Micro and Nano Systems Letters

REVIEW

Open Access

Comprehensive study and scientific process to increase the accuracy in estimating the thermal conductivity of nanofluids containing SWCNTs and CuO nanoparticles using an artificial neural network

Mohammad Hemmat Esfe[1*], Fatemeh Amoozad[1], Hossein Hatami[2] and Davood Toghraie[3*]

Abstract

This investigation aimed to evaluate the thermal conductivity ratio (TCR) of SWCNT-CuO/Water nanofluid (NF) using experimental data in the T range of 28–50 ℃ and solid volume fraction range of SVF = 0.03 to 1.15% by an artificial neural network (ANN). MLP network with Lundberg-Marquardt algorithm (LMA) was utilized to predict data (TCR) by ANN. In the best case, from the set of various structures of ANN for this nanofluid, the optimal structure was chosen, which consists of 2 hidden layers, the first layer with the optimal structure consisting of 5 neurons and the second layer containing 7 neurons. Eventually, for the optimal structure, the R^2 coefficient and MSE are 0.9999029 and 6.33377E-06, respectively. Based on all ANN information, MOD is in a limited area of − 3% < MOD < + 3%. Comparison of test, correlation yield, and ANN yield display that ANN evaluates laboratory information more exactly.

Keywords SWCNT-CuO nanoparticles, Thermal conductivity ratio

Introduction

Nowadays, polymer nanofibers and metal oxides are prepared with the help of electrospinning (E-spin) techniques. Nanoparticles (NPs) produced by the E-spin technique are used in fields such as sensor development, decontamination, energy storage, biomedicine, nanofluids and catalysts, etc. [1–3]. The suspension liquid, in which the constituent solid particle is less than 100 nm is nanofluid (NF) [4]. Due to the improved properties of the dispersion of nanoparticles in liquids, the published papers in the past two decades in the field of NFs are increasing sharply. The thermal conductivity (TC) that is acquired using adding nanoparticles to the base fluid [5–10], the basis for many innovations is in heat transfer intensification [11–13]. This is used in various parts of the industry such as cooling and heating, electricity generation, and transportation [14–19]. The impact of NF on heat inverters can be reducing the size of the heating system and reducing the amount of fluid in circulation [20]. The thermal attributes and efficiency of NFs HT with different combinations were studied by many scientists. Table 1 lists some of the research on NF heat transfer. Esfe et al. [12] researched properties of TC, dynamic

*Correspondence:
Mohammad Hemmat Esfe
Davood Toghraie
Toghraee@iaukhsh.ac.ir
[1] Nanofluid Advanced Research Team, Tehran, Iran
[2] Department of Mechanical Engineering, Lorestan University, Khorramabad, Iran
[3] Department of Mechanical Engineering, Khomeinishahr Branch, Islamic Azad University, Khomeinishahr, Iran

Table 1 Summary of research that investigated the NFs heat transfer properties

NPs	Base fluid	SVF (%)	Conditions	Max. heat transfer enhancement (%)	Ref.
Al_2O_3	Water	0.2–2.5	Re = 700–2050	41	[21]
MWCNT		0.5–1.5	Re = 150–15000	2	[22]
CuO		0.03–0.7	Flow rate = 1.5–3.5 lpm	53%	[23]
TiO_2		0.2	Re = 5000–17000	11	[24]
TiO_2	Water-EG	0.5–1	Re = 800–23000	24	[25]
Al_2O_3	Water	Up to 2.5%	Re = 750–8500	345	[26]

viscosity and Nusselt number of MgO/water NF. TC is increased up to 23%.

To model attributes like viscosity and TC of NFs, mathematical correlations can be presented based on the obtained experimental data. But recently, software and coding techniques such as ANNs were used for this purpose [27–34]. ANN has different applications in different industries and different scientific disciplines. Some applications of ANNs are shown in Fig. 1.

Today, researchers are looking for a way to achieve the best results in the shortest time and at the lowest cost. Many studies in various scientific and engineering fields were carried out by ANN [35–37]. Malika et al. [38] investigated the efficiency of a sonophotocatalytic reactor and the removal of toxic particles from industrial wastewater with $Al(OH)_3$-MWCNT HNF suspension with Ti + 4 coating using RSM and ANN methods. The ANN with multi-layer perceptron method and R^2 value = 0.999 confirmed the success of the experimental findings. Due to the significant differences related to the properties of different nanofluids and time-consuming experimental experiments, the need for methods such as ANN became more apparent. Table 2 shows some modeling of ANNs for TC of nanofluids.

Today, the need to use the ANN to estimate and forecast the relatively complex attributes of nanofluids is not hidden from anyone. Efforts to optimize the ANN or other post-processing methods could be the basis for the next generation of research by researchers to address the widespread use of nanofluids. Different types of ANNs have targeted and imitated only a part of the learning and adaptation capabilities of the human brain, including multilayer perceptron model (MLP), radial neural network (RBF), support vector machines (SVM) and Hopfield ANN. However, one of the most basic models used for data estimation is the multi-layer perceptron network, which simulates the transfer function of the human brain. In this study, experimental data were extracted from reference [44]. Therefore,

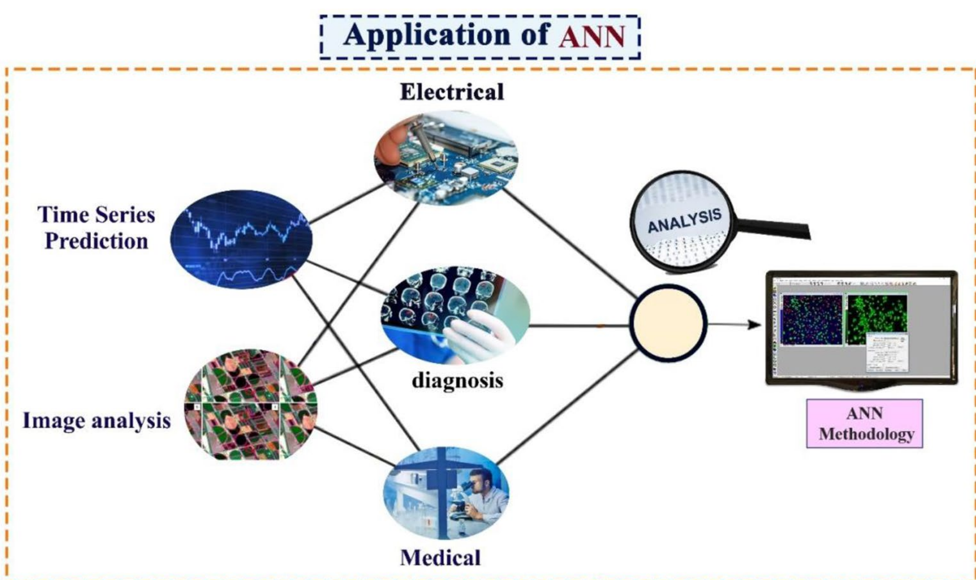

Fig. 1 Some applications of ANNs

Table 2 Some modeling of ANNs for TC of nanofluids

Ref.	NPs	Base fluid	accuracy	Description
[39]	Al_2O_3	EG	$R^2 = 0.9997$	The SVF was 0–2% by and T = 25–60° C
[40]	The Al_2O_3, ZnO-CuO	Water	The proposed ANN model had up to 2% error	SVF and T were considered as inputs and ANN as TC outputs
[41]	Al_2O_3-TiO_2- CuO	(CMC)	The average TC prediction data error was 1.6% with a maximum 5.8% error	TC of NFs does not show a significant increase for SVF up to 1.5%
[42]	MWCNTs	Oil (a-olefin)	AAD% = 2.79	ANN results are compared with other models
		Decene (DE)	AAD% = 2.5	
		Distilled water (DW)	AAD% = 3.64	
		EG	AAD% = 1.86	
[43]	ZnO	EG	$R^2 > 0.99$	MLP-ANNs were used and 40 data were utilized for training, testing, and validation

