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Prediction of dynamic viscosity of a hybrid nano-lubricant by an optimal artificial neural network☆

Masoud Afrand [a,*], Karim Nazari Najafabadi [a], Nima Sina [a], Mohammad Reza Safaei [b], A.Sh. Kherbeet [c], Somchai Wongwises [d,*], Mahidzal Dahari [e]

[a] Department of Mechanical Engineering, Najafabad Branch, Islamic Azad University, Najafabad, Iran
[b] Department of Mechanical Engineering, Faculty of Engineering, University of Malaya, 50603 Kuala Lumpur, Malaysia
[c] Department of Mechanical Engineering, KBU International College, 47800 Petaling Jaya, Selangor, Malaysia
[d] Fluid Mechanics, Thermal Engineering and Multiphase Flow Research Lab. (FUTURE), Department of Mechanical Engineering, Faculty of Engineering, King Mongkut's University of Technology Thonburi, Bangmod, Bangkok 10140, Thailand
[e] Department of Electrical Engineering, Faculty of Engineering, University of Malaya, 50603 Kuala Lumpur, Malaysia

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ABSTRACT

In this paper, at first, a new correlation was proposed to predict the relative viscosity of MWCNTs-SiO_2/AE40 nano-lubricant using experimental data. Then, considering minimum prediction error, an optimal artificial neural network was designed to predict the relative viscosity of the nano-lubricant. Forty-eight experimental data were used to feed the model. The data set was derived to training, validation and test sets which contained 70%, 15% and 15% of data points, respectively. The correlation outputs showed that there is a deviation margin of 4%. The results obtained from optimal artificial neural network presented a deviation margin of 1.5%. It can be found from comparisons that the optimal artificial neural network model is more accurate compared to empirical correlation.

1. Introduction

Oil is a lubricant that is used in industrial applications for many years. The main task of oil is to reduce friction in moving parts. It also inhibits corrosion, improves sealing and cleans the engine. It is also used as a coolant in numerous applications and can remove excess heat away from moving parts. Since adding the nano-sized materials can increase the thermal conductivity of fluids, many researchers have focused on this subject. In recent decades, the thermal conductivity and heat transfer rate of the dispersions of nano-sized materials in common fluids, called nanofluids, have been investigated in many studies [1–10]. These studies have shown that the thermal conductivity of nanofluids is greater than common fluids and is a function of temperature, solid volume fraction, size and shape of nanoparticles, and properties of base fluids and nanoparticles.

However, the thermophysical properties of the fluids also are affected by the adding nanoparticles to the fluid base. Among these properties, viscosity is an important parameter for calculating the required pumping power. It affects the Reynolds and Rayleigh number values, which are very essential characteristics for convective heat transfer. In this regard, many researchers have investigated the viscosity of nanofluids, and have reported that the viscosity of nanofluids is dependent on temperature, concentration, size and shape of nanoparticles, and specifications of base fluids and nanoparticles [11–20].

In recent years, attention has been given to use novel nanofluids, called hybrid nanofluids, combined with various nanoparticles to enhance the thermo-physical properties of common fluids. For example, the thermo-physical properties of several water-based hybrid nanofluids containing Cu–Cu_2O, Ag–TiO_2, Cu–TiO_2, Ag–MgO, MWCNT–SiO_2, MWCNT–Ag, MWCNT–Fe_2O_3, and Fe_3O_4–Ag have been reported by different researchers [21–29].

However, there is a need to do several experiments for obtaining the thermophysical properties of nanofluids at different temperatures and nanoparticles concentrations, which are time-consuming and costly. Therefore, to avoid the costs of experiments, soft computing methods have been used to predict the thermophysical properties of nanofluids. Among these methods, we can point to curve-fitting, artificial neural network (ANN), fuzzy logic and genetic algorithm as the most widely used methods. In this regard, numerous studies have been performed on thermal conductivity of various nanofluids by employing soft computing methods. Some of the studies worth mentioning are the research studies of Papari et al. [30], Hojjat et al. [31], Longo et al. [32], Ariana et al. [33] and Hemmat Esfe et al. [34–40]. Nevertheless, there are few works for the viscosity of nanofluids by using soft computing methods. For example, Mehrabi et al. [41] established a new model for predicting

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* Corresponding authors.
E-mail addresses: masoud.afrand@pmc.iaun.ac.ir, masoud_afrand@yahoo.com (M. Afrand), somchai.won@kmutt.ac.th (S. Wongwises).

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the effective viscosity of Al_2O_3, CuO, TiO_2 and SiO_2 water-based nanofluids using an FCM-ANFIS based on experimental data. They considered the nanoparticles size, solid volume fraction and temperature as the design parameters. Their comparisons revealed that the estimated results agreed with the experimental findings. Karimi et al. [42] suggested a neural network based on genetic algorithm to predict the nanofluids viscosity. They optimized the neural network parameters by employing the genetic algorithm. Temperature and concentration of nanoparticles were considered as input variables. Their results showed that the proposed model was in agreement with experiments. Recently, Hemmat Esfe et al. [43] predicted the dynamic viscosity and thermal conductivity of ferromagnetic nanofluid by designing an artificial neural network (ANN). They used experimental results that include temperature and concentration diameter of particles as input variables. Their results showed that the neural network was able to track the data. The ANN outputs also revealed the maximum error of 2% and 2.5% in predicting the thermal conductivity and dynamic viscosity, respectively.

