Journal of Chemical and Petroleum Engineering 2021, 55(1): 163-175
DOI: 10.22059/jchpe.2021.303675.1317

RESEARCH PAPER

An Intelligent Approach to Predict the Viscosity of Water/Glycerin Containing Cu Nanoparticles: Neuro-Fuzzy Inference System (ANFIS) Model

Reza Beigzadeh*

Department of Chemical Engineering, Faculty of Engineering, University of Kurdistan, Sanandaj, Iran

Received: 30 May 2020, Revised: 20 December 2020, Accepted: 14 February 2021

Abstract

The ability to approximate the nanofluid properties such as viscosity, thermal conductivity, and specific heat capacity will greatly assist in the modeling and design of nanofluidic systems. The purpose of this study was to present an adaptive neuro-fuzzy inference system (ANFIS) model for estimating the viscosity of Water/Glycerin nanofluid-containing Cu nanoparticles. The model inputs consist of two variables of temperature and volume concentration of nanofluids which have a great influence on the nanofluid viscosity. The experimental data were divided into two categories: training (three-quarters) and testing (a quarter of the data). The grid partition and subtractive clustering approaches were employed to determine the ANFIS configuration. The mean value of the relative error of 5.18% and the root mean square error of 0.0794 were obtained by comparing the target and model output values for the testing data. Proper matching of ANFIS prediction results with the test data set indicates the validity of the model. In addition, an empirical correlation was developed based on the form presented in the literature. The constants of the equation were determined by the genetic algorithm (GA) searching technique. The comparison of the prediction accuracy of the two models showed the complete superiority of the ANFIS.

Keywords:
ANFIS,
Cu,
Genetic Algorithm,
Heat Transfer,
Nano Fluid,
Viscosity

Introduction

In passive heat transfer enhancement (HTE) techniques, increasing heat transfer rate is accomplished by various methods such as surface roughness [1], tube inserts [2], and complex geometry [3] to increase turbulence intensity. However, the poor thermal conductivity of liquids is always considered a weakness in heat exchangers. In an attempt to overcome this problem, an idea was to add some solid particles to the fluid based on the fact that the solids had higher thermal conductivity. Using particles in millimeters or micro sizes in the liquids leads to channel blockage due to the poor stability of the suspensions. To solve this problem, the size of the additives was reduced to the nanometer particles. Nanofluids are mixtures of solids and liquids that contain nanoparticles with sizes typically 1 to 100 nm suspended in the liquid. Suspended metallic or nonmetallic nanoparticles can improve the heat transfer properties of the base fluid [4].

The empirical correlations for estimating the physical properties of nanofluids have been considered in the literature [5]. Bardool et al. [6] used a viscosity model based on friction theory to estimate the viscosity of nanofluids. The friction viscosity model was developed for

* Corrresponding author:
Email: r.beigzadeh@uok.ac.ir (R. Beigzadeh)

nanofluids using Peng-Robinson (PR) and Esmaeilzadeh-Roshanfekr (ER) equations of state (EoS). The results of the proposed model were compared with correlations developed by Einstein [7], Brinkman [8], and Lundgren [9], and the model's superiority was proved. Alawi et al. [10] presented a model for estimating the thermal conductivity and viscosity of metallic oxides nanofluids. The metallic oxides nanofluids including Al_2O_3, CuO, SiO_2, and ZnO were investigated. The effects of nanoparticle concentration, temperature, and nanoparticle shapes were investigated. They observed that the nanoparticle's shape has a major effect on the thermos-physical properties of the studied nanofluids. Akilu et al. [11] measured the viscosity, electrical and thermal conductivity for β-SiC in ethylene glycol and propylene glycol nanofluids. The effect of temperature and concentration on each base liquid was investigated. Based on the obtained experimental data, an empirical relation was proposed to estimate these nanofluid properties.

The artificial neural network (ANN) modeling technique has been successfully employed to approximate the nonlinear and complex relations. Recently, the ANNs are applied to estimate the behavior of the properties of nanomaterials. The prediction of nanofluid properties by neural networks was investigated in the literature [12]. Akhgar et al. [13] developed ANNs for estimating the thermal conductivity of MWCNT-TiO2/ Water-Ethylene glycol nanofluid. ANN models can find and distinguish information and rules between the empirical data using their training procedure. The viscosity of a hybrid nano-lubricant was modeled by Afrand et al. [14]. The results of their comparison with empirical correlations showed that the ANN was superior in the prediction of target data. Jang [15] developed an efficient model by the combination of the neural network and fuzzy logic. The result of this combination is well-known as the adaptive neuro-fuzzy inference system (ANFIS). The combining of ANN with other artificial intelligence (AI) models (e.g. genetic algorithms and fuzzy logic) leads to improved performance in comparison with individual ANN [16]. Alarifi et al. [17] used particle swarm optimization (PSO) and genetic algorithm (GA) thermos-physical properties of Al_2O_3-MWCNT/Oil nanofluid. The modeling results indicate that the ANFIS-PSO model is more accurate than ANFIS-GA. Mehrabi et al. [18] predicted the alumina-water nanofluid thermal conductivity by ANFIS and GA-polynomial ANN. Alrashed et al. [19] performed an experimental and numerical study about the thermos-physical properties of carbon-based nanofluids. The ANFIS, ANN, and regression were developed to estimate the properties.

