Q1 # Advanced big-data/machine-learning techniques for optimization and performance enhancement of the heat pipe technology – A review and prospective study

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Abstract

A heat pipe (HP) is a passive heat transfer device able to transmit heat a few meters or several hundred meters away from the heat source without use of external energy. This paper presents a critical review of the HP technologies. It is found that the heat transfer performance of a HP is highly dependent upon its geometrical and operational conditions, whilst the existing computerized analytical and numerical models for the HP require a huge number of parametrical data inputs, and therefore is extremely time-consuming and impractical. Furthermore, the measurement results of the HPs vary time by time and show certain disagreement with the simulation prediction, giving a high uncertainty in characterisation of the HP. Development of a machine learning algorithm and associated models based on the structured HP database is a solution to tackle these challenges, which is able to provide the dimensionless and multiple-factors-considering solution for HP structural optimization and performance prediction. A review on big-date/machine-learning technology for HP application was undertaken, indicating that a database covering the HP parametrical data, operational variables and associated performance results has not yet been established. Challenges for the HP structural optimization and performance prediction using the big-data-trained machine learning technology lie in: (1) complex and unregulated HP data; (2) unidentified analytic algorithm for HP structural optimization; and (3) unidentified data-driven algorithm for HP performance prediction. This review-based study provides the potential future research directions for development of the big-data-trained machine learning technology for HP structural optimization and performance prediction.

Keywords: Heat pipe; Big data; Machine learning; Optimization; Prediction; Algorithm

Abbreviations: ANN, Artificial Neural Networks; ANFIS, Artificial Neuro Fuzzy Inference System; CRAC, Computer Room Air-conditioning; CLPHP, Closed Loop Pulsating Heat Pipe; DI, Deionized; FPMHP, Flat-plate Micro Heat Pipe; GA, Genetic Algorithm; HP, Heat Pipe; HPSCs, Heat Pipe Solar Collectors; LR, Linear Regression; NoSQL, Not Only SQL; OLPHP, Open Loop Pulsating Heat Pipe; RSM, Response Surface Methodology; SVM, Support Vector Machine; SVR, Support Vector Regression; TRN, Thermal Resistance Network

Nomenclature

B bayesian network

b bias parameter

C regularization constant

G directed acyclic graphs

L latent heat

L loss function

M merit number

w connection weight

σ_l surface tension

ρ_l liquid density

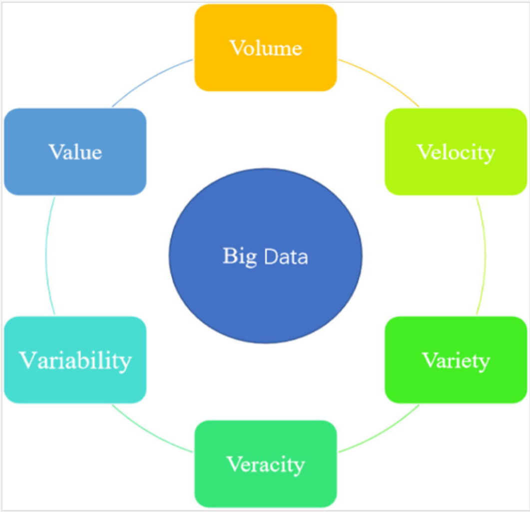
μ_l viscosity

1 Introduction

A heat pipe (HP) [1] is an efficient two-phase heat transfer device which can transport huge amounts of heat over long distances (up to several hundred meters) with a small temperature gradient using the latent heat of evaporation. In this regard, HP offers good prospects of use in electronic cooling and applications such as data centre cooling due to the high heat transport capacity. Several parameters have critical impact on HP's thermal performance including filling ratio, working fluid, inclination angle, structure parameters, etc [2]. Previous studies have been conducted to improve their thermal performance by applying different approaches such as using nanofluids [3], changes in structure [4], etc. Vivek et al. [5] mainly studied seven geometric parameters of satellite heat pipe operated with ammonia and methanol for the multi-objective optimization. They found that lengths of condenser section, evaporator section, and vapour core diameter are the important geometrical parameters causing a strong conflict between the objective functions. Lurie et al. [6] proposed a topology optimization approach to determine an optimal geometry of a wick sintered inside a flat plat heat pipe. Utilizing the simplified 2D thermal and hydrodynamic models, they obtained the optimization results for HPs with different lengths and thicknesses, which could achieve the increased heat transfer capability up to twice. All studies indicate that the design and optimization of the HP under different circumstances are very difficult and time-consuming. Previous relevant studies based on experiments, simulations and analysis have generated huge volumes of data associated with HPs, while combining these data with the advanced AI technology, e.g., machine learning, has potential to develop the accurate, multiple-factors-inclusive, and data-reflective HP structural optimization and performance prediction models, which would help design of the high performance HP to enable achieve the maximized heat transport capacity with the least capital cost.

Big data is usually described as the large volumes of high velocity, complex and variable data that require big data technology to enable the capture, storage, distribution, management, and analysis of the information [7,8]. Typically, big data is characterised with six aspects referred to as the 6 V's, i.e., volume, velocity, variety, veracity, variability and value, which is shown in Fig. 1. Volume [9,10] refers to the massive amounts of data. The size of data typically ranges from petabytes to zettabytes. Velocity [8] refers to the rate at which data are generated and the speed at which it should be analysed and acted upon. The data velocity is positively associated with the data value and data veracity. Variety [11] refers to the structural heterogeneity in a dataset, and now data can be of many different forms, e.g., structured, semi-structured, and unstructured data. Veracity [12] refers to the quality and reliability of the data. Variability [7] refers to that the data can flow at different rates. Value [13] refers to the extraction of valuable insights and information from the data.

Fig. 1



Six V's of Big Data.

Big data need efficient processes to turn high volumes of fast-moving and diverse data into meaningful insights, which usually involve big data management and analytic technology; this is viewed as a sub-process in the overall process of insight extraction from big data [14]. The current era of big data has witnessed a much broader spectrum of the application of big data technology in other industries such as manufacturing, services, financial, etc. Li et al. [15] proposed an energy economy model for guiding the future application of big data to modelling. They thought that the issues surrounding data collection costs, ownership and privacy need to be solved and modelers must look dispassionately at the basic dynamic assumptions, datasets and the big data collection and analysis tools underpinning the models. Arias et al. [16] presented an electric vehicle charging demand forecasting model, combining the historical traffic data and weather data with big data technology. The model could be the foundation for the research on the impact of charging electric vehicles on the power system. Walch et al. [17] developed a methodology that could estimate the technical photovoltaics potential for individual roof surfaces, combining Machine Learning algorithms, Geographic Information Systems and physical models. The uncertainty estimation could be applied to the large-scale assessment of future energy systems with decentralized electricity grids.

HPs experimental data like operational variables and performance parameters, as data sets or 'samples', could play a role in machine learning model training. Machine learning is defined as an approach to simulate human learning and allow computers to identify and acquire knowledge from the real world, and to improve the performance of some tasks based on this new knowledge [18]. The machine learning technology can handle high dimensional data, and extract hidden relationships within data in complex and dynamic environments [19]. It means that a successful machine learning model can identify the relationship between the input and output parameters from enough 'samples' which is almost impossible to represent by experimental or simulation methods.

Several popular machine learning algorithms involve linear regression, artificial neural networks, support vector machines and support vector regression, decision tree, etc [20]. In terms of the model establishment, many researchers would consider utilization of the machine learning algorithms, such as ANN, owing to its high efficiency [21]. As a new computational model, ANN [22] has rapid and large uses for handling various complex real world issues, and its popularity lies in information processing characteristics to learning power, high parallelism, fault tolerance, nonlinearity, noise tolerance, and capabilities of generalization [23,24].

In this paper, the following issues will be addressed: (1) Characterisation of the thermal performance parameters of the HPs; (2) The classification and management of the big data including acquisition, analysis and storing; (3) The classification of machine learning algorithms, and (4) Analysis of the previous research on HP structural optimization and performance prediction using machine learning technology.

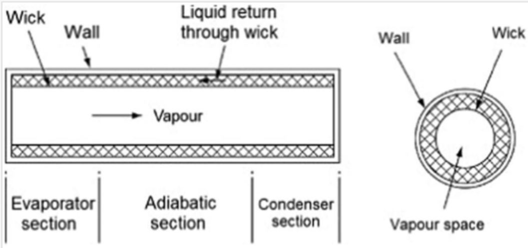
2 Characterisation of the HP thermal performance

The heat transfer capacity of a HP is limited by the geometrical and operational parameters, including the filling ratio, properties of the working fluid, inclination angle, structural dimensions, as well as the application occasion of the HP. These parameters will be investigated, thus forming the foundation for establishment of the dedicated HP database.

2.1 Operation principle

HPs have the advantage of driving passively with the natural circulation of the working fluid, which changes between the liquid and vapour phases without any additional energy input. The schematic of a HP [24,25] is shown in Fig. 2, and its working mechanisms including evaporation, adiabatic transfer and condensation. Heat passes through the evaporator section and provides the required thermal energy for evaporation of working fluid. Then, the vapor moves towards the adiabatic section then the condenser section, where the vapor turns into liquid by emitting its thermal energy. The liquid then returns to the evaporator section via the capillary wick structure, and the cycle continues.

Fig. 2



Schematic of a typical HP [25].

2.2 Performance parameters

The most relevant performance parameters of a HP include the type of a working fluid, filling ratio, inclination angle, as well as the geometrical sizes of the HP. These are illustrated as below:

2.2.1 Selection of the appropriate working fluids

With decades of research and development, a variety of working fluids ranging from cryogenic liquids to liquid metals [27] for the HPs have been identified and applied. The typical HP working fluids are pentane, acetone, methanol, ethanol, heptane, etc., and the selection of HP working fluids should take into account a number of factors, which including melting point, boiling point at atmospheric pressure and useful range [28,29].

During the fluid selection, a number of issues should be considered: (1) Compatibility with the wall and wick materials [30]; (2) Good thermal stability; (3) Wettability of the wall and wick materials; (4) Appropriate vapour pressures at the operational temperatures; (5) High latent heat; (6) High thermal conductivity; (7) Low liquid and vapour viscosities; (8) High surface tension; and (9) Acceptable freezing or pour point.

To ensure that the device starts at a minimum temperature difference between the evaporation zone and the compensation chamber, the pressure and temperature differences should be considered. The working fluid selection also should take into account the heat transfer limitations including sonic, capillary, viscous, entrainment and boiling limit. According to Reay [31], the convenient criteria to choose an acceptable working fluid in most cases is to compare the figure of merit number (M). The figure of merit is defined as a function of the surface tension σ_l, the latent heat L, the liquid density ρ_l and viscosity μ_l, which is expressed in Eq. (1). The larger merit number will lead to a higher heat transfer capacity.

$$\mathrm{M} = \frac{\sigma_l L \rho_l}{\mu_l} \tag{1}$$

2.2.2 Filling ratio of the working fluid

The thermal performance of a HP system could be highly affected by the refrigerant filling ratio [32], which is defined as the ratio of the working fluid volume to the evaporator volume. A lower filling ratio results in the dry-out phenomenon occurring in the evaporation part, while a high filling ratio results in the high flow resistance due to the mixture of the liquid and vapour from boiling [33].