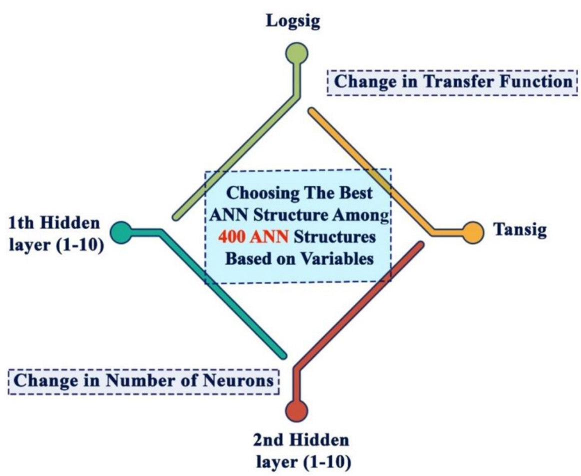

Fig. 2 Choosing the best structure for ANNs

in the current investigations, the focus was on increasing the accuracy and optimization of the ANN structure in estimating the TC of NFs. For this purpose, ANN training was performed using experimental data [45] on TC of SWCNT (25)-CuO (75%)/Water NF based on changes in SVF and temperature, and then ANN output with data. Experiments were compared and its deviation was carefully evaluated. To increase the accuracy, about 400 species of different ANN structures have been studied and based on the results, the best structure was selected and its output was based on the analysis of the current investigation (See Fig. 2). The experimental data set includes 40 data, but to predict the viscosity of the nanofluid in the ANN with two hidden layers and 10 neurons in each layer, a set of 400 neural network structures is designed. The results of this research will be used to develop the available data for the exploitation of hybrid nanofluids in industrial equipment. The results show the importance of ANN optimization in estimating properties and its much higher accuracy than the classical model.

About ANN

ANNs are mathematical tools that can model complex functions by mimicking the behavior of biological nervous networks. ANNs are utilized in various scientific courts because of their high ability to reproduce and model nonlinear processes. One of the applications of ANNs is the ability to model multivariate problems to solve complex problems [46, 47]. ANNs are one of the best nonlinear methods, due to the high accuracy method. ANNs are utilized to solve challenges of intricate modeling like estimating and template diagnosis. With advances in software engineering, scientists use artificial intelligence software like ANNs to model viscosity and TC [48, 49]. Past research review displays that providing an experimental relationship and designing data using ANN is the appropriate method. These methods can replace laboratory methods. Therefore, in this study, for the first time, the TCR of the SWCNT-CuO (25:75)/Water nanofluid versus temperature and SVF [45] was designed by ANNs. In this method, ANNs with lots of neurons and various transfer functions have been evaluated and optimal ANN is chosen. The most common type of used ANN to solve the regression problem is the MLP [50, 51]. Utilized ANN in current investigation is an MLP and the utilized algorithm to train this network is LMA. Functions of sigmoid transfer were considered on neurons in the latent layers. Figure 3 displays best structure from 400 structures investigated to forecast TCR.

The ANN topology was proposed in Fig. 4 to design and TCR of nanofluid. Generally, 40 experimental information was utilized for ANN training. The MLP algorithm was also used for ANN and the TCR was selected as the ANN output.

Different ANN structures were analyzed to choose the best ANN structure. Various structure's accuracy of ANNs has been presented in Table 3. The best value

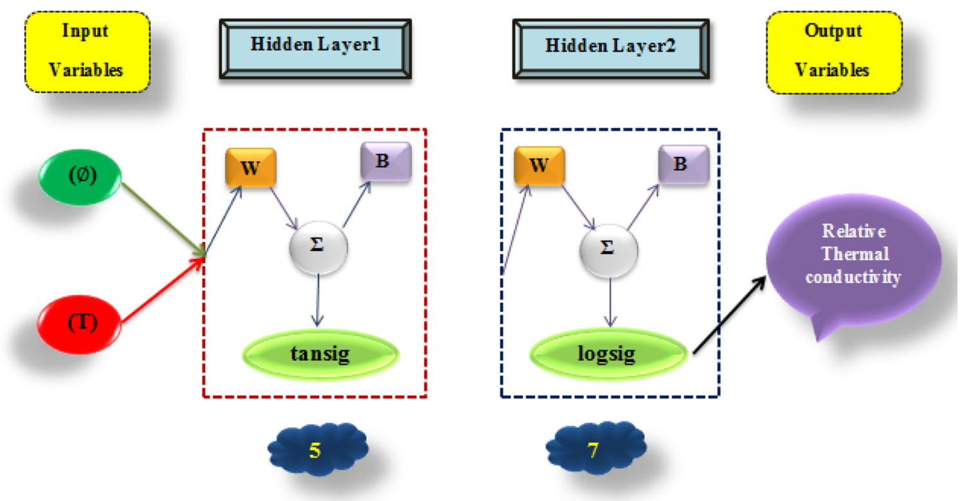

Fig. 3 The best ANN

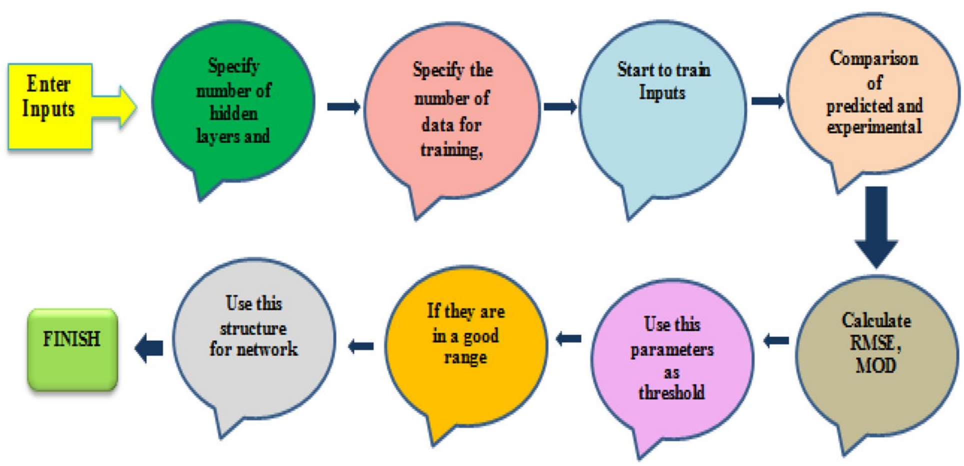

Fig. 4 Flowchart to achieve the optimal ANN

of R^2 is 0.999903, which is related to the fourteenth structure in Table 3.

