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Original Research Paper

Modeling thermal conductivity enhancement of metal and metallic oxide nanofluids using support vector regression

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ABSTRACT

Enhancing thermal conductivity of nanofluids is an important objective in heat transfer applications. Experimental measurement of thermal conductivity is time consuming, laborious and expensive. One of the common ways to address these limitations involves developing theoretical models to study thermo-physical properties of nanofluid. However, most classical and empirical models fail in predicting experimental results with good precision. In this study, we developed support vector regression (SVR) models that are capable of predicting the thermal conductivity enhancement for metallic and metallic-oxide nanofluids. The accuracy and reliability of the developed models were assessed using statistical parameters such as correlation coefficient (R^2), root mean square error (RMSE) and mean absolute error (MAE). The models were characterized with very high correlation coefficients of 99.3 and 96.3% for the metallic and metallic oxide nanofluids, respectively. While the RMSE obtained were 1.11 and 1.33 for the metallic and metallic oxide nanofluids, respectively. In addition, the results of the models were compared with Hamilton-Crosser (HC) model and other empirical models. The SVR models performed much better than all the models examined. Furthermore, the effects of temperature, volume fractions, nanoparticle size & type and basefluids types were correlated with experimental data in order to assess the performance of the developed models. The results indicate that SVR predictions were accurate and better than common theoretical models.

1. Introduction

Rapid industrialization expansion has inspired the design of highly efficient energy systems and as a consequence, the energy dissipation requirement of these new systems necessitates the use of advanced cooling fluids in order to maintain optimum performance of the systems [1,2]. Prior to the seminal work of Choi [3] on the enhancement of thermal conductivity of fluids, common liquids such as water, engine oil and ethylene glycol were used as coolants in industrial applications. However, these materials exhibit relatively low thermal conductivity which imposes limitation on systems' performance. Choi's introduction of nanofluids thus becomes very significant as it paved way to circumvent this challenge. Following his discovery, research efforts towards synthesis of novel nanofluids, measurement and prediction of the thermo-physical properties of nanofluid have seen significant increase till date [4,5].

Nanofluids are unique class of fluids which are formulated by addition of nano-sized particles into a common cooling fluids such as water or ethyl glycol. The resultant effect of adding nanoparticles to cooling fluids is improvement of the thermo-physical properties of the fluid. Nano-sized particles can be metals, metallic/non-metallic oxides or carbon nanotubes, with size ranging from 1 to 100 nm [6]. Nanoparticles exhibit high thermal conductivity due to their large surface-area-to-volume ratio [7]. Therefore, addition of nanoparticles into base fluids (cooling liquid) raises the thermal conductivity of the base fluid significantly [5,8]. This property makes nanofluids to be extremely important for many practi-

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cal engineering applications such as heat transfer, solar collectors, heat exchangers, heat pipes and electronics, fuel cell, and refrigerators.

Thermal conductivity is one of the most desirable properties of nanofluids [9]. It is understood that when the thermal conductivity of nanofluids increases, its heat transfer capability increases accordingly, consequently leading to an increase in the heat exchange efficiency of the nanofluid [10,11]. Therefore, thermal conductivity enhancement plays a central role in nanofluid research. There has been numerous experimental and theoretical studies in this field [9,12–14]. Investigating thermal conductivity enhancement via experimental approach is a quite reliable and effective means. However, the procedure is usually time-consuming, laborious and expensive [15,16]. Also, there are methodical problems associated with measurements of certain parameters such particle size, and volume concentration [17,18]. These limitations make theoretical studies necessary. Also, in order to fully understand the science of nanofluid, there has to be harmony between the experimental and theoretical studies. Unfortunately, nanofluid offers a major theoretical problem because experimental values of thermal conductivity differ by one order of magnitude from many theoretical models.

To this end, many classical and empirical models have been formulated to correlate the enhancement of thermal conductivity with experimental studies. The existing classical models that are used for prediction of thermal conductivity enhancement include Maxwell [19], Hamilton-Crosser [20], Nan [21], etc. Details of these models can be found in the literatures [15,22,23]. It is a fact the classical models and their derivatives suffer from underestimation of measured thermal conductivity [22,24]. One possible reason is that most of the models are derived from advanced parameters which are not regular features associated with nanofluids. Hence, this limits their general applicability in predicting emerging nanofluids [25].

