PERFORMANCE ANALYSIS OF CONSTANT CONDUCTANCE HEAT PIPES USING ARTIFICIAL NEURAL NETWORKS

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ABSTRACT

Study was carried out for optimizing the working fluid quantity in a heat pipe. A heat pipe with 28.4 mm outer diameter and 893 mm length was designed and tested with water as working fluid for different thermal loads to assess the performance of heat pipe. The temperature distribution along the heat pipe was measured and recorded using the thermocouples. The performance of the heat pipe was quantified in terms temperature difference, transmitting heat and thermal resistance. The amount of liquid filled was varied and the variation of the thermal performance of heat pipe is observed. Finally, optimum liquid fill ratio is identified in terms of lower temperature difference and thermal resistance with maximum heat transfer rate.

The artificial neural network use for the proposed model was developed with Matlab 2009 software by using backpropagation architecture.The artificial neural networks model which is used to predict the effect of fill ratio of working fluid (distillated water) at varying heat input on thermal performance of constant conductance heat pipe (CCHP).Artificial Neural Networks predicated of CCHP shows the ranges of fill ratio (85%-90%) of working fluid (distillated water) of wick volume have minimum thermal resistance and temperature difference and maximum transmitting heat.In the present work, the maximum error between theneural prediction and experimental values is within ±10.80 %.

تحليلتأثير نسبة الملء علىأداء الأنبوب الحراري الثابت الموصلية باستخدام الشبكات العصبية الاصطناعية

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الخلاصة

قد أجريت الدراسة لتحسين كمية المائع في الأنبوب الحراري. تم تصميم الأنبوب الحراري بقطر خارجي 28.4 ملم وطول 893 ملم واختباره مع الماء كمائع تشغيل عند أحمال حرارية مختلفة لتقيم أداءالأنبوب الحراري. توزيع درجات الحرارة على طول الأنبوب الحراري تم قياسها وتسجيلها باستخدام المزدوجات الحرارية . مقدار أداءالأنبوب الحراري هو من حيث الفرق في درجات الحرارة والحرارة المنتقلة والمقاومة الحرارية. عند تغير كمية السائل المعبأ لوحظ تباين الأداء الحراري للأنبوب الحراري. وأخيرا تم تحديد نسبة ملء الأمثل للسائل اقل فرق في درجات الحرارة واقل مقاومة حرارية.

تم استخدام الشبكة العصبية الاصطناعية المستخدمة التي طورت في النموذج المقترح مع برنامج ماتلاب 2009 باستخدام طريقة backpropagation. النموذج الصناعي للشبكات العصبية التي تستخدم للتنبؤ تأثير نسبة ملء السائل (الماء المقطر) عند أحمال حرارية متغيرة على الأداء الحراري للأنبوبالحراري الثابت الموصلية (CCHP).

لقد تنبأت الشبكة العصبية الاصطناعية للأنبوب الحراري الثابت الموصلية (CCHP) آن مدى نسبة ملء (85 ٪ -90 ٪) لمائع التشغيل (الماء المقطر) من حجم الفتيل يمتلك اقل مقاومة حرارية واقل فرق في درجة الحرارة وأعلى انتقال للحرارة.في العمل الحالي، الخطأ الأقصى بين التنبؤ العصبية والقيم التجريبية ضمن ± 10،80 ٪

INTRODUCTION

A heat pipe is a simple device that can quickly transfer heat from one point to another. They are often referred to as the superconductors of heat as they possess an extraordinary heat transfer capacity and rate with almost no heat loss [1]. The heat transfer takes place by repeated cycles of condensation and evaporation of the working fluid within a sealed system [2]. Hence the heat pipe transfers higher amount of heat compared to normal conductors, with a less temperature difference and can be operated over a wide range of temperature (100K–1000K) according to type of working fluid [3]. They are found particularly useful as cooling means for modern electronic devices, which are manufactured for high performance and high degree of integration [4].heat pipes have advantages over many traditional heat-exchange devices when (1) heat has to be transferred isothermally over relatively short distances, (2) low weight is essential (the heat pipe is a passive pumping device and therefore does not require a pump), (3) fast thermal-response times are required, and (4) low maintenance is mandatory [5].

ANN could offer an alternative approach for modeling constant conductance heat pipe (CCHP). 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)[6]. Applying ANN to thermal systems is still not very popular, and definitely needs more research. This approach has not been applied for modeling CCHP so far. This paper intends to analyze thermal behaviour of CCHP by applying ANN.

ARTIFICIAL NEURAL NETWORKS (ANN)

An ANN is a processing device, either 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 [7].

The key feature of ANNs over conventional regression analysis is that they employ nonlinear mathematics and therefore can be used to model highly complex and nonlinear systems such as heat pipes (HPs) [8].

A fully connected feed-forward multi-layer configuration using resilient back propagation learning algorithm has been employed in this study. This type of ANN has a strong ability to express complex nonlinear mapping and has already found wide ranging applications [7].

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 (**Fig.1**)[7].

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 [9].

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 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 pure line activation function. For all other nodes, a sigmoid function is used as activation function. This function can perform nonlinear input-output transformation actions and is normally used in most applications. Further details are available in [7,9].

EXPERIMENTATION

The heat pipe was fabricated using a copper tube of 893 mm length and 26.6mm inner diameter (**Fig.2**). Electrical heater wending on evaporator section for length 80 mm and 230V, 25W capacity was used for providing the required heat source at the evaporator(**Fig.3**). The evaporator and adiabatic sections of the heat pipe are insulated using glass wool to minimize the heat loss through these portions (**Fig.4**). Variable power supply and wattmeter were provided to control and measure the power input respectively. Waterjacket of length 150mm, width 88 mm, and thickness 80mm was round on the condenser end (**Fig. 5**).Eleven Digital Thermometers (*K type thermocouple*) are used to measure temperature distribution along the pipe out shell in nine different areas as shown in **Fig.6**, the input and output temperature of the water jacket was measured by two digital K-type thermometers as shown in **Fig.5**. The digital K-type thermometers calibration consists of recording the temperature measured by a standardized thermometer, both in a constant temperature bath.

Temperature difference between evaporator and condenser is taken as the arithmetic average of the temperate measured along the heat pipe as shown in **Fig. 6**(T_1 ,$T_2 T_3$,T_7 ,T_8 *and* T_9)hence

$$T_e - T_c = \left(\frac{T_1 + 2T_2 + 2T_3}{5}\right) - \left(\frac{T_9 + 2\,T_8 + 2T_7}{5}\right) \quad (1)$$

Experiments were conducted with 25%, 50%, 75% and 100% fill ratio of wick volume run. Its performance is considered as the base for the evaluation of heat pipe. The transient tests were conducted on the heat pipe, in which the heater is put “on” and the temperature rise was observed at regular intervals till the steady state is achieved,

Experiments were repeated for different heat inputs with different fill ratios(*fill ratio is the ratio of working fluid volume to wick space volume*) of fluid and various plots were drawn to study the performance of heat pipe to optimize the fluid inventory.

