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ORIGINAL ARTICLE

Combination of RSM and NSGA-II algorithm for optimization and prediction of thermal conductivity and viscosity of bioglycol/water mixture containing SiO_2 nanoparticles

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Abstract The fluids containing nanoparticles have enhanced thermo-physical characteristics in comparison with conventional fluids without nanoparticles. Thermal conductivity and viscosity are thermo-physical properties that strongly determine heat transfer and momentum. In this study, the response surface method was firstly used to derive an equation for the thermal conductivity and another one for the viscosity of bioglycol/water mixture (20:80) containing silicon dioxide nanoparticles as a function of temperature as well as the volume fraction of silicon dioxide. Then, NSGA-II algorithm was used for the optimization and maximizing thermal conductivity and minimizing the nanofluid viscosity. Different fronts were implemented and 20th iteration number was selected as Pareto front. The highest thermal conductivity (0.576 W/m.K) and the lowest viscosity (0.61 mPa.s) were obtained at temperature on volume concentration of (80 °C and 2%) and (80 °C without nanoparticle) respectively. It was concluded that the optimum thermal conductivity and viscosity of nanofluid could be obtained at maximum temperature (80 °C) or a temperature close to this temperature. An increase in the volume fraction of silicon dioxide led to the

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enhancement of thermal conductivity but the solution viscosity was also increased. Therefore, the optimum point should be selected based on the system requirement.

1. Introduction

Optimization is the art of finding the best answer among existing conditions. It is highly important in the engineering systems design to minimize the cost and maximizing the net profit (Hemmat Esfe et al., 2017b). The optimization of different systems has been attracted by many researchers and engineers in recent years (Zhang et al., 2021; Zou, 2021).

Heat transfer processes have a key role in many industries such as electricity production, air conditioning, cars, solar collectors, and so on (Azmi et al., 2013; Delavari and Hashemabadi, 2014; Kuznetsov and Nield, 2010; Qin et al., 2014; Sonawane et al., 2011; Wang et al., 2010). Thermal conductivity is considered as one of the most vital parameters where there is a fluid and it has substantial effect on the system heat transfer (Sonawane et al., 2011). Using nanofluid is one of the emerging technologies for the improvement of heat transfer in engineering systems. The suspension of nanoparticles in a fluid has the potential in cooling fluid due to creation of higher thermal conductivity. The effective parameters on the thermal conductivity can be found according to the type of base fluid (Hemmat Esfe et al., 2015). The nanofluids are usually used in heat exchangers. The nanofluids can increase heat transfer coefficient 50–60% at optimum operating conditions (Hemmat Esfe et al., 2017b).

A fluid containing nanoparticles with a size of less than 100 nm is called nanofluid and it was firstly used by Choi (Choi and Eastman, 1995). The nanoparticles could be metal oxide, metal sulfide, carbide, nitrite, and carbon materials such as carbon nanotube, graphene, and so on (Huminic and Huminic, 2012). Although the nanofluids improve thermal conductivity, they can also affect the rheological behaviour of solution such as the viscosity of solution. Rheological behaviour of different nanofluids including ZnO-Ag (50%-50%)/water hybrid Newtonian nanofluid (Ruhani et al., 2019), hybrid tungsten oxide (WO_3)-MWCNTs/engine oil (Aghahadi et al., 2019), nanofluid containing oxide nanoparticle (Saeedi et al., 2018) has been investigated experimentally. Also, the nanofluids can cause fouling of tubes, friction and precipitation (Hemmat Esfe et al., 2016; Moradi et al., 2019). Determination of nanofluid viscosity containing SiO_2 or Al_2O_3 was experimentally conducted and response surface model was used to generate an equation for the viscosity as a function of volume concentration ad temperature. It was found that the viscosity increases with nanoparticle concentration and reduces with the system temperature (Abdullah et al., 2021). Moreover, suction and dual stretching effect on the dynamics of various hybrid nanofluids was investigated by Shah et al. (Shah et al., 2020a). According to (Elnaqeeb et al., 2021; Koriko et al.; Shah et al., 2021), more accurate simulation of fluid conveying nanoparticles is achievable when the viscosity and thermal conductivity are assumed to vary with nanoparticle's radius, volume fraction and most especially temperature.

Determination of thermal conductivity and viscosity of various nanofluids as well as influence of various parameters such as temperature, concentration, and ultrasonic time on these two properties have been investigated separately. There are a few research studies to investigate the interaction of these two parameters on the thermo-physical properties (Hemmat Esfe et al., 2017c; Sonawane and Juwar, 2016). Therefore, it will be highly important these two parameters in a system simultaneously.

A number of research studies has been performed in recent years in this regard. Effect of temperature (26 – 50 °C) and the hybrid nanoparticles volume fraction (SWCNT-ZnO (30%-70%)) (0.05% −1.6%) in ethylene glycol–water (60%-40%) base fluid on the nanofluid thermal conductivity was studied by Safe et al. (Hemmat Esfe et al., 2017a). Then, neural network was used for determination of a relationship between temperature as well as volume fraction and the nanofluid thermal conductivity and viscosity. It was found that the thermal conductivity is much more affected by the nanoparticles volume fraction in comparison with temperature. It was concluded that there was 45% increasing in thermal conductivity at temperature and volume fraction of 50 °C and 1.6% respectively (Hemmat Esfe et al., 2017a). Akilu et al. (Akilu et al., 2017) synthesised titanium oxide-copper oxide/carbon (TiO_2-CuO/C) using wet-mixing protocol, then, the nanoparticles dispersed in ethylene glycol (EG) as a base fluid. The maximum increase in thermal conductivity and viscosity was obtained 16.7%, and 80% at 2.0% volume fraction and temperature of 40.25 °C. The change in nanofluid pH was proposed as one of the methods for holding the nanoparticles dispersed in the fluid.

