A comprehensive review on the application of nanofluid in heat pipe based on the machine learning: Theory, application and prediction

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Abstract

This paper ~~firstly~~ introduces three paramount factors i.e. viscosity, thermal conductivity and stability that affect the application of mono and hybrid nanofluids in heat pipes. ~~Secondly, t~~The applications of nanofluids in various types of heat pipes are reviewed and the mechanism of heat transfer enhancement or inhibition is summarized. ~~Thirdly, t~~The applications of machine learning in nanofluids (thermal conductivity and dynamic viscosity) and heat pipes charged with nanofluids are presented. ~~Finally, the challenges and opportunities are presented as the main contribution of this review paper including key findings in the form of conclusions.~~ The main challenges include: (1) difference and uncertainty on thermal conductivity and viscosity, as well as undesirability on stability property of nanofluid; (2) lack of comprehension of time-dependent property of heat pipes; (3) limitation of predictive models based on machine learning; and (4) lack of an appropriate standard for selecting the appropriate machine learning algorithm. To tackle the above imminent challenges, further opportunities are revealed including: (1) exploring the mechanism at nanoscale and establishing unified standards, as well as exploring the effect of surfactant and smaller particle size; (2) focusing on the nanoparticle deposition layer; (3) establishing the large, exclusive ~~large~~ databases and expanding the input variables; and (4) defining specific standard by horizontal comparison and using more advanced algorithms. This review-based study provides the guidelines for the development of heat pipes charged with nanofluids and establishes the foundation for the application of machine learning technology in heat pipes and nanofluids.

Keywords:

Heat pipe, Nanofluid, Machine learning, Theory, Application, Prediction

Nomenclature

b Bias Value

e_k Loose Variable for the kth x

f Neuron's state

Knf Thermal conductivity of nanofluid

Kbf Thermal conductivity of base fluid

n_j Input value of jth neurons

w Weight Vector

X Input Vector

x Characteristic Vector

μ_{nf} Viscosity of nanofluid

μ_{bf} Viscosity of base fluid

ω_{ji} Weight Vector

γ Margin Parameter

Abbreviation

ANN Artificial Neural Network

ANFIS Adaptive Neuro-fuzzy Inference System

BP Back Propagation

CART Category and Regression Tree

CHPSO Conjugate Hybrid Particle Swarm Optimization

CNN Convolutional Neural Network

CNTs Carbon Nanotubes

COOH-GnP Carboxyl-functionalized Graphene Nanoplatelet

COOH-MWCNT Carboxyl-functionalized Multi-Walled Carbon Nanotube

DI Deionization

DW Distilled Water

DWCNT Double-Walled Carbon Nanotube

EG Ethylene Glycol

EO Ethylene Oxide

ETSC Evacuated Tube Solar Collector

GA Genetic Algorithm

GMDH Group Method of Data Handling

GNP Graphene Nanoplatelet

ICA Imperialist Competitive Algorithm

LHP Loop Heat pipe

LM Levenberg–Marquardt

LSSVM Least-square Support Vector Machine

MAE Mean Absolute Error

mLHP Miniature Loop Heat Pipe

MLP Multi-layer Perceptron

MSE Mean Square Error

MWCNT Multi-Walled Carbon Nanotube

MWCNT-Cys Multi-Walled Carbon Nanotube with Cysteine

MWCNT-GA Multi-Walled Carbon Nanotube with Gum Arabic

PAC Probably Approximately Correct

PHP Pulsating Heat Pipe

PSO Particle Swarm Optimization

PV/T Photovoltaic/Thermal

RBF Radial Basis Function

RF Random Forest

RNN Recurrent Neural Network

SDS Sodium Dodecyl Sulphate

SEM Scanning Electron Microscope

SOM Self-organizing Maps

SVM Support Vector Machine

TEM Transmission Electron Microscope

THP Thermosyphon Heat Pipe

TPCT Two-phase Closed Thermosyphon

UV/vis Ultraviolet–visible Spectroscopy

XRD X-ray Diffraction

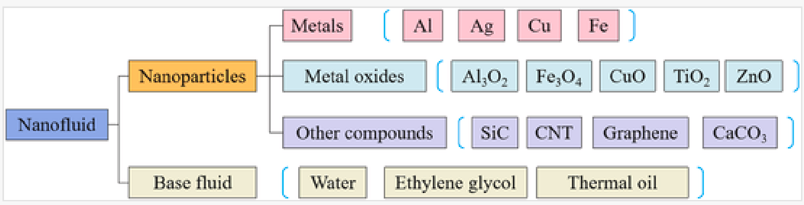
1 Introduction

Heat pipes are one of the most efficient passive heat transfer technologies [1]. A heat pipe transports heat by phase change of the working fluid and has a high effective thermal conductivity (several thousand times higher than copper rod [2]), and an extremely low effective thermal resistance (0.05–0.4 °C/W [3]). The thermo-physical properties of the working fluids significantly affect heat transfer performance of heat pipes especially in the evaporator [4–6]. Several conventional working fluids have shown poor heat transfer characteristics, owing to their lower thermal conductivity. Therefore, an innovative working fluid is needed to enhance the transfer performance of the heat pipes [7].

Nanofluid, a colloidal mixture of conductive nanoparticles in the base fluid, shows higher thermal conductivity than conventional coolant and has a wide application prospect [8–11]. Thermo-physical properties (especially thermal conductivity and viscosity) affect heat transfer and flow behaviour. The major parameters influencing the nanofluid properties such as particle structure, shape, size, fluid type, temperature, surfactant and PH value etc., have been widely investigated [12–14]. Besides, the preparation of a stable suspension of nanofluid is paramount before implementing it in the application, as better stability will improve the efficiency of heat transfer equipment and reduce the size and fabrication cost of the equipment. Several results have been reported on various types of combinations of base fluids and nanoparticles. Some common base fluids and nanoparticles are illustrated in Fig. 1. The conventional nanofluids either have a good rheological property or a better thermal network. Recently, hybrid nanofluid, a homogeneous mixture of two or more nanoparticles type, has gained significant attention from researchers because of its encouraging improvement in thermo-physical, thermal transfer and hydrodynamic properties [15–19].

alt-text: Fig. 1

Fig. 1



Common base fluids and nanoparticles.

The application of nanofluids in heat pipes can be one of the most interesting techniques for heat transfer enhancement [20,21]. A plethora of studies have reported that the nanofluids can improve the boiling thermal transfer due to the modification of heated surface characteristics (e.g., size of cavities, surface wettability and roughness) by the nanoparticles depositing on the wall, as well as the changes of thermo-physical properties of the nanofluids (e.g., thermal conductivity and capillary force) [22–29]. Meanwhile, many attempts have been made to combine the advantages of nanofluids and heat pipes to obtain a higher heat transfer coefficient [30,31]. However, the micro factors in nanofluids such as instant clustering, particle charge condition and micro motion, contribute to the complicated thermo-physical properties of nanofluids and complex heat transfer mechanisms for heat pipes [32,33]. These problems lead to difficulties in obtaining accurate value and variation law, which should be determined by pre-experiments before designing the heat pipes with nanofluids, thus seriously limiting the development of nanofluids in heat pipes.

With the strong nonlinear mapping ability, machine learning algorithms such as Artificial Neutral Network (ANN) and Support Vector Machine (SVM) could provide the dimensionless and multiple-factors-considering solution, which can effectively tackle the above problems. Available studies have shown that the favourable confidence and high accuracy of the prediction model depend on selecting appropriate algorithms as well as considering all influencing factors [34–37]. However, in the previous studies, there is no agreement on the selection of the algorithm and the structure of the model. Therefore, it is imperative to review previous research to extract the significant knowledge.

The data of several publications on nanofluids, heat pipes and machine learning acquired in the Web of Science for the decade from 2010 to 2019 indicates that the publications on nanofluids are an order of magnitude less on the combination of nanofluids and heat pipes than on nanofluids. Besides, machine learning publications involving heat pipes or nanofluids are scarce [38–45]. In addition, the application of nanofluids in heat pipes has been reviewed only in a few number of articles, but not involving hybrid nanofluids. Furthermore, it is noteworthy that there is no review on the machine learning applied in heat pipes charged with nanofluids. However, uncertainty and nonlinearity of the heat transfer performance of heat pipes charged with nanofluids impede its potential practical applications. Therefore, it is significant to review machine learning techniques applied in this field to tackle the above-mentioned problems.

The originality of the systematic review involves presenting the application of hybrid nanofluids in heat pipes, pointing out the potential application of machine learning in heat pipes charged with nanofluids which is significant to tackle the uncertainty and nonlinearity of the heat transfer performance of pipes with nanofluids, and identifying the main challenges and opportunities on the application of nanofluids in heat pipes. This paper firstly introduces three main factors i.e., viscosity, thermal conductivity and stability that affect the application of mono and hybrid nanofluids in heat pipes. Secondly, the applications of nanofluids in various types of heat pipes are reviewed and the mechanism of heat transfer enhancement or inhibition is summarized. Thirdly, the applications of machine learning in nanofluids (thermal conductivity and dynamic viscosity) and heat pipes charged with nanofluids are represented. Finally, this review-based paper provides the challenges and opportunities to form the framework for future work and it also covers crucial findings in the form of conclusions.

