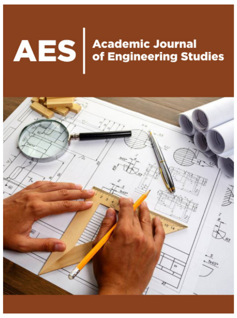
Crimson Publishers
Wings to the Research

Review Article

A Review of Applications Artificial Intelligence in the Nanofluid Domain Hybrid AI Algorithms

ISSN: 2694-4421



Mohammed BEKHTI* and Rachid SAIM

Laboratory of Energetics and Applied Thermic (ETAP), Algeria

***Corresponding author:** Mohammed BEKHTI, Laboratory of Energetics and Applied Thermic (ETAP), Algeria

Submission: July 12, 2021

Published: July 23, 2021

Volume 2 - Issue 3

How to cite this article: Mohammed BEKHTI, Rachid SAIM. A Review of Applications Artificial Intelligence in the Nanofluid Domain Hybrid AI Algorithms. Academic J Eng Stud. 2(3). AES.000537. 2021.
DOI: 10.31031/AES.2021.2.000537

Abstract

This paper presents the applications Artificial intelligence in the field of nanofluidic Hybrid AI algorithms. Are becoming beneficial as alternative methods to conventional approaches or as components of embedded systems. They have been used to solve complex applied problems in different fields and are becoming increasingly popular at present. In this survey, for the first time, a comprehensive review of AI algorithms developed to study different nanofluid related problems is conducted. The contributions presented in this paper reveal the strong potential of AI methods as prediction and optimization tools in nanofluids, investigated different aspects of nanofluids in applications such as electronic cooling, solar systems, heat exchangers, microchannels, refrigeration systems, and MCPs. In addition, challenges and directions for future research in the area of using AI techniques in nanofluids are presented and discussed.

Keywords: Artificial intelligence; Nanofluid; Hybrid AI algorithms

Abbreviations: ANFIS: Adaptive Neuro-Fuzzy Inference System; ANN: Artificial Neural Networks; GA: Genetic Algorithms

Introduction

The development of artificial intelligence as an academic discipline dates back to the 1950s, when scientists and researchers began to consider the possibility of machines processing intellectual abilities similar to those of human beings. The term “artificial intelligence” itself was coined in 1956 by a Massachusetts Institute of Technology professor, JOHN MCCARTHY. MCCARTHY created the term for a conference that was held in the same year. The conference was called the Dartmouth Conference by researchers in AI, made AI a distinct discipline. The conference also defined the major goals of AI: to understand and model human thought processes and to design machines that mimic that behaviour. Much of the AI research in the period between 1956 and 1966 was theoretical in nature. The first AI program, Logic Theorist (presented at the Dartmouth Conference) proved mathematical theorems. Several other programs were developed later taking advantage of AI, such as “Sad Sam”, (written by Robert K. Lindsay in 1960) which included simple English sentences and was able to draw conclusions from facts learned in a conversation. The conclusions drawn depended on data called a Knowledge Base (KB) in AI. Another was ELIZA, a program developed in 1967 by Joseph Weizenbaum at MIT that was able to simulate a therapist’s responses to patients. With increasingly successful demonstrations of the feasibility of AI, the focus of AI research changed. Researchers have focused on solving specific problems in areas of possible AI application. This shift in research focus has resulted in the current definition of AI as “a variety of research areas concerned with extending the ability of computers to perform tasks that resemble those performed by human beings," as V. Daniel Hunt puts it in his 1988 article "The Development of Artificial Intelligence" (Andriole 52). Some of the most interesting areas of current AI research include expert systems, neural networks, and robotics [1]. On the other hand, there are several reasons why AI paradigms are used in nanotechnology research. Nanotechnology suffers from the physical limitations of its working scale, where the physics is completely different from that of the macroscopic world. This means that the correct interpretation of the results obtained from any system or device at this scale is one of the problems faced in nanotechnology [2].

Nanofluids have been introduced as a modern and interesting type of nanotechnology-based heat transfer liquids and have been developed considerably in the last two decades. They possess the highest thermal conductivity and superior convective heat transfer compared to conventional fluids. Therefore, nanofluids have been studied significantly by many researchers to examine their capabilities to overcome the challenges of cooling technology and thermal management due to the excellent characteristics of nanofluids. In this regard, many review articles have also been published in the last decade, which has studied different aspects of nanofluids in applications such as electronic cooling, solar systems, heat exchangers, microchannel, refrigeration systems and PCMs [3]. The present of this paper can be considered as a guideline applications Artificial intelligence in the field of nanofluids Hybrid AI algorithms.

Hybrid Artificial Intelligence Algorithms

Various unique AI methods have been used in nanofluids, simple algorithms often have limitations such as slow prediction rate and large error. Recently, researchers have introduced methods that combine at least two AI approaches. These algorithms are called hybrid artificial intelligence systems and are implemented to overcome the limitations of single algorithms and to improve the efficiency of the predictor. For example, ANNs will only allow input to output reasoning and this can be overcome by applying Adaptive Neuro-Fuzzy Inference System (ANFIS) and by combining different AI algorithms, the advantages of each of the algorithms can be used combinations of ANNs with GA and combinations of GA with decision making approaches. Various combinations of AI algorithms have been employed in the field of nanofluids [3].

