International Communications in Heat and Mass Transfer 116 (2020) 104645

Contents lists available at ScienceDirect

International Communications in Heat and Mass Transfer

journal homepage: www.elsevier.com/locate/ichmt

Using of Artificial Neural Networks (ANNs) to predict the thermal conductivity of Zinc Oxide–Silver (50%–50%)/Water hybrid Newtonian nanofluid

Wei He[a], Behrooz Ruhani[b], Davood Toghraie[c], Niloufar Izadpanahi[c], Navid Nasajpour Esfahani[d], Arash Karimipour[b], Masoud Afrand[e,f,*]

[a] Engineering Research Center of Fujian University for Marine Intelligent Ship Equipment, Minjiang University, Fuzhou 350108, China
[b] Department of Mechanical Engineering, Najafabad Branch, Islamic Azad University, Najafabad, Iran
[c] Department of Mechanical Engineering, Khomeinishahr Branch, Islamic Azad University, Khomeinishahr, Iran
[d] Kennesaw State University, Department of Mechanical Engineering, MD # 9075, 840 Polytechnic Lane Marietta, GA 30060, United States of America
[e] Laboratory of Magnetism and Magnetic Materials, Advanced Institute of Materials Science, Ton Duc Thang University, Ho Chi Minh City, Vietnam
[f] Faculty of Applied Sciences, Ton Duc Thang University, Ho Chi Minh City, Vietnam

ARTICLE INFO

Keywords:
Artificial Neural Networks (ANNs)
Thermal conductivity
Hybrid Newtonian nanofluid

ABSTRACT

In this study, after generating experimental data points of Zinc Oxide (ZnO)–Silver (Ag) (50%–50%)/Water nanofluid, an algorithm is proposed to calculate the best neuron number in the Artificial Neural Network (ANN), and the performance and correlation coefficient for ANN has been calculated. Then, using the fitting method, a surface is fitted on the experimental data, and the correlation coefficient and performance of this method have been calculated. Finally, the absolute values of errors in both methods have been compared. It can be seen that the best neuron number in the hidden layer is 7 neurons. We concluded that both methods could predict the behavior of nanofluid, but the fitting method had smaller errors. Also, the ANN method had better ability in predicting the thermal conductivity of nanofluid based on the volume fraction of nanoparticles and temperature. Finally, we found that, in ANN, all outputs, the maximum absolute value of error is 0.0095, and the train performance is 1.6684e-05.

1. Introduction

Nanofluids have had many problems, such as deposition, impurity, corrosion, and increasing pressure drop, until the idea of using nano-sized particles was first put forward by Maxwell in 1881 and a major revolution in heat transfer was created in the fluids [1]. Nanofluids are fine-grained particles between 1 and 100 nm suspended in a base fluid. Typically, nanoparticles of metals such as copper, aluminum, potassium, silver, and oxides, as well as MWCNT and SWCNT and base fluids, are also predominantly of relatively low conductivity fluids. They are used as heat transfer conductors. Nanoparticles are much more stable than larger particles such as microparticles and have a higher surface area of contact with the fluid [2–10]. Recently, Artificial Neural Networks (ANNs) are widely used in many scientific and engineering fields. These networks have shown their potential in predicting the nonlinear or complex behavior of systems. The history of ANNs refers to the 1940s. During this decade, Warren McCulloch and Walter Pitts created a simple model based on the algorithms which were named threshold logic, and then in 1956, Rochester Holland and Duda introduced neural network machines. In 1958, Rosenblatt worked on pattern recognition, which led to perceptron. In 4965, Ivakhneko and Lapa published the first networks, including many layers [11–17].

Yousefi and Mohammadiyan Nezhad [18] and Hemmat Esfe et al. [19] obtained the thermal conductivity of Al_2O_3 nanofluids using ANN. They found that there is a good agreement between the theoretical and the experimental values of the thermal conductivity of the Al_2O_3/water nanofluid and correlation coefficient. Mechiri et al. [20] modeled using ANN the thermal conductivity of Cu−Zn nanofluids. They found that these models were in good agreement with the experimental data. Hemmat Esfe et al. [21] studied the thermal conductivity of Al_2O_3/water–EG (40–60%) nanofluid. They showed that the trained ANN had provided a good agreement between the predicted values and experimental data. Hosseinian Naeini et al. [22] predicted the thermal conductivity of Fe_2O_3/water nanofluid based on ANN. Their results show

* Corresponding author at: Ton Duc Thang University, Ho Chi Minh City, Vietnam.
E-mail address: masoud.afrand@tdtu.edu.vn (M. Afrand).

https://doi.org/10.1016/j.icheatmasstransfer.2020.104645

Table 1
Specifications of ZnO nanoparticles [36].

Density (gcm^{-3})	Color	Shape	Specific surface (m^2g^{-1})	Size (nm)	Purity	Particle
5.606	Milk white	Spherical	20–60	10–30	%99+	ZnO

Table 2
Specifications of Ag nanoparticles [36].

Bulk density ($grcm^{-3}$)	Color	Shape	Specific surface (m^2g^{-1})	Size (nm)	Purity	Particle
10.5	Black	Spherical	20–16	30–50	%99+	Silver

