Computational Modeling of Transport in Porous Media Using an Adaptive Network-Based Fuzzy Inference System

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ABSTRACT: This investigation is conducted to study the integration of the artificial intelligence (AI) method with computational fluid dynamics (CFD). The case study is hydrodynamic and heat-transfer analyses of water flow in a metal foam tube under a constant wall heat flux (i.e., 55 kW/m²). The adaptive network-based fuzzy inference system (ANFIS) is an AI method. A 3D CFD model is established in ANSYS-FLUENT software. The velocity of the fluid in the x-direction (Ux) is considered as an output of the ANFIS. The x, y, and z coordinates of the node’s location are added to the ANFIS step-by-step to achieve the best intelligence. The number and type of membership functions (MFs) are changed in each step. The training process is done by the CFD results on the tube cross-sections at different lengths (i.e., z = 0.1, 0.2, 0.3, 0.4, 0.6, 0.7, 0.8, and 0.9), while all data (including z = 0.5) are selected for the testing process. The results showed that the ANFIS reaches the best intelligence with all three inputs, five MFs, and "gbellmf"-type MF. At this condition, the regression number is close to 1.

1. INTRODUCTION

Open-cell metal froths were discovered within thermal transfer as a result of their solid mixing proportion and high porosity. The heat sinks in metal froths were investigated by Zhao et al. Also, the methane-hydrogen chemical reactions over the catalytic surfaces capped with metal froths were discussed by Dhamrat et al. The upgraded tubes are metal foam-occupied that are widely tested. The numerical and experimental investigations on the single-phase convection-heat-transfer behavior of metal foam-occupied channels possessing various structures have been done by several studies. Variables such as the porosity of metal froths, channel geometry, and pore density affecting the thermal transport and fluid flow were extensively studied.

Currently, ANNs (artificial neural networks), ANFIS (adaptive network-based fuzzy inference system), and intelligence algorithms such as ant colony and differential algorithms were gradually common for simulating engineering problems with a significant decrease in the calculation time. Nevertheless, their use in energy-related studies and problems with a significant decrease is restricted. It was proved that ANFIS is a robust method as it includes the ANN’s greater abilities and the neuro-fuzzy architectures.

ANFIS’s architecture is a combination of artificial neural and fuzzy logic network methods. This model can learn complicated associations in terms of the experimental or input computational pattern data. In the present work, the ANFIS model involves three inputs (x-direction, y-direction, and z-direction) and three membership functions (MFs) for each input. The distribution functions are then anticipated utilizing the first-order Sugeno fuzzy model.

The CFD modeling is an applicable tool for the prediction of fluid flow characteristics. CFD models have their own expenses, specifically in complex cases (i.e., turbulent flows, complex geometries, dense meshes, 3D analysis, and so on). Recently, some research works have shown the effect of artificial intelligence (AI) algorithms on facilitating the CFD modeling. Artificial intelligence algorithms can do the machine learning (ML). In this way, the AI algorithms capture the general pattern of the output based on different inputs. Once the best intelligence is obtained, there is no need for the CFD to solve the complicated governing equations anymore, and the AI algorithms predict the output corresponding to any values of new input on the domain.