Adaptive Neuro-fuzzy Inference System (ANFIS)

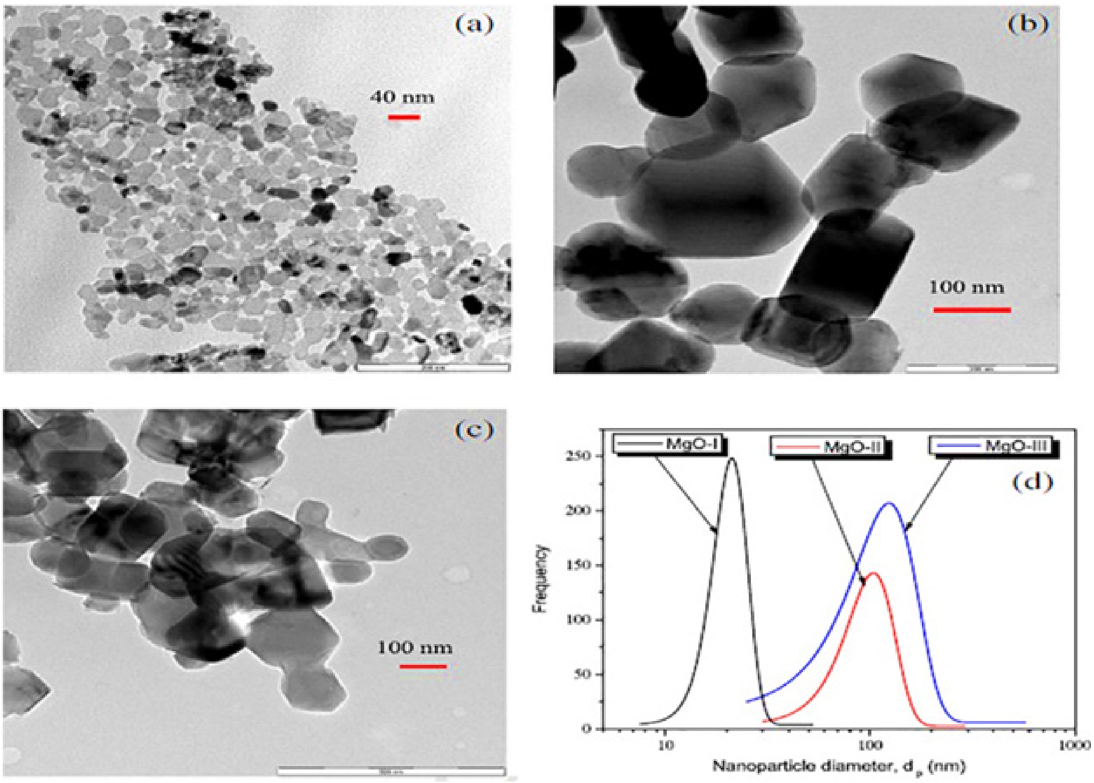


Figure 1: TEM image of MgO and particle size distribution (a) MgO-I (b) MgO-II (c) MgO-III (d) particle size distribution [5].

ANNs and fuzzy logic algorithms have advantages and disadvantages. However, an ANFIS that is developed by combining an ANN and a fuzzy logic method can recover the disadvantages of both approaches and develop an effective algorithm for engineering system modeling. ANFIS uses training methods developed from an ANN to find appropriate fuzzy rules and fuzzy membership functions. In ANFIS, a training approach is aligned with an integrated training method. The ANFIS structure consists of five layers, in which the first hidden layer is used to map the input parameter to each member. In the second layer, the normoperator T is used to evaluate the antecedent of the rules. The third hidden layer normalizes the strengths of the rules, followed by a fourth hidden layer in which the realizations of the rules are computed. Finally, the last layer computes the output and the sum of all signals entering this layer. ANFIS has been used to study the characteristics of nanofluids in some research contributions. Shanbedi et al. [4] employed ANFIS to predict the thermal resistance and heat transfer performance of a Two-Phase Closed Thermosiphon (TPCT). Dispersions of pristine carbon nanotubes and functionalized nanotubes containing ethylene diamine were applied as nanofluids. The experimental results regarding the performance of TPCT were modelled by the ANFIS approach. A comparison was made between the results with 5 mathematical criteria. These criteria proposed that the modelling via ANFIS is reliable, so that it can be developed for other cases. In Study by Adio et al. [5] found the optimal energy required to prepare MgO-ethylene glycol nanofluids by modifying the ultrasonic energy input in the synthesis process. The nanofluids were characterized and their viscosity was measured in terms of volume concentration, temperature and particle size. The size distribution of the nanoparticles and the Transmission Electron Microscopy (TEM) image are shown in the Figure 1. The average sizes of the nanoparticles were ~21, ~105 and ~125nm, which are shown in the figure as MgO-I, MgO- II and MgO-III respectively. ANFIS was used to model the viscosity as a function of the mentioned parameters. The results had good consistency with the experimental results.

Aminossadati et al. [6] numerically studied on mixed convection in a cavity filled with an alumina-water nanofluid. The bottom and top walls of the cavity were kept at different temperatures, while the vertical walls were thermally isolated. An ANFIS method was designed trained and validated using data obtained from a numerical simulation. The results proved that ANFIS can be effectively applied to estimate the fluid temperature, velocity, and amount of heat exchange, with reduced computational time and no reduction in accuracy. The aim of the study by Mehrabi et al. [7] presented models to estimate the viscosity of nanofluids using ANFIS with the use of experimental results. Apparent viscosity was chosen as the target parameter, while temperature, volume fraction and particle diameter were assumed as input parameters. The estimated viscosities were compared with empirical results for 4 different nanofluids including alumina AL_2O_3, Titanium dioxide TiO_2, Copper Oxide CuO and Silicon dioxide SiO_2, and with water as the base liquid. The results obtained from the suggested ANFIS model showed appropriate consistency with the empirical results.

Combinations of ANN with GA

The hybrid AI system combines ANN with GA have focused on creative methods to couple ANN modules with GA. Research efforts also focus on methods to introduce ANNs for easier tuning and development by GA, techniques to replace gas with neural training approaches, and probabilities to incorporate new methods from evolutionary computing. The combination of GA with ANN has also been used in the area of nanofluids. The study goal of Vakili et al. [8] modeled the viscosity of graphene nanofluid using MLP neural network and GA. To obtain the empirical data, the nanofluid was used at volume fractions of 0.025 to 0.1 wt% and temperatures of 20 to 60 °C. The combination of genetic algorithms with ANN was used to improve the learning process. The results revealed that the obtained model was consistent with the empirical results. Karimi et al. [9] introduced a GA-based ANN to predict the viscosity of nanofluids. GA was applied to optimize the ANN factors. The viscosity of eight nanofluids at temperatures between 238.15K and 343.15K with volume fraction up to 9.4% was studied. The results proved that the model shows good agreement with the experimental data. Moreover, the results revealed that the model has better accuracy than the usual correlations. Salehi et al. [10] presented the models for evaluating the thermal characteristics of a water-Ag nanofluid inside a closed two-phase thermosiphon employing an optimized ANN via a genetic algorithm. The ANN was used to predict the heat transfer performance and resistance of a thermosiphon under a magnetic field. The volume fraction, magnetic field strength, and input power were considered as input variables, while the thermal resistance and heat transfer efficiency were taken as the outputs. The results were compared with the experimental results and it was concluded that the results obtained from ANN are accurate. The trial and error technique is time consuming and the ANN architecture obtained may not be optimal. To solve this problem, as observed, ANNs based on genetic algorithms have been used in nanofluids, in which the ANN parameters are optimized by GA. In the field of nanofluids, in general, GA has been used to determine the weights of ANNs as well as to design their structure, while no studies have been conducted in which GA is used to find an optimal formation rule for ANNs. This idea can be followed in the future to find optimal learning algorithms to improve the prediction task in nanofluids.