Silica nanoparticles have been used in many applications because it has some advantages including low cost, hydrophilic, large surface area per volume, high biocompatibility, and low polydispersity index. Using SiO_2 nanoparticles in nanofluids application has been investigated widely and it can be found in literature in more detail (Shah et al., 2020b). It was found that it possesses some benefits such as minimal pressure drop, maximum increase in heat transfer, appropriate suspension stability, and better rheological and thermal specifications in comparison with other nanoparticles (Muhammad et al., 2021; Shah et al., 2020b). Zyla and Fal (Żyła and Fal, 2017) investigated thermophysical properties of SiO_2–ethylene glycol nanofluids and there was a linear increase in thermal conductivity and viscosity with an increase in the nanoparticle volume fraction.

The data should be firstly modelled for the optimization of discrete experimental data. Response surface method and neural network are two common methods which are used for the modelling experimental data and determination of objective functions (Hemmat Esfe et al., 2017c). Using neural network has been widely used for the optimization of nanofluid systems (Akhgar et al., 2019; Faridzadeh et al., 2014; Goodarzi et al., 2019; Rostami et al., 2021; Shahsavar et al., 2019; Toghraie et al., 2019; Zadeh and Toghraie, 2018). Many algorithms such as GA‘ ICA‘ PSO, and NSGA-II have been used for the optimization of thermal conductivity, viscosity, pressure drop, and so on (Ahrar and Djavareshkian, 2017; Hemmat Esfe et al., 2017b). The optimization can be mono-objective or multi-objective. In mono-objective optimization, the aim is optimization of one objective function. Then, effect of operating parameters on the function value is investigated. However, more than one objective function involves optimization simultaneously (Hemmat Esfe et al., 2017b). Using NSGA-II algorithm for the optimization of thermo-physical properties of bioglycol and water fluid containing silicon oxide nanoparticles will be the novelty of the current study. Experimental data used in this study were taken from literature (Abdolbaqi et al., 2016). The nanofluids were prepared by SiO_2 nanoparticle dispersion (0.5%-2%) in various base fluids like 30:70% and 20:80% by volume of bioglycol/water mixtures. For 20%:80% of bioglycol/water, the amount of 7.2% increase in thermal conductivity was observed in the volume concentration of 2.0% at a temperature of 70 °C (Abdolbaqi et al., 2016). Firstly, the experimental data was used to determine the thermal conductivity and viscosity equations as function of temperature and volume fraction by the response surface method.

2. Modelling using RSM

The response surface methodology (RSM) is a common statistical and mathematical approach for modelling and analysing a system in which the response of interest is affected by different variables and the aim of this approach is the optimization of the response (Aydar, 2018). The main benefit of this approach is decreasing the number of experiments and proposing a mathematical equation between dependant and independent variables in the system. The RSM uses statistical techniques like multiple regressions. For example, the first-order linear regression with two variables can be expressed as follows (Aydar, 2018):

$$y = \beta_0 + \beta_1 x_1 + \beta_2 x_2 + \varepsilon \tag{1}$$

where β_0, β_1, and β_2 are coefficients of the regression model. The symbols x_1 and x_2 are independent variables and y denotes dependent variable or response. The ε is the error of model. The least-square method is used for the determination of coefficients of the regression model as follows (Aydar, 2018):

$$ss_E = \sum_{n}^{i=1} (y_i - y_u)^2 = \sum_{n}^{i=1} e_i^2 = e^T e \tag{2}$$

It can be simplified using the following assumption:

$$y_i - y_u = e_i \tag{3}$$

The σ^2 can be written as follows:

$$\sigma^2 = \frac{ss_E}{n-p} \tag{4}$$

where n and p are the numbers of experiment and regression coefficients. Based on the following assumption (Eq. (6)), the SS_E can be expressed as follows (Aydar, 2018):

$$X^T X b = X^T y \tag{5}$$

$$SS_E = y^T y - b^T X^T y \tag{6}$$

The equation (8) is considered for the calculation of the sum of squares (Aydar, 2018).

$$SS_T = y^T y - \frac{\left(\sum_{i=1}^{n} y_i\right)^2}{n} = \sum_{i=1}^{n} y_i^2 - \frac{\left(\sum_{i=1}^{n} y_i\right)^2}{n} \tag{7}$$

The accuracy of the regression model is evaluated by the following equation:

$$R^2 = 1 - \frac{SS_E}{SS_T} \tag{8}$$

It is not suitable to use R^2 when new variables are added to the model. It is common to use adjusted R^2 when it is required to add new variables into the model (Aydar, 2018):

$$R^2_{adj} = 1 - \frac{SS_E/(n-p)}{SS_T/(n-1)} = 1 - \frac{n-1}{n-p}\left(1 - R^2\right) \tag{9}$$

3. Multi-object optimization using NSGA II

In this study, a non-dominated sorting genetic algorithm (NSGA-II) was used for the determination of optimal values of dynamic viscosity and thermal conductivity. Apart from

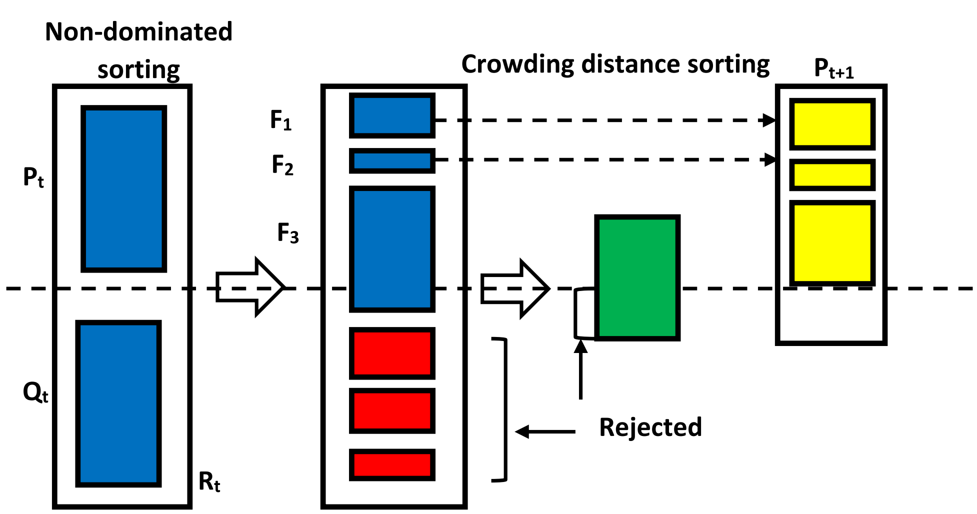

Fig. 1 NSGA-II algorithm structure.

