodes and the square nodes are represent parameters nodes that have to be learnt.

For the training of the ANFIS network, there is a forward pass and a backward pass. The forward pass propagates input vectors through the network layer by layer. In the backward pass, the error is sent back through the network in a similar manner to back propagation [13].

Layer 1: The output of each node is:

O1, i=μAi(x) for i =1, 2.

O1, i=μBi−2(y) for i=3, 4.

So, the O1, i(x) is essentially the membership grade for x and y. The membership functions could be anything but for illustration purposes we will use the bell shaped function, that is,

$$\mu_A(x) = \frac{1}{1 + \left|\frac{x - c_i}{a_i}\right|^{2bi}} \tag{7}$$

where a_i, b_i, c_i are parameters to be known. These are the premise parameters.

Layer 2: Every node in this layer is fixed. This is where the t-norm is used to 'AND' the membership grades – for example the product:

$$O_{2,i} = w_i = \mu_{Ai}(x)\mu_{Bi}(y) \quad \text{i} = 1, 2 \tag{8}$$

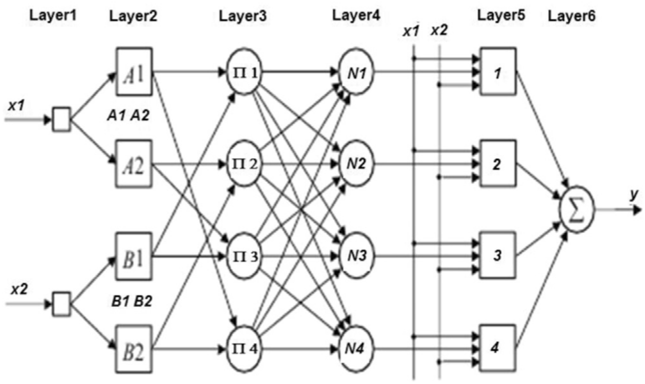


Fig. 2. Construction of Neuro fuzzy.

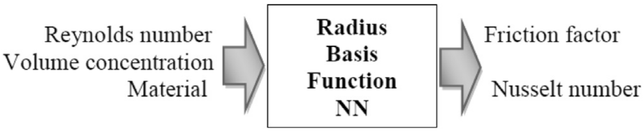


Fig. 3. Neuro-fuzzy for heated tube.

Layer 3: It contains fixed nodes which calculate the ratio of firing strengths of the rules:

$$O_{3,i} = w_i = \frac{w_i}{w_1 + w_2} \quad \text{for} \quad i = 1, 2 \tag{9}$$

Layer 4: The nodes in this layer are adaptive and perform consequent of the rules:

$$O_{4,i} = w_i f_i = w_i\left(P_i x + q_i y + r_i\right) \quad \text{for} \quad i = 1, 2 \tag{10}$$

The parameters in this layer (pi, qi, ri) are to be determined and are referred to as the consequent parameters.
Layer 5: There is a single node here that computes the overall output:

$$O_{5,i} = \sum_{i=1}^{2} w_i f_i = \frac{\sum_{i=1}^{2} w_i f_i}{\sum_{i=1}^{2} w_i} \tag{11}$$

This is how, typically, the input vector is fed through the network layer by layer.

3.2. Modeling of heated tube

In this study, the neuro-fuzzy systems with the CFD analysis for specified flow regimes in horizontal single-phase flow has been conducted. Fig. 3 shows effective predicting of output parameters based on a proper selected inputs and outputs of Neuro-Fuzzy, structure of the network and training of it using appropriate data should be done with almost care.

In the present study, three inputs are selected as Reynolds number (Re), concentration of volume (φ) and nanofluid materials; and on another hand the output node representing the friction factor and Nusselt number.

To train ANN models with the results of the CFD, network architecture was required; first the entire training data file was randomly divided into training and testing data sets.

About 90% of the data and 55 patterns were used to train the different network architectures and remaining 5 patterns which used for testing to verify the prediction ability of each training ANFIS model as shown in Table 1.