Combinations of GA with Decision Making Approaches

In multi-attribute optimization methods, a group of states is reached as the optimal case, while they have no preference over each other. Thus, some researchers have combined GA with different decision making methods to facilitate the selection procedure between different optimal points. The study of Bahiraei et al. [11] that attributes of water-Al2O3 nanofluid in a tube and shell heat exchanger. The schematic of the helical baffles used as well as the overlap parameter and helix angle are shown in the Figure 2. The pressure drops and heat transfer increased with increasing baffle overlap and volume fraction and reducing helix angle. In order to determine the cases with the highest heat transfer and lowest pressure loss, optimization was performed on the ANN model by GA coupled with a decision making method (i.e. Trade-off Programming). The results revealed that even when a small pressure drop is considerably vital to the decision maker, nanofluids with large volume fractions can be used. Furthermore, when both low pressure drop, and high heat transfer are crucial, low helix angles can be used.

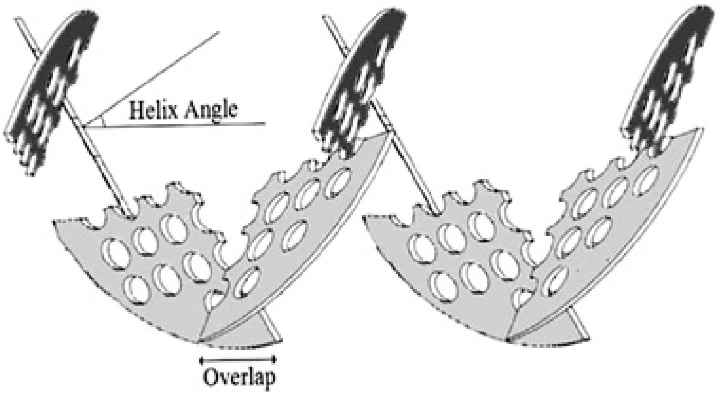


Figure 2: Diagram of the helical deflectors [11].

The study by Bahiraei & Hangi [12] that conducts the efficiency of a water-based Mn\Zn ferrite nanofluid inside a double tube heat exchanger in the presence of a quadrupole magnetic field. The nanofluid flowed on the tube side, while the hot water flowed on the ring side (Figure 3). The particle distribution was not uniform so that the concentration was lower near the walls. However, the use of the magnetic field led to a more uniform distribution of the nanoparticles. Optimization was performed via GA coupled with a trade-off programming method, which is a decision approach, to achieve the highest overall heat transfer coefficient with the lowest pressure drop. The optimal values were determined against various states for the relative importance of the objective functions to the designer's views.

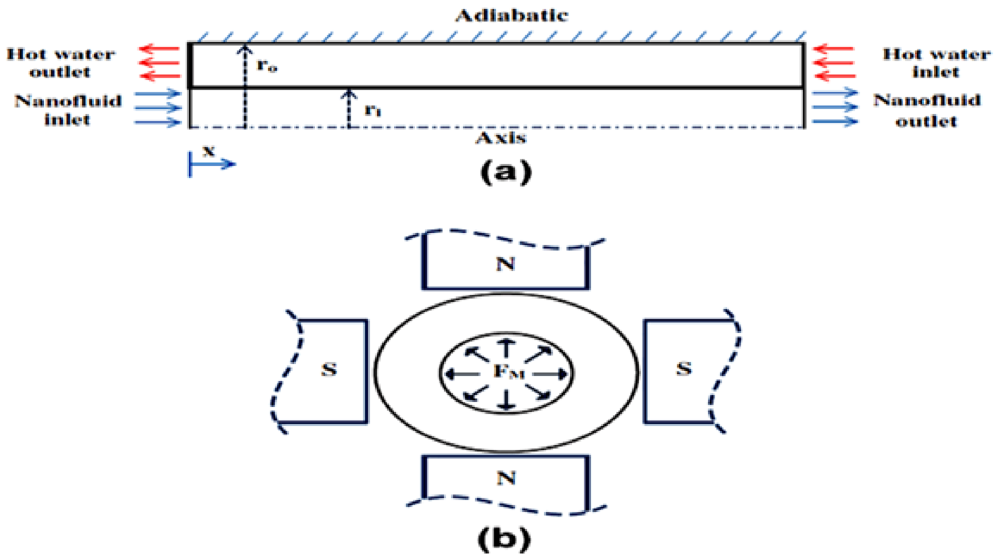


Figure 3: The heat exchanger studied in [12] (a) longitudinal cross section and (b) Cross section.

Application Artificial Intelligence Algorithms

Application of AI algorithms in solar energy applications with nanofluids

Recently, there has been an increasing demand in the use of renewable energy. This type of energy is sustainable, generates zero or minor greenhouse gas emissions and will never run out, which has a negligible effect on the environment. Solar energy is the oldest energy source ever used with a large supply. In some of the studies that have used nanofluids in solar energy applications, AI algorithms have been applied for modeling and optimization. Mohammad Zadeh et al. [13] introduced efficient solar collector optimization and modeling in a numerical study. The method used in the modeling employed a parabolic trough collector absorber tube, a fully developed flow, and a synthetic alumina oil nanofluid. A hybrid optimization approach involving a genetic algorithm and sequential quadratic programming was adopted in the optimization procedure. The optimization problem involved maximizing a non-dimensional relationship including pressure drop and Nusselt number with Reynolds and Richardson numbers applied as design constraints.