Researchers have studied the filling ratio of the working fluid for different HPs. The recommended filling ratio of a heat pipe system should be at least 50% of the volume of the evaporator [33]. Ling et al. [34] experimentally studied the impact of filling ratio on a closed-loop HP system with separated micro-channel evaporator and condenser as a cooling device, showing that the optimal filling ratio was in the range 88–101%. Babu et al. [35] studied the thermal performance of a pulsating heat pipe, by CFD simulation and experiments, showing that the filling ratio of 60% led to a smaller thermal resistance. Molan et al. [36] experimentally investigated the effect of the filling ratio on the thermal performance of a multi-turn pulsating heat pipe, indicating that the optimal filling ratio may be in the range 48.8–66.1%. Ding et al. [37] mainly studied the filling ratio and Freon types as the influence factors of the loop HP system used in data centre cooling and analysed the relationship between the heat transfer capacity and filling ratio varying from Freon types. Ling et al. [38] for the first time, applied smooth and rough porous copper fiber sintered sheets into a loop HP system. They investigated the influence of filling ratio, highlighting that a filling ratio at 30% of the deionized water was the optimal combination for their designed loop HP. Chang et al. [39] established a CFD model to simulate the evaporator of a micro-channel separated heat pipe. The simulation results showed that the optimal refrigerant filling ratio was in the range 68–100%. Li et al. [40] experimentally investigated the thermal and electrical performance of a solar photovoltaic/loop-heat-pipe water heating system with different refrigerant filling ratios, showing that filling ratio at 30% was conductive to improve solar thermal efficiency of this system and filling ratio at 40% was conductive to improve electrical efficiency. He et al. [41] theoretically and experimentally studied the operational performance of a novel heat pump assisted solar facade loop-heat-pipe water heating system, which was charged with R600a as working fluid at the filling ratio of 35%. Zhou et al. [42] presented a miniature loop HP employing deionized water as the working fluid. The filling ratio of 37% was selected owing to the consideration of the start-up characteristics. From the above references, it can be observed that the best filling ratio changes with type of working fluid and structure of HP, which is outlined in Table 1.

Table 1

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Comparison of the filling ratio of the working fluid in different HPs.

References	Material/working fluid	Filling ratio
Ling et al. [34]	/R22	88%-101%
Babu et al. [35]	copper tube/acetone	60%
Molan et al. [36]	stainless steel/helium	48.8%- 66.1%
Ding et al. [37]	copper tube/R134a	71%
Ling et al. [38]	copper/deionized water	30%
Chang et al. [39]	/R22	68%-100%
Li et al. [40]	/refrigerant	30%-40%
He et al. [41]	/R134a	35%
Zhou et al. [42]	/deionized water	37%

2.2.3 Inclination angle

The inclination angle of a heat pipe, defined as the angle between the heat pipe axis and the horizontal datum, is very important to the systems with spatial changes in position [43]. As the inclination angle increases from 0° to 60°, the evaporator section moves towards the ground, leading to an easy return of the refrigerant from the condenser to the evaporator, owing to the combined effect of the gravitational and capillary forces. As a result, the efficiency of the heat pipe would increase. However, further increase in the inclination angle would lead to the reduced heat transport capacity, which is because that the gravitational forces will oppose the movement of evaporated fluid from the evaporator section to the condenser section [44].

Researchers have studied the different inclination angle of the HPs. Aly et al. [43] investigated the performance of a helically-micro-grooved heat pipe working with water-based alumina nanofluid, showing that the inclination angle of 60° leads to the best thermal performance of the heat pipe using water or nanofluid. ChNookaraju et al. [44] investigated the thermal performance of a sintered-wick heat pipe at various inclination angles with gravity-assisted tilt, showing that the maximum heat transport capacity takes place at 60° gravity-assisted tilt followed by 90°. Alammar et al. [45] used CFD simulation to investigate the performance of the two-phase closed thermosiphon at the five fill ratios of working fluid and five inclination angles. They found that the best fill ratio and inclination angle were 65% and 90° respectively. Reji et al. [46] tested the thermosyphon heat pipe under various angles of inclination with two working fluids, i.e., water and aluminium nanofluid. The results showed the peak efficiency of 88% was obtained at an inclination angle of 60°. Rahman et al. [47] investigated the heat transfer performance of an OLPHP. They found that using the OLPHP as an integrated structure would achieve higher thermal conductance to the host substrate, while the optimal inclination is 45°. Tharayil et al. [48] investigated the performance of cylindrical heat pipes at various inclinations (−90° to +90°). They found that for the cylindrical heat pipe at an inclination of −45°, the maximum heat transfer coefficients of the evaporator and condenser were 3876 W/m^2 K and 1698 W/m^2 K. Wang et al. [49] studied the effect of liquid filling ratio and inclination angle on the performance of a novel FPMHP. They found that when the inclination angle increased from 20° to 90°, FPMHP performance was considerably improved. Wang et al. [50] designed a novel concentric condenser heat pipe array and found that the array provided a better heat transfer performance and better maximum heat transport capacity, at the operating temperature of 80 °C and the inclination angle of 60°. Jahan et al. [51] studied the effect of inclination angle and working fluid on the heat transfer performance of a CLPHP and found that the inclination operating angle changes the internal flow patterns and the best performance of CLPHP is obtained at 75°. From the above references, it can be concluded that the best inclination angle for any heat pipe depends on many other factors such as geometry, heat input, type of liquid and operating conditions. These are outlined in Table 2.

Table 2

Best inclination angle of different HPs.

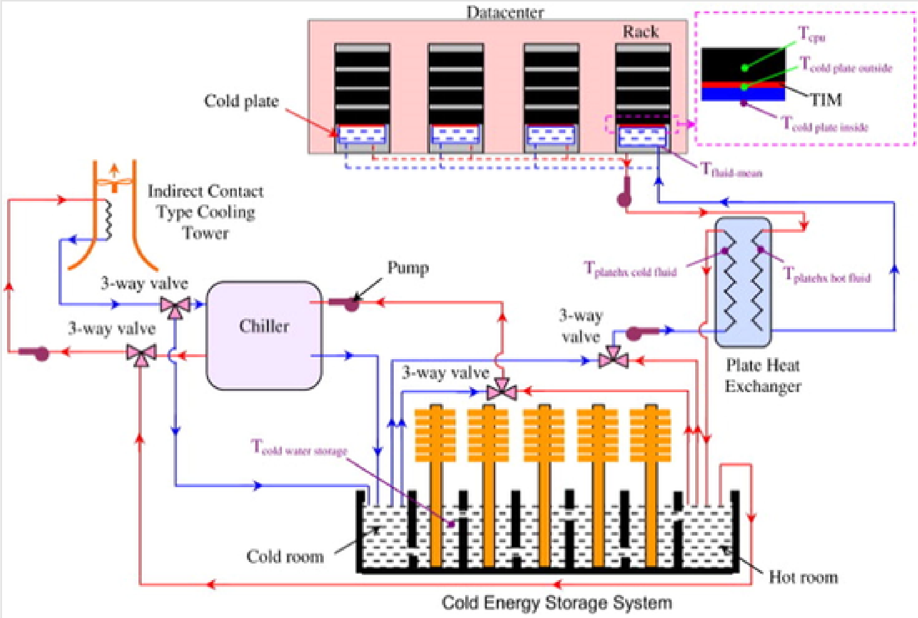
References	Type of heat pipe	Inclination angle
Aly et al. [43]	Helically-micro-grooved heat pipe	60°
ChNookaraju et al. [44]	Sintered-wick heat pipe	60°
Alammar et al. [45]	Two-phase closed thermosiphon	90°
Reji et al. [46]	Thermosiphon heat pipe	60°
Rahman et al. [47]	Open-loop pulsating heat pipe	45°
Tharayil et al. [48]	Cylindrical and Flattened hat pipe	−45°
Wang et al. [49]	Novel flat-plate micro heat pipe	90°
Wang et al. [50]	Concentric condenser heat pipe array	60°
Jahan et al. [51]	Closed-loop pulsating heat pipe	75°

2.2.4 Structural parameters

These heat pipes have different structures e.g. micro-channel, thermosyphon, and pulsating ones, different combination forms e.g. separated and integrated ones, different driving modes e.g. pump-driven, PCM-assisted and gravity-assisted [52]. All these brought about significant variation in heat transport capacity and operational condition.