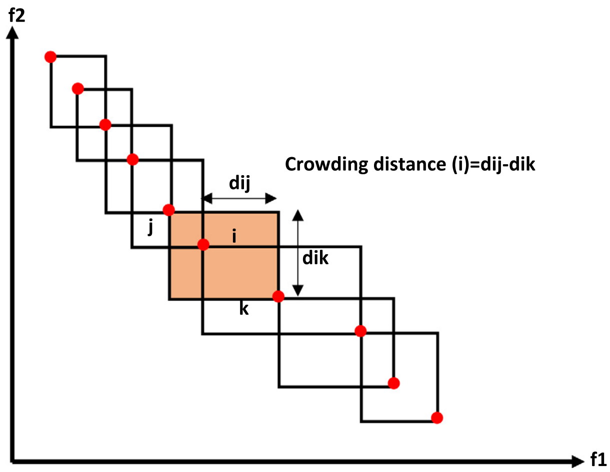

Fig. 2 structure of crowding distance function.

non-dominated sorting and crowding distance functions, this algorithm also uses mutation and crossover functions. The crossover function is the most important in the NSGA-II algorithm (Aydar, 2018). The combination of the two parent's genetic information to create new offspring is done by the crossover function. Moreover, maintenance of genetic diversity from a generation of a population of genetic algorithm chromosomes to the next is carried out by mutation function.

The primary distinction between NSGA-II and genetic algorithms is that they use different functions for the optimization of the system parameters. The structure of NSGA-II algorithm is provided in Fig. 1. The non-dominated sorting as well as crowding distance functions play key role in population generation and modification and improve the algorithm performance (Deb et al., 2002).

The non-dominated sorting function compares different answers in different rows and columns and selects a member which satisfies the optimal conditions. For example, the aim of this paper to find a member which has the lowest dynamic viscosity and the highest thermal conductivity. The selected member must have the highest value in the row which has the constant viscosity and the lowest value in the column which has the constant thermal conductivity. In the last step, the crowding distance is used for the modification of new generations' answers. The main duty of this function is that maintaining an external archive and select a global optimum position (Yusoff et al., 2011). The schematic of the crowding distance function is shown in Fig. 2.

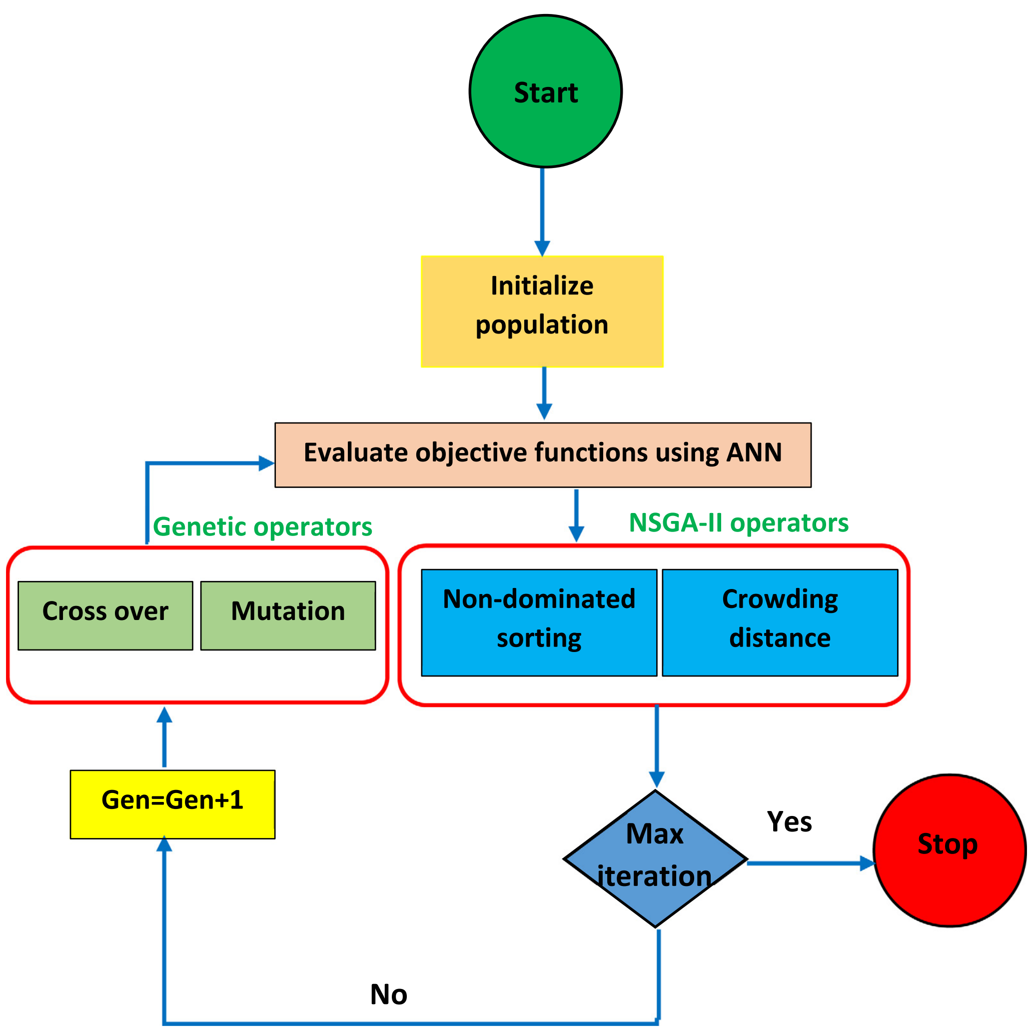

Fig. 3 NSGA-II algorithm flowchart.

