Revolutionizing Nanofluid Viscosity Prediction: A Deep Learning-based Smart Generalized Model

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Abstract

This research presents a unique method for estimating nanofluid viscosity by building a smart generalized model on top of a deep neural network (DNN). The DNN model was trained using the nadam optimization approach on a large experimental dataset that contained Alumina (Al₂O₃) nanoparticles. Non-linearities may be automatically learned by the proposed DNN model from a training dataset. This paper details the innovative aspects of this investigation and how they combine with the benefits of deep learning. To the author’s knowledge, no prior attempt was made to predict viscosity using a model based on deep learning. The comprehensive investigation of this DNN model’s efficiency demonstrates that it outperforms all competing models while also avoiding their pitfalls. Additionally, our DNN model provides remarkably accurate predictions on unseen data and can be trained in a fraction of the time mandatory by conventional data-driven models. This intelligent model has also been subjected to a sensitivity study. With a coefficient of determination of 0.9999, our unique DNN-based smart model is the best at predicting the viscosity of nanofluids.

Keywords

Nanofluid, Deep learning, Viscosity, Alumina, Nanoparticles

Introduction

Thermophysical qualities play a major role in making nanofluids a prominent aspect of nanotechnology. Preparing nanofluids involves dispersing nanoscale components like nanosheets or nanoparticles in a base fluid like water, oil, fuel, ethylene glycol, etc. [1]. The tunable characteristics and very stable dispersion of nanofluids have been the focus of a great deal of recent study. Nanotechnology has several uses in medicine and technology, such as engine cooling, lubricants, solar water heating, etc. Nanomaterials have the potential to improve the system’s overall performance [2]. It lessens the need for bulky components and boosts the durability of mechanical parts. Many different types of industry, nuclear reactors, electronics, and even some branches of biomedical engineering make extensive use of nanofluids because of their superior thermal characteristics. The thermal system is a significant area of use for nanofluids [3]. Afterwards, several scientists shifted their attention to nanofluid viscosity due to its numerous practical applications. The internal friction of a nanofluid is described by its viscosity, making it a crucial thermophysical characteristic.
Several models of computer-assisted artificial intelligence (AI)

There has been a significant uptick in the number of literatures interested in the study of AI. Due to the various benefits of artificial neural networks (ANNs) including rapid processing speeds, cheap data storage, and low resource requirements, this AI technology is quickly becoming the center of attention. Due to its fast performance and accuracy in calculating thermophysical parameters and the dynamic viscosity of nanofluids, the soft computing technique has been employed in several studies. To investigate how temperature affects the viscosity of nanofluids, the authors [4] suggested a radial basis function-based viscosity prediction model for water-based nanofluids. Using three models, researchers [5] shown that ANN-MLP (multilayer perceptron) outperforms MPR (Multivariate polynomial regression) and ANN-MLP in forecasting the viscosity of silver/water-based nanofluids. MPR and MLP were the other two models.

An extensive review of the available machine learning techniques for modelling the dynamic viscosity of nanofluids [6]. Predictions of dynamic viscosity may be made based on several characteristics such as concentration, temperature, nanostructure size, and shear rate. This research [7] indicates that ANN-based models are superior to correlations when it comes to generating predictions, and that the quality of the models' predictions is affected by the ANN's structure. Researchers [8] focus on developing a universal model for predicting nanofluid viscosities. It has also been suggested that the available data from different investigations might help in formulating a more universal model.

