EASR

Engineering and Applied Science Research

https://www.tci-thaijo.org/index.php/easr/index

Published by the Faculty of Engineering, Khon Kaen University, Thailand

A quick review of the applications of artificial neural networks (ANN) in the modelling of thermal systems

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Received 21 July 2021
Revised 11 September 2021
Accepted 28 September 2021

Abstract

Thermal systems play a main role in many industrial sectors. This study is an elucidation of the utilization of artificial neural networks (ANNs) in the modelling of thermal systems. The focus is on various heat transfer applications like steady and dynamic thermal problems, heat exchangers, gas-solid fluidized beds, and others. Solving problems related to thermal systems using a traditional or classical approach often results to near feasible solutions. As a result of the stochastic nature of datasets, using the classical models to advance exclusive designs from the experimental dataset is often a function of trial and error. Conventional correlations or fundamental equations will not proffer satisfactory solutions as they are in most cases suitable and applicable to the problems from where they are generated. A preferable option is the application of computational intelligence techniques focused on the artificial neural network model with different structures and configurations for effective analysis of the experimental dataset. The main aim of current study is to review research work related to artificial neural network techniques and the contemporary improvements in the use of these modelling techniques, its up-and-coming application in addressing variability of heat transfer problems. Published research works presented in this paper, show that problems solved using the ANN model with regression analysis produced good solutions. Limitations of the classical and computational intelligence models have been exposed and recommendations have been made which focused on creative algorithms and hybrid models for future modelling of thermal systems.

Keywords: Artificial neural networks, Thermal systems, Classical models, Computational intelligence

Nomenclature

W_{k1}	This defines the neuron weigh or possible connection strength from first neuron
W_{k2}	Weight This defines the neuron weigh or possible connection strength from second neuron
W_{k3}	This defines the neuron weigh or possible connection strength from third neuron
W_{kn}	This defines the neuron weigh or possible connection strength from n neuron
X_1	This defines available Input from first neuron to the kth neuron
X_2	This defines available Input from second neuron to the kth neuron
X_n	This defines available Input from n neuron to the kth neuron
j	This represents the Index for input value
n	This presents the index for source of dumpsites
k	Index classifying the connecting route of neuron
U_k	Combiner output in linear form as a result of input signal
V_k	Combiner in a linear form with bias serving as support to the input signal
Y_k	Over-all output

1. Introduction

In many engineering applications, heat is exchanged between two fluids which are at different temperatures and separated by a solid wall. The device used for this purpose is called a heat exchanger. Heat exchangers are used either individually or as components of large thermal systems in a wide variety of commercial, industrial, and household applications such as space heating, air-conditioning, power production, refrigeration, manufacturing processes, waste heat recovery, chemical processing, electronic chip cooling, etc. The

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doi: 10.14456/easr.2022.45

use of heat exchangers in these applications provides an opportunity to provide the needed thermal energy required and thus improve the system or process efficiency, thus saving energy [1]. All heat exchangers operate under the same fundamental principles irrespective of their types and designs. These principles are the Zeroth law, and the First and Second Laws of thermodynamics. The Zeroth law concerns itself with temperature as a characteristic of thermodynamic systems in thermal equilibrium. It states that thermodynamic systems in thermal equilibrium have the same temperature, this means that, if two systems 'A' and 'B' are individually in thermal equilibrium with a third system 'C', then 'A' and 'B' are in equilibrium with each other; and all three systems are of the same temperature. The First Law of Thermodynamics concerns itself with internal energy (U) as another property of thermodynamic systems. It describes the influence of heat and work on the internal energy of a system and its surrounding's energy. The first law, also referred to as the Law of Conversation of Energy states that energy cannot be created or destroyed, it is only transferred to another thermodynamic system or converted to another form (e.g., heat or work). The Second Law of Thermodynamics concerns itself with entropy (S) as an additional property of thermodynamic systems and describes the directional nature of heat flow in thermodynamic systems.

Analytical and experimental studies are used in the research area to investigate the performance of various systems, which consume more time and more expensive. The soft computing techniques are implemented in many studies in order to minimize the cost. ANN as a part of artificial intelligence technology is represented one of the most useful tool for optimization, prediction, and other tasks since it saves time and produces more accurate results than other methods [2]. Scientists in the fields of science and engineering employ this technique. In the last decade, the ANN approach has grown in popularity in mechanical engineering fields and the energy sector. In the past 2 decades, many researchers have implemented ANN in many research areas [3]. ANN was used in the field of forecasting the electrical energy consumption for a building [4], combustion processes [5], refrigeration and heat pumps systems [6], milling process [7] , heat exchangers [8, 9], solar systems design [10], solid desiccant systems [11] , hybrid energy systems [12], solar collector systems [13, 14], nuclear engineering [15], solar thermal systems [16], solar air heaters [17], PV applications [18, 19], chemical process control [20], atmospheric sciences [21], solar energy systems [22], renewable energy systems [23], solar radiations [24], thermal science and engineering [25] , wind-PV power systems [26] .

It has been observed that the challenge with any prediction process is the precision or accuracy of the technique. It has also been seen that there are various difficulties owing to the system's complexity. However, there are a variety of prediction and computational approaches that may be used to address estimation problems and obtain the optimum forecast accuracy. Many techniques, mostly in the disciplines of thermal systems, are utilised for performance prediction and estimate, including analytical methods, statistical methods, and artificial intelligence methods. ANN approach is most common for system performance predictions, because of its high accuracy and capacity to solve nonlinear issues, neural networks are the most extensively used. During data analysis, this approach can potentially learn from previous patterns.

Form the literature review of ANN technique in various applications, it is found that there is no separate review on using of ANN technique in thermal systems. In this paper, a short review of various heat transfer applications and the applicability of artificial neural networks in modelling of these systems is presented. The main objectives of present review article are to summarize the applications of the artificial neural networks (ANN) predictive models in various thermal systems and to find out research gaps and recommendations for future studies.