2 Properties of nanofluids: thermal conductivity, viscosity and stability

The thermal conductivity, viscosity and stability of nanofluids are regarded as the primary factors that affect thermal systems with nanofluids. Up to date, there have been plenty of investigations. In this section, in order to provide a deep view about improving the thermal performance of heat pipes charged with nanofluids, some influencing factors on thermal conductivity and viscosity are reported and the stability of nanofluids used in the heat pipes is briefly discussed.

2.1 Thermal conductivity of nanofluids

This section reports some influencing factors on thermal conductivity, such as particle volume fraction, temperature, particle material, particle size, particle shape, base fluid and other influencing factors.

2.1.1 Thermal conductivity of conventional nanofluids

The influencing factors on thermal conductivity have been discussed. Summary is given below, and some typical studies about the thermal conductivity of conventional nanofluids are summarized in Table 1.

(i) *Particle volume fraction:* The enhancement of thermal conductivity increases with particle concentration. However, the increasing rate is different [46–48].

(ii) *Temperature:* The thermal conductivity of nanofluids increases with temperature, due to the clustering and Brownian motion of nanoparticles. More drastic Brownian motion could enhance the thermal conductivity. However, the clustering harms Brownian motion. Therefore, the rise of temperature seems to not invariably contribute to the improvement of thermal conductivity, and the results are reversed at times [49,50].

(iii) *Particle material:* Generally, the higher thermal conductivity of nanoparticles results in greater enhancement in the thermal conductivity of nanofluids in the same volume loading. There are three classes of nanoparticles in general. The first class is advanced structural materials such as CNTs, graphene, which have extremely high thermal conductivity and may be favourable to obtain better dispersion, fluidity and applicability in a lower particle loading. Next is some metallic materials with high thermal conductivity such as Ag, Au, Fe, Cu, which show noticeable strengthening properties. The last class is the non-metallic and metallic compound such as ZnO, SiC, SiO_2, Al_2O_3, CuO, which shows better stability and chemical inertness, but lower thermal conductivity, compared with the above-mentioned one. However, the value of thermal conductivity of nanofluids is very different even for the same kind. Nevertheless, there is great uncertainly for a certain kind of nanofluid in a specific application, since the thermal conductivity of nanofluids is affected by some other factors such as aggregation, interfacial nanolayer, Brownian motion, surface charge state and thermal resistance of nanoparticles [51–53].

(iv) *Particle size:* The thermal conductivity of nanofluids has a downward trend with the increment of particle size. Brownian motion and liquid layering around nanoparticles are two significant mechanisms for the enhancement of thermal conductivity of nanofluids. The above mechanisms in the smaller size of particle are extremely active and provide more contribution to the thermal conductivity of nanofluids. However, this conclusion is a speculative hypothesis and cannot be strictly verified, since the above mechanisms are difficult to be quantized and experimentally measured [49,54].

(v) *Particle shape:* Most nanoparticles are spherical and cylindrical shapes. Cylindrical particle exhibit higher thermal conductivity compared with spherical particle [55,56].

(vi) *Base fluid:* The mechanism of the influence of base fluid on thermal conductivity is complicated. This is because higher thermal conductivity is contributed by lower thermal conductive base fluid. However, high viscous fluids obstruct the Brownian motion due to higher stable nanofluid [57–59].

(vii) *Other factors:* In preparation of the nanofluids, some other factors also influence the thermal conductivity of nanofluids such as standing time, ultrasonic time, ~~p~~PH value and surfactant. ~~p~~PH value and surfactant can improve the dispersion stability and thermal conductivity [60,61]. Generally, the moderate sonication is recommended, since the rigorous sonication time may contribute to the collapsing of nanoparticles and the brief sonication causes particle agglomerations [58,62].

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Table 1

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Some typical studies on thermal conductivity of conventional nanofluids.

Nanofluids	Diameter (nm)	Volume fraction (%)	Temperature (°C)	K_{nf}/K_{bf}

Au/water [46]	10–70	0.00013–0.001	30–60	1.03–1.08
DWCNT/water [47]	5	0.75–1	Room	1.03–1.08
Cu/water [48]	26	1–2	30–60	1.14–1.24
Cu/water [143]	50–300	0.1–0.2	Room	1.04–1.24
Al_2O_3/water [49]	29–36	6–6.1	20–37	1.134–1.34
Al_2O_3/water [50]	36	2–10	27.5–34.7	1.08–1.29
Fe_3O_4/water [144]	6.7	1–3	10–40	1.028–1.151
SiC/water [145]	170	1–4	23–70	1.04–1.225
Cu/water [146]	25	0.2–0.8 (wt)	Room	1.13–1.18
Cu/EG [62]	<10	0.01–0.56	Room	1.002–1.410
Fe3O4/water [52]	6.7	6.3	Room	4
CuO/water [60]	25	0.03–0.30	Room	1.02–1.12
CNTs/water [53]	20–60	0–0.84	10–70	1.05–1.32

2.1.2 Thermal conductivity of hybrid nanofluids

In the previous section, effective parameters affecting the thermal conductivity of conventional nanofluids were mentioned. Therefore, this section mostly focuses on the thermal conductivity of hybrid nanofluids. Some typical studies about the thermal conductivity of hybrid nanofluids are summarized in Table 2.

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Table 2

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Some typical studies on thermal conductivity of hybrid nanofluids.

Nanoparticles	Base fluid	Volume fraction (%)	Temperature (°C)	K_{nf}/K_{bf}
Cu/MWCNT [66]	DI water and EG	0.006–0.03	26.5–48.9	1.04–3.554
Al_2O_3–Cu [65]	Water	0.1–2	Room	1.005–1.12
SiO_2/MWCNT [64]	DI water	0.1–1 (wt)	27–40	1.06–1.17
MWCNT-GA, MWCNT-Cys MWCNT-Ag [67]	Water	0.5–1 (wt)	30–80	1.11–1.30
Ag/SiO_2 [63]	Water	1.5–3.5	15–40	1.01–1.03

The thermal conductivity of hybrid nanofluids is dependent on the thermal conductivity of mono nanoparticles [63]. Baghbanzadeh et al. [64] measured thermal conductivity of three types of nanofluids namely silica nanospheres, MWCNT and hybrid nanostructures based water nanofluids. It can be concluded that MWCNT based water nanofluids exhibited the highest increment, followed by hybrid nanofluids and silica. This is due to the thermal conductivity of the particles which is about 1.38 W/(m•K) for silica and 3000 W/(m•K) for MWCNT. Furthermore, Suresh et al. [65] compared thermal conductivity of Al_2O_3–Cu/water and Al_2O_3/water nanofluids. The authors reiterated that the thermal conductivity enhancement of hybrid nanofluids is significantly higher than none-hybrid nanofluids. Meanwhile, the hybrid nanofluid's thermal conductivity ratio had a linear relationship with the particle's volume concentration. Generally, the thermal conductivity of hybrid nanofluids is similar to conventional nanofluids [65,66]. Amiri et al. [67] observed that the thermal conductivity in the same particle loading and temperature abided by this order: MWCNT-Ag > MWCNT-Cys > MWCNT-GA > Ag/water > water. Meanwhile, temperature and particle loading are significant to thermal conductivity enhancement. Similar to conventional nanofluids, viscosity and thermal conductivity of base fluid have an effect on the thermal conductivity of hybrid nanofluids. In addition, the different hybrid combination of base fluids also affects the thermal conductivity of nanofluids [68]. Ma et al. [69] investigated the effect of base fluids mixture ratios on thermal conductivity enhancement (Al_2O_3–CuO/EG-W, Al_2O_3–Cu/EG-W and Al_2O_3–TiO_2/EG-W). It was concluded that the thermal conductivity linearly decreased while the EG concentration increased because the thermal conductivity of water was higher than that of EG. Sundar et al. [70] studied the thermal conductivity of nanofluids that Co_3O_4-GO hybrid nanoparticles dispersed in different base fluids such as, EG, water, (20 EG:80 W), (40 EG:60 W) and (60 EG:40 W). The thermal conductivity abided by this order water > (40 EG:60 W) > (60 EG:40 W) > EG.

2.2 Viscosity of nanofluids

The viscosity of nanofluids is also an extremely important factor that determines the pumping power, flow resistance and even the availability of nanofluids. This section reports several influencing factors on viscosity such as volume loading, temperature, particle size and other influencing factors.

2.2.1 Viscosity of conventional nanofluids

Table 3 provides some typical experimental data about the viscosity of conventional nanofluids in various research and the summary is given below.

(i) *Volume loading:* A consensus that the viscosity of nanofluids increases with the increment of volume loading can be reached since almost all results support it [71,72]. CNTs nanofluid is regarded as a seriously promising working fluid due to the tremendous potential enhancement of thermal conductivity. Some studies have reported that adding an extremely slight amount of CNTs causes an unexpected reduction in the viscosity of the base fluid [73].

(ii) *Temperature:* The viscosity is expected to decrease at a high temperature due to weak intermolecular forces of attraction between base fluid and nanoparticles interface [74]. However, the effective viscosity ratios are variable in diverse research [75,76].