Numerical studies were conducted to verify the ANFIS model results. Number of CFD data was used in order to improve ANFIS model, for training and the remainder for testing performance. The relative error results of ANFIS model are shown in Tables 2 and 3, for training data, where the relative error (*MR%*) for variable *G* and the mean relative error (*MAR%*) were estimated as [9]:

$$MR\% = \frac{\left|G_{CFD} - G_{ANFIS}\right|}{G_{CFD}} \tag{12}$$

$$MAE\% = \frac{1}{N}\sum_{i=1}^{N}\left(MR\%\right)_i \tag{13}$$

Table 1
Sample of training data.

Re	Volume concentration	Materials	Frication factor	Nusselt number
3000	0.01	1	0.2536	53
6000	0.01	1	0.1976	55
9000	0.01	1	0.1416	58
12,000	0.01	2	0.0912	61
15,000	0.01	2	0.0654	64
18,000	0.01	2	0.0553	67
21,000	0.01	3	0.0302	70
24,000	0.01	3	0.0376	74
27,000	0.01	3	0.0351	77

Table 2
Ccomparison of ANFIS with CFD of friction factor data.

Re	Volume concentration	Materials	Frication factor CFD	Friction factor ANFIS	Error %
3000	0.01	1	0.2363	0.2342	0.8921
33,000	0.01	1	0.0379	0.0376	0.7385
3000	0.01	2	0.2459	0.2411	1.9608
33,000	0.01	2	0.0380	0.0373	1.7316
3000	0.01	3	0.2499	0.2465	1.3645
33,000	0.01	3	0.0381	0.0375	1.5631
3000	0.02	1	0.2375	0.2338	1.5397
33,000	0.02	1	0.0382	0.0379	0.6517
3000	0.02	2	0.2405	0.2378	1.1292
33,000	0.02	2	0.0385	0.0380	1.3341
3000	0.02	3	0.2413	0.2387	1.0861
33,000	0.02	3	0.0387	0.0381	1.4433
				MR	1.2862
				MAR	0.1232
		Time per test	183 s	0.00926 s	

Table 3
Ccomparison of ANFIS with CFD of Nusselt number data.

Re	Volume concentration	Materials	Nusselt number CFD	Nusselt number ANFIS	Error %
3000	0.01	1	61	60	1.639344262
33,000	0.01	1	70	69	1.428571429
3000	0.01	2	67	67	0
33,000	0.01	2	74	73	1.351351351
3000	0.01	3	73	72	1.369863014
33,000	0.01	3	83	82	1.204819277
3000	0.02	1	81	80	1.234567901
33,000	0.02	1	89	89	0
3000	0.02	2	85	84	1.176470588
33,000	0.02	2	96	95	1.041666667
3000	0.02	3	90	90	0
33,000	0.02	3	108	107	0.925925926
				MR	0.97477
				MAR	0.1123
		Time per test	183 s	0.00926 s	

4. CFD analysis

4.1. Simulation study

ANSYS/FLUENT software is using to simulate governing equations of turbulent forced convection heat transfer in a horizontal tube with constant heat flux. Computational fluid dynamics (CFD) has the ability to deal with a wide range of simulating engineering problems related to heat transfer by means of the numerical solution. The governing equations included continuity, momentum and energy equations [17]:

$$\nabla\cdot\left(\rho_{nf}.\,u\right) = 0 \tag{14}$$

$$\nabla\cdot\left(\rho_{nf}uu\right) = -\nabla P + \nabla\cdot\left(\mu_{nf}\nabla u\right) \tag{15}$$

$$\nabla\cdot\left(\rho_{nf}C_{nf}uT\right) = \nabla\cdot\left(k_{nf}\nabla T\right) \tag{16}$$

Equations are solved iteratively using the segregated solver and a pressure correction equation which used to ensure the momentum and mass conservation. A SIMPLE scheme was adopted for the treatment of pressure. Turbulent viscous (k-ε) model was employed. For all simulations performed in this work, converged solutions were considered for residuals lower than 1×10^{-6} for all the governing equations.

