A NOVEL CELL BY CELL ARTIFICIAL NEURAL NETWORKS APPROACH FOR PREDICTING THE TEMPERATURE OF STEADY STATE, INCOMPRESSIBLE, LAMINAR FLOWS

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ABSTRACT

A cell-by-cell artificial neural network approach is used to predict the temperature field of steady-state, incompressible, laminar flows in a two-dimensional computational domain. The temperature field is characterized by the initial flow velocity, fluid temperature and the temperature of the wall boundaries. Two types of neural network architectures are developed in this research, namely cascade-forward and feedforward models. Both models are trained using Levenberg-Marquardt and Bayesian regularization backpropagation algorithms. The training data for the models are obtained by solving the Navier-Stokes equations for steady-state, incompressible, heat conducting laminar flow in two-dimensional domain using commercial ANSYS Fluent software. The results show that the predicted values produced by the ANN models are in good agreement with the CFD simulation data. Even though the introduction of artificial neural networks at the cell level increases the complexity of the training process, this drawback is compensated by the increase in flexibility (generality) of the models. More importantly, the results show that the cell-by-cell artificial neural network approach is capable of providing an accurate prediction of the temperature field for the fluid flow investigated in this research, as indicated by the statistical indices used to evaluate the performance of prediction models. The feedforward ANN model trained using the Bayesian regularization backpropagation algorithm gives the most accurate predictions among all models.

Keywords: Artificial neural networks, Computational fluid dynamics, Conjugate heat transfer, cell-by-cell approach

INTRODUCTION

Regardless of the high cost and time consuming, laboratory experiments are considered an appropriate method for understanding the behaviors of fluid flow. Similar to the numerical methods, laboratory techniques are efficient and reliable, but they do not require solving the complex mathematical models of the flow. Solving fluid model numerically requires all the boundary conditions in the geometrical domains to be formulated precisely with respect to the computational domain. Despite the progress in computational techniques in fluid dynamics, the computational time for the simulation is considerably large when urgent responses are required. In fluid dynamics, a relatively accurate and immediate results are required for efficient responses.

Knowledge of the thermal behavior of fluid flows is of utmost importance owing to its various range of applications such as gas turbine engines, electronics thermal management, microfluidic devices, as well as heating, ventilating and air-conditioning (HVAC) systems. In gas turbine engines, the secondary air system provides cooling air to the disks, blades and for brush sealing of the bearing chambers.

Thermal characteristics of secondary air can affect the efficiency and the environmental aspects of gas turbines [1]. Thermal energy storage based on the energy exchanges between a heat transfer fluid flows and a phase changing materials.

Both experimental and numerical techniques have been widely used by scientists and researchers in the heat transfer and fluid flow community in order to gain insight into the thermal behavior of fluid flows. Even though experimental techniques are usually reliable, these techniques are very time-consuming and costly. With advancements in computing hardware and software over the years, numerical techniques using computational fluid dynamics (CFD) have made it possible for scientists and researchers to probe into the thermal behavior and underlying physics of fluid flows within a shorter time frame compared to experimental techniques. However, even though CFD techniques are capable of attaining faster results compared to experimental techniques, numerical techniques are still somewhat time-consuming. Patankar and Spalding [2], who verified their algorithm by computing the flow field parameters in a square duct with moving walls, noted an increase in the total simulation time. Solving the Navier-Stokes energy equation increases the computational cost dramatically. The complexity of numerical problems increased over the years owing to the increasing demand for high thermal sensitivity, precision and accuracy in a variety of heat transfer and fluid flow applications.

Artificial neural network (ANN) is a powerful tool that is capable of solving complex problems and attaining faster results due to its flexibility and automatic perceptions. Unlike other numerical techniques, ANN is capable of dealing with problems where there is lack of a proper physical model and problems in which uncertainties are present. More importantly, ANN is a promising method that can be used to predict the thermal behavior of fluid flows. The basic idea of ANN is to attach a group of arrays representing the inputs to an equivalent output array. When new inputs are entered, the ANN predicts the outputs instantaneously by applying what it has been trained.

ANN has been employed to solve a variety of heat transfer and fluid flow problems, particularly those in which uncertainties are present. Benning et al. [3, 4] implemented neural networks trained using the backpropagation algorithm to predict the flow field variables of steady, isothermal flows around a solid cylinder. A hybrid artificial intelligence model was developed to predict the flow field over a range of Reynolds numbers from 1 to 60. The algorithm was improved by integrating ANN with conventional numerical techniques [3, 5]. Valyuhov et al. [6-8] promoted the method of weighted residuals (MWR) to solve Navier-Stokes equations. The MWR algorithm makes use of neuron estimations to solve the Navier-Stokes equations by computing the velocity components and pressure on a Cartesian grid. ANN models have also been implemented successfully in recent years to predict the thermal behaviour of Nano fluids [9-11].

The existing works on ANN models are focus on the overall computational domain under special flow conditions. The main drawback of these approaches is that many of the flow characteristics may not be captured because of the approaches are limited to the learning procedure for the whole geometry. Even though some studies make use of a cost function strategy to improve the flexibility of the model and enforce the boundary conditions, this strategy only partially overcomes the disadvantages of complex geometries.

In this research, a novel method based on artificial neural networks is proposed to predict the temperature field of a fluid flow, in which the computational domain is divided into an equal number of cells with equal size and uniform spacing (similar to a Cartesian grid) and the temperature is predicted on a cell-by-cell basis. The design and development of the cell-by-cell ANN approach is described in detail in this paper, beginning with a description on the governing equations for incompressible, laminar flows in a two-dimensional computational domain and the discretization of the independent variables on a staggered grid. Two neural network architectures are developed in this research (cascade-forward and feedforward ANN models) and these models are trained using the Levenberg-Marquardt and Bayesian regularization backpropagation algorithms. The Levenberg–Marquardt algorithm [12, 13], provides a fast and stable numerical solution for training small and medium sized ANN problems. The Bayesian regularization training algorithm shows better performance than the Levenberg-Marquardt algorithm. The advantage of a Bayesian regularization artificial neural network is its ability to reveal potentially complex relationships [14]. The ANN models are evaluated using a number of statistical indices in order to determine the capability and accuracy of the ANN models in predicting the temperature field of the fluid flow investigated in this research.

METHODOLOGY

In a neural network, the computational nodes are represented by neurons in the hidden layers. The number of hidden layers and the number of neurons within each hidden layer will change according to the complexity of the tasks executed by the ANN model [15, 16]. A clear understanding of the problem and well defined model with clear independent variables leads to decent neural network design. The flexibility of Neural network models for particular application leads to more difficulty in the designing phase due to the specific features of the application. There are various choices have to be decided, but very few guidelines to help the programmer through them. Some assistances can be found in the literature [17-21], but these guidelines are applicable for certain applications and they have never been endorsed for alternative applications.

