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in

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by

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(Rajesh Kumar)

ABSTRACT

The continuous increase in power density and miniaturization of modern electronic systems has intensified the demand for advanced thermal-management technologies capable of dissipating high heat fluxes while maintaining thermal reliability and energy efficiency. Although microchannel heat sinks have emerged as one of the most effective cooling technologies for electronic applications, their performance is often constrained by the competing requirements of heat-transfer enhancement, pressure-drop minimization, and thermodynamic efficiency. Consequently, the development of optimized cooling architectures capable of achieving superior thermo-hydraulic and exergetic performance remains a critical challenge in electronic cooling.

To address this challenge, convergent-divergent microchannel heat sinks (CD-MCHS) were selected as the baseline cooling architecture because the periodic flow acceleration and deceleration induced by convergent-divergent passages can enhance fluid mixing, suppress thermal boundary-layer growth, and improve heat-transfer performance. The present research develops an integrated computational framework combining Computational Fluid Dynamics (CFD), Artificial Neural Networks (ANN), the Non-Dominated Sorting Genetic Algorithm-II (NSGA-II), and the Technique for Order Preference by Similarity to Ideal Solution (TOPSIS) for the multi-objective optimization of CD-MCHS. The optimization objective was to maximize thermal performance while minimizing entropy generation and thermodynamic irreversibility.

The first phase of the investigation focused on the optimization of the baseline CD-MCHS geometry. The TOPSIS-selected configuration achieved a 20.1% enhancement in heat-transfer performance and a 38.1% reduction in entropy generation compared with the conventional straight microchannel. Furthermore, the optimized geometry reduced the outlet temperature by approximately 8 K while exhibiting the lowest exergy destruction ratio (8.53%) and the highest exergy efficiency (91.47%). These findings demonstrate that geometric optimization alone can significantly enhance cooling performance while simultaneously improving thermodynamic behavior.

Building upon the optimized CD-MCHS platform, three complementary passive enhancement strategies representing geometric modification (micro-pillars), coolant modification (tri-hybrid nanofluids), and porous-medium augmentation were systematically investigated to explore different mechanisms of thermal-performance

enhancement. For each enhancement strategy, ANN surrogate models were developed and coupled with NSGA-II and TOPSIS to identify the optimal configurations based on thermo-hydraulic and exergetic performance criteria.

The optimized micro-pillar-enhanced CD-MCHS achieved a 71.45% increase in heat-transfer performance with only a 15.64% increase in entropy generation, while reducing the maximum wall temperature by approximately 3.5 K. The optimized tri-hybrid nanofluid composition enhanced heat transfer by 16.36% while maintaining the lowest thermodynamic penalty among the enhancement techniques and reducing the maximum wall temperature by 1.89 K. In contrast, the optimized porous-medium configuration delivered the highest cooling capability, achieving a 265.65% increase in heat-transfer performance and approximately 7 K reduction in maximum wall temperature relative to the non-porous channel. However, this substantial thermal enhancement was accompanied by significantly higher entropy generation and exergy destruction due to increased flow resistance within the porous matrix.

A comprehensive comparative assessment revealed that the three passive enhancement strategies represent distinct thermal-management philosophies. Porous media maximized cooling capability, whereas tri-hybrid nanofluids minimized thermodynamic penalties. The micro-pillar-enhanced CD-MCHS effectively bridged these two extremes by delivering substantial heat-transfer enhancement with moderate entropy-generation and exergetic penalties. Consequently, the micro-pillar configuration emerged as the most balanced passive enhancement strategy, offering the most favorable compromise among cooling effectiveness, thermodynamic efficiency, and pumping-power requirements.

Overall, the present research demonstrates that the optimization of advanced microchannel heat sinks should not be guided solely by heat-transfer enhancement but must simultaneously consider hydrothermal and thermodynamic performance. The proposed CFD-ANN-NSGA-II-TOPSIS framework provides a robust methodology for the design and optimization of next-generation thermal-management systems. Furthermore, the findings establish convergent-divergent microchannel heat sinks as a promising platform for high-performance electronic cooling and provide practical design guidelines for advanced computing, power-electronic, and other energy-intensive applications.

Keywords: ANN, CFD, Convergent-divergent microchannel heat sink, Electronic cooling, Entropy generation, Exergy analysis, Hydrothermal performance, Micro-pillars, Multi-objective optimization, NSGA-II, Porous media, TOPSIS, Tri-hybrid nanofluid.

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NOMENCLATURE

Latin Symbols

Symbol	Description	Unit
3-D	Three dimensional	-
A_h	Convective heat transfer area	m^2
C_i	Relative closeness coefficient	-
C_p	Specific heat capacity	$J\ kg^{-1}\ K^{-1}$
d_p	Pore diameter	μm
D_h	Hydraulic diameter	mm
E_d	Exergy destruction rate	W
E_{in}	Energy input rate	W
E_{out}	Energy output rate	W
f	Friction factor	-
f_{Ag}	Volume fraction of Ag nanoparticles	%
$f_{Al_2O_3}$	Volume fraction of Al_2O_3 nanoparticles	%
f_{CuO}	Volume fraction of CuO nanoparticles	%
Gen	Generation number	-
H_T	Total height of microchannel heat sink	mm
h_{av}	Average heat transfer coefficient	$W\ m^{-2}\ K^{-1}$
k	Thermal conductivity	$W\ m^{-1}\ K^{-1}$
L_T	Total length of microchannel heat sink	mm
M_c	Material code	—
N_1	Number of parallel channels	—
N_2	Number of channels arranged in series	—
N_p	Population size	—
Nu	Nusselt number	—
P	Wetted perimeter	mm
P_c	Pillar count	—
P_d	Pillar geometry code	—
P_o	Pillar offset	μm
ΔP	Pressure drop	Pa
PP	Pumping power ($\Delta P \times Q$)	W

q''	Applied heat flux	W m^{-2}
Q	Volume flow rate through a unit channel	$\text{cm}^3 \text{s}^{-1}$
Q_t	Total volume flow rate	$\text{cm}^3 \text{s}^{-1}$
R	Correlation coefficient	—
R^2	Coefficient of determination	—
Re	Reynolds number	—
R_{th}	Thermal resistance	K W^{-1}
S_g	Entropy generation rate	W K^{-1}
T	Temperature	K
V	Velocity	m s^{-1}
W_T	Total width of microchannel heat sink	mm

Greek Symbols

Symbol	Description
α	Top-to-bottom width ratio
β	Bottom-to-pitch width ratio
γ	Channel-to-total height ratio
δ	Throat-to-channel height ratio
ε	Porosity
η_{ex}	Exergy efficiency
μ	Dynamic viscosity
ρ	Density
Γ	Solid-liquid interface
ϕ	Nanofluid concentration
ϕ_T	Total nanoparticle volume fraction

Subscripts

Subscript	Description
av	Average
b	Bulk mean
f	Fluid
hnf	Hybrid nanofluid
in	Inlet

out	Outlet
s	Solid
w	Wall

Abbreviations

Abbreviation	Description
ANN	Artificial Neural Network
CD	Convergent-Divergent
CFD	Computational Fluid Dynamics
CV	Coefficient of Variation
DOE	Design of Experiments
EDR	Exergy Destruction Ratio
GA	Genetic Algorithm
LHS	Latin Hypercube Sampling
MAE	Mean Absolute Error
MAPE	Mean Absolute Percentage Error
MCHS	Microchannel Heat Sink
NSGA-II	Non-dominated Sorting Genetic Algorithm II
RSM	Response Surface Methodology
RMSE	Root Mean Square Error
TOPSIS	Technique for Order Preference by Similarity to Ideal Solution

CHAPTER 1

INTRODUCTION

1.1 Background and Motivation

The rapid evolution of modern electronic technologies has intensified the demand for advanced thermal management solutions. Emerging applications such as high-performance computing, artificial intelligence, data centers, advanced communication systems, electric vehicles, aerospace and avionics systems, as well as power electronics, increasingly require compact devices capable of delivering exceptional computational and operational performance. However, the continuous trend toward miniaturization, higher integration density, and increased functionality has resulted in unprecedented power densities and heat generation rates, making efficient heat dissipation a critical challenge for the reliability, performance, and longevity of modern electronic systems [1].

The trend toward miniaturization has enabled billions of transistors to be integrated within a single semiconductor chip. While this advancement has considerably enhanced computational capability, it has also intensified the problem of heat accumulation within limited physical dimensions. Historically, the growth in transistor density has closely followed Moore's law, which states that the number of transistors integrated onto a chip approximately doubles every two years [2]. As illustrated in Figure 1.1, transistor density has increased exponentially over the past several decades, reflecting remarkable progress in semiconductor manufacturing and device integration. Although this trend has enabled exceptional improvements in processing power and functionality, it has simultaneously resulted in higher power densities and greater heat generation within increasingly compact architectures. Consequently, heat fluxes exceeding 100 W/cm^2 are commonly encountered in advanced electronic devices, while substantially higher thermal loads are anticipated in next-generation computing and power electronic applications [3].

Excessive temperature rise adversely affects the performance, reliability, and lifespan of electronic components. Elevated operating temperatures increase electrical resistance, accelerate material degradation, induce thermal stresses, and contribute to the formation

of localized hot spots. These effects not only reduce system efficiency but may also lead to performance deterioration and premature device failure. Therefore, maintaining acceptable operating temperatures has become a critical requirement for ensuring the safe and reliable operation of modern electronic equipment [4].

Conventional air-cooling techniques, including heat sinks and forced convection systems, have been widely employed for thermal management because of their simplicity and low implementation cost. However, the relatively low thermal conductivity and heat capacity of air limit their ability to dissipate the high heat fluxes generated by contemporary electronic devices. As thermal loads continue to increase, conventional cooling approaches often become inadequate, necessitating the development of more effective thermal management technologies [5].

To address these challenges, several advanced cooling techniques have been proposed, including heat pipes, jet impingement cooling, spray cooling, phase-change cooling, and liquid-cooling systems. Among these technologies, microchannel heat sinks (MCHSs) have emerged as one of the most promising solutions for high-heat-flux applications. Owing to their large surface-area-to-volume ratio, compact size, and superior heat transfer characteristics, microchannel heat sinks can dissipate substantial amounts of heat while satisfying the stringent space constraints of modern electronic systems [6].

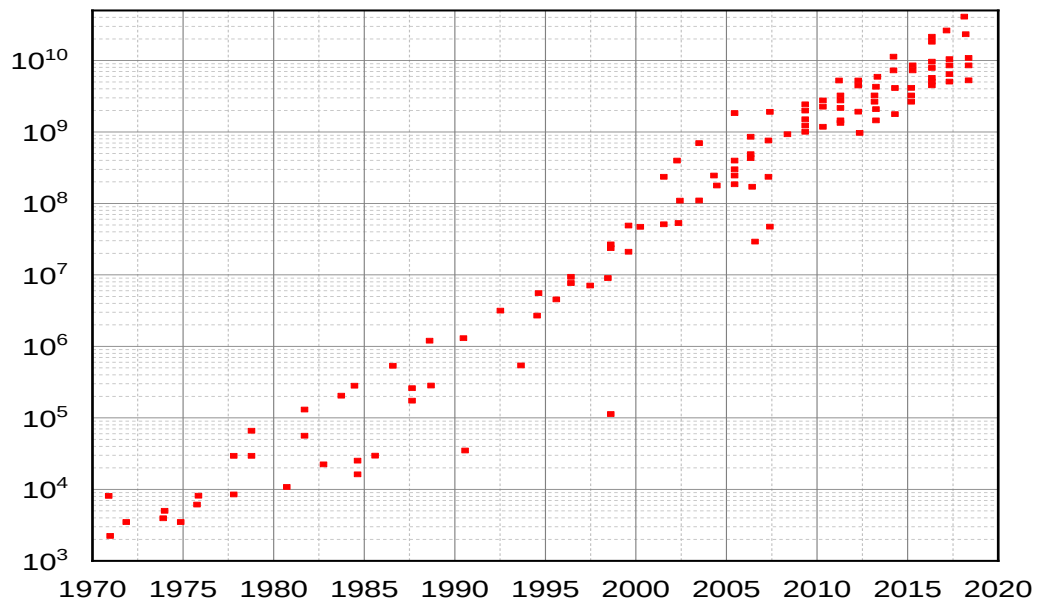


Figure 1.1: Historical evolution of transistor density in semiconductor devices [3]

1.2 Thermal Management Market Growth and Reliability Challenges

The increasing thermal demands of modern engineering systems have significantly elevated the importance of thermal management technologies. This growing importance is reflected in the continuous expansion of the global thermal management market, which was valued at approximately USD 10.12 billion in 2015 and has experienced substantial growth in subsequent years. The projected market expansion indicates the increasing dependence of modern industries on effective heat dissipation technologies to ensure the reliable operation of electronic devices, power systems, energy conversion equipment, and advanced manufacturing processes. Therefore, thermal management has evolved from a supplementary design consideration to a key technological enabler for next-generation engineering applications [7].

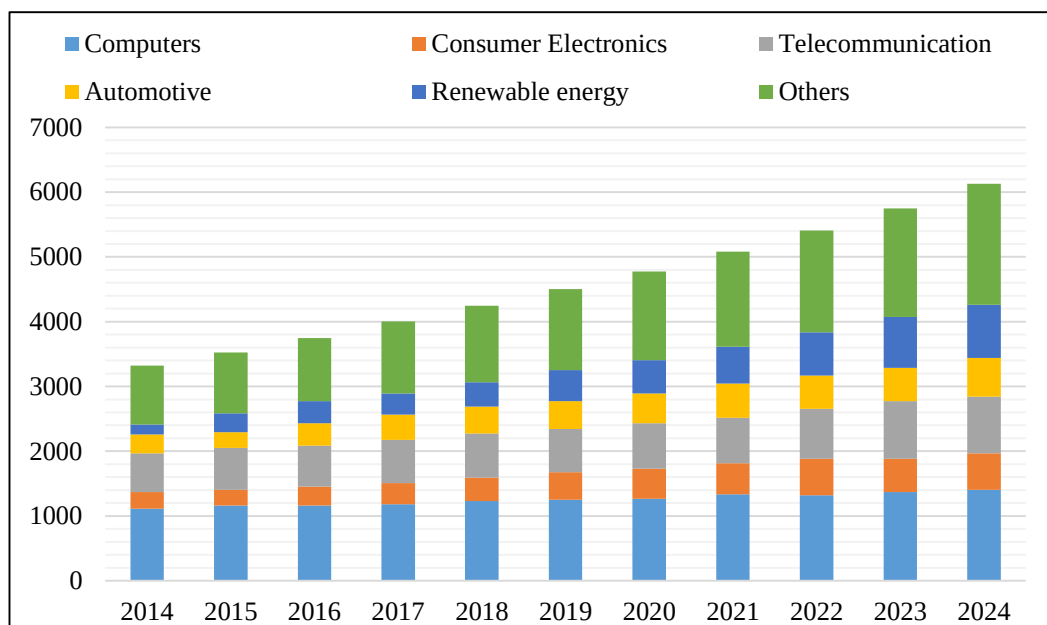


Figure 1.2: Growth trend of the global thermal management market [8]

Figure 1.2 depicts the projected growth of the global thermal management market, highlighting the increasing importance of advanced cooling technologies in modern engineering applications. This growth is primarily driven by the escalating thermal loads associated with high-performance electronic and energy systems. As device miniaturization continues alongside increasing power densities, greater amounts of heat are generated within confined spaces, necessitating efficient thermal management solutions to ensure system reliability, performance, and longevity [9].

Among the various factors affecting electronic device reliability, operating temperature is recognized as one of the most influential. Elevated temperatures accelerate material

degradation processes and significantly reduce component lifetime. The relationship between device reliability and operating temperature can be described by Black's equation, which correlates the median time to failure (MTF) with temperature [10]:

$$MTF = AJ^{-n} \exp\left(\frac{E_a}{K_B T}\right) \quad (1.1)$$

Where A is a material-dependent constant, J denotes the current density, E_a represents the activation energy, K_B is the Boltzmann constant, and T is the absolute operating temperature. The exponential dependence of the MTF on temperature indicates that even a relatively small increase in operating temperature can cause a significant reduction in device lifespan. This relationship highlights the critical importance of effective thermal management in ensuring long-term reliability and preventing premature failure of electronic components.

The reliability of electronic devices is highly sensitive to operating temperature, as many degradation processes are thermally activated. Elevated temperatures accelerate electromigration in metallic interconnects, dielectric breakdown of insulating layers, material diffusion, solder joint fatigue, and oxidation-related degradation. Furthermore, temperature gradients and repeated thermal cycling generate significant thermal stresses due to the mismatch in thermal expansion coefficients among constituent materials. These mechanisms progressively deteriorates the structural, mechanical, and electrical integrity of electronic components, leading to performance degradation, increased failure probability, and reduced operational lifespan. Therefore, maintaining the chip temperature below the recommended operating limit of approximately 85°C is essential for ensuring reliable and long-term operation of electronic systems [11].

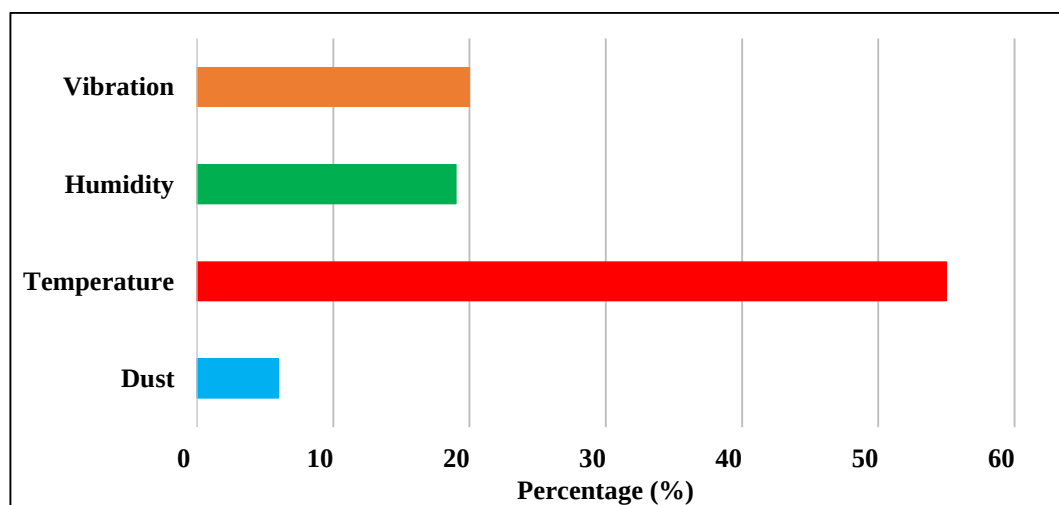


Figure 1.3: Contribution of various factors to electronic device failure [12]

As shown in Figure 1.3, excessive temperature is responsible for approximately 55% of electronic device failures, representing the single largest contributor among all failure-inducing factors. This observation clearly demonstrates that temperature control is a critical requirement for enhancing device reliability, extending service life, and preventing premature system failure [12].

1.3 Emerging Cooling Technologies for Modern Electronics

The continuous increase in heat flux and power density has driven the development of various advanced cooling technologies for electronic thermal management. Conventional air-cooling techniques, although simple and cost-effective, are often inadequate for high-heat-flux applications. Consequently, several alternative cooling approaches have been developed, including heat pipes, jet impingement cooling, spray cooling, phase-change cooling, liquid cooling, and microchannel heat sinks [13]. Figure 1.4 presents the major cooling technologies used in modern electronic thermal management.

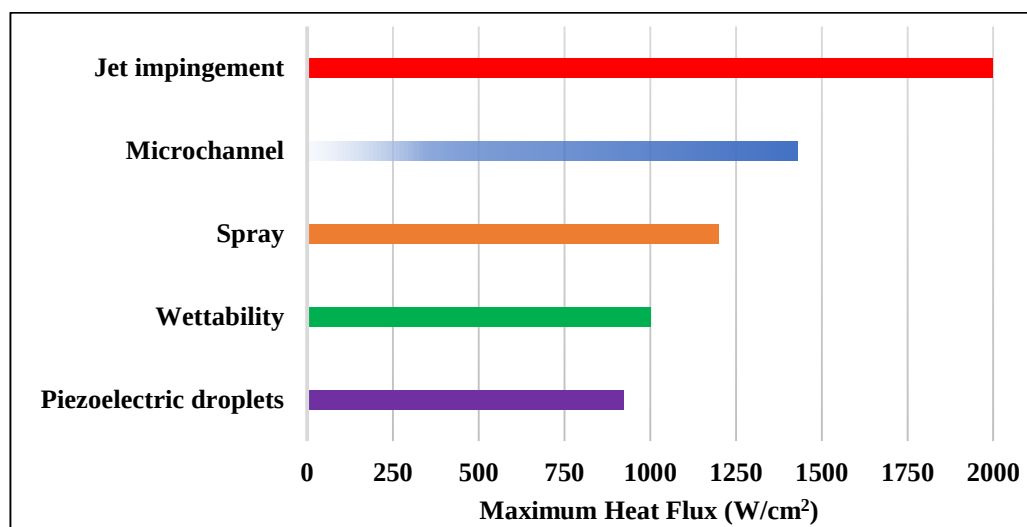


Figure 1.4: Emerging cooling technologies for modern electronic systems [14]

Each cooling technology offers a unique balance between heat dissipation capability, thermal uniformity, compactness, and operational complexity. Heat pipes offer efficient passive heat transport, whereas jet impingement and spray cooling provide high local heat transfer rates suitable for hotspot mitigation. Phase-change cooling technologies further enhance thermal performance through latent heat absorption. Among these approaches, liquid-cooled microchannel heat sinks have attracted considerable attention due to their ability to dissipate high heat fluxes within a compact footprint, making them particularly suitable for next-generation electronic cooling applications [15].

1.4 Microchannel Heat Sinks: An Advanced Cooling Solution

Microchannel heat sinks (MCHSs) have emerged as one of the most promising thermal management technologies for dissipating high heat fluxes in compact electronic systems. Their superior cooling capability is primarily attributed to the large surface-area-to-volume ratio and enhanced convective heat transfer characteristics of microscale flow passages, which enable efficient heat removal within limited space. These advantages make MCHSs particularly attractive for applications where conventional cooling techniques are unable to meet stringent thermal requirements [16].

The concept of microchannel-based cooling was first introduced by Tuckerman and Pease in 1981, who demonstrated that reducing channel dimensions to the microscale could dramatically enhance heat dissipation while maintaining low surface temperatures [17]. This pioneering work established microfabricated heat sinks as a viable solution for advanced thermal management and laid the foundation for extensive research in microchannel cooling technologies.

Since then, continuous developments in microfabrication and thermal engineering have accelerated the adoption of MCHSs across a wide range of high-heat-flux applications. Today, they are extensively employed in high-performance computing systems, data-center servers, power electronic modules, electric vehicle converters, high-power laser devices, and aerospace electronics. Owing to their exceptional thermal performance, compact architecture, and scalability, MCHSs have become a focal point of modern electronic cooling research [18]. A typical microchannel heat sink cooling system is schematically illustrated in Figure 1.5.

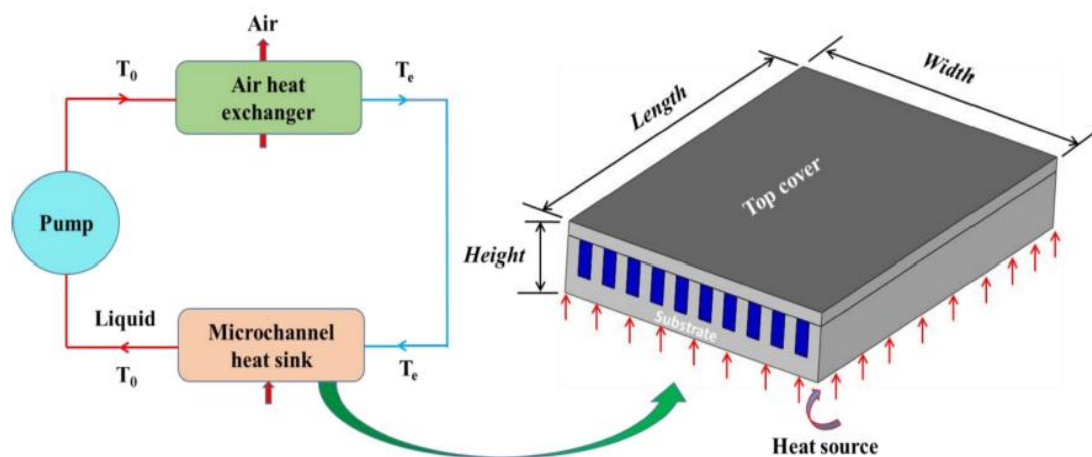


Figure 1.5: Schematic of the microchannel heat sink cooling system [19]

A typical microchannel heat sink consists of an array of microscale flow passages fabricated within a thermally conductive substrate and integrated into a closed-loop liquid cooling system. Heat generated by the electronic component is first conducted through the solid substrate and subsequently transferred to the coolant flowing within the microchannels through a conjugate heat transfer (CHT) process involving simultaneous heat conduction in the solid and forced convection in the fluid. This conjugate heat transfer process enables efficient heat extraction from the heated surface, resulting in enhanced thermal performance and reduced thermal resistance [20].

The heated coolant exiting the microchannel heat sink is continuously circulated through the cooling loop by a pump and directed toward a heat exchanger, where the absorbed thermal energy is dissipated to the surrounding environment. The cooled working fluid is subsequently returned to the microchannel heat sink, thereby establishing a continuous closed-loop circulation system. This integrated heat removal mechanism enables sustained temperature regulation under high heat flux conditions, making microchannel heat sinks highly effective for advanced electronic thermal management applications [21].

1.4.1 Classification of Channels

Channels are commonly classified based on their hydraulic diameter, which serves as a fundamental parameter for distinguishing flow passage scales and characterizing fluid flow behavior. Several classification schemes have been proposed in the literature, among which those developed by Mehendale et al. and Kandlikar and Grande are the most widely recognized. As presented in Table 1.1, flow passages are categorized into conventional channels, minichannels, microchannels, transitional channels, and nanochannel according to their hydraulic diameter range. Such classifications provide a standardized framework for identifying channel scales and facilitate the analysis and comparison of thermal-fluid transport phenomena across different channel regimes.

Table 1.1: Classification of channels based on hydraulic diameter

Mehendale et al. [22]		Kandlikar and Grande [23]	
Microchannels	$1\mu\text{m} < D_h \leq 100\mu\text{m}$	Molecular nanochannel	$\leq 0.1\mu\text{m}$
Mini-channels	$100\mu\text{m} < D_h \leq 1\text{mm}$	Transitional microchannels	$0.1\mu\text{m} < D_h \leq 10\mu\text{m}$
Compact Passages	$1\text{mm} < D_h \leq 6\text{mm}$	Microchannels	$10\mu\text{m} < D_h \leq 200\mu\text{m}$
Conventional Passages	$D_h > 6\text{mm}$	Mini-channels	$200\mu\text{m} < D_h \leq 3\text{mm}$
		Conventional passages	$D_h > 3\text{mm}$

1.4.2 Overview of Microchannel Heat Sink Studies

Since the pioneering work of Tuckerman and Pease, microchannel heat sinks have attracted extensive research attention owing to their exceptional capability for dissipating high heat fluxes. Early investigations primarily focused on understanding the fundamental fluid flow and heat transfer behavior within conventional straight microchannels, thereby establishing the scientific foundation for microchannel-based cooling technologies.

As illustrated in Figure 1.6, MCHS research can broadly be categorized into convective heat transfer studies and fluid flow studies. These investigations aim to characterize the transport phenomena governing microchannel performance and provide essential insights for the design of efficient cooling systems.

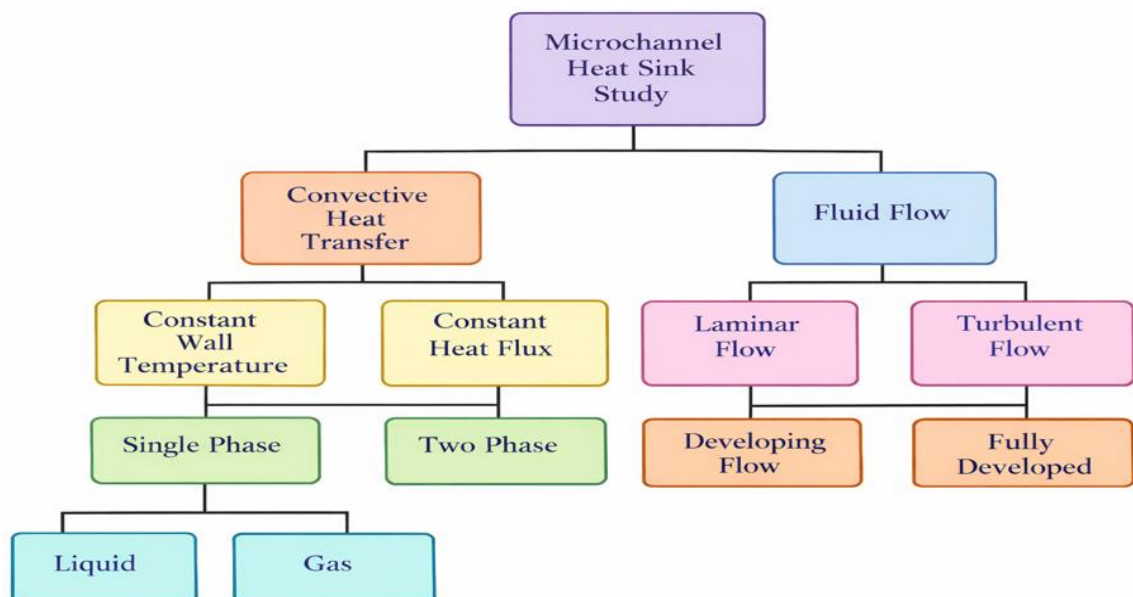


Figure 1.6: Classification of microchannel heat sink studies [24]

Depending on the scope of investigation, MCHS studies are commonly performed under constant heat flux or constant wall temperature boundary conditions and may involve either single-phase or two-phase cooling configurations. Furthermore, fluid flow and heat transfer analyses are generally conducted in laminar or turbulent flow regimes and may consider developing or fully developed flow conditions, depending on the application and operating parameters.

1.4.3 Applications of Microchannel Heat Sinks

The remarkable heat dissipation capability and compact architecture of microchannel heat sinks have enabled their widespread adoption across numerous high-heat-flux

applications. Their ability to effectively remove large amounts of heat within confined spaces makes them particularly suitable for modern electronic and energy systems, where thermal management plays a crucial role in ensuring performance, reliability, and operational stability. Table 1.2 summarizes some of the major application areas of microchannel heat sinks and their associated thermal management requirements.

Table 1.2: Major applications of microchannel heat sinks in high-heat-flux thermal management [25]

Application Area	Thermal Challenge	Role of MCHS
High-Performance Computing Systems	High processor power density and hotspot formation	Efficient chip cooling and temperature regulation
Data Centers and Servers	Large heat generation from densely packed processors	Enhanced thermal management and energy-efficient operation
Power Electronics	High thermal loads in IGBTs, MOSFETs, and power converters	Improved heat dissipation and device reliability
Electric Vehicles (EVs)	Thermal management of power converters and battery systems	Temperature control and performance enhancement
High-Power Laser Systems	Intense localized heat generation	Prevention of thermal degradation and instability
Aerospace and Avionics Electronics	High thermal loads under stringent size and weight limitations	Lightweight cooling with efficient heat dissipation

As evident from Table 1.2, microchannel heat sinks have emerged as a versatile cooling technology across a broad spectrum of electronic, energy, and transportation applications. Their capability to manage high heat fluxes while maintaining compact system dimensions has established them as a key enabling technology for next-generation thermal management systems.

1.4.4 Advantages of Microchannel Heat Sinks

Microchannel heat sinks offer several advantages that have established them as one of the most promising cooling technologies for high-heat-flux thermal management applications. The major advantages are summarized as follows [26]:

- **High Heat Removal Capability**

Microchannel heat sinks can dissipate extremely high heat fluxes due to their enhanced convective heat transfer characteristics, making them suitable for advanced electronic cooling applications.

- **Large Surface-Area-to-Volume Ratio**

The microscale dimensions provide a substantially increased heat transfer area, facilitating efficient thermal energy exchange between the heated surface and the coolant.

- **Low Thermal Resistance**

The short heat conduction path and effective fluid-solid interaction enable rapid heat extraction, resulting in reduced thermal resistance and improved cooling performance.

- **Compact and Lightweight Configuration**

Their small size allows seamless integration into miniaturized electronic devices without significantly increasing system dimensions or weight.

- **Enhanced Temperature Control**

Efficient heat removal helps maintain lower operating temperatures and suppress hotspot formation, thereby improving device reliability and performance.

- **Design Flexibility**

Thermal performance can be tailored through modifications in channel geometry, substrate materials, and coolant selection to satisfy specific application requirements.

1.4.5 Challenges and Limitations of Microchannel Heat Sinks

Despite their superior thermal performance, microchannel heat sinks are associated with several challenges that must be addressed to ensure efficient implementation [27].

- **High Pressure Drop**

The small hydraulic diameter of microchannels results in increased flow resistance, leading to significant pressure losses and higher pumping power requirements.

- **Flow Maldistribution**

Non-uniform coolant distribution among parallel channels can create localized hotspots and reduce overall thermal performance.

- **Manufacturing Complexity**

Fabrication of microscale channel structures frequently requires advanced manufacturing techniques, increasing production cost and process complexity.

- **Clogging and Fouling Susceptibility**

The narrow flow passages are vulnerable to particle deposition, fouling, and blockage, which may adversely affect long-term performance and reliability.

- **Thermal Stress and Reliability Issues**

Large temperature gradients and repeated thermal cycling can induce thermal stresses within the substrate, potentially affecting structural integrity and service life.

- **Coolant Management Requirements**

The use of liquid-cooling systems necessitates additional components such as pumps, and heat exchangers, increasing system complexity and maintenance requirements.

These limitations have motivated extensive research efforts toward the development of advanced microchannel configurations capable of simultaneously enhancing heat transfer while minimizing hydraulic penalties.

1.5 Common Substrate Materials for Microchannel Heat Sinks

The thermal performance of a microchannel heat sink is influenced not only by its flow characteristics but also by the properties of the solid substrate through which heat is conducted before being transferred to the coolant. Consequently, the selection of an appropriate substrate material plays a crucial role in determining heat spreading capability, thermal resistance, structural integrity, and overall cooling effectiveness.

Table 1.3: Commonly used substrate materials in microchannel heat sink fabrication

Substrate Material	Thermal Conductivity	Major Advantages	Key Limitations
Silicon [28]	~130-150 W/mK	Excellent compatibility with microfabrication processes and high dimensional accuracy	Brittle nature and relatively high fabrication cost
Copper [29]	~380-400 W/mK	Outstanding thermal conductivity and heat spreading capability	Higher weight and susceptibility to corrosion
Aluminum [30]	~200-240 W/mK	Lightweight, cost-effective, corrosion resistant, and easy to manufacture	Lower thermal conductivity than copper

A variety of materials have been employed in the fabrication of microchannel heat sinks, including silicon, copper, aluminum, ceramics, and polymer-based materials. Each material possesses distinct characteristics in terms of thermal conductivity, mechanical strength, corrosion resistance, manufacturability, weight, and cost. Therefore, the choice of substrate material is often governed by the specific thermal and operational

requirements of the intended application. Table 1.3 summarizes the commonly used substrate materials and their key properties.