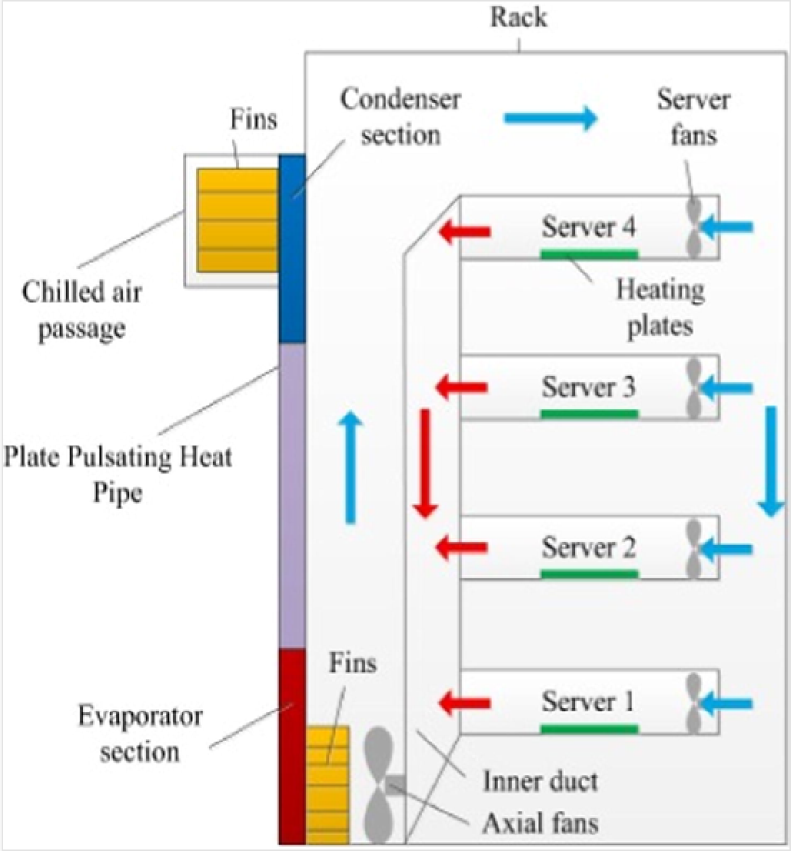
Researchers have studied the wide application in various industrial and engineering practices. Ding et al. [53] analysed the components of a separated heat pipe system and found that the evaporator of the system can soon absorb heat, leading to little local hot spots inside the data centre room. The total entrant dissipation of the separated heat pipe system was 48.3% lower than the CRAC system. Zhou et al. [54] developed a pump-driven loop heat pipe for small-sized data centre and it can save over 20% energy if the indoor temperature was maintained at 18–25 °C. If 74.2% of the Chinese cities adopted this technology, the annual energy saving rate will reach over 30% [55]. Tian et al. [56] designed a two-stage heat pipe loops that are combined with water loop and coupled with serially connected multi cold sources. This system can dynamically and effectively adjust the cooling load distribution and reduce cooling cost by around 46% compared to the CARC system. Liu et al. [57] developed a hybrid cooling system that combines the dew-point evaporative coolers with heat pipes and the average annual COP of the ideal systems was around 34, leading to annual energy savings of nearly 90% compared to vapour compression cooling system. Wang et al. [58] designed the integrated heat pipe system which integrates the heat pipe cycle with the vapour compression cycle and operates simultaneously. The results showed that the power usage efficiency of the data centre using this system can be 0.3 lower than that using the conventional air-cooling systems in cold areas. Behi et al. [59] designed the phase change material (PCM) assisted heat pipe for electronics cooling. The study revealed that the PCM assisted heat pipe provided up to 86.7% of the required cooling load in the working power ranging from 50 W to 80 W. Sun et al. [60] proposed the thermoelectric cooling system integrated with the gravity-assistant heat pipe for cooling electronic devices. This system increased the cooling capacity by approximately 73.54% and the electricity consumption was reduced by 42.2%, compared to the thermoelectric cooling system. Singh et al. [61] studied the design and economics of the thermal control system for data centre using heat-pipe-based cold energy storage system, which is shown in Fig. 3. The results showed that this system can save around 3 million dollars each year for a data centre with heat capacity of 8,800 kW. Ling et al. [62] proposed the water-cooled multi-split heat pipe system to cool the space in modular data centres and found that the optimum refrigerant filling rate was in the range 33–42% with cooling capacity ranging from 6100 W to 6200 W. Dang et al. [63] proposed a closed rack cooling system with pulsating heat pipe and carried out the numerical study of its heat transfer performance, which is shown in Fig. 4. The results showed that the temperature of the CPU would decrease and the temperature distribution of the CPU would be uniform.

Fig. 3



Data centre facility with heat-pipe-based cold energy storage system [61].

Fig. 4



Schematic of the closed rack cooling system with pulsating heat pipe [63].

Utilizing different types or structures of HP could dynamically meet specific onsite requirements for material compatibility and temperature ranges and significantly save energy. From the above references, comparison of different structures of HP with different drive modes is presented in Table 3.

Table 3

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Comparison of different HPs with different driving modes.

Reference	Structure	Driving mode
Ding et al. [53]	Separated heat pipe	Gravity
Zhou et al. [54]	Pump-driven loop heat pipe	Pump
Tian et al. [56]	Two-stage heat pipe	Gravity
Liu et al. [57]	Micro-channel separated heat pipe	Pump

Wang et al. [58]	Integrated heat pipe	Gravity
Behi et al. [59]	PCM-assisted heat pipe	Capillary
Sun et al. [60]	Gravity-assisted heat pipe	Gravity
Singh et al. [61]	Thermosyphon	Gravity
Ling et al. [62]	Multi-split heat pipe	Gravity
Dang et al. [63]	Pulsating heat pipe	Pressure difference

3 A review-based study of big data technology

Big data technology has already widely used in other industries such as manufacturing, services, financial, etc. This section will review the multi-category big data technology and explore the possibility of utilizing big data technology to deal with the HP data.

3.1 Previous researches on big data technology and its application

The HP data usually comes from experiments or field testing. These massive amounts of tabular data often contain different types of parameters, representing different physical meanings. It is a challenge to find valuable information to form a complex and diverse dataset. Some previous researches are presented. Shafieian et al. [64] developed various data-based models to simulate the performance of the HPSCs. They found that the ANN was the best method to predict the performance of the HPSCs, and the highest difference between the experimental and theoretical thermal efficiencies was observed in autumn and winter, which are 3.56% and 3.55% respectively. Ayompe et al. [65] used the data obtained from a field trial installation to analyse the thermal performance of a solar water heating system with heat pipe. They found that the annual average solar fraction, collector efficiency and system efficiency were 33.8%, 63.2% and 52.0% respectively. Nookaraju et al. [66] utilized the historical data to present the convective heat transfer coefficient of a hybrid wick heat pipe, and RSM was utilized to optimise the model. The result showed that the ideal working conditions were acquired at the mass flow rate of 0.04 kg/s, tilt angle of 15° and heat input of 176 W.

From the above references, the optimization of heat pipes mainly utilized the massive historical or experimental data, lacking more professional technology to sort out and analyse these huge amount of data [67]. This means that an appropriate big data technology should be identified and studied in order to provide the dimensionless and multiple-factors-considering solution for HP structural optimization and performance prediction.

3.2 Comparison of different forms of big data

According to different varieties, the big data can be classified into three different forms, i.e., structured, unstructured data, and semi-structured. Structured data [7], which constitutes only 5% of all existing data, is usually defined with the fixed attributes, type, and format. Compared to unstructured or semi-structured data, the processing of structured data is relatively simpler and more straightforward.

Unstructured data [68] is any stored information that comes with different sizes, that contains information expressed as a single concept in many different ways, that is not neatly packaged into spreadsheet cells, that cannot be assigned a numeric value, or that does not conform in any way to a specific data standard.

Semi-structured data [69] is a continuum between the fully-structured and unstructured data, which does not conform to strict standards. The basic characteristic is that they are “self-describing”, which means that the information generally associated with the schema is specified directly within data. Different forms of big data are compared in Table 4 [70,71]
.

Table 4

Comparison of different forms of big data.

Type	Advantage	Disadvantage	Examples
Structured	Simple, easy processing, and straightforward	Scarce	Tabular data found in spreadsheets or relational databases
Unstructured	Easy to collect	Various types, and difficult to extract	Text, images, audio and video
Semi-structured	Information can be represented by different types of data, and contain implied pattern information	Lacking strict type constraint of data, and irregular structure	Extensible Mark-up Language (XML), textual language for exchanging data on the Web

3.3 Comparison of different big data technologies

The big data technologies [72] represent the technologies to efficiently deal with huge data feeds, due to the capability to process data in a variety of environments, e.g., batch, and stream.

3.3.1 Technologies based on batch processing

The batch-based processing technologies [14], ideal for processing large, bounded, persistent and not-time-sensitive datasets requiring significant computation, including Apache Hadoop, Dryad, and Tableau.

Apache Hadoop [14,73] is a batch processing tool that provides scalability and fault-tolerance. This technology has the advantages of quick retrieval, searching log data and fast insertion. Thus, it becomes one of the most popular big data technologies. However, the disadvantages of the Apache Hadoop are the restrictive programming model, joint multiple datasets, hard cluster management, single master node and unobvious configuration of the nodes.

Dryad [11], based on the dataflow graph processing, is a popular programming model which consists of a cluster of computing nodes, and a computer cluster used to run the programs in a distributed manner. It has the advantages of graph generation, processing schedules, handling errors in a cluster, and handling user-defined policies. The programmers don't need to know about parallel programming with the help of Dryad framework. However, the disadvantages of the Dryad are unsuitable for the iterative and nesting programme, and difficult to convert irregular computing into a data flow graph [14,74].

Tableau [75] is utilized to process large amounts of datasets, which consists of the Tableau Desktop, Tableau Public, and Tableau Server. Tableau Desktop is to visualise data. Tableau Server provides browser-based analytics, and Tableau Public creates interactive visuals. Tableau has the advantages of great data visualisation, low-cost solutions to upgrade, excellent mobile support and convenient to present big data analytic results. However, the disadvantages of the Tableau lie in the lack of predictive capabilities, risky security, and changing management issues [14,76].

3.3.2 Technologies based on stream processing

The technologies based on stream processing [74] are ideal to handle a large volume of real-time data. It could be very low latency while processing the data from a large volume of data and overcome the challenges when dealing with a huge volume of data, high speed of data and the time dimension. The stream-based technologies include Storm, SQL Stream s-Server, and Splunk.

Storm [11,77] is a free and open technology applied to real-time computation system, which makes it easy to reliably process unbounded streams of data. The Storm cluster is comprised of master and worker nodes which are implemented through nimbus and supervisor, two types of daemons. Storm has the advantages of easy to operate, which ensure that all the data will be processed, efficient, scalable and fault-tolerant. However, the disadvantages of the Storm are poor performances in reliability, efficiency, and manageability [14,74].

SQL Stream [78] is a big data platform that is designed for processing large-scale streaming data in real-time and focuses on intelligent and automatic operations of streaming big data. The new version of SQL Stream is SQL Stream s-Server that is developed to perform better in data gathering, conversion and sharing of real-time data. It has advantages of low cost, scalable for high-volume and high-velocity data, low latency, rich analytics and better performances in real-time data collection, transformation and sharing. However, the disadvantage of the SQL Stream s-Server is the high complexity [11,14,74].

Splunk [74] is an intelligent and real-time platform for exploiting information from machine-generated big data, which also gives users the facility to access, monitor and analyse data through the web interface. Splunk has the advantages of great performance from security to business analytics to infrastructure monitoring, indexing structured or unstructured machine-generated data, real-time searching, reporting analytical results and dashboards. However, the disadvantages of Splunk are high setup costs and high complexity [11,14].

In general, the batch-based processing technologies can be very efficient where data is collected, stored, and processed, and the results are produced in batches. But it has limitations in terms of resource utilisations and real-time processing capabilities. In contrast, stream-based processing technologies mostly focus on the velocity of data and help to process data in a very short time.

3.4 Big data management and analytics

The real challenge for big data is that the variety of sources makes it hard to deal with the information [79]. Thus, to turn high volumes of fast-moving and diverse data into meaningful insights, the data acquisition and processing contains two main parts [7]: data management referring to data acquiring, store, preparation and retrieval, and analytics referring to acquiring intelligence from big data.

There is a current approach for big data management and database design which could be divided into the following several steps [80]:

(1) Data capture: Many data are recorded from diverse data generating sources. The principle of data capture [81] is the separation of data from author interpretations, extensive and flexible capabilities for phase identification, well-structured capture of metadata related to sample characterisation, and quantitatively defined uncertainties.

(2) Data cleaning and storage: The objective in this phase is to store the data in a structured form suitable for analysis. The cloud database [82] may be a great solution to store and process data, residing on a private, public or hybrid cloud computing infrastructure platform. After collecting data in different databases of the physical layers, all the data will be hosted on a cloud platform.

