Artificial Neural Network with Multilayer Perceptron Model for the Prediction of Thermal Parameters of Nano Particle Coated Miniature Loop Heat Pipe Using Experimental Data

James Graham Steward [a], L. Godson Asirvatham [a], A. Hepzibah Christinal [a], S. Jebasingh [a], S. Manova [a]

[a] *Karunya Institute of Technology and Sciences, Coimbatore, India*

Abstract

The present study deals with the prediction of transfer parameters of a miniature loop heat pipe using Artificial Neural Network (ANN). The outcome of various coating thicknesses on heat transfer coefficient, thermal conductivity, and thermal resistance is predicted using Multilayer Perceptron (MLP) approach. The experimental data for different coating thicknesses are given as input to the ANN model and the heat transfer parameters are predicted. 80% and 20% of the total experiment data are used as training and testing data accordingly. High accuracy between experimental and the predicted values for the heat transfer parameters (R2 =0.98) are observed. Based on the results, the root means square error (RMSE) values of 1.77%, 17.9%, and 8.79% respectively are observed for thermal resistance, thermal conductivity, and heat transfer coefficient. This study establishes the ANN model with multilayer perceptron as an alternative method to estimate the heat transfer parameters thereby reducing the cost and time in the thermal characteristic study of miniature loop heat pipes.

Keywords

Miniature loop heat pipe, Thermal characteristic, Artificial neural network

1. Introduction

Loop heat pipes are special types of heat pipes used in the removal of heat stress generated in electronic devices [1]. Thermal conductivity and heat capacity are the parameters that influence heat transfer coefficient which also affects the dimension, flow pattern, and viscosity of the nanofluid. In recent years LHP with different nanofluids are studied widely by many researchers [2] as it possesses all the thermal properties of conventional heat pipes and more importantly due to its efficiency in heat transfer. Several examinations have been undertaken by analysts on the effect of using nanofluids or by the coating of nano particles on the boiling surface of heat pipes. The experimental study involves meticulous preparation of nanoparticle-coated heat pipes and recording thermal characteristic of the heat pipes under the various thickness of nanoparticle coating upon the boiling surface of the heat pipes [3]. The conventional method of thermal behavior of loop heat pipes has limitations in the calculation and predictions. As an alternative method, the ANN technique is found to be a promising technique with significantly less error and validation of the parameters with MLFNN predictions [12]. In this paper, we propose an ANN model with Multilayer Perceptron (MLP) to obtain the Heat Transfer Coefficient, Thermal Conductivity, and Thermal Resistance of the Loop Heat Pipe where the working fluid is water [5]. In [3] the authors employ the feed-forward ANN method to predict thermal resistances of a closed vertical meandering pulsating heat pipe. In [Deshpande, Purva, et al] the authors determine the changes in heat rate and boiler efficiency in thermal plants using sensitivity coefficients. The study

WCES-2022: Workshop on Control and Embedded Systems, April 22 – 24, 2022, Chennai, India.
EMAIL: hepzia@yahoo.com (A. Hepzibah Christinal)
ORCID: 0000-0003-3965-3183 (A. Hepzibah Christinal)

was also useful in improving the efficiency of the boiler.

In [Esfe, Mohammad Hemmat, et al] the authors evaluate dynamic viscosity and thermal conductivity of ferromagnetic nanofluids including parameter temperature, particle diameter, and solid volume fraction.

2. Summary of the Experimental Work

In [18], the authors coated copper nanoparticles on the mLHP and studied the consequence of coating of nanoparticle on the thermal characteristic of heat pipes. In the following, we briefly summarize [18] the experimental details to calculate the three different parameters of miniature loop heat pipe. In order to analyze the reaction of coating thickness on the parameters, the authors fabricated mLHPs with six types of coating thicknesses (0 nm, 100nm, 200nm, 300nm, 400nm, and 500nm). The evaporator with or without nanoparticles was compared using distilled water which was utilized as a fluid working for finding out the performance of transfer of heat in the loop heat pipe. The filling ratioof 30% on the total volume was engaged which is the optimum for this design in all heat pipes [9]. The testing of heat pipes in a vertical orientation to provide gravity-assisted operation. Water at 25 LPH is made to flow through the condenser at 25 c. Using the heater block and dimmest at the heat load was pertained to the evaporator. After a few minutes, various points in mLHPs get to steady-state temperature. For every 5 seconds, the temperature was calculated by a data logger and computer. Only after 30 minutes, the heat load was changed to ensure 20 minutes of steady-state operation. The input heat differs from 20 W to 380 W. For each step, there was a 40 W increase. The application of heat loads was given the load was decreased to zero above all. The mLHPS were removed from the experimental arrangement once it reaches room temperature. Each of the loop heat pipes was tested at different temperatures at three different time instances to confirm the average value of temperatures. These procedures were repeated for all five heat pipes. The variation was found to be 1.5%. A stability test was conducted with a 400 mm coated pipe for evaluating the stability and strength four times.

