Neural Network Modeling of Parallel-Plain Fin Heat Sink

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Abstract

The paper aims at optimizing the heat sink dimensions by maximizing the heat dissipation and minimizing thermal resistance and pressure drop. In this paper, a Neural network model is built for a parallel-plain fin heat sink. The model is developed using an experimental data from the literature. In addition, a quadratic model equation of the affecting parameters is constructed and analyzed using Response Surface Methodology for determining the important factors affecting the performance of the heat sink, and the quadratic effect of every factor by using design of experiment, analysis of variance and regression analysis. The results of the neural network model are compared with the experiment and it is shown that the error does not exceed 13.54%. This value is considered small and acceptable for such system.

Keywords: Heat sink; Parallel-plain fin; Neural network; Response surface methodology.

Introduction and literature review

Electronic devices are used in many appliances that we are using every day, they generate massive amount of heat which causes total damage to the device's components. The damage can be prevented if the excessive heat is removed. This can be accomplished by installing a heat sink. A heat sink is a simple device that depends on conduction from electronic chips to the heat sink base, conduction from base to the surface area and followed by convection to the surrounding medium. It is designed such that heat dissipation is maximized and consequently thermal resistance and change in pressure between the two mediums are minimized.

Recently several studies focused on finding the optimum design parameters and selection of heat sink with high thermal performance. Shah et al. (2004) presented a numerical analysis study of the performance of an impingement heat sink aiming at evaluating the possibility of improving the heat sink performance by improving the air flow characteristics near the center of the heat sink. The analysis compared between ten different fin geometries and several different heat sink base thickness values. Cimtalay and Fulton (1994) have presented multiobjective optimization trade off problem to find the optimum parameters of heat sink in electronic printed board assembly. They used compromise decision support problem with constraints to optimize cost, heat and geometrical aspects. Chiang (2005) presented an effective method for predicting and optimizing the cooling performance of the parallel-plain fin heat sink module based on Taguchi method and analysis of variance.

The main objective of their study was to obtain the lowest value of the highest temperature (or thermal resistance). Other study for Chiang (2007) presented a systematic experimental design based on the response surface methodology (RSM) with quadratic model and four factors on parallel plate fin heat sink with ANOVA analysis. Chiang and Chang (2006) investigated the effect of design parameters on the thermal performance on the pin fin heat sink by means of RSM with quadratic model and four factors. Chou et al., (2009) proposed the optimum design of a parallel plate heat sink using fuzzy grey relations and orthogonal arrays design of experiment which combines the fuzzy logic theory with the grey relational system. Chiang et al., (2006) presented the optimum design for a pin fin heat sink using the grey fuzzy logic based on the orthogonal arrays. Liu (2005) studied fuzzy optimum natural convection fin array design with constant heat transfer coefficient. In his work, the heat transfer rate was maximized for a given fin volume and array width in accordance with a prescribed tolerance. The author performed a comparison between the fuzzy model and the non-fuzzy optimum model.

Naphon and Sookkasem (2007) presented a numerical study of the heat transfer characteristics of the in line and staggered taper pin fin heat sink under constant heat flux conditions. They also presented an experimental verification to analyze the problem. Yang and Peng (2009) presented a numerical study to investigate the effects of fin shape on the thermal performances of the heat sink with un-uniform fin width designs with an impingement cooling. Khan et al. (2008) presented a case study where they used an evolutionary optimization method for the determination of the optimal heat sink dimensions by maximizing the heat dissipation capabilities, such that the optimized dimensions are within realistic manufacturing constraints. Husain and Kim (2009a) presented single objective optimization of micro channel heat sink based on the surrogate methods. They showed that pressure and/or pumping power constrained optimization limits the applicability pumping source used at the micro-level. In another study, Husain and Kim (2009b) presented an optimization study for a mixed (electroosmotic and pressure-driven) flow microchannel heat sink with the help of three-dimensional numerical analysis, surrogate methods, and the multi-objective evolutionary algorithm. They considered two design variables; the ratio of the microchannel width-to-depth and the ratio of the fin width-to-depth.

