UNIVERSITI PUTRA MALAYSIA

PREDICTIVE MODELLING OF NANOFLUIDS THERMOPHYSICAL PROPERTIES USING MACHINE LEARNING

ALADE IBRAHIM OLANREWAJU

PREDICTIVE MODELLING OF NANOFLUIDS THERMOPHYSICAL PROPERTIES USING MACHINE LEARNING

By

ALADE IBRAHIM OLANREWAJU

Thesis Submitted to the School of Graduate Studies, Universiti Putra Malaysia, in Fulfilment of the Requirements for the Degree of Doctor of Philosophy

March 2021

DEDICATION

This thesis is dedicated to my late parents (Mr Tajudeen Alade & Mrs Abiodun Felicia Alade). Without their vision and supports, this work would not have been completed.

Abstract of thesis presented to the Senate of Universiti Putra Malaysia in fulfilment of the requirement for the degree of Doctor of Philosophy

PREDICTIVE MODELLING OF NANOFLUIDS THERMOPHYSICAL PROPERTIES USING MACHINE LEARNING

By

ALADE IBRAHIM OLANREWAJU

March 2021

Chairman : Mohd Amiruddin Abd Rahman, PhD
Faculty : Science

Nanofluid plays significant roles in different application areas as a result of its enhanced thermal properties. Thus, studying the thermophysical properties of nanofluids has enormous technological benefits. Traditionally, the evaluations of these properties have been undertaken by experimental approaches which can be time-consuming, laborious and costly. Consequently, many researchers have developed empirical models to predict nanofluids properties. Unfortunately, many of these models grossly underestimate or overestimate the experimental values of the thermophysical properties. Hence, there is a need to develop a better approach to overcome the stated problems with the empirical models. In this regards, there have recently been series of efforts aimed at developing machine learning (ML)-based models to address the above challenges. This thesis aimed to develop machine learning algorithms to estimate the thermophysical properties of commonly used nanofluids. The machine learning algorithms used in this thesis comprise support vector regression (SVR) and artificial neural network (ANN) developed in a MATLAB computing environment. The optimization of the machine learning parameters was conducted using the Genetic Algorithm or the Bayesian Optimization Algorithm techniques. The first part of the thesis deals with modelling and prediction of the viscosity of nanofluids while the second part deals with modelling the specific heat capacity of nanofluids. For the viscosity, a systematic study of various factors that affect the viscosity of nanofluids was conducted, the results showed that an accurate prediction of viscosity of nanofluids can be accomplished using the following input parameters; volume fraction of the nanoparticles, the fluid temperature, the size of the nanoparticles, and the density of the nanoparticles. Furthermore, the four-input BSVR model proposed in this thesis showed over 50 per cent improvement in results over the five-input ANN-based model already presented in the literature and at the same time exhibits significantly improved accuracy over the existing empirical models.

For the specific heat capacity study, the following nanofluids were modelled; Al_2O_3-water, Al_2O_3-ethylene glycol (EG), CuO-water, nitrides-ethylene glycol (EG). The results of the machine learning models for each of the nanofluids were compared with simple mixing theory (model I) and thermal equilibrium based model (model II) to highlight the accuracy of the proposed techniques. For the Al_2O_3-water nanofluid, the model accuracy as measured by root mean square error (RMSE) obtained for the model I, model II, and the developed GA/SVR are 4.39×10^{-1} J/gK, 6.67×10^{-2} J/gK, and 1.4×10^{-3} J/gK, respectively. The GA/SVR results for Al_2O_3-water exhibits better accuracy than model I and Model II. In the case of Al_2O_3-EG nanofluids, the developed technique comprises of hybridization of Bayesian optimization algorithm with support vector regression (BSVR). The RMSE values obtained are 1.75×10^{-1} J/gK, 2.77×10^{-2} J/gK and 4.7×10^{-3} J/gK for the Model I, Model II and BSVR model, respectively. The BSVR exhibited at least an order(s) magnitude improvement for the prediction of Al_2O_3-EG nanofluids compared to both existing models. A similar improvement in accuracy was obtained using machine learning for the CuO-water and nitrides-ethylene glycol (EG) nanofluids. The machine models developed in this thesis are significantly better than the other existing theoretical models for all the classes of nanofluid modelled. In summary, this thesis demonstrates that machine learning-based approaches can provide more precise prediction results for specific heat capacity and viscosity of nanofluids than existing empirical/classical models. These results will be useful for experimentalists working on nanofluids design and applications.
.

Abstrak tesis yang dikemukakan kepada Senat Universiti Putra Malaysia sebagai memenuhi keperluan untuk ijazah Doktor Falsafah

PEMODELAN RAMALAN SIFAT FIZIKAL HABA NANO BENDALIR MENGGUNAKAN PEMBELAJARAN MESIN

Oleh

ALADE IBRAHIM OLANREWAJU

Mac 2021

Pengerusi : Mohd Amiruddin Abd Rahman, PhD
Fakulti : Sains

Nano bendalir memainkan peranan penting dalam pelbagai bidang aplikasi untuk mempertingkatkan sifat haba. Oleh itu, kajian tentang sifat fizikal haba memberi banyak faedah dalam teknologi. Penilaian sifat-sifat yang dilakukan secara tradisional boleh memakan masa yang agak lama, sukar dan agak mahal. Kesannya, ramai penyelidik telah mengembangkan model empirik untuk meramal sifat nano bendalir. Namun demikian, kebanyakan model ini mendapat kurang anggaran atau terlebih anggaran nilai eksperimen sifat fizikal haba. Oleh itu, perkembangan yang lebih baik perlu dilakukan dalam menangani masalah dalam meramal sifat nano bendalir. Dengan itu, terdapat beberapa kajian telah dilakukan tertumpu kepada perkembangan model berasaskan pembelajaran mesin untuk mengatasi masalah yang telah dinyatakan di atas. Tesis ini bertujuan untuk mengembangkan penggunaan pembelajaran mesin dalam menganggar sifat fizikal haba bagi nano bendalir yang biasa digunakan. Algoritma pembelajaran mesin yang digunakan dalam tesis ini merangkumi mesin vektor sokongan (SVR) dan rangkain neural buatan (ANN) yang telah dibangunkan meggunakan persekitaran pengkomputeran MATLAB. Pengoptimuman parameter pembelajaran mesin telah dibuat menggunakan teknik algoritma Genetik atau algoritma pengoptimuman bayesan. Bahagian pertama tesis ini berkenaan dengan kelikatan nano bendalir dan bahagian kedua adalah berkenaan dengan kajian kapasiti haba nano bendalir. Untuk kelikatan, kajian sistematik terhadap beberapa faktor yang mempengaruhi kelikatan nano bendalir dilakukan dan hasilnya menunjukkan bahawa ramalan kelikatan nano bendalir yang tepat dapat dicapai dengan menggunakan parameter input berikut; pecahan isipadu zarah nano, suhu bendalir, ukuran zarah nano, dan ketumpatan zarah nano.

Tambahan pula, empat input bagi model BSVR yang diusulkan dalam tesis ini menunjukkan peningkatan hasil lebih daripada 50 peratus berbanding model berasaskan lima input bagi ANN yang telah dibentangkan dalam literatur dan pada masa yang sama memperlihatkan peningkatan ketepatan yang ketara berbanding model empirikal yang sedia ada. Untuk kajian kapasiti haba tertentu, nan bendalir berikut dimodelkan; Al_2O_3-

air, Al_2O_3-etilina glikol (EG), CuO-air, nitrida-etilena glikol (EG). Hasil model pembelajaran mesin untuk setiap nano bendalir dibandingkan dengan teori pencampuran sederhana (model I) dan model berdasarkan keseimbangan haba (model II) untuk menonjolkan ketepatan teknik yang dicadangkan. Untuk Al_2O_3-air, ketepatan model yang diukur dengan punca min ralat kuasa dua (RMSE) yang diperoleh untuk model I, model II, dan perkembangan GA/SVR masing-masing ialah 4.39×10^{-1} J/gK, 6.67×10^{-2} J/gK, and 1.4×10^{-3} J/gK. Hasil ketepatan GA/SVR bagi Al_2O_3-air lebih baik dari model I dan Model II. Bagi kes Al_2O_3-EG, teknik yang dikembangkan terdiri daripada penghibridan algoritma pengoptimuman Bayesan dengan regresi vektor sokongan (BSVR). RMSE yang diperoleh masing-masing adalah 1.75×10^{-1} J/gK, 2.77×10^{-2} J/gK and 4.7×10^{-3} J/gK untuk Model I, Model II dan model BSVR. BSVR menunjukkan sekurang-kurangnya sedikit peningkatan magnitud untuk ramalan Al_2O_3-EG berbanding dengan kedua-dua model yang sedia ada. Peningkatan ketepatan yang serupa diperoleh menggunakan pembelajaran mesin untuk CuO-air dan nitrida-etilena glikol (EG). Perkembangan model mesin dalam tesis ini jauh lebih baik daripada model teori lain yang sedia ada untuk semua jenis model nano bendalir. Kesimpulannya, tesis ini menunjukkan bahawa pendekatan berasaskan pembelajarn mesin dapat memberikan hasil ramalan yang lebih tepat untuk kapasiti haba dan kelikatan nano bendalir tertentu jika dibandingkan dengan model empirikal yang sedia ada. Hasil ini akan berguna bagi para eksperimental yang mengusahakan reka bentuk dan penemuan nano bendalir.

ACKNOWLEDGEMENTS

First, I wish to express my gratitude to Almighty Allah for giving me the opportunity to complete this dissertation. Second, I would like to thank my late mother and father for their tremendous effort on me and their vision to educate me and my siblings even with the very limited resources at their disposal. Without their efforts, I will not be in a position to complete the thesis. May Allah continue to show His mercy on them. Third, the understanding of my family; Kamilat Mopelola (my wife), Ibrahim Ibraheem (son) and Fatima Ibrahim (daughter) also played a key role in the successful completion of this thesis.

Lastly, I would like to appreciate the effort of my supervisory team including Dr Mohd Amiruddin Abd Rahman, Associate Professor Dr. Zulkifly Abbas and Dr Yazid Yaakob. They all supported me morally and academically during the period of my candidature. Their continuous encouragement played a significant role in the completion of the thesis. An important mentor worthy of acknowledgement is Dr Tawfik Saleh. I deeply appreciate his commitment to nurturing students’ growth.