(3) Data integration and aggregation: The SQL or NoSQL database is a current approach for large and distributed data management and database design. SQL database is a logical choice for the management of data containing fixed or rarely changeable structure. NoSQL database is mainly to deal with the fast processing of vast quantities of unstructured data. Hybrid SQL/NoSQL database would be a popular solution for parallel use of different database types [83].

(4) Query processing, data modelling and analysis: Data mining [84] is a set of techniques to extract precious information from data. However, most of the data mining-based methods are still not mature enough for practical applications, and it is therefore necessary to develop universal, automatic and domain knowledge-driven data mining-based methods.

(5) Data interpretation and visualisation: Due to the complexity of data, it is crucial to choose proper data representation tools, e.g., graphical interfaces, to visualise big data. The use of data interpretation and visualisation tools [85] can help to consume, explore and understand complex data.

Utilizing the above big-data technology and HP database, the machine learning model could provide the multiple-factors-considering solution, which would significantly reduce the computational time, simplify the calculation process, and improve the accuracy of the simulation results. Furthermore, it could provide a simpler, straight-forward and comprehensive mathematical relationship among the HP geometrical and operational variables and resultant parameters.

4 A comprehensive study of machine learning technologies

Machine learning technologies are considered as a suitable method for the HP design, structural optimization and performance prediction. Several popular machine learning algorithms would be presented in this section, but the most appropriate approach will be compared and finally selected.

4.1 Characteristics of machine learning

The machine learning algorithm is fed by a series of input/attribute '$\mathbf{x}$' and related output/label '$\mathbf{y}$'. The purpose is to estimate a mapping relationship $\mathbf{f}(\mathbf{x})$ which could minimise the value of loss function $\mathbf{L}(\mathbf{y}, \mathbf{f}(\mathbf{x}))$, and use the $\mathbf{f}(\mathbf{x})$ as a data-driven model to map new attribute $\mathbf{x}$ to unknown $\mathbf{y}$.

Aiming at the overfitting problem in machine learning algorithms, the common operation for databases is divided into 'training set' and 'testing set', and the model performance for both datasets is evaluated to remit the overfitting problems. There are four common strategies to confront overfitting problems, which are bias-variance relationship weight decay, learning rate decay, cross validation and regularization. The performance of the model could be evaluated by different metrics, such as mean bias error, coefficient of variation of root mean square error and mean absolute percentage error.

4.2 Comparison of different machine learning algorithms

Several popular machine learning algorithms will be presented including linear regression, artificial neural networks, support vector machines, and decision tree etc. Different machine learning algorithms are compared in Table 5.

Table 5

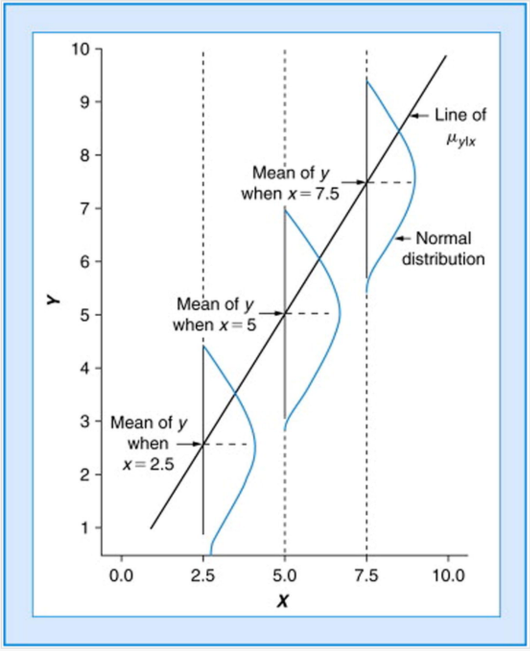
The table layout displayed in this section is not how it will appear in the final version. The representation below is solely purposed for providing corrections to the table. To preview the actual presentation of the table, please view the Proof.

Comparison of different machine learning algorithms.

Algorithm	Advantage	Disadvantage
Linear regression	Good comprehensibility	More computation time in training phase
Artificial neural network	Conducting non-linear mapping and classification	Analysis results cannot be ascertained
Support vector machine	Applicable to classification tasks	More data to prove effectiveness
Decision tree	Enhance the prediction accuracy, Decrease the computational time	More nodes to test effectiveness

The linear regression model (see Fig. 5) predicts the linear combination of attributes [86]. Its target function has a very simple basic vector form and the linear model has good comprehensibility that is not easily available in complex models. Classical linear regression models include logistic regression and linear discriminant analysis. Logistic regression is a type of generalised linear model. Linear discriminant analysis is a classic dimension reduction technique. The basic idea is to project the sample space into a low-dimensional space.

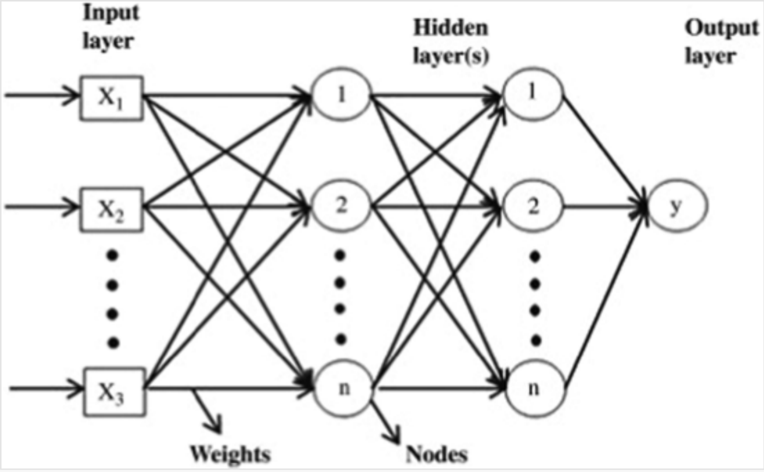
Fig. 5



General schematic representation of linear regression model [86].

Artificial Neural Networks (ANN) is widely cited in the prediction and calculation of complex systems due to its advantages in non-linear regression and classification [87]. Basically, ANN (see Fig. 6) is a black-box data-driven method enabling conducting non-linear mapping between the input and output variable sets without considering their physical interpretation. The error backpropagation learning algorithm is one of the most typical learning algorithms which is based on the gradient descent strategy. Other commonly-used neural networks include radial basis function neural network, adaptive resonance theory neural network, self-organizing map neural network, and recurrent neural network.

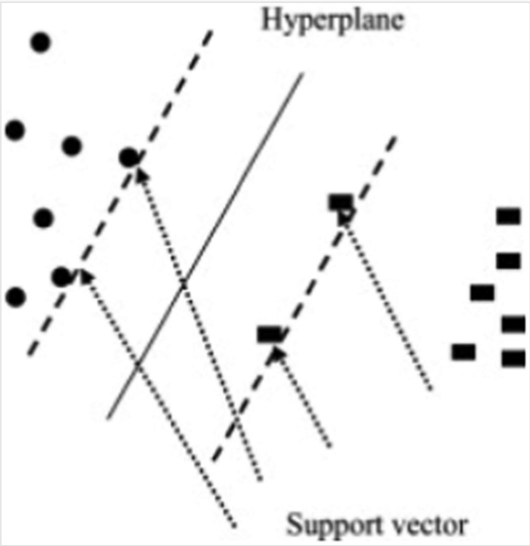
Fig. 6



General structure of ANN [87].

Support Vector Machine (SVM) (see Fig. 7) is a kernel learning technique showing excellent performance in classification tasks [88,89]. The objective is to find a hyperplane in high-dimensional space, which represents the maximum margin between any two instances of two types of training data points or maximizes the correlation function when it cannot be separated. Support Vector Regression (SVR) is based on SVM and applied to resolve the regression problems.

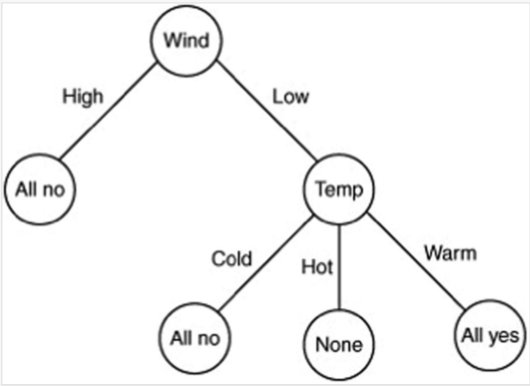
Fig. 7



General structure of SVM [89].

Decision tree is a machine learning method for making decisions based on the tree structure and it partitions the dataset on the given attribute in order to calculate the information gain (see Fig. 8) [90]. Generally, a decision tree contains a root node, several internal nodes, and several leaf nodes. The root node contains the whole sample space, each internal point corresponds to an attribute test to select the sub-branch of the tree, and the leaf node corresponds to the decision result. The path from the root node to the leaf node corresponds to a decision test sequence [91]. According to the method of selecting the best attribute of dividing nodes, the decision tree method can be divided into three main catalogues, i.e., ID3, C4.5, and classification regression decision tree.

Fig. 8



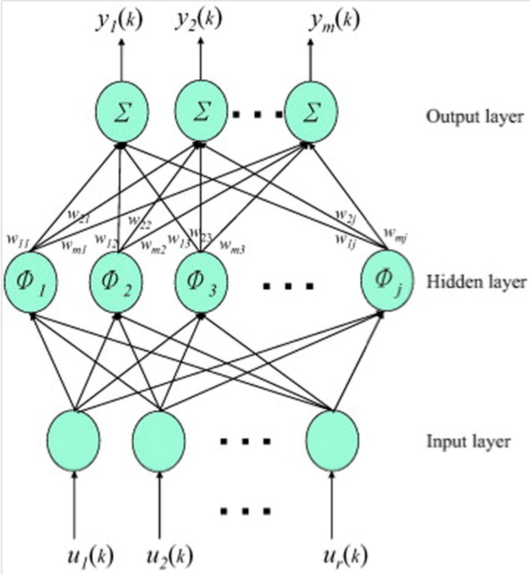
General structure of decision tree [90].

5 Previous research in HP characterisation using machine learning technologies

Some researchers conducted the characterisation, structural optimization and performance prediction of HP using machine learning technologies including classification and regression techniques.

