# Optimization, Modeling of Thermal Conductivity and Viscosity of Cu/Engine Oil Nanofluids by NSGA-II Using RSM

*Mohammad Hemmat Esfe*[1], *Sayyid Majid Motallebi* [2,*]

[1]Department of Mechanical Engineering, Imam Hossein University, Tehran, Iran

[2,*]Department of Chemical Engineering, Kermanshah University of Technology, Kermanshah, Iran

Email: sayyidmajidmotallebi@gmail.com

## Abstract

This study provides the optimization of thermophysical properties of Cu/engine oil nanofluid. In this optimization, the objective functions were determined with the experimental data of viscosity and TC of nanofluid using RSM. Two equations for predicting thermal conductivity (TC) and viscosity data were presented which can accurately predict these properties. The NSGA-II method was used for multi-objective optimization (Mo-O) and Pareto's front was introduced to study optimal viscosity and TC responses. According to the results, the highest TC and the lowest viscosity occurs when the temperature and solid volume fraction (SVF) of the nanoparticle are at their maximum values. Among the results, those with the highest TC and the lowest viscosity are referred to as optimal points.

**Keywords:** Nanofluid; Viscosity; Thermal Conductivity; Optimization; Cu/Engine Oil.

## 1. Introduction

Among various applications of nanofluids, many items such as automotive coolers, electronic coolants, solar energy systems, antibacterial applications and polymer membrane fuel cells can be pointed [1-6]. Among the thermophysical properties of the fluid, TC and dynamic viscosity play an important role in the heat transfer behavior. The addition of nanoparticles increases the TC and dynamical viscosity of nanofluid [7-13]. A review of studies on viscosity and TC of nanofluids is presented in Table 1.

**Table 1.** Studies on the viscosity and TC of nanofluids.

| Author | Type of nanofluid | The effect | Conclusion |
|---|---|---|---|
| Águila et al.[14] | Cu-PCM | Thermal conductivity and viscosity | Increasing the temperature from 30 to 40 ℃ leads to a linear reduction in thermal conductivity. The rheological behavior of fluids also exhibits a quasi-plastic behavior. |
| Kakavand et al.[15] | MWCNTs-SiC/Water-EG | Thermal conductivity | At solid volume fraction of 0.75%, thermal conductivity increased to 28.86%. |
| Alirezaie et al.[16] | Fe and MgO in Ethylene Glycol | Thermal conductivity | Temperature, SVF, nanoparticle diameter, specific heat capacity, and density of nanoparticles play an important role in determining thermal conductivity. |
| Dalkılıç et al.[17] | $SiO_2$-Graphite/water | viscosity | The highest viscosity increase to 36.12% was in a nanofluid with a concentration of 2% at 15 °C. |
| Hemmat et al.[18] | MWCNT–MgO/water–EG | Thermal conductivity | The MWCNT-MgO/water-EG nanofluid has better price-performance value, but the MWCNT-CuO (10-90%)/water-EG nanofluid has a higher thermal conductivity. |

In order to predict the thermal and rheological behavior of nanofluids, researchers have investigated various methods of modeling such as ANN, GA and RSM method. The results of modeling can be useful for use in other studies and reduce the cost of testing [19-20]. In Table 2, some studies have been reviewed on the modeling of Nano-fluid properties.

**Table 2.** Some modeling in the field of nanofluid properties.

| Author | Type of nanofluid | The effect | Modeling method | Conclusion |
|---|---|---|---|---|
| Hemmat et al.[21] | NSGA-II coupled with RSM | Thermal conductivity and viscosity | NSGA-II coupled with RSM | Maximum thermal conductivity and minimum viscosity occur at the highest SVF and temperature. |
| Rejvani et al.[22] | NSGA-II | Thermal conductivity and viscosity | NSGA-II | As the temperature rises, the viscosity of the nanofluids decreases at all SVFs and their thermal conductivity increases. |
| Longo [23] | ANN | viscosity | ANN | The average absolute error percentage of predicted data was 4.15%. |
| Alrashed [24] | ANN ANFIS | Thermal conductivity and viscosity | ANN ANFIS | Has the lowest values of MAPE and RMSE in predicting the thermal conductivity and |

| | | | | |
|---|---|---|---|---|
| | | | | viscosity of both types of nanofluids. |
| Rostamian et al.[25] | ANN | Thermal conductivity | ANN | Comparison of the accuracy of the neural network model and proposed correlation showed that the neural network can predict the nanofluid thermal conductivity more accurately. |