Theoretical models for estimating viscosity of fluids of various types

The authors [9] who originally suggested developing a theoretical model to foretell the viscosity of nanofluids. The volume concentration of nanoparticles used in practical applications is extremely low (φ 2 %), this model demonstrates a linear connection between the dynamic viscosity of nanofluids and the percentage volume of particles. The model may be expressed in this way,

\[ \mu_{nf} = \mu_{bf}(1 + 2.5\varphi) \quad (1) \]

\[ \mu_{nf} = \frac{\mu_{bf}}{(1-\varphi)^{2.5}} \quad (2) \]

By including the impact of the interaction between particles and the Brownian motion of isotropic stiff spherical particles [10, 11],

\[ \mu_{nf} = \mu_{bf}(1 + 2.5\varphi + 6.2\varphi^2) \quad (3) \]

Taylor series expansion was utilized as [12],

\[ \mu_{nf} = \mu_{bf} \left(1 + 2.5\varphi + \frac{25}{4} \varphi^2 + O(\varphi^3) \right) \quad (4) \]

Another model was presented by authors [13] as,

\[ \mu_{nf} = \frac{\mu_{bf}}{(1-2.5\varphi)} \quad (5) \]

Various theoretical models of viscosity prediction may be found in a plethora of other published works. However, most of these models only function under certain oversimplified assumptions. Therefore, these models generate an enormous discrepancy between theoretical and experimental estimates of the nanofluids’ viscosity throughout the full range of particle concentration.

Empirical models

Since the dawn of the era of nanofluids, several studies on the topic of predicting viscosity have been initiated. All these studies have helped match experimental data to basic mathematical connections of various types. Empirical models are the name for these techniques [13].

\[ \mu_{nf} = \mu_{bf}(1 + 7.3\varphi + 123\varphi^2) \quad (6) \]

The viscosity of ethylene was analysed, and they provided a correlation model that can be written as, glycol nanofluid [14],

\[ \mu_{nf} = \mu_{bf}(1 + 10.5\varphi + (10.6\varphi)^2) \quad (7) \]

Nanoparticle size (S), volume percent, and temperature were used by authors [15] to establish a link. The model may be expressed as follows:

\[ \frac{\mu_{nf}}{\mu_{bf}} = \frac{1 + a_1\exp\left(\frac{S}{R}ight) + a_2\exp\left(\frac{S}{R}\right)^2 + a_3\exp\left(\frac{S}{R}\right)^3 - a_4\exp\left(\frac{S}{R}\right)^4}{1 + a_5\exp\left(\frac{S}{R}\right) + a_6\exp\left(\frac{S}{R}\right)^2 + a_7\exp\left(\frac{S}{R}\right)^3 - a_8\exp\left(\frac{S}{R}\right)^4} \quad (8) \]

Some other models based on empirical correlations have been introduced into the literature in recent years. Authors [16] reveal that these empirical correlation models provide results that significantly depart from the experimented data.

Novelty of the Present Study

As a result of its success in fields as diverse as voice, computer vision, and natural language processing, deep learning has exploded in popularity over the past several decades. Deep learning is becoming the foundational answer for even the biggest tech businesses like Google, Facebook, etc. Due to its revolutionary impact on AI, the notion of deep learning has recently gained widespread attention. DNN take their cues from the way the human brain is built and works. Models trained with deep learning can pick up on non-linearities on their own. The DNN models’ deep hidden layers allow for gradual category learning.

Many factors influence the dynamic viscosity of nanofluids. This is why it is difficult to precisely forecast viscosity using any of the techniques. Using advanced optimization strategies in tandem with machine learning techniques has been shown to improve model quality in the current evaluation [17]. The performance of the prediction model was also shown to be affected by activation function, both the number of neurons in each layer and the depth of the network.

This work presents the novel idea of a DNN-based model for accurately predicting the viscosity of nanofluids, acknowledging the limits of previously established theoretical and empirical correlations and computer-aided viscosity prediction methods. There hasn't been any attempt to use a deep learning network-based model to forecast the nanofluids’ viscosity, as far as the author is aware. The increasing accessibility of
experimental data is a driving factor behind the use of deep learning to predict nanofluid viscosity. When given a huge data collection, a DNN can effectively retrieve previously concealed information. Baidu’s head scientist and a Google Brain project leader, Andrew Ng, made this claim. To use a rocket analogy, the deep learning models are the engine, and the massive quantities of data we have at our disposal are the fuel. Since the amount of data is expanding exponentially and the complexity of the data is increasing, a generalized smart model is required to predict the experimental data of nanofluids viscosity. However, most current data-driven models rely on a very basic form of ANN. When compared to more basic ANN models, DNN provide more accurate predictions thanks to their use of big datasets and powerful computing engines like Graphics Processing Units (GPUs). The subsequent parts will provide further evidence of this reality.