In this paper, a neural networks model for the parallel plate heat sink is developed aiming at finding optimal dimensions of the heat sink. The heat sink dimensions and parameters to be studied are height of heat sink (H), thickness of each plate (T), and the gap between the plates (S). The neural networks model adopts the results of the experiment conducted by Chiang (2007). The rest of the paper is organized as follows; section 2 presents the heat sink model under consideration. Section 3 presented a summary of the experiment developed by Chiang (2007). The results of this experiment are used in this study to develop the Neural networks model. Section 4 presents the Neural network model for the heat sink under consideration. Section 5 presents the results of the response surface methodology in finding the important parameter affecting the heat sink. Results and discussion are presented in section 6. Section 7 presents the conclusion remarks and suggested future work.

1. Heat Sink Model

In this study an optimization procedure is developed in order to find the optimum dimensions of the heat sink that minimizes both the pressure drop across the heat sink and the thermal resistance of the heat sink. The heat sink dimensions and parameters to be studied are height of heat sink (H), thickness of each plate (T), and the gap between the plates (S). The thermal resistance of the heat sink is an important parameter that should be considered in designing the heat sink. It is given by the following equation,

$$R_{th} = \frac{\Delta T}{Q}$$

Where ΔT is the temperature difference between the highest temperature of the heat sink base, and the temperature in the inlet section, Q is the heat dissipation produced by the heating unit. Another important parameter is the pressure drop which is given by the following equation,

$$\Delta P = P_{in} - P_{out}$$

Where P_{in} is the average pressure in the inlet of test section and P_{out} is the average pressure in the outlet of test section.

2. Experimental Setup

Figure 1 shows the parallel plate heat sink under consideration. Chiang (2007) conducted an experiment for obtaining the thermal performance of parallel plate heat sink consists of heating unit, cooling chamber, tested heat sink and measuring devices. The results of this experiment will be used in this paper in developing the neural networks model. The parameters that will be considered are the height of the heat sink (H), the thickness of each fin (T) and the gap between fins (S).

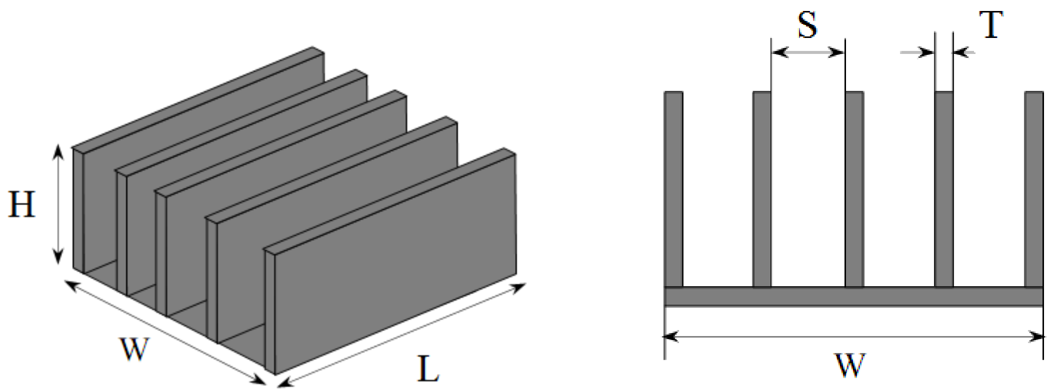

Figure 1: The parallel plate heat sink.

Figure 2 shows the experimental setup developed by Chiang (2007). The heat sink is made of Aluminum with thermal conductivity of 209*W/mK*, the heating unit supplied the heat sink with heat load of 40*W* to simulate heat generated by electronic chips. The heat sink has a simulated cooling fan installed on top to allow exchange between surrounding air and heat sink. Thermal resistance is measured by using a thermocouple and data acquisition system while the pressure change is measured by static pressure tapping. By changing the heat sink dimensions, several readings on thermal resistance and pressure drop were measured. For more details on the experiment conducted the reader can refer to Chiang (2007).