A conjugate heat transfer problem typically involves heat diffusion because of the temperature gradients and convective heat transfer present in the fluid flow. In this research, the flow is considered to be incompressible and laminar within the computational domain Ω. This flow is governed by the Navier-Stokes equations (momentum, continuity and energy equations) as a function time. Assuming that external forces and heat sources are negligible, the two-dimensional Navier-Stokes equations are given as follows:

Momentum equation:

$$\frac{1}{\rho}\frac{\partial p}{\partial x} = \frac{1}{Re}\left(\frac{\partial^2 u}{\partial x^2}+\frac{\partial^2 u}{\partial y^2}\right)-\left(u\frac{\partial u}{\partial x}+v\frac{\partial u}{\partial y}+\right) \quad (1)$$

$$\frac{1}{\rho}\frac{\partial p}{\partial x} = \frac{1}{Re}\left(\frac{\partial^2 v}{\partial x^2}+\frac{\partial^2 v}{\partial y^2}\right)-\left(u\frac{\partial v}{\partial x}+v\frac{\partial v}{\partial y}+\right) \quad (2)$$

Continuity equation:

$$\frac{\partial u}{\partial x}+\frac{\partial v}{\partial y}=0 \ \ in\,\Omega \quad (3)$$

Energy equation:

$$\left(\frac{\partial(uT)}{\partial x}+\frac{\partial(vT)}{\partial y}\right) = \frac{1}{Re}\frac{1}{Pr}\left(\frac{\partial^2 T}{\partial x^2}+\frac{\partial^2 T}{\partial y^2}\right) \quad (4)$$

The steady-state solver is chosen to eliminate the effect of time from the partial differential equations above, whereby the independent variables are x, y and t. The solution of the partial differential equations is dependent on the boundary conditions and initial conditions for each case. The velocity vector (u,v) in Equation (1) represents the dependent variable (ANN output) whereas the position vector (x,y) and initial velocity (u_0) represent the independent variables (ANN inputs). The velocity boundary conditions are consider as non-slip wall condition for all cases. The temperature (T) in Equation (3) represents the dependent variable (ANN input) whereas the position vector (x,y) and wall temperature (T_w) boundary condition represent the independent variables (ANN inputs). The initial condition variable (i.e. fluid temperature) is neglected since the initial fluid temperature is kept constant for all cases.

The solution of the differential equations depends on the boundary conditions and initial conditions of each case. From the momentum equations, the velocity vector (u,v) is considered the dependent variables (ANN outputs). Position vector (x,y) and initial velocity condition represent the independent variables (ANN inputs).

Cell-by-cell approach (CBC)

Whenever a numerical method is used such as the finite difference method, discretization is necessary in order to solve the system of partial differential equations, i.e. Equations (1) and (3). The analytical solution of Equations (1), (2) and (3) gives the values of the flow field variables at any point in the flow. In a numerical method, these equations are replaced by a system of algebraic equations. The numerical solution of this system of algebraic equations gives the values of the flow field variables at discrete points in the flow. Once the computational domain is discretized into an equal number of cells with equal size and uniform spacing, the computation of the flow field variables takes place in each cell and the discrete results are then combined to provide the solution for the entire computational domain. The number of cells in the Cartesian mesh is 11654 cells with the values of Local Truncation Error is 0.00246. Figure 1 shows the computational domain of the temperature field discretized on a staggered grid. In this grid, the normal velocity components are stored at the borders of the cell, whereas the temperature and pressure values are stored at the center of the cells [21]. The initial conditions and boundary conditions are assigned to the belt of ghost cells outside the domain. The purpose of these ghost cells is to assist in computing the solutions of the Naiver-Stokes equations including the energy equation throughout the domain from the outer border cells.