Although the ANFIS has already been employed by a few studies in combination with the CFD, there are still many unknown aspects to be unlocked. For example, there is no investigation regarding the effect of ANFIS parameters such as...
the number of iterations, number of data, percentage of trained data, number of inputs, number of MFs, types of MFs, and so forth on the best intelligence. The other studies in the literature simply used ANFIS in combination with CFD tools. They did not do any sensitivity tests. To the authors’ best knowledge, this is the first time the ANFIS is considered for the prediction of velocity of water flow in a porous medium. In addition, the sensitivity test was made for the first time for finding the proper values of input number, MF, and the type of MF at the best intelligence. The main aim of this study is to discover the ability of the ANFIS to contribute to the CFD for velocity prediction of the incompressible flow, such as water, in porous media. Therefore, in this study, the efficiency of artificial intelligence (AI) in cooperation with CFD prediction is investigated. For this purpose, water flow inside an aluminum metal foam tube warming up through the wall is simulated by the ANSYS-FLUENT CFD package. This modeling does not involve a simple use of the CFD package. All fluid and porous medium parameters are adjusted properly based on the papers in the literature. The temperature-dependent thermophysical properties of water are added to the CFD model by a user-defined code (UDF) written in the C programming language. The porous medium parameters including the porosity, permeability, pore size, and so forth are considered in the model. The porous media are considered homogeneous and isotropic. The equilibrium thermal model is used for the energy equation. The velocity of the fluid in the x-direction (Ux) is considered as the output of the ANFIS, while the x, y, and z coordinates of the node’s location are the inputs. The efficiency of artiﬁcial intelligence method (AI) in cooperation with CFD prediction is investigated. For this purpose, water flow inside an aluminum metal foam tube warming up through the wall is simulated by the ANSYS-FLUENT CFD package. This modeling does not involve a simple use of the CFD package. All fluid and porous medium parameters are adjusted properly based on the papers in the literature. The temperature-dependent thermophysical properties of water are added to the CFD model by a user-defined code (UDF) written in the C programming language. The porous medium parameters including the porosity, permeability, pore size, and so forth are considered in the model. The porous media are considered homogeneous and isotropic. The equilibrium thermal model is used for the energy equation. The velocity of the fluid in the x-direction (Ux) is considered as the output of the ANFIS, while the x, y, and z coordinates of the node’s location are the inputs. The efficiency of the number of inputs, the number of MFs, and the type of MF on the ANFIS efficiency are assessed.

2. SIMULATION METHODOLOGY

2.1. CFD Approach. The test was performed for an incompressible consistent state, three-dimensional, and turbulent flow in a pipe entirely occupied by a permeable medium, in which the permeable medium is saturated with a single-phase Newtonian fluid. Then, the fluid is introduced into the pipe with a uniform temperature T0 and a uniform velocity uw. It is presumed that the heat flux at the wall is continuous. Porous characteristics such as the porous medium, porosity, permeability, and PPI are aluminum, 0.8, 5 × 10^{-8} m^2, and 10, respectively. The final mass, energy, and momentum equations are given in refs, and they can be also written as follows

Continuity equation

\[
\frac{\partial \rho}{\partial t} + \nabla \cdot (\rho \vec{u}) = 0
\]  

(1)

Momentum equation

\[
\frac{1}{\epsilon} \frac{\partial \rho \vec{u}}{\partial t} + \frac{1}{\epsilon} \nabla \cdot (\rho \vec{u} \vec{u}) = -\nabla P + \epsilon \vec{g} + \frac{1}{\epsilon} \nabla [\mu \nabla \cdot (\nabla \vec{u} + (\nabla \vec{u})^T)]
\]  

(2)

Energy equation

\[
\frac{\partial \rho H}{\partial t} + \nabla \cdot (\rho \vec{u} H) = \nabla [k_e (\nabla T)]
\]  

(3)

The effective thermal conductivity can be determined as follows

\[
k_e = (1 - \epsilon)k_s + \epsilon k_f
\]  

(4)

where \(k_s\) and \(k_f\) are the solid porous material and fluid conductivities, respectively.

The following equations for water properties are used

\[
\rho_f = 2446 - 20.674 T + 0.11576 T^2 - 3.12895 \times 10^{-4} T^3
\]  
\[
+ 4.0505 \times 10^{-7} T^4 - 2.0546 \times 10^{-10} P^5
\]  

(5)

Viscosity

\[
\mu_f = A \left( \frac{B}{T - C} \right)
\]  

(6)

where A = 2.414 × 10^{-5}, B = 247.8, and C = 140.

Specific heat

\[
(C_p)_f = \exp \left\{ \frac{8.29041 - 0.012557 T}{1 - (1.52373 \times 10^{-7}) T} \right\}
\]  

(7)

2.2. CFD Validation Test. As there are not enough investigations on turbulent forced convection of water in a metal foam tube, the velocity profile of this study is compared with that from Ameri et al.’s study which considered the Fe3O4/water nanofluid flow in a heated metal foam tube. According to Figure 1, there is a good agreement between both velocity profiles as a function of radial coordinate.

