COMPUTATIONAL STUDY OF THERMAL PERFORMANCE OF ADAPTIVE STRUCTURES

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ABSTRACT

Artificial Intelligence can be used in design of adaptive structures for data-driven modelling, design of intelligent control algorithms, predictive analytics, and design optimization. Adaptive structures for thermal management of electronic devices refer to systems or components that can dynamically adjust their shape, properties, or configurations to optimize heat dissipation and regulate the temperature in electronic devices. The current study is based on the application of adaptive structures for heat transfer augmentation. These structures are designed to enhance cooling efficiency, prevent overheating, and ensure reliable operation of electronic components. Thermal simulation of adaptive structures is highly interdisciplinary, involving aspects of mechanical engineering, materials science, control systems, and numerical methods. The proposed heat sink changes its shape and hence exposed surface area in accordance with changes insurrounding conditions to cater to variable heat dissipation requirements by various thermal systems. A cylindrical heat sink with radial fins having a unique design feature of variable heat transfer area is studied for thermal performance. The objective of this study includes studying the numerical pattern of the effect on heat dissipation by changing the surface area. Two sets of dimensions of the model are taken for numerical simulation, and the change in heat transfer coefficient with respect to a gradual increase in the surface area is analysed.

KEYWORDS

Intelligent systems, Adaptive structures, Heat sinks, Variable heat transfer rate, Numerical modelling.

1. INTRODUCTION

Thermal management plays a crucial role in a wide range of engineering applications. It ensures component reliability and longevity, performance optimization, energy efficiency, ensures safety and assures performance consistency. To meet these objectives, fixed shape thermal management devices have used in the past. However, these fixed shape, fixed area thermal management devices have some inherent shortcomings. These mechanisms may not effectively dissipate heat in all operating conditions or under varying thermal loads. As these devices are designed for specific thermal scenarios or operating ranges, making them less adaptable to varying heat loads, ambient temperatures, or transient events. In addition, these structures may tend to overcool or undercool components, leading to suboptimal performance, energy wastage, or unnecessary wear on cooling systems. These drawbacks of the static thermal management devices generate the motivation for incorporating adaptive structures in thermal management devices promising

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enhanced performance, efficiency, and flexibility in managing heat transfer. Adaptive structures offer the ability to dynamically respond and adapt to changing thermal conditions and can significantly improve heat dissipation and thermal conductivity. These structures become more significant in view of the fact that thermal engineers have only two options to handle a dynamic thermal situation- change in convective surface area and change in heat transfer coefficient, the latter being costly in implementation [1]. In nature, both zoological and botanical species display area varying characteristics for adaptive thermal management which becomes source for the proposed design [2,3].

By dynamically adjusting their properties based on the prevailing thermal conditions, adaptive structures can optimize heat transfer, reduce energy consumption, and minimize wasteful cooling or heating. This energy-saving potential is crucial in applications where energy efficiency is a key concern, such as data centres, electric vehicles, or renewable energy systems. They can also respond to variations in heat loads, ambient temperatures, or thermal gradients, ensuring effective thermal management across a wide range of operating conditions. This adaptability is particularly beneficial in applications that experience varying thermal environments, such as spacecraft, industrial processes, or outdoor electronic devices. Adaptive structures also enhance the fault tolerance and resilience of thermal management systems. By dynamically redistributing heat or altering heat transfer paths, adaptive structures can mitigate localized hotspots, temperature gradients, or thermal stress, minimizing the risk of component failures. This capability improves the overall reliability and robustness of the system.

The proposed work studies the computational thermal analysis of an adaptive thermal dissipation system which consists of cylindrical heat sink with radial fins and is aimed to create an adaptive mechanism to achieve variable heat transfer rate as thermal systems are required to dissipate heat with variable rate as per environmental and operational requirements. The radial fins are made of two symmetric parts which can slide over each other, allowing to control projected heat transfer area. The commercial CFD software Fluent is used to solve the governing equations in order to obtain the heat transfer and fluid flow characteristics. The authors assessed the effects of the fin thickness, fin pitch and fin height on the thermo-fluidic behaviour of the extended surface. The temperature profile and heat transfer coefficient of all the possible configurations has been calculated and compared against each other for the most efficient thermal performance.