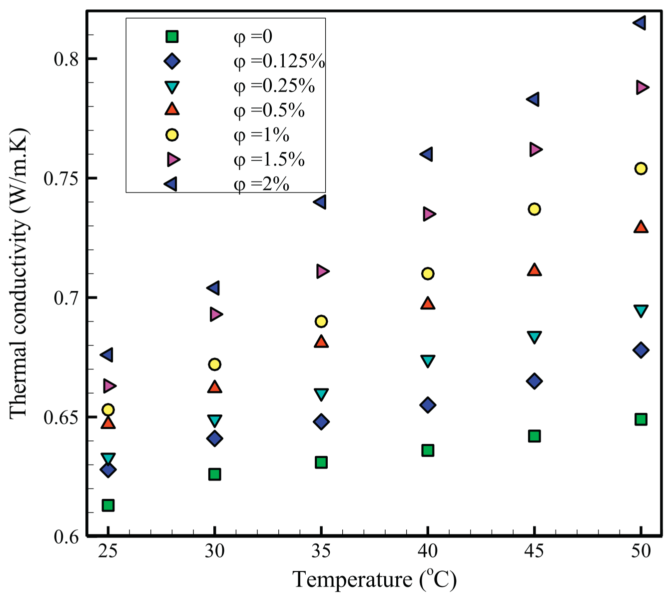

Fig. 1. Thermal conductivity of nanofluid versus temperature

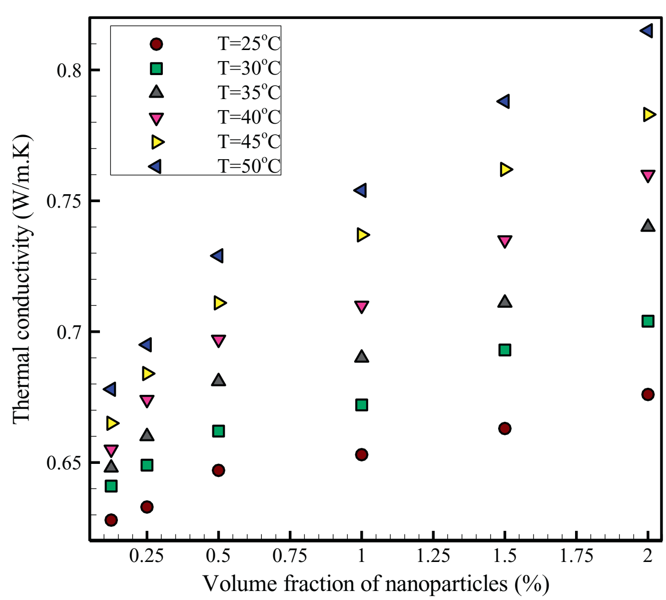

Fig. 2. Thermal conductivity of nanofluid versus ϕ

that ANN is capable of predicting nanofluid thermal conductivity with excellent precision. Aghayari et al. [23] predicted the thermal conductivity of Fe_3O_4 / water nanofluid by ANN. They concluded that the ANN is an effective method for the prediction of the thermal

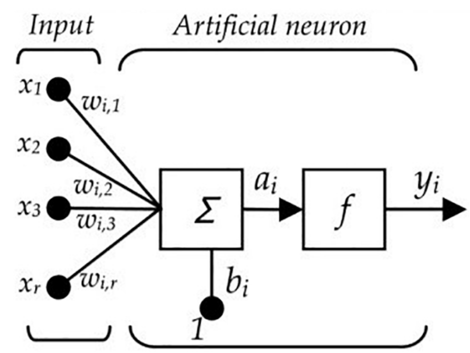

Fig. 3. Mathematical model of a neuron.

conductivity of nanofluid. Ahmadloo and Azizi [24] obtained the thermal conductivity and viscosity of $MnFe_2O_4$ nanofluid using an ANN. They showed that the ANN is very good tool to predict the properties of nanofluids. Tahani et al. [25] predicted the thermal conductivity of Graphene oxide/water nanofluid using ANN. Their results show that their model can precisely predict the thermal conductivity of the nanofluid. Kamalesh et al. [26] predicted the thermal conductivity of nanofluids containing TiO_2 with different base fluids such as -Water, Ethylene Glycol, and Engine Oil nanofluids. They observed that the ANN data are in good agreement with experimental results. Hojjat [27] predicted the Nusselt number of non-Newtonian nanofluids using ANN. They found that ANN predicts the Nusselt number of nanofluids more accurately than the previously proposed correlation. Mohamed and Habashy [28] modeled the thermal conductivity of Al_2O_3 and TiO_2 /Propylene Glycol nanofluid using ANN. They found that the ANN data are consistent with experimental data. Mohamed [29] modeled properties of MgO and SiO_2–TiO_2 / ethylene glycol nanofluids using ANN. They found that the ANN model can be utilized as an efficient tool to predict the properties of nanofluids.

In this paper, we predict the thermal conductivity of Zinc Oxide–Silver (50%–50%)/Water hybrid Newtonian nanofluid using ANNs. After generating experimental data points of nanofluid, an algorithm is proposed to calculate the best neuron number in the ANN, and the performance and correlation coefficient for ANN has been calculated. Then, using the fitting method, a surface is fitted on the experimental data, and the correlation coefficient and performance of this method have been calculated, and finally, the absolute values of errors in both methods have been compared.

2. Experimental procedure

Te transient hot-wire method using KD2-Pro and KS1 probe was used to calculate the thermal conductivity of nanofluid [30–33]. To calculate the thermal conductivity, the required masses must first be obtained, such as the mass calculation, and after stabilizing with considerations in determining the thermal conductivity, we place the probe in the mixture for 2 min for each experiment [34–36]. It must be borne

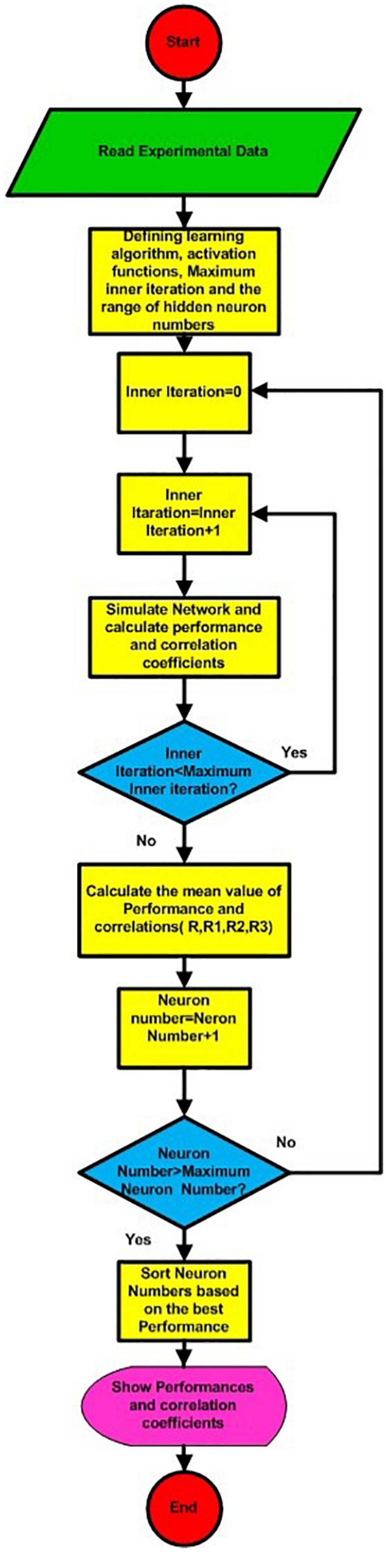

Fig. 4. The proposed algorithm to find the best neuron number

in mind that in order to obtain the correct results, considerations must be taken into consideration, including that the water should be perfectly vertical and fixed without clamping. The device must be calibrated prior to the test, and a temperature bath can also be used to keep the temperature constant during the data collection [37,38]. Tables 1 and 2 show the properties of nanoparticles.

