Study of Heat Transfer Characteristics of Cooling Fins using Artificial Neural Network

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Abstract - *Fin is an extended surface from an object to enhance the heat transfer by increasing heat transfer surface area. Method which are used to obtain heat transfer characteristics of fin are finite difference method, finite volume difference (CFD analysis), energy balance method etc. This project is to introduce a new method to find out heat transfer characteristics using Artificial Neural Network. It is a new type of computing system which works similar to human brain. Artificial neurons play a significant role in this work. An artificial neuron is a mathematical function conceived as a model of biological neurons. The artificial neuron receives one or more inputs and sums them to produce an output. Usually each input is separately weighted, and the sum is passed through a non-linear function known as an activation function. Circular type fin is analyzed here. The assumptions made are constant base temperature, steady state condition and no radiation heat transfer*

Key Words: Annular fin, Heat transfer characteristics, CFD analysis, Artificial neural network, Artificial neurons.

1. INTRODUCTION

We have already studied various methods to find heat transfer rate, heat flux and temperature distribution by energy balance method which is very difficult to apply in circular fins. We need to consider cylindrical coordinates and assumptions, to do that which is difficult and time consuming. Next methods are finite element method and finite volume method (CFD analysis). These are faster and accurate than traditional method but also time consuming and good capacity computers are needed.

Here we are introducing a new method called artificial neural network which is a latest trending technology in artificial intelligence. Artificial neural networks (ANN) are computing systems which is inspired by the biological neural networks that constitute animal brains. The neural network itself is not an algorithm, but rather a framework for many different machine learning algorithms to work together and process complex data inputs. Such systems "learn" to perform tasks by considering examples, generally without being programmed with any task-specific rules. There are three steps in ANN which are learning, testing and validation. For learning sufficient data samples are required, which should represent overall parameter range. Data sample set within the parameter range and with equal weightage is created using a statistical method called Latin hypercube sampling. And the corresponding output of parameters is got from CFD steady state thermal analysis. Testing is done with trained result and validation by results unknown by neural network. Here ANN model is created in python programming language using Keras library.

1.1 Literature survey

Many research works have been published in the field of fin analysis. Both experimental and numerical studies are there. B M Niroop Kumar, et al. (2014) in (Journal of Hydraulic Engineering) published “Study of thermal characteristics of cylinder fin by varying geometry and material”[1]. They studied various fin geometry and material which has maximum fin efficiency. Geometry selected to study are circular, rectangular and curved. From that they found that circular fin geometry have more heat dissipation rate than other geometry. Also best material is aluminum alloy 6061. Pulkit Sagar, et al. (2016) in (Journal of Heat Transfer) published “Heat transfer analysis and optimization of annular fins of varying geometry” [2]. In this work they studied various fin geometries such as concave shaped fin convex shaped fin and straight fin of same material and fin length. They observed that convex type fin have more heat transfer rate than all other types but material needed for convex and concave shaped fin are more than straight fin. Sathishkumar, et al. (2016) in (Journal of Heat Transfer) published “Design and thermal analysis on cylinder fins by modifying its material and geometry” [3]. They did research on fin materials such as aluminum alloy A6061, A2014 and C443. Out of this heat transfer rate is temperature distribution is higher in case of alloy A6061. Their application is in the air cooled engine cylinder. Yaddanapudi Sai et al. (2016) in (Journal of Heat Transfer) published “Design and Optimization of circular Fin Using Taguchi Technique” [4]. From this optimization work they specified proper parameters and their operational ranges but velocity of air is not considered which also have influence of heat transfer rate. The parameters they analyzed are fin thickness, fin number, fin radius and fin pitch. Anas A. Rahman et al. (2018) in (Journal of Heat and Mass Transfer) published “Prediction of oscillatory heat transfer coefficient for a thermo-acoustic heat exchanger through artificial neural network technique” [5]. In this paper they successfully conducted application of artificial neural network in heat transfer problem. They predicted oscillatory heat transfer characteristics of a thermo-acoustic heat exchanger with high accuracy. The average error percentage for predicted value of heat transfer coefficient is only 3.2%. C.K. Tan et al. (2009) in (Journal of Applied Thermal Engineering) published "Artificial neural network modeling of the thermal performance of a compact heat exchanger" [6]. They also predicted the heat transfer characteristics with an accuracy of 95% with the original value. More research work are published in both fin application and application of artificial neural network in heat transfer problems. M. Mohanraj et al. (2014) in (International Journal of Thermal Sciences) published "Applications of artificial neural networks for thermal analysis of heat exchangers" [7]. Devendra J Waghulde et al. (2017) in (International Research Journal of Engineering and Technology) published "Effect of fin thickness and geometry on engine cylinder fins" [8]. They conducted experimental and numerical simulations on cylinder fins. This paper is used to validate the present project.