2. Literature Review

The miniaturization trend in the electronics industry and ever-increasing demand for electric vehicles, led by a sharp increase in demand for portable devices and continuously increasing concerns about climate change, have posed fresh challenges to thermal engineers. The common element to these contemporary and essential challenges is their efficient thermal management. This would ensure their success and shape the future of technology and transportation. Thermal management engineers and researchers have adopted a plethora of methods to meet these objectives [4]. In an imminent departure from conventional thermal management systems, the research community has already started looking for alternate designs [5]. This has led to the shift of focus to adaptive thermal management devices due to their ability to dynamic heat transfer optimization, thermal energy storage, and release, flexible and variable thermal conductivity, adaptive insulation, etc. [6,7]. It has been an established practice to carry out computational fluid dynamics simulations before the first prototype is made, as it accurately predicts temperature distribution, heat transfer rates, hot spots, air flow patterns, and heat flux rates [8]. To further reduce the design to product lead time, several Multiphysics and multi-scale simulations are being carried out using state-of-the-art techniques like deep learning [9].While adaptive structures offer promising solutions for thermal management, addressing challenges and limitations like design complexity, actuation power, and energy requirements, actuation speed and response time, material properties and durability, sensing and control accuracy, integration and compatibility, scalability, reliability, and manufacturing constraints require further research, technological advancements, and interdisciplinary collaboration. These structures can further be integrated with functional materials like Shape Memory Alloy to make them completely autonomous and passive in operations [10].

3. Geometrical Description of the Model

The simulated heat sink model consists of a heat source on which constant heat flux condition is applied. It also consists of n number of radial fins, which is connected to the periphery of the cylindrical surface. The model is designed to be able to open the fins to increase the surface area. Further, each radial fin is made of two layers (as would be shown in Figure 3), where one layer can slide over the other prismatically, thereby providing more control over the convective surface area to suit variable thermal management requirements.

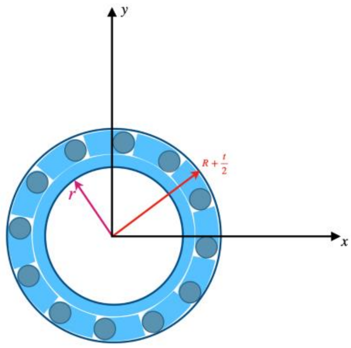

Figure 1. Adaptive fin in closed configuration

The geometry of the cross-section of the model of closed fins and opened fins are shown in the figures 1 and 2 respectively (for n = 12). The radius of the inner cylindrical surface is$r$. The radius of the imaginary cylinder that passes through the centres of the revolute joints of the fins is$R$. The thickness of each fin is$t$. The outward surface of the fin has a radius of$R+\frac{t}{2}$ and the inner surface of the fin has a radius of$R-\frac{t}{2}$. The parametric equations of the curves along the outer and the inner edges of the right most fin as shown in figure 2, are given by equations (1) and (2), respectively, where the parameterθ ranges from 0 toα, where$\alpha=\frac{\pi}{n}$, where$n$ is the number of fins andθ is measured from negative y-axis, as shown in Figure 2.

$$(x,y)=\left(R-\frac{t}{2}+\left(R+\frac{t}{2}\right)\cos\theta, R-\frac{t}{2}+\left(R+\frac{t}{2}\right)\sin\theta\right) \tag{1}$$

$$(x,y)=\left(R-\frac{t}{2}+\left(R-\frac{t}{2}\right)\cos\theta, R-\frac{t}{2}+\left(R-\frac{t}{2}\right)\sin\theta\right) \tag{2}$$

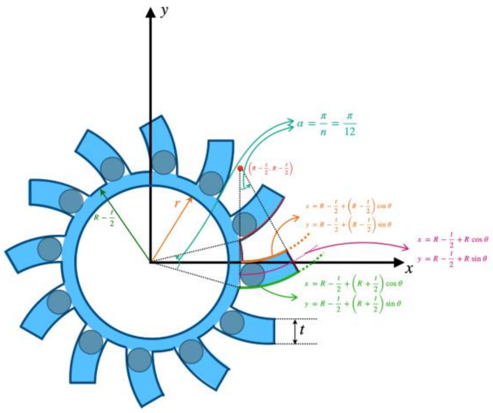

Figure 2. Geometry of the model

4. COMPUTATIONAL METHOD

Computation here involves solving of Navier-Stokes' equations that consist of five unknowns, namely the three velocities in all the three directions (x, y and z directions), the pressure and the temperature, at each point in the domain. Solving this analytically is extremely difficult and hence numerical methods such as Finite Element Method, Finite Volume Method, etc., where the entire domain is discretised into several small elements within which the variation of the variables is assumed to be a piece-wise smooth variation such as a piece-wise linear variation.