Fig. 1 shows the thermal conductivity of ZnO–Ag (50%–50%)/water nanofluid versus the temperature at a different volume fraction of nanoparticles (ϕ). By examining Fig. 1, it is found that the temperature is a very important factor, and its absence in classical relations results in a severe deviation from the results. As is evident, in the same volume fraction of nanoparticles, the increase in temperature leads to a significant increase in the thermal conductivity, which can be attributed to the particle motion. Increasing the temperature also reduces the thickness of the nanolayers. An increase in the volume fraction of nanoparticles means an increase in solid particles with a higher thermal conductivity in the fluid, but this factor is very sensitive because it can

Table 3
the sorted performance of ANN.

Neuron number	All performance	Train performance	Validation performance	Test performance
7	1.66842E-05	1.9928E-05	7.02973E-06	1.01197E-05
6	2.53201E-05	4.27217E-05	7.08254E-06	1.39949E-05
8	2.67636E-05	3.72297E-05	1.54128E-05	1.22122E-05
10	5.16584E-05	6.35924E-05	2.83999E-05	2.67475E-05
9	6.65934E-05	0.000145768	2.50699E-05	2.33706E-05
11	8.85316E-05	0.000159682	3.11479E-05	4.21055E-05
13	0.00010083	8.37181E-05	5.09442E-05	6.64435E-05
12	0.000103278	0.000149718	5.15384E-05	5.02473E-05
14	0.000116032	0.000113141	6.07801E-05	7.03651E-05
16	0.000122764	0.000130041	8.54952E-05	5.85793E-05
17	0.000164122	7.70419E-05	0.00012896	9.69136E-05
20	0.000186899	8.44163E-05	0.000147952	0.00011064
21	0.000189859	0.000209087	9.14271E-05	0.000113215
15	0.00020094	9.18948E-05	0.000139643	0.00013048
19	0.00023814	0.000186925	0.000132355	0.000152656
18	0.000268679	0.000164963	0.000256382	0.000119985
26	0.000277923	5.30575E-05	0.000266743	0.00015663
24	0.000308507	0.000104027	0.000279234	0.000171314
25	0.000437917	0.000378468	0.000269537	0.000254883
29	0.000443407	0.000193274	0.000386333	0.000242925
22	0.000446951	0.0002837	0.000320342	0.000261723
23	0.000547646	0.000535497	0.00036653	0.000283079
28	0.00062304	0.000565875	0.000510438	0.000277368
31	0.000828442	0.000578526	0.000669521	0.000423905
30	0.000892451	6.58194E-05	0.000848129	0.000537854
27	0.001038771	0.000573702	0.000666674	0.000680144

Table 4
The correlation coefficient between experimental data and ANN outputs.

Neuron number	Train	Validation	Test	All
7	0.998858	0.996431	0.992235	0.997229
6	0.997714	0.993361	0.993335	0.996094
8	0.99808	0.990556	0.986502	0.995403
10	0.99628	0.976468	0.9723	0.990737
9	0.991725	0.988002	0.980302	0.988838
11	0.990529	0.971793	0.949107	0.984973
13	0.994856	0.962871	0.92478	0.981649
12	0.990109	0.953693	0.935731	0.981757
14	0.992247	0.965814	0.937327	0.980551
16	0.992465	0.940734	0.938425	0.978838
17	0.995218	0.919542	0.917722	0.974696
20	0.994962	0.918033	0.842023	0.969619
21	0.98922	0.930349	0.876552	0.968641
15	0.99415	0.953847	0.902133	0.973103
19	0.988741	0.913137	0.858394	0.957623
18	0.989665	0.909689	0.863462	0.959195
26	0.997094	0.902279	0.865209	0.956127
24	0.993417	0.918562	0.819586	0.954342
25	0.976994	0.862376	0.836948	0.932107
29	0.990211	0.827144	0.839676	0.933185
22	0.983465	0.83137	0.8381	0.929744
23	0.973943	0.799716	0.818153	0.925055
28	0.963816	0.78568	0.870399	0.917491
31	0.967506	0.712917	0.684246	0.87945
30	0.995866	0.778671	0.741102	0.88756
27	0.960664	0.77931	0.770808	0.895945

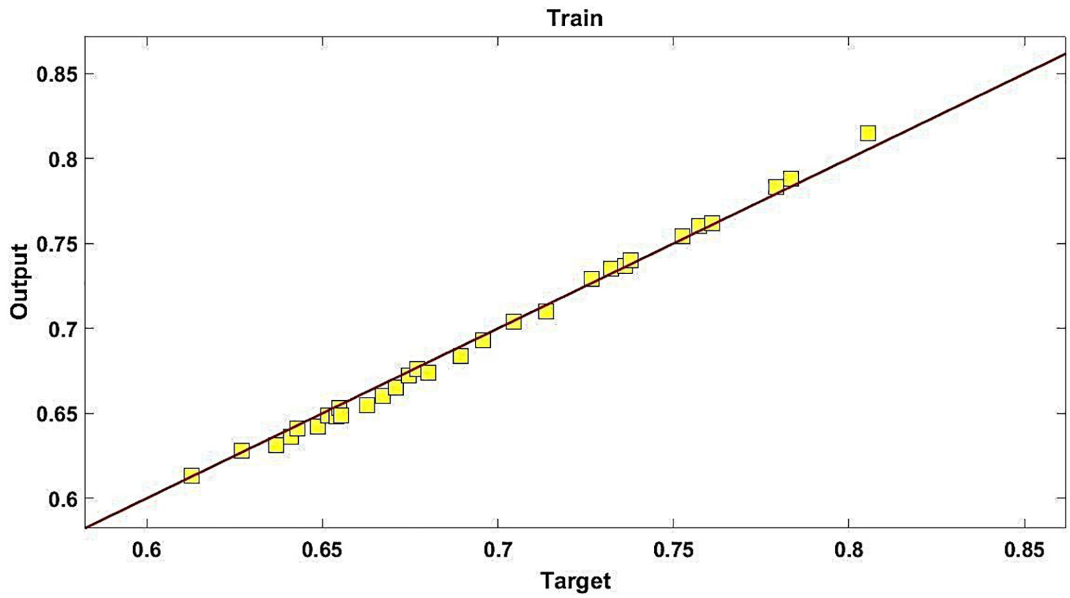

Fig. 5. ANN train outputs.