The results indicated that the heat exchange increment shows a direct relationship with volume fraction while it demonstrates an inverse relationship with temperature. In an analytical research, Risi et al. [14] proposed an innovative Transparent Parabolic

Solar Collector (TPTC) operating with a nanofluid. A conventional PTC is shown in the Figure 4. Transparent receivers as well as nanofluid are able to directly adsorb solar radiation due to the very large surface area of nanoparticles. The model was applied to run an optimization method with the use of GA. The simulations revealed that the highest solar/thermal transfer efficiency TPTC was 62.5% for a volume fraction of 0.3% and an exit temperature of 650 °C. Toghyani et al. [15] theoretically examined the efficiency of an integrated Rankine power cycle equipped with a parabolic trough solar system and a thermal storage system using 4 different nanofluids. The impact of solar intensity, dead-state temperature as well as particle concentration on the cycle efficiency was evaluated. The GA was used to optimize the power output. It was shown that by increasing the volume fraction, the exergy efficiency increases. At higher dead-state temperatures, higher solar irradiation caused a significant increase in power output. After performing an analytical study, Ahmadi Boyaghchi et al. [16] optimized a new refrigeration system combined with a flat plate solar collector. LiBr-H2O was used as a fluid pair in the cascade absorption part, while R134a, R1234ze, R1234yf, R407C and R22 coolants were used in the vapor compression part and CuO-water nanofluid was used as a heat transfer fluid in the collector subsystem. The thermal and exergy coefficients and total cost rate were chosen as objective functions. NSGA-II was implemented to obtain the final solutions. The modeling showed that R134a was the optimal refrigerant from the exergy and energy point of view.

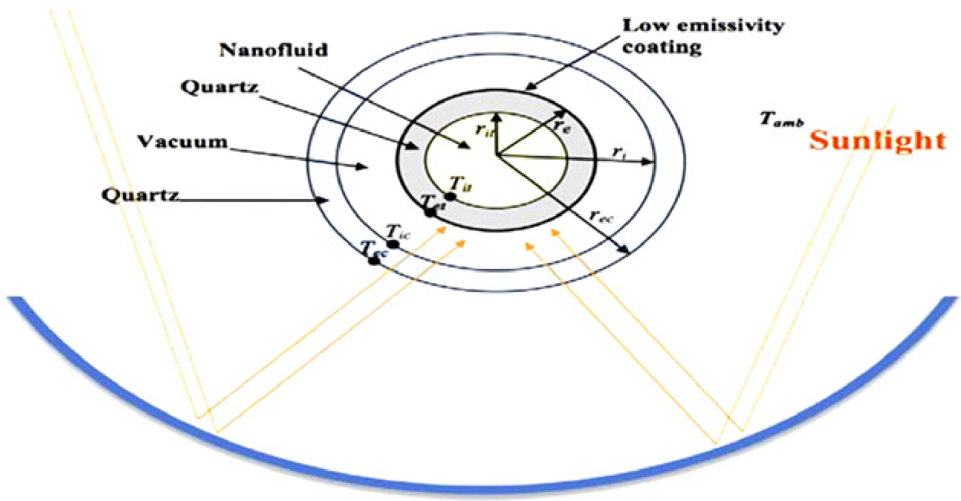


Figure 4: Schematic of a solar PTC [14].

Application of artificial intelligence algorithms to electronic cooling with nanofluids

Power and solid-state electronic devices have found many applications in commercial, residential, military and space environments. Nowadays, these systems are commonly used in automobiles, televisions, computers, phones, etc. Due to their extensive use, electronic components must operate reliably under a wide range of environmental conditions. One of the main causes that influence reliability is thermal management. The difference between input and output energy in an electronic device is converted into heat, which must be dissipated properly to avoid overheating and chip failure. Proper cooling in electronics still remains a problem that needs to be studied as it becomes an important enabling industry for the next development of electronics. To this end, some researchers have used nanofluids in electronic cooling, and the capabilities of AI have been used in some of the studies conducted in this area. Mital et al. [17] analytically studied the thermal characteristics of a rectangular channel liquid block with nanofluid flow for electronics cooling (Figure 5). The model was applied to estimate the pumping power and thermal resistance as a function of flow velocity, channel width, particle concentration, and wall width. The variables were optimized using a genetic algorithm with a constant value of pumping power as a constraint, and the lowest thermal resistance as an objective function. Minimized thermal resistances had only a minor benefit because solid nanoparticles increased energy consumption. Kargar et al. [18] used a neural network and CFD to evaluate the efficiency of two microchips in a cavity filled with a copper-water nanofluid. Heat exchange occurred due to free convection between the heated microchips attached to the right and left walls. The results obtained from the CFD simulation were used to form the ANN. Comparison of the results obtained from the CFD and those obtained from the neural network proved that the neural network accurately estimates the cooling of the microchips. The geometries applied for electronics cooling are miniature and are often in the micrometer range. Therefore, the possibility of channel clogging and particle agglomeration in these systems is high and therefore nanofluids with appropriate stability must be used for this purpose. In addition, the pressure drop intensifies considerably by reducing the channel size and therefore, low viscosity nanofluids are suggested for use in electronics cooling. With respect to many of the parameters affecting electronics cooling with nanofluids, ANNs and other AI algorithms can be effective for prediction and optimization of attributes in this area.

