Prediction of Nanofluid Temperature Inside the Cavity by Integration of Grid Partition Clustering Categorization of a Learning Structure with the Fuzzy System

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ABSTRACT: In this study, a quadratic cavity is simulated using computational fluid dynamics (CFD). The simulated cavity includes nanofluids containing copper (Cu) nanoparticles. The L-shaped thermal element exists in this cavity to produce heat distribution along with the domain. Results such as fluid velocity distribution in two dimensions and the fluid temperature field were generated as CFD simulation results. These outputs were evaluated using an adaptive neuro-fuzzy inference system (ANFIS) for learning and then the prediction process. In the training process related to the ANFIS method, x coordinates, y coordinates, and fluid temperature are three inputs, and the fluid velocity in line with y is the output. During the learning process, the data have been classified using a clustering method called grid clustering. In line with the attempt to rise ANFIS intelligence, the alterations in the number of input parameters and of membership structure have been analyzed. After reaching the highest level of intelligence, the fluid velocity nodes were predicted to be in line with y, especially cavity nodes, which were absent in CFD simulations. The simulation findings indicated that there is a good agreement between CFD and clustering approach, while the total simulation time for learning and prediction is shorter than the time needed for calculation using the CFD method.

1. INTRODUCTION

The past few decades have witnessed an increase in the attention of fluid flow in the industrial domain size in different engineering applications including lubrication technology, nuclear reactors, pharmaceuticals, cooling of electronic devices, processing foods, and membrane sequestration.1–7 A large number of research studies has been carried out to study the flow field and thermal distribution in different shapes of lid-driven cavities, while the main area of concern has been fluids with a thermal performance which is relatively low.8–11 Still, there is an increasing demand for cooling systems with high performance which require a specific agent with a high heat transfer rate. Choi12 introduced nanofluids as highly effective coolant fluids that outperformed standard pure fluids as to heat exchange performance. Given the highly sophisticated thermal and fluid behavior of nanofluids, different models have been introduced for estimating the specifications of nanofluids, including thermophysical properties.13–15 The design of the models is based on heat transfer, Brownian dynamics, and nanoparticle geometry along with the interaction of pure fluid and nanoparticles.15–20

There are recent reports about thermal distribution in lid-driven cavities which states that nanofluids can change the thermal behavior of fluid in the domain. Authors in ref.21 examined the thermal behavior of Cu-water nanofluids in the cavity by using the numerical method. The authors concluded that with increasing amounts of nanoparticles, the heat transfer rate increases. Moreover, they demonstrated that the direction of sliding walls and Richardson number were effective in the performance of the cavity in terms of heat transfer. In a similar study by Muthtamilselvan et al.,22 a lid-driven cavity filled with Cu-water nanofluids was examined in terms of the transport mechanism of mixed convection in a numerical way. The numerical results supported that adding pure water with Cu nanoparticles improved the thermal performance of the cavity. The laminar mixed convection flows were examined numerically by Talebi et al.23 using the Cu-water nanofluid fed into a cavity. The results showed that when Reynolds numbers are fixed, the flow field and thermal distribution of the nanofluid are affected by the amount of solids in the fluid, particularly at very high Rayleigh numbers.24,25

It is notable that improving heat transfer using nanofluids is still a complicated problem. According to ref.26 and,1 the
augmentation or decrease in heat transfer was because of the changes in the models employed to find the properties of nanofluids. Therefore, there is a need for further studies on computational fluid dynamics (CFD) to model nanofluid properties in a more reliable manner. Such modeling, still, is time-consuming and needs more funding. The recent development in the field is more emphasized on the learning process with an artificial neural cell algorithm called the artificial neural network (ANN) and integration of this method with the fuzzy system\(^7\)\(^{-}\)\(^{10}\) for solving engineering problems with shorter computation time. Still, the application of these methods in studies on thermal energy distribution is highly limited.\(^{31}\)\(^{-}\)\(^{32}\) The adaptive neuro-fuzzy inference system (ANFIS) is known as a reliable method because it includes the ANN superior features and the neuro-fuzzy architectures.\(^{33}\)\(^{-}\)\(^{35}\)

The ANFIS structure represents the ANN and fuzzy logic methodologies. A key feature of the ANFIS is its capability to train complex relationship using the pattern data.\(^{13}\)\(^{38}\)\(^{-}\)\(^{39}\) For nonlinear system modeling, the input space is divided by the ANFIS into several local regions. A simple local model is created for each local region using linear functions of adjustable coefficients. Therefore, ANFIS utilizes fuzzy membership functions (MFs) for dividing each input dimension.\(^{38}\) It is possible to activate many local regions at the same time to cover the input space by overlapping MFs. A critical role is played by the resolution of partitioning of the input space to determine ANFIS ability for approximation. This is carried out based on the MF count in the ANFIS and the number of layers.