With regards to the superior performance of nanofluids in heat exchangers, it would be very useful to provide an accurate predictive model for their thermo-physical properties. This study aims to model and estimate the viscosity of water-glycerin nanofluid containing Cu nanoparticles with different temperatures and volume concentrations. An adaptive neuro-fuzzy inference system was developed to approximate the viscosity of Cu-Water/Glycerin nanofluid. The viscosity has been studied within the temperature range of 20°C-80°C and volume concentration range of 0.22 %–1 %. The optimum structure of the ANFIS was determined by grid partition and subtractive clustering approaches. Finally, the developed ANFIS was compared with genetic algorithm (GA) based polynomial correlations in terms of accuracy of the viscosity estimation. The suitable prediction results indicate that the model can be used for other nanofluids (e.g. Hybrid nanofluids) with high precision.

Data preprocessing and modeling procedure

The fuzzy logic systems trained by the neural network based on the principles of artificial neural network training known as the adaptive neuro-fuzzy inference system (ANFIS). The ANFIS is employed in different chemistry and chemical engineering fields due to the ability to recognize the complex relationship between variables. The ANFIS is composed of layers that are associated with specific rules. The interconnected structure provides a reasonable relationship between input-output variables. The number of rules and membership functions for the ANFIS structure should be determined by an optimization technique which will be described in the following sections. In addition, the prediction ability of the genetic algorithm (GA) based correlations was investigated.

Experimental data collection

Recently, the enhanced thermal properties of nanofluids in heat transfer applications have attracted much attention [20, 21]. The accurate predictive models for the nanofluid properties are very useful to reduce laboratory efforts. In the study, the experimental data related to the viscosity of the copper-based Water-Glycerin nanofluids, which were collected by Chaitanya Lahari et al [22], used for developing artificial intelligence (AI) models. The viscosity of nanofluids with a base solution of water and glycerol in the ratio of 70 to 30 containing copper nanoparticles was measured. The two-step dispersion synthesis technique is used to make nanoparticles smaller than 50 nm in size and mixed with Water-Glycerin as the base fluid. The viscosity values of these nanofluids were measured in vitro at different temperatures of 20, 40, 60, and 80°C using the DV 2T model Brookfield Viscometer. Also, three different concentrations of copper nanoparticles in the base fluid were considered as 0.2٪, 0.6٪, and 1 ٪ values. Water-glycerin base fluid viscosity was also measured at these temperatures. The more detailed explanations about experimental data were presented in Ref. [22].

Adaptive neuro-fuzzy modeling

Artificial neural networks (ANNs) resemble biological nervous structures (i.e. human brain) and can learn and understand complex relations. Neural networks contain many simple processing units (neurons) in the interconnected structure to generate a network by weights and biases. ANN components will be modified regularly to reduce the deviation values between the network output and target data [23]. The neural networks are highly suggested as a method for estimating the main parameters in engineering systems. ANNs and fuzzy systems are the subgroups of artificial intelligence. Fuzzy logic schemes work by reasoning and have an advanced level of computational structures in comparison with ANNs. However, the fuzzy systems are not able to learn and therefore they cannot adjust their components. A combination of the neural network and the fuzzy system was introduced by Jang [15] which is known as adaptive neuro-fuzzy inference system (ANFIS). The neuro-fuzzy model benefits the advantages of both methods. The developed ANFIS can find objective data values from inputs associated with suitable precision. The ANFIS comprises two parts (antecedent and conclusion) connected by using a set of fuzzy if-then rules. The first-order Sugeno inference model is used in the present study. In the model, the typical rules have the following form:

$$\text{If } (x_1 \text{ is A}) \text{ and } (x_2 \text{ is B}) \text{ then } f=px_1+qx_2+r \quad (1)$$

where A and B are fuzzy sets, and x_1 and x_2 are input variables. In addition, p, q, and r are the first-order polynomial parameters and obtained using the training process.

As shown in Fig. 1, the ANFIS architecture comprises five layers such as fuzzification, implication, normalization, defuzzification, and summation (total output) layer. The input signals are transferred to the first layer which is named the fuzzification layer. Different membership functions (MFs) in this layer product membership grades from the input variables. The second layer is called the implication layer. Each fixed node in the layer states the rules and number of the Sugeno fuzzy inference system. The output of each layer node (w_i) is the multiplication of membership degrees from the previous layer. The third layer (normalization) computes the normalized ignition level for each rule ($\overline{w}_i$). In the fourth layer which named as the defuzzification layer, the normalized ignition level multiplied by a specific function of inputs ($\bar{w}_i f_i$). Finally, there is a single node in the last layer (summation) which is indicated with $\sum$. The outputs of nodes in the fourth layer are added to each other and the final ANFIS output is calculated.

The premise and consequent parameters are two sets of modifiable parameters in the ANFIS model which are found during the training process. The consequent factors can be obtained with the least square approximation through forwarding pass and the premise factors can be adjusted by the gradient descend in the backward pass [24]. In the present study, two techniques including the grid partition and subtractive clustering were applied to find the best ANFIS configuration. In the grid partition method, the membership function (MF) types (Gaussian, combination Gaussian, generalized bell, triangular, Π-shaped, and trapezoidal) and rules number are determined through the trial-and-error. On the other hand, in the subtractive clustering approach, the parameters related to the method (range of influence, squash actor, accepted ratio, and rejected ratio) should be determined.