2. Heat transfer applications

Heat can be transferred by different means, it could be by conduction, convection, radiation, and or a mix of the above mentioned. The heat flow can be through a free stream or flows over surfaces or through conduits. The passage through which the heat flows could be smooth or enhanced. Smooth heat exchanger tubes are the tubes with fluid flow without any obstruction or demarcation of the flow passage [27], while the enhanced heat exchanger tubes are those that incorporate inserts or swirl in the flow area for the sole purpose of improving heat transfer [28]. These kinds of flows have been seen in various applications of heat transfer and there is also heat transfer phenomenon by phase change. A great challenge facing the researchers and developers is to enhance the performance of the heat transfer systems. Considering the high cost of energy and the need towards more efficient heat transfer units with minimum energy and materials consumption, many researchers focused on the techniques of heat transfer enhancement to achieve that [29, 30]. The heat exchanger is represented as one of the most popular heat transfer systems, which is involved in many industrial sectors like heating, ventilation, and air conditioning (HVAC), power stations, automobiles, aviation, and other applications. For heat exchangers, heat transfer enhancement techniques can be active, passive, and combined techniques, as summarized in Figure 1. The active techniques consume some external power to achieve heat transfer augmentation, such as in fluids injection [31-35], fluids suction, vibrating tubes, and swirling fans [36, 37]. As for passive techniques, there is no need for an external power source to achieve the enhancement in heat transfer as in the case of corrugated tubes [29, 38-52], dimpled tubes [53-56], twisted-tape inserts [28, 57-79], wired-coiled inserts [80-84] conical tubes [84-86], vortex generators inserts [87, 88], and nanoparticles additives [14, 15, 89-94]. To reemphasize, various geometries include transverse ribs with twisted tape, axial rib with screw tape, inclined limbs, helical tapes [58, 59]. These various shapes (techniques) depend on increasing the turbulence levels and disrupting the fluid flow's thermal boundary layer, leading to more mixing for the fluid flow and enhancing the heat transfer [95]. However, the penalty to pay is increase in pressure drop [57, 65], particularly in the turbulent flow regime. The pressure drop increased as a result of the demarcation of the flow passage. In an effort to achieve a compromise between laminar flow regime with characteristics of low heat transfer and pressure drop and turbulent flow regime with high heat transfer and pressure drop, Meyer and Abolarin [28] reported enhanced tube experiments conducted in the transitional flow regime, where the heat transfer was found higher than the laminar flow regime and the pressure drop lower than the turbulent flow regime. The geometric can be classified according to the flow types: the free stream, flows over surfaces or internal flows [42, 63, 96-99]. Kaood et al. studied numerically the effect of various corrugation shapes of tube surface on thermal-hydraulic characteristics of turbulent water flow inside tube subjected to constant heat flux within a range of Reynolds number from 5,000 to 61,000 [95, 100]. Rectangular, triangular, curved, and trapezoidal corrugated tubes were involved in the study. Corrugated tubes provided a superior effect on heat transfer enhancement and performance evaluation criteria compared with the traditional smooth tubes. Followed by another study, Kaood and Hassan [50] reported the effect of a combination between the various corrugation shapes and various nanofluids as a two passive techniques of heat transfer enhancement on the thermal-hydraulic characteristics of turbulent nanofluids flow inside a tube subjected to constant heat flux within a range of Reynolds number from 5,000 to 40,000. Various fluids (water "DW", SiO_2/DW Al_2O_3/DW, and GNP-SDBS/DW) and tube geometries with (rectangular, triangular, curved, and trapezoidal ribs) are studied using a validated numerical model.

In another form of geometry modification, Essam and Kaood [101] investigated the effect of converting the traditional straight tubes of the double pipe heat exchanger into conical tubes on thermal-hydraulic characteristics of various turbulent nanofluids flow inside tube subjected to constant heat flux within a range of Reynolds number from 7,000 to 35,000. Multiple studies used the Artificial Neural Network (ANN) predictive models with the computational fluid dynamics (CFD) models to make a comprehensive and optimized investigations on many thermal systems [6, 102-120]. Balcilar et al. [106] studied using ANN the boiling and condensation processes of R134a through smooth and corrugated tubes. Nasr and Khalaj [121] reported using ANN the effect of the combination between the corrugated tubes with the twisted tape insert on the friction factor and heat transfer coefficient. Zheng et al. [122] investigated using numerical CFD model and Artificial Neural Network (ANN) predictive model the sensitivity of discrete inclined ribs fitted a flat heat exchanger tube on the heat transfer enhancement. Multi-objective optimization, Artificial Neural Networks ANN, and genetic algorithms were used to study the characteristics of the nanofluid flow in flat tubes using CFD by Safikhan et al. [123]. Taymaz and Islamoglu [124] investigated the thermal characteristics of laminar airflow in a converging-diverging tube using a back-propagation neural network.