The CFD modeling region for heat transfer and fluid flow phenomena in pipes could be done as follows:

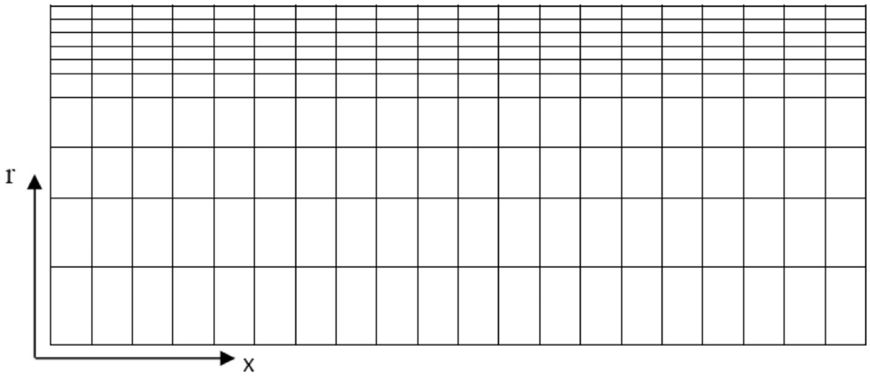


Fig. 4. Mesh generated model.

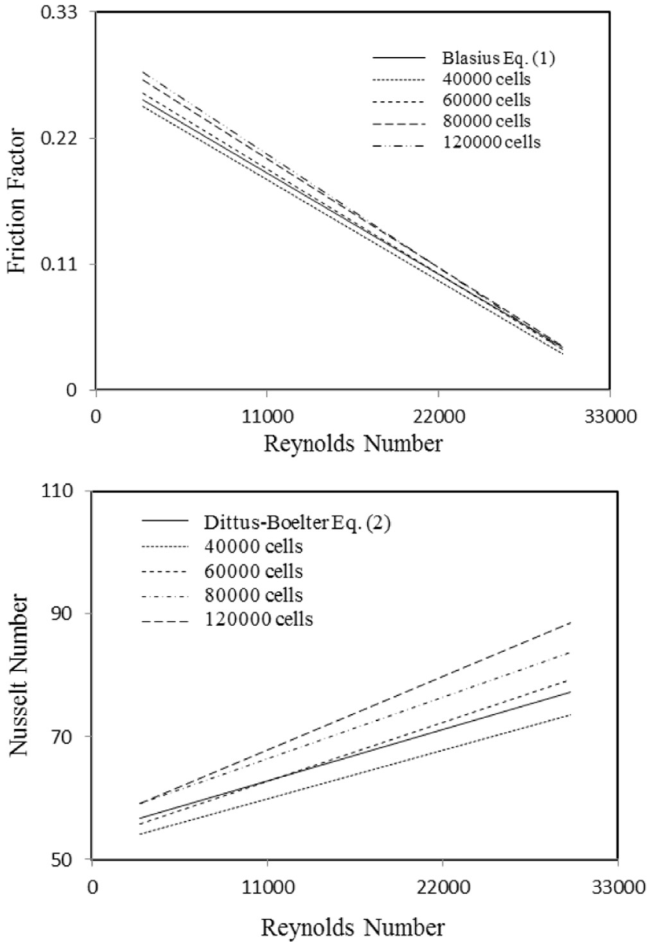


Fig. 5. Grid independent test.

I. Preprocess stage, the geometry of heated tube region was constructed and computational mesh was generated in GAMBIT. GAMBIT model as shown in Fig. 4, used to describe problem which graph and mesh the section test with size of (2000 $\times$ 30) and 2000 with length of pipe, 30 with radius.

II. It followed by the heated tube model, boundary conditions, and other appropriate parameters were defined in models setup and solving stage.

III. Finally the results could be obtained by ANSYS/FLUENT iterations which led to converged criteria. The friction factor and Nusselt number through the pipe could be obtained throughout the computational domain in the post-process stage.