Results and discussion

Figure 5 displays the trend of MSE changes related to TCR in the selected structure from among the 400 ANN structures for different stages. In Fig. 5, the MSE has the lowest MSE in the test phase compared to other phases, which is 6.33377E-06 according to Eq. 1,

$$MSE = \frac{1}{N}\sum_{i=1}^{N}(k_{rel}|_{Exp} - k_{rel}|_{Pred})^2 \tag{1}$$

As mentioned, a value of R^2 close to 1 demonstrates a close communication between TCR laboratory information and predicted information from ANN. According to correlation curves for different stages in 4 separate sections in Fig. 6, it can be seen that the amount of R^2 for all information in the current ANN is higher than 0.9. Regression coefficient results in Fig. 6a are more

Table 3 Characteristics of top 14 ANN structures

Case num	Num. of hidden neurons	Transfer function		Regression			
		Function1	Function2	R	Train R	Val R	Test R
1	[1 1]	Tansig	Tansig	0.980636	0.990243	0.9986	0.970701
2	[1 1]	Tansig	Logsig	0.982659	0.983369	0.925103	0.989236
3	[1 2]	Logsig	Tansig	0.985406	0.981134	0.993419	0.984336
4	[1 3]	Tansig	Logsig	0.986581	0.990757	0.984235	0.98257
5	[2 1]	Tansig	Tansig	0.995615	0.997098	0.992525	0.998934
6	[2 1]	Logsig	Tansig	0.996408	0.997992	0.996166	0.992992
7	[2 1]	Tansig	Logsig	0.997169	0.997745	0.999489	0.996758
8	[2 2]	Tansig	Tansig	0.997928	0.99867	0.998473	0.990627
9	[2 5]	Tansig	Tansig	0.998127	0.999235	0.999203	0.994305
10	[2 7]	Tansig	Tansig	0.998351	0.998545	0.997819	0.998492
11	[2 9]	Tansig	Logsig	0.998588	0.999069	0.997443	0.999077
12	[2 10]	Logsig	Tansig	0.998746	0.999733	0.999319	0.984129
13	[3 6]	Tansig	Tansig	0.999819	0.999979	0.999508	0.995985
14	[5 7]	Tansig	Logsig	0.999903	0.999999	0.999716	0.999643

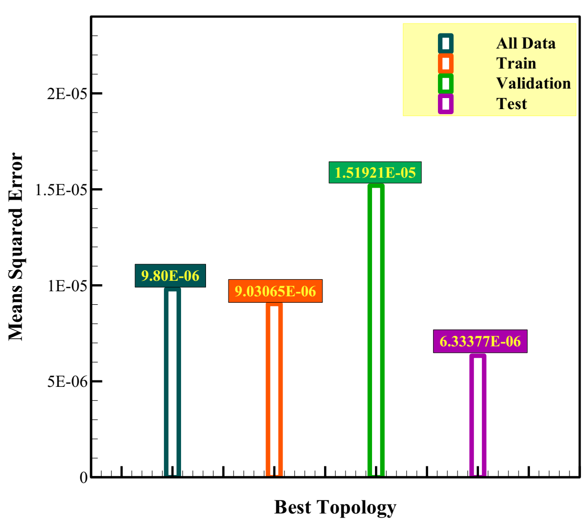

Fig. 5 MSE in terms of latent layer neurons

important for all data, which belongs to the last (14) proposed topology and is equal to 0.9999029.

In Fig. 7, the experimental data set and TCR data according to different temperatures and SVFs are used to model the ANN. Examination of forecasted information of ANN with outcomes of tests in 4 antiseptic parts shows that based on this figure, there is good agreement between ANN outputs and TCR tests and modeled data accurately predicts tests.

Figure 8 displays ANN adaptation outcomes obtained from training, test stages, and validation with laboratory tantamount information set in SVF = 0.03% to 1.15% through the ANN procedure. As displayed in Fig. 8, all points forecasted using ANN match experimental points that indicate high precision and suitable performance of ANNs in forecasting laboratory information. According to Fig. 8, there is a close correlation between train stages and all data, which shows predicted TCR data accuracy.

The comparison among the experimental information for TCR and the cases forecasted using ANN, simultaneously due to the changes of temperature and SVF, is better shown in Fig. 9. As you can see in Fig. 9, all forecasted points using ANN correlate well with a laboratory data point, but based on the contour of the visible changes in

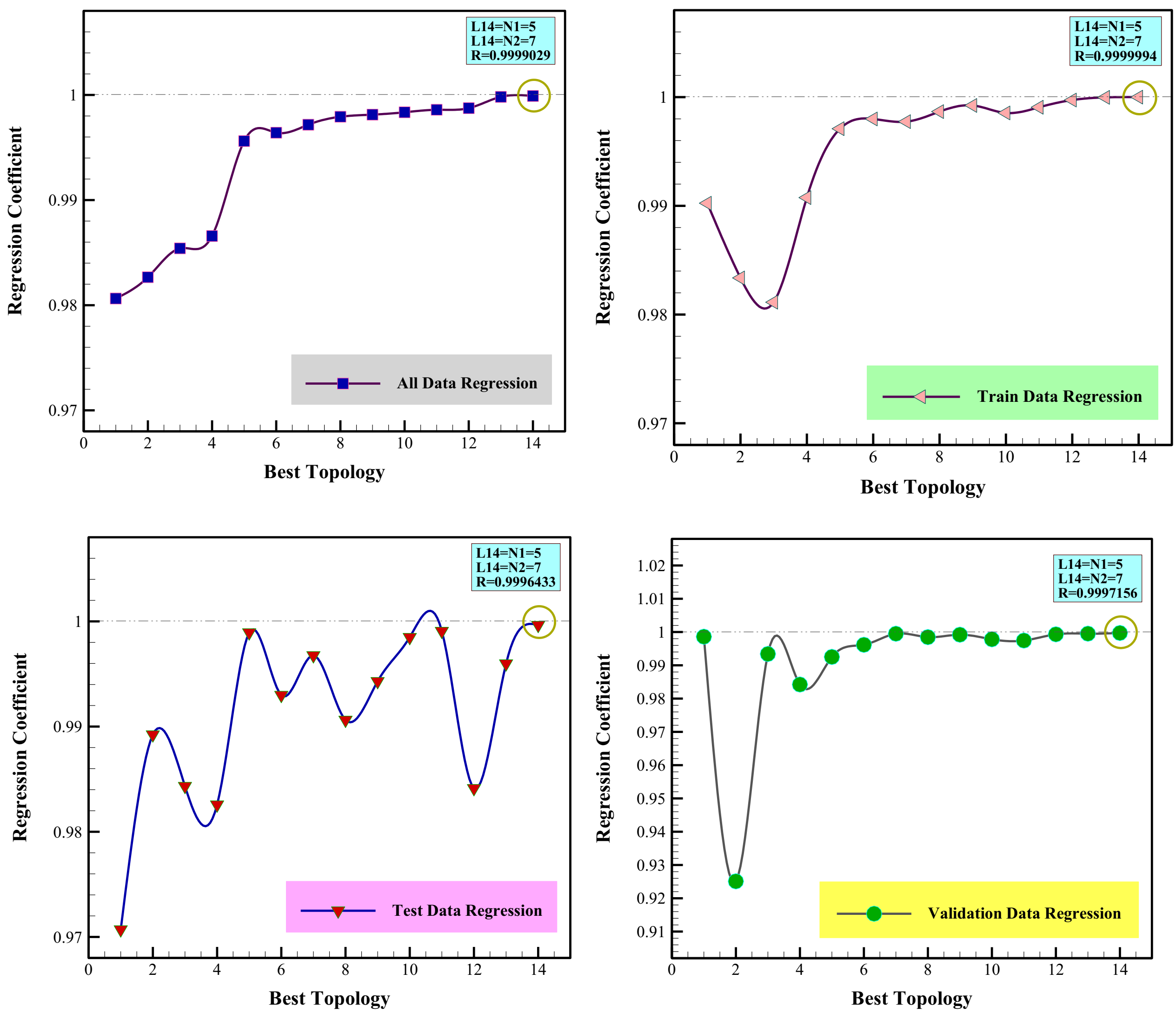

Fig. 6 Regression coefficient in latent layer neurons terms

this figure, the black square area marked on the figure has the highest correlation between the data, which is related to different temperatures and SVF, and more precisely the SVFs between 0.23% -0.95% and temperatures between 28 and 38 C make up this area.