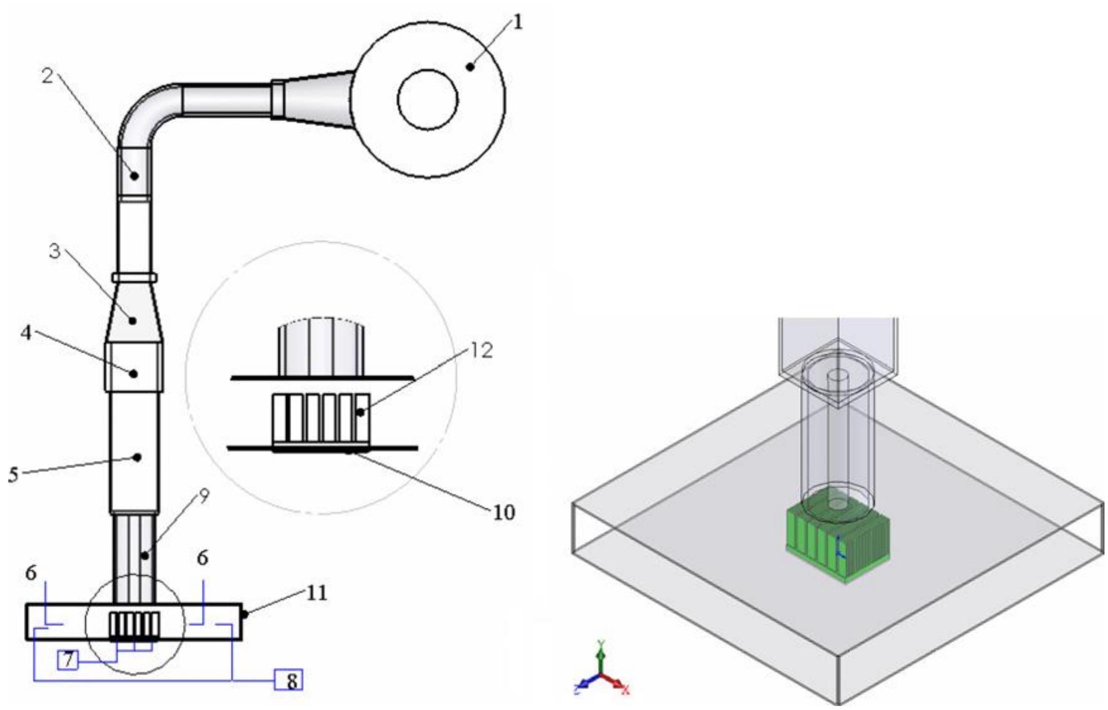

Figure 2: Experimental setup (Chiang (2007)).

Chiang (2007) represented the values of the parameters under consideration by considering the central composite design (CCD). Each parameter takes three levels low, medium and high levels. Table 1 shows the levels of the three parameters considered in this study. These parameters are selected with maximum and minimum boundaries and coded in the values of [-1(low), 0(mid), 1(high)] for simplicity.

Parameter	Levels		
	-1(low)	0(mid)	+1(high)
Fin height, H	45	52.5	60
Fin thickness, T	1	1.5	2
gap between fins, S	3	4	5

Table 1: Design parameters levels as represented by Chiang (2007).

The data obtained from the experiment conducted by Chiang (2007) are both the thermal resistance (R_{th}) and the pressure drop between the two mediums (ΔP). The results are shown in Table 2. The first three design parameters are the fin height, the fin thickness and the gap between the fins. These three parameters will be considered in this study.

Table 2: Data obtained from experiment conducted by Chiang (2007).

Run no.	Design parameters			Experimental results	
	H	T	S	R_{th}	ΔP
1	-1	-1	-1	0.4238	26.27
2	+1	-1	-1	0.2673	16.57
3	-1	+1	-1	0.4301	26.66
4	+1	+1	-1	0.2751	17.05
5	-1	-1	+1	0.4257	26.39
6	+1	-1	+1	0.2692	16.69
7	-1	+1	+1	0.4322	26.79
8	+1	+1	+1	0.2772	17.18
9	-1	-1	-1	0.4272	26.48
10	+1	-1	-1	0.2708	16.78
11	-1	+1	-1	0.4335	26.87
12	+1	+1	-1	0.2786	17.27
13	-1	-1	+1	0.4291	26.60
14	+1	-1	+1	0.2727	16.90
15	-1	+1	+1	0.4356	27.02
16	+1	+1	+1	0.2807	17.41
17	-1	0	0	0.4901	30.38
18	+1	0	0	0.1787	11.07
19	0	-1	0	0.3498	21.68
20	0	+1	0	0.3641	22.57
21	0	0	-1	0.3553	22.02
22	0	0	+1	0.3593	22.27
23	0	0	0	0.3550	22.01
24	0	0	0	0.3619	22.43
25	0	0	0	0.3569	22.12
26	0	0	0	0.3568	22.12
27	0	0	0	0.3568	22.12
28	0	0	0	0.3570	22.13
29	0	0	0	0.3568	22.12
30	0	0	0	0.3566	22.11

