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Viscosity of Alumina Water-Based Nanofluids Modeling by Artificial Neural Network

M. Auriemma and A. Iazzetta

Istituto Motori, C.N.R, NA 80125, Italy;
m.auriemma@im.cnr.it, a.iazzetta@im.cnr.it

Abstract

Objectives: To develop efficient models for the prediction of viscosity of nanofluids. **Methods/Statistical Analysis**: Artificial Neural Network (ANN) toolbox for Matlab and an experimental data set of effective viscosity of alumina water-based nanofluids are used. ANN is mathematical model of artificial intelligence product, inspired by the structure and functioning of the human nervous system. Experimental data set are divided into two groups: train and test. The train instructed ANN and the results were compared with the test. **Findings:** ANN viscosity results were compared with the experimental data points. The expected values were in excellent agreement with the measured ones, viewing that the developed model is accurate and has the great ability for predicting the viscosity. *0.9994* and *0.9998* are the values of *R2* linear regressions for training and testing data set, respectively and *2.7187*10-4* and *1.2461*10-4* are respective values of mean square errors. **Applications:** Artificial Neural Networks to model thermal characterization of nanofluids.

Keywords: Alumina Water-Based, Artificial Neural Network, Experimental Data, Nanofluids, Viscosity

1. Introduction

The correct prediction of Artificial Neural Network (ANN) depends by structure of neural network used, and from data set used for training. After step of training, the neural network achieves adequate generalization ability and the ability to predict an output result as close as possible to the real one, without input stimulus is equal to the examples given.

Nowadays ANN is used for thermal characterization of nanofluids and in particular for prediction of non-linear behavior of viscosity.

Numerous researches have presented benefits using nanofluids in heat transfer tools[1-3]. After publication of two pioneers scientific articles[4,5] many researches were concentrated on potential applications, nanofluid synthesis and thermal conductivity prediction models[6] only few studies[7-9] were conducted on the viscosity of nanofluids. However, increase of viscosity due to the suspension of nanoparticles becomes a key issue in many engineering application. Therefore, analysis and value of viscosity are essential[10] and at the same time challenging to determine because of hydrodynamic interactions and of particle-particle interactions of nanoparticles in the dispersions.

This paper was planned in two interconnecting sections. In the first section, we presented background of the principal theoretic models of viscosity and we discussed about different parameters affecting the viscosity as nanoparticle volume fraction, size, shape and temperature. However, links between these parameters are not yet known, and this does not allow preparation of stable nanofluids, with characteristics and desired properties. In addition, the analytical models developed to predict viscosity underestimate or overestimates the experimental results and it do not possible obtain satisfactory predictions. At the end, so far, the only method to obtain certain or very reliable results is the experimental method, but it is very costly both in terms of time and costs.

**Author for correspondence*

In the second section, for all problems above described, we focused about design and use of neural networks as efficient tool to characterize nanofluids from viscosity standpoint. The experimental data, collected during first phase, are used as input to develop the neural network. So the network learns to recognize the unknown relation between the input variables (volume concentration, size and the temperature) and output (viscosity of nanofluid), until becoming able to predict the solution also when output does not it is known.

Neural Network Toolbox for Matlab is used in this study; it is a software package to design, to train, and to test the neural networks performance using the functionality of the application Matlab. It provides several functions for the development of a variety of networks such as feed forward back propagation, perceptions, self-organized, hop field networks, recurrent networks, Elman etc. To speed up training and handle large data sets, we distributed computations and data across multi-core processors, GPUs, and computer clusters using Parallel Computing Toolbox.

The objective was to model the viscosity of nanofluids by using artificial intelligent techniques as well as optimization of convection heat transfer of nanofluids in such a way to achieve the maximum heat transfer performance. Aim was to propose accurate model for effective viscosity of nanofluids by using ANN and input-output experimental data.

2. Background Studies

Although, analysis of theoretical models and experimental results has been done[11] it still needs more attention because no theoretical formula is until now able to predict carefully the nanofluid viscosity and mostly experimental results did not have good agreement with theoretical models.

