

Investigating and Modeling the Factors Affecting Thermal Optimization and Dynamic Viscosity of Water Hybrid Nanofluid/Carbon Nanotubes via MOPSO using ANN

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Abstract: Optimization is to find the best answer among existing situations. Optimization is used in the design and maintenance of many engineering systems to minimize costs or maximize profits. Due to the widespread use of optimization in engineering, this topic has grown a lot. In this paper, the optimization of multi-objective of Water Hybrid Nanofluid/Carbon Nanotubes is investigated. Multi-Objective Particle Swarm Optimization (MOPSO) algorithm has been used in order to maximize thermal conductivity and minimum viscosity by changing the temperature (300 to 340 °k) and the volume fraction (0.01 to 0.4%) of nanofluid. Artificial Neural Network (ANN) modeling of experimental data has been used to obtain the values. Parto fronts, the optimal points and different values are 20 members and 15 iterations, and in order to compare the results optimization process on the first, fifth, tenth fronts, a relation has been proposed to predict the viscosity and Parto fronts in the optimization process. The aim of the study was to optimize nanofluid to reduce viscosity and increase thermal conductivity.

Keywords: Thermal Conductivity, Optimization Algorithm, Viscosity, Parto Front, Nanofluid.

1. Introduction

Due to their properties, nanofluids have found many applications, which makes it important to study these properties. Also, because these properties depend on the viscosity of nanoparticles in the base fluid, the nanofluid properties can be adjusted by changing the viscosity of nanoparticles. The structure and principles of multi-objective optimization methods are the same as single-objective optimization methods, but in a way the number of variables and objective functions in these methods is increased and they are used to find an optimal answer collection [1,2]. Hemmat et al. Optimized the nanofluid multi-objective with the aim of reducing costs and increasing the heat transfer coefficient [3]. Sonawane et al. Optimized nanoscale to increase thermal conductivity and reduce viscosity in heat exchangers [4]. Das et al. Conducted studies to determine the thermal conductivity changes of nanofluids with temperature. These used water nanomaterials/aluminum oxide and water/copper oxide in their experiments. The results of their experiments showed a direct dependence of thermal conductivity on temperature. The increase in thermal conductivity of water/copper oxide nanofluids was greater than the increase observed in water nanomaterials aluminum oxides. The researchers cited random and irregular nanofluid movements in the solution as a possible cause of the increase in thermal conductivity, as the nanofluids could easily move in the solution [5]. Potra et al. Investigated the effect of temperature on the thermal properties of nanofluids. The researchers used nanoscale water/aluminum oxide in their experiments. The results clearly showed that with increasing temperature, the effective thermal conductivity of the nanofluid improves. The dynamic viscosity of nanoscale decreases significantly with increasing temperature [6]. Zhao et al. investigated the effect of nanoscale size suspended on the thermal conductivity of nanofluids. For this purpose, nanofluids from alumina nanofluid suspensions with diameters of 36 and 47 nanometers (1 to 6 percent in water preparation is a volumetric nanofluid fraction). The specimens were irradiated with ultrasonic waves for 51 minutes. It has been observed that the thermal conductivity of these nanofluids increases with increasing volume of nanoscale, and the increase in temperature also increases the thermal conductivity of the specimens [7]. The use of nanofluids in heat transfer has many benefits, such as reducing heat exchangers, improving heat transfer efficiency, and reducing radiation. By using nanofluids in the pumping process, more energy can be saved [12]. There are four fluid thermophysical properties that change with the addition of nanofluid to the base fluid. These properties include density, viscosity, thermal conductivity and specific heat. Different researchers have expressed differing views on the effect of nanoscale addition on the values of these properties. However, the addition of nanofluids increases these properties except for the specific heat, which decreases with the addition of nanofluids. The percentage of this increase depends on various factors such as the volume of the nanoscale, the properties of the nanoscale, the properties of the base fluid and the temperature. Table 1 presents optimization shows the properties of nanofluids performed by optimization algorithms.