3. *Neural Network Model of Heat Sink*

Since the data obtained from the experiment conducted by Chiang (2007), which are shown in Table 2 is in the form of pairs of inputs and outputs, it can be used to build the neural network model by training the network using these data and then produce a general model of the heat sink that can be used to measure the thermal performance by inputting the dimensions of the heat sink.

The network is built with three inputs (H, T and S) and two outputs (R_{th} and ΔP) with one hidden layer that contains three neurons, so the design is 3-3-2 network. The training data are the data from Chiang's experiment which are presented in table 2. Figure 3 demonstrates the relationship between the training data and the network output after training. As can be seen from Figure 3 the error between the training data (target) and the NN output is small and the points almost fit. This may be improved by several factors such as increasing the number of epochs, increasing learning rate, decreasing goal, etc.

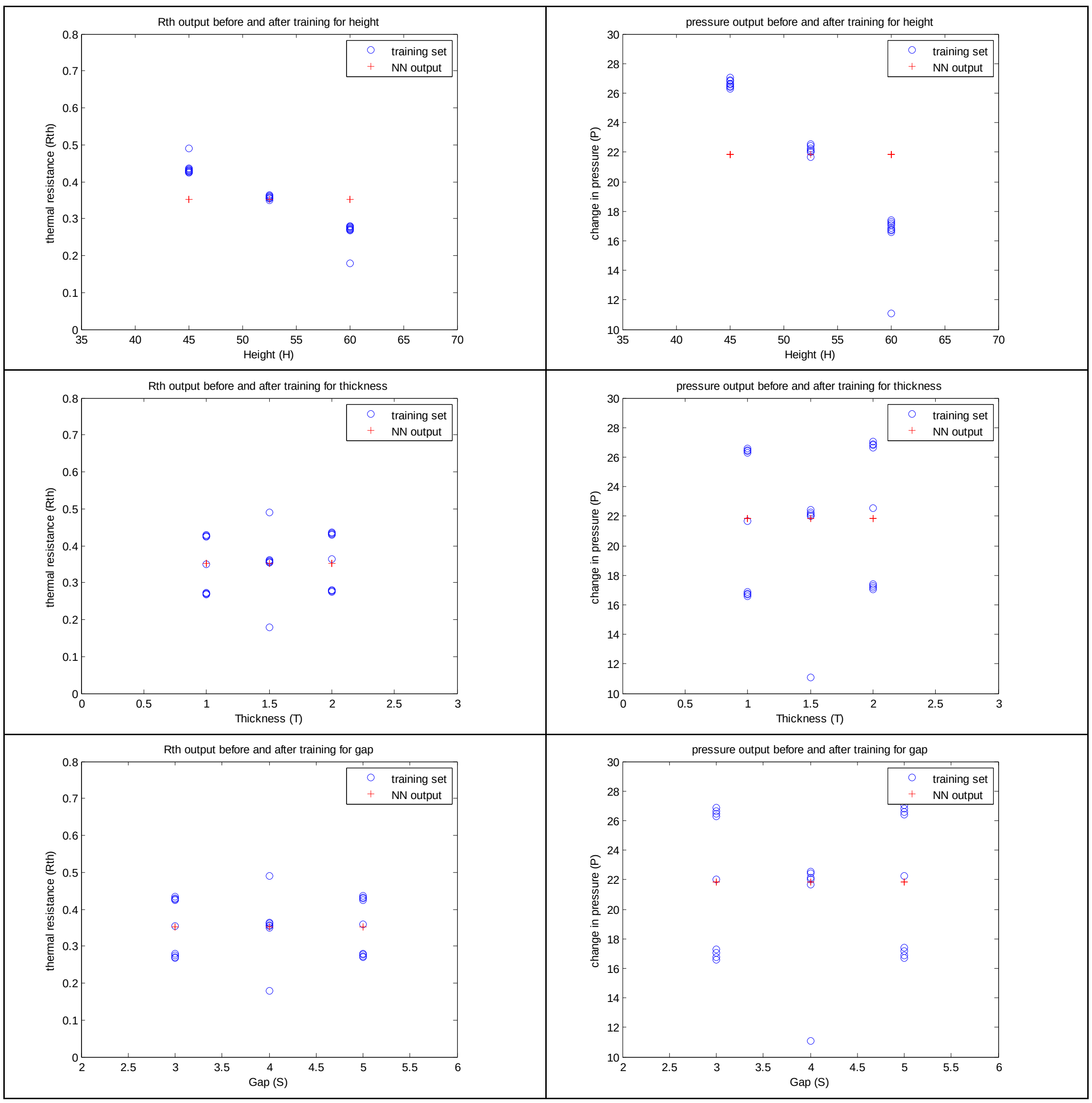

Figure 3: Training set versus NN output for every input and output

The heat sink Neural networks model for parallel plate can be generalized for any input values. Figure 4 illustrated the Simulink representation of the neural network model for the parallel plate heat sink, where the inputs are entered as a column vector and the outputs are calculated based on the neural network model and will be displayed. The figure shows the outputs for the given inputs [60; 2; 3].

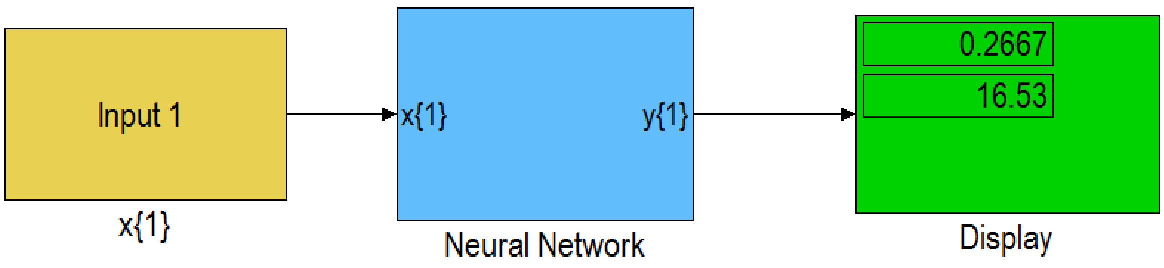

Figure 4: Simulink Neural network representation.

4. Response Surface Methodology