In this research, a smart data-driven viscosity prediction model that makes use of the deep learning approach was discovered. At first, a high-level explanation of what deep learning is has been provided. Next, a DNN is trained with the given data to make predictions about the viscosity of Al$_2$O$_3$ water nanofluid. Analyzing the values of statistical criteria like $R^2$, AARD, and RMSE provides evidence for the reliability of this model’s performance. Finally, this model has been used to conduct a sensitivity analysis.

**Viscosity Prediction Using a Modeled DNN**

As a concept, “deep learning” was initially introduced in 1986 by authors [18]. The elegant Universal Approximation Theorem relies heavily on the notion of DNN, which is just a ML technique based on ANN [19]. The deep learning strategy has proven to be effective in revealing hidden non-linear patterns in the data set of interest. Viscosity data from genuine trials has grown significantly, demonstrating that deep learning is the best method for gleaning insights from such massive datasets. With an input layer, an output layer, and potentially several fully-connected hidden layers in between, feed forward neural networks are the most common type of DNN. Layers at both ends-input and output-are connected to the information at hand. Taking the function $y: IR^p$ as input, we may deduce the network process. We develop IRq, which takes input from p neurons and outputs to q neurons, as shown in Figure 1. Therefore, the strength of the connection between neuron I in layer n and neuron j in layer n+1 is represented by the parameter $w_{ij}^n$. A neuron's output may be understood as the linear sum of the results from the neurons in the layer.

$$y_{mn}^n = \phi^n \left( \sum_{j=1}^{k} w_{mj}^n y_{jm}^{n-1} \right) + b_m^n$$

Where

- $\phi^n$ is the activation function among $(n-1)$-th and n-th layer; and
- $b_m$ is the bias of the n-th layer.

The network process can also be stated in matrix form as

$$\vec{y}_n = \phi^n (W^n \vec{y}^{n-1}) + \vec{b}_n \text{ for } n = 1, 2, \ldots, N,$$

Where

- $W^n = [w_{ij}^n]$ is the weightage matrix;
- $\vec{y}_n = [y_j^n]$ output column vectors;
- $\vec{y}^{n-1} = [y_j^{n-1}]$ input column vectors; and
- $\vec{b}_n = [b_j^n]$ bias of the n-th layer column vectors.

Methods have been explored and added to the model to provide the best possible forecast. The nanofluid viscosity is calculated using the particle size, density, temperature, base fluid viscosity, and nanoparticle volume percent, all of which are inputs to the proposed model. In this study, the 10-fold cross validation technique was used instead of the conventional practice of separating the original dataset into experimented and validation datasets. These days, we can get the most out of our training and validation data with this cross-validation strategy. Overfitting is avoided, and test and validation data are not mixed. This is why cross-validation has become the method of choice. The following is a generalized formula for doing 10-fold cross-validation calculations.

1. Divide D at random into 10 about equal-sized halves.
2. $Err = \frac{1}{10} \sum_{k=1}^{10} Err_k$.
3. For $k$ from 1 to 10 do.
4. $T \leftarrow D \setminus R$.
5. Use $T$ to train the model.
6. $R \leftarrow$ Partition $k$ from $D$.
7. $Err_k$ employed the trained model to predicted $R$.

