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RSM and ANN Modeling Techniques to Forecast How Various Parameters will Affect the Improvement of Electronics Cooling using Radial Heat Sink.

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Abstract:

This research provides the mathematical modeling for temperature difference for natural convection using Response Surface Methodology (RSM) and Artificial Neural Network (ANN) based modelling. Length of fin (L), height of fin (H), number of fins (N) and the heat input (Q) for the Radial heat sink are the parameters selected under natural convection heat transfer. Looking at the pattern of the data, feed forward back propagation type neural network is chosen. The RSM mathematical model of temperature difference is used to compare the performance of the created ANN models. ANN Simulations proved to be successful in terms of agreement with actual values of experimentation. ANN simulations perform accurate to validate the experimental results and the results obtained from the RSM for the output under natural convection. The optimum values for the dimensional parameters namely length of fin, height of the fin, number of fins are obtained by RSM method. Also the optimum operating parameter that is heat input for minimum temperature difference is obtained.

Keywords: Response Surface Methodology, Artificial Neural Network, Radial heat sink

1. Introduction

Electronic devices, e.g. projector, high electricity semiconductors devices, LED, chips, and so forth require efficient cooling techniques for dissipation of heat in a constrained place. Those devices have to be maintained at low and appropriate temperature for their efficient working. So the heat dissipation from those gadgets will become critical factor. One of the answers to do away with the warmth from such devices is to use Radial heat sink in free or forced convection. This examine the overall performance of radial heat sink underneath compelled convection is investigated. The one-of-a-kind parameters that are considered for the study of radial warmness sink are wide variety of fins, top of the fin, length of the fin, pace of air and the heat enter.

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The semiconductor industry has been aggressively reducing device size over the past decades. This has led to a significant increase in power density within these devices. The rising power density necessitates advanced thermal management solutions to prevent device failure. Chip operating power has been rapidly increasing, with a wide range from 100W to 400W. The demand for high computing power has resulted in increased chip heat flux as shown in figure 1 and 2.

Due to increasing power density, modern chips require advanced thermal management systems. High chip temperatures lead to mechanical failures like stress, debonding, and fracture. Most electronic device failures occur during operation due to excessive heat. [3]

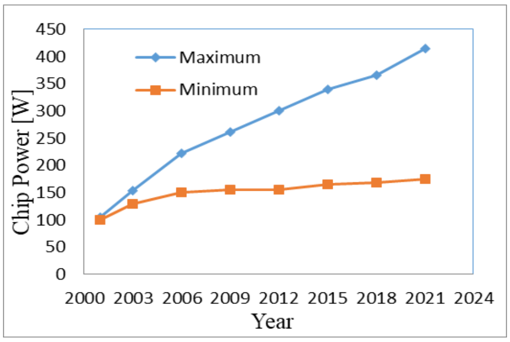

Figure 1 High Performance Chip Power Trends [1]

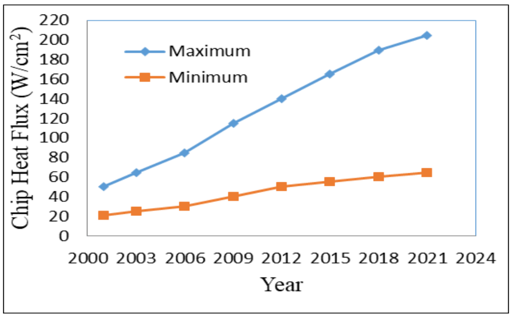

Figure 2 High Performance Chip Heat Flux Trends [1]

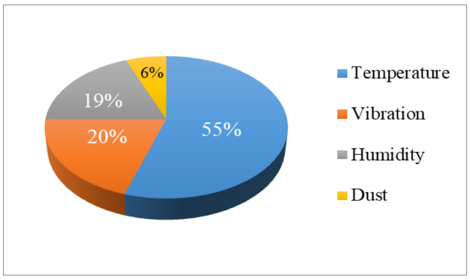

Figure 3 Failures in Electronic Components [2]

Thermal management is crucial for electronic devices due to increasing power density. It is categorized into active and passive cooling methods. Active cooling uses mechanical means for efficient heat removal but requires energy, is costly, and prone to malfunctions.