This thesis was submitted to the Senate of the Universiti Putra Malaysia and has been accepted as fulfilment of the requirement for the degree of Doctor of Philosophy. The members of the Supervisory Committee were as follows:

Mohd Amiruddin bin Abd Rahman, PhD
Senior Lecturer
Faculty of Science
Universiti Putra Malaysia
(Chairman)

Yazid bin Yaakob, PhD
Senior Lecturer
Faculty of Science
Universiti Putra Malaysia
(Member)

Zulkifly bin Abbas, PhD
Associate Professor
Faculty of Science
Universiti Putra Malaysia
(Member)

ZALILAH MOHD SHARIFF, PhD
Professor and Dean
School of Graduate Studies
Universiti Putra Malaysia

Date: 12 August 2021

Declaration by graduate student

I hereby confirm that:

- this thesis is my original work;
- quotations, illustrations and citations have been duly referenced;
- this thesis has not been submitted previously or concurrently for any other degree at any institutions;
- intellectual property from the thesis and copyright of thesis are fully-owned by Universiti Putra Malaysia, as according to the Universiti Putra Malaysia (Research) Rules 2012;
- written permission must be obtained from supervisor and the office of Deputy Vice-Chancellor (Research and innovation) before thesis is published (in the form of written, printed or in electronic form) including books, journals, modules, proceedings, popular writings, seminar papers, manuscripts, posters, reports, lecture notes, learning modules or any other materials as stated in the Universiti Putra Malaysia (Research) Rules 2012;
- there is no plagiarism or data falsification/fabrication in the thesis, and scholarly integrity is upheld as according to the Universiti Putra Malaysia (Graduate Studies) Rules 2003 (Revision 2012-2013) and the Universiti Putra Malaysia (Research) Rules 2012. The thesis has undergone plagiarism detection software

Signature: ________________________ Date: _______________

Name and Matric No: Alade Ibrahim Olanrewaju, GS51846

TABLE OF CONTENTS

LIST OF TABLES

LIST OF FIGURES

LIST OF APPENDICES

LIST OF ABBREVIATIONS

AARD	absolute average relative error
ANN	artificial neural network
R^2	coefficient of correlation
DI	deionised
d_n	density of nanoparticles
EG	ethylene glycol
MLP	multilayer perception
PG	propylene glycol
S	size of nanoparticles
SVR	support vector regression
T	temperature
μ_{bf}	viscosity of basefluids
μ_{nf}	viscosity of nanofluids
φ_p, V_f	volume fraction of nanoparticles
b	bias term
C	box constraint
d	degree of polynomial.
ϵ	epsilon
$\|\ \ \|$	Euclidean norm
$f(x)$	objective function to minimize

CHAPTER 1

INTRODUCTION

1.1 Overview

Energy is one of the core issues at the centre of the world's attention that physicists, chemists, material scientists, engineers and others are constantly seeking innovative means to ensure its optimum management [1]. Fundamentally, the development of methodologies for heat transfer enhancement and reduction of energy losses in the traditional and new energy sources are key components in dealing with the problems of energy wastage and harvesting [2]. Over the past few decades, researchers have pursued the use of extended-surface thermal control techniques, which include fins and microchannel in various electromechanical systems such as refrigerating, air-conditioning and cooling systems [2]. However, further improvement in terms of heat transfer enhancement using these techniques is limited due to geometric constraints in designs.

This limitation has paved way for the invention of a novel heat transfer approach that could enhance the capability of the existing heat transfer methodologies. The new mechanism involves controlling the thermal property of the cooling fluids through the suspension nanoparticles in conventional cooling fluids such as water, ethylene glycol, propene glycol, engine oil, transformer oil. Because the thermal conductivities of nanoparticles are substantially higher than conventional fluids. The introduction of a controlled amount of nanoparticles can dramatically increase the heat transfer ability of the base fluids [3]. These innovative fluids referred to as "nanofluids" was proposed by Choi in 1995 [4]. In their seminar work, they highlighted that when nanoparticles are suspended in base fluids, there is a three-fold thermal conductivity improvement in the base fluids. When such fluids are used in heat transfer equipment, the rate of heat transfer of the equipment doubles without increasing its pumping power. Using a conventional base fluid, a comparable increase in the rate of heat transfer is obtained by increasing the pumping power 10 times. This demonstrates that with nanofluids, energy optimization can be accomplished.

Since the invention, studies on nanofluids continue to grow in leaps and bounds. Currently, over 2500 journal articles have been published in the year 2020 which covers a broad spectrum of interests such as experimental, theoretical, pure and applied research. The impacts of nanofluids have been investigated in several different areas such as solar technology [5], automobile [6], refrigeration [7], heat exchangers [8]. Because of the central role played by thermophysical properties of nanofluids in the mentioned applications, many studies have been devoted to measuring the thermophysical property of nanofluids such as thermal conductivity, viscosity, density, specific heat capacity and thermal diffusivity. Amongst these properties, thermal conductivity and viscosity are the most investigated properties while the density and specific heat capacity of nanofluids have received lesser attention to date [9]. It is important to mention that these thermophysical properties are interrelated, they are connected through one relation or the other. In other words, to fully characterize a thermal fluid for potential applications, the values of the thermophysical properties must be known [10].

The most reliable ways to determine the values of the thermophysical properties of nanofluids is via experimental measurements. However, there are specific challenges in relying exclusively on these methods. Examples of these challenges include, preparation of very stable nanofluids is not trivial, the cost of nanomaterials and measuring equipment can be significant for lab with limited funding and the process of preparing and measuring the nanofluids can be intensive especially when large samples are involved [11]. Modelling the thermophysical properties has been adopted as a way to mitigate some of the challenges mentioned above. Numerous classical models and empirical models have been developed in the literature in an attempt to forecast the thermal properties of the nanofluids [12]. In many instances, they are inadequate to accurately model the experimental results due to underlying assumptions used in their formulation [11]. To reduce the forecasting errors obtained from classical or empirical models, researchers have turned to machine learning techniques to predict nanofluids properties [11].

1.2 Machine Learning: A New Frontier in Science

Learning from data is one of the most attractive sciences in the 21st century with applications covering a gamut of disciplines such as astronomy, finance, engineering. Machine learning (ML) can uncover hidden insight from data using algorithms to learn the relationship between inputs and output [13]. Machine learning teaches the computer to derive insight from existing data thereby presenting interesting opportunities which allow for future prediction of structure-property in material science and engineering. Interestingly, ML has shown superhuman capabilities in many real-life practical tasks [14] such as a self-driving car [15], image classification [16], [17] and Playing Go [18]. Many aspects of our daily life such as email/spam classification [19]–[22], fraud detection [23], image and speech recognition have been simplified by the use of ML algorithm.

Laboratories across the globe generate phenomena amount of data on daily basis. This reality has made the use of ML for various applications quite popular recently. In a nutshell, ML presents us with a unique opportunity to learn something new from existing data. This thesis is formulated against the backdrop of the excellent opportunities which ML techniques offer in applied science. Specifically, the application of ML to the modelling of the thermophysical properties of nanofluids is the main focus of this thesis. Figure 1-1 shows the number of studies on nanofluids where ML techniques have been employed. As observed, there is a growing trend in the application of ML in the study of nanofluids.

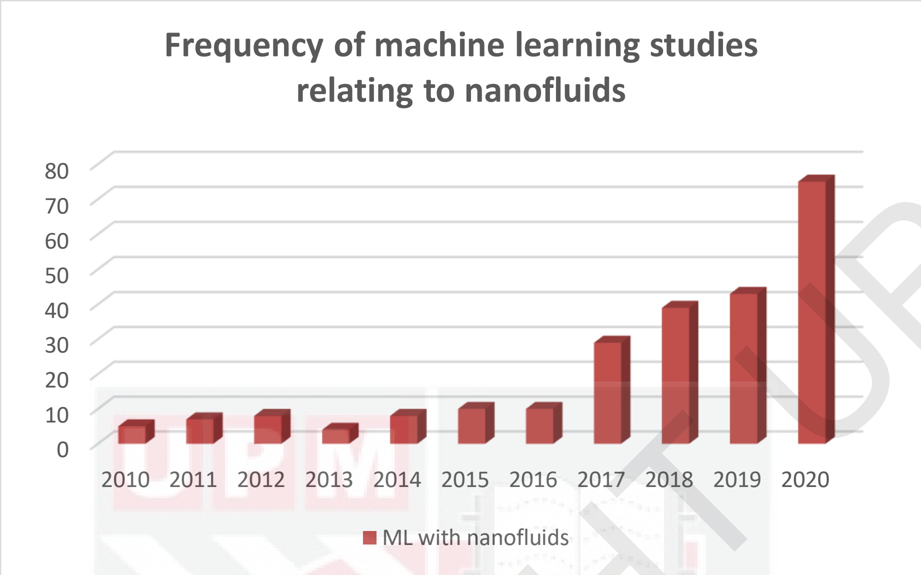

Figure 1.1 : Frequency of application of machine learning to nanofluid studies (Science direct, Sept 2020)

1.3 Problem Statement

To gain insight into the suitability of different nanofluids for heat transfer applications, the knowledge of thermophysical properties is very paramount. Over the years, the values of these properties have been obtained using the experimental approach. However, since the process of synthesis and measurements of nanofluid properties is intensive, time-consuming and costly. Therefore, a rapid estimation of the thermophysical property using ML techniques has become a highly attractive tool [24]. This thesis focuses on employing ML techniques for improving the prediction accuracy of the thermophysical property of nanofluids. This approach is justified because the existing classical models exhibit large prediction errors from the experimental [24]. Therefore, it is essential to formulate predictive models capable of accurate estimation of these properties without the need to conduct experiments frequently.

1.4 Research Objectives

The goal of this thesis is to be able to make highly accurate predictions of nanofluids properties to a degree superior to the available classical models by using ML algorithms with optimization techniques. The main objective of this thesis is to formulate predictive models for viscosity and specific heat capacity of nanofluids using ML algorithms.

The following are the specific objectives that this thesis addresses;

I. Modelling and prediction of viscosity of nanofluids using artificial neural network and Bayesian support vector regression algorithm. Under this objective, a systematic investigation of the influence of various parameters on viscosity prediction was conducted.

II. Modelling and prediction of specific heat capacity of nitrides nanoparticles suspended in ethylene glycol using Bayesian support vector regression. The nitrides nanoparticles considered are aluminum nitride, titanium nitrides and silicon nitrides.

III. Modelling and prediction of specific heat capacity of Al_2O_3 nanoparticles suspended in water using hybrid genetic algorithm and support vector regression.

IV. Modelling and prediction of specific heat capacity of aqueous nanofluids of copper oxide using support vector regression and artificial neural network optimized with bayesian optimization.

V. Modelling and prediction of the specific heat capacity of alumina/ ethylene glycol nanofluids using support vector regression model optimized with bayesian optimization.

1.5 Structure of the thesis

This thesis is structured as a publication-based dissertation where each of the above research objectives represents research chapters that are already published in international journals. The general structure of the thesis is described as follows.

Chapter one introduces the innovative fluids referred to as nanofluids. This chapter also covers research objectives and the significance of the proposed study.

Chapter two examines the literature reviews covering existing ML-based studies on the thermophysical properties of nanofluids.

Chapter three covers the modelling and prediction of relative viscosity of diverse nanofluids using artificial neural network and support vector regression optimized by Bayesian algorithm. The effect of various commonly used descriptors was also investigated to know the best set of descriptors that yield the most accurate results. A comparison of the developed models with the existing ANN model and the theoretical models was conducted in this chapter.

Chapter four discusses the modelling of the specific heat capacity of aluminum nitrides, titanium nitrides, and silicon nitrides all dispersed in ethylene glycol using the support vector regression and Bayesian optimization.

Chapter five deals with modelling the specific heat capacity of Al_2O_3 in water. This chapter discusses the application of support vector regression coupled with a genetic algorithm.

Chapter six examines the use of artificial neural network and support vector regression model for predicting the specific heat capacity of aqueous CuO nanofluids. A Comparison was made between the predictive performance of the artificial neural network and the support vector regression model. Both SVR and ANN were optimized using Bayesian optimization.

Chapter seven deals with the accurate modelling and prediction specific heat capacity of alumina suspended in ethylene glycol using support vector regression hybridized with Bayesian optimization.

Chapter eight provides the general conclusion and future recommendations relating to the use of ML for predicting the thermophysical properties of nanofluids.

It is essential to point out that for each of the above research objectives, the developed models for the nanofluids materials were benchmarked with the appropriate existing models to highlights the improvement in accuracy obtained using ML techniques over the existing theoretical models.

1.6 Significance of the study

The focus of this thesis has to do with deriving insights and patterns from experimental data to make accurate predictions of nanofluids properties using ML algorithms. Specifically, this thesis provided ML-based models that can rapidly and accurately estimate the viscosity of a wide range of nanofluids. Furthermore, for specific nanofluids with technological importance, ML models were selectively developed for predicting the specific heat capacity of the nanofluids from basic input parameters. In general, ML-based results obtained show a greater accuracy compared to the traditional modelling approaches like correlations-based or empirical-based models that predict the thermophysical properties of nanofluids with lesser accuracy. The ability to predict nanofluids properties with high accuracy facilitates the fast and reliable design of heat transfer applications.