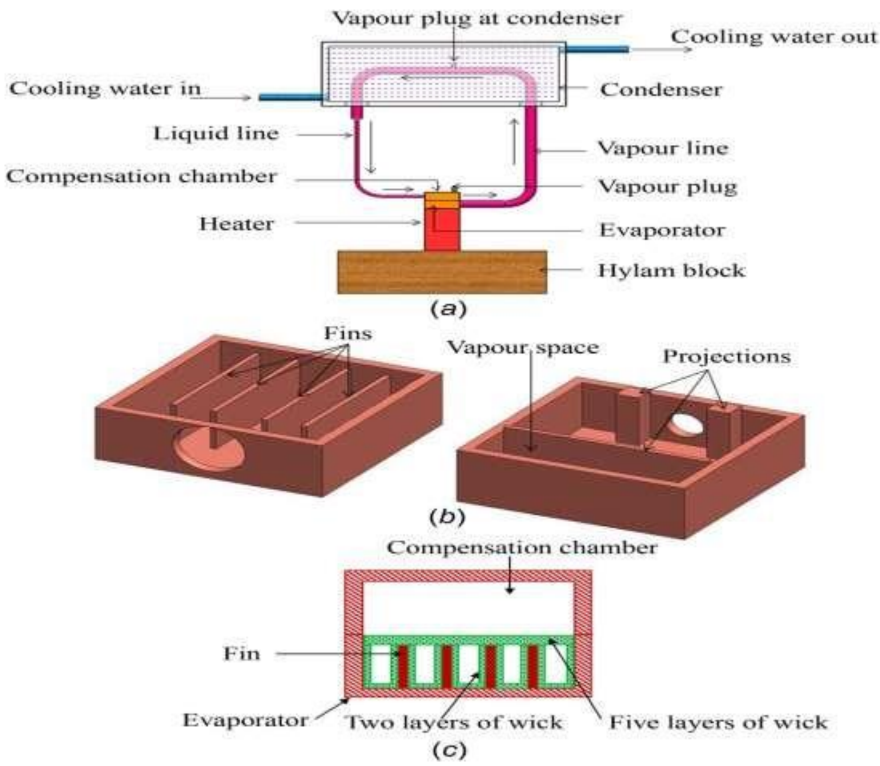


Figure 1: (a) Miniature Loop Heat Pipe-Heater Assembly (b)Evaporator and CC, and (c) schematic of the evaporator. (Reprinted with permission from Tharayil et al. [6]. Copyright 2016 by Elsevier).

The values of the experimentation were recorded for each pipe by the data logger. The various data recorded due to the impact of nanoparticles coating and heat load were plotted in the table. The values were recorded for the criterion such as thermal resistance, thermal conductivity, temperature, and heat load by coating thickness for each evaporator surface. In this present study, the data collected from the experimental study were utilized for modeling ANN and to evaluate the thermal parameters in miniature loop heat pipes [18].

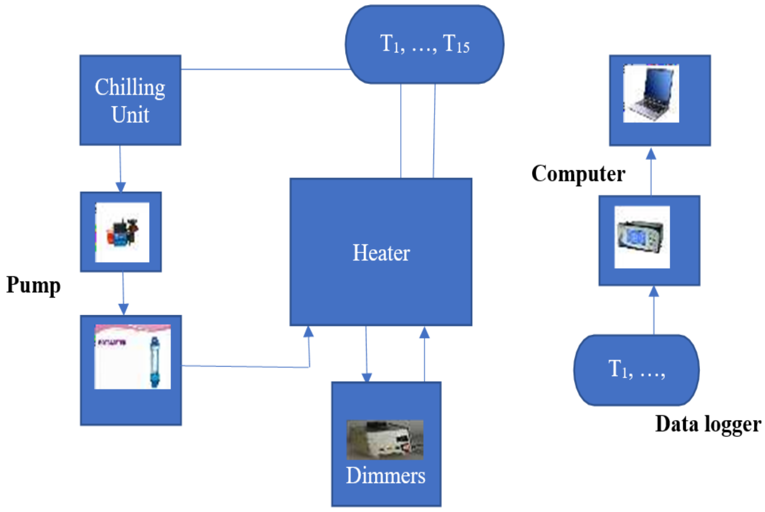
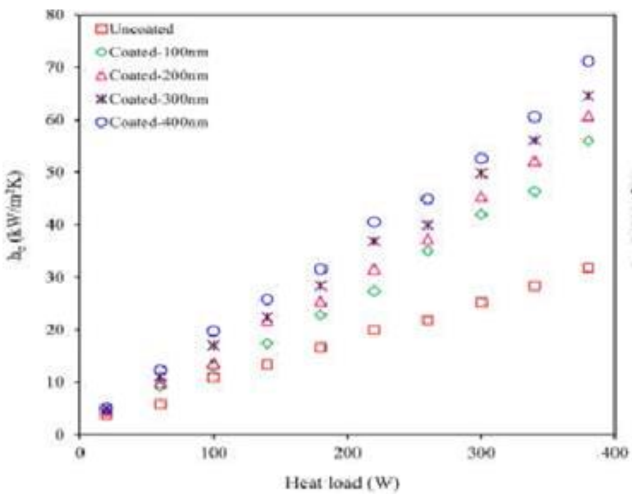


Figure 2: Experimental Setup



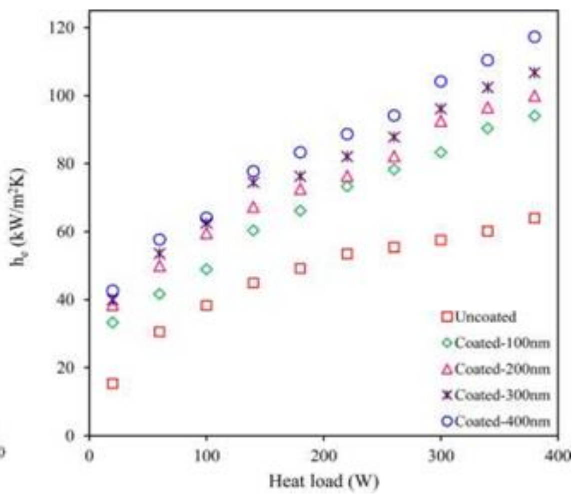
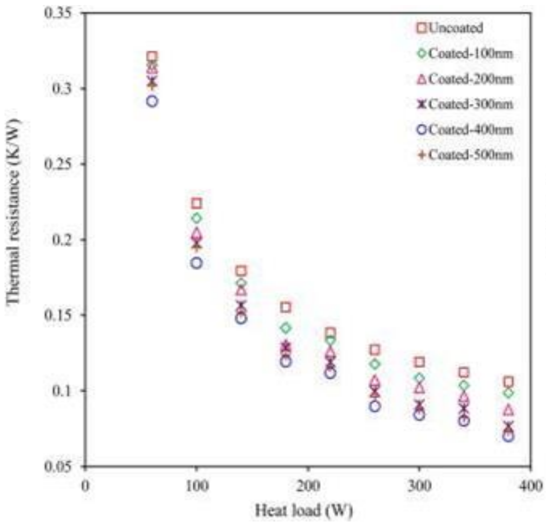