Passive cooling relies on heat conduction and convection, is energy-efficient and suitable for space-constrained devices but has limitations.

Scott [3] classified all the methods into four broad categories in order of increasing heat transfer effectiveness, for the temperature difference between the surfaces and the ambient is 80°C and also compared the methods as shown in figure 4.

- Natural convection and radiation (155-1550 W/m^2),
- Forced air-cooling (800-16000 W/m^2),
- Forced liquid cooling (11000-930000 W/m^2), and
- Liquid evaporation (15500-1400000 W/m^2).

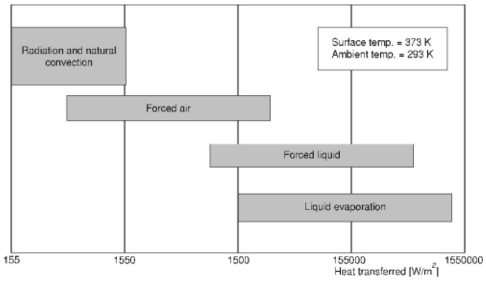

Figure 4 Ranges of Conventional Heat Transfer Modes [3]

2. Design of Experimentation

Thermal management is indispensable for the development of advanced electronics and is essential in competitive power density environments. Despite advancements in cooling technologies and tools, constraints and design requirements remain significant. The primary challenge is cost-effectiveness. Cooling solutions must reduce overall package and system costs while maintaining competitiveness.

The geometrical view of the radial heat sink is shown in figure 5. The performance of this heat sink is to be studied for varying parameters under natural and forced convection. The circular base of the heat sink makes it to be useful for cooling of LED and other electronics components having circular base.

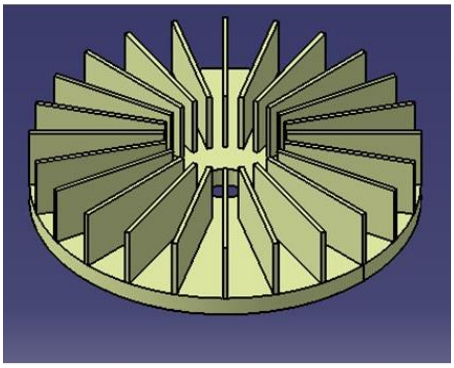

Figure 5 Radial Heat Sink with a Circular Base and Rectangular Fins

2.1 Selection of the Geometrical Parameters of Radial Heat Sink

The literature available on the radial heat is very limited so according to the dimensions mostly used for the rectangular array heat sink the corresponding geometrical dimensions are selected for the present study. As the effect of the design parameter on the performance of heat sink is the motto of present study so the outer diameter of the base of the heat sink is selected as 160 mm which most of the previous researcher have taken as the base length of square heat sink. Then according to the base outer diameter of the heat sink the other design parameters are selected which are given in table 1. As per the present trends of the power usage for the electronics devices the heat inputs for the experimentation under natural convection are selected in the range of 40W, 60 W, 80 W, 100 W, and 120 W.

Table 1 Heat Sink Parameters

Parameter		
Length of fin L	Height of fin H	Number of fin N
40 mm	20 mm	22
50 mm	25 mm	26
60 mm	30 mm	30

The present study focuses upon the thermal performance of radial heat sink subjected to natural convection. The main objectives of the current research work are as follows:

- To study the natural convection heat transfer for a heat sink with a circular base and rectangular fins, experimentally and numerically.
- To analyze the experimental data using RSM and ANN. To obtain the mathematical model for the heat sink under natural convection using RSM. Numerically validation of experimental data with RSM and ANN.