Model	Correlation	Remark
Einstein	$\mu_{nf}=\mu_f(1+2.5\,\phi)$	Valid for very low volume concentrations ($\phi \le 0.02$) and spherical particles
Brinkman	$\mu_{nf}=\mu_f\left(\frac{1}{(1-\phi)^{2.5}}\right)$	
Batchelor	$\mu_{nf}=\mu_f(1+2.5\phi+6.5\phi^2)$	
Abu-Nada et al.	$\mu_{\phi,0_1}=\exp\left(3.003-0.04203\,T-0.5445\,\phi+0.0002553\,T^2+0.0524\,\phi^2-\frac{1.622}{\phi}\right)$	The viscosity in these equations is expressed in centi poise (cP), the temperature in °C.
	$\mu_{T,\phi 0}=-0.6967+\left(\frac{15.937}{T}\right)+1.238\,\phi+\left(\frac{1356.14}{T^2}\right)-0.259\,\phi^2-30.88\left(\frac{\phi}{T}\right)$	
	$-\left(\frac{19652.74}{T^2}\right)+0.01593\,\phi^3+4.38206\left(\frac{\phi^2}{T}\right)+147.573\left(\frac{\phi}{T^2}\right)$	
	$\mu_{\phi,0_2}=-81.1+98.75\ln(T)-45.23\ln^2(T)+9.71\ln^3(T)-0.946\ln^4(T)+0.03\ln^5(T)$	
Abedian and Kachanov	$\mu_{nf}=\mu_f\left(\frac{1}{1-2.5\,\phi}\right)$	Newtonian fluid with a single rigid spherical particle
Masoud Hosseini et al.	$\mu_{nf}=\mu_f\exp\left[m+\alpha\left(\frac{T}{T_0}\right)+\beta(\phi)+\gamma\left(\frac{d_p}{1+R}\right)\right]$	For Al_2O_3-water nanofluids (Based on Nguyen et al. experimental data)
	$\alpha=-0.485,\beta=14.94,\gamma=0.0105$	
	$m=0.72,\ T_0=20\ ^\circ C,\ R=1\ nm$	
Ward model	$\mu_{nf}=\mu_f[1+(2.5\phi)+(2.5\phi)^2+(2.5\phi)^3+(2.5\phi)^4+\cdots]$	
Renewed Ward (RW) model	$\mu_{nf}=\mu_f[1+(2.5\phi_1)+(2.5\phi_1)^2+(2.5\phi_1)^3+(2.5\phi_1)^4+\cdots]$	
	$\phi_1=\phi'\left(1+\frac{h}{r}\right)^3$	

Figure 1. Main theoretical models of nanofluids viscosity.

In fact, it is note that most theoretical models, shown in Figure 1, underestimate or overestimate the experimental results and it do not possible obtain satisfactory predictions.

Starting by literature critical reading, it was seen that nanofluids viscosity depends by numerous parameters[12] as base fluids, nanoparticle volume fraction, particle size, particle shape, temperature, surface charge, particle material, Brownian motion of nanoparticles, effect of clustering, nano-layer and dispersion techniques.

Among above parameters, the three most important that we select as input data in the ANN are particle size, volume concentration and temperature. In fact, numerous experimental studies[13] shows that these parameters are most important identifiers on effects of nanofluids viscosity. Below we summarize main experimental tests from literature carried out, for each of these parameters.

2.1 Effect of Particle Size

However, in the literature all experimental results show that the viscosity of nanofluids varies with the particle size,

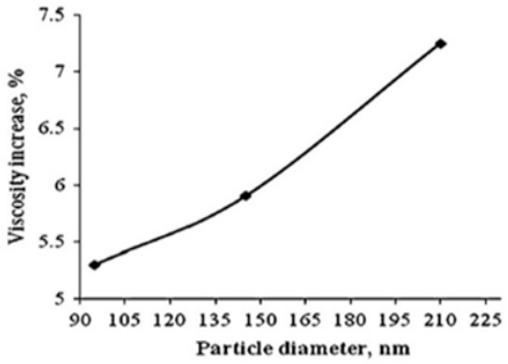

Figure 2. Increase in viscosity with increase in particle size[14].