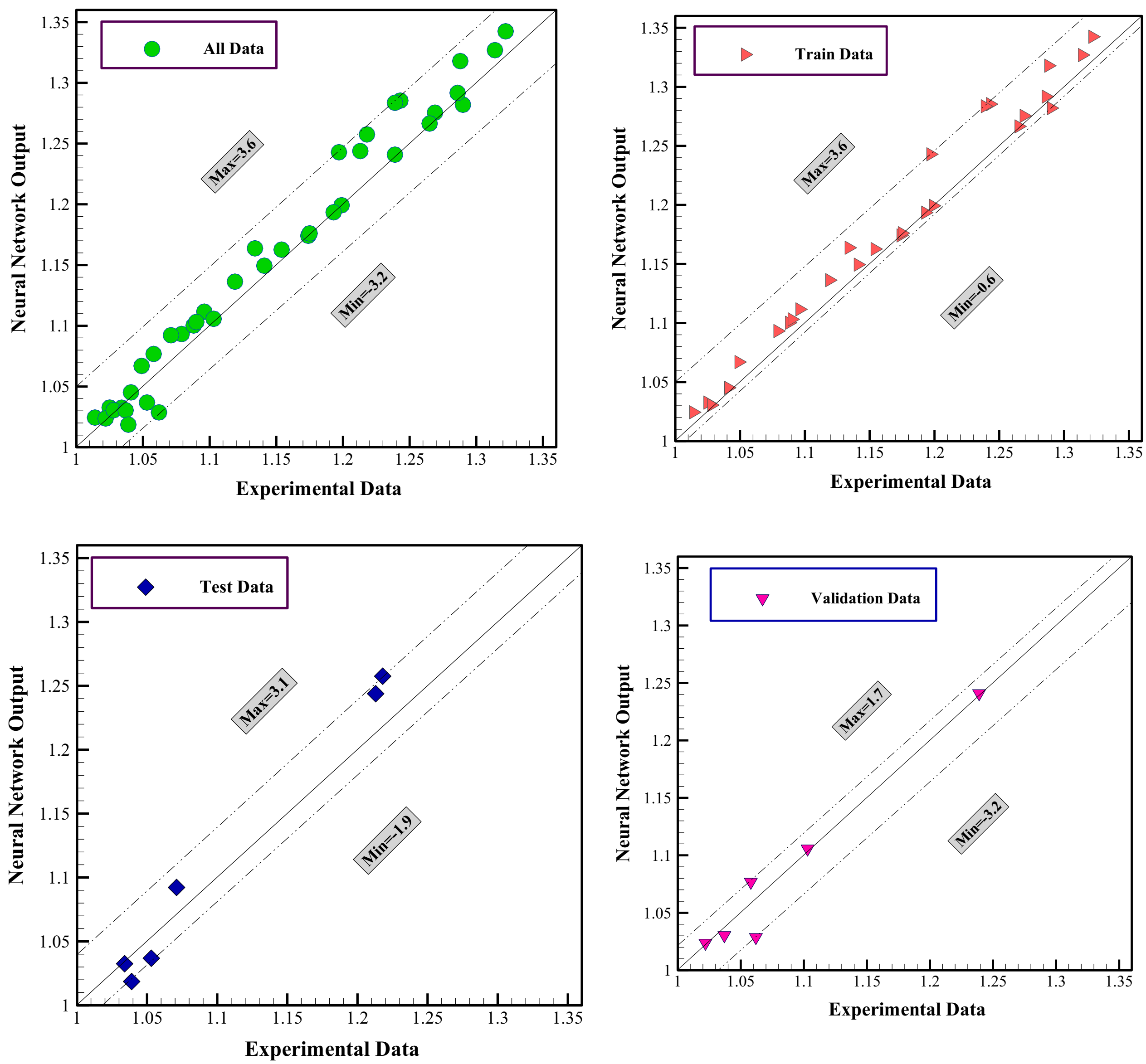

Fig. 7 Examination of forecasted information of ANN with outcomes of tests in four antiseptic parts

Figure 10 displays the error values in predicting TCR amounts of the hybrid nanofluid at different Ts. According to Fig. 10, the maximum error is between 0.033 and − 0.045. This displays high precision of TCR of the information predicted from the ANN model.

Figure 11 shows the histogram of TCR data errors for the three steps in the ANN. In Fig. 11, most of the data errors are near the zero line and in the ± 0.02 range. The least error with the highest frequency belongs to the training stage is − 0.001422943.

