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Artificial Neural Network Modelling of Nanofluid Heat Transfer Performance in Radiator †

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Abstract

ANN-based optimization is used for the prediction of thermal performance for various applications. This research work utilized the artificial neural network (ANN) model for the thermal enhancement of a radiator using diverse concentrations of nanofluid. The heat characteristic is affected by many factors like the shape and percentage of nanofluid concentration. The findings show that the proposed ANN model gives a significant amount of prediction with an accuracy of more than 90%. The developed ANN model demonstrated more capability for forecasting the thermal enhancement of the nanofluid. The R^2 value was 0.9959 for the heat transfer rate (Q). For the Nusselt number (Nu), it was 0.9964, and it was 0.9976 for the heat transfer coefficient (h), respectively. The corresponding RMSE values were 15.2974, 0.3017, and 5.9899, while the MAE values were 10.6077, 0.2425, and 4.4748, respectively. These findings verify that the nonlinear relationship between the Reynolds number, nanofluid concentration, inlet and exit temperatures, mass flow rate, and heat transfer efficiency can be accurately represented by the ANN model. The ANN model can be effectively employed as a predictive and optimization tool for determining suitable operating conditions for enhanced heat transfer.

Keywords: nanofluid; artificial neural network (ANN); heat transfer

1. Introduction

The demand to improve the heat transfer rate from thermal equipment for an effective cooling process is growing by the day. This is despite the fact that numerous ways to increase the heat transfer rate are already accessible, such as incorporating a machine learning algorithm (artificial neural network), and employing nanofluids to make the radiator more compact and effective. A nanofluid refers to a non-soluble metallic and non-metallic particle in a base fluid such as water or another fluid.

Common machine learning techniques are used for the prediction of heat transfer characteristics. Several academics explore using machine learning methods, such as ANN, for model establishment due to their great efficiency as shown in Figure 1.

Now the ANN has vast applications due to its solving capabilities for complex real-world problems, leading to its popularity. The parallel running capability, correction in iterations, and parameter control make it popular. Because of the artificial neural network's simplicity and adaptability, and the availability of a variety of training techniques, it has grown increasingly demanding. In the human brain, the processors are connected to one another by weighted linkages, via which impulses can travel. A neuron produces output

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parameters after receiving numerous input parameters from other neurons in accordance with the weights of their connections. The feed-forward neural network has become the most common in engineering applications due to its straightforward structure and ease of mathematical analysis [1]. There are input layers, many hidden layers, and output layers in this ANN design. The input nodes receive a set of input parameters for the feed-forward process, and the data is transmitted via the network to the output layer nodes. The nodes use sigmoid activation functions to carry out nonlinear input–output transformations. P. Naphon has done research on the mathematical underpinnings of the training and testing processes for the optimal ANN [2].