Table 1. Optimization shows the properties of nanofluids performed by optimization algorithms.

Author(s)	Nanofluid	Characteristic	Methods	Years
Zhao et al.[7]	Alumina-Water	Thermal conductivity, viscosity	ANN	2017
Abadi et al.[8]	Al ₂ O ₃	Thermal conductivity	ANN and GRG	2017
Ameer et al.[9]	microwave	Optimization of microwave-assisted	ANN	2017
Huang et al.[10]	ultrasound	ultrasound-assisted	RSM and ANN	2017
Ohale et al.[11]	alumina	factor evaluation	RSM and ANN	2017
Sabour et al.[16]	simultaneous	optimization of multiple	ANN and RSM	2017
Moslemi et al. [17]	Nanotube	Multi-objective Optimization	RSM	2020

In the present paper, in order to maximize thermal conductivity and minimum viscosity by changing the temperature (300 to 340°k) and volume fraction (0 to 1%) of nanofluid motor oil using laboratory optimization algorithm, laboratory studies and modeling have been performed. Modeling was performed using an artificial neural network and the results were given as an objective function to the optimization algorithm. According to a review of research, the nanofluid motor oil in the thermophysical conditions of the problem has not yet been studied in laboratory and Artificial Neural Network (ANN) modeling. Nanoscale has been analyzed at different volume and temperature fractions and a new relation has been proposed for its viscosity. Experimental data and data obtained from the Artificial Neural Network are mutually acceptable, indicating the high accuracy of the relation.

2. Particle swarm optimization (PSO)

The PSO algorithm is a social search algorithm modeled on the social behavior of bird groups. In 2002, Eberhart and Kennedy were first introduced by the PSO as an uncertain search method for functional optimization. The algorithm was inspired by the mass movement of birds looking for food. The algorithm was first used to discover patterns governing the simultaneous flight of birds and the sudden change in their path and the optimal deformation of the group. In PSO, particles flow in the search space. The relocation of particles in the search space is influenced by the experience and knowledge of themselves and their neighbors. So the position of another particle mass affects how a particle is searched. The result of modeling this social behavior is the process of searching for particles that tend toward successful areas. The particles learn from each other and, based on the knowledge gained, move towards their best neighbors. PSO's work is based on the principle that at any given moment, each particle finds its place in the search space according to the best place it has ever been and the best. It adjusts the location of the whole neighborhood [13].

Steps to Particle Swarm Optimization Algorithm (PSO):

- 1) Initial value Give the initial value to a population of particles with random positions and velocities in dimension D in the search space.
- 2) The estimate for the suitability of each particle in this population.
- 3) Calculate the velocity of each particle with relation 2 and move to the next position based on relation 3.
- 4) Stopping the algorithm if it reaches a certain stop criterion, otherwise go to step 2.

$$v_j^i[t+1] = wv_j^i[t] + c_1r_1(x_j^{i,best}[t] - x_j^i[t]) + c_2 + r_2(x_j^{g,best}[t] - x_j^i[t]) \quad (1)$$