1.2 Problem definition

The primary objective is to study heat transfer characteristics of cooling fins using artificial neural network method. Also we will calculate the average heat flux value using artificial neural network and the accuracy in calculated value. For this work we had arrived at some assumptions they are, steady state condition, constant inner wall or base temperature, no radiation heat transfer and not considering roughness of selected material. Now the parameters selected and their operating ranges are:

- Fin thickness (mm): 1 - 4.
- Fin length (mm): 10 - 20.
- Number of fins: 9 - 14.
- Air velocity(m/s): 10 – 40

2. NUMERICAL SIMULATION

2.1 Geometric model

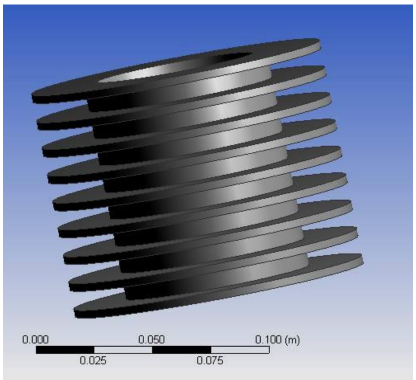

Fig -1: Geometric model of annular fin in one case

Fig. 1 shows the geometric model of annular fin constructed within the specified parameters. It was created in Ansys 16.2 Steady state thermal design modeler. The material selected is aluminum alloy 6061 as per literature review. The axial length is 100 mm, bore or inner cylinder diameter is 68 mm, outer cylinder diameter is 80 mm, cylinder wall-thickness is 6 mm, fin length (from outer cylinder) is 18 mm, fin thickness is 3.5 mm and number of fins is 9.

2.2 Meshing

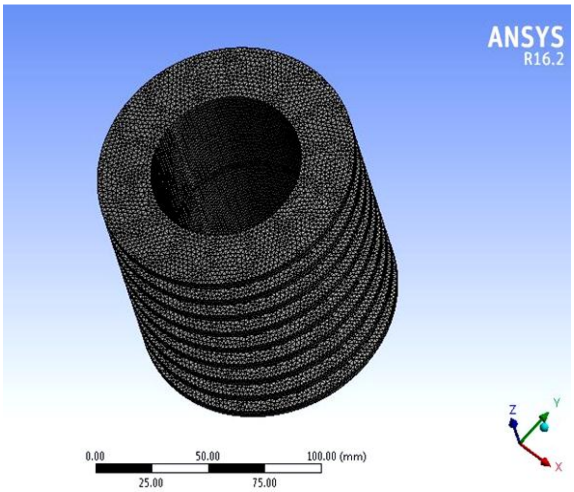

Fig-2: Meshing of the model

Fig. 2 shows the mesh created in the generated geometry. Mesh obtained is tetrahedral element. No. of element is 254790 with an element quality of 0.82717 and skewness of 0.21657. These values are finalized after conducting grid independency study. Face meshing and edge sizing are done for increasing mesh quality.