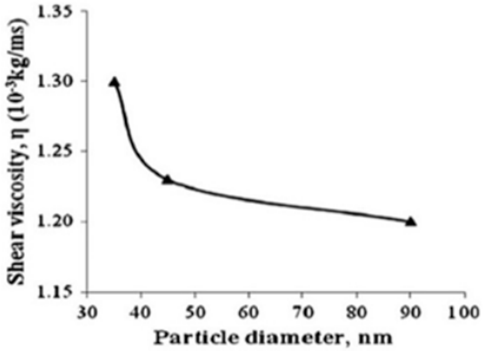

Figure 3. Decrease in viscosity with increase in particle diameter[15].

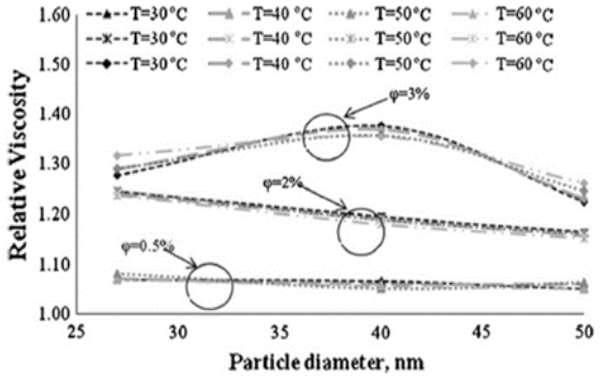

Figure 4. Viscosity is not a function of particle diameter[16].

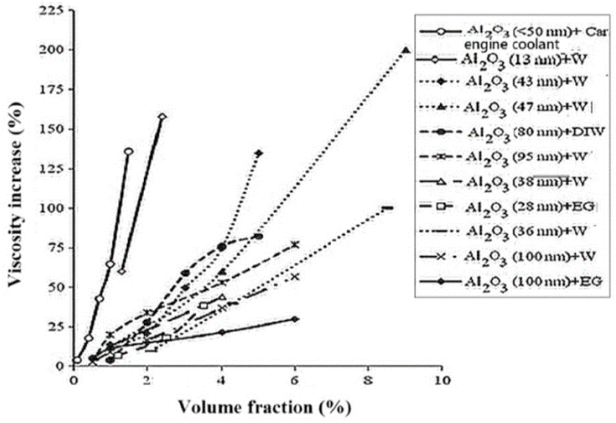

Figure 5. Change in viscosity with rise in volume fraction[17]

Relationship between the viscosity and the particle size is not yet known. Certain authors[14] contend that the viscosity of nanofluids at different particle sizes increases with the increase in particle size (Figure 2), however, some contradictions exist parallel to this trend, because others authors say[15] that viscosity decreases with the increase in particle diameter (Figure 3).

The experimental analysis of others[16] was also different. Their results showed that nanofluid viscosity was not a function of nanoparticle diameter (Figure 4).

Nevertheless, in summary, the literature shows that it is not possible to find a well-defined relationship between the viscosity of a generic nanofluid and the size of the nanoparticles dispersed. When you have available so many experimental data, a possible way can be use of appropriate techniques of soft computing, as neural network.

2.2 Effect of Volume Concentration

A considerable number of papers are published about consequences of volume concentration of particle on the viscosity.

Between all of us, we report in Figure 5[17] effects of volume fraction or volume concentration on viscosity of Al2O3 nanofluids.

Although, almost all papers showed that increasing nanoparticle volume fraction in the fluid increased the viscosity, however, a general relationship between viscosity and volumetric concentration is not yet largely obvious. Therefore also for the volumetric fraction, use of neural networks it seems appropriate.

2.3 Effect of Temperature

Clearly, temperature is a parameter of more critical and influential for viscosity of nanofluids. Most experimental results indicate a descending trend in viscosity with an increase in temperature. Figure 6[18] shows the viscosity vs. temperature, in graph viscosity decreases with a rise in temperature.

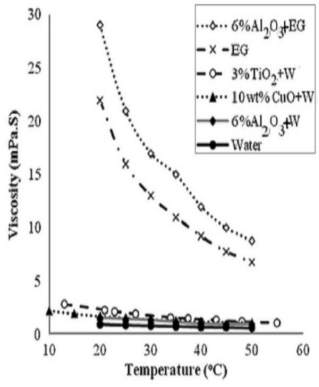

Fig. 6 Viscosity decreases with rise in temperature [2]

Figure 6. Viscosity decreases with rise in temperature[17].