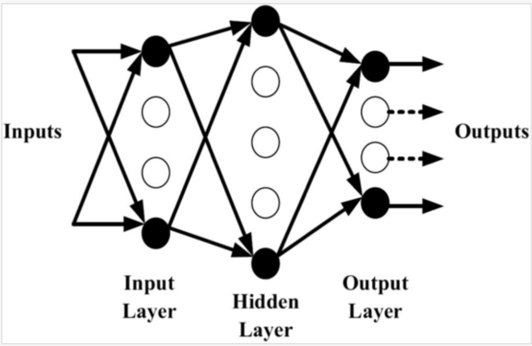
For the classification techniques, it is generally used to predict a discrete response that means the data can be categorized, labelled or separated into specific group or classes. Lee and Chang [92] used a nonlinear autoregressive model with exogenous neural networks (see Fig. 9) to predict the thermal dynamic performance of a pulsating heat pipe. The study was carried out in both the time and frequency domains, and the result showed the effect of the heating source on the condensation process by temperature responses. Chen et al. [93] developed a mathematical model for a CLPHP. The model, based on an approach of the nonlinear autoregressive moving average, provided the relationship between the response temperature differences between evaporator, adiabatic, and condenser. Jokar et al. [94] used a multilayer perceptron neural network (see Fig. 10) and genetic algorithm to investigate and optimise the pulsating heat pipes. The model was trained using the experimental data, and the results revealed that the optimum values of the inputs including the filling ratio, input heat flux to the evaporator and inclined angle were 38.25%, 39.93 W and 55° respectively. Malekan et al. [95] used multilayer feed-forward neural network, adaptive neuro-fuzzy inference system and group method of data handling type neural network to predict the thermal resistance of a closed-loop oscillating heat pipe. The root-mean-square error of the three methods was 0.05, 0.05, and 0.05 respectively. Ahmadi et al. [96] created four models, including multilayer perceptron, radial bias function, conjugated hybrid of particle swarm optimization and adaptive neuro-fuzzy inference system, to predict the thermal resistance of the pulsating heat pipes. The results indicated that the radial bias function model was able to predict the thermal resistance more accurately, and the R-squared and root mean squared error values for this model were 0.9892 and 0.0650, respectively. Qian et al. [97] proposed a heat transfer prediction model based on the extreme gradient boosting algorithm to choose the suitable geometry and cooling methods of the oscillating heat pipes for enhancing the heat transfer. The results showed that the mean absolute percentage error varied from 0.01% to 13.09% under the training set range of 4550–22,750 W/m^2. Elghool et al. [98] used the response surface methodology to determine the optimum geometry of the heat pipe heat sink to improve the performance of the thermo-electric generator. The results showed that the efficiency after the optimization was 3% respectively, which was improved by 36.7% compared to the previous results.

Fig. 9



Schematic view of a exogenous neural network [92].

Fig. 10

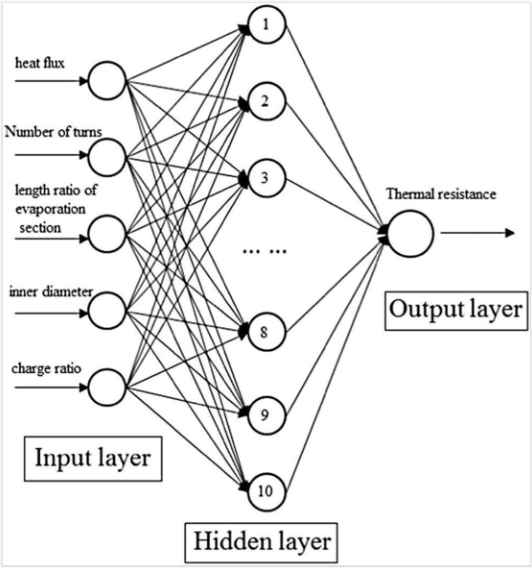


Schematic of a feed forward multi-layer neural network [94].

For the regression techniques, it is generally used to predict continuous responses that means working with a data range or if the nature of the response is a real number such as temperature. E et al. [99] used the ANN and grey relational analysis to study the heat transfer performance of an oscillating heat pipe. It was identified that the developed model could predict the performance with the maximum error of 4%. Patel et al. [100] developed a model for a pulsating heat pipe based on feed-forward backpropagation neural network and regression/correction analysis approach. The dataset for the ANN development comprised 1652 experimental data which were collected from the literature (2003–2017). Linear and power-law regression correlations were developed for input heat flux in terms of dimensionless Kutateladze number. Wang et al. [101,102] used the ANN (see Fig. 11) to analyse the performance of the pulsating heat pipes with different working fluids under diverse operating conditions. The root-mean-square error and the correlation coefficient of the ANN model were 0.01 and 0.98 respectively. Maddah et al. [103] used the ANN for a heat pipe heat exchanger with CuO/water nanofluid as the working fluid. The thermal performance, filling ratio, the concentration of nanofluid and input power were predicted by the model with the maximum error of 0.99. Liang et al. [104] established a back-propagation neural network model which was parameterized by genetic algorithm for thermal performance prediction of the miniature revolving heat pipes. The results showed that the established model could achieve the best prediction accuracy with the square of correlation coefficient of 0.92599. Qu et al. [105] used non-linear analysis to investigate the behaviour of the wall temperature oscillations in a closed-loop pulsating heat pipe. Results showed that all the calculated positive largest Lyapunov exponents were found to be less than 0.1, representing the weak chaos characteristics of the pulsating heat pipe. Shanbedi et al. [106] proposed an ANN (see Fig. 12) to estimate the thermal efficiency and resistance of thermosyphon with nanofluid. Combining neural networking and generic algorithm methods together, the R-values of MLP-ANN model were obtained over 0.99. Salehi et al. [107] designed an optimized ANN to predict the heat transfer of thermosyphon charged with silver/water nanofluid. They found that the thermal efficiency and resistance estimated by the multi-layer perception neural network were accurate. Kahani et al.

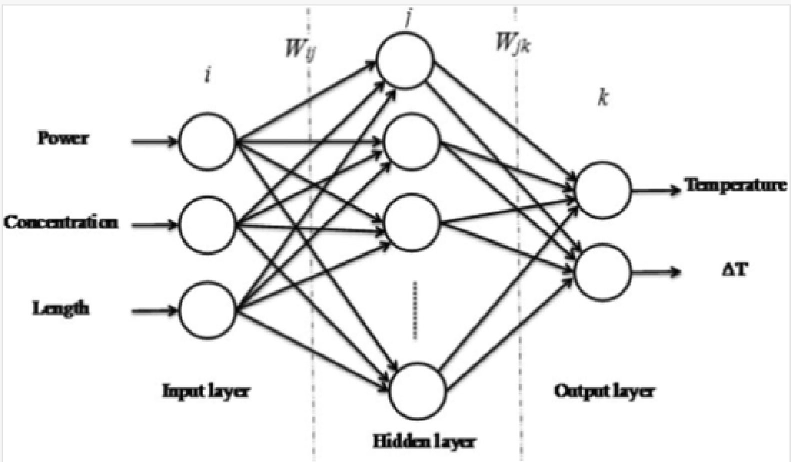
[108] designed an optimized ANN to predict the thermal performance of thermosyphon charged with Al_2O_3/water nanofluid. The R-squared value is 0.9822 which means that the output data of the model were sufficiently close to experimental data. Facao et al. [109] designed an ANN model to estimate two types of hybrid HPSCs (tube heat pipe type and plate heat pipe type) based on the results from mathematical models. The significant advantage of the model was that convergence was not an issue compared with mathematical models, and the outputs were obtained instantaneously.

Fig. 11



Schematic of ANN model [101].

Fig. 12



Schematic of MLP structure [106].

The above-mentioned research works have been summarised in Table 6.

Table 6

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Summary of the research works.

References	Input parameters	Machine learning algorithm	Output parameters
Lee and Chang [92]	Structural geometry, heating source	Nonlinear autoregressive model with exogenous neural network	Temperature response
Chen et al. [93]	Structural geometry	Nonlinear autoregressive moving average model with exogenous inputs	Temperature differences in different sections
Jokar et al. [94]	Input heat flux to evaporator, filling ratio, inclination angle	Multilayer perceptron neural network and genetic algorithm	Thermal resistance
Malekan et al. [95]	Heat input, thermal conductivity of working fluids, ratio of inner diameter to length	Multilayer feed-forward neural network, adaptive neuro-fuzzy inference system, group method of data handling types neural network	Thermal resistance
Ahmadi et al. [96]	Filling ratio, thermal conductivity, inclination angle, lengths of adiabatic, condenser and evaporator sections, heat input, inner and outer diameters	Multilayer perceptron, radial bias function, conjugated hybrid of particle swarm optimization and adaptive neuro-fuzzy inference system	Thermal resistance
Qian et al. [97]	Jakob number, Karman number, Prandtl number, Bond number, Morton number, heat flux, evaporator temperature, geometric parameters	Heat transfer prediction model based on the extreme gradient boosting algorithm	Effective heat transfer coefficient
Elghool A et al. [98]	Fin length and height	Response surface methodology	Power output, efficiency, cost
E et al. [99]	Charge ratio, inner diameter, inclination angle	ANN and grey relational analysis	Performance
Patel et al. [100]	Structural geometry	Feed-forward backpropagation neural network and regression/correction analysis	Input heat flux
Wang et al. [102,103]	Structural geometry, ratio of evaporation section length to diameter	ANN	Performance
Maddah et al. [103]	Structural geometry	ANN	Thermal performance, filling ratio, concentration of working fluid and input power
Liang et al. [104]	Jacob number, Bond number, Prandtl number, Froude number, filling ratio	Back-propagation neural network model and genetic algorithm	Thermal performance
Qu et al. [105]	Filling ratios, heating power, Jakob number, Karman number, inclination angle, Prandtl number	Non-linear analyses	Thermal resistance
Shanbedi et al. [106]	Weight fraction of nanofluid, Input power	ANN, Generic algorithm	Thermal efficiency and resistance
Salehi et al. [107]	Volume fraction of nanofluid, Inlet power	ANN	Thermal efficiency and resistance
Kahani et al. [108]	Input power, Filling ratio, Volume concentration of nanofluid, Mass rate	ANN	Thermal efficiency
Facao et al. [109]	Solar radiation, Inlet gas, water, ambient temperature, Evaporator and condenser length, Water and gas mass flow rate	ANN	Efficiency and heat output

6 Challenges – current status and deficiency

This review-based study proposes the possibility of developing the big-data-trained machine learning approaches, which would be able to achieve better, faster and reliable simulation, optimization and performance prediction results for the HPs. To enable this, a number of identified scientific challenges need to be tackled. These are detailed below.

6.1 Lack of suitable sampling methods for complex and redundant HPs experimental data

There are many sources of HP experimental data, which can be measured from the field or derived from theoretical studies. With many different meanings and structures of these experimental data from different sources, selection of the suitable data resource, and integration and transformation of the HP data will be the priority issues to be tackled. Generally, HPs data is arranged in a form of tabular layout, which needs to be extracted and pre-processed to lay the foundation for subsequent works. However, the data extraction form is predefined, and some useful data might be missed likely in this extraction process. Different structures and types of HP's data lead to different data characteristics which implies that the process of the data acquiring would lack the selection standards, sorting standards and suitable sampling methods.