2.3 Boundary conditions

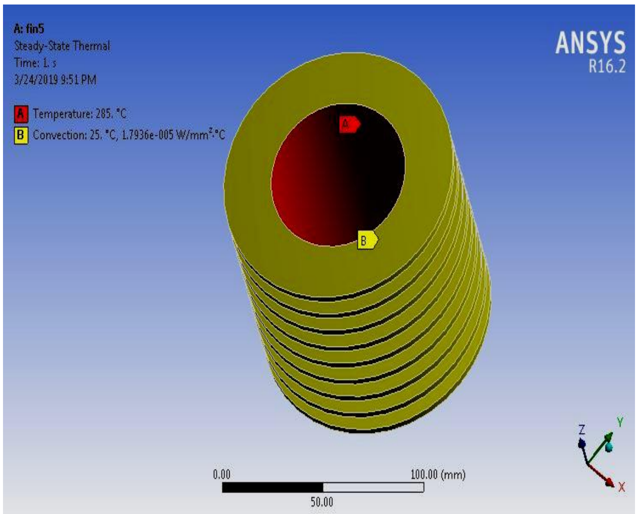

Fig-3: Boundary conditions

The boundary conditions applied are: inner wall or base temperature as 285^{0}C, surrounding air temperature as 25^{0}C and for the velocity 15 m/s, heat transfer coefficient or film coefficient is 1.7936 x10^{5}W/m^{0}C. All the above described data is shown in fig. 3. The all process such as geometric modeling, meshing, and simulation are done in Ansys Steady state thermal analysis. And the corresponding output that is average heat flux is calculated using CFD post by transferring simulation result to CFD post.

2.4 Validation

The model validation is done based on an experimental work conducted by Devendra J Waghulde[8]. It is done by repeating their numerical work and the temperature at fin tip is measured. The tip temperature from experimental work and numerical simulation is compared with this current work.

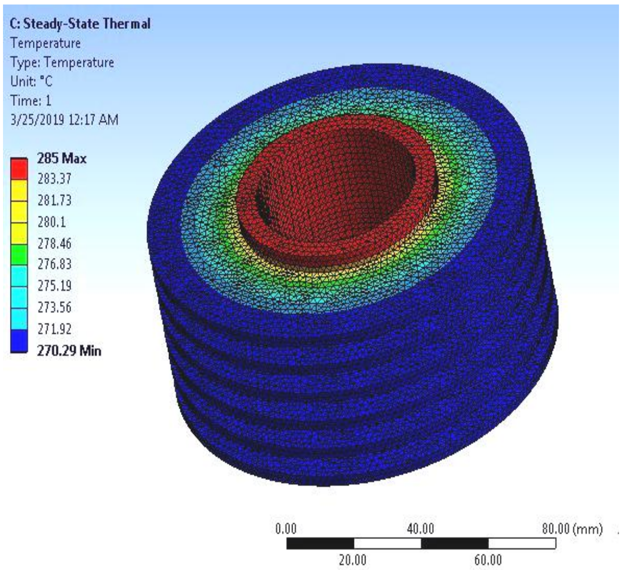

Fig-5: Temperature contour from the study

From the experimental work, they got fin tip temperature as 266.83^{0}C and the result from their numerical simulation is 269.5^{0}C. Now from the present work we got the numerical simulation result as 270.2^{0}C at fin tip. The average error percentage between their experimental value and present simulation result is 1.28%.

2.5 Simulation result

In this work we have conducted 40 simulation results corresponding to 40 combinations (given equal weightage within the range) of parameters. Out of that a single case is explained for the time being and all 40 simulation results are shown in table 1.