A Response Surface Methodology (RSM) is a collection of statistical and mathematical procedures that relates between the process parameters and the desired response and is useful in modeling and analysis problems that needs to be optimized. RSM can be used for finding a quadratic model that has the main effect, interaction effect and the quadratic effect of every factor by using design of experiment, analysis of variance and regression analysis. The RSM will be used in this work to determine the important parameters that affect the systems response.

The factors considered for RSM design are height (H), thickness (T) and gap (S), while the responses are thermal resistance (R_{th}) and pressure change (ΔP).The design will be three factors and two responses with one replicate, two levels (low (-1) and high (1)) and six central points. The type of RSM is central composite design (CCD). The total number of runs is 20 as shown in Table 3. The data are obtained from Table 2.

Table 3: design for the heat sink model using Minitab

↓	C1	C2	C3	C4	C5	C6	C7	C8	C9
	StdOrder	RunOrder	PtType	Blocks	A	B	C	Rth	P
1	5	1	1	1	-1	-1	1	0.4257	26.39
2	19	2	0	1	0	0	0	0.3566	22.11
3	8	3	1	1	1	1	1	0.2807	17.41
4	3	4	1	1	-1	1	-1	0.4301	26.66
5	7	5	1	1	-1	1	1	0.4322	26.79
6	6	6	1	1	1	-1	1	0.2692	16.69
7	17	7	0	1	0	0	0	0.3568	22.12
8	13	8	-1	1	0	0	-1	0.3553	22.02
9	18	9	0	1	0	0	0	0.3570	22.13
10	1	10	1	1	-1	-1	-1	0.4238	26.27
11	4	11	1	1	1	1	-1	0.2751	17.05
12	9	12	-1	1	-1	0	0	0.4901	30.38
13	16	13	0	1	0	0	0	0.3568	22.12
14	20	14	0	1	0	0	0	0.3568	22.12
15	15	15	0	1	0	0	0	0.3569	22.12
16	10	16	-1	1	1	0	0	0.1787	11.07
17	14	17	-1	1	0	0	1	0.3593	22.27
18	2	18	1	1	1	-1	-1	0.2708	16.78
19	12	19	-1	1	0	1	0	0.3641	22.57
20	11	20	-1	1	0	-1	0	0.3498	21.68