1.6 Overview of Heat Transfer Enhancement Techniques

Although microchannel heat sinks offer excellent heat dissipation capability, the increasing thermal demands of modern high-heat-flux systems have necessitated further improvements in their thermal-hydraulic performance. Consequently, numerous heat transfer enhancement techniques have been proposed to augment heat transfer while maintaining acceptable hydraulic characteristics.

These techniques are broadly categorized into active, passive, and hybrid methods based on the mechanism employed to augment heat transfer [31].

- **Active methods:** Active methods require external energy input to enhance heat transfer performance. The enhancement is typically achieved through mechanisms such as surface vibration, flow pulsation, electrostatic fields, magnetic fields, or mechanical mixing. Although these techniques can significantly improve heat transfer, their practical implementation is often limited by increased system complexity, higher energy consumption, and additional maintenance requirements [32].
- **Passive methods:** Passive methods enhance heat transfer without requiring any external power input. These techniques primarily rely on modifications in channel geometry, surface features, or coolant characteristics to promote fluid mixing, disrupt thermal boundary layers, and increase heat transfer rates. Owing to their simplicity, reliability, low operating cost, and ease of implementation, passive enhancement techniques have emerged as the most widely adopted approach for improving the thermal-hydraulic performance of microchannel heat sinks [33].
- **Hybrid methods:** Hybrid enhancement techniques combine two or more active and/or passive approaches within a single cooling system to achieve synergistic improvements in thermal performance. Common examples include the integration of geometrical modifications, micro-pillars, or porous media with nanofluids. Although these techniques can provide superior heat transfer enhancement, they are often associated with increased design complexity and hydraulic penalties [34].

As shown in Table 1.4, a wide range of enhancement techniques have been proposed to improve the thermal performance of microchannel heat sinks. Among these approaches, passive enhancement techniques have attracted the greatest research interest owing to their

simplicity, reliability, and ability to improve heat transfer without external energy input. Therefore, the following sections focus on the major passive enhancement strategies employed in microchannel heat sinks.

Table 1.4: Classification of heat transfer enhancement techniques for microchannel heat sinks [35]

Active Techniques	Passive Techniques	Hybrid Techniques
Surface & Fluid Vibration	Geometry Modification	Active-Passive Integration
Flow Pulsation	Rough/Treated Surfaces	Geometry Modify + Nanofluids
Electrostatic/ Magnetic Field	Micro-Pillars / Pin Fins	Micro-Pillars + Nanofluids
Mechanical Agitation	Fluid Additives (Nanofluids)	Porous Media + Nanofluids
Synthetic Jets	Porous Media	
	Secondary Flow Generators	

1.6.1 Geometrical Modification Techniques

Among the various passive enhancement approaches, geometrical modification is one of the most widely investigated and effective methods for improving the thermal-hydraulic performance of microchannel heat sinks. By altering the channel configuration, flow passage characteristics, or cross-sectional area, the fluid flow behavior can be manipulated to enhance mixing, disrupt thermal boundary layer development, and improve heat transfer. These modifications influence the transport mechanisms within the microchannel and can significantly affect thermal performance and pressure drop characteristics [36]. Over the years, numerous geometrical configurations have been proposed to enhance cooling effectiveness in microchannel heat sinks. The most commonly investigated geometries include straight, wavy, serpentine, bifurcated, fractal, and convergent-divergent channels, as illustrated in Figure 1.7.

As shown in Figure 1.7, geometrical modifications can be broadly categorized into curved geometries, branching geometries, and variable-area geometries. These configurations enhance thermal performance through different mechanisms, including flow redistribution, boundary layer interruption, secondary flow generation, and increased fluid mixing [37]. Among the various geometrical configurations proposed in the literature, convergent-divergent microchannels have attracted considerable attention owing to their ability to simultaneously improve heat transfer and flow distribution. Consequently, understanding the underlying enhancement mechanisms associated with geometrical

modifications is essential for the development of high-performance microchannel cooling systems [38].

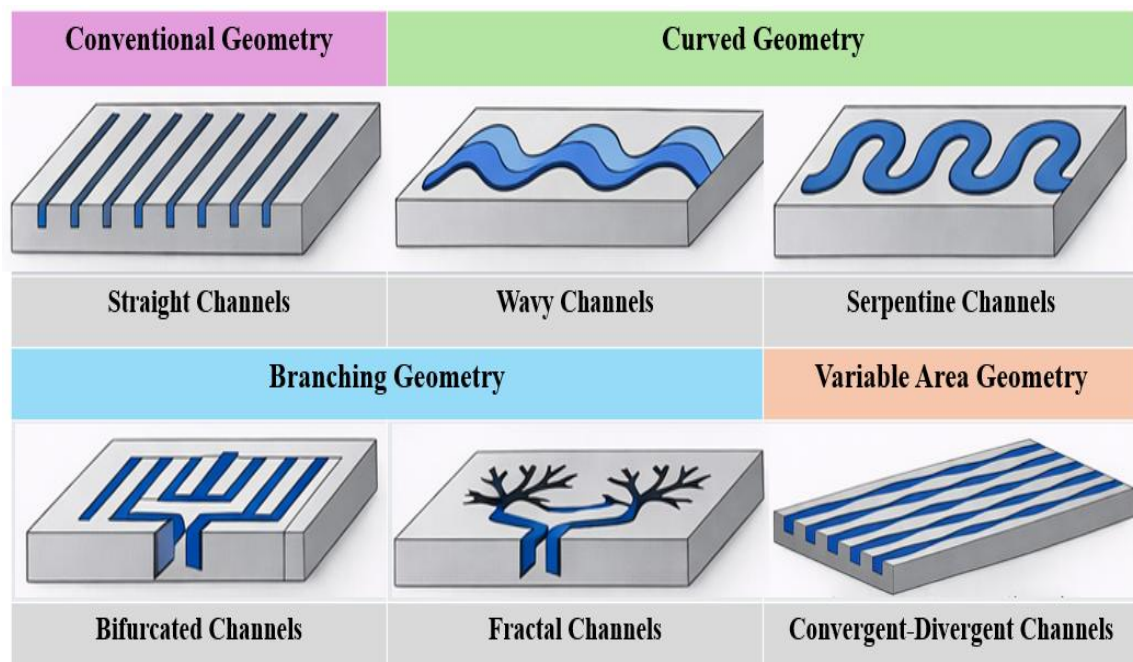


Figure 1.7: Representative geometrical configurations used for heat transfer enhancement in microchannel heat sinks [37]

1.6.2 Micro-Pillars as a Passive Heat Transfer Enhancement Technique

Micro-pillars, also referred to as pin fins, have emerged as an effective passive enhancement technique for improving the thermal performance of microchannel heat sinks. These structures are strategically integrated within the flow passage to modify the flow field and intensify fluid-solid interactions. By introducing localized flow disturbances, micro-pillars enhance fluid mixing, disrupt thermal boundary layer development, and promote the transport of thermal energy from the heated surface to the coolant [39].

In addition to increasing the available heat transfer surface area, micro-pillars generate secondary flow structures and localized vortices that improve coolant renewal near the heated walls. These mechanisms contribute to enhanced convective heat transfer and improved temperature uniformity throughout the microchannel [40]. Owing to their effectiveness and ease of integration, micro-pillars have been extensively investigated in various geometrical configurations (circular, square, diamond, elliptical, and streamlined shapes) and arrangements to optimize thermal-hydraulic performance [41].

Despite their thermal advantages, the insertion of micro-pillars alters the flow resistance within the channel and may result in an increased pressure drop. Therefore, the design and arrangement of micro-pillars require careful consideration to achieve an optimal balance between heat transfer enhancement and hydraulic performance [42].

1.6.3 Nanofluids as a Passive Heat Transfer Enhancement Technique

Nanofluids have emerged as one of the most promising passive enhancement techniques for improving the thermal performance of microchannel heat sinks. These engineered fluids are produced by dispersing nanoscale particles within conventional base fluids such as water, ethylene glycol, or their mixtures. The concept was first introduced by Choi in 1995 to overcome the inherently low thermal conductivity of conventional coolants and enhance heat transfer capability in advanced thermal management systems [43].

The incorporation of nanoparticles modifies the thermophysical properties of the base fluid, particularly thermal conductivity, resulting in improved heat transport characteristics. Furthermore, particle-fluid interactions, Brownian motion, and micro-scale mixing mechanisms contribute to enhanced convective heat transfer. Consequently, nanofluids have attracted considerable attention for high-heat-flux cooling applications, including microchannel heat sinks, advanced electronics, and computing systems [44].

As illustrated in Figure 1.8, working fluids employed in microchannel heat sinks have evolved from conventional base fluids to advanced nanofluids with increasingly complex compositions. Based on the type and number of dispersed nanoparticles, nanofluids can be categorized as mono nanofluids and hybrid nanofluids. While mono nanofluids contain a single nanoparticle and hybrid nanofluids combine multiple nanoparticles to exploit the complementary advantages of their individual constituents [45].

The superior cooling capability of nanofluids is attributed to enhanced heat transport characteristics and improved thermal-hydraulic performance. However, challenges such as particle agglomeration, long-term stability, increased viscosity, and the associated pressure-drop penalty continue to influence their practical implementation. Nevertheless, owing to their significant thermal enhancement potential, hybrid and tri-hybrid nanofluids have emerged as promising working fluids for next-generation microchannel cooling systems [46]. As a result, continued research efforts are focused on optimizing nanoparticle composition and concentration to maximize heat transfer enhancement while minimizing hydraulic penalties.

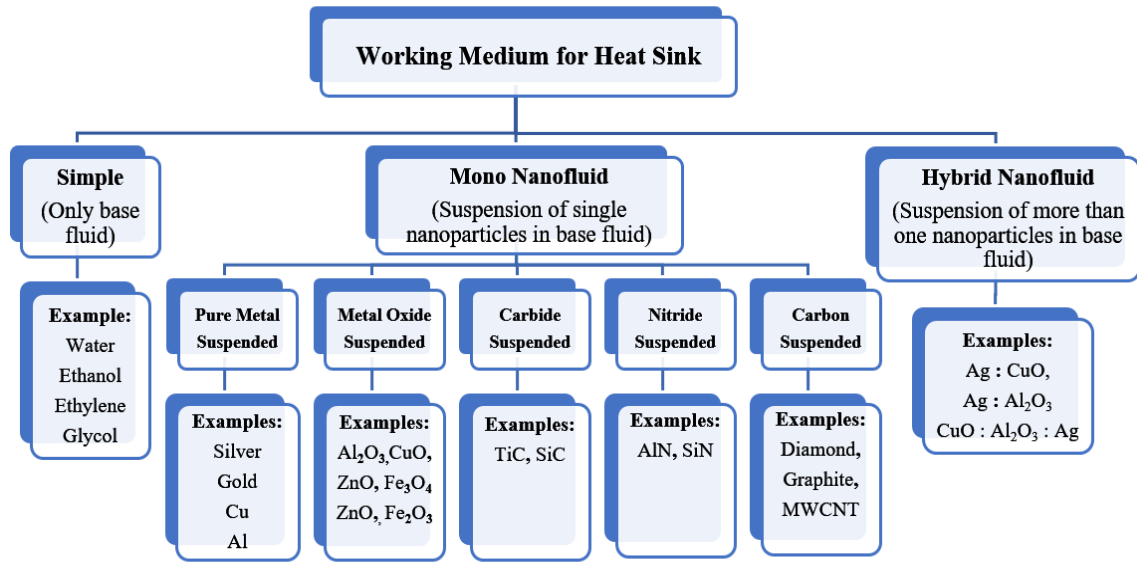


Figure 1.8: Classification of working fluids used in microchannel heat sinks [47]

1.6.4 Porous Media as a Passive Heat Transfer Enhancement Technique

Porous media have emerged as an effective passive enhancement technique for improving the thermal performance of microchannel heat sinks. A porous medium consists of a solid matrix containing interconnected pores through which the coolant can flow. When integrated into microchannels, porous structures substantially increase the available heat transfer surface area and strengthen fluid-solid interactions, thereby enhancing thermal transport within the cooling system [48].

The superior heat transfer characteristics of porous media are primarily attributed to their large specific surface area and complex flow pathways. As the coolant permeates through the porous region, fluid mixing is intensified and thermal boundary layer development is suppressed, resulting in enhanced convective heat transfer and improved temperature uniformity. Consequently, porous-media-integrated microchannels have attracted considerable attention for high-heat-flux electronic cooling applications [49].

The thermal-hydraulic performance of porous media is largely governed by structural parameters such as porosity and permeability. Porosity represents the fraction of void space available for fluid flow, whereas permeability characterizes the ease with which the coolant can pass through the porous structure. These parameters strongly influence heat transfer enhancement, flow distribution, and pressure-drop characteristics, making them critical considerations in porous media design. Furthermore, an appropriate balance between porosity and permeability is essential for achieving optimal thermo-hydraulic performance in practical applications [50].

Despite their significant thermal advantages, porous structures introduce additional flow resistance and may lead to increased pressure losses. Therefore, the successful implementation of porous media requires a careful balance between heat transfer augmentation and hydraulic performance. Owing to their remarkable capability for enhancing thermal transport, porous media continue to be widely explored as a promising solution for next-generation microchannel cooling systems.

1.7 Optimization Techniques for Microchannel Heat Sink Design

The performance of microchannel heat sinks is influenced by numerous interdependent design parameters, including channel geometry, operating conditions, substrate properties, and coolant characteristics. Owing to the complex interactions among these variables, modifications aimed at improving one performance metric often affect others. Consequently, the design of high-performance microchannel heat sinks requires a systematic optimization framework capable of identifying optimal trade-offs among thermal, hydraulic, and thermodynamic performance criteria [51].

Optimization techniques have therefore become indispensable tools for the design and development of advanced thermal management systems. These approaches enable efficient exploration of the design space and facilitate the identification of configurations that simultaneously satisfy multiple performance requirements. Depending on the underlying methodology, optimization strategies employed in thermal-fluid engineering can be broadly categorized into conventional mathematical methods, evolutionary algorithms, surrogate-based approaches, hybrid intelligent optimization frameworks, and multi-criteria decision-making techniques [52].

As summarized in Table 1.5, optimization methodologies have evolved from traditional mathematical approaches toward more advanced data-driven and hybrid frameworks capable of handling highly nonlinear multi-variable problems. While evolutionary algorithms provide robust global search capabilities, their direct coupling with computationally intensive numerical simulations often results in substantial computational expense. To overcome this limitation, surrogate-assisted optimization approaches have gained considerable attention by enabling rapid performance prediction while maintaining acceptable accuracy. These approaches significantly reduce the number of expensive numerical evaluations, thereby improving computational efficiency and facilitating the exploration of larger and more complex design spaces [53, 54].

Table 1.5: Classification of optimization techniques used for microchannel heat sink design [55]

Optimization Category	Common Techniques	Major Characteristics
Classical Optimization	- Gradient-Based Methods - Sequential Quadratic Programming	Fast convergence but may converge to local optima
Evolutionary Optimization	- Genetic Algorithm (GA) - NSGA-II - Particle Swarm Optimization	Global search capability; effective for complex multi-objective optimization
Surrogate-Based Optimization	- Response Surface Methodology - Kriging - ANN	Rapid performance prediction and reduced computational effort
Hybrid Optimization Frameworks	- ANN-GA - ANN-PSO - ANN-NSGA-II	Combines prediction efficiency with global optimization capability
Multi-Criteria Decision-Making (MCDM)	- TOPSIS - AHP - VIKOR	Facilitates selection of the best compromise solution from Pareto-optimal designs

Among the available surrogate models, Artificial Neural Networks (ANNs) have emerged as powerful tools for capturing complex nonlinear relationships between design variables and performance responses. When integrated with the Non-Dominated Sorting Genetic Algorithm II (NSGA-II), ANN models enable efficient multi-objective optimization and facilitate the generation of Pareto-optimal solutions. Furthermore, decision-making techniques such as the Technique for Order Preference by Similarity to Ideal Solution (TOPSIS) provide a systematic approach for identifying the most suitable compromise solution from the obtained Pareto front [56, 57].

Consequently, the integration of ANN, NSGA-II, and TOPSIS has emerged as a robust and efficient optimization framework for advanced thermal-fluid systems. This combined approach offers rapid performance prediction, effective multi-objective optimization, and rational decision-making, making it particularly suitable for the design and optimization of high-performance microchannel heat sinks.

1.8 Fabrication of Microchannel Heat Sinks

The advancement of microchannel heat sinks has been closely associated with the development of microfabrication technologies capable of producing microscale flow passages with high dimensional accuracy. Owing to their small characteristic dimensions and intricate geometrical features, the fabrication process plays a crucial role in determining the structural integrity, surface quality, and overall thermal-hydraulic performance of MCHSs [58, 59].

Early microchannel heat sinks were primarily manufactured using conventional fabrication techniques such as chemical etching, precision machining, electrical discharge machining (EDM), and laser micromachining. These methods enabled the production of a variety of channel geometries and significantly contributed to the widespread adoption of MCHSs in electronic cooling applications [60]. However, the increasing demand for compact thermal management systems and enhanced cooling performance has highlighted the limitations of traditional manufacturing approaches in producing highly complex internal structures.

Recent advances in manufacturing technologies have led to the emergence of additive manufacturing (AM) as a promising alternative for the fabrication of next-generation microchannel heat sinks. Unlike conventional subtractive processes, AM enables the layer-by-layer construction of components directly from computer-aided design (CAD) models, offering unprecedented design freedom and geometric flexibility. This capability facilitates the fabrication of intricate microchannel architectures and integrated thermal management structures that are difficult to achieve by traditional techniques [61, 62].

Among various additive manufacturing approaches, Direct Metal Laser Sintering (DMLS) has attracted significant attention owing to its ability to fabricate complex metallic microchannel configurations with high precision. Other techniques, including stereolithography (SLA) and LCD-based photopolymerization, have also been explored for the development of micro-scale thermal management devices and rapid prototyping applications [63-65]. Consequently, modern fabrication technologies have expanded the design possibilities of microchannel heat sinks and accelerated the development of advanced cooling solutions for high-heat-flux electronic systems.

1.9 Objectives and Performance Requirements of Advanced Microchannel Heat Sink

The design of advanced microchannel heat sinks is driven by the need to satisfy multiple thermal, hydraulic, and thermodynamic performance requirements simultaneously. The primary objective is to maximize heat removal capability while maintaining a low and uniform substrate temperature, thereby mitigating hotspot formation and enhancing the reliability of electronic components. Effective coolant distribution throughout the microchannel network is equally important to ensure uniform cooling and prevent localized thermal degradation.

From a hydraulic perspective, pressure drop should be minimized to reduce pumping power consumption and improve overall system efficiency. In addition, thermodynamic considerations such as minimizing entropy generation and maximizing exergy efficiency have become increasingly important for the development of sustainable and energy-efficient thermal management systems. Consequently, the design of advanced microchannel heat sinks requires a careful balance between heat transfer enhancement, flow resistance, temperature uniformity, and thermodynamic performance, particularly in high-heat-flux electronic cooling applications.

The discussions presented in this chapter highlight the growing importance of advanced microchannel heat sinks for addressing the escalating thermal challenges associated with modern high-performance electronic systems. Although substantial progress has been achieved through developments in channel geometries, passive heat transfer enhancement techniques, optimization methodologies, and advanced fabrication technologies, achieving a desirable balance between heat transfer enhancement, hydraulic performance, temperature uniformity, and thermodynamic efficiency remains a significant challenge. Consequently, the development of innovative microchannel configurations and systematic optimization strategies continues to attract considerable research interest. To identify existing knowledge gaps and establish the foundation for the present investigation, a comprehensive review of the relevant literature is presented in the following chapter.

1.10 Organization of the Thesis

The thesis is organized into seven chapters, each addressing a specific aspect of the research.

Chapter 1: Introduction presents the background and motivation for advanced thermal management systems, with particular emphasis on microchannel heat sinks. The chapter discusses the thermal challenges associated with modern electronic devices, the

fundamentals of microchannel cooling, heat transfer enhancement techniques, optimization approaches, fabrication methods, and the performance requirements of advanced microchannel heat sinks.

Chapter 2: Literature Review provides a comprehensive review of the existing literature related to microchannel heat sinks, convergent-divergent channel configurations, porous media, nanofluids, and thermal-hydraulic performance enhancement techniques. The chapter critically analyzes previous studies, identifies existing research gaps, and establishes the objectives of the present investigation.

Chapter 3: Research Methodology describes the computational framework adopted in this study. The chapter presents the geometrical modeling of the microchannel heat sink, governing equations, boundary conditions, numerical procedures, grid independence analysis, validation methodology, and performance parameters employed for thermal-hydraulic evaluation.

Chapter 4: Optimization Techniques and Selection Framework presents the surrogate-assisted optimization methodology employed in the present work. The chapter discusses the development of Artificial Neural Network (ANN) models, multi-objective optimization using the Non-Dominated Sorting Genetic Algorithm II (NSGA-II), and the application of the Technique for Order Preference by Similarity to Ideal Solution (TOPSIS) for selecting the optimal design from the Pareto-optimal solutions.

Chapter 5: Results and Discussion presents a detailed analysis of the thermal-hydraulic and thermodynamic performance of the proposed convergent-divergent microchannel heat sink configurations. The effects of design parameters, porous media, and tri-hybrid nanofluids are systematically investigated. Furthermore, the optimization results and the characteristics of the optimal configurations are critically discussed.

Chapter 6: Conclusions summarizes the major findings, contributions, and outcomes of the research. The chapter highlights the significance of the proposed enhancement and optimization strategies for advanced thermal management applications.

Chapter 7: Limitations and Future Scope discusses the limitations of the present study and provides recommendations for future research directions aimed at further improving the performance of advanced microchannel heat sink systems.

The thesis concludes with a list of references and appendices containing supplementary information, computational details, and supporting data relevant to the study.

CHAPTER 2

LITERATURE REVIEW

The continuous pursuit of higher computational capability, increased integration density, and enhanced functionality in modern electronic systems has intensified the challenges associated with thermal management. Although microchannel heat sinks (MCHS) have established themselves as one of the most effective cooling technologies for high-heat-flux applications, the ever-increasing thermal demands of next-generation electronic devices continue to drive the need for further performance enhancement. Consequently, extensive research efforts have been devoted to overcoming the inherent limitations of conventional microchannel configurations, including thermal boundary layer development, flow maldistribution, excessive pressure losses, and thermodynamic irreversibilities.

To address these challenges, researchers have explored a broad spectrum of enhancement strategies aimed at improving the thermo-hydraulic and thermodynamic performance of microchannel heat sinks. The resulting body of literature has progressively evolved from conventional channel design modifications toward more sophisticated passive enhancement techniques involving micro-scale flow-disrupting structures, advanced working fluids, porous materials, and intelligent optimization frameworks. These developments have significantly expanded the design possibilities of microchannel cooling systems and have contributed to substantial improvements in cooling capability, temperature uniformity, energy utilization, and overall thermal performance.

Among the various enhancement approaches reported in the literature, passive techniques have received particular attention because of their simplicity, reliability, and ability to improve heat transfer without external energy input. Geometrical modifications have been widely employed to alter flow structures, generate secondary flows, and periodically interrupt thermal boundary layer growth. Similarly, micro-pillars and pin-fin structures have been introduced to intensify fluid mixing and increase fluid-solid interaction, while nanofluids and hybrid nanofluids have emerged as promising working fluids owing to their superior thermophysical properties. Furthermore, porous media have demonstrated

considerable potential for thermal enhancement through their large specific surface area and improved heat exchange characteristics. Parallel to these developments, advances in computational intelligence, machine learning, and multi-objective optimization techniques have enabled the systematic exploration of complex design spaces and the identification of optimal configurations capable of balancing competing performance objectives.

Despite the remarkable progress achieved in this field, the enhancement of thermal performance is frequently accompanied by undesirable hydraulic and thermodynamic penalties, including increased pressure drop, higher pumping power requirements, and elevated entropy generation. Consequently, achieving an optimal balance between heat transfer augmentation and flow resistance remains one of the most significant challenges in the design of advanced microchannel heat sinks. Moreover, the coupled effects of channel geometry, passive enhancement structures, advanced working fluids, porous media, and optimization methodologies remain an active area of research, particularly for high-heat-flux electronic cooling applications where thermal efficiency and energy utilization are equally important.

Therefore, a comprehensive and critical assessment of the existing literature is essential to establish the current state of knowledge, evaluate the effectiveness of various enhancement strategies, identify unresolved challenges, and reveal the research gaps that motivate the present investigation. Accordingly, this chapter presents a detailed review of the published literature related to microchannel heat sinks, with particular emphasis on heat transfer enhancement through geometrical modifications, passive enhancement techniques involving micro-pillars, hybrid nanofluids, and porous media, modern optimization methodologies, as well as fabrication techniques employed for improving thermo-hydraulic and thermodynamic performance.

2.1 Heat Transfer Enhancement through Design Modifications

Microchannel geometry plays a decisive role in governing fluid flow behavior, thermal boundary layer development, pressure drop characteristics, and overall heat transfer performance. Consequently, numerous geometrical modifications have been proposed to improve the thermo-hydraulic performance of microchannel heat sinks. These modifications enhance heat transfer through mechanisms such as flow acceleration and deceleration, secondary flow generation, boundary layer interruption, fluid redistribution,

and enhanced fluid mixing. The earliest investigations primarily focused on simple straight microchannels with rectangular and circular cross-sections, which served as benchmark configurations for evaluating thermal and hydraulic performance. However, the limitations associated with boundary layer growth and restricted fluid mixing in these conventional geometries motivated the development of advanced channel designs. As a result, a wide variety of modified geometries, including zigzag, bifurcated, wavy, fractal, ribbed, cavity-assisted, and converging-diverging microchannels, have been extensively investigated to achieve superior heat transfer performance while maintaining acceptable hydraulic characteristics.

Straight microchannel heat sinks (MCHSs) have been widely adopted as baseline cooling configurations due to their simple geometry, ease of fabrication, and predictable flow characteristics. Nevertheless, the streamlined nature of the flow promotes continuous thermal boundary layer development, resulting in a gradual decline in heat transfer performance along the channel length. **Ganesh et al. [66]** reported that the progressive growth of the thermal boundary layer in conventional straight microchannels significantly limits heat transfer enhancement, thereby motivating the development of advanced geometrical configurations capable of improving fluid mixing and periodically disturbing the boundary layer.

Ali et al. [67] numerically investigated the thermal performance of a circular microchannel heat sink and reported that the circular geometry provides a relatively uniform flow distribution and lower hydraulic resistance owing to the absence of sharp corners. However, the predominantly streamlined flow within the channel promotes continuous thermal boundary layer development, limiting fluid mixing and consequently restricting heat transfer enhancement.

Javed et al. [68] employed a two-phase numerical model to examine nanofluid transport in wavy microchannels and highlighted the limitations of homogeneous single-phase approaches in predicting thermal performance. Their results demonstrated that nanoparticle migration leads to non-uniform concentration distributions, which significantly affect heat transfer behavior. The study further showed that higher nanoparticle volume fractions and smaller particle diameters improve thermal performance, while the synergistic effect of nanofluids and wavy channel geometry resulted in nearly a threefold enhancement in Nusselt number relative to water flowing through straight microchannels.

Peng et al. [69] designed and experimentally evaluated a zigzag-serpentine microchannel heat sink to investigate the influence of channel incidence angle on thermo-hydraulic performance. The results indicated that reducing the zigzag angle enhanced flow characteristics and reduced thermal resistance, with the 30° configuration exhibiting the best overall thermo-hydraulic performance. In contrast, the 45° configuration provided superior temperature uniformity. The authors also reported that the integration of serpentine passages improved hydraulic performance relative to conventional straight-channel designs.

Fadi et al. [70] numerically investigated the thermo-hydraulic performance of zigzag microchannel heat sinks over a Reynolds number range of 250–1500. The periodic changes in flow direction generated flow disturbances and enhanced fluid mixing, resulting in a significant reduction in thermal resistance. The study reported a 26–51% decrease in thermal resistance compared to conventional straight microchannels. Nevertheless, the improved thermal performance was accompanied by a 40–120% increase in pumping power due to the higher flow resistance associated with the zigzag configuration.

Rodrigo et al. [71] numerically investigated the thermo-hydraulic performance of a fractal microchannel heat exchanger integrated with sinusoidal channel walls under laminar flow conditions. The study examined the effects of wave amplitude and the number of sinusoidal waves on heat transfer and flow characteristics. Their results indicated that increasing the Reynolds number, wave amplitude, and number of waves improved heat transfer performance by enhancing fluid mixing, although at the expense of higher pumping power. Moreover, bifurcated fractal configurations exhibited lower power consumption than non-bifurcated channels, demonstrating that the combination of fractal branching and sinusoidal geometries can effectively balance heat transfer enhancement and hydraulic performance.

Lu et al. [72] investigated the thermal performance of fractal-shaped microchannel heat sinks with different branching levels. The branching architecture was designed to improve coolant distribution and increase the effective heat transfer area. The results indicated that increasing the branching level significantly reduced both the average temperature and peak temperature of the heat sink. The study demonstrated the potential of biomimetic fractal geometries for achieving enhanced temperature control and thermal uniformity.

Fathi et al. [73] numerically examined bifurcated divergent microchannel heat sinks incorporating bifurcation plates of constant cross-section, variable width, and variable height to evaluate their thermo-hydraulic characteristics. Their results revealed that bifurcated divergent configurations produce lower pressure drop penalties than conventional parallel microchannels while maintaining competitive heat transfer performance. Based on the performance index, the bifurcated divergent designs outperformed parallel microchannels, with variable-height bifurcation plates providing the highest overall thermo-hydraulic performance. The study highlighted the potential of combining channel divergence and flow bifurcation to improve cooling efficiency in microchannel heat sinks.

Farzaneh et al. [74] analyzed bifurcating microchannel heat sinks with and without reverting loops to assess the influence of branching on thermo-hydraulic performance. Their findings showed that increasing the number of branches improved coolant distribution and reduced thermal resistance throughout the heat sink. Compared with non-bifurcated configurations, one- and two-branch reverting microchannels reduced the maximum dimensionless temperature by approximately 10% and 20%, respectively. In addition, pressure drop decreased by nearly 25% and 30%, highlighting the effectiveness of bifurcation in simultaneously improving thermal and hydraulic performance.

Wang et al. [75] numerically investigated a microchannel heat sink incorporating various cavity geometries and straight rib structures to enhance thermo-hydraulic performance. The effects of cavity dimensions, rib configurations, and Reynolds number on the Nusselt number, friction factor, and thermal enhancement efficiency were systematically evaluated. Using an artificial neural network coupled with a multi-objective genetic algorithm, the authors identified an optimal design featuring rectangular-rounded straight ribs, which exhibited the best overall performance with an average thermal enhancement efficiency approximately 9.7% higher than that of the non-ribbed configuration. The study highlighted the effectiveness of combining cavity and rib structures with optimization techniques for improving microchannel heat sink performance.

Zhu et al. [76] proposed a novel microchannel heat sink incorporating periodic gradual expansions and sudden contractions using backward trapezoidal grooves. The geometrical modification was intended to periodically disturb the thermal boundary layer and promote fluid mixing within the channel. Their results revealed a substantial enhancement in heat transfer performance, with the Nusselt number increasing by as much as 2.23 times that

of a smooth microchannel. However, the enhanced thermal performance was accompanied by increased pressure losses and viscous resistance. The optimum performance was achieved at a groove angle of 15° and a Reynolds number of 442.

Shi et al. [77] optimized the geometrical parameters of a microchannel heat sink incorporating secondary flow channels with the objective of simultaneously reducing thermal resistance and pumping power. A comprehensive parametric investigation was performed to evaluate the influence of different design variables on thermo-hydraulic performance. The authors reported that the width ratio (α) was the most influential parameter, resulting in reductions of up to 28.7% in thermal resistance and 22.9% in pumping power compared with conventional microchannel designs. The study highlighted the effectiveness of secondary flow passages in improving overall cooling performance while maintaining hydraulic efficiency.

Kuppusamy et al. [78] developed a microchannel heat sink incorporating alternating slanted passages between adjacent channels to improve fluid communication and disrupt boundary layer development. The introduced passages promoted flow redistribution and intensified mixing between neighboring channels. As a result, the overall thermal performance increased by approximately 146%, while thermal resistance decreased by 76.8% compared with a conventional microchannel heat sink. The study demonstrated the effectiveness of inter-channel flow interaction as a passive heat transfer enhancement strategy.

Liu et al. [79] examined a rectangular microchannel heat sink integrated with longitudinal vortex generators (LVGs) to enhance heat transfer through vortex-induced mixing. The generated vortical structures continuously disrupted the thermal boundary layer and improved near-wall fluid transport. Their results showed that heat transfer increased by 9–21% under laminar flow conditions and by 39–90% under turbulent flow conditions. However, these benefits were achieved at the expense of higher pressure losses, with pressure drop increases ranging from 34–83% in laminar flow and 61–169% in turbulent flow.

Duryodhan et al. [80] investigated the cooling performance of converging and diverging microchannel heat sinks to evaluate the influence of channel geometry on thermo-hydraulic characteristics. The study compared the flow and heat transfer behavior of variable-area microchannels with conventional straight channels. Their results demonstrated that converging microchannels provide superior heat transfer performance,

achieving nearly 35% higher heat transfer rates than diverging configurations. This enhancement was primarily attributed to favorable flow acceleration and improved conjugate heat transfer effects, which strengthened thermal transport between the solid substrate and the coolant.

Tahir and Yilmaz [81] numerically investigated a converging-diverging microchannel operating within a Reynolds number range of 100–600. The periodic variation in channel cross-section caused repeated flow acceleration and deceleration, resulting in continuous disruption and redevelopment of the thermal boundary layer. This mechanism significantly enhanced convective heat transfer, leading to Nusselt number improvements of up to 400% compared with a conventional parallel channel. The study confirmed the strong potential of converging-diverging geometries for high-performance thermal management applications.

Kumar et al. [82] investigated a converging-diverging microchannel heat sink with the objective of enhancing thermal performance while minimizing thermodynamic losses. The study evaluated both heat transfer and entropy generation characteristics and employed a TOPSIS-based optimization framework to identify the optimal design. The baseline converging-diverging configuration improved heat transfer by 40.6% but also increased entropy generation by 108.8%. However, the optimized design achieved a 70.3% reduction in entropy generation with only a 14.6% sacrifice in heat transfer performance, resulting in superior overall thermal and exergetic efficiency.

Overall, the reviewed studies demonstrate that geometric modification is an effective strategy for enhancing the thermo-hydraulic performance of microchannel heat sinks through improved fluid mixing, boundary-layer disruption, flow redistribution, and secondary-flow generation. Among the various geometric modifications, converging-diverging microchannels have emerged as one of the most promising configurations due to their capability to periodically redevelop the thermal boundary layer while maintaining a relatively simple geometry. However, despite their significant heat transfer enhancement potential, challenges associated with increased pressure drop and thermodynamic losses continue to motivate further investigation and optimization of converging-diverging microchannel heat sinks.

2.2 Passive Heat Transfer Enhancement Techniques for Microchannel Heat Sinks

2.2.1 Micro-Pillar-Assisted Microchannel Heat Sinks

Micro-pillars have emerged as an effective passive heat transfer enhancement technique in microchannel heat sinks owing to their ability to increase the heat transfer surface area, disrupt thermal boundary layer development, and promote fluid mixing. The presence of micro-pillars within the flow passage generates local flow disturbances and secondary vortical structures, which enhance fluid-solid interaction and improve convective heat transfer. However, the associated enhancement in thermal performance is often accompanied by an increase in flow resistance, making pillar geometry and arrangement critical design parameters.