![Figure 1. Velocity profiles for the present study and Ameri et al.’s study: Adapted in part with permission from [Ameri, M.; Amani, M.; Amani, P., Thermal performance of nanofluids in metal foam tube: Thermal dispersion model incorporating heterogeneous distribution of nanoparticles. Advanced Powder Technology 2017, 28 (10), 2747–2755]. Copyright [2020] [ELSEVIER].](https://dx.doi.org/10.1021/acsomega.0c04497)

2.3. ANFIS Model. ANFIS is an artificial intelligence method for extremely nonlinear and complicated problems. Herein, the utilized ANFIS structure includes two inputs and five layers, where the Takagi-Sugeno fuzzy system was used as the FIS. For elucidating the procedure of ANFIS, it was taken into consideration that the FIS includes one output (F) and two inputs (x1,x2). Normally, the fuzzy rules can be reported as follows

Rule 1

\[
\text{if } x_1 \text{ is } I_1 \text{ and } x_2 \text{ is } I_2 \text{ and etc. ; then }
\]  

\[
F_1 = a_{1}x_1 + b_{1}x_2 + \ldots + r_1
\]  

(8)

Rule 2
if $x_1$ is $I_2$ and $x_2$ is $I_2$ and etc.; then

$$F_2 = a_2x_1 + b_2x_2 + \ldots + r_2$$

(9)

where $x_1$ and $x_2$ represent the inputs. $a_1$, $b_1$, $r_1$, $a_2$, $b_2$, and $r_2$ denote the output ($O$) function parameters. $I_1$, $I_2$, $J_1$, and $J_2$ represent the MFs for inputs ($x_1$ and $x_2$). ANFIS’s fundamental configuration is a feedforward network containing five layers with different functions.

Each layer’s function is provided in refs. 46, 47. By the input nodes in layer 1, the membership association including the output and input functions of this layer is given by

$$\mu_i(I) = \mu_i(I), \quad i = 1, 2$$

(10)

$$\mu_i(J) = \mu_i(J), \quad i = 1, 2$$

(11)

The output in rule nodes or layer 2 is the product of input signals given by

$$F_{i,1} = W_i = \mu_i(I)\mu_i(J), \quad i = 1, 2$$

(12)

where $\mu_i(I)$ and $\mu_i(J)$ denote the MFs. The weight function in the normalized layer or the third layer is under normalization as follows

$$F_{i,3} = W = \frac{W_i}{W_1 + W_2}, \quad i = 1, 2$$

(13)

In the consequent nodes or the fourth layer as the defuzzy layer, the former layer’s output is multiplied with the function of the Sugeno fuzzy rule

$$F_{i,4} = \prod_f = w(a_i x + b_i x_2 + \ldots + r_i), \quad i = 1, 2$$

(14)

Within the output node with one node (layer 5), the summation of all outputs of each rule from the final layer is determined as

$$F_{3,i} = \sum_{i=1}^{n} w_f = \frac{\sum_{i=1}^{n} w_f}{\sum_{i=1}^{n} w_i}$$

(15)

3. RESULTS AND DISCUSSION

Water forced convection inside a metal foam tube under a constant wall heat flux (i.e., $55 \text{kw/m}^2$) is simulated using the ANSYS-FLUENT CFD package. Among all CFD results, the velocity of the fluid in the x-direction is selected as an output of ANFIS artificial intelligence. Three nodal fluid locations in the tube (i.e., $x$, $y$, and $z$) are considered as the inputs and are added to the ANFIS model step-by-step to achieve the best intelligence. In addition to this, the number and type of MFs are changed in each step. The training process is done by the CFD results on the metal foam tube at different cross sections (i.e., $z = 0.1, 0.2, 0.3, 0.4, 0.6, 0.7, 0.8,$ and $0.9$). In other words, 70% of the CFD results are used in the training process, while all data (including $z = 0.5$) are selected for the testing process.