Figure 3: Condenser heat transfer coefficient versus heat load
Figure 4: Evaporator heat transfer coefficient versus heat load



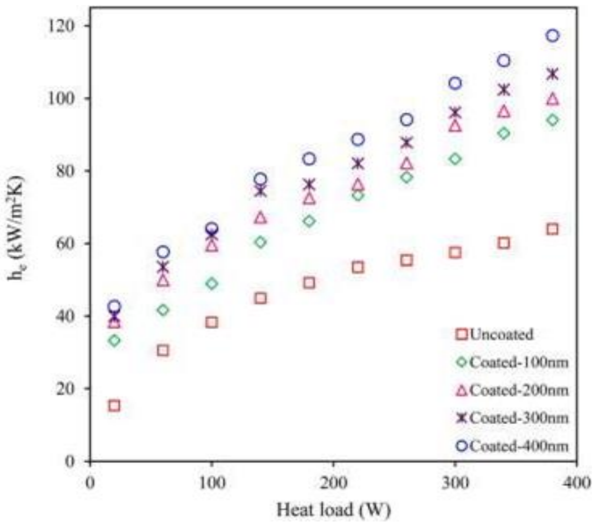


Figure 5: Thermal resistance versus heat load
Figure 6: Evaporator heat transfer coefficient versus heat load

The graph shown in Fig 3 represents the condenser heat transfer coefficient versus heat load taken while experimenting. The graph shown in Fig 4 represents the Evaporator Coefficient Vs Heat load. Also, Fig 5 and Fig 6 represent the thermal resistance Vs Heat load and Evaporator Heat transfer Coefficient Vs Heat Load respectively.

3. Artificial Neural Networks with Multilayer Perceptron (ANN-MLP)

ANN is a bio-inspired computational model abstracting the function of brain processing and analyzing the huge amount of information received [10]. The model has been successfully applied in solving computationally hard problems in the computer science field. ANN model consists of several nodes (neurons) and links connecting the nodes for communication between the nodes. There are three layer such as an input, hidden and an output layer (Fig 7), which are all determined through trial and error. The input layer perceives which is then refined by the hidden layer and ahead dispatched to the output layer. We use the Multilayer Perceptron (MLP) model to forecast the thermal characteristics of the mhlp in this paper. [7].

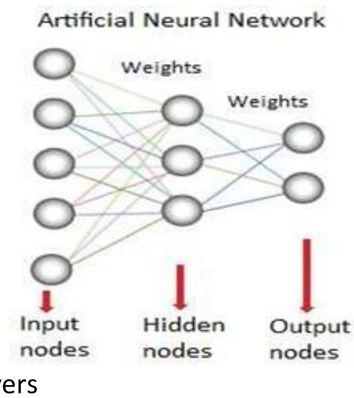


Figure 7: ANN model with three layers

The input given to the ANN model is processed by the nodes, which is communicated to other nodes of the model through the links and an output is produced [5]. The links between the nodes are assignedweights which controls the flow of information between the nodes. If the output produced has errors, then the weights associated with the links are altered and the model improves the output produced by providing suitable feedback to the network of nodes. The ANN computational model has the capacity of learning from the input data [6]. The MLP uses supervised learning which has backpropagation method for training the data. For a detailed discussion on the functioning of model, the reader may referthe article [15]. Figure 8 illustrate the step-by-step process of applying the model in the evaluation of thermal parameters of the miniature loop heat pipes.

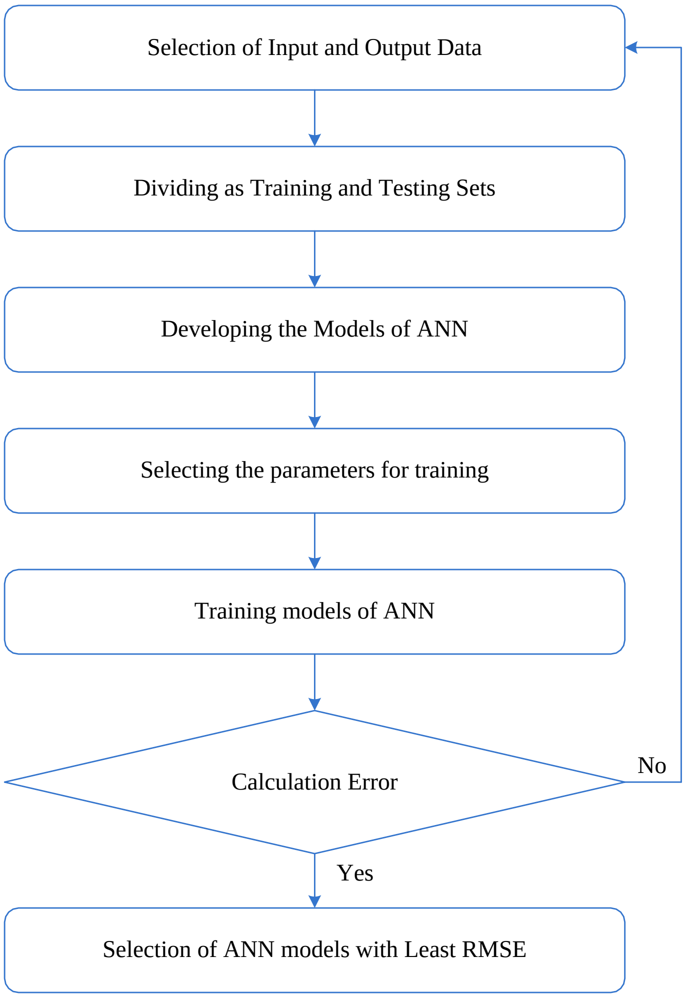


Figure 8: Flowchart

4. Prediction of Parameter by Applying ANN Techniques using MATLAB

The goal of this research is to use data from experimental results to estimate heat transfer coefficient, thermal conductivity, and thermal resistance. [20]. The ANN-MLP is constructed usingthe customized MATLAB code. The following input parameters are considered for modelling the ANN: Temperature (T_e), Heat load(W), Number of turns(N), Condenser length (L_c), Evaporator Length (L_e), Thermal Resistance (R_{th}). The observation of our dataset is given as input in the inputlayer. Randomly the weights are initialized. Now in feed propagation the neurons are activated andthe activated neurons are limited by the weights, which are propagated continuously until it attainsthe predicted value [17]. The predicted value is analyzed on the basis of original result and the flawis measured. The error is now back propagated in to the model for attaining better accuracy of the prediction of parameters. According to the error the weights are updated by decision of learning [19]. After each observation of enforcement learning the weights are updated. Finally, the whole training set is passed and epochs are generated.

