East European Journal of Physics. 3. 479-489 (2023)
DOI:10.26565/2312-4334-2023-3-54 ISSN 2312-4334

PREDICTION OF VISCOSITY OF COBALT FERRITE/SAE50 ENGINE OIL BASED NANOFLUIDS USING WELL TRAINED ARTIFICIAL NEUTRAL NETWORK (ANN) AND RESPONSE SURFACE METHODOLOGY (RSM)†

Malik Muhammad Hafeezullah[a,c], Abdul Rafay[b], Ghulam Mustafa[d], Muhammad Khalid[b]*, Zubair Ahmed Kalhoro[c], Abdul Wasim Shaikh[a], Ahmed Ali Rajput[b]

[a]*Institute of Computer Science and Mathematics, University of Sindh, Jamshoro, Pakistan*
[b]*Department of Physics, University of Karachi, 75270, Karachi, Pakistan*
[c]*Department of Mathematics, Balochistan University of Information Technology, Engineering and Management Sciences, Quetta, Pakistan*
[d]*Department of Physics, NED University of Engineering and Technology, 75270, Karachi, Pakistan*
**Corresponding Author e-mail: mkhalid@uok.edu.pk*
Received May 16, 2023; revised July 1, 2023; accepted July 6, 2023

Heat transmission by ordinary fluids such as pure water, oil, and ethylene glycol is inefficient due to their low viscosity. To boost the efficiency of conventional fluids, very small percent of nanoparticles are added to the base fluids to prepare nanofluid. The impact of changing in viscosity can be used to investigate the rheological properties of nanofluids. In this paper, ($CoFe_2O_4$)/engine oil based nanofluids were prepared using two steps standard methodology. In first step, $CoFe_2O_4$ (CF) were synthesized using the sol-gel wet chemical process. The crystalline structure and morphology were confirmed using X-Ray diffraction analysis (XRD) and scanning electron microscopy (SEM), respectively. In second step, the standard procedure was adapted by taking several solid volume fractions of CF as Ø = 0, 0.25, 0.50, 0.75, and 1.0 %. Such percent of concentrations were dispersed in appropriate volume of engine oil using the ultrasonication for 5 h. After date, the viscosity of prepared five different nanofluids were determined at temperatures ranging from 40 to 80 °C. According to the findings, the viscosity of nanofluids (μ_{nf}) decreased as temperature increased while increased when the volume percentage of nanofluids Ø raised. Furthermore, total 25 experimental observations were considered to predict viscosity using an artificial neural network (ANN) and response surface methodology (RSM). The algorithm for building the ideal ANN architecture has been recommended in order to predict the fluid velocity of the CF/SAE-50 oil based nanofluid using MATLAB software. In order to determine the validation of the predicted model, the mean square error (MSE) was calculated as 0.0136 which corresponds to the predicted data is well correlated with experimental data.
Keywords: *Cobalt Ferrite; Nanofluids; Viscosity; Solid volume fraction; ANN; RSM*
PACS: 47.63.-b, 61.46.+w, 07.05.Mh, 05.40.Jc, 66.20.Ej

1. INTRODUCTION

Nanofluid is a form of fluid formed by dispersing nano-sized particles in a base fluid [1]. These nanofluids have gotten a lot of interest in the last few decades for their applications in microelectronics, transportation, solar, nuclear, and space technology [2].Base fluids such as motor oil, water, and ethylene glycol were commonly employed as heat transporting fluids in a variety of industries [3]. By distributing nanoparticles in a normal fluid such as water, motor oil, and ethylene glycol, high heat conductive nanofluids can be formed, according to Choi [4]. The most important attribute of a nanofluid is its viscosity, which is related with heat transfer. It is obvious that when the volume percentage of nanoparticles increases, convective heat transmission increases [5]. As a result, accurate numbers for nanofluid viscosity are critical for industrial nanofluid demand [6].

Einstein created analytical methods for forecasting a mixture's viscosity in 1906, Brinkman in 1952, and Batchelor in 1977, but those models, which are based on the colloidal theory and contain particles on the order of micrometre, failed to predict the viscosity of the mixture numerous times. As a result, a new model based on nanofluid viscosity has been proposed. The majority of them were based on nanoparticle interfacial layers [7] and Brownian nanofluids nanoparticles in ordinary liquids [8]. Brownian motion has been discovered to be the cause of additional energy transmission of nano particles. Convection explains the relative mobility between nanoparticles and based fluids, according to Jang and Choi's first model, which is based on Brownian motion. Ravi Prasher, on the other hand, demonstrated that Choi and Jang's correlation is inaccurate, and he produced a new viscosity of nanofluid correlation [9]. Masoumi et al. construct an enhanced correlation [10] for nanofluid viscosity using the Ravi Prasher Correlation [11]. Yang et al. found a temperature influence on the viscosity of nanofluids. They experimented using graphene as a nanomaterial. They discovered that when temperature rises, viscosity decreases [12]. Chen et al. investigated the similar impact of MWCNT-distilled water nanofluid at temperatures ranging from 278 K to 338 K and discovered that beyond 338 K, the viscosity ratio increases dramatically [13].

He and colleagues observed that the viscosity of nanofluid increased with particle size. However, Lu and Fan observed that as particle radius grows, so does the viscosity of the nanofluid decreases [14, 15]. Chevalier et al. evaluated

† ***Cite as:*** M.M. Hafeezullah, A. Rafay, G. Mustafa, M. Khalid, Z.A. Kalhoro, A.W. Shaikh, A.A. Rajput, East Eur. J. Phys. 3, 479 (2023), https://doi.org/10.26565/2312-4334-2023-3-54

the viscosity of SiO2-Ethanol nanofluid for particle sizes and discovered that the viscosity increases as the diameter of the nanoparticles decreases [16]. According to [17] Chevalier et al. experimentally investigated that viscosity increases abnormally with increasing volume concentrations. The viscosity of nanofluid grows as the volume concentration increases, after the volume concentration of 0.4%, according to Lu and Fan. Chen et al. discovered that viscosity increases as the volume concentration increases [18]. According to Mahbubul et al. no correlation can estimate viscosity values across a wide range of particle volume concentrations [19].

Using various modelling tools, some researchers anticipated the rheological behavior of nanofluid [20]

To synthesize and assess nanofluid thermophysical characteristics such as viscosity [21] (Fig.1), special equipment and experiments, as well as a significant amount of time and money, are required [22].