Wang et al. [83] numerically investigated the thermo-hydraulic performance of microchannels incorporating triangular, circular, and diamond-shaped pillar geometries. The study demonstrated that the introduction of micro-pillars significantly improves fluid mixing and thermal transport, resulting in nearly a twofold increase in the heat transfer coefficient compared with conventional microchannels. Among the investigated geometries, triangular pillars exhibited the best thermal performance, achieving the highest Nusselt number owing to their stronger flow disturbance and enhanced boundary layer disruption. The results highlighted the significant influence of pillar geometry on microchannel heat transfer enhancement.

Rajalingam and Chakraborty [84] numerically examined microchannel heat sinks integrated with circular, aerofoil, and elliptical micro-pillars to evaluate the effect of pillar shape on cooling performance. Their findings revealed that the elliptical pillar configuration maintained the lowest interface temperature among all the cases considered, indicating superior thermal performance. The streamlined profile of the elliptical pillars facilitated effective heat transfer while mitigating excessive hydraulic losses, demonstrating the importance of geometric optimization in micro-pillar-based microchannel heat sinks.

Kumar et al. [85] investigated the influence of airfoil-shaped pillars in a jet-impinged microchannel heat sink operating at Reynolds numbers up to 2000. The study focused on the effect of pillar aspect ratio on thermal performance and reported that increasing the height-to-diameter ratio substantially improved cooling effectiveness. The optimized configuration reduced the base temperature by approximately 44%, increased the convective heat transfer coefficient by nearly 24%, and enhanced the Nusselt number by about 16%. These findings confirmed the strong dependence of thermo-hydraulic performance on pillar geometry and dimensional characteristics.

Ci et al. [86] numerically investigated microchannel heat sinks equipped with diamond, airfoil, and cylindrical pin-fin geometries under extremely high heat flux conditions ranging from 4000 to 8000 W/cm². The presence of pin-fins generated strong secondary flow structures and intensified fluid mixing, leading to substantial improvements in heat transfer performance. Among the investigated configurations, the optimized design achieved a heat dissipation capability of 7300 W/cm², a heat transfer coefficient of 661.6 kW/m²·K, and a remarkably low thermal resistance of 0.0059 K·cm²/W. These results demonstrated the effectiveness of pin-fin-assisted microchannels for next-generation ultra-high heat flux thermal management systems.

Chenyang et al. [87] numerically analyzed conjugate heat transfer in an elliptical pin-fin microchannel heat sink to evaluate the influence of geometric parameters on thermo-hydraulic performance. Their findings showed that flow velocity and fin transverse width significantly affect heat transfer enhancement and pressure losses. The study further established empirical correlations for Nusselt number and friction factor, providing useful guidelines for the design of optimized elliptical pin-fin microchannel heat sinks.

Justina et al. [88] examined the flow and thermal characteristics of inline and staggered pin-fin microchannel arrays. The study revealed that pin diameter and fin spacing play dominant roles in governing vortex formation, flow stability, and pressure loss characteristics. Their results indicated that staggered arrangements with appropriately selected pin dimensions can effectively reduce pressure losses while maintaining favorable thermal performance.

Wang et al. [89] numerically investigated pillar-embedded microchannel heat sinks and reported that pillar height is a critical design parameter influencing the trade-off between heat transfer enhancement and hydraulic resistance. By modifying local flow acceleration and thermal boundary layer thickness, the pillars significantly improved cooling performance. The study identified an optimum pillar height of approximately 260 μm, which minimized chip temperature without introducing excessive pressure drop.

Jatau et al. [90] numerically studied a microchannel heat sink incorporating centrally arranged square pin-fins for thermal management of high-concentration photovoltaic systems. The investigation revealed that both pin-fin density and coolant flow rate strongly affect cell temperature, temperature uniformity, and net electrical output. The authors identified an optimal pin-fin configuration that provided effective cooling while avoiding excessive pumping power requirements.

Yifan et al. [91] examined porous pin-fin heat sinks for liquid cooling of high-power data-center processors. Their results showed that a sparse-to-dense pin-fin arrangement enhances heat transfer while simultaneously reducing flow resistance and pumping power consumption. The optimized configuration reduced chip temperature by 13.4°C and significantly lowered entropy generation, demonstrating the suitability of porous pin-fin structures for next-generation electronic cooling systems.

Zhang et al. [92] experimentally investigated a fractal-distributed jet microchannel heat sink integrated with micro pin-fins under heat fluxes ranging from 200 to 400 W/cm². The incorporation of pin-fins improved coolant distribution and reduced flow maldistribution within the fractal network, thereby enhancing temperature uniformity across the heated surface. The study further demonstrated that optimizing the pin-fin height effectively suppressed hotspot formation under non-uniform heating conditions, making the proposed design particularly suitable for high-power electronic cooling applications.

Fadi et al. [93] numerically investigated straight microchannel heat sinks equipped with square sidewall fins to evaluate the influence of fin dimensions and channel geometry on thermo-hydraulic performance. The study demonstrated that fin size, fin spacing, and channel dimensions strongly affect the balance between thermal resistance and pumping power. Using a figure-of-merit analysis, the authors identified intermediate fin dimensions as the most effective configuration for achieving enhanced overall performance.

Husain et al. [94] proposed a hybrid microchannel heat sink integrating micro-pillars with jet impingement cooling to exploit the synergistic interaction between impinging jets and pillar-induced flow disturbances. The study demonstrated substantial improvements in heat transfer performance compared with conventional microchannel designs. Moreover, optimal jet spacing and stand-off ratios were identified to simultaneously minimize thermal resistance and pumping power.

Farzad et al. [95] experimentally investigated bubble dynamics in a microchannel containing a 150 µm micro-pillar to understand the influence of pillar geometry on two-phase flow behavior. Using high-speed visualization and micro-particle image velocimetry, the authors identified distinct flow regimes, including discrete bubbles, attached ligaments, and transitional flow patterns. The study revealed that slit angle and liquid-gas flow rates strongly influence bubble formation and transport mechanisms, providing valuable insights into the design of pillar-assisted microchannels for boiling heat transfer applications.

Chen et al. [96] explored mixed pillar-cavity microchannel structures under flow boiling conditions to investigate the combined influence of cavities and pillars on phase-change heat transfer. The authors reported that cavities promoted bubble nucleation, while the micro-pillars suppressed vapor film formation and facilitated liquid rewetting of the heated surface. This synergistic interaction significantly enhanced boiling heat transfer performance and improved thermal stability. Furthermore, the thermal enhancement was found to be strongly dependent on pillar height and cavity depth, emphasizing the need for careful geometric optimization.

Jin et al. [97] optimized pin-fin geometries in a hybrid microchannel heat sink designed for hotspot mitigation. Through a multi-objective optimization framework and TOPSIS-based decision-making approach, the authors identified an optimal pin-fin configuration that effectively enhanced local boundary layer disruption while preserving smooth flow characteristics. The optimized design reduced thermal resistance by 16.5% and pumping power by 62.9% compared with conventional configurations.

Zhou et al. [98] introduced butterflyfish-inspired biomimetic micro-pillars for microchannel heat sinks and investigated their thermo-hydraulic characteristics. Inspired by natural flow-control mechanisms, the proposed pillar geometry enhanced fluid mixing while reducing flow resistance. Compared with conventional solid pillars, the biomimetic design improved the Nusselt number by up to 16.5% and reduced pressure drop by 16.7%, demonstrating the effectiveness of nature-inspired geometries for advanced thermal management applications.

Collectively, the available literature indicates that micro-pillars and pin-fin structures substantially improve the thermal performance of microchannel heat sinks by enhancing fluid mixing, increasing heat transfer surface area, and disrupting thermal boundary layer growth. Nevertheless, the associated increase in flow resistance necessitates careful optimization of pillar geometry, size, arrangement, and operating conditions to achieve an optimal balance between heat transfer enhancement and hydraulic performance.

2.2.2 Hybrid Nanofluids in Microchannel Heat Sinks

Hybrid nanofluids have emerged as a promising class of advanced working fluids for microchannel heat sinks owing to their ability to combine the favorable thermophysical properties of multiple nanoparticles. By utilizing two or more nanoparticle species within a single base fluid, hybrid nanofluids can simultaneously enhance thermal conductivity,

convective heat transfer, and energy efficiency beyond the capabilities of conventional mono-nanofluids. Consequently, extensive research efforts have been directed toward evaluating their thermo-hydraulic and thermodynamic performance in microchannel cooling applications.

Krishna et al. [99] investigated the performance of a water-based MWCNT-CuO hybrid nanofluid with nanoparticle concentrations ranging from 1% to 3%. Their results demonstrated that the hybrid nanofluid outperformed the corresponding mono-nanofluids, achieving a maximum Nusselt number enhancement of approximately 4.68% compared to CuO/water and 12.64% compared to MWCNT/water at a concentration of 3%. Moreover, the thermal enhancement was achieved with only a marginal increase in pressure drop, indicating the potential of hybrid nanofluids for efficient heat transfer augmentation.

Zhai et al. [100] examined the thermo-hydraulic and thermodynamic characteristics of an Al_2O_3 - TiO_2 /water hybrid nanofluid in a microchannel heat sink. The study revealed that the addition of hybrid nanoparticles significantly improved thermal performance, resulting in a 23.53% increase in the Nusselt number and a 9.73% reduction in pressure drop. Furthermore, the optimized configuration reduced system irreversibility by nearly 64% while achieving an exergy efficiency of approximately 88%, highlighting the advantages of hybrid nanofluids from both thermal and thermodynamic perspectives.

Qu et al. [101] investigated a microchannel heat sink utilizing Fe_3O_4 /graphene-water hybrid nanofluids with nanoparticle concentrations ranging from 0.1% to 0.5%. Employing a multi-objective particle swarm optimization (MOPSO) framework, the authors demonstrated that appropriate selection of nanoparticle concentration and operating conditions can simultaneously reduce thermal resistance and pressure drop. The study highlighted the potential of optimization-driven hybrid nanofluid design to overcome the conventional trade-off between heat transfer enhancement and hydraulic performance.

Zhang et al. [102] employed machine-learning-based multi-objective optimization techniques to evaluate the performance of various hybrid nanofluids in microchannel cooling systems. Their results indicated that optimal thermo-hydraulic performance is generally achieved at nanoparticle volume fractions exceeding 1.5% and operating temperatures between 40°C and 50°C. Among the investigated nanofluids, the CeO_2 /ZnO-MWCNT hybrid nanofluid exhibited the most favorable overall performance,

demonstrating the effectiveness of combining advanced nanomaterials with intelligent optimization approaches.

Tang et al. [103] investigated a jet-impingement microchannel heat sink using Cu-Al₂O₃/water hybrid nanofluids with nanoparticle concentrations up to 2%. The incorporation of hybrid nanoparticles significantly improved thermal performance, reducing thermal resistance by 23.4% and lowering surface temperature by approximately 8.1 K. However, the enhanced cooling capability was accompanied by a considerable increase in pumping power, which varied from 0.22 W to 2.1 W with increasing Reynolds number and nanoparticle concentration. The study emphasized the importance of balancing thermal enhancement against hydraulic penalties in hybrid nanofluid applications.

Chu et al. [104] numerically investigated the thermo-hydraulic performance of AlN-Al₂O₃/water hybrid nanofluids in circular microchannel heat sinks. Their results showed that increasing nanoparticle concentration enhanced heat transfer performance owing to improved thermal conductivity; however, the enhancement was accompanied by higher frictional losses. The study highlighted the inherent trade-off between thermal augmentation and hydraulic resistance in hybrid nanofluid-based cooling systems.

Ghachem et al. [105] examined hybrid nanofluid flow in a cross-flow micro heat exchanger and evaluated the influence of nanoparticle concentration and flow conditions on thermal efficiency. The authors reported that thermal performance improved with increasing nanoparticle loading, particularly at higher flow velocities. Nevertheless, the effectiveness of the hybrid nanofluid was found to be strongly dependent on both geometric and operating parameters, emphasizing the importance of system-level optimization.

Tang et al. [106] performed multi-objective optimization of a hybrid nanofluid jet-impingement microchannel heat sink using an integrated ANN-NSGA-II-TOPSIS framework. Their optimized design achieved a substantial enhancement in heat transfer performance, with the Nusselt number increasing by nearly 48.7% while significantly improving temperature uniformity. Although the optimized configuration exhibited higher frictional losses, the study demonstrated the effectiveness of machine-learning-assisted optimization for advanced nanofluid cooling systems.

Mohammad et al. [107] numerically investigated a ribbed microchannel heat sink employing graphene oxide-cobalt oxide/water hybrid nanofluids. The combined effect of

rib-induced flow disturbance and enhanced thermophysical properties of the hybrid nanofluid resulted in improved convective heat transfer and temperature uniformity. The authors reported a notable reduction in thermal resistance with only a moderate increase in pressure drop, demonstrating the synergistic benefits of geometric modification and hybrid nanofluids.

Zahid et al. [108] evaluated heat sink configurations integrated with alumina nanoparticle-enhanced phase change materials for passive thermal management applications. Their results indicated that the incorporation of nanoparticles significantly reduced peak operating temperatures and extended the effective cooling duration. The study demonstrated the potential of nanoparticle-enhanced thermal storage materials for improving temperature regulation in high-power electronic systems.

Arshad et al. [109] experimentally compared the performance of circular and rectangular micro pin-fin heat sinks operating with mono and hybrid nanofluids. The rectangular configuration exhibited superior thermo-hydraulic performance owing to improved flow distribution and heat transfer characteristics. Among the tested working fluids, graphene nanoplatelet-based nanofluids provided the highest thermal enhancement and performance evaluation criterion, confirming their suitability for advanced micro-scale cooling applications.

Maatki et al. [110] numerically analyzed the flow and heat transfer behavior of Al_2O_3 -Cu hybrid nanofluids in a baffled microchannel heat sink. The study revealed that increasing nanoparticle concentration and Reynolds number improved heat transfer performance by intensifying fluid mixing and thermal transport. Their findings confirmed the effectiveness of combining hybrid nanofluids with flow-disrupting geometrical features for enhanced thermal management.

Alizadeh et al. [111] investigated the combined influence of twisted turbulator and hybrid nanofluids on the thermo-hydraulic performance of a heat exchanger. The incorporation of hybrid nanoparticles significantly increased the Nusselt number and improved exergy efficiency, although higher pressure losses were observed. The results demonstrated that hybrid nanofluids can effectively enhance both thermal and thermodynamic performance when employed in conjunction with turbulence-promoting structures.

Rajaei et al. [112] examined the application of hybrid nanofluids in microchannel heat sinks for photovoltaic-thermal cooling systems. Their study reported improvements in thermal regulation, exergy efficiency, and electrical performance compared with

conventional water-based cooling. The findings highlighted the potential of hybrid nanofluids for integrated thermal management and energy conversion applications.

Khaleduzzaman et al. [113] experimentally investigated Al_2O_3 -water nanofluids in a rectangular minichannel heat sink and evaluated both energetic and exergetic performance. The study revealed that increasing nanoparticle concentration enhanced heat transfer effectiveness and exergy efficiency, indicating the capability of nanoparticle-enhanced coolants to improve overall system performance.

Ren et al. [114] numerically studied a tree-root-inspired sinusoidal cold plate employing nanofluids for lithium-ion battery thermal management. The biomimetic flow architecture improved coolant distribution and heat dissipation relative to conventional channel designs. Optimization of nanoparticle concentration further enhanced thermal performance while maintaining acceptable hydraulic characteristics, demonstrating the benefits of integrating advanced geometries with nanofluid cooling.

Arshad et al. [115] numerically investigated mono and hybrid nanofluids in a staggered micro pin-fin heat sink subjected to constant heat flux conditions. Their results showed that graphene nanoplatelet-based nanofluids delivered the best overall thermo-hydraulic performance, with significant improvements in heat transfer coefficient, performance evaluation criterion, and thermal resistance. The study emphasized the combined influence of pin-fin arrangements and nanofluid properties on cooling effectiveness.

Mohammadi et al. [116] analyzed laminar nanofluid flow in circular tubes under slip-flow conditions using Al_2O_3 and SiO_2 nanoparticles dispersed in HFE7000. The authors reported that slip boundary conditions reduced pressure losses while simultaneously improving thermodynamic performance through lower entropy generation. The study provided valuable insights into the application of nanofluids in microscale cooling systems where rarefaction effects become important.

Wang et al. [117] investigated nanoparticle deposition behavior in microchannel heat sinks employing Al_2O_3 , Au, and CNT-based nanofluids. Their analysis showed that larger particle diameters, higher flow velocities, lower inlet temperatures, greater particle densities, and increased base-fluid viscosity effectively suppress nanoparticle deposition. The authors further reported that heat flux variations exert only a minor influence on heat transfer and deposition characteristics but can reduce pressure drop by approximately 10.57%. The study highlighted nanoparticle deposition as a critical factor affecting the long-term performance and reliability of nanofluid-based microchannel cooling systems.

Collectively, these studies demonstrate that hybrid nanofluids can substantially enhance the thermal performance of microchannel heat sinks through improved thermophysical properties and heat transport mechanisms. Nevertheless, challenges related to increased pumping power, nanoparticle deposition, long-term stability, and optimization of nanoparticle concentration remain important considerations for their practical implementation in advanced thermal management systems.

2.2.3 Porous Media-Assisted Microchannel Heat Sinks

Porous media have emerged as a promising passive enhancement technique for microchannel heat sinks owing to their large specific surface area and superior fluid-solid interaction characteristics. The incorporation of porous structures within microchannels enhances heat transfer by increasing the effective heat transfer area, promoting fluid mixing, and improving thermal diffusion. However, the associated increase in flow resistance necessitates careful optimization of porosity, permeability, and porous medium distribution to achieve a favorable balance between thermal enhancement and hydraulic performance.

Hunt et al. [118] investigated the influence of high-conductivity porous media on the thermal performance of microchannel heat sinks through numerical and experimental analyses. Their results demonstrated that the incorporation of porous materials significantly reduces wall temperature and enhances heat transfer performance. The study reported heat transfer improvements of nearly 200-400% compared with non-porous configurations, highlighting the substantial potential of porous structures for advanced thermal management applications.

Saravanan et al. [119] numerically investigated microchannel heat sinks partially and fully filled with porous media to evaluate the influence of porous material placement on thermo-hydraulic performance. Their results revealed that configurations with porous inserts located at the channel center or near the sidewalls outperform fully porous designs. The study reported an approximately 12% improvement in the figure of merit (FOM), demonstrating that strategic placement of porous media can effectively enhance heat transfer while mitigating excessive pressure losses.

Sathish and Jayavel [120] numerically analyzed porous-fin microchannel heat sinks with porosities ranging from 0.40 to 0.80 and varying permeability values. The authors observed that porous fins consistently provide superior thermal performance compared

with conventional solid fins due to improved heat transfer between the coolant and heated surface. The optimum performance was achieved at a porosity of 0.4 and a permeability of 10^{-8} m^2 , indicating that lower porosity combined with higher permeability offers the most effective heat dissipation characteristics.

Kumar et al. [121] investigated a porous-assisted microchannel heat sink and employed an NSGA-II-based multi-objective optimization framework to identify optimal porous medium characteristics. Their results demonstrated remarkable thermal enhancement, with the optimized design achieving approximately 515.12% improvement in the Nusselt number and an 83.65% reduction in entropy generation. Furthermore, the incorporation of porous media significantly reduced wall temperatures and enabled substantially higher heat transfer rates than conventional non-porous microchannels, highlighting the strong potential of porous structures for advanced thermal management applications.

Dai and Liu [122] proposed a graded-porosity microchannel heat sink in which porosity gradually increased along the flow direction. The study demonstrated that a stepwise porosity distribution provides superior thermo-hydraulic performance compared with uniformly porous structures by simultaneously enhancing heat transfer and reducing hydraulic penalties. Their findings emphasized the importance of spatial porosity distribution in optimizing the overall performance of porous microchannel heat sinks.

Liu et al. [123] examined a staggered porous solid-fin microchannel configuration with porosity values ranging from 0.80 to 0.97. The porous fin arrangement enhanced coolant mixing and improved thermal interaction between the fluid and solid domains, resulting in a 47% increase in the heat transfer coefficient. In addition, the design reduced pressure drop by approximately 18.4% and achieved an overall performance enhancement of nearly 57%, demonstrating its suitability for high-performance cooling applications.

Zhiao et al. [124] optimized a partially porous liquid-cooling plate using an integrated RSM–NSGA-II–TOPSIS framework to determine the optimal porous medium characteristics. The study investigated the influence of porosity and porous filling ratio on thermal management performance and identified an optimal configuration with a porosity of 0.87 and a filling ratio of 80.25%. The optimized design achieved a maximum cell temperature of 31.29°C while simultaneously improving temperature uniformity, highlighting the effectiveness of porous medium optimization in thermal management systems.

Wang et al. [125] proposed a gradient porous heat sink (GPHS) and evaluated its performance relative to a conventional homogeneous porous heat sink (HPHS). The graded porosity arrangement improved coolant distribution and thermal transport throughout the channel. As a result, the GPHS configuration achieved significantly higher Nusselt numbers than the homogeneous design, demonstrating the effectiveness of non-uniform porosity distributions in enhancing heat transfer performance.

Dai et al. [126] investigated the influence of porous medium characteristics on the hydrothermal performance of porous microchannel heat sinks. Their analysis revealed that pore size, porosity, and spatial distribution are key parameters governing thermal and hydraulic behavior. The study emphasized that appropriate optimization of porous medium properties can substantially improve overall cooling performance while minimizing hydraulic penalties.

Goharkhah et al. [127] numerically studied magnetite nanofluid flow through porous heat sinks and assessed the combined influence of nanoparticle concentration and porous medium characteristics. Their results indicated that thermal performance improves considerably at lower porosities and flow rates, particularly when higher nanofluid concentrations are employed. The study highlighted the synergistic interaction between porous structures and nanofluids for enhanced heat transfer applications.

Rashidi et al. [128] investigated porous materials for thermal management of lithium-ion battery systems and evaluated the effects of porosity and pore density on temperature regulation. The authors reported that decreasing porosity reduces battery surface temperature, whereas increasing pore density can adversely affect cooling performance due to permeability-related flow resistance. Their findings emphasized the importance of balancing porosity and permeability in porous thermal management systems.

Francisco et al. [129] proposed a porous-fin microchannel heat sink capable of generating cross-flow within the porous structure to simultaneously enhance conductive and convective heat transfer. Numerical results demonstrated an approximately 17% increase in the Nusselt number compared with conventional configurations. The study highlighted the effectiveness of porous fins in improving thermal transport for high-performance electronic cooling applications.

Arshad et al. [130] analyzed a water-cooled micro-porous heat sink incorporating aluminum metal foam and investigated the effects of porosity and pore density on hydrothermal performance. Their results revealed that lower porosity and moderate pore

density significantly improve heat transfer characteristics, reducing thermal resistance by more than 60%. The optimized porous configuration delivered nearly four times higher overall performance than a conventional non-porous heat sink under comparable pressure-drop conditions.

Zhou et al. [131] developed an optimization framework for porous-media-enhanced heat transfer systems and employed neural-network-assisted modeling to identify optimal porous medium parameters. The optimized design improved heat dissipation while maintaining acceptable flow resistance and achieved energy savings of approximately 26.8%. The study demonstrated the effectiveness of combining porous media design with data-driven optimization methodologies.

Yifan et al. [132] investigated porous pin-fin heat sinks for liquid cooling of high-power data-center processors. Their results showed that a sparse-to-dense fin arrangement enhances heat dissipation, reduces flow resistance, and lowers pumping power requirements. The optimized configuration reduced chip temperature by 13.4°C while achieving a high performance factor and reduced entropy generation, indicating the suitability of porous pin-fin structures for next-generation data-center cooling systems.

Collectively, the available literature demonstrates that porous media can significantly enhance the thermo-hydraulic performance of microchannel heat sinks through increased heat transfer area, improved fluid-solid interaction, and enhanced thermal diffusion. Nevertheless, the effectiveness of porous-assisted cooling systems is strongly influenced by porosity, permeability, spatial distribution, and filling ratio. Therefore, careful optimization of porous medium characteristics remains essential for achieving maximum thermal enhancement while maintaining acceptable hydraulic and thermodynamic performance.

2.3 Optimization Techniques for Microchannel Heat Sinks

The thermo-hydraulic performance of microchannel heat sinks is governed by a complex interaction among geometric parameters, operating conditions, coolant properties, and enhancement structures. Although various passive enhancement techniques can substantially improve heat transfer, they often introduce additional pressure losses and pumping power requirements. Consequently, achieving an optimal balance between thermal enhancement and hydraulic performance has become a critical design challenge. In recent years, advanced optimization techniques, including Response Surface

Methodology (RSM), Artificial Neural Networks (ANN), Genetic Algorithms (GA), Non-Dominated Sorting Genetic Algorithm-II (NSGA-II), and Technique for Order Preference by Similarity to Ideal Solution (TOPSIS), have been widely employed to identify optimal microchannel configurations capable of satisfying multiple and often conflicting performance objectives.

Yildizeli et al. [133] employed the NSGA-II algorithm to optimize the hydrothermal performance of a rectangular microchannel heat sink. The study generated a set of Pareto-optimal solutions representing different trade-offs between thermal and hydraulic objectives. Their findings demonstrated that no single design can simultaneously maximize all performance criteria, and the final configuration must be selected according to the specific design requirements and operational priorities.

Yang et al. [134] proposed an advanced multi-stage optimization framework for a hybrid microchannel heat sink incorporating a manifold configuration and secondary oblique channels. The methodology integrated Optimal Latin Hypercube Sampling, Pareto analysis, Response Surface Methodology, NSGA-II, and TOPSIS to systematically explore the design space. The optimized configuration achieved an 18.83% reduction in thermal resistance without increasing pumping power, demonstrating the effectiveness of combining statistical and evolutionary optimization techniques for thermal management applications.

Kose et al. [135] performed a comprehensive conjugate heat transfer analysis of rectangular, triangular, and trapezoidal microchannel heat sinks coupled with NSGA-II optimization. By comparing the Pareto fronts generated for different channel geometries, the authors concluded that the rectangular microchannel configuration provides superior overall hydrothermal performance. The study demonstrated the usefulness of multi-objective optimization for evaluating competing design alternatives and identifying the most effective geometry.

Wang et al. [136] developed an optimized microchannel heat sink incorporating cavity structures and straight ribs to improve thermal performance. The optimization framework combined Artificial Neural Networks with a Multi-Objective Genetic Algorithm to determine the optimal geometrical parameters. Their results revealed that a rectangular-rounded straight-rib configuration provides the best overall performance, achieving a thermal enhancement efficiency approximately 9.7% higher than that of non-ribbed designs. The study highlighted the effectiveness of combining machine-learning tools with

evolutionary optimization algorithms for the development of high-performance microchannel heat sinks.

Xie et al. [137] analyzed a disk-shaped microchannel heat sink integrated with baffles for electronic cooling applications. Using Response Surface Methodology in conjunction with Artificial Neural Networks and Genetic Algorithms, the authors identified optimized configurations that significantly improved thermo-hydraulic performance. The optimized design reduced thermal resistance by nearly 49.47% while simultaneously lowering pressure drop by approximately 30.36% relative to the baseline configuration, highlighting the potential of intelligent optimization techniques in heat sink design.

Dadda et al. [138] investigated air-cooled plate-fin heat sinks using a combination of experimental measurements, CFD simulations, and ANN-based surrogate modeling. Their results showed that staggered segmented fins reduced thermal resistance by approximately 46.8% compared to conventional configurations. Furthermore, the ANN model exhibited excellent predictive accuracy ($R^2 > 0.99$), enabling rapid evaluation of design alternatives and facilitating efficient optimization of heat sink performance.

Cui et al. [139] integrated artificial neural networks with multi-objective optimization algorithms to obtain Pareto-optimal solutions for a slot-jet impingement microchannel heat sink. Subsequently, the TOPSIS decision-making approach was employed to identify the most balanced design considering both thermal and hydraulic performance. The optimized configuration maintained the maximum substrate temperature below 73°C under a heat flux of 200 W/cm² while limiting the pressure drop to 5.7 kPa, demonstrating the effectiveness of ANN-assisted multi-criteria optimization for advanced thermal management systems.

Le et al. [140] applied Response Surface Methodology (RSM) to investigate the performance of a multi-nozzle microchannel heat sink equipped with circular fins. The developed predictive model accurately estimated both heat transfer and pressure drop characteristics across the design space. Their analysis revealed that increasing fin diameter promotes vortex generation and fluid mixing, leading to a significant enhancement in thermal performance. The study highlighted the capability of statistical optimization techniques in identifying favorable fin geometries for microchannel heat sinks.

Hou et al. [141] employed a genetic algorithm to optimize a heat sink incorporating a paraffin-copper foam composite phase change material. The optimization process simultaneously considered charging duration and heat sink mass as conflicting objectives.

The optimized configuration achieved a substantial improvement in the charging-time-to-mass ratio compared to the baseline design, demonstrating the potential of evolutionary optimization techniques for enhancing latent heat thermal storage systems.

Mieczkowski et al. [142] performed thermodynamic optimization of a copper heat sink with U-shaped microchannels designed for high-power laser diode cooling. Using the Entropy Generation Minimization (EGM) approach, the authors evaluated a large number of geometric configurations to identify the design with minimum irreversibility. The optimized heat sink reduced entropy generation significantly while improving thermodynamic efficiency and lowering the maximum device temperature, highlights the usefulness of second-law-based optimization methodologies in thermal system design.

Zhai et al. [143] numerically investigated several micro heat sink configurations incorporating different cavity and rib arrangements and assessed their performance using both thermal and exergy-based criteria. The study demonstrated that geometric optimization plays a critical role in balancing heat transfer enhancement and hydraulic losses. Among the investigated configurations, the design featuring triangular cavities and triangular ribs exhibited the best overall thermo-hydraulic performance within the considered Reynolds number range.

Collectively, these studies demonstrate that modern optimization methodologies have become indispensable tools for the design and development of advanced microchannel heat sinks. The integration of machine learning, surrogate modeling, evolutionary algorithms, and multi-criteria decision-making techniques enables efficient exploration of complex design spaces and facilitates the identification of configurations that simultaneously enhance heat transfer, reduce pressure losses, and improve overall system performance. Nevertheless, further research is required to develop optimization frameworks capable of simultaneously incorporating geometric modifications, porous media, micro-pillars, advanced working fluids, and thermodynamic performance indicators within a unified design environment.

2.4 Fabrication Techniques for Microchannel Heat Sinks

The practical implementation of microchannel heat sinks depends not only on their thermo-hydraulic performance but also on the feasibility and accuracy of the manufacturing process. The fabrication technique influences channel dimensions, surface roughness, structural integrity, manufacturing cost, and overall thermal performance.

Consequently, considerable research has been devoted to developing efficient fabrication methods capable of producing microchannels with high dimensional accuracy and complex geometries.

Gábor et al. [144] developed a refined fabrication technology for the integration of microchannel heat sinks with electronic devices at the package level. The proposed manufacturing process allowed the fabrication of different channel layouts while supporting the incorporation of active electronic components within the cooling structure. Experimental evaluation using an advanced thermal characterization method confirmed the practicality of the fabricated microchannel cooling system. The study highlighted the importance of fabrication-process development for achieving reliable and compact chip-level thermal management solutions.

Zhou et al. [145] demonstrated an all-laser fabrication approach for silicon-based microchannel heat sinks, in which laser processing was employed for channel engraving, inlet and outlet drilling, as well as bonding with a quartz cover plate. The proposed method significantly simplified the manufacturing process and reduced fabrication time to less than two hours. Furthermore, the fabricated microchannels exhibited hydrophilic surface characteristics that promoted boiling heat transfer, achieving a critical heat flux of 55.2 W/cm². The study highlighted the potential of laser-based fabrication for rapid and cost-effective production of high-performance microchannel heat sinks.

Nor et al. [146] fabricated a pin-fin-integrated rectangular microchannel heat sink using lithographic techniques and assessed the influence of fabrication quality on thermal performance. The authors employed SEM and EDX analyses to verify the dimensional accuracy and material characteristics of the fabricated microstructures. Their experimental investigation revealed that higher operating temperatures resulted in enhanced heat transfer rates owing to increased thermal driving forces. The study highlighted the capability of lithography for producing complex microchannel geometries while also identifying fabrication precision as a critical factor influencing the successful deployment of advanced pin-fin microchannel heat sinks.

Zhang et al. [147] developed an efficient multi-wire sawing with diamond wire (MWSDW) process for manufacturing ultra-high aspect ratio microchannel heat sinks with dual-scale micro-textured surfaces. Their results showed that the proposed fabrication method offers excellent machining quality while overcoming the high cost and low productivity associated with conventional manufacturing techniques. The generated

micro-textures enhanced convective heat transfer by increasing the effective heat transfer area, with the influence becoming more pronounced at higher mass fluxes. The optimized microchannel configuration exhibited the lowest thermal resistance and pressure drop, demonstrating that surface-texture engineering through advanced manufacturing techniques can significantly improve both thermal performance and large-scale manufacturability of microchannel heat sinks.

Kong et al. [148] developed an additively manufactured manifold–microchannel heat sink using laser powder bed fusion technology and evaluated its thermo-hydraulic performance experimentally and numerically. The monolithic fabrication approach enabled the integration of a complex three-dimensional manifold network with high-aspect-ratio microchannels, promoting improved coolant distribution and heat removal. The fabricated heat sink exhibited low thermal resistance and pressure-drop characteristics while dissipating high heat fluxes, demonstrating the advantages of additive manufacturing for producing compact and geometrically sophisticated cooling devices. The authors further proposed design improvements based on numerical and experimental analyses to enhance the performance of future manifold microchannel heat sinks.

Yang et al. [149] presented a comprehensive review of additively manufactured microchannel heat sinks (AM-MCHSs) for advanced thermal management applications. The authors highlighted that additive manufacturing enables the fabrication of complex geometries that are difficult to achieve using conventional microfabrication techniques, including topology-optimized structures, triply periodic minimal surfaces, bio-inspired flow networks, and multi-layered channel architectures. The review further discussed recent advancements in printable materials, multi-material integration, machine-learning-assisted design optimization, and experimental performance evaluation. The authors concluded that additive manufacturing offers significant potential for reducing thermal resistance and improving temperature uniformity; however, challenges related to fabrication accuracy, material properties, surface quality, and large-scale implementation remain important areas for future research.

Deng et al. [150] comprehensively reviewed recent developments in enhanced microchannels for two-phase microchannel heat sinks, with particular emphasis on both thermal performance and fabrication aspects. The authors demonstrated that flow-disruption structures, re-entrant cavities, porous coatings, and nanostructured surfaces can significantly improve boiling heat transfer and delay critical heat flux limitations.

Furthermore, the review systematically compared various fabrication techniques, including etching, laser processing, micro-EDM, sintering, chemical vapor deposition, and 3D printing, outlining their advantages and limitations. The study emphasized that fabrication capability remains a key factor governing the practical implementation and commercialization of advanced microchannel cooling technologies.

Joy et al. [151] presented a comprehensive review of microchannel fabrication technologies, including laser beam machining, micro-milling, electrical discharge machining (EDM), lithography, injection molding, and dry/wet etching techniques. The authors emphasized that fabrication parameters, channel geometry, and surface quality play crucial roles in determining the thermal and hydraulic performance of microchannel heat sinks. Their review further highlighted that the selection of an appropriate fabrication method, working fluid, and design configuration is essential for achieving reliable and efficient thermal management systems.

Collectively, these studies demonstrate that advancements in fabrication technologies have enabled the development of increasingly complex microchannel geometries while maintaining the dimensional precision required for high-performance thermal management applications. Nevertheless, challenges related to manufacturing cost, scalability, surface quality, and fabrication accuracy continue to influence the practical deployment of advanced microchannel heat sinks.