It is critical to find an effective and comprehensive pattern set for training the ANFIS.\(^{39}\)\(^{-}\)\(^{41}\) In the case where an incomplete set (where not every possible condition is met) is chosen as the ANFIS training set, the network’s capability to deal with an unknown condition will be attenuated. To improve the capability, a learning set of the ANFIS must be as wide as possible over the whole space of the input–output data set. Here, the results of the CFD simulation are obtained as a part of the study for training the models. In this study, with the subtractive clustering method, the flow field and thermal field in the cavity domain are categorized. For better accuracy of the method, different function structures and input parameters are used during the learning process. After the learning process, the CFD results and the ANFIS method are compared with the standard deviation (StD) method, and then, the CFD and ANFIS flow field and thermal distribution are compared with each other. The multiphase flow modeling is used to show the behavior of the nanofluid in the matrix phase. This type of modeling enables us to analyze the hydrodynamics between nanoparticles and the primary fluid/phase. In this study, as a novelty, the interaction between phases is simulated with the CFD method. After modeling of nanofluids in the domain, a machine-learning method, such as the ANFIS method, is used to model nanofluids with a faster modeling algorithm. The machine-learning method is the interface modeling between CFD and the optimization process to reduce the time of optimization during process engineering.

2. METHODOLOGY

2.1. CFD Method. As shown in Figure 1, a vertical square enclosure with relevant physical parameters is provided. Constant temperature conditions are considered for the right and left vertical boundaries. The value of one is considered for their various dimensionless values between them.\(^3\)\(^5\)\(^{-}\)\(^{43}\) The temperature of the left boundary is higher than the right one and is considered to be a hot boundary.\(^2\)\(^0\) The solid boundaries are exposed to constant conditions, and adiabatic conditions are considered for the bottom and top boundaries. The interaction of nanoparticles with the matrix phase is simulated by the cubic-interpolated pseudo particle (CIP) method, and different nanoparticles are used during validation of the CFD study with the existing analytical solution. In the cavity, the shear flow can appear in the domain and the shear mechanism can be changed, and the break-up process during mixing can be defined and modeled. Therefore, we use simple geometry to define the heat source or shear mechanism for simulation of the mixing process. In this work, for the first time, the nanofluid contains Cu in water. CIP is employed for minimizing the numerical diffusion of a high-order Navier–Stokes equation for two-dimensional problems.

The equations of vorticity and energy have been obtained based on the dimensionless analysis\(^{46}\) in which the thermal diffusivity is calculated as follows\(^2\)\(^0\):

\[
\alpha_{nf} = \frac{k_{nf}}{(\rho c_p)_{nf}}
\]

(1)

According to a reference temperature, the following relation is considered for the effective density of a fluid with suspended particles\(^4\)\(^4\):

\[
\rho_{nf} = (1 - \phi)\rho_1 + \phi\rho_2
\]

(2)

where \(\phi\), \(\rho_1\), and \(\rho_2\) stand for the volume fraction of suspended particles, pure fluid density, and particle density, respectively. The effective viscosity for a nanofluid is provided by Brinkman. This nanofluid includes pure water with viscosity \(\mu_c\). Brinkman also provided a dilute suspension of spherical, solid, and small particles\(^4\)\(^5\).
\[ \mu_{nl} = \frac{\mu_f}{(1 - \varphi)^{1.5}} \] (3)

Wasp developed the effective stagnant thermal conductivity for the solid–liquid mixture as follows:

\[ k_{nf}^{eff} = \frac{k_s + 2k_f - 2\varphi(k_f - k_s)}{k_s + 2k_f + \varphi(k_f - k_s)} \] (4)

The CIP model is applied for solving the advection term, which is necessary for solving vorticity, and further details can be found in ref 16. Several factors including the thermal conductivity as well as the heat capacity of both the ultrafine particles and the pure fluid, the nanofluid viscosity, the flow arrangement, and the volume fraction of solids particles are the key factors affecting the Nusselt number of the nanofluids. The nanofluid local Nusselt number is derived as follows:

\[ Nu_y = -\left( \frac{K_{nf}^y}{K_f^y} \right) \frac{\partial \theta}{\partial X} \] (5)

and

\[ Nu_z = -\left( \frac{K_{nf}^z}{K_f^z} \right) \frac{\partial \theta}{\partial Y} \] (6)

The mean Nusselt number is defined as follows:

\[ Nu_{avg} = \int_0^1 Nu_y \, dy + \int_0^1 Nu_z \, dx \] (7)

