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A novel nonlinear regression model of SVR as a substitute for ANN to predict conductivity of MWCNT-CuO/water hybrid nanofluid based on empirical data

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HIGHLIGHTS

- Propose a nonlinear regression model of Support Vector Regression (SVR).
- A substitution for ANN to predict the thermal conductivity.
- According to the empirical data of MWCNT-CuO/water hybrid nanofluid.

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ABSTRACT

An ideal regression method should have several characteristics including precision, accuracy and generalization. In many studies in the field of nanofluid, the precision of models is more highlighted. Nevertheless, a lack of generalization may lead to over fitted models. In this paper, two nonlinear regression methods, namely the ANN and SVR are employed to predict the thermal conductivity of MWCNT-CuO/water hybrid nanofluid with temperature and volume fraction. It is seen that precision of SVR & ANN approaches are able to be compared. However, SVR generalization is more convenient, compared to ANN because SVR method utilizes less parameters. Hence SVR can show better persistence to overfitting in little-size datasets compared to ANN. Therefore, SVR is more authentic approach for the regression with little-size datasets.

1. Introduction

Several examples can be mentioned for the substances at nano scales level such as electronic devices, medicine, ventilation and MEMS. Metal or non-metal nanoparticles are usually added to the base fluids to produce a mixture called nanofluid. These mentioned nanoparticles must be dispersed through the base liquid in a suitable way to generate a homogeneous mixture. Higher amount of nanoparticles thermal conductivity leads to increase the mixture thermal conductivity which it can be estimated as the main reason of using nanofluid. This fact causes the significant increase in conduction heat transfer through the mixture; however the nanofluid convention heat transfer can be invigorated due to Brownian motions of nanoparticles. Better quality of producing the nanofluid in aspect of thermal conductivity, encourage

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Table 1
The input-target dataset, k $\left(\frac{W}{mK}\right)$ [14].

		T(°C)					
		25	30	35	40	45	50
ϕ (%)	0.05	0.655	0.662	0.670	0.684	0.696	0.707
	0.1	0.674	0.685	0.693	0.705	0.723	0.730
	0.15	0.689	0.701	0.710	0.723	0.737	0.751
	0.2	0.705	0.717	0.728	0.744	0.758	0.770
	0.4	0.736	0.748	0.763	0.780	0.799	0.809
	0.6	0.766	0.777	0.788	0.810	0.829	0.840

researchers to apply the hybrid nanoparticles. Less concentration of hybrid nanoparticles also leads to less cost beside more efficiency. Moreover various types of the base liquids can be examined which it depends on the working conditions. It should be mentioned that surfactant substances should be used as the hydrophilic factor for the some nanoparticles dispersed through the base liquid layers [1–15].

The working temperature of nanofluid beside the shape, diameter and volume fraction of nanoparticles can affect its behavior; as a regard the type of the base fluid should also be involved. However each one of these mentioned factors might have a significant influence on the mixture thermal and hydrodynamic properties such as viscosity, thermal conductivity and density. A large number of works can be addressed in this way [16–31].

As a result it is necessary to have a complete knowledge of a nanofluid thermo-physical properties especially for the new types. Thermal efficiency, pumping power and heat transfer rate are some examples for the nanofluid usage which usually are reported though the literature. Due to high cost of experimental studies concerned nanofluid, several works can be referred using the numerical approaches. Propose a correlation and then validation of its performance, are the favorite topics for the researchers in the field of nanofluids & composites [32–49].

The experimental studies encounter some difficulties which implies several specified points usually would be evaluated. Therefore the numerical optimization/interpolation approaches should be employed to present the fluid behavior at each desired condition. Commonly the "Artificial Neural Network" (ANN) method is used to estimate the thermo-physical conditions of nanofluid according to the experimental results [50–72].

It is well known that Artificial Neural Network (ANN) is the most famous regression approach because of its universal approximation capability. A multi-layer feed-forward artificial neural network with finite amount neurons in hidden-layer, can predict each relationship between the dependent and independent parameters of a desired variable. ANN involves several disadvantages as follows in addition of its appropriate performance:

- Select ANN structure and desired training algorithm would be empirical.
- Results would be affected significantly by the initial conditions.
- Much amount of model variables (weights and biases) would be necessary.
- Models of the resultant would not be same.
- Great value of dataset would be necessary to satisfy the training stage.
- Overfitting would happen simply and frequently which decreases model generalization.

Now the problem is to find a substitution approach for ANN with the higher capability and less disadvantages. Present work claims that SVR seems to have more suitable performance between too many developed machine learning approaches.

2. Problem definition: goal of the proposed model

In many studies in the field of nanofluid, the precision of models is more highlighted. Nevertheless, a lack of generalization may lead to overfitted models. In this paper, two nonlinear regression methods, namely the ANN and SVR are employed to predict the thermal conductivity of MWCNT-CuO/water hybrid nanofluid with temperature and volume fraction. Hence A new nonlinear regression model is proposed to predict the nanofluid thermal conductivity according to temperature and nanoparticles volume fraction.

Two independent variables of temperature & volume fraction of nanoparticles and one dependent variable of thermal conductivity k(W/(mK)) are included through the model. The input-goal has 36 samples shown in Table 1 at $T = 25, 30, 35, 40, 45, 50$ (°C) and $\phi = 0.5, 0.1, 0.15, 0.2, 0.4, 0.6$ (%) [14].