The Experimental results shown in **Fig. 7** and **Fig. 8** of CCHP with water as working fluids are taken to train and validate the ANN.

ARTIFICIAL NEURAL NETWORK MODELLING

The back-propagation networks are most useful for problems involving forecasting and pattern recognition [9]. The type of ANN used in the model of the present work is known as back propagation networks, and are made up of a large number of interconnected neurons. The neurons are arranged in layers: one input layer, one output layer, and two hidden layers between the input layer and the output layer. Each neuron in the input layer is connected to every neuron in the hidden layer which in turn is connected to the neuron in the output layer. There is no connection between neurons in the same layer. The connection between two neurons is called synapse, and each synapse has a strength or weight attached to it which influences the output of the neuron. Neurons in the input layer receive the input variables. The neurons in the hidden layer receive the output of the input neurons and a non-linearity in the relationship between input and output parameters is introduced at the hidden neuron. The output of the hidden neuron is sent to the output neuron. The predicted output is compared to the desired output and the error is sent back to the hidden layer to improve the prediction [7,9].

NEURAL NETWORK ARCHITECTURE

The artificial neural network used for the proposed model is developed with Matlab 2009 software by using backpropagation architecture [9].

The artificial neural network model which is used to predict the effect of fill ratio of working fluid (distillated water) at varying heat input on thermal performance of constant conductance heat pipe (CCHP), the network is trained for temperature difference between evaporator and condenser (Te-Tc) and heat transfer rate (Qe).

The inputs are the heat input to heat pipe (QE), fill ratio of working fluid of wick volume(F.R. %) and length heat pipe to outer radius of heat pipe ratio (L/ro) and outputs are the temperature difference between evaporator and condenser (Te-Tc) and heat transfer rate (Qe). The randomly selected data used to train and test the first neural network are 54 and 25 respectively.In this way the heat pipe performance is quantified for a lower thermal resistance. If Q_e is the heat transfer rate in the system and $\Delta T = T_e - T_c$ is the temperature drop across the heat pipe (*from equation 1*) then the thermal resistance R_{th} is given by,

$$R_{th} = \frac{T_e - T_c}{Q_e} \qquad (2)$$

OPTIMIZATION TECHNIQUE AND ERROR ESTIMATES

During the training process, the network weights are continuously adjusted till the difference between the predicted output and experimental value is minimized, i.e. the error function defined as the sum of squares of the difference between predicted and experimental value on all the data reaches a set limit or the number of predetermined training operations are completed. A critical factor in developing a robust model is the numerical optimization technique applied for minimizing the error. Neural network functions depend non-linearly on their weights and so the minimization of the corresponding error function requires the use of iterative non-linear optimization algorithms. These algorithms make use of the derivatives of the error function with respect to the weights of the network. Resilient backpropagation algorithm is the optimization technique employed in building of present artificial neural networks. After completing the training process, the model is tested using another batch of data which has not been used in the training set [7,9].

The following statistical parameters of significance are calculated at the end of the training and testing calculations:

1. *Correlation coefficient* (*R*): is a measure of how the actual and predicted values correlate to each other. The goal is to maximize the value of *R*.

R=1-COV (3)

Where: *COV*Coefficient of Variation

2. *Mean square error* (MSE): is a statistical measure of the differences between the values of the outputs in the training set and the output values the network is predicting. The goal is to minimize the value of MSE.

$$MSE = \frac{1}{N}\sum(d_j - y_j)^2 \quad (4)$$

Where:

d_j Neural network target

y_j Neuron output

The statistical parameters used to give a description for good training for artificial neural network modeling in the present model are mean square error ($MSE=4*10^{-4}$) and correlation coefficient (R=0.99974).

NUMBER OF HIDDEN LAYERS AND NODES IN EACH HIDDEN LAYER

The choice of the number of hidden layers and number of nodes in the hidden layer depends on the network application. Two hidden layers are used in the neural networks modelling of the present study because it performs significantly better than one hidden layer. Although, using a single hidden layer might be sufficient in solving many functional approximation problems, some other problems may be easier to be solved with two hidden layers configuration [9].

The number of nodes in the hidden layer will be selected according to the following rules:

1. The maximum error of the output network parameters should be as small as possible for both training patterns and testing patterns.
2. Mean square error should be small as much as possible.

The optimal configurations in two hidden layers networks with minimum mean square error (MSE) and maximum correlation coefficient are 18:9 (18 nodes in the first hidden layer and 9 nodes in the second hidden layer) for the present ANN model.

PREDICATION THE EFFECT OF FILL RATIO OF WORKING FLUID (F.R.)

The artificial neural network modelling is used to prediction of the effect of fill ratio of working fluid that represented by temperature difference between evaporator and condenser (Te-Tc) and heat transfer rate (Qe). The data presented to train and test the proposed network are taken from the results of testing the heat pipe with different fill ratio of working fluid and variation of heat input. The architecture of neural network for this model is given in **Fig. 9**. It consists of three nodes in the input layer, two hidden layers are chosen which gives minimum mean square error (MSE) and maximum correlation coefficient, the first hidden layer has (18) nodes, and the second hidden layer has (9) nodes. The output layer has two nodes which were represented by temperature difference between evaporator and condenser (Te-Tc) and heat transfer rate (Qe).

The decision function used for the first hidden layer is (*logsig*) and second hidden layer is (*tansig*), and for the output layer is (*purelin*). These functions were chosen for first hidden, second hidden and the output was obtained by trial and error until the best performance was achieved by approaching the minimum values of mean square error and maximum correlation coefficient. The results obtained of temperature difference between evaporator and condenser (Te-Tc) and heat transfer rate (Qe) by artificial neural network predictions are shown to be agreed well against experimental values. i.e. correlation coefficient, R=0.99974 as shown in **Fig. 10** and **Fig.11** .

The ANN predicated results have good agreed with the experimental results of the present work. **Fig. 12** shows the ANN predicated of temperature difference between evaporator and condenser (Te-Tc) with varying fill ratio of working fluid (distillated water) at constant sink temperature (Ts=15 ^{o}c) and the heat input (QE=10 w and QE=20 w). Where the minimum temperature difference seemed at fill ratio 85% and 87% because this fill ratio thermal balance between the mass of working fluid in wick regain and the mass of vapor in vapor regain inside the heat pipe.**Fig.13** shows the maximum heat transfer rate seemed at fill ratio 90% and

95%. With increasing heat input to evaporator section cause more evaporation. And this need to increase the flow rate the mass of working fluid in wick regain because the wick not efficient.**Fig. 14** shows the thermal resistance with varying fill ratio of working fluid at constant sink temperature (Ts=15 ^{o}c) and the heat input (QE=10 w and QE=20 w), the minimum thermal resistance seemed at fill ratio 87%. Also the thermal resistance decrease with increasing the heat input.