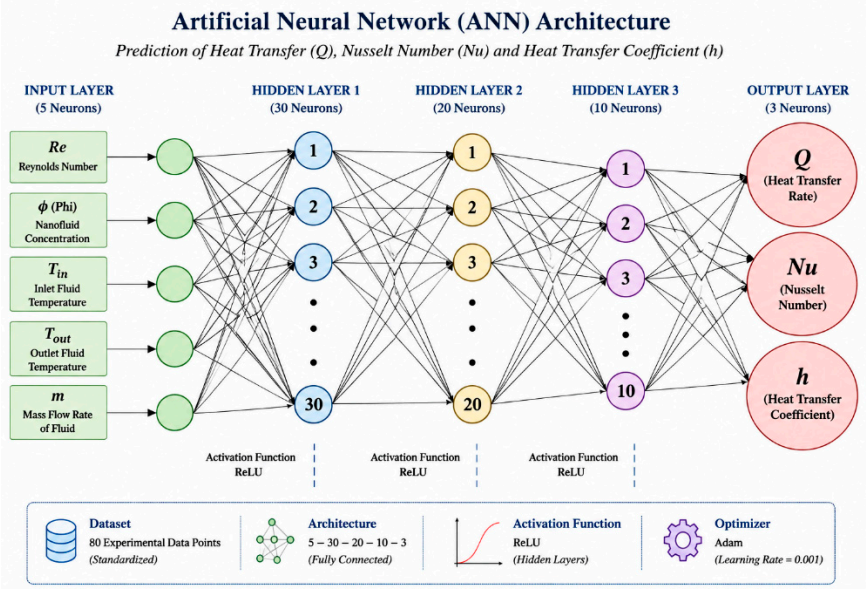


Figure 1. Proposed NN architecture for heat transfer prediction.

ANN is the use of a mathematical method to get to a problem's solution by finding the relationship between input and output parameters with assumed weight. The ANN models the predictions and controls them over more and more epochs. The main advantage of ANN is that it does not show the code, so it is traded as a black box model.

Heat transmission was investigated using ANN. The objective of this research was to find a prominent solution of the thermal performance of a radiator using structured ANN. Experimental study: To improve the effective use of ANN in heat transfer research, a brief explanation of ANN modelling to forecast the heat transfer coefficient and Nusselt number for radiator tubes is provided. And ANN can be used in a large variety of thermal applications effectively [3].

The ANN initializes with random weights of input parameters. Then the parameter weights are refined with each epoch, which is referred to as forward and reverse bias [4]. After the investigation of the ANN model, the mean error for training is near to 0.457% while the testing data shows an error of 0.478% [5].

2. Methodology

The nanofluid was prepared with nanoparticles in a base fluid with the addition of a surfactant and stabilizer. The use of a magnetic stirrer followed by ultrasonication ensured the proper mixing of the nanofluid. The ANN technique was utilized for finding the basic property of the nanofluid. An aluminum nanoparticle was produced using a two-step method with stability-focused parameter variation as shown in Figure 2. The nanoparticle size affects the effectiveness of a nanofluid [6–11]. Thus, its average size was kept constant,

30–35 nm. The purity of Al_2O_3 was varied from 99% to 99.5%. The amount of Al_2O_3 nano-powder needed to prepare different nanofluid concentrations is displayed in Table 1.

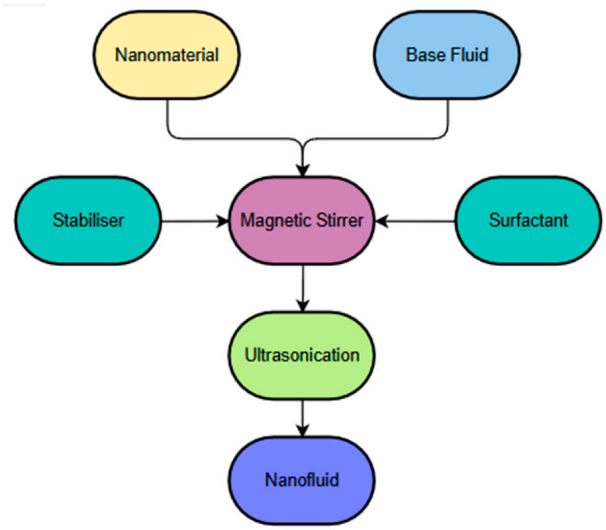


Figure 2. Flow diagram for nanofluid preparation.

Table 1. The amount of nano-powder needed for various compositions.

Sr. No.	Material	Volume Concentration (%)	Weight of Nanoparticles (Grams)
1	Al_2O_3	0.01	0.004
2		0.02	0.008
3		0.03	0.012
4		0.04	0.016

Sodium Dodecyl Sulphate (SDS) [12,13] was used as a well-known surfactant for nanofluids. It reduces the partial pressure between the base fluid and the nanoparticles. A stabilizer was also used for stabilization using pH adjustment of the base fluid as shown in Figure 3. The thermophysical properties are mostly affected by the stabilization of the nanofluid. After preparation of the nanofluid, to prevent agglomerations in the fluid, the solution was sonicated for five to six hours at a frequency of 10 KHz using an ultrasonic sonicator. To avoid a rise in the nanofluid temperature, a 5 to 10 min pause was taken during the sonication procedure.