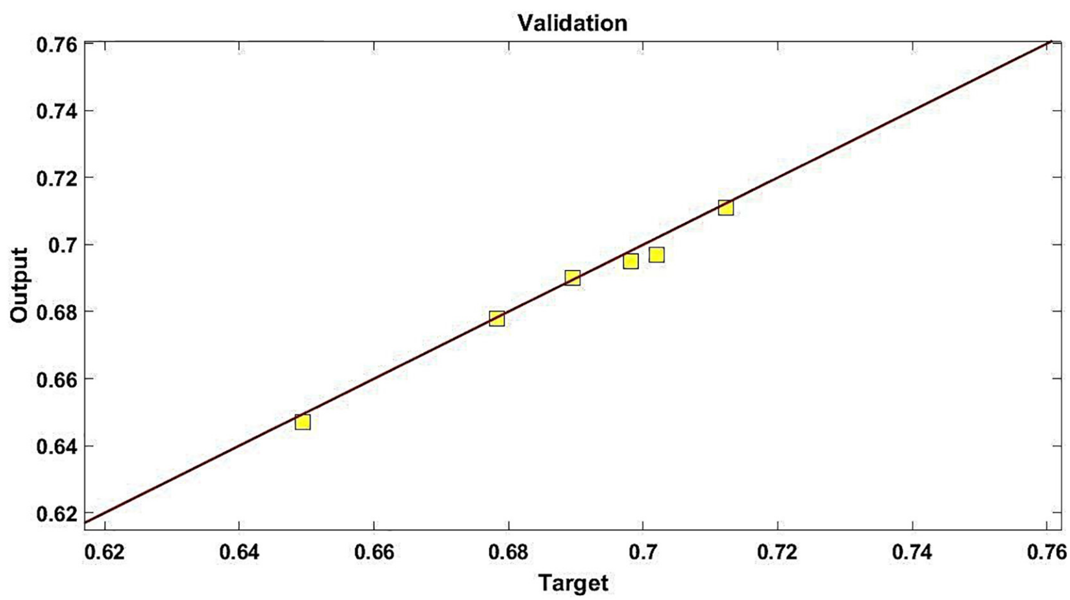

Fig. 6. ANN validation outputs.

increase as long as it does not cluster and settle. Nanoparticles and their accumulation decrease the thermal capability of nanofluids. The highest increase in thermal conductivity is related to the highest temperature and the highest volumetric percentage. In low volume fractions of nanoparticles, the effect of temperature is almost lower, but with the increasing volume fraction of nanoparticles, the temperature changes further on the nanofluid. It was also found that the relationship between thermal conductivity and volume fraction of nanoparticles is almost linear.

Fig. 2 shows the thermal conductivity of ZnO–Ag (50%–50%)/Water nanofluid versus ϕ at different temperatures. Fig. 2 shows that by increasing the ϕ at all temperatures, we have an increase in thermal conductivity. This increase is more pronounced in a lower volume fraction of nanoparticles. The main reason could be the increase in Brownian motion and the collision of more particles as well as the increase in energy exchange due to more collisions. However, at higher temperatures, the intermolecular bonds become looser, and the fluid becomes more thermally stable. On the other hand, in a very low ϕ, the thermal conductivity shows low sensitivity to temperature, but with the increasing ϕ, the temperature difference increases and changes significantly in this coefficient.

3. Artificial Neural Networks (ANNs) method

In this study, the different ϕ and temperatures have been used to measure the thermal conductivity of ZnO–Ag (50%–50%)/water nanofluid. ANNs are often judged by their performance. ANN's performance is considered as the Mean Square Error (MSE). Error is the difference between the experimental data and the calculated values by ANN. In Eq.1 the MSE has been presented,

$$MSE = \frac{1}{n}\sum_{i=1}^{n}(Y_i - \hat{Y}_i)^2 \tag{1}$$

In Eq. 1, n is the number of experimental data points, Y_i is the target, and $\hat{Y}_i$ is the predicted target.

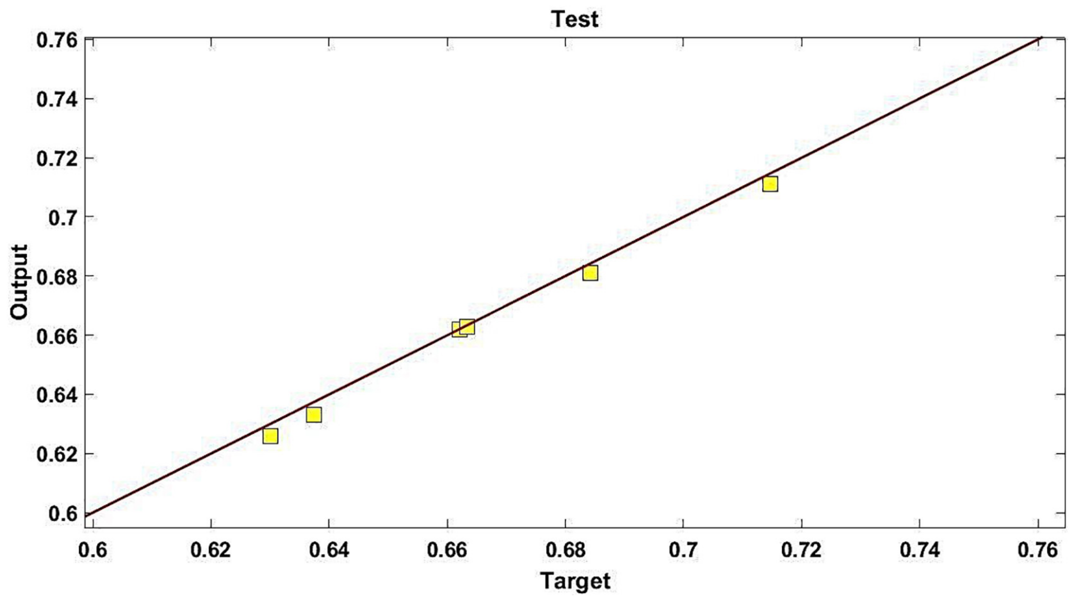

Fig. 7. ANN test outputs.