All experimental results focused in this brief previous literature review, highlight difficulty to synthesize the considered topic.

We can conclude that viscosity assessment of generic nanofluid is complex issue methodologically and experimentally. It is also true, that the tool is very expensive in terms of both cost and time.

For above reasons, intelligent use of neural networks can be valuable support together to experimental test to estimate of the viscosity of nanofluids.

3. Artificial Neural Networks (ANN)

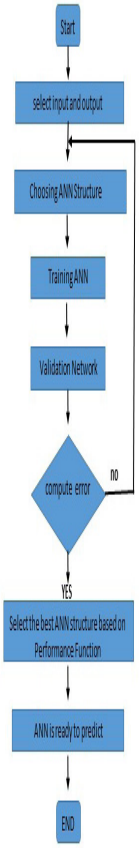

Figure 7. ANN process flow chart.

In this study, ANN is used to predict the effective viscosity of Alumina Water-Based Nanofluid. A computer program was executed with Matlab R2014B software.

For modeling, the feed forward multilayer perception neural network has been used. This network is very common in engineering applications and it has a good aptitude in estimating non-linear relations. Figure 7 shows the network training process used. Necessary data for training were collected from literature. Indeed, between numerous experimental data for Al2O3 water-based nanofluids viscosity are reported in literature, we chose those shown in Table1.

Table 1. Physical and operating conditions of used experimental data sets.

Temperature (°C) Volume Fraction Diameter	Viscosity (mPa.S) Reference Number of Experimental data
4°-60° **1.4%.** **43nm**	0.48-1.41 Pastoriza-Gallego et al.[18] 42
7.52°-54.40° **2%.** **25 nm**	0.74-1.51 Kwek et al[19] 30
13.88°-55.49° **0.5%** **30nm**	0.64-0.99 Tavman et al[20] 25
6.09°-55.84° **2 %** **95 nm**	0.59-1.05 Anoop et al[21] 30
23°-54,99° **9%** **36nm**	1.95-4.25 Nguyen et al.[8] 23
23°-63,07° **7%** **36nm**	1-2.43 Nguyen et al.[8] 23
22.55-59.99 **9,4%** **47nm**	2.24-4.8 Nguyen et al.[8] 15
23.05-64.15 **7%** **47nm**	0.97-2.29 Nguyen et al.[8] 18

In fact, it denotes physical, operating conditions and references for all experimental data sets used.

Out of the 208 data obtained from literature, 166 of the data are used for network training, while the remaining 42 data are used for network test and validating.

Finally, for calculating performance of training results we used mean square error (MSE) and the linear regressions (R2) using the following equations:

$$MSE = \frac{1}{N}\sum_{t=1}^{N}(t_j - o_j)^2 \quad (1)$$

$$R^2 R^2 = 1 - \left[\frac{\Sigma_j (t_j - o_j)^2}{\Sigma_j (o_j)^2}\right] \quad (2)$$

Where t is a target value, o is an output value, and N is a pattern.

The network with minimum MSE and maximum R2 is proposed as best model. We planned network with three layers and algorithm Leven berg-Marquardt back propagation is used to train the network; one input layer, one hidden layer, and one output layer were used.

The hidden layer performs the computations in the network. Table 2 shows the range of the input parameters in ANN. Three parameters affecting the viscosity were considered as inputs, including temperature, volume fraction nanoparticles and diameter nanoparticles. ANN was then trained so that to predict the viscosity as outputs.

In Figure 8 Neural network architecture is given. In feed forward networks, neurons are arranged from input to output in order layers and transmission from one level to another is only available for the next layer.

Table 2. The range of the input parameters in ANN.

