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Thermal Performance Analysis and Optimization of Pin-Fin Heat Sink Using CFD, Taguchi Method, and Machine Learning

A Kalyan Charan[1],*, C Venkateshwar Reddy[1], C.N Rohit Sai[2], K. Someshwar Rao[2]

Abstract

Efficient thermal management is essential for improving the performance and reliability of modern engineering systems and electronic devices. This study presents the design, simulation, and optimization of a pin-fin heat sink using SolidWorks for three-dimensional modeling and ANSYS for thermal and computational fluid dynamics (CFD) analysis. Four different pin-fin geometries, namely square, pentagon, octagon, and circular fins, are considered to evaluate their thermal performance under varying operating conditions. Aluminum is selected as the heat sink material, while air is used as the cooling fluid. The thermal analysis is carried out for inlet temperatures ranging from 400 K to 550 K and airflow velocities varying from 5 m/s to 8 m/s. The performance of each configuration is evaluated in terms of heat transfer coefficient and Nusselt number. The simulation results indicate that increasing airflow velocity significantly enhances heat dissipation due to improved convective heat transfer, while temperature variation has a comparatively smaller influence on thermal performance. To determine the optimal combination of operating parameters, the Taguchi optimization technique with an L16 orthogonal array is implemented using Minitab. Signal-to-noise (S/N) ratio analysis are performed to identify the most influential factors affecting heat transfer behavior. The statistical analysis confirms that airflow velocity is the dominant parameter influencing thermal efficiency, followed by fin geometry. Among the tested configurations, the square pin-fin arrangement exhibits the best thermal performance compared to the other fin shapes. The results show that the optimal operating condition is achieved at an inlet temperature of 400 K and airflow velocity of 8 m/s, where the heat transfer coefficient reaches approximately 40 W/m²K. The square pin-fin geometry demonstrates superior heat dissipation characteristics due to its improved surface interaction with airflow. The findings also reveal that higher airflow velocities improve convective cooling effectiveness, making airflow management a critical factor in heat sink design. In addition to numerical simulation and statistical optimization, a machine learning approach based on Linear Regression (LR) is developed to predict thermal performance and validate the simulation outcomes. The generated CFD dataset is used for training and testing the predictive model, and the predicted values show good agreement with simulation results. The proposed integrated approach combining CFD analysis, Taguchi optimization, and machine learning provides an efficient and reliable framework for enhancing pin-fin heat sink performance while reducing computational time and repeated simulation effort in thermal management applications.

Keywords: Pin-fin heat sink, CFD analysis, thermal management, Taguchi method, ANOVA, linear regression, machine learning, heat transfer coefficient

***Author for Correspondence**
A Kalyan Charan
E-mail: agirkalyan@gmail.com

[1]Assistant Professor, Department of Mechanical Engineering, Matrusri Engineering College, Saidabad, Hyderabad, India
[2]Student, Department of Mechanical Engineering, Matrusri Engineering College, Saidabad Hyderabad, India

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INTRODUCTION

In modern engineering applications, heat generation has become a major challenge owing to the rapid development of high-performance and compact systems [1]. Devices such as computers, laptops, electronic circuits, automobiles, industrial machines, and power systems generate significant amounts of heat during operation [2]. If this heat is not removed properly, it can lead to overheating, reduced efficiency, malfunctioning of components, and shorter system life [3]. Therefore, effective thermal management has become an essential requirement in many engineering fields [4].

One of the most commonly used cooling devices for thermal management is a heat sink [5]. A heat sink absorbs heat from a hot surface and transfers it to the surrounding air [6]. The performance of a heat sink mainly depends on how efficiently it can dissipate heat [7]. Different types of fin structures are used to improve heat transfer [8]. Among them, pin-fin heat sinks are widely preferred because they provide a large surface area for heat transfer and allow airflow in multiple directions [9]. The fins increase the contact area between the solid surface and air, thereby improving cooling performance [10].

The thermal performance of a pin-fin heat sink depends on several factors, such as the fin geometry, airflow velocity, temperature conditions, and material properties [11]. Different fin shapes can produce different airflow patterns and heat transfer characteristics [12]. Some fin configurations improve turbulence and enhance heat transfer, whereas others reduce the pressure drop and improve airflow movement [13]. Hence, selecting an appropriate fin design is crucial for achieving efficient cooling performance [14].

Traditionally, engineers relied on experimental methods to study heat transfer and evaluate heat sink performance [15]. Although experiments provide accurate results, they require physical models, laboratory setups, skilled manpower, and considerable time and cost [16]. With advancements in computer technology, Computational Fluid Dynamics (CFD) has become a powerful tool for thermal analysis and design optimization [17]. CFD allows engineers to numerically simulate fluid flow and heat transfer phenomena without conducting large numbers of physical experiments [18]. This helps visualize the temperature distribution, airflow patterns, velocity contours, and heat transfer behavior within the system [19].

CFD analysis provides several advantages, such as reduced development costs, shorter design cycles, and a better understanding of thermal behavior [20]. However, performing CFD simulations for several combinations of design parameters can be computationally expensive and time-consuming [21]. To overcome this limitation, optimization techniques are used to identify the best parameter combinations efficiently [22]. The Taguchi method is a widely used optimization approach [23]. The Taguchi method is a statistical design of experiments technique that reduces the number of experiments or simulations while providing reliable results [24]. It helps in determining the most influential parameters and identifying optimal operating conditions with minimum effort [25].

In addition to CFD and optimization techniques, Machine Learning (ML) has emerged as a modern and efficient approach for engineering analysis and prediction [26]. Machine learning models can learn patterns from simulation data and predict system performance without repeatedly running simulations [27]. In this project, a Linear Regression model was used to predict the thermal performance of pin-fin heat sinks based on parameters such as geometry, airflow velocity, and temperature conditions [28]. The use of machine learning significantly reduces the computational time and supports faster decision-making during the design process [29].

The present study combined CFD analysis, optimization techniques, and machine learning methods to improve the thermal performance of pin-fin heat sinks [30]. CFD is used to analyze airflow and temperature distribution, the Taguchi method is applied to optimize design parameters, and machine learning is used for the prediction of performance [31]. This integrated approach helps develop an efficient and reliable thermal management system while reducing the overall analysis time and cost [32].

The outcomes of this study can be applied in various engineering fields, such as electronic cooling systems, automotive thermal management, industrial machinery, heat exchangers, and aerospace applications [33]. Thus, the study contributes to the development of efficient cooling technologies for modern engineering systems [34].