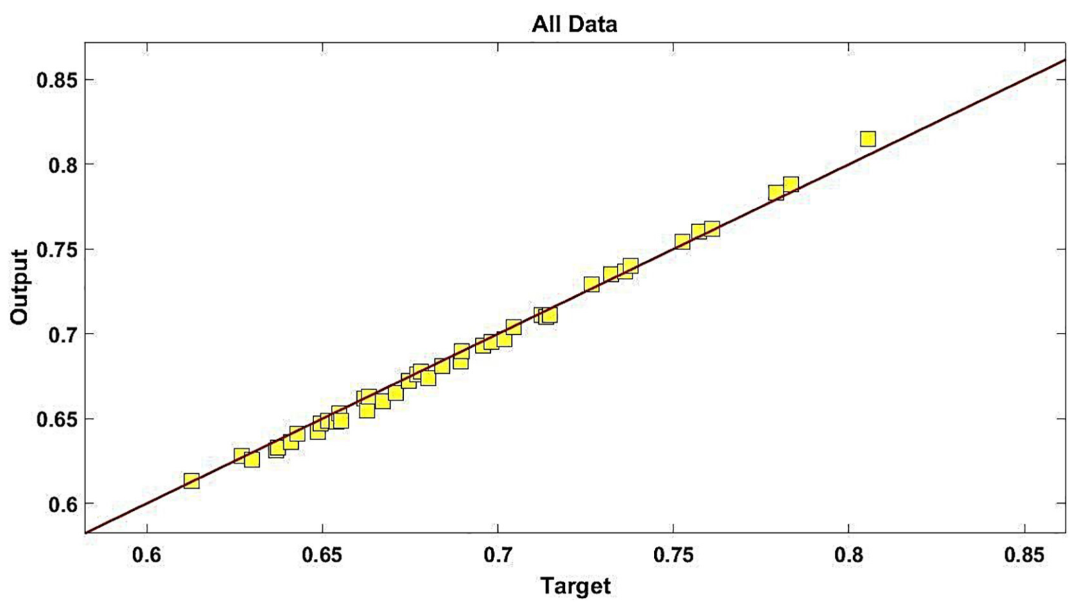

Fig. 8. ANN all outputs.

Table 5
the coefficients of the fitted surface.

Coefficients	p00	p10	p01	p20	p11	p30	p21
Numerical Values	0.579263154	0.009537	0.001481	−0.06677	0.003572	0.026872	−0.00082

In ANN's the value of MSE is called performance, and it should be near zero. A mathematical model of a real neuron is depicted in Fig. 3, which consists of weights, bias, and activation function.

In this model, x_i is the i_{th} input, $w_{i,\ r}$ is the weight of r_{th} data point related to the i_{th} neuron, b_i is the bias of neuron and f is the activation function. The process of data in neurons is presented in Eq.2.

$$Y_i = f\left(\sum_{j=1}^{n} w_{ij}x_j + b_i\right) \tag{2}$$

In this study, the activation function of all layers (except of the last one) is tansig. The tansig is presented in Eq.3. The activation function of the last layer is purelin,

$$\tan sig\,(n) = \frac{2}{1 + e^{-2n}} - 1 \tag{3}$$

The learning algorithm for this ANN is Levengerg-Marquardt. This algorithm was presented by Kenneth Levenberg in the 1940s and then it rediscovered by Donald Marquardt in the 1960s. The Levenberg Marquardt is one of the most common and powerful algorithms in the learning process of ANNs.

Experimental data is categorized into three main parts, including train, validation, and test randomly. The train data consists of 70% of points, validation 15%, and test also consists of 15% of data. In the

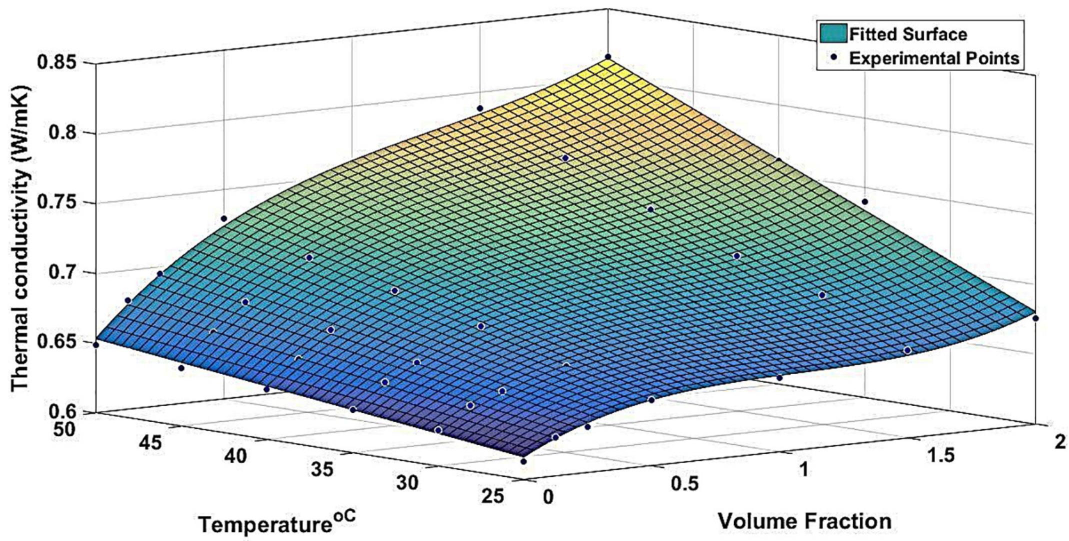

Fig. 9. the fitted surface.