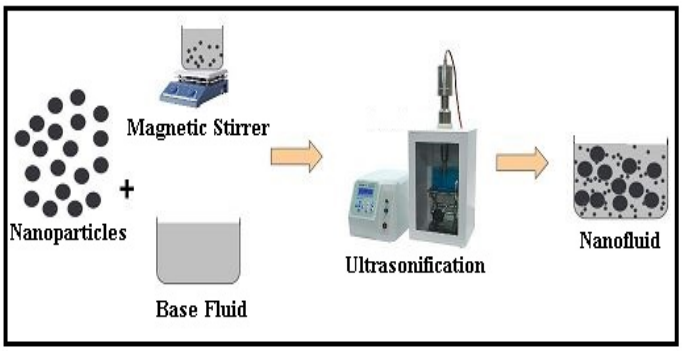

Figure 1. Special apparatus for the preparation of nanofluids

There are numerous research studies that may be utilized to determine the viscosity of nanofluids. Hajir-Karimi et al. investigated the viscosities of several nanoparticles in the temperature range 238.15–343.15 K, using a total number of eight nanoparticles, with a nanoparticle volume fraction of up to 9.4%. An effective and precise artificial neural network based on genetic algorithm (GA) is modelled for forecasting nanofluid viscosity using computational intelligence approaches. To optimize the neural network variables, the genetic algorithm (GA) is applied. As input data for computational intelligence models, they employed nanofluid temperature, nanoparticle size, nanoparticle percentage and nanofluid density. The nanofluid viscosity was the resulting data. The findings demonstrate that the GA-NN model matches the actual data effectively, with an absolute deviation of 2.48 % and a high degree of correlation value (R = 0.98).[23]. Majid Gholizadeh et al. properly calculated the viscosity of thermodynamic nanofluids using a robust artificial intelligence technique known as random forest (RF). Temperature, solid volume percentage, base fluid viscosity, nanoparticle size, and nanoparticle density were used to build the model. In addition, 2890 data points were gathered. They utilised (R = 0.989, RMSE = 0.139, MAPE = 4.758 %) rather than the MLP (R = 0.915, RMSE = 0.377, MPE = 16.194 %) and the SVR (R = 0.941, RMSE = 0.315, MAPE = 7.895 %) for model accuracy. They produced an effective model based on comparative findings with other approaches [24]. Praveen Kanti et al. used a modern computational intelligence strategy, ANN and MGGP, to enhance experimentally recorded dynamic viscosity data of nanofluids. This study looked at the dynamic viscosity of a water-based stable fly-ash nanofluid and a fly ash–Cu (80-20 % by volume) hybrid nanofluid at temperatures ranging from 30 to 60°C. The viscosity of flue-ash nanofluid is determined utilizing MGGP modeling (R = 0.99988, RMSE = 0.0019, and MAPE = 0.25 %). Furthermore, experiment also showed that the MGGP approach excels at predicting flue ash-Cu/Water hybrid nanofluid viscosity (R = 0.9975, RMSE = 0.0063, and MAPE = 0.664 %) [25]. Abdullah et al. examined the viscosity of MWCNT-COOH nanoparticles in water at temperatures ranging from 20 to 50° C and solid volume fractions ranging from 0 to 0.2%. As a result of the experimental results, the unique connection that predicts the relative thermophysical properties of the nanofluids was established. An adaptive neuro-fuzzy inference system (ANFIS) and the finest artificial neural network (ANN) were built in addition to nonlinear regression for the least prediction error. 120 experimental measurements were submitted to the model. Several theoretical models, predicted outcomes, and experimental findings were all compared. ANN has an RMSE of 0.46618, but ANFIS has an RMSE of 0.49062, and the mean absolute percentage error (MAPE) of ANN and ANFIS is 0.00023 and 0.00047, respectively [26]. To predict the viscosity of nanoparticles, Ahmedi et. al. used optimization techniques to simulate the fluid viscosity of silver (Ag)-water nanofluid: multivariable polynomial regression (MPR), artificial neural network–multilayer perceptron (ANN-MLP), and multivariate adaptive regression splines (MARS). Size of the particles, temperature, and silver nanoparticle concentration are the most essential input elements examined in the modelling approach. The ANN-MLP, MARS, and MPR techniques have R^2 values of 0.9998, 0.9997, and 0.9996, respectively.[27]

By forecasting thermophysical qualities, scholars utilized artificial neural network simulation to perform their researches by the least amount of money and time feasible. A summary regarding the various authors have done the work using the nanofluids with different mathematical model are shown in Table 1.

In their investigation the artificial neural network model employed by Baranitharan et al. is presented schematically in (Fig. 2). An artificial neural network (ANN) is a computing approach that understands the relationship between input and

output by using neurons and their connections. Input neurons send data to buried layer neurons for processing. The data is then sent from the hidden neurons to the output neurons for processing. The letters "w" and "b" in this image reflect the amount of weight and bias, respectively (Fig. 2).

Table 1. Summary of the researches conducting by ANN, MLP and RSM using various nanofluids

Scholar	Nanofluid	Technique	Objective
Bahirai et al. [30]	Several Nanofluids (analysis)	ANN and hybrid Al algorithm	Nanofluids thermal characteristics.
Zhao et al. [31]	Several Nanofluids (analysis)	ANN	Predicting the viscosity of a substance in order to use it in a radiator.
Vakili et al. [32]	Water based grapheme.	MLP-genetic algorithm	Viscosity
Vakili et al. [33]	Water based CNT.	Levenberg–Marquardt algorithm	Thermal properties
Heideri et al.[34]	Al_20Si0_2 and CuO nanoparticles dispersed in water.	ANN	Viscosity
Alirezai et al. [35]	Multiwall carbon nanotube.	MLP	Dynamic Viscosity
Esfe et.al. [36]	Oil based hybrid nanofluid.	RSM	Viscosity of nanoparticles-based oil.
Esfe et.al [37]	MgO-MWCNT (75–25%)/10W40	RSM	Thermophysical properties
Esfe et al. [38]	Co_3O_4/EG (40/60) aqueous nanofluid.	RSM	Optimization of Viscosity.
Esfe et.al.[39]	CNT nanofluids.		
Maqsood et.al.[40]	Multi-walled CNT nanofluids.	ANN and RSM	Thermophysical properties.
Esfe et al.[41]	Water based nanofluids.	ANN and RSM	Thermophysical properties.

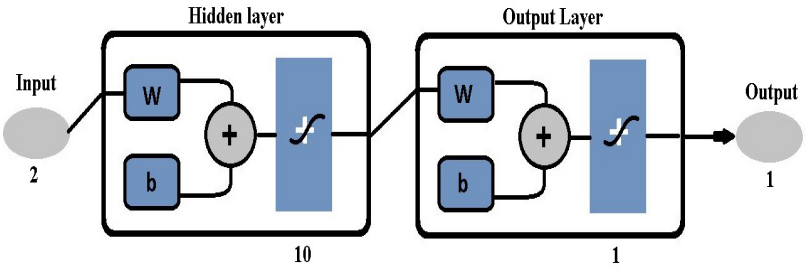

Figure 2. A schematic diagram of an artificial neural network

Many models for determining effective viscosity values have been established in the past. Some researchers, such as Einstein [42] provided a theoretical model for forecasting nanofluid relative viscosity. When SVF is less than 0.20 percent, the Einstein model (Eq.1) yields more accurate findings, and it is based on the notion that solid suspended particles in the base fluid are spherical:

$$\mu_{nf} = (1 + 2.5\emptyset)\mu_{bf}. \quad (1)$$

Where 'μ' stands for viscosity, 'φ' for SVF, and the abbreviations "nf" and "bf" stand for nanofluid and base fluid, respectively. Wang et al. [21] also gave the model for estimating relative viscosity shown below

$$\mu_{nf} = (1 + 7.3\emptyset + 123\emptyset^2)\mu_{bf}. \quad (2)$$

Also, H. De Bruijin[43] proposed a model to predict the relative viscosity of nanofluids containing spherical nanoparticles:

$$\mu_{nf} = (1 - 2.5\emptyset + 1.552\emptyset^2)\mu_{bf}. \quad (3)$$

On the other hand, current theoretical models fail to detect the viscosity of nanoparticles. Nanofluids were predicted by Wang et al (1999) as a function of nanoparticle kind, particle size, volume percent, and temperature. A laboratory-based study is presented in this paper to analyze the viscosity of a Cobalt Ferrite (40-80°C)/SAE 50 Engine oil based nanofluid. Temperature and solid volume fraction (SVF) were employed as inputs in an ANN with two related hidden layers, and viscosity was used as an output. The ANN findings and the experimental results are likewise at variance. After this, the trial outcomes were compared to the RSM model and the ANN approach.