LITERATURE REVIEW

Many researchers have studied the thermal performance of pin-fin heat sinks because of their importance in cooling electronic and industrial systems. Kumar et al [9]. and Sharma et al [10]. showed that fin geometry, fin arrangement, and airflow velocity significantly affect the heat transfer performance. Circular, square, and polygonal fins have been commonly analyzed, and staggered fin arrangements have been found to improve turbulence and cooling efficiency. Researchers have also observed that increasing the surface area enhances heat dissipation, but it may also increase the pressure drop and energy consumption.

Several studies have focused on the application of Computational Fluid Dynamics (CFD) in thermal analysis. Patel et al [17]., Reddy et al [18]., and Rao et al [18]. demonstrated that CFD is an effective tool for studying airflow distribution, temperature contours, and heat transfer behavior. CFD helps engineers visualize the thermal performance and reduces the need for costly experiments. However, the simulation accuracy depends on proper meshing, boundary conditions, and solver settings. Many researchers have also noted that CFD simulations require considerable computational time.

Optimization techniques have also been widely applied to thermal systems. Researchers such as Jain et al [22]. and Mehta et al [24]. used the Design of Experiments (DOE) and statistical methods to identify important design parameters while reducing the number of experiments. Among these methods, the Taguchi method has become popular because it uses orthogonal arrays and signal-to-noise ratio analysis to identify optimal conditions efficiently.

Recently, machine learning techniques have been introduced in the field of thermal engineering. Saxena et al [26]. and Agrawal et al [26]. showed that machine learning models can accurately predict the thermal performance using simulation data. These methods reduce the computational effort and provide faster predictions than repeated CFD simulations [27].

From the literature review, it was observed that most researchers focused on individual techniques such as CFD, optimization, or machine learning separately. Very few studies have combined all these methods. Therefore, this study integrates CFD analysis, optimization techniques, and machine learning to improve the thermal performance prediction of pin-fin heat sinks.

Methodology

Different pin-fin heat sink geometries, such as circular, square, pentagonal, and octagonal fins, were modeled using SolidWorks software [28]. All configurations were designed with equal cross-sectional areas and fin heights to ensure an accurate comparison of the thermal performance [29]. The developed CAD models were imported into the ANSYS Workbench for CFD analysis [30].

Thermal simulations were performed using ANSYS Fluent under steady-state conditions [31]. Boundary conditions including velocity inlet, pressure outlet, and constant heat flux at the base plate were applied. Fine meshing near the fin surfaces was used to improve the accuracy of the airflow and heat transfer analysis [32].

Taguchi optimization was performed using Minitab software to reduce the number of simulation runs and identify the best parameter combination [33]. An L16 orthogonal array was selected by considering parameters such as fin geometry, airflow velocity, and temperature. A signal-to-noise ratio analysis was used to evaluate the thermal performance.

The heat transfer characteristics were analyzed using the Reynolds number, Nusselt number, and heat transfer coefficient calculations. A Linear Regression machine learning model was also developed to predict the thermal performance efficiently and reduce repeated CFD simulations [34].

RESULTS AND DISCUSSION

Four pin-fin geometries (circular, square, pentagonal, and octagonal) were designed using SolidWorks and analyzed using ANSYS Fluent under steady-state conditions. CFD simulations were performed with appropriate boundary conditions and fine meshing. Taguchi optimization using Minitab and an L16 orthogonal array was applied to identify the optimal parameters. A Linear Regression machine learning model was also developed to predict the thermal performance and reduce repeated CFD simulations.

Four different pin-fin geometries, namely circular, square, pentagonal, and octagonal fins, were designed using SolidWorks software. To ensure a fair comparison of the thermal performance, all the fin configurations were maintained with equal cross-sectional areas and identical fin heights (Figure 1).

The Taguchi Design of Experiments (DOE) method was applied to optimize the thermal performance of the pin-fin heat sink while minimizing the number of simulation runs. The selected input parameters included the fin geometry, temperature, and airflow velocity (Table 1). An L16 orthogonal array was generated using Minitab software for systematic experiments. Signal-to-noise (S/N) ratio analysis was performed using the “larger-the-better” criterion because higher heat transfer coefficient values are preferred for improved cooling performance.

The CAD models were imported into the ANSYS Workbench for Computational Fluid Dynamics (CFD) analysis. ANSYS Fluent was used to perform steady-state thermal simulations. Appropriate boundary conditions, such as velocity inlet, pressure outlet, and constant heat flux at the base plate, were applied (Figure 2). Fine meshing and inflation layers near the fin surfaces were used to accurately capture the airflow and thermal boundary layer effects (Figure 3).

The heat transfer performance was evaluated using standard convective heat transfer equations. Important parameters such as Reynolds number, Nusselt number, and heat transfer coefficient were calculated for all cases. Based on the Reynolds number calculations, the airflow conditions were identified as laminar flow (Table 2).

Table 1. Taguchi parameters.

S.N.	Shape	Temperature	Velocity
L1	Circle	400 K	5 m/s
L2	Circle	450 K	6 m/s
L3	Circle	500 K	7 m/s
L4	Circle	550 K	8 m/s
L5	Pentagon	400 K	6 m/s
L6	Pentagon	450 K	5 m/s
L7	Pentagon	500 K	8 m/s
L8	Pentagon	550 K	7 m/s
L9	Square	400 K	7 m/s
L10	Square	450 K	8 m/s
L11	Square	500 K	5 m/s
L12	Square	550 K	6 m/s
L13	Octagon	400 K	8 m/s
L14	Octagon	450 K	7 m/s
L15	Octagon	500 K	6 m/s
L16	Octagon	550 K	5 m/s

