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Research Article

Proposing an Adaptive Neuro-Fuzzy System-Based Swarm Concept Method for Predicting the Physical Properties of Nanofluids

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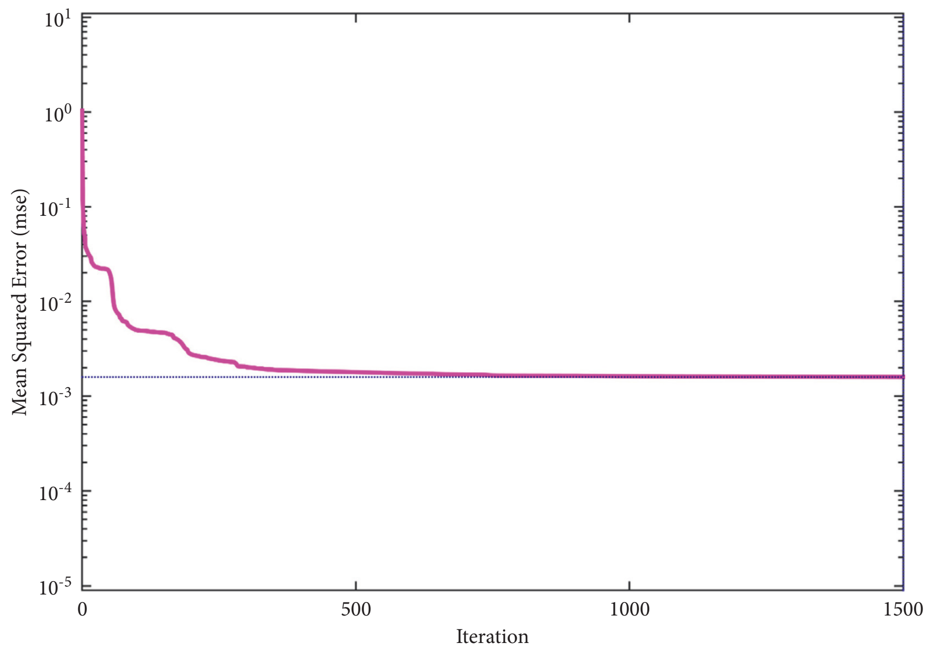
This paper employs dispersed nanoparticles (NPs) to build an adaptive neuro-fuzzy system (ANFIS) for predicting their thermal conductivity (TC) and viscosity according to the most important input data including concentration, size, the thickness of the interfacial layer, and intensive properties of NPs. In this regard, we gather an extensive and comprehensive data set from different sources. Here, the ANFIS model factors are optimized by using the particle swarm optimization (PSO) technique. Afterward, the obtained results are compared with previously published models which did a better job in predicting target values. In the following, to investigate the validity of our proposed model, statistical and graphical techniques are employed and it was proved that this model is efficient to evaluate the output values. Amounts of results obtained from the PSO-ANFIS model evaluation are 0.988 and 0.985 for the R2 and 0.0156 and 0.0876 for root mean squared error (RMSE) of TC ratio and viscosity ratio values, respectively, letting out a valid forecast of targets. Finally, by performing various statistical analyzes, it can be said that this model shows a high ability to predict target values and can be considered a good alternative to previous models.

1. Introduction

The colloids of engineered NPs distributed uniformly in base fluids are called nanofluids (NFs) [1–3]. The thermophysical, transport, and other characteristics of NFs are distinct from those of conventional fluids [4–6]. For example, adding modest amounts of NPs may result in a substantial increase in thermal conductivity [7]. Numerous theoretical and experimental studies established formulations for the change of viscosity and TC [4, 5, 8–20]. Established formulas describe the effect of nanofluid TC and viscosity on a variety of factors, including volume fraction, the type of base fluid, the particle shape and size, the temperature, the surface charge, pH, the particle nature, the Brownian motion of NPs, dispersion, clustering, and monolayer approaches [1, 4, 6, 8, 21, 22]. In most studies, the viscosity and TC are determined by size and concentration of one type of NF. However, there is much disagreement between experimental results and theoretical theories. There are currently no acceptable mathematical models for describing the temperature behavior of a NF [23, 24].