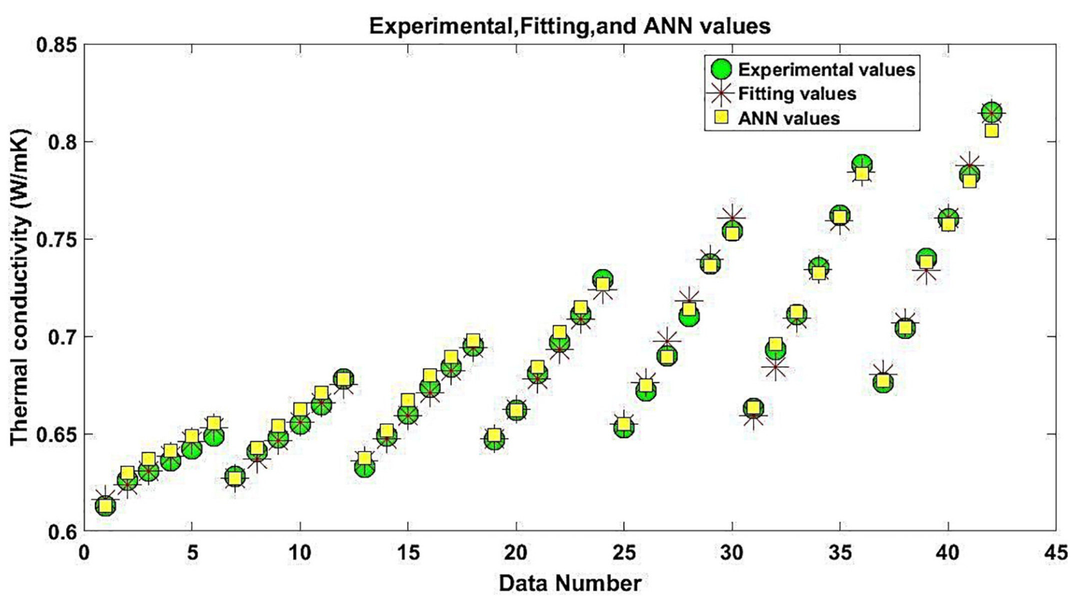

Fig. 10. the experimental, ANN and surface fitting outputs.

current study, an algorithm is used to find the best neuron number in the hidden layer. The proposed algorithm is depicted in Fig .4.

In the presented algorithm, for each neuron number in the hidden layer, the ANN is simulated several times, and during each iteration, the performance is calculated, and then the mean value of the performance of iterations is considered as the performance of that neuron number. In this algorithm, the neuron numbers have been changed from 8 to 31 neurons. The number of inner iterations is 20 times. The results of this algorithm are shown in Table 3, in which the best neuron numbers are sorted based on the performance values. Not only the performances of all experimental data points are calculated, but also the train, validation, and test performances are presented.

It can be seen that the best neuron number in the hidden layer is 7 neurons. To judge better about the outputs, another criterion, which is called the correlation coefficient, is used. The correlation coefficient determines the compatibility between inputs and outputs. The correlation coefficient is calculated by Eq.4,

$$\rho U,\, V = \frac{E[(U-\mu_U)(V-\mu_V)]}{\sigma_U \sigma_Y} \tag{4}$$

In Eq.4, $U$and V are targets and outputs, respectively.μ_U is the mean of U and μ_V is the mean value of $V$and σ_U, σ_V are considered as the standard deviations of U *and* V, respectively. Also, the correlation coefficient for train, test, validation, and all data points are presented in Table 4.

Considering Table 4, it can be seen that for a network with 7 neurons in the hidden layer has the best overall correlation coefficient for train, validation, test, and all data points. The train, validation, and test outputs of the optimum ANN are presented in Figs. 5 to 8. In Fig. 5, ANN train outputs are displayed. In ANN train outputs, the maximum absolute value of error is 0.0095, and the train performance is 1.9928e-05.

In Fig. 6, ANN validation outputs are displayed. In ANN validation outputs, the maximum absolute value of error is 0.0050, and the train performance is 7.0307e-06.

In Fig. 7, ANN test outputs are displayed. In ANN Test outputs, the maximum absolute value of error is 0.0045, and the train performance is 1.0120e-05.

In Fig. 8, ANN's all outputs are displayed. In ANN All outputs, the maximum absolute value of error is 0.0095, and the train performance

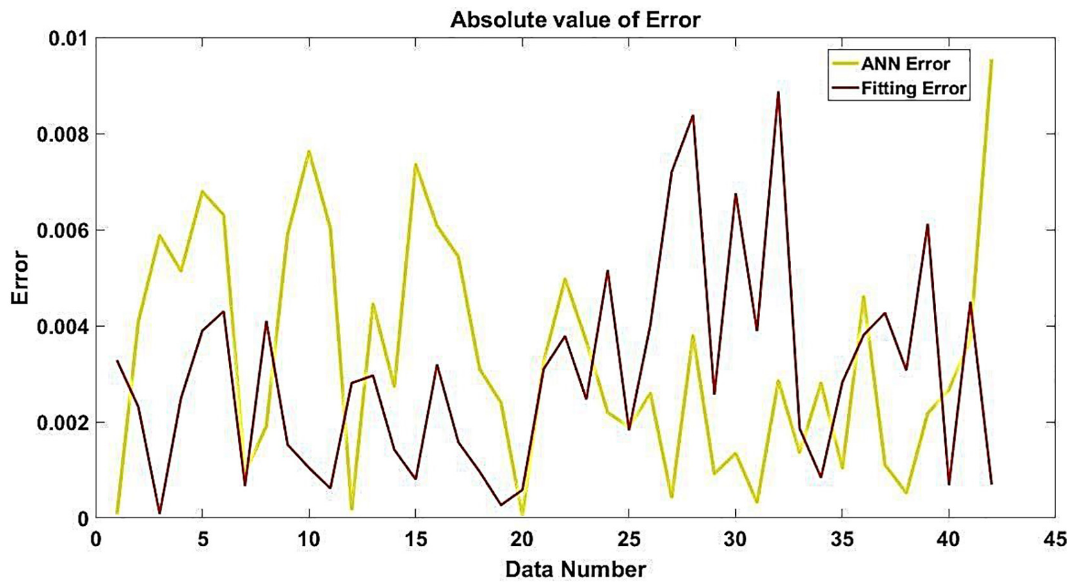

Fig. 11. the absolute value of ANN and correlation method.

is 1.6684e-05.

4. Surface fitting

Considering the experimental data points, there are two inputs (Volume fraction of nanoparticles and temperature) and there is only one output (Thermal conductivity). Using a surface fitting method, the surface has been generated. By applying functions with different orders, the best results are related to a third-order function for volume fraction and a first order for temperature. The fitted surface has been presented in Eq.5.

Fittedsurface (x,y) = p00 + p10*x + p01*y + p20*x^2 + p11*x*y + p30*x^3 + p21*x^2*y (5).