Because of numerous applications of engine oil, mentioned above, the study of rheological behavior of engine oil seems very necessary. However, only a few works have been done on thermo-physical properties of engine oils [44–48]. On the other hand, literature survey reveals that there is no any reported work about modeling of dynamic viscosity of MWCNTs-SiO_2/SAE40 hybrid nano-lubricant using artificial neural network. Hence, in the present study, for the first time, a new correlation has been proposed to predict the relative viscosity of MWCNTs–SiO_2/AE40 hybrid nano-lubricant using a set of experimental data. Then, an accurate and efficient artificial neural network has been designed to predict the relative viscosity of the hybrid nano-lubricant.

2. Methodology

2.1. Experimental

Forty-eight experimental data for the relative viscosity of a hybrid nano-lubricant covering a volume fraction ranging from 0 to 1% and a temperature ranging from 25 to 60 °C have been used for developing models (Fig. 1) [49]. The hybrid nano-lubricant is made up of a combination of multi-walled carbon nanotubes and silica dispersed in SAE40 engine oil. The properties of the nano-materials used for nano-lubricant data are presented in Table 1.

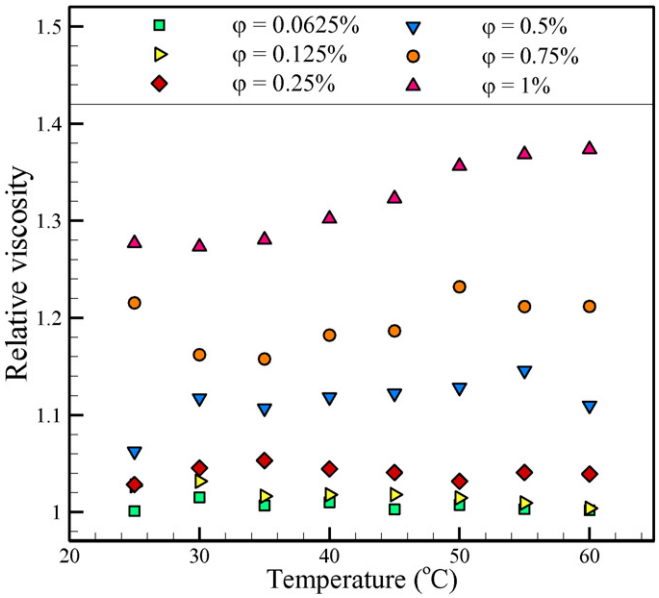

Fig. 1. Relative viscosity versus temperature for various solid volume fractions [49].

Table 1
Properties of the nano-materials used for nano-lubricant data.

Characteristic	Value	
	MWCNTs	SiO_2
Purity	>97%	>99%
Color	Black	White
Size	Outer diameter: 5–20 (nm) Inner diameter: 3–5 (nm) Length: 50 (μm)	20–30 (nm)
Bulk density:	0.27 (g/cm^3)	<0.10 (g/cm^3)
True density	~2.1 (g/cm^3)	2.4 (g/cm^3)
Specific surface area (SSA)	233 (m^2/g)	180–600 (m^2/g)

2.2. Proposing new experimental correlation

In this section, a new experimental correlation has been proposed as a function of temperature and solid volume fraction. To attain a precise correlation, the curve-fitting has been performed employing the Marquardt–Levenberg algorithm [50] to find the coefficients of the temperature and solid volume fraction. This algorithm examines the parameters that minimize the sum of the squared differences between the experimental data and predicted values of the relative viscosity of the nano-lubricant (see Eq. (1)).

$$S = \sum_{i=1}^{n} (y_i - \hat{y}_i)^2 \tag{1}$$

where S is the sum of the squared differences, and y_i and $\hat{y}_i$ are respectively the experimental and the predicted values of the relative viscosity.

The correlation, attained by aforementioned algorithm, can estimate the relative viscosity of the hybrid nano-lubricant which is known as

$$\mu_r = \frac{\mu_{nf}}{\mu_{bf}} = 0.00337 + exp\left(0.07731\,\varphi^{1.452}T^{0.3387}\right) \tag{2}$$

where μ_r, μ_{nf} and μ_{bf} are, respectively, the relative viscosity, the nanofluid viscosity and the base fluid viscosity. Moreover, T is the temperature of the nanofluid in °C and φ is the solid volume fraction in %.

2.3. Architecture of artificial neural network

Recently, the artificial neural network (ANN) has been used widely to predict the nonlinear systems because of its significant advantages such as high precision, low cost and time. The human brain is the main idea behind ANN, which is a parallel processing network to determine the complex nonlinear relationships between input variables and output parameters [51,52].

The ANN architecture presents the connections between the neurons and the layers. The weights and biases on the connections are determined using the learning algorithm. The ANN consisted of an output layer and a hidden layer. In this study, the transfer function of the hidden layer has been considered as the tangent-sigmoid, while pureline function was used for the output layer. Eq. (3) presents the tangent-sigmoid transfer function as follows:

$$f(x) = \frac{1}{1 + \exp(-x)} \tag{3}$$

Since a Levenberg–Marquardt generally leads to better outputs [53–54], the Levenberg–Marquardt training algorithm has been employed to model the rheological behavior of MWCNTs–SiO_2/AE40 nano-lubricant. In this study, a feed forward network has been used as the training algorithm (see Fig. 2). There are two input variables including solid volume fraction (φ) and temperature (T). The ANN output parameter is the relative viscosity (μ_r). Forty-eight experimental data,