Input	Range
Temperature	4°-64,15° °C
Volume Fraction Np	0.5% - 9,4%
Diameter NP	25 – 47 nm

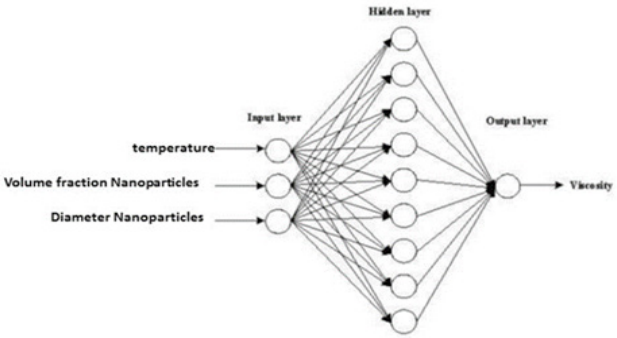

Figure 8. The system architecture used in the ANN model.

The data went in the input layer then in the hidden layer and finally in the output layer where they were processed and the results were combined to the outer world. Already it has been shown that a three layers feed forward ANN can approximate any continuous function at the wanted accuracy level provided that an adequate number of neurons are included in the hidden layer.

In the end, all the input data were normalized to the range of (0-1) with aim to deal efficiently with the data.

4. Results and Discussion

For modeling viscosity of alumina water-based nanofluids, a three layers ANN with feed forward Leven berg-Marquardt back propagation network were used. The input layer has three neurons (temperature, volume fraction and diameter of nanoparticles) hidden layer has nine neurons and output layer has one neuron (viscosity).

As shown in Figures 9 and 10, the R2 values of the ANN viscosity model are 0.9994 and 0.9998 for training and test data sets respectively. Their mean square error (MSE) values are 2.7187*10-4 and 1.2461*10-4.

Accurate predictions based on a high R2 value and a low MSE value prove that proposed ANN is an efficient model for the design of viscosity of nanofluids; it is reliable and easily extensible to different nanofluids from those investigated.

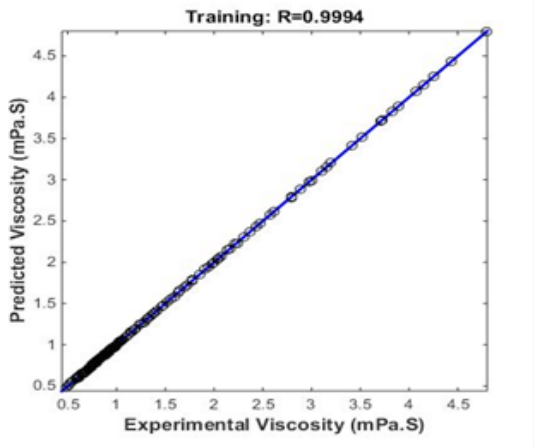

Figure 9. Training for ANN proposed.

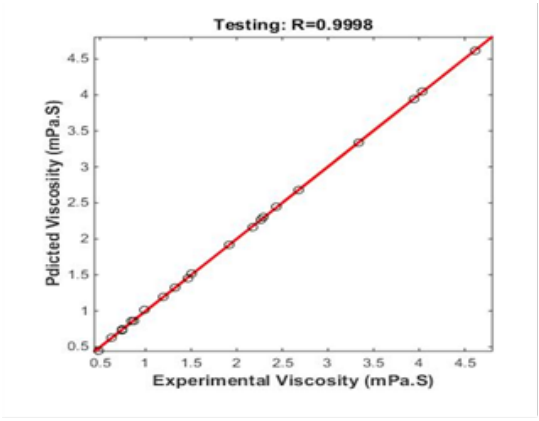

Figure 10. Test for ANN proposed.

In fact, the proposed ANN viscosity model successfully increases the prediction possibility of viscosity of alumina water-based nanofluids at various conditions.

Figures 11 and 12 show the experimental results of experimental data[18- 21,5] and correlations for an Al_2O_3– water nanofluid with a particle size, volume concentration and temperature shown in Table 1 compared with the ANN proposed model. The proposed ANN model is well matched with the experimental data for all experimental data set. The experimental data were divided into two subsets as 80% for training and 20% for testing purposes.