3. Numerical approach: SVR concept

SVM is a supervised learning approach for the classification and regression steps; in which input space is mapped through the feature domain and then it is resolved by the optimization method. SVM involves the powerful theoretical concepts and suitable generalization, accuracy and precision which works with nonlinear conditions [28]. The type of SVM called Support Vector Regression (SVR) was presented to estimate the function [29]. SVR implies the nice resistance on overfitting and good in little-size datasets beside the suitable generalization. As a result, it can be considered as the best approach to regression.

In the following parts, a short glance on SVR is provided at first; then SVR is applied to predict the present sample nanofluid thermal conductivity. At the end, the incomes of SVR and ANN are evaluated with one another.

Assume the training input-goal dataset of (x_i, y_i) for $i = 1, \ldots, n$ while $x_i \in \Re^d$ & $y_i \in \Re$. A linear regression approach is presented as [30]:

$$y = \omega.x + b \tag{1}$$

In which $\omega \in \Re^d$ & $b \in \Re$. The goal is to estimate the linear regression for the last equation with highest flatness and deviation ε from y_i at $i = 1, \ldots, n$ which means,

$$\begin{gathered}\text{min: } \frac{1}{2}\left\|\omega\right\|^2 \\ \text{s.t.: } \begin{cases} y_i - \omega.x_i - b \leq \varepsilon \\ \omega.x_i + b - y_i \leq \varepsilon \end{cases} \text{for } i = 1, \ldots, n \end{gathered} \tag{2}$$

In some cases, it may not practical to gain an answer for the previous optimization object. Hence precision condition of ε is able to be relaxed with the variables of ξ_i & ξ_i^*. It should be mentioned that variables must not be let to be increased in order to keep the precision,

$$\begin{gathered}\text{min: } \frac{1}{2}\left\|\omega\right\|^2 + \gamma \sum_{i=1}^{n}\left(\xi_i + \xi_i^*\right) \\ \text{s.t.: } \begin{cases} y_i - \omega.x_i - b \leq \varepsilon + \xi_i \\ \omega.x_i + b - y_i \leq \varepsilon + \xi_i^* \\ \xi_i \geq 0 \\ \xi_i^* \geq 0 \end{cases} \text{for } i = 1, \ldots, n \end{gathered} \tag{3}$$

In which $\gamma > 0$ implies to agreement among the flatness and suitable deviations. Now the optimization approach is followed by presenting the Lagrange multipliers as $\alpha_i > 0, \alpha_i^* > 0, \eta_i > 0$ & $\eta_i^* > 0$:

Lagrangian:

$$\begin{aligned} L = {} & \tfrac{1}{2}\left\|\omega\right\|^2 + \gamma \sum_{i=1}^{n}\left(\xi_i + \xi_i^*\right) \\ & - \sum_{i=1}^{n}\alpha_i\left(\varepsilon + \xi_i - y_i + \omega.x_i + b\right) - \sum_{i=1}^{n}\alpha_i^*\left(\varepsilon + \xi_i^* + y_i - \omega.x_i - b\right) \\ & - \sum_{i=1}^{n}\eta_i\xi_i - \sum_{i=1}^{n}\eta_i^*\xi_i^* \end{aligned} \tag{4}$$

Partial deviations must be omitted from the Lagrangian, considering the parameters of ω, b, ξ_i & ξ_i^*,

$$\begin{aligned} \frac{\partial L}{\partial \omega} &= \omega - \sum_{i=1}^{n}\left(\alpha_i^* - \alpha_i\right)x_i \\ \frac{\partial L}{\partial b} &= \sum_{i=1}^{n}\left(\alpha_i^* - \alpha_i\right) \\ \frac{\partial L}{\partial \xi_i} &= \gamma - \alpha_i - \eta_i \\ \frac{\partial L}{\partial \xi_i^*} &= \gamma - \alpha_i^* - \eta_i^* \end{aligned} \tag{5}$$

Eq. (6) is achieved for the optimization object by substitution of Eq. (5) in (4) [30],

$$\begin{gathered}\text{min: } -\frac{1}{2}\sum_{i,j=1}^{n}\left(\alpha_i - \alpha_i^*\right)\left(\alpha_j - \alpha_j^*\right)\left(x_i.x_j\right) - \varepsilon\sum_{i=1}^{n}\left(\alpha_i + \alpha_i^*\right) + \sum_{i=1}^{n}y_i\left(\alpha_i - \alpha_i^*\right) \\ \text{s.t.: } \begin{cases} \sum_{i=1}^{n}\left(\alpha_i - \alpha_i^*\right) = 0 \\ 0 \leq \alpha_i \leq \gamma \\ 0 \leq \alpha_i^* \leq \gamma \end{cases} \end{gathered} \tag{6}$$

Table 2
Error percentage of original experimental results versus those of SVR model for k $\left(\frac{W}{mK}\right)$.