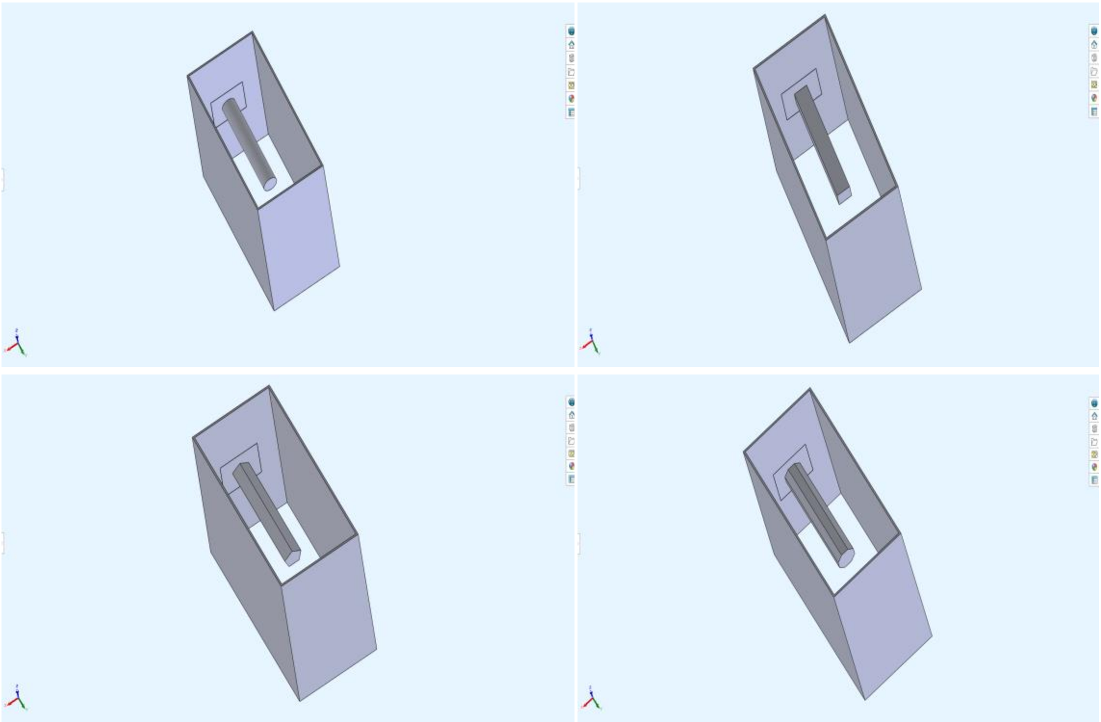
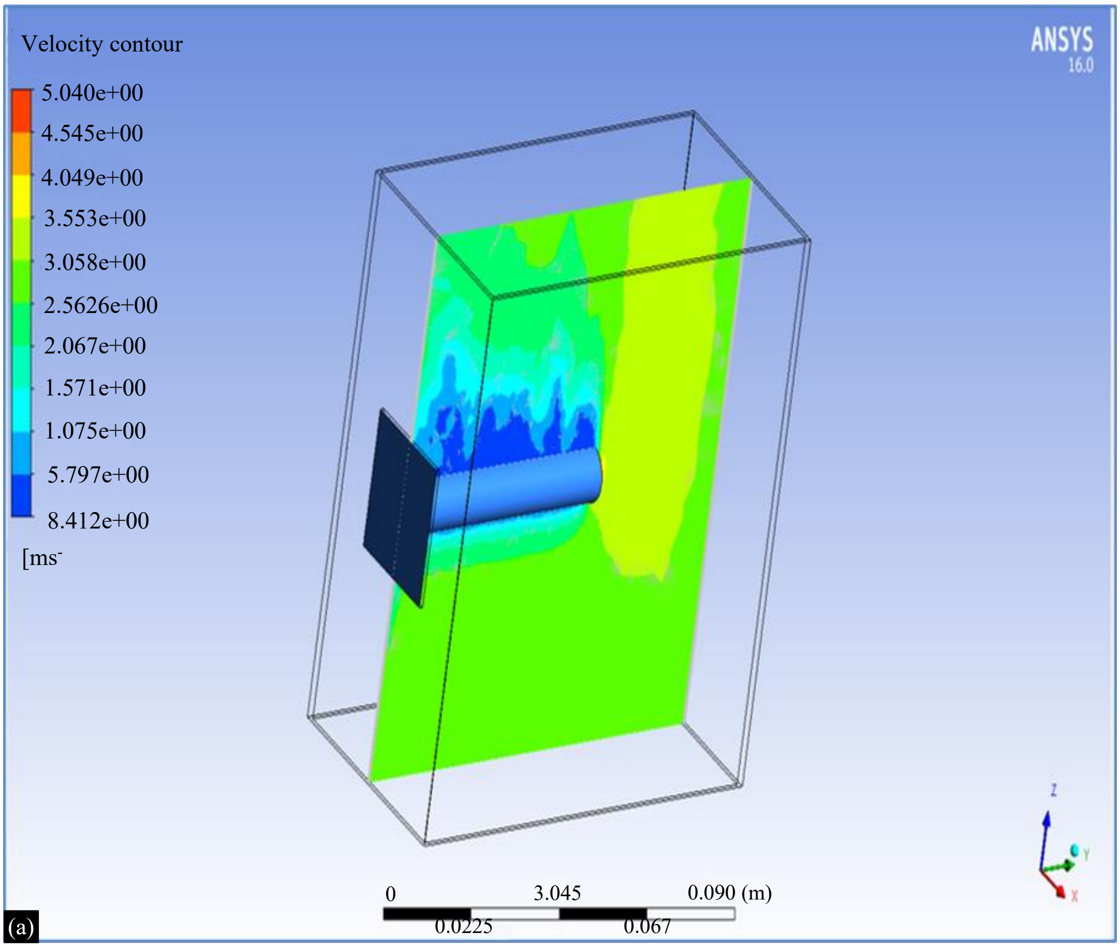
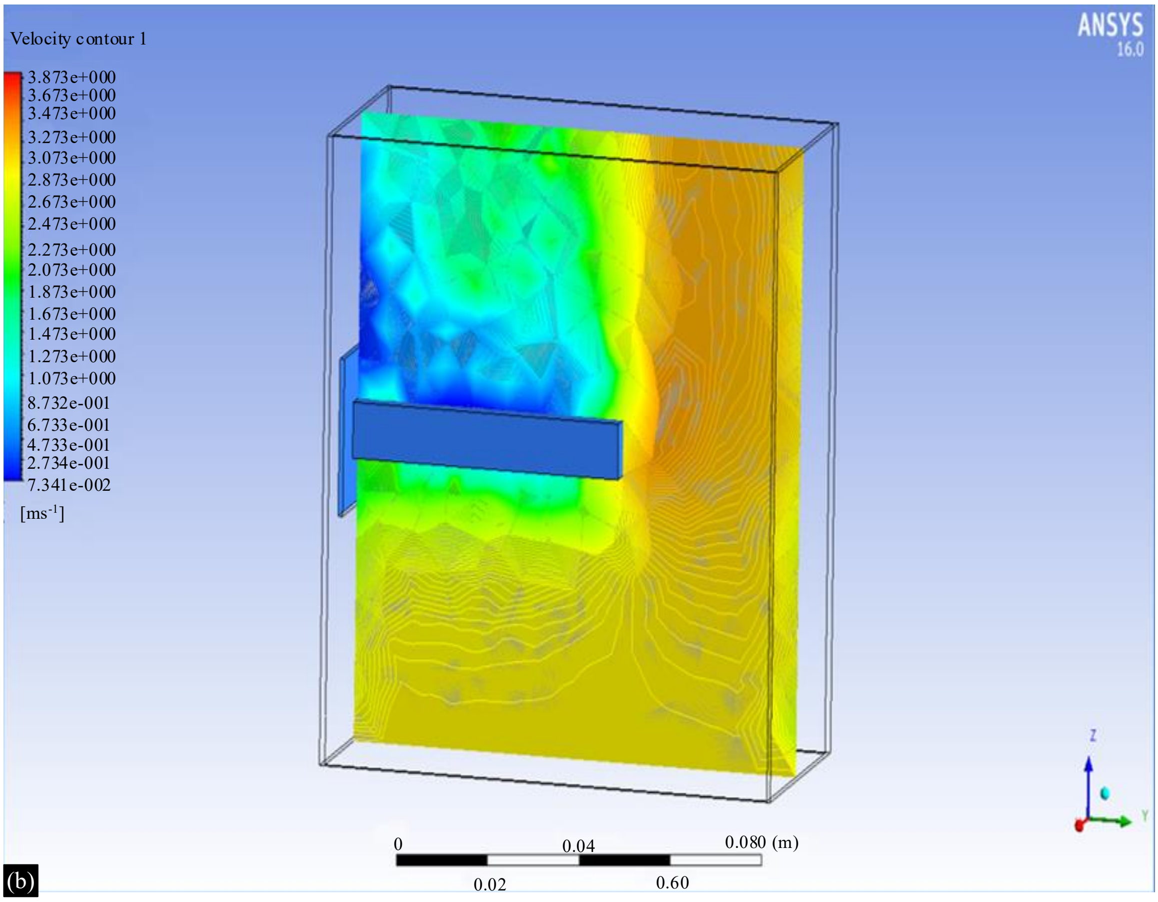