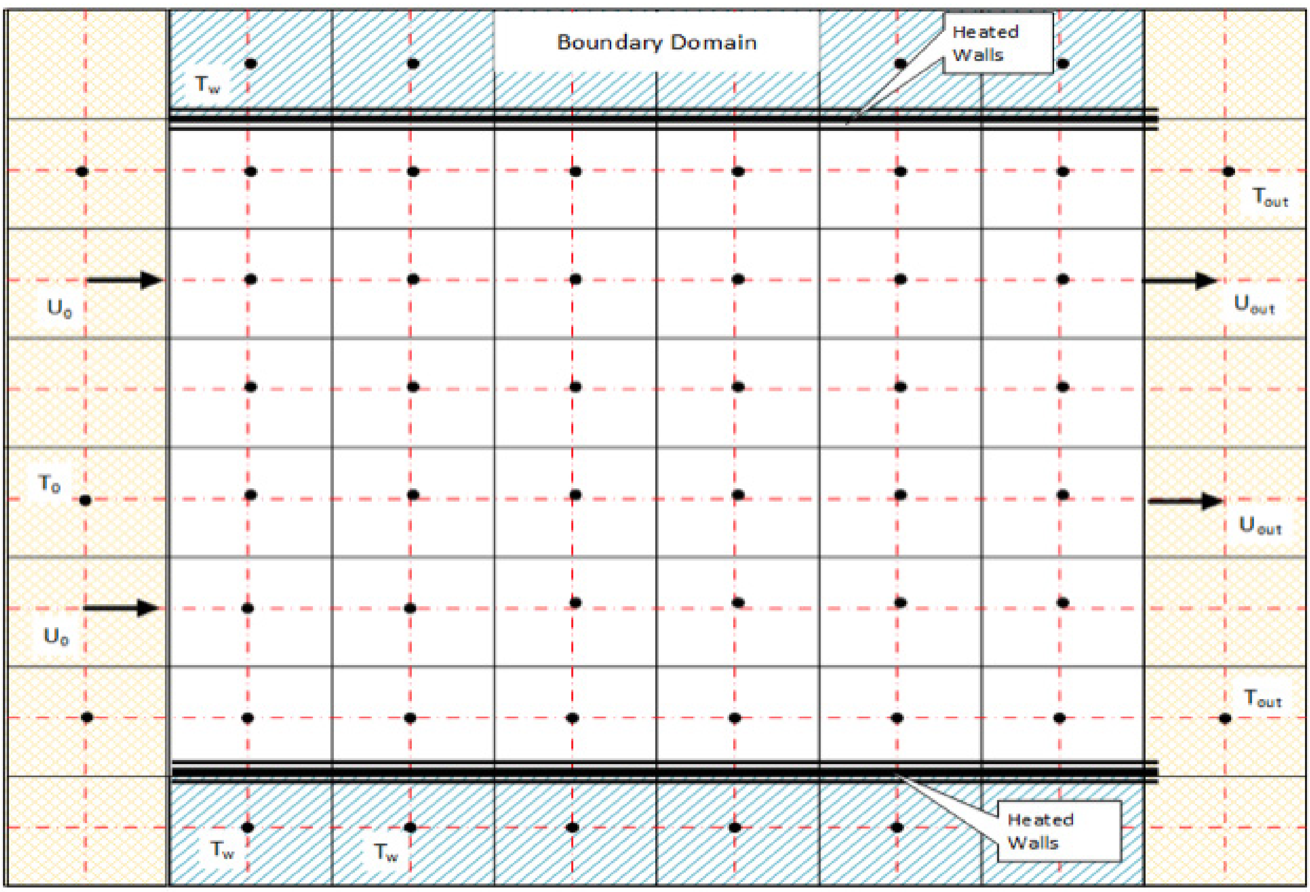

Figure 1 Computational domain for the temperature field

The discretization process is also applied to transform the space domain from continuous to discrete. The cell-by-cell ANN approach is then introduced to predict the temperature field of the flow. Using this approach, the computations take place locally at the cell level – however, it shall be noted that the model has been trained prior to running the simulation. The independent variables are discretized using a grid similar to the staggered grid in the finite difference method. *Figure 2* shows how each cell receives the value of the independent variable from the three adjacent cells. The entire computational domain is covered using this technique. Similar to other numerical techniques, an interpolation procedure is used to compute the missing values of the dependent variable in the spaces in between the computational domain. The Reynold number range for the 2-D model is between (1150, 2000) with velocity (0.08, 0.15) m/s.

It is possible to produce a decent neural network design when one has a clear understanding of the physical problem and a well-defined model with clear independent variables. The primary variables that control the behavior of the flow field at the cell level are the position vector (x, y) of the cell, the velocity vector (u, v) and temperature (T). All of the cells in the Cartesian grid are identical and spaced at an equal distance from each other, which reduces the influence of the position vector (x, y). Figure 3 shows the input layer (independent variables) and their interconnection with the output layer through the hidden layer of the ANN model.