		T(°C)					
		25	30	35	40	45	50
ϕ (%)	0.05	0.01	0.08	0.14	0.20	0.05	0.09
	0.1	0.01	0.27	0.03	0.06	0.47	0.09
	0.15	0.20	0.00	0.26	0.33	0.43	0.00
	0.2	0.13	0.17	0.05	0.26	0.07	0.23
	0.4	0.07	0.07	0.05	0.05	0.05	0.14
	0.6	0.00	0.17	0.24	0.09	0.04	0.01

The variables corresponded to Eq. (1), are achieved from the last optimization equation,

$$\begin{aligned} \omega &= \sum_{i=1}^{n} \left(\alpha_i - \alpha_i^*\right) x_i \\ b &= \frac{1}{2}\left\{\min\left(y_i - \omega.x_i\right) + \max\left(y_i - \omega.x_i\right)\right\} \end{aligned} \tag{7}$$

Now it is assumed a nonlinear object, which means the input x is primary moved from the input domain to the feature domain by the function of $\phi(x)$. Then, input–output relationship is corresponded by the linear regression as follows:

$$y = \omega.\phi(x) + b \tag{8}$$

By the same procedure, the next optimization expression is achieved:

$$\begin{aligned} &\min: -\frac{1}{2}\sum_{i,j=1}^{n}\left(\alpha_i - \alpha_i^*\right)\left(\alpha_j - \alpha_j^*\right) K\left(x_i, x_j\right) - \varepsilon\sum_{i=1}^{n}\left(\alpha_i + \alpha_i^*\right) + \sum_{i=1}^{n} y_i\left(\alpha_i - \alpha_i^*\right) \\ &\text{s.t.:} \begin{cases} \sum_{i=1}^{n}\left(\alpha_i - \alpha_i^*\right) = 0 \\ 0 \le \alpha_i \le \gamma \\ 0 \le \alpha_i^* \le \gamma \end{cases} \end{aligned} \tag{9}$$

K represents the kernel function which must contains the specified characteristics. Various types of kernel functions can be found through the literature, however the Radial Basis Function (RBF) Kernel can be addressed as the suitable one among them,

$$K\left(x_i, x_j\right) = \exp\left(-\frac{\left\|x_i - x_j\right\|^2}{2\sigma^2}\right) \tag{10}$$

where σ^2 represents the kernel variable. A quadratic programming problem was shown in Eq. (9). The most famous approach to solve it, would be the Least Squares-Support Vector Machine (LS-SVM) among the various available methods. LS-SVM corresponds to the linear objects instead of quadratic ones. Moreover an optimization method of simplex can be employed for it which leads to achieve the variables of Eq. (8):

$$\begin{aligned} \omega &= \sum_{i=1}^{n}\left(\alpha_i - \alpha_i^*\right)\phi\left(x_i\right) \\ b &= \frac{1}{2}\left\{\min\left(y_i - \omega.\phi\left(x_i\right)\right) + \max\left(y_i - \omega.\phi\left(x_i\right)\right)\right\} \end{aligned} \tag{11}$$

4. Results

At first step, SVR is applied by the simplex optimization approach and using RBF kernel. The variables of σ^2 & γ are demonstrated using Coupled Simulated Annealing (CSA). Fig. 1 shows the present model obtained results for the input-target dataset. Moreover the regression of original experimental data versus proposed numerical model of SVR are illustrated in Fig. 2. The regression slope and bias are around one and zero respectively, which implies the model can closely trace the goal data through the trained objects. Table 2 involves the deviation percentage between the original experimental results and those of proposed model of SVR. It is observed that SVR shows the nice precision.

Second step is provided by the results from SVR in comparison with ANN composed of one hidden layer and an output layer. Hidden layer involves fifteen "tansig" neurons and output layer involves the linear neurons while Levenberg–Marquardt backpropagation algorithm is applied as the learning algorithm. Fig. 3 represents the regression of ANN and also the deviation between original experimental results versus those of ANN are presented in Table 3. It is seen that ANN involves the appropriate precision through the trained samples which implies that SVR & ANN precisions are comparable.

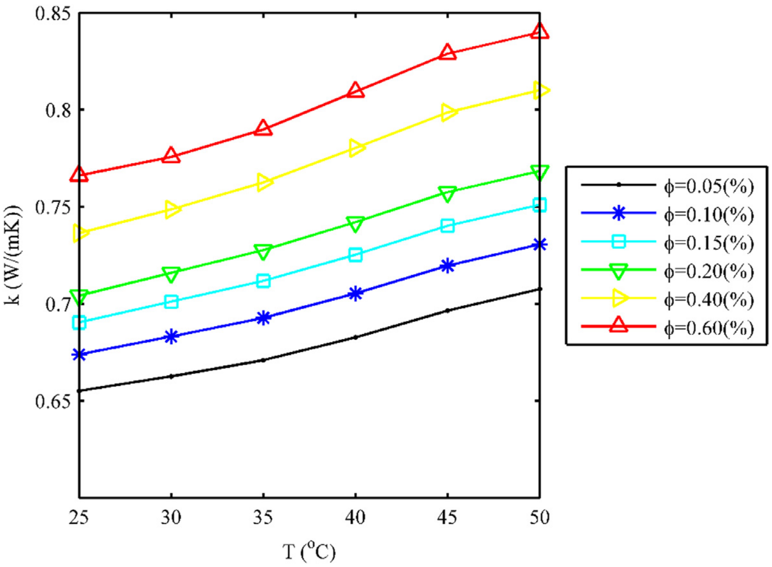

Fig. 1. Validation of SVR obtained data for input-target dataset.