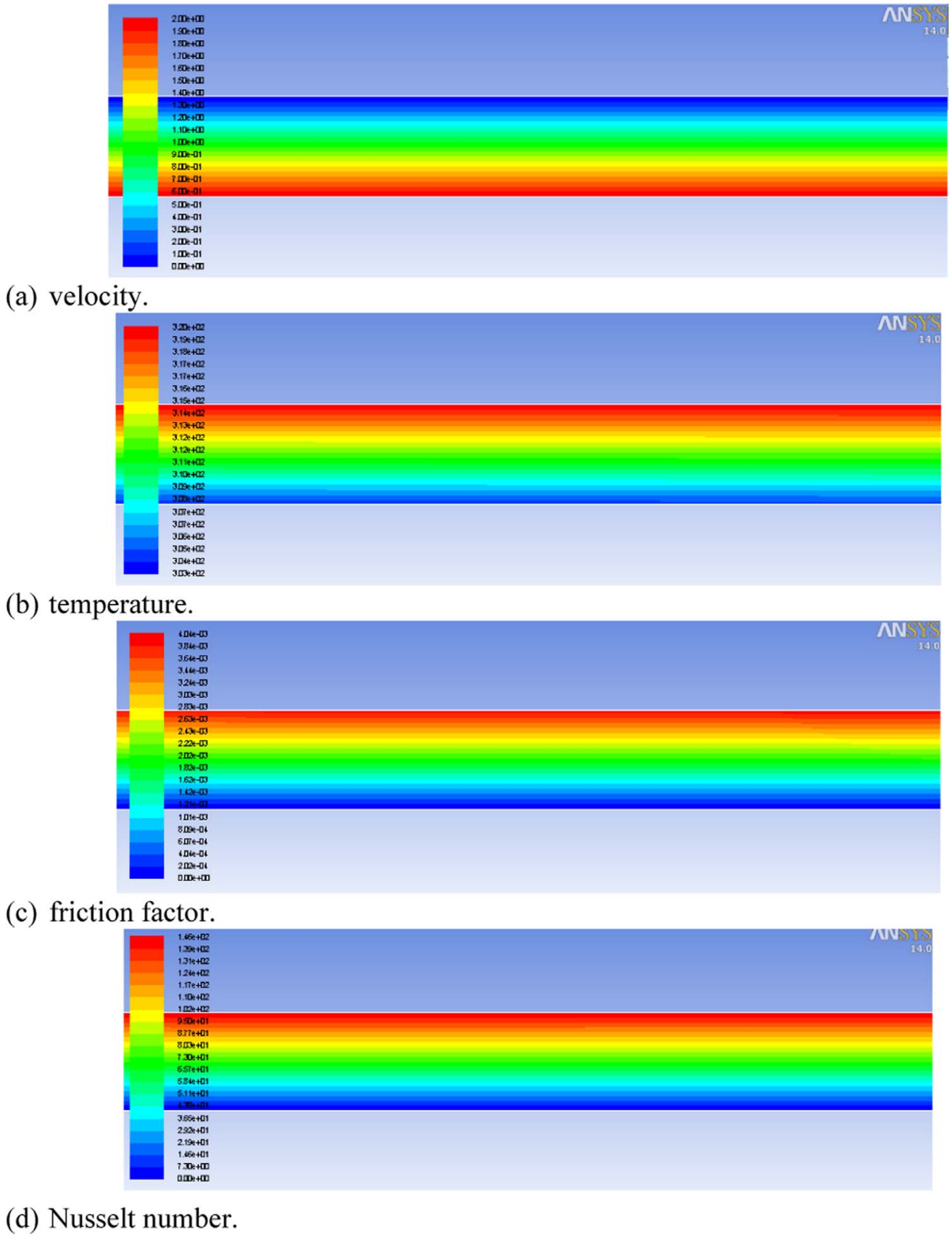


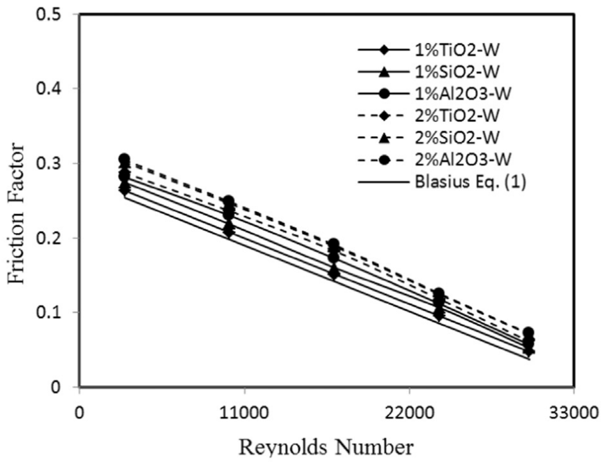
Fig. 6. CFD analysis contours: (a) velocity (b) temperature (c) friction factor and (d) Nusselt number.

4.2. Boundary conditions

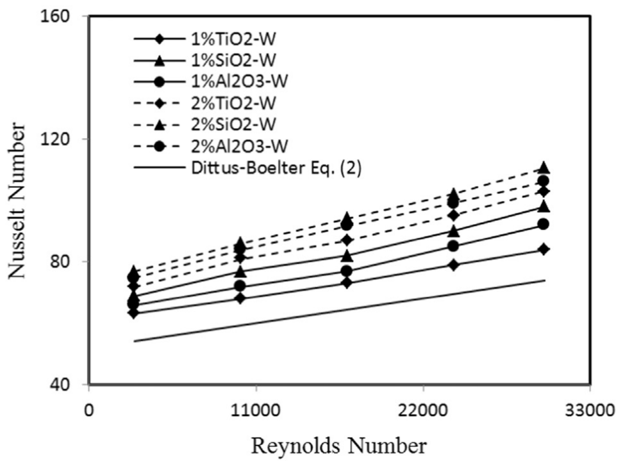
Three types of nanoparticles (Al_2O_3, SiO_2 and TiO_2) suspended in water with volume concentrations of 1% and 2% at a base temperature of 25 °C were used as the input fluids. For verification, water is also used as the working fluid. CFD studies were performed with a uniform velocity profile at the inlet, and a pressure outlet condition is used at the outlet of the system. The wall of the tube is assumed to be perfectly smooth. The Reynolds number was