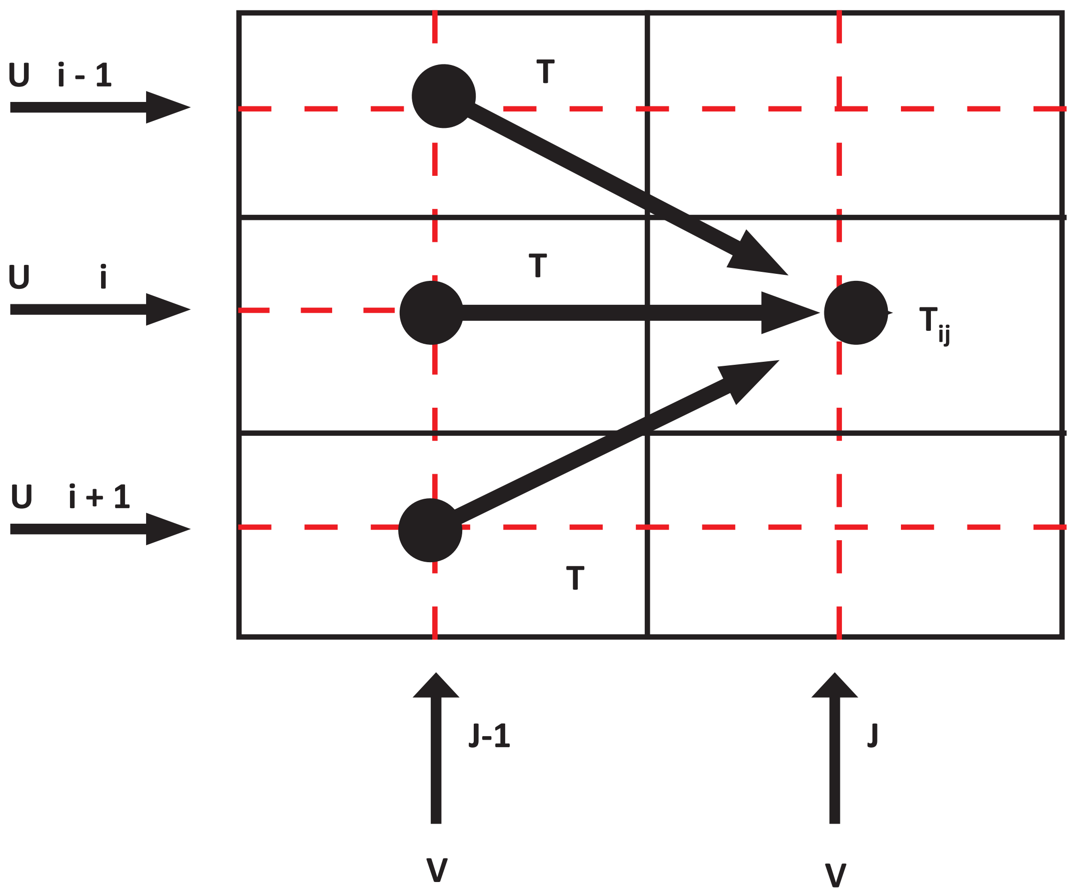

Figure 2 Schematic diagram of the of cell-by-cell approach

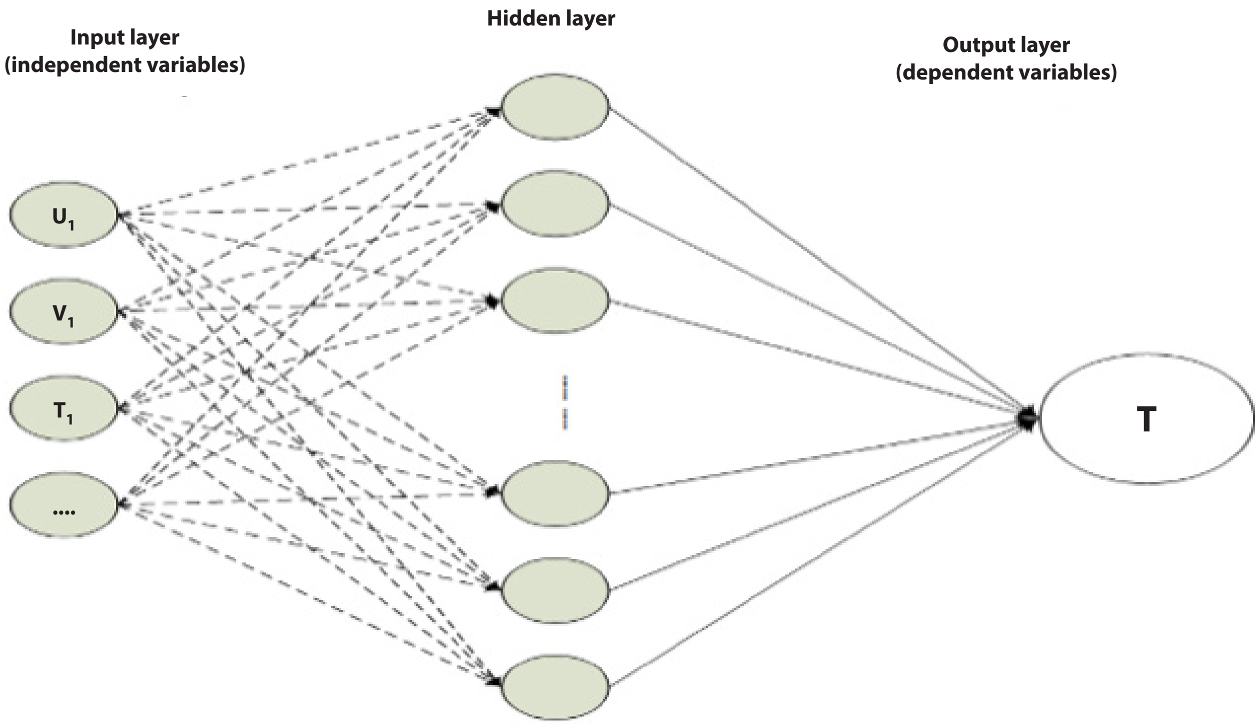

Figure 3 Schematic diagram of CBC for temperature

CBC Model implementation approach

Two ANN models are selected and tested to determine the capability of each model in predicting the temperature field of steady-state, incompressible, laminar flows in a two-dimensional computational domain. The architecture of the cascade-forward and feedforward ANN model is illustrated in Figure 4 and Figure 5, respectively. As mentioned previously, a portion of the data set is used to test each ANN model after training to determine the differences between the predicted data and simulation data. The cascade-forward and feedforward ANN models are developed to emulate the behavior of a fluid particle. Based on the assumption that there is only one inlet, the energy is transferred from the first particle to the second particle in the forward direction. In steady-state, laminar flows, the momentum shifts from one particle to the adjacent particle in the forward direction. Each ANN model analyses the input energy from three previous particles and then computes the resultant total energy. This simple energy conservation approach is analogous to the data flow in cascade-forward and feedforward networks. There is no back flow in steady-state, laminar flows and likewise, there are no feedback loops in cascade-forward and feedforward networks. The cascade-forward ANN model is proposed to measure the echo of the initial energy on the molecules and the weight of the other energy routes.

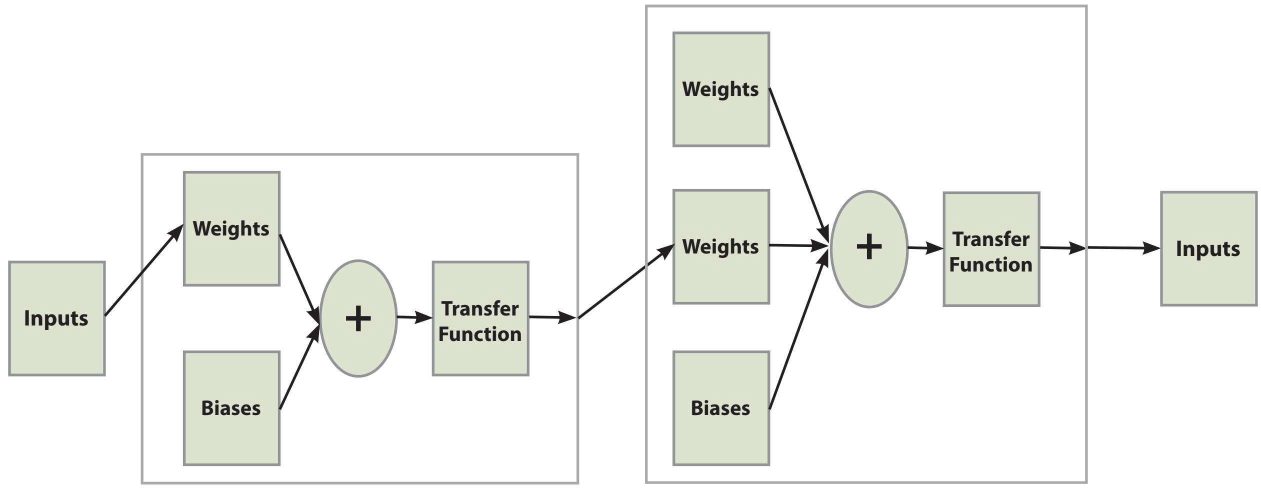

Figure 4 Architecture of the cascade-forward ANN

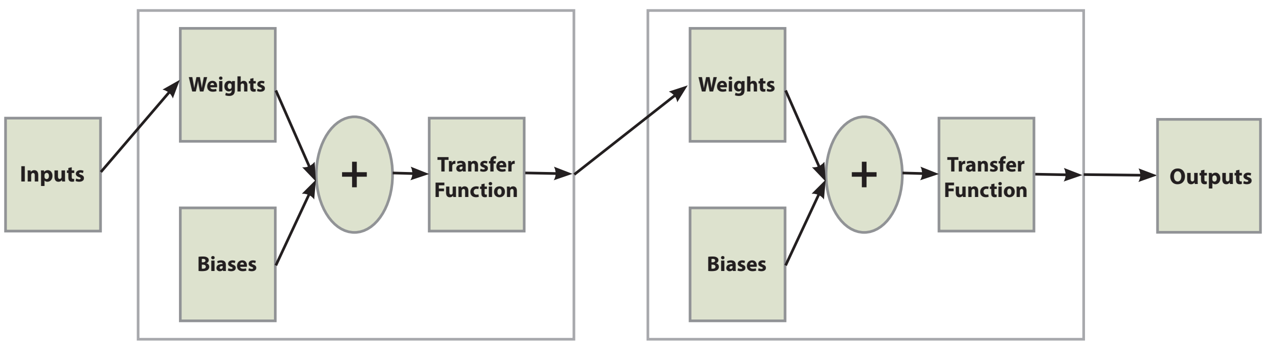

Figure 5 Architecture of the feedforward ANN

The results of the experiment used to select the optimum number of hidden neurons are shown in Figure 6. The results show the variations of the MSE, RMSE and MAE values with respect to the number of hidden neurons for the feedforward ANN model. The first objective of this experiment is to confirm that the increase in the number of hidden neurons will not improve the outcomes of the model [22, 23] and this evident from Figure 6, whereby the error values actually increase when the number of hidden neurons exceeds 20 due to overfitting problem. The mean square error smallest value achieved when 15 hidden neurons are used, but the ratio of the error value change between 11 neurons and 20 neurons is small. The root mean square error gradient shows the increasing value of the error for one neuron is insignificant in the range from minimum value at 11 hidden neurons to 20 hidden neurons. In the interval between 15-20 neurons the upward sloping line for the mean absolute error increasing value from the lowest value can be neglected. Therefore, the error minimum values are reached when choosing an ANN model with 15 hidden neurons. The second objective of this experiment is to determine the differences between the predicted data and simulation data. Regression analysis is carried out in order to determine how well the cascade-forward and feedforward models fit with the simulation data.

