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Prediction and Comparative Analysis of Thermal Conductivity of Jatropha Oil-based Hybrid Nanofluid by Multivariable Regression and ANN

Amol J. Asalekar[1,2,*], D.V.A. Rama Sastry[3]

Abstract

In the present study, a multivariable regression (MR) and artificial neural network (ANN) method was used to predict the thermal conductivity of Jatropha oil-based ZnO-Ag hybrid nanofluid. Firstly, the ZnO-Ag hybrid nanoparticles were synthesized and mixed in the jatropha oil to prepare various nanofluids at different volume concentrations (F) ranging from 0.05 to 0.20%. The stability and thermal conductivity of the prepared nanofluids were investigated. Wide ranges of temperature and volume concentration as input data were used to predict the output parameters as thermal conductivity. In comparison with the multivariable regression, the artificial neural network (ANN) models, predict thermal conductivity values that are remarkably similar to the experimental values by offering a lower mean square error. This approach also aids with the issue of guesswork in figuring out the neural network layer's hidden structure.

Keywords: ANN, Thermal conductivity, hybrid nanofluid, Jatropha oil

INTRODUCTION

Hybrid nanofluids (HYNF) are gaining popularity due to the combined effects of nanoparticles, which provide them with superior heat transfer abilities than base fluids and conventional nanofluids [1]. The heat transmission qualities of hybrid nanofluids are strongly influenced by their thermophysical properties. As a result, thorough research of thermophysical characteristics is necessary before employing them in industrial applications. Nanofluids are employed as coolants in various production processes in industrial settings [2]. A heat dissipation area is a crucial need in manufacturing businesses during cutting operations since it may provide beneficial outcomes in terms of cutting tool life, energy consumption, and production rates. For proper heat dissipation, Thermal conductivity is one of the most important properties investigated in various research papers which describe their ability to conduct heat. One common approach to measuring thermal conductivity using the experimental method is the hot wire method. Based on the experimental values, many researchers develop mathematical models to predict the thermal conductivity of a hybrid nanofluid.

In late times, various researchers have employed various mathematical models such as regression, ANN, ANFIS, etc. to simulate the thermophysical properties of nanofluids under various circumstances. Much research has been published related to models and theories to investigate the thermal conductivity of hybrid nanofluids by curve fitting or multivariable regression. ANN can be used to model thermal conductivity measurements by learning the relationship between the input variables and the output values. Compared to other

***Author for Correspondence**
Amol J. Asalekar

[1]Research Scholar, Department of Mechanical Engineering, Koneru Lakshmaiah Educational Foundation, Green Fields, Vaddeswaram, Guntur, Andhra Pradesh, India
[2]Assistant Professor, School of Mechanical Engineering, MIT Academy of Engineering, Alandi Pune, Maharashtra-, India
[3]Associate Professor, Department of Mechanical Engineering, Koneru Lakshmaiah Educational Foundation, Green Fields, Vaddeswaram, Guntur, Andhra Pradesh, India

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modeling methods, ANN has several major advantages, including its fast-processing speed, availability of multiple training algorithms, and ability to solve complex equations. The speed of ANNs is a major advantage over other modeling methods, as they can process data quickly and provide accurate predictions [3]. Additionally, ANNs offer a range of training algorithms to choose from, providing flexibility in the modeling process. The ability of ANNs to solve complex equations makes them well-suited for modeling complicated relationships between input variables and output values [3]. Using 3 inputs such as temperature, nanoparticle volume fraction, and nanoparticle cluster average size, Giovanni A. Longo et al. [4] investigated the thermal conductivity of the Aluminum oxide-water nanofluids and developed the ANN model. Balla et al [5] investigated the application of ANN, the parameters of which were modified by a back propagation learning approach, and predicted the thermal conductivity ratio of alumina-water-based nanofluids. The prediction and modeling of the Thermal Conductivity Ratio (TCR) of various nanofluids was also the focus of the work of several other researchers [6–8].

As hybrid nanoparticles, a variety of metallic (Al, Au, Ag, Cu, Fe, and Sn), nonmetallic (ZnO, Al_2O_3, TiO_2, CuO, and Fe_3O_4), and carbon nanotube nanoparticles are combined. They have been dispersed in various base fluids such as water, ethylene glycol, and vegetable oil to enhance the thermo-physical properties [9]. However, the methods related to predicting the thermal conductivity of hybrid nanofluids with Jatropha oil as a base fluid are still under investigation. Jatropha belongs to the "Euphorbiaceae" family and is a type of perennial shrub or small tree that can withstand drought. It can thrive in difficult and arid soil conditions and can be found growing naturally in tropical and subtropical regions. The plant has a 50-year cycle for seed production and is versatile, with several applications that provide significant benefits to both humans and industry.