2. METHODOLOGY

2.1. X-Ray diffraction and Scanning electron Microscopy

To do this, the sol-gel method [44] was used to create cobalt ferrite nanoparticles ($CoFe_2O_4$). The structure was confirmed using X-Ray diffraction analysis (Fig.3) [45]. The composition of prepared Cobalt spinel ferrite is confirmed by the EDX [46]. Using the Scherer formula (eq.4), the particle size was measured to be 15 nm. The form and size of the particles were determined using scanning electron microscopy and the grain size of the particles is analyzed by histogram (Fig.4) [47].

$$D = \frac{0.94\,\lambda}{\beta \cos\theta}. \tag{4}$$

where “β” is the full width and half maximum, “λ" is the X-ray wavelength, and "θ" is the angle suspended.

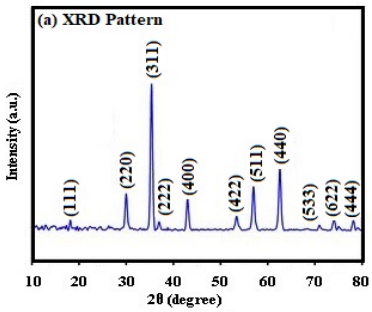

Figure 3. XRD pattern of cobalt spinel ferrite nanoparticles

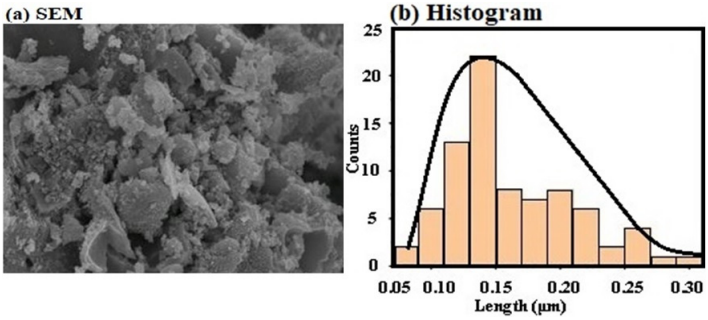

Figure 4. (a) SEM image and (b) grain size distribution of cobalt spinel ferrite nanoparticles

2.2. Surface Modification

To begin, mill the cobalt ferric oxide nanoparticles and then make an 80 ml orthoxylene in a 20 ml oleic acid solution volume by volume ratio. The Stirring was done of the prepared solution for a few hours to achieve a homogeneous condition. On the other hand, 2 gm of milled particles, were added to 98 gm of orthoxylene, stirred continuously for surface modification, and placed on a heated plate. The modified particles are filtered away, and then particles are added to the oleic acid solution.

2.3. Preparation of Nanofluids

The dried powder is then mixed with SAE 50 engine oil in predetermined proportions to make different samples with varied solid volume fractions, such as 0, 0.25, 0.50, 0.75, and 1.0% solid volume fraction. To make the concentrated solutions that are necessary, the weight of solid Cobalt nanoparticles and the oil SAE 50 is specified in (Table 2), which were calculated by using the relation given in **(Eq. 5).** Stir all the solution samples to obtain the stability of cobalt-based nanoparticles in engine oil. The experimental work was summarized in a flow chart that was supplied in order to acquire the greatest understanding of it (Fig.5).

$$\emptyset = \frac{m_{NP}}{m_{NP}+m_{oil}} \times 100. \tag{5}$$

Table 2. The composition weights for the preparation of different volume fractions of sample

Number of samples	Solid volume fraction (%)	Mass of cobalt nanoparticles (g)	Mass of oil (g)
1	0.00	0.000	49.83
2	0.25	0.137	49.69
3	0.50	0.275	49.55
4	0.75	0.4125	49.005
5	1.00	0.550	49.77

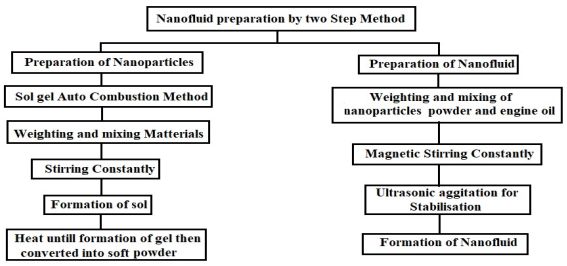

Figure 5. Flow chart to represents the preparation of cobalt spinel ferrite-based engine oil based nanofluids in two steps methods

Finally, using the free-falling technique, the viscosity of the prepared samples is determined experimentally by using relation given in **(Eq.6).**

$$\eta = KT(\rho_1 - \rho_2). \tag{6}$$

where "k" is the proportionality constant, "T" is the average time taken by the free fall body through the fluid between two fixed points, and "ρ_1", "ρ_2" are the densities of ball and sample fluid respectively. The experimental viscosity is found to be correlated with the input parameters temperature and solid volume percent in (Fig. 6).

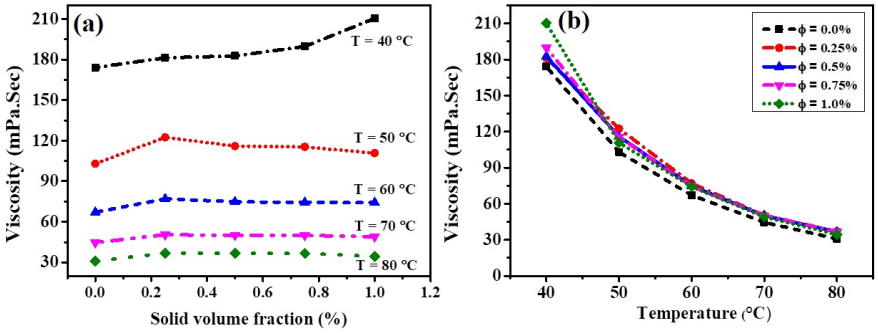

Figure 6. Experimental values of viscosity using various volume fractions of cobalt ferrites based nanofluids with effect of (a) temperature and (b) solid volume fraction

2.4 Artificial Neural Network (ANN)

One of the technologies used to study human brain activity is artificial neural networks. Many numerical methods inspired by the human brain have been presented in the subject of Artificial Neural Networks. Many industries have used the models provided to tackle a wide range of scientific and practical issues. There are many other ANN architectures, such as the well-known multilayer perceptron (MLP). This strategy was used to develop the present neural network. Many training approaches may be employed to train the ANN, and one of the most prevalent (the Levenberg-Marquardt approach) is used in this work.

In systems with various input parameters, neural networks are also utilized to anticipate output data. The viscosity of Cobalt Ferrite/SAE 50 Engine oil based nanofluids was investigated in this research using two input parameters which are SVF and Temperature. The ANN approach predicts output data by obtaining the problem's input parameters and training neurons based on a number of inputs and calculating their weight and bias; errors are gathered during the testing and validation stages. The most optimal ANN structure is shown in (Fig. 7). The ideal structure contains two inputs, nine neurons in the first hidden layer, five neurons in the second hidden layer, and one output.