REFERENCES

[1] D. Wen, G. Lin, S. Vafaei, and K. Zhang, “Review of nanofluids for heat transfer applications,” *Particuology*, vol. 7, no. 2, pp. 141–150, 2009.

[2] M. Raja, R. Vijayan, P. Dineshkumar, and M. Venkatesan, “Review on nanofluids characterization, heat transfer characteristics and applications,” *Renew. Sustain. Energy Rev.*, vol. 64, pp. 163–173, Oct. 2016.

[3] A. Hemmati-Sarapardeh, A. Varamesh, M. Nait Amar, M. M. Husein, and M. Dong, “On the evaluation of thermal conductivity of nanofluids using advanced intelligent models,” *Int. Commun. Heat Mass Transf.*, vol. 118, p. 104825, Nov. 2020.

[4] C. SUS., “Enhancing thermal conductivity of fluids with nano- particles.,” *Dev Appl Non Newt. Flows.*, pp. 231:99–105, 1995.

[5] A. H. Elsheikh, S. W. Sharshir, M. E. Mostafa, F. A. Essa, and M. K. Ahmed Ali, “Applications of nanofluids in solar energy: A review of recent advances,” *Renew. Sustain. Energy Rev.*, vol. 82, pp. 3483–3502, Feb. 2018.

[6] S. M. Peyghambarzadeh, S. H. Hashemabadi, M. Naraki, and Y. Vermahmoudi, “Experimental study of overall heat transfer coefficient in the application of dilute nanofluids in the car radiator,” *Appl. Therm. Eng.*, vol. 52, no. 1, pp. 8–16, Apr. 2013.

[7] A. Bhattad, J. Sarkar, and P. Ghosh, “Improving the performance of refrigeration systems by using nanofluids: A comprehensive review,” *Renewable and Sustainable Energy Reviews*, vol. 82. Elsevier Ltd, pp. 3656–3669, 01-Feb-2018.

[8] M. N. Pantzali, A. A. Mouza, and S. V. Paras, “Investigating the efficacy of nanofluids as coolants in plate heat exchangers (PHE),” *Chem. Eng. Sci.*, vol. 64, no. 14, pp. 3290–3300, 2009.

[9] I. M. Shahrul, I. M. Mahbubul, S. S. Khaleduzzaman, R. Saidur, and M. F. M. Sabri, “A comparative review on the specific heat of nanofluids for energy perspective,” *Renew. Sustain. Energy Rev.*, vol. 38, pp. 88–98, 2014.

[10] G. Żyła and J. Fal, “Viscosity, thermal and electrical conductivity of silicon dioxide–ethylene glycol transparent nanofluids: An experimental studies,” *Thermochim. Acta*, vol. 650, pp. 106–113, Apr. 2017.

[11] A. Zendehboudi, R. Saidur, I. M. Mahbubul, and S. H. Hosseini, “Data-driven methods for estimating the effective thermal conductivity of nanofluids: A comprehensive review,” *Int. J. Heat Mass Transf.*, vol. 131, pp. 1211–1231, Mar. 2019.

[12] H. Khodadadi, S. Aghakhani, H. Majd, R. Kalbasi, S. Wongwises, and M. Afrand, “A comprehensive review on rheological behavior of mono and hybrid nanofluids: Effective parameters and predictive correlations,” *Int. J. Heat Mass Transf.*, vol. 127, pp. 997–1012, Dec. 2018.

[13] T. Law and J. Shawe-Taylor, “Practical Bayesian support vector regression for financial time series prediction and market condition change detection,” *Quant. Financ.*, vol. 17, no. 9, pp. 1403–1416, Sep. 2017.

[14] J. Schmidt, M. R. G. Marques, S. Botti, and M. A. L. Marques, “Recent advances and applications of machine learning in solid-state materials science,” *npj Comput. Mater.*, vol. 5, no. 1, 2019.

[15] M. Daily, S. Medasani, R. Behringer, and M. Trivedi, “Self-Driving Cars,” *Computer (Long. Beach. Calif).*, vol. 50, no. 12, pp. 18–23, Dec. 2017.

[16] J. Peña, P. Gutiérrez, C. Hervás-Martínez, J. Six, R. Plant, and F. López-Granados, “Object-Based Image Classification of Summer Crops with Machine Learning Methods,” *Remote Sens.*, vol. 6, no. 6, pp. 5019–5041, May 2014.

[17] S. Amini, S. Homayouni, A. Safari, and A. A. Darvishsefat, “Object-based classification of hyperspectral data using Random Forest algorithm,” *Geo-Spatial Inf. Sci.*, vol. 21, no. 2, pp. 127–138, Apr. 2018.

[18] D. Silver *et al.*, “Mastering the game of Go with deep neural networks and tree search,” *Nature*, vol. 529, no. 7587, pp. 484–489, 2016.

[19] H.-Y. Li, S.-N. Zhao, S.-Q. Zang, and J. Li, “Functional metal–organic frameworks as effective sensors of gases and volatile compounds,” *Chem. Soc. Rev.*, vol. 49, no. 17, pp. 6364–6401, 2020.

[20] E. G. Dada, J. S. Bassi, H. Chiroma, S. M. Abdulhamid, A. O. Adetunmbi, and O. E. Ajibuwa, “Machine learning for email spam filtering: review, approaches and open research problems,” *Heliyon*, vol. 5, no. 6, p. e01802, Jun. 2019.

[21] S. Zhao, Z. Xu, L. Liu, and M. Guo, “Towards Accurate Deceptive Opinion Spam Detection based on Word Order-preserving CNN,” Nov. 2017.

[22] A. Bhowmick and S. M. Hazarika, “Machine Learning for E-mail Spam Filtering: Review,Techniques and Trends,” *Comput. Sci. Math.*, Jun. 2016.

[23] J. Błaszczyński, A. T. de Almeida Filho, A. Matuszyk, M. Szeląg, and R. Słowiński, “Auto loan fraud detection using dominance-based rough set approach versus machine learning methods,” *Expert Systems with Applications*, 01-Jan-2021. .

[24] M. Bahiraei, S. Heshmatian, and H. Moayedi, “Artificial intelligence in the field of nanofluids: A review on applications and potential future directions,” *Powder Technology*, vol. 353. Elsevier B.V., pp. 276–301, 15-Jul-2019.

[25] M. Hemmat Esfe, H. Rostamian, D. Toghraie, and W. M. Yan, "Using artificial neural network to predict thermal conductivity of ethylene glycol with alumina nanoparticle: Effects of temperature and solid volume fraction," *J. Therm. Anal. Calorim.*, vol. 126, no. 2, pp. 643–648, 2016.

[26] A. Maleki, A. Haghighi, M. Irandoost Shahrestani, and Z. Abdelmalek, "Applying different types of artificial neural network for modeling thermal conductivity of nanofluids containing silica particles," *J. Therm. Anal. Calorim.*, pp. 1–10, Apr. 2020.

[27] I. O. Alade, T. A. Oyehan, A. Bagudu, I. K. Popoola, and S. O. Olatunji, "Modeling thermal conductivity enhancement of metal and metallic oxide nanofluids using support vector regression," *Adv. Powder Technol.*, vol. 29, no. 1, pp. 157–167, 2017.

[28] M. Hemmat Esfe, M. Afrand, W. M. Yan, and M. Akbari, "Applicability of artificial neural network and nonlinear regression to predict thermal conductivity modeling of Al<inf>2</inf>O<inf>3</inf>-water nanofluids using experimental data," *Int. Commun. Heat Mass Transf.*, vol. 66, pp. 246–249, 2015.

[29] A. Zendehboudi and R. Saidur, "A reliable model to estimate the effective thermal conductivity of nanofluids," *Heat Mass Transf. und Stoffuebertragung*, vol. 55, no. 2, pp. 397–411, 2019.

[30] G. A. Longo, C. Zilio, E. Ceseracciu, and M. Reggiani, "Application of Artificial Neural Network (ANN) for the prediction of thermal conductivity of oxide–water nanofluids," *Nano Energy*, vol. 1, no. 2, pp. 290–296, 2012.

[31] S. A. Angayarkanni and J. Philip, "Review on thermal properties of nanofluids: Recent developments," *Adv. Colloid Interface Sci.*, vol. 225, pp. 146–176, Nov. 2015.

[32] B. Barbés, R. Páramo, E. Blanco, and C. Casanova, "Thermal conductivity and specific heat capacity measurements of CuO nanofluids," *J. Therm. Anal. Calorim.*, vol. 115, no. 2, pp. 1883–1891, 2014.

[33] X. Wang, X. Yan, N. Gao, and G. Chen, "Prediction of Thermal Conductivity of Various Nanofluids with Ethylene Glycol using Artificial Neural Network," *J. Therm. Sci.*, 2019.

[34] A. Maleki, M. Elahi, M. E. H. Assad, M. Alhuyi Nazari, M. Safdari Shadloo, and N. Nabipour, "Thermal conductivity modeling of nanofluids with ZnO particles by using approaches based on artificial neural network and MARS," *J. Therm. Anal. Calorim.*, pp. 1–12, Feb. 2020.

[35] A. Maleki, A. Haghighi, M. Irandoost Shahrestani, and Z. Abdelmalek, “Applying different types of artificial neural network for modeling thermal conductivity of nanofluids containing silica particles,” *J. Therm. Anal. Calorim.*, pp. 1–10, Apr. 2020.

[36] M. Ghazvini, H. Maddah, R. Peymanfar, M. H. Ahmadi, and R. Kumar, “Experimental evaluation and artificial neural network modeling of thermal conductivity of water based nanofluid containing magnetic copper nanoparticles,” *Phys. A Stat. Mech. its Appl.*, p. 124127, Jan. 2020.

[37] R. Agarwal, K. Verma, N. K. Agrawal, and R. Singh, “Comparison of Experimental Measurements of Thermal Conductivity of Fe2O3 Nanofluids Against Standard Theoretical Models and Artificial Neural Network Approach,” *J. Mater. Eng. Perform.*, vol. 28, no. 8, pp. 4602–4609, Aug. 2019.

[38] A. Zendehboudi and R. Saidur, “A reliable model to estimate the effective thermal conductivity of nanofluids,” *Heat Mass Transf. und Stoffuebertragung*, vol. 55, no. 2, pp. 397–411, Feb. 2019.

[39] I. M. Mahbubul, R. Saidur, and M. A. Amalina, “Latest developments on the viscosity of nanofluids,” *Int. J. Heat Mass Transf.*, vol. 55, pp. 874–885, 2012.

[40] P. C. Mishra, S. Mukherjee, S. K. Nayak, and A. Panda, “A brief review on viscosity of nanofluids,” *Int. Nano Lett.*, vol. 4, no. 4, pp. 109–120, Dec. 2014.

[41] D. Toghraie, M. H. Aghahadi, N. Sina, and F. Soltani, “Application of Artificial Neural Networks (ANNs) for Predicting the Viscosity of Tungsten Oxide (WO3)-MWCNTs/Engine Oil Hybrid Nanofluid,” *Int. J. Thermophys.*, vol. 41, no. 12, p. 163, Dec. 2020.

[42] N. Parashar, N. Aslfattahi, S. M. Yahya, and R. Saidur, “An artificial neural network approach for the prediction of dynamic viscosity of MXene-palm oil nanofluid using experimental data,” *J. Therm. Anal. Calorim.*, no. 0123456789, 2020.