CONCLUSIONS

1. The experimental results of the fill ratio (volume ofworking fluid to heat pipe wick volume) is shown to have maximum effect on the performance of heat pipe with respect to the temperature difference.
2. The experimental resultsshown the fill ratio of working fluid 87% of volume of wick show better results in terms of increased transmitting heat, decreased thermal resistance and reduced temperature difference across the evaporator and condenser.
3. ANN predicated of CCHP shows the range of fill ratio(85%-90%) of working fluid (water) of wick volume have minimum thermal resistance, minimum temperature difference and maximum transmitting heat.
4. The ANN predicated results have good agreed with the experimental results of the present work.

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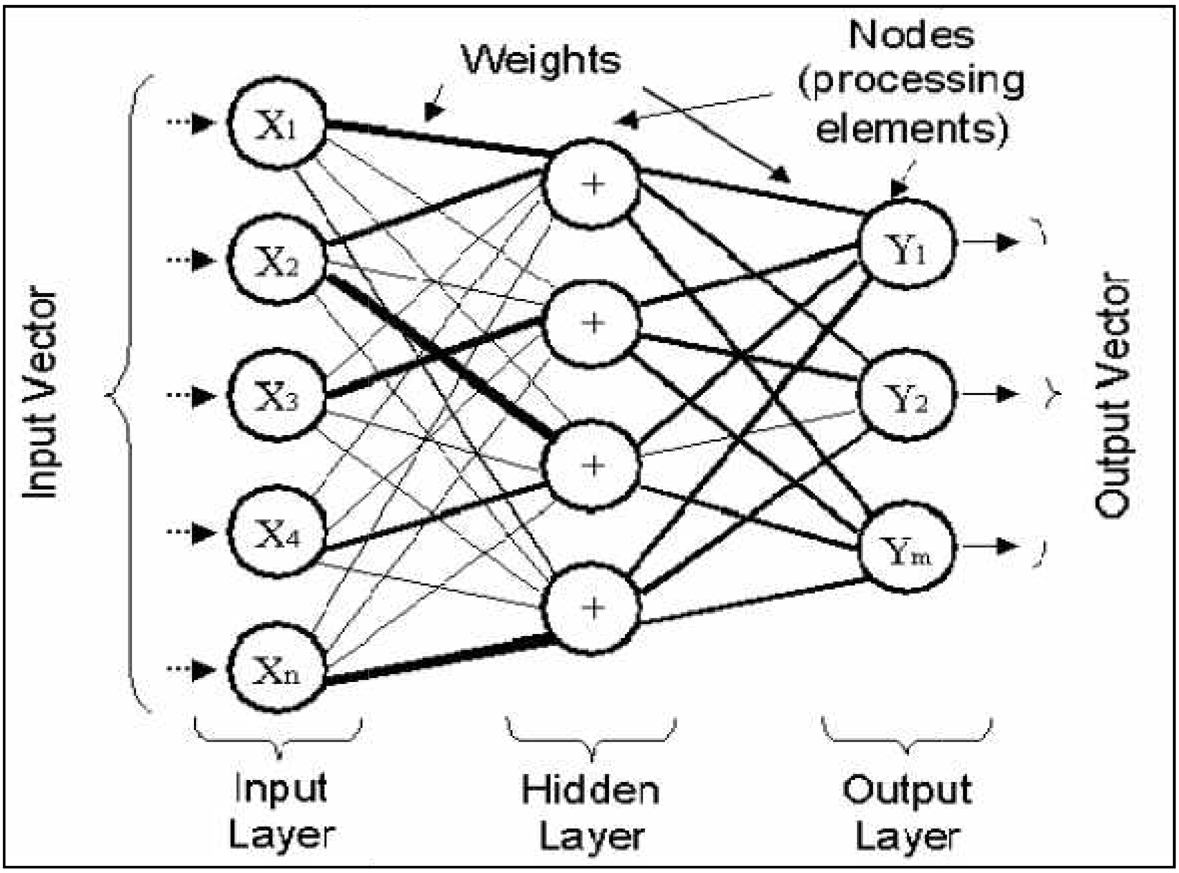

Fig.1: Basic ANN architecture [7]

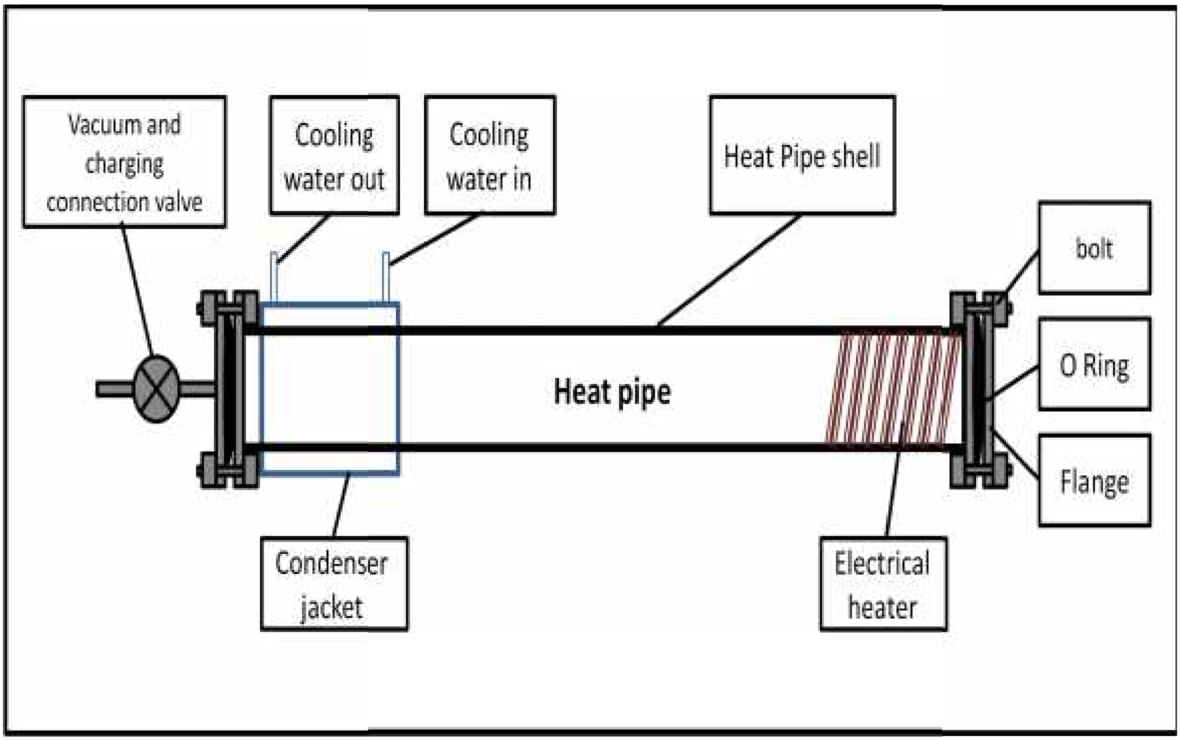

Fig.2: Heat pipe construction [Present work]