Recently, researchers have turned to Artificial Neural Network (ANN) to model the behaviour of nanofluids due to the above mentioned limitation of existing models [10,15,18]. Literature survey reveals that ANN has been extensively used to study nanofluids with much improved performance compared to classical and empirical models [17,26,27]. However, when dealing with limited experimental data as in the case of nanofluid research, ANN is largely disadvantageous [10]. For this reason, support vector regression (SVR) is a viable computational tool that performs very well in the presence of few dataset [28]. Also, there are reports that support vector machine (SVM) performs better than ANN in some studies [29–31]. Surprisingly, researchers have made very limited use of SVM in the prediction of thermo-physical properties of nanofluids despite its superior generalization ability when dealing with few dataset. To the best of our knowledge, the only study that has employed support vector machine in the study of thermo-physical properties of nanofluids is the work of Meybodi et al. [26], wherein they predicted viscosity of water-based nanofluids using least square support vector machine (LSSVM).

The paper sought to bridge the gap between measured thermal conductivity and theoretical prediction by using a computational intelligence approach. We developed data-driven computational models that are capable of predicting thermal conductivity enhancement of nanofluids with high accuracies. A five-input and a four-input support vector machine models have been developed for metallic oxides and metal-based nanofluids, respectively. The accuracies of the models were benchmarked with experimental results to validate the robustness of the models. The results obtained are very promising with correlation coefficient of up to 99.3% between the predicted and experimental values. In other to justify the superiority of the developed models, we compared the results obtained from our studies with previous models (Hamilton-Crosser [32], Peterson & Li [33], Pak & Choi [34] and Timofeeva [35]. Also, the effects of suspension temperature, volume fraction, nanoparticle size, base fluid and nanoparticle types on thermal conductivity of nanofluids were studied using the developed support vector regression (SVR) models. This work highlights the applicability of SVR in prediction of thermal conductivity enhancement of nanofluids.

The remaining part of this work is organized as follow; Section 2 contains description of the proposed technique. Section 3 contains empirical studies which include description of datasets, experimental set-up and optimization strategy. Section 4 presents results and discussion while Section 5 contains the conclusion of this work.

2. Brief description of the proposed techniques

SVR is a robust computational algorithm derived from statistical learning theory (SLT). The framework of SVR was developed by Vapnik in 1995 [36]. In order to minimize error, SVR makes use of Structural Risk Minimization (SRM) principle, which has proven to be better than traditional Empirical Risk Minimization (ERM) principle employed by conventional neural networks [37]. The main idea in SRM involves minimizing the upper bound on the expected risk thereby increasing SVR ability to generalize well in the presence of few data-point and descriptive features [29].

The fundamental idea in SVR entails mapping the inputs into a high-dimensional feature space by nonlinear transformation mapping function that is defined by inner product function. This allows a linear regression to be performed in the high dimensional space.

For the implementation of the SVR, Vapnik introduced the ε-insensitive loss function for which errors below $\varepsilon > 0$, determined *a priori* are not penalized [38,39].

$$|k_r - f(\mathrm{x_i})|_\varepsilon = \max\{0, |k_r - f(\mathrm{x_i})| - \varepsilon\} \quad (1)$$

SVR algorithm selects a function that estimates the actual value of target as close as possible to the reference value with a precision ε, which measures the flatness of generalized pattern and the maximum permitted deviations of the targets from the estimated values for all the given training dataset [29]. The input parameters are then mapped via a Gaussian kernel nonlinear mapping function onto n-dimensional feature space for which a linear model given in (2) is to be estimated.

$$f(\mathrm{x}) = \tilde{\omega}\Phi(\mathrm{x}) + \mathrm{b} \quad (2)$$

where $\tilde{\omega}$, $\Phi \in \mathrm{R^N}$, $\mathrm{b} \in \mathrm{R}$; based on supplied training data $\{\mathrm{x_i}, k_{ei}\}$: i = 1, 2, 3 … n. $\mathrm{R^N}$ is the space containing the patterns of the input parameters. $\tilde{\omega}$ is the weight of the function and b is a bias factor.

Small test error is sought by minimizing the regularized risk function,

$$\frac{1}{2}\|\tilde{\omega}\|^2 + C \cdot R_{emp}(f) \quad (3)$$

The complexity of the model is influenced by $\|\tilde{\omega}\|^2$ and the empirical risk $\mathrm{R_{emp}}(f)$ is given as

$$R_{emp}(f) = \frac{1}{n}\sum_{i=1}^{n}|k_e - f(\mathrm{x}_i)|_\varepsilon \quad (4)$$

For the purpose of getting a small risk, SLT imposes the requirement of controlling the duo of the training error and complexity of the model whereby the data is described using a simple model. SVR achieves these objectives through the minimization of the $\|\tilde{\omega}\|^2$ and measuring the deviation of the training data lying outside the loss function with a non-negative slack variables. Hence, the resulting optimization problem is

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