3. Response Surface Methodology

The RSM is a statistical technique which is widely accepted for experimental analysis. RSM proceed with carrying out statistically designed experiments followed by evaluating the coefficients in a mathematical model and predict the response and examine the sufficiency of the model. This technique is very useful to model and predict the effect of input variables on the output. [71]

The important steps in the RSM are as follows,

- Defining the independent input and output variables.
- Conducting the experiments and develop the regression equation.
- Analysis of Variance (ANOVA) for the independent input variables to validate the model.

Mathematical modeling is a relationship between input and output variables. It gives the organized illustration of the experimental data and explains the variation of response as a function of input variables. Mathematical models are generally are of first order or second order regression equation. Response surface methodology uses multiple regressions to build the experimental models. The least square method is used to estimate the regression coefficients. Minitab 17 is used for estimating the regression coefficient and formulating the response surface regression equation. Analysis of Variance (ANOVA) checks the appropriateness of the mathematical models. ANOVA test is performed to verify the fitness of the model. Residual plots are plotted to confirm the assumptions of the ANOVA. [62]

3.1. Regression Equations for the Radial Heat Sink

The mathematical model developed with the help of RSM in Minitab -17 for radial heat sink under natural convection for temperature difference is given by equation 2.1. The temperature difference equation is of second order equation in terms of length of fin (L), height of fin (H), number of fins (N) and the heat input (Q)

3.2 Regression Equation for Temperature Difference under Natural Convection:

$$\Delta T = 144.2 - 1.91 L - 4.02 H - 4.54 N + 1.221 Q + 0.01292 L*L + 0.0980 H*H + 0.0547 N*N - 0.000692 Q*Q - 0.0087 L*H + 0.0371 L*N - 0.00089 L*Q - 0.01810 H*Q - 0.00435 N*Q \quad \textbf{(3.1)}$$

To validate the regression equations, residual plots are plotted for the heat sink under natural convection for temperature difference between the surface temperature of heat sink and the ambient temperature as shown in figure 6.

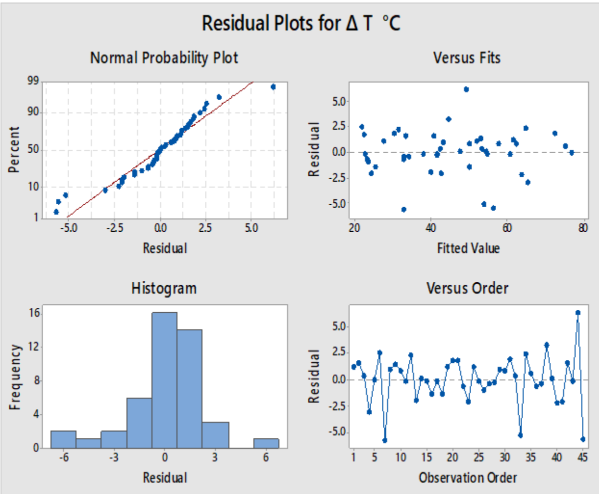

Figure 6 Residual Plots for Temperature Difference under Natural Convection

3.3 Significance of R Square, R Square Adjusted and R Square Predicted

R square measures the percentage of variance of response as per the regression equation. The value of R square should be closer to one for the better assessment of regression equation to fit the trail data. Higher the value of R square means the model fits the data better. The R square adjusted and R square predicted should be closer to each other. Adjusted R square accounts for the number of predictors in the model and is useful to compare model with different number of predictors. Predicted R square indicates how well the model predicts response for new observations. Larger the value of predicted R square suggest the model of greater predictive ability. [76,]

Table 2 Summary of ANOVA for Δ T

Sr. No.	Factors	Δ T (°C) for Natural Convection
1	R^2 (%)	97.97
2	Adj. R^2 (%)	97.13
3	Pre. R^2 (%)	95.83

Table 4.1 gives the summary of ANOVA for temperature difference for natural obtained by RSM in Minitab-17. The R square is 97.97 which is very close to 100%, this indicates that the model is fitted well with the experimental data.