Figure 1. Fin shapes namely circular, square, pentagonal, and octagonal fins are designed with equal cross-sectional area.

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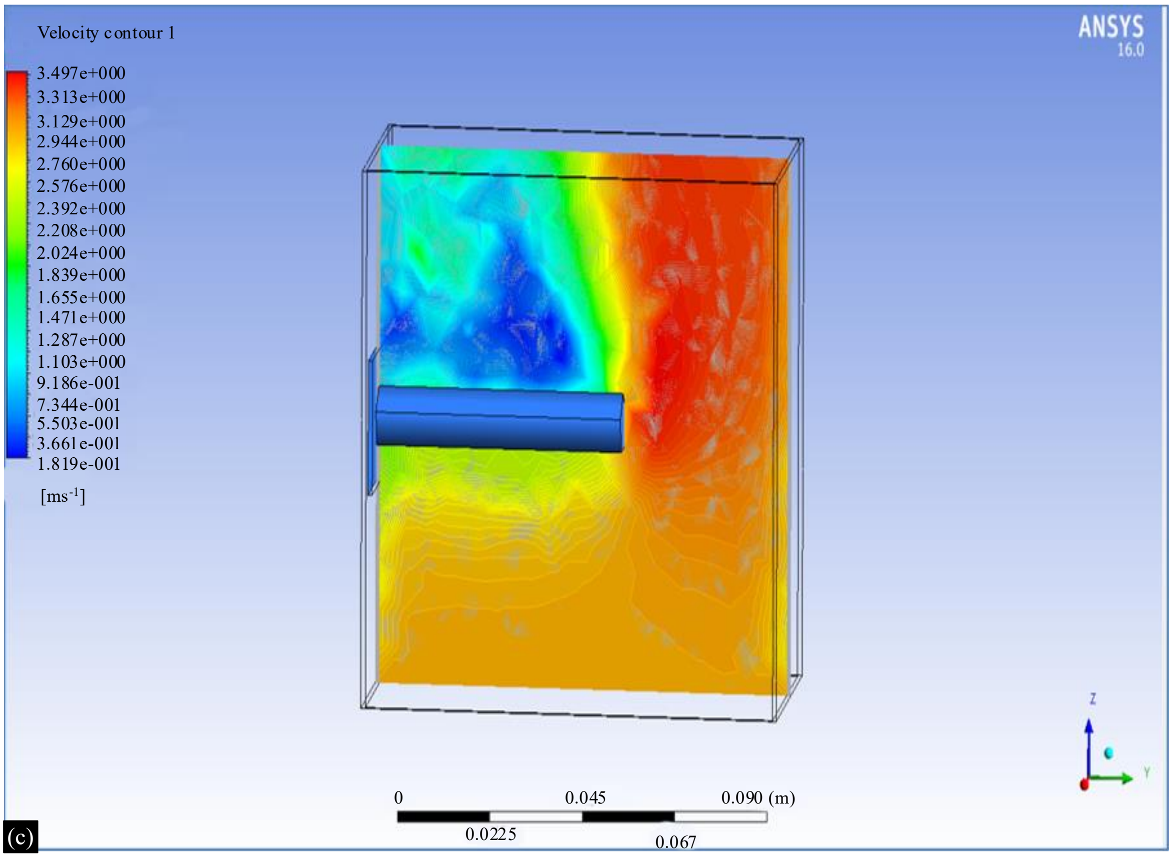