[43] M. Gholizadeh, M. Jamei, I. Ahmadianfar, and R. Pourrajab, “Prediction of nanofluids viscosity using random forest (RF) approach,” *Chemom. Intell. Lab. Syst.*, vol. 201, p. 104010, Jun. 2020.

[44] D. Yadav, P. Dansena, S. K. Ghosh, and P. K. Singh, “A unique multilayer perceptron model (ANN) for different oxide/EG nanofluid’s viscosity from the experimental study,” *Phys. A Stat. Mech. its Appl.*, vol. 549, p. 124030, Jul. 2020.

[45] D. Toghraie, N. Sina, N. A. Jolfaei, M. Hajian, and M. Afrand, “Designing an Artificial Neural Network (ANN) to predict the viscosity of Silver/Ethylene glycol nanofluid at different temperatures and volume fraction of nanoparticles,” *Phys. A Stat. Mech. its Appl.*, vol. 534, Nov. 2019.

[46] M. Ramezanizadeh, M. A. Ahmadi, M. H. Ahmadi, and M. Alhuyi Nazari, “Rigorous smart model for predicting dynamic viscosity of Al2O3/water nanofluid,” *J. Therm. Anal. Calorim.*, vol. 137, no. 1, pp. 307–316, Jul. 2019.

[47] M. H. Ahmadi, B. Mohseni-Gharyehsafa, M. Farzaneh-Gord, R. D. Jilte, R. Kumar, and K. Chau, “Applicability of connectionist methods to predict dynamic viscosity of silver/water nanofluid by using ANN-MLP, MARS and MPR algorithms,” *Eng. Appl. Comput. Fluid Mech.*, vol. 13, no. 1, pp. 220–228, Jan. 2019.

[48] M. H. Ahmadi, B. Mohseni-Gharyehsafa, M. Ghazvini, M. Goodarzi, R. D. Jilte, and R. Kumar, “Comparing various machine learning approaches in modeling the dynamic viscosity of CuO/water nanofluid,” *J. Therm. Anal. Calorim.*, vol. 139, no. 4, pp. 2585–2599, Feb. 2020.

[49] A. Aminian, “Predicting the effective viscosity of nanofluids for the augmentation of heat transfer in the process industries,” *J. Mol. Liq.*, vol. 229, pp. 300–308, Mar. 2017.

[50] E. Gholami, B. Vaferi, and M. A. Ariana, “Prediction of viscosity of several alumina-based nanofluids using various artificial intelligence paradigms - Comparison with experimental data and empirical correlations,” *Powder Technol.*, vol. 323, pp. 495–506, Jan. 2018.

[51] F. Yousefi, H. Karimi, and M. M. Papari, “Modeling viscosity of nanofluids using diffusional neural networks,” *J. Mol. Liq.*, vol. 175, pp. 85–90, 2012.

[52] M. Mehrabi, M. Sharifpur, and J. P. Meyer, “Viscosity of nanofluids based on an artificial intelligence model,” *Int. Commun. Heat Mass Transf.*, vol. 43, pp. 16–21, 2013.

[53] S. Atashrouz, G. Pazuki, and Y. Alimoradi, “Estimation of the viscosity of nine nanofluids using a hybrid GMDH-type neural network system,” *Fluid Phase Equilib.*, vol. 372, pp. 43–48, 2014.

[54] N. Zhao, X. Wen, J. Yang, S. Li, and Z. Wang, “Modeling and prediction of viscosity of water-based nanofluids by radial basis function neural networks,” *Powder Technol.*, vol. 281, pp. 173–183, 2015.

[55] M. Bahiraei, M. Hosseinalipour, K. Zabihi, and E. Taheran, “Using Neural Network for Determination of Viscosity in Water-TiO 2 Nanofluid,” *Adv. Mech. Eng.*, vol. 4, p. 742680, 2012.

[56] M. Hemmat Esfe, S. Saedodin, N. Sina, M. Afrand, and S. Rostami, “Designing an artificial neural network to predict thermal conductivity and dynamic viscosity of ferromagnetic nanofluid,” *Int. Commun. Heat Mass Transf.*, vol. 68, pp. 50–57, 2015.

[57] M. Hemmat Esfe, M. R. Hassani Ahangar, M. Rejvani, D. Toghraie, and M. H. Hajmohammad, "Designing an artificial neural network to predict dynamic viscosity of aqueous nanofluid of TiO2 using experimental data," *Int. Commun. Heat Mass Transf.*, vol. 75, pp. 192–196, 2016.

[58] M. H. Ahmadi, B. Mohseni-Gharyehsafa, M. Ghazvini, M. Goodarzi, R. D. Jilte, and R. Kumar, "Comparing various machine learning approaches in modeling the dynamic viscosity of CuO/water nanofluid," *J. Therm. Anal. Calorim.*, vol. 139, no. 4, pp. 2585–2599, Feb. 2020.

[59] A. S. Dalkilic *et al.*, "Prediction of graphite nanofluids' dynamic viscosity by means of artificial neural networks," *Int. Commun. Heat Mass Transf.*, vol. 73, pp. 33–42, 2016.

[60] M. Afrand, A. Ahmadi Nadooshan, M. Hassani, H. Yarmand, and M. Dahari, "Predicting the viscosity of multi-walled carbon nanotubes/water nanofluid by developing an optimal artificial neural network based on experimental data," *Int. Commun. Heat Mass Transf.*, vol. 77, pp. 49–53, 2016.

[61] N. Zhao and Z. Li, "Experiment and Artificial Neural Network Prediction of Thermal Conductivity and Viscosity for Alumina-Water Nanofluids," *Materials (Basel).*, vol. 10, no. 5, p. 552, May 2017.

[62] G. A. Longo, C. Zilio, L. Ortombina, and M. Zigliotto, "Application of Artificial Neural Network (ANN) for modeling oxide-based nanofluids dynamic viscosity," *Int. Commun. Heat Mass Transf.*, vol. 83, pp. 8–14, 2017.

[63] M. Hemmat Esfe, H. Rostamian, S. Esfandeh, and M. Afrand, "Modeling and prediction of rheological behavior of Al2O3-MWCNT/5W50 hybrid nano-lubricant by artificial neural network using experimental data," *Phys. A Stat. Mech. its Appl.*, vol. 510, pp. 625–634, 2018.

[64] E. Gholami, B. Vaferi, and M. A. Ariana, "Prediction of viscosity of several alumina-based nanofluids using various artificial intelligence paradigms - Comparison with experimental data and empirical correlations," *Powder Technol.*, vol. 323, pp. 495–506, 2018.

[65] H. R. Ansari, M. J. Zarei, S. Sabbaghi, and P. Keshavarz, "A new comprehensive model for relative viscosity of various nanofluids using feed-forward back-propagation MLP neural networks," *Int. Commun. Heat Mass Transf.*, vol. 91, no. December 2017, pp. 158–164, 2018.

[66] M. H. Ahmadi *et al.*, "Precise smart model for estimating dynamic viscosity of SiO 2 /ethylene glycol-water nanofluid," *Eng. Appl. Comput. Fluid Mech.*, vol. 13, no. 1, pp. 1095–1105, 2019.

[67] M. Afrand *et al.*, "Prediction of dynamic viscosity of a hybrid nano-lubricant by an optimal artificial neural network," *Int. Commun. Heat Mass Transf.*, vol. 76, pp. 209–214, 2016.

[68] M. Amani, P. Amani, A. Kasaeian, O. Mahian, I. Pop, and S. Wongwises, “Modeling and optimization of thermal conductivity and viscosity of MnFe2O4 nanofluid under magnetic field using an ANN,” *Sci. Rep.*, vol. 7, no. 1, pp. 1–13, 2017.

[69] M. Hemmat Esfe, M. Bahiraei, and O. Mahian, “Experimental study for developing an accurate model to predict viscosity of CuO–ethylene glycol nanofluid using genetic algorithm based neural network,” *Powder Technol.*, vol. 338, pp. 383–390, 2018.

[70] M. K. Meybodi, S. Naseri, A. Shokrollahi, and A. Daryasafar, “Prediction of viscosity of water-based Al2O3, TiO2, SiO2, and CuO nanofluids using a reliable approach,” *Chemom. Intell. Lab. Syst.*, vol. 149, pp. 60–69, Dec. 2015.

[71] A. Hemmati-Sarapardeh, A. Varamesh, M. M. Husein, and K. Karan, “On the evaluation of the viscosity of nanofluid systems: Modeling and data assessment,” *Renew. Sustain. Energy Rev.*, vol. 81, no. March 2017, pp. 313–329, 2018.

[72] M. Hemmat Esfe, M. Reiszadeh, S. Esfandeh, and M. Afrand, “Optimization of MWCNTs (10%) – Al2O3 (90%)/5W50 nanofluid viscosity using experimental data and artificial neural network,” *Phys. A Stat. Mech. its Appl.*, vol. 512, pp. 731–744, 2018.

[73] M. Hemmat Esfe, A. Tatar, M. R. H. Ahangar, and H. Rostamian, “A comparison of performance of several artificial intelligence methods for predicting the dynamic viscosity of TiO2/SAE 50 nano-lubricant,” *Phys. E Low-Dimensional Syst. Nanostructures*, vol. 96, no. July 2017, pp. 85–93, 2018.

[74] M. H. Ahmadi, A. Ghahremannezhad, K.-W. Chau, P. Seifaddini, M. Ramezannezhad, and R. Ghasempour, “Development of Simple-to-Use Predictive Models to Determine Thermal Properties of Fe2O3/Water-Ethylene Glycol Nanofluid,” *Computation*, vol. 7, no. 1, p. 18, Mar. 2019.

[75] M. Ramezanizadeh, M. A. Ahmadi, M. H. Ahmadi, and M. Alhuyi Nazari, “Rigorous smart model for predicting dynamic viscosity of Al2O3/water nanofluid,” *J. Therm. Anal. Calorim.*, vol. 137, no. 1, pp. 307–316, 2019.

[76] M. H. Ahmadi, A. Baghban, M. Ghazvini, M. Hadipoor, R. Ghasempour, and M. R. Nazemzadegan, “An insight into the prediction of TiO2/water nanofluid viscosity through intelligence schemes,” *J. Therm. Anal. Calorim.*, vol. 139, no. 3, pp. 2381–2394, Feb. 2020.

[77] E. Heidari, M. A. Sobati, and S. Movahedirad, “Accurate prediction of nanofluid viscosity using a multilayer perceptron artificial neural network (MLP-ANN),” *Chemom. Intell. Lab. Syst.*, vol. 155, pp. 73–85, 2016.

[78] H. O'Hanley, J. Buongiorno, T. McKrell, and L. Hu, "Measurement and Model Validation of Nanofluid Specific Heat Capacity with Differential Scanning Calorimetry," *Adv. Mech. Eng.*, vol. 4, p. 181079, Jan. 2012.

[79] S.-Q. Zhou and R. Ni, "Measurement of the specific heat capacity of water-based Al2O3 nanofluid," *Appl. Phys. Lett.*, vol. 92, no. 9, p. 093123, Mar. 2008.

[80] R. S. Vajjha and D. K. Das, "Specific Heat Measurement of Three Nanofluids and Development of New Correlations," *J. Heat Transfer*, vol. 131, no. 7, p. 071601, 2009.

[81] D. P. Kulkarni, D. K. Das, and R. S. Vajjha, "Application of nanofluids in heating buildings and reducing pollution," *Appl. Energy*, vol. 86, no. 12, pp. 2566–2573, Dec. 2009.

[82] R. S. Vajjha, D. K. Das, and B. M. Mahagaonkar, "Density Measurement of Different Nanofluids and Their Comparison With Theory," *Pet. Sci. Technol.*, vol. 27, no. 6, pp. 612–624, Mar. 2009.