Figure 3. Nanofluid stirring with a magnetic stirrer.

3. Development of ANN Model

The ANN was developed by analogy with the human brain system. In this research, the preferred model was the Levenberg–Marquardt algorithm. The input parameters were set for Reynolds number = Re, nanofluid concentration phi (Ø), inlet temperature of fluid (Tin), outlet fluid temperature (Tout), and mass flow rate of fluid = m. The parameters evaluated were the heat transfer (Q), heat transfer coefficient (h), and Nusselt number (Nu). The dataset consisted of different nanofluid concentrations (Ø) from 0.01 to 0.025. The inlet temperature varied from 50 to 90 °C. Five input parameters, namely the Reynolds number (Re), nanofluid concentration (Φ), inlet temperature (Tin), outlet temperature of the fluid (Tout), and mass flow rate (m), were used as input variables. Some parameters like the heat transfer rate (Q), heat transfer coefficient (h), and Nusselt number (Nu) were considered as the three output parameters. Prior to ANN modelling, the input and output data were normalized to improve the training performance [14–19]. An input layer with five neurons, two hidden layers, with ten and twenty neurons, respectively, was used. An output layer with three neurons, representing Q, Nu, and h, made up the created ANN. The LBFGS optimization algorithm was used to train the network, while the ReLU activation function was used for the hidden layers [20,21]. The developed ANN model provided excellent prediction accuracy, with coefficient of determination (R^2) values of 0.9959 for Q, 0.9964 for Nu, and 0.9976 for h, demonstrating its suitability for predicting and optimizing the heat transfer performance of the nanofluid.

Formulae

$$Re = 4m/\pi Dh\mu \quad (1)$$

$$Q = m\ Cp\ \Delta T \quad (2)$$

$$Q = hA\Delta T \quad (3)$$

$$Q = h(\pi DhL)\ \Delta T \quad (4)$$

$$Nu = hDh/K \quad (5)$$

4. Results and Discussion

The ANN model was developed and validated with the experimental data. The training and testing data was split with 70:30% variation [22–25]. The validation was done using randomized data. Figure 4 shows a neural network training methodology.

An artificial neural network (ANN) was formed to estimate the thermal performance parameters of the nanofluid heat transfer system, namely the heat transfer rate (Q), Nusselt number (Nu), and heat transfer coefficient (h). The input layer consisted of five experimentally measured operating parameters: the Reynolds number (Re), nanofluid concentration (ϕ), inlet temperature (Tin), outlet temperature (Tout), and mass flow rate (m). These parameters were selected because they directly influence the fluid-flow and heat transfer characteristics of the system [26–29]. The developed network consisted of three fully connected hidden layers containing 30, 20, and 10 neurons, respectively, resulting in an overall 5–30–20–10–3 ANN architecture [30]. The nonlinear link between the input operating parameters and the thermal performance characteristics was captured.

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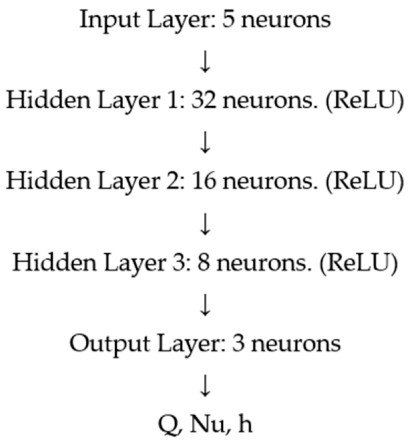


Figure 4. Structure of the ANN.