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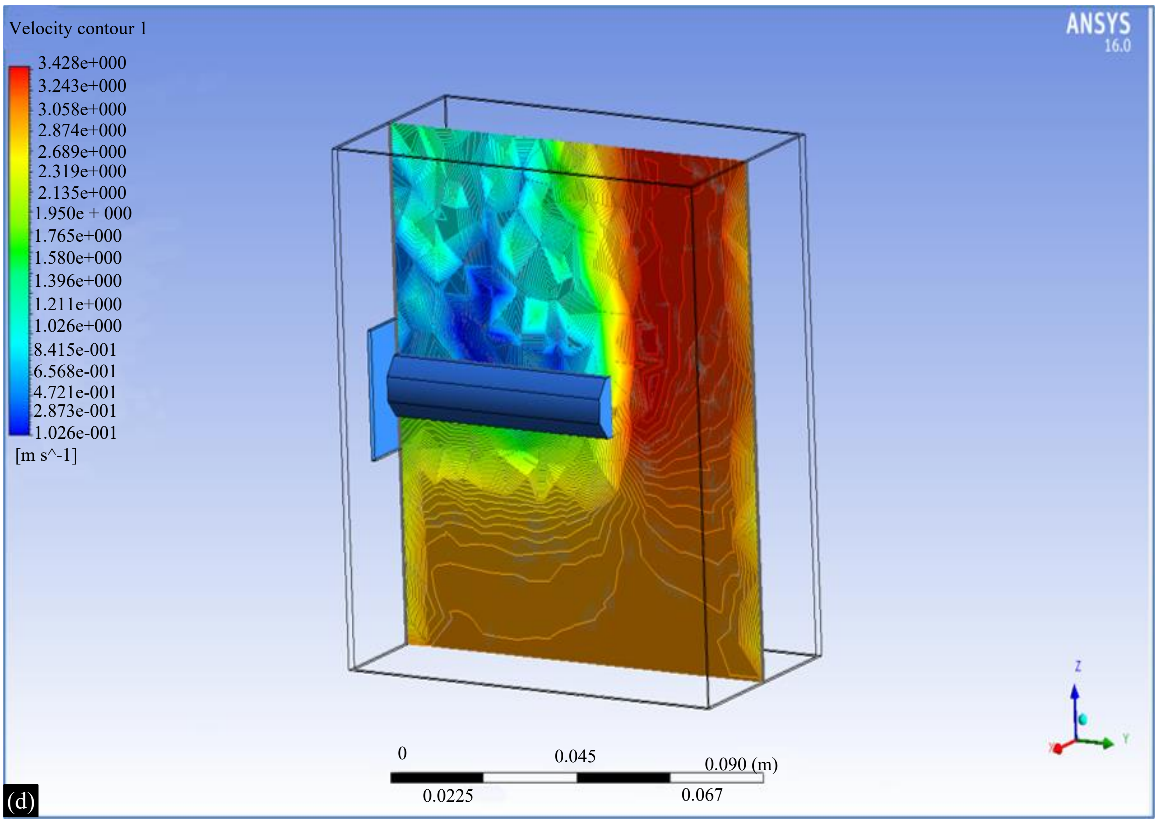
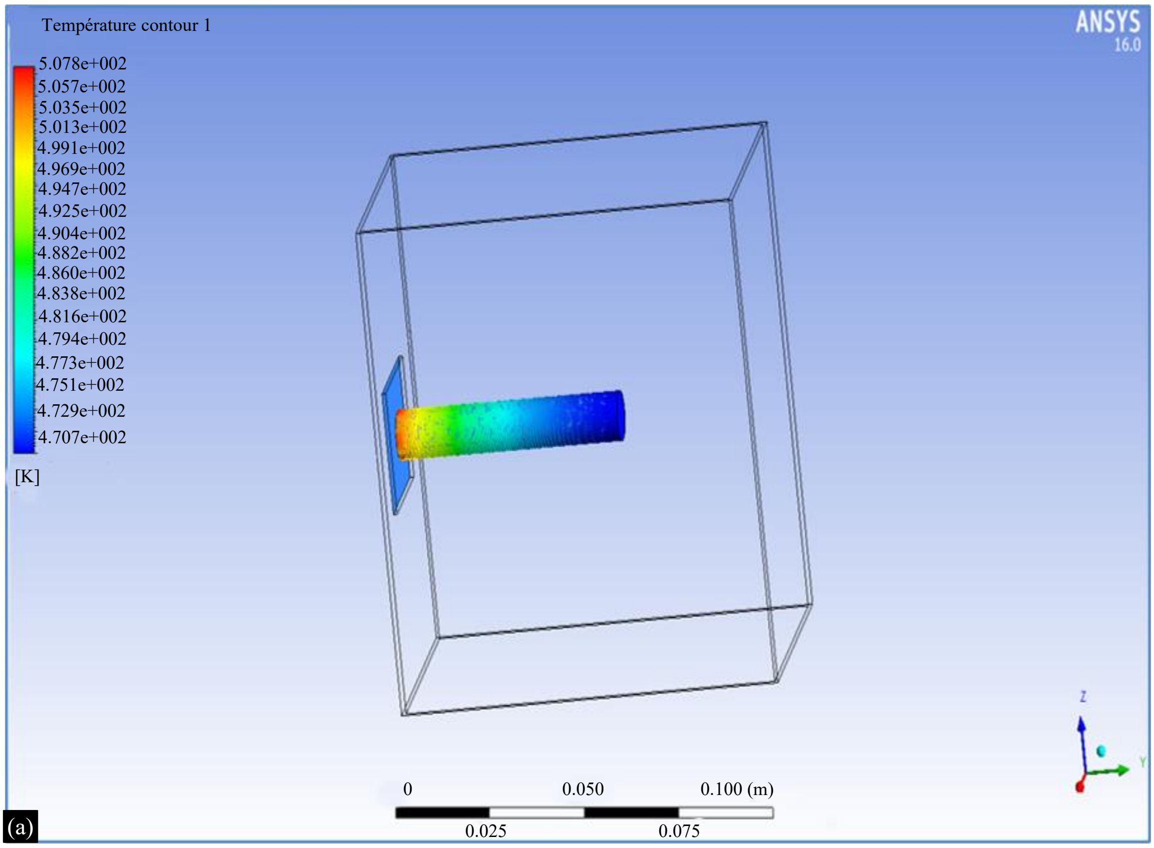
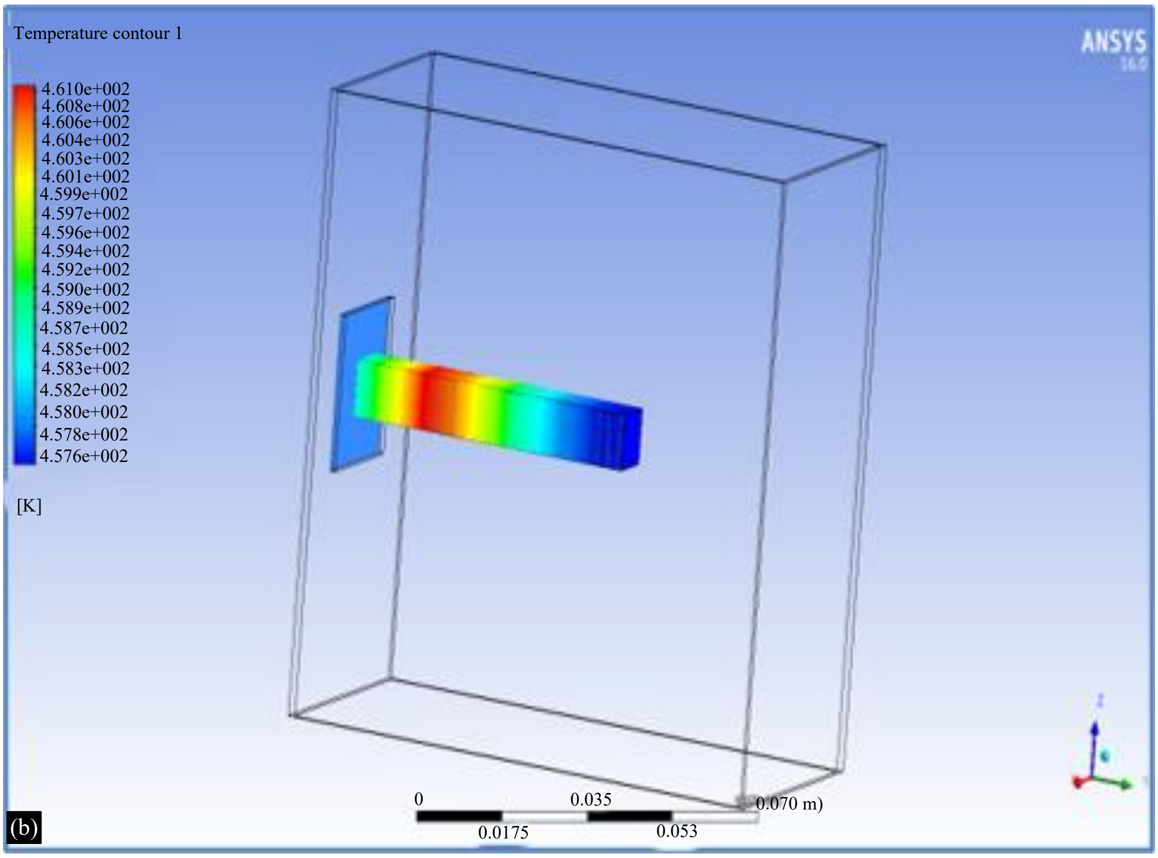