(iii) *Particle size:* The effects of particle size are contradictory in a great number of reports. Such discrepancies are mostly due to complexity in instrument calibration and experimental procedures [77,78].

(iv) *Particle shape:* The viscosity with rod-like nanoparticles is significantly higher than spherical ones [79].

(v) *Other factors:* Other factors also influence the viscosity of nanofluids such as ~~p~~PH value, base fluid and surfactant. ~~p~~PH value can alter the dispersion and stability of nanofluids, furthermore lead to variation in viscosity [80]. The effects of surfactant on viscosity of nanofluids are ambiguous. Some researchers report that although surfactants can bring the increment in viscosity [76], others report that some surfactants increase viscosity only slightly and even present drag reduction [81]. Sunder et al. [82] revealed that higher viscosity base fluid contributed more enhancement of viscosity since the viscosity of nanofluids abided by this order 60:40% EG/W > 40:60% EG/W > 20:80% EG/W.

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Table 3

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Some typical studies on dynamic viscosity of conventional nanofluids.

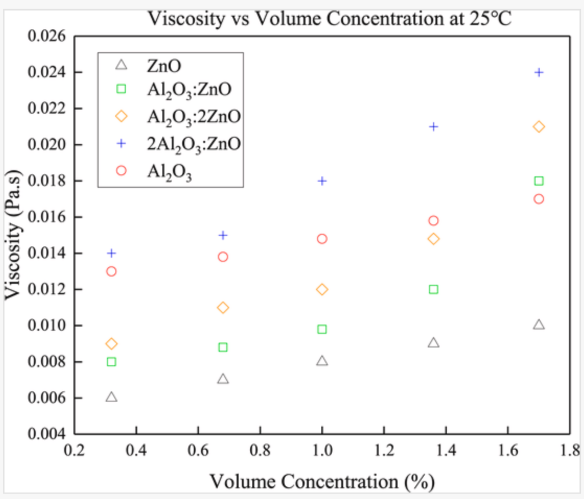
Nanofluid	Size (nm)	Volume fraction (%)	Temperature (°C)	Viscosity ratio (μ_{nf}/μ_{bf})
Al_2O_3/water [147]	43	0.33–5	Room	1–2.36827
Al_2O_3/water [148]	28	5–6.17	Room	1.855–1.765
Al_2O_3/water [72]	13	1.3–2.78	Room	1.615–2.59
CuO/ethylene [71]	29	1–6.12	−35-50	1.102–3.032
CNTs/water [73]	15–30	0.2–1	6–65	0.930–1.706

2.2.2 Viscosity of hybrid nanofluids

Generally, similar to thermal conductivity, the viscosity of hybrid nanofluids is similar to conventional nanofluids [83]. Xian et al. [84] compared the viscosity of mono (COOH-GnP) and hybrid (TiO_2-(COOH-GnP)) nanofluids. It can be concluded that viscosity increases with the increment of concentration and decreases with the growth of temperature in both mono and hybrid nanofluids. Wole-Osho et al. [85] performed an experimental investigation on the viscosity of Al_2O_3–ZnO/water hybrid nanofluids in three mixture ratios. A comparison made between the viscosity of hybrid nanofluids, and corresponding mono fluids is shown in Fig. 2. As can be seen, a combination of different nanoparticles can result in different properties compared with mono nanoparticles. The variations in properties require further investigations on hybrid nanoparticles. Similar to the conventional nanofluids, higher viscosity of the base fluid contributes more enhancement on the viscosity. Kumar et al. [86] investigated the viscosity of Al_2O_3–CuO (50/50) hybrid nanofluids in various mixture ratios of ethylene glycol and propylene glycol base fluid. It was concluded that hybrid nanofluid in 30% propylene glycol as binary base fluid contributed 16.2% higher viscosity compared to pure propylene glycol.

alt-text: Fig. 2

Fig. 2



A comparison made between the viscosity of hybrid nanofluids and corresponding mono fluids [85].

2.3 Stability of nanofluids

Stability is the major hindrance to nanofluid practical application. Akbari and Saidi [87] revealed that the more stable nanofluid achieves better thermal performance, while the less stable nanofluid provides a worse thermal performance than water. Different approaches to prepare more stabilized nanofluids were used by researchers. For this purpose, stability enhancement methods and stability evaluation methods are commonly followed. Table 4 shows stability techniques, stability duration and stability evaluation methods used by some researchers.

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Table 4

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Stability techniques, stability duration and stability evaluation methods used by some researchers.

Nanofluid	Method of preparation	Stability enhancement techniques		Stability duration & characterization used to evaluate stability
		Dispersion method	pH value/surfactant	

GNP/water [88]	Two step method	Ultrasonication for 5 min and functionalization by diazonium salt		Maximum sedimentation of 16% after 480 h and remaining steady up to 840 h.
Graphite/water [149]	Two step method	Ultrasonication		Stability after 21 days. Zeta potential analysis is used to check the stability of nanofluid.
Al_2O_3/water,Al_2O_3/EG [97]	Two step method	Ultrasonication for 60 min		No sedimentation occurred within 64 days.
Al2O3/water [150]	Two step method		Silane as the surface modifier. PH was adjusted to 9.1	
Ag/water [98]	One step method			Stability for more than 85 days. Nanofluids after preparation is left for 8 h to examine their stability and spectral absorbance analysis by UV/vis spectrophotometer
Graphene oxide nanofluids [106]	One step method		Sodium dodecyl sulphate (SDS)	Characterized by TEM.
MWNTs-OH nanofluids [109]	Two step method	Ultrasonication for 60 min		Stability was examined using a density measurement method

In various stability enhancement approaches, techniques like changing ~~p~~PH values, surfactant addition and ultrasonication are used. Considering nanofluids applied into heat pipes, researchers used these techniques to improve the stability of nanofluids.

In various stability evaluation approaches, techniques like spectral absorbance analysis, Zeta potential, centrifugation and sedimentation method are used to evaluate the stability of nanofluids. Besides, some characterization methods like TEM, SEM and XRD are used to identify the morphology of nanoparticles.

In summary, it can be concluded that the thermal conductivity and viscosity of nanofluids depend on several parameters and have the difference and uncertainty even for the same kind, since the thermal conductivity and viscosity of nanofluids are simultaneously affected by a multitude of factors, particularly micro factors for instance clustering, particle charge condition and micro motion etc. The thermal conductivity of nanofluids with advanced materials, e.g., graphene, CNTs, gold, is generally higher than that of the conventional nanofluids. Furthermore, these kinds of particles may be favourable to obtain better dispersion, fluidity and applicability in a low particle loading. Hitherto, the stability of nanofluids is not desirable. Meanwhile, a combination of different nanoparticles can result in different properties compared with mono nanoparticles. The variations in properties require further investigations on hybrid nanoparticles.

3 Application of nanofluids in various types of heat pipes

Since different heat pipes have different structure characteristics, it is imperative to compare the heat transfer effect and mechanism of nanofluids in different types of heat pipes. The application of nanofluids in heat pipes can be divided into three categories based on working fluid reflux power, such as conventional heat pipe, pulsating heat pipe, and closed two-phase thermosyphon. The first category namely conventional heat pipes are the heat pipes with capillary forces provided by sintered, meshes and micro-grooved metallic materials. The second category is pulsating heat pipes which is a self-sustained thermal driven oscillating heat pipe. The third category is the closed two-phase thermosyphon that the driven force of the fluid reflux is gravity. In this section, the application for conventional and hybrid nanofluids in three types of heat pipes is discussed and the mechanism of heat transfer enhancement or inhibition is summarized.

3.1 Application of conventional nanofluids in heat pipes

In this section, the application of conventional nanofluids in heat pipes (conventional heat pipe, closed two-phase thermosyphon and pulsating heat pipe) is discussed. Some typical studies about the thermal conductivity of conventional nanofluids are summarized in Table 5.

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Table 5

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The application of conventional nanofluid in heat pipes.