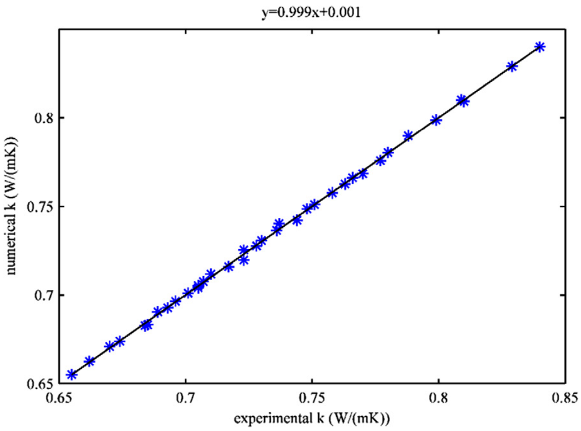

Fig. 2. Regression of original experimental results versus those of SVR numerical model.

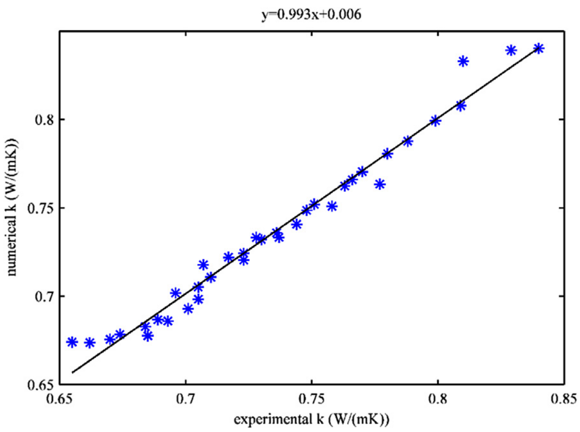

Fig. 3. Regression of original experimental results versus those of ANN numerical model.

Table 3
Error percentage of original experimental results versus those of ANN model for k $\left(\frac{W}{mK}\right)$.

		T(°C)					
		25	30	35	40	45	50
ϕ (%)	0.05	2.83	1.74	0.83	0.18	0.82	1.50
	0.1	0.65	1.10	1.02	0.03	0.35	0.28
	0.15	0.33	1.17	0.10	0.17	0.51	0.13
	0.2	0.97	0.69	0.70	0.45	0.94	0.05
	0.4	0.03	0.08	0.09	0.07	0.04	0.16
	0.6	0.01	1.79	0.04	2.75	1.20	0.02

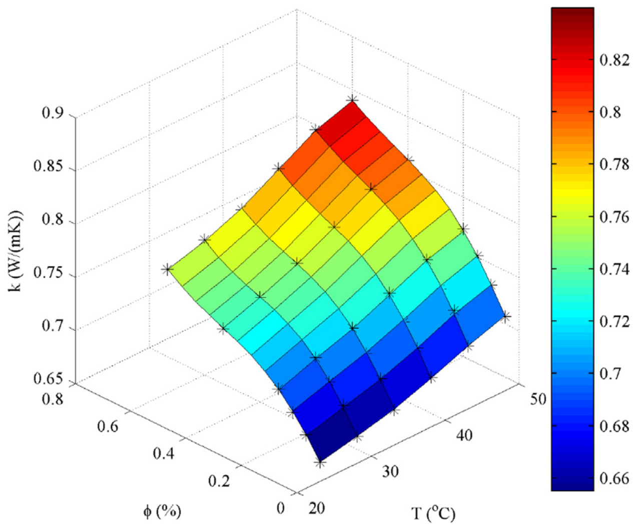

Fig. 4. Nanofluid thermal conductivity from SVR versus temperature and nanoparticles volume fraction (asterisks: input-target dataset).

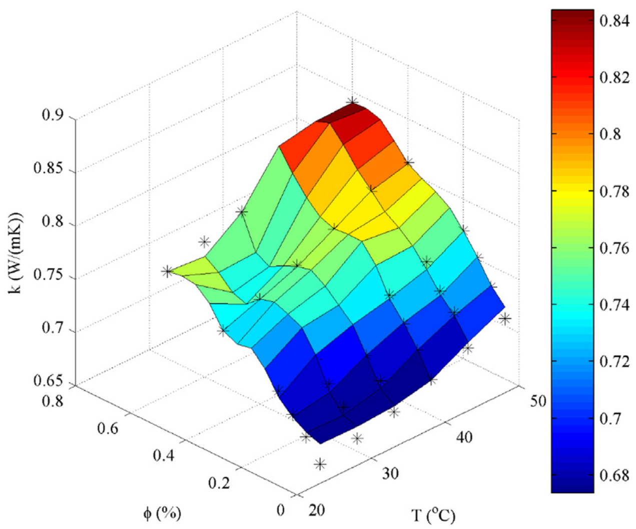

Fig. 5. Nanofluid thermal conductivity from ANN versus temperature and nanoparticles volume fraction (asterisks: input-target dataset).