Recently, the use and application of artificial intelligence methods in various sciences have been seen repeatedly [25–29]. The quantitative structure-property-activity relationships method is among the most interesting and widely used approaches for developing mathematical relationships between target characteristics and aspects of the chemical composition [30, 31]. The method is often referred to as "nano-QSAR" or "nano-QSPR" when used with NPs [32, 33]. Since 2009, several nano-QSAR/QSPR models have been created for inorganic NPs [33]. In spite of the importance of this endeavor and the interesting findings of available nano-QSAR/QSPR models, there is yet no uniform approach to offer a coherent definition for a diverse array of



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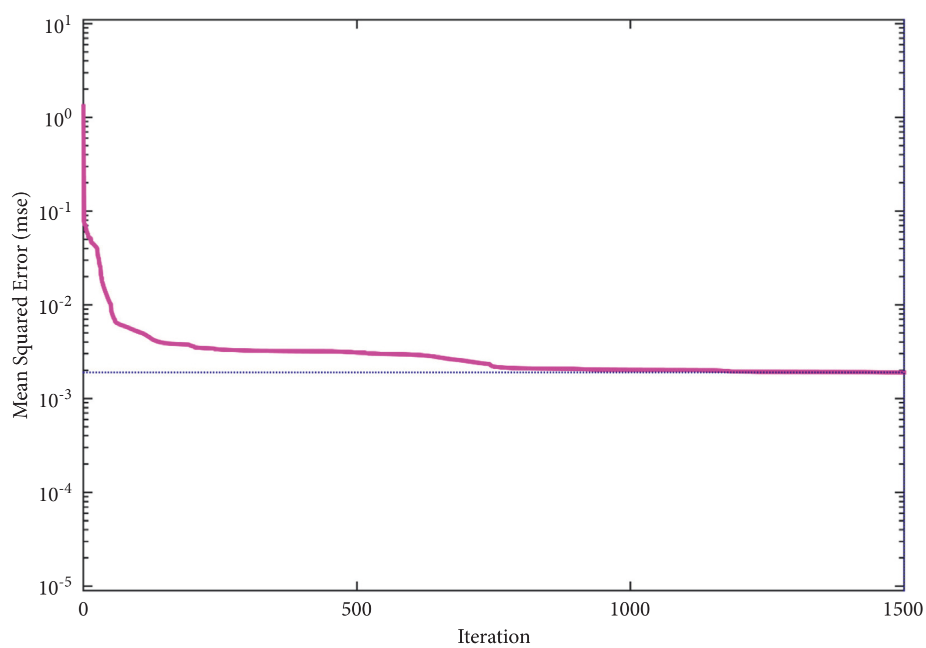


(b)

Figure 1: Mean squared error values according to the number of iterations for two parameters TC ratio and relative viscosity.

nanoscale structures. Additionally, direct characterization of dispersed-phase particles can be performed utilizing molecular dynamics models, which are not appropriate for rapid prediction for screening applications [12]. Several studies have been performed on the effects of chemical composition on the viscosity and TC of NFs employing the QSPR technique [34, 35]. Each of them used a simplified model of the NF structure [34]. For instance, we described NF structures using the so-called “liquid drop” model in earlier works. But the model’s application was limited by (i) a lack of variety (five different NPs were examined) and (ii) a low volume percentage (NPs concentration lies within 0.01–0.55%) [34].

The present research aims to provide a thorough examination of viscosity and TC utilizing a hierarchical mixture of newly created descriptors that describe the composition of NFs at various organizational levels. This project aims to develop a unifying expert system capable of predicting viscosity and TC of various NFs at various sizes and concentrations using PSO-ANFIS. The predicted TC