The dataset, the training set, and the test set are denoted by $D$, $T$, and $R$. The data normalization technique specified by is applying for both the training and testing datasets [21].

$$x' = \frac{x - \mu}{\sigma}$$

Where $x'$ is the standard deviation of the input variable, the meaning of the training dataset’s column vectors, and $x$ is the input variable itself. To minimize the effect of data outliers, normalization is an essential step in the deep learning process. After carefully weighing the pros and cons of various activation functions, the ReLU activation function is applying to the layers of the recommended DNN model. As a piecewise linear function, CNNs frequently employ ReLU [22]. The vanishing

![Figure 1: An outline of the DNN model for viscosity prediction.](image-url)
gradient problem may be avoided, and convergence can be sped up by using the ReLU activation function. The authors [23], who developed the deep learning technique for solar power energy prediction, emphasized the benefits of utilizing ReLU as an activation function. We compute many loss functions to help you select the best one for your prediction model.

**Optimization of DNN model parameters: a comparative analysis of various approaches**

To improve a deep learning model’s efficiency, a robust learning algorithm is crucial. Several well-known optimization techniques have been shown in the literature to be particularly effective in resolving the difficulties associated with DNN models due to their robust update rules. In this analysis, the Nadam optimizer used to train the projected DNN model is likened against Adam, RMSprop, and other SGD variations [24]. Three SGD optimizers, Adam, Nadam, and RMSprop, have been found to outperform the rest. The Nadam optimizer is employed in this study for the purpose of adjusting the parameters of the suggested DNN model to reduce the Mean Square Error (MSE) to a minimum value. The formula for the MSE is given in equation 12.

\[
MSE = \frac{1}{N} \sum_{k=1}^{N} (\mu_{true,k} - \mu_{pred,k})^2
\]

Where

- \(\mu_{true,k}\) true values of the \(k\)th input data.
- \(\mu_{pred,k}\) predicted values of the \(k\)th input data.

According to authors [25] the parameters of RBF are often updated by a trial-and-error method, and the majority of MLP models have been constructed using a single optimization technique, most frequently Levenberg-Marquardt (LM). To evaluate which learning approach yields the most accurate optimizer for the proposed DNN model, we conduct extensive experiments with four different approaches. Figure 2 depicts this comparison as a function of MSE and epoch count. In this respect, we consider the situation to be over when the sum squared error reaches 103. The convergence performance of several SGD approaches has been shown to be quite low. However, using Adam and Nadam algorithms, a satisfactory convergent solution may be reached with a little number of iterations. Nadam is a hybrid of Adam and NAG. In this situation, Adam takes on NAG’s modified motion [26].

**DNN**

The network structure of a DNN model is one of the essential aspects that influences its performance. The efficiency of the DNN model may be enhanced by modifying its number of hidden layers and the number of neurons present in each layer. Table 1 provides information on the optimum DNN model that was created and utilized to forecast the nanofluids’ viscosity in the current study (Figure 3 and figure 4).

The following section calculates and evaluates the existing model using various statistical criteria.

**Results and Discussion**

In this part, the significant implications of the important factors used in the technique to conclude the viscous of nanofluids.

**Data collection**

Accurate results from the DNN model may be obtained with the collection of precise data from various experimental operations. When dealing with a small dataset, most machine learning techniques fail to produce accurate estimates of value. Multiple experiments produce copious amounts of information. The prediction model requires this massive data set for training and testing; thus, its collection is essential. A total of 2400 viscosity measurements were utilized to create the data set for this investigation. Four hundred of them are Alumina nanofluids dissolved in water. In addition, it is crucial to keep...
data collecting consistent to avoid introducing further bias into the forecasting process. In contrast to most preexisting models, the authors of this study took advantage of data gathering uniformity.

**Evaluation of prediction accuracy**

As was previously indicated, the model’s precision is sensitive to a wide range of inputs. Figure 1 shows the relationship between the nanofluid’s viscosity and the density of nanoparticle, percentage volume of nanofluid, size of nanoparticle, temperature, and base fluid viscosity. On a scatter plot, the vertical axis represents the projected viscosity from the deep learning network, while the horizontal axis represents the experimental viscosity. The data points in figure 5a for training and figure 5b for testing are all, with a small number of exceptions, extremely near to the y = x line. The suggested DNN model does not appear to be overfitting based on this evidence.