Fig.3: The evaporator section of heat pipe [Present work]

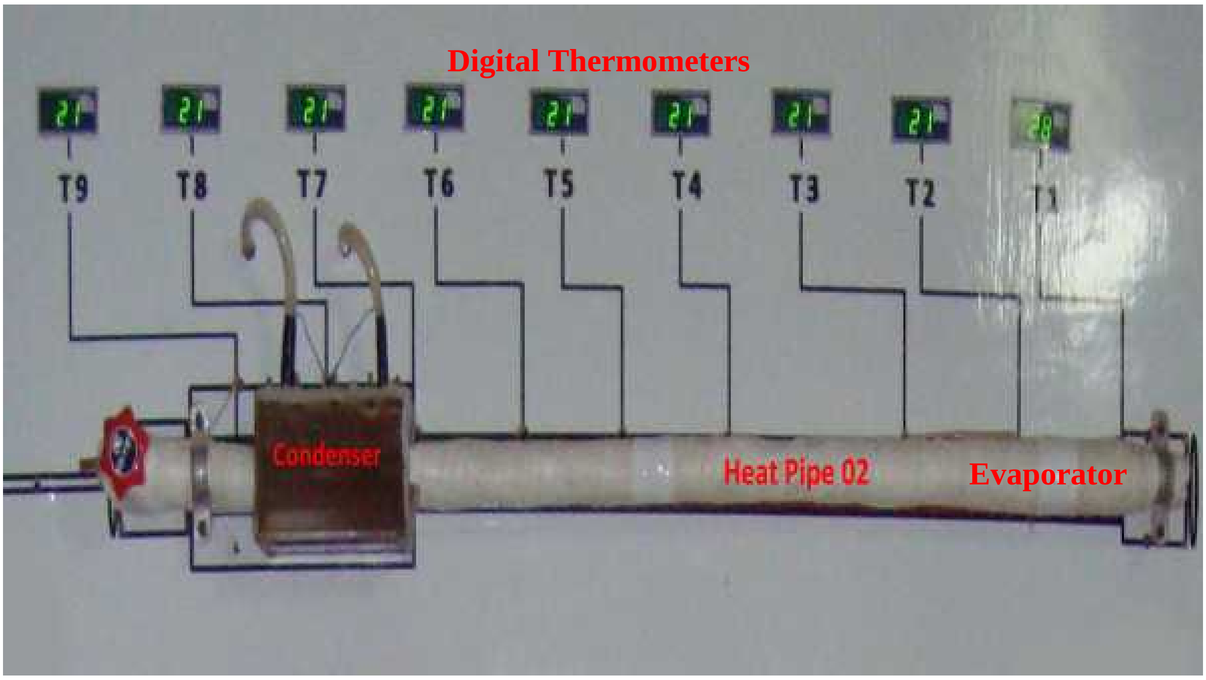

Fig.4: Experimental rig [Present work]

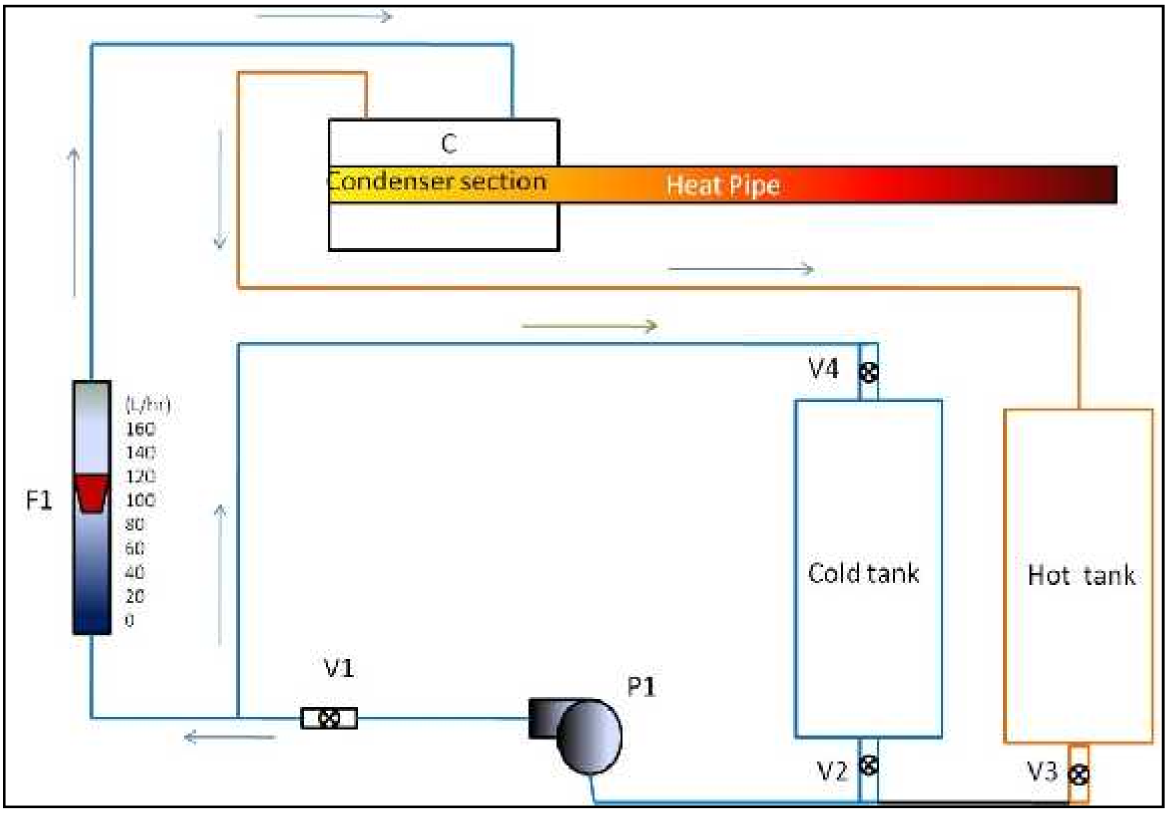

Fig.5: Cooling System of heat pipe [Present work]