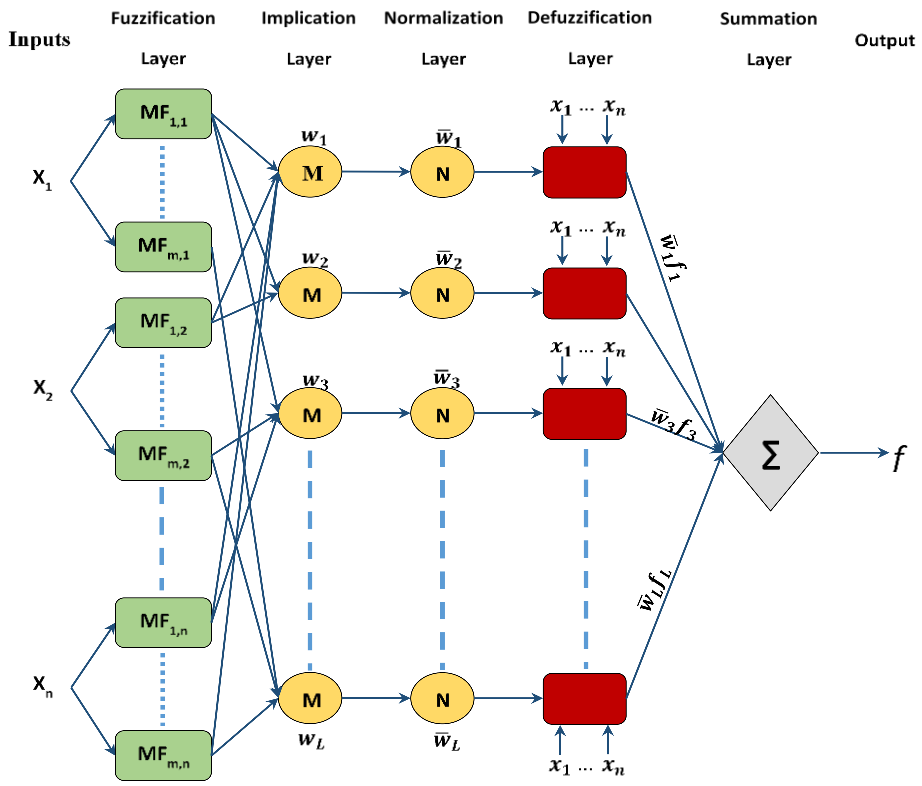

Fig. 1. The ANFIS architecture

In the study, it was attempted to develop an ANFIS model for approximating the viscosity of Water/Glycerin nanofluid containing Cu nanoparticles. The input parameters for the ANFIS are the important and effective variables on viscosity including temperature and volume concentration of nanofluids. The network training was performed by three-quarters of data points and the rest were used for the model validation. The validation (testing) data were randomly selected and the high accuracy of the model for predicting these data guarantees the accuracy of the model estimation for other data (extrapolation). The hybrid-learning scheme was employed to obtain the optimal parameters. In the method, the gradient and least mean square approximation are used simultaneously [15].

Genetic algorithm modeling

The genetic algorithm (GA) as a subgroup of artificial intelligence is a numerical heuristic search. The GA is inspired by Charles Darwin's theory of the natural evolution process. The algorithm states the procedure of natural selection in which the most suitable individuals are chosen to reproduce for producing offspring of the next generation. GA typically has shown to be an appropriate choice for approximation based on the regression [25, 26]. This method can solve min-max problems rapidly, after exploring a small section of the possible answers.

Five steps are considered in a genetic algorithm including initialization, fitness assignment, selection, crossover, and mutation. Fig. 2 illustrates the flow chart related to the genetic algorithm steps. The first step is defining a set of solutions (chromosomes) as the initial population. The fitness function specified the fitness grade of each individual. The chance that an individual will be chosen for reproduction is based on the grade. The pairs of individuals (parents) are selected according to the fitness grade. In the crossover phase, the selected parent chromosomes generate children. In some of the new children, some genes maybe have a genetic mutation.

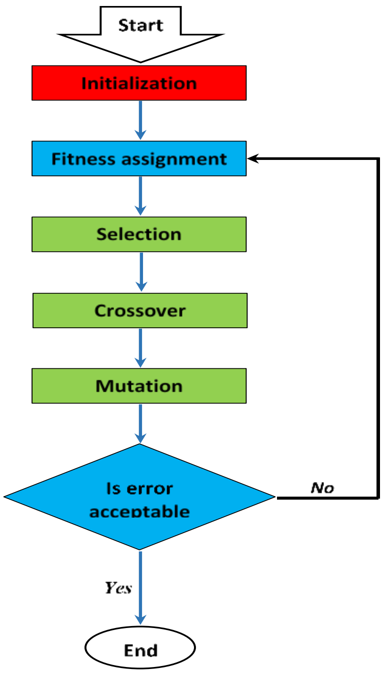

Fig. 2. Flowchart of the genetic algorithm

Finally, the termination criteria control the number of generations in which there are no meaningfully different from the previous generation.