Figure 2 describes the whole steps in this study for the prediction of water velocity in the x-direction ($U_x$) in the porous pipe by the ANFIS. The $x$, $y$, and $z$ coordinates of the nodes are selected, as the first to the third inputs. In addition, the velocity of the nanofluid in the x-direction is defined as the output. The grid partition clustering is selected as the type of data clustering and for generating the primary FIS. For the FIS algorithm, parameters such as the number of data, the number of iterations, and the percentage of data for the training process are determined. For grid partition clustering parameters, the number of MFs and the type of MF must be defined. In this study, a sensitivity test is conducted to find out the proper values of input number, the number of MFs, and the type of MF for the best intelligence of the ANFIS. Therefore, the intelligence process of the ANFIS is done through a loop until the intelligence is achieved; the training of the CFD data is done; the
regression number (R), the coefficient of determination ($R^2$), the mean standard error (MSE), the root mean standard error (RMSE), and the standard error (STD) are recorded for different input numbers, MF numbers, and MF types. The intelligence condition is related to the lowest errors and the highest $R$. The velocity predictions of the DEFIS are validated with those of the CFD modeling. Once the results have been validated, the ANFIS predicts the water velocity on the cross-section plate that does not exist in the learning process.

Figure 3 shows the values of $R^2$ of the training and testing processes by changing the number of inputs, number of MFs, and the type of MF. At first, it should be noted that there is a relationship between the number of inputs and the number of MFs and the number of rules. The number of MFs to the power of the number of rules is equal to the number of rules. For
example, for two inputs and three MFs, the number of rules is equal to 9. At the first glance, it is shown that the \( R^2 \) values increase by the MF number. Therefore, for all types of MFs, the highest value of \( R^2 \) is related to the maximum amount of MF number. For one and two inputs, the values of \( R^2 \) are not that much (i.e., around 0.02). As the number of inputs increases to three, the maximum values of \( R^2 \) for each type of MF jump to around 0.98. This means that the ANFIS gets closer to the best intelligence for three inputs. According to Figure 3c, among different types of MFs, the best intelligence is achieved by the “gbellmf” MF (\( R^2 = 0.97 \)). The detailed analysis and comparisons of \( R \), \( R^2 \), MSE, RMSE, MEAN, and STD of the training and testing processes can be found in the “Supporting Information”. Thus, the highest value of \( R^2 \), in other words, the best intelligence could be seen once again for three inputs, five MFs, and the “gbellmf” MF type.

Figure 4a,b depicts the ANFIS training and testing regression for the condition where the best intelligence is achieved (i.e., the input number is three, MF number is five, and MF type is “gbellmf”). At this condition, the regression numbers are close to 1 for both training and testing processes.

A comparison is made between the CFD and ANFIS predictions of \( U_x \), as shown in Figure 5. The results reveal that there is a good agreement between the predicted results of both methods. Figure 6 illustrates this comparison in another way. According to Figure 6, the output data obtained by both CFD and ANFIS methods are shown versus the inputs.

The final comparison is made between the \( U_x \) prediction at a length of 0.5 m that resulted from the CFD and that from the ANFIS (Figure 7). Similar results are seen again by both predictions. Therefore, it can be concluded that the ANFIS model has reached the best intelligence and the model is able to predict the \( U_x \) in each randomly selected node. Totally, the results revealed that the ANFIS cannot be simply used for learning the CFD data. A sensitivity test is needed for finding the ANFIS parameters at the best intelligence. These parameters differ from one study to another, and the parameters must be adjusted in each case study.

According to Figure 8, a comparison is made between the predictions of two artificial algorithms: one is the ANFIS that was used in this study and the other one is GAFIS (genetic algorithm-based fuzzy interface system). Figure 9 describes this comparison based on the CFD results. The black line represents the CFD results, while the blue and red lines represent the ANFIS and GAFIS predictions, respectively. Magnifying the graph lines in the three sections A, B, and C shows that the ANFIS predictions are closer to the CFD results than to the GAFIS ones. For a quantitative comparison, the standard error deviations of GAFIS and ANFIS from CFD are estimated as \( 1.9 \times 10^{-5} \) and \( 1.77 \times 10^{-5} \), respectively.