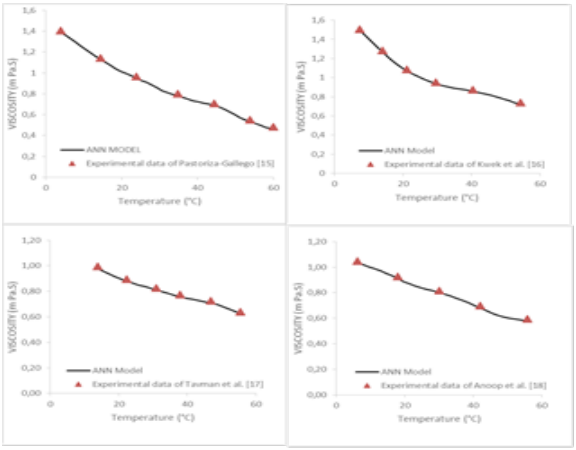

Figure 11. ANN model and experimental data comparison for references data[18-21].

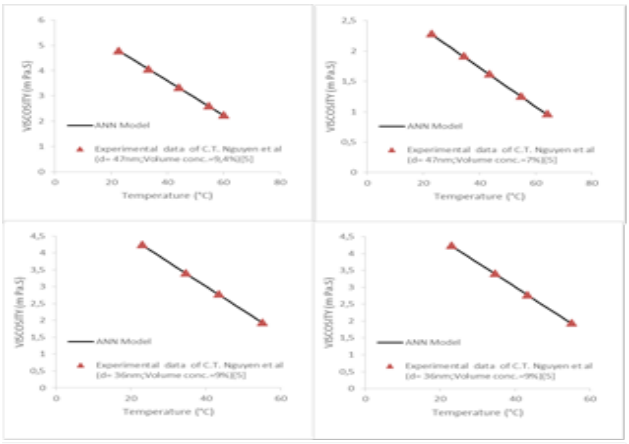

Figure 12. ANN model and experimental data comparison for reference data[8].

5. Conclusion

Artificial neural networks (ANN) were used to predict the viscosity of alumina water-based nanofluids. The viscosity is considered one of more significant thermophysical properties of a nanofluid, especially in thermal applications where heat transfer and fluid flow take place.

The ANN approach was used for modelling the viscosity of nanofluids as function of particle size, volume concentration and temperature. The objective of this paper was to develop an ANN model to predict the viscosity of oxide–water nanofluids, based on own experimental data and then validated against data coming also from other authors to exploit the consistency of the modelling approach. The ANN modelling techniques work as a black box to establish the relation- ship between input and output values.

A literature review of experimental data of the viscosity of nanofluids showed that particle size, volume concentration and temperature were the three most important variables that determined viscosity. Therefore, experimental data points for Al2O3, nanoparticles with water as base fluid were obtained from literature to model the viscosity of nanofluids by using particle size, volume concentration and temperature as input for the ANN method.

The viscosity results ANN were compared with the experimental data points. The expected values were in excellent agreement with the measured ones, viewing that the developed model is accurate and has the great ability for predicting the viscosity. The linear regressions R2 0.9994 and 0.9998 are the values of the ANN viscosity model for training and testing data set, respectively, 2.7187*10-4 and 1.2461*10-4 are the values of mean square error respectively.

6. References

1. Karimipour A, Mirtalebi SS, Afrand M. Using Nanofluid in Lid Driven Shallow Enclosure at Particular Richardson Number: Investigation the Effect of Velocity Ratio, Indian Journal of Science and Technology. 2014; 7(5):698–704.
2. Mostafavinia N, Eghvay S, Hassanzadeh A. Numerical Analysis of Melting of Nano-Enhanced Phase Change Material (NePCM) in a Cavity with Different Positions of Two Heat Source-Sink Pairs, Indian Journal of Science and Technology. 2015; 8(S9):49–61.