In the present work, this algorithm was used to develop polynomial correlations due to its superiority in achieving global min-max over traditional methods. Based on the empirical data, a correlation between the viscosity (μ), temperature (T), and volume concentration of nanofluids (φ) is found using the GA technique. For this attempt, the following polynomial equation is considered according to the related literature [27, 28]:

$$\mu = \mu_b (1 + C_1\varphi + C_2\varphi^2 + C_3\varphi^3 + C_4\varphi^4 + C_5\varphi^5) \quad (2)$$

where μ_b is the viscosity of the base fluid (Water-Glycerin in 70:30 ratio) which has a temperature dependence.

The error function from experimental data and approximated values defined by the root mean square error:

$$E(C_1,C_2,C_3,C_4,C_5)=\sqrt{\frac{\sum_{i=1}^{N}\left(\mu_i^{Experimental}-\mu_i^{Approximated}\right)^2}{N}} \tag{3}$$

where N is the number of data points. The GA was employed to obtain the optimum constant values (C_i) of the assumed polynomial correlation.

Values of 500 and 0.8 were specified for the initial population and the crossover fraction, respectively. Two elite offspring (the best answer of every generation) were considered in the GA searching process.

Results and discussion

In this study, an adaptive neuro-fuzzy inference system (ANFIS) and genetic algorithm (GA) models were developed to estimate the viscosity of a nanofluid with an aqueous solution of glycerin containing copper nanoparticles based on temperature and volume concentration of nanoparticles. Providing a precise model for viscosity estimation would be very useful given its importance in the design of nanofluidic systems. Four criteria of accuracy include the root mean square error (RMSE), mean relative error (MRE), the sum of squared error (SSE), and the absolute fraction of variance (R^2) were used to select the optimum models.

$$\mathrm{RMSE}=\sqrt{\frac{\sum_{i=1}^{N}(t_i-y_i)^2}{N}} \tag{4}$$

$$\mathrm{MRE}\,(\%)=\frac{100}{N}\sum_{i=1}^{N}\left(\frac{|t_i-y_i|}{t_i}\right) \tag{5}$$

$$\mathrm{SSE}=\sum_{i=1}^{N}(t_i-y_i)^2 \tag{6}$$

$$R^2=1-\frac{\sum_{i=1}^{N}(t_i-y_i)^2}{\sum_{i=1}^{N}(t_i)^2} \tag{7}$$

in which t is the target (experimental data) and y is the approximated value.

Adaptive neuro-fuzzy modeling results

The ANFIS using a large number of adjustable parameters can learn and recognize the complex relationship between viscosity and input variables. Different fuzzy inference system configurations were designed and investigated using two kinds of partitioning techniques including grid partition and subtractive clustering. The trained ANFIS performance was evaluated with a test data group which was not used in the training process.

In the subtractive clustering method, the main parameters including the range of influence (ROI), squash factor (SF), accept ratio (AR) and reject ratio (RR) should be optimized. The procedure proposed by Cakmakci [29] was used for this purpose. Three parameters were held constant and the fourth parameter was changed until its optimal value was determined. The RMSE values related to the test data set were considered as the criterion for selecting the optimal model. Fig. 3 illustrates the variations of RMSE with different clustering parameters. The ranges of ROI=0.45-0.65, SF=1.20-1.35, AR=0.45-0.55, and RR=0.1-0.2 were investigated. The figure shows that AR and RR have no significant effect on the ANFIS performance. Finally, the values of 0.61, 1.25, 0.5, and 0.15 were selected for ROI, SF, AR, and RR, respectively. The minimum testing RMSE of 0.4199 was achieved for ANFIS modeling by the subtractive clustering method.