In this study, Ansys Fluent has been used for thermo-fluidic simulation due to its superiority over its counterpart in many aspects. It offers a wide scope of integration with Artificial Intelligence (AI) techniques. This would substantially improve the simulation procedure in terms of optimization of the design, autonomous control of the simulation, predictive modelling. It has potential to further improve the simulation procedures by uncertainty quantification, process automation and data driven insights [11-14]. It also provides a robust and efficient solver for solving the governing equations of fluid flow, including the Navier-Stokes equations. It incorporates advanced numerical algorithms that enable accurate and reliable predictions of fluid behaviour. Fluent provides various models to simulate different modes of heat transfer, such as conduction, convection, and radiation. It offers a wide range of boundary conditions and material properties to represent the thermal behaviour of systems accurately [15]. It becomes a natural candidate for thermo-fluidic simulation due to its ability to handle Multiphysics simulations efficiently, extensive material database, and advanced pre-processing and post-processing. Its extensive usage across industries has resulted in a vast amount of application-specific knowledge and validation, making it a trusted tool for thermal simulation. A Python script is written in SpaceClaim of ANSYS that can produce geometric model for any given fraction. The model is then automatically imported for meshing, solution and post-processing, using another Python code. During the solving process for each fraction,ANSYS Fluent is made to run 10 iterations and get the value of average heat transfer coefficient, and to rerun it for 10 more iterations and get the value, and so on, until the last 10 such values happen to be unchanging of the order of 1 decimal point. Then it terminates and collects the value and goes for the same analysis with an incremented fraction. This way, an approximate value of the average heat transfer coefficient is computed for each fraction from 0.1 to 0.9 at a step size of 0.01.

5. RESULTS AND DISCUSSIONS

Forced heat transfer analysis is done in ANSYS Fluent by assuming the following parameters, for the movable layer of the fin varying from 0.1 to 0.9 of a fraction with respect to the stationary layer of the fin:

Material properties:

Table 1. Material properties of Aluminium and Air.

S. No.	Property	Value
1	Density of Aluminium	$2719\ kg\ m^{-3}$
2	Specific Heat of Aluminium	$871 J\ Kg^{-1} K^{-1}$
3	Thermal Conductivity of Aluminium	$202.4\ W\ m^{-1} K^{-1}$
4	Density of air	$1.225\ Kg\ m^{-3}$
5	Specific Heat of Air	$1006.43\ J\ Kg^{-1} K^{-1}$
6	Thermal Conductivity of Air	$0.0242\ W\ m^{-1} K^{-1}$
7	Viscosity of Air	$1.7894 \times 10^{-5}\ Kg\ m^{-1} s^{-1}$
8	Velocity of inlet air	$5\ m\ s^{-1}$
9	Input heat flux	$10000\ W\ m^{-2}$

Dimensions:

Table 2. Dimensions of the model.

S. No.	Dimension	Value
1	R	$0.6\ m$
2	r	$0.45\ m$
3	w	$1.2\ m$
4	n	8
5	t	0.15

The SpaceClaim model for 0.5 fraction is shown in Figure 3.

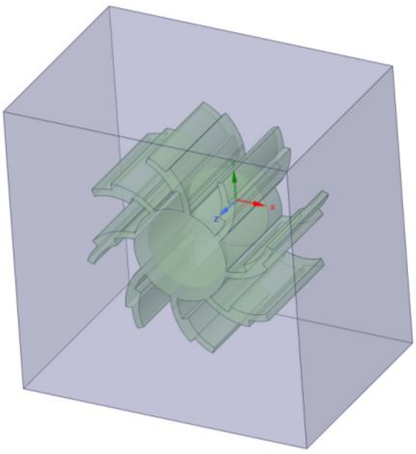

Figure 3. SpaceClaim geometry model of the fin system along with its fluid domain.