In this study, a mathematical model framework is constructed to forecast the effect of nanofluid temperature and concentration on numerous thermo-physical parameters of ZnO-Ag hybrid nanofluids. The comparative analysis has been analyzed between a multivariable regression (MR) and artificial neural network (ANN)) for thermal conductivity measurement.

METHODOLOGY

In this research, initially, the ZnO-Ag hybrid nanoparticles have been synthesized by wet chemical method and dispersed in the jatropha vegetable oil in various volume concentrations. The prepared vegetable oil-based hybrid nanofluid is characterized by stability and thermal conductivity measurement

Preparation of Ag-ZnO Vegetable Oil-based Hybrid Nanofluid

ZnO-Ag hybrid nanoparticles were synthesized by the wet chemical method. The complete synthesis process and its characterization were described in previous research [10]. The synthesized nanoparticles dispersed in the jatropha vegetable oil. The produced nanofluid was ultrasonically treated for 30 minutes at 30 W and 60 kHz after 30 minutes of stirring at 600 rpm. Then, the letters A (0.05%), B (0.10%), C (0.15%), and D (0.20%) are used to define the nanofluid samples, in volume concentration, respectively. The details about the base fluid and nanoparticles were represented in Tables 1 and 2.

Table 1. Properties of Prepared hybrid nanoparticles

Color	**Brown**
Size	10–50 nm
Shape	Hexagonal

Table 2. Properties of Jatropha oil

Properties	**Values**
Kinematic viscosity	8.65 m^2/s

Viscosity index	206
Flash point	252°C
Pour point	-12°C
Thermal conductivity	0.168 W/mK

Characterization of Prepared Hybrid Nanofluid

In the present study, initially, the prepared hybrid nanofluid is characterized for stability with zeta potential value. Zeta potential is a key parameter for the stability measurement of nanofluids (Zeta potential analyzer) Nanofluids are suspensions of nanoparticles in a base fluid, and their stability is essential for their practical applications in various fields, such as thermal management, lubrication, and energy storage. The zeta potential of nanofluids can be measured using techniques such as electrophoresis or laser Doppler velocimetry. A high absolute value of zeta potential indicates high stability of the nanofluid, as the electrostatic repulsion between the particles will prevent them from aggregating and settling. Conversely, a low absolute value of zeta potential indicates low stability and a higher likelihood of particle aggregation and settling. Using a thermal property analyzer with an isothermal bath (Model: KD2 Pro, Make: Decagon Device, USA), the effective thermal conductivity of the nanofluids was determined. The stainless-steel sensor needle (KS-1) used for measurement was 6 cm (about 2.36 in) long and had a 0.13 cm diameter. To calibrate the sensor needle, the thermal conductivity of several well-known fluids, including DI water and glycerin, was measured. Glycerin and distilled water have thermal conductivities of 0.63 W/mK and 0.292 W/mK, respectively. The sensor needle may be used to test the fluids' thermal conductivity between 0.02 and 2 W/mK with an accuracy of ± 5%. KD2 Pro uses a transient line heat source system and replaceable sensors to test thermal conductivity, resistance, diffusivity, and volumetric-specific heat. On both single-needle type and dual-needle type sensors, it uses the complete exponential integral solution to the heat flow equation. During both the heating and cooling processes of the calculation, data are collected, and a statistical non-linear least-square-inverse process is carried out to conform the data to differential equation solutions to find precise heat and thermal conductivity values. Fitting data on heating and cooling minimizes the influence of the sample temperature drift on the thermal property values obtained.

Data Processing and Models

Multivariable regression models involve multiple predictor variables included on the right side of the model equation, enabling the assessment of the relationships between various variables while adjusting for potential confounders. This statistical model is useful for analyzing the independent relationships between multiple factors. In contrast, a simple linear regression model involves a single predictor variable and a continuous outcome, whereas a multivariable linear regression model involves multiple predictors and a continuous outcome. Due to its simplicity, many researchers choose to employ this modeling technique when analyzing thermal conductivity problems.

$$y = \alpha + x_1\beta_1 + x_2\beta_{21} + \cdots + x_k\beta_k + \epsilon \quad (1)$$

When x is the single predictor in the basic regression model, x1, x2,..., xk are the predictors in the multivariable model, and y is a continuous dependent variable.

