Indian Journal of Science and Technology Vol. 3 No. 4 (Apr. 2010) ISSN: 0974- 6846

Performance analysis on modeling of loop heat pipes using artificial neural networks

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Abstract

The absence of mechanical moving parts, simplicity and robustness of loop heat pipes (LHPs) has prompted many satellite manufacturers to employ LHPs as primary thermal control systems. The acknowledgement of temperature dynamics of LHP plays a vital role in conception, optimization and control of the same. The overall thermal conductance varies not only with the power input, sink temperature and ambient conditions, but also with the previous history of its operation. In this connection, the present work is focused on a different approach for modeling LHPs. Experimental data for a vertical loop heat pipe made of copper, with two different working fluids, *viz*., water and ethanol for a range of heat inputs and fill ratios is collected from the literature. An artificial neural network (ANN) is trained with the collected test data and validated. Fully connected feed forward multilayer configuration (MLFFN) with momentum back propagation algorithm is adopted for the ANN. The MLFFN architecture consists of two input nodes representing the parameters heat input and fill ratio, and a single output node representing the thermal resistance of the LHP. The MLFFN predictions were validated within the domain of total available experimental data. This study also emphasizes that the understanding of the physical phenomena of LHP to be modeled by ANN is a prerequisite for getting acceptable results. As there is a serious limitation of conventional techniques for understanding the LHP physical phenomena and thermal behaviour, ANN approach appears to be very promising, if sufficient experimental data is available covering the entire range of system operation.

Keywords: Loop heat pipes, artificial neural network, modelling.

Introduction

LHPs are being developed for thermal control of micro electronic equipment. It can be readily integrated with different systems to maintain uniform temperature. There exist no reliable tools to design a LHP for a given micro electronic cooling requirement. ANN could offer an alternative approach for modeling LHPs. ANNs have been extensively studied during the past two decades and successfully applied in different areas especially where non-linear effects are predominant (Sen & Yang, 2000). Applying ANN to thermal systems is still not very popular, and definitely needs more research. This approach has not been applied for modeling LHPs so far. This paper intends to analyze thermal behaviour of LHPs by applying ANN.

Artificial neural networks

An ANN is a processing device, an algorithm or actual hardware, the design of which is motivated by the design and functioning of the human brain (biological neural cells & neurons) and components thereof. This design motivation is what distinguishes ANNs from other mathematical techniques. It is a kind of mathematical tool, similar to regression analysis. The key feature of ANNs over conventional regression analysis is that they employ non-linear mathematics and there fore can be used to model highly complex and non-linear systems such as LHPs. A fully connected feed forward multi-layer configuration using back propagation momentum learning algorithm has been employed in this study. This type of ANN has a strong ability to express complex non-linear mapping and has already found wide ranging applications (Sen & Yang, 2000).

The architecture of this type of ANN usually consists of an input layer, some hidden layers and an output layer. Each layer has some nodes representing artificial neurons. Each node is interconnected to the nodes of its preceding layer through adaptable weights and no lateral, self or back connection is allowed. Individual neurons have limited ability of calculation and expression but when they connect with each other, the whole network achieves ability to model complex functions. A network accepts an input vector and generates a response in the form of an output vector as shown in Fig.1.

Training of the network involves the iterative refinement of the associated 'weights' such that the pre-specified error condition is minimized. Training patterns are composed of a group of matching input and output vectors. The learning algorithm uses these sets of input and output vectors to train a network. It measures the difference between the desired output vector to the current actual output vector and the resulting error back propagates to alter the connecting weights in the direction of reducing the error. This process runs many times until the error is within the required level. Then the network holds the weights constant and becomes a valid model

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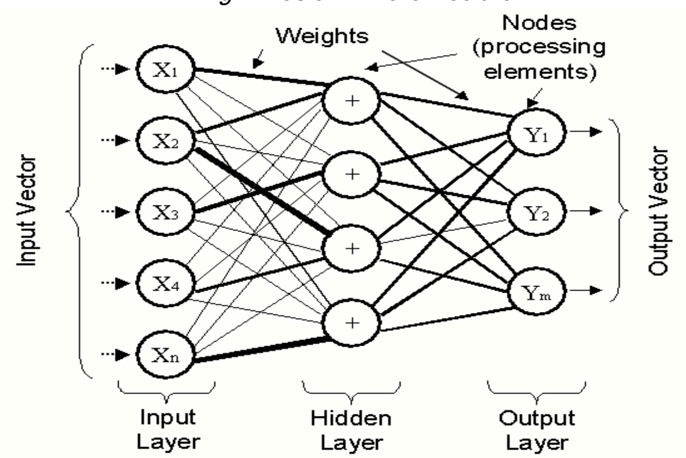
for prediction. As stated earlier, each neuron or node performs a very simple calculation. It sums all its inputs multiplied by their respective weights, then a squashing function is applied to this value. In this study, an identity function is used for output activation. For all other nodes, a sigmoid function is used as activation function. This function can perform non-linear input-output transformation actions and is normally used in most applications.