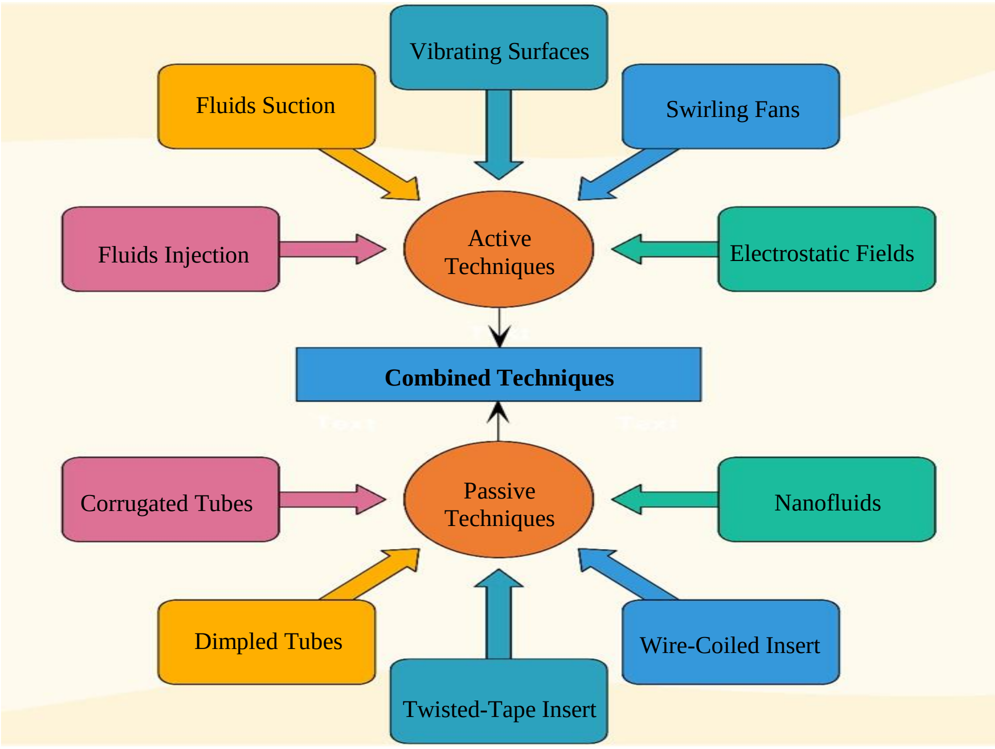

Figure 1 Techniques of heat transfer enhancement.

Heating, ventilation, and air conditioning (HVAC) systems consist of complicated structures that combine heat and mass transfer devices, such as boilers, chillers, heating/cooling coils, and supply air ducts. Many researchers used the Artificial Neural Network (ANN) predictive models to study many characteristics and simulate the different supervisory and local loop control strategies to improve the energy consumption efficiency of many thermal systems as in the case of Heating, ventilation, and air conditioning (HVAC) systems [125, 126]. There are three major classes of modeling methods defined, and they include data-driven, physics-based, and so-called "grey box" techniques. Using data-driven approaches, a system's behavior can be closely approximated with the aid of linear and nonlinear functions based on measurements of the input and output variables. Among these models are well-known techniques such as frequency-domain models with dead time and data mining algorithms (e.g., ANN and SVM), statistical models (e.g., ARX, ARMAX, and ARIMA), and FL models (e.g., FAN and ANFIS) [36]. However, physics-based models depend on the full understanding of the mechanism and the laws that control it. Building models with physics-based approaches more closely mimics the framework and offers a greater capacity for generalization. If the conditions vary from the training data, data-driven models begin to degrade. Grey box models are a relatively new methodology that combines physics-based and data-driven modeling approaches. A grey box model describes the overall structure of the model using physical laws and then uses calculated data to find the model's parameters. Many optimization techniques, such as least squares, gradient descent, and GA, are also used for parameter recognition [36].

Various studies used Artificial Neural Network (ANN) predictive models in nuclear energy systems as one of the most critical and sensitive types of thermal systems as in nuclear power plants [38-44]. In this way, this technique is used for pattern recognition, for optimization of artificial control, and fault diagnosis. Although there are some difficulties face the researchers due to ANN is still a fresh technology without sufficient validation [38]. Geometry plays a very important role in effective transfer of heat. Geometry modification is represented as one of the most popular passive technique of heat transfer enhancement.

2.1 Flows through channels

Researchers have studied horizontal, inclined, and vertical plane conduits for the effects of mixed convection [27, 127-131]. Mixed convection is the phenomenon that combines the free convection and forced convection systems for the transfer of heat [132, 133]. These channels maybe straight walled, micro scaled or irregular geometries. Micro scale heat transfer has been studied by many. They used micro-channel of different shaped heat sinks and then optimised the thermal performance. This found particular applications in electronics cooling [134-137]. de Vega, García-Hernando and Venegas [138] reported a cooling study conducted with a membrane absorber fabricated from a stainless-steel microchannel. The study focused on the comparison of water-cooled absorber and adiabatic absorber. The results indicate that the absorption rates of these two scenarios are different. For the water-cooled scenario, the absorption rate was reported to be 0.005 kg/m^2s, while for the adiabatic type it was 0.003 kg/m^2s.

2.2 Energy storage applications

Energy storage channels may contain phase change materials (PCMs) developed to improve energy storage [139-143]. Gholaminia, Rahimi and Ghaebi [144] numerically investigated energy storage improvement by placing a PCM in a tube-in-tube heat exchanger. The variables considered include types of PCMs, working fluid temperature, tube geometry and fins on the heat exchanger surface. The relevant heat transfer equations were solved using the Crank-Nicolson solution in MATLAB software. It was found that PCMs with capability of higher latent heat are capable of stored heat at lower temperature. As the temperature of the working fluid increased, the difference in temperature between the PCM and the fluid increased, so was the stored energy and storage speed. When the influence of fins was investigated, it was reported that the energy stored increased with number of fins on the heat exchanger. In a numerical study, Deng, Li, Zhang, Yao and Shen [145], reported the influence of heat transfer fluid temperature on charging performance of pure and composite PCMs. The study found that heat transfer was enhanced, and uniform latent heat storage was accomplished with the PCMs. In an experimental study reported in the work of Mehta, Vaghela, Rathod and Banerjee [146], a shell and tube channel type of heat exchanger equipped with spiral fins was investigated with possible latent heat storage unit. Study investigated the influence of the spiral fins on the rate of charging and discharging of the unit. The PCM used was stearic acid, while the working fluid was water. To successfully measure the PCM temperatures, a total of 45 thermocouples were installed on the shell annulus. It was found that the spiral fins led to melting and solidification enhancement thus improved the energy storage of the PCM in the channel. Furthermore, the spiral fins resulted in the reduction of time of charging by 41.48% and discharging by 22.16%. In a channel heat exchanger fabricated from a double-spiral coil, Lin, Ling, Zhang and Fang [147] investigated storage technology suitable for solar thermal with sebacic acid as the PCM and oil as working fluid. The study found out that the sebacic acid is a promising PCM for enhancing heat transfer in the double-spiral coil heat exchanger channel.