Vakili et al. [26] predicted the TC of the graphene/deionized water at weight percent from 0.00025, 0.0005, 0.001 and 0.005 using a multi-layer perceptron (MLP) ANN. They showed the high accuracy of ANN (ANN) compared to other experimental and theoretical modeling by comparing the results of modeling results with experimental data and MLP modeling results. Since performing experimental processes to determine the TC of graphene nanofluid is costly, the use of ANN model was recommended in this study.

Hemmat et al. [27] investigated the optimization of nanofluid with double-walled carbon nanotubes (DWCNTs)/water. The experimental data of their thermal performance coefficients were obtained for various SVFs of nanoparticles and Re number. They provided the appropriate equations to achieve the lowest cost pattern with respect to the desirable thermal performance. The results showed that the cost of the first replication has been reduced by 38%. The maximum thermal performance coefficient was obtained at the nanoparticle SVF of 0.365 and the Re number of 23.712.

Tahani et al. [28] examined the prediction of the TC of the nanofluid with graphene/deionized oxide nanotubes using ANN and experimental data. They found that the proposed model has a high accuracy with respect to the values of statistical indicators. The RMSE value was 0.03, the MAPE value was 0.006%, and the R2 was 99.9%. Since experimental research is usually time-consuming and its equipment is expensive, they suggested using the above method to predict the TC of the nanoparticle containing graphene.

In this paper, the Mo-O has been used by NSGA- II to obtain the highest TC along with the lowest viscosity of Cu-engine oil, which was studied by Aberoumand and Jafarimoghaddam [29]. Also, two models have been proposed to predict TC and viscosity of nanofluid by using RSM.

## 2. Simulation

### 2.1. RSM

The design of experiment (DOE) method can be used as a guide and reference for researchers to improve the production process. DOE is a practical solution for determining the effect of input parameters on output. Also, Design Expert software has been considered as a useful tool for designing experiments, providing relationships and analyzing results. The RSM is used in this software. RSM is a powerful mathematical tool for developing and optimizing processes. RSM is a method for developing or optimizing the process and by integrating mathematical and statistical methods. The input variable is known as an independent variable, which is determined according to process constraints. This study investigated the statistical modeling of the statistical process using RSM statistical modeling. The approximation model is usually derived from the experimental data of the process, so it is known as experimental model. The first-order regression model has been shown by Eq.1 [30]:

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

In this linear model, the unknown parameters of $\beta_0$, $\beta_1$ and $\beta_2$ are called regression coefficients. Independent variables $x_1$ and $x_2$ are also known as predictive variables or regressions. y is the objective function (dependent variable). This model in the matrix symbol is as Eq.2:

$$Y = X\beta + \varepsilon \tag{2}$$

Where Y is vector of the observations, X is matrix of the levels of the independent variables, b is vector of the regression coefficients, and ε is vector of random errors.

There are several methods for assessing the accuracy of linear regression models such as Least Squares Estimators. The sum of squares of residuals is presented as Eq.3:

$$SS_E = \sum_{i=1}^{n} (y_i - \hat{y}_i)^2 = \sum_{i=1}^{n} e_i^2 = e^T e \tag{3}$$

Since $X^T X b = X^T y$ the formula for computing $SS_E$ may be appeared as:

$$SS_E = y^T y - b^T X^T y \tag{4}$$

Eq.5 is known as the error or residual sum of squares.