4. Artificial Neural Network (ANN)

The regression equation has been achieved based on experimental data for the dependent π terms for natural convection and forced convection. In such complex phenomenon involving non-linear kinematics where in the validation of regression equation is not in close proximity, it becomes necessary to formulate Artificial Neural Network (ANN) Simulation of the observed data. Simulation consists of three layers. First layer is known as input layer. Number of neurons in input layer is equal to the number of independent variables. Second layer is known as hidden layer. Number of neurons in hidden layer is equal to the number of independent variables. The third layer is output layer. It contains one neuron as one of dependent variables. Multilayer feed forward topology is decided for the network.

4.1 Procedure for Formation of ANN Simulation

MATLAB software is selected for developing ANN simulation. The various steps followed in developing the algorithm to form ANN are as under.

i. The observed data from the experimentation is separated into two parts viz. input data or the data of independent pi terms and the output data or the data of dependent pi terms. The input data and output data are imported to the program respectively.

ii. The input and output data is read by pre-standard function and appropriately sized. Function pre-standard is pre-processes the data so that the mean is 0 and standard deviation is 1.

iii. In pre-processing step the input and output data is normalized using mean and standard deviation.

iv. Looking at the pattern of the data, feed forward back propagation type neural network is chosen.

v. This network is then trained using the training data. The computation errors in the actual and target data are computed and then the network is simulated.

3.2 ANN for Temperature Difference under Natural Convection

The ANN program given in appendix 'E' is executed for temperature difference under natural convection.

The first step in ANN is to train the data. Figure 9 represents the training of network for prediction of temperature difference. The train function outputs the trained network and history of the training performance. The errors for the temperature difference under natural convection are plotted by the (MATLAB) software with respect to training epoch. The means square error for temperature difference under natural convection obtained by MATLAB software is 0.0298604.

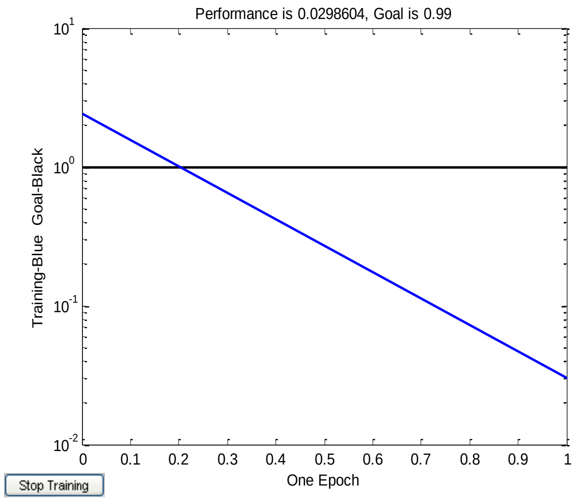

Figure 9 Training of the Network for ΔT under Natural Convection

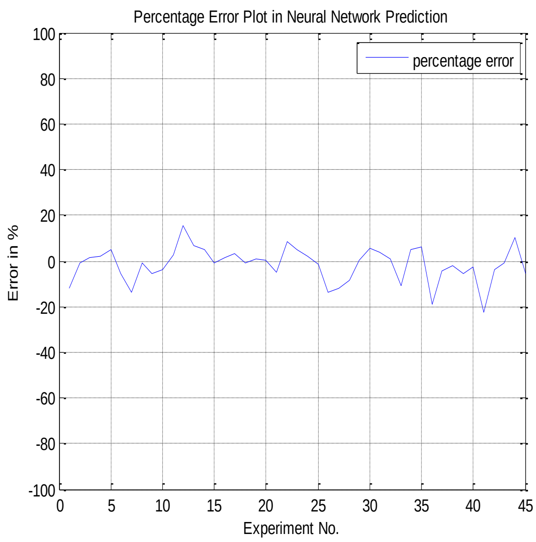

Figure 10 Percentage Error Plot Predictions for the Network for ΔT under Natural Convection

The percentage error between the experimental results and ANN predicted values for temperature difference under natural convection is shown in figure 10.