Tables S1–S3 (Supporting Information) illustrate the \( R \), \( R^2 \), MSE, RMSE, MEAN, and STD of the training and testing processes by changing the number of inputs, number of MFs, and the type of MF. As the number of inputs increases, all types of errors decrease for all numbers and types of MFs in both training and testing processes. For lower input numbers (i.e., 1 and 2) all kinds of error values are not sensitive to the number and type of MF. Besides, for one and two inputs, the values of \( R \) and \( R^2 \) are not that much (i.e., around 0.2 and 0.02, respectively). As the number of inputs increases to three, the values of \( R \) and \( R^2 \) jump to around 0.98. This means that the ANFIS gets closer to the best intelligence for three inputs. The best intelligence is achieved by the “gbellmf” MF. In almost all cases, “gbellmf” shows the least error. Besides increasing the number of MFs, all types of errors decrease. For instance, as the number of MFs increases from two to five, the MSE and STD decreased, respectively, from \( 7.71 \times 10^{-9} \) to \( 3.03 \times 10^{-10} \) and from \( 8.78 \times 10^{-5} \) to \( 1.74 \times 10^{-5} \). Therefore, the highest values of \( R \) and \( R^2 \) (i.e., 0.98 and 0.97, respectively) and the lowest MSE, RMSE, and STD (i.e., \( 3.14 \times 10^{-10} \), \( 1.77 \times 10^{-10} \), and \( 1.77 \times 10^{-10} \), respectively) are achieved for three inputs, five MFs, and the “gbellmf” MF type.

4. CONCLUSIONS

The present study tries to investigate the ability of the artificial intelligence (AI) method in cooperation with the computational fluid dynamics (CFD). For this purpose, a 3D water flow in an aluminum metal foam tube under a constant wall heat flux (i.e., \( 55 \ kW/m^2 \)) is considered as a case study. The ANFIS is employed as the AI method. The simulation is done using the
ANSYS-FLUENT CFD package. The velocity of the fluid in the x-direction (Ux) is selected as an output of ANFIS artificial intelligence. The nodal locations of the fluid in the metal foam tube (i.e., x, y, and z) are considered as the inputs. The number of inputs of the ANFIS model is increased step-by-step to achieve the best intelligence. In addition to this, the number and type of MF are changed in each step. The training process is done by the CFD results on the tube cross sections at different lengths (i.e., z = 0.1, 0.2, 0.3, 0.4, 0.6, 0.7, 0.8, and 0.9), while all data (including z = 0.5) are selected for the testing process.

The following conclusions can be drawn as a result of this investigation:

- Increase in the number of inputs, all types of errors decrease for all numbers and types of MFs in both training and testing processes.
- For lower input numbers (i.e., one and two), all kinds of error values are not sensitive to the number and type of MF.
- In the number of MFs, all types of errors decrease.
- For input number equal to three, MF number equal to five, and "gbellmf"-type MF, the best intelligence is achieved.
- For the best intelligent conditions, the regression numbers are close to 1 for both training and testing processes.
- The ANFIS model with the best intelligence is able to predict the Ux in each randomly selected node.

Figure 5. (a) Validation of the training process of ANFIS intelligence when the number of inputs is three and the type of MF is gbellmf. (b) Validation of the testing process of ANFIS intelligence when the number of inputs is three and the type of MF is gbellmf.
Figure 6. (a) Comparison of ANFIS prediction and CFD output nodes based on the first and second inputs. (b) Comparison of ANFIS prediction and CFD output nodes based on the first and third inputs. (c) Comparison of ANFIS prediction and CFD output nodes based on the second and third inputs.
Figure 7. Velocity by ANFIS prediction (left side) using absent data in the learning process and the real velocity plot (right side) based on CFD outputs.

Figure 8. Correlation coefficient of the best results of ANFIS and GAFIS methods.

Figure 9. Pattern recognition ANFIS and GAFIS predictions.
ASSOCIATED CONTENT

Supporting Information
The Supporting Information is available free of charge at https://pubs.acs.org/doi/10.1021/acsomega.0c04497.

R, R², MSE, RMSE, MEAN, and STD of the training and testing processes with changes in the number of inputs, number of MFs, and the type of MF (PDF)

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Notes
The authors declare no competing financial interest.

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