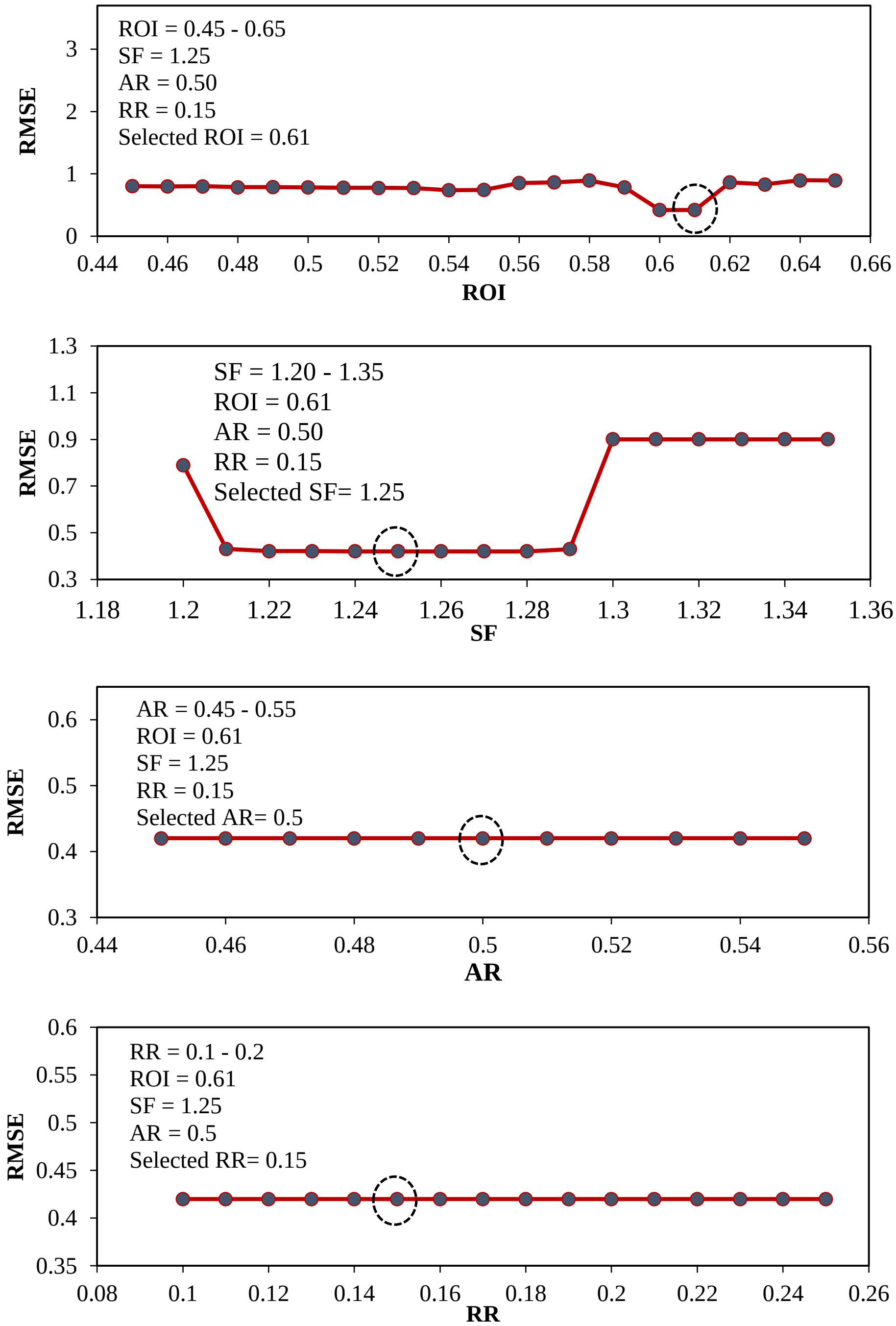

Fig. 3. Effects of clustering parameters on the prediction accuracy of the ANFIS model

On the other hand, in the grid partition technique, the best membership function (MF) type and the optimum number of rules were found by trial-and-error. The performances of various ANFIS model arrangement is shown in Fig. 4.

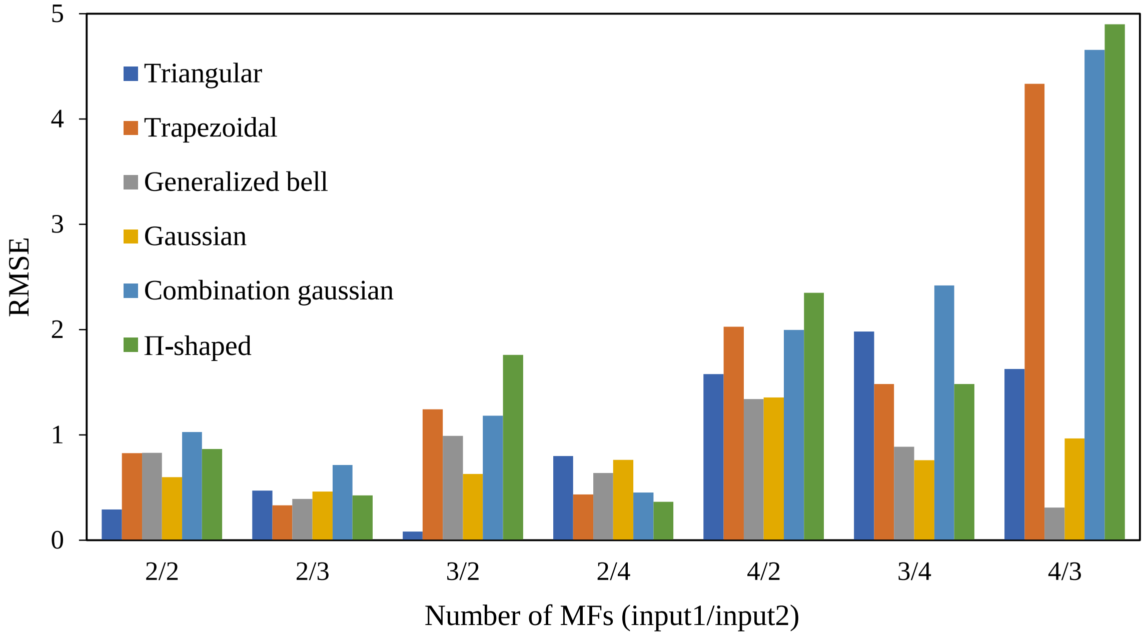

Fig. 4. Testing RMSE for different ANFIS configuration

As seen in the figure, using more MFs and rules leads to the complexity of the model and its lower accuracy. ANFIS with 3 and 2 MFs for the first and second variables, respectively, has the best accuracy (RMSE=0.0830). In addition, the triangular membership function was selected which the related fuzzy sets of the two input variables are indicated in Fig. 5.The triangular function defined as follows:

$$\mu(x) = \begin{cases} 0, & x \leq a \\ \dfrac{x-a}{m-a}, & a < x \leq m \\ \dfrac{b-x}{b-m}, & m < x < b \\ 0, & x \geq b \end{cases} \tag{8}$$

where a and b are the lower and upper limit, respectively, and m is a value between a and b.