Figure 2. (a)–(d) Velocity contours for selected circular, square, pentagonal, and octagonal fin configurations.

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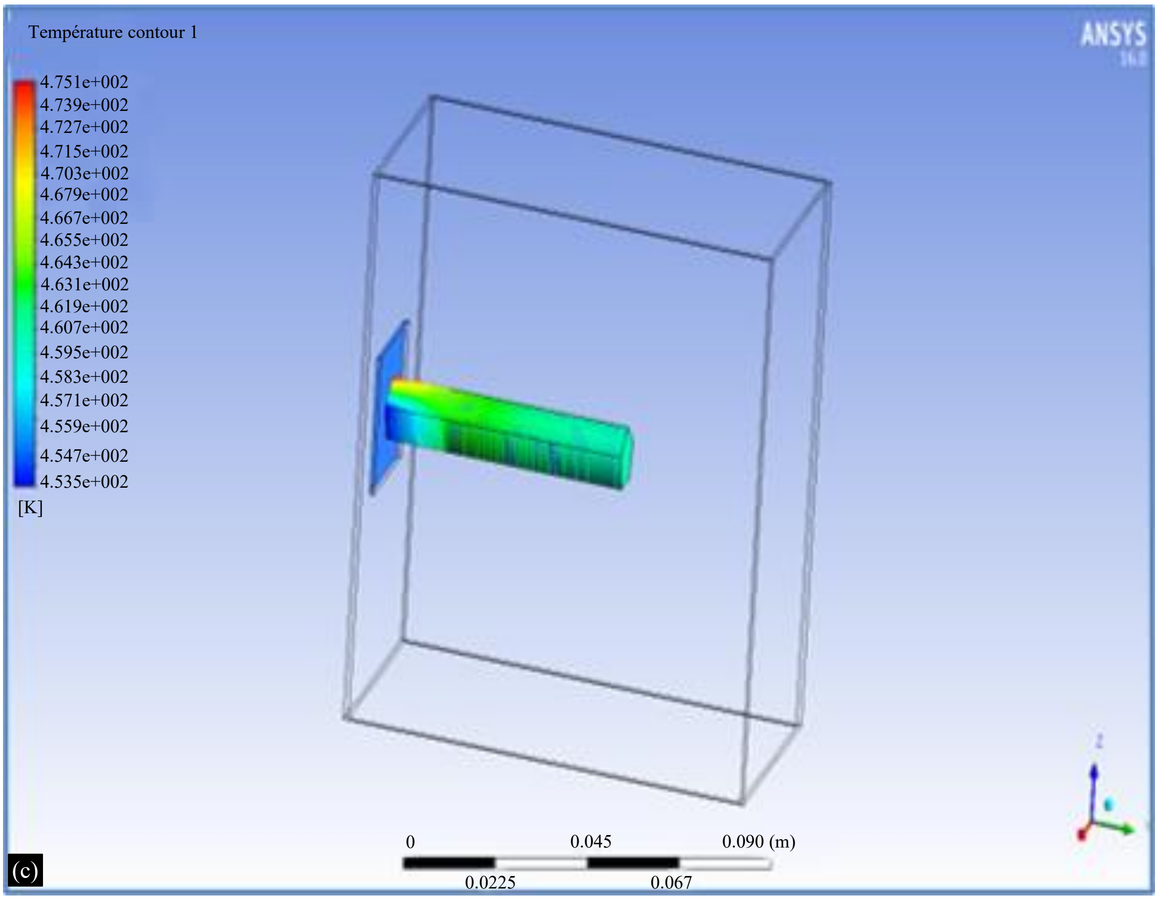
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4.595e+002
4.583e+002
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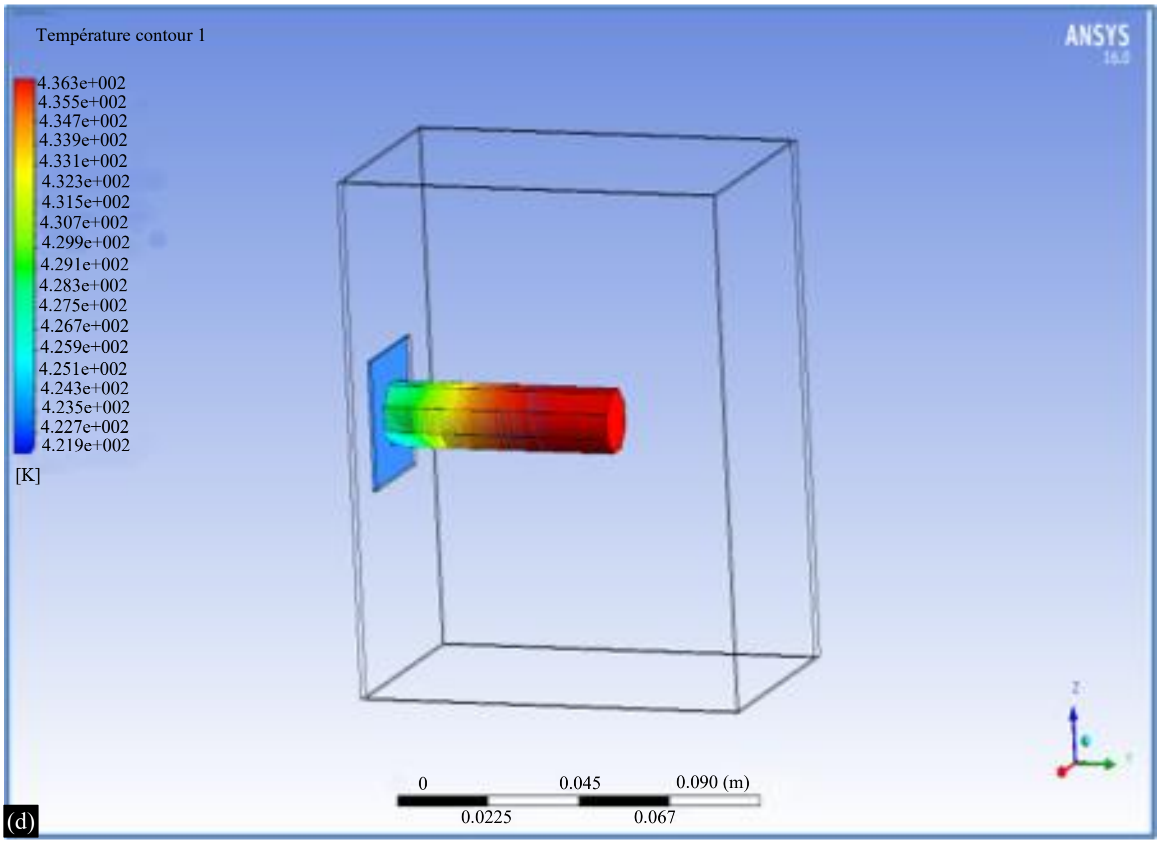