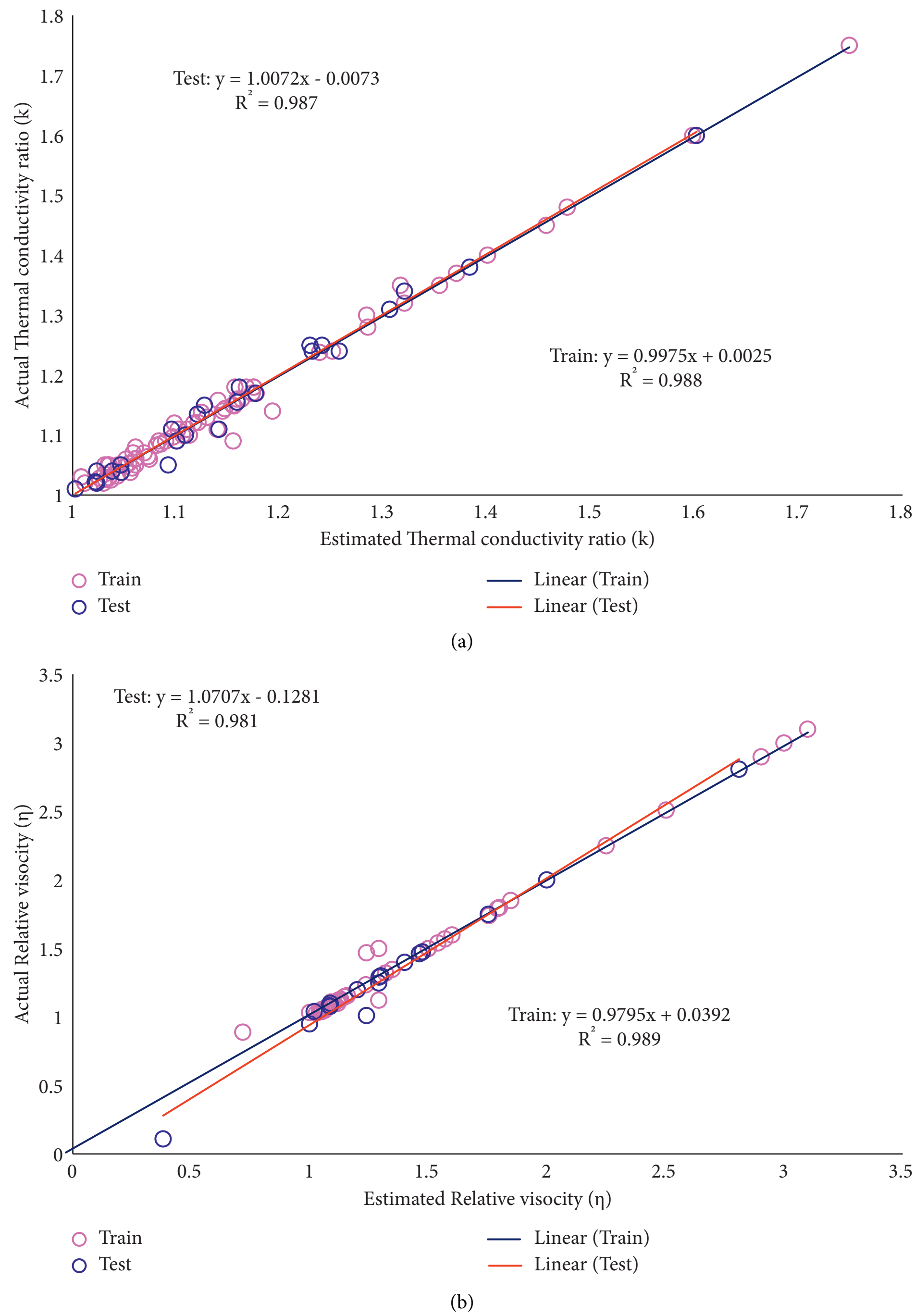


Figure 2: Regression analysis on the (a) TC ratio and (b) relative viscosity of NFs data related to training and testing phases.