varied from 3000 to 30,000 at each iteration step as input data while, the friction factor and Nusselt number are the output data.

5. Results and discussion

Grids independence was determined using commercial software and it was found for 60,000 cells (2000×30), with subdivisions in the horizontal and vertical directions of the tube. To determine the most suitable size of the mesh faces, a



(a) Friction Factor.



(b) Nusselt Number.

Fig. 7. CFD data with different Reynolds Number: (a) friction factor, (b) Nusselt number.

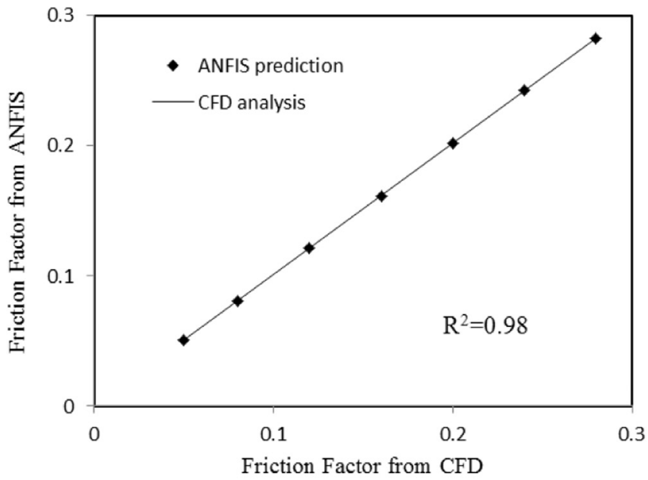
grid independence test was performed for the physical model. In this study, rectangular cells were used to mesh the tube as shown in Fig. 5.