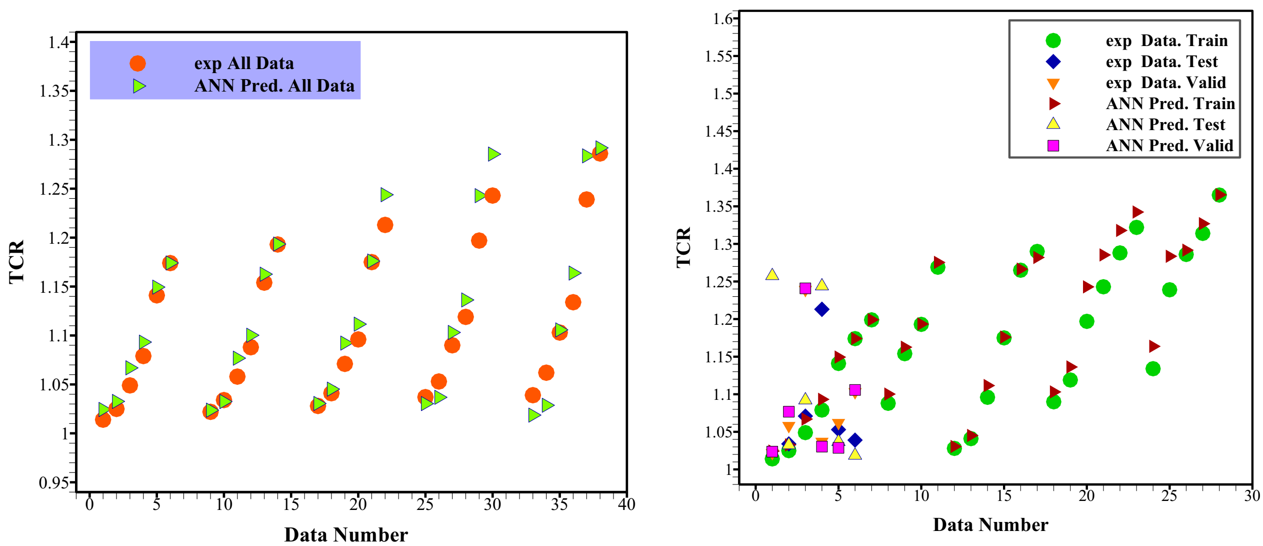

Fig. 8 ANN accuracy

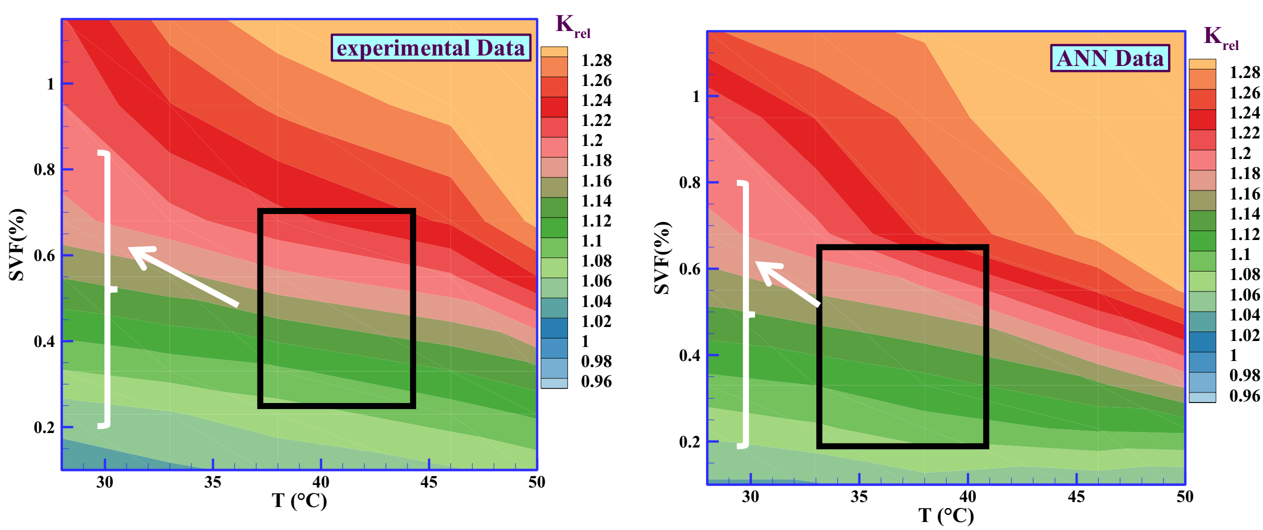

Fig. 9 Investigation of simultaneous T and SVF effect on TCR

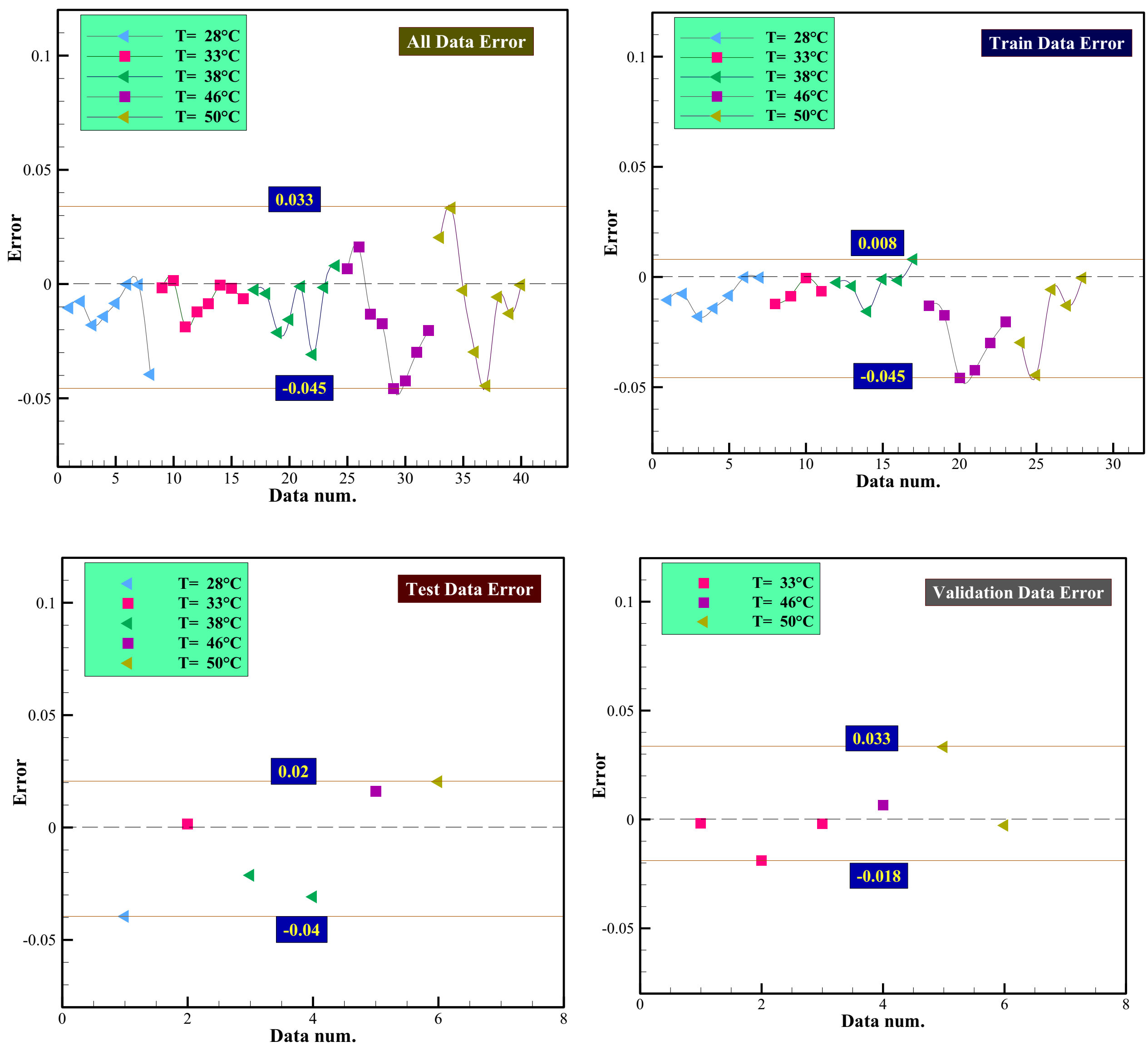

Fig. 10 Calculated errors

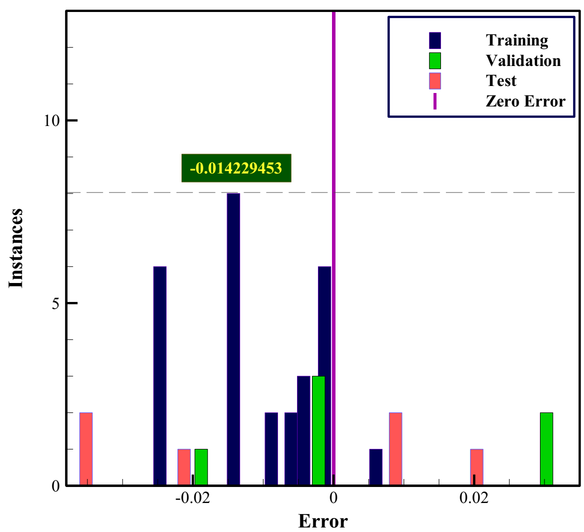

Fig. 11 Histogram plot

In Eq. 2, the formula for computing MOD of forecasted ANN information and laboratory information is provided. These data MOD at various SVFs are displayed in Fig. 12. MOD doesn't exceed 3.1 to − 3.8. The validation stage has the lowest MOD.

$$\mathrm{MOD}(\%) = \frac{k_{Pre-}k_{Exp}}{k_{Exp}} \times 100 \tag{2}$$

To evaluate the TCR of tNF, an experimental relation based on measured parameters for the TCR is presented [52]:

$$\mathrm{TCR} = 1 + 0.764481\mathrm{SVF} + 0.018689\mathrm{T} - 0.46215 \tag{3}$$

In Fig. 13, two methods of data forecasting, suggested new relationships, and ANN design are compared according to forecasting laboratory information. This comparison was performed at T = 50–33 ℃ and various SVFs. As displayed, the ANN procedure has a greater ability to forecast information. With increasing SVF and T, the TCR of computational data was more distant from experimental information, but ANN information is consistent with laboratory data ANN simulation is more precise than computational data.