Chiang (2007) summarizes the seven steps that are used for determination of the design parameters with optimal performance characteristics. These steps are summarized as follows (Chiang, 2007):

1. Defining the independent input variables and desired responses with the design constraints.
2. Adopting the face centered to plan the experimental design.
3. Performing the regression analysis with the quadratic model of response surface.
4. Calculating the statistical analysis of variance (ANOVA) for the independent input variables and to find the parameter significantly affects the desired response.
5. Determining the situation of the quadratic model of the response surface and to decide whether the model of RSM needs screening variables or no.
6. Obtaining the optimal machining parameters with the design constraints using the sequential approximation optimization (SAO) method.
7. Conducting confirmation experiment and verify the optimal machining parameters setting.

5. *Results and Discussion*

6.1 The Neural Network Model Results

A simulation procedure is carried out to evaluate both outputs using the neural networks model after training. The results of the Neural network model are compared with the experimental results developed by Chiang (2007). Table 4 illustrated a comparison between the results of the Neural network model and the experimental values in R_{th} and ΔP for 10 experiments. As can be seen from Table 4 the error is very small and does not exceed 14% for both R_{th} and ΔP.

Table 4: Comparisons between NN model and experimental values in R_{th} and ΔP.

Number	H (mm)	T (mm)	S (mm)	Experimental value		NN value		% Error in	
				R_{th}	ΔP	R_{th}	ΔP	R_{th}	ΔP
1	45	1	3	0.4238	26.27	0.4312	26.73	1.716	1.72
2	52.5	1.5	4	0.3566	22.11	0.3573	22.15	0.196	0.18
3	60	2	5	0.2807	17.41	0.27	16.74	3.96	4
4	60	2	3	0.2751	17.05	0.2667	16.53	3.15	3.14
5	45	2	5	0.4322	26.79	0.4402	27.29	1.817	1.83
6	45	1.5	4	0.4901	30.38	0.4361	27.03	12.38	12.39
7	52.5	1.5	3	0.3553	22.02	0.3546	21.98	13.54	0.182
8	52.5	1	3	0.3498	21.68	0.3459	21.44	1.13	1.12
9	60	1	5	0.2727	16.9	0.2599	16.11	4.92	4.9
10	60	1.5	5	0.2692	16.69	0.2647	16.41	1.7	1.7

6.2 The Response Surface Methodology (RSM) Results

RSM is employed and the results of the analysis of variance (ANOVA) shows that for the thermal resistance (R_{th}), the important factors in order are A, A^2, C^2, B^2, B, C, BC and AB while AC is neglected compared to others. Where A represents the height (H), B represents the thickness (T) and C represents the gap (S). So mainly, the liner parameters and the quadratic parameters are significant while the interaction parameters are not that significant. For the pressure drop (ΔP), the important factors in order are A, A^2, C^2, B^2, B, C, BC and AB, while AC is neglected compared to others. So mainly, the liner parameters and the quadratic parameters are significant while the interaction parameters are not that significant. The results are tabulated in Tables 5 and 6. The regression models for R_{th} and ΔP in coded units are:

$$Rth = 0.354499 - 0.09274 * A + 0.00429 * B + 0.0012 * C - 0.016623 * A^2 + 0.005927 * B^2 + 0.006277 * C^2 + 0.000375 * AB + 0.000925 * BC$$

$$\Delta P = 21.9745 - 5.749 * A + 0.267 * B + 0.077 * C - 1.0314 * A^2 + 0.36 * B^2 + 0.3886 * C^2 + 0.025 * AB + 0.00575 * BC$$

Table 5: RSM results for R_{th}.

Response Surface Regression: Rth versus A, B, C

The analysis was done using coded units.