5. Results and Discussion

The table listed below are the predicted values using ANN and they are plotted in a table. The Values which are predicted are MSE, PSNR, R, RMSE, NRMSE, Mape.

Table 4.1: Heat Transfer Coefficient_H_C

	Total Hidden layers	Total neurons in hidden layers	Total No. of neurons	Correlation Coefficient of data for Training	Correlation Coefficient of data for testing	Correlation Coefficient for overall data	Results MSE PSNR R RMSE NRMSE Mape
1	1	3	7	0.98131	0.96338	0.97664	37.784049912735995, 32.357718545958080, 0.964950230940293, 6.146873181767783, 0.092101785762178, 17.55157628
2	2	4(3,1)	8	0.97879	0.93169	0.97353	34.894155416014240, 32.703276698151925, 0.954749499686177, 5.907127509713519, 0.105371521757287, Inf
3	2	5(3,2)	9	0.9798	0.98325	0.98056	16.000176195166350, 36.089555957015385, 0.987181264904587, 4.000022024335160, 0.065746581596567, Inf
4	3	6(2,2,2)	10	0.9441	0.87687	0.92899	92.511135465475800, 28.468863494246450, 0.895277348876716, 9.618270918698215, 0.171816200762741, Inf
5	3	7(3,2,2)	11	0.97465	0.9928	0.97537	20.047827220982820, 35.110130500997740, 0.975498408176007, 4.477480007881980, 0.073594345954668, Inf
6	3	8(3,3,2)	12	0.96255	0.94846	0.95857	66.152825638083950, 29.925319615837100, 0.929043890653997, 8.133438733898716, 0.114297902387559, Inf
7	3	9(3,3,3)	13	0.98129	0.99104	0.98289	8.761551822771107, 38.704993268026930, 0.991211632318807, 2.959991861943392, 0.048652068736742, Inf

Table 4.2: Thermal Conductivity H_E

	Total Hidden layers	Total neurons in hidden layers	Total no. of neurons	Correlation Coefficient of data for training	Correlation Coefficient of data for testing	Correlation Coefficient for overall data	Results MSE PSNR R RMSE NRMSE Mape
1	1	3	7	0.97287	0.90786	0.97287	1.348006631824366e+02, 26.833883320531480, 0.966505259790726, 11.610368778916394, 0.116103687789164, Inf
2	2	4(3,1)	8	0.976	0.98258	0.97721	44.382660546522274, 31.658670281354997, 0.990363171898819, 6.662031262799828, 0.066620312627998, Inf
3	2	5(3,2)	9	0.97419	0.99252	0.97679	1.312368389942967e+02, 26.950245995612990, 0.964349419657705, 11.455864829610059, 0.097679611439376, Inf
4	3	6(2,2,2)	10	0.97282	0.89779	0.96792	1.159585597069651e+02, 27.487775484174620, 0.978932518739079, 10.768405625112988, 0.155883115592255, 16.20655434
5	3	7(3,2,2)	11	0.97294	0.92877	0.96836	1.326799558437884e+02, 26.902750425546998, 0.976706308650227, 11.518678563263600, 0.144326256900935, 18.80000751
6	3	8(3,3,2)	12	0.9239	0.92533	0.92206	2.044068143763205e+02, 25.025849909477840, 0.945538778485724, 14.297091115899082, 0.148695695433168, Inf
7	3	9(3,3,3)	13	0.98361	0.98921	0.98121	17.952095483159848, 35.589652113709896, 0.996860128752723, 4.236991324414041, 0.057716814118159, 5.207988507

Table 4.3: Thermal Resistance R_t

	Total Hidden layers	Total neurons in hidden layers	Total no. of neurons	Correlation Coefficient of data for training	Correlation Coefficient of data for testing	Correlation Coefficient for overall data	Results MSE PSNR R RMSE NRMSE Mape
1	1	3	7	0.96655	0.97448	0.9671	43.137837421745600, 31.782219915279946, 0.970340707187143, 6.567940120140073, 0.088302502287444, 2.551676661021013
2	2	4(3,1)	8	0.97673	0.98729	0.97797	12.758283476160496, 37.072881133619400, 0.991637846251108, 3.571873944606738, 0.046545138710017, 6.970743991709018
3	2	5(3,2)	9	0.97145	0.94119	0.96647	57.611320578981630, 30.525725305365160, 0.962941817466203, 7.590212156388096, 0.114482837954572, 7.290600765185099
4	3	6(2,2,2)	10	0.97538	0.9821	0.9746	16.001471637375610, 36.089204347994276, 0.990137282784463, 4.000183950442231, 0.056788528541201, 6.786050844727903
5	3	7(3,2,2)	11	0.98471	0.9781	0.98093	65.739101281370920, 29.952565983174573, 0.953861391604532, 8.107965298480927, 0.104457166947706, 16. 728962865294204
6	3	8(3,3,2)	12	0.9742	0.97584	0.97406	36.929866162412935, 32.457026271414065, 0.976228971663768, 6.076994829882031, 0.078636061463277, 5.673455509985892
7	3	9(3,3,3)	13	0.99454	0.99808	0.99501	1.777331966742656, 45.633118087746816, 0.998844059334908, 1.333166143713024, 0.017472688646304, 2.164644920109018

The correlations available in the literature for the performance of looped heat pipes are similarly the same from the data predicted and the input parameters are within the range. Thus, ANN method has more advantages than obtaining the values through experimental methods. Artificial Neural Networks are used to estimate the performance of tiny Loop Heat Pipes in order to make the prediction accurate and reliable [19]. The iterative constructive error method is integrated with the statistical error method by comparing ANN models. The optimum ANN type is found to be the multilayer perceptron with back propagation structure.