The obtained fuzzy rules of the developed ANFIS model and optimum consequent parameters are tabulated in Table 1.

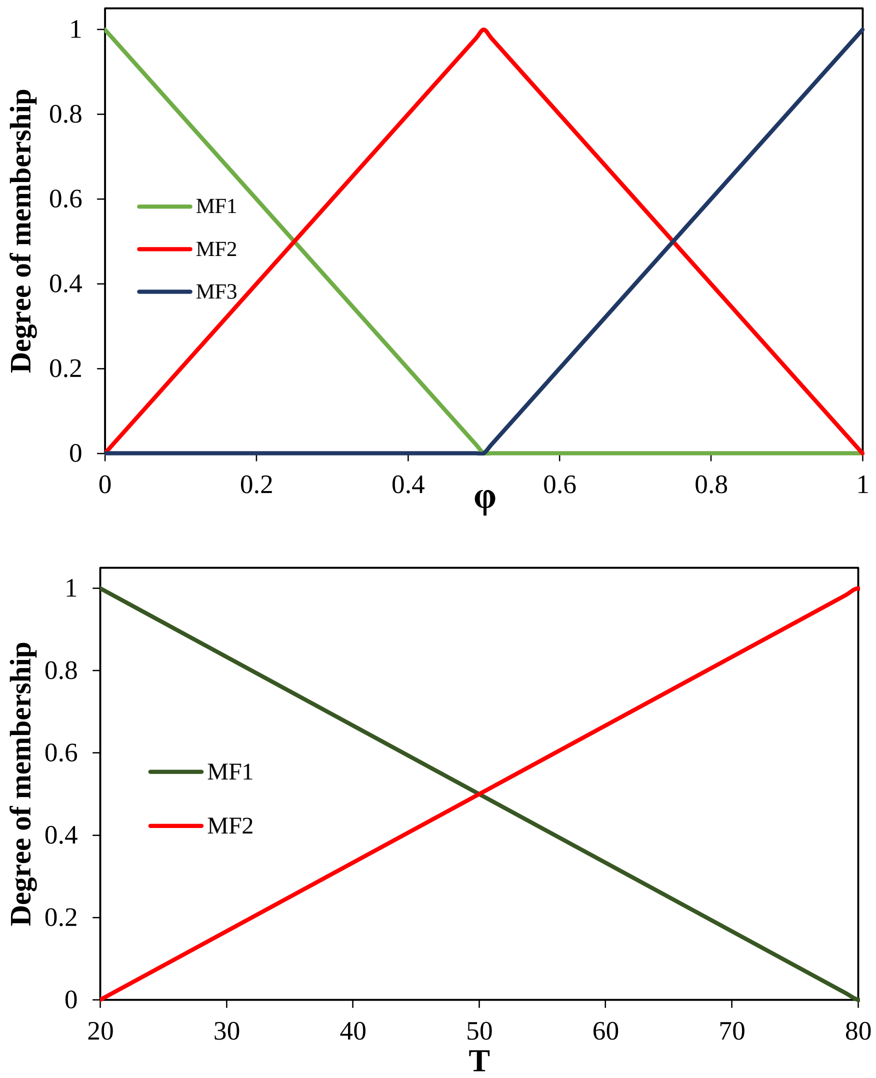

Fig. 5. Fuzzy sets of the input variables

Table 1. Fuzzy rules related to the optimum ANFIS configuration

Rule number	Rule description
1	if (φ is φ MF1) and (T is T MF1) then (μ=2.14φ-0.01187T+2.719)
2	if (φ is φ MF1) and (T is T MF2) then (μ=0.8058φ+0.01727T-0.6796)
3	if (φ is φ MF2) and (T is T MF1) then (μ=-0.9719φ+0.05619T+3.137)
4	if (φ is φ MF2) and (T is T MF2) then (μ=-1.544φ+0.03275T-0.783)
5	if (φ is φ MF3) and (T is T MF1) then (μ=1.723φ+0.03648T+1.323)
6	if (φ is φ MF3) and (T is T MF2) then (μ=0.01689φ+0.02443T-0.33)

Polynomial correlation-based genetic algorithm

The genetic algorithm was used to provide an empirical correlation for approximating the viscosity of the nanofluid as a function of temperature and volume concentration. The form of the polynomial equation (Eq. 2) was considered according to the phenomenological argument and investigated literature [27, 28]. After using the experimental data points, the correlation constants (C_i) were optimized for different equation orders. Table 2 reports the prediction accuracy of the polynomial correlations with different orders (1 to 5). As shown in the table, the third-order equation has the least error (RMSE=0.4931). Using the constants presented in the table, the following equation was obtained:

$$\mu = \mu_b (1 + 1.95\varphi - 3.395\varphi^2 + 1.969\varphi^3) \quad (9)$$

Table 2. The constants and accuracy of polynomial equations with different orders