At the end, trained SVR and ANN are applied to evaluate the non-trained inputs to examine the model generalization. The predicted thermal conductivity by SVR and ANN at various temperature and nanoparticles volume fraction are presented in Figs. 4 and 5. It is seen that SVR produces a smooth surface; however ANN makes a distorted one. ANN involves the generalization object due to surface distortion that would not physically sensible. This fact is because of the acquired ANN overfitting which is commonly happens in ANN with little-size training and much amount of variables. It should be mentioned that it is possible for ANN to decrease the approach variables with no losing of accuracy. Hence, it is not easy to keep ANN precision and generalization with little-size datasets. It means SVR can present higher accurate outcomes because of using the less amounts of variables in LSR. Therefore SVR can be estimated as the better reliable approach for the regression schemes with little-size datasets.

5. Conclusion

In this paper, two nonlinear regression methods, namely the ANN and SVR were employed to predict the thermal conductivity of MWCNT-CuO/water hybrid nanofluid with temperature and volume fraction. Hence A new nonlinear regression model was proposed to predict the nanofluid thermal conductivity according to temperature and nanoparticles volume fraction.

It was seen that precision of SVR & ANN methods can be compared togeother. SVR generalization was more suitable than ANN because SVR approach used less parameters. Hence SVR could demonstrate further resistance to overfitting in small-size datasets compared with ANN. Hence, SVR was more reliable method for the regression of small-size datasets.

References

[1] S.M. Aminossadati, A. Raisi, B. Ghasemi, Effects of magnetic field on nanofluid forced convection in a partially heated microchannel, Int. J. Non-Linear Mech. 46 (10) (2011) 1373–1382.
[2] A. Karimipour, New correlation for nusselt number of nanofluid with $Ag/Al_2O_3/Cu$ nanoparticles in a microchannel considering slip velocity and temperature jump by using lattice Boltzmann method, Int. J. Therm. Sci. 91 (2015) 146–156.
[3] H.C. Brinkman, The viscosity of concentrated suspensions and solutions, J. Chem. Phys. 20 (4) (1952) 571-571.
[4] M.R. Safaei, A. Karimipour, A. Abdollahi, T.K. Nguyen, The investigation of thermal radiation and free convection heat transfer mechanisms of nanofluid inside a shallow cavity by lattice Boltzmann method, Physica A 509 (2018) 515–535.
[5] A. Karimipour, A. Taghipour, A. Malvandi, Developing the laminar MHD forced convection flow of water/FMWNT carbon nanotubes in a microchannel imposed the uniform heat flux, J. Magn. Magn. Mater. 419 (2016) 420–428.
[6] A. Karimipour, A.H. Nezhad, A. D'Orazio, M.H. Esfe, M.R. Safaei, E. Shirani, Simulation of copper–water nanofluid in a microchannel in slip flow regime using the lattice Boltzmann method, Eur. J. Mech. B Fluids 49 (2015) 89–99.
[7] M. Baratpour, A. Karimipour, M. Afrand, S. Wongwises, Effects of temperature and concentration on the viscosity of nanofluids made of single-wall carbon nanotubes in ethylene glycol, Int. Commun. Heat Mass Transfer 74 (2016) 108–113.
[8] M. Bahrami, M. Akbari, A. Karimipour, M. Afrand, An experimental study on rheological behavior of hybrid nanofluids made of iron and copper oxide in a binary mixture of water and ethylene glycol: non-newtonian behavior, Exp. Therm Fluid Sci. 79 (2016) 231–237.
[9] M.H. Esfe, W.M. Yan, M. Akbari, A. Karimipour, M. Hassani, Experimental study on thermal conductivity of DWCNT-ZnO/water-EG nanofluids, Int. Commun. Heat Mass Transfer 68 (2015) 248–251.
[10] C.H. Chon, K.D. Kihm, S.P. Lee, S.U. Choi, Empirical correlation finding the role of temperature and particle size for nanofluid (Al_2O_3) thermal conductivity enhancement, Appl. Phys. Lett. 87 (15) (2005) 153107.
[11] S.M. Hosseini, M.R. Safaei, M. Goodarzi, A.A. Alrashed, T.K. Nguyen, New temperature, interfacial shell dependent dimensionless model for thermal conductivity of nanofluids, Int. J. Heat Mass Transfer 114 (2017) 207–210.
[12] Y. Xuan, Q. Li, Investigation on convective heat transfer and flow features of nanofluids, J. Heat transfer 125 (1) (2003) 151–155.
[13] M.H. Esfe, S. Wongwises, A. Naderi, A. Asadi, M.R. Safaei, H. Rostamian, M. Dahari, A. Karimipour, Thermal conductivity of CU/TiO_2–water/EG hybrid nanofluid: experimental data and modeling using artificial neural network and correlation, Int. Commun. Heat Mass Transfer 66 (2015) 100–104.
[14] 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. Thermal Anal. Calorimetry 129 (2) (2017) 859–867.
[15] M.H. Esfe, S. Saedodin, A. Naderi, A. Alirezaie, A. Karimipour, S. Wongwises, M. Goodarzi, M. bin Dahari, Modeling of thermal conductivity of ZnO-EG using experimental data and ANN methods, Int. Commun. Heat Mass Transfer 63 (2015) 35–40.
[16] S.S. Harandi, A. Karimipour, M. Afrand, M. Akbari, A. D'Orazio, An experimental study on thermal conductivity of F-MWCNTs–Fe_3O_4/EG hybrid nanofluid: effects of temperature and concentration, Int. Commun. Heat Mass Transfer 76 (2016) 171–177.
[17] M. Jourabian, A.A.R. Darzi, D. Toghraie, O. aliAkbari, Melting process in porous media around two hot cylinders: numerical study using the lattice Boltzmann method, Physica A 509 (2018) 316–335.
[18] M.H. Esfe, H. Rostamian, M. Rejvani, M.R.S. Emami, Rheological behavior characteristics of ZrO_2-MWCNT/10w40 hybrid nano-lubricant affected by temperature, concentration, and shear rate: an experimental study and a neural network simulating, Physica E 102 (2018) 160–170.
[19] M.H. Esfe, A. Naderi, M. Akbari, M. Afrand, A. Karimipour, Evaluation of thermal conductivity of COOH-functionalized MWCNTs/water via temperature and solid volume fraction by using experimental data and ANN methods, J .Thermal Anal. Calorimetry 121 (3) (2015) 1273–1278.
[20] A.A. Nadooshan, M.H. Esfe, M. Afrand, Prediction of rheological behavior of SiO_2-MWCNTs/10W40 hybrid nanolubricant by designing neural network, J .Thermal Anal. Calorimetry 131 (3) (2018) 2741–2748.
[21] M. Mehrali, E. Sadeghinezhad, S.T. Latibari, M. Mehrali, H. Togun, M.N.M. Zubir, S.N. Kazi, H.S.C. Metselaar, Preparation, characterization, viscosity, and thermal conductivity of nitrogen-doped graphene aqueous nanofluids, J. Mater. Sci. 49 (20) (2014) 7156–7171.
[22] K. Hornik, M. Stinchcombe, H. White, Multilayer feedforward networks are universal approximators, Neural Netw. 2 (5) (1989) 359–366.
[23] A.A. Alrashed, A. Karimipour, S.A. Bagherzadeh, M.R. Safaei, M. Afrand, Electro-and thermophysical properties of water-based nanofluids containing copper ferrite nanoparticles coated with silica: experimental data, modeling through enhanced aNN and curve fitting, Int. J. Heat Mass Transfer 127 (2018) 925–935.
[24] M.H. Esfe, M.R.H. Ahangar, M. Rejvani, D. Toghraie, M.H. 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.
[25] K. Hornik, Approximation capabilities of multilayer feedforward networks, Neural Netw. 4 (2) (1991) 251–257.
[26] D.J. MacKay, Bayesian interpolation, Neural Comput. 4 (3) (1992) 415–447.
[27] Martin T. Hagan, Howard B. Demuth, Mark H. Beale, Orlando De Jesús, Neural Network Design, second ed., Martin Hagan, 2014.
[28] N. Cristianini, J. Shawe-Taylor, An Introduction to Support Vector Machines, Cambridge University Press, 2000.
[29] H. Drucker, C.J. Burges, L. Kaufman, A.J. Smola, V. Vapnik, Support vector regression machines, in: Advances in Neural Information Processing Systems, 1997, pp. 155–161.
[30] D. Basak, S. Pal, D.C. Patranabis, Support vector regression, Neural Inf. Process.-Lett. Rev. 11 (10) (2007) 203–224.