The pattern of failure shown in figure 6a applies to both the training and testing stages. We find that throughout several iterations of data, the loss on experimented or prediction data is quite close to the loss on experimenting data. After the turn of the twentieth century, the trend becomes more pronounced, it has been observed. This Keras deep learning model allows you to pause training at any time via a callback. This callback method is a fascinating idea. When the validation error exceeds a certain threshold, we can halt the training process. Figure 6b demonstrates the root mean square error (RMSE) calculations performed at each level of the training and testing procedures. As a result, the suggested DNN model has been seen to avoid the overfitting problem. This DNN model is helpful for predicting nanofluid viscosity even without access to actual experimental data. Differences between measured and predicted viscosity values are used to characterize the modelling error in this study.

The statistical metric known as the coefficient of determination (R²) is the mean of the R² values obtained by doing 10-fold cross validation. Table 2 shows that the proposed DNN model performed well on average throughout experimented and predicted using 10-fold cross validation, and that the model successfully captured all the outliers in the response data. Table 2 shows that the R² and RMSE for the current model are both at their maximums of 0.9999 at epoch 500 during training, and 0.0130 at epoch 500 during testing. After 495 - 500 epochs in training and testing, the DNN model achieves a high degree of accuracy in predicting the nanofluid viscosity.

**Prediction accuracy of the new DNN model compared to other models**

Figure 1 and figure 2 show the proposed DNN in action, demonstrating its process in making precise forecasts. There is a strong causal relationship between the percentage of nanoparticle volume and many of the indicated theoretical models and correlations. Our DNN-based model for predicting viscosity has been compared to both experimental data and other, more well-established models that take into consideration the volume fractional changes brought on by nanoparticles. Figure 7 depicts this inferred comparison. Other current models fail to predict the viscosity properly across a large range of particle volume percent, but as can be seen in the figure, the projected...
values of the DNN models precisely correspond with the actual data. It also demonstrates that the viscosity of nanofluids dramatically increases with the concentration of nanoparticles. It has been shown that the models with expected results outperform the empirical model [27]. The viscosity of an Alumina-H_{2}O nanofluid containing a small percentage volume of nanoparticles may be predicted with high accuracy using the model [28].

However, the suggested DNN model outperforms the state-of-the-art models by a wide margin when it comes to predicting the viscosity of any of the nanofluids. The innovative DNN-based viscosity prediction model may find widespread use if it can reliably predict the viscous of H_{2}O-based nanofluids.

This demonstrates that the proposed DNN model is well-trained and predicted changes in nanofluid viscosity in response to changes in nanoparticle volume fraction and temperature.

Conclusions

For some water-based nanofluids as those containing Alumina nanoparticles, a cutting-edge data-driven viscosity prediction model was built in the current work using deep learning. The suggested deep learning-based network was built with 2400 data, 400 of which were Alumina. The current model takes as inputs the base fluid viscosity, nanoparticle density, size of nanoparticles, temperature, percentage volume of nanoparticles and outputs the nanofluid viscosity. The following are some of the results of the present inquiry:

This research uses a cutting-edge, deep-learning-based strategy to estimate the viscosity of nanofluids in water, such as Alumina nanoparticles. Two thousand and four hundred data used to train the proposed deep learning-based network came from Alumina. The density of the nanoparticles, the volume fraction of the nanoparticles, the size of the nanoparticles, the temperature, and the viscosity of the base fluid are all considered while modelling the nanofluid's viscosity.

Since the acquired value of R^{2} is more than 0.9999, the outcomes of the current inquiry may be relied upon as being predictive. The suggested DNN model may also be trained to automatically learn non-linearities.

To forecast the viscosity of any other type of nanofluid, a DNN model of a similar sort may be simply created using the dataset of experimental research. It is important to note that applying this current deep learning-based model on a big dataset is necessary to obtain a positive outcome.

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Conflict of Interest

None.

References


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