$$x_j^i[t+1] = x_j^i[t] + v_j^i[t+1] \quad (2)$$

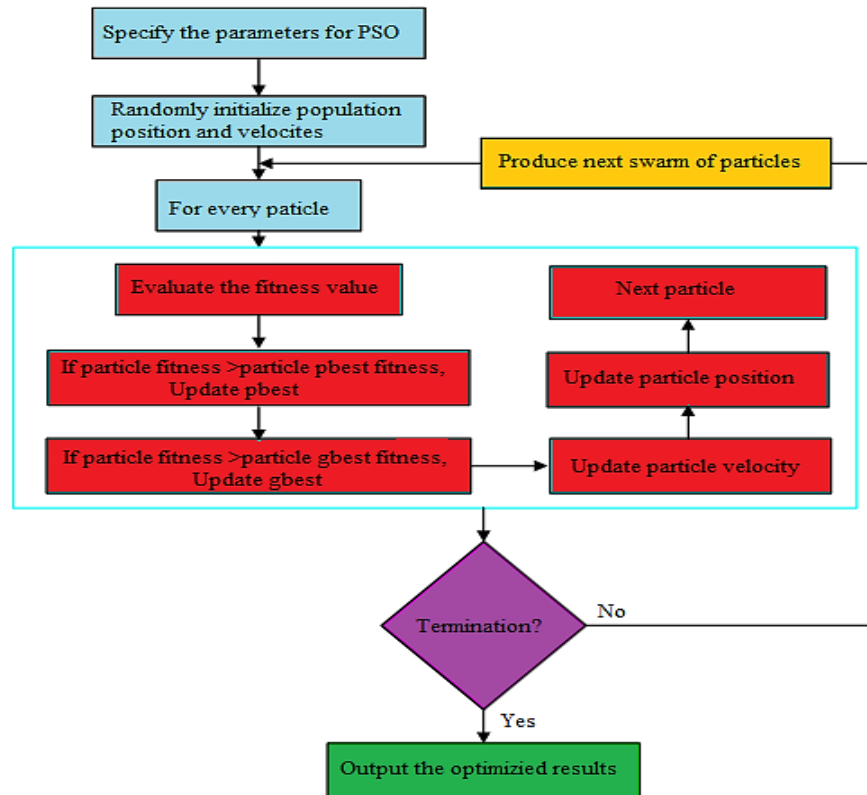


Fig. 1. PSO flowchart.

Benefits of PSO over other optimization methods:

- ❖ It is a zero-order procedure and does not require heavy mathematical operations such as grading.
- ❖ A population-based approach. (Using distributed calculations)
- ❖ Computational load is acceptable.
- ❖ Convergence is relatively fast.

Comparison of PSO with evolutionary algorithms:

- ❖ Unlike evolutionary algorithms in PSO, there is no selection operation. That means nothing
- ❖ One of the particles) Responses (not deleted and only the value of each particle changes.
- ❖ PSO does not use the principle of generational survival.
- ❖ There is no Cross Over in PSO.
- ❖ In PSO, there is a kind of mutation.
- ❖ In PSO, the relation between local and global search can be determined with the help of weights [14].

Multi-Objective Particle Swarm Optimization (MOPSO)

- ❖ Create a primary population
- ❖ Separate the unwanted members of the population and store them in Rep.
- ❖ Scheduling the discovered target space.
- ❖ Each leader elects a leader from among the members of the Rep and makes his move.
- ❖ The best performance of each particle is updated.
- ❖ Involuntary members of the current population are added to the Rep.
- ❖ Remove the defeated members of Rep.
- ❖ If the number of Rep members exceeds the specified capacity, we delete the additional members.
- ❖ If the termination conditions are not met, return to (3) and otherwise (end) [15].