Table 1 ANOVA analysis of the thermal conductivity and dynamic viscosity for RSM.

Source	Sum of squares		df		Mean square		F value		P value	
	K_{nf}	μ_{nf}	K_{nf}	μ_{nf}	K_{nf}	μ_{nf}	K_{nf}	μ_{nf}	K_{nf}	μ_{nf}
model	0.011	3.67	7	6	$1.63e^{-3}$	0.61	1018	2195	> 0.0001	> 0.0001
φ	$4.15e^{-3}$	0.094	1	1	$4.15e^{-3}$	0.094	2578	337.80	> 0.0001	> 0.0001
T	$1.31e^{-3}$	0.32	1	1	$1.31e^{-3}$	0.32	812	1157.22	> 0.0001	> 0.0001
Φ.T	$4.24e^{-6}$	$5.41e^{-3}$	1	1	$4.23e^{-6}$	$5.41e^{-3}$	2.63	19.44	0.1192	0.0002
T^2	$1.65e^{-5}$	0.15	1	1	$1.65e^{-5}$	0.15	10.23	531.53	0.0042	> 0.0001
T^3	$7.69e^{-5}$	$7.45e^{-3}$	1	1	$7.69e^{-5}$	$7.45e^{-3}$	47.77	26.78	> 0.0001	> 0.0001
Φ^2	$3.34e^{-5}$	–	1	–	$3.34e^{-5}$	–	20.71	–	0.0002	–
Φ^2.T	$4.73e^{-6}$	–	1	–	$4.73e^{-6}$	–	2.93	–	0.1008	–
Φ.T^2	–	$9.56e^{-4}$	–	1	–	$9.56e^{-4}$	–	3.43	–	0.0767
Residual	$3.54e^{-5}$	$6.40e^{-3}$	22	23	1.61e-6	$2.78e^{-4}$				
Cor total	0.012	3.67	29	29						

Crowding distance for each member is obtained based on the first and last members as follows (Yusoff et al., 2011):

$$d_{ij} = \frac{|f_1^k - f_1^j|}{f_1^{max} - f_1^{min}}, d_{ik} = \frac{|f_2^k - f_2^j|}{f_2^{max} - f_2^{min}} CD_i = d_{ij} + d_{ik} \quad (10)$$

Fig. 3 shows general NSGA-II algorithm flowchart. It can be seen that the neural network technique is used for the optimization in NSGA-II algorithm for the determination of the fitness function. In addition, the population generation is performed using crossover and mutation operators. The number of iterations in NSGA-II optimization algorithm was defined in the last section of the algorithm.

4. Results and discussion

4.1. RSM results

The experimental data reported in the literature (Abdolbaqi et al., 2016) was used to derive thermal conductivity and dynamic viscosity equations as a function of operating parameters. It was obtained using Design-Expert software. The derived thermal conductivity and viscosity equations can be expressed as follows:

$$K_{nf} = 5.4686e^{-1} + 2.1675e^{-2} \times \phi - 3.59e^{-3} \times T - 2.52e^{-3} \times \phi^2 + 8.34e^{-5} \times T^2 - 4.87e^{-7} \times T^3 \quad (11)$$

$$\mu_{nf} = 3.40544 + 1.736e^{-1} \times \phi - 9.0417e^{-2} \times T - 1.112e^{-3} \times T \times \phi + 1.07e^{-4} \times T^2 - 4.796e^{-6} \times T^3 \quad (12)$$

where K_{nf}, μ_{nf}, T, and φ are nanofluid thermal conductivity (W/m.K), nanofluid viscosity (mPa.s), temperature (° C), and volume fraction of nanoparticles (%). The volume ratio of bio-glycol/water (W) mixtures was 20:80%.

To investigate the accuracy of RSM model and obtained equations, F-value, P-value as well as coefficient of variation was determined. Moreover, the analysis of Variance (ANOVA) approach was used to calculate these parameters. Based on the ANOVA analysis, the model developed for the determination of the thermal conductivity and viscosity is valid, when the F value > 1 and the P-value < 0.05. The results were provided in Table 1. From Table 1, it could be