The corresponding temperature distribution and heat transfer coefficient distribution are shown in Figure 4 and Figure 5, respectively.

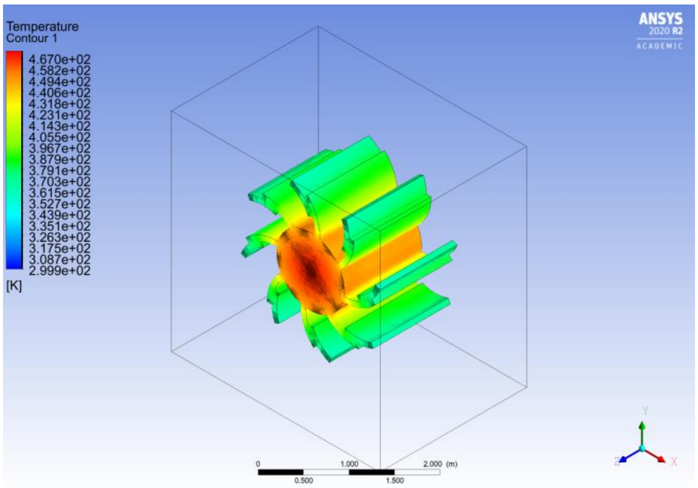

Figure 4. Temperature profile for 0.5 fraction configuration.

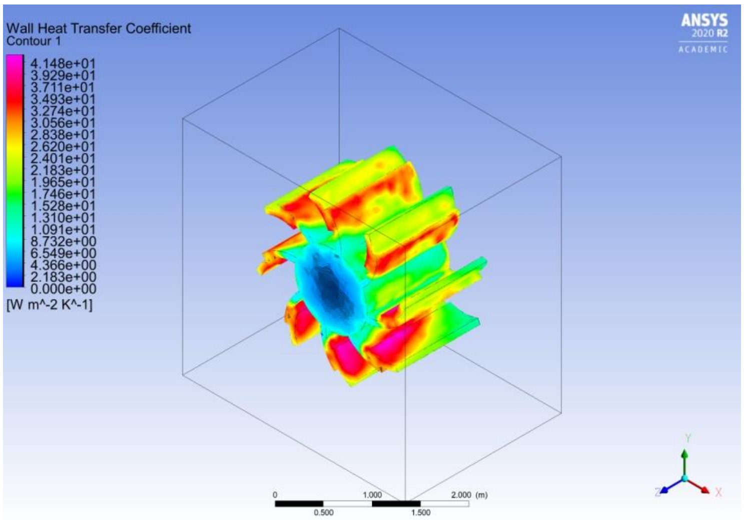

Figure 5. Wall heat transfer coefficient profile for 0.5 fraction configuration.

The average heat transfer coefficient is calculated to be about 21.1345 W/m^2K. Since CFD consists of non-linear partial differential equations, the criterion for convergence of average heat transfer coefficient through iterations that is considered for this analysis is that the average heat transfer coefficient is assumed to have converged when the rounded value up to 1 decimal place doesn't change continuously for 10 sets of 10 iterations each (100 iterations inspected at every 10 iterations). The average heat transfer coefficient has been calculated for all the cases with sliding fraction changing from 0.1 to 0.9, and the result is shown in Figure 6.

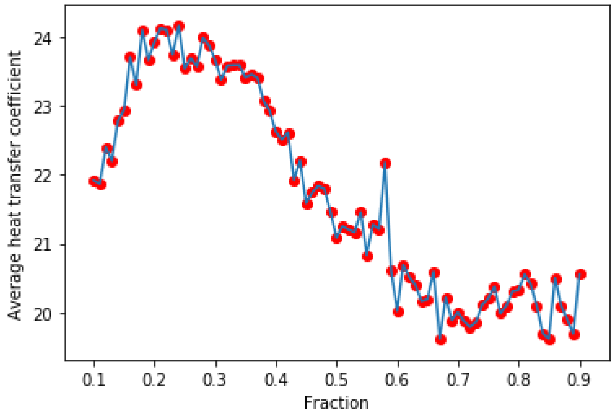

Figure 6. Variation in average heat transfer coefficient with increase in exposed surface area for large-sized model.