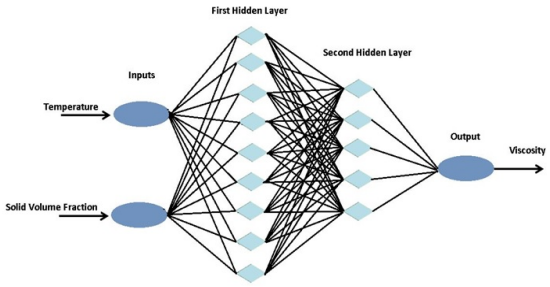

Figure 7. The design of the most ideal ANN network

The formulas in Eq. 7, 8 and 9 may be used to compute the most efficient number of hidden layers, neuron counts in each layer, neuron weighting, and the optimal combination of transfer functions.

$$\mathrm{MSE} = \frac{1}{N}\sum_{i=1}^{n}\left(T_{ij} - \mathrm{P_{ij}}\right)^2, \tag{7}$$

$$\mathrm{MAE} = \frac{1}{\mathrm{N}}\sum_{i=1}^{n}\left(\mathrm{T_{ij}} - \mathrm{P_{ij}}\right), \tag{8}$$

$$\mathrm{R^2} = \frac{\sum_{i=1}^{\mathrm{N}}(\mathrm{T_{ij}}-\mathrm{T})^2 - (\mathrm{P_{ij}}-\mathrm{P})^2}{\sum_{i=1}^{\mathrm{N}}(\mathrm{T_{ij}}-\mathrm{T})^2}. \tag{9}$$

where T_{ij} and P_{ij} are the expected and estimated values, and the total number of observations is N.

2.5. Mathematical Correlation Model

The exact viscosity of nanofluid cannot be predicted using theoretical models. As a result of analyzing the experimental data and applying the RSM method, a new quadratic equation for predicting viscosity has been constructed (Eq. 10). Experimental data was used to predict viscosity changes when SVF and temperature varied, as well as curve

fitting rates. The correlation coefficient R^2 of this equation is 0.9663, indicating that the prediction is correct based on the experimental results.

$$\mu = 8.62 - 3.95T + 0.3412\emptyset - 0.2504T\emptyset + 1.25T^2 - 0.1313\emptyset^2 + 1.25T^2 - 0.1313\emptyset^2 \quad (10)$$

The results acquired by analysis variance indicate the correctness of the expected model using response surface technique. In the recommended equation (Eq. 7), the relevance of each variable is shown in (Tables 4 and 5). The parameter's relevance in the equation is high if the p-value is less than 0.05; if the p-value is more than 0.05, the parameter's importance in the equation is low, and the parameter's effect can be removed from the equation.

Table 4. ANOVA for nanofluid viscosity

Source	Square sum	Df	Square Mean	F-value	p-value
Design	99.500	5	9.90	576.52	<0.0001 **Significant**
A-TEMP	93.840	1	93.84	2718.71	< 0.0001
B-SVF	0.6983	1	0.6983	20.23	0.0028
AB	0.2508	1	0.2508	7.27	0.0308
A^2	4.320	1	4.32	125.24	< 0.0001
B^2	0.0476	1	0.0476	125.24	0.2785
Residual	0.2416	7	0.0345	1.38	
Cor Total	99.740	12			

Table 5. The present numerical model's evaluation of variance

Std. Dev.	0.1858	**R^2**	0.9976
Mean	9.14	**Adjusted R^2**	0.9958
C.V. %	2.03	**Predicted R^2**	0.9767
		Adeq Precision	68.0720

Fig. 8 (a) shows the excellent agreement between the experimental and predicted daya using the RSM developed model which reveal the accuracy of the developed model.

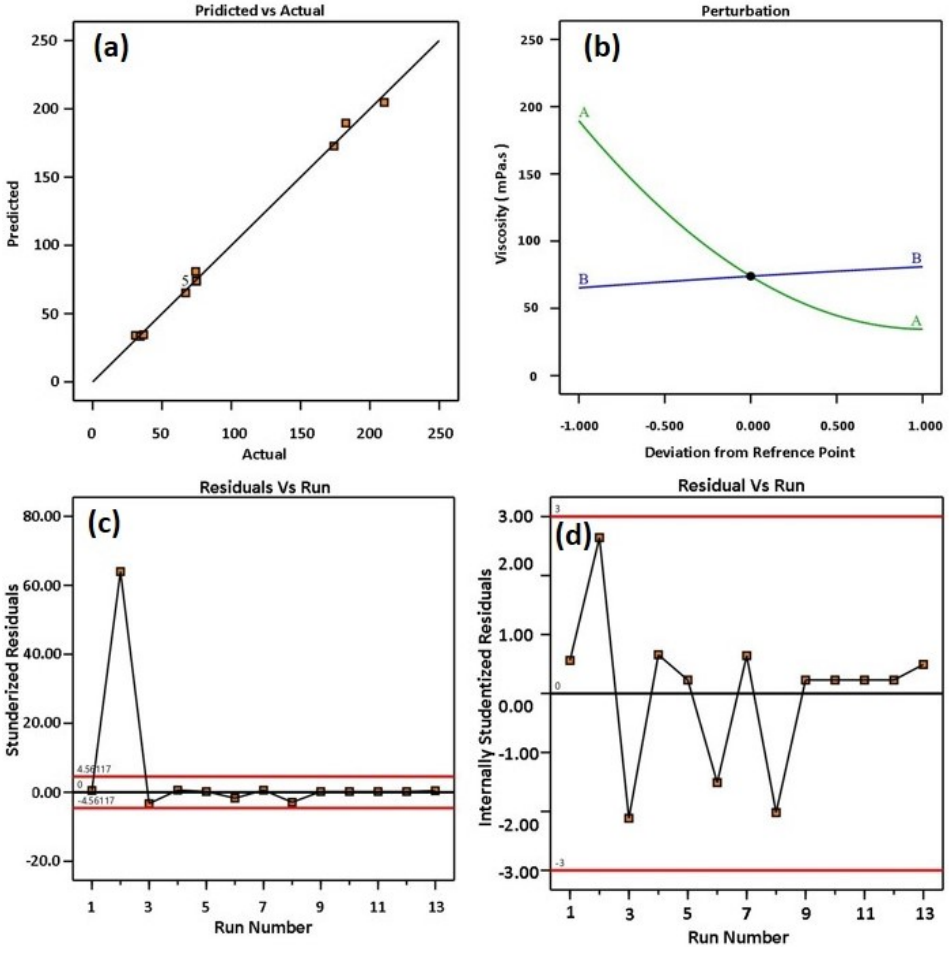

Figure 8. Experimental validation with RSM results

Fig. 8 (b) represent the graph between the deviation bwteen the reference point and viscosity. This graph is provide the central point (O) of the deviation which ultemetialy gives the overall influence of all process factors on the response function. The contrast effect of two factors such as solid volume fraction and temperature at the referece point provides the operating range's of the perturbation presented graph. The residual graph based on run number nad projected data can be seen in Fig. 8 (c). Only one data points at runs 2 is out from the other data points in between the red lines which is clear evidence the developed theoretical model has a significant and well adapted to predict the viscosity of the nanofluids. No abnormality in the random distribution of residuals can be seen in Fig. 8 (d)

3. RESULTS AND DISCUSSION

3.1. ANN Accuracy Evaluation

The coefficients were obtained using the Levenberg-Marquardt learning procedures, which were utilized to train the network. In this case, the neural network repeats the prediction cycle, altering the weight and bias as well as the training stage to achieve the desired error rates. In this study, the error value is fully provided in (Table 3), which shows the relationship between eq. 7 and 9. The fact that R^2 is so near to 1 (0.9999) demonstrates the constructed neural network's exceptional accuracy (Fig. 9).