Type of heat pipe	Type of nanofluids	Parameters affecting thermal behaviours						Maximum reduction of Thermal resistance
		Concentration	Thermal conductivity (W/m.K)	Viscosity (mPa.s)	Input power/w	Inclination/°	Filling ratio	
Sintered heat pipe [88]	DS-GNP/water	2 vol%-5 vol%	0.62–0.73	0.50–1.07	20–120	0–70	30%–60%	26.4%
Sintered heat pipe [90]	CuO/water and Al_2O_3/water	0.5–1.5 wt%	0.613–0.645	0.36–0.88	10–160	0–90		25.51%
Sintered heat pipe [96]	Cu/water	1-2 wt%			25–150			21.7%
Helically-micro-grooved heat pipe [95]	Al_2O_3/water				10–65	0–90	20%–80%	18.2%
Horizontal micro-grooved heat pipe [89]	CuO/water	0.5 wt%-2 wt%			10–100			39%
Rectangular grooved wick heat pipes [94]	Al_2O_3/water	0-1 vol%			40–80			57.7%
Micro-grooves heat pipe [91]	CuO/water	1 wt%	0.61–0.78	0.81–0.85		0–90	50%	50%
Mesh wick heat pipe [93]	Al_2O_3/water	0.25 vol%-1.5 vol%			10–60		20%–90%	40%
Mesh sick heat pipe [150]	Al_2O_3/water	5 wt%-10 wt%	0.62–0.72.	0.57–1.34	7.5–45			50%

mesh Wick heat pipe [97]	Al_2O_3/water, Al_2O_3/EG, TiO_2/water, TiO_2/EG and ZnO/EG	1 vol%-5 vol%	0.25–0.73		10–30			87%
Copper mesh heat pipe [149]	Graphite/water	0.5 wt%-1.2 wt%	0.61–0.81	1.0–2.0	30–180	0–90		46%
Mesh wick heat pipe [98]	Ag/water	0.0008 wt%-0.0032 wt%	0.65–1.15	0.79–0.80				65.29%
Thermosyphon [100]	Bauxite nanofluid	1 wt%-4 wt%			200–400			24.3%
Thermosyphon [101]	Al_2O_3/water							24%
Thermosyphon [102]	TiO_2/water	0.1–0.3 vol%	0.50–0.79		5–20	30–90		36.67%
Thermosyphon [104]	Graphene/water	0.02 wt%-0.1 wt%			4–12	30–90		50%
Pulsating heat pipe [108]	Ag/water	100 ppm–450 ppm			5–85		20%–80%	33%
Pulsating heat pipe [110]	GNP/water	1.2–16.7 vol%	0.65–0.8	0.6–1.3	10–100		45%–90%	83.6%
Pulsating heat pipe [112]	Graphene oxide/water	0.25–1.5 g/lit	0.63–0.65	0.93–1.11	10–70			40%
Pulsating heat pipe [113]	Graphene/ethanol-water	0.1–1 mg/ml	0.34–0.52	0.55–2	20–60			25.16

3.1.1 Application of nanofluids in conventional heat pipes

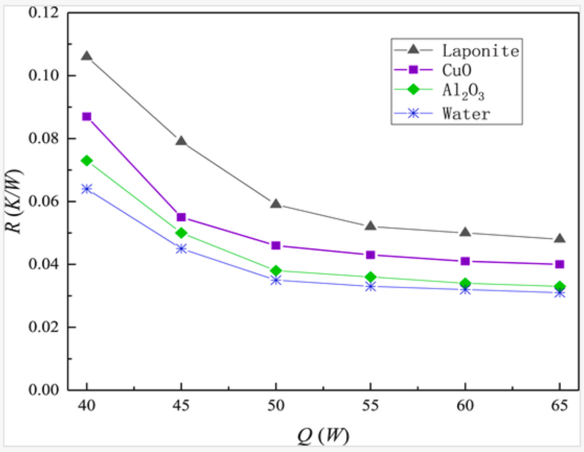
For the conventional heat pipes, the addition of nanoparticles in the base fluid can greatly improve the heat transfer performance of heat pipes, including GNP [88], CuO [89–91], Al_2O_3 [92–95], Cu [96], ZnO/TiO_2 [97] and Ag [98]. The mechanism of heat transfer enhancement can be concluded for three reasons. The first reason is the enhancement of effective thermal conductivity of nanofluids. The second reason is the reduction of the solid-liquid contact angle of nanofluids, thus increasing the capillary force in heat pipes. The third reason is the formation of a thin porous layer on the surface of heat pipes, increasing the solid-liquid wettability and capillary force. Furthermore, there exists an optimal nanoparticle concentration to balance the capillary force and flow drag force [94]. Vijayakumar et al. [90] revealed that the optimum concentration of nanofluid in a heat pipe was dependent on the particle types and the thermal resistance of heat pipe is reduced with the growth of concentration of nanofluids. Putra et al. [99] proved that capillary pressure and gravity affect the thermal performance of LHPs. The thermal resistance of the LHP charged with nanofluids was less than one charged with pure water. Wang et al. [98] demonstrated that the heat transfer performance and start-up of heat pipe with Ag–H_2O nanofluids have been improved compared with DI water. The Ag–H_2O nanofluids with a low viscosity and a high thermal conductivity are expected to be the most promising working fluid. Yang et al. [89] explored the heat transfer characteristic of a micro-grooved heat pipe filled with CuO nanofluids. The results revealed that the heat transfer coefficients of the evaporator section could be enhanced by about 46% and the maximum enhancement rate of critical heat flux could be 30% compared with pure water.

3.1.2 Application of nanofluids in closed two-phase thermosyphons

Various nanofluids have been explored for use in the closed two-phase thermosyphon, including bauxite/water [100], Al_2O_3/water [101], TiO_2/water [102], graphene/water [100,103–105], graphene oxide/water [106]. The effect of nanofluids on heat transfer characteristics of thermosyphon is complex. Most results reported an enhancement of heat transfer and few reported a deterioration of heat transfer. Its heat transfer characteristics are similar to the pool boiling characteristics. The sediment layer can enhance the number of nucleation sites, whereas slurry sediments will decrease the half cone angle or mouth radius of the cavity and decrease the number of nucleation sites. Cacua et al. [101] revealed that both the effect of the nanoparticle deposition and surfactant on the boiling heat transfer mechanism had to be taken into account to explain the improvement of THP thermal performance. Wlazlak et al. [106] observed that graphene oxide nanofluids enhanced heat transfer of a thermosyphon at low heat loads and this enhancement was limited to the evaporator. Zhao et al. [105] revealed that the addition of 0.05 wt% graphene/water nanofluid could cause a 15.1% reduction of start-up time compared with water. Khandekar et al. [107] demonstrated that the thermal resistance of thermosyphon with nanofluids was higher compared with pure water (Fig. 3), due to the increment of wettability and entrapment by nanoparticles in the grooves of the surface.

alt-text: Fig. 3

Fig. 3



The thermal resistance of thermosyphon with nanofluids and water [107].

3.1.3 Application of nanofluids in pulsating heat pipes

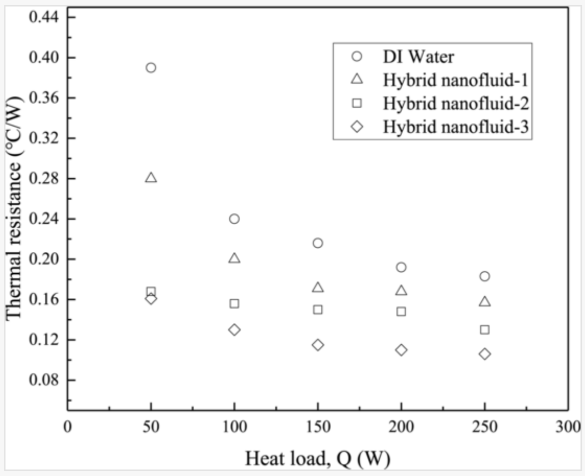
The addition of nanoparticles in base fluid can improve the heat transfer of the PHP by experimental and numerical analysis [108–113]. The heat resistance decreases with the increment of the temperature of PHP with nanofluids compared to that without nanoparticles. The mechanism was considered for two reasons. Firstly, the increment of temperature results in higher thermal conductivity as well as stronger oscillating motion of nanoparticle. In addition, the formation of a thin layer of porous sediments on the surface of PHP will enhance the thermal performance of PHP. Xu et al. [111] proposed a three-dimensional numerical model to investigate the thermal transfer characteristics of Ag/water nanofluids. The results revealed that the time for the maximum inflection point of the thermal resistance of the heat pipe was shortened. Moreover, the heat transfer characteristics of the heat pipe were affected by the heat input and filling ratio. Zhou et al. [110] reported that the maximum reduction of thermal resistance by 83.6% was achieved in the PHP charged with a 2 vol% GNP nanofluid in comparison with pure water at the same heat power (80 W) and filling ratio (62%).

3.2 Application of hybrid nanofluids in heat pipes

To date, the effect of hybrid nanofluids on heat pipes has been investigated in a few studies, which has an uncertainty. Meanwhile, different volume concentrations and different combinations of nanoparticles can affect the thermal transfer performance of the heat pipes [114,115]. Ramachandran et al. [116] studied different nanofluid systems (Ag/water, Al_2O_3/water and Ag–Al_2O_3/water hybrid nanofluids). The results proved that the hybrid nanofluid system was not much effective compared to the mono nanofluid system Fig. 4. Zufar et al. [117] revealed that the hybrid nanofluids shorten the start-up time of PHP and lower heat power could achieve start-up pulsations compared with water. Xu et al. [118] investigated the effect of different nanoparticle mixture ratios of Al_2O_3–TiO_2/H_2O hybrid nanofluids on the heat transfer performance of TPCT. The results indicated that the 25% Al_2O_3 + 75% TiO_2–H_2O hybrid nanofluid contributed to the best transfer performance and was effective compared to the mono nanofluid system.

alt-text: Fig. 4

Fig. 4



The effect of heat load on the thermal resistance of heat pipe [116].

Based on the above analysis, nanofluids can extremely improve the heat transfer of heat pipes (thermal resistance was reduced by 18.2%–87%), and nanofluids with high thermal conductivity and low viscosity are most welcome in application. Advanced nanomaterials, e.g., graphene, GNTs, Ag, exhibit higher heat transfer enhancement of heat pipes compared to metal oxides. Meanwhile, there exists an optimum concentration for nanofluids. Hybrid nanofluids can lead to high thermal performance of heat pipes. However, the study on the thermal characteristics of heat pipes filling with hybrid nanofluids is still in the initial stage. More research need to be carried out.