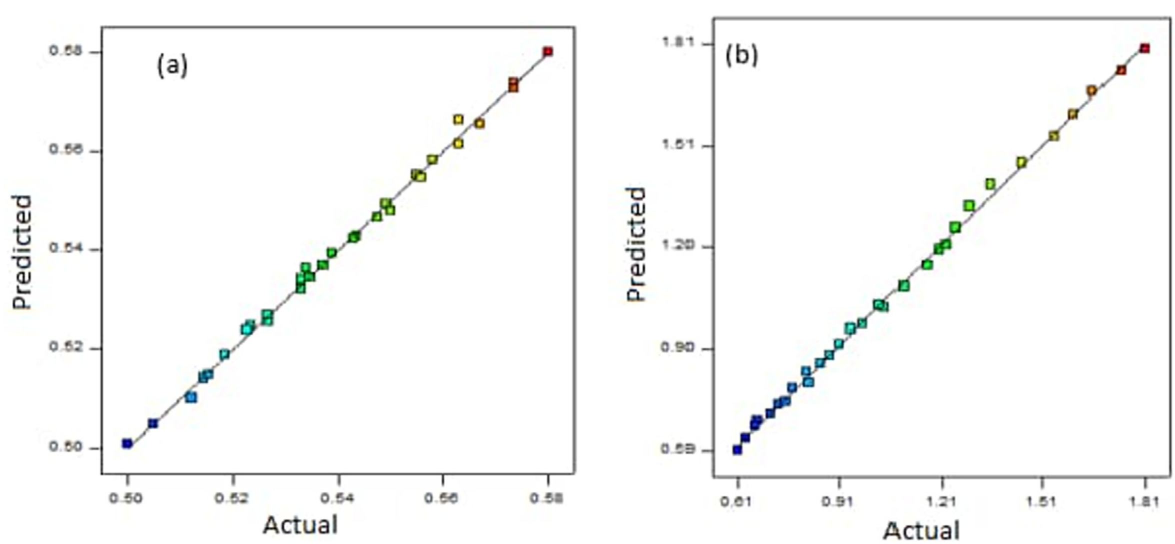

Fig. 4 (a) Predicted thermal conductivity (W/m.K) as well as (b) dynamic viscosity (mPa.s) (x-axis) against the experimental data (y-axis) for bioglcol/water nanofluid.

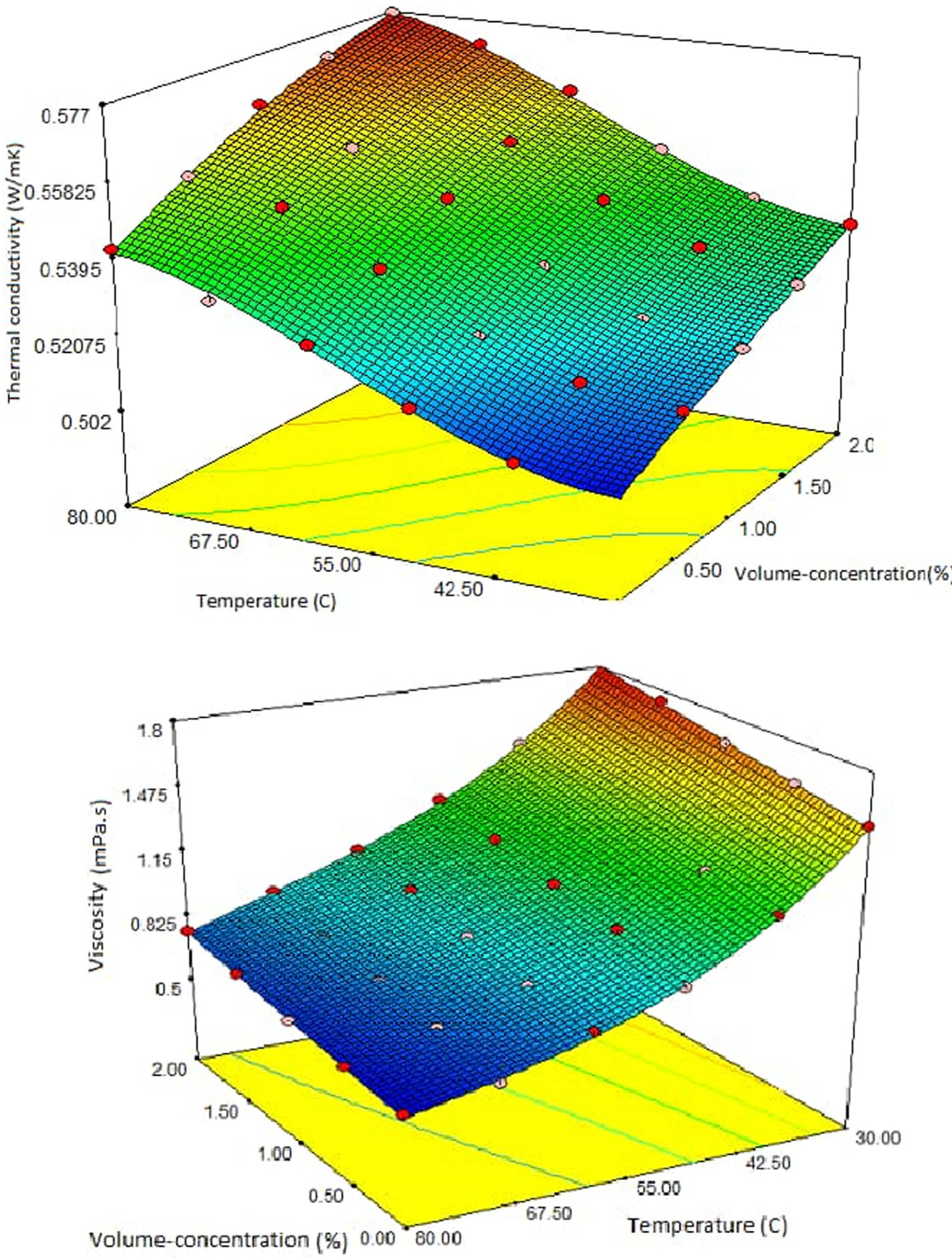

Fig. 5 3D response surface plots as function of temperature as well as nanoparticles volume fraction.

concluded that thermal conductivity, as well as dynamic viscosity, has been estimated accurately with the model due to the higher amount of F-value while the amount of P-value are lower (<0.001). The P-value less than 0.1 means that the model terms is significant. As it can be seen, most of the parameters are significant for both thermal conductivity as well as dynamic viscosity.

The statistical deviation between experimental data and predicted values by the developed model was evaluated by the coefficient of determination (R^2). The value equal to 1 or a number close to one means that the developed model is accurate. The value of R^2 and adjusted R^2 are 0.9943 and 0.9918 for the thermal conductivity and 0.9921 and 0.9902 for the viscosity respectively. The adjusted R^2 is much more reliable than R^2 value due to affecting any bias in the system on its value. In the current study, both adjusted R^2 and R^2 values are almost same indicating the developed model accuracy.