2.5 Summary of Literature Review

The extensive body of literature reviewed in this chapter demonstrates that microchannel heat sinks have evolved into one of the most effective thermal management solutions for high-heat-flux electronic systems owing to their compact size, high surface-area-to-volume ratio, and superior heat removal capability. Nevertheless, conventional straight microchannels suffer from progressive thermal boundary layer development, limited fluid mixing, and non-uniform temperature distribution, which restrict their thermal performance under increasingly demanding operating conditions. Consequently, considerable research efforts have been directed toward developing advanced microchannel configurations and enhancement strategies to overcome these limitations. Among the various geometrical modifications proposed in the literature, converging-diverging microchannels have emerged as a promising approach for improving heat transfer performance. The periodic variation in channel cross-section promotes repeated

flow acceleration and deceleration, resulting in continuous thermal boundary layer disruption and enhanced fluid mixing. Several studies have reported substantial improvements in heat transfer characteristics compared with conventional straight channels. However, these benefits are often accompanied by increased pressure drop and thermodynamic losses, indicating the need for further refinement of converging-diverging microchannel designs.

In addition to geometric modifications, passive enhancement techniques such as micro-pillars, pin-fins, ribs, cavities, and porous media have been extensively investigated. The incorporation of micro-pillars structures enhances the effective heat transfer area and promotes secondary flow generation, thereby improving convective heat transfer. Similarly, porous media have demonstrated significant potential for augmenting heat dissipation through enhanced fluid-solid interaction and enlarged heat transfer surfaces. Although these techniques substantially improve thermal performance, their effectiveness is strongly dependent on geometric parameters and is frequently associated with increased hydraulic resistance. Therefore, achieving an optimal balance between thermal enhancement and pressure-drop penalty remains a critical challenge.

The use of hybrid nanofluids has also attracted considerable attention as an advanced cooling strategy. Owing to their improved thermophysical properties, hybrid nanofluids have demonstrated superior heat transfer performance compared with conventional coolants and mono-nanofluids. Numerous investigations have reported enhancements in Nusselt number, heat transfer coefficient, and thermal resistance characteristics. However, issues related to increased viscosity, pumping power requirements, nanoparticle deposition, and long-term stability continue to influence their practical implementation. As a result, the selection of appropriate nanoparticle combinations, concentrations, and operating conditions remains an important area of research.

Recent studies have increasingly adopted optimization methodologies such as Response Surface Methodology (RSM), Artificial Neural Networks (ANN), Genetic Algorithms (GA), Non-Dominated Sorting Genetic Algorithm-II (NSGA-II), Multi-Objective Particle Swarm Optimization (MOPSO), and TOPSIS to improve microchannel heat sink performance. These techniques have proven effective in identifying optimal configurations that simultaneously consider multiple conflicting objectives, including heat transfer enhancement, pressure-drop reduction, and thermodynamic efficiency. Nevertheless, most optimization studies have focused on a limited set of design variables

or a single enhancement strategy, leaving substantial opportunities for more comprehensive optimization frameworks.

Overall, the reviewed literature indicates that significant progress has been achieved through the use of converging-diverging microchannels, micro-pillars, porous media, hybrid nanofluids, and advanced optimization techniques. However, the majority of existing investigations have examined these enhancement approaches independently. Comprehensive studies integrating converging-diverging geometries with micro-pillars, porous media, and advanced hybrid nanofluids within a unified optimization framework remain relatively limited. Furthermore, the coupled influence of these enhancement mechanisms on thermo-hydraulic performance, entropy generation, and overall system efficiency has not yet been systematically explored. Therefore, the development of an integrated and optimized converging-diverging microchannel heat sink capable of simultaneously maximizing heat transfer while minimizing hydraulic and thermodynamic penalties remains a significant research challenge. Addressing this gap forms the primary motivation for the present investigation.

2.6 Research Gaps

Although substantial progress has been achieved in the development of microchannel heat sinks for high-heat-flux thermal management applications, the available literature reveals several unresolved challenges that continue to limit their overall thermo-hydraulic and thermodynamic performance. Existing investigations have largely focused on individual enhancement techniques, such as geometric modification, flow-disrupting structures, porous media, advanced working fluids, or optimization approaches. While these studies have provided valuable insights into specific enhancement mechanisms, a comprehensive understanding of their combined influence within converging-diverging microchannel heat sinks remains limited. Furthermore, the complex interactions among flow structures, heat transfer augmentation mechanisms, pressure-drop characteristics, and thermodynamic irreversibilities have not been systematically explored. Therefore, several important research gaps can be identified from the available literature:

- Limited studies have been conducted on a convergent-divergent microchannel heat sink with flow obstacles (pillars, ribs, and cavities).
- There has been limited research on the performance evaluation of convergent-divergent microchannel heat sinks incorporating mono/hybrid nanofluids.

- The hydrothermal performance of convergent-divergent microchannel heat sinks utilizing porous media (either fully or partially filled) has received little attention.
- There is also significant scope for investigating the combined application of nanofluids and porous media within convergent-divergent microchannel heat sinks to exploit potential synergistic enhancement effects.
- Limited research exists on advanced multi-objective optimization frameworks for systematic performance enhancement and decision-making in convergent-divergent microchannel heat sink design.

2.7 Objectives of the Research

Based on the research gaps identified in the preceding section, the present investigation aims to enhance the thermo-hydraulic performance of convergent-divergent microchannel heat sinks for high-performance electronic cooling applications through the incorporation of passive heat transfer enhancement techniques, advanced working fluids, and optimization methodologies. The study seeks to develop a comprehensive understanding of the flow and heat transfer mechanisms associated with these enhancement strategies and to identify configurations capable of achieving superior thermal performance with minimum hydraulic penalty. The specific objectives of the present research are as follows:

1. Numerical analysis of convergent-divergent microchannel heat sink with and without pillars.
2. To investigate the hydrodynamic and heat transfer characteristics of convergent-divergent microchannel heat sink with nanofluids.
3. To investigate the hydrodynamic and heat transfer characteristics of convergent-divergent microchannel heat sink with porous media.
4. Optimize the hydrothermal performance of the convergent-divergent microchannel heat sink.

CHAPTER 3

RESEARCH METHODOLOGY

3.1 Research Framework

The present research is aimed at enhancing the hydrothermal and exergetic performance of convergent-divergent microchannel heat sinks (CD-MCHS) for high heat-flux electronic cooling applications. To achieve this objective, a systematic research framework has been developed that integrates numerical modelling, passive heat-transfer enhancement techniques, and multi-objective optimization to identify thermally efficient and thermodynamically sustainable microchannel configurations.

The investigation is conducted in a progressive manner, beginning with the development of a baseline convergent-divergent microchannel heat sink, which serves as the reference configuration for subsequent analyses. Building upon this baseline design, three passive enhancement approaches, namely micro-pillar integration, hybrid nanofluid cooling, and porous-media-assisted flow enhancement, are independently incorporated and evaluated. These enhancement strategies are selected based on the research gaps identified in Chapter 2 and their demonstrated potential for improving heat transfer performance in microscale thermal management systems.

The hydrothermal and thermodynamic performances of the proposed configurations are assessed using appropriate first-law and second-law performance indicators. The numerical database generated from the simulations is subsequently utilized to develop an integrated optimization and decision-making framework for identifying optimal design solutions under competing performance objectives. The overall research framework adopted in the present study is presented in Figure 3.1.

Figure 3.1 illustrates the overall workflow followed throughout the present investigation. The proposed framework establishes a systematic pathway for evaluating the influence of various passive heat-transfer enhancement techniques on the hydrothermal and thermodynamic performance of convergent-divergent microchannel heat sinks. By

integrating numerical analysis, performance assessment, and optimization within a unified framework, the study enables a comprehensive comparison of the investigated enhancement strategies. Such an approach facilitates the identification of configurations that simultaneously enhance heat transfer performance and reduce thermodynamic irreversibilities, thereby contributing to the development of efficient and sustainable thermal management solutions for next-generation electronic cooling applications.

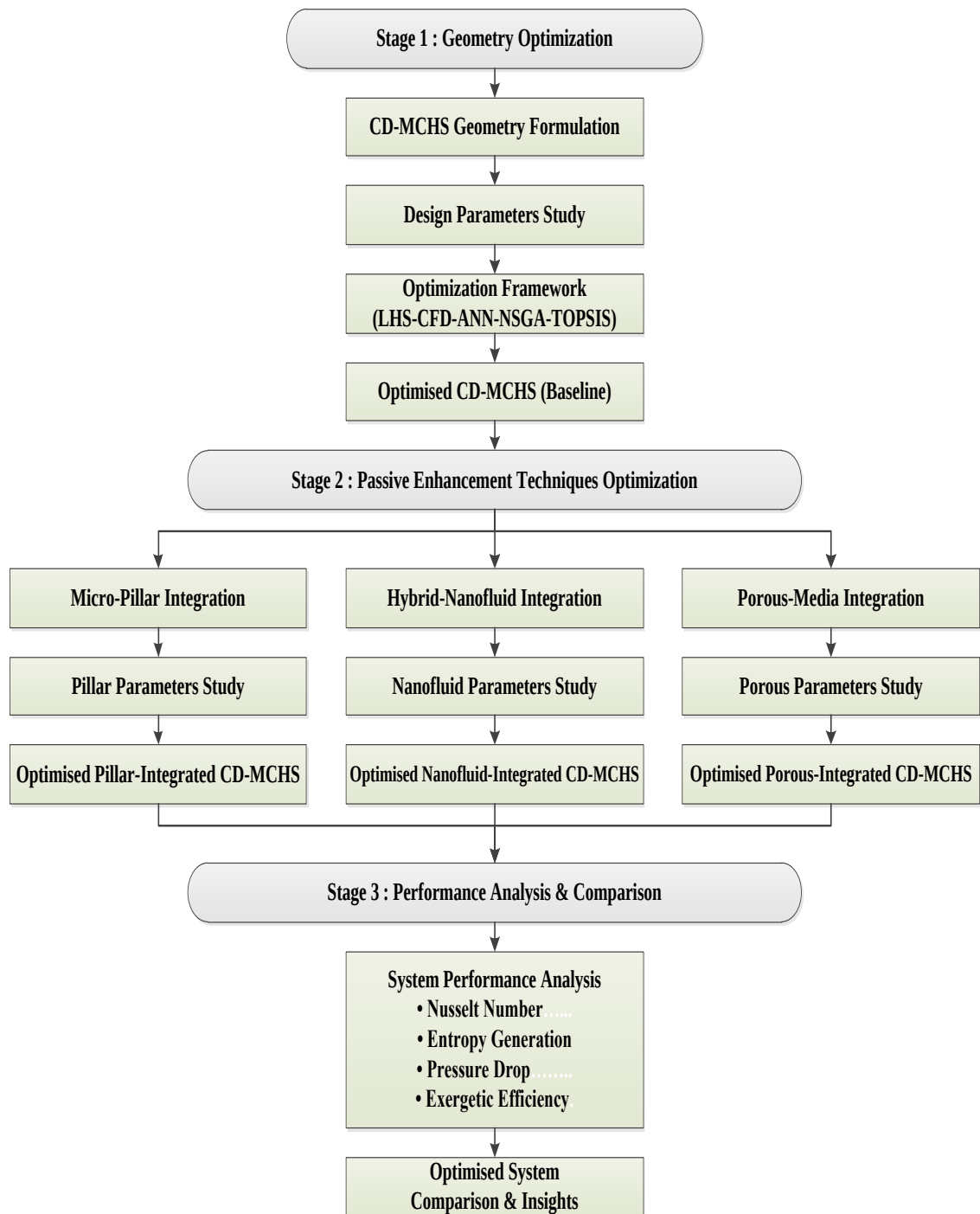


Figure 3.1: Overall research framework of the present study

3.2 Problem Description

This section describes the physical model, geometric configuration, and operating conditions considered in the present investigation. A convergent-divergent microchannel heat sink is adopted as the baseline configuration and serves as the reference model for all subsequent analyses. The proposed configuration is designed to enhance fluid mixing and promote periodic redevelopment of the thermal boundary layer, thereby improving heat transfer performance under high heat-flux operating conditions. The baseline geometry is subsequently utilized for the incorporation of various passive enhancement techniques, including micro-pillars, hybrid nanofluids, and porous media, investigated in later stages of the study.

3.2.1 Baseline Convergent-Divergent Microchannel Heat Sink Configuration

A three-dimensional convergent-divergent microchannel heat sink (CD-MCHS) is considered in the present study. The microchannel possesses a trapezoidal cross-section throughout its length, while a periodic convergent-divergent profile is incorporated along the flow direction. The overall dimensions of the heat sink are $10 \text{ mm} \times 10 \text{ mm} \times 1 \text{ mm}$ (length $\times$ width $\times$ height), which are representative of compact cooling devices employed in modern electronic systems. The heat sink is fabricated from copper owing to its high thermal conductivity and widespread use in electronic cooling applications, while deionized water is employed as the baseline working fluid.

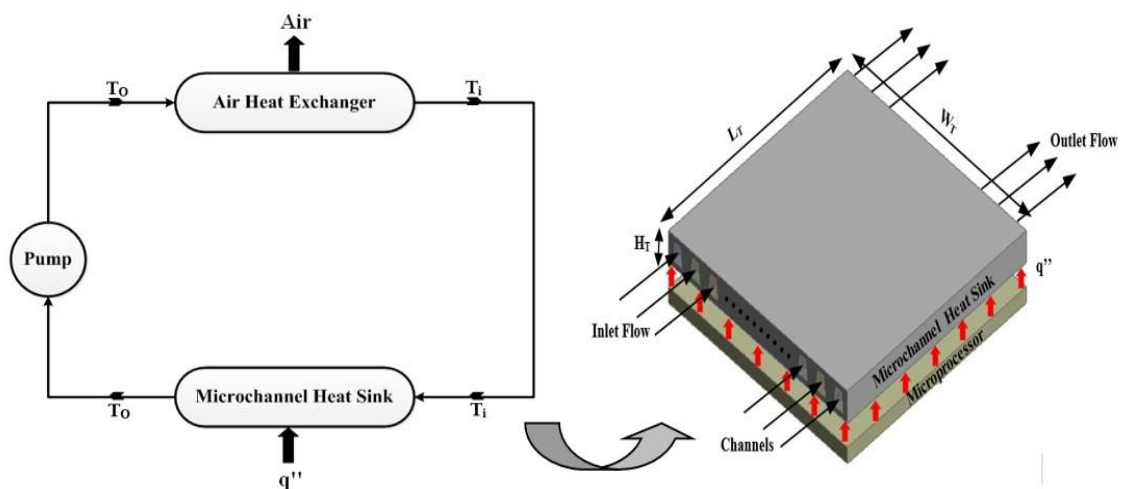


Figure 3.2: Schematic representation of the convergent-divergent microchannel heat sink cooling system

As shown in Figure 3.2, the microchannel heat sink forms an integral part of a closed-loop liquid-cooling system, wherein the coolant absorbs heat generated by the electronic device and subsequently transports it for dissipation to the surroundings. The heat sink consists of N_1 parallel microchannels distributed uniformly across the substrate width, with each microchannel comprising N_2 successive convergent-divergent segments along the flow direction, forming a periodically varying flow passage. The periodic variation in channel cross-section promotes repeated acceleration and deceleration of the coolant, resulting in continuous disruption and redevelopment of the thermal boundary layer, thereby enhancing convective heat transfer.

A uniform heat flux of 150 W/cm^2 is applied at the bottom surface of the heat sink to represent the thermal load generated by high-power electronic components. All remaining external surfaces are considered thermally insulated. The coolant enters the microchannels at an inlet temperature of 298 K and exits through the outlet after absorbing heat from the substrate.

Owing to the geometric periodicity and symmetry of the microchannel arrangement, the computational domain is reduced to a representative unit cell without affecting the accuracy of the numerical solution. This approach substantially decreases computational cost while preserving the essential flow and heat transfer characteristics of the complete heat sink. The corresponding unit microchannel configuration and flow domain adopted for the numerical simulations are illustrated in Figure 3.3.

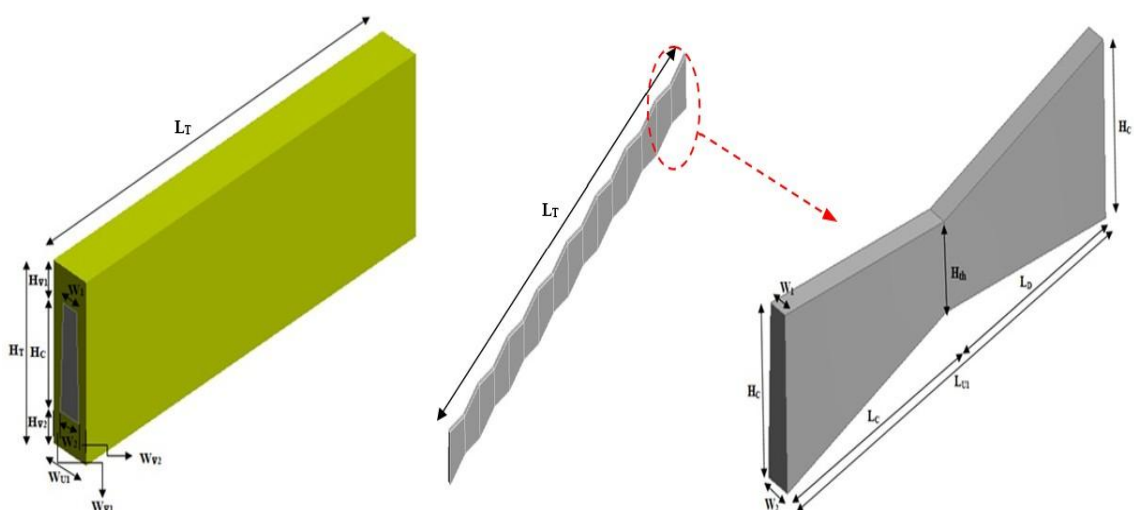


Figure 3.3: Geometric configuration of the representative unit microchannel heat sink and corresponding computational domain

The geometric characteristics of the CD-MCHS are defined using seven independent design parameters, namely Reynolds number (Re), top-to-bottom width ratio (α), bottom-to-pitch width ratio (β), channel-to-total height ratio (γ), throat-to-channel height ratio (δ), number of parallel channels (N_1), and number of convergent-divergent segments arranged in series (N_2). These parameters govern the flow distribution, heat transfer characteristics, and overall hydrothermal performance of the microchannel heat sink. The constant geometric dimensions and state design-variable considered in the present investigation are summarized in Table 3.1.

Table 3.1: Description of constant and state design variables of the CD-MCHS

Type of Variable	Symbol	Description	Value
Constant	L_T	Total length of microchannel heat sink	10 mm
	W_T	Total width of microchannel heat sink	10 mm
	H_T	Total height of microchannel heat sink	1 mm
State	W_{U1}	Pitch width	$\frac{W_T}{N_1}$
	L_{U1}	Pitch length	$\frac{L_T}{N_2}$
	W_1	Top width of the channel	$\alpha \cdot W_2$
	W_2	Bottom width of the channel	$\beta \cdot W_{U1}$
	H_c	Height of the channel	$\gamma \cdot H_T$
	H_{th}	Height of the throat	$\delta \cdot H_c$

To ensure geometric consistency and physical feasibility throughout the design space, appropriate geometric constraints are imposed on the channel dimensions and substrate thicknesses. These constraints maintain symmetry of the flow passage and prevent the generation of unrealistic geometric configurations during the optimization process. The adopted constraints are presented in Table 3.2.

Table 3.2: Design constraints of the study

S. No.	Mathematical Expression
1	$W_{V1} = W_{V2} \ ; \ W_{V1} + W_2 + W_{V2} = W_{U1}$
2	$H_{V1} = H_{V2} \ ; \ H_{V1} + H_c + H_{V2} = H_T$
3	$L_c = L_D \ ; \ L_c + L_D = L_{U1}$

Table 3.3 presents the thermophysical properties of the materials employed in the present investigation at a reference temperature of 298 K. The thermophysical properties of the copper substrate are assumed to remain constant throughout the numerical simulations. In contrast, the properties of the working fluid are treated as temperature-dependent and are evaluated using the appropriate correlations presented in the subsequent sections of this chapter.

Table 3.3: Thermo-physical properties of the substrate employed in the microchannel heat sink [82]

Particle	k (W/mK)	ρ (kg/m ³)	C_p (J/kg.K)	μ (kg/m.s)
Copper	401	8933	385	-
Pure Water	0.613	997	4179	0.000855

The geometric configuration, operating conditions, and material properties presented in this section constitute the baseline model adopted throughout the present investigation. This reference configuration provides a consistent basis for the comparative assessment of the enhancement techniques considered in the subsequent sections.

3.2.2 Micro-Pillar-Integrated CD-MCHS Configuration

To further enhance the hydrothermal performance of the baseline convergent-divergent microchannel heat sink, passive heat-transfer enhancement through the integration of micro-pillars is investigated. Micro-pillars are incorporated within the flow domain of the optimized baseline configuration to promote flow disturbance, enhance fluid mixing, and increase the effective heat transfer area for convection. In addition, the presence of micro-pillars alters the local flow structure and promotes repeated redevelopment of the thermal boundary layer, thereby improving heat transfer from the heated substrate to the coolant. These mechanisms collectively contribute to enhanced thermal transport characteristics while maintaining the inherent advantages of passive cooling techniques.

The micro-pillars are embedded within the microchannel and are oriented normal to the flow direction, extending across the local channel height. A perfect thermal contact is assumed between the micro-pillars and the substrate material, thereby allowing efficient conduction of heat from the solid domain to the coolant flowing through the microchannel. The incorporation of micro-pillars within the convergent-divergent passage provides an

effective means of intensifying fluid-solid thermal interaction and is therefore expected to improve the overall hydrothermal performance of the microchannel heat sink.

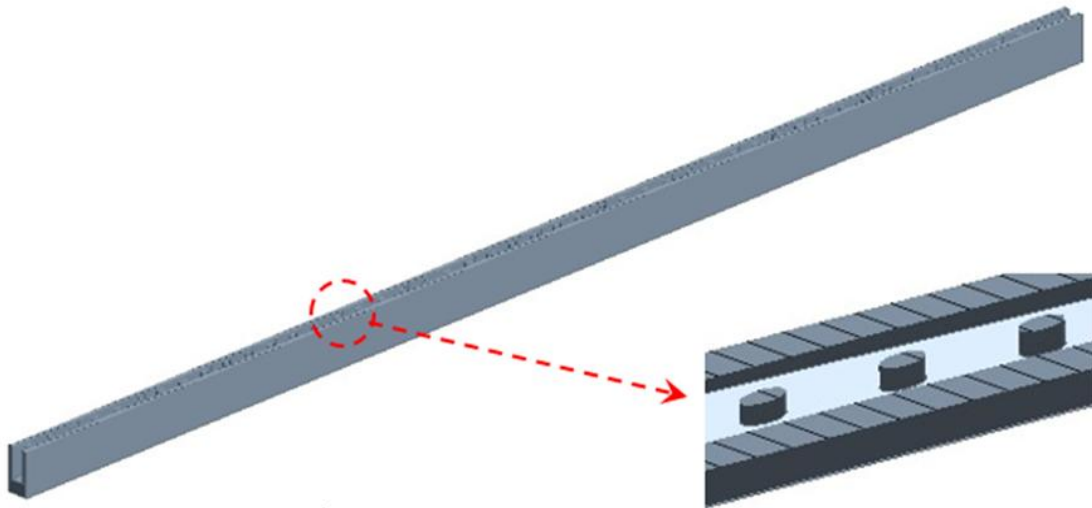


Figure 3.4: Schematic representation of micro-pillars integrated within the CD-MCHS flow domain

As illustrated in Figure 3.4, the micro-pillars are strategically positioned within the convergent-divergent flow passage to interact directly with the coolant stream. The presence of these structures modifies the local flow field, generating flow acceleration, wake formation, and enhanced mixing in their vicinity. Consequently, the thermal boundary layer development is altered, resulting in improved convective heat transfer performance compared with the baseline configuration.

To investigate the influence of pillar geometry on hydrothermal performance, four different micro-pillar cross-sectional geometries are considered, namely elliptical, circular, square, and rhombic configurations, as illustrated in Figure 3.5. The elliptical micro-pillar is selected as the reference geometry and is characterized by a semi-major axis $a = 25 \mu\text{m}$ and a semi-minor axis $b = 12.5 \mu\text{m}$.

In addition to the pillar geometry, the spatial arrangement of the micro-pillars is carefully designed to maximize fluid–structure interaction within the microchannel. Successive micro-pillars are positioned alternately on either side of the channel centreline, resulting in a staggered arrangement that creates a zigzag flow path for the coolant. This offset configuration promotes lateral fluid motion and repeated interaction between the core flow and the channel walls, thereby enhancing fluid mixing and facilitating continuous redevelopment of the thermal boundary layer. The combined effect of pillar geometry and

staggered arrangement is expected to improve the overall hydrothermal performance of the CD-MCHS.

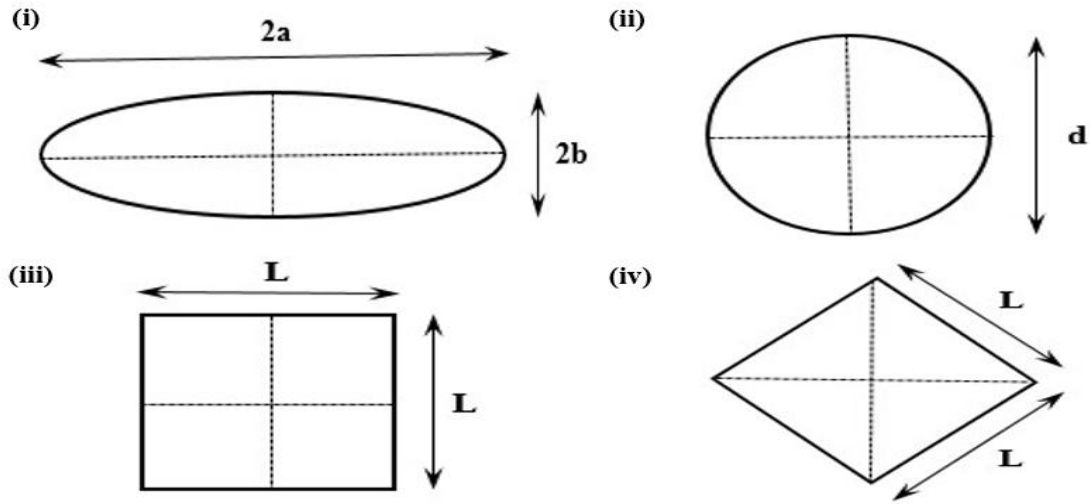


Figure 3.5: Cross-sectional geometries of micro-pillars considered in the present study under equivalent-perimeter criterion: i) elliptical, ii) circular, iii) square, and iv) rhombic

To ensure a meaningful comparison among the different pillar geometries, an equivalent-perimeter criterion is adopted. Under this approach, all micro-pillar configurations possess an identical wetted perimeter, thereby maintaining a comparable fluid-solid interaction area while isolating the influence of geometric shape on the hydrothermal behaviour of the microchannel.

The perimeter of the reference elliptical micro-pillar is evaluated using the relation [152]:

$$P_e = \pi(a + b) \left[1 + \frac{3h}{10 + \sqrt{4 - 3h}} \right] \quad (3.1)$$

$$h = \left(\frac{a-b}{a+b} \right)^2 \quad (3.2)$$

The equivalent-perimeter criterion is expressed as:

$$P_e = P_c = P_{s,r} \quad (3.3)$$

Where P_e , P_c , and $P_{s,r}$ represent the perimeters of the elliptical, circular, and square/rhombic micro-pillars, respectively.

The characteristic dimensions of the circular, square, and rhombic micro-pillars are subsequently determined from the equivalent-perimeter criterion. Consequently, all pillar geometries possess approximately the same wetted perimeter, allowing the effect of shape-induced flow modification to be investigated independently of variations in fluid-solid contact area.

The micro-pillar configuration is further parameterized using key design variables such as pillar geometry, nanoparticle volume fraction, pillar count, and spatial arrangement, including pitch, offset, and axial positioning. The pillar shape is treated as a discrete design variable $P_d \in [1-4]$ for integration into the optimization framework, where $P_d = 1$ represents elliptical, $P_d = 2$ circular, $P_d = 3$ square, and $P_d = 4$ rhombic geometry. A $\text{Fe}_3\text{O}_4/\text{water}$ nanofluid is used as the working fluid, and perfect thermal contact between the substrate and micro-pillars is assumed.

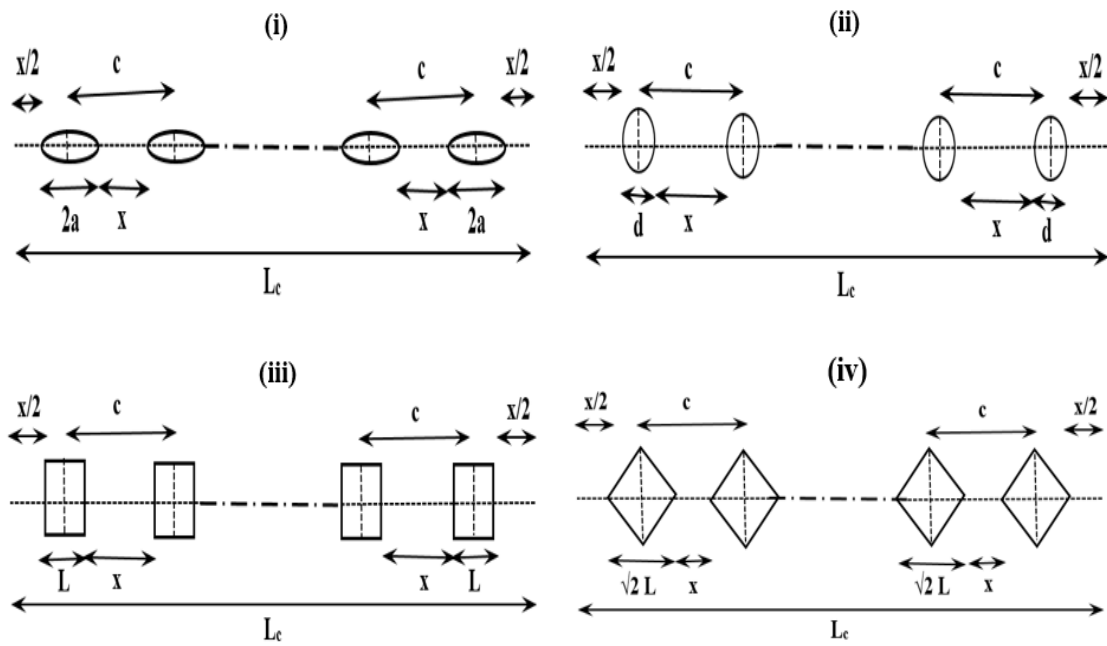


Figure 3.6: Spatial arrangement of micro-pillar arrays within CD-MCHS: i) elliptical, ii) circular, iii) square, iv) rhombic

Figure 3.6 presents the spatial arrangement of micro-pillar arrays within the convergent-divergent microchannel. The distribution is defined based on the converging length L_c and the number of pillars n in each segment. A uniform arrangement is maintained, where the surface-to-surface spacing, centre-to-centre pitch, and axial positions of the pillars are systematically determined using Eqs. (3.4)-(3.7):

Surface-to-surface spacing between adjacent micro-pillars is defined as:

$$x = \frac{L_c}{n} - D_g \quad (3.4)$$

The centre-to-centre pitch between adjacent micro-pillars is then expressed as:

$$c = x + D_g \quad (3.5)$$

The axial location of the centre of the i^{th} micro-pillar array measured from the channel inlet is determined by:

$$e_i = \frac{L_c}{2n} + (n - 1) * c \quad (3.6)$$

Finally, the total number of micro-pillars in the computational domain, accounting for all convergent-divergent segments, is given by:

$$P_c = 16 * n \quad (3.7)$$

In the above relations, D_g represents the characteristic dimension of the selected micro-pillar geometry, corresponding to $2a$ for the elliptical configuration, d for the circular configuration, L for the square configuration, and $\sqrt{2}L$ for the rhombic configuration. These geometric relations ensure a uniform pillar distribution throughout the microchannel and provide a systematic framework for evaluating the influence of pillar shape and arrangement on hydrothermal performance.

The micro-pillar-integrated CD-MCHS configuration described in this section constitutes the physical model adopted for investigating the influence of pillar geometry and spatial arrangement on the hydrothermal and exergetic performance of the microchannel heat sink. The resulting configuration provides the basis for the subsequent numerical analysis and optimization studies presented in this thesis.

3.2.3 Hybrid Nanofluid-Based CD-MCHS Configuration

To further enhance the thermal performance of the convergent-divergent microchannel heat sink, a hybrid nanofluid is employed as the working coolant. The use of hybrid nanofluids has emerged as an effective passive heat-transfer enhancement technique owing to their superior thermophysical properties compared with conventional base fluids and mono-nanofluids. By combining nanoparticles with different thermal characteristics, hybrid nanofluids can simultaneously improve thermal conductivity and energy transport capability, thereby enhancing convective heat transfer within microscale cooling systems. In the present study, a water-based tri-hybrid nanofluid consisting of copper oxide (CuO), aluminium oxide (Al_2O_3), and silver (Ag) nanoparticles is considered. The selection of these nanoparticles is motivated by their favourable thermal properties and their demonstrated potential for improving heat transfer performance in electronic cooling applications. The hybrid nanofluid is circulated through the optimized CD-MCHS configuration to evaluate its influence on the hydrothermal and thermodynamic behaviour of the system.

To simplify the numerical analysis, the hybrid nanofluid is assumed to be homogeneous, stable, and uniformly dispersed throughout the flow domain. The effects of particle agglomeration, sedimentation, and slip velocity between the nanoparticles and the base fluid are neglected. Consequently, a single-phase approach is adopted, wherein the nanofluid is treated as an equivalent homogeneous fluid possessing effective thermophysical properties.

The formulation of the hybrid nanofluid configuration is governed by several design variables, including the total nanoparticle volume fraction and the individual volume fractions of CuO, Al₂O₃, and Ag nanoparticles. This parameterization enables a systematic investigation of the influence of nanoparticle concentration and composition on the thermal and hydraulic performance of the microchannel heat sink.

Table 3.4: Thermophysical properties of the nanoparticles [21]

Particle	k (W/mK)	ρ (kg/m ³)	C_p (J/kg.K)
CuO	76	6500	533
Al ₂ O ₃	40	3970	769
Ag	429	10500	237

The thermophysical properties of the constituent nanoparticles used in the present study are summarized in Table 3.4. The effective thermophysical properties of the hybrid nanofluid are determined using established correlations reported in the literature. The mathematical formulations employed for evaluating the effective density, specific heat capacity, thermal conductivity, and dynamic viscosity of the hybrid nanofluid are presented in the subsequent sections of this chapter.

The hybrid nanofluid-based CD-MCHS configuration described in this section serves as the physical model for investigating the influence of nanoparticle concentration and composition on the hydrothermal and exergetic performance of advanced microchannel heat sinks. The resulting configuration provides the basis for the subsequent numerical analysis and optimization studies presented in this thesis.

3.2.4 Porous-Media-Assisted CD-MCHS Configuration

To further improve the hydrothermal performance of the convergent-divergent microchannel heat sink, porous media is incorporated as an additional passive heat-

transfer enhancement technique. Unlike the micro-pillar configuration, the incorporation of porous media does not alter the physical geometry of the microchannel. Instead, the fluid domain is treated as a porous region characterized by specified porosity, pore diameter, permeability, and inertial resistance parameters. The introduction of porous structures increases the effective fluid-solid contact area and promotes enhanced thermal interaction between the coolant and the heated substrate.