Furthermore, it can be found that no general correlations exist in heat pipes charged with nanofluids, since the thermal performance of heat pipes depend not only on the thermal properties of nanofluids, such as nanoparticle size, thermal conductivity, viscosity and stability, but also on the operating condition and structural parameters. It is extremely arduous to find accurate relationships among different heat pipe types and experimental setups. There is a lack of comparability between different experimental works conducted by different groups even under similar experimental conditions. Machine learning technology could shed a light on tackling the complexity of nanofluids heat transfer and provide guidance for the optimal design of various types of heat pipes.

4 Machine learning: thermal conductivity, viscosity and thermal performance of heat pipes with nanofluids

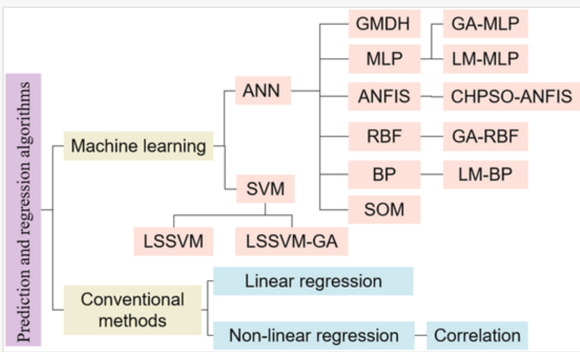
The confidence and accuracy of the predictive model depend on selecting appropriate algorithms and considering all influential factors. Therefore, in this section, the mechanisms of ANNs and LSSVM are elaborately introduced to provide deep insight, and the applications of machine learning approaches in modelling thermal conductivity, viscosity of nanofluids and thermal performance of heat pipes charged with nanofluids are discussed.

4.1 Machine learning methods

In engineering problems and systems, the regression type of machine learning approach is often used to recognize the association between input and output variables of a system. The machine learning predicting the viscosity and thermal conductivity of nanofluids as well as performance of heat pipes mainly includes ANNs and LSSVM. Among them, ANNs are acceptable for large sample cases, because they have the ability to model complex nonlinear relationship and generalization, although they have a high demand for computing resources. LSSVM is acceptable for small samples, which is arduous to deal with large samples. The general classification of these used approaches is explained and represented in Fig. 5.

alt-text: Fig. 5

Fig. 5



Categories of regression algorithms.

4.1.1 Artificial neural networks

ANNs have a set of linked neurons relating the input data to appropriate output by statistical weights. Fig. 6 illustrates the schematic structures for a typical ANN. In ANNs models, $X = [x_1, x_2, x_3, ..., x_n]^T$, n_j is presented as an input value of jth neurons:

$$n_j = \sum_{i=1}^{n} \omega_{ji} x_i \tag{1}$$

where ω_{ji} is the weight vector between the ith neuron and the jth neuron, f indicates the neuron's state:

$$y_j = f(n_j) = f\left(\sum_{i=1}^{n} \omega_{ji} x_i\right) \tag{2}$$

alt-text: Fig. 6

Fig. 6

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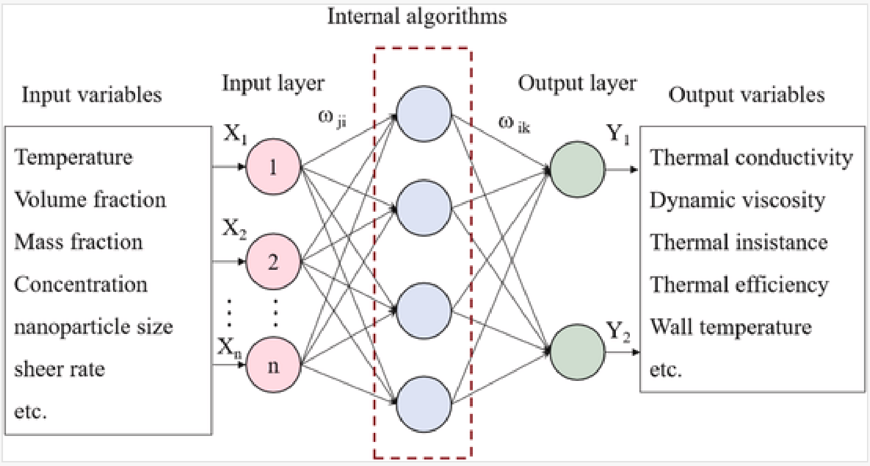

Structure of ANN topology.

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According to the employed algorithm, various functions are developed as activation function. Feed-forward ANNs such as MLP-ANN and RBF have been widely used in the scientific area. This type of network consists of various neurons in three distinct layers including: an input layer which attains the input data; one or more inter-layers, namely hidden layers which carry out the processing step; and an output layer which is connected to the forecasted output result with predefined weight functions. In general, the structure parameters of these networks such as the number of neurons and layers should be pre-determined and significantly influence the accuracy and time consumption. Moreover, GMDH does not need to pre-determine the structural parameters such as the number of the hidden layer and the number of active neurons, due to the self-regulation feature. ANFIS combines the functions of neural network and fuzzy reasoning system, and it has the advantages of high processing speed, self-learning ability and easy to solve nonlinear problems with fuzzy logic. In addition, large samples size is the pre-condition of the employment of ANN. Several optimization algorithms such as PSO, LM, ICA and GA are employed in ANN for minimizing the error. Details of these algorithms are represented in Refs. [36,119].

4.1.2 Least square Support Vector Machines

SVM-based algorithms have a cost function. A more accurate result can be achieved by minimizing the cost function. The main advantage of SVMs is relatively simple and straightforward optimization, which is due to the existence of their convex objective function, and it is suitable for the small sample size or high-dimensional data. Its performance is mainly up to the kernel function. To overcome this restriction that the SVM method cannot address the overfitting problems, the LSSVM method is developed to make it feasible to overcome the overfitting. Generally, the LSSVM nonlinear function is,

$$f(\mathrm{x}) = w^T x + b \tag{3}$$

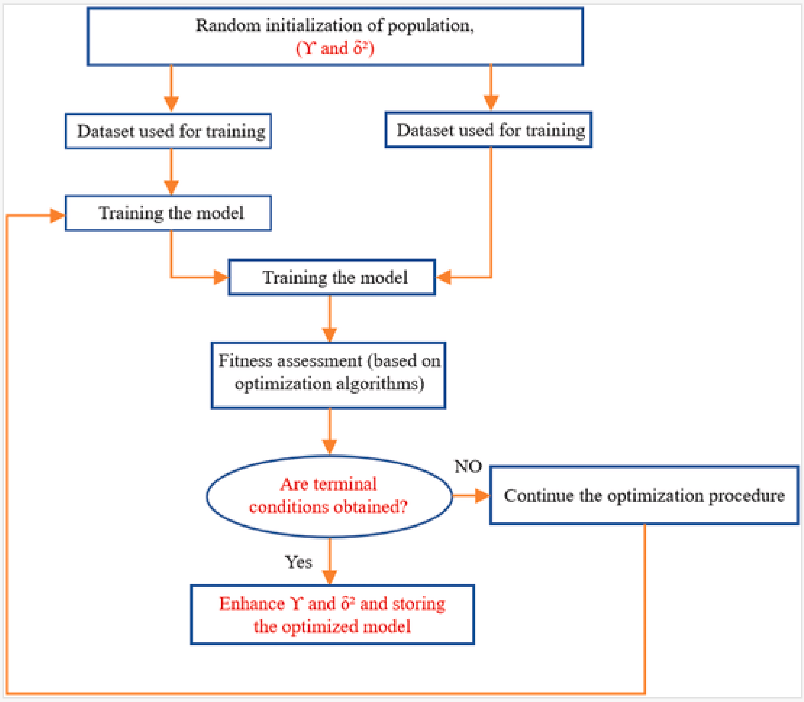
To minimize the topology, the fitting error function is defined to solve the regression problem:

$$Min\ J(w, e) = \frac{1}{2} w^T w + \gamma \sum_{k=1}^{m} e_k^2 \tag{4}$$

The general process of LSSVM-based methods is demonstrated in Fig. 7. In the modelling process, the step in which the obtained model is evaluated by optimization algorithms is crucial to achieving an accurate model. GA and PSO are the most applicable optimization algorithms.

alt-text: Fig. 7

Fig. 7



Process of LSSVM models.

4.2 Prediction of thermal conductivity by machine learning approaches

The thermal conductivity and viscosity which are affected by a multitude of factors and have complexity and uncertainty should be determined by pre-experiments before designing the thermal system used with nanofluids. Machine learning in the area to perform prediction is extremely pivotal since the number of experiments is reduced and then the costs are reduced. The review on the application of machine learning methods in predicting the thermal conductivity of conventional and hybrid nanofluids is carried out.