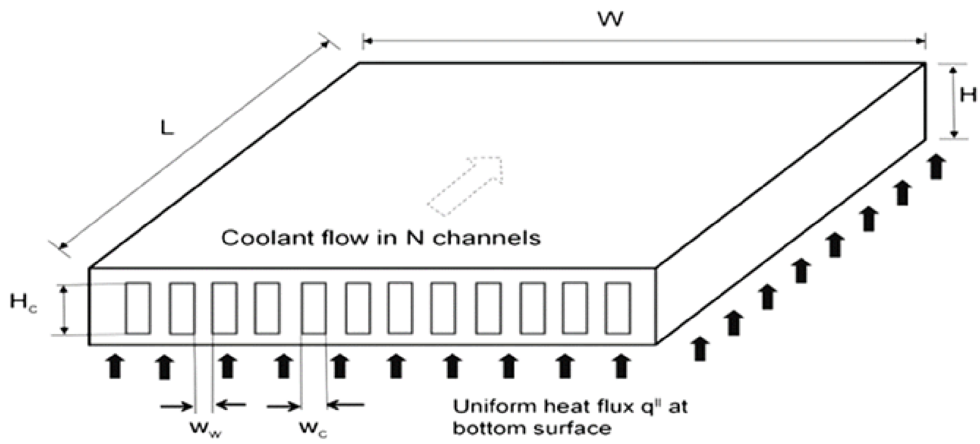


Figure 5: The heat sink under study [17].

Application of AI algorithms in heat exchangers operating with nanofluids

Heat exchangers have already proven to be important equipment for heat transfer systems in many technical fields. To improve the efficiency of heat exchangers, nanofluids are newly applied as working fluids. Due to the excellent attributes of nanofluids, research in this area has seen considerable development. AI algorithms have been applied to investigate the attributes of nanofluids inside heat exchangers in some studies. In a numerical effort, Bahiraei et al. [19] studied the thermal-hydraulic characteristics of alumina-water nanofluid in a shell-and-tube heat exchanger equipped with helical baffles. The influence of volume fraction and Reynolds number on pressure drop and heat transfer was examined. Increasing Reynolds number and particle concentration increased both pressure drop and heat transfer. Friction factor and Nusselt number models were developed as a function of particle concentration and Reynolds number per ANN. The ANN predicted the output parameters with appropriate accuracy.

Bahiraei et al. [20] numerically evaluated convective flow and heat transfer of a non-Newtonian nanofluid in a double tube heat exchanger model. Reducing the particle diameter and increasing the volume fraction increased the pressure drop and convective heat transfer. Using the data obtained from the simulations, an ANN model was designed to estimate the pressure drop and convective heat transfer coefficient as a function of radius ratio, volume fraction, and nanoparticle diameter. In addition, GA was used to achieve the optimal conditions regarding the designer's viewpoints. Exergy analysis of heat exchangers using AI algorithms is suggested as a really suitable future area for optimization of weight, size, baffle configuration and cost of heat exchangers operating with nanofluids. Moreover, heat exchangers operating with nanofluids are exposed to severe fouling which can depend on many parameters such as flow velocity, particle concentration, temperature, etc. To date, no studies have been conducted on fouling of heat exchangers operating with nanofluids via AI algorithms. Since many factors affect fouling, it is proposed to utilize the capabilities of AI, especially ANNs in this area.

Application of AI algorithms for hybrid nanofluids

Hybrid nanofluids are novels that are synthesized by suspending different nanoparticles as a mixture or composite in base liquids. The motivation for the production of hybrid nanofluids is the improvement of heat transfer with enhanced thermal conductivity of these nanofluids as well as the use of some special features. For example, functionalization of carbon nanotubes with other types of nanoparticles can integrate the characteristics of CNTs with these nanoparticles, which can lead to innovative materials with new chemical, thermal and physical characteristics as well as interesting applications. In some investigations, AI methods have been used to study hybrid nanofluids. Hemmat E et al. [21] presented a model for predicting the thermal conductivity of SWCNTs-MgO/EG hybrid nanofluids through a neural network. The hybrid nanofluids were experimentally synthesized and tested at concentrations between 0.05 and 2%.

Photographs and XRD patterns of MgO and SWCNT are shown individually in the Figure 6. The ANN correlation revealed a high degree of accuracy. Comparison of the results of this research and single particle nanofluids indicated that the interaction of particles in hybrid nanofluids acts in a positive direction, namely the improvement of thermal conductivity. Rostamian et al. [22] investigated the variations of thermal conductivity of CuO/SWCNTs-EG/water hybrid nanofluid as a function of volume fraction and temperature via neural network modeling. CNTs were mixed with CuO nanoparticles in equal volume (50:50) in an experimental work. Thermal conductivity modeling was performed by ANN by applying experimental data. The ANN model correctly estimated the thermal conductivity of the nanofluids. Afrand et al. [23] obtained a neural network model to estimate the relative viscosity of the MWCNTs-SiO_2/AE40 hybrid nanofluid using the experimental data. The concentration and temperature of the particles were considered as input parameters. The results obtained from ANN showed a margin of deviation of 1.5% from the empirical results (Figure 7). It was concluded from comparisons that the optimal neural network model is accurate in predicting the outputs. It can be noted that studies that have used AI algorithms for hybrid nanofluids, have often investigated the thermophysical properties of these nanofluids. With the further development of hybrid nanofluids in the future, the use of different AI algorithms is proposed to model and optimize the convective heart transfer of these modern nanofluids as well.

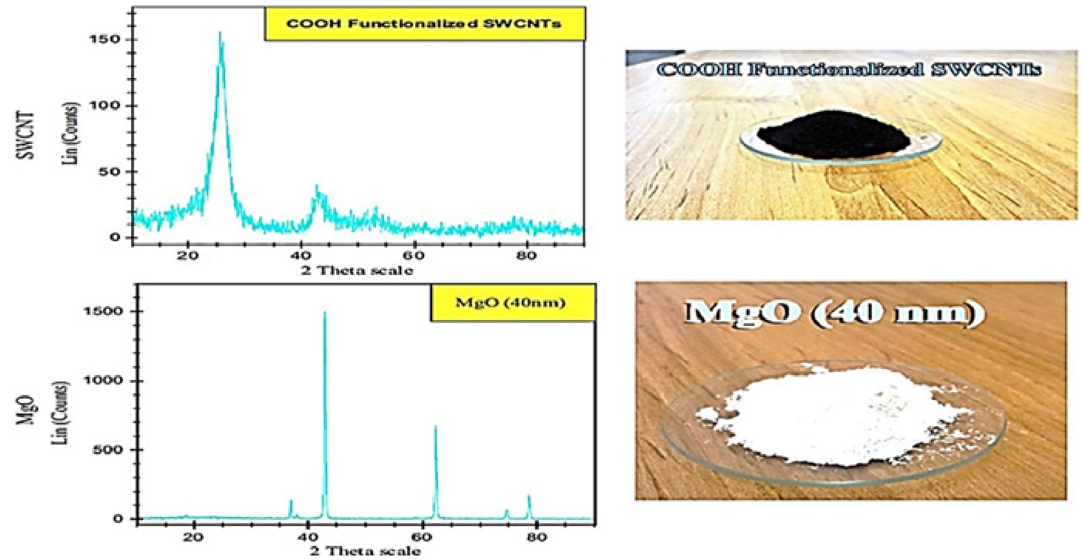


Figure 6: XRD analysis of nanopowder [21].