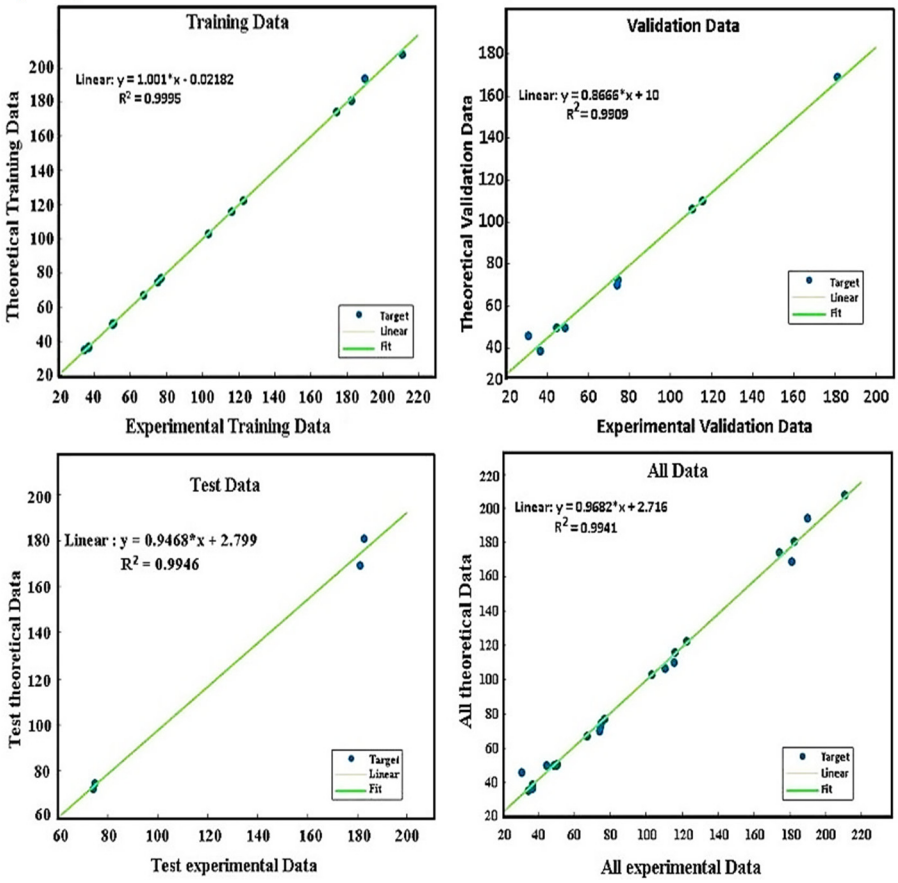

Figure 9. Confirmation of ANN results with experimental results

Table 3. The results of an ANN model to measure viscosity of cobalt ferrite / SAE 50 Engine Oil

Train Step accuracy analysis	
3.896 x 10^{-6}	MSE
0.037611	MAE
0.9995	R^2
Test step accuracy	
0.3122	MSE
4.028138	MAE
0.9946	R^2
Total accuracy analysis by ANN predicted topology	
0.9941	R^2

The experimental data is compared to the ANN's predicted data in the Fig. 10. In this comparison, the trial, train, and total network data were compared. The ANN's projected values are well-trained, resulting in appropriate test data, validation, and total data correctness, as shown in this diagram.

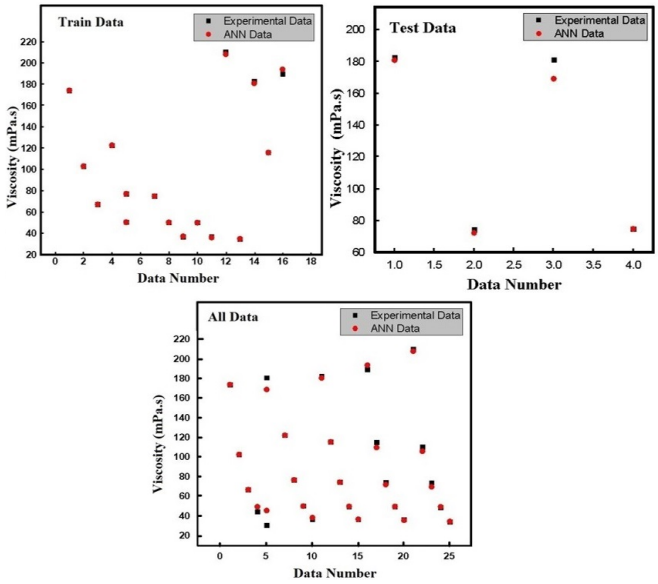

Figure 10. The correlation of intended ANN outputs with the experimental set of data during training, testing, and all data phases

3.2 Prediction Accuracy of Artificial Neural network against Mathematical Model

The validation of the ANN and RSM techniques in estimating viscosity at different temperature and solid volume fractions is compared in this section. The ANN forecast, on the other side, closely matches the patterns of experimental results. It can be concluded that the prediction of ANN method is better than the RSM prediction with experimental results. The outcomes of the ANN and RSM are compared in (Fig.11)

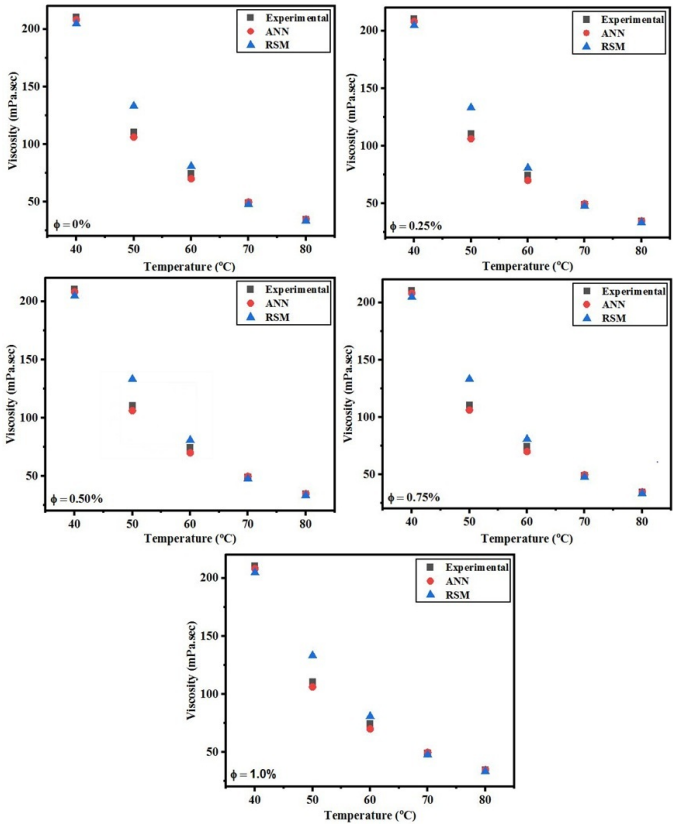

Figure 11. RSM and ANN predictions of viscosity compared with experimental values

