1. Introduction

An Artificial Neural Network (ANN) is made up of neurons that work together to solve a problem [1, 2, 3, 4]. Heat transfer fluids have various industrial applications. Conventional cooling fluids are inherently poor in heat due to their low thermal conductivity [5, 6]. Research and development activities to improve the thermal properties of fluids and phase change materials (PCMs) were always ongoing [7, 8, 9, 10]. Metallic solids and non-metallic materials have a much higher thermal conductivity than conventional cooling fluid. Hence, an innovative idea is to add solid particles to traditional cooling fluids to increase their thermal conductivity. Therefore, predicting the rheological behavior and heat transfer properties of nanofluids is a practical goal. Due to the high cost of heat transfer tests, it is not possible to repeat one test for different data, so predicting the results of one test for different amounts of untested data is an important issue. Due to the accurate results obtained from ANNs in predicting values, the use of this method in predicting the values of untested data has been considered in this article. In this method, by having a limited number of input data and their desired output, the network can be trained in such a way that for a wide range of input data, the desired output can be predicted with great accuracy [7, 8, 9, 10]. With advances in computer science and software, researchers using computational methods such as ANNs, Fuzzy logic, and genetic algorithms tried to model the $k_{nf}$. ANNs were used by many researchers in various engineering systems to model the thermophysical properties of nanofluids.

Safaei et al. [11] investigated the effect of temperature and $\phi$ on the $k_{nf}$ of ZnO–TiO$_2$/ethylene glycol nanofluid using ANN and curve fitting. Their results showed that there is a good agreement between results so that the model of ANN can predict the $k_{nf}$.
ANN method to predict the thermophysical properties of different nanofluids. They showed that with the inputs of temperature, \( \phi \), type, and size of nanomaterial, the ANN model illustrated a good consistency with the experimental data. He et al. [22] predicted the \( k_{nf} \) of ZnO–Ag/Water nanofluid using an ANN method. They found that an ANN method had a better ability in predicting the \( k_{nf} \). Zahmatkesh et al. [23] investigated entropy generation of nanofluid flow in the stagnation point by impinging on the cylinder axes with constant wall heat flux and uniform transpiration.

A review of previous research shows that providing empirical relationships and modeling with the help of ANNs is a suitable method that was considered by many researchers. These methods can replace repeated tests, which are time-consuming and costly. In this study, optimal ANN is obtained by considering the number of different neurons in the hidden layer and considering the least prediction error. Based on the research and studies of the authors, no research has been done on the \( k_{nf} \) of cerium oxide/ethylene glycol nanofluid using ANN.

### 2. Experimental results

In the present study, the hot wire method is used to measure the \( k_{nf} \) using a thermal analyzer KD2-Pro. Cerium oxide nanoparticles are suspended in \( \phi = 0, 0.25, 0.5, 0.75, 1, 1.5, 2 \) and 2.5% in the ethylene glycol base fluid. The \( k_{nf} \) of nanofluids at \( T = 25, 30, 35, 40, 45, \) and 50 °C was obtained experimentally [8]. The diameter of nanoparticles of cerium oxide is 10–30 nm and their bulk density is 0.8–1.1 g/cm³. In this experiment, a two-step method using ultrasonic and magnetic stirrer has been used to produce the Cerium oxide - ethylene glycol nanofluids. To produce the nanofluids in different \( \phi \), the mass of nanoparticles is measured using a digital scale with an accuracy of 0.001 g. The weighted nanoparticles are poured into the base fluid and mixed with a magnetic stirrer for 5 h. The resulting mixture is then exposed to ultrasonic waves and size of nanomaterial, the ANN model illustrated a good consistency with the experimental data. He et al. [22] predicted the \( k_{nf} \) of ZnO–Ag/Water nanofluid using an ANN method. They found that an ANN method had a better ability in predicting the \( k_{nf} \). Zahmatkesh et al. [23] investigated entropy generation of nanofluid flow in the stagnation point by impinging on the cylinder axes with constant wall heat flux and uniform transpiration.

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**Table 1. The neuron numbers based on the best performance.**