2.2. ANFIS Method. The ANFIS is an effective fuzzy system designed to predict how complicated nonlinear systems behave. The ANFIS method is a combination of neural network and fuzzy system. The learning part is the responsibility of neural cells because of the great ability of this method in learning different phenomena. After the learning process, the method transfers all information of learning to the fuzzy structure system, and the fuzzy system can predict the process behavior. There are three different fuzzy reasonings in which if-then rules were proposed by Takagi and Sugeno. These were used in the ANFIS structure. Figure 2 illustrates the structure used by the ANFIS method to predict hydrodynamic specifications in the cavity. Here, X coordinate, Y coordinate, and nanofluid temperature were adopted to achieve nanofluid velocity (in Y coordinate) as the output. At the first layer, the inputs were divided into different numbers of MFs. Then, at the second layer, the input signals generated by the first layer were multiplied using AND rule and the node function. For example, the ith rule’s function is as follows:

\[ w_i = \mu_{\tilde{X}}(X)\mu_{\tilde{Y}}(Y)\mu_C(T) \] (8)

where \( w_i \) stands for the outputing signal of the node at the second layer and \( \mu_{\tilde{X}} \), \( \mu_{\tilde{Y}} \), and \( \mu_C \) represent the input signals generated from implemented MFs on inputs, X coordinate (X), Y coordinate (Y), and nanofluid temperature (T), to the node of the second layer, respectively. At the third layer, the relative value of the firing strength of each rule is obtained. The total size of all rules’ firing power is as follows:

\[ w_i = \frac{w_i}{\sum w_i} \] (9)

where \( \bar{w}_i \) represents the called normalized firing strengths. The fourth layer uses the function of a consequence according to the
If-then rule introduced in ref 54. Therefore, the node function is as follows:

\[ \pi_f = \pi_0 (p X + q Y + r T + s) \]  

(10)

where \( p, q, r, \) and \( s \) (known as consequent parameters) stand for the if-then rules’ parameters.

3. RESULTS AND DISCUSSION

In this article, the CFD method outputs were analyzed as inputs and outputs of learning processes of ANFIS methods in different requirements considering the number of inputs and MFs. Some hypotheses have been created in order to start the ANFIS method which are as follows:

- In heat transfer, Grashof number (Gr) is dimensionless in which GR is 71,000.
- In nanofluids, the value shows the nanoparticle percentage which is 20%.
- The P-value conveys the data percentage in the ANFIS training process.
- The Epoch frequency is 750.
- Generalized bell-shape MF (gbellmf) is an MF and has been used in this study.
- At the beginning of the learning process, the \( x \) coordinate is considered as the first input, while velocity in \( y \) is considered as the output, and the number of MFs equals to 2 in the training process.

Figure 3a,b shows the StD error training and testing processes equal to 0.0355. Next, the learning process occurs with the increase in MFs from 2 to 3 and 4. In this process, the change in the Std value was low which demonstrates a slight increase in ANFIS intelligence. According to this failure in increasing MFs of the system intelligence, the number of inputs changed from 1 to 2, and also, the \( y \) coordinate was considered to be the second input.

The learning process is fulfilled by fixing the number of MFs to 2. Considering Figure 4a for the training process and Figure 4b for the testing process, the Std value in training and testing processes equals to 0.03422 and 0.034749, respectively. Considering the previous condition, the Std value did not change a lot. Hence, the number of MFs increases from 2 to 3 and 4. Then, testing and training processes were performed once again. The results showed an appropriate change and increase in the Std value, where MFs equal to 4. An increase in the Std value for training and testing processes equals to 0.012898 and 0.012855, respectively. Then, in order to attain higher intelligence in the ANFIS method, the number of input effects from 2 to 3 was analyzed; also, the fluid temperature was considered to be the third input. The learning process was completed separately for number of MFs 2, 3, and 4. The results are shown in Figure 5a for the training process and in Figure 5b for the testing process.

The input numbers increased from 2 to 3, while the number of MFs equaled to 2, but there was no significant difference when MFs equal to 4. However, there is an increase in Std. Now, if MFs change from 3 to 4, there is a significant increase in Std. Therefore, in the training and testing process, we have 0.015964 and 0.0016816, respectively. Considering these two numbers,
the chances of error are less and we can see complete intelligence in the ANFIS method (see Figure 6).

In Figure 7, the degree of membership can be seen. Using the appropriate intelligence in ANFIS, the absent points in ANFIS learning would be predicted and also compared with the CFD results, in which, the appropriate correspondence between the CFD output and ANFIS method can be illustrated (see Figure 8).

Another ability of the ANFIS is to predict points that are absent in the CFD simulation of fluid flow, and it can provoke appropriate ability in stopping complex CFD method calculations (see Figure 9).

4. CONCLUSIONS

In this study, the ANFIS method has been employed to train the thermal and fluid field in the cavity calculated by the CFD method. The grid partition clustering method was used for clustering the fluid and thermal field in the domain. The flow and thermal distribution in the cavity were simulated with the clustering method and then compared with the CFD results. Additionally, the effects of changing parameters such as the number of inputs and MFs were analyzed in ANFIS intelligence. We have reached complete intelligence by changing ANFIS intelligence parameters. We finally predicted the velocity in the domain and compared the results with CFD outputs. The
positive effect of combining ANFIS and CFD methods in nano fluid studies in a cavity shows that smart modeling can be a good alternative to predict the flow and thermal distribution in the industrial domains with inexpensive computational time.

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