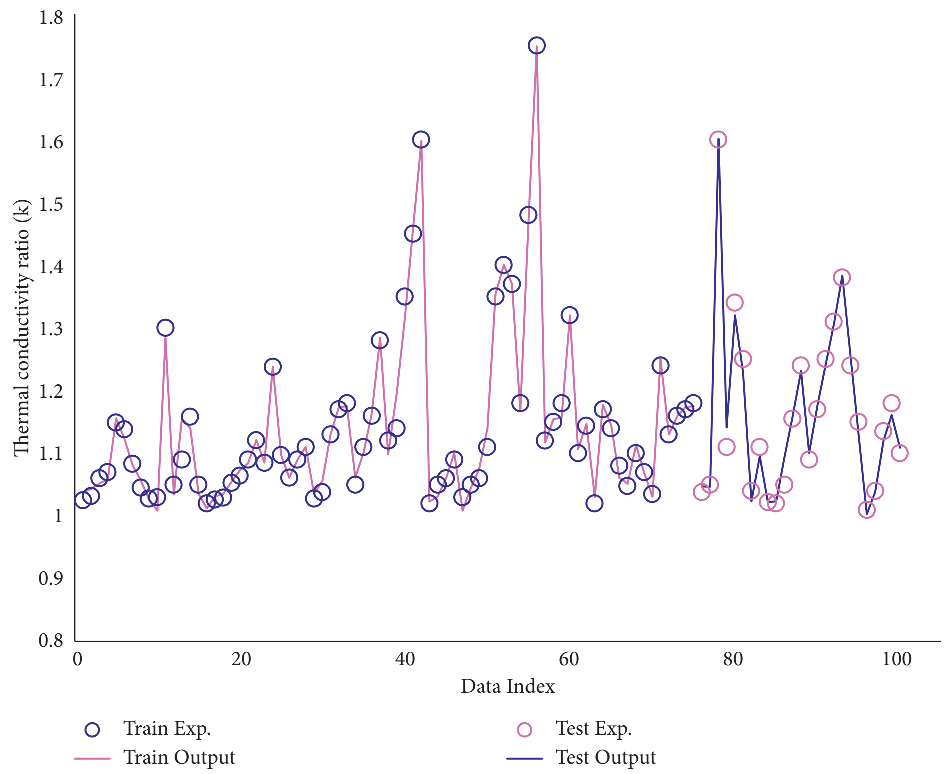
and viscosity of NFs using the suggested mathematical model are compared to experimental test data published in the literature in this study and compared with models already presented by previous researchers.

2. Methodology

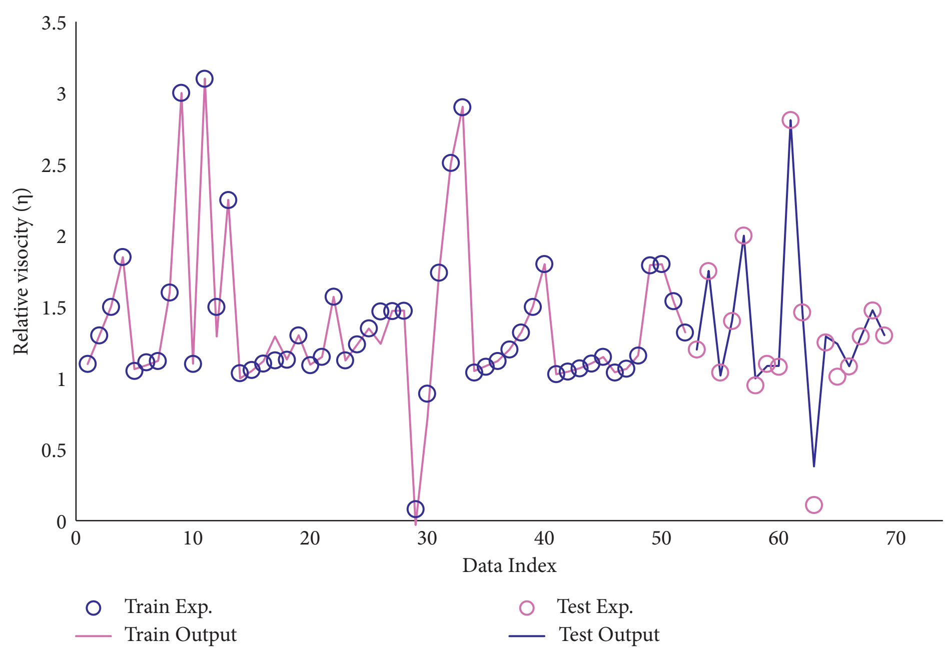
2.1. (ANFIS) Model Description. In 1993, Jang [36] proposed adaptive neuro indistinct inference network (ANIIN) for the first time, as a combination of the synthetic neural system (SNS) and indistinct inference network (IIN). Here, a fuzzy inference system has four underlying parts which must be studied [37]. The first part consists of the fuzzy if-then rules defined by Takagi-Sugeno type in a "if A then B" structure. These rules are characterized by proper membership functions (MFs). There are various MFs. In this research, we utilize the Gaussian type MF as follows [38–40]:

$$\mu_{Ai} = a_i \exp\left[\left(\frac{x - c_i}{a_i}\right)^2\right], \quad (1)$$

where c_i and a_i are the indicator units.



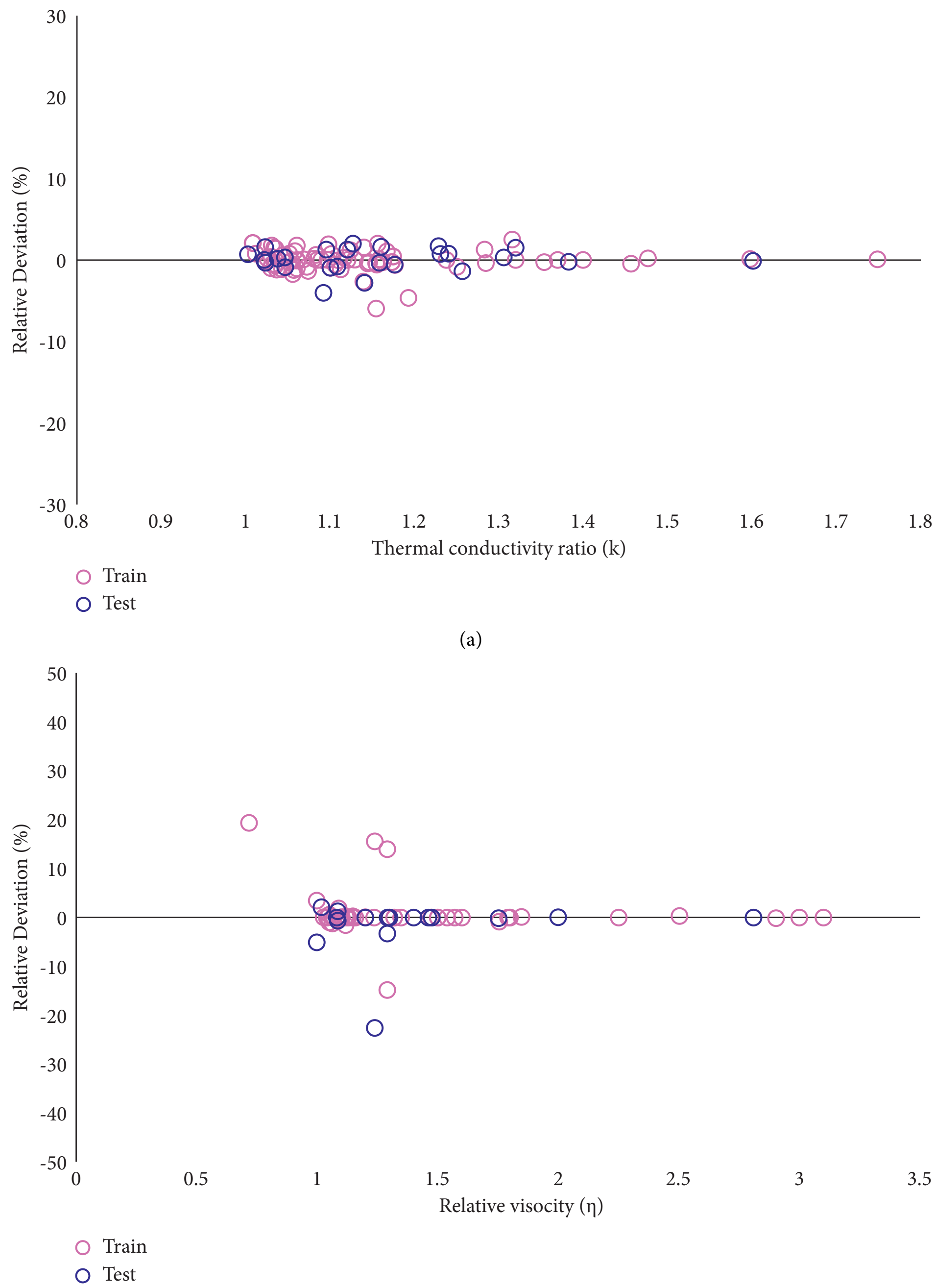
(a)