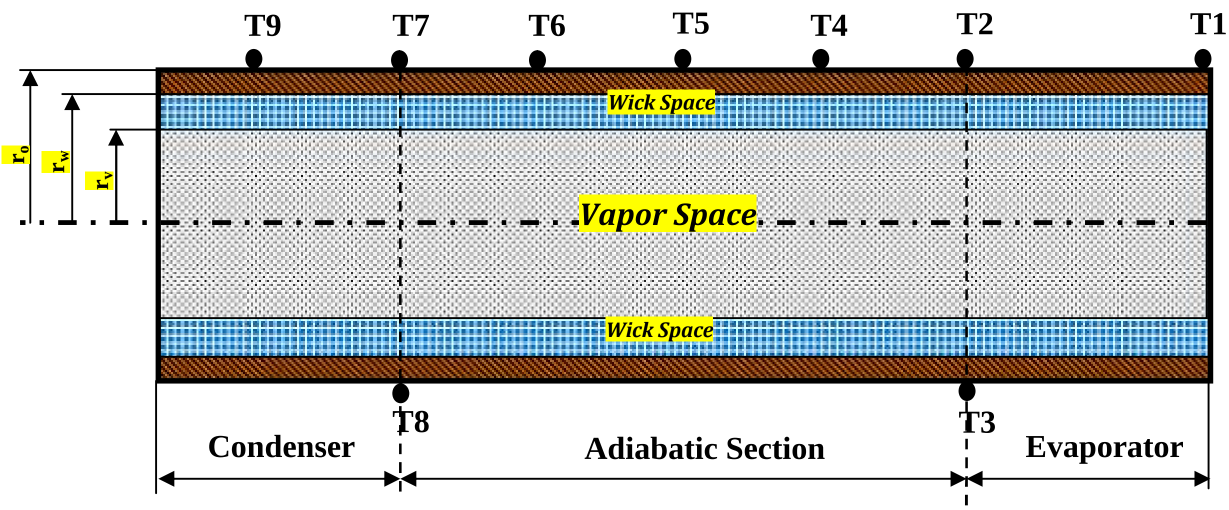

Fig.6: heat pipe thermocouples locations[Present work]