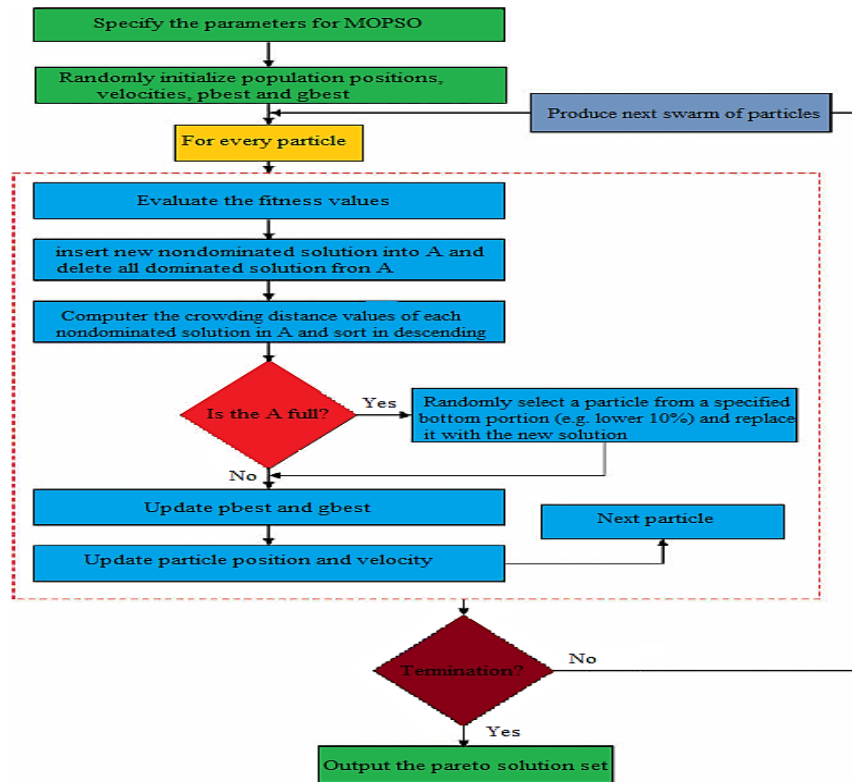


Fig. 2. MOPSO flowchart.

3. Results and Discussion

Artificial Neural Network are systems that work on the basis of empirical data. The human brain has a set of 1011 living neurons that make up a very complex structure of tissues and chemical interactions. Some neural structures are associated with humans from birth, and others are shaped by human experiences throughout life. Scientists are currently at the beginning of the path to recognizing neural networks and are only focusing on how the set works. According to the discoveries, all living neural functions, such as memory, are saved in the neurons and the connections between them. Learning means starting a new relation between males or changing existing relations. Neural networks use two basic properties of neural networks, including mesentery and parallelism of structure, and are comprehensively used to simulate systems, especially nonlinear ones. The neural network in complex systems provides the right solutions.

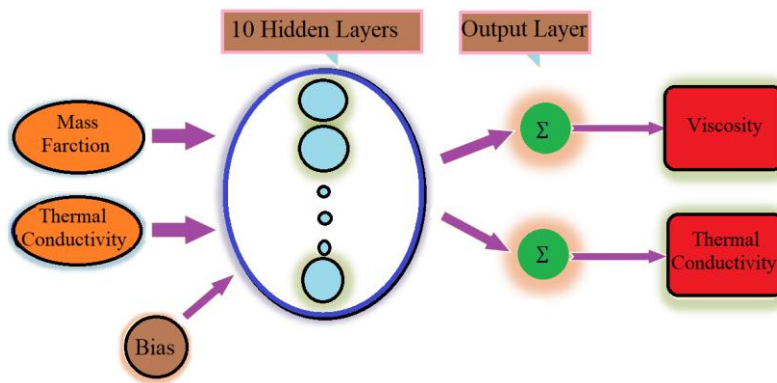


Fig. 3. Three-layer perceptron neural network for viscosity modeling and thermal conductivity.

A neural network of 10 neurons in the hidden layer and a neuron in the output layer for viscosity and thermal conductivity models. The number of hidden layer lights is determined experimentally and is based on the mean error of the maximum squares to predict viscosity and thermal conductivity and provide a comparison between neural network and experimental data. Weights and biases are determined by the Levenberg Marquardt algorithm. It should also be noted that the transfer function was performed in the hidden layer of the sigmoid (logsig) function and the purelin linear function for the outer layer [16]. Figures 4 and 5 shows the mean square error for different data from the evaluation sequence in relation to viscosity and thermal conductivity. If the value of MSE for evaluation data increases in a particular iteration, it will be broken as a result, and this iteration process ends when the best result is introduced as the output. Figures 6 and 7 shows comparison of experimental results of nanofluid thermal conductivity and viscosity with data obtained from artificial neural network.