(b)

Figure 3: Simultaneous viewing of laboratory and modeled data of the (a) TC ratio and (b) relative viscosity of NFs related to training and testing phases.

In the second part, indistinct decisions are made by indistinct rules. Then, in the third and fourth parts, fuzzification and defuzzification fulfillment are done, respectively [41, 42]. The fuzzification unit has a responsibility to increase data amounts to the fuzzy amounts [43, 44]. The type of Takagi and Sugeno fuzzy rules are as follows (to evaluate data of the x and y as well as the production of f, two first-order polynomials are studied) [45, 46]:



(a)

(b)

Figure 4: Relative deviation analysis of the (a) TC ratio and (b) relative viscosity of NFs. Furthermore, the validity of the proposed model is measured by statistical factors. To predict errors, R^2, RMSE, MSE, STD, and MRE are used in Table 1 [55–59].

$$\textit{Rule 1}:\ if\ x\ is\ A1\ and\ y\ is\ B1,\ then\ f1 = p1x + q1y + r1, \tag{2}$$

$$\text{Rule 2}:\ if\ x\ is\ A2\ and\ y\ is\ B2,\ then\ f2 = p2x + q2y + r2, \tag{3}$$

where B and A are optimization techniques and indistinct units, respectively. These are required to be employed for optimization of the linear indicators, i.e., p, q, and r. In this study, this optimization is performed by the PSO technique

Table 1: Statistical parameters obtained to estimate the accuracy of the PSO-ANFIS model.

Parameter	Phase	R2	MRE (%)	MSE	RMSE	STD
TC ratio	Train	0.989	0.829	0.000208729	0.0144	0.0112
	Test	0.987	1.056	0.000243615	0.0156	0.0101
	Total	0.988	0.886	0.000217451	0.0156	0.0110
Relative viscosity	Train	0.990	4.110	0.003234137	0.0569	0.0538
	Test	0.981	16.556	0.007665055	0.0876	0.0816
	Total	0.985	7.176	0.004325812	0.0876	0.0616