In Eq.5, x represents ϕ and $y$represents temperature. The coefficients of this function have been shown in Table 5.

In Fig. 9 the fitted surface has been shown. The MSE in surface fitting method is 1.8518e-05. The correlation coefficient in surface fitting method is 0.9971.

In Fig. 10 the experimental ANN and surface fitting outputs have been shown. It can be seen that both methods can predict the thermal conductivity of nanofluid.

In Fig. 11, the absolute value of error of ANN and fitting method has been compared. It can be seen that the ANN method has smaller absolute value of error compared to the surface fitting method.

5. Conclusion

In this study, after generating the experimental data for different volume fraction of nanoparticles ranges (0, 0.125, 0.25, 0.5, 1, 1.5 and 2%) and temperatures (25, 30, 35, 40, 45, 50), thermal conductivity of ZnO–Ag (50%–50%)/water nanofluid has been predicted by two methods including ANN and surface fitting method. In the ANN method, an algorithm is proposed to find the best neuron numbers of the hidden layer. Also, the correlation coefficient for train, validation, and test data has been calculated. In the fitting method, a surface has been fitted on the experimental data points, and then the correlation coefficient of this method has been calculated. Finally, the absolute value of errors for both methods has been compared.

- The best neuron number in the hidden layer is 7 neurons.
- Both methods could predict the behavior of nanofluid, but the fitting method had smaller errors.
- The MSE in the surface fitting method is 1.8518e-05. The correlation coefficient in the surface fitting method is 0.9971.
- In ANN All outputs, the maximum absolute value of error is 0.0095, and the train performance is 1.6684e-05.
- The ANN method had better ability in predicting the thermal conductivity of ZnO–Ag (50%–50%)/water nanofluid based on the $\phi$and temperature.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Acknowledgement

This study is supported by the Fujian Province Natural Science Foundation (No: 2018J01506), and University-industry cooperation program of Department of Science and Technology of Fujian Province (No.2019H6018), and Fuzhou Science and Technology Planning Project (No: 2018S113, 2018G92), and the Educational Research Projects of Young Teachers of Fujian Province (No. JK2017038, JAT170439) , and the 2017 Outstanding Young Scientist Training Program of Colleges in Fujian Province.

References

[1] J.C.A. Maxwell, Treatise on Electricity and Magnetism, second ed., 1 Clarendon Press, Oxford, UK, 1881.

[2] B. Ruhani, D. Toghraie, M. Hekmatifar, M. Hadian, Statistical investigation for developing a new model for rheological behavior of ZnO–Ag (50%–50%)/Water hybrid Newtonian nanofluid using experimental data, Phys. A Statistical Mech. Appl. 525 (2019) 741–775.

[3] A. Moradi, D. Toghraie, A.H.M. Isfahani, A. Hosseinian, An experimental study on MWCNT–water nanofluids flow and heat transfer in double-pipe heat exchanger using porous media, J. Therm. Anal. Calorim. (2019), https://doi.org/10.1007/s10973-019-08076-0.

[4] M. Keyvani, M. Afrand, D. Toghraie, M. Reiszadeh, An experimental study on the thermal conductivity of cerium oxide/ethylene glycol nanofluid: developing a new correlation, J. Mol. Liq. 266 (2018) 211–217.

[5] A.H. Saeedi, M. Akbari, D. Toghraie, An experimental study on rheological behavior of a nanofluid containing oxide nanoparticle and proposing a new correlation, Phys. E Low-Dimensional Syst. Nanostruct. 99 (2018) 285–293.

[6] A. Akhgar, D Toghraie, an experimental study on the stability and thermal conductivity of water-ethylene glycol/TiO_2-MWCNTs hybrid nanofluid: developing a

new correlation, Powder Technol. 338 (2018) 806–818.

[7] A. Deris Zadeh, D. Toghraie, Experimental investigation for developing a new model for the dynamic viscosity of silver/ethylene glycol nanofluid at different temperatures and solid volume fractions, J. Therm. Anal. Calorim. 131 (2018) 1449–1461.

[8] A. Afshari, M. Akbari, D. Toghraie, M. Eftekhari Yazdi, Experimental investigation of rheological behavior of the hybrid nanofluid of MWCNT–alumina/water (80%)–ethylene-glycol (20%), J. Therm. Anal. Calorim. 132 (2018) 1001–1015.

[9] M. Ahmadi Esfahani, D. Toghraie, Experimental investigation for developing a new model for the thermal conductivity of silica/water-ethylene glycol (40%–60%) nanofluid at different temperatures and solid volume fractions, J. Mol. Liq. 232 (2017) 105–112.

[10] M.H. Aghahadi, M. Niknejadi, D. Toghraie, An experimental study on the rheological behavior of hybrid Tungsten Oxide (WO_3)-MWCNTs/Engine Oil Newtonian nanofluids, J. Mol. Struct. 1197 (5) (2019) 497–507.

[11] M. Hemmat Esfe, H. Rostamian, M. Afrand, A. Karimipour, M. Hassani, Modeling and estimation of thermal conductivity of MgO–water/EG (60:40) by artificial neural network and correlation, Int. Commun. Heat Mass Transfer 68 (2015) 98–103.

[12] M. Hemmat Esfe, S. Saedodin, A. Naderi, A. Alirezaie, A. Karimipour, S. Wongwises, M. Goodarzi, M. Dahari, Modeling of thermal conductivity of ZnO-EG using experimental data and ANN methods, Int. Commun. Heat Mass Transfer 63 (2015) 35–40.

[13] S. Oveissi, S.A. Eftekhari, D. Toghraie, Longitudinal vibration and instabilities of carbon nanotubes conveying fluid considering size effects of nanoflow and nanostructure, Phys. E Low-Dimensional Syst. Nanostruct. 83 (2016) 164–173.

[14] H. Noorian, D. Toghraie, A.R. Azimian, The effects of surface roughness geometry of flow undergoing Poiseuille flow by molecular dynamics simulation, Heat Mass Transf. 50 (1) (2014) 95–104.

[15] M. Hemmat Esfe, H. Hajmohammad, D. Toghraie, H. Rostamian, O. Mahian, S. Wongwises, Multi-objective optimization of nanofluid flow in double tube heat exchangers for applications in energy systems, Energy 137 (2017) 160–171.