Eqs. (11) and (12) were used for the calculation of predicted values for the thermal conductivity as well as dynamic viscosity. Fig. 4 ((a) and (b)) presents the predicted value by the developed model for the thermal conductivity as well as viscosity vs. experimental data of thermal conductivity and dynamic viscosity of bioglycol/water nanofluid. It was observed that there is a great agreement between the predicted values by

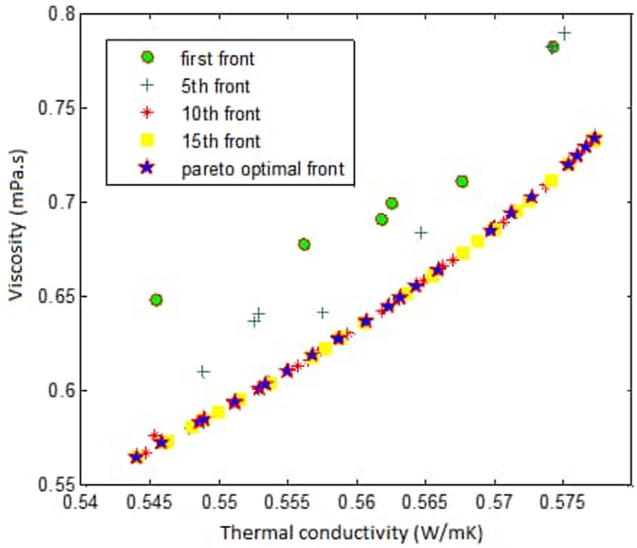

Fig. 6 Thermal conductivity (x-axis) and dynamic viscosity (y-axis) reslut were obtained by NSGA-II.

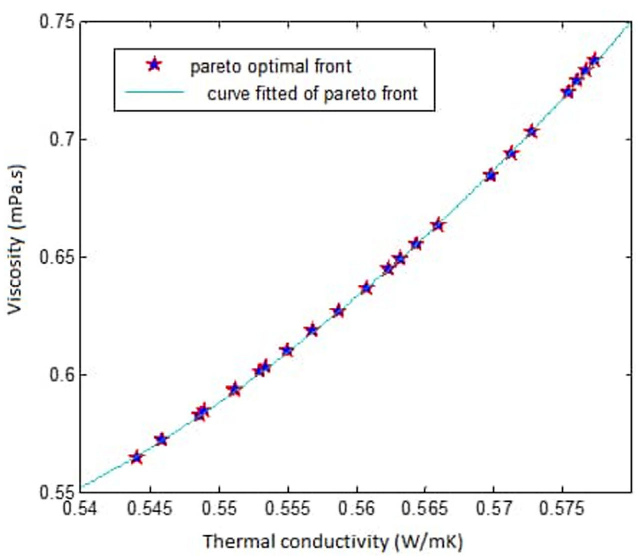

Fig. 7 Pareto optimal front.

the developed model and experimental data. Therefore, it could be concluded that the developed model by response surface method is reliable for the prediction of thermal conductivity and dynamic viscosity values.

Three-dimensional response surface plots that provide the influence of each parameter on the thermal conductivity and viscosity are given in Fig. 5. There is a decrease in viscosity with increasing temperature while the thermal conductivity was increased by increasing temperature for all volume concentrations. The maximum viscosity of 1.814 mPa.s was obtained at temperature and volume concentration of 30 °C and 2% but the minimum viscosity (0.61 mPa.s) was for the solution without nanoparticles and the temperature of 80 °C. In terms of thermal conductivity, the lowest (0.501 W/m.K) and highest (0.576 W/m.K) thermal conductivities were found at temperature and volume concentration of (30 °C and 0%) and (80 °C and 2%) respectively. Furthermore, addition of nanoparticles in the fluid was increased the amount of both thermal conductivity and viscosity. Also, it should be noted that influence of temperature is much more significant than volume fraction on both thermal conductivity and viscosity. Similar findings were obtained in literature in a system with a base fluid of water and cobalt-oxide (ND-Co_3O_4) nanoparticles (Hemmat Esfe et al., 2016).

Table 2 Optimum points obtained by NSGA-II optimization method for bioglycol/water (20–80) nanofluid.

Viscosity (mPa.s)	Thermal conductivity (w/m.K)	Temperature (°C)	Volume Conc. (%)
0.735	0.577	79.901	2.000
0.564	0.544	80.000	0.000
0.568	0.545	79.990	0.047
0.636	0.560	79.950	0.838
0.574	0.546	80.000	0.120
0.664	0.566	79.990	1.178
0.603	0.553	79.990	0.450
0.643	0.561	79.953	0.924
0.611	0.555	80.000	0.560
0.650	0.563	80.000	1.025
0.655	0.564	79.998	1.071
0.670	0.567	80.000	1.269
0.617	0.556	80.000	0.630
0.597	0.552	79.998	0.383
0.695	0.571	80.000	1.543
0.660	0.565	80.000	1.139
0.645	0.562	80.000	0.958
0.701	0.572	79.990	1.615
0.678	0.568	80.000	1.341
0.626	0.558	79.966	0.729
0.709	0.573	79.968	1.710
0.704	0.572	80.000	1.650
0.719	0.575	79.999	1.833
0.578	0.547	79.999	0.159

4.2. NSGA II results

Multi-object optimization was performed on the bioglycol/water nanofluid containing SiO_2 nanoparticles. NSGA II algorithm was implemented by applying different iteration times including first, fifth, tenth, fifteenth, and twentieth and 25 members of population. The optimization results for different iteration times were provided in Fig. 6. The twentieth iteration time is considered as Pareto front. It is seen that the first and fifth fronts are undefeated, and the system is not able to reach stability by applying these fronts. But, the system was achieved stability at the 10th front. The 15th and 20th fronts were also obtained to show this stability.