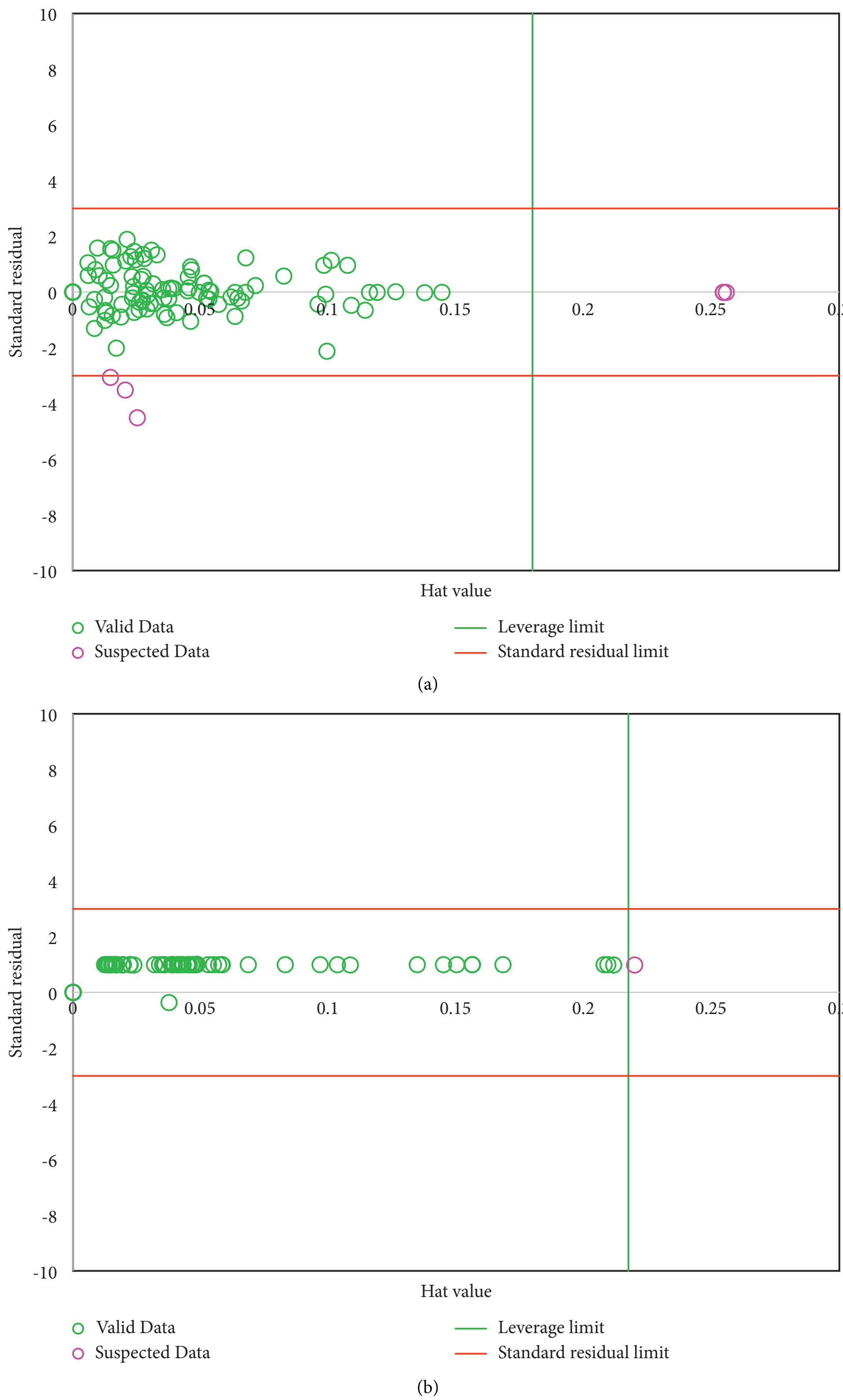


Figure 5: William's plots for data related to the (a) TC ratio and (b) relative viscosity of NFs.

[47–49]. So, to calculate the ultimate production in a five-layer mechanism, the ANFIS model is used. Thus, production for each layer is presented as follows [50, 51]:

$$1st\, layer\text{:}\ O_{1,i} = \mu_{Ai}(x), \tag{4}$$

$$2nd\ \text{layer:}\ O_{2,i} = w_i = \mu_{Ai}(x) \times \mu_{Bi}(y), \tag{5}$$

Figure 6: Sensitivity analysis for data related to the (a) TC ratio and (b) relative viscosity of NFs.

$$3rd\,\text{layer: } O_{3,i} = w\Delta_i = \frac{w_i}{\sum w_i}, \tag{6}$$

$$4th\,layer\text{: } O_{4,i} = w\Delta_i \times f_i = w\Delta_i\left(p_i x + q_i y + r_i\right), \tag{7}$$

$$\begin{aligned} 5th\,\text{layer: } O_{5,i} &= \text{overall output} = \sum_{i=1}^{N} w\Delta_i \\ &= 1\, w\Delta_i\, f_i = \frac{\sum_i w_i f_i}{\sum_i w_i}, \end{aligned} \tag{8}$$

where w_i is the standardized volley vigor.