Porous media has attracted considerable attention in advanced thermal management applications owing to its large specific surface area and superior heat-spreading capability. The presence of a porous matrix facilitates heat transfer by providing additional conductive and convective pathways within the flow domain. Furthermore, the porous structure promotes a more uniform temperature distribution and improves heat dissipation from the heated surface, making it a promising approach for high heat-flux electronic cooling applications.

In the present study, the porous medium is integrated throughout the flow passage of the optimized CD-MCHS configuration. The porous matrix acts as an extended heat-transfer structure that facilitates thermal energy transport from the heated substrate to the coolant while simultaneously modifying the flow resistance characteristics within the microchannel. Consequently, the overall thermal performance of the system can be improved through enhanced fluid-solid thermal interaction.

For numerical modelling, the porous medium is assumed to be homogeneous, isotropic, rigid, and non-deformable. The flow through the porous region is represented using the Darcy-Forchheimer approach, which accounts for both viscous and inertial resistance effects within the porous matrix. In addition, local thermal equilibrium (LTE) between the fluid and solid phases is assumed, implying that both phases remain at the same local temperature. Under this assumption, a single energy equation is sufficient to describe heat transfer within the porous domain.

The porous-media-enhanced configuration is parameterized using several geometric and material variables, including porosity (ϵ), pore diameter (d_p), and porous material type. Porosity governs the available flow volume and fluid-solid contact area within the porous structure, whereas pore diameter significantly influences permeability and flow resistance characteristics. These parameters collectively determine the hydrothermal behaviour of the porous microchannel heat sink and therefore constitute important design variables within the present investigation.

In addition to the porous structure parameters, the porous material itself is treated as a discrete design variable within the optimization framework. The material selection variable is represented by $M_c \in [1-4]$, where $M_c = 1$ represents copper, $M_c = 2$ aluminium, $M_c = 3$ bronze, and $M_c = 4$ nickel. These materials are selected owing to their distinct thermophysical properties and widespread use in thermal management applications. The inclusion of material selection as a design variable enables a systematic assessment of the influence of solid matrix properties on the hydrothermal and thermodynamic performance of the porous-media-assisted CD-MCHS.

Table 3.5: Thermophysical properties of the porous substrates [152]

Particle	k (W/mK)	ρ (kg/m ³)	C_p (J/kg.K)
Copper	401	8933	385
Aluminum	170	2787	883
Bronze	26	8666	343
Nickel	90	8908	444

Table 3.5 summarizes the thermophysical properties of the porous materials employed in the present investigation. The effective thermophysical properties of the porous medium, together with the permeability and inertial resistance coefficients required for the Darcy-Forchheimer formulation, are evaluated using established correlations reported in the literature. The corresponding mathematical formulations are presented in the subsequent sections of this chapter.

The porous-media-assisted CD-MCHS configuration described in this section constitutes the physical model adopted for investigating the influence of porous structure characteristics and material selection on the hydrothermal and exergetic performance of the microchannel heat sink. The resulting configuration provides the basis for the subsequent numerical analysis and optimization studies presented in this thesis.

3.3 Mathematical Formulation

The baseline and enhanced configurations described in the preceding sections constitute the physical models investigated in the present study. To predict the fluid flow, heat transfer, and thermodynamic behaviour within these configurations, a comprehensive numerical model is developed based on the fundamental principles of conservation of

mass, momentum, and energy. Prior to formulating the governing equations, a set of simplifying assumptions is introduced to facilitate the numerical analysis while preserving the essential physical characteristics of the problem. The mathematical formulation subsequently incorporates the governing transport equations, thermophysical property models, porous-medium formulations, and performance evaluation criteria required for the hydrothermal and exergetic assessment of the proposed microchannel heat sink configurations. The details of the mathematical model are presented in the following sections.

3.3.1 Modelling Assumptions

The following assumptions are adopted for the numerical modelling of the baseline and enhanced CD-MCHS configurations. Where applicable, additional assumptions specific to micro-pillar, hybrid nanofluid, and porous-media configurations are also incorporated:

- Three-dimensional single-phase fluid flow is considered.
- The coolant is incompressible, and the flow is laminar.
- Flow is considered under steady-state conditions.
- All channels are identical; hence, a single representative channel with adjacent solid substrate is analyzed.
- Body forces, viscous dissipation, and thermal radiation effects are neglected.
- Temperature-dependent thermophysical properties are applied to fluid, while solid properties remain constant.
- The ambient (dead state) temperature is assumed equal to the inlet fluid temperature.
- All walls except the heat-flux surface are adiabatic, so the energy input is fully carried away by the coolant.
- The micro-pillars are assumed to be in perfect thermal contact with the heat sink substrate; therefore, thermal contact resistance at the pillar-substrate interface is neglected.
- Nanoparticle agglomeration, sedimentation, and slip velocity effects are neglected.
- Local thermal equilibrium (LTE) is assumed within the porous medium.

The above assumptions are consistent with those widely adopted in numerical investigations of microscale electronic cooling systems and are considered appropriate for modelling the baseline as well as the enhanced CD-MCHS configurations investigated in

the present study. These assumptions provide a reasonable balance between computational efficiency and physical realism while preserving the dominant transport mechanisms governing fluid flow and heat transfer within the microchannel heat sinks.

3.3.2 Governing Equations

The fluid flow and heat transfer characteristics within the baseline and enhanced CD-MCHS configurations are governed by the fundamental conservation equations of mass, momentum, and energy. The governing equations are formulated under the assumptions presented in the previous section and are applied to the fluid and solid domains as appropriate. For conjugate heat transfer analysis, the fluid and solid domains are coupled at the fluid-solid interface through the continuity of temperature and heat flux.

The continuity equation expressing conservation of mass is given by [82]:

$$\nabla \cdot V = 0 \quad (3.8)$$

For the non-porous flow domain, momentum conservation equation is expressed as [82]:

$$\rho_f (V \cdot \nabla) V = -\nabla P + \mu_f \nabla^2 V \quad (3.9)$$

For the porous-medium configuration, the momentum equation is modified using the Darcy-Forchheimer model to account for viscous and inertial resistance effects within the porous matrix and is written as [38]:

$$\frac{\rho_f}{\varepsilon^2} (V \cdot \nabla) V = -\nabla P + \frac{\mu}{\varepsilon} \nabla^2 V - \frac{\mu}{K_p} V - \frac{C_f \rho_f}{\sqrt{K_p}} |V| \quad (3.10)$$

The energy conservation equation governing heat transfer within the fluid domain is given by [82]:

$$(\rho C_p)_f V \cdot \nabla T = \nabla \cdot (k_f \nabla T) \quad (3.11)$$

Heat conduction within the solid substrate is described by the steady-state energy equation [82]:

$$k_s (\nabla^2 T) = 0 \quad (3.12)$$

In the above equations, V denotes the velocity vector, P represents pressure, T is temperature, ρ is density, μ is dynamic viscosity, k is thermal conductivity, C_p is specific heat capacity, ε is porosity, K_p is permeability, and C_f is the inertial resistance coefficient. The subscripts f and s refer to the fluid and solid domains, respectively.

3.3.3 Thermophysical Property Models

The accuracy of the numerical predictions strongly depends upon the appropriate evaluation of thermophysical properties. Different thermophysical property models are therefore adopted for the working fluids and porous media considered in the present study, including pure water, mono-nanofluids, hybrid nanofluids, and porous-medium configurations.

3.3.3.1 Temperature-Dependent Properties of Water

The thermophysical properties of water are evaluated as functions of temperature using established correlations available in the literature. The density, dynamic viscosity, thermal conductivity, and specific heat capacity are calculated using the following relations [82]:

$$\rho_f = 2446 - 20.674T + 0.1157T^2 - 3.1289 * 10^{-4}T^3 + 4.0505 * 10^{-7}T^4 - 2.055 * 10^{-10}T^5 \quad (3.13)$$

$$\mu_f = 2.414 * 10^{-5} * 10^{\left(\frac{247.8}{T-140}\right)} \quad (3.14)$$

$$C_{pf} = 8958.9 - 40.535T + 0.11243T^2 - 1.04 * 10^{-4}T^3 \quad (3.15)$$

$$k_f = -1.13 + 9.71 * 10^{-3}T - 1.31 * 10^{-5}T^2 \quad (3.16)$$

The above correlations are valid over the temperature range encountered during the present simulations and enable accurate representation of the variation of water properties with temperature.

3.3.3.2 Mono-Nanofluid Property Models

For the micro-pillar-enhanced configuration, Fe₃O₄/water nanofluid is employed as the working coolant. A single-phase approach is adopted, and the effective thermophysical properties are determined using established mixture relations [121].

$$(\rho)_{nf} = (1 - \varphi)\rho_f + \varphi * \rho_{np} \quad (3.17)$$

$$(C_p)_{nf} = \left((1 - \varphi)(\rho * C_p)_f + \varphi(\rho * C_p)_{np} \right) / \rho_{nf} \quad (3.18)$$

$$k_{nf} = k_f \left[\frac{((k_{np} + 2k_f) - 2\varphi(k_f - k_{np}))}{((k_{np} + 2k_f) + \varphi(k_f - k_{np}))} \right] \quad (3.19)$$

$$\mu_{nf} = \mu_f(1 + 2.5\varphi), \varphi \leq 2\% \quad (3.20)$$

In the above relations, φ denotes the nanoparticle volume fraction, while the subscripts f , np , and nf represent the base fluid, nanoparticle, and nanofluid, respectively.

3.3.3.3 Hybrid Nanofluid Property Models

For the hybrid nanofluid-based CD-MCHS configuration, a water-based CuO-Al₂O₃-Ag tri-hybrid nanofluid is considered. The effective thermophysical properties are evaluated by combining the contributions of the individual nanoparticle species according to the following mixture models relations [110].

$$\sum_{j=1}^3 f_j = 100 \quad (3.21)$$

$$j = \begin{cases} 1 ; CuO \\ 2 ; Al_2O_3 \\ 3 ; Ag \end{cases} \quad (3.22)$$

$$\Phi_i = \frac{f_j \Phi_T}{100} \quad (3.23)$$

$$(\rho)_{hnf} = \sum_{i=1}^3 \Phi_i \rho_i + (1 - \Phi_T) \rho_f \quad (3.24)$$

$$\sum_{i=1}^3 \Phi_i = \Phi_T \quad (3.25)$$

$$(C_p)_{hnf} = \frac{1}{\Phi_T} \sum_{i=1}^3 \Phi_i (\rho C_p)_i + (1 - \Phi_T) (\rho C_p)_f \quad (3.26)$$

$$k_{\Phi i} = k_f \left[\frac{((k_i + 2k_f) - 2\Phi_i(k_f - k_i))}{((k_i + 2k_f) + \Phi_i(k_f - k_i))} \right] \quad (3.27)$$

$$k_{hnf} = \frac{1}{\Phi_T} \sum_{i=1}^3 \Phi_i k_{\Phi i} \quad (3.28)$$

$$\mu_{\Phi i} = \mu_f (1 + 2.5\Phi_i) \quad (3.29)$$

$$\mu_{hnf} = \frac{1}{\Phi_T} \sum_{i=1}^3 \Phi_i \mu_{\Phi i} \quad (3.30)$$

Here, Φ_T represents the total nanoparticle volume fraction, f_j denotes the percentage contribution of the j^{th} nanoparticle species, and Φ_i corresponds to the effective volume fraction of each constituent nanoparticle.

3.3.3.4 Porous-Medium Properties

For the porous-media-assisted CD-MCHS configuration, effective thermophysical properties are employed to represent the combined behaviour of the fluid and solid phases within the porous matrix. Under the assumption of local thermal equilibrium (LTE), the effective density, volumetric heat capacity, and thermal conductivity are calculated as follows [121]:

$$\rho_{eff} = \varepsilon \cdot \rho_f + (1 - \varepsilon) \cdot \rho_s \quad (3.31)$$

$$(\rho C_p)_{eff} = \varepsilon (\rho C_p)_f + (1 - \varepsilon) (\rho C_p)_s \quad (3.32)$$

$$k_{eff} = \varepsilon \cdot k_f + (1 - \varepsilon) \cdot k_s \quad (3.33)$$

In the above relations, ε denotes the porosity of the porous medium, while the subscripts f , s , and eff represent the fluid phase, solid phase, and effective porous-medium properties, respectively.

The thermophysical property models presented in this section provide the material parameters required for solving the governing equations and evaluating the hydrothermal and thermodynamic performance of the various CD-MCHS configurations investigated in the present study.

3.3.4 Permeability and Inertial Coefficient Formulations

The Darcy-Forchheimer momentum model employed for the porous-media-assisted CD-MCHS requires the evaluation of permeability and inertial resistance coefficients to characterize flow transport within the porous matrix. These parameters are determined using the well-established Ergun correlations based on the porosity and pore diameter of the porous medium [152].

$$K_P = \frac{\varepsilon^3 d_p^2}{180 \cdot (1 - \varepsilon)^2} \quad (3.34)$$

$$C = \frac{1.75(1 - \varepsilon)}{\varepsilon^3 d_p} \quad (3.35)$$

$$Da = \frac{K_P}{D_h^2} \quad (3.36)$$

Where K_P denotes the permeability of the porous medium, C represents the inertial resistance coefficient, ε is the porosity, d_p is the pore diameter, D_h is the hydraulic diameter of the microchannel, and Da is the Darcy number. The Darcy number provides a measure of the relative influence of permeability on fluid flow within the porous domain and is widely used to characterize transport phenomena in porous microchannel systems.

3.4 Performance Evaluation Metrics

To quantitatively assess the hydrothermal and thermodynamic performance of the proposed microchannel heat sink configurations, several first-law and second-law performance indicators are employed. The selected parameters enable a comprehensive evaluation of heat transfer enhancement, flow resistance characteristics, thermal management effectiveness, and thermodynamic irreversibilities. The mathematical formulations adopted in the present study are presented in the following sections.

3.4.1 Heat Transfer Characteristics

The heat transfer performance of the microchannel heat sink is evaluated using the average Nusselt number, which represents the ratio of convective to conductive heat transfer across the fluid domain. The average Nusselt number is expressed as [121]:

$$Nu_{av} = \frac{h_{av}(D_h)_{eq}}{K_f} \quad (3.37)$$

Where h_{av} denotes the average convective heat transfer coefficient, k_f is the thermal conductivity of the working fluid, and $(D_h)_{eq}$ represents the equivalent hydraulic diameter of the convergent-divergent microchannel.

The average convective heat transfer coefficient is determined from [121]:

$$h = \frac{Q_f}{A_h \Delta T_m} = \frac{q''}{T_w - T_b} \quad (3.38)$$

Where q'' is the imposed heat flux, T_w is the average temperature of the heated wall, and T_b represents the bulk fluid temperature.

The bulk fluid temperature is evaluated as [121]:

$$T_b = \frac{T_{in} + T_{out}}{2} \quad (3.39)$$

For the convergent-divergent microchannel, an equivalent hydraulic diameter is employed to account for the variation in cross-sectional dimensions along the flow direction and is calculated as [121]:

$$(D_h)_{eq} = \frac{(D_h)_{in} + (D_h)_{th} + (D_h)_{out}}{3} \quad (3.40)$$

The hydraulic diameters at the inlet/outlet and throat sections are respectively determined from [121]:

$$(D_h)_{in, out} = \frac{2(W_1 + W_2)H_c}{(W_1 + W_2) + 2\sqrt{\left(\frac{W_2 - W_1}{2}\right)^2 + (H_c)^2}} \quad (3.41)$$

$$(D_h)_{th} = \frac{2(W_1 + W_2)H_{th}}{(W_1 + W_2) + 2\sqrt{\left(\frac{W_2 - W_1}{2}\right)^2 + (H_{th})^2}} \quad (3.42)$$

The Reynolds number, used to characterize the flow regime, is defined as [121]:

$$Re = \frac{\rho_f U_{in} (D_h)_{in}}{\mu_f} \quad (3.43)$$

Where ρ_f , μ_f , and U_{in} denote the fluid density, dynamic viscosity, and inlet velocity, respectively.

3.4.2 Pressure Drop and Pumping Power

The hydrodynamic performance of the microchannel is assessed using pressure drop, friction factor, and pumping power. The pressure drop across the microchannel is evaluated from [121]:

$$\Delta P = P_{in} - P_{out} \quad (3.44)$$

Where P_{in} and P_{out} represent the area-averaged pressures at the inlet and outlet sections, respectively.

The pumping power required to overcome the flow resistance is calculated as [121]:

$$\Omega = Q \cdot \Delta P \quad (3.45)$$

Where Q denotes the volumetric flow rate.

The Darcy friction factor is determined from [121]:

$$f = \frac{2\Delta P(D_h)_{eq}}{\rho_{hn} U_{in}^2 L_T} \quad (3.46)$$

Where L_T represents the total channel length.

3.4.3 Thermal resistance

Thermal resistance is employed to quantify the ability of the microchannel heat sink to dissipate heat from the heated substrate. A lower thermal resistance indicates superior thermal management performance. The thermal resistance is defined as [121]:

$$R_{th} = \frac{T_{w,max} - T_{in}}{q''} \quad (3.47)$$

Where $T_{w,max}$ denotes the maximum temperature attained on the heated surface.

3.4.4 Entropy generation

Entropy generation analysis is performed to quantify thermodynamic irreversibilities associated with heat transfer and fluid friction within the microchannel. The logarithmic mean fluid temperature is first calculated as [121]:

$$T_{av} = \frac{T_{out} - T_{in}}{\ln\left(\frac{T_{out}}{T_{in}}\right)} \quad (3.48)$$

The total entropy generation rate is expressed as the sum of thermal and frictional contributions [121]:

$$(S_g)_{Total} = (S_g)_{Thermal} + (S_g)_{Frictional} \quad (3.49)$$

The thermal entropy generation component is evaluated from:

$$(S_g)_{Thermal} = \frac{q''^2 \pi (D_h)_{eq}^2 L_T}{Nu_{av} \cdot k_f T_{av}^2} \quad (3.50)$$

Whereas the frictional entropy generation component is calculated as:

$$(S_g)_{Frictional} = \frac{32\dot{m}^3 f L_T}{\pi^2 \rho_f^2 T_{av} (D_h)^5} \quad (3.51)$$

The entropy generation analysis provides valuable insight into the sources of thermodynamic losses and enables identification of configurations that minimize system irreversibilities.

3.4.5 Exergetic efficiency

To evaluate the thermodynamic effectiveness of the proposed cooling configurations, an exergy-based analysis is performed. Exergy analysis considers both the quantity and quality of energy and provides a rigorous measure of useful energy utilization.

The rate of thermal energy supplied to the microchannel heat sink is given by [38]:

$$E_{in} = \dot{q} A_b \quad (3.52)$$

The useful thermal energy carried away by the coolant is determined as [38]:

$$E_{out} = \dot{m} C_p (T_{out} - T_{in}) \quad (3.53)$$

The exergy destruction rate associated with system irreversibilities is expressed as [38]:

$$E_d = T_o S_{gen} \quad (3.54)$$

Where T_o denotes the ambient (dead-state) temperature.

The exergy destruction ratio is defined as [38]:

$$EDR = \frac{E_d}{E_{out}} \quad (3.55)$$

Finally, the exergetic efficiency of the microchannel heat sink is evaluated as [38]:

$$\eta_{ex} = \frac{E_{out}}{E_{in}} \quad (3.56)$$

For idealized conditions with negligible energy losses, the exergetic efficiency may alternatively be expressed as [38]:

$$\eta_{ex} = 1 - EDR \quad (3.57)$$

The exergy analysis complements the hydrothermal assessment by quantifying the extent of useful energy recovery and identifying configurations that simultaneously enhance thermal performance and reduce thermodynamic losses.

3.5 Boundary Conditions

The boundary conditions employed in the numerical simulations are selected to accurately represent the operating conditions encountered in high heat-flux electronic cooling

applications. The same set of hydrodynamic and thermal boundary conditions is applied to all baseline and enhanced CD-MCHS configurations to ensure a consistent and meaningful comparison of their hydrothermal and exergetic performances. The inlet flow conditions, outlet pressure, imposed heat load, and wall boundary treatments are established based on the physical configuration described in Section 3.2.

The coolant enters the microchannel through the inlet section at a prescribed velocity corresponding to the desired Reynolds number and a uniform temperature of 298 K. At the outlet, a pressure-outlet condition is imposed with the gauge pressure fixed at atmospheric reference conditions. A uniform heat flux of 150 W/cm² is applied at the bottom surface of the heat sink to simulate the thermal load generated by high-power electronic devices. All remaining external surfaces are assumed to be thermally insulated, thereby restricting heat transfer to the coolant flowing through the microchannel.

Table 3.6: Boundary conditions in various regions of the CD-MCHS

Zone	Boundary Condition	Expression	Nature
CD-MCHS Inlet	Velocity Inlet	• $x = 0 \text{ mm}; u = U_{in}$	Hydrodynamic
		• $x = 0 \text{ mm}; T = T_{in} = 298 \text{ K}$	Thermal
CD-MCHS Outlet	Pressure Outlet	• $x = 10 \text{ mm}; P_{out} = 0 \text{ Pa (gauge)}$	Hydrodynamic
Bottom Wall	Heat flux (Constant.)	• $z = 0 \text{ mm}; q'' = 150 \text{ W/cm}^2$	Thermal
Sidewalls	Symmetry and Adiabatic	• $\frac{\partial T_s}{\partial n} = 0$	Thermal
Interface	No-Slip and Stationary	• $u = v = w = 0$	Hydrodynamic
		• $-k_s \frac{\partial T_s}{\partial n} = -k_f \frac{\partial T_f}{\partial n}$	Thermal
		• $(T_f)_r = (T_s)_r$	

At the fluid-solid interfaces, no-slip conditions are imposed for fluid flow, while conjugate heat transfer is enforced through continuity of temperature and heat flux across the interface. The complete set of boundary conditions adopted in the present investigation is summarized in Table 3.6.

The above hydrodynamic and thermal boundary conditions are applied consistently across all investigated configurations, including the baseline, micro-pillar-enhanced, hybrid nanofluid-based, and porous-media-assisted CD-MCHS models. Such a consistent implementation facilitates a reliable comparative assessment of the influence of different passive enhancement strategies on the hydrothermal and exergetic performance of the microchannel heat sink.

3.6 Numerical Methodology

The numerical simulations are performed using the commercial computational fluid dynamics (CFD) package ANSYS Fluent. The governing equations describing the conservation of mass, momentum, and energy are solved using the finite volume method (FVM) under the prescribed hydrodynamic and thermal boundary conditions. The finite volume framework is particularly suitable for microscale heat transfer applications because it ensures local conservation of mass, momentum, and energy within each computational control volume. The adopted numerical methodology enables the simultaneous prediction of fluid flow, heat transfer, and thermodynamic behaviour within the baseline and enhanced convergent-divergent microchannel heat sink configurations. Furthermore, the numerical framework provides the flexibility to incorporate different passive enhancement techniques, including micro-pillars, nanofluids, and porous media, within a unified computational environment.

The computational domain is discretized using a structured hexahedral mesh to ensure high numerical accuracy and efficient convergence characteristics. Structured grids are particularly suitable for microchannel heat transfer simulations owing to their superior orthogonality, reduced numerical diffusion, and improved control over mesh quality compared with unstructured discretization schemes. As illustrated in Figure 3.6, a predominantly structured mesh topology is employed throughout the computational domain. To accurately resolve the steep velocity and temperature gradients that develop near the solid boundaries, local mesh refinement is applied in the vicinity of the channel walls and fluid-solid interfaces. Particular attention is given to the near-wall regions, where significant variations in thermal and hydrodynamic boundary layers occur. A comparatively coarser mesh is maintained within the core flow region to achieve an appropriate balance between computational accuracy and computational cost. This

meshing strategy ensures reliable prediction of both flow and heat transfer characteristics while maintaining acceptable computational efficiency.

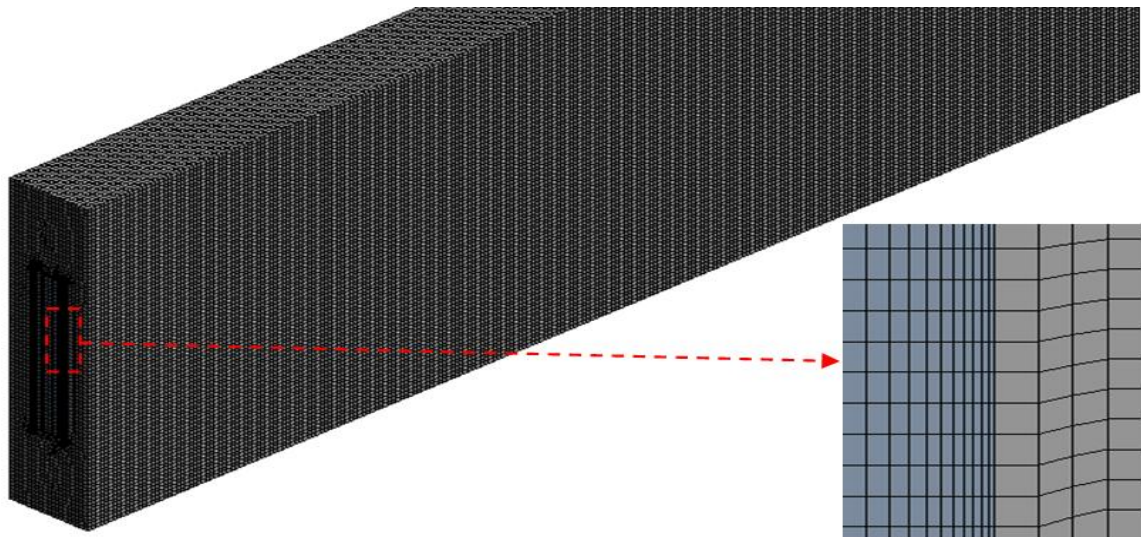


Figure 3.7: Structured hexahedral grid representation of the computational domain with local grid refinement near the channel walls

The pressure-based solver available in ANSYS Fluent is employed for the numerical solution of the governing equations. Pressure-velocity coupling is achieved using the Semi-Implicit Method for Pressure-Linked Equations (SIMPLE) algorithm, which provides stable and efficient convergence for incompressible laminar flows. Spatial gradients are evaluated using the Least-Squares Cell-Based scheme, while pressure interpolation is performed using the PRESTO! formulation. The momentum and energy equations are discretized using second-order upwind schemes to improve spatial accuracy and minimize numerical diffusion. The selection of higher-order discretization schemes ensures an accurate representation of flow and thermal transport phenomena within the convergent-divergent microchannel, particularly in regions characterized by strong velocity and temperature gradients.

To enhance solution stability and convergence behaviour, appropriate under-relaxation factors are employed during the iterative solution process. The values adopted for the present simulations are summarized in Table 3.7. Numerical convergence is considered to be achieved when the scaled residuals of the continuity and momentum equations decrease below 10^{-5} , while the residual of the energy equation falls below 10^{-8} . These stringent convergence criteria ensure accurate prediction of both hydrodynamic and thermal fields within the microchannel.

Table 3.7: Numerical schemes and solution control parameters employed in the present study

Category	Parameter	Method / Value
Mesh Configuration	Mesh Type	Structured Hexahedral Mesh
	Mesh Refinement	At fluid-solid interface
Numerical Solver	Solver Type	Pressure-Based Solver
	Numerical Method	Finite Volume Method (FVM)
Pressure–Velocity Coupling	Coupling Scheme	SIMPLE
Spatial Discretization	Gradient	Least-Squares Cell-Based
	Pressure	PRESTO!
	Momentum	Second-Order Upwind
	Energy	Second-Order Upwind
Under-Relaxation Factors	Pressure	0.2
	Momentum	0.6
	Energy	1
Convergence Criteria	Continuity Residual	10^{-5}
	Momentum Residuals	10^{-5}
	Energy Residual	10^{-8}

The numerical methodology described above is applied consistently to all investigated configurations, including the baseline CD-MCHS, micro-pillar-enhanced CD-MCHS, hybrid nanofluid-based CD-MCHS, and porous-media-assisted CD-MCHS. The resulting numerical framework provides a robust platform for evaluating the hydrothermal and exergetic performance of the proposed thermal management strategies.

3.7 Grid Independence Study

The accuracy and reliability of computational fluid dynamics (CFD) simulations are significantly influenced by the quality and resolution of the computational mesh. In microchannel heat sinks, steep velocity and temperature gradients develop in the vicinity of the solid-fluid interfaces, making adequate mesh refinement essential for accurate prediction of hydrothermal performance. An excessively coarse mesh may lead to numerical diffusion and inaccurate estimation of heat transfer and pressure-loss characteristics, whereas excessive mesh refinement increases computational cost without

providing a corresponding improvement in solution accuracy. Therefore, a systematic grid independence study is performed to ensure that the numerical predictions are independent of mesh resolution.

For this purpose, a sequence of progressively refined structured hexahedral meshes is generated for the reference computational domain. The average heat transfer coefficient (h_{av}) and thermal resistance (R_{th}) are selected as the monitoring parameters because they directly represent the thermal performance of the microchannel heat sink. The variation of these parameters with mesh refinement is illustrated in Figure 3.7.

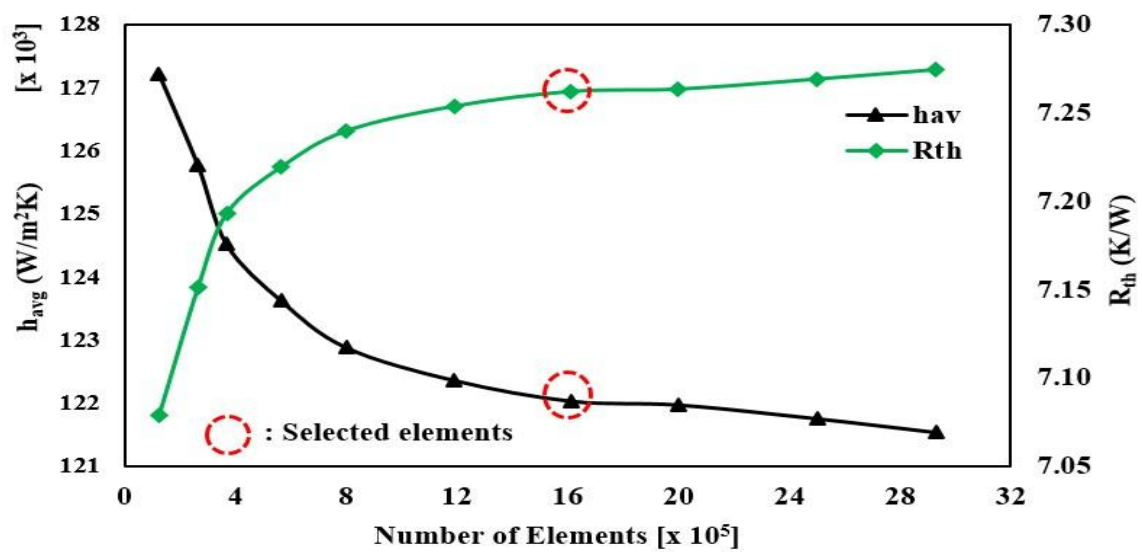


Figure 3.8: Grid independence assessment of the reference study based on average heat transfer coefficient and thermal resistance

As shown in Figure 3.7, both h_{av} and R_{th} exhibit noticeable variations at lower mesh densities. However, as the mesh is progressively refined, the variations diminish and the solution gradually approaches an asymptotic convergence region. Beyond approximately 1.61×10^6 elements, only marginal changes are observed in the monitored parameters, indicating that the numerical solution becomes insensitive to further mesh refinement.

To establish a quantitative criterion for mesh independence, the relative variation of the monitored parameters between two successive mesh levels is evaluated. The numerical solution is considered grid-independent when the variation in two successive refinement levels for both h_{av} and R_{th} remains under 0.25%. Based on this criterion, the mesh containing approximately 1.61×10^6 elements satisfies the prescribed tolerance and is

therefore selected for all subsequent simulations. This mesh provides an appropriate balance between computational efficiency and numerical accuracy.

3.7.1 Grid Convergence Index (GCI) Analysis

Although mesh independence provides qualitative evidence of solution convergence, a quantitative estimate of discretization uncertainty is necessary to assess the numerical accuracy of the simulations. Therefore, the Grid Convergence Index (GCI) methodology proposed by Roache is employed to evaluate the uncertainty associated with spatial discretization.

Since the GCI formulation is based on Richardson extrapolation, its application is most reliable when the numerical solution lies within the asymptotic convergence region. Accordingly, the GCI analysis is performed using the refined mesh levels corresponding to the asymptotic portion of the convergence curve, while the coarser meshes are excluded from the calculation.

The relative discretization error between two successive mesh levels is defined as [153]:

$$e = \frac{\phi_{fine} - \phi_{coarse}}{\phi_{fine}} \quad (3.58)$$

Where ϕ denotes the monitored variable (i.e., h_{av} or R_{th}).

The grid refinement ratio is calculated as [153]:

$$r = \left(\frac{N_{fine}}{N_{coarse}} \right)^{1/3} \quad (3.59)$$

Where N represents the total number of computational elements.

The Grid Convergence Index for the fine mesh is evaluated as [153]:

$$GCI = F_s \frac{|e|}{r^p - 1} \quad (3.60)$$

Where F_s is the safety factor (taken as 1.25 for three or more meshes), and p is the order of convergence, assumed as 1.97 in accordance with the second-order discretization scheme employed in the present study.

The calculated GCI values corresponding to the monitored parameters are presented in Table 3.8. A monotonic reduction in GCI is observed with increasing mesh refinement, indicating stable and consistent convergence behaviour. For the selected mesh containing approximately 1.61×10^6 elements (Mesh-7), the GCI values associated with h_{av} and R_{th} are found to be 0.40 % and 0.11 %, respectively. These low GCI values indicate that the numerical uncertainty arising from spatial discretization is negligible. Furthermore, the

progressive reduction in GCI with successive mesh refinement confirms stable convergence behaviour and demonstrates that the numerical solution lies within the asymptotic convergence region.