Conclusion

In this study, the use of an ANN to evaluate the TCR of SWCNT (25)-CuO (75)/Water hybrid NF is presented. Use of ANN was done at SVF = 0.03% and T = 28–50 ℃ to 1.15%. SVF and T were selected as input variables of ANN, while TCR values were selected as output. To design the ANN, the MLP model with LMA training with 2 transfer functions has been used. To obtain the best topology, many analyses of different structures of MLP were performed. It was found that the developed ANN provides a precise forecast of TCE amounts with R^2 and

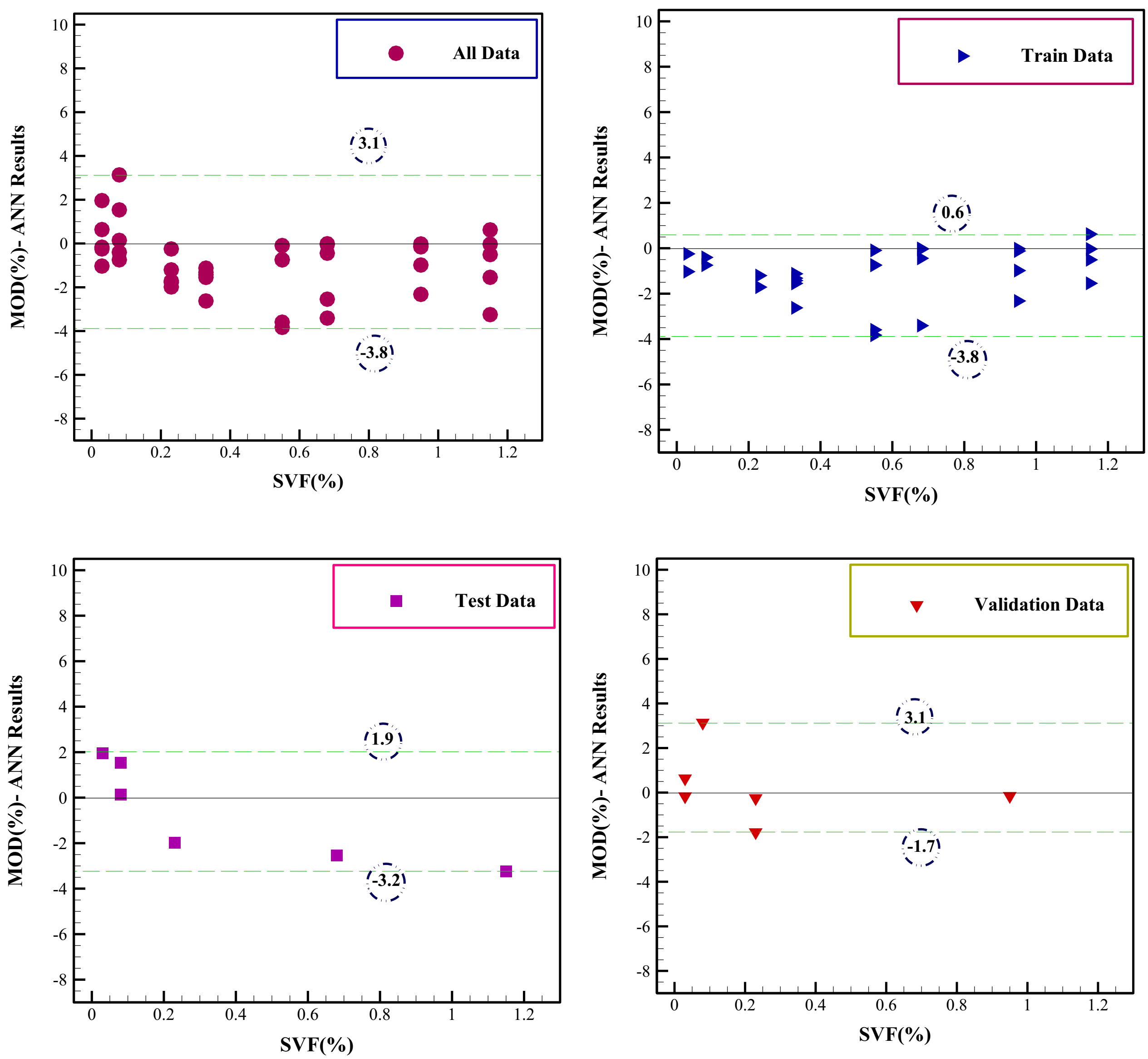

Fig. 12 Margin of deviation

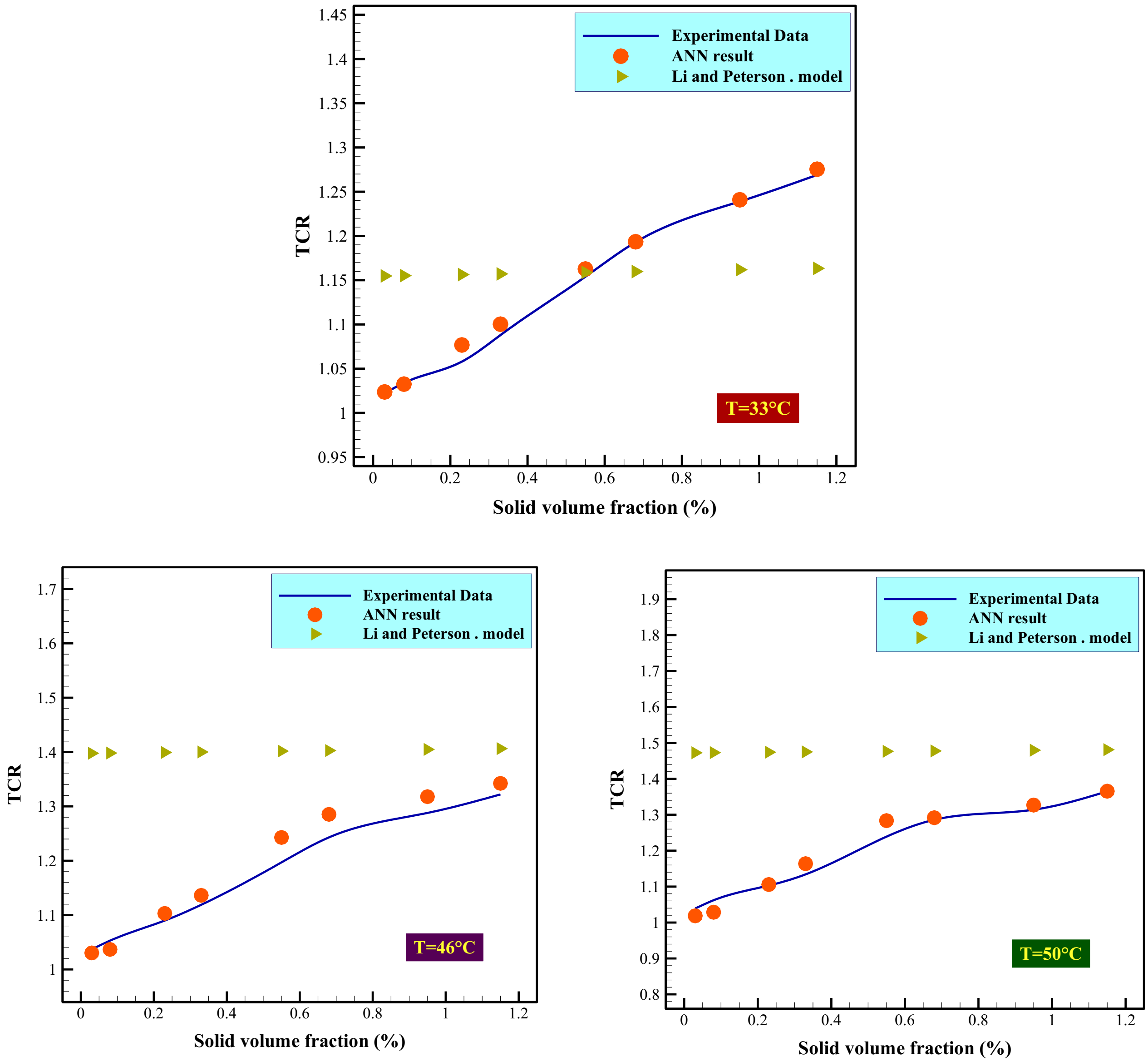

Fig. 13 Curve-fitting on experimental data

MSE of 0.9999029 and 6.33377E-06, respectively. The highest frequency of MOD values was in the range of less than − 3% < MOD < + 3%. A comparison of the TCR test with ANN data and mathematical calculation data output shows the high capability and precision of ANN in modeling TCR information. From the comparison and analysis and examination of proposed model data compared to experimental data, it can be concluded that there is a good match between data and to save money and time, ANN can determine TCR of NFs with high accuracy.

Acknowledgements
Not applicable.

Author contributions
Not applicable.

Funding
Not applicable.

Availability of data and materials
Not applicable.

Declarations

Ethics approval and consent to participate
Not applicable.

Consent for publication
Not applicable.

Competing interests
Not applicable.

Received: 6 October 2023 Accepted: 17 December 2023
Published online: 10 January 2024