Unbiased estimator of X can be shown as Eq.6:

$$\sigma = \frac{SS_E}{n-p} \tag{5}$$

Where n is the number of measurements and represents the number of regression coefficients.

The total sum of squares is:

$$SS_T = y^T y - \frac{(\sum_{i=1}^{n} y_i)^2}{n} = \sum_{i=1}^{n} y_i^2 - \frac{(\sum_{i=1}^{n} y_i)^2}{n} \tag{6}$$

Eq.7 has been presented to calculate the total sum of squares.

Then the coefficient of determination ($R^2$) has been calculated by Eq.8:

$$R^2 = 1 - \frac{SS_E}{SS_T} \tag{7}$$

The investigation of Eq.8 shows that the values of $R^2$ are between zero and one. The closer it is to the unit, the higher the accuracy of the model.

In some studies, $R_{adj}^2$ is also evaluated as Eq.9:

$$R_{adj}^2 = 1 - \frac{SS_E/n-p}{SS_T/n-1} = 1 - \frac{n-1}{n-p}(1-R^2) \tag{8}$$

$R_{adj}^2$ Decreases by highly increase the parameter.

### 2.2. Regression model

The regression models of the RSM for determining the TC and viscosity of the Cu/engine oil nanoparticles, studied by Aberoumand and Jafarimoghaddam [29], have been shown Eq.10 and 11:

$$K_{nf} = 0.148928189 + 0.070452536 * phi - 0.000858593 * T + 0.001482324 * phi * T - 0.252294359 * phi^2 + 1.07655E-05 * T^2 - 0.000591119 * phi^2 * T - 4.12579E-06 * phi * T^2 + 0.177513333 * phi^3 - 4.86548E-08 * T^3 \tag{9}$$

$$\mu_{nf} = 3871.941168 + 764.1531501 * phi - 130.6783731 * T - 16.20129806 * phi * T - 134.9668743 * phi^2 + 1.489507577 * T^2 + 0.97370388 * phi^2 * T + 0.08805177 * phi * T^2 + 31.7975 * phi^3 - 0.005680515 * T^3 \tag{10}$$

After modeling based on experimental data of RSM tests, analysis of variance (ANOVA) of TC and viscosity relationships have been presented in Tables 3 and 4, respectively. The viscosity and TC models have the regression coefficient $R^2 = 0.9904$ and $R^2 = 0.9924$, respectively. This means that the accuracy of the response surface model is acceptable. The significance of the regression model is determined by the large F value for the TC and viscosity model (respectively 115.0404 and 204.952) and the small P-value.

**Table 3.** Analysis of variance (ANOVA) for TC of nanofluid

| Source | Sum of Squares | df | Mean Square | F Value | p-value , Prob > F |
|---|---|---|---|---|---|
| **Model** | 0.003222 | 9 | 0.000358 | 115.0404 | 6.66E-09 significant |
| **A-phi** | 4.91E-06 | 1 | 4.91E-06 | 1.578322 | 0.237558 |
| **B-T** | 2.07E-05 | 1 | 2.07E-05 | 6.637145 | 0.027593 |
| **AB** | 0.000115 | 1 | 0.000115 | 37.02933 | 0.000118 |
| **$A^2$** | 0.000145 | 1 | 0.000145 | 46.64079 | 4.57E-05 |
| **$B^2$** | 5.41E-06 | 1 | 5.41E-06 | 1.738118 | 0.216775 |
| **$A^2B$** | 3.37E-05 | 1 | 3.37E-05 | 10.84139 | 0.008114 |
| **$AB^2$** | 6.97E-06 | 1 | 6.97E-06 | 2.238203 | 0.165514 |
| **$A^3$** | 0.000219 | 1 | 0.000219 | 70.4982 | 7.69E-06 |
| **$B^3$** | 6.82E-07 | 1 | 6.82E-07 | 0.219052 | 0.649797 |
| **Residual** | 3.11E-05 | 10 | 3.11E-06 | | |
| **Cor Total** | 0.003254 | 19 | | | |
| **Standard deviation = 0.001764201** | | | | | |
| **$R^2$ (Adequate) = 0.990433952, $R^2$ (Predicted) = 0.877608099, $R^2$ (Adjusted) = 0.981824509** | | | | | |