Figure 3. (a)–(d)Temperature contours for selected circular, square, pentagonal, and octagonal fin configurations.

Table 2. Taguchi L16 array results.

S.N.	**Shape**	**Temperature**	**Velocity**	**T in (air inner temperature)**	**T out (air outer temperature)**	**T fin(overall fin temperature)**	**T f (film temperature)=** $\frac{Tin+Tout+Tfin}{3}$
L1	Circle	400 K	5m/s	300 K	335 K	375 K	336 K
L2	Circle	450 K	6m/s	300 K	409 K	425 K	378 K
L3	Circle	500 K	7m/s	300 K	354 K	468 K	374 K
L4	Circle	550 K	8m/s	300 K	368 K	516 K	394 K
L5	Pentagon	400 K	6m/s	300 K	411 K	363 K	350 K
L6	Pentagon	450 K	5m/s	300 K	441 K	463 K	401 K
L7	Pentagon	500 K	8m/s	300 K	388 K	414 K	367 K
L8	Pentagon	550 K	7m/s	300 K	370 K	512 K	394 K
L9	Square	400 K	7m/s	300 K	341 K	363 K	334 K
L10	Square	450 K	8 m/s	300 K	300 K	409 K	336 K
L11	Square	500 K	5 m/s	300 K	329 K	457 K	362 K
L12	Square	550 K	6 m/s	300 K	324 K	507 K	377 K
L13	Octagon	400 K	8 m/s	300 K	498 K	328 K	375 K
L14	Octagon	450 K	7 m/s	300 K	518 K	370 K	396 K
L15	Octagon	500 K	6 m/s	300 K	526 K	423 K	416 K
L16	Octagon	550 K	5 m/s	300 K	527 K	470 K	432 K

Table 3. Coefficient of heat transfer results.

S.N.	T f (film temperature) = (Tin+Tout+Tfin)/3	Reynolds number (Re_x)	Nusselt number (Nu_x)	Heat transfer coefficient (h)
L1	336 K	1.951×10^3	12.871	30.9
L2	378 K	2.223×10^3	13.753	33.0072
L3	374 K	2.590×10^3	14.845	35.63
L4	394 K	2.707×10^3	15.176	36.42
L5	350 K	2.178×10^3	13.6	35.1
L6	401 K	1.815×10^3	12.415	32.04
L7	367 K	2.750×10^3	15.296	37.47
L8	394 K	2.412×10^3	14.326	36.97
L9	334 K	2.609×10^3	14.37	38.91
L10	336 K	2.760×10^3	15.309	38.45
L11	362 K	1.729×10^3	12.117	32.82
L12	377 K	2.675×10^3	13.274	35.95
L13	375 K	3.260×10^3	17.547	36.32
L14	396 K	3.0125×10^3	16.009	33.06
L15	416 K	2.580×10^3	14.816	30.63
L16	432 K	2.151×10^3	13.528	27.96

***Sample Calculation**: (Table 3).*

L_1= (400 = Temperature, 5= velocity)

$T_{in} = 300\ K,\ T_{out} = \frac{127+543}{2} = 335\ K$

$T_s = \frac{352+400}{2} = 375.5$

Film Temperature:

$T_{film} = \frac{300+335+375.5}{3} = 336.8\ K$

Using heat transfer data at film temperature (300–400 K):

$Pr = 0.676,\ d = 10\ mm,\ p = 1.225\ kg/m^3,\ k = 0.024$ W/mKm, $\mu = 31.88\times10^{-6}$

Reynolds Number:

$Re = \frac{ud\rho}{\mu}$

$Re = \frac{5\times10\times10^{-3}\times1.225}{31.88\times10^{-6}}$

$Re = 1921.26\times10^3$

Since, $Re<5\times10^5$, flow is laminar (Figure 4).