During the process of hydrogen charging into metal hydrides, heat is released. This heat is usually needed to be quickly removed so as to ensure the rate of charging is rapid as expected. In an effort to store hydrogen, Wang, Prasad and Advani [148] inserted an helical coil heat exchanger in order to remove the heat generated during the hydrogen charging process. Using Ansys Fluent 12.1, a three-dimensional mathematical model was formulated to determine the transient heat as well as mass transfer in a cylindrical reservoir where the heat exchanger was inserted. The results show that the rate of absorption increased with convective heat transfer. Similarly, Keshari and Maiya [149] inserted an heat exchanger tube with fins fabricated from copper in to an hydrogen absorption process with metal hydride with the sole aim of using the heat exchanger to remove the heat generated during the absorption process.

2.3 Single phase flow

Richter do Nascimento, Mariani and Coelho [150] using a plate-fin heat exchanger and fins with offset strip demonstrated numerical approach optimisation at different mass flow rates. The focus of the study was to optimise effectiveness, volume and pressure drop while hot and cold working fluids flowed through the counter-flow heat exchanger. Using the Non-Dominated Sorting Genetic Algorithm-III of neural networks, the effectiveness as well as the volume led to pressure drop reduction over a range of 55.4-72.3% in the counter-flow heat exchanger.

As helical or spiral coiled heat exchangers have found numerous applications in nuclear industries because of the coil arrangement in heat transfer improvement, using an helical coil shell and tube heat exchanger, Delgado, Porter, Hassan and Anand [151] conducted a pressure drop experimental investigation over a range of Reynolds number in the fully turbulent flow regime. The Reynolds number was over the range of 8500 and 11700.

Aasi and Mishra [152] reported an empirical study combined with an artificial neural network of a three-fluid heat exchanger subjected to a cross-flow. To enhance this heat exchanger, plain rectangular fins were placed on the inside. Influence of the fins on the friction factors, Colburn j-factors as well as effectiveness ratio as a function of Reynolds numbers and flow arrangements were investigated and reported. The study used the ANN model to predict the experimental data was found that employing the ANN provided better prediction as compared with conventional regression analysis.

In the determination of exergy efficiency and performance, Abu-Hamdeh, Almitani and Alimoradi [153] conducted a numerical fluid flow in a sector-by-sector and tube-in-tube heat exchanger with helical coils. The efficiency and performance were reported as a function of Reynolds number, dimensionless coil diameter and pitch. It was found that the exergy efficiency was reduced by 21-26% when the dimensionless coil diameter was doubled. Furthermore, the exergy coefficient of performance was reduced by 8-15% when a heat exchanger with semi-circle cross-section was investigated. As a result, the study recommended the use of the heat exchanger with semi-circle and quadrant-circle cross-sections in the place of the regular tube-in-tube. The study developed new correlations for the efficiency and performance of this heat exchange setup.

Heat exchanger also allow for the flow of different working fluids for the purpose of achieving the desired heat transfer. some of the working fluids in use include nanofluid of different nano particles, concentration and physical properties [154], water [155].

2.4 Two-phase flow

Two phase flows cover the areas of condensation, boiling, and nanofluid flow and is a very important heat transfer application in the industry. Many papers [90, 103, 156-162] have been published in this area. For example, Qiu and Zhang [162] reported an investigation of pressure drops in a two-phase flow experiment as R600a/3GS oil flowed in a circular heat exchanger tube with inner diameter of 8 mm. The study investigated the influence of the oil concentration ranging from 0-4%, mass flux ranging from 150-300 $kg.m^{-2}.s^{-1}$ on the pressure drop. The use of the oil in this two-phase channel flow experiment resulted in the improvement of pressure drop by a maximum of 60%. As such it was concluded that the correlation generated from the study could be used for when there is a need to predict the pressure drop of R600a/oil mixture in the design of a refrigeration system. This in particular relates to the design and operation of the various components that make up the refrigeration system (condenser, evaporator, etc).

It is very important to note that in two-phase flow ANN has been used to develop and predict dimensionless heat transfer coefficient correlations in the form of Nusselt number. In an helical evaporator with double pipe, Parrales, Hernández-Pérez, Flores, Hernandez, Gómez-Aguilar, Escobar-Jiménez and Huicochea [163] presented an investigation that developed two Nusselt number correlations using ANN from an experimental data of 1109 values. One Nusselt number correlation was developed or the annulus while the other Nusselt number was developed for the inner section of the pipe. The correlations were developed to enable the determination of coefficients of heat transfer in the each of the sections of the double-pipe vertical and helical evaporator. The working fluid whose properties was used to develop the mathematical correlation was water. The modified Wilson plot method was used to determine the Nusselt in the annular section of the pipe. This method was thereafter solved using ANN. The input variables considered in the correlations are Reynolds number, Prandtl number as well as three neurons in the hidden layer. The inner Nusselt number was developed using Rohsenow equation and thereafter solved by ANN. The input variables to the ANN solution were Jackob liquids and Prandtl number as well as one neuron in the hidden layer. The two correlations were found to meet the dimensionless characteristics of Nusselt number. The weights and biases of the correlations were determined using Levenberg-Marquart algorithm. In the inner and outer layers, the study used the hyperbolic and linear transfer functions respectfully. The accuracy of the of the Nusselt number correlation for the flow in the inner section was reported to be 4%, while that of the annulus was determined to be 0.2%.