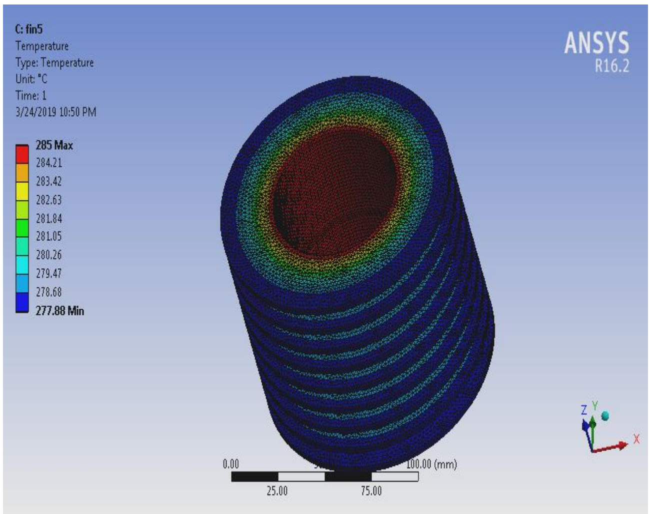

Fig-6: Temperature contour

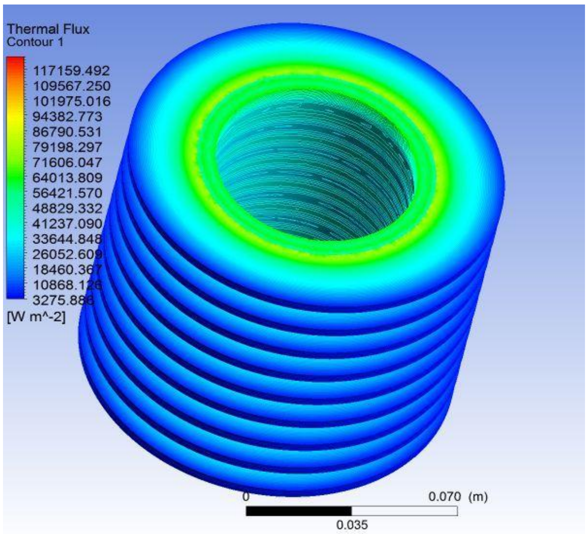

Fig-7: Heat flux contour

The heat flux contour shown is the average heat flux, that's why there is a yellow circle. As the air velocity is taken in x direction, temperature is taken away from area of first contact. So the heat flux is not uniform. That's why average heat flux is calculated. By applying boundary conditions as shown in fig-3, the average heat flux value calculated by CFD post is 29477.2 W/m^2. Similarly 39 more simulations are done.

Sl. no	Fin-length (mm)	Fin thickness (mm)	Air velocity (m/s)	No. of fins	Heat flux (W/m^2)
1	11	3.0	10	20	22712.6
2	14	1.5	30	13	61332.7
3	11	2.5	30	9	30736.5
4	16	2.0	10	10	31942.3
5	11	3.5	10	11	15288.3
6	14	3.5	35	10	44880.1
7	15	2.0	25	14	57774.1
8	18	3.5	10	9	29477.2
9	19	3.0	25	12	65678.4
10	16	1.5	13	15	50952.1

11	11	3.5	35	12	33817.8
12	16	1.0	15	12	56306.2
13	18	3.5	35	10	66924.5
14	12	2.0	20	9	27932.5
15	13	4.0	35	13	41527.9
16	17	2.0	12	10	38068.5
17	13	3.5	15	14	26770.6
18	14	4.0	15	11	26071.4
19	17	2.5	10	11	33612.6
20	15	1.5	20	13	54364.9
21	12	2.5	11	25	33974.5
22	17	2.0	20	10	53593.7
23	13	3.5	30	9	35398.4
24	13	1.5	30	10	47822.5
25	12	2.0	15	11	26699.1
26	12	1.5	10	11	22543.8
27	16	2.5	15	13	41562.3
28	19	3.0	20	10	54158.9
29	15	2.5	25	13	51298.9
30	10	1.0	13	15	25945.6
31	17	3.0	25	12	55439.1
32	12	1.0	25	12	45441.7
33	10	4.0	15	10	15845.6
34	18	2.5	30	13	75611.5
35	12	2.0	10	25	35422.8
36	17	3.0	10	11	30918.8
37	14	3.0	25	14	43911.5
38	10	2.5	30	12	30052.7
39	11	3.5	10	30	27881.5
40	11	3.0	20	11	23834.5

Table-1: Data samples for training, testing and validating ANN

Out of these, 35 data samples are selected for training the neural network and rest for validating. Testing of a neural network is done by trained data and the validation is done by network unknown data.