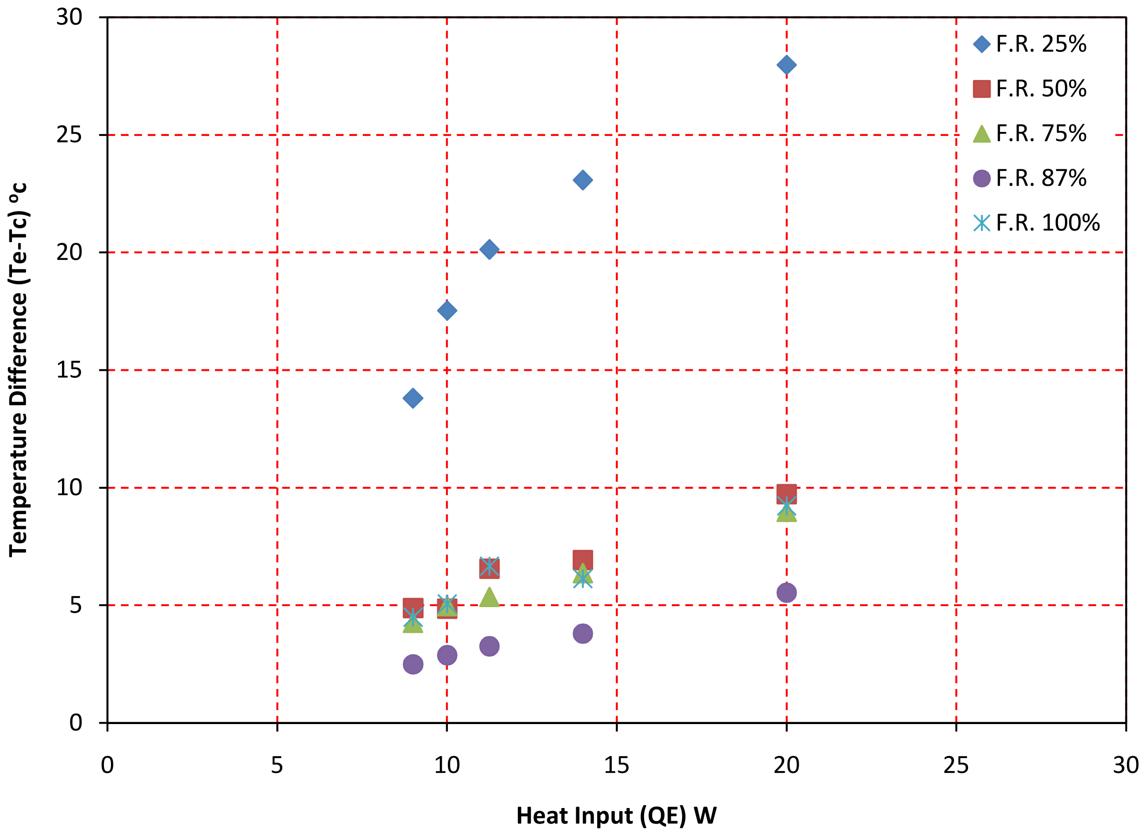

Fig.7: Temperature vs. heat input with variation of fill ratio for heat input

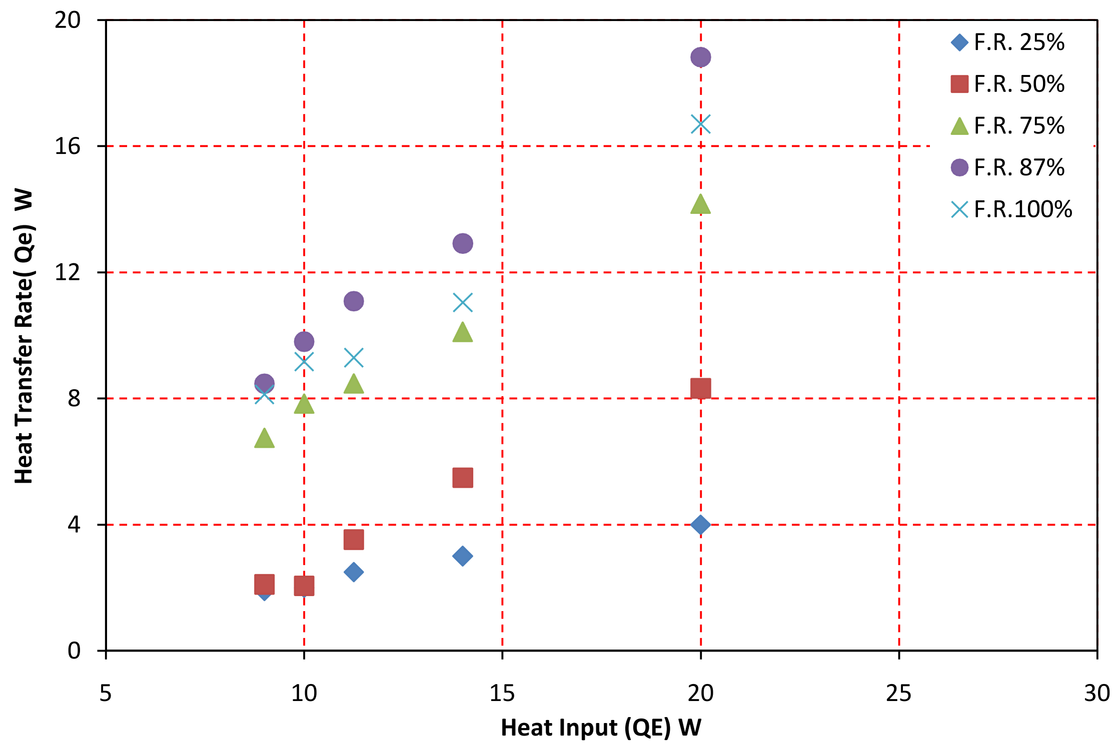

Fig.8: Heat transfer rate with heat input for different working fluid Fill ratio.