In another study using ANN in a two-phase flow, Parrales, Colorado, Díaz-Gómez, Huicochea, Álvarez and Hernández [164], developed two correlations for void fraction with water as working fluid in a helical vertical coils. The input variables to the first correlation are viscosity ratio, density ratio, curvature ratio and vapour fraction with two neurons in the hidden layer. In the second model and for the purpose of simplification, the curvature ratio was not included, however the developed was accompanied with two neurons in the hidden layer. These models were validated on variations heat exchangers. An application was on steady state data obtained from two evaporators with double pipes with heat transformer with absorption capability, while another application was on the design and prototype of steam generator with full-scale helical coil.

2.5 Thermosyphon

This system is a passive method of heat exchange and it functions by natural convection and by principle does not require a mechanical pump, it often occurs across a temperature gradient such as solar chimney [165, 166], biomass heat engine [167], residential and commercial heating and cooling systems [168-172] etc.

Goswami and Das [167] developed a thermoelectric generator using a biomass engine waste heat. The waste heat was recovered and used to recharge an uninterrupted power source with 12 V, more experiments conducted on this system was the parametric investigation on an octagonal-shaped thermosyphon in a two-phase mode. The maximum temperature gradient of the system was 40.12 °C at the optimum thermosyphon filling ratio of 0.496. The system generated a total power of approximately 1 W at a conversion efficiency of 2.218%.

In an investigation to compare the complex mechanism of heat transfer of conventional with check valve closed loop thermosyphon, Thongdaeng, Pipatpaiboon and Donmuang [173] reported a flow visualization study conducted. The check valve close loop thermosyphon was fabricated from a pyrex tube of 11.6 mm inner diameter, the length of the evaporator and condenser was 300 mm each. The purpose of the study was to improve the efficiency of a liquid-vapour flow separation by installing a check valve to alter the flow behaviour. It was found that the check valve type had a maximum heat transfer of 195.73 W, while that of the conventional type was 126.18 W.

Bahiraei, Gharagozloo, Alighardashi and Mazaheri [168] presented a thermosyphon made from a finned cooper tube for possible application in a residential and commercial refrigeration system. The working fluid circulated was methanol. The authors located an environmental chamber capable of reproducing atmospheric temperature of -5 °C on the refrigerator. For different temperatures the study compared the speed of the fan and filling ratio of the thermosyphon. It was found that the number of fans used was influenced by the inner temperature of the refrigerating system.

Vasiliev, Grakovich, Rabetsky, Vassiliev and Zhuravlyov [170] conducted experiments with long thermosyphon technologies that could be coupled to the ground for all year-round heating or cooling of ground surfaces and as well reduce thermal resistance. These thermosyphons could find applications in the heat exchangers found in heating of residential buildings, runways, roadsides, railways, air conditioning etc. Different working fluids such as water, propane, ammonia, and isobutene were circulated in the thermosyphons. Two types were discussed; the first was the polymeric loop two-phase, while the second was the vapour-dynamic thermosyphons. When compared, the vapour-dynamic was found to have lower thermal resistance.

2.6 Solar radiation

Solar radiation is found to reach the surface of the earth by diffuse solar radiation, reflected radiation, direct (beam) solar. Its availability can be studied by measurements from a radiation monitoring network or based on physical formulae and constants. Solar energy has been applied in engineering problems some of the applications include solar water heater, solar air heaters, solar generators and refrigerators [174, 175]. In an application for concentrated solar power, Yao, Zhu, Guo, Yang, Zhang, Ren and Wu [176], considered a multi-phase heat exchanger in a two-dimensional study of metal hydride reactor. The focus of the study was to determine the performance as well as the feasibility to the solar application. It was found that to sustain constant heat flux, the fluid velocity must be in accordance with the metal hydride's thermal conductivity. When compared with a single-phase heat exchanger, the heat flux of the multi-phase was reported to be 3 times more.

Abu-Hamdeh, Bantan, Khoshvaght-Aliabadi and Alimoradi [177], installed rectangular ribs on the inside of a curved absorber tube to overcome the problems of non-uniform wall temperature boundary condition and thermal stress from solar radiation. The study numerically investigated the influence of the ribs height while varying the mass flow rate in the laminar flow regime. The result of the study indicated that the insertion of the ribs led to enhancement of heat absorption by 48% as compared with a smooth curved absorber tube without the rectangular rib. Unfortunately, the insertion of the rib increased the pressure drop by 89%.

2.7 Solar air heater

Of recent, investigations around the application of ANN in solar air heater has dominated the heat transfer field [16, 178-184]. Ghritlahre [178], considered three different techniques which are multi-linear regression, group method data handling and ANN for the prediction of solar air heaters' exergy efficiency. Each model was used to analyse about 210 sets of experimental data on two solar collectors, one with an enhanced surface and the other with a smooth surface. These models and surfaces were tested with working fluid flowing over the range of 0.007 kg/s to 0.0222 kg/s. The independent variables considered were temperatures (room, inlet, bulk and plate), wind direction and speed, mass flow rate, solar intensity and elevation and relative humidity. The output variable was the exergy efficiency. The results of the study showed that out of the three models investigated, the ANN model showed the best performance. For the ANN room mean square value was 0.0085 with a correlation coefficient of 0.99981. The correlation coefficient of the remaining two models were 0.98977 and 0.97693 respectively.

In the prediction of heat performance solar air heater, Ghritlahre, Chandrakar and Ahmad [16] reported an ANN investigation for an enhanced heat exchanger with arc shaped wire rib and for a smooth tube. The study identified that previous studies had relied on parameters from system, operating and metrology for the prediction of thermal performance but not with relevant input parameters. Therefore, the study developed an ANN model with relevant input variables with 10 to 20 neurons in order to find optimal model. The result of the study shows that ANN-II with 8-14-1 demonstrated the best model. From all the relevant input variables considered, mass flow rate was the only one found to be the most effective.