**Table 4.** Analysis of variance (ANOVA) for viscosity of nanofluid.

| Source | Sum of Squares | df | Mean Square | F Value | p-value Prob > F |
|---|---|---|---|---|---|
| Model | 83116.56 | 9 | 9235.174 | 204.952 | 2.73E-13 significant |
| **A-phi** | 0.426757 | 1 | 0.426757 | 0.009471 | 0.923853 |
| **B-T** | 3347.576 | 1 | 3347.576 | 74.29124 | 5.69E-07 |
| **AB** | 1188.856 | 1 | 1188.856 | 26.38374 | 0.000151 |
| **$A^2$** | 33.50835 | 1 | 33.50835 | 0.743636 | 0.403029 |
| **$B^2$** | 15027.26 | 1 | 15027.26 | 333.4932 | 3.67E-11 |
| **$A^2B$** | 36.70857 | 1 | 36.70857 | 0.814657 | 0.382014 |
| **$AB^2$** | 382.8338 | 1 | 382.8338 | 8.496056 | 0.011306 |
| **$A^3$** | 8.448491 | 1 | 8.448491 | 0.187494 | 0.671607 |
| **$B^3$** | 943.2737 | 1 | 943.2737 | 20.93365 | 0.000432 |
| **Residual** | 630.8424 | 14 | 45.06017 | | |
| **Cor Total** | 83747.41 | 23 | | | |
| **Standard deviation = 6.712687379** | | | | | |
| **$R^2$ (Adequate) = 0.99246732, $R^2$ (Predicted) = 0.974054457, $R^2$ (Adjusted) = 0.987624883** | | | | | |

The regression graph of the Expert design software to evaluate the quality of these model functions, has been illustrated in Fig.s (1-a) and (1-b), based on experimental results for TC and nanofluid viscosity functions. The results indicate that the experimental values have a good agreement with the predicted values.

**Fig.1.** Comparison of the experimental results and predicted values (a) TC (b) Viscosity.

The residual graphs of experimental data and predicted results of TC and viscosity with RSM have been shown in Fig.s 2a and 2b. The coordination of the modeling results with the actual value shows the accuracy. The low amount of residual values indicates the accuracy of prediction models.

**Fig.2.** Residuals of the experimental results and predicted values (a) TC (b) Viscosity.

Fig.s (3a) and (3b) show three-dimensional TC and viscosity diagrams based on the temperature and SVF of nanoparticles. As it is known, the temperature has a direct effect on TC and inversely affect the nanofluid viscosity. But the volume fraction has a direct effect on both thermophysical properties.

**Fig.3.** Three-dimensional response surface graphs of (a) TC (b) Viscosity.

Fig.s (4a) and (4b) respectively show TC and viscosity contours, based on the temperature and SVF of nanoparticles. The results show that the effect of nanoparticle SVF on TC is much higher than nanofluid viscosity. At temperatures above 80 °C, the SVF has a slight effect on nanofluid viscosity. Also, according to Fig, with increasing SVF, temperature has a great influence on the TC of the nanofluid.

**Fig.4.** Contour response surface graphs of (a) TC (b) Viscosity.

## 3. Multi-objective optimization of Viscosity and TC

In this study for reducing viscosity and increasing TC, Mo-O by NSGA II was presented for Cu/engine oil nanofluid, which was studied by Aberoumand and Jafarimoghaddam [29]. NSGA II was first introduced by Deb in 1994 [31].