[31] M.H. Esfe, M. Bahiraei, M.H. Hajmohammad, M. Afrand, Rheological characteristics of MgO/oil nanolubricants: experimental study and neural network modeling, Int. Commun. Heat Mass Transfer 86 (2017) 245–252.
[32] M. Afrand, A.A. Nadooshan, M. Hassani, H. Yarmand, M. Dahari, Predicting the viscosity of multi-walled carbon nanotubes/water nanofluid by developing an optimal artificial neural network based on experimental data, Int. Commun. Heat Mass Transfer 77 (2016) 49–53.
[33] R. Ranjbarzadeh, A.M. Isfahani, M. Afrand, A. Karimipour, M. Hojaji, An experimental study on heat transfer and pressure drop of water/graphene oxide nanofluid in a copper tube under air cross-flow: applicable as a heat exchanger, Appl. Therm. Eng. 125 (2017) 69–79.
[34] M. Afrand, K.N. Najafabadi, M. Akbari, Effects of temperature and solid volume fraction on viscosity of SiO_2-MWCNTs/SAE40 hybrid nanofluid as a coolant and lubricant in heat engines, Appl. Therm. Eng. 102 (2016) 45–54.
[35] M. Nojoomizadeh, A. D'Orazio, A. Karimipour, M. Afrand, M. Goodarzi, Investigation of permeability effect on slip velocity and temperature jump boundary conditions for FMWNT/water nanofluid flow and heat transfer inside a microchannel filled by a porous media, Physica E 97 (2018) 226–238.
[36] S.A. Sajadifar, A. Karimipour, D. Toghraie, Fluid flow and heat transfer of non-newtonian nanofluid in a microtube considering slip velocity and temperature jump boundary conditions, Eur. J. Mech. B Fluids 61 (2017) 25–32.
[37] O.A. Akbari, H.H. Afrouzi, A. Marzban, D. Toghraie, H. Malekzade, A. Arabpour, Investigation of volume fraction of nanoparticles effect and aspect ratio of the twisted tape in the tube, J .Thermal Anal. Calorimetry 129 (3) (2017) 1911–1922.
[38] M. Afrand, D. Toghraie, A. Karimipour, S. Wongwises, A numerical study of natural convection in a vertical annulus filled with gallium in the presence of magnetic field, J. Magn. Magn. Mater. 430 (2017) 22–28.
[39] O.A. Akbari, D. Toghraie, A. Karimipour, A. Marzban, G.R. Ahmadi, The effect of velocity and dimension of solid nanoparticles on heat transfer in non-newtonian nanofluid, Physica E 86 (2017) 68–75.
[40] M. Afrand, A. Karimipour, A.A. Nadooshan, M. Akbari, The variations of heat transfer and slip velocity of FMWNT-water nano-fluid along the micro-channel in the lack and presence of a magnetic field, Physica E 84 (2016) 474–481.
[41] M.H. Esfe, S.S.M. Esforjani, M. Akbari, A. Karimiopour, Mixed-convection flow in a lid-driven square cavity filled with a nanofluid with variable properties: effect of the nanoparticle diameter and of the position of a hot obstacle, Heat Transfer Res. 45 (6) (2014) 563–578.
[42] M. Akbari, M. Afrand, A. Arshi, A. Karimipour, An experimental study on rheological behavior of ethylene glycol based nanofluid: proposing a new correlation as a function of silica concentration and temperature, J. Molecular Liquids 233 (2017) 352–357.
[43] M. Mahmoodi, M.H. Esfe, M. Akbari, A. Karimipour, M. Afrand, Magneto-natural convection in square cavities with a source–sink pair on different walls, Int. J. Appl. Electromagn. Mech. 47 (1) (2015) 21–32.
[44] O. Soltani, M. Akbari, Effects of temperature and particles concentration on the dynamic viscosity of MgO-MWCNT/ethylene glycol hybrid nanofluid: experimental study, Physica E 84 (2016) 564–570.
[45] M.H. Esfe, M. Akbari, A. Karimipour, Mixed convection in a lid-driven cavity with an inside hot obstacle filled by an Al_2O_3–water nanofluid, J. Appl. Mech. Technical Phys. 56 (3) (2015) 443–453.
[46] M.H. Esfe, S. Niazi, S.S.M. Esforjani, M. Akbari, Mixed convection flow and heat transfer in a ventilated inclined cavity containing hot obstacles subjected to a nanofluid, Heat Transfer Res. 45 (4) (2014) 309–338.
[47] M.H. Esfe, A. Ghadi, S.M. Esforjania, M. Akbari, Combined convection in a lid-driven cavity with an inside obstacle subjected to Al_2O_3-water nanofluid: effect of solid volume fraction and nanofluid variable properties, Acta Phys. Polonica A. 124 (4) (2013) 665–672.
[48] M. Afrand, S. Rostami, M. Akbari, S. Wongwises, M.H. Esfe, A. Karimipour, Effect of induced electric field on magneto-natural convection in a vertical cylindrical annulus filled with liquid potassium, Int. J. Heat Mass Transfer 90 (2015) 418–426.
[49] A. Zareie, M. Akbari, Hybrid nanoparticles effects on rheological behavior of water-EG coolant under different temperatures: an experimental study, J. Molecular Liquids 230 (2017) 408–414.