References

1. Thenmozhi S, Dharmaraj N, Kadirvelu K, Kim HY (2017) Electrospun nanofibers: new generation materials for advanced applications. Mater Sci Eng, B 217:36–48
2. Callister WD Jr, Rethwisch DG (2020) Fundamentals of materials science and engineering: an integrated approach. John Wiley & Sons, Hoboken
3. Roseti L, Parisi V, Petretta M, Cavallo C, Desando G, Bartolotti I, Grigolo B (2017) Scaffolds for bone tissue engineering: state of the art and new perspectives. Mater Sci Eng, C 78:1246–1262
4. Xuan Y, Li Q (2003) Investigation on convective heat transfer and flow features of nanofluids. J Heat transfer 125(1):151–155
5. Ghozatloo A, Rashidi AM, Shariaty-Niasar M (2014) Effects of surface modification on the dispersion and thermal conductivity of CNT/water nanofluids. Int Commun Heat Mass Transfer 54:1–7
6. Ghanbari M, Rezazadeh G (2021) A MEMS-based methodology for measurement of effective density and viscosity of nanofluids. Eur J Mech-B/Fluids 86:67–77
7. Cao Y, Khan A, Abdi A, Ghadiri M (2021) Combination of RSM and NSGA-II algorithm for optimization and prediction of thermal conductivity and viscosity of bioglycol/water mixture containing SiO2 nanoparticles. Arab J Chem 14(7):103204
8. Mousavi SM, Ehteshami B, Darzi AAR (2021) Two-and-three-dimensional analysis of Joule and viscous heating effects on MHD nanofluid forced convection in microchannels. Therm Sci Eng Prog 25:100983
9. Dezfulizadeh A, Aghaei A, Joshaghani AH, Najafizadeh MM (2021) An experimental study on dynamic viscosity and thermal conductivity of water-Cu-SiO2-MWCNT ternary hybrid nanofluid and the development of practical correlations. Powder Technol 389:215–234
10. Hosseini SMS, Dehaj MS (2021) An experimental study on energetic performance evaluation of a parabolic trough solar collector operating with Al2O3/water and GO/water nanofluids. Energy 234:121317
11. Fereidoon A, Saedodin S, Hemmat Esfe M, Noroozi M (2013) Evaluation of mixed convection in inclined square lid-driven cavity filled with Al2O3/water nano-fluid. Eng Appl Comput Fluid Mech 7(1):55–65
12. Esfe MH, Saedodin S (2015) Turbulent forced convection heat transfer and thermophysical properties of Mgo–water nanofluid with consideration of different nanoparticles diameter, an empirical study. J Therm Anal Calorim 119(2):1205–1213
13. Derakhshan MM, Akhavan-Behabadi M (2015) An empirical study on fluid properties and pressure drop of nanofluid flow inside inclined smooth and microfin tubes. Int Commun Heat Mass Transf 65:111–116
14. Amini S, Khosrojerdi M, Nosouhi R, Behbahani S (2014) An experimental investigation on the machinability of Al2O3 in vibration-assisted turning using PCD tool. Mater Manuf Processes 29(3):331–336
15. Hussein AM, Bakar RA, Kadirgama K, Sharma KV (2014) Heat transfer enhancement using nanofluids in an automotive cooling system. Int Commun Heat Mass Transfer 53:195–202
16. Ijam A, Saidur R (2012) Nanofluid as a coolant for electronic devices (cooling of electronic devices). Appl Therm Eng 32:76–82
17. Wang X, Luo L, Xiang J, Zheng S, Shittu S, Wang Z, Zhao X (2021) A comprehensive review on the application of nanofluid in heat pipe based on the machine learning: theory, application and prediction. Renew Sustain Energy Rev 150:111434
18. Stalin P M J, Arjunan T, Matheswaran M, Kumar P M, Sadanandam N. Investigations on thermal properties of CeO2/water nanofluids for heat transfer applications. Mater Today: Proceedings, 2021.
19. Yashawantha KM, Vinod AV (2021) ANFIS modelling of effective thermal conductivity of ethylene glycol and water nanofluids for low temperature heat transfer application. Therm Sci Eng Prog 24:100936
20. Motahari K, Abdollahi-Moghaddam M, Rezaei A, Abdollahi Moghaddam M, Rezaei A. "An experimental investigation of reduced water consumption of coolers using various concentrations of CuO/water nanofluid instead of pure water."
21. Heris SZ, Esfahany MN, Etemad SG (2007) Experimental investigation of convective heat transfer of Al2O3/water nanofluid in circular tube. Int J Heat Fluid Flow 28(2):203–210
22. Sarafraz M, Hormozi F (2016) Heat transfer, pressure drop and fouling studies of multi-walled carbon nanotube nano-fluids inside a plate heat exchanger. Exp Thermal Fluid Sci 72:1–11
23. Duangthongsuk W, Wongwises S (2009) Heat transfer enhancement and pressure drop characteristics of TiO2–water nanofluid in a double-tube counter flow heat exchanger. Int J Heat Mass Transf 52(7–8):2059–2067
24. Azmi W, Sharma K, Sarma P, Mamat R, Najafi G (2014) Heat transfer and friction factor of water based TiO2 and SiO2 nanofluids under turbulent flow in a tube. Int Commun Heat Mass Transfer 59:30–38
25. Azari A, Derakhshandeh M (2015) An experimental comparison of convective heat transfer and friction factor of Al2O3 nanofluids in a tube with and without butterfly tube inserts. J Taiwan Inst Chem Eng 52:31–39
26. Hussein AM (2016) Adaptive neuro-fuzzy inference system of friction factor and heat transfer nanofluid turbulent flow in a heated tube. Case Stud Therm Eng 8:94–104
27. Vakili M, Yahyaei M, Kalhor K (2016) Thermal conductivity modeling of graphene nanoplatelets/deionized water nanofluid by MLP neural network and theoretical modeling using experimental results. Int Commun Heat Mass Transfer 74:11–17