| Neuron number | All Performance | Train Performance | Validation Performance | Test Performance |
|---------------|----------------|-------------------|------------------------|-----------------|
| 7             | 1.5776E-06     | 2.3580E-07        | 4.9837E-06             | 4.8816E-06      |
| 9             | 3.1080E-06     | 8.2889E-06        | 6.3693E-06             | 6.5715E-06      |
| 8             | 3.2208E-06     | 4.0468E-06        | 1.0701E-05             | 1.0740E-05      |
| 10            | 3.3097E-06     | 4.9502E-06        | 1.2772E-05             | 8.6275E-06      |
| 6             | 4.2963E-06     | 1.0811E-06        | 5.7806E-06             | 1.2705E-05      |
| 12            | 5.1926E-06     | 6.2598E-06        | 1.7218E-05             | 1.7190E-05      |
| 13            | 5.3821E-06     | 7.9878E-06        | 1.4669E-05             | 1.9757E-05      |
| 11            | 5.8240E-06     | 1.2878E-06        | 9.7508E-06             | 1.7640E-05      |
| 14            | 5.8982E-06     | 5.6439E-06        | 2.2569E-06             | 2.0484E-05      |
| 15            | 6.1336E-06     | 5.3589E-07        | 2.2403E-07             | 2.2493E-06      |
| 16            | 6.5536E-06     | 9.4103E-08        | 2.0861E-08             | 2.0738E-08      |
| 17            | 6.8034E-06     | 5.5578E-06        | 2.7039E-04             | 2.4123E-05      |
| 18            | 8.4312E-06     | 6.8150E-06        | 3.7141E-05             | 3.1174E-05      |
| 19            | 8.9345E-06     | 1.0596E-06        | 3.6981E-06             | 2.6471E-05      |
| 20            | 9.3704E-06     | 1.0525E-06        | 3.7199E-06             | 2.9060E-06      |
| 21            | 1.1304E-05     | 4.0083E-07        | 4.6149E-06             | 4.6921E-05      |
| 22            | 1.4705E-05     | 2.9578E-07        | 7.9629E-05             | 5.1374E-05      |
| 23            | 1.6221E-05     | 3.5282E-07        | 7.9938E-05             | 6.1502E-05      |
| 24            | 1.6243E-05     | 1.6531E-06        | 5.8578E-05             | 6.1068E-05      |
| 25            | 1.7951E-05     | 4.6695E-07        | 8.8753E-05             | 6.6787E-05      |
| 26            | 2.5428E-05     | 1.7534E-06        | 9.4892E-06             | 9.6312E-06      |
| 27            | 2.5622E-05     | 1.6531E-06        | 5.3301E-06             | 5.6566E-05      |
| 28            | 2.8135E-05     | 3.3077E-07        | 1.0001E-06             | 8.2091E-06      |
| 29            | 3.2563E-05     | 1.8785E-06        | 1.0001E-06             | 8.2091E-06      |
| 30            | 4.4218E-05     | 1.4604E-06        | 0.0002E-05              | 0.0001E-05      |
| 31            | 4.6896E-05     | 5.2020E-06        | 0.0001E-05              | 0.0001E-05      |
and controlling the acid at a point far from the isoelectric point (IEP). The resulting nano fluid had good stability and no sediment or sediment was observed in the period before the test.

Experimental data for k_{nf} and TCR of this nano fluid are shown in Figures 1 and 2. The experiments are performed in T = 25 °C-50 °C for φ = 0-2.5%. The experiments show that with increasing φ and temperature, the TCR of nanofluid increases. It is also observed that when the experiments are performed at high temperatures, the rate of increase in k_{nf} due to the change in the φ is much higher than the change in the same amount of φ change at low temperatures. Also, at higher φ, the changes in the k_{nf} of the nano fluid are much more pronounced due to the temperature change. The results show that for low φ at any constant temperature, increasing the particle concentration causes a significant

| Table 2. The targets and ANN outputs. |
|--------------------------------------|
| Target | ANN Outputs |
| 0.249  | 0.248869742 |
| 0.254  | 0.254049596 |
| 0.256  | 0.256055544 |
| 0.26   | 0.261904563 |
| 0.266  | 0.266180316 |
| 0.25   | 0.253673565 |
| 0.258  | 0.258279925 |
| 0.262  | 0.262426936 |
| 0.269  | 0.267093963 |
| 0.272  | 0.272648095 |
| 0.28   | 0.278838674 |
| 0.256  | 0.251847956 |
| 0.263  | 0.262796111 |
| 0.267  | 0.267978975 |
| 0.274  | 0.273196641 |
| 0.278  | 0.279115194 |
| 0.288  | 0.284628844 |
| 0.261  | 0.266977896 |
| 0.27   | 0.270117368 |
| 0.274  | 0.276391129 |
| 0.292  | 0.282339601 |
| 0.287  | 0.286897927 |
| 0.296  | 0.291452426 |
| 0.268  | 0.268195517 |
| 0.278  | 0.277162977 |
| 0.282  | 0.282185061 |
| 0.287  | 0.286652187 |
| 0.292  | 0.292253007 |
| 0.301  | 0.300497803 |
| 0.278  | 0.278258237 |
| 0.286  | 0.286089525 |
| 0.29   | 0.290810375 |
| 0.297  | 0.29624572 |
| 0.303  | 0.30163645 |
| 0.312  | 0.312625127 |
| 0.29   | 0.289731512 |
| 0.297  | 0.29724906 |
| 0.302  | 0.301925847 |
| 0.31   | 0.30700263 |
| 0.314  | 0.313967513 |
| 0.325  | 0.324781612 |