Table 3.8: Grid convergence index (GCI) analysis for h_{av} and R_{th} for the selected mesh levels in the asymptotic convergence region

S. No.	Elements	Nodes	r	$(e)_{h_{av}}$	$(GCI)_{h_{av}}$	$(e)_{R_{th}}$	$(GCI)_{R_{th}}$
Mesh 4	566250	614732	1.120	-0.0060	3.01 %	0.0028	1.38 %
Mesh 5	799370	863496	1.139	-0.0043	1.81 %	0.0019	0.82 %
Mesh 6	1190952	1277550	1.103	-0.0027	1.58 %	0.0012	0.73 %
Mesh 7	1613430	1714502	1.074	-0.0005	0.40 %	0.0001	0.11 %
Mesh 8	2000000	2123121	-	-	-	-	-

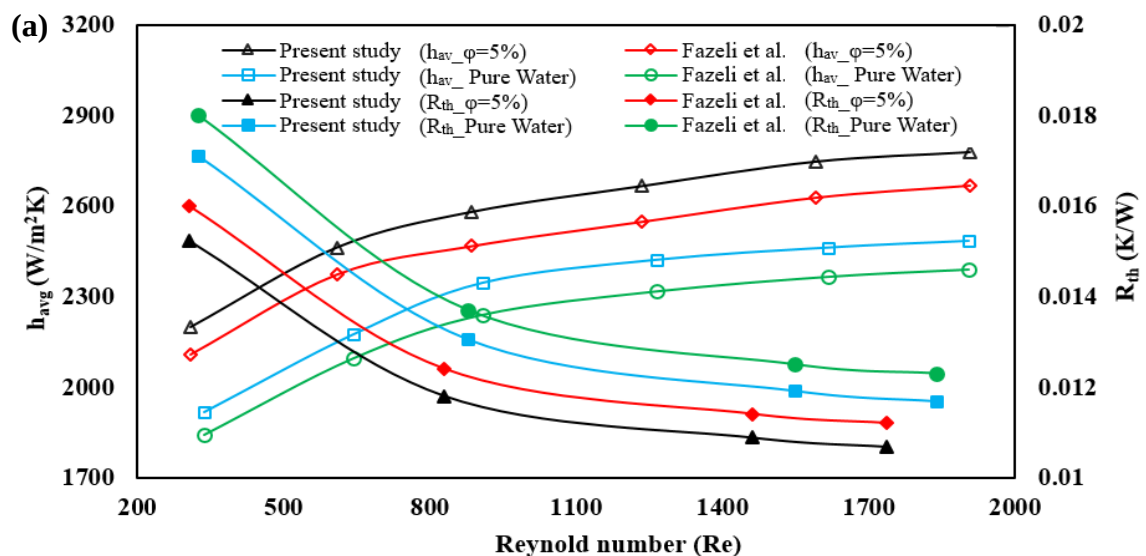
Based on the combined evidence obtained from the grid independence assessment and GCI analysis, the mesh comprising approximately 1.61×10^6 elements is adopted for all subsequent numerical simulations. The selected mesh ensures reliable prediction of the hydrothermal and exergetic performance of the investigated CD-MCHS configurations while maintaining reasonable computational cost.

3.8 Model Validation

The accuracy and reliability of the present numerical framework are established through validation against independent experimental investigations reported in the literature. Since the predictive capability of a numerical model forms the foundation for all subsequent analyses, it is essential to demonstrate that the developed computational methodology can accurately reproduce experimentally observed thermal and hydrodynamic behaviour. To ensure a comprehensive assessment, the present model is validated using two separate experimental studies involving different working fluids, geometrical configurations, and thermal performance indicators. The selected validation cases encompass a broad range of flow and heat-transfer conditions, thereby enabling evaluation of the numerical framework under diverse operating environments. Such a multi-case validation approach provides a rigorous assessment of the developed computational model, enhances confidence in the accuracy of the numerical predictions, and establishes its applicability for the hydrothermal and exergetic analysis of CD-MCHS.

In the first validation study, the experimental work reported by Fazeli et al. [154] is reproduced by reconstructing the corresponding computational domain using the geometric dimensions, material properties, and operating conditions provided in the original study. The validation is performed for both pure-water and nanofluid cooling conditions to examine the capability of the numerical model in predicting thermal transport behaviour under different coolant compositions. The average heat transfer coefficient and thermal resistance are selected as the validation parameters because they directly characterize the thermal performance of the cooling system. The numerical predictions are compared with the corresponding experimental measurements over a range of Reynolds numbers representative of practical electronic cooling applications.

To further evaluate the robustness of the developed numerical framework under a different geometric configuration, a second validation study is performed using the experimental data reported by Wang et al. [155]. Unlike the first validation case, Wang et al. investigated microchannels incorporating pin-fin structures, which introduce additional flow disturbances, wake formation, and fluid-mixing effects. Consequently, this validation case provides a more stringent assessment of the model's ability to predict the complex transport phenomena associated with flow-obstruction-based heat-transfer enhancement techniques. The corresponding microchannel configurations are reconstructed using the reported geometric and operating parameters, and the average Nusselt number is selected as the validation parameter. The comparison is carried out over a range of Reynolds numbers to examine the capability of the numerical model to accurately predict convective heat-transfer characteristics in pin-fin-enhanced microchannel systems.



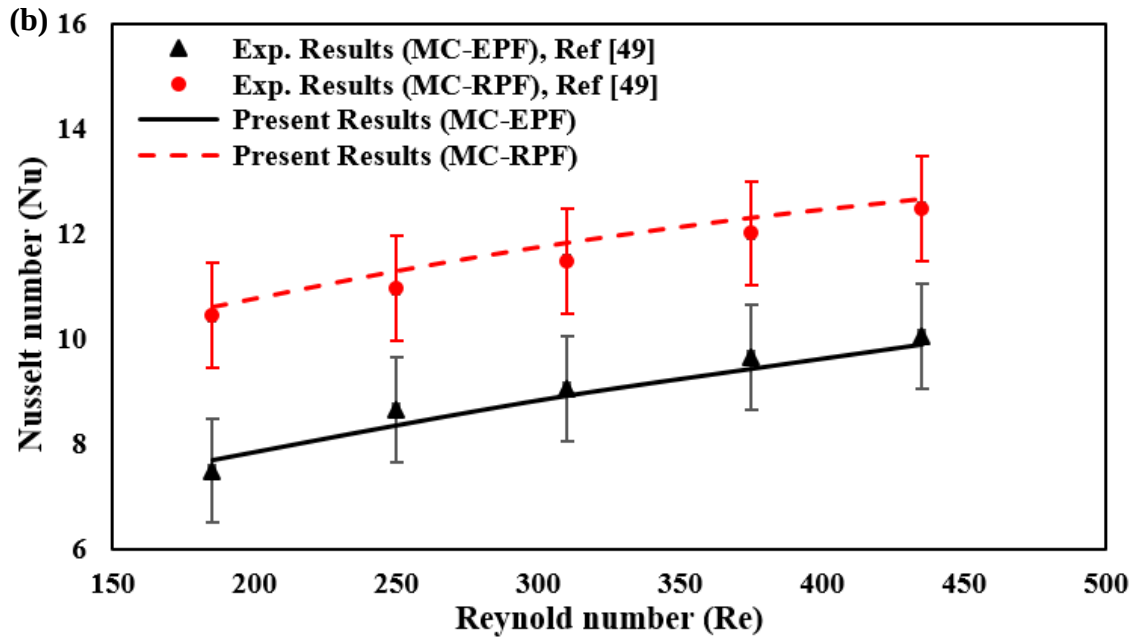


Figure 3.9: Experimental validation of the present numerical model using data from (a) Fazeli et al. [154] and (b) Wang et al. [155]

The comparisons between the numerical predictions and experimental measurements are presented in Figure 3.8. Figure 3.8 (a) illustrates the variation of the average heat transfer coefficient and thermal resistance with Reynolds number for both pure-water and nanofluid cases reported by Fazeli et al. It can be observed that the numerical results closely follow the experimental trends throughout the investigated operating range. The predicted heat transfer coefficients increase with increasing Reynolds number, while the corresponding thermal resistance decreases, consistent with the experimentally observed behaviour. Furthermore, the model successfully captures the enhancement in thermal performance associated with nanofluid cooling, demonstrating its capability to accurately represent the underlying heat-transfer mechanisms.

Similarly, Figure 3.8 (b) presents the comparison between the computed and experimental Nusselt numbers obtained from the pin-fin microchannel study of Wang et al. The numerical predictions exhibit excellent agreement with the experimental data over the entire Reynolds number range considered. The model accurately reproduces both the magnitude and trend of the measured Nusselt number, indicating that the governing equations, boundary conditions, and numerical schemes employed in the present study are capable of reliably capturing the convective heat-transfer behaviour in microchannels containing flow-disturbing structures.

For both validation studies, the deviations between the numerical predictions and experimental measurements remain within $\pm 5\%$, which is generally considered acceptable for conjugate heat-transfer simulations involving complex microscale flow and thermal transport phenomena. The close agreement obtained across different geometries, working fluids, and performance indicators demonstrates the robustness and predictive capability of the developed numerical framework.

In addition, the numerical uncertainty associated with spatial discretization has been independently assessed through the grid independence and Grid Convergence Index (GCI) analyses presented in Section 4.7, which confirmed that the selected computational mesh lies within the asymptotic convergence region with negligible discretization error. Therefore, the combined evidence from experimental validation and numerical uncertainty assessment establishes the accuracy and reliability of the present computational framework. The validated model is consequently employed for the subsequent hydrothermal, exergetic, and optimization investigations presented in this thesis.

CHAPTER 4

OPTIMIZATION TECHNIQUES AND DECISION-MAKING FRAMEWORK

4.1 Overview

The design of advanced microchannel heat sinks involves multiple geometric, operating, and material parameters that simultaneously influence thermal, hydraulic, and thermodynamic performance. Although numerical simulations provide detailed insight into the underlying transport phenomena, the identification of optimal designs through direct parametric investigation becomes increasingly challenging as the dimensionality of the design space increases. Furthermore, many performance indicators of practical interest are inherently conflicting. For instance, strategies that enhance heat transfer often increase flow resistance and pumping power requirements, while approaches aimed at reducing thermodynamic irreversibilities may adversely affect thermal performance. Consequently, the design of high-performance microchannel heat sinks represents a complex multi-objective optimization problem requiring a systematic decision-making methodology.

Traditional optimization approaches based solely on direct CFD evaluations become computationally expensive when a large number of design variables and objective functions are involved. Therefore, an efficient surrogate-assisted optimization framework is adopted in the present study to facilitate rapid exploration of the design space while maintaining prediction accuracy. The framework integrates Design of Experiments (DOE), Artificial Neural Networks (ANN), multi-objective evolutionary optimization, and decision-making techniques to identify optimal microchannel configurations under competing performance objectives.

The present chapter describes the optimization and decision-making framework employed throughout this thesis. The methodology combines Latin Hypercube Sampling (LHS) for database generation, CFD simulations for performance evaluation, ANN-based surrogate modelling for rapid prediction, the Non-dominated Sorting Genetic Algorithm-II (NSGA-II) for multi-objective optimization, and the Technique for Order Preference by Similarity

to Ideal Solution (TOPSIS) for final design selection. Together, these techniques provide a comprehensive platform for identifying thermally efficient and thermodynamically sustainable microchannel heat sink designs.

4.2 Overall Optimization Framework

The optimization methodology adopted in the present study consists of a sequence of interconnected stages designed to systematically explore the design space and identify optimal configurations. Direct integration of CFD simulations with evolutionary optimization algorithms is computationally prohibitive because thousands of function evaluations are typically required during the optimization process. To overcome this limitation, surrogate modelling is employed to replace the computationally expensive CFD simulations during the optimization stage. The overall optimization and decision-making framework adopted in the present investigation is illustrated in Figure 4.1.

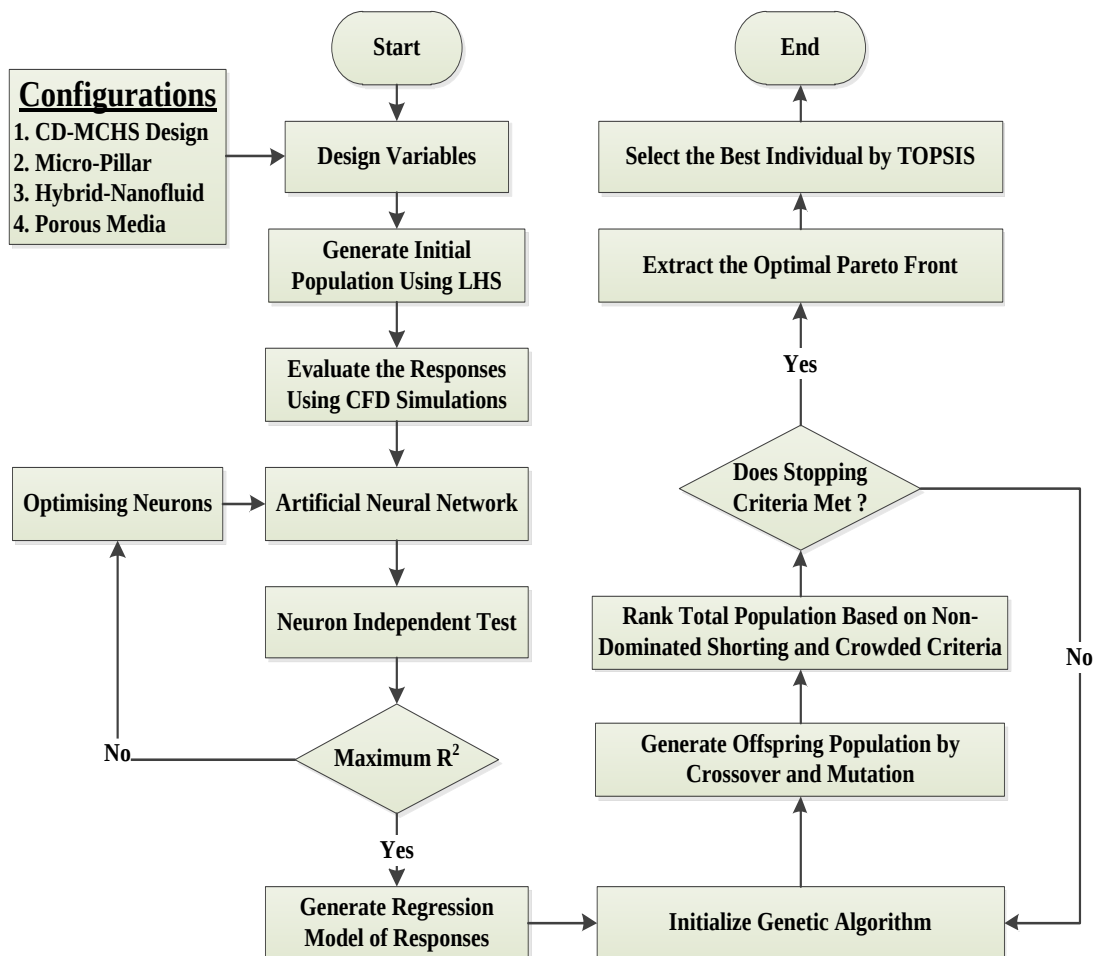


Figure 4.1: Integrated optimization and decision-making framework adopted in the present study

As shown in Figure 4.1, the optimization process begins with the definition of design variables, objective functions, and associated constraints. Latin Hypercube Sampling is subsequently employed to generate representative sample points within the design space. Each sampled design is evaluated using CFD simulations to establish a comprehensive performance database describing the hydrothermal and thermodynamic characteristics of the microchannel heat sink.

The generated database is then utilized to train and validate ANN-based surrogate models capable of rapidly predicting the performance parameters of interest. The trained ANN models are subsequently coupled with the NSGA-II algorithm to perform multi-objective optimization and generate a set of Pareto-optimal solutions. Finally, TOPSIS is employed to rank the Pareto-optimal solutions and identify the most balanced design according to the specified performance criteria.

4.3 Formulation of the Optimization Problem

The optimization of advanced microchannel heat sinks involves the simultaneous consideration of multiple design variables and competing performance objectives. Owing to the complex interactions between geometric parameters, operating conditions, and enhancement strategies, the identification of an optimal design cannot be achieved through conventional trial-and-error approaches. Consequently, the optimization problem is formulated as a multi-objective design task in which thermal performance enhancement and thermodynamic irreversibility minimization are pursued simultaneously within prescribed design constraints.

In the present study, separate optimization formulations are developed for the baseline convergent-divergent microchannel heat sink (CD-MCHS), micro-pillar-enhanced CD-MCHS, hybrid-nanofluid-based CD-MCHS, and porous-media-assisted CD-MCHS configurations. Although each configuration possesses a distinct set of design variables, a common optimization philosophy is adopted to facilitate a consistent assessment of the different enhancement strategies.

The vector of design variables may generally be expressed as:

$$X = [x_1, x_2, \dots, x_n] \quad (4.1)$$

Where X denotes the set of independent design variables defining a particular microchannel configuration, and n represents the total number of design variables considered in the corresponding optimization process.

Depending on the enhancement technique under investigation, the design variables may include geometric parameters, flow conditions, micro-pillar characteristics, nanoparticle composition, nanoparticle concentration, porous-medium properties, and material selection variables. The permissible ranges of these variables are selected based on physical feasibility, manufacturing considerations, numerical stability requirements, and the research gaps identified in the literature review.

To ensure a uniform basis for comparison among the investigated configurations, the optimization objectives are formulated in terms of maximizing heat-transfer performance while minimizing thermodynamic irreversibilities. Although a common optimization philosophy is adopted throughout the present study, the specific design variables and constraints differ according to the enhancement strategy under consideration. Therefore, separate optimization formulations are developed for the baseline CD-MCHS, micro-pillar-enhanced CD-MCHS, hybrid-nanofluid-based CD-MCHS, and porous-media-assisted CD-MCHS configurations. The corresponding optimization problems are presented in the following sections.

4.3.1 Baseline CD-MCHS Optimization Problem

The baseline CD-MCHS optimization problem aims to identify the optimal combination of geometric and operating parameters that maximizes heat-transfer performance while minimizing entropy generation. The selected design variables govern the channel geometry and flow characteristics and therefore play a significant role in determining the hydrothermal and thermodynamic behaviour of the microchannel heat sink. By simultaneously considering these parameters within a multi-objective optimization framework, it becomes possible to establish an appropriate balance between enhanced heat-transfer capability and reduced thermodynamic irreversibility.

The optimization formulation adopted for the baseline configuration is expressed as:

$$\left\{ \begin{array}{l} \mathbf{Max} \, U_1(X) = f_1 \\ \mathbf{Min} \, U_2(X) = f_2 \\ \text{Where;} \\ X = (\text{Re}, \alpha, \beta, \gamma, \delta, N_1, N_2) \\ f_1 = -\frac{Nu}{Nu_{ref}} \\ f_2 = -\frac{S_{gen}}{(S_{gen})_{ref}} \end{array} \right. \quad (4.2)$$

Table 4.1: Design variables and their corresponding bounds and step-size for the baseline CD-MCHS optimization problem

Variable	Description	Range	Step-Size
Re	Reynolds number	100-500	100
α	Top-to-bottom width ratio	0.50-1.50	0.25
β	Bottom-to-pitch ratio	0.40-0.80	0.10
γ	Channel-to-height ratio	0.40-0.80	0.10
δ	Throat-to-channel ratio	0.20-0.60	0.20
N ₁	Parallel channels	30-70	10
N ₂	Series channels	04-12	02

4.3.2 Micro-Pillar-Enhanced CD-MCHS Optimization Problem

To evaluate the influence of micro-pillar geometry and arrangement on hydrothermal and thermodynamic performance, a separate optimization formulation is developed for the micro-pillar-enhanced CD-MCHS configuration. The incorporation of micro-pillars introduces additional design variables associated with pillar geometry and spatial arrangement. Accordingly, the optimization problem is formulated to determine the optimal micro-pillar configuration. The optimization problem is defined as:

$$\left\{ \begin{array}{l} \text{Max } U_1(X) = f_1 \\ \text{Min } U_2(X) = f_2 \\ \text{Where;} \\ X = (P_d, \varphi, P_c, P_o) \\ f_1 = -\frac{Nu}{Nu_{ref}} \\ f_2 = -\frac{S_{gen}}{(S_{gen})_{ref}} \end{array} \right. \quad (4.3)$$

Table 4.2: Design variables, permissible ranges, and step sizes employed in the optimization of the micro-pillar-enhanced CD-MCHS configuration

Variable	Description	Range	Step-Size
P _d	Pillar shape index	01-04	01
φ	Nanoparticle concentration	01-03 %	01
P _c	Pillar count	32-80	16
P _o	Offset parameter	0-15 μ m	05

Note: P_d is a discrete design variable representing the micro-pillar geometry, where $P_d = 1$ denotes an elliptical pillar, $P_d = 02$ a circular pillar, $P_d = 03$ a square pillar, and $P_d = 04$ a rhombic pillar.

4.3.3 Hybrid-Nanofluid-Based CD-MCHS Optimization Problem

The optimization formulation for the hybrid-nanofluid-based CD-MCHS aims to determine the optimal coolant composition and operating conditions that maximize thermal performance while minimizing entropy generation. The inclusion of hybrid nanoparticles modifies the effective thermophysical properties of the coolant and consequently influences both heat-transfer and flow characteristics. The optimization problem is therefore formulated as:

$$\left\{ \begin{array}{l} \text{Max } U_1(X) = f_1 \\ \text{Min } U_2(X) = f_2 \\ \text{Where;} \\ X = (\Phi_T, f_{CuO}, f_{Al_2O_3}, f_{Ag}) \\ f_1 = -\frac{Nu}{Nu_{ref}} \\ f_2 = -\frac{S_{gen}}{(S_{gen})_{ref}} \end{array} \right. \quad (4.4)$$

Table 4.3: Design variables, permissible ranges, and step sizes employed in the optimization of the hybrid-nanofluid-based CD-MCHS configuration

Variable	Description	Range	Step-Size
Φ_T	Total nanoparticle volume fraction	0.5-2.0 %	0.50
f_{CuO}	Volume fraction of CuO nanoparticles	50-65 %	05
$f_{Al_2O_3}$	Volume fraction of Al_2O_3 nanoparticles	20-35 %	05
f_{Ag}	Volume fraction of Ag nanoparticles	15-30 %	05

Note: f_{CuO} , $f_{Al_2O_3}$, and f_{Ag} represent the relative volume fractions of CuO, Al_2O_3 , and Ag nanoparticles, respectively, and satisfy $f_{CuO} + f_{Al_2O_3} + f_{Ag} = 100 \%$.

4.3.4 Porous-Media-Assisted CD-MCHS Optimization Problem

For the porous-media-assisted CD-MCHS, the optimization formulation incorporates porous-medium structural parameters and material-selection variables to investigate their

influence on heat-transfer enhancement and thermodynamic behaviour. The optimization seeks to identify porous configurations that provide an effective balance between enhanced thermal performance and the additional flow resistance introduced by the porous structure. The effects of porosity, pore diameter, and porous material are simultaneously considered during the optimization process. The optimization problem is expressed as:

$$\left\{ \begin{array}{l} \text{Max } U_1(X) = f_1 \\ \text{Min } U_2(X) = f_2 \\ \text{Where;} \\ X = (\varepsilon, d_p, M_c) \\ f_1 = -\frac{Nu}{Nu_{ref}} \\ f_2 = -\frac{S_{gen}}{(S_{gen})_{ref}} \end{array} \right. \quad (4.5)$$

Table 4.4: Design variables, permissible ranges, and step sizes employed in the optimization of the porous-media-assisted CD-MCHS configuration

Variable	Description	Range	Step-Size
ε	Porosity	0.40-0.85	0.15
d_p	Pore diameter	08-32 μm	08
M_c	Porous material index	01-04	01

Note: M_c is a discrete design variable representing the porous material, where $M_c = 01$ denotes copper, $M_c = 02$ aluminium, $M_c = 03$ bronze, and $M_c = 04$ nickel.

4.4 Design of Experiments Using Latin Hypercube Sampling

The optimization of advanced microchannel heat sinks involves a large number of design variables, resulting in a high-dimensional design space. Direct evaluation of all possible combinations of these variables through CFD simulations would require a prohibitively large computational effort. Therefore, an efficient sampling strategy is required to generate a representative database while minimizing the number of simulations. In the present study, a Design of Experiments (DOE) approach based on Latin Hypercube Sampling (LHS) is adopted for this purpose.

LHS is a stratified statistical sampling technique that enables efficient exploration of multidimensional design spaces while maintaining a relatively small sample size.

Compared with conventional random sampling methods, LHS provides improved coverage of the design domain and reduces the likelihood of clustering of sample points within specific regions. Consequently, it has become one of the most widely adopted sampling techniques for surrogate-based optimization studies.

The fundamental principle of LHS is to divide the range of each design variable into a number of equally probable intervals and then randomly select one sample from each interval. The sampled values of all design variables are subsequently combined in such a manner that the entire design space is uniformly represented. This approach ensures that the generated samples capture the variability of the design variables while avoiding redundant sampling and unnecessary computational expense.

In the present study, LHS is employed to generate representative design configurations for the baseline CD-MCHS, micro-pillar-enhanced CD-MCHS, hybrid-nanofluid-based CD-MCHS, and porous-media-assisted CD-MCHS optimization problems. The generated sample points are subsequently evaluated through CFD simulations to establish comprehensive databases describing the hydrothermal and thermodynamic performance of the investigated configurations.

The numerical databases obtained from the CFD simulations serve as the foundation for the development of ANN-based surrogate models. By providing a well-distributed set of training samples throughout the design space, LHS contributes to improving the predictive capability and generalization performance of the surrogate models used in the subsequent optimization process.

4.5 Artificial Neural Network Based Surrogate Modelling

4.5.1 Need for Surrogate Modelling

Although CFD simulations provide accurate predictions of fluid flow and heat transfer characteristics, their direct integration with evolutionary optimization algorithms requires thousands of function evaluations and consequently leads to substantial computational cost. To overcome this limitation, surrogate models are employed to approximate the relationship between design variables and performance parameters while significantly reducing computational effort.

Among the available surrogate modelling techniques, Artificial Neural Networks (ANN) have demonstrated excellent capability in capturing highly nonlinear relationships and

complex interactions among design variables. Owing to their strong approximation capability and computational efficiency, ANN are adopted in the present study to establish predictive models for the hydrothermal and thermodynamic performance parameters.

4.5.2 ANN Architecture

An Artificial Neural Network is a data-driven computational model inspired by the structure and functioning of biological neural systems. The ANN employed in the present study consists of three primary layers: an input layer, one or more hidden layers, and an output layer.

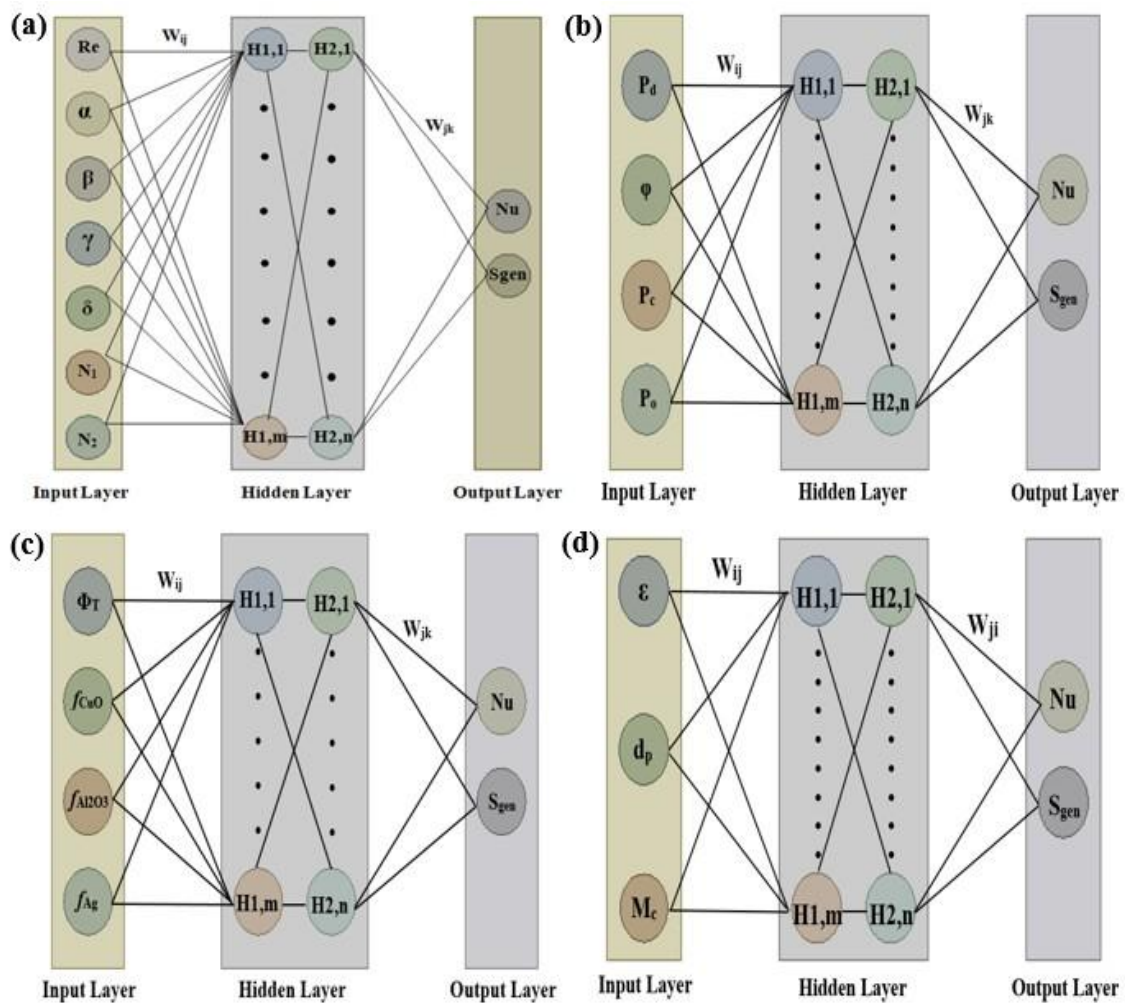


Figure 4.2: ANN architectures developed for the investigated optimization problems: (a) baseline CD-MCHS, (b) micro-pillar-enhanced CD-MCHS, (c) hybrid-nanofluid-based CD-MCHS, and (d) porous-media-assisted CD-MCHS

The input layer receives the design variables generated through the LHS procedure, while the output layer predicts the corresponding performance parameters obtained from CFD

simulations. The hidden layer establishes nonlinear relationships between the input and output variables through interconnected neurons and weighted connections.

As illustrated in Figure 4.2, separate ANN architectures are developed for each optimization problem to accommodate the corresponding sets of design variables. Although the input variables differ among the investigated configurations, all ANN models employ a feed-forward network structure and are trained to predict the two objective functions, namely the average Nusselt number and total entropy generation. The optimal number of hidden neurons is determined through a neuron-independence study to achieve high prediction accuracy while minimizing the risk of overfitting.

The hidden layers serve as nonlinear processing units that capture the complex relationships between the design variables and the corresponding performance parameters embedded within the CFD-generated database. During the training process, the connection weights and bias terms are iteratively updated to minimize the prediction error between the ANN outputs and the target values obtained from numerical simulations. Consequently, the trained ANN models function as computationally efficient surrogate models capable of accurately reproducing CFD predictions while significantly reducing the computational effort required during the optimization process.

4.5.3 Mathematical Formulation of ANN

The ANN establishes a nonlinear mapping between the input design variables and the corresponding performance parameters through interconnected neurons arranged in successive layers. Each neuron receives information from the neurons of the preceding layer, processes the received signals through weighted connections and bias terms, and transmits the resulting output to the subsequent layer.

The net input received by the j^{th} neuron can be expressed as:

$$Z_j = \sum_{i=1}^n w_{ij}x_i + b_j \quad (4.6)$$

Where x_i denotes the input variable, w_{ij} represents the connection weight between the i^{th} and j^{th} neurons, and b_j is the bias associated with the j^{th} neuron.

The weighted input is subsequently transformed through an activation function to introduce nonlinearity into the network. The output of the j^{th} neuron is therefore given by:

$$a_j = f(z_j) \quad (4.7)$$

Where $f(\cdot)$ denotes the activation function and a_j represents the neuron output.

The outputs generated by the hidden neurons are combined in the output layer to produce the final ANN prediction according to:

$$y_k = f\left(\sum_{j=1}^m w_{jk}a_j + b_k\right) \quad (4.8)$$

Where y_k denotes the predicted output parameter and m represents the number of neurons in the hidden layer.

During the training process, the connection weights and bias terms are iteratively adjusted to minimize the prediction error between the ANN outputs and the target values obtained from CFD simulations. Through this learning process, the ANN develops an accurate approximation of the underlying relationship between the design variables and the corresponding hydrothermal and thermodynamic performance parameters.

4.5.4 ANN Training and Performance Assessment

The CFD-generated database obtained from the Latin Hypercube Sampling procedure is employed for the development of the ANN surrogate models. Prior to training, the input and output datasets are normalized to improve numerical stability and facilitate efficient network convergence. The available data are subsequently divided into three subsets comprising 70% training data, 15% validation data, and 15% testing data. Such a division ensures adequate model learning while simultaneously providing independent datasets for monitoring generalization performance and evaluating prediction accuracy.

The ANN models are developed using the MATLAB Neural Network Toolbox. Network training is performed using the Levenberg-Marquardt (LM) backpropagation algorithm, which is widely recognized for its rapid convergence and high prediction accuracy in nonlinear regression problems. The hidden neurons employ a hyperbolic tangent sigmoid (tansig) activation function, whereas a linear (purelin) activation function is used in the output layer to generate continuous predictions of the performance parameters.

During the training process, the connection weights and bias terms are iteratively updated to minimize the prediction error between the ANN outputs and the target values obtained from CFD simulations. The validation dataset is employed to monitor network generalization and prevent overfitting, while the testing dataset is used to evaluate the predictive capability of the final trained model using previously unseen data.

The predictive performance of the ANN models is assessed using statistical indicators such as the correlation coefficient (R), coefficient of determination (R^2), mean absolute error (MAE), Root Mean Square Error (RMSE), and Mean Absolute Percentage Error

(MAPE). These indicators provide quantitative measures of the agreement between the ANN predictions and the corresponding CFD results [152].

$$R = \frac{\sum_{i=1}^n (y_i - \bar{y})(\hat{y}_i - \bar{\hat{y}})}{\sqrt{\sum_{i=1}^n (y_i - \bar{y})^2} \sqrt{\sum_{i=1}^n (\hat{y}_i - \bar{\hat{y}})^2}} \quad (4.9)$$

$$R^2 = 1 - \frac{\sum_{i=1}^n (y_i - \hat{y}_i)^2}{\sum_{i=1}^n (y_i - \bar{y})^2} \quad (4.10)$$

$$MAE = \frac{1}{n} \sum_{i=1}^n |y_i - \hat{y}_i| \quad (4.11)$$

$$RMSE = \sqrt{\frac{1}{n} \sum_{i=1}^n (y_i - \hat{y}_i)^2} \quad (4.12)$$

$$MAPE = \frac{100}{n} \sum_{i=1}^n \left| \frac{y_i - \hat{y}_i}{y_i} \right| \quad (4.13)$$

Where, y_i = Actual (CFD) value

$\hat{y}_i$ = Predicted (ANN) value

$\bar{y}$ = Mean of actual value

$\bar{\hat{y}}$ = Mean of predicted value

n = Number of data points

A high value of R^2 together with low RMSE and MAPE values indicates strong predictive capability of the ANN model and confirms its suitability for surrogate-based optimization. The trained ANN models are subsequently integrated with the NSGA-II algorithm to perform multi-objective optimization of the investigated CD-MCHS configurations.

4.6 Multi-Objective Optimization Using NSGA-II

The optimization of advanced microchannel heat sinks involves multiple conflicting objectives that must be considered simultaneously. In the present study, enhancement of heat-transfer performance and minimization of entropy generation are treated as competing objectives. Since improvement in one objective may adversely affect the other, a multi-objective optimization approach is required to identify the best compromise solutions.

To address this challenge, the Non-dominated Sorting Genetic Algorithm-II (NSGA-II) is employed. NSGA-II is one of the most widely used evolutionary optimization algorithms owing to its ability to efficiently identify a diverse set of Pareto-optimal solutions while maintaining good convergence characteristics. The algorithm combines non-dominated sorting and crowding-distance evaluation to guide the search towards the optimal region of the design space while preserving solution diversity.

The trained ANN surrogate models developed in Section 4.5 are integrated with NSGA-II as a fitness function to perform the optimization process. The use of ANN models eliminates the need for repeated CFD evaluations during optimization and significantly reduces the associated computational cost.

4.6.1 Pareto Optimality and Non-Dominated Sorting

The fundamental concept underlying NSGA-II is Pareto optimality. A solution is considered Pareto-optimal if no other feasible solution exists that improves one objective without simultaneously deteriorating at least one of the remaining objectives. Consequently, the optimization process generates a set of non-dominated solutions known as the Pareto front, representing the best trade-offs among the competing objectives. For a multi-objective optimization problem, the objective vector may be expressed as:

$$F(X) = [f_1(X), f_2(X), \dots, f_m(X)] \quad (4.14)$$

Where $F(X)$ denotes the set of objective functions and X represents the vector of design variables.