3. Auriemma M, Iazzetta A. Numerical Analysis of Melting of Paraffin Wax with Al2O3, ZnO and CuO Nanoparticles in Rectangular Enclosure, Indian Journal of Science and Technology. 2016; 9(3):1–8.
4. Masuda H, Ebata A, Teramae K, Hishinuma N. Alteration of Thermal Conductivity and Viscosity of Liquid by Dispersing Ultra-Fine Particles (dispersion of c-Al2O3, SiO2 and TiO2 ultra-fine particles), NetsuBussei (Japan). 1993; 4(4):227–33.
5. Choi SUS. Eastmen JA. Enhancing Thermal Conductivity of Fluids with Nanoparticles, ASME Congress and Exposition. 1995; 1–8.
6. Mahbubul IM, Saidur R, Amalina MA. Latest Developments on the Viscosity of Nanofluids, International Journal of Heat and Mass Transfer. 2012; 55(4):874–85.
7. Pak BC, Cho YI. Hydrodynamic and Heat Transfer Study of Dispersed Fluids with Submicron Metallic Oxide Particles, Experimental Heat Transfer: A Journal of Thermal Energy Generation, Transport, storage and Conversion. 1998; 11(2):151–70.
8. Nguyen CT, Desgranges F, Roy G, Galanis N, Maré T, Boucher S, Angue Mintsa H. Temperature and Particle-Size Dependent Viscosity Data for Water-Based Nanofluids — Hysteresis Phenomenon, International Journal of Heat and Fluid Flow. 2007; 28(6):1492–506.
9. Chen H, Witharana S, Jin Y, Kim C, Ding Y. Predicting Thermal Conductivity of Liquid Suspensions of Nanoparticles (Nanofluids) based on Rhenology, Particuology. 2009; 7(2):151–57.
10. Yang JC, Li FC, Zhou WW, He YR, Jiang BC. Experimental Investigation on the Thermal Conductivity and Shear Viscosity of Viscoelastic-Fluid-Based Nanofluids, International Journal of Heat and Mass Transfer. 2012; 55(11-12):3160–66.
11. Mishra PC, Mukherjee S, Nayak SK, Panda A. A Brief Review on Viscosity of Nanofluids, Review International Nano Letters. 2014; 4(4):109–20.
12. Meyer JP, Nwosu PN, Sharifpur M, Ntumba T. Parametric Analysis of Effective Viscosity Models for Nanofluids, Proceedings of the ASME 2012 International Mechanical Engineering Congress and Exposition (IMECE2012), Houston, USA; 2012. p. 1149–57.
13. Mukesh Kumar PC, Kumar J, Suresh S. Review on Nanofluid Theoretical Viscosity Models, International Journal of Engineering Innovation and Research. 2012; 1(2):182–88.
14. He Y, Jin Y, Chen H, Ding Y, Cang D, Lu H. Heat Transfer and Flow Behaviour of Aqueous Suspensions of TiO2 Nanoparticles (Nanofluids) Flowing Upward Through a Vertical Pipe, International Journal of Heat Mass Transfer. 2007; 50(11-12):2272–81.
15. Lu W-Q, Fan Q-M. Study for the Particle's Scale Effect on some Thermo-physical Properties of Nanofluids by a Simplified Molecular Dynamics Method, Engineering Analysis with Boundary Elements. 2008; 32(4):282–89.
16. Prasher R, Song D, Wang J, Phelan P. Measurements of Nanofluid Viscosity and its Implications for Thermal Applications, Applied Physics Letters. 2006; 89(13):108–33.
17. Mahbubul IM, Saidur R, Amalina MA. Latest Developments on the Viscosity of Nanofluids, International Journal of Heat Mass Transfer. 2012; 55(4):874–85.
18. Pastoriza-Gallego MJ, Casanova C, Páramo R, Barbés B, Legido JL. A Study on Stability and Thermo-Physical Properties (density and viscosity) of Al2O3 in Water Nanofluid, Journal of Applied Physics. 2009; 106(6):301–08.
19. Kwek D, Crivoi A, Duan F. Effects of Temperature and Particle Size on the Thermal Property Measurements of Al2O3–Water Nanofluids, Journal of Chemical and Engineering Data. 2010; 55(12):5690–95.
20. Tavman I, Turgut A, Chirtoc M, Schuchmann HP, Tavman S. Experimental Investigation of Viscosity and Thermal Conductivity of Suspensions Containing Nanosized Ceramic Particles, Archives of Materials Science and Engineering. 2008; 34(2):99–104.
21. Anoop KB, Kabelac S, Sundararajan T, Das SK. Rheological and Flow Characteristics of Nanofluids: Influence of Electroviscous Effects and Particle Agglomeration, Journal of Applied Physics. 2009; 106:909.