Fig. 7 presents the Pareto front (20th front) for the two-objective optimization of thermal conductivity and viscosity for the bioglycol/water (20–80) nanofluid containing SiO_2 nanoparticles. The Non-dominated sorting, as well as crowding distance functions, were used to obtain these results. In Pareto front all obtained points are optimum. Also, it should be noted that the points are non-superior to each other. The designer can select each of these points based on the system requirement. In Fig. 7, the horizontal axis is the thermal conductivity and vertical axis is the viscosity. The fitted curve was also obtained for the Pareto front and its second-order equation can be written as follows:

$$\mu_{nf} = 3.4K_{nf}^2 - 0.95K_{nf} - 0.94 \quad (13)$$

Table 2 shows multi-object optimization results for the enhancement of thermal conductivity and minimizing viscosity for bioglycol/water (20–80) nanofluid containing SiO_2 nanoparticles. According to Table 2, it is possible to find what is the system viscosity at optimum operating conditions in terms of thermal conductivity and vice versa. Also, what the needed temperature and volume fraction are for achieving a certain thermal conductivity as well as dynamic viscosity of the system. For example, the system viscosity is 0.564 mPa.s and 0.735 mPa.s for the lowest (0.544 W/m.K) and highest (0.577 W/m.K) thermal conductivities respectively. Furthermore, the optimum condition is obtained at the highest temperature (80 °C) or a temperature close to this temperature.

5. Conclusion

In this study, nanofluid optimization in terms of thermal conductivity as well as dynamic viscosity was performed using response surface method and NSGA-II optimization approach. Firstly, the equations were obtained for the thermal conductivity and dynamic viscosity as function of operating condition using response surface method. Then, NSGA-II optimization approach was used for minimizing viscosity and maximizing thermal conductivity of the nanofluid. The results showed that increasing temperature increases the thermal conductivity, but the viscosity was decreased. There was also an increase in both thermal conductivity as well as dynamic viscosity with increasing the amount SiO_2 nanoparticles volume fraction. The optimal values for the thermal conductivity and dynamic viscosity were found at the maximum temperature in the system and optimum SiO_2 can be selected based on the process requirement.

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.

References

Abdolbaqi, M.K. et al, 2016. Experimental investigation and development of new correlation for thermal conductivity and viscosity of BioGlycol/water based SiO_2 nanofluids. Int. Commun. Heat Mass 77, 54–63.

Abdullah, M.Z., Nasir, F.M., Abdul Majid, M.F.M., 2021. Empirical viscosity modeling for SiO_2 and Al_2O_3 nanofluids using the response surface method. J. Adv. Res. Fluid Mechanics Thermal Sci. 75 (3), 63–72.

Aghahadi, M.H., Niknejadi, M., Toghraie, D., 2019. An experimental study on the rheological behavior of hybrid Tungsten oxide (WO_3)-MWCNTs/engine oil Newtonian nanofluids. J. Mol. Struct. 1197, 497–507.

Ahrar, A.J., Djavareshkian, M.H., 2017. Computational investigation of heat transfer and entropy generation rates of Al_2O_3 nanofluid with Buongiorno's model and using a novel TVD hybrid LB method. J. Mol. Liq. 242, 24–39.

Akhgar, A., Toghraie, D., Sina, N., Afrand, M., 2019. Developing dissimilar artificial neural networks (ANNs) to prediction the thermal conductivity of MWCNT-TiO_2/Water-ethylene glycol hybrid nanofluid. Powder Technol. 355, 602–610.

Akilu, S., Baheta, A.T., Sharma, K.V., 2017. Experimental measurements of thermal conductivity and viscosity of ethylene glycol-based hybrid nanofluid with TiO_2-CuO/C inclusions. J. Mol. Liq. 246, 396–405.

Aydar, A.Y., 2018. Utilization of Response Surface Methodology in Optimization of Extraction of Plant Materials, in: Statistical Approaches With Emphasis on Design of Experiments Applied to Chemical Processes. Intechopen: 3324.

Azmi, W.H., Sharma, K.V., Mamat, R., Anuar, S., 2013. Nanofluid properties for forced convection heat transfer: an overview. J. Mech. Eng. Sci. 4, 397–408.

Choi, S.U.S., Eastman, J.A., 1995. Enhancing thermal conductivity of fluids with nanoparticles. Mater. Sci. 231, 99–105.

Deb, K., Pratap, A., Agarwal, S., Meyarivan, T., 2002. A fast and elitist multiobjective genetic algorithm: NSGA-II. IEEE Trans. Evolut. Comput. 6 (2), 182–197.

Delavari, V., Hashemabadi, S.H., 2014. CFD simulation of heat transfer enhancement of Al_2O_3/water and Al_2O_3/ethylene glycol nanofluids in a car radiator. App. Thermal Eng. 73 (1), 380–390.

Elnaqeeb, T., Animasaun, I.L., Shah, N.A., 2021. Ternary-hybrid nanofluids: significance of suction and dual-stretching on three-dimensional flow of water conveying nanoparticles with various shapes and densities. Zeitschrift für Naturforschung A 76 (3), 231–243.

Faridzadeh, M.R., Toghraie, D.S., Niroomand, A., 2014. Analysis of laminar mixed convestion in an inclined square lid-driven with a nanofluid by using artifical neural network. Heat Transfer Res. 45 (4), 361–390.

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

Hemmat Esfe, M., Abbasian Arani, A.A., Firouzi, M., 2017a. Empirical study and model development of thermal conductivity improvement and assessment of cost and sensitivity of EG-water based SWCNT-ZnO (30%:70%) hybrid nanofluid. J. Mol. Liq. 244, 252–261.

Hemmat Esfe, M., Hajmohammad, H., Moradi, R., Abbasian Arani, A.A., 2017b. Multi-objective optimization of cost and thermal performance of double walled carbon nanotubes/water nanofluids by NSGA-II using response surface method. App. Thermal Eng. 112, 1648–1657.

Hemmat Esfe, M., Hajmohammad, M.H., Razi, P., Ahangar, M.R.H., Arani, A.A.A., 2016. The optimization of viscosity and thermal conductivity in hybrid nanofluids prepared with magnetic nanocomposite of nanodiamond cobalt-oxide (ND-Co_3O_4) using NSGA-II and RSM. Int. Commun. Heat Mass 79, 128–134.