The relationship average absolute percent deviation (AAD) is used to compare expected and observed data in (Eq.11).

$$\text{AAD\%} = \frac{1}{N}\sum_{i=1}^{n}\frac{\mu\,\text{exp}-\mu\ \text{pre}}{\mu\,\text{exp}}\ X\ 100. \tag{11}$$

Eq. 11 specifies the number of experiments (N), experimental calculated viscosity (exp), and expected viscosity (pre). Calculations revealed that the AAD% is 1.7112%, indicating that the results are accurate. Fig. 12 (a) depicts the experimental data that back up ANN predictions. Maximum margin of deviation (MOD) percent reported (-7% and 9%). The symbol placement on the bisector line also indicates whether the experimental data matches the neural network's predicted outcomes. Fig.12 (b) depicts the experimental data that back up RSM predictions, that's confirmed the RSM prediction is correlated with the experimental values. Maximum margin of deviation (MOD) percent reported (-8% and 10%) for RSM. The comparison of MOD% for ANN was observed less than the MOD% observed in RSM, indicates that the ANN model much better than RSM.

Another method for comparing experimental data with data produced from the suggested correlation is to use Eq.12 to calculate the percentage of data deviation from experimental data.

$$\text{MOD\%} = 1 - \frac{\mu\text{Pred}}{\mu\text{Exp}}. \tag{12}$$

Another comparison chart for nf versus temperature and Solid volume fraction is shown in 3D space to evaluate the trained ANN method for estimating the viscosity μ_{nf}. (Fig. 13a). Fig. 13b depicts another 3D space for estimating viscosity using the RSM model. We may deduce from the diagram that a well-trained ANN can be utilized to simulate viscosity. Furthermore, solid volume fraction has a larger impact on viscosity than temperature, which has a smaller impact on the output values.

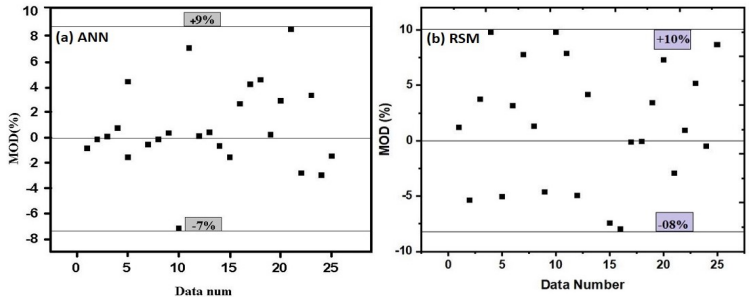

Figure 12. Margin of deviation for RSM and ANN projected data compared with experimental data

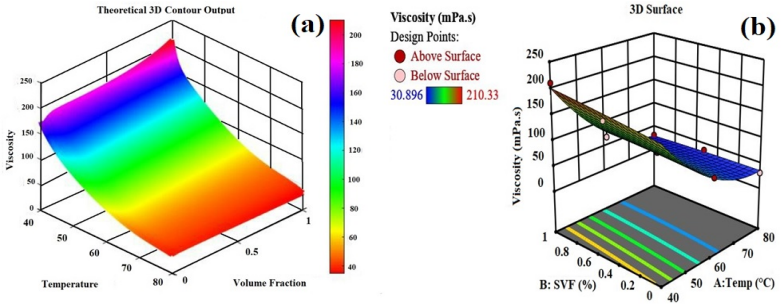

Figure 13. 3D graph of viscosity against temperature and SVF using the (a) ANN and (b) RSM methodology

4. CONCLUSION

Under this research, 25 experimental results for the viscosity of cobalt ferrite/SAE 50 engine oil based nanofluids in all temperature ranges from 40, 50, 60, 70, and 80°C, at SVFs of 0, 0.25, 0.50, 0.75, and 1.0%, were tried to compare with the simulated values by the neural network, with their insignificant difference (-7%, +9%) representing a precise model for forecasting nanofluid viscosity. The sample's viscosity is significantly influenced by the parameters of the nanoparticle's temperature and solid volume fraction (SVF), therefore an increase in SVF across the range results in a notable increase in viscosity. For all SVF ranges, rising temperature will result in a decrease in dynamic viscosity. From a collection of 25 ANN data, the best optimum structure was chosen after analysis by two hidden layers that each had 9 and 5 neurons. For the first and second hidden layers, respectively, logsig and tansig are the ideal transfer functions. Another appropriate technique to use the RSM method was to build a mathematical relationship between the input parameters temperature and solid volume percentage. The correlation model's accuracy ($R^2 = 0.9663$) was lower than the neural network model's ($R^2 = 0.9941$). Furthermore, the experimental findings were compared to the data collected from the RSM and neural network data. The gap between experimental and anticipated model data is quite small, with the greatest difference occurring at temperature 50°C and SVF of 1.0. The MOD% for ANN was observed to be lower than the MOD% for RSM suggests that ANN is a much better model than RSM for predicting the viscosity.

Acknowledgments

The authors extend their appreciation to the Researchers Supporting grant number (DRG-2021-22/190), University of Karachi, Karachi, Pakistan

Data Availability Statement

The datasets generated or analyzed during the current study are available from the corresponding author on reasonable request.