The various statistical indicator such as R-squared and mean squared error (MSE) values are taken into consideration to get the optimal model for thermal conductivity. The following is a list of the equations related to these parameters Eq. (2) to (3).

$$R - squared = 1 - \frac{(\sum_{i=1}^{N}(k_{exp} - k_{predicted})_i^{\ 2}}{(\sum_{i=1}^{N} k_{exp})_i^{\ 2}} \quad (2)$$

$$MSE = \frac{1}{N}\,(\sum_{i=1}^{N}(\,k_{exp} - k_{predicted})_i^{\ 2} \quad (3)$$

In a later stage, the experimental data was processed by ANN method. Artificial neural networks (ANNs) are a type of data processing model that mimics the neural networks of the human brain. ANNs are composed of interconnected artificial neurons, each with unique input/output (I/O) characteristics that allow for various calculations or partial actions. Compared to other mathematical models, ANNs can present computer modeling of experimental data faster and with greater accuracy. The benefits of ANNs include their simplicity, ability to derive non-linear relationships from training data, and capability to model multivariate problems. These features make ANNs effective for solving complex relationships between variables. Although ANN has many advantages, there are also several disadvantages such as overfitting, data resources, computational facility accuracy, etc, Figure 1 shows an architecture of ANN for two inputs and one output.

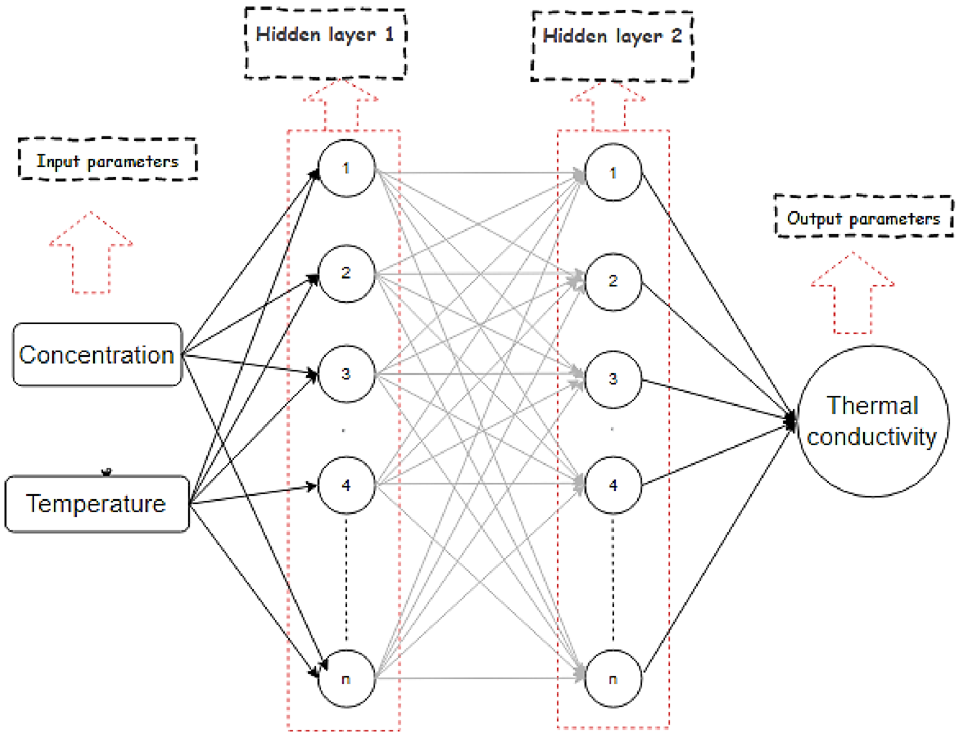

Figure 1. Architecture of ANN for two inputs.

RESULTS AND DISCUSSION

In this research, the ZnO-Ag hybrid nanofluid was prepared and characterized for stability and thermal conductivity analysis. Based on the measured value, the mathematical model based on multivariable regression and artificial neural network model has been developed and comparative analysis was described in the following paragraphs.