6. Best Performance in heat transfer coefficient H_c Graph

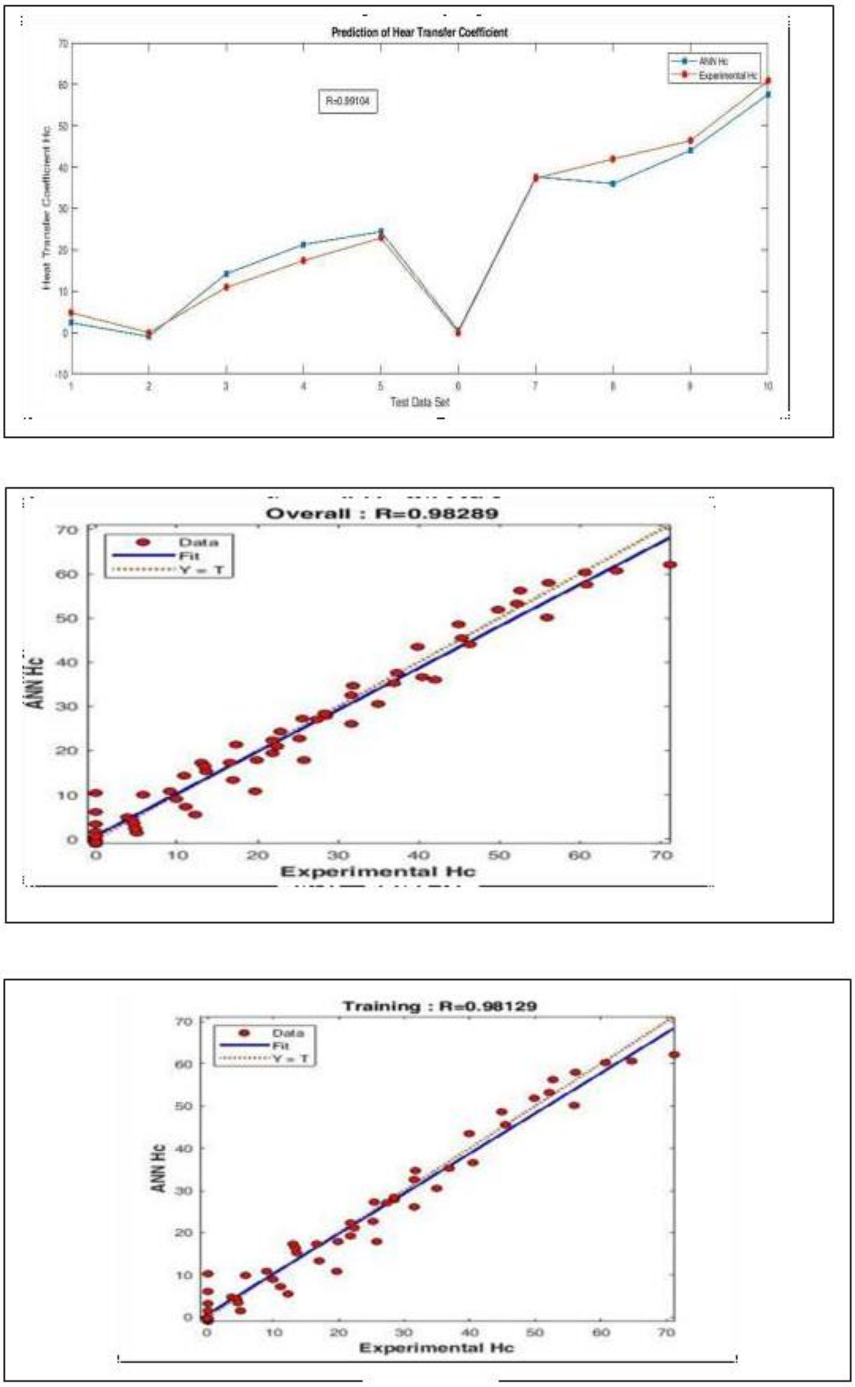


Figure 9 (a): Heat Transfer coefficient anticipated by ANN model with the test data
Figure 9 (b): Regression Graph of the overall data
Figure 9 (c): Training data sets predicted by ANN

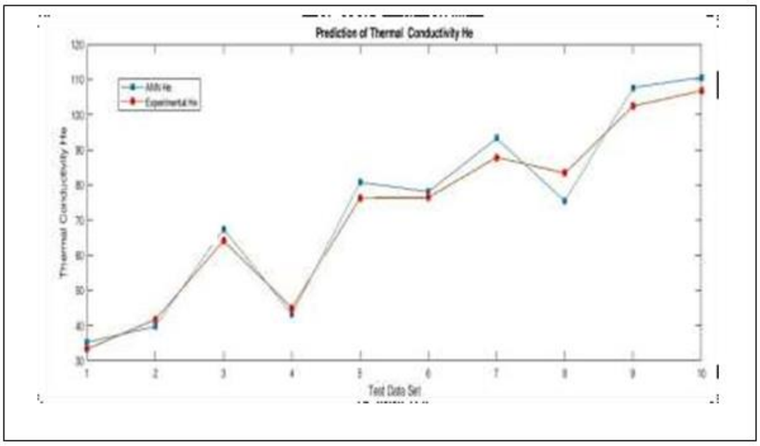
7. Best performance thermal conductivity H_e graph

The heat transfer coefficient anticipated by ANN model with the test data is indicated in Fig 9(a). The inputs given to evaluate the heat transfer coefficient were heat load, number of coating and temperature. From the graph we infer that the values predicted by ANN is identical with the data. The blue line gives the values obtained using ANN and the red line illustrates the data for experimentation.The test data are indicated along the X -axis then heat transfer coefficients are plotted along the Y-axis.Graph shown in Fig 9 (b) is the regression graph of the overall data. The relationship between the experimental data and training data set is represented graphically. The ratio of training set data and testing data was 70% and 30% respectively. The dotted lines passing through the data set is given as Y=T and the blue line denotes the fit. The red dots represent the experimental data.