The output layer corresponded to Q, Nu, and h, thereby enabling the ANN to find the heat transfer performance. The network weights and biases were optimized using the Adam optimization algorithm, which provides efficient gradient-based learning for nonlinear regression problems [31–33]. The ANN model was pre-trained using the available experimental values and subsequently evaluated using independent test data to assess its predictive capability. The obtained results demonstrate that the ANN can effectively form the curvilinear relationship between the Reynolds number, nanofluid concentration, temperature conditions, mass flow rate, and resulting heat transfer parameters. Therefore, the proposed ANN architecture provides a reliable computational approach for predicting Q, Nu, and h, and can be utilized to reduce the requirement for extensive experimental investigations while facilitating the performance analysis of nanofluid-based systems. The performance of the model was tested by different calculating methods like the mean absolute error, mean square error, root mean square error, etc., through advanced Python 3.14.8 code [34]. Here different machine learning algorithms were selected for the training and testing purpose so that we could compare the outputs of different models for the prophecy of heat transfer (Q), heat transfer coefficient (h), and Nusselt number (Nu). The estimated time taken by the algorithm is also indicated in Table 2.

Table 2. Results for performance validation of different ANN models.

Output	ANN Method	RMSE	R^2	MSE	MAE	Speed (obs/s)	Training Time (s)
Q	ANN (30-20-10)	35.21	0.97	1239.76	25.93	14,644.64	0.0446
Nu	ANN (30-20-10)	0.55	0.98	0.3046	0.43	16,205.11	0.0586
h	ANN (30-20-10)	18.74	0.97	351.52	16.17	16,582.94	0.0493

4.1. ANN Prediction Results

The artificial neural network (ANN) was used to forecast the three output parameters using four input parameters. The output parameters were the heat transfer rate (Q), Nusselt number (Nu), and heat transfer coefficient (h), and the Reynolds number (Re), nanofluid concentration (ϕ), inlet temperature (Tin), outlet temperature (Tout), and mass flow rate (m) were used as input parameters. The 80 available experimental variations were divided into training and testing datasets in an 80:20 ratio. A feed-forward ANN with a 5–30–20–10–1 architecture was employed, with ReLU activation and the Adam optimization algorithm. The prediction performance was evaluated using the RMSE, R^2, MSE, and MAE. For the test dataset, the ANN achieved R^2 values of 0.9785, 0.9880, and 0.9763 for Q, Nu, and h, respectively. The corresponding RMSE values were 35.2103, 0.5519, and 18.7491, while the MAE values were 25.9321, 0.4340, and 16.1738, respectively. The additional 5-fold cross-

validation produced mean R^2 values of 0.9861 for Q, 0.9800 for Nu, and 0.9724 for h, which shows the effectiveness of the ANN model.

4.1.1. ANN Training Loss vs. Epoch Graph

- ANN model used;
- Inputs: Re, Φ, Tin, Tout, m;
- Outputs: Q, Nu, h;
- Architecture: 5–20–10–3;
- Hidden layers: 2;
- Neurons: 20 and 10;
- Activation: ReLU;
- Training: Adam optimizer;
- Epochs: 1000;
- Training/test split: 80/20.

The training-loss curve validates the convergence nature of the developed ANN model during the learning process. A rapid decrease in training loss is observed during the initial epochs, indicating that the ANN quickly learns the nonlinear relationship between the input and output parameters. The above graph represents the ANN training loss as the epochs are increased. The graph clearly indicates that, as the epochs move from 0 to 200, the solution converges to 0 loss. The ANN loss is nearly constant at epoch levels more than 400 iterations as shown in Figure 5.