RESULTS AND DISCUSSION

The regression between the predicted data and simulation data for the cascade-forward and feedforward ANN model obtained from the validation phase is shown in Figure 7 and Figure 8, respectively. It is evident from the ANN predicted data show good agreement with the CFD simulation data under the same training conditions. Two different Artificial Neural Network training algorithms are applied to the model, Bayesian regulation backpropagation (BRB) and Levenberg-Marquardt backpropagation (LMB). For the Bayesian regularization, the lowest correlation coefficient (R) is found to be 0.99978 and 0.99974 for the cascade-forward and feedforward ANN model, respectively. For Levenberg-Marquardt, the lowest correlation coefficient (R) is found to be 0.99668 for the feedforward and 0.99613 for cascade-forward ANN model, as shown in Figure 9 and Figure 10, respectively. Based on Pan et al. [24] the Levenberg-Marquardt algorithm is usually faster than Bayesian regularization, although it does require more memory than other algorithms. The influence of the training methods is greater than the influence of ANN architectures, the Bayesian regulation backpropagation generalizes well comparing other algorithms. It can be seen that the correlation coefficient is very high (close to +1.0) for both models, indicating that there is a strong correlation between the predicted data and simulation data. Based on the correlation coefficient values, it can be deduced that the cascade-forward ANN model predicts the temperature field with a little higher accuracy compared to the feedforward ANN model.

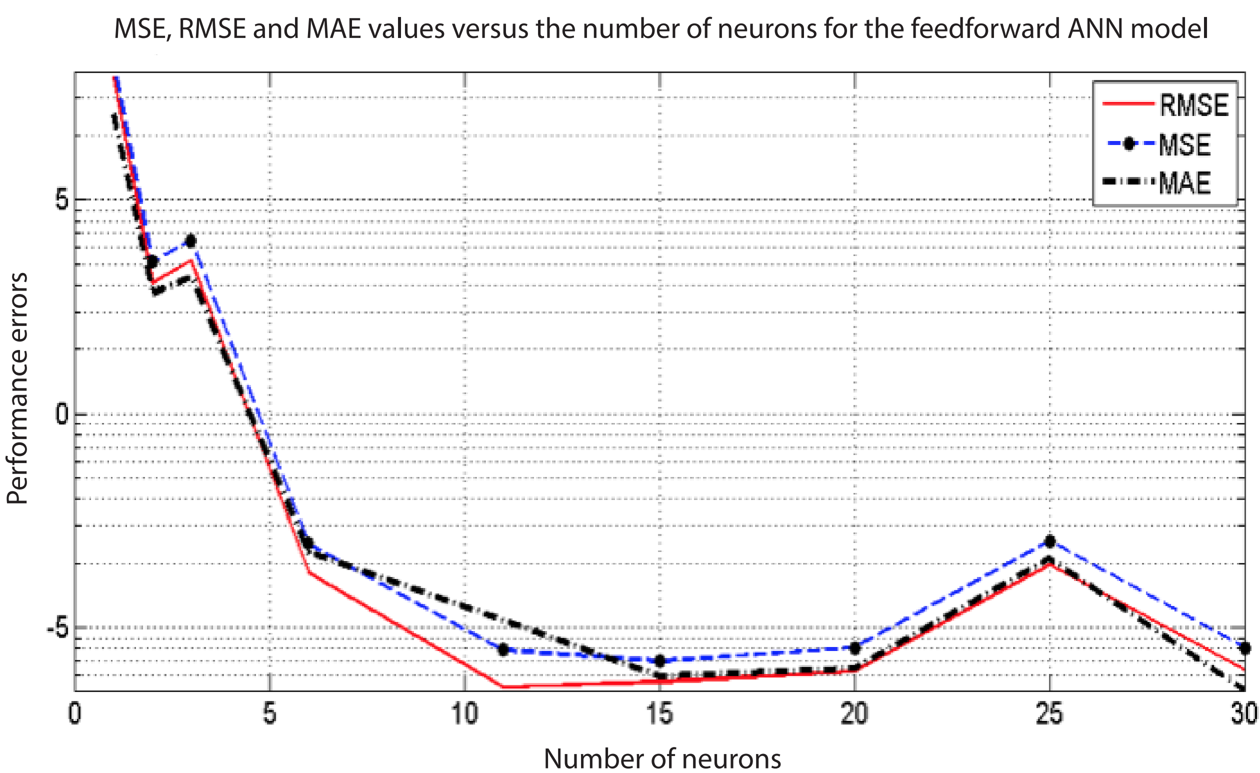

Figure 6 Variations vs the number of hidden neurons

For Bayesian regulation backpropagation (BRB) training:

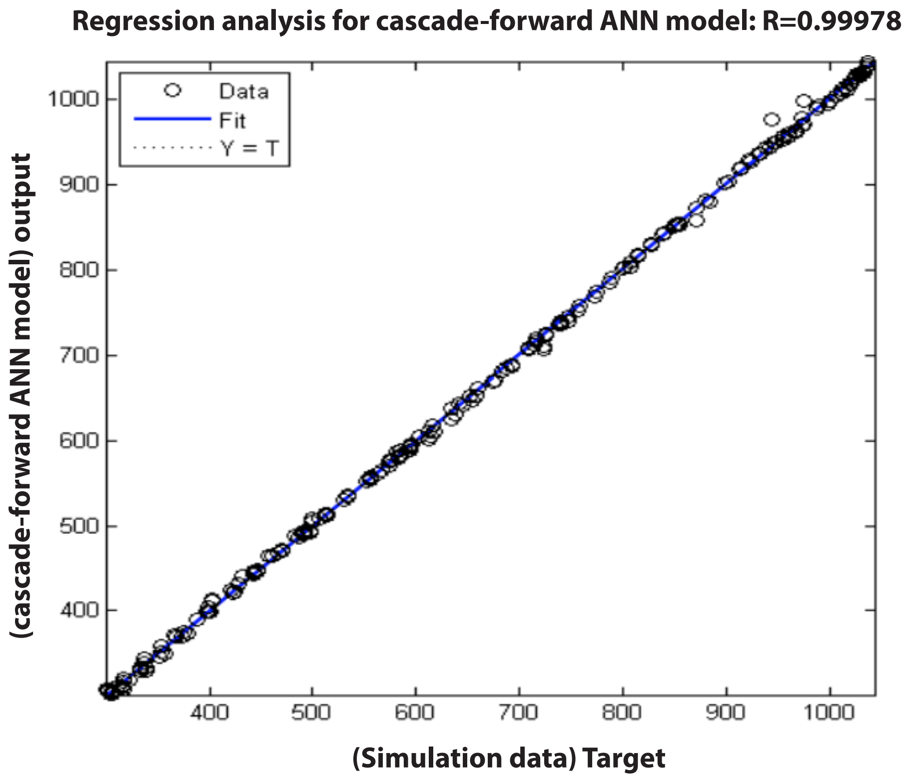

Figure 7 Regression analysis in the validation phase for the cascade-forward ANN model