Fig.1. Basic ANN architecture



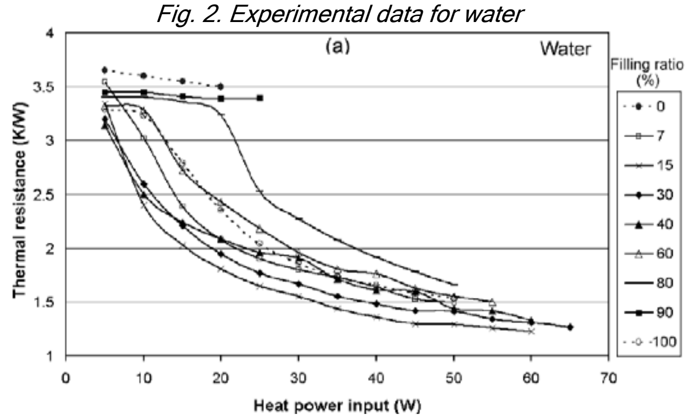
Characteristics of LHP

A given LHP has two operational extremities with respect to filling ratio (liquid volume/total LHP volume), i.e., 0% filled or an empty device and 100% filled equivalent to a single-phase thermosyphon (Khandekar *et al.,* 2003). It is obvious that at 0% fill ratio, an LHP structure with only bare turbes and no working fluid, is a pure conduction mode heat transfer device and obviously has a very high undesirable thermal resistance. A100% fully filled LHP is identical in operation to a single-phase thermosyphon. Since there exist no bubbles in the tube, pulsating effects are obviously non-existent but substantial heat transfer can take place due to liquid circulation in the tubes by thermally induced buoyancy. In between these two limits the device functions in a pulsating mode. In this pulsating operational mode, there exist three distinct regions:

Near 100% fill ratio: In this mode there are only very few bubbles present, the rest being all liquid phase. These bubbles are not sufficient to generate the required perturbations and the overall degree of freedom is very small. The buoyancy induced liquid circulation, which was present in a 100% filled LHP, gets hindered due to additional surface-tension-generated friction of the bubbles. Thus the performance of the device is seriously hampered and the thermal resistance much higher than for the 100% filled LHP.

Near 0% fill ratio: In this mode there is very little liquid to form enough distinct slugs and there is a tendency towards dry-out of the evaporator. The operational characteristics are unstable and undesirable.

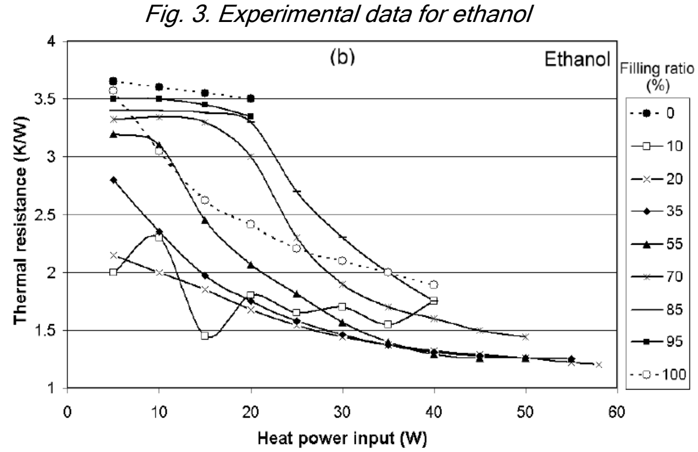
Fig. 2. Experimental data for water



LHP true working range: Between 10% to 90% fill ratio, the LHP operates as a true pulsating device. The exact range will differ for different working fluids, operating parameters and construction. It can be clearly stated that the underlying physics guiding the mechanism of heat transfer in a LHP is entirely different in different modes of operation as explained above. In the absence of 'apriori' knowledge of this fact, ANN modeling may prove to be quite misleading.

The Experimental results shown in Fig. 2 and Fig. 3 of copper bent tube LHP with water and ethanol as working fluids are taken from (Khandekar *et al.,* 2003) to train and validate the ANN.