The comparison of experimental data and ANN prediction for temperature difference under natural convection is shown in figure 11. The curves for the experimental data and ANN data are very closed which indicates the agreement of the ANN results with experimental results.

The comparison of experimental data and ANN prediction for temperature difference under natural convection is shown in figure 11.

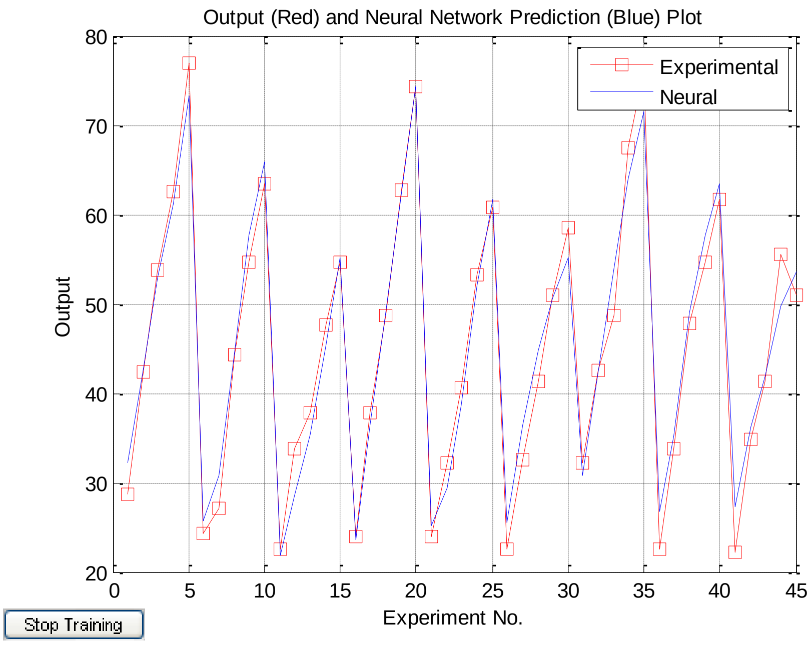

Figure 11 Graph of Comparison with Experimental Data Base and Neural Prediction for the Network for ΔT under Natural Convection

The curves for the experimental data and ANN data are very closed which indicates the agreement of the ANN results with experimental results.

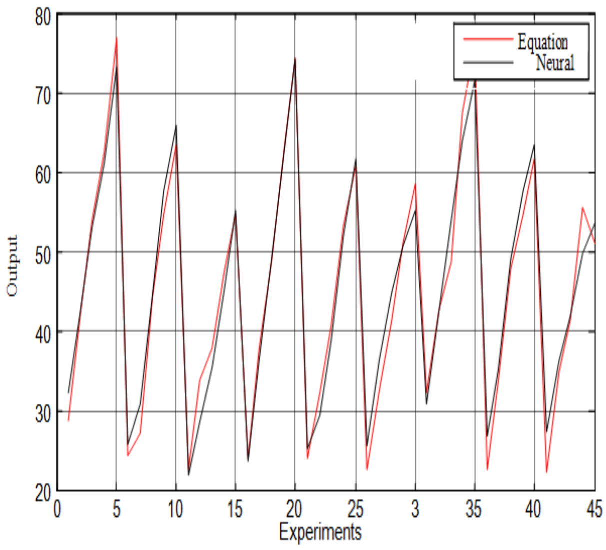

Figure 12 Graph of Comparison with Equation Data Base and Neural Base for the Network for ΔT under Natural Convection

Figure 12 shows the comparison of data obtained by the RSM equation and ANN data. Again both curves are following each other and are close to each other.

The percentage error between the RSM equation based data and the ANN prediction data for temperature difference under natural convection is shown in figure 13.