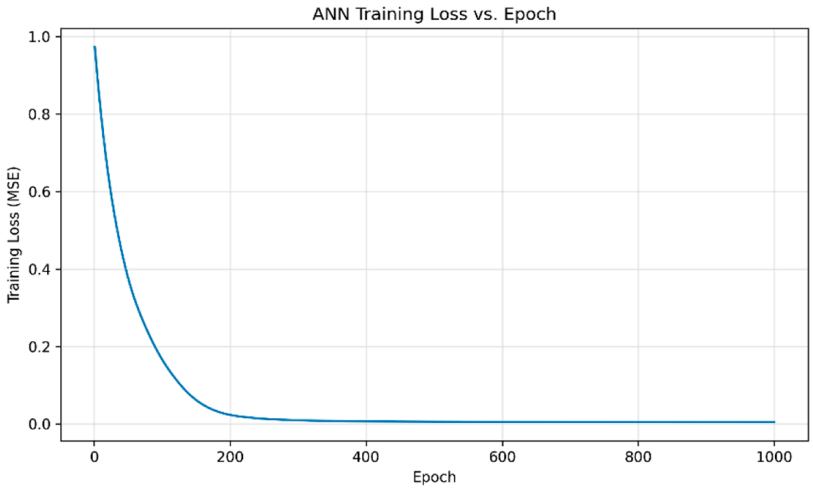


Figure 5. Graph of ANN training loss vs. epochs.

4.1.2. The Experimental Versus ANN-Predicted Heat Transfer Rate (Q) Graph

There is a strong relation between the experimental and ANN-predicted heat transfer rate (Q) plot as shown in Figure 6. Most of the data points are distributed close to the 45° reference line, which shows a good agreement between the experimental and ANN results. The obtained R^2 value of 0.9574 confirms that the ANN successfully captures the variation in heat transfer rate. The deviations show the nonlinear interaction among the Reynolds number, nanofluid concentration, temperature, and mass flow rate. Overall, the results demonstrate that the ANN model provides a reliable prediction of Q within the investigated operating range.

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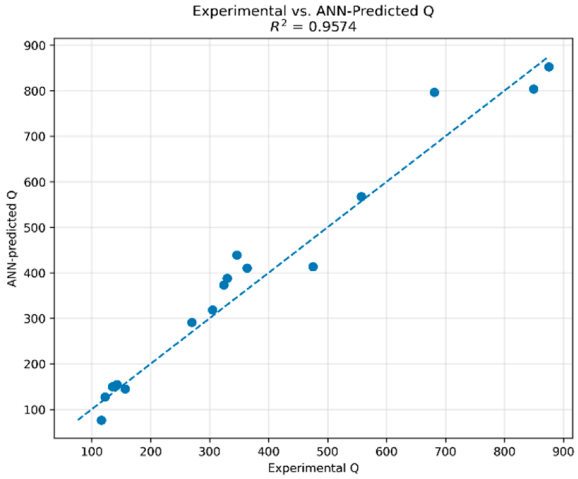


Figure 6. Experiential vs. ANN graph of heat transfer (Q).

4.1.3. Experimental vs. ANN-Predicted h Graph

The experimental versus ANN-predicted heat transfer coefficient (h) plot shows the strongest agreement among the three predicted output parameters as shown in Figure 6. The majority of the data points lie very close to the 45° reference line, indicating high calculated accuracy. The ANN achieved an R^2 value of 0.9801, which demonstrates an excellent correlation between the experimental and predicted h values. The low scattering of the points shows that the ANN model is comparatively more accurate. Only limited deviations are observed at some operating conditions near 200–250 values. Therefore, the developed ANN model is particularly effective for predicting the heat transfer coefficient of the investigated nanofluid as shown in Figure 7.