[83] H. E. Patel, T. Sundararajan, and S. K. Das, "An experimental investigation into the thermal conductivity enhancement in oxide and metallic nanofluids," *J. Nanoparticle Res.*, vol. 12, no. 3, pp. 1015–1031, Mar. 2010.

[84] M. U. Sajid and H. M. Ali, "Recent advances in application of nanofluids in heat transfer devices: A critical review," *Renew. Sustain. Energy Rev.*, vol. 103, no. December 2018, pp. 556–592, 2019.

[85] M. Sahaluddin, I. O. Alade, M. O. Oyedeji, and U. S. Aliyu, "A machine learning-based model to estimate the density of nanofluids of nitrides in ethylene glycol," *J. Appl. Phys.*, vol. 127, no. 20, p. 205105, May 2020.

[86] F. Nasirzadehroshenin *et al.*, "Modeling of heat transfer performance of carbon nanotube nanofluid in a tube with fixed wall temperature by using ANN–GA," *Eur. Phys. J. Plus*, vol. 135, no. 2, p. 217, Feb. 2020.

[87] A. Einstein, "Eine neue Bestimmung der Moleküldimensionen," *Ann. Phys.*, vol. 324, no. 2, pp. 289–306, 1906.

[88] G. K. Batchelor, "The effect of Brownian motion on the bulk stress in a suspension of spherical particles," *J. Fluid Mech.*, vol. 83, no. 1, pp. 97–117, Nov. 1977.

[89] H. C. Brinkman, "The Viscosity of Concentrated Suspensions and Solutions," *J. Chem. Phys.*, vol. 20, no. 4, pp. 571–571, Apr. 1952.

[90] B. C. Pak and Y. I. Cho, "Hydrodynamic and heat transfer study of dispersed fluids with submicron metallic oxide particles," *Exp. Heat Transf.*, vol. 11, no. 2, pp. 151–170, 1998.

[91] C. T. Nguyen *et al.*, “Viscosity data for Al2O3–water nanofluid—hysteresis: is heat transfer enhancement using nanofluids reliable?,” *Int. J. Therm. Sci.*, vol. 47, no. 2, pp. 103–111, Feb. 2008.

[92] M. Chandrasekar, S. Suresh, and A. Chandra Bose, “Experimental investigations and theoretical determination of thermal conductivity and viscosity of Al2O3/water nanofluid,” *Exp. Therm. Fluid Sci.*, vol. 34, no. 2, pp. 210–216, Feb. 2010.

[93] M. H. Ahmadi, A. Baghban, M. Sadeghzadeh, M. Hadipoor, and M. Ghazvini, “Evolving connectionist approaches to compute thermal conductivity of TiO2/water nanofluid,” *Phys. A Stat. Mech. its Appl.*, vol. 540, p. 122489, Feb. 2020.

[94] I. O. Alade, M. A. A. Rahman, and T. A. Saleh, “An approach to predict the isobaric specific heat capacity of nitrides/ethylene glycol-based nanofluids using support vector regression,” *J. Energy Storage*, vol. 29, no. February, p. 101313, 2020.

[95] I. O. Alade, M. A. Abd Rahman, A. Bagudu, Z. Abbas, Y. Yaakob, and T. A. Saleh, “Development of a predictive model for estimating the specific heat capacity of metallic oxides/ethylene glycol-based nanofluids using support vector regression,” *Heliyon*, vol. 5, no. 6, 2019.

[96] I. O. Alade, M. A. Abd Rahman, and T. A. Saleh, “Modeling and prediction of the specific heat capacity of Al 2 O 3 /water nanofluids using hybrid genetic algorithm/support vector regression model,” *Nano-Structures & Nano-Objects*, vol. 17, pp. 103–111, Feb. 2019.

[97] S. M. S. Murshed, K. C. Leong, and C. Yang, “Investigations of thermal conductivity and viscosity of nanofluids,” *Int. J. Therm. Sci.*, vol. 47, no. 5, pp. 560–568, May 2008.

[98] J. H. Lee *et al.*, “Effective viscosities and thermal conductivities of aqueous nanofluids containing low volume concentrations of Al2O3 nanoparticles,” *Int. J. Heat Mass Transf.*, vol. 51, no. 11–12, pp. 2651–2656, Jun. 2008.

[99] C. T. Nguyen *et al.*, “Temperature and particle-size dependent viscosity data for water-based nanofluids - Hysteresis phenomenon,” *Int. J. Heat Fluid Flow*, vol. 28, no. 6, pp. 1492–1506, Dec. 2007.

[100] I. Tavman, A. Turgut, M. Chirtoc, H. P. Schuchmann, and S. Tavman, “Experimental investigation of viscosity and thermal conductivity of suspensions containing nanosized ceramic particles,” 2008.

[101] M. K. Meybodi, A. Daryasafar, M. M. Koochi, J. Moghadasi, R. B. Meybodi, and A. K. Ghahfarokhi, “A novel correlation approach for viscosity prediction of water based nanofluids of Al2O3, TiO2, SiO2 and CuO,” *J. Taiwan Inst. Chem. Eng.*, vol. 58, pp. 19–27, 2016.

[102] S. W. Lee, S. D. Park, S. Kang, I. C. Bang, and J. H. Kim, "Investigation of viscosity and thermal conductivity of SiC nanofluids for heat transfer applications," *Int. J. Heat Mass Transf.*, vol. 54, no. 1–3, pp. 433–438, Jan. 2011.

[103] W. Duangthongsuk and S. Wongwises, "Measurement of temperature-dependent thermal conductivity and viscosity of TiO2-water nanofluids," *Exp. Therm. Fluid Sci.*, vol. 33, no. 4, pp. 706–714, Apr. 2009.

[104] M. Lal and S. Kundan, "Experimental study on thermal conductivity and viscosity of Al2O3-nanotransformer oil," *Int. J. Theor. Appl. Res. Mech. Eng.*, vol. Volume-2, pp. 2319 – 3182, 2013.

[105] Z. Jia-Fei, L. Zhong-Yang, N. Ming-Jiang, and C. Ke-Fa, "Dependence of Nanofluid Viscosity on Particle Size and pH Value," *Chinese Phys. Lett.*, vol. 26, no. 6, p. 066202, 2009.

[106] T. Haisheng, Chen Yulong, Ding Chunqing, "Rheological behaviour of nanofluids," *New J. Phys.*, vol. 9, p. 367, 2007.

[107] J. Chevalier, O. Tillement, and F. Ayela, "Rheological properties of nanofluids flowing through microchannels," *Appl. Phys. Lett.*, vol. 91, no. 23, p. 233103, Dec. 2007.

[108] M. J. Pastoriza-Gallego, C. Casanova, J. L. Legido, and M. M. Piñeiro, "CuO in water nanofluid: Influence of particle size and polydispersity on volumetric behaviour and viscosity," *Fluid Phase Equilib.*, vol. 300, no. 1–2, pp. 188–196, Jan. 2011.

[109] L. S. Naik, M.T Sundar, "Investigation into Thermophysical Properties of Glycol based CuO Nanofluid for Heat Transfer Applications," *World Acad. Sci. Eng. Technol.*, vol. 59, pp. 440–446, 2011.

[110] P. K. Namburu, D. P. Kulkarni, D. Misra, and D. K. Das, "Viscosity of copper oxide nanoparticles dispersed in ethylene glycol and water mixture," *Exp. Therm. Fluid Sci.*, vol. 32, no. 2, pp. 397–402, Nov. 2007.

[111] N. Jamshidi, M. Farhadi, D. D. Ganji, and K. Sedighi, "Experimental Investigation on the Viscosity of Nanofluids," *Int. J. Eng.*, vol. 25, no. 3, pp. 201–209, 2012.

[112] V. Y. Rudyak, S. V. Dimov, and V. V. Kuznetsov, "On the dependence of the viscosity coefficient of nanofluids on particle size and temperature," *Tech. Phys. Lett.*, vol. 39, no. 9, pp. 779–782, Sep. 2013.

[113] S. Q. Zhou, R. Ni, and D. Funfschilling, "Effects of shear rate and temperature on viscosity of alumina polyalphaolefins nanofluids," *J. Appl. Phys.*, vol. 107, no. 5, p. 054317, Mar. 2010.

[114] V. N. Vapnik, "An Overview of Statistical Learning Theory," 1999.

[115] R. Martinčič, I. Kuzmanovski, A. Wagner, and M. Novič, “Development of models for prediction of the antioxidant activity of derivatives of natural compounds,” *Anal. Chim. Acta*, vol. 868, pp. 23–35, 2015.

[116] T. A. Oyehan, M. A. Liadi, and I. O. Alade, “Modeling the efficiency of TiO2 photocatalytic degradation of MTBE in contaminated water: a support vector regression approach,” *SN Appl. Sci.*, vol. 1, no. 5, p. 386, May 2019.

[117] S. Liu, H. Tai, Q. Ding, D. Li, L. Xu, and Y. Wei, “A hybrid approach of support vector regression with genetic algorithm optimization for aquaculture water quality prediction,” *Math. Comput. Model.*, vol. 58, pp. 458–465, 2013.

[118] I. O. Alade, I. A. Olumegbon, and A. Bagudu, “Lattice constant prediction of A2XY6 cubic crystals (A = K, Cs, Rb, TI; X = tetravalent cation; Y = F, Cl, Br, I) using computational intelligence approach,” *J. Appl. Phys.*, vol. 127, no. 1, p. 015303, Jan. 2020.

[119] A. J. Smola and B. Schölkopf, “A tutorial on support vector regression,” *Stat. Comput.*, vol. 14, no. 3, pp. 199–222, 2004.

[120] V. Gueorguiev and D. Moodley, “Hyperparameter Optimization for Astronomy: Taking the Astronomer Out of the Loop HPO for ASTCVS,” 2017.

[121] B. Shahriari, K. Swersky, Z. Wang, R. P. Adams, and N. De Freitas, “Taking the Human Out of the Loop: A Review of Bayesian Optimization,” *Proc. IEEE*, vol. 104, no. 1, 2015.

[122] L. Cornejo-Bueno, E. C. Garrido-Merchán, D. Hernández-Lobato, and S. Salcedo-Sanz, “Bayesian optimization of a hybrid system for robust ocean wave features prediction,” *Neurocomputing*, vol. 275, pp. 818–828, 2018.

[123] J. Ahn, E. Ko, and E. Y. Kim, “Highway traffic flow prediction using support vector regression and Bayesian classifier,” in *2016 International Conference on Big Data and Smart Computing, BigComp 2016*, 2016, pp. 239–244.

[124] A. Jalali, J. Azimi, and X. Fern, “Exploration vs Exploitation in Bayesian Optimization,” *ArXiv*, p. 1204.0047, 2012.

[125] J. Snoek, H. Larochelle, and R. P. Adams, “Practical Bayesian Optimization of Machine Learning Algorithms,” in *Advances in Neural Information Processing Systems 25 (NIPS 2012)*, 2012, pp. 2951–2959.

[126] I. O. Alade, M. A. Abd Rahman, and T. A. Saleh, “Predicting the specific heat capacity of alumina/ethylene glycol nanofluids using support vector regression model optimized with Bayesian algorithm,” *Sol. Energy*, vol. 183, pp. 74–82, May 2019.

[127] J. Lancaster, R. Lorenz, R. Leech, and J. H. Cole, "Bayesian optimization for neuroimaging pre-processing in brain age classification and prediction," *Front. Aging Neurosci.*, vol. 10, no. FEB, Feb. 2018.

[128] P. I. Frazier, "A Tutorial on Bayesian Optimization," *ArXiv*, p. 1807.02811, 2018.