3. ARTIFICIAL NEURAL NETWORK

Artificial neural network is a type of computing system which works similar to a biological brain. An artificial neuron is a mathematical function which resembles a model of biological neurons. Artificial neurons are elementary units in an artificial neural network. The artificial neuron receives one or more inputs and sums them to produce an output. Usually each input is separately weighted, and the sum is passed through a non-linear function known as an activation function. Here the activation function used is Relu- rectified linear unit. It is just $R(x) = max(0,x)$ that is, if $x < 0$, $R(x) = 0$ and if $x >= 0$, $R(x) = x$. Hence as seeing the mathematical form of this function we can see that it is very simple and efficient. This is unlike the tanh (hyperbolic tan) and sigmoid activation function that require the use of an exponential calculation.

3.1 Neural network training and testing

Before training, the 35 data set is normalized to a value between 0 and 1. This is done for the easiness of computation. And corresponding de-normalization is done to obtain actual value at final step. Now from the combination of input parameters and corresponding result values, the network tries to learn. Learning is actually a creation of better algorithm which gives most accurate result. Each neuron in the hidden layer will try to have a threshold value which act as a barrier to control the forward movement for calculation of result. After a number of iterations it will create proper weights to hidden neurons and finally a better algorithm is created. Learning in a neural network is closely related to how we learn in our regular life.

Based on the difference between the actual value and the output value by the network, an error value is computed and sent back through the system. For each layer of the network, the error value is analyzed and used to adjust the threshold and weights for the next input. In this way, the error keeps becoming marginally lesser each run as the network learns how to analyze values. The procedure described above is known as back propagation, and is applied continuously through a network until the error value is kept at a minimum.

Now it will give some values which are calculated using the algorithm it created during learning. Surely there will be some error associated with it. And we calculate the average percentage error in the predicted value. So here I am taking all 35 data samples to test the ANN. And the ANN calculated some values corresponding to each 35 heat flux value with some error associated with it.

Sl.no	Trained value	Tested value	Error percentage
1	41527.9	41419.2	0.26
2	54364.9	54100.5	0.48
3	31942.3	31933.4	0.02
4	51298.9	50680.7	1.21
5	15845.6	15934.1	0.56
6	54158.9	53672.5	0.89
7	53593.7	53302.2	0.54
8	41562.3	42648.6	2.61
9	22543.8	22981.6	1.94
10	45441.7	45790.4	0.76
11	26071.4	26125.1	0.21
12	47822.5	48002.9	0.37
13	15288.3	15413.2	0.81
14	30736.5	31213.7	1.55
15	35398.4	35664.8	0.75
16	26699.1	25441.9	1.71
17	33817.8	34492.5	1.99
18	55439.1	55257.4	0.32
19	33612.6	33853.8	0.71
20	57774.6	57944.2	0.29
21	27932.5	27993.1	0.21
22	29477.2	29498.4	0.07
23	75611.5	74828.5	1.03

24	61332.7	62131.7	1.29
25	26770.6	27116.2	1.29
26	44880.1	44680.2	0.44
27	56306.2	55836.5	0.83
28	65678.4	65551.8	0.19
29	66924.5	66471.2	0.67
30	35422.8	35621.7	0.56
31	22712.6	22980.2	1.17
32	50952.1	51184.4	0.45
33	38068.5	38143.9	0.19
34	33974.5	33637.4	0.99
35	25945.6	25614.5	1.27

Table-2: Variation in trained and tested value

The average error percentage in evaluated values is 0.9037%. And therefore the ANN evaluated the values with an accuracy of 99.09%. This implies that the created ANN is ready for validation. Fig -8 indicates the variation between trained value and tested value of heat flux.