Fig. 3. Experimental data for ethanol



Modelling of LHP using ANN

Model for water as working fluid

A total of 58 sets of data, for fill ratios ranging from 15% to 80% is taken from Fig. 2 to train the ANN and 29 sets of data, for fill ratios 0%, 7%, 90% & 100% are used for validation of the network. Two major parameters that affect the thermal resistance are the heat load and the fill ratio, hence both were considered as inputs to the network. The overall thermal resistance, based on heater temperature and the cooling air temperature, is the network output.

Fig. 4. Trained MLFFN output for water

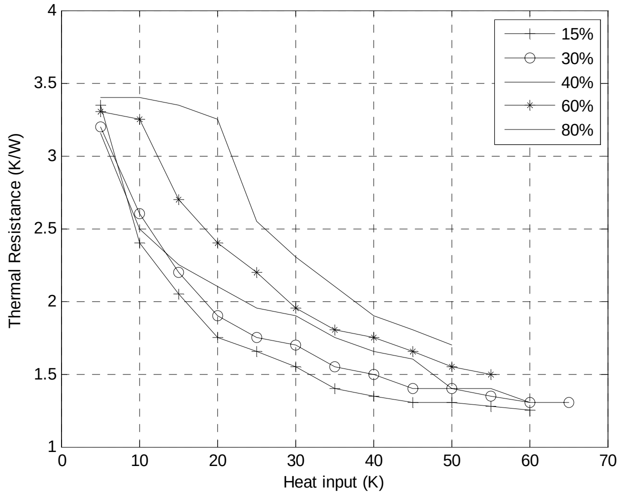


Fig. 5. Validation for water at 0% fill ratio

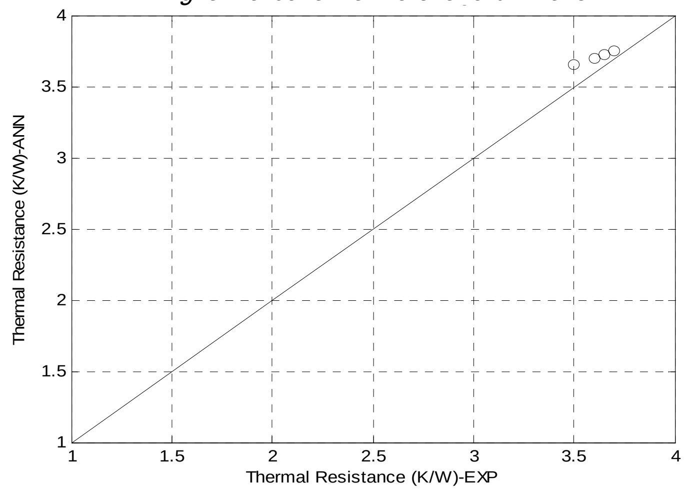


Fig. 6. Validation for water at 7% fill ratio

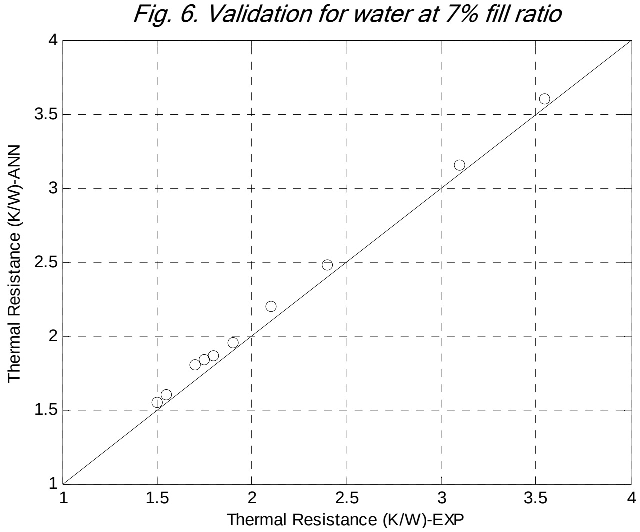


Fig. 7. Validation for water at 90% fill ratio

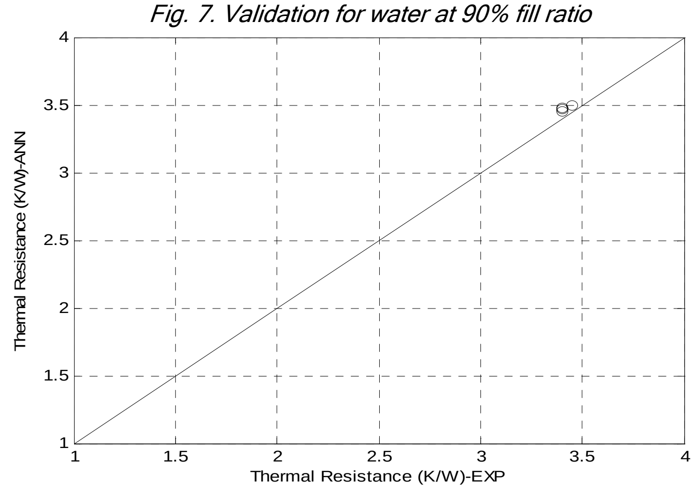


Fig. 8. Validation for water at 100% fill ratio

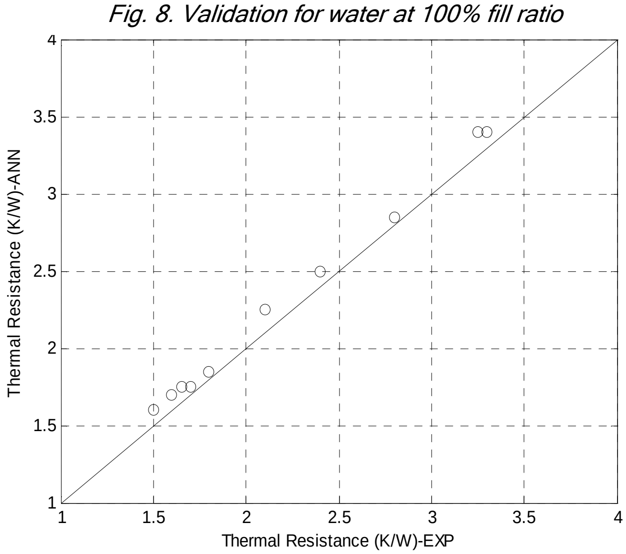


Fig. 9. Trained MLFFN output for ethanol

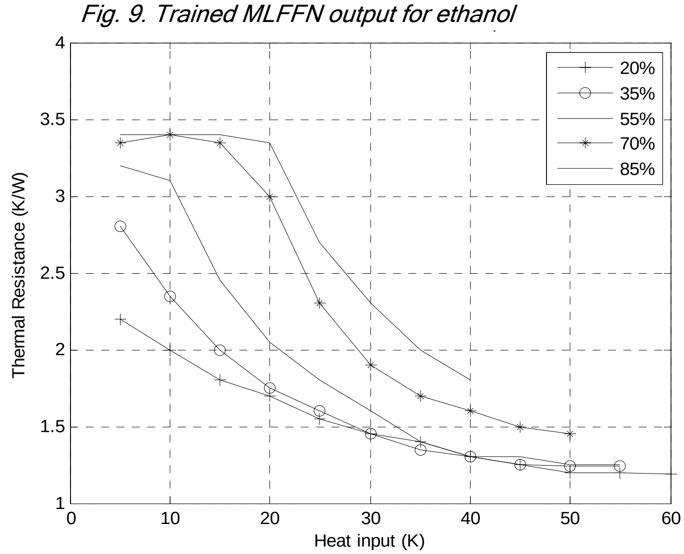


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Fig.10. Validation for ethanol at 0% fill ratio