Nusselt Number:

$Nu = 0.332\ (Re)^{0.5}\ (Pr)^{0.333}$

$Nu = 0.332\ (1.951)^{0.5}\ (0.676)^{0.333}$

$Nu = 12.871$

Heat Transfer Coefficient:

$Nu = \frac{hd}{k}$

$12.871 = \frac{h\times10\times10^{-3}}{0.024}$

$h = 30.9 W/m^2K$

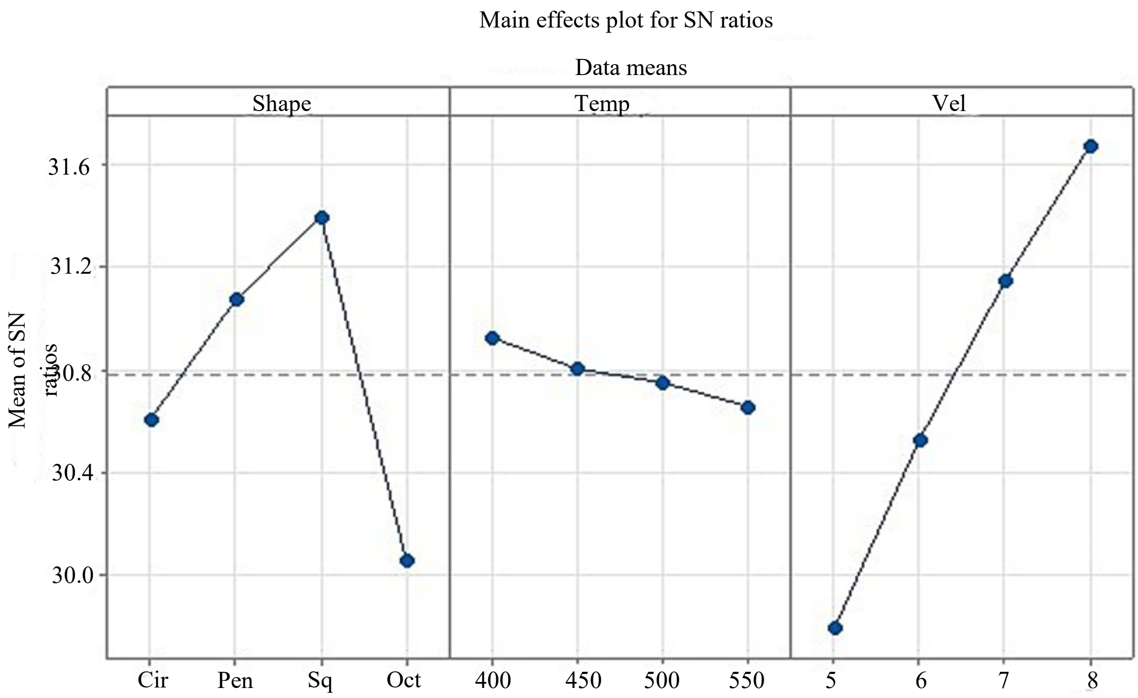

Figure 4. Main effects plot for SN ratios.

Table 4. Predicted heat transfer coefficient values.

S.N.	Actual h	Predicted h
L1	30.90	30.90
L2	33.0072	33.00
L3	35.63	35.10
L4	36.42	37.20
L5	35.10	35.10
L6	32.04	33.00
L7	39.47	38.10
L8	36.97	36.00
L9	38.91	38.91
L10	38.45	40.20
L11	32.82	36.51
L12	35.95	38.40
L13	36.32	36.32
L14	33.06	34.22
L15	30.63	32.12
L16	27.96	30.02

The optimal results were obtained at an inlet temperature of 400 K and an airflow velocity of 8 m/s. The outlet temperature from the CFD analysis was 878.205 K, and the film temperature was calculated to be 518.03 K. Using the air properties at this temperature, the Reynolds number was calculated as (Re 2.4×10^3), indicating laminar flow conditions. The Nusselt number was obtained as (Nu = 14.353). Using the Nusselt number relation, the convective heat transfer coefficient was calculated to be approximately (h 40 2 K). The results indicate improved thermal performance under the optimized operating conditions.

A Linear Regression machine learning model was developed to predict the heat transfer coefficient using the fin geometry, temperature, and airflow velocity as input parameters. The general equation for linear regression is as follows:

$$y = \beta_0 + \beta_1 x_1 + \beta_2 x_2 + \cdots + \beta_n x_n$$

where y = predicted output (heat transfer coefficient, h), β_0 = intercept, $\beta_1, \beta_2 + \cdots + \beta_n$ = coefficients of input variables, $x_1 + x_2 + \cdots + x_n$ = input features (temperature, velocity, shape, etc.) (Table 4).

The dataset generated from the CFD simulations was used to train and test the model. The predicted values showed good agreement with the actual CFD results. The machine learning approach significantly reduced computational time and minimized the need for repeated CFD simulations.

CONCLUSION

The results confirmed that the thermal performance of pin-fin heat sinks is mainly influenced by the airflow velocity and fin geometry. Among all the parameters, the airflow velocity had the greatest effect on heat transfer, as a higher velocity improved convective cooling. The fin geometry also plays an important role, with the square pin-fin configuration providing better thermal performance than the circular, pentagonal, and octagonal fins.

The analysis also showed that the inlet temperature had a smaller effect on the performance than the velocity and fin shape. The optimal conditions identified were an inlet temperature of 400 K and airflow velocity of 8 m/s, where the heat sink achieved a heat transfer coefficient of approximately 40 W/m²K, indicating effective cooling performance.

The Taguchi optimization method and signal-to-noise ratio analysis successfully identified the best parameter combination while reducing the number of simulation runs. The CFD-generated dataset was reliable and useful for detailed thermal analysis and prediction modeling.

The machine learning approach using Linear Regression proved to be effective for predicting thermal performance. The model accurately predicted the heat transfer characteristics without requiring repeated CFD simulations. Overall, the results show that increasing the airflow velocity and selecting an appropriate fin geometry significantly improve heat dissipation and thermal management efficiency.

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