The graph in fig 9(c) shows the training data sets predicted by ANN. The training results has showed regression coefficient (R) up to 0.98129. The experimental data was trained with 70% of the data for the training set. Minor deviation was observed from the experimental data.

The graph in fig (d) shows the result of the testing done. These testing was done with 30% of the input parameters. The regression value of the testing data was 0.99104. The data obtained were observed to be accurate with the experimental values. The tested data was fitted with linear equation which shows the accuracy of the prediction and the dotted lines are represented by Y=T.

8. Best performance in thermal conductivity He graph



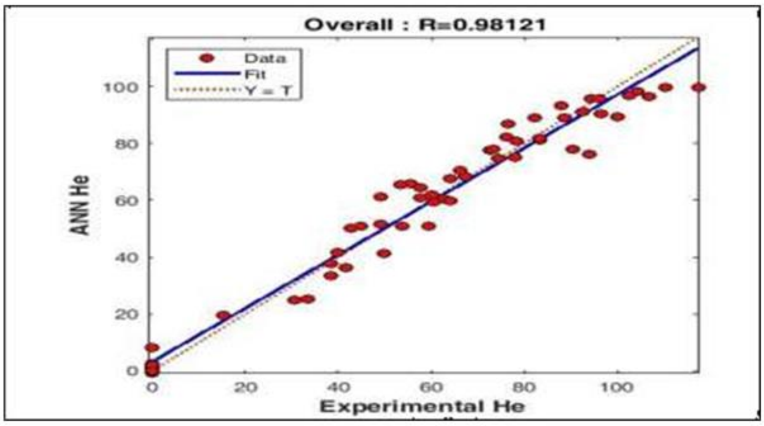
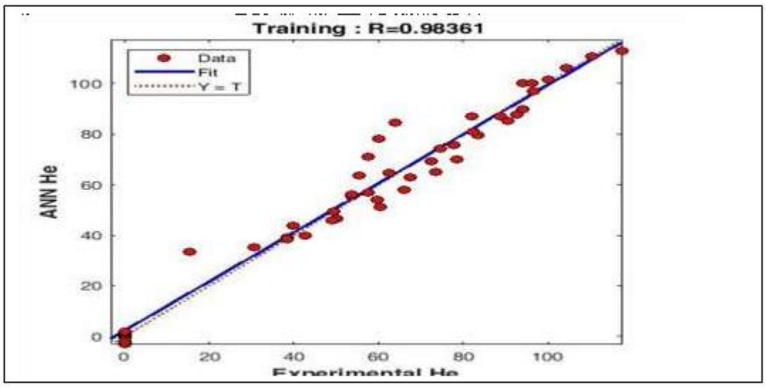


Figure 10: Graphs of Thermal Conductivity He – ANN - 3 Hidden Layers 13 Neurons
(a) Prediction He Graph (b) Regression Graph Overall data



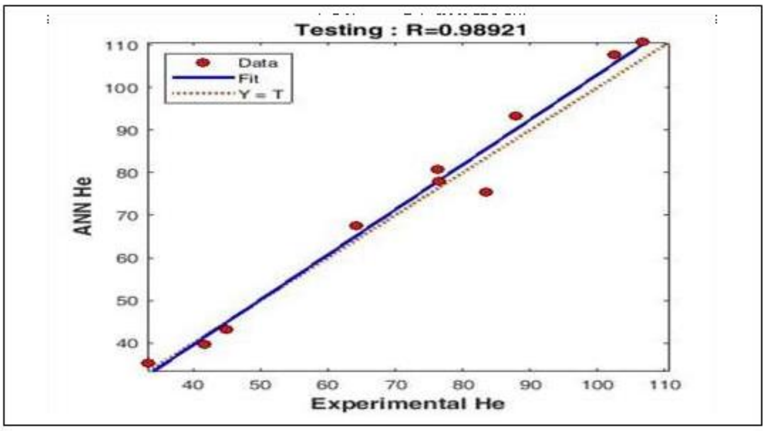
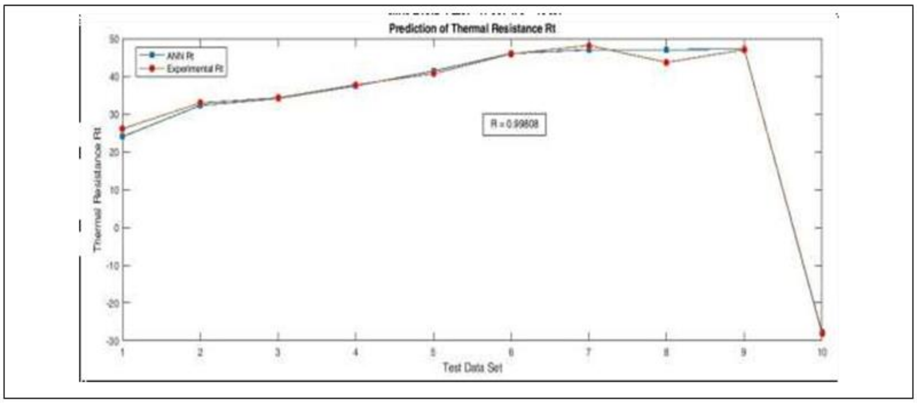


Figure 10: Graphs of Thermal Conductivity He – ANN - 3 Hidden Layers 13 Neurons
(c) Regression Graph ofTraining Data (d) Regression Graph of Data for testing

The thermal conductivity parameter evaluated by ANN with the test data is indicated in Fig 10 (a). From the graph we infer that the predicted data is approximately same as that of the test data. The linear relationship of entire data shown is given in the graph (Fig 10 (b)) for the thermal conductivity. Also, we find that the straight line fits the data linearly. The blue line is the best fit of thedata which shows the accuracy when comparing with the experimental data.