From theory, we predict that as the moving layer slides out, because of the increase in convective surface area it could be more effective. However, as it is further increased, the conduction from the stationary fin to the moving fin may decrease because of the reduction in the area of contact between them, thereby reducing the efficiency. In the graph, we can observe that the average heat transfer coefficient increases initially but decreases as the fraction reaches 0.9. From the graph, the maximum heat transfer coefficient is reached when the fraction is around 0.22. The graph shows that the improvement in the heat dissipation characteristics is observed as the exposed convective area increases. However, this improvement in thermal dissipation characteristics is observed only for a limited increase in surface area, beyond which there is little or no significant improvement. This guides the thermal management designer in finalizing the actuation limits without incurring additional resources for undesirable part of the actuation.

5.1. Analysis of a Scaled-Down Model

The dimensions used in the first analysis are for representational purposes only and are meant to validate the concept. A scaled-down model with practical dimensions and thermal parameters has been discussed in this sub-section. The scaled-down dimensions are shown in Table 2.

Table 3. Dimensions of the scaled-down model.

S. No.	Dimension	Value
1	R	$40\ mm$
2	r	$30\ mm$
3	w	$30\ mm$
4	n	8
5	t	$10\ mm$

The geometry of this scaled-down model for 0.5 fraction is shown in Figure 7.

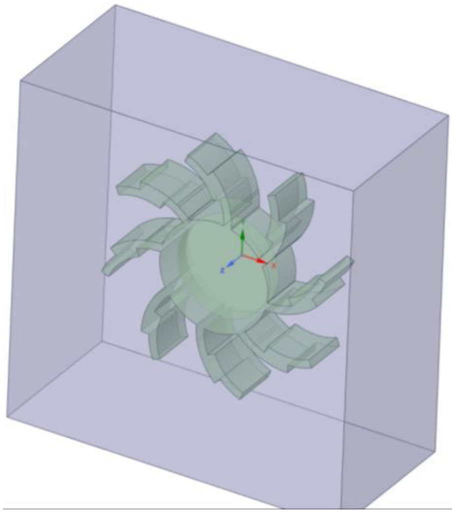

Figure 7. SpaceClaim geometry of the scaled-down model of the fin system along with its fluid domain.

The temperature distribution and the heat transfer distribution of the scaled-down model are shown in Figure 8 and Figure 9, respectively.

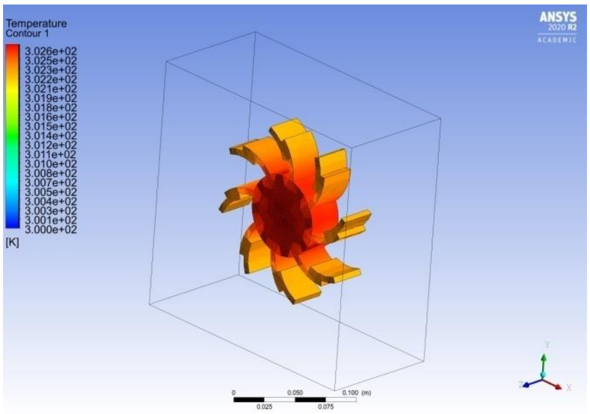

Figure 8. Temperature profile for 0.5 fraction configuration of the scaled-down model.

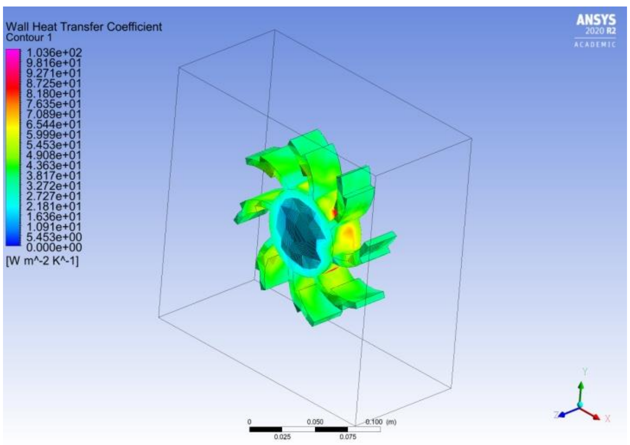

Figure 9. Wall heat transfer coefficient profile for 0.5 fraction configuration of the scaled-down model.