4.2.1 Prediction of thermal conductivity of conventional nanofluids

Machine learning has been widely employed to predict the thermal conductivity of nanofluids [120–124]. Some typical studies on machine learning in thermal conductivity of nanofluids and their corresponding R^2 values used for evaluating the model confidence are summarized in Table 6. It is seen that temperature, concentration and nanoparticle size, were commonly taken as the input variables. The maximum R^2 value is 0.99, although a low value of 0.875 is also noticed. In some cases, R^2 is not enough to validate the results obtained and other measures such as MSE may also be applied to confirm the validation of the predictions. The neural network structure such as number of hidden layers and neurons, and weight coefficient should be precisely designed in a particular problem to improve the prediction accuracy. Hemmat Esfe et al. [123] predicted the thermal conductivity of Al_2O_3/water nanofluids by utilizing the MLP-ANN and mathematical correlation. The results indicated that the ANN model was more accurate compared with mathematical correlation, based on these statistical criteria of R-squared and MSE. Tahani et al. [124] demonstrated the accuracy of the ANN model was acceptable because the R^2 value was 0.999. Ariana et al. [37] predicted the thermal conductivity of Al_2O_3/water nanofluid by utilizing the MLP-ANN. The results indicated that the MSE for the test and training stage was 6.3×10^{-4} and 3.3×10^{-4},respectively which prove the high accuracy of the model.

alt-text: Table 6

Table 6

The table layout displayed in this section is not how it will appear in the final version. The representation below is solely purposed for providing corrections to the table. To preview the actual presentation of the table, please view the Proof.

Machine learning research in thermal conductivity of conventional nanofluids.

Nanofluid	Input variables	Algorithms	R-squared value
Al_2O_3/water [123]	Temperature, concentration	Correlation, MLP	0.991, 0.99988
COOH-MWCNTs/antifreeze [151]	Temperature, concentration	Correlation, ANN	0.988
MgO/water [152]	Temperature, concentration	Correlation, ANN	
Al_2O_3/EG, Al_2O_3/water [36].	Size, temperature, concentration	GMDH	0.9958, 0.9462
Al_2O_3/water [37]	Size, temperature, concentration	MLP	0.971875
Twenty-six nanofluids [153]	Size, temperature, concentration	ANN	0.9309
Al_2O_3/water-EG [154]	Temperature, concentration	Correlation, ANN	0.9955, 0.9993
Al_2O_3/water [126]	Size, temperature, concentration	LSSVM, LM-BP, SOM	0.89999, 0.87575, 0.88125
CuO/EG [127]	Size, temperature, concentration	LSSVM-GA, GMDH	0.991, 0.994
Al_2O_3/water-EG [120]	Temperature, concentration	ANN	0.9974
CuO/water-EG [121]	Temperature, concentration	Correlation, ANN	
CNTs/water [122]	Temperature, concentration	Correlation, ANN	

Considering more influential factors contribute to more precise results [36]. For instance, Longo et al. [125] presented two ANN models for predicting the thermal conductivity of oxide-water nanofluids. One of them accounts for the effect of temperature, particle loading and thermal conductivity of nanoparticles, while the other one accounts for the effect of nanoparticle size in addition to the above-mentioned factors, which exhibits better performance.

Several novel models, such as coupling optimizing intelligence methods and optimal algorithms, can contribute to higher accuracy. For instance, Ahmadi et al. [126] presented two models, LSSVM-GA model and GMDH model, to estimate the thermal conductivity of CuO/EG nanofluid. The results showed that the R-squared values for the LSSVM-GA model and GMDH model were 0.994 and 0.991. In another research [127], LSSVM-GA and GMDH were used to predict the thermal conductivity of Al_2O_3/water. The results revealed that these algorithms are appropriate tools for estimating thermal conductivity.

4.2.2 Prediction of thermal conductivity of hybrid nanofluids

Similar to the conventional nanofluids, several studies have been proposed to predict the thermal conductivity of hybrid nanofluids [128,129]. Machine learning research in thermal conductivity of hybrid nanofluids are listed in Table 7. The model structure also affects predictive accuracy and ability [35]. For instance, Hemmat Esfe et al. [34] proposed a 2-layer ANN model for thermal conductivity ratio of MWCNT-SiO_2/EG nanofluids. The results revealed that the structure with 10 neurons in each layer contributed to the highest accuracy. Kannaiyan et al. [130] proposed a MLP-ANN model for thermal conductivity of Al_2O_3–SiO_2/water hybrid nanofluids. The results revealed that the structure, which chose two hidden layers, with 10 neurons in each layer, was optimal.

alt-text: Table 7

Table 7

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Machine learning research in thermal conductivity of hybrid nanofluids.

Nanofluid	Input variables	Algorithms	R^2 value
Al_2O_3–SiO_2/water [130]	Temperature, concentration	MLP	
CuO-SWNTs/EG-water [155]	Temperature, concentration	Correlation, MLP	
Cu–TiO_2/water-EG [156]	Temperature, concentration	Correlation, MLP	0.995, 0.999
MWCNT-SiO_2/EG [34]	Temperature, concentration	Correlation, MLP	0.9864, 0.9977
CNT-Fe_3O_4/water [157]	Temperature, concentration	MLP	0.999
Cu–Zn/water [119]	Temperature, concentration	Correlation, ANFIS	

4.3 Prediction of viscosity by machine learning approaches

In this section, a review on the application of machine learning methods in predicting the viscosity of conventional and hybrid nanofluids is carried out.

4.3.1 Prediction of viscosity of conventional nanofluids

Some typical studies on machine learning in viscosity of nanofluids and their corresponding R^2 values used for evaluating the model confidence are summarized in Table 8. It is seen that temperature and concentration were commonly taken as the input variables. The maximum R^2 value is 0.99, although a low value of 0.96 is also noticed. The neural network structure and weight coefficient should be precisely designed in a particular problem to improve the prediction accuracy. Esfe et al. [131] proposed an ANN model to estimate the dynamic viscosity of TiO_2/water. The ANN model utilized one hidden layer with four neurons, which was extremely accurate with R-squared value of 0.9998. Kumar et al. [132] reported a structure which chose 6 neurons in hidden layers based on the results of testing various structures and MSE value of above mentioned structure was 0.01118.

alt-text: Table 8

Table 8

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Machine learning research in viscosity of conventional nanofluids.

Nanofluid	Input variables	Method(s)	R-square value(s)
ZnO-EG [158]	Temperature, concentration	Correlation	
MWCNT/water [159]	Temperature, concentration	ANN	
TiO_2/water [131]	Temperature, concentration	Correlation, ANN	0.999
Fe_3O_4/paraffin [160]	Temperature, concentration, shear rate	GMDH	0.96
Fe-EG [133]	Temperature, concentration	Correlation, ANN	
Fe_2O_3/water [135]	Temperature, concentration, size	CHPSO-ANFIS, MLP, GA-RBF, LSSVM	0.9974,0.9970, 0.9982,0.9930
Different nanofluids [161]	Temperature, concentration, size	Hybrid GMDH	0.995

Considering more influential factors contribute to more precise results [133]. For instance, Esfe et al. [134] predicted the dynamic viscosity of Fe/water nanofluids at different sizes (37, 71 and 98 nm), temperature and volume fraction, by utilizing the ANN. The results indicated that considering the size of nanostructure as another input variable led to more accuracy and comprehensive model.

Different algorithms are compared to obtain an optimal prediction model. For instance, Ahmadi et al. [135] predicted the dynamic viscosity of Fe_2O_3/water nanofluids at different sizes, temperatures and volume fractions by utilizing the GHPSO ANFIS, MLP, GA-RBF, and LSSVM. The results indicated that the maximum value of R-squared among the above-mentioned approaches belonged to GA-RBF, namely 0.9982.

4.3.2 Prediction of viscosity of hybrid nanofluids

The machine learning approaches for estimating the viscosity of hybrid nanofluids and their corresponding R-squared values used for evaluating the model confidence are listed in Table 9. The model structure also affects predictive accuracy and ability. For instance, Esfe et al. [136] proposed an ANN model for dynamic viscosity of Al_2O_3 -MWCNT/5W50 nanofluids. The results revealed that the structure with 35 neurons provided the highest accuracy. Moghaddari et al. [137] designed the ANN model in which the designed hidden layer had 20 neurons, and R-squared value for the model was 0.9897.

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Table 9

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Machine learning research in viscosity of hybrid nanofluids.

Nanofluid	Input variables	Method(s)	R-square value(s)
MgO-MWCNT/EG [158]	Temperature, concentration	Correlation	
MWCNT-Si O_2/AE40 [162]	Temperature, concentration	Correlation, ANN	
SiO_2-MWCNT/10W40 [138]	Temperature, concentration, Shear rate	ANN	0.9948
CuO-MWCNT/SAE 5W-50 [163]	Temperature, concentration	Correlation, ANN	0.998, 0.9998
Various nanofluids including MWCNTs [137]	Temperature, concentration, viscosity of base	ANN	0.9897
Al_2O_3-MWCNT/5W50 [136]	Temperature, concentration	Correlation, ANN	0.982, 0.998

In addition to temperature and concentration, the shear rate and viscosity of base fluids were also regarded as input variables. For example, Nadooshan et al. [138] predicted the dynamic viscosity of SiO_2-MWCNT/10W40 nanofluids at different shear rates, temperatures and concentrations by utilizing the ANN. The results indicated that the MSE and R-squared values were 1.94×10^{-4} and 0.9948 respectively. Utilizing the ANN, Moghaddari et al. [137] predicted the dynamic viscosity of various hybrid nanofluids including MWCNTs. The R-squared value for ANN model was 0.9897.