Estimated Regression Coefficients for Rth

Term	Coef	SE Coef	T	P
Constant	0.354499	0.01090	32.530	0.000
A	-0.092740	0.01002	-9.251	0.000
B	0.004290	0.01002	0.428	0.678
C	0.001200	0.01002	0.120	0.907
A*A	-0.016623	0.01912	-0.870	0.405
B*B	0.005927	0.01912	0.310	0.763
C*C	0.006277	0.01912	0.328	0.749
A*B	0.000375	0.01121	0.033	0.974
A*C	-0.000000	0.01121	-0.000	1.000
B*C	0.000925	0.01121	0.083	0.936

S = 0.0317001 PRESS = 0.0777026
R-Sq = 89.64% R-Sq(pred) = 19.91% R-Sq(adj) = 80.32%

Analysis of Variance for Rth

Source	DF	Seq SS	Adj SS	Adj MS	F	P
Regression	9	0.086974	0.086974	0.009664	9.62	0.001
Linear	3	0.086206	0.086206	0.028735	28.60	0.000
Square	3	0.000760	0.000760	0.000253	0.25	0.858
Interaction	3	0.000008	0.000008	0.000003	0.00	1.000
Residual Error	10	0.010049	0.010049	0.001005		
Lack-of-Fit	5	0.010049	0.010049	0.002010	113760.66	0.000
Pure Error	5	0.000000	0.000000	0.000000		
Total	19	0.097023				

Table 6: RSM results for ΔP.

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Response Surface Regression: P versus A, B, C

The analysis was done using coded units.

Estimated Regression Coefficients for P

Term          Coef  SE Coef       T      P
Constant   21.9745   0.6762  32.498  0.000
A          -5.7490   0.6220  -9.243  0.000
B           0.2670   0.6220   0.429  0.677
C           0.0770   0.6220   0.124  0.904
A*A        -1.0314   1.1861  -0.870  0.405
B*B         0.3686   1.1861   0.311  0.762
C*C         0.3886   1.1861   0.328  0.750
A*B         0.0250   0.6954   0.036  0.972
A*C         0.0025   0.6954   0.004  0.997
B*C         0.0575   0.6954   0.083  0.936


S = 1.96692    PRESS = 299.125
R-Sq = 89.63%  R-Sq(pred) = 19.79%  R-Sq(adj) = 80.29%


Analysis of Variance for P

Source          DF   Seq SS   Adj SS   Adj MS          F      P
Regression       9  334.240  334.240   37.138       9.60  0.001
  Linear         3  331.282  331.282  110.427      28.54  0.000
  Square         3    2.927    2.927    0.976       0.25  0.858
  Interaction    3    0.031    0.031    0.010       0.00  1.000
Residual Error  10   38.688   38.688    3.869
  Lack-of-Fit    5   38.688   38.688    7.738  193438.12  0.000
  Pure Error     5    0.000    0.000    0.000
Total           19  372.928
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In Table 7 the results of the RSM methodology is compared with the results of the experiment conducted by Chiang (2007). As can be seen the resulted height of the heat sink (H) is the same as the one in the experiment with zero error, in the other hand the resulted thickness (T) and gab between fins(S) showed variation from that of the experimental values with error of 4.78% and 13.85% respectively. This error is acceptable. From the ANOVA analysis, the most important factor that affects the thermal performance of the heat sink is the height then thickness then gap.

Table 7: Results of the RSM compared with experimental results

	RSM	Experimental	Error
H (mm)	60	60	0%
T (mm)	1.1238	1.07	4.78%
S (mm)	3.8537	3.32	13.85%

6. Conclusion

In this study a parallel plate heat sink was modeled using neural network. The responses of the heat sink that are under study are thermal resistance and pressure change between the inside and the outside while the parameters design are height, thickness and gap between fins.

Neural network model is developed using experimental data from the literature, the results of the Neural network model showed maximum error of less than 13.54% compared with the experimental results. The neural network may be trained with a larger number of examples but care should be taken to avoid overtraining.

Response surface methodology is employed for determining the important factors affecting the performance of the heat sink, and the quadratic effect of every factor by using design of experiment, analysis of variance and regression analysis. The optimum dimensions that minimize thermal resistance and pressure change as obtained by response surface methodology are, height of 60 mm, thickness of 1.1238 mm and gap between fins of 3.8537 mm. with a maximum error of 13.85% compared with the experimental data. It is found that the height is the most important factor affecting the thermal performance.

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