NSGA-II ranks the candidate solutions according to their dominance relationships and classifies them into successive Pareto fronts. Solutions belonging to the first front are non-dominated and therefore represent the most desirable candidates in the population. The remaining solutions are subsequently assigned to lower-ranked fronts according to their level of dominance. This non-dominated sorting procedure enables systematic ranking of the candidate solutions and guides the evolutionary search towards the Pareto-optimal region of the objective space.

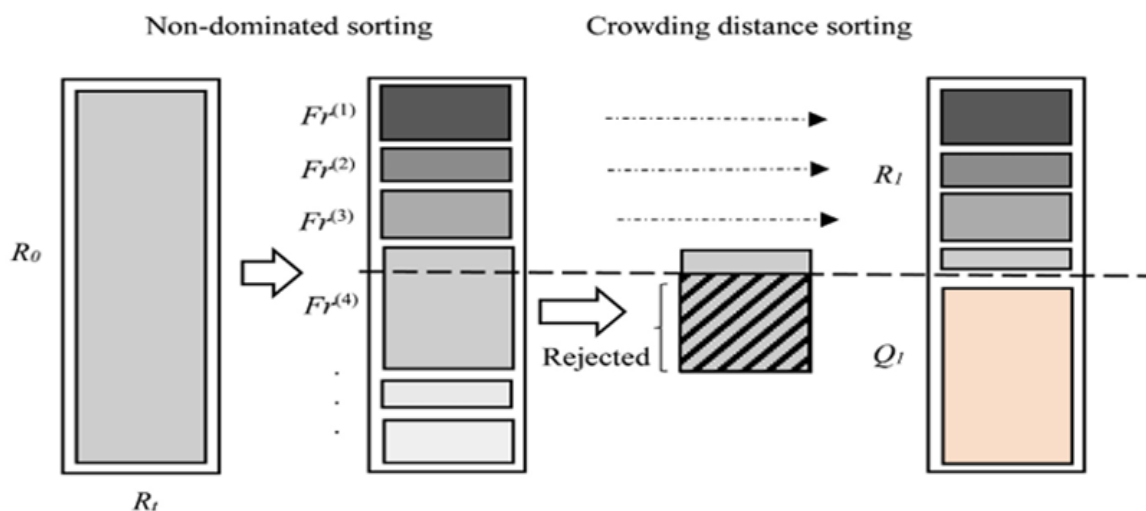


Figure 4.3: Flowchart of NSGA-II execution at each iteration

To maintain diversity among the non-dominated solutions, NSGA-II further incorporates a crowding-distance mechanism during the selection process. The combined procedure of non-dominated sorting and crowding-distance evaluation is schematically illustrated in Figure 4.3.

4.6.2 Crowding Distance and Genetic Operations

To maintain a well-distributed Pareto front, NSGA-II employs a crowding-distance mechanism that estimates the relative density of solutions surrounding a given individual in the objective space. Solutions located in less crowded regions are preferred during the selection process, thereby preserving diversity across the Pareto front.

The evolutionary search is performed through selection, crossover, and mutation operations. Selection identifies superior candidate solutions based on their Pareto rank and crowding distance, whereas crossover and mutation generate new offspring solutions and promote exploration of the design space. Through repeated evolution over successive generations, the population gradually converges towards the optimal Pareto front.

4.6.3 Implementation of NSGA-II for CD-MCHS Optimization

In the present study, NSGA-II is coupled with the developed ANN surrogate models to perform multi-objective optimization of the baseline CD-MCHS, micro-pillar-enhanced CD-MCHS, hybrid-nanofluid-based CD-MCHS, and porous-media-assisted CD-MCHS configurations. The optimization process is initiated by generating an initial population within the prescribed design-variable bounds, after which the objective functions are evaluated using the trained ANN models.

The candidate solutions are subsequently ranked based on Pareto dominance, and successive populations are generated through the evolutionary operations of selection, crossover, and mutation. Through repeated iterations, the population gradually converges towards the Pareto-optimal region of the objective space, resulting in a set of non-dominated solutions representing the best trade-offs among the competing objectives.

The optimization procedure is independently applied to each investigated configuration using the corresponding design variables and constraints defined in Section 4.3. The resulting Pareto-optimal solutions constitute the feasible design space and provide the basis for identifying the most suitable configuration according to the specified performance criteria.

Since all Pareto-optimal solutions are equally optimal from a dominance perspective, an additional decision-making technique is required to select a single preferred design. Accordingly, the Technique for Order Preference by Similarity to Ideal Solution (TOPSIS) is employed to rank the Pareto-optimal solutions and determine the final optimal configuration, as discussed in the following section.

4.7 Multi-Criteria Decision-Making Using TOPSIS

The NSGA-II optimization procedure yields a set of Pareto-optimal solutions that represent the best trade-offs among the competing objective functions. Although all solutions located on the Pareto front are considered optimal from a dominance perspective, practical engineering design generally requires the selection of a single preferred configuration for implementation. Consequently, an additional decision-making framework is required to identify the most balanced solution among the available Pareto-optimal alternatives.

In the present study, the Technique for Order Preference by Similarity to Ideal Solution (TOPSIS) is employed for this purpose. TOPSIS is a widely used multi-criteria decision-making (MCDM) technique that ranks candidate solutions based on their geometric proximity to an ideal best solution and their distance from an ideal worst solution. The fundamental principle of TOPSIS is that the preferred alternative should simultaneously possess the shortest distance from the positive ideal solution and the greatest distance from the negative ideal solution. Owing to its simplicity, computational efficiency, and ability to incorporate the relative importance of multiple objectives, TOPSIS has been extensively adopted in engineering optimization problems. The overall TOPSIS procedure adopted in the present study is illustrated in Figure 4.4.

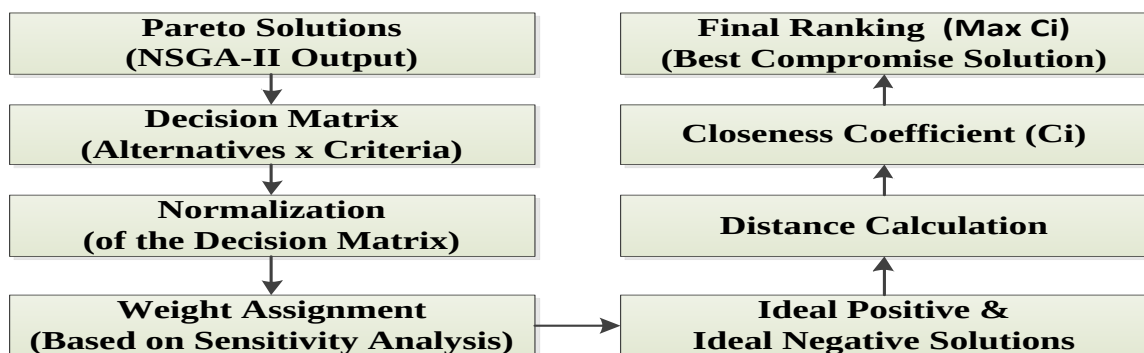


Figure 4.4: TOPSIS method framework

The TOPSIS implementation consists of the following steps [152]:

Step 1: Construction of the Decision Matrix

The Pareto-optimal solutions obtained from NSGA-II are arranged in the form of a decision matrix:

$$X = [x_{ij}] \quad (4.15)$$

Where $i = 1, 2, \dots, M$ denotes the Pareto-optimal alternatives and $j = 1, 2, \dots, N$ represents the objective functions. Each element x_{ij} corresponds to the performance value of the i^{th} alternative with respect to the j^{th} objective.

Step 2: Normalization of the Decision Matrix

Since the objective functions may possess different units and magnitudes, the decision matrix is normalized using vector normalization:

$$r_{ij} = \frac{x_{ij}}{\sqrt{\sum_{i=1}^m x_{ij}^2}} \quad (4.16)$$

This transformation eliminates dimensional inconsistencies and allows all objectives to be evaluated on a common basis.

Step 3: Weighted Normalized Matrix

The relative importance of the objective functions is incorporated through weighting factors w_j , yielding the weighted normalized matrix:

$$v_{ij} = w_j \times r_{ij} \quad (4.17)$$

The weighting factors may be determined based on engineering judgment, sensitivity analysis, or specific design requirements.

Step 4: Determination of Ideal Solutions

The positive ideal solution V^+ and negative ideal solution V^- are subsequently determined as:

$$V^+ = \{v_1^+, v_2^+, \dots, v_N^+\} \quad (4.18)$$

$$V^- = \{v_1^-, v_2^-, \dots, v_N^-\} \quad (4.19)$$

Where v_j^+ and v_j^- represent the best and worst attainable values of the j^{th} objective, respectively.

Step 5: Distance Calculation

The Euclidean distances of each alternative from the positive and negative ideal solutions are calculated as:

$$D_i^+ = \sqrt{\sum_{j=1}^n (v_{ij} - v_j^+)^2} \quad (4.20)$$

$$D_i^- = \sqrt{\sum_{j=1}^n (v_{ij} - v_j^-)^2} \quad (4.21)$$

Where D_i^+ and D_i^- denote the distances from the positive and negative ideal solutions, respectively.

Step 6: Closeness Coefficient and Ranking

The relative closeness coefficient of each alternative is then determined as:

$$C_i = \frac{D_i^-}{D_i^+ + D_i^-} \quad (4.22)$$

Finally, the Pareto-optimal alternatives are ranked according to their closeness coefficients, and the optimal compromise solution is selected as:

$$A_{opt} = \arg \max(C_i) \quad (4.23)$$

The alternative possessing the highest closeness coefficient is considered the most balanced design because it simultaneously exhibits the greatest proximity to the ideal solution and the largest separation from the non-ideal solution.

By integrating TOPSIS with the NSGA-II-generated Pareto front, the proposed optimization framework enables objective and quantitative selection of the final design configuration while accounting for the competing hydrothermal and thermodynamic performance criteria. The selected optimal solutions obtained through this procedure are presented and discussed in the subsequent chapters.

CHAPTER 5

RESULTS AND DISCUSSION

The present chapter discusses the results obtained from the numerical simulations, surrogate-model development, multi-objective optimization, and decision-making framework established in the preceding chapters. The objective is to systematically evaluate the effectiveness of different enhancement strategies in improving the hydrothermal and thermodynamic performance of convergent-divergent microchannel heat sinks (CD-MCHS) for high heat-flux electronic cooling applications. The discussion focuses not only on the magnitude of performance enhancement achieved but also on the underlying physical mechanisms governing heat transfer, fluid flow, and thermodynamic behaviour within the microchannel heat sink.

To facilitate a clear interpretation of the results, the chapter is organized into five major sections. First, the baseline CD-MCHS configuration is optimized to establish a reference design and identify the influence of key geometric and operating parameters on heat-transfer enhancement and entropy generation. Subsequently, three passive enhancement strategies, namely micro-pillar integration, hybrid nanofluid utilization, and porous-media incorporation, are independently investigated and optimized using the ANN-NSGA-II-TOPSIS framework. For each enhancement technique, the Pareto-optimal solutions, TOPSIS-selected compromise design, flow and thermal characteristics, and exergetic performance are analyzed and discussed in detail.

Finally, a comprehensive comparative assessment is performed to evaluate the relative merits and limitations of the investigated enhancement strategies. The comparison not only quantifies the achievable improvements in thermal and exergetic performance but also provides a unified understanding of the mechanisms responsible for transport enhancement and entropy-generation reduction. Such an assessment enables the identification of the most effective strategy for practical implementation in advanced electronic cooling systems and provides valuable design guidelines for the development of next-generation microchannel heat sinks operating under high heat-flux conditions. The organization adopted for the Result and Discussion chapter is illustrated in Figure 5.1.

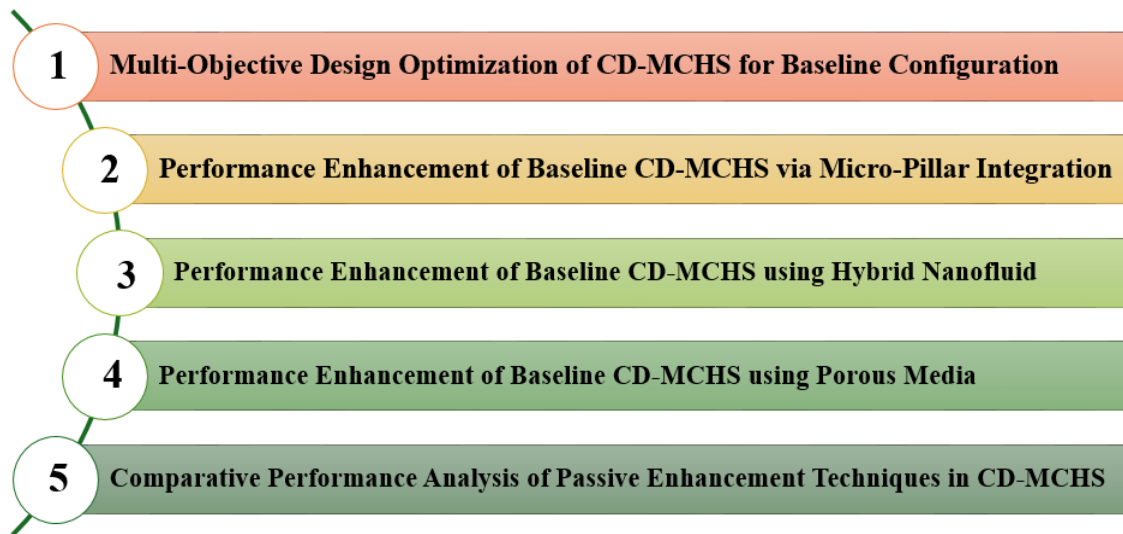


Figure 5.1: Organization of the results and discussion framework adopted in Chapter 5

5.1 Multi-Objective Design Optimization of CD-MCHS for Baseline Configuration

The baseline convergent-divergent microchannel heat sink (CD-MCHS) serves as the reference configuration for all enhancement strategies investigated in the present study. Prior to incorporating micro-pillars, hybrid nanofluids, and porous media, it is essential to establish an optimized baseline design capable of delivering improved thermal performance while maintaining favorable thermodynamic characteristics. Such an optimization not only identifies the influence of key design parameters on system performance but also provides a benchmark for assessing the effectiveness of subsequent enhancement techniques. The detailed results obtained through the CFD-ANN-NSGA-II-TOPSIS framework are presented and discussed in the following sections.

5.1.1 Design Variables and Optimization Objectives

The hydrothermal and thermodynamic performance of the baseline CD-MCHS is governed by seven independent design variables, namely Reynolds number (Re), top-to-bottom width ratio (α), bottom-to-pitch width ratio (β), channel-to-total height ratio (γ), throat-to-channel height ratio (δ), number of parallel channels (N_1), and number of channels arranged in series (N_2). These parameters collectively control the channel geometry, flow distribution, thermal boundary-layer development, and fluid acceleration within the convergent-divergent passages. Variations in these parameters therefore directly influence the heat-transfer and pressure-loss characteristics of the microchannel heat sink.

The performance of the heat sink is evaluated using two objective functions: the average Nusselt number (Nu) and total entropy generation (S_{gen}). The Nusselt number serves as a measure of convective heat-transfer enhancement and reflects the effectiveness of boundary-layer disruption and fluid mixing within the microchannel. In contrast, entropy generation quantifies the thermodynamic irreversibilities associated with heat transfer and fluid friction, thereby providing a second-law assessment of system performance.

The simultaneous optimization of these objectives creates a conflicting design scenario. Geometrical modifications that intensify fluid mixing and enhance heat transfer generally increase velocity gradients and pressure losses, leading to higher entropy generation. Conversely, configurations that minimize thermodynamic irreversibilities may suppress convective transport and reduce heat-transfer effectiveness. Consequently, identifying a balanced design requires a multi-objective optimization framework capable of simultaneously considering both thermal and thermodynamic performance criteria.

To facilitate a meaningful assessment of the optimization benefits, a baseline configuration was defined corresponding to a straight microchannel geometry characterized by $Re = 300$, $\alpha = 1.0$, $\beta = 0.5$, $\gamma = 0.5$, $\delta = 1.0$, $N_1 = 50$, and $N_2 = 6$. For this configuration, $\alpha = 1$ and $\delta = 1$ cause the convergent-divergent geometry to reduce to an equivalent straight microchannel with a rectangular cross-section. Consequently, this case serves as the reference configuration for evaluating the relative improvements achieved through the optimized CD-MCHS designs. Unless otherwise stated, the normalized objective functions presented in the optimization results are expressed with respect to this baseline configuration.

5.1.2 Exploration of Design Space and Initial CFD Database

To establish a representative optimization database, the design space defined by the seven independent variables was systematically sampled using the Latin Hypercube Sampling technique. LHS is particularly suitable for multi-variable optimization problems because it ensures a uniform distribution of sample points throughout the design domain while minimizing clustering and redundancy. As a result, the entire feasible design space can be explored efficiently using a limited number of numerical simulations, thereby reducing the computational burden associated with exhaustive parametric investigations.

Based on the prescribed ranges of the design variables, a total of 45 design configurations were generated using the LHS approach. Each configuration was subsequently evaluated

through three-dimensional numerical simulations to determine the corresponding values of the average Nusselt number and total entropy generation. The resulting CFD database forms the foundation for the development of ANN surrogate models and the subsequent multi-objective optimization process. The generated dataset provides a comprehensive representation of the design space and captures the variation of both objective functions over a wide range of geometric and operating conditions, thereby ensuring adequate coverage of the feasible solution domain.

Table 5.1: LHS-generated design variables and corresponding CFD responses for the baseline CD-MCHS

S. No.	Design Variable (Generated with LHS)							Corresponding Results	
	Re	α	β	γ	δ	N ₁	N ₂	Nu	S _{gen}
01	300	1.00	0.50	0.50	1.00	50	06	33.180	0.001155
02	300	0.75	0.60	0.60	0.80	60	12	39.649	0.001034
03	300	1.00	0.40	0.70	1.00	50	06	43.199	0.001103
04	400	1.50	0.60	0.80	0.60	50	04	46.607	0.001902
05	400	1.00	0.50	0.60	0.80	40	06	33.803	0.001738
06	200	1.25	0.50	0.40	0.80	60	08	26.909	0.001106
07	200	1.50	0.60	0.40	0.60	30	08	18.849	0.006030
08	300	1.25	0.60	0.70	1.00	30	10	34.599	0.004216
09	400	0.50	0.70	0.70	0.20	70	04	37.984	0.000937
10	200	0.50	0.70	0.50	0.60	70	08	30.720	0.000881
11	300	1.00	0.80	0.80	1.00	30	06	38.093	0.005306
12	300	1.00	0.40	0.60	0.60	50	08	31.658	0.001313
13	500	1.50	0.50	0.80	0.60	60	04	51.682	0.001826
14	100	1.25	0.60	0.40	0.40	40	10	16.002	0.004066
15	300	1.25	0.70	0.50	1.00	60	06	39.013	0.001000
16	300	1.00	0.70	0.70	0.40	50	06	35.624	0.002080
17	100	0.75	0.60	0.80	0.60	40	04	31.460	0.001962
18	400	1.50	0.50	0.70	1.00	40	06	42.687	0.002008
19	400	1.00	0.40	0.50	0.60	60	10	31.559	0.001904
20	200	0.50	0.70	0.50	0.80	60	12	30.611	0.000985
21	400	1.25	0.60	0.70	0.60	60	04	45.111	0.001401

Cont....

22	100	1.00	0.50	0.70	0.80	40	12	30.458	0.001776
23	200	1.25	0.50	0.50	0.60	40	12	23.160	0.002462
24	300	0.50	0.60	0.50	0.20	70	06	30.057	0.002580
25	400	0.75	0.50	0.70	0.80	70	12	47.915	0.003084
26	100	0.75	0.80	0.70	0.60	40	06	27.843	0.003382
27	200	0.75	0.40	0.60	0.80	40	08	27.922	0.003382
28	200	0.75	0.70	0.60	0.40	70	08	32.178	0.001152
29	200	1.25	0.60	0.50	0.60	30	06	20.806	0.001149
30	400	0.50	0.60	0.70	1.00	40	10	39.043	0.005640
31	400	1.00	0.80	0.60	0.80	60	12	41.281	0.001443
32	200	1.25	0.40	0.50	0.60	50	08	25.731	0.003045
33	500	0.75	0.70	0.70	0.20	50	10	27.177	0.001646
34	500	1.25	0.50	0.80	0.80	60	08	54.362	0.001583
35	300	0.75	0.80	0.80	0.80	40	04	40.910	0.001214
36	100	0.75	0.70	0.50	0.20	40	06	19.225	0.001865
37	400	1.50	0.40	0.70	0.40	50	06	39.543	0.002589
38	300	0.50	0.70	0.60	0.40	50	08	32.335	0.001916
39	500	1.00	0.70	0.40	0.80	60	04	33.053	0.001550
40	300	0.75	0.80	0.40	0.40	70	08	28.573	0.001401
41	200	0.75	0.70	0.50	0.20	50	10	23.964	0.001304
42	400	1.25	0.40	0.50	0.40	50	08	31.529	0.001646
43	200	1.00	0.60	0.60	0.40	60	10	30.185	0.001374
44	300	1.00	0.70	0.40	0.80	60	10	29.570	0.001440
45	400	1.00	0.50	0.70	0.80	50	12	43.118	0.001338

Table 5.1 summarizes the generated design configurations together with the corresponding objective-function values obtained from the CFD simulations. The wide variation observed in both Nusselt number and entropy generation indicates that the selected design variables exert a significant influence on the hydrothermal and thermodynamic behavior of the baseline CD-MCHS. Such variability is desirable from an optimization perspective because it enables the surrogate model to effectively capture the underlying relationships between the design variables and performance responses.

The Nusselt number obtained from the sampled designs varies considerably across the design space, reflecting the strong dependence of convective heat transfer on the geometric and operating parameters of the convergent-divergent microchannel. Configurations that promote stronger flow acceleration, repeated boundary-layer redevelopment, and enhanced fluid mixing generally exhibit superior heat-transfer performance. Conversely, designs that allow thermal boundary-layer growth with relatively weaker flow disturbances tend to produce lower Nusselt numbers.

A similar trend is observed for entropy generation, which is governed by the combined effects of thermal and frictional irreversibilities. Geometrical modifications that intensify fluid acceleration and increase velocity gradients enhance heat transfer but may simultaneously increase viscous dissipation, leading to higher entropy generation. In contrast, smoother flow passages with reduced velocity gradients generally lower frictional irreversibilities, resulting in reduced entropy production.

These observations indicate that the hydrothermal performance of the CD-MCHS is highly sensitive to the selected design variables and that improvements in heat-transfer capability are frequently accompanied by variations in thermodynamic irreversibility. The generated CFD database therefore provides a sufficiently diverse representation of the design space and captures the complex interactions among the governing parameters. Such characteristics are essential for developing reliable surrogate models capable of accurately reproducing the underlying CFD responses during the optimization process.

5.1.3 Development and Validation of ANN Surrogate Models

The CFD database generated through Latin Hypercube Sampling provides an accurate representation of the hydrothermal and thermodynamic behavior of the baseline CD-MCHS. However, direct utilization of CFD simulations during the optimization process would require a large number of objective-function evaluations, resulting in substantial computational expense. To overcome this limitation, Artificial Neural Network (ANN) surrogate models were developed to establish nonlinear relationships between the design variables and the corresponding objective functions. Once trained and validated, these surrogate models enable rapid prediction of system performance while significantly reducing the computational effort associated with repeated CFD evaluations.

Prior to ANN development, the variation of the objective functions within the generated CFD database was examined to assess the nature of the optimization problem. Since the

Nusselt number and entropy generation possess different magnitudes and units, both responses were normalized using Eq. (5.1) to facilitate direct comparison on a common scale. The normalization was performed solely for visualization purposes and to highlight the conflicting behavior of the objective functions within the sampled design space. The normalized objective functions used during NSGA-II optimization are defined separately with respect to the baseline straight-channel configuration introduced in Section 5.1.1.

$$X_{norm} = 2 * \left(\frac{X - X_{min}}{X_{max} - X_{min}} \right) - 1 \quad (5.1)$$

Where X represents the original response value, X_{norm} denotes the corresponding normalized response, and X_{min} and X_{max} represent the minimum and maximum values of the respective dataset, respectively.

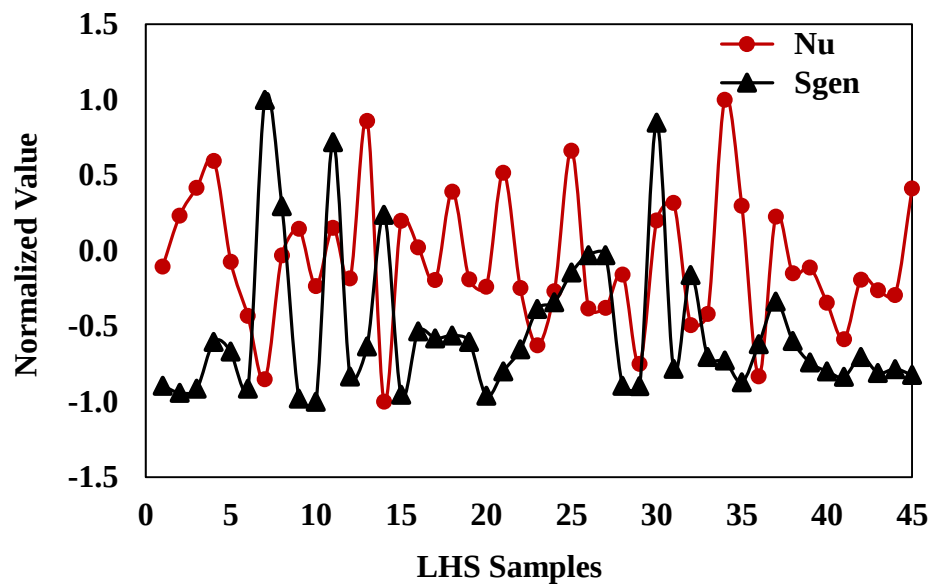


Figure 5.2: Normalized objective responses of the baseline CD-MCHS design space generated using LHS

Figure 5.2 clearly demonstrates the conflicting nature of the optimization objectives. Configurations exhibiting enhanced heat-transfer performance do not necessarily correspond to lower entropy generation, indicating that simultaneous improvement of both objectives cannot be achieved through a single design modification. This behavior highlights the necessity of adopting a multi-objective optimization strategy capable of identifying balanced solutions that satisfy both thermal and thermodynamic performance requirements.

To establish reliable surrogate models, separate ANN architectures were developed for the Nusselt number and entropy generation. The available CFD database was divided into

training, validation, and testing datasets consisting of 70%, 15%, and 15% of the total samples, respectively. The training dataset was employed to determine the network weights and biases, whereas the validation dataset was used to monitor the learning process and prevent overfitting. The testing dataset was subsequently utilized to independently evaluate the predictive capability of the trained networks.

The predictive accuracy of an ANN model is strongly influenced by the number of neurons employed within the hidden layers. Consequently, a neuron independence study was performed to identify the optimum network architecture for each objective function. The variation of the residual error with hidden-layer neurons is presented in Figure 5.3.

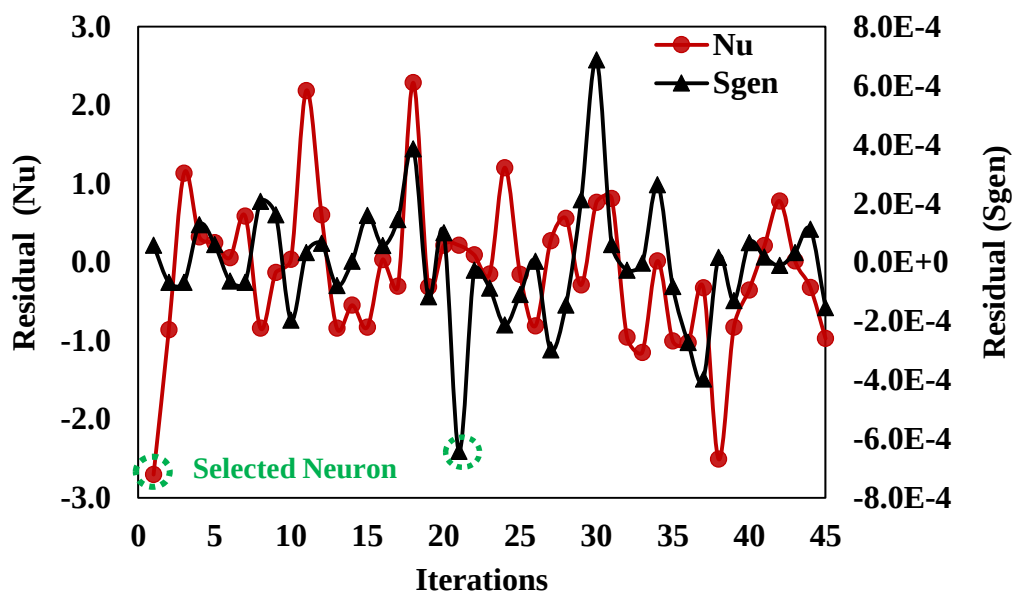


Figure 5.3: Neuron independence analysis for ANN development of baseline CD-MCHS responses

Figure 5.3 presents the variation of residual error with hidden-layer neurons for both objective functions. As the number of neurons increases, the prediction error initially decreases due to the improved learning capability of the network. However, beyond a certain limit, additional neurons provide only marginal improvements while increasing computational complexity. Consequently, the optimal network architecture was selected based on the minimum residual criterion.

The results indicate that the best-performing ANN architecture for predicting the Nusselt number consists of two hidden layers with five neurons each (5-5). Similarly, the optimum ANN model developed for entropy generation comprises two hidden layers with seven neurons each (7-7). These architectures provided the lowest residual errors while

maintaining excellent generalization capability and prediction accuracy. Accordingly, the selected ANN structures were adopted for subsequent model training and validation.

Following the selection of the network architecture, the ANN models were trained using the Levenberg–Marquardt backpropagation algorithm. This algorithm is widely recognized for its rapid convergence and superior performance in nonlinear regression problems involving relatively small and medium-sized datasets. During the training process, the network weights and bias terms were iteratively adjusted until the prediction error reached a minimum value while maintaining satisfactory generalization characteristics.

The predictive capability of the developed ANN surrogate models was subsequently evaluated using parity-plot analysis. Figures 5.4 and 5.5 compare the ANN-predicted responses with the corresponding CFD-generated values for the Nusselt number and entropy generation, respectively. The parity plots provide a direct assessment of model accuracy by illustrating the degree of agreement between the predicted and actual responses over the training, validation, testing, and overall datasets.

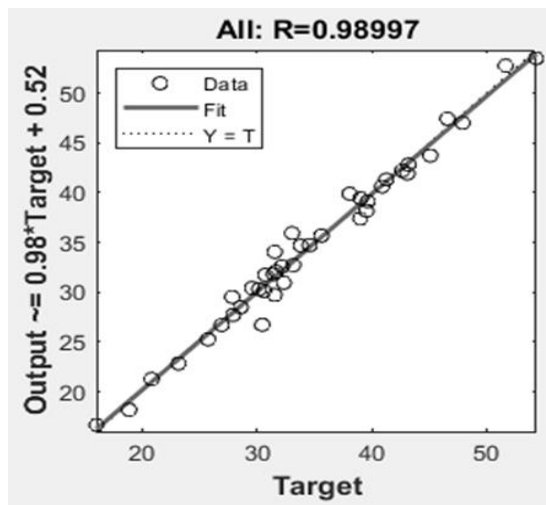


Figure 5.4: Parity plot between CFD and ANN predictions for Nusselt number of the baseline CD-MCHS

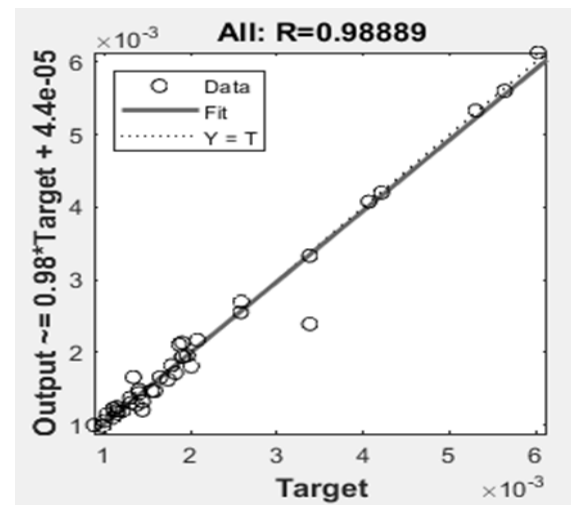


Figure 5.5: Parity plot between CFD and ANN predictions for entropy generation of the baseline CD-MCHS

As shown in Figures 5.4 and 5.5, the data points are closely distributed around the 45° parity line, indicating excellent agreement between the ANN predictions and CFD results. The strong clustering of the data along the line of perfect prediction demonstrates the ability of the developed ANN models to accurately capture the underlying nonlinear relationships between the design variables and responses. Furthermore, the consistent

agreement observed across the training, validation, and testing datasets confirms the robustness and generalization capability of the developed surrogate models.

To quantitatively evaluate the predictive performance of the ANN models, several statistical indicators were calculated. These include the correlation coefficient (R), coefficient of determination (R^2), root mean square error (RMSE), mean absolute error (MAE), and mean absolute percentage error (MAPE). The obtained statistical metrics are summarized in Table 5.2.

Table 5.2: Statistical validation metrics of ANN surrogate models for the baseline CD-MCHS.

S. No.	Performance metrics	Nusselt number	Entropy generation
01	R (Training)	0.9944	0.9865
02	R (Validation)	0.9958	0.9986
03	R (Test)	0.9439	0.9852
04	Overall R	0.9899	0.9888
05	Coefficient of determination (R^2)	0.9994	0.9984
06	Mean Absolute Error	0.7260	3.3×10^{-5}
07	Root Mean Squared Error	0.9551	5.1×10^{-5}
08	Mean Absolute Percentage Error	2.20 %	2.29 %

The statistical results reveal excellent predictive capability for both objective functions, characterized by correlation coefficients approaching unity and very low prediction errors. Such results indicate that the developed ANN models accurately reproduce the CFD-generated responses and can therefore serve as reliable surrogate models during the optimization stage. The close agreement observed between the ANN predictions and CFD data further confirms the ability of the developed networks to capture the complex nonlinear interactions among the governing design variables.

Based on the satisfactory parity-plot agreement and favorable statistical performance indicators, the developed ANN models were adopted as surrogate objective functions for the subsequent multi-objective optimization process. The use of ANN-based surrogate models substantially reduces the computational effort associated with repeated CFD evaluations while maintaining a high level of prediction accuracy. Consequently, the surrogate models enable efficient exploration of the design space and facilitate the identification of Pareto-optimal solutions through the NSGA-II optimization framework.