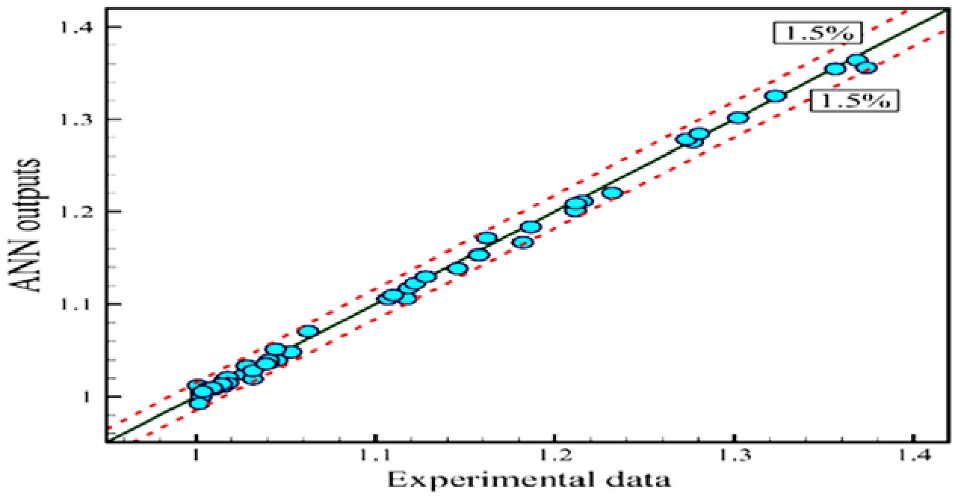


Figure 7: Comparison between experimental data and ANN results [23].

Application of AI algorithms for magnetic nanofluids

Magnetic nanofluids or ferrofluids are dispersions produced from non-magnetic base liquid and magnetic solid nanoparticles. In this new group of dispersions that are also called smart fluids, particle movement, heat exchange and fluid flow can be controlled using magnetic fields. Due to the excellent attributes of magnetic nanofluids, many researchers have conducted extensive research on these nanofluids. Some research papers have been published in which AI approaches have been implemented to evaluate the characteristics of magnetic nanofluids. Selimefendigil et al. [24] numerically investigated the effect of a magnetic dipole on the convective heat transfer of magnetic nanofluids inside an enclosure. A partial heating was attached to the left wall while the right wall remained at invariant temperature. The magnetic source was located outside the cavity. It was seen that the interaction between magnetic and free convection influences the hydrothermal characteristics. The magnetic field reduced local heat exchange in some locations, while enhancing it in others. Ultimately, a model was suggested to predict the heat transfer efficiency of the system using ANN. By mixing carbon nanotubes and magnetic nanoparticles in a base liquid, a new type of hybrid nanofluid can be synthesized. Such a ferrofluid benefits from the high thermal conductivity of CNTs in addition to the controllability of magnetite nanoparticles. In other words, in addition to possessing high thermal conductivity, such a hybrid nanofluid will also be controllable under magnetic fields. The study by Shahsavar & Bahiraei [25] experimentally measured the viscosity and thermal conductivity of a hybrid ferrofluid comprising both magnetite nanoparticles and CNTs at temperatures from 25 to 55 °C, Fe_3O_4 concentrations from 0.1% to 0.9% and CNT concentrations from 0 to 1.35%.

To avoid agglomeration, tetramethylammonium hydroxide and gum arabic were used to coat the magnetite nanoparticles and CNTs, respectively. The pictures of $FeCl_2$ solution and $FeCl_3$ solution, which were applied to synthesize the ferrofluid, as well as the picture of a hybrid ferrofluid instance are shown in the Figure 8. Based on the experimental results, two ANN models were designed to predict the viscosity and thermal conductivity. The obtained models had a good ability to estimate these properties. The review of the relevant literature indicates that correlations to predict the thermophysical properties of magnetic nanofluids are very rare. Therefore, it is essential to extend the models that can be used for the thermophysical properties of these nanofluids. Accordingly, it is suggested to apply ANRs to model the thermophysical properties of ferrofluids using experimental data, as the results obtained from numerical simulations are highly dependent on these properties.

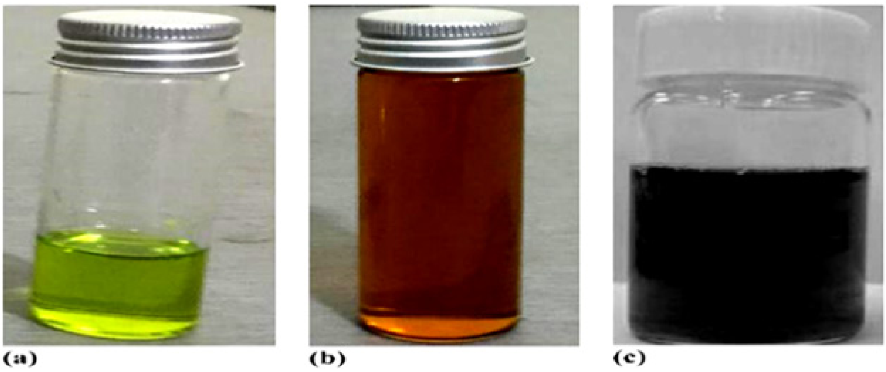


Figure 8: Photos of a) $FeCl_2$ solution, b) $FeCl_3$ solution, c) hybrid nanofluid sample [25].