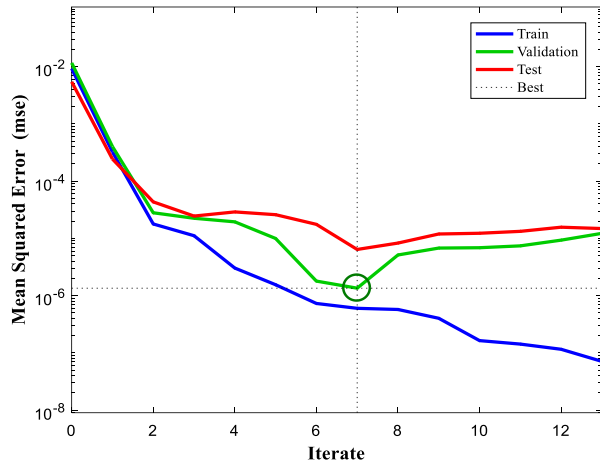


Fig. 4. ANN model performance diagram for thermal conductivity.

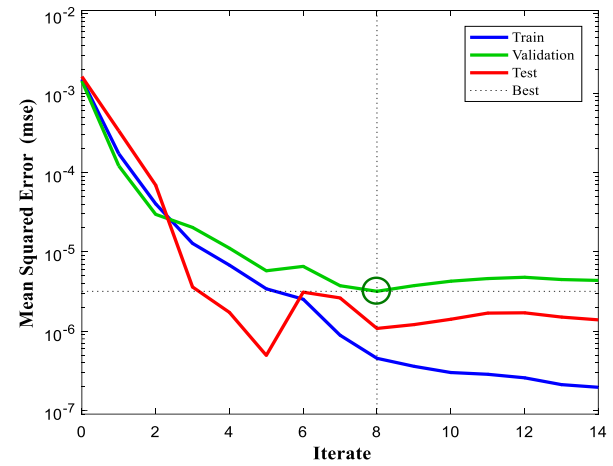


Fig. 5. ANN performance diagram for viscosity.

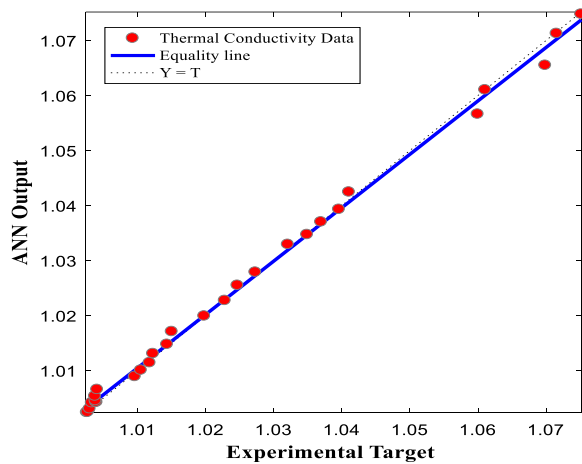


Fig. 6. Comparison of experimental results of nanofluid thermal conductivity.

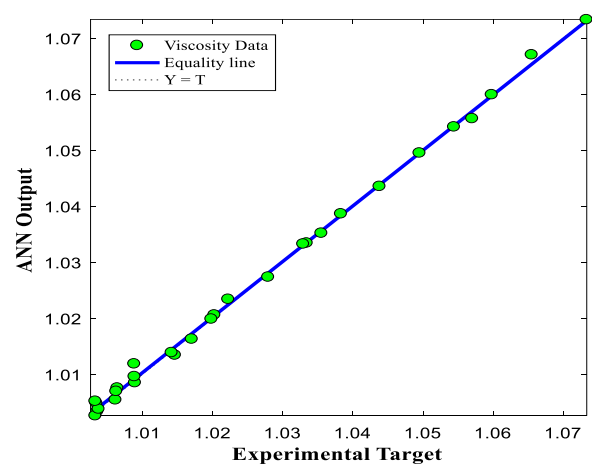


Fig. 7. Comparison of experimental results of nanofluid viscosity.