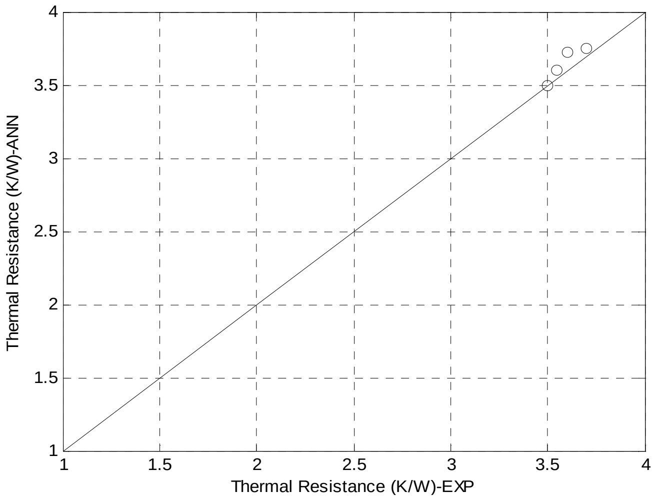


Fig.11. Validation for ethanol at 10% fill ratio

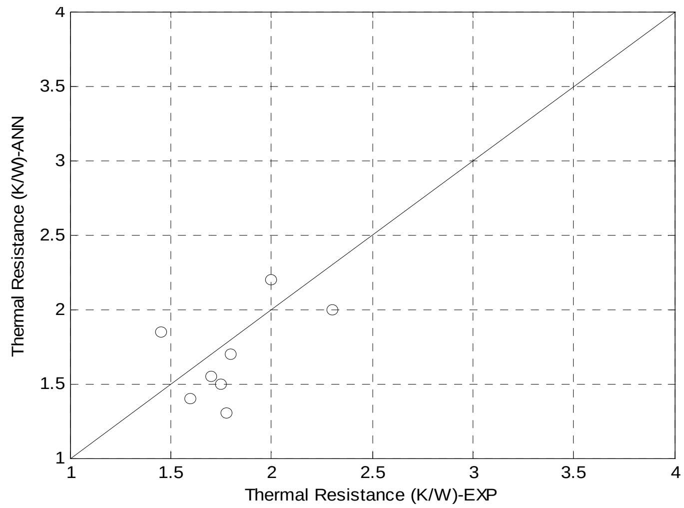


Fig.12. Validation for ethanol at 95% fill ratio

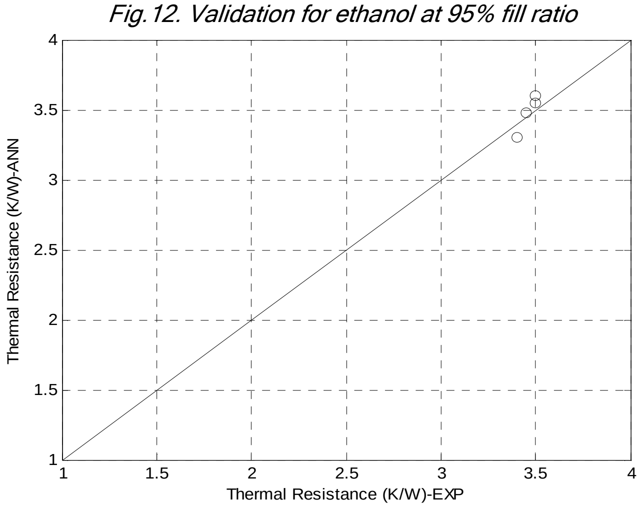


Fig.13. Validation for ethanol at 100% fill ratio

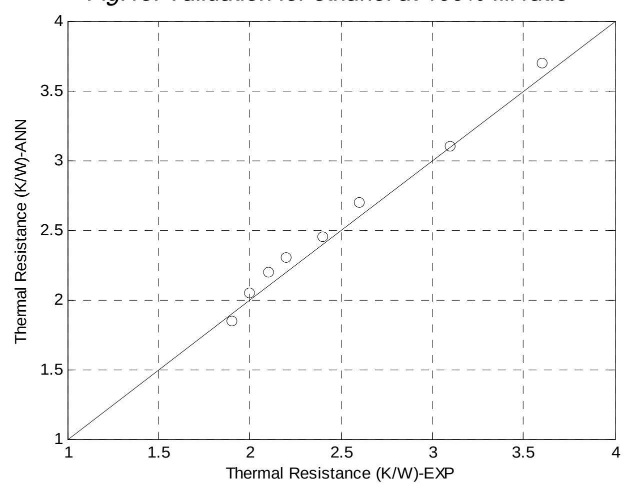


Fig.14. Prediction for water at 50% fill ratio

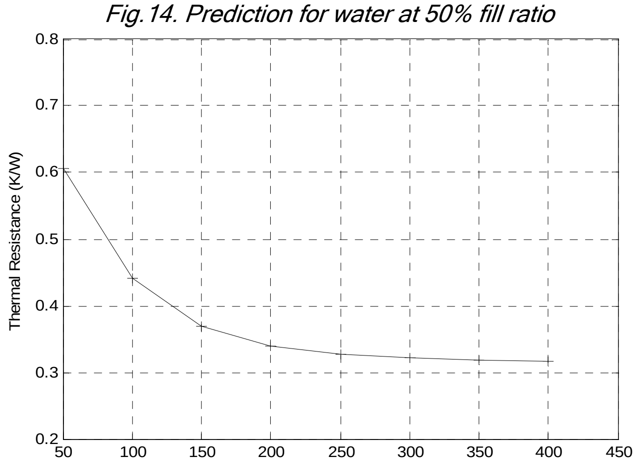
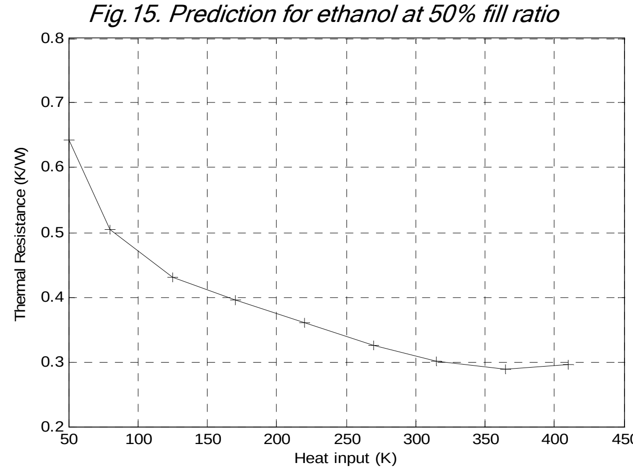


Fig.15. Prediction for ethanol at 50% fill ratio



Due to the scarcity of the available theory on selection of the network architecture, it is common practice to train various network architectures and then to choose the one which gives most accurate predictions for a given CPU time. In this work, Kolmogorov equation and Elm equation are tried in the network architecture and the Elm equation is found to be more suitable for this problem. After fixing the network architecture, 4 different configurations are studies as follows:(Input node- Hidden nodes- Output node) 2-1-1, 2-2-1, 2-3-1,2-5-1.

The best one with least errors between the ANN trained output data and the experimental data for the same number of epochs is 2-5-1. This configuration has two input nodes, corresponding to heat load and fill ratio, one hidden layer with 5 nodes, and the output layer consists of a single node, representing the thermal resistance.

The ANN was trained with the data representing the typical pulsating working range and the trained output is shown in Fig. 4. When compared to Experimental data the trained data scatters by an average of 3.5%. The next step is to validate the model and this is done by testing the network with new sets of data, which is not used during the training process. If the predicted data from the ANN model are close to the test data, then the network model is successful. Validation is done by 29 sets of data, which are kept aside for this purpose. A comparison between the ANN predicted data and the experimental data at 0%, 7%, 90% &100% fill ratios respectively is shown in Fig. 5-8 and the maximum possible error was found to be 6.7%.

Model for ethanol as working fluid:

A total of 50 sets of data, for fill ratios ranging from 20% to 85% is taken from Fig. 3 to train the ANN and 24 sets of data, for fill ratios 0%, 10%, 95% & 100% are used for validation of the network. The ANN with same architecture and configuration is trained with the data representing the typical pulsating working range and the trained output scatters by an average of 2.54%, compared to experimental data as shown in Fig. 9. The model is validated by 24 sets of new data, Fig. 10-13 gives the comparison between the ANN predicted data and the experimental data at 0%,10%,95% & 100% fill ratios respectively, and the maximum possible error was found to be 4.76% .

Prediction for water and ethanol at 50% fill ratio for a different range of heat input

The trained ANN model was applied to predict the thermal resistance of the same LHP at 50% fill ratio and heat input ranging between 50-450W, with water as working fluid. The predicted Thermal resistance values are shown in Fig.14 and15 describes the thermal resistance values predicted from the trained ANN at 50% fill ratio and heat input ranging between 50-450W, with ethanol as working fluid.

Conclusions

An MLFFN with momentum back propagation algorithm is successfully trained, validated and used for prediction at a different heat input range for an LHP with two different working fluids viz., water and ethanol. Since the conventional modeling of thermo-hydraulic behaviour of LHP is rather difficult, ANN based method appears to be a good tool, though there exists certain limitations. During the modeling, several uncertain choices such as the number of hidden layers, intern the number of nodes in each layer, the minimum number of training data sets, the initial values, the choice of test data etc., are critical in achieving successful ANN models.

In this study, only two parameters, ie, the heat input and the fill ratio were used as the input parameters. In practice, there exist various other parameters which affect the operation of LHP like, dimensions of the tube, inclination angle, physical properties of the working fluid etc., to consider all these parameters, abundant experimental data is required. While, ANN can effectively model highly complex and non-linear systems, it is equally difficult to obtain accurate and ample experimental data for such complex systems. Analysis of experimental data, to understand the physical phenomena helps in the network design, training and selection of learning algorithms to obtain a good quality ANN.

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