[129] M. Hemmat Esfe, M. H. Kamyab, M. Afrand, and M. K. Amiri, "Using artificial neural network for investigating of concurrent effects of multi-walled carbon nanotubes and alumina nanoparticles on the viscosity of 10W-40 engine oil," *Phys. A Stat. Mech. its Appl.*, vol. 510, pp. 610–624, 2018.

[130] A. Hemmati-Sarapardeh, A. Varamesh, M. M. Husein, and K. Karan, "On the evaluation of the viscosity of nanofluid systems: Modeling and data assessment," *Renew. Sustain. Energy Rev.*, vol. 81, pp. 313–329, 2018.

[131] H. Ahmadi and M. Rodehutscord, "Application of Artificial Neural Network and Support Vector Machines in Predicting Metabolizable Energy in Compound Feeds for Pigs," *Front. Nutr.*, vol. 4, Jun. 2017.

[132] B. C. Pak and Y. I. Cho, "HYDRODYNAMIC AND HEAT TRANSFER STUDY OF DISPERSED FLUIDS WITH SUBMICRON METALLIC OXIDE PARTICLES," *Exp. Heat Transf.*, vol. 11, no. 2, pp. 151–170, Apr. 1998.

[133] G. Huminic and A. Huminic, "Application of nanofluids in heat exchangers : A review," *Renew. Sustain. Energy Rev.*, vol. 16, no. 8, pp. 5625–5638, 2012.

[134] M. Bahiraei, R. Rahmani, A. Yaghoobi, E. Khodabandeh, and R. Mashayekhi, "Recent research contributions concerning use of nano fl uids in heat exchangers : A critical review," vol. 133, no. February 2017, pp. 137–159, 2018.

[135] T. T. Joy, S. Rana, S. Gupta, and S. Venkatesh, "Batch Bayesian optimization using multi-scale search," *Knowledge-Based Syst.*, vol. 187, Jan. 2020.

[136] J. Philip and P. D. Shima, "Thermal properties of nanofluids," *Adv. Colloid Interface Sci.*, vol. 183, pp. 30–45, 2012.

[137] S. K. Das and S. U. S. Choi, *A Review of Heat Transfer in Nanofluids*, vol. 41, no. 08. Elsevier Masson SAS, 2009.

[138] M. A. Hassan and D. Banerjee, "A soft computing approach for estimating the specific heat capacity of molten salt-based nanofluids," *J. Mol. Liq.*, vol. 281, pp. 365–375, May 2019.

[139] M. H. Ahmadi, A. Mirlohi, M. Alhuyi Nazari, and R. Ghasempour, "A review of thermal conductivity of various nanofluids," *J. Mol. Liq.*, vol. 265, pp. 181–188, Sep. 2018.

[140] S. M. S. Murshed and P. Estellé, "A state of the art review on viscosity of nanofluids," *Renew. Sustain. Energy Rev.*, vol. 76, pp. 1134–1152, Sep. 2017.

[141] K. Bashirnezhad *et al.*, "Viscosity of nanofluids: A review of recent experimental studies," *Int. Commun. Heat Mass Transf.*, vol. 73, pp. 114–123, Apr. 2016.

[142] G. Sadeghi, S. Nazari, M. Ameri, and F. Shama, "Energy and exergy evaluation of the evacuated tube solar collector using Cu2O/water nanofluid utilizing ANN methods," *Sustain. Energy Technol. Assessments*, vol. 37, Feb. 2020.

[143] H. Riazi, T. Murphy, G. B. Webber, R. Atkin, S. S. M. Tehrani, and R. A. Taylor, "Specific heat control of nanofluids: A critical review," *Int. J. Therm. Sci.*, vol. 107, pp. 25–38, 2016.

[144] B. Barbés *et al.*, "Thermal conductivity and specific heat capacity measurements of Al\textsubscript{2}O\textsubscript{3} nanofluids," *J. Therm. Anal. Calorim.*, vol. 111, no. 2, pp. 1615–1625, 2013.

[145] J. M. Smith and M. C. Van Ness, *Introduction to Chemical Engineering Thermodynamics McGraw-Hill, New York,*. 1987.

[146] J. Buongiorno, "Convective transport in nanofluids," *J. Heat Transfer*, vol. 128, no. 3, pp. 240–250, Mar. 2006.

[147] S. Q. Zhou and R. Ni, "Measurement of the specific heat capacity of water-based Al2 O3 nanofluid," *Appl. Phys. Lett.*, vol. 92, no. 9, p. 093123, Mar. 2008.

[148] T.-P. Teng and Y.-H. Hung, "Estimation and experimental study of the density and specific heat for alumina nanofluid," *J. Exp. Nanosci.*, vol. 9, no. 7, 2014.

[149] D. Cabaleiro, C. Gracia-fernández, J. L. Legido, and L. Lugo, "International Journal of Heat and Mass Transfer Specific heat of metal oxide nanofluids at high concentrations for heat transfer," *Int. J. Heat Mass Transf.*, vol. 88, pp. 872–879, 2015.

[150] C. Selvam, D. Mohan Lal, and S. Harish, "Thermal conductivity and specific heat capacity of water–ethylene glycol mixture-based nanofluids with graphene nanoplatelets," *J. Therm. Anal. Calorim.*, vol. 129, no. 2, pp. 947–955, Aug. 2017.

[151] I. Wole-Osho, E. C. Okonkwo, D. Kavaz, and S. Abbasoglu, "An experimental investigation into the effect of particle mixture ratio on specific heat capacity and dynamic viscosity of Al2O3-ZnO hybrid nanofluids," *Powder Technol.*, Jan. 2020.

[152] L.-P. Zhou, X.-Z. Du, B.-X. Wang, Y.-P. Yang, and X.-F. Peng, "On the Specific Heat Capacity of CuO Nanofluid," *Adv. Mech. Eng.*, vol. 2, p. 172085, 2009.

[153] Y. R. Sekhar and K. V. Sharma, “Study of viscosity and specific heat capacity characteristics of water-based Al2O3nanofluids at low particle concentrations,” *J. Exp. Nanosci.*, vol. 10, no. 2, pp. 86–102, 2015.

[154] M. A. Hassan and D. Banerjee, “A soft computing approach for estimating the specific heat capacity of molten salt-based nanofluids,” *J. Mol. Liq.*, vol. 281, pp. 365–375, May 2019.

[155] H. Khodadadi, S. Aghakhani, H. Majd, R. Kalbasi, S. Wongwises, and M. Afrand, “A comprehensive review on rheological behavior of mono and hybrid nanofluids: Effective parameters and predictive correlations,” *Int. J. Heat Mass Transf.*, vol. 127, pp. 997–1012, Dec. 2018.

[156] A. Zendehboudi, R. Saidur, I. M. Mahbubul, and S. H. Hosseini, “Data-driven methods for estimating the effective thermal conductivity of nanofluids: A comprehensive review,” *Int. J. Heat Mass Transf.*, vol. 131, pp. 1211–1231, Mar. 2019.

[157] M.-A. Ahmadi, M. H. Ahmadi, M. Fahim Alavi, M. R. Nazemzadegan, R. Ghasempour, and S. Shamshirband, “Determination of thermal conductivity ratio of CuO/ethylene glycol nanofluid by connectionist approach,” *J. Taiwan Inst. Chem. Eng.*, vol. 91, pp. 383–395, Oct. 2018.

[158] I. O. Alade, M. A. Abd Rahman, and T. A. Saleh, “Modeling and prediction of the specific heat capacity of Al2O3/water nanofluids using hybrid genetic algorithm/support vector regression model,” *Nano-Structures and Nano-Objects*, vol. 17, pp. 103–111, 2019.

[159] S. khosrojerdi, M. Vakili, M. Yahyaei, and K. Kalhor, “Thermal conductivity modeling of graphene nanoplatelets/deionized water nanofluid by MLP neural network and theoretical modeling using experimental results,” *Int. Commun. Heat Mass Transf.*, vol. 74, pp. 11–17, 2016.

[160] R. Gómez-Villarejo, P. Estellé, and J. Navas, “Boron nitride nanotubes-based nanofluids with enhanced thermal properties for use as heat transfer fluids in solar thermal applications,” *Sol. Energy Mater. Sol. Cells*, vol. 205, Feb. 2020.

[161] J. Antony Pradeep, S. Dhinesh kumar, D. Balasubramanian, and C. Author, “A Performance Comparision of Nanofluids Using Solar Flat Plate Collector and Flow is Simulated in Computational Fluid Dynamics (Cfd) Analysis,” 2017.

[162] G. Orrù, W. Pettersson-Yeo, A. F. Marquand, G. Sartori, and A. Mechelli, “Using Support Vector Machine to identify imaging biomarkers of neurological and psychiatric disease: A critical review,” *Neuroscience and Biobehavioral Reviews*, vol. 36, no. 4. pp. 1140–1152, Apr-2012.

[163] S. Salcedo-Sanz, J. L. Rojo-Álvarez, M. Martínez-Ramón, and G. Camps-Valls, “Support vector machines in engineering: an overview,” *Wiley Interdiscip. Rev. Data Min. Knowl. Discov.*, vol. 4, no. 3, pp. 234–267, May 2014.

[164] C. J. Lu, T. S. Lee, and C. C. Chiu, "Financial time series forecasting using independent component analysis and support vector regression," *Decis. Support Syst.*, vol. 47, no. 2, pp. 115–125, May 2009.

[165] A. Zendehboudi, M. A. Baseer, and R. Saidur, "Application of support vector machine models for forecasting solar and wind energy resources: A review," *J. Clean. Prod.*, vol. 199, pp. 272–285, Oct. 2018.

[166] A. J. Smola and B. Scholkopf, "A Tutorial on Support Vector Regression," 1998.

[167] A. A. Adewumi, T. O. Owolabi, I. O. Alade, and S. O. Olatunji, "Estimation of physical, mechanical and hydrological properties of permeable concrete using computational intelligence approach," *Appl. Soft Comput. J.*, vol. 42, pp. 342–350, 2016.

[168] T. A. Oyehan, I. O. Alade, A. Bagudu, K. O. Sulaiman, S. O. Olatunji, and T. A. Saleh, "Predicting of the refractive index of haemoglobin using the Hybrid GA-SVR approach.," *Comput. Biol. Med.*, vol. 98, pp. 85–92, 2018.

[169] M. Ghorbani, G. Zargar, and H. Jazayeri-Rad, "Prediction of asphaltene precipitation using support vector regression tuned with genetic algorithms," *Petroleum*, vol. 2, no. 3, pp. 301–306, 2016.

[170] L. M. Ghiringhelli, J. Vybiral, S. V. Levchenko, C. Draxl, and M. Scheffler, "Big data of materials science: Critical role of the descriptor," *Phys. Rev. Lett.*, vol. 114, no. 10, pp. 1–5, 2015.

[171] G. Żyła, J. P. Vallejo, and L. Lugo, "Isobaric heat capacity and density of ethylene glycol based nanofluids containing various nitride nanoparticle types: An experimental study," *J. Mol. Liq.*, vol. 261, pp. 530–539, Jul. 2018.

[172] F. Mashali *et al.*, "Thermo-physical properties of diamond nanofluids: A review," *International Journal of Heat and Mass Transfer*, vol. 129. Elsevier Ltd, pp. 1123–1135, Feb-2019.

[173] G. Huminic and A. Huminic, "Application of nanofluids in heat exchangers : A review," *Renew. Sustain. Energy Rev.*, vol. 16, no. 8, pp. 5625–5638, 2012.

[174] J. J. Brandner *et al.*, "Concepts and realization of microstructure heat exchangers for enhanced heat transfer," vol. 30, pp. 801–809, 2006.

[175] A. R. A. Khaled, M. Siddique, N. I. Abdulhafiz, and A. Y. Boukhary, "Recent advances in heat transfer enhancements: A review report," *Int. J. Chem. Eng.*, vol. 2010, no. 1, 2010.