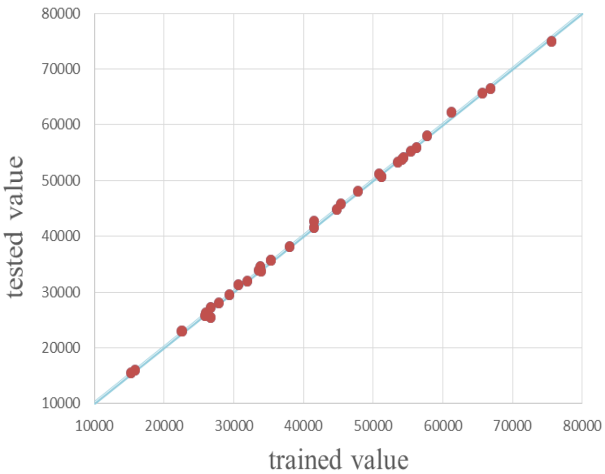

Fig-8: Graph showing variation in trained value and tested value of heat flux

3.2 Neural network validation and result

Validation of neural network is carried out using the 5 remaining data samples which are not used to train the network. So the network uses the already created algorithm to predict the unknown value. Now we have the actual value got from the CFD simulation and the network predicted value. Comparing these values we can calculate the error percentage associated with it. The table 3 shows the variation between actual value and predicted value. The graph shows the variation in these values is shown in fig. 9.

Sl. no	Actual value of heat flux	Predicted value of heat flux	Error percentage
1	30918.8	31956.2	3.35
2	43911.5	42718.6	2.71
3	30052.7	30188.1	0.45
4	27881.5	27302.5	2.07
5	23834.5	21863.4	8.26

Table-3: Variation between actual value and predicted value

Even though these 5 values are unknown to the created neural network model, it calculated the values much accurately. The average error percentage occurred while validating is 3.368%. Therefore the accuracy of created ANN is 96.6%. We can increase the accuracy by increasing number of training data samples. But we should have a limiting condition otherwise a problem called over fitting will occur.

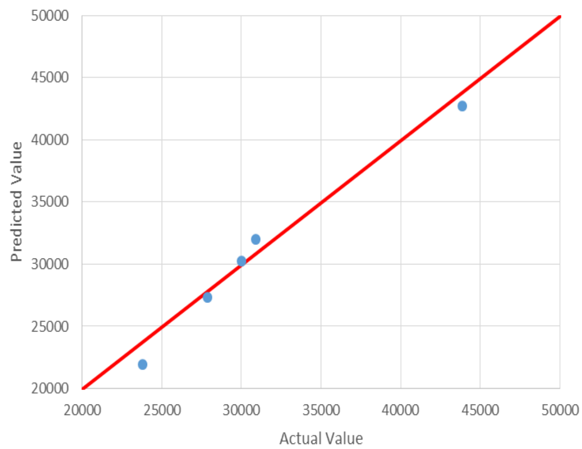

Fig-9: Graph shows the variation in actual value and predicted value

4. CONCLUSIONS

The study of heat transfer characteristics of circular cooling fins was conducted using Artificial Neural Network. In this work I have created a neural network model of configuration 4-6-8-4-1, which means it have four input neurons, three hidden layers and an output neuron that is heat flux. 40 data samples are created using CFD simulation by giving 40 design parameter combinations. From these 40 data samples 35 samples are taken to train the network and rest for validating the network.

After validating the network, the average error percentage for predicted value compared to actual value is only 3.368 % which means the created neural network is much accurate to handle these fin problems. It also proves that a well-trained neural network can predict accurate and very fast results. In this work the neural network is created using Keras library in Python programming language. It can also create in Matlab or even in C++. It is very easy to create in python language because there is a lot of supporting library files available in python programming language. A very accurate neural network can be used instead of traditional energy balance method and finite element methods for finding linear or non-linear heat transfer problems. Their ability to learn by example makes them very flexible and powerful. Furthermore there is no need to devise an algorithm in order to perform a specific task; i.e. there is no need to understand the internal mechanisms of that task. They are also very well suited for real time systems because of their fast response and computational times which are due to their parallel architecture.

ACKNOWLEDGMENT

I express my heartfelt gratitude to my project guide, Dr. Brijesh Paul, Professor, Department of Mechanical Engineering for his valuable guidance, support and encouragement during the course of the project and in the preparation of the report. I also extend my thanks and goodwill to my parents, friends, family members and well-wishers for their encouragement and support that helped me to overcome all difficulties.

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