### 3.1. General procedure of NSGA-II algorithm

The principles of the genetic algorithm were first introduced by John Holland (1958). Genetic algorithm is a general-purpose optimization algorithm, modeled on Darwin's evolutionary theory; this algorithm operates on a population of potential answers, and by applying the survival of the better, 8 provides a better approximation of the solution [32]. The genetic algorithm consists of the design of the original communities (chromosomes), 55 of the best individuals (the survival of the most deserving), and the intersection of the generations (the marriage of superior couples). Genetic algorithms are suitable for Mo-O due to the investigation of a set of possible solutions and also less sensitivity to a particular form of optimal points [31]. The general method is illustrated in Fig.6. The NSGA-II flowchart is illustrated in Fig.7.

**Fig.5.** Structure of NSGA-II.

**Fig.6.** Optimization flowchart.

## 4. Results

NSGA II has been used to obtain the highest TC along with the lowest viscosity of Cu/engine oil, which was studied by Aberoumand and Jafarimoghaddam [29]. This method demonstrates the effectiveness of the optimization algorithm. For the proposed optimization problem, the temperature (T) and SVF (φ) of nanoparticles are considered as design variables. The nanofluid TC and viscosity objective function was modeled using experimental data and RSM with a regression coefficient higher than 0.99. In addition, the powerful NSGA-II algorithm with an initial population of 20 was also used for implementing optimization. After implementing the 2-objective optimization process, a set of non-dominant results was obtained on the Pareto front and has been presented in Fig.8. According to the Fig, by maximizing an objective (TC), the other objective (viscosity) will be minimized. This often happens in multi-purpose optimization. As shown in Fig.8, all Pareto front points are optimal and have no advantage over each other. Researchers can choose any of the points according to their needs. According to the results, the highest TC occurs at higher temperatures and higher SVFs. Table 5 has presented the optimal results by the RSM.

**Fig.7.** Pareto optimal front.

**Table 5.** Optimum points of the Mo-O.

| Phi (%) | T (C) | K (W/m.k) | V (cp) |
|---|---|---|---|
| **0.957431** | 97.16299 | 0.162439 | 37.38207 |
| **0.555087** | 99.31627 | 0.154952 | 27.5083 |
| **0.957431** | 97.16299 | 0.162439 | 37.38207 |
| **0.546184** | 98.7815 | 0.154972 | 28.39495 |
| **0.767292** | 99.44144 | 0.155063 | 30.53843 |
| **0.929409** | 99.391 | 0.160527 | 35.1116 |
| **0.889053** | 99.36374 | 0.158441 | 33.80149 |
| **0.872066** | 99.29476 | 0.157726 | 33.35816 |
| **0.94301** | 99.23315 | 0.161372 | 35.72898 |
| **0.903984** | 99.38909 | 0.159147 | 34.2524 |
| **0.856064** | 99.37055 | 0.15713 | 32.81669 |
| **0.827335** | 99.42164 | 0.156246 | 31.98123 |
| **0.956431** | 98.84155 | 0.16229 | 36.50333 |
| **0.842785** | 99.40074 | 0.156693 | 32.41547 |
| **0.949169** | 99.03219 | 0.161785 | 36.1062 |
| **0.802163** | 99.12696 | 0.155652 | 31.71847 |
| **0.915414** | 99.37931 | 0.15974 | 34.64061 |
| **0.918809** | 99.32004 | 0.159927 | 34.80945 |
| **0.787064** | 99.40952 | 0.155363 | 31.01785 |
| **0.797901** | 99.42636 | 0.155564 | 31.24707 |

## 6. Conclusion

In this research for reducing viscosity and increasing TC, optimizing the thermophysical properties of Cu/engine oil is investigated. In this optimization, the objective functions are performed with the experimental data of viscosity and TC of the nanofluid using RSM. Two equations have been presented for predicting TC and viscosity data that can predict their performance well. Also NSGA-II method has been introduced to investigate the optimal response of viscosity and TC. According to the results the highest TC and the lowest viscosity occurs at maximum of temperature and SVF. Among the results, those with the highest TC and the lowest viscosity are referred to as optimal points.

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