Grid independence was checked using different grid systems, and four mesh sizes were considered, 40,000 cells (2000 × 20), 60,000 cells (2000 × 30) and 80,000 cells (2000 × 40) for pure water. The friction factor and Nusselt number were determined for all four mesh sizes, and the results all agreed with each other. All four-mesh sizes could have been used, and in the study undertaken, the mesh sizes with 60,000 cells was adopted because it was the best in terms of accuracy. Similar to the methodology has followed by Hussein et al. [18] to select the optimum mesh size.

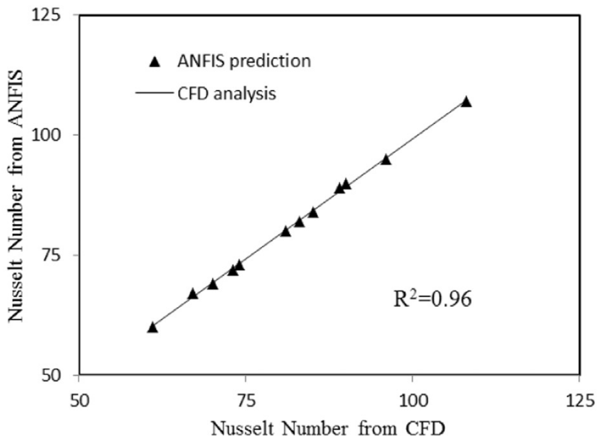
The assumption of this study was 1% and 2% nanofluids volume concentration at (25 °C) base temperatures which used as input fluids. For verification process, water was also employed as working fluid which carried out with uniform velocity profile at the inlet of the horizontal tube. The pressure outlet boundary condition was used at the outlet boundary. The wall of the pipe was assumed to be perfectly smooth with zero roughness height and a constant wall heat flux (5000 W/m^2) as wall boundary.

Fig. 6 shows contour of CFD data of (velocity, temperature, friction factor and Nusselt number) along axisymmetric tube for pure water. The velocity profile shown in Fig. 6(a) increases with the centerline of tube from zero near the Wall to the máximum value of 2 m/s at the center of tube. Likewise, Fig. 6(b, c and d) shows temperature, friction factor and Nusselt number increase with wall side when boundary layer is found till maximum value of 320, 0.004 and 146 respectively.

Fig. 7(a) shows the friction factor against Reynolds number with two concentration of volume for 3 types of nanofluids. It



(a) Friction Factor.



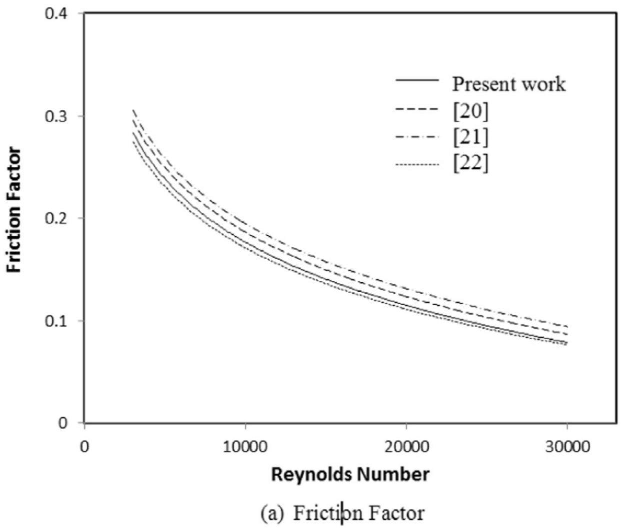
(b) Nusselt Number.