In the thermal performance prediction of a solar air heat with porous wire screen bed, Ghritlahre and Prasad [179] performed an ANN analysis using empirical data collected from the porous bed solar air heaters. In the study, two porous bed solar air heaters were considered. The first was the bed with unidirectional flow, while the second was the cross directional flow bed. The ANN model was developed using the thermal efficiency of the solar air heater and the Levenberg-Marquardt learning algorithm. To obtain an optimum topology, thirteen neuron hidden layer were used. The thermal efficiency of the unidirectional flow heater was compared with that that of the cross flow.

The unidirectional flow model resulted in coefficient of determination of 0.9994, while that cross directional flow was obtained as 0.9964. The low root mean square values obtained from the comparison of the ANN models on the unidirectional and cross flow indicated that ANN is capable of being used to determine the thermal performance of solar air heaters with porous wire beds. Other models used for the prediction of thermal performance in unidirectional flow in solar air heater with porous beds are multi-layer perception, multiple linear regression model, generalised regression neural network and radial basis function. These models were demonstrated in the work of Ghritlahre and Prasad [180] where 96 data obtained from experiments conducted were used to test these models with six input variables. The input parameters used are temperatures (input, fluid mean, and ambient), mass flow rate, wind speed and solar intensity for the generalised regression neural network, radial basis function, multi-layer perception and the multiple linear regression models. The only output variable considered was the thermal efficiency. Out of these four models the generalised regression neural network performed the best because it produced the least error and highest adjusted R^2 value of 0.99758 and root mean square vale of 0.00000593.

3. General application of an in thermal systems

Longo et al [108] predicted the heat transfer coefficient of refrigerant condensation in a herring bone type plate heat exchanger (BHPE). In their model they took consideration for the following: geometry of the plate, properties of the refrigerant in the saturated and superheated state, operating conditions. The resulting artificial neural network (ANN) model had a mean absolute percentage error (MAPE) of 3.6%. The MAPE represents a measure of the prediction accuracy of a predictive method in statistics. It is usually given in percentage. However, it is worthy of note that using MAPE alone as a criterion is meaningless because we need to account for how predictable a series is. For example, 9% MAPE is good for some series and bad for others. So care should be taken when evaluating ANN models [185]. From their study, they found that ANN models was better at forecasting than the compared BPHE analytical models [108]. Naphon et al. [186] presented a study to analyse nanofluid jet impingement pressure drop and heat transfer using ANN and computational fluid dynamics (CFD). Their study was in a micro-channel heat sink. The back propagation training algorithm of the Levenberg-Marquardt was used to get an optimal ANN model. The observed error was low. Liu et al [187] carried out an experimental study and applied ANN to heat transfer of pulsed spray cooling on a vertical surface. They observed that the heat flux increased with duty cycle and the accuracy of predictions was better than conventional correlations. Thanikodi et al [188] applied a hybrid neural network to model a shell and tube heat exchanger and they were able to predict the heat transfer rate. Mandavgane and Pandharipande [189] used ANN to estimate the exit temperature of both fluids taking inlet temperature conditions and flow rates as inputs. They found that an ANN model with three hidden layers of 4-15-15-15-2 had the best accuracy of 98-99.5% for training and test data. Karimi and Yousefi [190] presented a hybrid model of back propagation network (BPN) genetic algorithm (GA) for the purpose of predicting nanofluids density. The GA was used to optimize the parameters of the BPN and its accuracy. They studied four nanofluid for a range of temperature of 273-323 K and a volume fraction up to 10%. They obtained an absolute deviation of 0.13% and an R-squared value of greater than 0.98. They also observed that BPN-GA does better than radial base functions and the Pak and Cho's correlation with 64% and 95% enhancement. Souayeh et al [191] presented an ANN model for heat transfer and fluid flow. They developed a five-layer neural network to forecast thermohydraulic friction factor and Nusselt number, they used 4 hidden layers having 40 neurons was the best in terms of accuracy. Zhu et al. [192] generated data for flow boiling and condensation heat transfer in mini channels for refrigerant R134a. They used ANN models to forecast the heat transfer performance of both condensation and flow boiling. Islamoglu [107] predicted the heat transfer rate of wire-on-tube type heat exchanger by ANN. He suggested using it as a first stage for engineering design of the heat exchanger.

Xie et al [119] presented an ANN model for predicting overall heat transfer rate and outlet temperature differences in each side. The model was for a shell-and-tube heat exchanger with segmented baffles. They used the back propagation (BP) algorithm. They observed a less than 2% maximum deviation between predictions and results from experiment. Athani et al. [193] used back propagation ANN for predicting the heat transfer in porous medium. They observed that ANN was an accurate method. Rahman and Zhang [194] used ANN to predict oscillatory heat transfer coefficient. Their model had a 2-10-1 configuration. Their model was 3.2% average error percentage better than existing correlations. They stated that the subtle relationships between variables could be well modelled by ANN. They applied the model to thermoacoustic refrigerators. Ghritlahre and Prasad [184] used ANN to model heat transfer of roughened solar air heater. Their model was made from the Levenberg-Marquardt (LM) algorithm with feed-forward back propagation model. They found that an optimal result was obtained at hidden layer with 10 neurons. Diaz et al [195] simulated heat exchanger performance with ANN. They found their method to be better than the power-law correlation for heat transfer coefficient. Azizi and Ahmadloo [196] developed an ANN model to predict heat transfer coefficient of refrigerant (R134a). They used 440 data points for developing the model, the inputs to the model were the inclination angle, mean vapor quality, mass flux, saturation temperature. They confirmed the ability of ANN to make accurate predictions of heat transfer coefficient. Esfe [197] used ANN to model heat transfer and pressure drop of Ag/water nanofluid. In the ANN model the radial basis transfer function was adopted. The correlation coefficient for both Nusselt number and pressure drop was greater than 99%. Sablani et al [111] applied ANN to evaluate the heat transfer coefficient from having the temperature for a solid-fluid system. They studied the direct heat conduction problem (DHCP) of unsteady heat conduction in a semi-infinite plate having convection boundary condition and in a cube. In the first case, ANN was to predict the dimensionless heat transfer coefficient by having dimensionless temperature and in the second case it was to predict Biot number from non-dimensional temperature ratio and Fourier number. They then tested with unsteady experiments. Krzywanski and Nowak [198] was interested in the fluidized bed boiler's combustion chamber heat transfer coefficient by using ANN. They agreed that ANN give quick and accurate results.