[176] W. H. Choi SU, Singer DA, "Developments and applications of non-Newtonian flows.," *ASME FED.*, vol. 66, pp. 99–105, 1995.

[177] R. S. Vajjha and D. K. Das, “Specific Heat Measurement of Three Nanofluids and Development of New Correlations,” *J. Heat Transfer*, vol. 131, no. 7, p. 071601, 2009.

[178] D. K. Devendiran and V. A. Amirtham, “A review on preparation, characterization, properties and applications of nanofluids,” *Renew. Sustain. Energy Rev.*, vol. 60, pp. 21–40, 2016.

[179] M. U. Sajid and H. M. Ali, “Thermal conductivity of hybrid nanofluids: A critical review,” *Int. J. Heat Mass Transf.*, vol. 126, pp. 211–234, 2018.

[180] K. V. Wong and O. De Leon, “Applications of nanofluids: Current and future,” *Adv. Mech. Eng.*, vol. 2010, no. January 2010, 2010.

[181] M. Rafati, A. A. Hamidi, and M. Shariati Niaser, “Application of nanofluids in computer cooling systems (heat transfer performance of nanofluids),” *Appl. Therm. Eng.*, vol. 45–46, pp. 9–14, Dec. 2012.

[182] S. M. S. Murshed, K. C. Leong, and C. Yang, “Investigations of thermal conductivity and viscosity of nanofluids,” *Int. J. Therm. Sci.*, vol. 47, no. 5, pp. 560–568, May 2008.

[183] M. C. Lu and C. H. Huang, “Specific heat capacity of molten salt-based alumina nanofluid,” *Nanoscale Res. Lett.*, vol. 8, no. 1, pp. 1–7, 2013.

[184] S. Zhou and R. Ni, “Measurement of the specific heat capacity of water-based Al\textsubscript{2}O\textsubscript{3} nanofluid,” *Appl. Phys. Lett.*, vol. 92, no. 9, p. 93123, 2008.

[185] T. P. Teng and Y. H. Hung, “Estimation and experimental study of the density and specific heat for alumina nanofluid,” *J. Exp. Nanosci.*, vol. 9, no. 7, pp. 707–718, 2014.

[186] H. O’Hanley, J. Buongiorno, T. McKrell, and L. Hu, “Measurement and Model Validation of Nanofluid Specific Heat Capacity with Differential Scanning Calorimetry,” *Adv. Mech. Eng.*, vol. 4, p. 181079, 2012.

[187] R. Ghasempour, M. A. Nazari, M. H. Ahmadi, O. Mahian, and M. A. Ahmadi, “A proposed model to predict thermal conductivity ratio of Al2O3/EG nanofluid by applying least squares support vector machine (LSSVM) and genetic algorithm as a connectionist approach,” *J. Therm. Anal. Calorim.*, vol. 0123456789, 2018.

[188] M. Vakili, S. Khosrojerdi, P. Aghajannezhad, and M. Yahyaei, “A hybrid artificial neural network-genetic algorithm modeling approach for viscosity estimation of graphene nanoplatelets nanofluid using experimental data,” *Int. Commun. Heat Mass Transf.*, vol. 82, pp. 40–48, 2017.

[189] M. Hemmat Esfe, M. R. Hassani Ahangar, M. Rejvani, D. Toghraie, and M. H. Hajmohammad, "Designing an artificial neural network to predict dynamic viscosity of aqueous nanofluid of TiO2 using experimental data," *Int. Commun. Heat Mass Transf.*, vol. 75, pp. 192–196, 2016.

[190] G. Żyła and J. Fal, "Experimental studies on viscosity, thermal and electrical conductivity of aluminum nitride–ethylene glycol (AlN–EG) nanofluids," *Thermochim. Acta*, vol. 637, pp. 11–16, 2016.

[191] B. Barbés *et al.*, "Thermal conductivity and specific heat capacity measurements of Al\textsubscript{2}O\textsubscript{3} nanofluids," *J. Therm. Anal. Calorim.*, vol. 111, no. 2, pp. 1615–1625, 2013.

[192] P. Kojić and R. Omorjan, "Chemical Engineering Research and Design Predicting hydrodynamic parameters and volumetric gas – liquid mass transfer coefficient in an external-loop airlift reactor by support vector Predrag Koji ´," *Chem. Eng. Res. Des.*, vol. 5, pp. 398–407, 2017.

[193] L. Jiang, M. Diao, H. Xue, and H. Sun, "Energy Dissipation Prediction for Stepped Spillway Based on Genetic Algorithm–Support Vector Regression," *J. Irrig. Drain. Eng.*, vol. 144, no. 4, p. 04018003, Apr. 2018.

[194] X. Z. Li and J. M. Kong, "Application of GA-SVM method with parameter optimization for landslide development prediction," *Nat. Hazards Earth Syst. Sci.*, vol. 14, no. 3, pp. 525–533, 2014.

[195] H. Karimi and F. Yousefi, "Application of artificial neural network–genetic algorithm (ANN–GA) to correlation of density in nanofluids," *Fluid Phase Equilib.*, vol. 336, pp. 79–83, 2012.

[196] C.-H. Wu, G.-H. Tzeng, and R.-H. Lin, "A Novel hybrid genetic algorithm for kernel function and parameter optimization in support vector regression," *Expert Syst. Appl.*, vol. 36, no. 3, pp. 4725–4735, 2009.

[197] K. S. Sajan, V. Kumar, and B. Tyagi, "Genetic algorithm based support vector machine for on-line voltage stability monitoring," *Int. J. Electr. Power Energy Syst.*, vol. 73, pp. 200–208, 2015.

[198] S. G. Patil, S. Mandal, and A. V. Hegde, "Genetic algorithm based support vector machine regression in predicting wave transmission of horizontally interlaced multi-layer moored floating pipe breakwater," *Adv. Eng. Softw.*, vol. 45, no. 1, pp. 203–212, 2012.

[199] T. A. Oyehan, S. O. Olatunji, I. O. Alade, A. Bagudu, M. A. A. Rahman, and T. A. Saleh, "Estimating the refractive index of oxygenated and deoxygenated hemoglobin using genetic algorithm – support vector regression model," *Comput. Methods Programs Biomed.*, vol. 163, pp. 135–142, May 2018.

[200] J. Li, B. Zhang, and J. Shi, “Combining a Genetic Algorithm and Support Vector Machine to Study the Factors Influencing CO2 Emissions in Beijing with Scenario Analysis,” *Energies*, vol. 10, no. 10, p. 1520, 2017.

[201] I. O. Alade, A. Bagudu, T. A. Oyehan, M. A. A. Rahman, T. A. Saleh, and S. O. Olatunji, “Estimating the refractive index of oxygenated and deoxygenated hemoglobin using genetic algorithm – support vector regression model,” *Comput. Methods Programs Biomed.*, 2018.

[202] D. K. Devendiran and V. A. Amirtham, “A review on preparation, characterization, properties and applications of nanofluids,” *Renew. Sustain. Energy Rev.*, vol. 60, pp. 21–40, 2016.

[203] D. Kumar and V. A. Amirtham, “A review on preparation , characterization , properties and applications of nano fl uids,” *Renew. Sustain. Energy Rev.*, vol. 60, pp. 21–40, 2016.

[204] M. H. Al-Rashed, G. Dzido, M. Korpyś, J. Smołka, and J. Wójcik, “Investigation on the CPU nanofluid cooling,” *Microelectron. Reliab.*, vol. 63, pp. 159–165, Aug. 2016.

[205] I. Sharifi, H. Shokrollahi, and S. Amiri, “Ferrite-based magnetic nanofluids used in hyperthermia applications,” *J. Magn. Magn. Mater.*, vol. 324, no. 6, pp. 903–915, Mar. 2012.

[206] E. Tombácz, D. Bica, A. Hajdú, E. Illés, A. Majzik, and L. Vékás, “Surfactant double layer stabilized magnetic nanofluids for biomedical application,” *J. Phys. Condens. Matter*, vol. 20, no. 20, p. 204103, May 2008.

[207] A. Kasaeian, A. T. Eshghi, and M. Sameti, “A review on the applications of nanofluids in solar energy systems,” *Renew. Sustain. Energy Rev.*, vol. 43, pp. 584–598, Mar. 2015.

[208] K. Farhana *et al.*, “Improvement in the performance of solar collectors with nanofluids — A state-of-the-art review,” *Nano-Structures and Nano-Objects*, vol. 18. Elsevier B.V., 01-Apr-2019.

[209] A. H. A. Al-Waeli, M. T. Chaichan, H. A. Kazem, and K. Sopian, “Comparative study to use nano-(Al2O3, CuO, and SiC) with water to enhance photovoltaic thermal PV/T collectors,” *Energy Convers. Manag.*, vol. 148, pp. 963–973, 2017.

[210] J. J. Michael and S. Iniyan, “Performance of copper oxide/water nanofluid in a flat plate solar water heater under natural and forced circulations,” *Energy Convers. Manag.*, vol. 95, pp. 160–169, May 2015.

[211] F. A. Boyaghchi, M. Chavoshi, and V. Sabeti, “Optimization of a novel combined cooling, heating and power cycle driven by geothermal and solar energies using the water/CuO (copper oxide) nanofluid,” *Energy*, vol. 91, pp. 685–699, Nov. 2015.

[212] S. Soltani, A. Kasaeian, H. Sarrafha, and D. Wen, “An experimental investigation of a hybrid photovoltaic/thermoelectric system with nanofluid application,” *Sol. Energy*, vol. 155, pp. 1033–1043, 2017.

[213] M. A. Ariana, B. Vaferi, and G. Karimi, “Prediction of thermal conductivity of alumina water-based nanofluids by artificial neural networks,” *Powder Technol.*, vol. 278, pp. 1–10, 2015.

[214] M. Hemmat Esfe, M. R. H. Ahangar, D. Toghraie, M. H. Hajmohammad, H. Rostamian, and H. Tourang, “Designing artificial neural network on thermal conductivity of Al2O3–water–EG (60–40 %) nanofluid using experimental data,” *J. Therm. Anal. Calorim.*, pp. 1–7, May 2016.

[215] F. Yousefi, H. Karimi, and M. M. Papari, “Modeling viscosity of nanofluids using diffusional neural networks,” *J. Mol. Liq.*, vol. 175, pp. 85–90, 2012.

[216] A. Rajabpour, F. Y. Akizi, M. M. Heyhat, and K. Gordiz, “Molecular dynamics simulation of the specific heat capacity of water-Cu nanofluids,” *Int. Nano Lett.*, vol. 3, no. 1, p. 58, 2013.

[217] A. Mohebbi, “Prediction of specific heat and thermal conductivity of nanofluids by a combined equilibrium and non-equilibrium molecular dynamics simulation,” *J. Mol. Liq.*, vol. 175, pp. 51–58, Nov. 2012.

[218] H. O’hanley, J. Buongiorno, T. Mckrell, and L.-W. Hu, “Measurement and Model Validation of Nanofluid Specific Heat Capacity with Differential Scanning Calorimetry,” *Adv. Mech. Eng.*, vol. 2012, 2012.

[219] I. O. Alade, M. A. Abd Rahman, and T. A. Saleh, “Modeling and prediction of the specific heat capacity of Al2O3/water nanofluids using hybrid genetic algorithm/support vector regression model,” *Nano-Structures and Nano-Objects*, vol. 17, pp. 103–111, May 2019.

[220] M. Karami, M. A. Akhavan-bahabadi, S. Delfani, and M. Raisee, “Experimental investigation of CuO nano fl uid-based Direct Absorption Solar Collector for residential applications,” *Renew. Sustain. Energy Rev.*, vol. 52, pp. 793–801, 2015.