6.2 No appropriate big data technology for processing HPs' data

Big data technologies have been generally applied to the internet industry and now gradually applied to the manufacturing industry. However, no specific big data technology has been developed for processing the HPs data owing to the selection criteria for an appropriate big data technology is not in existence. It should also be noted that with different functions of big data technologies, the framework of data processing tools based on big data platform are different. Although many tool packages in popular programming languages like R and Python are in rapid development, it is still lack appropriate and stable development tools for non-professionals.

6.3 No appropriate standard for selecting machine learning algorithm to establish HP model

During the previous works, many researchers conducted the performance prediction of HP using a machine learning algorithm. However, big dataset establishment and associated machine learning training approaches were not well addressed, and the appropriate machine learning algorithms for HP structural optimization and performance prediction were not appropriately investigated, which are the essential research gaps in existence. At present, the ANN is a commonly used machine learning algorithm for HP simulation and optimization. However, comparison among the ANN and other algorithms have not yet been undertaken, and the most appropriate machine learning algorithm has not yet identified.

6.4 Lack of a suitable method to interface big data technology and machine learning technology

The works on applying big data technology and machine learning technology are substantial. However, careful consideration should be made on when and how to apply machine learning approaches to big data. Meanwhile, it is also urgent to solve the problem of how to find a suitable method to connect machine learning approach with big data technology and deal with the relationship between machine learning model and database. The number of samples required for machine learning model training needs to be confirmed, because using more samples is not always necessarily the best. Some machine learning approaches perform well under different sizes of training data, while the prediction performance of many others fluctuates largely with the training size.

7 Opportunities for future works

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

7.1 Data munging for HPs experimental data

Most HP's data (geometric structure parameters, experimental data, performance parameters, etc.), acquired by previous research work, are massive, heterogeneous and inconsistent. Hence, a new tool, based on big data technologies, should be explored which can capture, analyse and store HP's experimental data according to the selection standards and sampling methods. It could achieve data munging, which commonly includes data exploration, transformation, enrichment exploiting metadata, cleaning or scrubbing the data which are not required for getting the underlying trends of data, and then data validation. So that the machine learning model, based on the structured HP database, could optimise the HP structure and predict its performance in both multi-variable and multi-objective optimisations.

7.2 Developing the way of combining multiple big data technologies for data analysis and processing

Most HP's experimental data need to be pre-processed, but big data technology is diverse, with many overlap functions and has its advantages and disadvantages. Some processing technologies could be very efficient where data is collected, stored and processed, and results are produced in batches, while others mostly focus on the velocity of data and help to process data in a very short period. Thereby integrating the advantages of multiple big data technologies, the advanced technology with high computational efficiency and accuracy need to be developed in different application scenarios.

7.3 Selecting the best machine learning approach by horizontal comparison

More data per feature and balanced data can help improve the performance of the machine learning models. Meanwhile, an appropriate machine learning approach to establish the HP model is worthy to be further investigated, in respect to the reliable design and the stochastic uncertainty-based performance analysis. So it is necessary to horizontally compare the advantages and disadvantages of ANN and other machine learning approaches to choose the suitable approach. Attention should be paid to a number of issues including the fine tuning of the algorithm parameters and problem objectives, the modification of the governing equations, and the accurate uncertainty quantification of scenario parameters, etc.

7.4 Exploring how to design an integrated system connecting the machine learning model with HP database

It is needed to seriously consider the sampling size for the data training, because more data could carry errors that lead to overfitting issues and misleading biases. Using more is not necessarily the best and a certain number of representatives 'samples' from the HP database need to be extracted for training the model and optimizing the algorithm.

The future studies are suggested to focus on the development of integrated system, with the aim of configuring advanced learning algorithms for the accurate surrogate model with less training epochs and simpler neural network, accurate quantifications of multi-diversified scenario parameters, and generic HP multi-objective optimization methodologies. The further studies could work on novel systematic configurations with the flexible switch on operating modes, the advanced system structural design and the advanced optimization methodology flexibly integrating advanced optimization algorithms.

8 Conclusions

A critical review on the use of big-data/machine-learning technologies for HP structural optimization and performance prediction is presented. This study addresses several important issues, including (1) characterisation of the operational parameters of HP to evaluate the requirements of establishing HP database; (2) review of the big data technologies; (3) review of the machine learning technologies and the application of several popular machine learning algorithms in the HP sector; and (4) challenges and opportunities in developing big-data-trained machine learning model for the HP structural optimization and performance prediction.

Given the current development status and challenges, the opportunities for further development big-data trained machine learning model for HP structural optimization and performance prediction are outlined as: (1) data munging for HPs experimental data; (2) developing the way to combine multiple big data technologies for data analysis and processing; (3) selecting the best machine learning approach by horizontal comparisons; (4) exploring how to design an integrated system connecting the machine learning models with HP databases.

This review-based study will contribute to applying big-data/machine-learning technologies to the structure optimization and performance prediction of HP and identifying the current status and potential problems remaining in this regard, with practicality and relevance for researchers who wish to harness the power of big-data/machine-learning technologies, thus creating significant energy saving benefits.

Q4 Uncited references

[26].

Declaration of Competing Interest

I, Xudong Zhao, hereby **declare** that I have no pecuniary or other personal **interest**, direct or indirect, in any matter that raises or may raise a conflict with my duties as a Professor and Director of the Centre for Sustainable Energy Technologies, University of Hull.

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Q5 References

The corrections made in this section will be reviewed and approved by a journal production editor. The newly added/removed references and its citations will be reordered and rearranged by the production team.

[1] Reay D., Kew P.A., McGlen R.J. Heat pipes: theory, design and applications. 6th ed. UK: Elsevier Ltd.; 2014.

[2] Alizadeh H., Ghasempour R., Shafii M.B., Ahmadi M.H., Yan W.-M., Nazari M.A. Numerical simulation of PV cooling by using single turn pulsating heat pipe. Int J Heat Mass Tran 2018;127:203–208. doi:10.1016/j.ijheatmasstransfer.2018.06.108.

[3] Gandomkar A., Saidi M.H., Shafii M.B., Vandadi M., Kalan K. Visualization and comparative investigations of pulsating ferro-fluid heat pipe. Appl Therm Eng 2017;116:56–65. doi:10.1016/j.applthermaleng.2017.01.068.

[4] Ebrahimi M., Shafii M.B., Bijarchi M.A. Experimental investigation of the thermal management of flat-plate closed-loop pulsating heat pipes with interconnecting channels. Appl Therm Eng 2015;90:838–847. doi:10.1016/j.applthermaleng.2015.07.040.

[5] Pater V.K. An efficient optimization and comparative analysis of ammonia and methanol heat pipe for satellite application. Energ Convers Manage 2018;165:382–395. doi:10.1016/j.enconman.2018.03.076.

[6] Lurie S.A., Rabinskiy L.N., Solyaev Y.O. Topology optimization of the wick geometry in a flat plate heat pipe. Int J Heat Mass Tran 2019;128:239–247. doi:10.1016/j.enconman.2018.03.076.

[7] Gandomi A., Haider M. Beyond the hype: Big data concepts, methods, and analytics. Int J Inf Manage 2015;35(2):137–144. doi:10.1016/j.ijinfomgt.2014.10.007.

[8] Ghasemaghaei M. Understanding the impact of big data on firm performance: the necessity of conceptually differentiating among big data characteristics. Int J Inf Manage 2021;57:102055. doi:10.1016/j.ijinfomgt.2019.102055.

[9] Bello-Orgaz G., Jung J.J., Camacho D. Social big data: Recent achievements and new challenges. Inform Fusion 2016;28:45–59. doi:10.1016/j.inffus.2015.08.005.

[10] Ghasemaghaei M., Calic G. Does big data enhance firm innovation competency? The mediating role of data-driven insights. J Bus Res 2019;104:69–84. doi:10.1016/j.jbusres.2019.07.006.

[11]

Chen C.L.P., Zhang C.Y. Data-intensive applications, challenges, techniques and technologies: a survey on Big Data. Inform Sciences 2014;275:314–347. doi:10.1016/j.ins.2014.01.015.

[12] Lozano M.G., Brynielsson J., Franke U., Rosell M., Tjörnhamma E., Varga S., et al. Veracity assessment of online data. Decis Support Syst 2020;129:113132. doi:10.1016/j.indmarman.2020.03.015.

[13] Elia G., Polimeno G., Solazzo G., Passiante G. A multi-dimension framework for value creation through Big Data. Ind Mark Manage 2020;90:617–632. doi:10.1016/j.indmarman.2020.03.015.

[14] Yaqoob I., Hashem I.A.T., Gani A., Mokhtar S., Ahmed E., Anuar N.B., et al. Big data: from beginning to future. Int J Inf Manage 2016;36(6):1231–1247. doi:10.1016/j.ijinfomgt.2016.07.009.

[15] Li F.G.N., Bataille C., Pye S., O'Sullivan A. Prospects for energy economy modelling with big data: hype, eliminating blind spots, or revolutionising the state of the art? Appl Energ 2019;239:991–1002. doi:10.1016/j.apenergy.2019.02.002.

[16] Arias M.B., Bae S. Electric vehicle charging demand forecasting model based on big data technologies. Appl Energ 2016;183:327–339. doi:10.1016/j.apenergy.2016.08.080.

[17] Walch A., Castello R., Mohajeri N., Scartezzini J.-L. Big data mining for the estimation of hourly rooftop photovoltaic potential and its uncertainty. Appl Energ 2020;262:114404. doi:10.1016/j.apenergy.2019.114404.

[18] Portugal I., Alencar P., Cowan D. The use of machine learning algorithms in recommender systems: a systematic review. Expert Syst Appl 2018;97:205–227. doi:10.1016/j.eswa.2017.12.020.

[19] Carvalho T.P., Soares F.A.A.M.N., Vita R., Francisco R.d.P., Basto J.P., Alcalá S.G.S. A systematic literature review of machine learning methods applied to predictive maintenance. Comput Ind Eng 2019;137:106024. doi:10.1016/j.cie.2019.106024.

[20] Wu J., Zhao Y. Machine learning technology in the application of genome analysis: a systematic review. Gene 2019;705:149–156. doi:10.1016/j.gene.2019.04.062.

[21] Paturi U.M.R., Cheruku S. Application and performance of machine learning techniques in manufacturing sector from the past two decades: a review. Mater Today: Proc 2021;38:2392–2401. doi:10.1016/j.matpr.2020.07.209.

[22] Abiodun O.I., Jantan A., Omolara A.E., Dada K.V., Mohamed N.A., Arshad H. State-of-the-art in artificial neural network applications: a survey. Heliyon 2018;4(11):e00938. doi:10.1016/j.heliyon.2018.e00938.

[23] Ghritlahre H.K., Prasad R.K. Application of ANN technique to predict the performance of solar collector systems - a review. Renew Sust Energ Rev 2018;84:75–88. doi:10.1016/j.rser.2018.01.001.