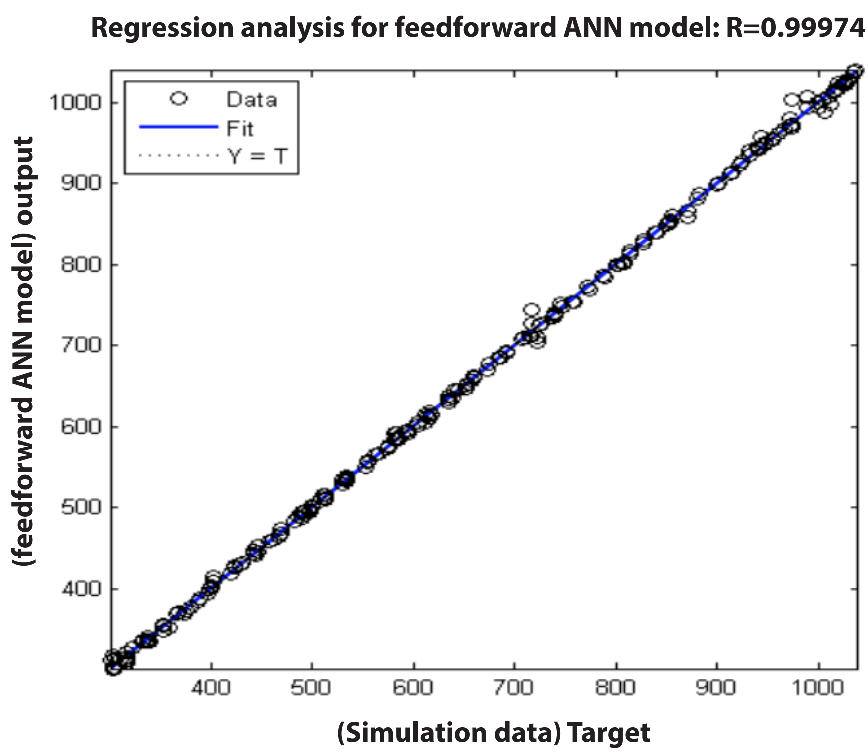

Figure 8 Regression analysis in the validation phase for the feedforward ANN model

For Levenberg-Marquardt backpropagation (LMB) training:

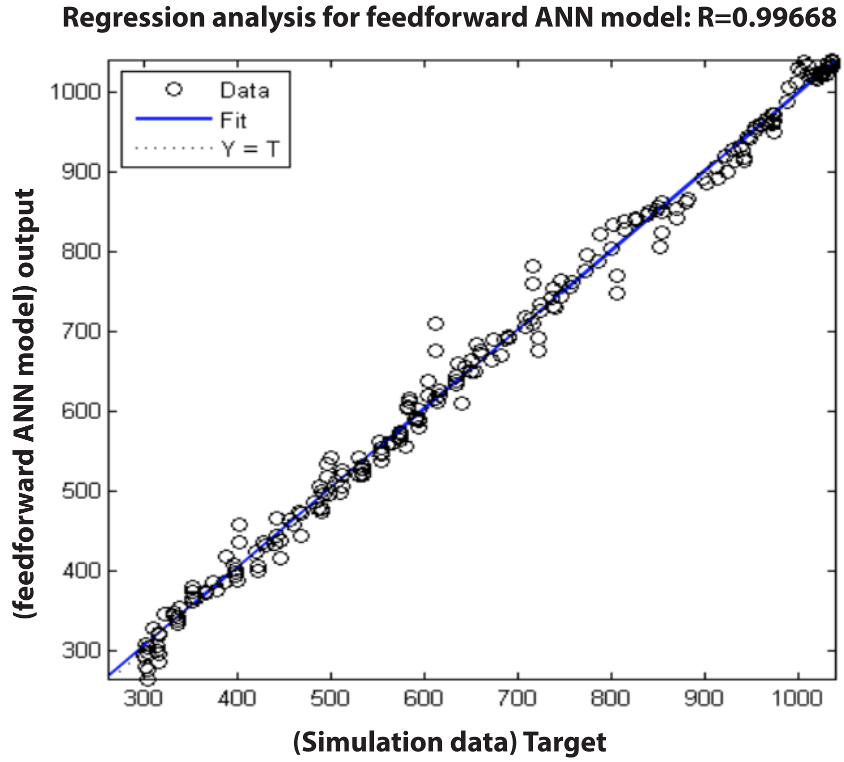

Figure 9 Regression analysis in the validation phase for the feedforward ANN model

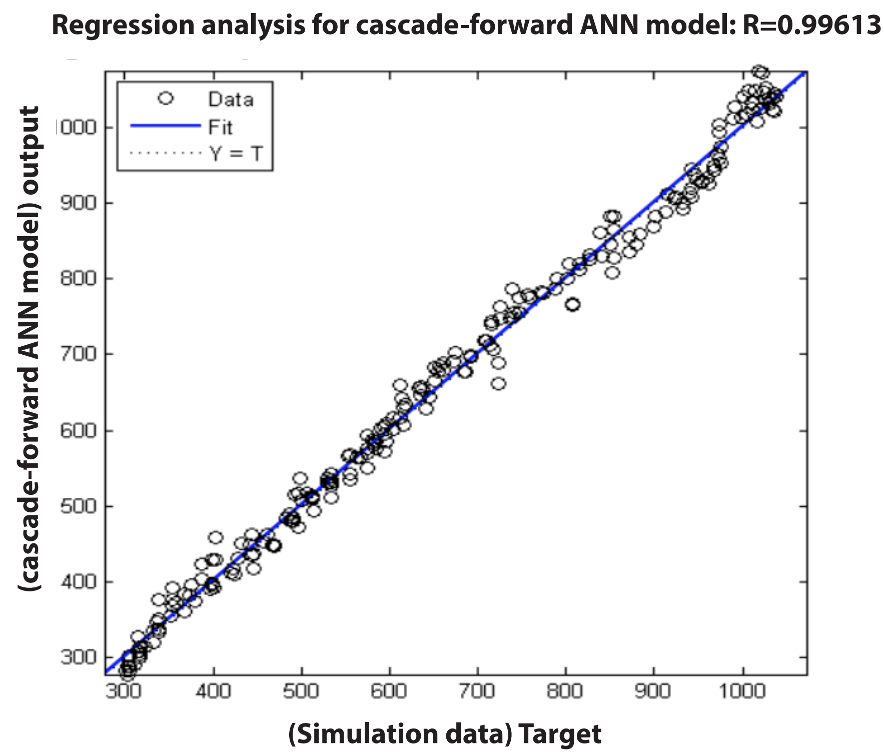

Figure 10 Regression analysis in the validation phase for the cascade-forward ANN model under (LMB) training

The performance of the cascade-forward and feedforward ANN models trained using the Levenberg-Marquardt and Bayesian regularization training algorithms is evaluated using a number of statistical indices. These parameters indicate the deviation of the predicted values from the simulation values. These statistical indices along with the statistical boundaries of the network training phase will help one to determine if there is overfitting in the ANN models. In general, the lower the statistical index values, the better the prediction model will be. It can be deduced that the feedforward ANN model outperforms the cascade-forward ANN model – however, verification is needed to clarify this matter. In addition, the feedforward ANN model trained using the Bayesian regularization algorithm has higher prediction accuracy compared to the same model trained using the Levenberg-Marquardt algorithm. The results are in a good agreement with the results of former applications indicating the same behavior [25].