4.4 Prediction of performance of heat pipes charged with nanofluids

Machine learning has been applied to predict the thermal performance of heat pipes charged with nanofluids and proved to be an extremely powerful and efficient predictive tool. Limited studies on the application of machine learning in heat pipes charged with nanofluids are listed in Table 10. Different nanoparticles including CNT, CNT-Ag, Ag, Al_2O_3, and Fe_3O_4 are considered. Thermal efficiency, thermal resistance and temperature were considered the output variables. The input variables include operating conditions (input power magnetic field strength, mass rate in condenser section and filling ratio), the properties of nanofluids (concentration and thermal conductivity) and structure of heat pipes (the ratio of inner diameter to the length). Presently, the heat pipe in this field of study is mainly thermosyphon and pulsating heat pipe. Kahani and Vatankhah [139] designed an optimized MLP-ANN to predict the thermal performance of thermosyphon heat pipe charged with Al_2O_3/water nanofluids. The results showed that volume concentration was the paramount parameter for estimating the thermosyphon performance. Several novel models coupling optimizing intelligence methods and optimal algorithms are considered for predicting the performance of heat pipes charged with nanofluids. Shanbedi et al. [140] proposed a LM-ANN model to estimate the thermal performance of thermosyphon heat pipe with CNT/water and CNT-Ag/water nanofluids. The results obtained were in reasonable agreement with the experimental results. The GA-MLP model was used to predict the thermal efficiency and resistance of thermosyphon with Ag/water nanofluids at a magnetic field by Salehi et al. [141]. Some algorithms were compared by Malekan et al. [142]. The results revealed that the MLP model presented the best predictive performance, followed by ANFIS, and GMDH.

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Table 10

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Machine learning research in thermal performance of heat pipes charged with nanofluids.

Method	Heat pipe	Nanofluid	Input variables	Output variables	R^2
LM-MLP [140]	Thermosyphon	CNT/water and CNT-Ag/water	Input power and concentration	Temperature	
GA-MLP [141]	Thermosyphon	Ag/water	Magnetic field strength, concentration and input power	Thermal efficiency and thermal resistance	
MLP [139]	Wickless heat pipe	Al_2O_3/water	Input power, concentration, filling ratio and mass rate in condenser section	Thermal efficiency of wickless heat pipe	0.9822
MLP, ANFIS and GMDH [142]	Pulsating heat pipe	Fe_3O_4/water and γFe_2O_3/water	heat power, thermal conductivity and the ratio of inner diameter to the length	Thermal resistance	

Based on the above analysis, it can be concluded that machine learning approaches, especially ANNs, could provide significant information on the thermal performance of heat pipes with nanofluids. Prediction accuracy can be improved by combining the optimization algorithms (PSO and GA) and intelligent methods, and considering more input variables such as particle size. Furthermore, the structure of ANN is required to be optimized for the best fit in each case, and the most appropriate method for predictive modelling might be different in different case studies.

5 Challenges – current status and deficiency

The combination of nanofluids and heat pipes is efficient and practical, which could be another attractive new subject in thermal systems. To enable this, several identified scientific challenges need to be tackled. These are detailed below.

5.1 Challenges in the properties of nanofluids

In the properties of nanofluids, the main challenges focus on difference and uncertainty on thermal conductivity and viscosity of nanofluids, undesirability on stability property of nanofluid, as well as inadequate cognition on the mechanism and characteristics of hybrid nanofluids.

5.1.1 Difference and uncertainty on thermal conductivity and viscosity of nanofluids

There are difference and uncertainty on thermal conductivity and viscosity of nanofluids even for the same kind, since the thermal conductivity and viscosity of nanofluids are simultaneously affected by a multitude of factors particularly micro factors for instance clustering, particle charge condition and micro motion etc. The difference and uncertainty lead to hardly getting accurate design value and variation law, thus seriously hindering the more popular application of nanofluids.

5.1.2 Undesirability on stability property of nanofluids

The stability of nanofluids is critical to maintaining the constant thermal performance of nanofluids and heat transfer performance of systems applied with nanofluids. The agglomeration tendency and sedimentation of nanoparticles increase with time, thus thermal performance decreases with time. Several research have focused on improving the stability, but the results are still undesirable. In addition, the effects of surfactant on thermo-physical performance (thermal conductivity and viscosity) of nanofluids are ambiguous. Some researchers report that although surfactants can improve the dispersion, they also cause the increment in viscosity and decrement in thermal conductivity. Others report that some surfactants improve the dispersion and thermal conductivity and increase viscosity only slightly and even present drag reduction.

5.1.3 Inadequate cognition on the mechanism and characteristics of hybrid nanofluids

A noticeable thermal conductivity enhancement of hybrid nanofluids compared to normal nanofluids has been reported. However, the complex heat transfer and rheological mechanisms of hybrid nanofluids have not been sufficiently understood. So far, several types of hybrid nanoparticles have been investigated, such as: Al_2O_3/CNT, Cu–TiO_2, CNT-Au and many more. Each nanoparticle presents its characteristics. The selection of nanoparticles is significant for the thermal conductivity and stability of hybrid nanofluids. This is because the combination of nanoparticles with better stability but low thermal conductivity and better thermal conductivity might improve the thermal conductivity and stability of nanofluids. However, what nanomaterials and what proportion will contribute to the hybrid nanofluid exhibiting the best thermal performance is not yet clear.

5.2 Challenges in the application of nanofluids in heat pipes

In the application of nanofluids in heat pipes, the major challenges include no appropriate standard for selecting the nanofluids in heat pipes, lack of comprehension of the time-dependent property of heat pipes charged with nanofluids and application of nanofluids in heat pipes restricted in terms of technology, economic and environment.

5.2.1 No appropriate standard for selecting the nanofluids in heat pipes

Nanofluids with high thermal conductivity and low viscosity are welcome in application. However, the increment in thermal conductivity is invariably at the expense of viscosity. Meanwhile, it is unclear what kind of nanofluids is most suitable for various types of heat pipes under different application scenarios.

5.2.2 Lack of comprehension of the time-dependent property of heat pipes charged with nanofluids

The agglomeration tendency and sedimentation of nanoparticles increase with operation time, thus thermal performance of heat pipes charged with nanofluids will deteriorate. However, time-dependent properties of heat pipes charged with nanofluids are rather rarely investigated. Without a clear comprehension of the time-dependent property for heat transfer performance of heat pipes charged with nanofluids, the heat pipes charged with nanofluids will not be widely applied.

5.2.3 Application of nanofluids in heat pipes restricted in terms of technology, economic and environment

Firstly, the technical standards such as filling rate and inclination angle of heat pipes charged with nanofluids and evaluation standards have not yet been formulated, which also hinder their application at the industry level. Secondly, the cost of nanofluids is a paramount issue for the wide application of nanofluids, and if the cost is too high (compared to the benefits) it will also hinder the application of nanofluids. Finally, the application of nanoparticles affects the environment in both positive and negative ways. On the one hand, nanofluid has a multitude of benefits for the environment such as fuel-saving, saving raw materials and wood preservatives. On the other hand, there are also potential risks and devastating effects on the environment. For instance, nanoparticles in the air can cause air pollution and ozone layer depletion, and it might disturb the soil environment and aquatic ecosystem by interfering with the composition of microbial population. To date, there are few literatures on evaluating heat pipes charged with nanofluids from technical, economic and environmental aspects.

5.3 Challenges in the predictive models based on machine learning

In the predictive models based on machine learning, there are some problems including limitation of predictive models based on machine learning approaches, little attention on data volume as indicator and the difficulty in determination of data volume, and no appropriate standard for selecting the most precise machine learning method.

5.3.1 Limitation of predictive models based on machine learning

Established by the machine learning, the predictive models are only applicable to their own experimental scope under a specific condition, which may eclipse the predictive models. Utilizing the predictive model, it could be easy and accurate to identify the optimum concentration of nanofluids before application without pre-experiments and numerical calculations. However, if the predictive model is not universal, then the main purpose of the model that reduces calculation time and the cost of pre-experiments will not be achieved. Meanwhile, there are some available models that only consider limited influencing factors, without considering the shape and type of nanoparticles, which may affect the accuracy and comprehensiveness of the models.

5.3.2 Little attention on data volume as indicator and difficulty in determination of data volume

In addition to the accuracy of prediction, the data volume is also a significant indicator for evaluating machine learning methods. However, little attention is current being paid to the data volume issue. The sampling size is vital in machine learning approach. It is necessary to seriously consider the size of the data that are used to train the model, since more data could carry high expenses in data production and collection, while small sized data may easily lead to random or systematic errors during the model training, which might obscure the internal regularity of subject. A balance of compromise between the cost and sample size should be identified before building the sampling data.