Hemmat Esfe, M. et al, 2017c. Optimization, modeling and accurate prediction of thermal conductivity and dynamic viscosity of stabilized ethylene glycol and water mixture Al_2O_3 nanofluids by NSGA-II using ANN. Int. Commun. Heat Mass 82, 154–160.

Hemmat Esfe, M., Saedodin, S., Wongwises, S., Toghraie, D., 2015. An experimental study on the effect of diameter on thermal conductivity and dynamic viscosity of Fe/water nanofluids. J. Thermal Anal. Calori. 119 (3), 1817–1824.

Huminic, G., Huminic, A., 2012. Application of nanofluids in heat exchangers: A review. Ren. Sustain. Energy Rev. 16 (8), 5625–5638.

Koriko, O.K., Adegbie, K.S., Shah, N.A., Animasaun, I.L. and Olotu, M.A., Numerical solutions of the partial differential equations for investigating the significance of partial slip due to lateral velocity and viscous dissipation: The case of blood-gold Carreau nanofluid and dusty fluid. Num. Meth. Partial Differen. Eq. n/a(n/a).

Kuznetsov, A.V., Nield, D.A., 2010. Natural convective boundary-layer flow of a nanofluid past a vertical plate. Int. J. Thermal Sci. 49 (2), 243–247.

Moradi, A., Toghraie, D., Isfahani, A.H.M., Hosseinian, A., 2019. An experimental study on MWCNT–water nanofluids flow and heat transfer in double-pipe heat exchanger using porous media. J. Thermal Anal. Calori. 137 (5), 1797–1807.

Muhammad, N.M., Che Sidik, N.A., Saat, A., Abdullahi, B., 2021. Effect of nanofluids on heat transfer and pressure drop characteristics of diverging-converging minichannel heat sink. CFD Let. 11 (4), 105–120.

Qin, Y., Darus, A. and Sidik, N., 2014. Numerical analysis on natural convection heat transfer of a heat sink with cylindrical pin fin. J. Adv. Res. Fluid Mech.

Rostami, S., Toghraie, D., Shabani, B., Sina, N., Barnoon, P., 2021. Measurement of the thermal conductivity of MWCNT-CuO/water hybrid nanofluid using artificial neural networks (ANNs). J. Thermal Anal. Calori. 143 (2), 1097–1105.

Ruhani, B., Toghraie, D., Hekmatifar, M., Hadian, M., 2019. Statistical investigation for developing a new model for rheological behavior of ZnO–Ag (50%–50%)/Water hybrid Newtonian nanofluid using experimental data. Physica A: Statist. Mech. its Appl. 525, 741–751.

Saeedi, A.H., Akbari, M., Toghraie, D., 2018. An experimental study on rheological behavior of a nanofluid containing oxide nanoparticle and proposing a new correlation. Physica E: Low-dimensional Sys. Nanostruct. 99, 285–293.

Shah, N.A. et al, 2021. Significance of nanoparticle's radius, heat flux due to concentration gradient, and mass flux due to temperature gradient: The case of Water conveying copper nanoparticles. Sci. Rep. 11 (1), 1882.

Shah, N.A. et al, 2020a. Significance of suction and dual stretching on the dynamics of various hybrid nanofluids: Comparative analysis between type I and type II models. Physica Scripta 95, (9) 095205.

Shah, T.R., Ali, H.M., Janjua, M.M., 2020b. On aqua-based silica (SiO_2–water) nanocoolant: Convective thermal potential and experimental precision evaluation in aluminum tube radiator. Nanomaterials 10 (9), 1736.

Shahsavar, A., Khanmohammadi, S., Toghraie, D., Salihepour, H., 2019. 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 Al_2O_3 nanoparticles. J. Mol. Liq. 276, 850–860.

Sonawane, S. et al, 2011. An experimental investigation of thermo-physical properties and heat transfer performance of Al_2O_3-Aviation Turbine Fuel nanofluids. App. Thermal Eng. 31 (14), 2841–2849.

Sonawane, S.S., Juwar, V., 2016. Optimization of conditions for an enhancement of thermal conductivity and minimization of viscosity of ethylene glycol based Fe_3O_4 nanofluid. App. Thermal Eng. 109, 121–129.

Toghraie, D., Sina, N., Jolfaei, N.A., Hajian, M., Afrand, M., 2019. Designing an Artificial Neural Network (ANN) to predict the viscosity of Silver/Ethylene glycol nanofluid at different temperatures and volume fraction of nanoparticles. Physica A: Statist. Mech. Appl. 534, 122142.

Wang, Y.-Z., Li, F.-M., Kishimoto, K., 2010. Scale effects on thermal buckling properties of carbon nanotube. Physics Let. A 374 (48), 4890–4893.

Yusoff, Y., Ngadiman, M.S., Zain, A.M., 2011. Overview of NSGA-II for optimizing machining process parameters. Procedia Eng. 15, 3978–3983.

Zadeh, A.D., Toghraie, D., 2018. Experimental investigation for developing a new model for the dynamic viscosity of silver/ethylene glycol nanofluid at different temperatures and solid volume fractions. J. Thermal Anal. Calorim. 131 (2), 1449–1461.

Zhang, Y., Hong, M., Li, J., Ren, J., Man, Y., 2021. Energy system optimization model for tissue papermaking process. Comput. Chem. Eng. 146, 107220.

Zou, L., 2021. Design of reactive power optimization control for electromechanical system based on fuzzy particle swarm optimization algorithm. Microproc. Microsys. 82, 103865.

Żyła, G., Fal, J., 2017. Viscosity, thermal and electrical conductivity of silicon dioxide–ethylene glycol transparent nanofluids: An experimental studies. Thermochimica Acta 650, 106–113.