Verification cases

A test case is used to verify the capability of the ANN models in predicting the temperature field of fluid flows using a different data set. The computational domain remains the same, whereby the same number of Cartesian cells is used for the CFD simulation and ANN models. The boundaries of the ghost cells are added to initiate the computations from the boundary conditions as well as to include the initial computational domain. The regression between the predicted data and simulation data for the cascade-forward and feedforward ANN model is shown in Figure 11, 12 under (BRB) training and Figure 13, under (LMB) training respectively. It can be observed that the predicted data show good agreement with the simulation data, whereby the correlation coefficient (R) is 0.99964 and 0.99982 for the cascade-forward and feedforward ANN model, respectively. The results of the verification phase conform to those from the validation phase, with a regression difference of less than 4.5×10^{-04}.

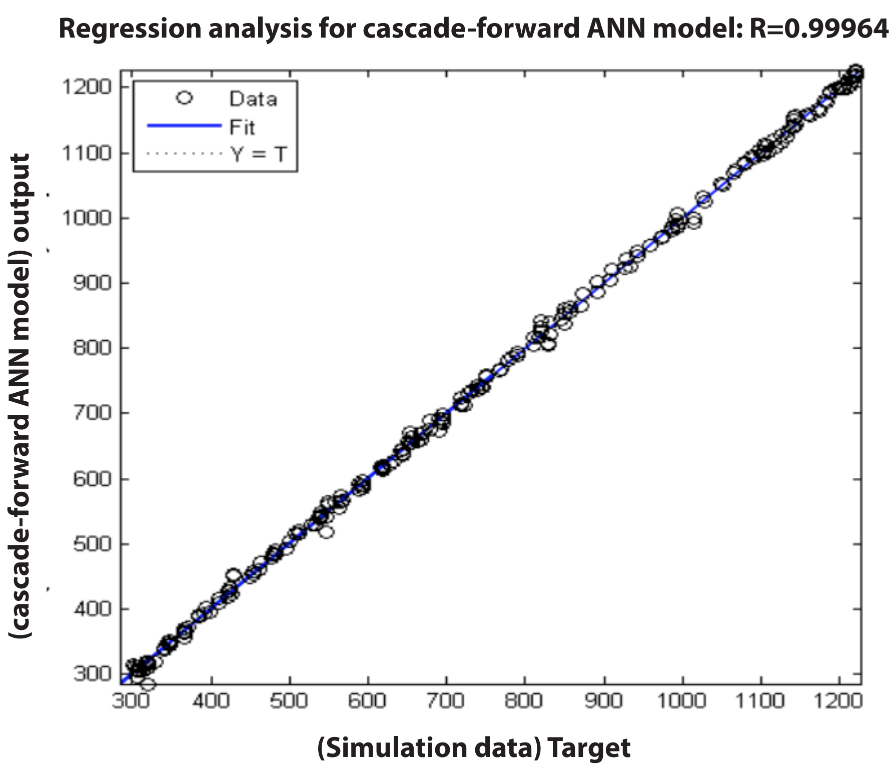

Figure 11 Regression analysis in the verification phase for the cascade-forward ANN model under (BRB) training

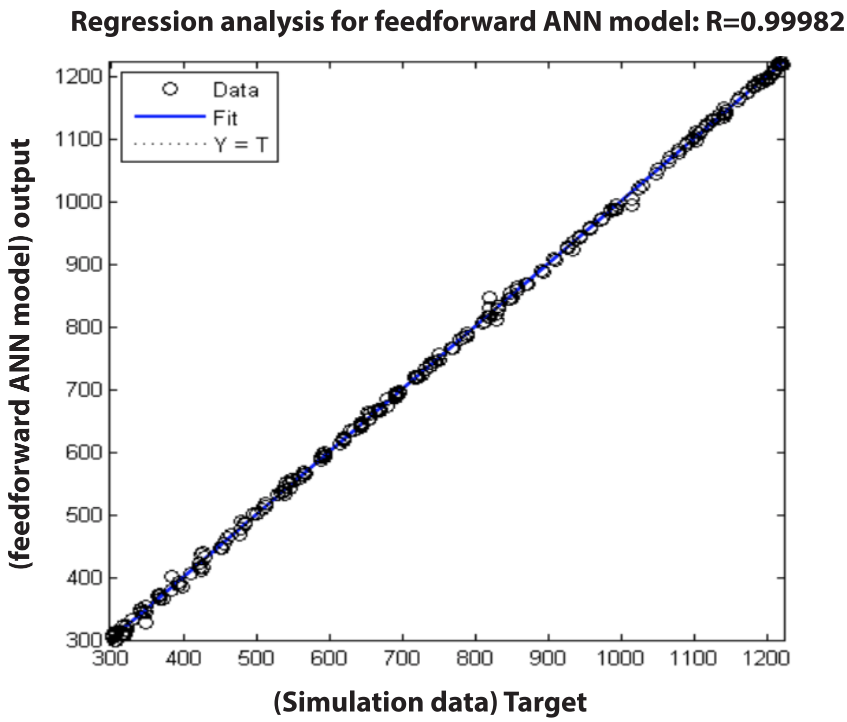

Figure 12 Regression analysis in the verification phase for the feedforward ANN model under (BRB) training

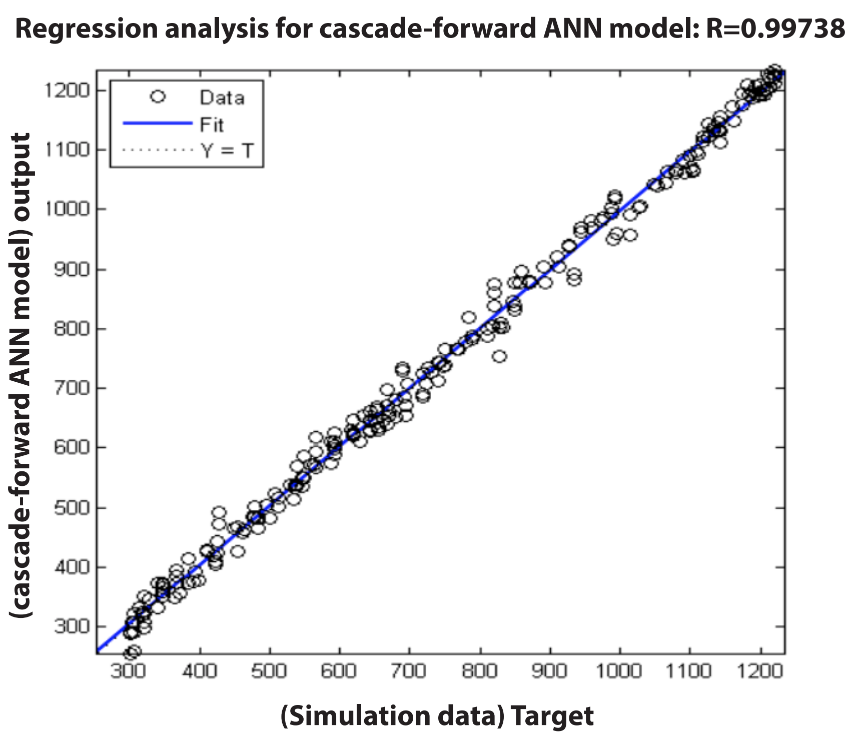

Figure 13 Regression analysis in the verification phase for the cascade-forward ANN model under (LMB) training