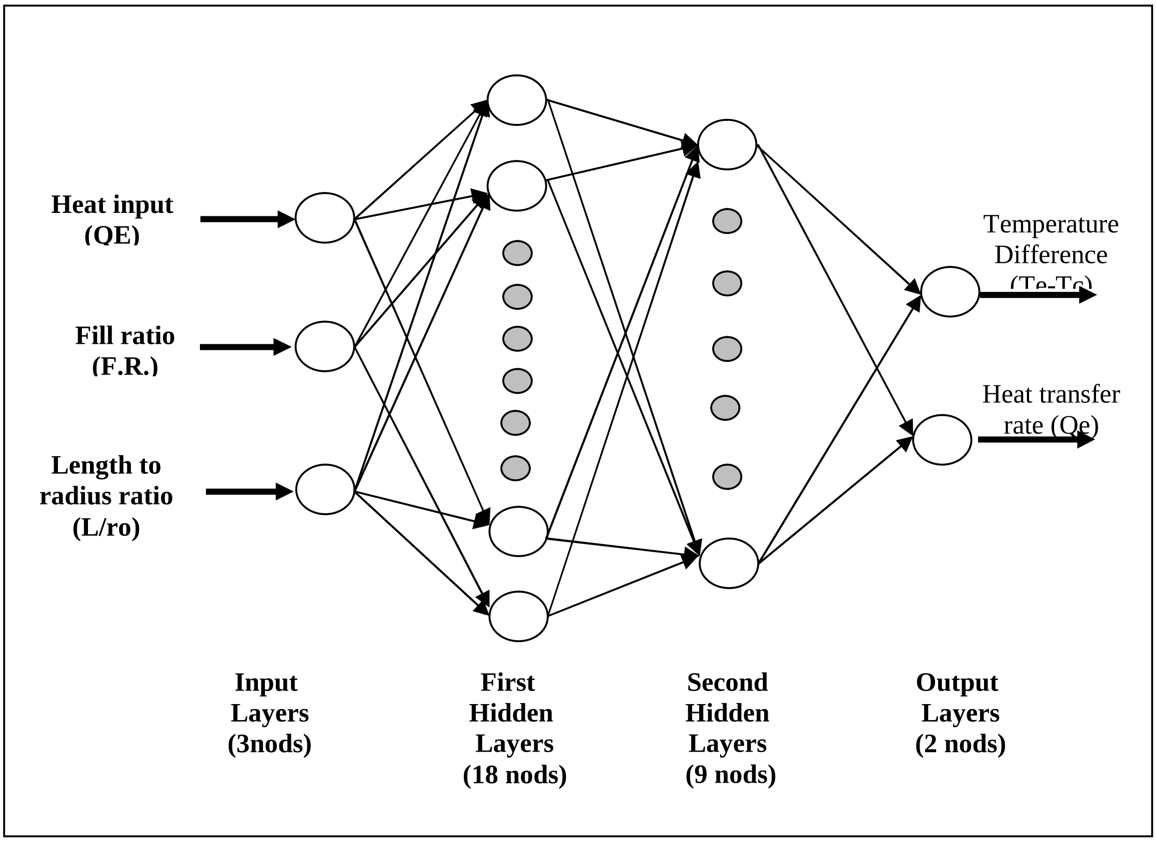

Fig.9: The architecture of neural network

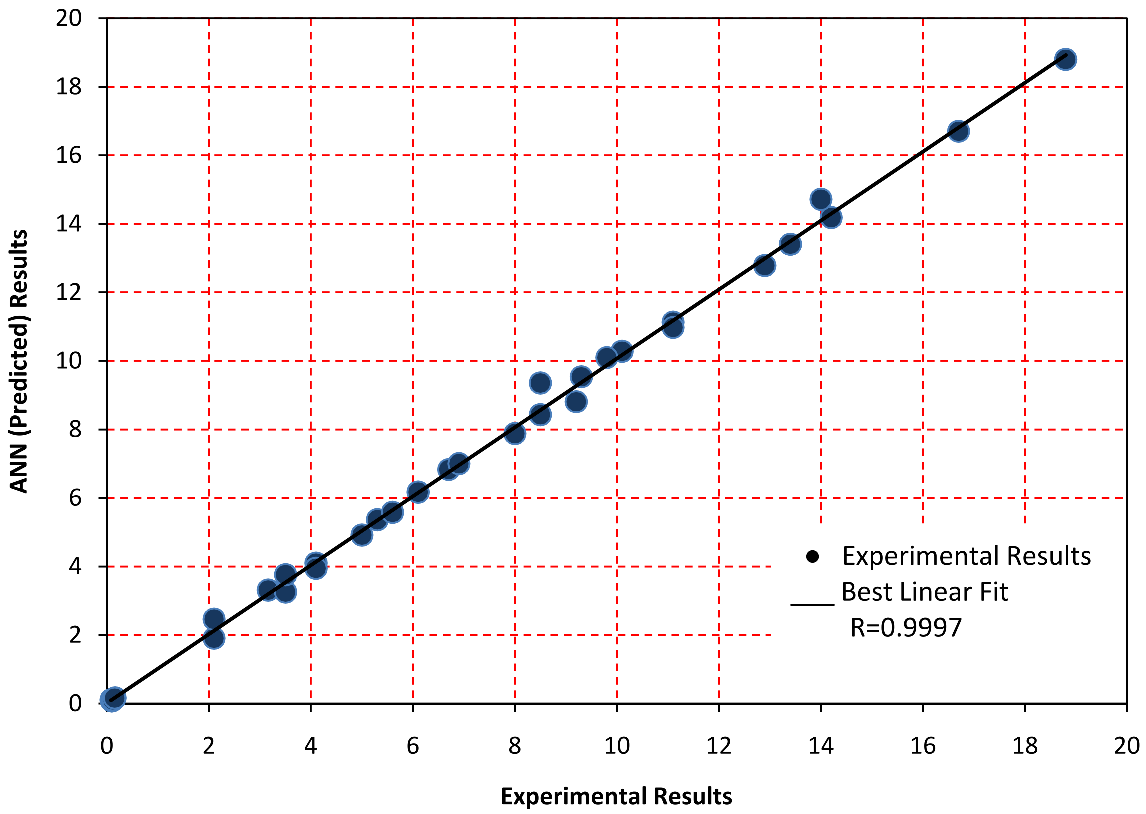

Fig.10: Comparison between ANN results and experimental results of heat transfer rate (Qe) using Resilliantbackpropagation algorithm

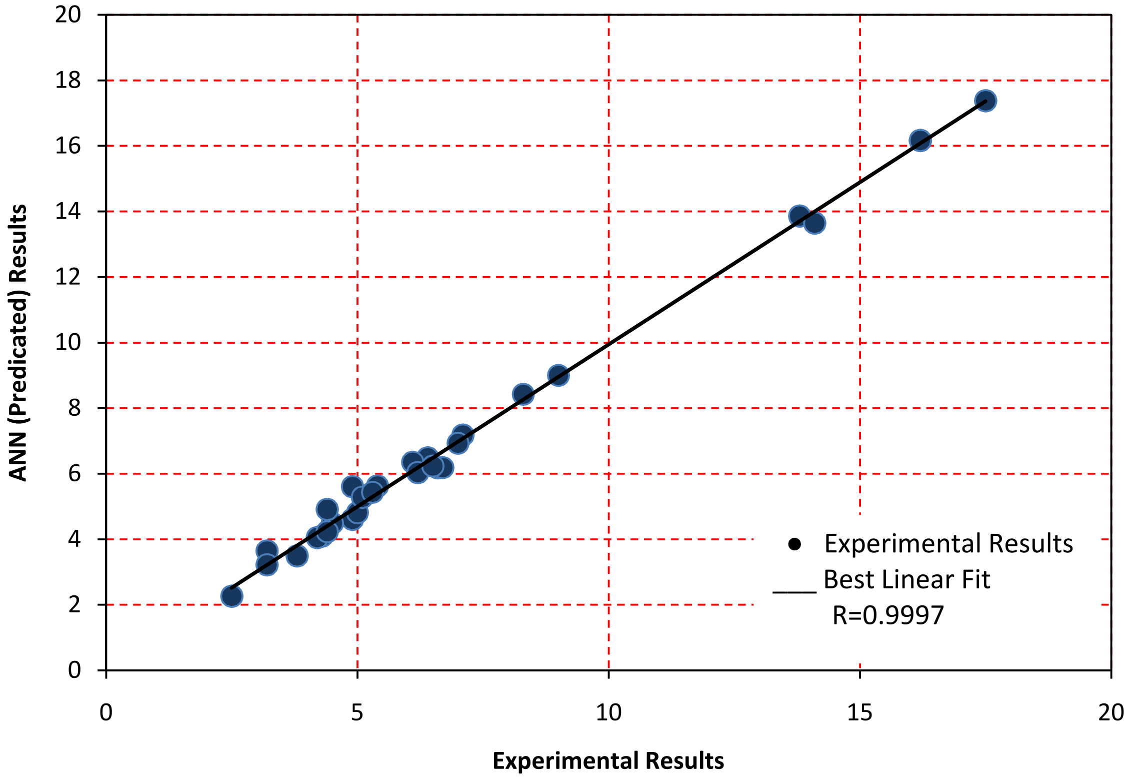

Fig.11: Comparison between ANN results and experimental results of temperature difference (Te-Tc) using Resilliantbackpropagation algorithm

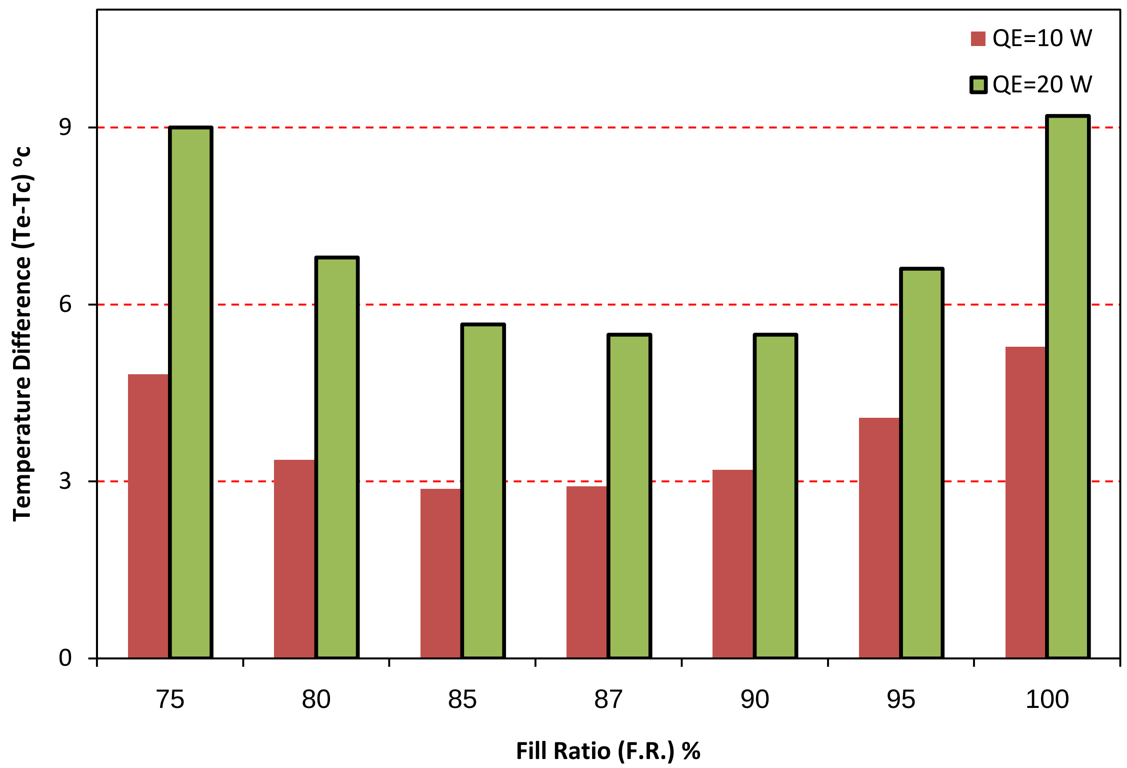

Fig.12: ANN predicated results of temperature difference between evaporator and condenser (Te-Tc) with varying fill ratio of working fluid at variation of heat input