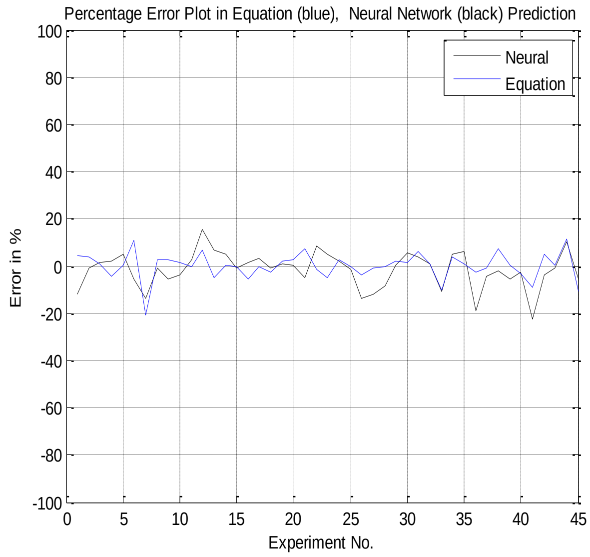

Figure 13 Graph of Comparison of Percentage Error with Equation Base and Neural Network Prediction for the Network for ΔT under Natural Convection

Figure 14 shows the comparison of experimental results and the RSM equation based results. Both the curves are closed to each other and validate the results for temperature difference under natural convection.

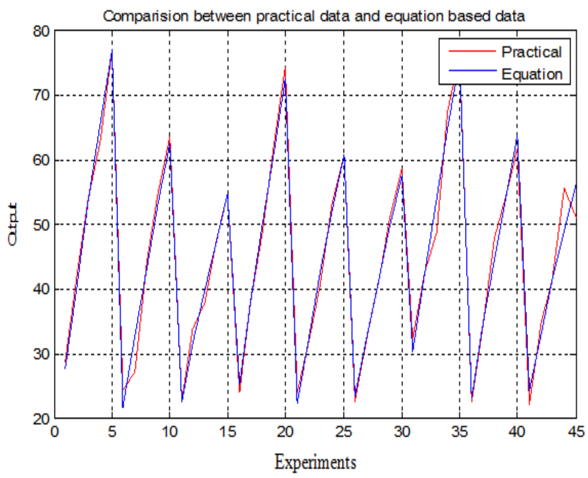

Figure 14 Graph of Comparison of Experimental Base and Equation Based Network Prediction for the Network for ΔT under Natural Convection

These graphs are a representation of the natural convection using ANN Simulation. From the above comparison of phenomenal response by a conventional approach and ANN simulation it seems to be that the curve obtained by dependent pi term temp for natural convection are overlapping due to the less percentage of error which is on the positive side and gives an accurate relationship between ANN simulation and Experimental data.

ANN simulations have been developed for temperature difference under natural convection. These simulations proved to be successful in terms of agreement with actual values of experimentation. So it can be concluded that ANN simulation perform accurate to validate the experimental results and the results obtained from the RSM for the output under natural.

The Response Surface Methodology (RSM) and Artificial Neural Network (ANN) methods are used for developing the mathematical models numerically for the heat sink successfully. The results from the RSM and ANN are compared with the experimental data to estimate responses. Also RSM and ANN methods are compared with experimental data for their predictive competences. The comparison of RSM and ANN methods for the radial heat sink under natural is analyzed. The comparison of experimental data with the RSM regression equation and the ANN prediction for the temperature difference under natural convection is shown in figure 15.