Conflict of interest

The authors declare that they have no conflict of interest

REFERENCES

[1] A. Kasaeian, A.T. Eshghi, and M. Sameti, "A review on the applications of nanofluids in solar energy systems," Renewable and Sustainable Energy Reviews, **43**, 584-598 (2015). https://doi.org/10.1016/j.rser.2014.11.020
[2] I. Nkurikiyimfura, Y. Wang, and Z. Pan, "Heat transfer enhancement by magnetic nanofluids - a review," Renewable and Sustainable Energy Reviews, **21**, 548-561 (2013). https://doi.org/10.1016/j.rser.2012.12.039
[3] S. Angayarkanni, and J. Philip, "Review on thermal properties of nanofluids: Recent developments," Advances in Colloid and Interface Science, **225**: 146-176. 2015. https://doi.org/10.1016/j.cis.2015.08.014
[4] M. Raja, R. Vijayan, P. Dineshkumar, and M. Venkatesan, "Review on nanofluids characterization, heat transfer characteristics and applications," Renewable and Sustainable Energy Reviews, **64**, 163-173 (2016). https://doi.org/10.1016/j.rser.2016.05.079
[5] S.K. Das, S.U. Choi, and H.E. Patel, "Heat transfer in nanofluids—a review," Heat transfer engineering, **27**(10), 3-19 (2006). https://doi.org/10.1080/01457630600904593
[6] T. Maré, S. Halelfadl, S. Van Vaerenbergh, and P. Estellé, "Unexpected sharp peak in thermal conductivity of carbon nanotubes water-based nanofluids," International Communications in Heat and Mass Transfer, **66**, 80-83 (2015). https://doi.org/10.1016/j.icheatmasstransfer.2015.05.013
[7] Y.L. Zhai, G.D. Xia, X.F. Liu, and Y.F. Li, "Heat transfer enhancement of Al_2O_3-H_2O nanofluids flowing through a micro heat sink with complex structure," **66**, 158-166 (2015). http://dx.doi.org/10.1016%2Fj.icheatmasstransfer.2015.05.025
[8] M.A. Sheremet, I. Pop, and M.M. Rahman, "Three-dimensional natural convection in a porous enclosure filled with a nanofluid using Buongiorno's mathematical model," International Journal of Heat and Mass Transfer, **82**, 396-405 (2015). https://doi.org/10.1016/j.ijheatmasstransfer.2014.11.066
[9] Jang, S.P. and S.U.S. Choi, "Role of Brownian motion in the enhanced thermal conductivity of nanofluids," Appl. Phys. Lett. **84**(21), 4316-4318. (2004). https://doi.org/10.1063/1.1756684
[10] S.K. Das, and S.U.S. Choi, "A review of heat transfer in nanofluids," Advances in Heat transfer, **41**, 81-197 (2009). https://doi.org/10.1016/S0065-2717(08)41002-X
[11] D.S. Udawattha, M. Narayana, and U.P.L. Wijayarathne, "Predicting the effective viscosity of nanofluids based on the rheology of suspensions of solid particles," **31**(3), 412-426 (2019). https://doi.org/10.1016/j.jksus.2017.09.016
[12] Y. Yang, Z.G.Z., E.A. Grulke, W.B. Anderson, and G. Wu, "Heat transfer properties of nanoparticle-in-fluid dispersions (nanofluids) in laminar flow," **48**(6), 1107-1116 (2005). https://doi.org/10.1016/j.ijheatmasstransfer.2004.09.038
[13] M. Gupta, R. Kumar, N. Arora, S. Kumar, and N. Dilbagi, "Forced convective heat transfer of MWCNT/water nanofluid under constant heat flux: an experimental investigation," Arabian Journal for Science and Engineering, **41**(2), 599-609 (2016). https://doi.org/10.1007/s13369-015-1699-5
[14] W.-Q. Lu, and and Q.-M. Fan, "Study for the particle's scale effect on some thermophysical properties of nanofluids by a simplified molecular dynamics method," **32**(4), 282-289 (2008). https://doi.org/10.1016/j.enganabound.2007.10.006
[15] K.V. Wong, and O. De Leon, "Applications of nanofluids: current and future," Advances in mechanical engineering, **2**, 519659 (2010). https://doi.org/10.1155/2010/519659
[16] A. Patra, M.K. Nayak, and A. Misra, "Viscosity of nanofluids-A Review," International Journal of Thermofluid Science and Technology, **7**(2), 070202 (2020). https://doi.org/10.36963/IJTST.2020070202
[17] M.J. Pastoriza-Gallego, C. Casanova, J.L. Legido, and M.M. Piñeiro, "CuO in water nanofluid: influence of particle size and polydispersity on volumetric behaviour and viscosity," **300**(1-2), 188-196 (2011). https://doi.org/10.1016/j.fluid.2010.10.015
[18] T.X. Phuoc, M. Massoudi, and R.-H. Chen, "Viscosity and thermal conductivity of nanofluids containing multi-walled carbon nanotubes stabilized by chitosan," International Journal of Thermal Sciences, **50**(1), 12-18 (2011). https://doi.org/10.1016/j.ijthermalsci.2010.09.008
[19] P.K. Namburu, D.K. Das, K.M. Tanguturi, and R.S. Vajjha, "Numerical study of turbulent flow and heat transfer characteristics of nanofluids considering variable properties,' **48**(2), 290-302 (2009). https://doi.org/10.1016/j.ijthermalsci.2008.01.001
[20] J. Li, C. Zhou, G. Wang, and D. Zhao, "Study on rheological behavior of polypropylene/clay nanocomposites," Journal of applied polymer science, **89**(13), 3609-3617 (2003). https://doi.org/10.1002/app.12643
[21] M. Gupta, V. Singh, R. Kumar, and Z. Said, "A review on thermophysical properties of nanofluids and heat transfer applications," Renewable and Sustainable Energy Reviews, **74**, 638-670 (2017). https://doi.org/10.1016/j.rser.2017.02.073
[22] R. Saidur, K. Leong, and H.A. Mohammed, "A review on applications and challenges of nanofluids," Renewable and sustainable energy reviews, **15**(3), 1646-1668 (2011). https://doi.org/10.1016/j.rser.2010.11.035
[23] H. Karimi, F. Yousefi, and M.R. Rahimi, "Correlation of viscosity in nanofluids using genetic algorithm-neural network (GA-NN)," Heat and mass transfer, **47**(11), 1417-1425 (2011). http://dx.doi.org/10.1007%2Fs00231-011-0802-z
[24] M. Gholizadeh, M. Jamei, I. Ahmadianfar, and R. Pourrajab, "Prediction of nanofluids viscosity using random forest (RF) approach," Chemometrics and Intelligent Laboratory Systems, **201**, 104010 (2020). https://doi.org/10.1016/j.chemolab.2020.104010
[25] P.K. Kanti, K.V. Sharma, K.M. Yashawantha, and S. Dmk, "Experimental determination for viscosity of fly ash nanofluid and fly ash-Cu hybrid nanofluid: Prediction and optimization using artificial intelligent techniques," Energy Sources, Part A: Recovery, Utilization, and Environmental Effects, 1-20 (2021). https://doi.org/10.1080/15567036.2021.1877374
[26] A.A.A.A. Alrashed, M.S. Gharibdousti, M. Goodarzi, L.R. de Oliveira, M.R. Safaei, and E.P.B. Filho, "Effects on thermophysical properties of carbon based nanofluids: experimental data, modelling using regression, ANFIS and ANN," International Journal of Heat and Mass Transfer, **125**, 920-932 (2018). https://doi.org/10.1016/j.ijheatmasstransfer.2018.04.142
[27] M.H. Ahmadi, B. Mohseni-Gharyehsafa, M. Farzaneh-Gord, R.D. Jilte, and R. Kumar, "Applicability of connectionist methods to predict dynamic viscosity of silver/water nanofluid by using ANN-MLP, MARS and MPR algorithms," Engineering Applications of Computational Fluid Mechanics, **13**(1), 220-228 (2019). https://doi.org/10.1080/19942060.2019.1571442
[28] M.H. Esfe, S. Saedodin, M. Bahiraei, D. Toghraie, O. Mahian, and S. Wongwises, "Thermal conductivity modeling of MgO/EG nanofluids using experimental data and artificial neural network," Journal of Thermal Analysis and Calorimetry, **118**(1), 287-294 (2014). https://doi.org/10.1007/s10973-014-4002-1