Wang et al [199] presented a study on pulsating heat pipes where they used ANN with 5 input parameter and 10 hidden layers. The filling ratio, number of turns, inner diameter, evaporation section length ratio, heat flux were the inputs. They obtained a correlation coefficient greater than 99%. Giannetti et al. [200] predicted the two-phase refrigerant distribution using ANN. They suggested that a reverse ANN may be helpful in achieving a design of a target take-off-ratio.

Ewim et al. [103] used ANN to predict the heat transfer coefficient under condensation in an enhanced inclined tube. They observed that ANN was able to make good predictions. The inputs to the ANN were the inclination angle, vapour quality, and the mass velocity.

4. Classical models

One of the fields in which thermal systems can be studied is device recognition. Creating a good model helps the designer to create controllers with better response times, precision, and energy consumption. The model may also be used to evaluate the system's internal behaviour and possibly suggest mechanical changes or innovative designs, depending on its structure. To create models of thermal systems, classical and computational intelligence models have been employed Tian et al. [201]. Classical models through the use of grey-box continuous-time model based on heat equation by Tillman et al., [202], and intelligence models that use black-box structures based on linear regressions, such as ARX or ARMAX [201, 202]. Despite these challenges, every one of the previously presented structures is not sufficient for overhauling the internal behaviour of these systems. While some of the models have a physical basis, they are unable to model those variables of interest, such as heat fluxes or stored thermal energy for a deeper understanding of system performance variables. These variables are extremely helpful in recognizing vital components and studying mechanical improvements that could reduce system energy consumption and improved thermal system management. However, design and research improvement based on the classical model applications are less effective in meeting the required system performance. The limitation of the technique is the fact that it only gives a physical analogy of process operations that affects the assessment for design improvement. Models in general are mainly used to improve comprehension of an operation in a system. They can also assist with device overhaul [203, 204].

Classical and or Creative analysis are two methods for modelling systems. These modelling techniques have their collection of analytics and advantages. Modelling has been very effective in providing design and organisational ingenuity when properly implemented. A method or a device can be visualized using physical or cold flow models. They have been used in the past to analyse systems like steady and dynamic thermal problems, heat exchangers, gas-solid fluidized beds, and others such as fuel tubing, burner design, boiler simulations, gas flow evaluations via air pollution equipment, and other processes. Classical and CAD model applications in the design process has been and it continues to be prevalent. For instance, boiler system is modelled after the design of a device, such as a steam boiler, has reached a certain stage in order to validate the design and layout. Many designed applications, such as the ones just mentioned, still depend on classical models. Physical scaling down of processes and components has proven to be very efficient, but physical or classical modelling is costly, less accurate and time-consuming. These factors drove the growth and progress of computerized intelligence and numerical modelling [202].

Furthermore, the classical model of heat conduction is well-established and based on the Fourier law of heat conduction and the first law of thermodynamics to predict and regulate the rate at which heat is conducted [203]. The Fourier law is known to be constitutive nature on heat flux that relates temperature gradient, the driving force and cause of heat-conduction, to the heat transfer rate [201, 203, 204]. The classical and standard framework for understanding heat-conduction processes consists primarily of two steps: Temperature fields acquisition of heat-conduction or measure data; acquiring heat and mass transfer rate and control methods through the Fourier law of heat conduction [205]. By applying the second law of thermodynamics to heat conduction, a traditional irreversible mechanism that satisfies both the first and second laws of thermodynamics, we go one step further than the classical theory of heat conduction. The essence of the second law of thermodynamics can be shown using a variety of expressions [206]. Each is usually more convenient to use for specific processes which are known as the increase in entropy principle [206].

5. Computational intelligence techniques in thermal systems

Besides, classical model analysis is the application of computer intelligence computational models such as Artificial Neural Networks, ANNs has been used in diverse area of applications [207]. An artificial neural network (ANN) is a part of a computational system that mimics how the human brain analyses and processes data. Artificial intelligence (AI) is built on this basis, and it solves problems that would be impossible or difficult to solve by the classical or statistical standard model. ANN models have personality features, potentially improving their performance as an increased dataset becomes available [208]. Thermal system and components parts, in general, suffer a gradual process of performance inefficiency over the process of operations having been exposed to various degradation agents and mechanisms. This deterioration phenomenon reduces the standard of achievement of thermal components until they are no longer able to completely meet their intended performance requirements. In this sense, service life and possible performance predictions are important because it allows for more logical use of the system which also gives way to appropriate planning for system maintenance actions. One way to ensure an adequate level of performance for a longer time and eventual costs of urgent repairs are reduced is the application of computational intelligence such as ANN. Thermal system performance prediction is neither a forthright nor simplistic task. This mechanism is comprehensive and required robust analysis for the beauty of the study to be satisfied since it involves a variety of variables that interact synergistically. There are various methodologies for ANN predictions since their application have emerged in recent decades, and they can be very useful in the decision-making process. They simply consist of the input variable, controlled and uncontrolled parametric variables using antecedence of available data variables. The network is usually consisting of input, hidden and output layers with input neurons connected through adapted weights.

6. Structure and methodology

Models for thermal analysis can be based on either steady-state or dynamic conditions. For example, to simulate thermal behaviour, steady-state and dynamic models can be based on experimental data or its intricate instinctive description [114]. As a modelling and prediction technique, an artificial neural network (ANNs) is considered very useful. Without using preconceptions, neural networks can map linear and non-linear dependencies in data [109, 209]. They are useful for forecasting thermal behaviour in in systems over short and long periods, with an emphasis on hourly energy consumption [210] and cost optimization [211, 212]. ANN has been used intensively as a CI technique based on its ability to perfectly harmonize input dataset based on decision variables to provide favorable output response. Model demonstration of the neuron and synaptic weight is presented (Figure 2), accurate prediction of the model is promising using MATLAB. According to [213, 214], Levenberg Marquardt Neural Network algorithm significantly outperforms other training algorithms like Resilient Back Propagation (RBP) and Scaled Conjugate Gradient (SCG) under Multi-Layer Perceptron Neural Networks (MLPN).