Order	C_1	C_2	C_3	C_4	C5	RMSE
1	0.577					0.5099
2	0.781	-0.239				0.5002
3	1.95	-3.392	1.969			0.4931
4	1.121	1.922	-7.888	5.392		0.4934
5	3.35	-7.26	3.751	1.924	-1.233	0.5179

Table 3. Comparison of ANFIS and GA prediction results

	Data type	Input variables						
Data Number	ANFIS	φ(%)	T(°)	Experimental μ(cp)	Predicted μ(cp)by ANFIS	Relative error (%)	Predicted μ(cp) by GA correlation	Relative error (%)
1	Training	1	20	3.77541	3.77541	0.00007	4.57504	21.180
2	Training	1	40	3.22459	3.22459	0.00002	2.62552	18.578
3	Testing	1	60	2.59508	2.51311	3.15856	1.70825	34.173
4	Training	1	80	1.64098	1.64098	0.00027	1.21209	26.137
5	Training	0.6	20	3.55902	3.55902	0.00018	4.11719	15.683
6	Testing	0.6	40	2.99836	3.00664	0.27610	2.36277	21.198
7	Training	0.6	60	2.17213	2.17214	0.00025	1.53730	29.226
8	Testing	0.6	80	1.22787	1.11515	9.17974	1.09079	11.164
9	Training	0.2	20	3.37213	3.37211	0.00073	3.80526	12.844
10	Training	0.2	40	2.51639	2.51641	0.00056	2.18376	13.219
11	Training	0.2	60	1.76885	1.76883	0.00121	1.42083	19.675
12	Testing	0.2	80	0.93279	1.00838	8.10370	1.00815	8.079
13	Training	0	20	2.49672	2.48148	0.61046	2.99610	20.001
14	Training	0	40	1.45410	1.49984	3.14566	1.71940	18.245
15	Training	0	60	0.95246	0.90673	4.80163	1.11870	17.454
16	Training	0	80	0.68689	0.70214	2.22056	0.79377	15.561
						MRE=1.97%		MRE=18.90%

Comparison of the models

Table 3 is presented to compare the accuracy of the developed models for predicting the experimental data. The acceptable prediction error related to the testing data points proved the validity of the ANFIS model. The MRE of 5.18% was obtained for the testing data set and the value of 1.97% was found for all data points. On the other hand, the MRE value of 18.9% was calculated for the third-order polynomial equation developed by GA. Four deviation values such as MRE, RMSE, SSE, and R^2 for the developed models are reported in Table 4. Although the accuracy of the developed ANFIS model is much higher, the developed correlations by GA can be employed to estimate the viscosity more efficiently.

Table 4. Deviations of the ANFIS and GA models

Model	MRE	RMSE	SSE	R2
ANFIS	1.97	0.04320	0.10192	0.99891
GA (Eq. 9)	18.90	0.49307	3.88992	0.99942

Conclusion

This study aimed to investigate the ability of modeling by an adaptive neuro-fuzzy inference system to estimate the viscosity of copper nanoparticles in the Water-Glycerin solution. In addition, polynomial equations with different orders were developed by the genetic algorithm searching procedure. The relevant laboratory data were collected at different temperatures and nanofluid concentrations to develop the models. The grid partition and subtractive clustering techniques were applied to find the optimum ANFIS configuration and the validity of the model was proved by the testing data set. The optimal ANFIS structure obtained by the grid partition has a lower prediction error value. The estimation precision of the ANFIS is more than the GA-based polynomial correlations. The MRE and RMSE of the ANFIS model are 1.97% and 0.0432, respectively, and the values for correlation are 18.9% and 0.4931. Nevertheless, using the GA-based correlation is easier than ANFIS that can be treated as an advantage of the GA correlation.

Nomenclature

a	upper limit of triangular function
b	lower limit of triangular function
C_i	constant
E	error function
N	number of data points
t	target data
T	temperature (°C)
x_i	input variables
y	predicted value

Greek Symbols

μ	dynamic viscosity
μ_b	dynamic viscosity of base fluid
φ	volume concentration of nanofluid

Abbreviations

ANFIS	adaptive neuro-fuzzy inference system
GA	genetic algorithm
MF	membership function
MRE	mean relative error
RMSE	root mean square error

References

[1] Van der Geer J, Hanraads JA, Lupton RA. The art of writing a scientific article. J. Sci. Commun. 2000;163(2):51-9.

[2] Lu H, Xu M, Gong L, Duan X, Chai JC. Effects of surface roughness in microchannel with passive heat transfer enhancement structures. International Journal of Heat and Mass Transfer. 2020 Feb 1;148:119070.