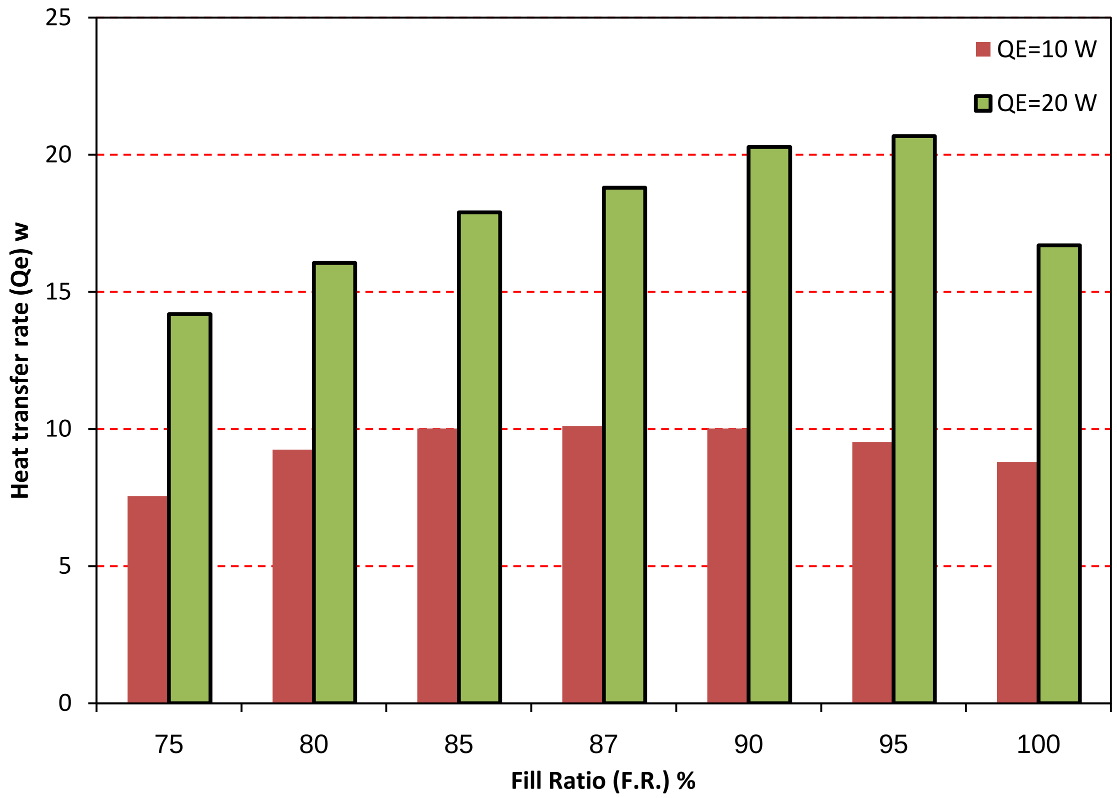

Fig.13: ANN predicated results of heat transfer rate with varying fill ratio of working fluid at variation heat input

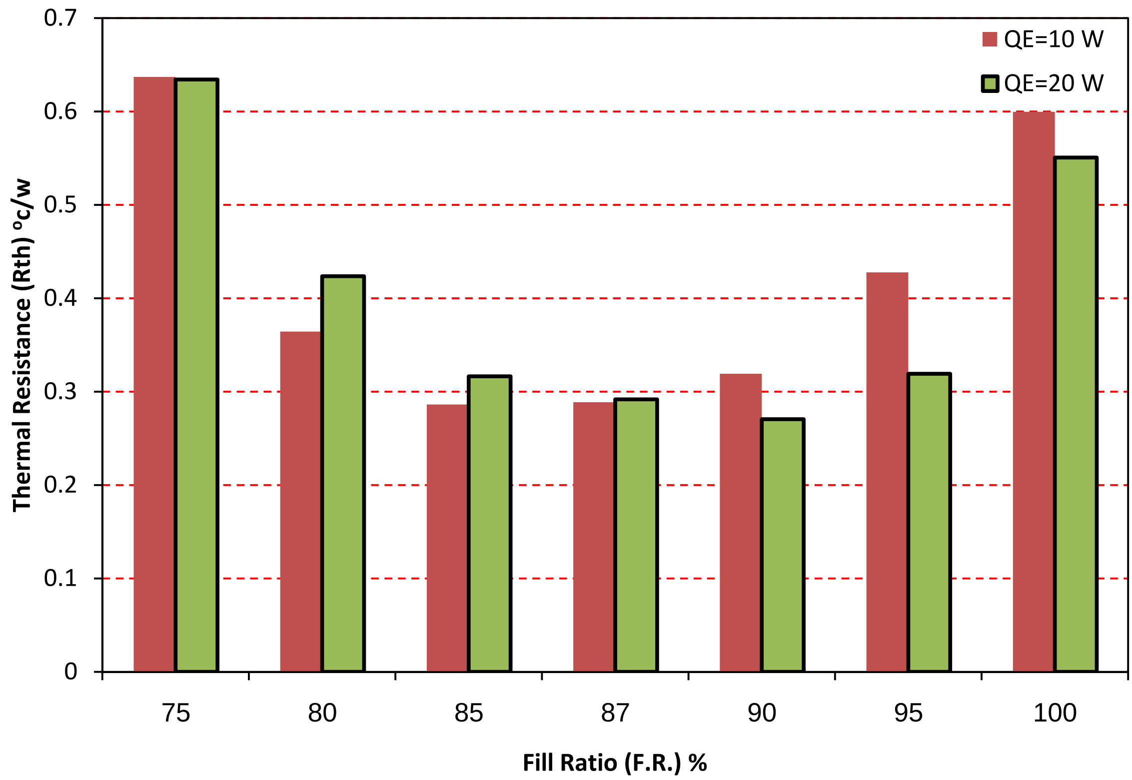

Fig.14: ANN predicated results of thermal resistance with varying fill ratio of working fluid at variation heat input