[29] N. Zhao, and Z. Li, "Experiment and artificial neural network prediction of thermal conductivity and viscosity for alumina-water nanofluids," Materials, **10**(5), 552 (2017). https://doi.org/10.3390/ma10050552
[30] M. Vakili, S. Khosrojerdi, P. Aghajannezhad, and M. Yahyaei, "A hybrid artificial neural network-genetic algorithm modeling approach for viscosity estimation of graphene nanoplatelets nanofluid using experimental data," International Communications in Heat and Mass Transfer, **82**, 40-48 (2017). https://doi.org/10.1016/j.icheatmasstransfer.2017.02.003
[31] M. Vakili, M. Karami, S. Delfani, and S. Khosrojerdi, "Experimental investigation and modeling of thermal radiative properties of f-CNTs nanofluid by artificial neural network with Levenberg–Marquardt algorithm," International Communications in Heat and Mass Transfer, **78**, 224-230 (2016). https://doi.org/10.1016/j.icheatmasstransfer.2016.09.011
[32] A.M Ghanadi, A.H. Nasab, D. Bastani, and A.A.S. Kordi, "The effect of nanoparticles on the mass transfer in liquid–liquid extraction," Chemical Engineering Communications, **202**(5), 600-605 (2015). https://doi.org/10.1080/00986445.2013.858037
[33] M. Abdollahi-Moghaddam, K. Motahari, and A. Rezaei, "Performance characteristics of low concentrations of CuO/water nanofluids flowing through horizontal tube for energy efficiency purposes; an experimental study and ANN modeling," Journal of Molecular Liquids, **271**, 342-352 (2018). https://doi.org/10.1016/j.molliq.2018.08.149
[34] M.H. Esfe, and S.M.S. Tilebon, "Statistical and artificial based optimization on thermo-physical properties of an oil-based hybrid nanofluid using NSGA-II and RSM," Physica A: Statistical Mechanics and its Applications, **537**, 122126 (2020). https://doi.org/10.1016/j.physa.2019.122126
[35] M.H. Esfe, M. Goodarzi, and S. Esfandeh, "Experimental investigation of c(75–25%)/10W40 as a new nano-lubricant," The European Physical Journal Plus, **136**(5), 605 (2021). https://doi.org/10.1140/epjp/s13360-021-01414-y
[36] M.H. Esfe, and M.H. Hajmohammad, "Thermal conductivity and viscosity optimization of nanodiamond-Co3O4/EG (40: 60) aqueous nanofluid using NSGA-II coupled with RSM," Journal of Molecular Liquids, **238**, 545-552 (2017). https://doi.org/10.1016/j.molliq.2017.04.056
[37] M.H. Esfe, and S. Alidoust, "Modeling and precise prediction of thermophysical attributes of water/EG blend-based CNT nanofluids by NSGA-II using ANN and RSM," Arabian Journal for Science and Engineering, **46**(7), 6423-6437 (2021).
[38] Maqsood, K., et al., Multi-objective optimization of thermophysical properties of multiwalled carbon nanotubes based nanofluids. Chemosphere, **286**, 131690 (2022). https://doi.org/10.1007/s13369-020-05086-1
[39] M.H. Esfe, M.H. Kamyab, "Mathematical monitoring of agglomeration effects on thermophysical properties of water-based nanofluids using MLP and RSM," Journal of Thermal Analysis and Calorimetry, **146**(2), 739-756 (2021). https://doi.org/10.1007/s10973-020-09996-y
[40] N. Zhao, and Z. Li, "Modeling and prediction of viscosity of water-based nanofluids by radial basis function neural networks," **281**, 173-183 (2015). https://doi.org/10.3390/app7040409
[41] O.A. Alawi, N.A.C. Sidik, H.W. Xian, T.H. Kean, and S.N. Kazi, "Thermal conductivity and viscosity models of metallic oxides nanofluids," **116**, 1314-1325 (2018). https://doi.org/10.1016/j.ijheatmasstransfer.2017.09.133
[42] D.-H. Chen, and X.-R. He, "Synthesis of nickel ferrite nanoparticles by sol-gel method," Materials Research Bulletin, **36**(7-8), 1369-1377 (2001). https://doi.org/10.1016/S0025-5408(01)00620-1
[43] M. Salavati-Niasari, F.Davar, M. Mazaheri, and M. Shaterian, "Preparation of cobalt nanoparticles from [bis (salicylidene) cobalt (II)]–oleylamine complex by thermal decomposition," Journal of Magnetism and Magnetic Materials, **320**(3-4), 575-578 (2008). https://doi.org/10.1016/j.jmmm.2007.07.020
[44] M. Scimeca, S. Bischetti, H.K. Lamsira, R. Bonfiglio, and E. Bonanno, "Energy Dispersive X-ray (EDX) microanalysis: A powerful tool in biomedical research and diagnosis," European journal of histochemistry, **62**(1), (2018). https://doi.org/10.4081/ejh.2018.2841
[45] W. Zhou, R. Apkarian, Z.L. Wang, and D. Joy, *"Fundamentals of scanning electron microscopy (SEM),"* in: *Scanning microscopy for nanotechnology*, edited by D. Joy, and Z.L. Wang, (Springer, NY, 2006), pp. 1-40.

ПРОГНОЗ В'ЯЗКОСТІ НАНОРІДИН НА ОСНОВІ КОБАЛЬТОВОГО ФЕРИТУ/SAE50 ТА МОТОРНОЇ ОЛИВИ ЗА ДОПОМОГОЮ НАВЧЕНОЇ ШТУЧНОЇ НЕЙТРАЛЬНОЇ МЕРЕЖІ (ANN) ТА МЕТОДОЛОГІЇ ВІДГУКУ ПОВЕРХНІ (RSM)

Малік Мухаммад Хафізуллах[a,c], Абдул Рафай[b], Гулам Мустафа[d], Мухаммад Халід[b], Зубайр Ахмед Калхоро[c], Абдул Васім Шайх[a], Ахмед Алі Раджпут[b]

[a]Інститут інформатики та математики, Університет Сінда, Джамшоро, Пакистан
[b]Кафедра фізики, Університет Карачі, 75270, Карачі, Пакистан
[c]Департамент математики, Белуджистанський університет інформаційних технологій, інженерії та менеджменту, Кветта, Пакистан
[d]Кафедра фізики, Університет інженерії та технології NED, 75270, Карачі, Пакистан

Передача тепла звичайними рідинами, такими як чиста вода, масло та етиленгліколь, є неефективною через їх низьку в'язкість. Щоб підвищити ефективність звичайних рідин, дуже малий відсоток наночастинок додається до базових рідин для приготування нанорідини. Вплив зміни в'язкості можна використовувати для дослідження реологічних властивостей нанофлюїдів. У цьому дослідженні нанорідини на основі ($CoFe_2O_4$)/моторна олива були виготовлені за стандартною методологією у два етапи. На першому етапі $CoFe_2O_4$ (CF) синтезували за допомогою золь-гель вологого хімічного процесу. Кристалічна структура та морфологія були підтверджені за допомогою рентгенівського дифракційного аналізу (XRD) та скануючої електронної мікроскопії (SEM), відповідно. На другому етапі стандартна процедура була адаптована, взявши кілька твердих об'ємних часток CF як Ø = 0, 0,25, 0,50, 0,75 і 1,0 %. Такі відсотки концентрацій диспергували у відповідному об'ємі моторного масла за допомогою ультразвукової обробки протягом 5 годин. Після цього в'язкість підготовлених п'яти різних нанофлюїдів визначали при температурах від 40 до 80 °C. Відповідно до отриманих даних, в'язкість нанофлюїдів (μnf) зменшувалася в міру підвищення температури, але збільшувалася, коли об'ємний відсоток нанофлюїдів Ø підвищувався. Крім того, було враховано 25 експериментальних спостережень для прогнозування в'язкості за допомогою штучної нейронної мережі (ANN) і методології відгуку поверхні (RSM). Алгоритм побудови ідеальної архітектури штучної нейронної мережі був рекомендований для прогнозування швидкості рідини нанофлюїду на основі нафти CF/SAE-50 за допомогою програмного забезпечення MATLAB. Щоб визначити правильність прогнозованої моделі, було розраховано середню квадратичну помилку (MSE) 0,0136.

Ключові слова: *ферит кобальту; нанофлюїди; в'язкість; тверда об'ємна частка; ANN; RSM*