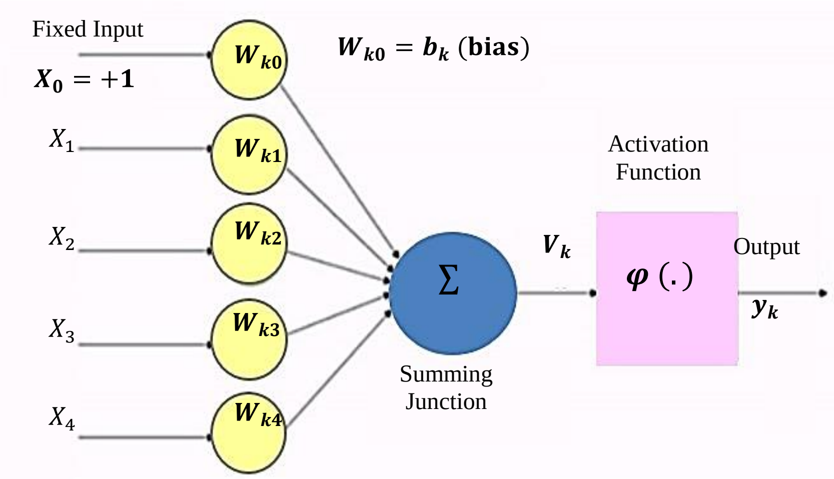

Figure 2 Strength of the connection of neurons with bias and activation junction [212]

Neural network model

$$U_k = \sum_{j=1}^{n} x_j w_{kj} \tag{1}$$

$$V_k = U_k + b_k \tag{2}$$

$$V_k = \sum_{j=1}^{n} x_j w_{kj} + b_k \tag{3}$$

$$Y_k = S_g F_n(V_k) \tag{4}$$

$$Y_k = \phi(.)V_k \tag{5}$$

$$Y_k = \phi(.)\sum_{j=1}^{n} x_j w_{kj} + b_k \tag{6}$$

7. Limitations of classical and CI models

Classical and or CI models are models improving the understanding of various aspects of thermal systems be it ovens, refrigerators, and other devices with heavy heating systems, blend combustion, but they all have their demerits. These demerits are based on many factors, including the complexity of model formulation, complexity of variables, the quality of operation data, the terrain of operation, analysis is slow. Modelling is critical for the design and understanding of different processes and parametric studies. They serve as a foundation for studying and visualizing a specific procedure. For several years, numerical and physical models have been used. However, some of the modelling limitations warrant further study, which is particularly relevant when considering thermal system [215, 216]. Hybrid models are strongly recommended due to their high computational power and faster response to optimal results.

8. Hybrid algorithms for thermal systems analysis

From the study, it is evident that modelling of thermal systems requires higher creative algorithms and hybrid methods, it is not enough to optimize and model systems using ANN, new algorithms and metaheuristic techniques are springing up. Much importantly is having the ability to hybridize models for problem solving. It has been shown in literature studies that hybrid algorithms is far superior to single models [212]. Therefore, from the investigation so far, the best solutions can be obtained by using comparative analytics of ANN with other hybrid models. Some useful hybrid metaheuristics for a more perfect representation of all facets of hybridization methodology for thermal systems and recommended for further studies include the evolutionary algorithm combined with bio-inspired algorithms, metaheuristics and constraint programming or metaheuristics with other creative algorithms like-Artificial Neural Network trained with Particle Swarm Optimization (PSO); PSO and Ant colony optimization (ACO) combined; Iterated local search (ILS) algorithm and PSO; guided local search (GLS) and Tabu Search (TS); Combined Fuzzy Logic and Artificial Neural Network-Adaptive Neuro Fuzzy Inference System (ANFIS); ANFIs and Genetic Algorithm (ANFIS-GA) and others.

9. Recommendations for future work

No doubt, the use of ANN has shown massive success in its applications in thermal systems. However, the following future work is recommended

1. The integration of ANN modelling into computational fluid dynamics (CFD) packages for more robust modelling applications
2. The use of ANN on identifying the prevailing flow pattern during two phase flow processes should be explored.
3. The application of ANN in the modelling of the flow of hybrid and magnetic nanofluids is an area that should be explored further.
4. The use of creative models, hybrid algorithms and metaheuristics have been identified as preferable modelling techniques for effective analysis of thermal systems and should be extensively explored.

10. Conclusion

This study is focused on the exposition of the applications of ANN in the modelling of thermal systems. Thermal devices, such as heat exchangers, ovens, refrigerators, and other devices with heavy heating systems, account for a significant portion of energy usage in both industrial and domestic settings. One of the greatest issues humans are currently faced with is the reducing global energy use, as a result of economic, environmental, and sustainability. Utilization of ANN in modelling of thermal systems has become necessary. Various heat transfer applications and analysis focused on the use of ANN for solving problems related to thermal systems have been investigated in this study. It was observed that solutions obtained using these methods require high level of improvement due to the complexity of dataset obtained from thermal devices. It was observed that MLPN with Levenberg-Marquardt Algorithm is much more suitable for analysis and outperforms other algorithms of MLPN like RBP and SCG. This study further identified improvements in the use of artificial neural network techniques and its up-and-coming applications for addressing variability of heat transfer problems. Limitations of the classical and CI models were further revealed, and recommendations have been made. For future studies, the use of creative models, hybrid algorithms and Metaheuristics have been identified as preferable modelling techniques for effective analysis of thermal systems.

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