By using the same criterion for convergence, the values of average heat transfer coefficient with varied fraction from 0.1 to 0.9 are shown in Figure 10.

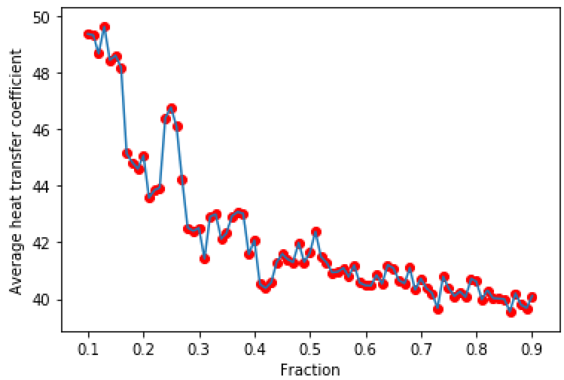

Figure 10. Variation in average heat transfer coefficient with increase in exposed surface area for scaled-down model.

5.2. Another Performance Indicator – Reciprocal of Thermal Resistance

Figure 10 shows how the average heat transfer coefficient is changing by varying the fraction from 0.1 to 0.9 with a step size of 0.01. From the plot, it can be observed that in the initial values of fraction the average heat transfer coefficient is locally fluctuating but globally it is reducing as the fraction reaches 0.9. From this plot alone, it is not very clear that the thermal enhancement is taking place, as the average heat transfer is decreasing contrary to what is being aimed. However, this is just the average convective heat transfer coefficient (h) which does not include the full consideration of actual area. If this average convective heat transfer coefficient is multiplied with the area, that gives the reciprocal of the thermal resistance. The surface area for a given fraction f_r is given by equation (3).

$$A = \left(6\pi R - \pi t + 4\pi R f_r + \frac{nt}{2}\right) w + \pi \left(R + \frac{t}{2}\right)^2 - \pi r^2 \quad (3)$$

The plot of the reciprocal of the thermal resistance vs the fraction, is shown in Figure 11.

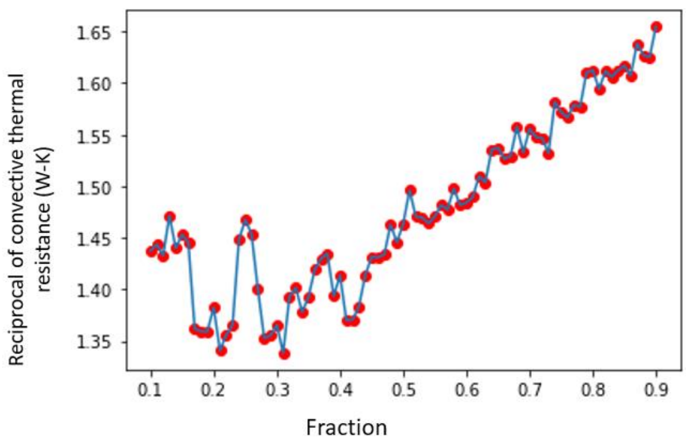

Figure 11. Variation in reciprocal of thermal resistance with increase in exposed surface area for scaled-down model.

From Figure 11, it is very clear that even though locally there are fluctuations the value of the reciprocal of the thermal resistance is globally increasing, which indicates the configuration with a larger exposed area is better in terms of thermal performance.

6. CONCLUSIONS

A variable surface model of the heat sink is presented in which the layers of the fin can slide relative to each other. An extensive numerical thermal analysis is performed in ANSYS for forced convection for fraction values ranging from 0.1 to 0.9 with a step size of 0.01, and the average heat transfer coefficient and the reciprocal of thermal resistance is also plotted. The plot shows that as the movable layer of the fin is opened outwards, the effective thermal dissipation ability is also enhanced, thus confirming the idea of its application to heat dissipation of heat sinks of variable thermal loading arising due to change in environmental and operational conditions. The proposed design can be integrated with functional materials which can respond to at least one stimulus in the nature which would make these heat sinks intelligent. Thermal data resulting from this study can be used by Machine learning and deep learning tools to assist thermal engineers in data driven design and design of intelligent control algorithms.

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