[50] O.A. Akbari, D. Toghraie, A. Karimipour, M.R. Safaei, M. Goodarzi, H. Alipour, M. Dahari, Investigation of rib's height effect on heat transfer and flow parameters of laminar water–Al_2O_3 nanofluid in a rib-microchannel, Appl. Math. Comput. 290 (2016) 135–153.
[51] H. Alipour, A. Karimipour, M.R. Safaei, D.T. Semiromi, O.A. Akbari, Influence of T-semi attached rib on turbulent flow and heat transfer parameters of a silver-water nanofluid with different volume fractions in a three-dimensional trapezoidal microchannel, Physica E 88 (2017) 60–76.
[52] O.A. Akbari, D. Toghraie, A. Karimipour, Numerical simulation of heat transfer and turbulent flow of water nanofluids copper oxide in rectangular microchannel with semi-attached rib, Adv. Mech. Eng. 8 (4) (2016) 1687814016641016.
[53] A. Behnampour, O.A. Akbari, M.R. Safaei, M. Ghavami, A. Marzban, G.A.S. Shabani, R. Mashayekhi, Analysis of heat transfer and nanofluid fluid flow in microchannels with trapezoidal, rectangular and triangular shaped ribs, Physica E 91 (2017) 15–31.
[54] O.A. Akbari, M.R. Safaei, M. Goodarzi, N.S. Akbar, M. Zarringhalam, G.A.S. Shabani, M. Dahari, A modified two-phase mixture model of nanofluid flow and heat transfer in a 3-D curved microtube, Adv. Powder Technol. 27 (5) (2016) 2175–2185.
[55] A.A.A. Arani, O.A. Akbari, M.R. Safaei, A. Marzban, A.A. Alrashed, G.R. Ahmadi, T.K. Nguyen, Heat transfer improvement of water/single-wall carbon nanotubes (SWCNT) nanofluid in a novel design of a truncated double-layered microchannel heat sink, Int. J. Heat Mass Transfer 113 (2017) 780–795.
[56] A.A. Ahmadi, E. Khodabandeh, H. Moghadasi, N. Malekian, O.A. Akbari, M. Bahiraei, Numerical study of flow and heat transfer of water-Al_2O_3 nanofluid inside a channel with an inner cylinder using eulerian–lagrangian approach, J. Thermal Anal. Calorimetry 132 (1) (2018) 651–665.
[57] A.A. Alrashed, O.A. Akbari, A. Heydari, D. Toghraie, M. Zarringhalam, G.A.S. Shabani, A.R. Seifi, M. Goodarzi, The numerical modeling of water/FMWCNT nanofluid flow and heat transfer in a backward-facing contracting channel, Physica B 537 (2018) 176–183.
[58] G. Ahmadi, O.A. Akbari, M. Zarringhalam, Energy and exergy analyses of partial repowering of a natural gas-fired steam power plant, Int. J. Exergy 23 (2) (2017) 149–168.
[59] A. Karimipour, S.A. Bagherzadeh, M. Goodarzi, A.A. Alnaqi, M. Bahiraei, M.R. Safaei, M.S. Shadloo, Synthesized $CuFe_2O_4/SiO_2$ nanocomposites added to water/EG: evaluation of the thermophysical properties beside sensitivity analysis & EANN, Int. J. Heat Mass Transfer 127 (2018) 1169–1179.
[60] M. Goodarzi, M.R. Safaei, H.F. Oztop, A. Karimipour, E. Sadeghinezhad, M. Dahari, S.N. Kazi, N. Jomhari, Numerical study of entropy generation due to coupled laminar and turbulent mixed convection and thermal radiation in an enclosure filled with a semitransparent medium, Sci. World J. 2014 (2014) 761745.
[61] M. Goodarzi, M.R. Safaei, A. Karimipour, K. Hooman, M. Dahari, S.N. Kazi, E. Sadeghinezhad, Comparison of the finite volume and lattice Boltzmann methods for solving natural convection heat transfer problems inside cavities and enclosures, in: Abstract and Applied Analysis (Vol. 2014), Hindawi, 2014, p. 762184.
[62] A. Karimipour, A. D'Orazio, M. Goodarzi, Develop the lattice Boltzmann method to simulate the slip velocity and temperature domain of buoyancy forces of FMWCNT nano particles in water through a micro flow imposed to the specified heat flux, Physica A 509 (2018) 729–745.
[63] M. Goodarzi, A. D'Orazio, A. Keshavarzi, S. Mousavi, A. Karimipour, Develop the nano scale method of lattice Boltzmann to predict the fluid flow and heat transfer of air in the inclined lid driven cavity with a large heat source inside, two case studies: pure natural convection & mixed convection, Physica A 509 (2018) 210–233.
[64] M. Nojoomizadeh, A. Karimipour, M. Firouzi, M. Afrand, Investigation of permeability and porosity effects on the slip velocity and convection heat transfer rate of Fe_3O_4/water nanofluid flow in a microchannel while its lower half filled by a porous medium, Int. J. Heat Mass Transfer 119 (2018) 891–906.
[65] A. Karimipour, M.H. Esfe, M.R. Safaei, D.T. Semiromi, S. Jafari, S.N. Kazi, Mixed convection of copper–water nanofluid in a shallow inclined lid driven cavity using the lattice Boltzmann method, Physica A 402 (2014) 150–168.