2.2. Input Attainment. In order to develop a trusty predictive tool, we require to utilize an inclusive data foundation. In a mechanism for progressing the model, we must investigate various factors which affect the production factor. In this mechanism, we apply a data foundation including data tips from formerly stated papers. Collected references to this data are given elsewhere [52].

2.3. Model Progression. To employ data foundation, they were randomly classified into testing and training units. The training data unit will create the construction of the forecasting model and the testing data unit measures the validity of the evaluated amounts. We see that the training data unit is containing 75% of the data, while the remaining is 25% and assigned to the test data unit. Then, the addendum formulation is used to represent the model progression with the standardized amounts as follows [53, 54]:

$$X_{\text{nor}} = \frac{X - X_{\text{min}}}{X - X_{\text{max}}} \times 2 - 1, \tag{9}$$

where max, nor, and *min* signs depict the maximum, normalized, and minimum amounts.

3. Results and Discussion

In this research, we create an ANFIS model with Gaussian MF operation to evaluate the output values. To test the MF factors, a PSO algorithm was used. Figure 1 shows the mean squared error values in terms of the number of iterations for two output target parameters of TC ratio and relative viscosity.

Figure 2 demonstrates the regression shape by planning the expected amounts versus the empirical amounts.

As you see in Figure 2, data points are gathered around the 45° line revealing the model's great ability to forecast the target values.

Figure 3 shows the great coincidence between expected and empirical amounts for every indicator number in the synchronous shape of the expected and empirical amounts.

Also, the relative deviation of expected and empirical amounts is shown in an aberrance plan in Figure 4. In this form, the mass of data points is set around the zero line, revealing the accurate anticipation of the output values.

To resolve the faraway data points, the force method may be used in some cases. In this technique, William's plot is used acquired from planning the normalized residuals versus hat amounts (hat amounts are acquired from oblique factors of the hat matrix) to mark the faraway data points out. The hat matrix (H) for a matrix of size $n \times m$ (X) is as follows [60–62]:

$$H = X\left(X^t X\right)^{-1} X^t, \tag{10}$$

where m and n are data parameters and the number of data points, respectively. A cut-off value for the normalized deposition and a force hat value (H∗) are defined to raise a possibility for the area of William's plot. In the following, the cut-off amount of 3 is explored for normalized residuals while the strength hat value is yielded by the following equation [59, 61, 63]:

$$H^* = 3\frac{k+1}{n}. \tag{11}$$

Also here, the feasibility region is restricted to $-3 < R < +3$ and $0 < H < H^*$, vertically and horizontally, respectively, and will be a squared area. Figure 5 shows William's plot. This figure demonstrates the statistical authority of the suggested PSO-ANFIS model, as the majority of data points are placed in the feasibility region of William's plot.

In order to determine the effect of each of the input variables on the target parameter, sensitivity analysis has been used [64]. More details about this analysis have been given in several articles [65–69]. In summary, in this method, a relevancy factor is calculated for each input variable that has a value between −1 and +1, and if this value is positive for a particular variable, it indicates the positive effect of this variable on the target parameter and vice versa. The next point that can be deduced from the relevancy factor is that the larger the absolute factor for a variable, the more effectively that variable affects the target parameter [60, 70, 71].

As can be seen from Figure 6, the density and size of NPs have the highest and lowest effects on TC, respectively. The following diagram shows that a volumetric concentration with a relevancy factor of +0.48 has the greatest effect on the viscosity of NFs and the density of nanoparticles has the least effect on this parameter.

4. Conclusions

In this research, statistical and graphical evaluation of the suggested PSO-ANFIS model demonstrates that this strategy has a superior capability to predict the outputs including the TC ratio and relative viscosity. The R2 values obtained by this model for these two parameters were set at 0.988 and 0.985, respectively, which indicates the high accuracy of this strategy in estimating outputs. Other analyzes employed in this paper included sensitization, visual observation, estimation of suspicious data, and determination of other statistical parameters. So, due to its reliability, it can be taken into account as a great predictive tool to be used in practical applications in related industries.

Data Availability

The references of experimental data used to support the findings of this study are included within the article.

Conflicts of Interest

The authors declare that they have no conflicts of interest.

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