[24] Kalogirou S.A. Artificial neural networks in renewable energy systems applications: a review. Renew Sust Energ Rev 2001;5(4):373–401. doi:10.1016/S1364-0321(01)00006-5.

[25] Shafieian A., Khiadani M., Nosrati A. A review of latest developments, progress, and applications of heat pipe solar collectors. Renew Sust Energ Rev 2018;95:273–304. doi:10.1016/j.rser.2018.07.014.

[26] Narcy M., Lips S., Sartre V. Experimental investigation of a confined flat two-phase thermosyphon for electronics cooling. Exp Therm Fluid Sci 2018;96:516–529. doi:10.1016/j.expthermflusci.2018.01.018.

[27] Chi SW. Heat pipe theory and practice. New York: McGraw-Hill B. Co.; 1976.

[28] Reay DA, Kew PA, McGlen RJ. Chapter 3 - Heat pipe components and materials. In: Reay DA, Kew PA, McGlen RJ, editors. Heat Pipes, 6th ed., Oxford; 2014, p. 65-94. .

[29] Reay DA, Kew PA, McGlen RJ. Appendix 1 - Working fluid properties. In: Reay DA, Kew PA, McGlen RJ, editors. Heat Pipes, 6th ed., Oxford; 2014, p. 227-237. DOI: 10.1016/B978-0-08-098266-3.

00017-0.

[30] Faghri A. Heat pipe science and technology. Global Digital Press 1995.

[31] Reay DA, Kew PA, McGlen RJ. Chapter 2 - Heat transfer and fluid flow theory. In: Reay DA, Kew PA, McGlen RJ, editors. Heat Pipes, 6th ed., Oxford; 2014, p. 15-64. DOI: 10.1016/B978-0-08-098266-3.00002-9.

[32] Ku J. Introduction to heat pipes, https://ntrs.nasa.gov/search.jsp?R=20150018080; 2015 [accessed 21 May 2020].

[33] Reay DA, Kew PA, McGlen RJ. Chapter 4 – Design guide. In: Reay DA, Kew PA, McGlen RJ, editors. Heat Pipes, 6th ed., Oxford; 2014, p. 95-104. DOI: 10.1016/B978-0-08-098266-3.00004-2.

[34] Ling L., Zhang Q., Yu Y., Liao S., Sha Z. Experimental study on the thermal characteristics of micro channel separate heat pipe respect to different filling ratio. Appl Therm Eng 2016;102:375–382. doi:10.1016/j.applthermaleng.2016.03.016.

[35] Babu E.R., Reddappa H.N., Gnanendra Reddy G.V. Effect of filling ratio on thermal performance of closed loop pulsating heat pipe. Mater Today: Proc 2018;5(10):22229–22236. doi:10.1016/j.matpr.2018.06.588.

[36] Li M., Li L., Xu D. Effect of filling ratio and orientation on the performance of a multiple turns helium pulsating heat pipe. Cryogenics 2019;100:62–68. doi:10.1016/j.cryogenics.2019.04.006.

[37] Ding T., Cao H., He Z., Li Z. Experiment research on influence factors of the separated heat pipe system, especially the filling ratio and Freon types. Appl Therm Eng 2017;118:357–364. doi:10.1016/j.applthermaleng.2017.02.085.

[38] Ling W., Zhou W., Yu W., Liu R., Hui K.S. Thermal performance of loop heat pipes with smooth and rough porous copper fibre sintered sheets. Energ Convers Manage 2017;153:323–334. doi:10.1016/j.enconman.2017.10.009.

[39] Yue C., Zhang Q., Zhai Z., Ling L. CFD simulation on the heat transfer and flow characteristics of a microchannel separate heat pipe under different filling ratios. Appl Therm Eng 2018;139:25–34. doi:10.1016/j.applthermaleng.2018.01.011.

[40] Li H., Hou P., Sun Y. Photoelectricity and photothermal performance experiment on solar photovoltaic/loop-heat-pipe water heating system. Trans Chinese Soc Agric Eng 2018;34(7):235–240. http://www.tcsae.org/nygcxb/ch/reader/view_abstract.aspx?file_no=20180730.

[41] He W., Hong X., Zhao X., Zhang X., Shen J., Ji J. Operational performance of a novel heat pump assisted solar façade loop-heat-pipe water heating system. Appl Energ 2015;146:371–382. doi:10.1016/j.apenergy.2015.01.096.

[42] Zhou G., Li J., Lv L. An ultra-thin miniature loop heat pipe cooler for mobile electronics. Appl Therm Eng 2016;109:514–523. doi:10.1016/j.applthermaleng.2016.08.138.

[43] Aly W.I.A., Elbalshouny M.A., El-Hameed H.M.A., Fatouh M. Thermal performance evaluation of a helically-micro-grooved heat pipe working with water and aqueous Al2O3 nanofluid at different inclination angle and filling ratio. Appl Therm Eng 2017;110:1294–1304. doi:10.1016/j.applthermaleng.2016.08.130.

[44] ChNookaraju B., KurmaRao P.S.V., Sarada S.N. Thermal analysis of gravity effected sintered wick heat pipe. Mater Today: Proc 2015;2(4–5):2179–2187. doi:10.1016/j.matpr.2015.07.230.

[45] Alammar A.A., Al-Dadah R.K., Mahmoud S.M. Numerical investigation of effect of fill ratio and inclination angle on a thermosiphon heat pipe thermal performance. Appl Therm Eng 2016;108:1055–1065. doi:10.1016/j.applthermaleng.2016.07.163.

[46] Reji A.K., Kumaresan G., Sarathi A., Saiganesh A.G.P., Kr S., Shelton M.M. Performance analysis of thermosyphon heat pipe using aluminum oxide nanofluid under various angles of inclination. Mater Today: Proc 2020. doi:10.1016/j.matpr.2020.04.247.

[47] Rahman M.L., Saha P.K., Mir F., Totini A.T., Nawrin S., Ali M. Experimental investigation on heat transfer characteristics of an Open loop Pulsating Heat Pipe(OLPHP) with fin. Procedia Eng 2015;105:113–120. doi:10.1016/j.proeng.2015.05.017.

[48] Tharayil T., Asirvatham L.G., Cassie C.F.M., Wongwises S. Performance of cylindrical and flattened heat pipes at various inclinations including repeatability in anti-gravity - a comparative study. Appl Therm Eng 2017;122:685–696. doi:10.1016/j.applthermaleng.2017.05.007.

[49] Wang G., Quan Z., Zhao Y., Wang H. Performance of a flat-plate micro heat pipe at different filling ratios and working fluids. Appl Therm Eng 2019;146:459–468. doi:10.1016/j.applthermaleng.2018.10.014.

[50] Wang X., Han X., Ling Q., He W., Lang Z. Experimental investigation of the thermal performance of a novel concentric condenser heat pipe array. Int J Heat Mass Tran 2015;82:170–178. doi:10.1016/j.ijheatmasstransfer.2014.11.045.

[51] Jahan S.A., Ali M., Islam M.D.Q. Effect of inclination angles on heat transfer characteristics of a closed loop pulsating heat pipe (CLPHP). Procedia Eng 2013;56:82–87. doi:10.1016/j.proeng.2013.03.092.

[52] Zhang H., Zhuang J. Research, development and industrial application of heat pipe technology in China. Appl Therm Eng 2003;23(9):1067–1083. doi:10.1016/S1359-4311(03)00037-1.

[53] Ding T., He Z.G., Hao T., Li Z. Application of separated heat pipe system in data center cooling. Appl Therm Eng 2016;109:207–216. doi:10.1016/j.applthermaleng.2016.08.025.

[54] Zhou F., Wei C., Ma G. Development and analysis of a pump-driven loop heat pipe unit for cooling a small data center. Appl Therm Eng 2017;124:1169–1175. doi:10.1016/j.applthermaleng.2017.06.108.

[55] Zhou F., Li C., Zhu W., Zhou J., Ma G., Liu Z. Energy-saving analysis of a case data center with a pump-driven loop heat pipe system in different climate regions in China. Energ Build 2018;169:295–304. doi:10.1016/j.enbuild.2018.03.081.

[56] Tian H, He Z, Li Z. A combined cooling solution for high heat density data centers using multi-stage heat pipe loops. Energ Buildings 2 015;94:177-188. DOI: 10.1016/j.enbuild.2015.03.002.

[57] Liu Y., Yang X., Li J., Zhao X. Energy savings of hybrid dew-point evaporative cooler and micro-channel separated heat pipe cooling systems for computer data centers. Energy 2018;163:629–640. doi:10.1016/j.energy.2018.07.172.

[58] Wang Z., Zhang X., Li Z., Luo M. Analysis on energy efficiency of an integrated heat pipe system in data centers. Appl Therm Eng 2015;90:937–944. doi:10.1016/j.applthermaleng.2015.07.078.

[59] Behi H., Ghanbarpour M., Behi M. Investigation of PCM-assisted heat pipe for electronic cooling. Appl Therm Eng 2017;127:1132–1142. doi:10.1016/j.applthermaleng.2017.08.109.

[60] Sun X., Yang Y., Zhang H., Si H., Huang L., Liao S., et al. C. Experimental research of a thermoelectric cooling system integrated with gravity assistant heat pipe for cooling electronic devices. Energy Procdia 2017;105:4909–4914. doi:10.1016/j.egypro.2017.03.975.

[61] Singh R., Mochizuki M., Mashiko K., Nguyen T. Heat pipe based cold energy storage systems for datacenter energy conservation. Energy 2011;36(5):2802–2811. doi:10.1016/j.energy.2011.02.021.

[62] Ling L., Zhang Q., Yu Y., Liao S. Experimental investigation on the thermal performance of water cooled multi-split heat pipe system (MSHPS) for space cooling in modular data centers. Appl Therm Eng 2016;107:591–601. doi:10.1016/j.applthermaleng.2016.07.006.

[63] Dang C., Jia L., Lu Q. Investigation on thermal design of a rack with the pulsating heat pipe for cooling CPUs. Appl Therm Eng 2017;110:390–398. doi:10.1016/j.applthermaleng.2016.08.187.

[64] Shafieian A., Parastvan H., Khiadani M. Comparative and performative investigation of various data-based and conventional theoretical methods for modelling heat pipe solar collectors. Sol Energy 2020;198:212–213. doi:10.1016/j.solener.2020.01.056.

[65] Ayompe L.M., Duffy A. Thermal performance analysis of a solar water heating system with heat pipe evacuated tube collector using data from a field trial. Sol Energy 2013;90:17–28. doi:10.1016/j.solener.2013.01.001.

[66] Nookaraju B.C., Sohail M., Karthikeyan R. Experimental investigation and optimization of process parameters of hybrid wick heat pipe using with RSM historical data design. Mater Today: Proc 2020. doi:10.1016/j.matpr.2020.05.634.