[3] Kumar B, Srivastava GP, Kumar M, Patil AK. A review of heat transfer and fluid flow mechanism in heat exchanger tube with inserts. Chemical Engineering and Processing-Process Intensification. 2018 Jan 1;123:126-37.
[4] Beigzadeh R, Ozairy R. Developing predictive models for analysis the heat transfer in sinusoidal wavy channels. Thermal Science and Engineering Progress. 2019 Dec 1;14:100425.
[5] Assael MJ, Antoniadis KD, Wakeham WA, Zhang X. Potential applications of nanofluids for heat transfer. International Journal of Heat and Mass Transfer. 2019 Aug 1;138:597-607.
[6] Yıldız Ç, Arıcı M, Karabay H. Comparison of a theoretical and experimental thermal conductivity model on the heat transfer performance of Al2O3-SiO2/water hybrid-nanofluid. International Journal of Heat and Mass Transfer. 2019 Sep 1;140:598-605.
[7] Bardool R, Bakhtyari A, Esmaeilzadeh F, Wang X. Nanofluid viscosity modeling based on the friction theory. Journal of Molecular Liquids. 2019 Jul 15;286:110923.
[8] Einstein A. A new determination of molecular dimensions. Annual Physics. 1906;19: 289–306.
[9] Brinkman HC. The viscosity of concentrated suspensions and solutions. The Journal of Chemical Physics. 1952 Apr;20(4):571-571.
[10] Lundgren TS. Slow flow through stationary random beds and suspensions of spheres. Journal of fluid mechanics. 1972 Jan;51(2):273-299.
[11] Alawi OA, Sidik NA, Xian HW, Kean TH, Kazi SN. Thermal conductivity and viscosity models of metallic oxides nanofluids. International Journal of Heat and Mass Transfer. 2018 Jan 1;116:1314-25.
[12] Akilu S, Baheta AT, Kadirgama K, Padmanabhan E, Sharma KV. Viscosity, electrical and thermal conductivities of ethylene and propylene glycol-based β-SiC nanofluids. Journal of Molecular Liquids. 2019 Jun 15;284:780-92.
[13] Kavitha R, Kumar PM, A Review on nanofluids thermal properties determination using intelligent techniques or soft computing tools. Int. J. Scientific Res. 2015; 463–465.
[14] Akhgar A, Toghraie D, Sina N, Afrand M. Developing dissimilar artificial neural networks (ANNs) to prediction the thermal conductivity of MWCNT-TiO2/Water-ethylene glycol hybrid nanofluid. Powder Technology. 2019 Oct 1;355:602-10.
[15] Afrand M, Najafabadi KN, Sina N, Safaei MR, Kherbeet AS, Wongwises S, Dahari M. Prediction of dynamic viscosity of a hybrid nano-lubricant by an optimal artificial neural network. International Communications in Heat and Mass Transfer. 2016 Aug 1;76:209-14.
[16] Jang JS. ANFIS: adaptive-network-based fuzzy inference system, IEEE Trans. Syst. Man. Cybern., 1993;23: 665–685.
[17] Beigzadeh R. Estimation of LLE Data for Binary Systems of N-Formylmorpholine with Alkanes Using Artificial Neural Network–Genetic Algorithm (ANN–GA) Model. Chemical Methodologies. 2019 Jan 1;3(1):67-82.
[18] Alarifi IM, Nguyen HM, Naderi Bakhtiyari A, Asadi A. Feasibility of ANFIS-PSO and ANFIS-GA models in predicting thermophysical properties of Al2O3-MWCNT/oil hybrid nanofluid. Materials. 2019 Jan;12(21):3628.
[19] Mehrabi M, Sharifpur M, Meyer JP. Viscosity of nanofluids based on an artificial intelligence model. International Communications in Heat and Mass Transfer. 2013 Apr 1;43:16-21.
[20] Alrashed AA, Gharibdousti MS, Goodarzi M, de Oliveira LR, Safaei MR, Bandarra Filho EP. Effects on thermophysical properties of carbon based nanofluids: experimental data, modelling using regression, ANFIS and ANN. International Journal of Heat and Mass Transfer. 2018 Oct 1;125:920-32.
[21] Toghraie D, Sina N, Jolfaei NA, Hajian M, Afrand M. 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: Statistical Mechanics and its Applications. 2019 Nov 15;534:122142.
[22] Meybodi MK, Naseri S, Shokrollahi A, Daryasafar A. Prediction of viscosity of water-based Al2O3, TiO2, SiO2, and CuO nanofluids using a reliable approach. Chemometrics and Intelligent Laboratory Systems. 2015 Dec 15;149:60-9.
[23] Lahari MC, Sai PS, Narayanaswamy KS, HaseenaBee P, Devaraj S, Sharma KV. Experimental determination of viscosity of Water-Glycerin based Cu nano-fluids. Materials Today: Proceedings. 2019 Jan 1;19:517-20.

[24] Tong RM. A control engineering review of fuzzy systems. Automatica. 1977 Nov 1;13(6):559-69.
[25] Beigzadeh R, Hajialyani M, Rahimi M. Heat transfer and fluid flow modeling in serpentine microtubes using adaptive neuro-fuzzy approach. Korean Journal of Chemical Engineering. 2016 May 1;33(5):1534-50.
[26] Goldberg DE, Genetic Algorithms in Search, Optimization, and Machine Learning, Addison-Wesley Longman Inc. 2000.
[27] Alade IO, Abd Rahman MA, Saleh TA. Modeling and prediction of the specific heat capacity of Al2 O3/water nanofluids using hybrid genetic algorithm/support vector regression model. Nano-Structures & Nano-Objects. 2019 Feb 1;17:103-11.
[28] Batchelor GK. The effect of Brownian motion on the bulk stress in a suspension of spherical particles. Journal of fluid mechanics. 1977 Nov;83(1):97-117.
[29] Chen H, Ding Y, Tan C. Rheological behaviour of nanofluids. New journal of physics. 2007 Oct 9;9(10):367.