[16] M. Hemmat Esfe, W. Yan, M. Afrand, M. Sarraf, D. Toghraie, M. Dahari, Estimation of thermal conductivity of Al_2O_3/water (40%)–ethylene glycol (60%) by artificial neural network and correlation using experimental data, Int. Commun. Heat Mass Transfer 74 (2016) 125–128.

[17] M. Hemmat Esfe, M.R. Hassani Ahangar, M. Rejvani, D. Toghraie, M. Hadi Hajmohammad, Designing an artificial neural network to predict dynamic viscosity of aqueous nanofluid of TiO_2 using experimental data, Int. Commun. Heat Mass Transfer 75 (2016) 192–196.

[18] Fakhri Yousefia, Somayeh Mohammadiyan Nezhad, Thermal Conductivity of Al_2O_3 Nanofluids Using Artificial Neural Network, 17th Iranian Chemistry Congress Vali-e-Asr University of Rafsanjan 1–3 September, (2014).

[19] Mohammad Hemmat Esfe, Masoud Afrand, Wei-Mon Yan, Mohammad Akbari, Applicability of artificial neural network and nonlinear regression to predict thermal conductivity modeling of Al_2O_3–water nanofluids using experimental data, Int. Commun. Heat Mass Transfer 66 (2015) 246–249.

[20] Sandeep Kumar Mechiri, V. Vasu, A. Venu Gopal, R. Satish Babu, Thermal conductivity of Cu-Zn hybrid newtonian nanofluids: experimental data and modeling using neural network, Procedia Engineering 127 (2015) 561–567.

[21] Mohammad Hemmat Esfe, Wei-Mon Yan, Masoud Afrand, M. Sarraf, Davood Toghraie, Mahidzal Dahari, Estimation of thermal conductivity of Al_2O_3/water (40%)–ethylene glycol (60%) by artificial neural network and correlation using experimental data, Int. Commun. Heat Mass Transfer 74 (2016) 125–128.

[22] A. Hosseinian Naeini, J. Baghbani Arani, A. Narooei, R. Aghayari, H. Maddah, Nanofluid thermal conductivity prediction model based on artificial neural network, Trans. Phenom. Nano Micro Scales 4 (2) (2016) 41–46.

[23] Reza Aghayari, Heydar Maddah, Ali Reza Faramarzi, Hamid Mohammadiun, Mohammad Mohammadiun, Comparison of the experimental and predicted data for thermal conductivity of Iron oxide nanofluid using artificial neural networks, Nanomed Res. J. 1 (1) (2016) 15–22.

[24] Mohammad Amani, Pouria Amani, Alibakhsh Kasaeian, Omid Mahian, Ioan Pop, Somchai Wongwises, Modeling and optimization of thermal conductivity and viscosity of $MnFe_2O_4$ nanofluid under magnetic field using an ANN, Sci. Rep. 7 (2017) 17369.

[25] M. Tahani, M. Vakili, S. Khosrojerdi, Experimental evaluation and ANN modeling of thermal conductivity of graphene oxide nanoplatelets/deionized water nanofluid, Int. Commun. Heat Mass Transfer 76 (2016) 358–365.

[26] Kamalesh Verma, Ravi Agarwal, R.K. Duchaniya, Ramvir Singh, Measurement and prediction of thermal conductivity of nanofluids containing TiO_2 nanoparticles, J. Nanosci. Nanotechnol. 17 (2) (2017) 1068–1075.

[27] Mohammad Hojjat, Modeling heat transfer of non-Newtonian nanofluids using hybrid ANN-metaheuristic optimization algorithm, J. Particle Sci. Technol. 3 (4) (2017) 233–241.

[28] R. Mohamed, D. Habashy, Thermal conductivity Modeling of propylene glycol - based nanofluid using artificial neural network, J. Adv. Phys. 14 (1) (2018) 5281–5291, https://doi.org/10.24297/jap.v14i1.7177.

[29] R.A. Mohamed, Modeling electrical properties of nanofluids using artificial neural network, Phys. Scr. 94 (10) (2019).

[30] P. Talebizadehsardari, A. Shahsavar, D. Toghraie, P. Barnoon, An experimental investigation for study the rheological behavior of water–carbon nanotube/magnetite nanofluid subjected to a magnetic field, Phys. A Statistical Mech. Appl. 534 (2019) 122129.

[31] A. Arabpour, A. Karimipour, D. Toghraie, O.A. Akbari, Investigation into the effects of slip boundary condition on nanofluid flow in a double-layer microchannel, J. Therm. Anal. Calorim. 131 (3) (2018) 2975–2991.

[32] B. Ruhani, P. Barnoon, D. Toghraie, Statistical investigation for developing a new model for rheological behavior of Silica–ethylene glycol/Water hybrid Newtonian nanofluid using experimental data, Phys. A Statistical Mech. Appl. 525 (2019) 616–627.

[33] M. Goodarzi, D. Toghraie, M. Reiszadeh, M. Afrand, Experimental evaluation of dynamic viscosity of ZnO–MWCNTs/engine oil hybrid nanolubricant based on changes in temperature and concentration, J. Therm. Anal. Calorim. 136 (2) (2019) 513–525.

[34] A. Shahsavar, S. Khanmohammadi, D. Toghraie, H. Salihepour, Experimental investigation and develop ANNs by introducing the suitable architectures and training algorithms supported by sensitivity analysis: Measure thermal conductivity and viscosity for liquid paraffin based nanofluid containing Al2O3 nanoparticles, J. Mol. Liq. 276 (2019) 850–860.

[35] H. Khodadadi, D. Toghraie, A. Karimipour, Effects of nanoparticles to present a statistical model for the viscosity of MgO-Water nanofluid, Powder Technol. 342 (2019) 166–180.

[36] N.N. Esfahani, D. Toghraie, M. Afrand, A new correlation for predicting the thermal conductivity of ZnO–Ag (50%–50%)/water hybrid nanofluid: an experimental study, Powder Technol. 323 (2018) 367–373.

[37] M. Zadkhast, D. Toghraie, A. Karimipour, Developing a new correlation to estimate the thermal conductivity of MWCNT-CuO/water hybrid nanofluid via an experimental investigation, J. Therm. Anal. Calorim. 129 (2) (2017) 859–867.

[38] D. Toghraie, S.M. Alempour, M. Afrand, Experimental determination of viscosity of water based magnetite nanofluid for application in heating and cooling systems, J. Magn. Magn. Mater. 417 (2016) 243–248.