Application of AI algorithms in second law analysis of nanofluids

Most of the research done on nanofluids has used the first law of thermodynamics to evaluate the behavior or fundamental thermal applications, which is not sufficient to disclose the energy efficiency of these types of systems. Indeed, the processes of energy exchange result in an irreversible increase in entropy. Therefore, although the quantity of energy is invariant, its quality decreases with its conversion into another form of energy to which less work is available. As a result, the rate of thermal entropy production increases with increasing particle diameter and wall heat flux, while it decreases with increasing concentration. The friction entropy production rate increased with increasing concentration, and reduced with increasing nanoparticle enlargement, while it changed insignificantly with improving wall heat flux. Finally, a model was proposed to predict the entropy production rates by ANN using the numerical data as learning models [3].

Application of AI algorithms for nanofluids with respect to nanoparticle migration

Particle migration in nanofluids has been trivially investigated in the studies performed and is certainly an open research topic requiring more studies. Particle migration can affect the characteristics of nanofluids significantly by disrupting the particle distribution and altering the thermophysical properties. In fact, particle migration occurs when nanoparticles do not follow the streamlines of the base fluid. Particle migration in nanofluids has been studied by some researchers. Some of these studies have been done by applying AI algorithms. In a numerical study, Bahiraei & Abdi [26] evaluated the entropy generation rates for the flow of a titanium dioxide-water nanofluid in a minitube regarding particle migration. A neural network model was designed to predict entropy generation amounts as a function of volume fraction, Reynolds number and particle diameter. The results revealed that particle migration significantly affects entropy production, especially for large particles and high volume fractions. The obtained ANN model estimated the outputs with appropriate accuracy.

Bahiraei et al. [27] evaluated the impacts of particle migration on the thermal characteristics of Al2O3 - water nanofluids by considering Brownian and thermophoresis forces through a numerical study. They presented an ANN model for the estimation of the convective heat transfer coefficient. Taking into account the influences of particle migration, a larger heat transfer coefficient was obtained and also the volume concentration in the central region of the tube was higher than that in the near wall. In addition, the proposed ANN model effectively estimated the convective heat transfer coefficient. It is also crucial to examine the attributes of nanofluids based on the second law of thermodynamics. As a result, some researchers have conducted the second law examination of nanofluids, and AI capabilities have been applied in some of these contributions.

Bahiraei & Mohammadi Majd [28] analyzed the second law of thermodynamics for the flow of water-alumina nanofluids inside a mini channel with triangular cross section via numerical simulations. The impacts of wall heat flux, Reynolds number, volume fraction and particle diameter were evaluated. Entropy generation due to heat transfer decreased as the volume fraction and Reynolds number were increased, while it increased with increasing nanoparticle diameter or wall heat flux. Friction-induced entropy generation, however, possessed an opposite trend. Entropy generation rate patterns were obtained via an a MLP neural network. The contours related to the total entropy generation rate obtained from this study for a volume fraction of 5% at a channel cross section are shown in

Figures 2 & 4 for three different Reynolds numbers. Heshmatian & Bahiraei et al. [29] examined the irreversibilities due to friction and heat transfer for the flow of a titania-water nanofluid inside a circular microtube with numerically calculated entropy generation rates.

Conclusion

It is concluded that in this review reveals that various AI approaches including ANNs, fuzzy logic and hybrid systems have been successfully used in the nanofluid domain. AI algorithms present easy formulation without requiring complete knowledge of the system, are simple to apply, adaptable and able to overcome long delays. ANN is used due to its accuracy while fuzzy logic is applied due to the simplicity of development and interpretation. In addition, GA is used to allow multiple potential answers to be produced. Hybrid AI algorithms in recent years show the notable success of these methods. The key factor in this is the synergy developed via intelligent mechanisms such as fuzzy logic, machine learning, ANNs and GA. Each of these approaches results in hybrid techniques with complementary reasoning and search methods that allow the application of domain knowledge to solve different problems.

The most important results of this paper as well as suggestions for future research are as follows:

1. Among the different thermophysical properties of nanofluids modeled by AI algorithms, most of the considerations have been attributed to viscosity and thermal conductivity, while less attention is given to other properties including density and specific heat. The study of other properties of nanofluids such as their optical properties using AI methods is strongly suggested.

2. Unlike common fluids, sparse relationships exist to predict convective heat transfer of nanofluids, and the need to develop accurate correlations via AI methods is strongly felt.

3. GA approaches are promising while suffering from the problem of too much complexity if the problem is too large. Moreover, since the selection in GA is performed stochastically.

4. In the field of nanofluids, GA has been generally used to determine the weights of ANNs as well as to design the structure, while no studies have been conducted in which GA is used to find an optimal training rule for ANNs. This idea can be followed in the future to find optimal training algorithms to improve the prediction task in nanofluids.

5. ANFIS has opened up a new avenue for understanding complex behaviors and phenomena in different domains related to nanofluids. However, ANFIS is not suitable for problems with many inputs because under such conditions, the number of fuzzy rules produced increases exponentially.

6. The results show that hybrid AI approaches are more efficient than simple approaches. Therefore, hybrid approaches can furthermore be tried for use in nanofluids.

7. The stability of nanofluids is a very critical issue that can be evaluated using ANN models.

8. Exergy analysis of heat exchangers using AI algorithms is suggested as a fantastic future area for optimizing the weight, size, baffle configuration and price of heat exchangers operating with nanofluids. Nanofluids via AI algorithms. Since there are many factors that affect fouling, it is proposed to utilize the capabilities of AI, especially ANNs.

References

1. Shubhendu SS, Vijay J (2013) Applicability of artificial intelligence in different fields of life. International Journal of Scientific Engineering and Research (IJSER) 1(1): 2347-3878.

2. Ly DQ, Paramonov L, Davidson C, Ramsden J, Wright H, et al. (2011) Nanotechnol Percept 7: 199-217.

3. Bahiraei M, Heshmatian S, Moayedi M (2019) Artificial intelligence in the field of nanofluids: A review on applications and potential future directions. Powder Technology 353: 276-301.