| Table 3. The correlation coefficients. |
|--------------------------------------|
| Neuron number | All correlation | Train correlation | Validation correlation | Test correlation |
|---------------|-----------------|-------------------|------------------------|-----------------|
| 7             | 0.995841024     | 0.998173095       | 0.992745855            | 0.985776848     |
| 8             | 0.991557586     | 0.993946135       | 0.987198567            | 0.982331411     |
| 9             | 0.99125482      | 0.996781847       | 0.97726202             | 0.98289868      |
| 10            | 0.991332507     | 0.996505672       | 0.979866767            | 0.983689681     |
| 6             | 0.990323195     | 0.993546552       | 0.994402106            | 0.985228158     |
| 12            | 0.986131563     | 0.994615009       | 0.979715431            | 0.994196883     |
| 13            | 0.985305959     | 0.994180948       | 0.978781279            | 0.940890185     |
| 11            | 0.984291185     | 0.990926614       | 0.98062136             | 0.940798198     |
| 14            | 0.984719914     | 0.995705511       | 0.970811281            | 0.951357078     |
| 17            | 0.983668381     | 0.995725551       | 0.954561963            | 0.955944203     |
| 15            | 0.982064016     | 0.992779679       | 0.961331405            | 0.951394652     |
| 16            | 0.982157255     | 0.99554427        | 0.965851012            | 0.95147009      |
| 20            | 0.977269443     | 0.994753864       | 0.915534813            | 0.909141478     |
| 19            | 0.977044132     | 0.992631817       | 0.92979117             | 0.949634088     |
| 21            | 0.979668155     | 0.996222334       | 0.93438673             | 0.858038105     |
| 26            | 0.963273098     | 0.997588564       | 0.861942949            | 0.886805016     |
| 24            | 0.95844383      | 0.99687083        | 0.891636222            | 0.921035698     |
| 23            | 0.956409625     | 0.988209968       | 0.824790841            | 0.827560728     |
| 22            | 0.950213722     | 0.99596403        | 0.91214046             | 0.838429906     |
| 25            | 0.932747198     | 0.987596691       | 0.892840863            | 0.680383719     |
| 27            | 0.935725292     | 0.96079977        | 0.915516146            | 0.847999379     |
| 29            | 0.932411052     | 0.99747013        | 0.813070501            | 0.77720659      |
| 30            | 0.923746252     | 0.987745609       | 0.725901943            | 0.737661413     |
| 31            | 0.888390218     | 0.988788998       | 0.714433614            | 0.733361773     |
| 28            | 0.890771214     | 0.961083664       | 0.65718834             | 0.755546111     |

| Table 4. The coefficients of the fitted surface. |
|-----------------------------------------------|
| Coefficient | Value                  |
| P00        | 0.2267                 |
| P10        | 0.0079                 |
| P01        | 0.0008362              |
| P20        | -0.008007              |
| P11        | 0.000624               |
| P90        | 0.00402                |
| P21        | -0.0001815             |

Figure 3. The architecture of ANN.
increase in the $k_{nf}$. However, at higher $\phi$, this increase indicates a lower slope. As the $\phi$ increases and the nanoparticles come together, clusters of nanoparticles are formed. By forming these clusters, heat can travel through these solid regions faster than when passing through the fluid, thus increasing the $k_{nf}$. In nanofluids with smaller nanoparticles, the occurrence of this phenomenon is more obvious. The joining of this phenomenon is more obvious, because in these nanofluids, at a certain $\phi$, the distance between the nanoparticles decreases with decreasing diameter and the Van der Waals absorption forces between the particles become more intense. On the other hand, it can be concluded that no considering the effective and important parameters such as temperature, particle diameter, and size and stabilization method in the relationships of estimation models, the $k_{nf}$ can make them inefficient and reduce their efficiency.

### 3. Artificial Neural Network

#### 3.1. The neuron numbers based on the best performance

Artificial Neural Networks (ANNs) are widely used in engineering projects. If these ANNs are designed accurately, they can predict the behavior of complicated systems including linear on non-linear behavior. In the current work, the inputs are $\phi$ which consists of ($\phi = 0, 0.25, 0.5, 0.75, 1, 1.5, 2$ and $2.5\%$) and temperature which includes ($T = 25, 30, 35, 40, 45$ and $50\,^\circ C$) and the goal is predicting $k_{nf}$ of nanofluid. The numbers of data points are 42. To predict the $k_{nf}$, a feed-forward network is designed. This network consists of three layers: An input layer, a hidden layer, and the output layer. The output layer has only one neuron (Because only one parameter should be predicted). For the hidden layer,
different neuron numbers have been tested and then the best neuron based on the performance has been selected and applied. In Table 1, the neuron numbers are sorted based on the best performance. In this table for each neuron number, the train, validation, test, and all performances are presented. It can be seen that a network with 7 neurons in the hidden layer has the best performance.