[66] A. Karimipour, A. D'Orazio, M.S. Shadloo, The effects of different nano particles of Al_2O_3 and ag on the MHD nano fluid flow and heat transfer in a microchannel including slip velocity and temperature jump, Physica E 86 (2017) 146–153.
[67] M. Esfandiary, B. Mehmandoust, A. Karimipour, H.A. Pakravan, Natural convection of Al_2O_3–water nanofluid in an inclined enclosure with the effects of slip velocity mechanisms: brownian motion and thermophoresis phenomenon, Int. J. Therm. Sci. 105 (2016) 137–158.
[68] M.H. Esfe, A.A.A. Arani, A. Karimiopour, S.S.M. Esforjani, Numerical simulation of natural convection around an obstacle placed in an enclosure filled with different types of nanofluids, Heat Transfer Res. 45 (3) (2014) 279–292.
[69] M. Nemati, A.R.S.N. Abady, D. Toghraie, A. Karimipour, Numerical investigation of the pseudopotential lattice Boltzmann modeling of liquid–vapor for multi-phase flows, Physica A 489 (2018) 65–77.
[70] E. Khodabandeh, M.R. Safaei, S. Akbari, O.A. Akbari, A.A. Alrashed, Application of nanofluid to improve the thermal performance of horizontal spiral coil utilized in solar ponds: geometric study, Renew. Energy 122 (2018) 1–16.
[71] A. Heydari, O.A. Akbari, M.R. Safaei, M. Derakhshani, A.A. Alrashed, R. Mashayekhi, G.A.S. Shabani, M. Zarringhalam, T.K. Nguyen, The effect of attack angle of triangular ribs on heat transfer of nanofluids in a microchannel, J. Thermal Anal. Calorimetry 131 (3) (2018) 2893–2912.
[72] E. Khodabandeh, A. Rahbari, M.A. Rosen, Z.N. Ashrafi, O.A. Akbari, A.M. Anvari, Experimental and numerical investigations on heat transfer of a water-cooled lance for blowing oxidizing gas in an electrical arc furnace, Energy Convers. Manage. 148 (2017) 43–56.