[221] P. Selvakumar and S. Suresh, “Convective performance of CuO/water nanofluid in an electronic heat sink,” *Exp. Therm. Fluid Sci.*, vol. 40, pp. 57–63, Jul. 2012.

[222] M. Hossein, A. Behnam, M. M. Ghazvini, and M. Goodarzi, “Comparing various machine learning approaches in modeling the dynamic viscosity of CuO / water nanofluid,” *J. Therm. Anal. Calorim.*, vol. 0123456789, 2019.

[223] S. H. Rostamian, M. Biglari, S. Saedodin, and M. Hemmat Esfe, “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.*, vol. 231, pp. 364–369, Apr. 2017.

[224] C. Cortes and V. Vapnik, “Support-Vector Networks,” *Mach. Learn.*, vol. 20, no. 3, pp. 273–297, 1995.

[225] V. N. Vapnik, “An Overview of Statistical Learning Theory,” 1999.

[226] K.-Y. Chen and C.-H. Wang, “Support vector regression with genetic algorithms in forecasting tourism demand,” *Tour. Manag.*, vol. 28, no. 1, pp. 215–226, Feb. 2007.

[227] A. A. Levis and L. G. Papageorgiou, “Customer Demand Forecasting via Support Vector Regression Analysis,” *Chem. Eng. Res. Des.*, vol. 83, no. 8, pp. 1009–1018, Aug. 2005.

[228] C. Cortes, V. Vapnik, and L. Saitta, “Support-Vector Networks Editor,” Kluwer Academic Publishers, 1995.

[229] C. J. C. Burges, “A Tutorial on Support Vector Machines for Pattern Recognition,” *Data Min. Knowl. Discov.*, vol. 2, pp. 121–167, 1998.

[230] J. R. Satti, D. K. Das, and D. Ray, “Specific heat measurements of five different propylene glycol based nanofluids and development of a new correlation,” *Int. J. Heat Mass Transf.*, vol. 94, pp. 343–353, Mar. 2016.

[231] G. Żyła, J. P. Vallejo, and L. Lugo, “Isobaric heat capacity and density of ethylene glycol based nanofluids containing various nitride nanoparticle types: An experimental study,” *J. Mol. Liq.*, vol. 261, pp. 530–539, Jul. 2018.

[232] S. M. Sohel Murshed and C. A. de Castro, “Conduction and convection heat transfer characteristics of ethylene glycol based nanofluids - A review,” *Appl. Energy*, vol. 184, pp. 681–695, 2016.

[233] O. Mahian, A. Kianifar, S. A. Kalogirou, I. Pop, and S. Wongwises, “A review of the applications of nanofluids in solar energy,” *Int. J. Heat Mass Transf.*, vol. 57, no. 2, pp. 582–594, 2013.

[234] Y. Varol, H. F. Oztop, and E. Avci, “Estimation of thermal and flow fields due to natural convection using support vector machines (SVM) in a porous cavity with discrete heat sources,” *Int. Commun. Heat Mass Transf.*, vol. 35, no. 8, pp. 928–936, Oct. 2008.

[235] N. S. Bondareva, M. A. Sheremet, H. F. Oztop, and N. Abu-Hamdeh, “Heatline visualization of MHD natural convection in an inclined wavy open porous cavity filled with a nanofluid with a local heater,” *Int. J. Heat Mass Transf.*, vol. 99, pp. 872–881, Aug. 2016.

[236] K. Khanafer and K. Vafai, “A review on the applications of nanofluids in solar energy field,” *Renew. Energy*, vol. 123, pp. 398–406, Aug. 2018.

[237] A. Zamzamian, M. KeyanpourRad, M. KianiNeyestani, and M. T. Jamal-Abad, “An experimental study on the effect of Cu-synthesized/EG nanofluid on the efficiency of flat-plate solar collectors,” *Renew. Energy*, vol. 71, pp. 658–664, 2014.

[238] F. V. Tooraj Yousefia, Ehsan Shojaeizadeh, and Sirus Zinadini, “An experimental investigation on the effect of Al2O3eH2O nanofluid on the efficiency of flat-plate solar collectors,” *Renew. Energy*, pp. 293–298, 2012.

[239] W. S. Sarsam, S. N. Kazi, and A. Badarudin, “A review of studies on using nanofluids in flat-plate solar collectors,” *Sol. Energy*, vol. 122, pp. 1245–1265, Dec. 2015.

[240] C. Link, H. O. Hanley, J. Buongiorno, T. Mckrell, and L. Hu, “Measurement and Model Validation of Nanofluid Specific Heat Capacity with Differential Scanning Calorimetry Accessed Measurement and Model Validation of Nanofluid Specific Heat Capacity with Differential Scanning Calorimetry,” *Adv. Mech. Eng.*, vol. 4, p. 181079, Jan. 2016.

[241] R. Sałat and K. Sałat, “The application of support vector regression for prediction of the antiallodynic effect of drug combinations in the mouse model of streptozocin-induced diabetic neuropathy,” *Comput. Methods Programs Biomed.*, vol. 111, pp. 330–337, 2013.

[242] H. Mori and D. Kanaoka, “Application of support vector regression to temperature forecasting for short-term load forecasting,” *IEEE Int. Conf. Neural Networks - Conf. Proc.*, pp. 1085–1090, 2007.

[243] S. R. Sain and V. N. Vapnik, “The Nature of Statistical Learning Theory,” *Technometrics*, vol. 38, no. 4, p. 409, 2006.

[244] M. A. Ahmadi and A. Bahadori, “Prediction performance of natural gas dehydration units for water removal efficiency using a least-square support vector machine,” *Int. J. Ambient Energy*, vol. 37, no. 5, pp. 486–494, 2016.

[245] C. H. Cheng and H. Y. Shiu, “A novel GA-SVR time series model based on selected indicators method for forecasting stock price,” *Proc. - 2014 Int. Conf. Inf. Sci. Electron. Electr. Eng. ISEEE 2014*, vol. 1, pp. 395–399, 2014.

[246] Z. Ramedani, M. Omid, A. Keyhani, B. Khoshnevisan, and H. Saboohi, “A comparative study between fuzzy linear regression and support vector regression for global solar radiation prediction in Iran,” *Sol. Energy*, vol. 109, pp. 135–143, Nov. 2014.

[247] Y. Varol, H. F. Oztop, A. Koca, and E. Avci, “Forecasting of entropy production due to buoyant convection using support vector machines (SVM) in a partially cooled square cross-sectional room,” *Expert Syst. Appl.*, vol. 36, no. 3, pp. 5813–5821, Apr. 2009.

[248] L. Olatomiwa, S. Mekhilef, S. Shamshirband, K. Mohammadi, D. Petković, and C. Sudheer, “A support vector machine–firefly algorithm-based model for global solar radiation prediction,” *Sol. Energy*, vol. 115, pp. 632–644, May 2015.

[249] D. Basak, S. Pal, and D. C. Patranabis, “Support Vector Regression,” vol. 11, no. 10, pp. 203–224, 2007.

[250] R. Martinez-Cantin, “Bayesian optimization with adaptive kernels for robot control,” *Proc. - IEEE Int. Conf. Robot. Autom.*, pp. 3350–3356, 2017.

[251] B. Barbés *et al.*, “Thermal conductivity and specific heat capacity measurements of Al2O3 nanofluids,” *J. Therm. Anal. Calorim.*, vol. 111, no. 2, pp. 1615–1625, Feb. 2013.

[252] E. Bellos and C. Tzivanidis, “Multi-criteria evaluation of a nanofluid-based linear Fresnel solar collector,” *Sol. Energy*, vol. 163, pp. 200–214, Mar. 2018.

[253] A. Radwan and M. Ahmed, “Thermal management of concentrator photovoltaic systems using microchannel heat sink with nanofluids,” *Sol. Energy*, vol. 171, pp. 229–246, Sep. 2018.

BIODATA OF STUDENT

Ibrahim Olanrewaju Alade was born in Lagos, Nigeria on the 14th March 1983. He attended the University of Lagos for his Bachelor's Degree where he graduated with a second-class upper division in 2008. In 2012, he commenced his Master of Science in physics from King Fahd University of Petroleum and Minerals where his research areas were thin films synthesis and application. He completed his M.Sc in physics in January 2015. In March 2018, he began his PhD studies in Applied Physics at Universiti Putra Malaysia. His contribution to search in various fields of applied science has been recognized through publications in high impact factor journals.

LIST OF PUBLICATIONS

Alade, Ibrahim Olanrewaju, Mohd Amiruddin Abd Rahman, and Tawfik A. Saleh. "An approach to predict the isobaric specific heat capacity of nitrides/ethylene glycol-based nanofluids using support vector regression." ***Journal of Energy Storage*** **29 (2020): 101313. Q1**

Alade, Ibrahim Olanrewaju, Mohd Amiruddin Abd Rahman, and Tawfik A. Saleh. "Predicting the specific heat capacity of alumina/ethylene glycol nanofluids using support vector regression model optimized with Bayesian algorithm." ***Solar Energy*** **183 (2019): 74-82. Q1**

Alade, Ibrahim Olanrewaju, Mohd Amiruddin Abd Rahman, and Tawfik A. Saleh. "Modeling and prediction of the specific heat capacity of Al2 O3/water nanofluids using hybrid genetic algorithm/support vector regression model." ***Nano-Structures & Nano-Objects*** **17 (2019): 103-111. Q1**

Alade, Ibrahim Olanrewaju, Mohd Amiruddin Abd Rahman, Zulkifly Abbas, Yazid Yaakob, and Tawfik A. Saleh. "Application of support vector regression and artificial neural network for prediction of specific heat capacity of aqueous nanofluids of copper oxide." ***Solar Energy*** **197 (2020): 485-490. Q1**

Alade, Ibrahim Olanrewaju, Mohd Amiruddin Abd Rahman, Amjed Hassan, and Tawfik A. Saleh. "Modeling the viscosity of nanofluids using artificial neural network and Bayesian support vector regression." ***Journal of Applied Physics*** **128, no. 8 (2020): 085306. Q2**

UNIVERSITI PUTRA MALAYSIA

STATUS CONFIRMATION FOR THESIS / PROJECT REPORT AND COPYRIGHT

ACADEMIC SESSION: ___________________

TITLE OF THESIS / PROJECT REPORT:

PREDICTIVE MODELLING OF NANOFLUIDS THERMOPHYSICAL PROPERTIES USING MACHINE LEARNING

NAME OF STUDENT: ALADE IBRAHIM OLANREWAJU

I acknowledge that the copyright and other intellectual property in the thesis/project report belonged to Universiti Putra Malaysia and I agree to allow this thesis/project report to be placed at the library under the following terms:

1. This thesis/project report is the property of Universiti Putra Malaysia.
2. The library of Universiti Putra Malaysia has the right to make copies for educational purposes only.
3. The library of Universiti Putra Malaysia is allowed to make copies of this thesis for academic exchange.

I declare that this thesis is classified as:

*Please tick (√)

☐	**CONFIDENTIAL**	(Contain confidential information under Official Secret Act 1972).
☐	**RESTRICTED**	(Contains restricted information as specified by the organization/institution where research was done).
☐	**OPEN ACCESS**	I agree that my thesis/project report to be published as hard copy or online open access.

This thesis is submitted for:

☐	**PATENT**	Embargo from _____________ until _____________ (date) (date)

Approved by:

_________________________ (Signature of Student)
New IC No/ Passport No.:

Date:

_________________________ (Signature of Chairman of Supervisory Committee)
Name:

Date:

[Note: If the thesis is CONFIDENTIAL or RESTRICTED, please attach with the letter from the organization/institution with period and reasons for confidentially or restricted.]