Stability Analysis Vegetable Oil-based Ag-ZnO Hybrid Nanofluid

The stability of nanoparticles in vegetable oil nanofluid is a crucial characterization, which is determined by the dispersion properties of nanoparticles in the base fluid. Visual tests were performed to measure the stability of the prepared nanofluids, by examining them for any signs of nanoparticle sedimentation or agglomeration. The results indicated that no nanoparticle aggregation or sedimentation was observed at the bottom of the flasks for a period of up to 15 days (about 2 weeks) for all of the tested nanofluids. According to the stabilization theory, increased electrostatic repulsion is often seen for high zeta potential values. Nanoparticle aggregation is inversely proportional to electrostatic repulsion in particles. It is claimed that exceptionally stable nanofluids have zeta potential values between 30 and 60 mV. The produced nanofluids' measured zeta potential values are shown in are in the range of at room temperature (25°C). The zeta potential values were well within the range of 30–60 mV (range for improved stability) = 0.05% to 0.2%, even though they decreased as the concentration of nanoparticles increased. The zeta potential value dropped to below 30 mV at the 0.2% volume concentration, however. Thus, the generated nanofluids with A volume concentration between 0.05% to 0.2% were thought to be stable and had good dispersal characteristics based on the zeta potential tests and visual observations. Hence, for further characterization, the nanofluids with volume concentrations of 0.05% to 0.20% were chosen.

Thermal Conductivity Analysis

As previously mentioned, hybrid nanoparticles were dissolved in a variety of base fluids at different fractions of 0.05%, 0.10%, 0.15%, and 0.2% by volume. The thermo-physical characteristics of these nanofluids were then determined using a KD2 Pro thermal analyzer. The accuracy was checked by EG and DI water in the range of +/- 2% accuracy. The effect of temperature (25°C–55°C) and volume concentration on its thermal conductivity was examined. An increased thermal conductivity was seen for increasing the values of the concentration of nanoparticles and temperature. It is found that for 0.20% volume concentration of nanoparticle, the maximum 16.8% enhancement in thermal conductivity compared with base fluid at 25°C was recorded. Due to the improved Brownian motion of the nanoparticles, the lattice vibration between molecules increases that causes the enhancement in the thermal conductivity.

The changes in relative thermal conductivity with temperature for various nanoparticles volume fractions (Figure 2). As can be noticed, the relative thermal conductivity increases slightly as the temperature rises for all investigated solid volume fractions. An increase in the relative thermal conductivity is more pronounced at high temperatures than at low ones. It is clear from that the solid volume fraction has a greater impact on the thermal conductivity of nanofluids concerning temperature. The presented graph showcases how thermal conductivity improves as a percentage of different temperatures and concentrations in a nanofluid. Higher temperatures and concentrations have a notable effect on the nanofluid's heat transfer capability. The most significant enhancement of 16.8% is observed at the highest temperature and concentration, highlighting the advantageous outcomes of incorporating nanoparticles into the base fluid regarding thermal conductivity.

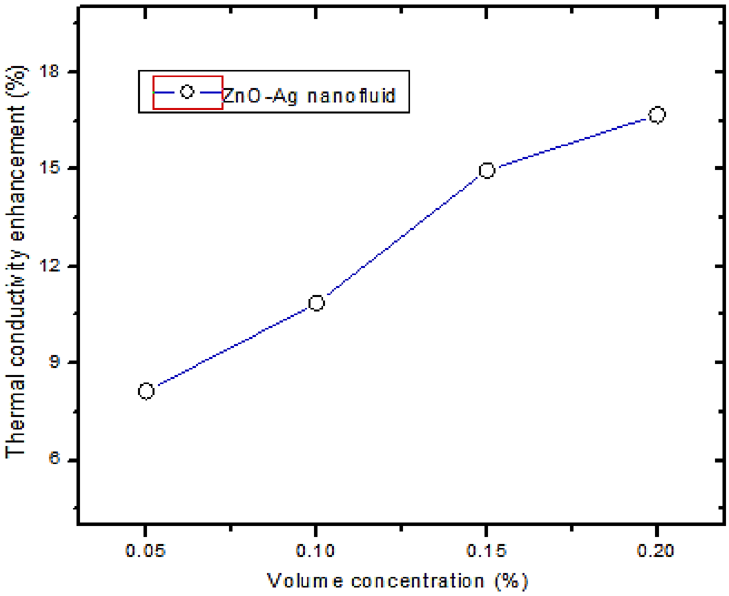

Figure 2. Thermal conductivity at different volume concentrations.