4. Shanbedi M, Amiri A, Rashidi S, Zeinali SH, Baniadam M (2015) Thermal performance prediction of two-phase closed thermosyphon using adaptive neurofuzzy inference system. Heat Transf Eng 36(3): 315-324.

5. Adio SA, Mehrabi M, Sharifpur M, Meyer JP (2016) Experimental investigation and model development for effective viscosity of MgO-ethylene glycol nanofluids by using dimensional analysis, FCM-ANFIS and GA-PNN techniques. Int Commun Heat Mass Transf 72: 71-83.

6. Aminossadati SM, Kargar A, Ghasemi B (2012) Adaptive network-based fuzzy inference system analysis of mixed convection in a two-sided lid-driven cavity filled with a nanofluid. Int J Therm Sci 52: 102-111.

7. Mehrabi M, Sharifpur M, Meyer JP (2013) Viscosity of nanofluids based on an artificial intelligence model. Int Commun Heat Mass Transf 43: 16-21.

8. Vakili M, Khosrojerdi S, Aghajannezhad P, Yahyaei M (2017) A hybrid artificial neural network-genetic algorithm modeling approach for viscosity estimation of graphene nanoplatelets nanofluid using experimental data. Int Commun Heat Mass Transf 82: 40-48.

9. Karimi H, Yousefi F, Rahimi MR (2011) Correlation of viscosity in nanofluids using genetic algorithm-neural network (GA-NN). Heat Mass Transf 47: 1417-1425.

10. Salehi H, Zeinali SH, Koolivand SM, Noei SH (2011) Designing a neural network for closed thermosyphon with nanofluid using a genetic algorithm. Braz J Chem Eng 28: 157-168.

11. Bahiraei M, Hangi M, Saeedan M (2015) A novel application for energy efficiency improvement using nanofluid in shell and tube heat exchanger equipped with helical baffles. Energy 93: 2229-2240.

12. Bahiraei M, Hangi M (2013) Investigating the efficacy of magnetic nanofluid as a coolant in double-pipe heat exchanger in the presence of magnetic field. Energy Convers Manag 76: 1125-1133.

13. Mohammad ZP, Sokhansefat T, Kasaeian AB, Kowsary F, Akbarzadeh A (2015) Hybrid optimization algorithm for thermal analysis in a solar parabolic trough collector based on nanofluid. Energy 82: 857-864.

14. De Risi A, Milanese M, Laforgia D (2013) Modelling and optimization of transparent parabolic trough collector based on gas-phase nanofluids. Renew Energy 58: 134-139.

15. Toghyani S, Baniasadi E, Afshari E (2013) Thermodynamic analysis and optimization of an integrated Rankine power cycle and nano-fluid based parabolic trough solar collector. Energy Convers Manag 121: 93-104.

16. Ahmadi BF, Mahmoodnezhad M, Sabeti V (2016) Exergoeconomic analysis and optimization of a solar driven dual-evaporator vapor

compression-absorption cascade refrigeration system using water/CuO nanofluid. J Clean Prod 139: 970-985.

17. Mital M (2013) Semi-analytical investigation of electronics cooling using developing nanofluid flow in rectangular microchannels. Appl Therm Eng 52: 321-327.
18. Kargar A, Ghasemi B, Aminossadati SM (2011) An artificial neural network approach to cooling analysis of electronic components in enclosures filled with nanofluids. J Electron Packag 133(1): 011010.
19. Bahiraei M, Hosseinalipour SM, Saeedan M (2015) Prediction of nusselt number and friction factor of water-Al2O3 nanofluid flow in shell-and-tube heat exchanger with helical baffles. Chem Eng Commun 202: 260-268.
20. Bahiraei M, Khosravi R, Heshmatian S (2017) Assessment and optimization of hydrothermal characteristics for a non-Newtonian nanofluid flow within miniaturized concentric-tube heat exchanger considering designer's viewpoint. Appl Therm Eng 123: 266-276.
21. Hemmat Esfe M, Alirezaie A, Rejvani M (2017) An applicable study on the thermal conductivity of SWCNT-MgO hybrid nanofluid and price-performance analysis for energy management. Appl Therm Eng 111: 1202-1210.
22. Rostamian SH, Biglari B, Saedodin S, Hemmat ES (2017) An inspection of thermal conductivity of CuO-SWCNTs hybrid nanofluid versus temperature and concentration using experimental data. ANN modeling and new correlation. J Mol Liq 231: 364-369.
23. Afrand M, Nazari NK, Sina N, Safaei MR, Kherbeet AS, et al. (2016) Prediction of dynamic viscosity of a hybrid nano-lubricant by an optimal artificial neural network. Int Commun Heat Mass Transf 76: 209-214.
24. Selimefendigil F, Oztop HF (2015) Numerical study and POD-based prediction of natural convection in a ferrofluids-filled triangular cavity with generalized neural networks. Num Heat Transf Part A 67: 1136-1161.
25. Shahsavar A, Bahiraei M (2017) Experimental investigation and modeling of thermal conductivity and viscosity for non-Newtonian hybrid nanofluid containing coated CNT/Fe_3O_4 nanoparticles. Powder Technol 318: 441-450.
26. Bahiraei M, Abdi F (2016) Development of a model for entropy generation of water-TiO_2 nanofluid flow considering nanoparticle migration within a minichannel. Chemom Intell Lab Syst 157: 16-28.
27. Bahiraei M, Hosseinalipour SM, Hangi M (2014) Prediction of convective heat transfer of Al_2O_3-water nanofluid considering particle migration using neural network. Eng Comput 31: 843-863.
28. Bahiraei M, Mohammadi MS (2016) Prediction of entropy generation for nanofluid flow through a triangular minichannel using neural network. Adv Powder Technol 27: 673-683.
29. Heshmatian S, Bahiraei M (2017) Numerical investigation of entropy generation to predict irreversibilities in nanofluid flow within a microchannel: Effects of Brownian diffusion, shear rate and viscosity gradient. Chem Eng Sci 172: 52-65.