The fig 11 (c), fig 11 (d) shows the graph of training data and testing data respectively using ANN model for thermal conductivity. Both graphs are almost accurate and the regression coefficient is 0.98.These graphs were generated using customized MATLAB coding.

9. Best performance in thermal resistance r_t graph



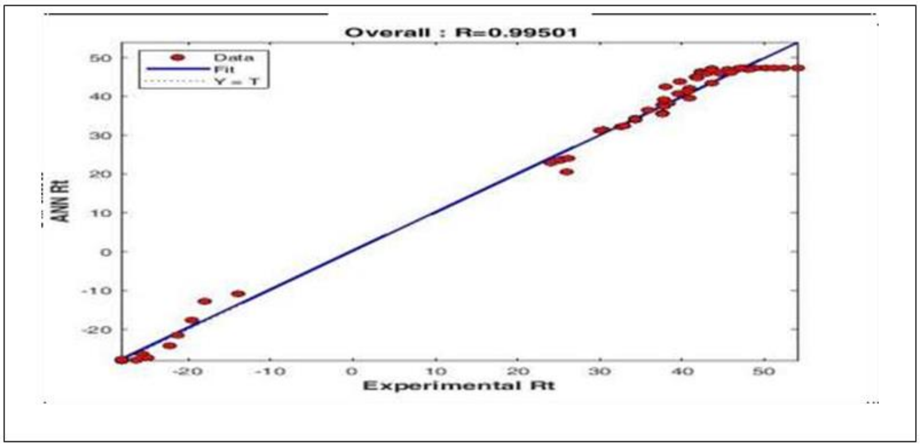
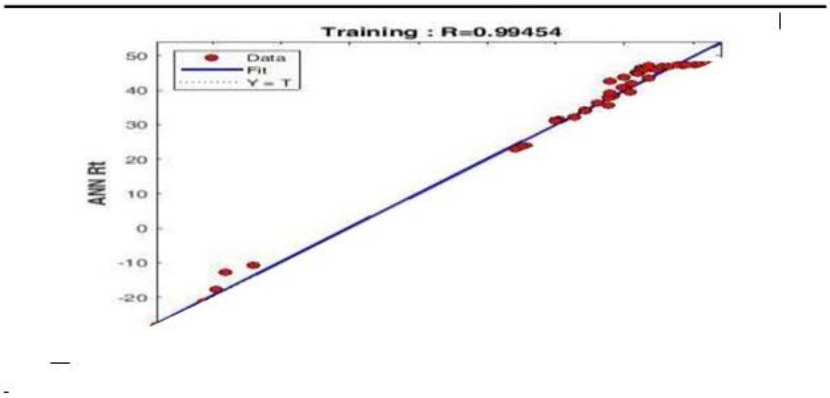


Figure 11: Graphs of Thermal Resistance Rt – ANN – Hidden Layers – 3, Neurons – 13
(a) Prediction RtGraph (b) Regression Graph of Overall Data

The first Graph shows the prediction of the Thermal Resistance. This Graph has proved its accuracy with the Experimental Data. The inputs given to predict are heat load, no of coating and temperature. There shows a decline at the last which shows the accuracy of the thermal resistance.

The Blue line shows the ANN and the red line shows the data for experimenatation. The X - Axis shows the test data and the Y-axis shows the heat transfer coefficient. These both are predicted and the Graph already proves its approximately accurate to the experimental data given. The Next graph shows Regression Graph the overall data. This Graph is the output after testing and training data set. The training set is taken 70% and testing as 30%. The dotted lines passing through is given as Y=T and the blue straight line denotes the Fit. The red dots represent the experimental data. The graph shown in fig 10 and 11 represents the best performance of the prediction of heat Transfer coefficient H_c, thermal conductivity H_e, thermal resistance R_t. We observe that both the experimental and ANN values coincide



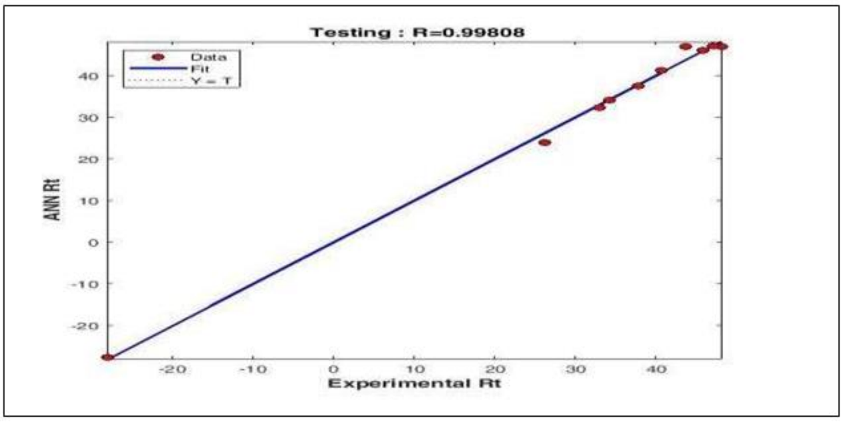


Fig. 11: Graphs of Thermal Resistance Rt – ANN – Hidden Layers – 3, Neurons – 13
(c) Regression Graph of Training data (d) Regression Graph of Testing data

The number of neurons and layers in the ANN model are critical factors in forecasting loop heat pipe performance. We have considered multiple sets of predictions with several number of neurons and hidden layers to obtain the best result. Initially we set the ANN system with a total of seven neurons in single layer mode and three hidden layer neurons. Subsequently the training of data was processed with two hidden layers and a total of eight neurons 5(3,2) in the hidden layer. Finally, training data was processed with nine neurons 5(3,2) having three hidden layers with different set of neurons as plotted in the table. The accuracy of the predicted data was high with the three hidden layers having 13 neuronsin total which was split as 9(3,3,3). Also, the mean square error of the predicted and experimental datais low when compared with other results.