5.3.3 No appropriate standard for selecting the most appropriate machine learning algorithm

The most appropriate method for predictive modelling might be different in different case studies. The standard for select the appropriate methods have not yet been established, which is the major challenge in the future. Presently, the ANN is a popular method for the nanofluids simulation and prediction. However, comparisons among all algorithms of various ANNs have not yet been undertaken and the most appropriate algorithm and structure have not yet been identified.

6 Opportunities for future works

To tackle the above challenges, further opportunities for future research and development are identified and these are outlined below:

6.1 Opportunities in the properties of nanofluid

Given the current development status and challenges, the solutions for the properties of nanofluids are outlined as, exploring the thermo-physical properties of nanofluids and establishing unified standards, improving the stability of nanofluids, and investigating the heat transfer mechanism and characteristics of hybrid nanofluids.

6.1.1 Exploring the thermo-physical properties and establishing unified standards

Micro factors such as clustering, particle charge condition and micro motion are the main reason for difference and uncertainty. Methodical research at nanoscale should be carried out to unveil the intricate mechanisms of thermo-physical properties. The different preparation method of nanofluid, thermal conductivity and viscosity measurement and characterization procedures are the main source of inconsistent data. Therefore, unified standards in these areas should be established to minimize difference. Meanwhile, the approach of preparation, the stability method, duration and evaluating method should be introduced in all studies.

6.1.2 Improving the stability of nanofluids

The stability of nanofluids is crucial to the long-term performance of heat pipes charged with nanofluids. More research is needed to explore the effect of surfactants on nanofluids. Both viscosity and thermal conductivity of nanofluid should be considered when selecting surfactants. In addition, further reducing the size of nanoparticles $(<10^{-9})$ and rational designing composition ratio of hybrid nanoparticles might find more stable particles than nanoparticles, and new mechanisms should be developed to avoid sedimentation and agglomeration.

6.1.3 Investigating the heat transfer mechanism and characteristics of hybrid nanofluids at nanoscale

The complex rheological changes and heat transfer mechanism of hybrid nanofluids have not been sufficiently understood. Therefore, more research at nanoscale is needed to understand them and make use of hybrid nanofluids in heat pipes. In addition, more experiments need to be performed to investigate the properties of various hybrid nanofluids because each nanoparticle presents its own characteristics. Therefore, we can identify what nanomaterials and proportion can contribute to hybrid nanofluids exhibiting the best thermal performance and employ them to various heat pipes.

6.2 Opportunities in the application of nanofluids in heat pipes

Given the current development status and challenges, the solutions for the application of nanofluids in heat pipes are outlined as, using advanced nanoparticles and conducting more systematic investigations, focusing on the nanoparticle deposition layer and life expectancy of heat pipes, and developing the heat pipes charged with nanofluids in technical, economic and environmental aspects.

6.2.1 Using advanced nanomaterials and conducting more systematic investigations

Some advanced and precious nanomaterials like CNT, Graphene, Au and Ag, achieve better dispersion and lower viscosity at very low concentration. Therefore, the application of those advanced nanoparticles could be a significantly promising direction. Meanwhile, more systematic and carefully planned investigations should be carried out to establish fundamental results for diverse heat pipes charged with different nanofluid species subjected to variable operating conditions and help to form the industry standard for selecting appropriate nanofluids in various cases.

6.2.2 Focusing on the nanoparticle deposition layer

The nanoparticle deposition layer is the main reason to significantly affect the heat transfer performance of heat pipes. The morphology and thickness of the nanoparticle deposition layer changed with operation time is not well understood, which should be intensively investigated to understand the time-dependent property of heat pipes charged with nanofluids. For instance, whether the deposition layer becomes thicker or maintains a constant thickness during the operation should be explored. Meanwhile, the life expectancy of heat pipes charged with nanofluids should also be considered. Before the heat transfer performance of heat pipes charged with nanofluids fail, it is necessary to replace the new nanofluids and clean the heat pipes timely.

6.2.3 Developing the heat pipes charged with nanofluids in technical, economic and environmental aspects

Before thermal systems applied with heat pipes and nanofluids transform from small-scale experiments to large-scale industrial production, the reliability of thermal systems must be evaluated in technical, economic and environmental aspects. Unified technical and evaluation standards should be formulated to promote mass production of heat pipes charged with nanofluids. More attention should be paid on low-cost production techniques which could provide great thermal performance of nanofluids. In addition, natural non-toxic and non-polluting nanoparticles are encouraged for the investigation, and green technologies should also be developed for preparation of nanoparticles or nanofluids.

6.3 Opportunities in the predictive models based on machine learning

Given the current development status and challenges, the solutions for the application of nanofluids in heat pipes are outlined as, establishing the large, exclusive ~~large~~ databases and expanding the input variables, serving the data volume as the evaluated indicator and verifying the adequacy of data volume, and defining specific standard by horizontal comparison and using the more advanced algorithm.

6.3.1 Establishing the large, exclusive ~~large~~ databases and expanding the input variables

Large, ~~E~~exclusive ~~large~~ databases for all thermo-physical properties of various nanofluids and the thermal performance of various heat pipes applied with nanofluids should be established and used to train the universal predictive models. Effort to establish the large databases can firstly be made including the advanced nanofluids and proper ranges of nanoparticles size and concentration. Utilizing the predictive model to identify the optimum nanoparticle concentration for each nanofluid must be the next step in heat pipes research. In addition, adding the input variables such as the particle type and shape not only could solve the limitation of prediction model, but also improve the comprehensiveness and accuracy of the model.

6.3.2 Serving the data volume as the evaluated indicator and verifying the adequacy of data volume

At the same prediction accuracy, if the amount of data required by the prediction model is small, the number of experiments and simulation calculations required will be reduced. Therefore, the data volume is also a significant indicator for evaluating machine learning methods, which should be paid more attention. The probably approximately correct (PAC) learning, which can measure the learnability of a specific machine learning algorithm with a specific sampling size, is recommended to verify the sufficiency of sampling size by minimal empirical risk.

6.3.3 Defining specific standard by horizontal comparison and using the more advanced algorithm

An appropriate machine learning approach to establish the predictive model is also the key to ensuring the performance of machine learning models. Therefore, more rigorous horizontal comparisons about the advantages and disadvantages of various machine learning approaches are needed to define the criteria to find their best range of applicability. Also, attention should be paid to a number of issues including the fine tuning of the algorithm structures and problem objectives, the modification of the governing equations, and the form of the input parameter, etc. In addition, with the rapid development of computer technology, more advanced machine learning (deep learning, e.g., convolutional neural network (CNN), recurrent neural network (RNN), etc.) technology has been applied to a multitude of fields, and has been proven to have better prediction effect than traditional algorithms. Therefore, the combination of large databases for nanofluids and the state-of-the-art machine learning technology will provide a new method for this field.

7 Conclusions

The thermal conductivity and viscosity of nanofluids depend on many parameters and have the difference and uncertainty. Advanced nanoparticles such as graphene, CNTs, etc., are encouraged to be explored due to high thermal conductivity and an unexpected reduction in the viscosity at low concentration. The different preparation methods of nanofluid, measurement and characterization procedures are the main source of difference and uncertainty on thermal conductivity and viscosity of nanofluids. Unified standards in these areas should be established to minimize difference. In addition, the effects of surfactant on thermo-physical performance of nanofluids are ambiguous. The stability of nanofluids can be improved by further reducing the size of nanoparticles ($<10^{-9}$) and rational designing composition ratio of hybrid nanoparticles.

For majority of heat pipes, the addition of nanoparticles can extremely increase the heat transfer (thermal resistance was reduced by 18.2%–87%) mainly due to the higher thermal conductivity of nanofluids and the increment of nucleation sites, and there exists an optimum concentration for nanofluids. However, it is unclear what kind of nanofluids is most suitable for various types of heat pipes under different application scenarios. Therefore, more systematic investigations should be carried out to help to form industry standard for selecting appropriate nanofluids in various cases.

Much work mentioned in this paper has demonstrated that machine learning approaches especially ANNs could give excellent prediction. Higher prediction accuracy can be achieved by coupling the optimization algorithms (PSO and GA) and the intelligent methods. However, the prediction model has limitations which could be addressed by establishing large, exclusive ~~large~~ databases and expanding the input variables such as the particle type and shape. Presently, the evaluation of the prediction model is only the prediction accuracy, and the data volume should also be considered. In this review, the PAC learning is recommended to verify the sufficiency of sample size by minimal empirical risk. However, the most appropriate method for predictive modelling might be different in different case studies. Therefore, more rigorous horizontal comparisons are needed, and more advanced machine learning such as CNN and RNN is encouraged to combine with large databases of nanofluids to form a universal model.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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Highlights

- There are some differences and uncertainties on thermal conductivity and viscosity of nanofluids.
- There is a lack of comprehension of the time-dependent property of heat pipes.
- There is a limitation of predictive models based on machine learning techniques.
- The mechanism of thermo-physical properties for nanofluids at nanoscale should be explored.
- The exclusive large databases should be established and the input variables should be expanded.

Queries and Answers

Q1

Query: Please confirm that the provided email “zwang@gdut.edu.cn” is the correct address for official communication, else provide an alternate e-mail address to replace the existing one, because private e-mail addresses should not be used in articles as the address for communication.
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Q2

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