According to the modeling performed on the nanoscale laboratory results of engine oil, the modeling parameters for the best network response are reported in Table 2. MSE shows for Mean Squared Error and MAE shows for Mean Absolute Error, and R shows for Regression Coefficient. The value of the regression coefficient is 0.9979, which is an acceptable value for data modeling. In order to achieve the optimal results, the desired algorithm has been implemented and presented in several stages and with different values of 20 members and 15 iterations. In this figure, in order to compare the optimization process of the results in the first, fifth, tenth and Pardo fronts, optimization is presented. Using the optimization obtained, it is possible to use the areas where the thermal conductivity is from 300 to 340°k. In each generation, the optimal values are optimized compared to the previous generation, and finally the best results are presented. This process indicates the correct operation of the optimization algorithm. With the help of the obtained curve, the optimal points of the thermal conductivity coefficient and the equivalent viscosity can be considered.

Table 2. Modeling parameters for the best network response.

MSE	4.36e-04
MAE	0.0021
Test performance	1.74e-03
Train performance	5.36e-05
Valid performance	3.44e-05
R	0.9979

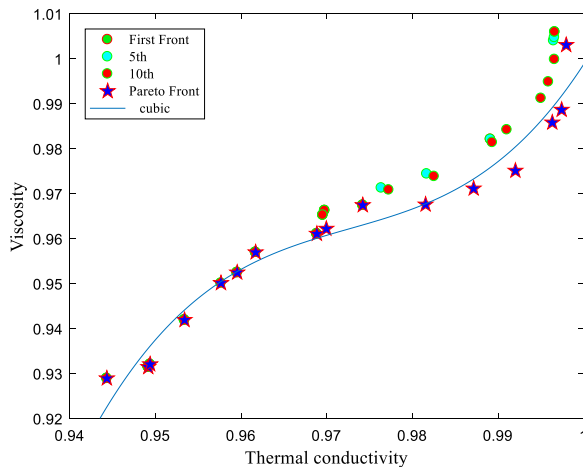


Fig. 10. Multipurpose Optimization Results Using MOPSO.

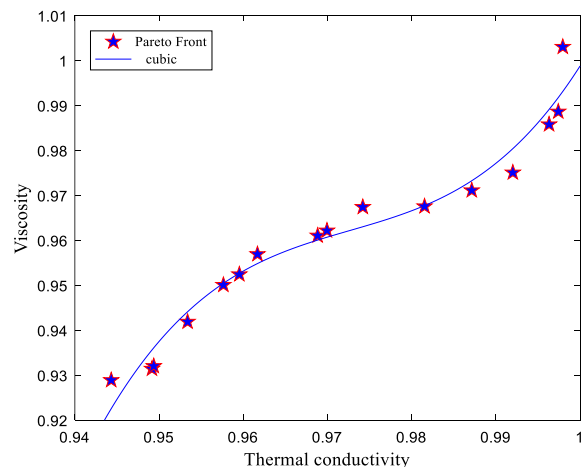


Fig. 9. Pareto optimal front.

Provide a new experimental relation:

To achieve the optimal point pattern with the ANN evaluation function to achieve the maximum thermal conductivity ratio (1) is presented. Below, using this relation, you can determine the minimum viscosity for a given thermal conductivity.

$$\text{Viscosity} = -14834x^3 + 5614/5x^2 - 64/544x + 4/6219$$

$$x = \text{Thermal Conductivity} \tag{3}$$

$$\text{Norm of residuals} = 0.02151$$

4. Conclusion

The aim of the study is to optimize nanofluid to reduce viscosity and increase thermal conductivity. This optimization was performed by determining the target functions and experimental data of viscosity and thermal conductivity of nanofluid and using artificial neural network. In this study, the structure of the neural network determined the thermal conductivity and viscosity by generating the input data of temperature and volume fraction. After the variables and objective functions defined in the MOPSO method, multi-objective optimization has been performed and the viscosity and thermal conductivity responses on the Pareto front have been introduced. The results show that the highest thermal conductivity and the lowest viscosity occur when a maximum temperature point of 340°C and a volume fraction (0.01 to 0.4%) are used. Among the results, the ones with the highest thermal conductivity and the lowest viscosity were selected as the best.

5. References

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