10. Conclusion

The prediction of thermal conductivity, coefficient of heat transfer and thermal resistance of miniature loop heat pipes has been studied using the novel method ANN with Multilayer perceptron technique. The results obtained shows that the predicted data is approximately same as the experimental results. The below tables show the prediction accuracy from the experimental results and the predicted results of heat transfer coefficient, thermal resistance and thermal conductivity. The results acquired by the MLP network developed are MSE(H_c)=8.76155 MSE(H_e)=17.95209, MSE(R_t)=1.77733. The prediction accuracy for heat transfer coefficient, thermal conductivity and thermal resistance are 98.02%, 98.01% and 98.04% respectively. Thus, the average divergence between the data for experimentation and values which are predicted is1.5%. The accuracy was high with the three hidden layers having 13 neurons in total which was split as 9(3, 3, 3). The mean square error for thermal resistance, thermal conductivity, heat transfer coefficient was given by 1.77%, 17.9% and 8.76 % respectively. Approximation is high when the neurons and the hidden layers are increased in the ANN model. It was discovered that in hidden layers maximising the total neurons improves the anticipated data outputs.

11. Acronyms

- MSE – Mean Square Error
- PSNR- Peak to Signal Noise Ratio
- R – Regression Coefficient
- RMSE- Root Mean Square Error
- NRMSE-Normalized Root Mean Square Error
- Mape-Mean Absolute Percentage Error

12. References

[1] Maydanik, Yu F. "Loop heat pipes." *Applied thermal engineering* 25.5-6 (2005): 635-657.

[2] Dutra, Thiago, and Roger R. Riehl. "Loop heat pipe: design and performance during operation." *AIP Conference Proceedings*. Vol. 699. No. 1. American Institute of Physics, 2004.

[3] Changdong, Lu, et al. "Experimental and computational analysis of a passive containment cooling system with closed-loop heat pipe technology." *Progress in Nuclear Energy* 113 (2019): 206-214.

[4] Launay, Stéphane, Valérie Sartre, and Jocelyn Bonjour. "Parametric analysis of loop heat pipe operation: a literature review." *International Journal of Thermal Sciences* 46.7 (2007): 621-636.

[5] Latha, A., et al. "Performance analysis on modeling of loop heat pipes using artificial neural networks." *Indian Journal of Science and Technology* 3.4 (2010): 463-467.

[6] Tharayil, Trijo, et al. "Effect of filling ratio on the performance of a novel miniature loop heat pipe having different diameter transport lines." *Applied Thermal Engineering* 106 (2016): 588-600.

[7] Heidari, Elham, Mohammad Amin Sobati, and Salman Movahedirad. "Accurate prediction of nanofluid viscosity using a multilayer perceptron artificial neural network (MLP-ANN)." *Chemometrics and intelligent laboratory systems* 155 (2016): 73-85.

[8] Dutra, Thiago, and Roger R. Riehl. "Loop heat pipe: design and performance during operation." *AIP Conference Proceedings*. Vol. 699. No. 1. American Institute of Physics, 2004.

[9] Heris, Saeed Zeinali, Mohsen Nasr Esfahany, and Gh Etemad. "Investigation of CuO/water nanofluid laminar convective heat transfer through a circular tube." *Journal of Enhanced Heat Transfer* 13.4 (2006).

[10] Heris, S. Zeinali, M. Nasr Esfahany, and S. Gh Etemad. "Experimental investigation of convectiveheat transfer of Al2O3/water nanofluid in circular tube." *International journal of heat and fluid flow* 28.2 (2007): 203-210.

[11] Heris, S. Zeinali, S. Gh Etemad, and M. Nasr Esfahany. "Experimental investigation of oxide nanofluids laminar flow convective heat transfer." *International communications in heat and masstransfer* 33.4 (2006): 529-535.

[12] Ku, Jentung. "Operating characteristics of loop heat pipes." *SAE transactions* (1999): 503-519.

[13] Lu, Lin, Lun-Chun Lv, and Zhen-Hua Liu. "Application of Cu-water and Cu-ethanol nanofluids ina small flat capillary pumped loop." *Thermochimica acta* 512.1-2 (2011): 98-104.

[14] Patel, Vipul M., and Hemantkumar B. Mehta. "Thermal performance prediction models for a pulsating heat pipe using Artificial Neural Network (ANN) and Regression/Correlation Analysis (RCA)." *Sādhanā* 43.11 (2018): 1-16.

[15] Peters, Teresa B., et al. "Design of an integrated loop heat pipe air-cooled heat exchanger for high performance electronics." *IEEE Transactions on Components, Packaging and ManufacturingTechnology* 2.10 (2012): 1637-1648.

[16] Qu, Jian, Hui-ying Wu, and Ping Cheng. "Thermal performance of an oscillating heat pipe with Al2O3–water nanofluids." *International Communications in Heat and Mass Transfer* 37.2 (2010):111-115.

[17] Rostampour, Vahid, et al. "Using Artificial Neural Network (ANN) technique for prediction of

apple bruise damage." *Australian Journal of Crop Science* 7.10 (2013): 1442-1448.

[18] Swain, Abhilas, and Mihir Kumar Das. "Artificial intelligence approach for the prediction of heat transfer coefficient in boiling over tube bundles." *Proceedings of the Institution of Mechanical Engineers, Part C: Journal of Mechanical Engineering Science* 228.10 (2014): 1680-1688.

[19] Tafarroj, Mohammad Mahdi, et al. "Artificial neural network modeling of nanofluid flow in a microchannel heat sink using experimental data." *International Communications in Heat and MassTransfer* 86 (2017): 25-31.

[20] Tharayil, Trijo, et al. "Effect of nanoparticle coating on the performance of a miniature loop heat pipe for electronics cooling applications." *Journal of Heat Transfer* 140.2 (2018).

[21] Vaferi, B., et al. "Artificial neural network approach for prediction of thermal behavior of nanofluidsflowing through circular tubes." *Powder technology* 267 (2014): 1-10.

[22] Manova, S., Asirvatham, L. G., Nimmagadda, R., Bose, J. R., & Wongwises, S. (2020). Feasibility of using multiport minichannel as thermosyphon for cooling of miniaturized electronic devices. *Heat Transfer*, *49*(8), 4834-4856.