The architecture of the best ANN is shown in Figure 3.

In this ANN the tangent sigmoid is considered as the activation function and Levenberg Marquardt as the learning algorithm. In Table 2, the predicted data points by the ANN were presented. More than two-thirds of the data points are used for train and the rest of the data points are divided into two parts equally and used for validation and test. In Table 2, the blue, green, and red colors refer to the train points, validation, and test data points, respectively. It can be seen that the predicted values are very close to the target data points. Another important criterion to judge the accuracy of results is the Correlation Coefficient. The correlation coefficient is defined as Eq. (1),

$\rho_{UV} = \frac{E[(U - \mu_U)(V - \mu_V)]}{\sigma_U \sigma_V}$  

(1)

In Eq. (1), $U$ is the target and $V$ is the predicted parameter, $\mu_U$ and $\mu_V$ are the mean values of $U$ and $V$ respectively. The standard deviations of $U$, $V$ are $\sigma_U$, $\sigma_V$. Also $\rho$ defines the correlation coefficient between the experimental and predicted values. In Table 3, the correlation coefficients for these neuron numbers are shown. In this table, the correlation coefficients also have been calculated for training, validation, test, and all data points. It can be seen that an ANN with 7 neurons in the hidden layer has a correlation coefficient very close to 1 and this proves that the outputs are compatible with experimental results.

3.2. Fitting method

The fitting method is another important method that is used for modeling the behavior of systems. In this work, a surface is fitted on the experimental data points in which, one axes are for temperature, one axes is for $\varphi$ and the third axes shows $k_{nf}$. To obtain an acceptable fitting result, combinatorial power functions were tested with different orders for temperature and $\varphi$ and finally, the best one is selected (Eq. (2)), i.e., a first-order for temperature and the third order for $\varphi$, $k(x,y) = p00 + p10*x + p01*y + p20*x2 + p11*x*y + p30*x3 + p21*x2*y$  

(2)

In Eq. (2), $x$ represents the $\varphi$ and $y$ represents the $k_{nf}$ of nanofluid, and $k(x,y)$ is the fitted result of $k_{nf}$. The coefficients of this function are shown in Table 4.

In Figure 4, the fitted surface is depicted. The dotted points are experimental data and the fitted surface is very close to these points. This surface depicts a better overview of the behavior of nanofluids. It can be seen that $k_{nf}$ has a direct relationship to temperature and $\varphi$. The maximum $k_{nf}$ occurs in the highest values of temperature and $\varphi$.

In Figure 5 the experimental data points, ANN outputs, and the fitted surface results are presented. It is found that both the ANN and fitting method have acceptable accuracy in predicting the $k_{nf}$ based on the temperature and $\varphi$. It can be seen that ANN and fitting methods are near the experimental data points, and both these methods are accurate enough to predict $k_{nf}$.

To have a better understanding of the results of these two methods, the errors of these methods are presented in Figure 6. In Figure 4 the absolute values of errors are shown. It was assumed that the experimental data are our reference values; however, the error of extracting the experimental data may be more than 0.003, and we tried to predict these reference values. It can be seen that both methods have small errors but the ANN in most data points has smaller errors.

4. Conclusion

In this paper, the $k_{nf}$ of cerium oxide/ethylene glycol nanofluid is predicted for different temperatures and $\varphi$ by ANN and fitting methods. The important results of the research can be summarized as follows:

- An ANN with 7 neurons has a correlation coefficient very close to 1 and this proves that the outputs are compatible with experimental results.
- The ANN could predict the thermal behavior of this nanofluid more accurately.
- Both methods have small errors but the ANN in most data points has smaller errors.
- This method can decrease the lab costs and can obtain $k_{nf}$ of this nanofluid for this range.

Figure 6. The error of ANN and fitting Method.
Declarations

Author contribution statement

Behrooz Ruhani, Mansour Taheri Andani, Azher M. Abed, Ghassan Fadhil Smaisim, Salema K. Hadrawi: Performed the experiments; Analyzed and interpreted the data; Conceived and designed the experiments; Contributed reagents, materials, analysis tools or data. Nima Sina, Davood Toghraie: Conceived and designed the experiments; Performed the experiments; Analyzed and interpreted the data; Contributed reagents, materials, analysis tools or data.

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Data availability statement

No data was used for the research described in the article.

Declaration of interest statement

The authors declare no conflict of interest.

Additional information

No additional information is available for this paper.

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