Fig. 8. ANFIS prediction to CFD analysis: (a) friction factor (b) Nusselt number.

appears that the friction factor increases with increasing of volume concentrations but decreases with increasing of Reynolds number. It was observed the friction factor of Al_2O_3 is higher than SiO_2 which is higher than TiO_2 nanofluids due to high viscosity of Al_2O_3 as compared to SiO_2 and TiO_2 nanofluids. Fig. 7(b) shows Nusselt number against Reynolds number with two concentration of volume for 3 types of nanofluids. It seems that Nusselt number increases with increasing of both volume concentrations and Reynolds number. It was found the Nusselt number values of SiO_2 are higher than Al_2O_3 and TiO_2 nanofluids due to high specific heat capacity of SiO_2 than Al_2O_3 and TiO_2 nanofluids. Similar results of [16,19] of friction factor and Nusselt number behavior with Reynolds number.

Tables 2 and 3 show comparison sample of friction factor and Nusselt number for a set of heated tube models that calculated by ANFIS and CFD analysis. It was observed that the accuracy of the ANFIS was slightly superior when compared to the CFD techniques on account of Maximum Error (MR) and Mean Average Error (MAE). The mean error is within the range of 1.2862–0.97477. The higher values of the maximum error of friction factor were approximately 0.128 and the mean average error was 0.1232 whereas, the higher values of the maximum error of Nusselt number were approximately 0.97477 and the mean average error was 0.1123. The computational time is the least, for the (ANN) prediction (0.00926 s) is much less as compared to the CFD which is (183 s). It means ANFIS can often obtain results in almost negligible time [9].

Fig. 8 shows the linear correlation among the response parameters obtained from ANFIS and CFD analysis. Fig. 8(a and b) indicated friction factor and Nusselt number from ANFIS model with them from CFD analysis. It seems that there are good agreement between ANFIS model and CFD analysis for both friction factor and Nusselt number data with R-square value less than 96%.



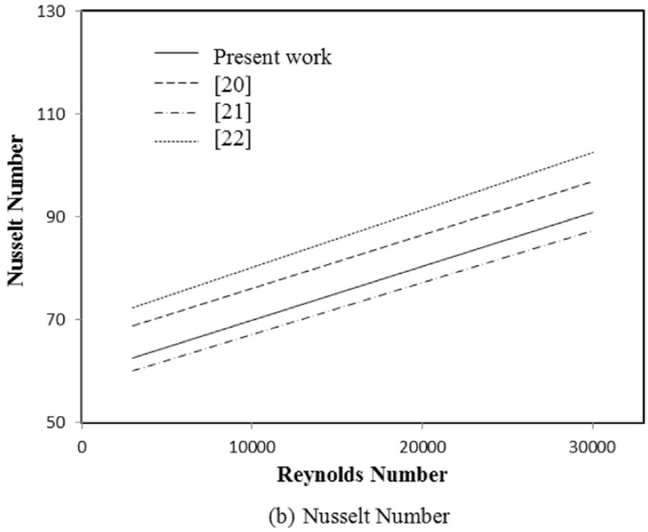


Fig. 9. Validation of CFD data.

Fig. 9 shows the validation of CFD data with the experimental data of [19–21]. It can be seen the good agreement of both friction factor and Nusselt number simulation data against the experimental data with deviation not more than 5%.

6. Conclusions

There are two parts in this article; the first is the numerical study of turbulent nanofluid flow in the circular heated tube. The influence of Reynolds number (Re), nanofluid volume concentration (ϕ) and the nanofluids type on the friction factor and Nusselt number were studied. The second part is included the intelligent study using ANFIS to find friction factor and Nusselt number through circular heated tube. It can be concluded that:

1. Friction factor increases with increasing of volume concentrations but decreases with increasing of Reynolds number.
2. Nusselt number increases with increasing of both volume concentrations and Reynolds number.
3. Al_2O_3 nanofluid has higher friction factor than SiO_2 and TiO_2, furthermore, SiO_2 nanofluid has higher Nusselt number than Al_2O_3 and TiO_2.
4. ANFIS is completed iterations with (0.00926 s) time but CFD is completed iterations with (183 s), so reducing time by using ANFIS for the case undertaken.
5. The prediction of the friction factor and Nusselt number with the ANFIS models is in good agreement with the CFD analysis with maximum error of less than 0.1282.

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