The Mathematical Model for Thermal Conductivity

Multivariable regression model (Curve fitting) can be a useful tool in determining the thermal conductivity of nanofluids, which are fluids that contain nanoparticles. The thermal conductivity of a nanofluid can be different from that of the base fluid due to the presence of nanoparticles, which can enhance or reduce heat transfer. In the curve fitting method, the experimental data is used to fit a mathematical model. The mathematical model is a function of the temperature, the concentration of the nanoparticles, in the base fluid After fitting the model to the data, you can use the model to estimate the thermal conductivity of the nanofluid at any given temperature and concentration. This can be useful for predicting the heat transfer properties of nanofluids and for designing heat transfer applications using nanofluids. It is important to note that the accuracy of the curve fitting method depends on the quality of the experimental data and the choice of the mathematical model. Therefore, it is important to carefully design the experiments and select an appropriate model for curve fitting. Equation (4) shows the mathematical model comes from the curve fitting model. Figure 3 shows variation in thermal conductivity by experiment or model by regression (curve fitting)

$$k= 0.000811048\ T + 0.259111\ ǿ + 0.141763 \quad (4)$$

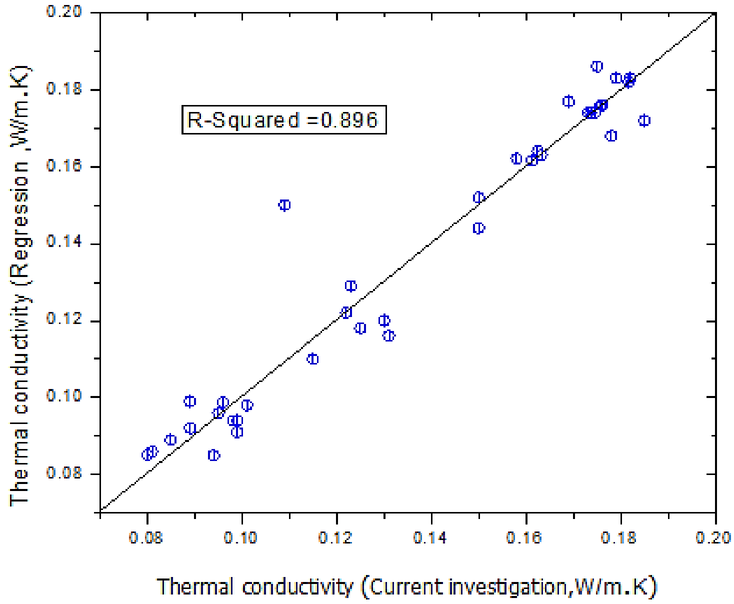

Figure 3. variation in Thermal conductivity by experiment or model by regression (curve fitting).

The accuracy in the form of statistical indicators such as MSE and R squared value is not up to the mark. The ANN method gives us a better prediction of the thermal conductivity value. The ANN network's inputs are the temperature of the nanofluid and the concentration of nanoparticles in the base fluid. The ideal number of neurons and the hidden layer are predicted in the current work using the trial-and-error approach to estimate the thermal conductivity model of a hybrid nanofluid. The model was developed using 100 experimental readings altogether. To expand the experimental data set and lower measurement error, several measurements are obtained at the same temperature and concentration. To avoid over-fitting the model, this is done. When a model is over-fitted, it accurately predicts the data from the training set but is unable to do so for the data from the test set. The network was trained using 70% of the available data, while 30% of the data was used for testing. The best number of hidden layers and neurons in those layers are determined using the hit-and-trial approach. Two distinct transfer functions, hyperbolic tangent sigmoid (TANSIG) and log sigmoid (LOGSIG), were used to identify the optimum performance for the hidden layers. The formula for the transfer functions utilized is shown in Eq. (5) to (7).

$$tansig\ (n) = \frac{2}{(1+e^{-2n})} - 1 \quad (5)$$

$$radbas\ (n) = e^{-n^2} \quad (6)$$

$$purelin\ (n) = n \quad (7)$$

The trials with a single hidden layer are represented by cases 1 to 17. In the hidden layer, only a single neuron is initially included [case 1 to case 10]. Regardless of the transfer function, the R-square value is quite low in these circumstances. The value of R-squared improves as the number of neurons grows. The value of the R-square does not increase significantly when a certain number of neurons are added. An additional hidden layer can be added to overcome this problem. Even though the second hidden layer has fewer neurons, the R-squared increases significantly. The transfer functions were examined in all feasible combinations. The findings of TANSIG-TANSIG [case 11] and LOGSIG-LOGSIG [case 12] were quite accurate. The R-squared again improves when increases for the TANSIG-TANSIG combination. For further neurons, this transfer function combination was used. To improve the model's accuracy, the number of neurons was raised even further. The addition of neurons beyond instance 12 did not result in a substantial increase in R-squared or MSE values, similar to the case of the first hidden layer.