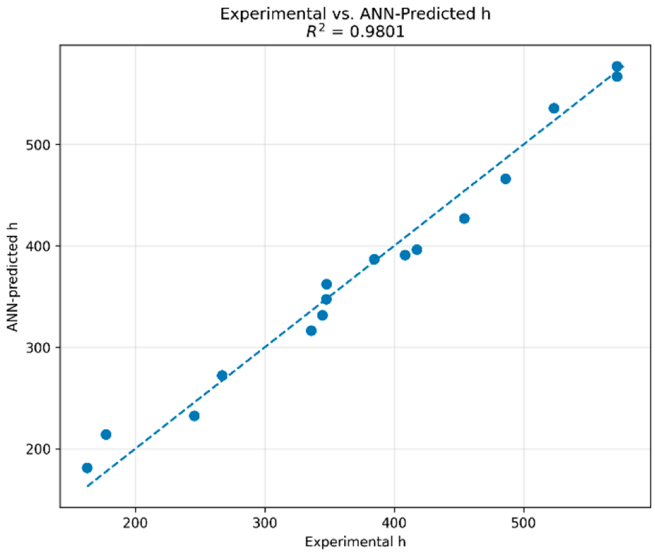


Figure 7. Experimental vs. ANN-predicted h graph.

4.1.4. Experimental vs. ANN-Predicted Nu

The experimental comparison with the ANN Nusselt number (Nu) indicates better experimental trends as shown in Figure 8. The predicted points are located near the ideal 45° line, demonstrating that the ANN effectively reproduces the experimental trend. The model achieved an R^2 value of 0.9486, indicating a strong predictive relationship. The relatively small scatter around the reference line suggests satisfactory prediction accuracy over the investigated range. The deviations could be associated with the complex nonlinear

influence of the Reynolds number and nanofluid concentration on convective heat transfer. Hence, the developed ANN can be considered an effective tool for predicting Nu.

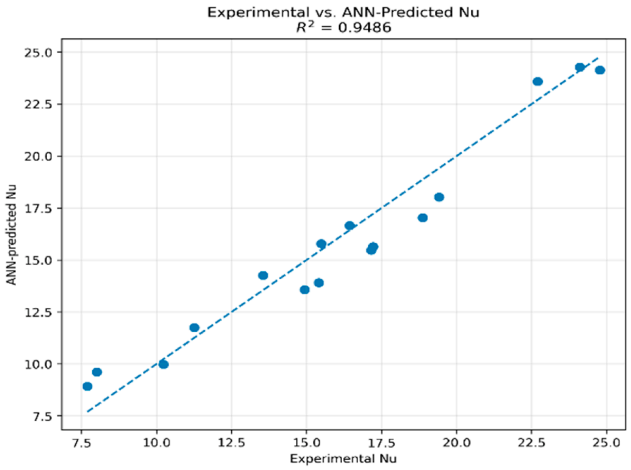


Figure 8. Experimental vs. ANN-predicted Nu graph.

5. Conclusions

An artificial neural network (ANN) was successfully developed to forecast thermal properties. The heat transfer rate (Q), Nusselt number (Nu), and heat transfer coefficient (h) of the nanofluid under different operating conditions were characterized. The five input parameters considered were the Reynolds number (Re), mass flow rate (m), nanofluid concentration (Φ), inlet temperature (Tin), and outlet temperature (Tout).

The R^2 values above 0.99 indicate that the ANN model is more effective for predicting thermal properties. Among the three responses, the estimation of the heat transfer coefficient (h) provided the highest accuracy, with an R^2 of 0.9976, followed by Nu (0.9964) and Q (0.9959). The relatively low RMSE and MAE values further confirm the reliability of the developed ANN model.

The ANN outcome also indicates that the nanofluid concentration and Reynolds number are important parameters influencing heat transfer performance. In general, increasing the nanofluid concentration enhances the predicted heat transfer characteristics, while an increase in Reynolds number promotes stronger fluid fraternization and convective heat transfer. The combined influence of the temperature and mass flow conditions is also effectively captured by the ANN model.

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Conflicts of Interest: The authors declare no conflicts of interest.

Abbreviations

Re	Reynolds number
m	Mass flow rate
D	Inner diameter of the tube
Q	Heat flow, Watts (heat transfer rate)
Cp	Specific heat capacity
ΔT	Temperature difference
A	Area, m^2
L	Length of the tube, m
Nu	Nusselt number
k	Thermal conductivity, W/m k

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