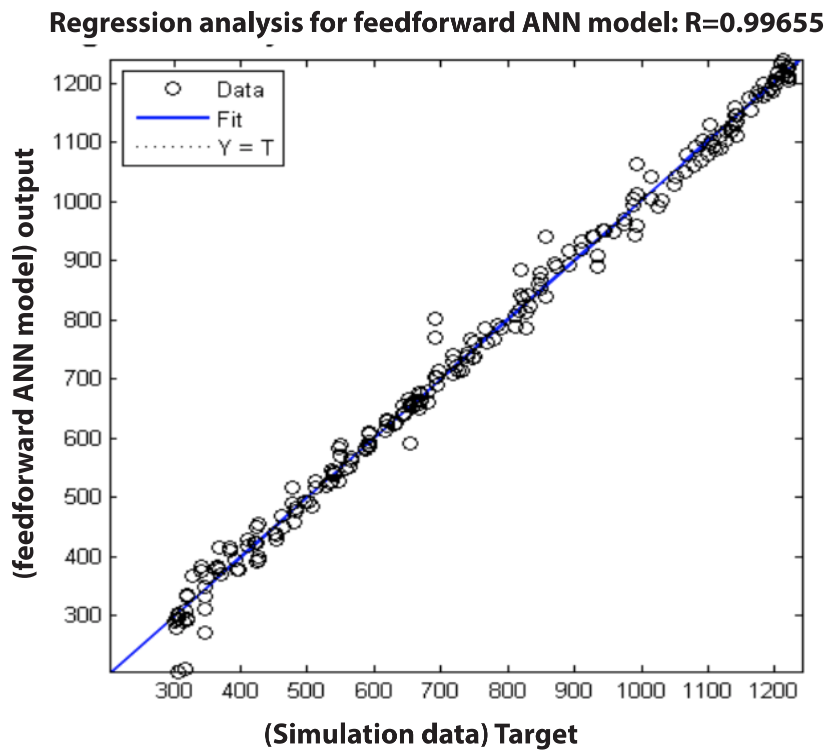

Figure 14 Regression analysis in the verification phase for the feedforward ANN model under (LMB) training

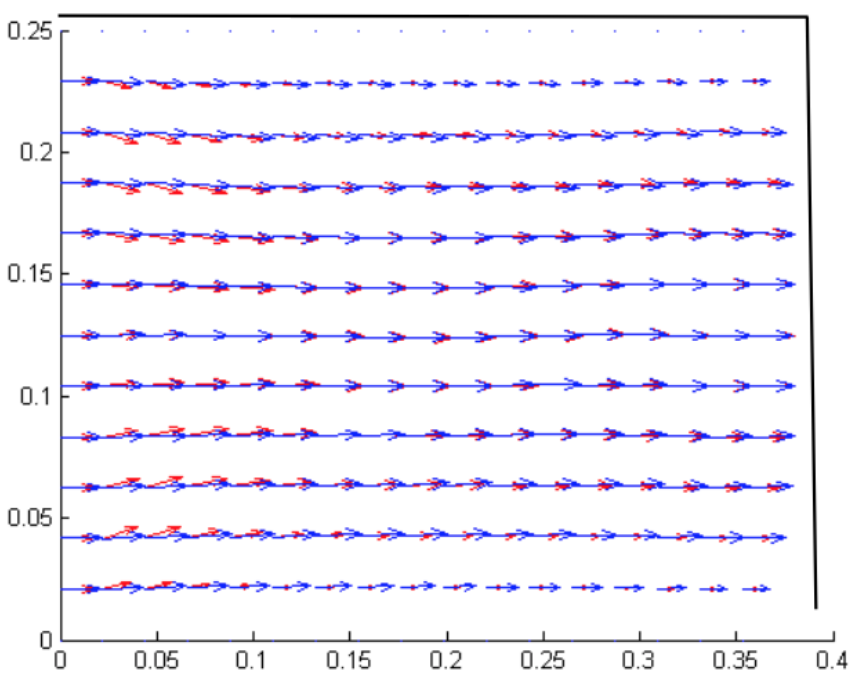

Figure 15 The differences between CFD simulation and the (ANN) velocity vectors

It can be seen that the values of the statistical indices in the verification phase are similar to those obtained from the validation phase. The statistical indices indicate that the cascade-forward and feedforward ANN models have good generalization capability. In general, the feedforward ANN model has superior performance compared to the cascade-forward ANN model in predicting the temperature field of two-dimensional, steady-state, incompressible, laminar flows since most of the statistical index values are lower for the feedforward ANN model. The feedforward ANN model trained using the Bayesian regularization algorithm also has higher prediction accuracy compared to the same model trained using the Levenberg-Marquardt algorithm. It shall be noted that even though the correlation coefficients of both models obtained from the verification phase are higher than those obtained from the validation phase, the statistical index values are higher for the verification phase. For the flow velocity vectors, the differences between the simulation data and the predictive data are showed in Figure 15.

CONCLUSION

In this research, a novel cell-by-cell ANN approach is proposed to predict the temperature field a steady-state, incompressible, laminar flow in a two-dimensional computational domain. Two types of ANN models have been developed in this research (cascade-forward and feedforward models) and trained using Levenberg-Marquardt and Bayesian regularization backpropagation algorithms. The predicted data generated by the ANN models are compared with those from CFD simulations. The results indicate that both ANN models are capable of predicting the temperature field of two-dimensional, steady-state, incompressible, laminar flows with reasonable accuracy (R=.099). However, the feedforward ANN model trained using the Bayesian regularization backpropagation algorithm gives the most accurate predictions among all models. Even though the introduction of ANN at the cell level increases the complexity of the models during the training phase, this drawback is compensated by the increase in flexibility (generality) of the models. Since most of the computational cost is associated with the training phase, the new approach is capable of computing the results within a fraction of the time taken by conventional numerical techniques. Hence, the new ANN approach can be used to predict the temperature field of fluid flows with an acceptable margin of error within a shorter time frame.

Since structured grids are more common compared to other types of grids, it is recommended that the cell-by-cell ANN approach is tested on structured grids in future work in order to reform the node-by-node approach. In addition, there is a need to test the new approach on transient flows and examine the prediction of temperature as a function of time. There is also a need to develop a robust ANN model to predict the temperature field in complex fluid flow problems which will lead to an increase in the number of inputs of the ANN model. Finally, the limitations of the cell-by-cell ANN approach developed in this research need to be examined in detail by implementing the approach on various types of fluid flows.

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