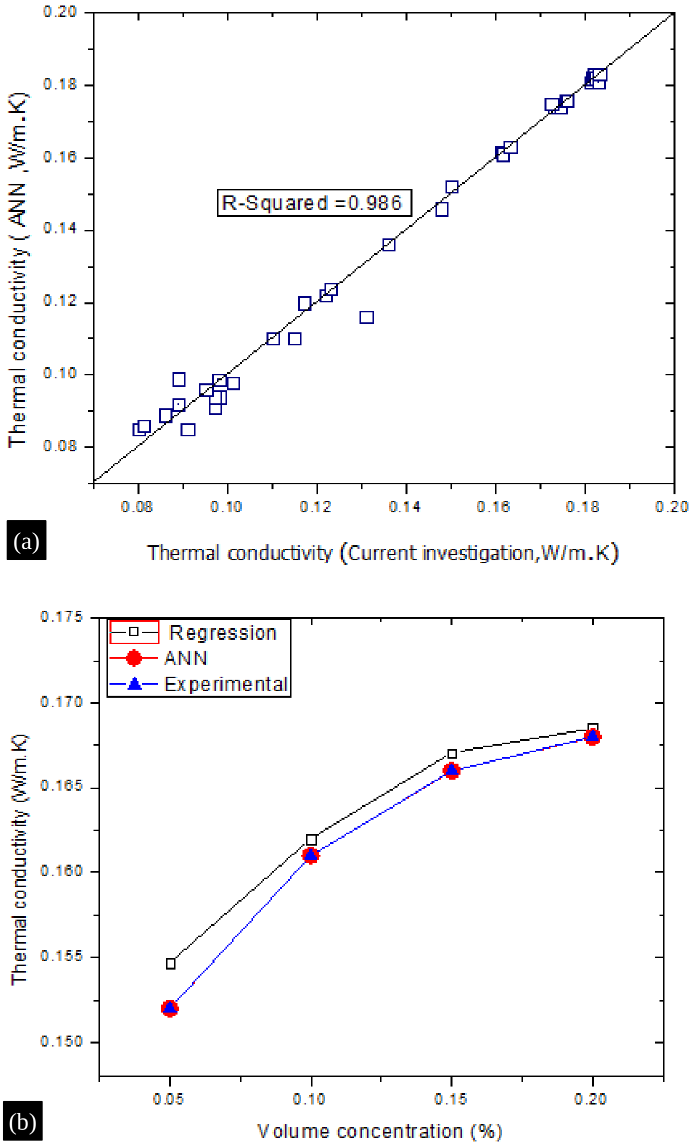

Figure 4. (a) Thermal conductivity by ANN vs Experimental values (b) comparative graph between ANN vs regression vs experimental values.

From Figure 4a, it is observed that the R-squared value for thermal conductivity measurement by multivariable correlation is lower than and ANN model. Also, the mean square error show lower in the case of ANN modeling. From Figure 4b, the thermal conductivity value by experimental measurement and ANN shows good agreement.

CONCLUSIONS

In the present study, ZnO-Ag nanoparticles-based vegetable oil nanofluid are prepared and its thermal conductivity was measured experimentally. Based on the experimental data, a multivariable regression (MR) and artificial neural network (ANN) were used to predict the effective thermal conductivity of jatropha oil-based ZnO-Ag hybrid nanofluid.

In contrast to the multivariable regression model, the ANN model could predict conductivity values that closely matched the experimental values by offering the lowest mean square error. This approach also aids with the issue of guesswork in figuring out the neural network layer's hidden structure.

This work shows that the artificial neural network modeling could be a powerful tool to predict the thermal conductivity ZnO-Ag nanoparticles-based vegetable oil nanofluid over highly nonlinear a wide temperature range and volume fraction which is difficult to achieve using conventional regression methods and ANN, especially for the lower volume fractions.

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