[67] Sivarajah U., Kamal M.M., Irani Z., Weerakkody V. Critical analysis of Big Data challenges and analytical methods. J Bus Res 2017;70:263–286. doi:10.1016/j.jbusres.2016.08.001.

[68] Berman JJ. 2 - Providing Structure to Unstructured Data. In: Berman JJ, editors. . 2018, P. 15-51. DOI: 10.1016/B978-0-12-815609-4.00002-9.

[69] Bergamaschi S., Castano S., Vincini M., Beneventano D. Semantic integration of heterogeneous information sources. Data Knowle Eng 2001;36(3):215–249. doi:10.1016/S0169-023X(00)00047-1.

[70] Giudice P.L., Musarella L., Sofo G., Ursino U. An approach to extracting complex knowledge patterns among concepts belonging to structured, semi-structured and unstructured sources in a data lake. Inform Sci 2019;478:606–626. doi:10.1016/j.ins.2018.11.052.

[71] Yang L., Zhou J., Mei H., Zhang Z., Feng Z. A method of extracting the semi-structured data implication rules. Procedia Comput Sci 2018;131:706–716. doi:10.1016/j.procs.2018.04.315.

[72] Amanullah M.A., Habeeb R.A.A., Nasaruddin F.H., Gani A., Ahmed E., Nainar A.S.M., et al. Deep learning and big data technologies for IoT security. Comput Commun 2020;151:495–517. doi:10.1016/j.comcom.2020.01.016.

[73] Polato I., Ré R., Goldman A., Kon F. A comprehensive view of Hadoop research—a systematic literature review. J Netw Comput Appl 2014;46:1–25. doi:10.1016/j.jnca.2014.07.022.

[74] Jan B., Farman H., Khan M., Imran M., Islam I.U., Ahmad A., et al. Deep learning in big data Analytics: a comparative study. Comput Electr Eng 2019;75:275–287. doi:10.1016/j.compeleceng.2017.12.009.

[75] Goranko V., Angelo A., Shkatov D. Tableau tool for testing satisfiability in LTL: implementation and experimental analysis. Electron Notes Theor Comput Sci 2010;262:113–125. https://doi:10.1016/j.entcs.2010.04.009.

[76] Cui Y., Kara S., Chan K.C. Manufacturing big data ecosystem: A systematic literature review. Roboti Cim-Int Manuf 2020;62:101861. doi:10.1016/j.rcim.2019.101861.

[77] Ficco M., Pietrantuono R., Russo S. Aging-related performance anomalies in the apache storm stream processing system. Future Gener Compu Sy 2018;86:975–994. doi:10.1016/j.future.2017.08.051.

[78] Sahal R., Breslin J.G., Ali M.I. Big data and stream processing platforms for Industry 4.0 requirements mapping for a predictive maintenance use case. J Manuf Syst 2020;54:138–151. doi:10.1016/j.jmsy.2019.11.004.

[79] Petcu D., Macariu G., Panica S., Crăciun C. Portable Cloud applications—from theory to practice. Future Gener Compu Sy 2013;29(6):1417–1430.

[80]

Gil D., Song I. Modeling and management of big data: challenges and opportunities. Future Gener Compu Sy 2016;63:96–99. doi:10.1016/j.future.2015.07.019.

[81] Wilthan B., Pfeif E.A., Diky V.V., Chirico R.D., Kattner U.R., Kroenlein K. Data resources for thermophysical properties of metals and alloys, Part 1: structured data capture from the archival literature. CALPHAD 2017;56:126–138. doi:10.1016/j.calphad.2016.12.004.

[82] Moutaib M., Fattah M., Farhaoui Y. Internet of things: energy consumption and data storage. Procedia Comput Sci 2020;175:609–614. doi:10.1016/j.procs.2020.07.088.

[83] Bjeladinovic S., Marjanovic Z., Babarogic S. A proposal of architecture for integration and uniform use of hybrid SQL/NoSQL database components. J Syst Software 2020;168:110633. doi:10.1016/j.jss.2020.110633.

[84] Zhao Y., Zhang C., Zhang Y., Wang Z., Li J. A review of data mining technologies in building energy systems: Load prediction, pattern identification, fault detection and diagnosis. Energy Built Environ 2020;1(2):149–164. doi:10.1016/j.enbenv.2019.11.003.

[85] Graves A. Techniques to reduce cluttering of RDF visualizations. Future Gener Compu Sy 2015;53:152–156. doi:10.1016/j.future.2014.11.005.

[86] Freund R.J., Wilson W.J., Mohr D.L. Statistical Methods. Elsevier; 2010. p. 321–374. doi:10.1016/B978-0-12-374970-3.00007-X.

[87] Sairamya N.J., Susmitha L., Thomas George S., Subathra M.S.P. Intelligent Data Analysis for Biomedical Applications. Elsevier; 2019. p. 253–273. doi:10.1016/B978-0-12-815553-0.00013-6.

[88] Cortes C., Vapnik V. Support-Vector Networks. Mach Learning 1995;20:273–297. https://link.springer.com/article/10.1023/A:1022627411411.

[89] Bhargava D., Vyas S., Bansal A. Advances in Computational Techniques for Biomedical Image Analysis. Elsevier; 2020. p. 133–144. doi:10.1016/B978-0-12-820024-7.00007-4.

[90] Akanbi O.A., Amiri I.S., Fazeldehkordi E. A Machine-Learning Approach to Phishing Detection and Defense. Elsevier; 2015. p. 35–43. doi:10.1016/B978-0-12-802927-5.00003-4.

[91] Murthy S.K. Automatic construction of decision trees from data: A multidisciplinary survey. Data Min Knowle Disc 1998;4(2):345–389.

[92] Lee Y.-W., Chang T.-L. Application of NARX neural networks in thermal dynamics identification of a pulsating heat pipe. Energ Convers Manage 2009;50(4):1069–1078. doi:10.1016/j.enconman.2008.12.008.

[93] Chen P.-H., Lee Y.-W., Chang T.-L. Predicting thermal instability in a closed loop pulsating heat pipe system. Appl Therm Eng 2009;29(8–9):1566–1576. doi:10.1016/j.applthermaleng.2008.07.007.

[94] Jokar A., Godarzi A.A., Saber M., Shafii M.B. Simulation and optimization of a pulsating heat pipe using artificial neural network and genetic algorithm. Heat Mass Transfer 2016;52(11):2437–2445. doi:10.1007/s00231-016-1759-8.

[95] Malekan M, Khosravi A, Goshayeshi HR, Assad MEH, Garcia Pabon. Thermal resistance modeling of oscillating heat pipes for nanofluids by artificial intelligence approach. J Heat Trans 2019;141(7):072402. https://doi.org/10.1115/1.4043569.

[96] Ahmadi M.H., Tatar A., Nazari M.A., Ghasempour R., Chamkha A., Yan W.-M. Applicability of connectionist methods to predict thermal resistance of pulsating heat pipes with ethanol by using neural networks. Int J Heat Mass Tran 2018;126:1079–1086. doi:10.1016/j.ijheatmasstransfer.2018.06.085.

[97] Qian N., Wang X., Fu Y., Zhao Z., Xu J., Chen J. Predicting heat transfer of oscillating heat pipes for machining processes based on extreme gradient boosting algorithm. Appl Therm Eng 2020;164:114521.

doi:10.1016/j.applthermaleng.2019.114521.

[98] Elghool A., Basrawi F., Ibrahim H., Ibrahim T., Ishak M., Yusof T.M., et al. Enhancing the performance of a thermo-electric generator through multi-objective optimization of heat pipes-heat sink under natural convection. Energ Convers Manage 2020;209:112626. doi:10.1016/j.enconman.2020.112626.

[99] E J.-Q., Li Y.-Q., Gong J.-k. Function chain neural network prediction on heat transfer performance of oscillating heat pipe based on grey relational analysis. J Cent South Univ 2011;18(5):1733–1737. doi:10.1007/s11771-011-0895-z.

[100] Patel V.M., Mehta H.B. Thermal performance prediction models for a pulsating heat pipe using Artificial Neural Network (ANN) and Regression/Correlation Analysis (RCA). Sādhanā 2018;43:184. doi:10.1007/s12046-018-0954-3.

[101] Wang X., Li B., Yan Y., Gao N., Chen G. Predicting of thermal resistances of closed vertical meandering pulsating heat pipe using artificial neural network model. Appl Therm Eng 2019;149:1134–1141. doi:10.1016/j.applthermaleng.2018.12.142.

[102] Wang X., Yan Y., Meng X., Chen G. A general method to predict the performance of closed pulsating heat pipe by artificial neural network. Appl Therm Eng 2019;157:113761. doi:10.1016/j.applthermaleng.2019.113761.

[103] Maddah H., Ghazvini M., Ahmadi M.H. Predicting the efficiency of CuO/water nanofluid in heat pipe heat exchanger using neural network. Int Commun Heat Mass 2019;104:33–40. doi:10.1016/j.icheatmasstransfer.2019.02.002.

[104] Liang F., Gao J., Xu L. Thermal performance investigation of the miniature revolving heat pipes using artificial neural networks and genetic algorithms. Int J Heat Mass Tran 2020;151:119394. doi:10.1016/j.ijheatmasstransfer.2020.119394.

[105] Qu J., Wu H., Cheng P., Wang X. Non-linear analyses of temperature oscillations in a closed-loop pulsating heat pipe. Int J Heat Mass Tran 2009;52(15–16):3481–3489. doi:10.1016/j.ijheatmasstransfer.2009.03.012.

[106] Shanbedi M., Jafari D., Amiri A., Heris S.Z., Baniadam M. Prediction of temperature performance of a two-phase closed thermosyphon using Artificial Neural Network. Heat Mass Transf 2013;49(1):65–73. doi:10.1007/s00231-012-1066-y.

[107] Salehi H., Zeinali Heris S., Koolivand Salooki M., Noei S.H. Designing a neural network for closed thermosyphon with nanofluid using a genetic algorithm. Braz J Chem Eng 2011;28(1):157–168. doi:10.1590/S0104-66322011000100017.

[108] Kahani M., Vatankhah G. Thermal performance prediction of wickless heat pipe with Al_2O_3/water nanofluid using artificial neural network. Chem Eng Commun 2019;206(4):509–523. doi:10.1080/00986445.2018.1505614.

[109] Facao J., Varga S., Oliveira A.C. Evaluation of the use of artificial neural networks for the simulation of hybrid solar collectors. Int J Green Energy 2004;1:337–352. doi:10.1081/IJGE-20033649.

Highlights

- Critical review of the heat pipe (HP) technologies was undertaken.

- Existing HP simulation models are extremely time-consuming and impractical.
- A big-data-trained HP machine learning algorithm is a solution.
- Challenges for the big-data-trained HP machine learning technology was investigated.
- The future research directions of the HP machine learning were outlined.

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