28. Yang Y-T, Tang H-W, Ding W-P (2016) Optimization design of microchannel heat sink using nanofluid by numerical simulation coupled with genetic algorithm. Int Commun Heat Mass Transfer 72:29–38
29. Chu Y-M, Ibrahim M, Saeed T, Berrouk AS, Algehyne EA, Kalbasi R (2021) Examining rheological behavior of MWCNT-TiO2/5W40 hybrid nanofluid based on experiments and RSM/ANN modeling. J Mol Liq 333:115969
30. Çolak AB (2021) A novel comparative analysis between the experimental and numeric methods on viscosity of zirconium oxide nanofluid: Developing optimal artificial neural network and new mathematical model. Powder Technol 381:338–351
31. Yang X, Boroomandpour A, Wen S, Toghraie D, Soltani F (2021) Applying artificial neural networks (ANNs) for prediction of the thermal characteristics of water/ethylene glycol-based mono, binary and ternary nanofluids containing MWCNTs, titania, and zinc oxide. Powder Technol 388:418–424
32. Tian S, Arshad NI, Toghraie D, Eftekhari SA, Hekmatifar M (2021) Using perceptron feed-forward artificial neural network (ANN) for predicting the thermal conductivity of graphene oxide-Al2O3/water-ethylene glycol hybrid nanofluid. Case Stud Thermal Eng 26:101055
33. Ji W, Yang L, Chen Z, Mao M, Huang J-N (2021) Experimental studies and ANN predictions on the thermal properties of TiO2-Ag hybrid nanofluids: consideration of temperature, particle loading, ultrasonication and storage time. Powder Technol 388:212–232
34. Li L, Zhai Y, Jin Y, Wang J, Wang H, Ma M (2020) Stability, thermal performance and artificial neural network modeling of viscosity and thermal conductivity of Al2O3-ethylene glycol nanofluids. Powder Technol 363:360–368
35. Malika M, Sonawane SS (2022) Ecological optimization and LCA of TiO2-SiC/water hybrid nanofluid in a shell and tube heat exchanger by ANN. Proc Inst Mech Eng, Part E: J Process Mech Eng. https://doi.org/10.1177/09544089221093304
36. Malika M, Sonawane SS (2022) MSG extraction using silicon carbide-based emulsion nanofluid membrane: Desirability and RSM optimisation. Colloids Surf, A 651:129594
37. Malika M, Sonawane SS (2022) The sono-photocatalytic performance of a Fe2O3 coated TiO2 based hybrid nanofluid under visible light via RSM. Colloids Surf, A 641:128545
38. Malika M, Sonawane SS (2021) The sono-photocatalytic performance of a novel water based Ti+ 4 coated Al (OH) 3-MWCNT's hybrid nanofluid for dye fragmentation. Int J Chem Reactor Eng 19(9):901–912
39. Pare A, Ghosh SK (2021) A unique thermal conductivity model (ANN) for nanofluid based on experimental study. Powder Technol 377:429–438
40. Hojjat M, Etemad SG, Bagheri R, Thibault J (2011) Thermal conductivity of non-Newtonian nanofluids: experimental data and modeling using neural network. Int J Heat Mass Transf 54(5–6):1017–1023
41. Papari MM, Yousefi F, Moghadasi J, Karimi H, Campo A (2011) Modeling thermal conductivity augmentation of nanofluids using diffusion neural networks. Int J Therm Sci 50(1):44–52

42. Esfe MH, Saedodin S, Naderi A, Alirezaie A, Karimipour A, Wongwises S, Goodarzi M, Bin Dahari M (2015) Modeling of thermal conductivity of ZnO-EG using experimental data and ANN methods. Int Commun Heat Mass Transf 63:35–40
43. Esfe MH, Ahangar MRH, Rejvani M, Toghraie D, Hajmohammad MH (2016) Designing an artificial neural network to predict dynamic viscosity of aqueous nanofluid of TiO2 using experimental data. Int Commun Heat Mass Transfer 75:192–196
44. Esfe MH, Alidoust S, Esfandeh S, Toghraie D, Hatami H, Kamyab MH, Ardeshiri EM (2023) Theoretical-experimental study of factors affecting the thermal conductivity of SWCNT-CuO (25: 75)/water nanofluid and challenging comparison with CuO nanofluids/water. Arab J Chem 16(5):104689
45. Esfe M H, Alidoust S, Esfandeh S, Toghraie D, Hatami H, Kamyab M H, Theoretical -Experimental study of factors affecting the thermal conductivity of SWCNT-CuO (25:75)/water nanofluid and challenging comparison with CuO nanofluids/water
46. Ahmadloo E, Azizi S (2016) Prediction of thermal conductivity of various nanofluids using artificial neural network. Int Commun Heat Mass Transfer 74:69–75
47. He W, Ruhani B, Toghraie D, Izadpanahi N, Esfahani NN, Karimipour A, Afrand M (2020) Using of artificial neural networks (ANNs) to predict the thermal conductivity of zinc oxide–silver (50%–50%)/water hybrid Newtonian nanofluid. Int Commun Heat Mass Transfer 116:104645
48. Afrand M, Esfe MH, Abedini E, Teimouri H (2017) Predicting the effects of magnesium oxide nanoparticles and temperature on the thermal conductivity of water using artificial neural network and experimental data. Physica E 87:242–247
49. Nazmi N, Rahman MAA, Yamamoto S-I, Ahmad SA (2019) Walking gait event detection based on electromyography signals using artificial neural network. Biomed Signal Process Control 47:334–343
50. Sayyad H, Manshad AK, Rostami H (2014) Application of hybrid neural particle swarm optimization algorithm for prediction of MMP. Fuel 116:625–633
51. Olmedo MTC, Paegelow M, Mas J-F, Escobar F (2018) Geomatic approaches for modeling land change scenarios. Springer, Berlin
52. Li CH, Peterson G (2006) "Experimental investigation of temperature and volume fraction variations on the effective thermal conductivity of nanoparticle suspensions (nanofluids)." J Appl Phys 99(8):084314

Publisher's Note