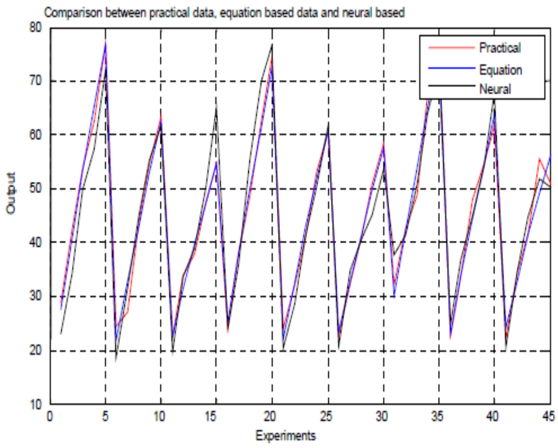

Figure 15. Graph of Comparison with Experimental Data Base, Neural Network Prediction and Equation Base Prediction for ΔT under Natural Convection

The closeness of the curves for experimental data, RSM equation based prediction and the Neural Network based prediction indicates that the experimental results are very much accurate and whatever may be the small difference between these values are due uncertainties during the experiments. In this way the experimental results for Comparison between practical data, equation based data and neural based Practical Equation Neural temperature difference under natural convection is validated with RSM and ANN technique.

Table 3 Comparison between Observed and Computed Values of Dependent Pi Term for Natural Convection

Dependent Pi term	Δ T °C Natural Convection
Mean Field	45.1220
Mean ANN	45.3730
Mean Model	45.0099

Table 6.3 shows the comparison between observed mean values and computed mean values of temperature difference for natural convection by RSM and ANN which are very close this validates the experimental values with RSM and ANN.

4.2 Optimization by Response Surface Methodology

The selection of optimum values of the design parameters for any heat sink is to improve the heat transfer enhancement. The mathematical techniques are used to obtain the optimized geometrical parameters of radial heat sink under natural and forced convection. Optimization is the process of finding the best result under given circumstances. It can be defined as the process of finding the conditions that give the maximum or minimum value of a function. Desirability is used to verify the feasibility of the optimization process. The value of desirability approaching one specifies that the optimization process is realistic and reasonable. [12]

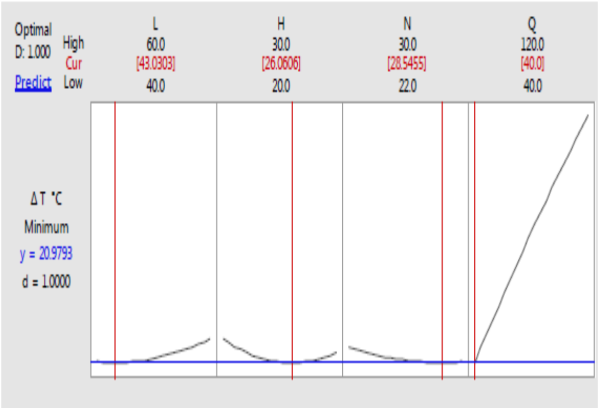

Figure 16 Optimal Plots for Radial Heat Sink under Natural Convection

The optimal plots for radial heat sink under natural convection for minimum temperature difference given by RSM are shown in figure 16. The optimum values are as length of fin is 43.03 mm, height of the fin 26.06 mm, number of fins is 28.54. The temperature difference will be minimum for minimum heat input so here also the optimal heat supplied is 40 W for minimum temperature difference.

Conclusions

Experimental investigations are carried out for the thermal performance of radial heat sink in the natural convection. The Taguchi method of design of experiments (DOE) is used to determine the influence of various parameters of radial heat sink on the temperature difference under natural convection. The various parameters examined are number of fins, fin length, fin height and heat flux.

The Mathematical modeling is done with Response Surface Methodology (RSM) to predict the temperature difference for natural convection. The predictions of the model matched with experimental results. The Response Surface Methodology (RSM) based regression model is validated with Artificial Neural Network (ANN) method. The results of these methodologies are compared for their predictive capabilities. The ANN results shows close matching between the RSM model output and experimental results. It has also been confirmed numerically that the results obtained from derived modeling equation are consistent with experimental results. By using RSM method the optimum dimensional parameters are obtained that are length of fin (43.03 mm), height of the fin (26.06 mm) and number of fins (28). Also the optimum operating parameter that is heat input for minimum temperature difference is obtained.

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