Accordingly, the trained ANN models were employed to represent the objective functions during the optimization process. The mathematical expressions defining the surrogate models for the average Nusselt number and total entropy generation are presented in Equations (5.2) and (5.3), respectively.

$$\begin{aligned} \text{Nu} = & 28.85 + 0.073 \cdot \text{Re} - 21.94 \cdot \alpha + 40.05 \cdot \beta - 46.03 \cdot \gamma - 37.36 \cdot \delta + 0.16 \cdot N_1 - 3.63 \cdot N_2 - \\ & 0.0001 \cdot \text{Re}^2 + 4.91 \cdot \alpha^2 - 31.27 \cdot \beta^2 + 12.32 \cdot \gamma^2 + 5.05 \cdot \delta^2 - 0.0061 \cdot N_1^2 + 0.037 \cdot N_2^2 + \\ & 0.016 \cdot \text{Re} \cdot \alpha - 0.023 \cdot \text{Re} \cdot \beta + 0.01 \cdot \text{Re} \cdot \gamma - 0.034 \cdot \text{Re} \cdot \delta + 0.0002 \cdot \text{Re} \cdot N_1 - 0.0005 \cdot \text{Re} \cdot N_2 \\ & + 1.76 \cdot \alpha \cdot \beta - 3.11 \cdot \alpha \cdot \gamma + 1.36 \cdot \alpha \cdot \delta + 0.10 \cdot \alpha \cdot N_1 + 0.72 \cdot \alpha \cdot N_2 - 7.66 \cdot \beta \cdot \gamma + 2.30 \cdot \beta \cdot \delta + \\ & 0.2 \cdot \beta \cdot N_1 + 0.11 \cdot \beta \cdot N_2 + 56.03 \cdot \gamma \cdot \delta + 0.49 \cdot \gamma \cdot N_1 + 2.02 \cdot \gamma \cdot N_2 + 0.23 \cdot \delta \cdot N_1 + 0.59 \cdot \delta \cdot N_2 \\ & + 0.012 \cdot N_1 \cdot N_2. \end{aligned} \quad (5.2)$$

$$\begin{aligned} S_{\text{gen}} = & 1.86\text{E-}02 - 8.54\text{E-}07 \cdot \text{Re} - 8.29\text{E-}04 \cdot \alpha + 1.11\text{E-}02 \cdot \beta - 9.18\text{E-}03 \cdot \gamma - 1.06\text{E-}02 \cdot \delta - \\ & 4.26\text{E-}04 \cdot N_1 - 4.68\text{E-}04 \cdot N_2 + 3.11\text{E-}10 \cdot \text{Re}^2 - 6.63\text{E-}05 \cdot \alpha^2 + 9.24\text{E-}03 \cdot \beta^2 + 2.71\text{E-}03 \\ & \cdot \gamma^2 + 3.34\text{E-}03 \cdot \delta^2 + 4.66\text{E-}06 \cdot N_1^2 + 9.50\text{E-}06 \cdot N_2^2 - 2.79\text{E-}06 \cdot \text{Re} \cdot \alpha - 2.03\text{E-}06 \cdot \text{Re} \cdot \beta - \\ & 8.01\text{E-}07 \cdot \text{Re} \cdot \gamma + 3.46\text{E-}06 \cdot \text{Re} \cdot \delta + 8.14\text{E-}08 \cdot \text{Re} \cdot N_1 - 8.46\text{E-}08 \cdot \text{Re} \cdot N_2 + 2.90\text{E-} \\ & 03 \cdot \alpha \cdot \beta + 3.66\text{E-}03 \cdot \alpha \cdot \gamma + 3.73\text{E-}05 \cdot \alpha \cdot \delta - 3.49\text{E-}05 \cdot \alpha \cdot N_1 + 4.78\text{E-}05 \cdot \alpha \cdot N_2 - 5.03\text{E-} \\ & 03 \cdot \beta \cdot \gamma - 1.45\text{E-}03 \cdot \beta \cdot \delta - 3.81\text{E-}04 \cdot \beta \cdot N_1 + 6.60\text{E-}05 \cdot \beta \cdot N_2 - 8.78\text{E-}04 \cdot \gamma \cdot \delta + 1.00\text{E-} \\ & 04 \cdot \gamma \cdot N_1 - 3.11\text{E-}05 \cdot \gamma \cdot N_2 + 7.06\text{E-}05 \cdot \delta \cdot N_1 + 2.20\text{E-}04 \cdot \delta \cdot N_2 + 2.86\text{E-}06 \cdot N_1 \cdot N_2. \end{aligned} \quad (5.3)$$

The validated ANN surrogate models therefore provide an efficient and computationally economical representation of the objective functions and are subsequently integrated with the NSGA-II optimization framework to identify Pareto-optimal CD-MCHS designs.

5.1.4 Selection of NSGA-II Parameters

The effectiveness of the NSGA-II algorithm largely depends on the selection of appropriate control parameters, particularly the population size and the number of generations. These parameters govern the exploration capability, convergence behavior, and diversity of the Pareto-optimal solutions. Therefore, a sensitivity analysis was conducted to identify suitable NSGA-II settings for the present optimization problem.

5.1.4.1 Population Size Analysis

The population size determines the number of candidate solutions available during each generation of the optimization process. A small population may limit the exploration of the design space and result in inadequate Pareto-front diversity, whereas an excessively

large population increases computational effort without providing significant improvements in solution quality.

To evaluate its influence, NSGA-II simulations were performed using different population sizes while maintaining identical optimization settings. The resulting Pareto fronts are presented in Figure 5.6.

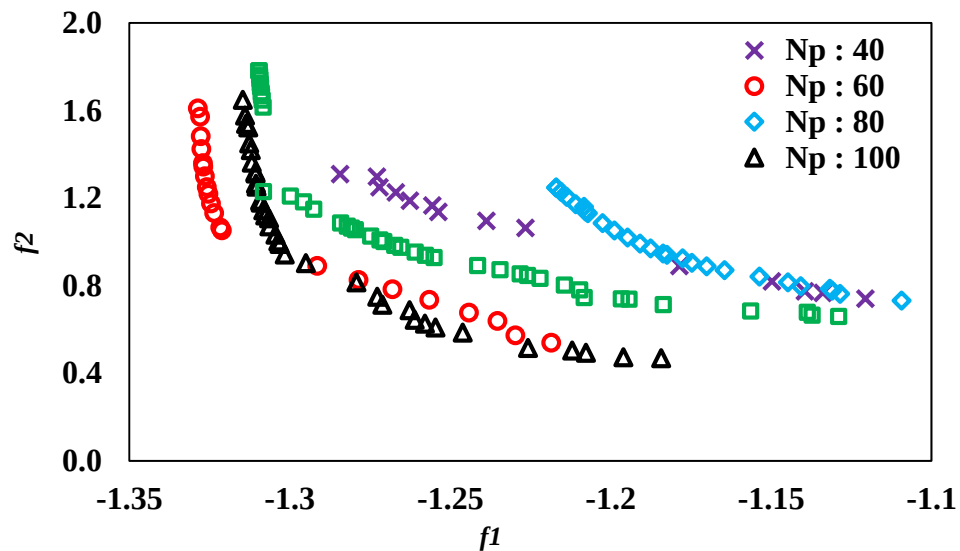


Figure 5.6: Influence of population size on Pareto-front development for baseline CD-MCHS optimization

As illustrated in Figure 5.6, increasing the population size improves the distribution and density of Pareto-optimal solutions. Smaller populations generate sparse solution sets and fail to adequately cover the objective space. In contrast, larger populations provide better exploration of the design domain and produce a more continuous Pareto front. It was observed that the improvement in Pareto-front quality becomes marginal beyond a population size of 100. Therefore, a population size of 100 was selected as an appropriate compromise between solution diversity and computational efficiency.

5.1.4.2 Generation Number Analysis

The number of generations controls the evolutionary progression of NSGA-II and influences the refinement of candidate solutions through selection, crossover, and mutation. Too few generations may lead to premature convergence and an incomplete Pareto front, whereas excessive generations increase computational cost with limited improvement. Using a population size of 100, a generation study was performed to assess convergence behaviour, and the resulting Pareto fronts are presented in Figure 5.7.

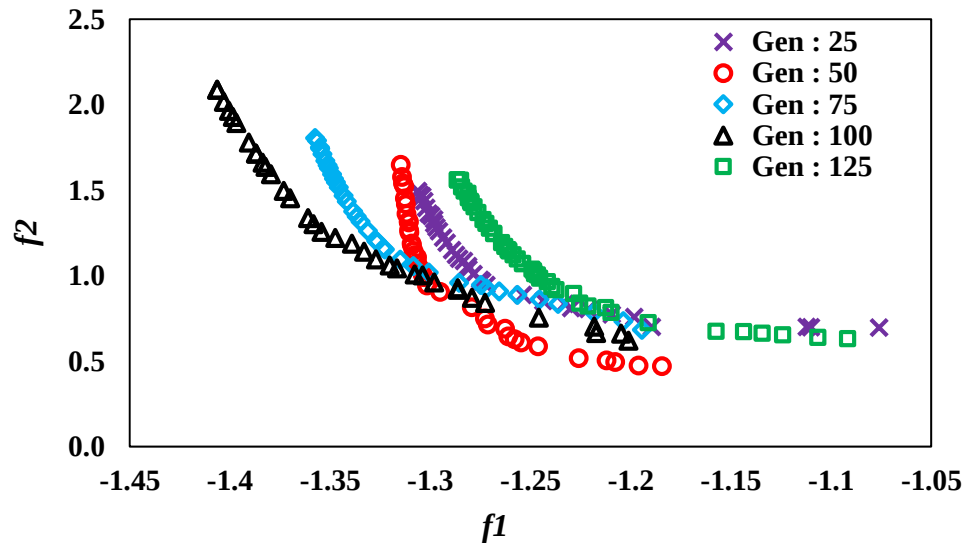


Figure 5.7: Influence of generation number on Pareto-front convergence for baseline CD-MCHS optimization

The results indicate that the Pareto front progressively improves as the number of generations increases. At lower generation numbers, the solutions remain relatively scattered and the trade-off between the objective functions is not fully developed. With increasing generations, the Pareto front becomes more uniform and converges toward a stable solution set. Beyond 100 generations, only negligible changes are observed in the Pareto-front distribution, indicating that convergence has been achieved. Consequently, 100 generations were adopted for all subsequent optimization studies.

5.1.4.3 Final NSGA-II Parameters

Based on the population size and generation number investigations, the final NSGA-II parameters employed for baseline CD-MCHS optimization are summarized in Table 5. 3.

Table 5.3: Final NSGA-II control parameters adopted for baseline CD-MCHS

Parameter		Parameter Value
Population (N_p)		100
Maximum Generation (Gen)		100
Reproduction / Selection	Tournament Selection (Rank and Crowding Distance)	
Pareto Fraction	0.35	
Crossover Rate	0.85	
Mutation Rate	0.10	

The selected parameter set provided a stable and well-converged optimization framework capable of generating a diverse set of Pareto-optimal solutions while maintaining computational efficiency. The validated ANN surrogate models together with the optimized NSGA-II settings were subsequently employed to identify the optimal trade-off solutions discussed in the following section.

5.1.5 Characterization of the Optimal Pareto Front

The final Pareto front was established following the selection of appropriate NSGA-II parameters, ensuring a well-converged and diverse set of non-dominated solutions. The optimization process simultaneously maximized the average Nusselt number and minimized total entropy generation, resulting in a set of Pareto-optimal designs representing different trade-offs between thermal enhancement and thermodynamic performance. The corresponding design-variable combinations and objective-function values are summarized in Table 5.4.

Table 5.4: Pareto-optimal design configurations and corresponding responses for the baseline CD-MCHS

S. No.	Pareto Design Variable (100 th Generation)							Corresponding Results	
	Re	α	β	γ	δ	N ₁	N ₂	Nu	S _{gen}
01	400	1.10	0.65	0.70	0.75	65	10	44.035	0.001265
02	400	1.05	0.65	0.70	0.75	65	09	43.807	0.001223
03	425	1.15	0.60	0.70	0.75	70	11	46.666	0.002412
04	400	0.95	0.65	0.70	0.75	60	08	42.229	0.000970
05	400	1.00	0.65	0.70	0.75	65	09	43.259	0.001156
06	400	0.75	0.65	0.70	0.70	60	08	39.975	0.000764
07	400	1.00	0.65	0.70	0.75	60	09	42.677	0.001060
08	400	0.90	0.65	0.70	0.75	60	08	41.336	0.000871
09	400	1.05	0.65	0.70	0.75	65	10	44.430	0.001371
10	400	0.80	0.65	0.70	0.70	60	08	40.417	0.000811
11	425	0.95	0.60	0.70	0.60	65	07	40.224	0.001378
12	400	0.90	0.65	0.70	0.65	60	07	39.986	0.000922
13	400	0.60	0.65	0.70	0.65	55	09	36.973	0.000612
14	400	0.65	0.65	0.70	0.65	60	08	38.339	0.000649

Cont....

15	400	0.70	0.65	0.70	0.65	60	07	39.312	0.000736
16	400	0.65	0.65	0.70	0.65	55	08	37.976	0.000635
17	400	0.85	0.65	0.70	0.65	60	07	39.636	0.000813
18	400	0.80	0.65	0.70	0.65	60	07	39.494	0.000794
19	450	1.25	0.60	0.70	0.70	70	08	44.572	0.001695
20	425	1.20	0.65	0.70	0.70	65	07	43.415	0.001220
21	425	1.20	0.65	0.70	0.70	65	08	44.351	0.001555
22	425	0.75	0.65	0.70	0.70	60	07	39.627	0.000789
23	425	1.15	0.65	0.70	0.70	60	07	41.993	0.001048
24	425	0.95	0.65	0.70	0.70	60	07	40.427	0.000907
25	425	1.10	0.65	0.70	0.70	60	07	41.694	0.001026
26	425	0.80	0.65	0.70	0.70	60	07	39.937	0.000849
27	425	1.00	0.65	0.70	0.70	60	07	41.016	0.000964
28	425	0.75	0.60	0.70	0.75	60	07	39.739	0.000864
29	425	0.90	0.60	0.70	0.75	65	07	42.017	0.001289
30	425	0.90	0.60	0.70	0.70	70	07	42.598	0.001943
31	400	0.70	0.65	0.70	0.70	60	08	39.854	0.000716
32	425	0.85	0.60	0.70	0.75	60	07	41.300	0.001110
33	425	0.80	0.60	0.70	0.75	60	07	41.102	0.001093
34	425	0.70	0.60	0.70	0.70	55	07	38.860	0.000807
35	425	0.85	0.60	0.70	0.75	65	07	41.384	0.001145

Table 5.4 demonstrates that the ANN-NSGA-II framework successfully identified multiple optimal design configurations distributed throughout the feasible design space. The Pareto solutions are characterized by different combinations of Reynolds number and geometric parameters, indicating that the hydrothermal performance of the CD-MCHS is governed by the coupled interaction of all design variables rather than any single parameter. The distribution of solutions further confirms that the optimization process effectively explored the design domain and converged toward several high-performance regions capable of satisfying different thermal and thermodynamic requirements. A closer examination of the Pareto-optimal solutions reveals a distinct trade-off between heat-transfer enhancement and entropy generation. Designs exhibiting superior thermal performance generally correspond to higher entropy-generation values, whereas

configurations associated with lower thermodynamic irreversibility tend to produce comparatively smaller Nusselt numbers. This behavior is physically expected because the mechanisms responsible for enhanced convective heat transfer, including intensified flow acceleration, repeated boundary-layer redevelopment, and stronger fluid mixing within the convergent-divergent passages, simultaneously increase viscous dissipation and fluid-friction irreversibilities.

Among the Pareto-optimal solutions, the highest thermal performance is achieved by Solution-03, which produces a Nusselt number of 46.666. However, this configuration also exhibits one of the largest entropy-generation values (0.002412), indicating a significant thermodynamic penalty associated with aggressive heat-transfer enhancement. In contrast, Solution 13 yields the minimum entropy-generation value of 0.000612, but the corresponding Nusselt number decreases to 36.973. These extreme solutions clearly demonstrate the conflicting nature of the optimization objectives and confirm that improvements in thermal performance cannot be achieved without influencing thermodynamic irreversibility.

The Pareto-optimal solutions also reveal important geometric trends. Configurations associated with higher Nusselt numbers generally occur at relatively larger values of the width ratio (α), increased Reynolds numbers, and larger channel counts (N_1 and N_2). Such parameter combinations promote stronger fluid acceleration and enhanced thermal boundary-layer disruption, thereby increasing convective heat transfer. Conversely, lower values of α are frequently associated with reduced entropy generation due to the suppression of excessive velocity gradients and frictional losses. These observations highlight the critical role of geometric optimization in controlling the balance between heat-transfer enhancement and thermodynamic efficiency.

To further visualize the trade-off characteristics of the optimization process, the Pareto front obtained through the ANN-NSGA-II framework is presented in Figure 5.8.

Figure 5.8 illustrates the non-dominated solution boundary separating feasible and infeasible regions of the objective space. Each point on the Pareto front represents an optimal design for which improvement in one objective can only be achieved at the expense of the other. The continuous nature of the Pareto front confirms the existence of multiple equally optimal solutions and demonstrates the inherently conflicting relationship between heat-transfer enhancement and entropy-generation minimization.

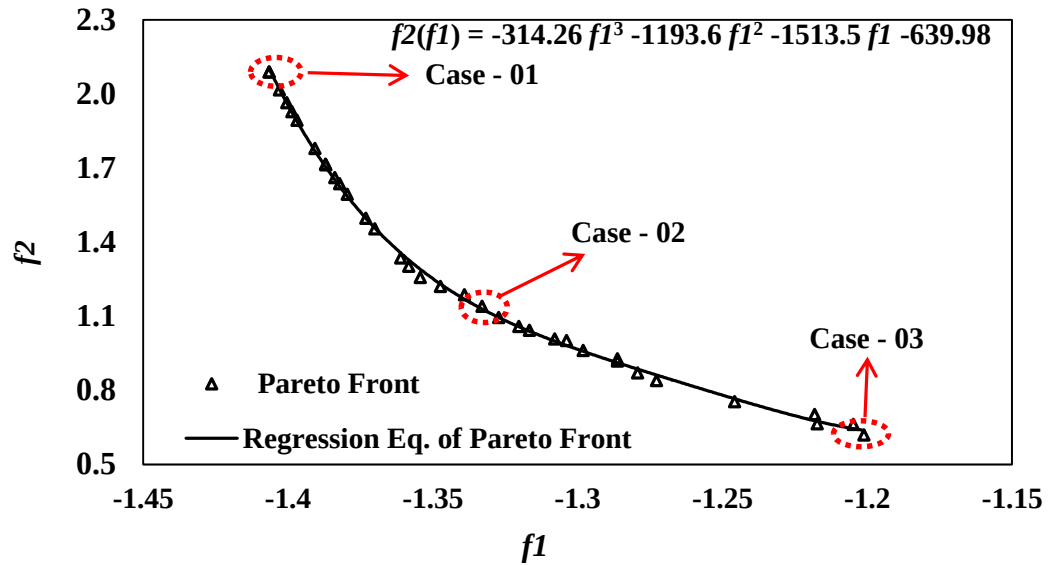


Figure 5.8: Pareto front with selected optimal solutions for the baseline CD-MCHS

Although the Pareto front successfully identifies the complete set of optimal trade-off solutions, it does not directly indicate which design should be selected for practical implementation. Therefore, representative solutions located at different regions of the Pareto front were selected for further evaluation to better understand their engineering significance. The corresponding performance comparison is presented in Table 5.5.

Table 5.5: Performance comparison of representative Pareto-optimal solutions for the baseline CD-MCHS relative to the reference configuration

Ref Study : (Re-300; α -1.00; β -0.50; γ -0.50; δ -1.00; N_1 -50; N_2 -06)	Nu ($f_1 = -1$)	S _{gen} ($f_2 = 1$)
Case – 01: (Re-425; α -1.15; β -0.60; γ -0.70; δ -0.75; N_1 -70; N_2 -11)	40.6 % ↑	108.8 % ↑
Case – 02: (Re-400; α -1.05; β -0.65; γ -0.70; δ -0.75; N_1 -65; N_2 -10)	33.9 % ↑	18.6 % ↑
Case – 03: (Re-400; α -0.70; β -0.65; γ -0.70; δ -0.70; N_1 -60; N_2 -08)	20.1 % ↑	38.1 % ↓

Table 5.5 compares three representative Pareto-optimal solutions corresponding to the maximum heat-transfer design (Case-01), an intermediate compromise design (Case-02), and a thermodynamically favorable design (Case-03). Relative to the baseline configuration, Case-01 provides the highest thermal enhancement, increasing the average Nusselt number by approximately 40.6%. However, this improvement is accompanied by a substantial increase of about 108.8% in entropy generation. Such behavior demonstrates the thermodynamic cost associated with maximizing heat-transfer performance.

Case-02 occupies an intermediate position on the Pareto front and achieves a more balanced thermo-hydraulic performance. The Nusselt number increases by approximately

33.9%, while the corresponding increase in entropy generation is limited to only 18.6%. This result indicates that significant thermal enhancement can be achieved without incurring excessive thermodynamic penalties, making this solution particularly attractive from an engineering standpoint.

In contrast, Case-03 is located near the entropy-generation-minimization region of the Pareto front. Although the heat-transfer enhancement is comparatively lower, the design still achieves an increase of approximately 20.1% in the Nusselt number while simultaneously reducing entropy generation by about 38.1% relative to the baseline configuration. This finding demonstrates that appropriate geometric modification of the CD-MCHS can improve thermal performance while reducing overall thermodynamic irreversibility.

The comparison of representative Pareto-optimal solutions clearly demonstrates that no single design simultaneously maximizes heat transfer and minimizes entropy generation. Consequently, an objective decision-making approach is required to identify the most balanced design among the available Pareto solutions. For this purpose, the Technique for Order Preference by Similarity to Ideal Solution (TOPSIS) was employed, as discussed in the following section.

5.1.6 Identification of the Best Compromise Design Using TOPSIS

Although the Pareto front successfully identifies the set of non-dominated solutions, it does not directly indicate which design should be selected for practical implementation. Each Pareto-optimal solution represents a different compromise between heat-transfer enhancement and entropy-generation minimization, and therefore the final design selection depends on the relative importance assigned to the optimization objectives. To address this limitation, the Technique for Order Preference by Similarity to Ideal Solution (TOPSIS) was employed as a multi-criteria decision-making tool to rank the Pareto-optimal solutions and identify the most balanced design.

The TOPSIS method evaluates each Pareto solution based on its relative proximity to an ideal solution and its distance from the corresponding negative ideal solution. In the present study, the average Nusselt number and total entropy generation were adopted as the decision criteria. Since the primary objective of a microchannel heat sink is efficient thermal management, a higher priority was assigned to heat-transfer enhancement than to entropy-generation minimization. Consequently, greater weight was assigned to the

Nusselt number while still maintaining sufficient consideration of thermodynamic performance.

To examine the robustness of the selected weighting strategy, a sensitivity analysis was conducted by systematically varying the weighting factors assigned to the objective functions. Five different weighting combinations ranging from (0.4, 0.6) to (0.8, 0.2) for (Nuavg, Sgen) were investigated. The resulting TOPSIS rankings for the leading Pareto-optimal solutions are summarized in Table 5.6.

Table 5.6: Sensitivity of TOPSIS rankings for the baseline CD-MCHS under different objective weight distributions

TOPSIS	W ₁ (0.4;0.6)		W ₂ (0.5;0.5)		W ₃ (0.6;0.4)		W ₄ (0.7;0.3)		W ₅ (0.8;0.2)	
Ranking	(C _i) ₁	DoE	(C _i) ₂	DoE	(C _i) ₃	DoE	(C _i) ₄	DoE	(C _i) ₅	DoE
01	0.9183	14	0.8881	31	0.8504	31	0.7918	31	0.7199	04
02	0.9170	16	0.8839	14	0.8400	06	0.7850	08	0.7160	08
03	0.9127	31	0.8811	16	0.8367	15	0.7848	06	0.7038	07
04	0.9103	13	0.8760	15	0.8365	14	0.7833	10	0.6972	10
05	0.9013	15	0.8712	13	0.8321	16	0.7754	15	0.6956	31

The results indicate that the ranking of the Pareto-optimal solutions remains relatively stable despite variations in the weighting scheme. In particular, DoE 31 consistently appears among the top five candidates for all investigated weighting combinations. More importantly, it achieves the highest ranking under three weighting distributions, namely (0.5, 0.5), (0.6, 0.4), and (0.7, 0.3). Even under the extreme weighting scenarios of (0.4, 0.6) and (0.8, 0.2), DoE 31 maintains competitive rankings of third and fifth positions, respectively. Such behavior demonstrates the robustness of this solution and indicates that its performance is relatively insensitive to moderate variations in decision-maker preference.

To further evaluate the stability of the selected design, the relative closeness coefficient (C_i) of DoE 31 was statistically analyzed for all weighting distributions. The corresponding results are presented in Table 5.7.

The statistical assessment reveals that the relative closeness coefficient of DoE 31 exhibits a mean value of 0.8277 with a standard deviation of 0.079, corresponding to a coefficient of variation of only 9.5%. The relatively low coefficient of variation indicates limited sensitivity to changes in weighting preference and confirms the stability of the selected

solution. Furthermore, the weighting distribution of (0.6, 0.4) produces a closeness coefficient that lies very close to the overall mean value, suggesting that this weighting combination provides a balanced representation of both objective functions. Accordingly, the weighting factors of 0.6 for Nu_{avg} and 0.4 for S_{gen} were adopted as the reference decision-making criteria for the present study, as they prioritize enhanced cooling performance while maintaining acceptable thermodynamic irreversibility.

Table 5.7: Relative closeness coefficient of the selected TOPSIS design for the baseline CD-MCHS under different weighting scenarios

S. No.	Weight (Nu , S_{gen})	Relative Closeness (C_i)
1	$W_1(0.4;0.6)$	0.9127
2	$W_2(0.5;0.5)$	0.8881
3	$W_3(0.6;0.4)$	0.8504 Selected
4	$W_4(0.7;0.3)$	0.7918
5	$W_5(0.8;0.2)$	0.6956
Mean (μ)		0.8277
Std. Dev. (σ)		0.079
Coefficient of variation (CV)		9.50%

Using the selected weighting distribution (Nu : 0.6; S_{gen} : 0.4), the relative closeness coefficients of all Pareto-optimal solutions were evaluated. The resulting TOPSIS ranking is illustrated in Figure 5.9.

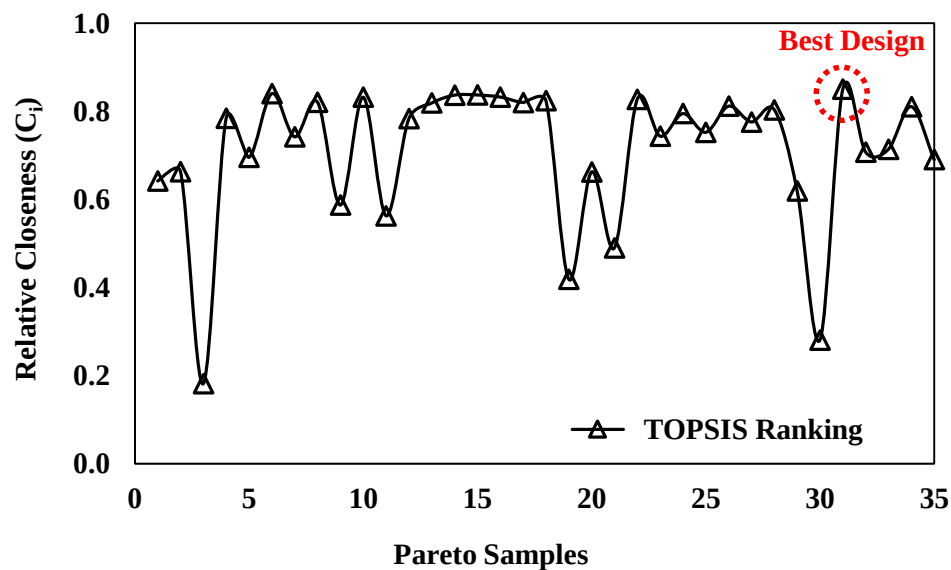


Figure 5.9: TOPSIS ranking of Pareto-optimal solutions for the baseline CD-MCHS

Figure 5.9 shows the variation of the relative closeness coefficient (C_i) for the Pareto-optimal solutions. Higher values of C_i indicate greater proximity to the ideal solution and therefore represent more desirable design alternatives. Although several Pareto solutions exhibit competitive performance, DoE 31 attains the highest relative closeness coefficient and is consequently identified as the most balanced design among the available Pareto-optimal solutions. This design corresponds to Case-03 identified in the previous section and occupies an intermediate region of the Pareto front where substantial heat-transfer enhancement is achieved without excessive entropy-generation penalties.

The optimal design identified through the TOPSIS analysis is characterized by the following parameter combination: $Re-400$; $\alpha-0.70$; $\beta-0.65$; $\gamma-0.70$; $\delta-0.70$; N_1-60 ; N_2-08 . To better understand the engineering significance of the selected configuration, its performance was compared with other representative Pareto-optimal solutions. The comparison is presented in Table 5.8.

Table 5.8: Comparative performance of the selected TOPSIS design for the baseline CD-MCHS relative to Pareto-optimal solutions and the reference configuration

Best TOPSIS Design	Nu (f_1)	S _{gen} (f_2)
Case – 01	14.6 % ↓	70.3 % ↓
Case – 02	10.3 % ↓	47.7 % ↓
Case – 03	-	-
Reference Study	20.1 % ↑	38.1 % ↓

The results indicate that the selected TOPSIS design provides the most favorable balance between heat-transfer enhancement and entropy-generation minimization. Compared with Case-01, the TOPSIS design sacrifices only 14.6% in the Nusselt number while reducing entropy generation by a substantial 70.3%. Similarly, relative to Case-02, a modest reduction of 10.3% in heat-transfer performance results in a significant 47.7% decrease in entropy generation. These observations demonstrate that a small compromise in thermal enhancement can yield considerable thermodynamic benefits. Furthermore, when compared with the reference study, the TOPSIS-selected design still achieves an approximately 20.1% increase in the average Nusselt number while simultaneously reducing entropy generation by 38.1%. Overall, the selected configuration offers the most balanced thermo-hydrodynamic performance among the Pareto-optimal solutions and was

therefore adopted as the optimized CD-MCHS design for subsequent hydrothermal and exergetic analyses.

5.1.7 Hydrothermal Characteristics of the Selected TOPSIS Design

To understand the physical mechanisms responsible for the improved performance of the optimized configuration, the temperature, velocity, and pressure distributions of the TOPSIS-selected design were compared with those of the reference straight microchannel. The corresponding longitudinal mid-plane contours are presented in Figure 5.10.

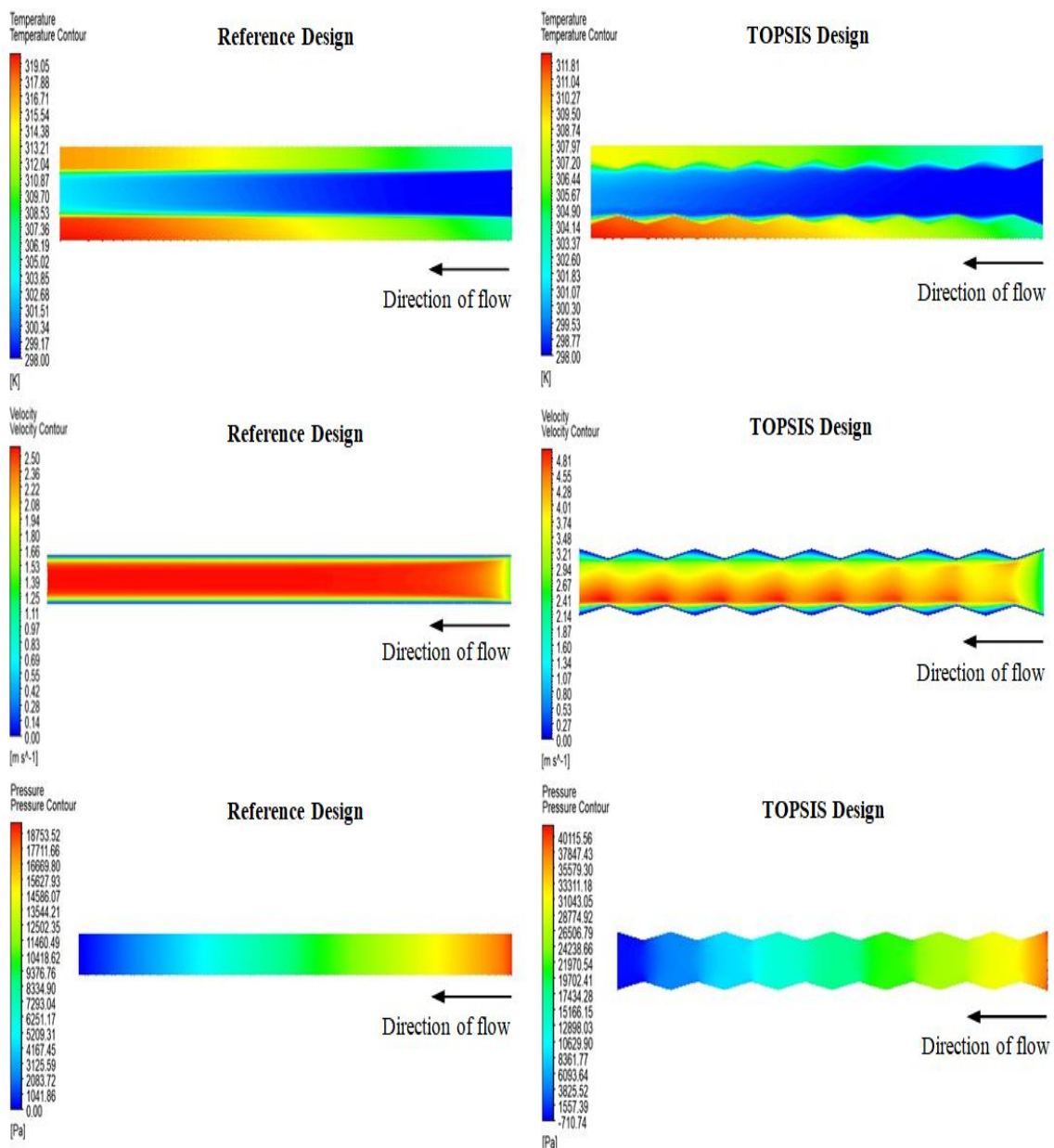


Figure 5.10: Comparison of temperature, velocity, and pressure distributions between the reference and TOPSIS-optimized baseline CD-MCHS

The temperature contours reveal a significant improvement in thermal performance for the optimized convergent-divergent channel. In the reference design, the fluid temperature gradually increases along the flow direction, reaching approximately 319 K near the outlet due to continuous thermal boundary-layer growth. In contrast, the optimized channel restricts the outlet temperature to approximately 311 K, corresponding to a reduction of nearly 8 K. This improvement is attributed to the repeated contraction and expansion sections, which periodically disrupt the thermal boundary layer and enhance fluid mixing, resulting in more uniform temperature distribution and improved heat removal.

The velocity contours further illustrate the enhancement mechanism. While the reference channel exhibits a relatively uniform velocity field with a peak velocity of about 2.5 m/s, the convergent-divergent geometry generates successive acceleration and deceleration regions, increasing the peak velocity to nearly 4.8 m/s. These periodic velocity fluctuations promote stronger momentum exchange and repeated boundary-layer redevelopment, thereby improving convective heat-transfer performance.

The pressure contours indicate that the improved thermal performance is accompanied by a hydraulic penalty. The pressure drop increases from approximately 1.9×10^4 Pa in the reference channel to nearly 4.0×10^4 Pa in the optimized design due to enhanced flow acceleration through the converging sections. Nevertheless, the substantial reduction in fluid temperature and improved heat-transfer capability demonstrate that the optimized geometry effectively enhances thermo-hydraulic performance and justifies the associated increase in pressure loss.

5.1.8 Exergetic Performance Evaluation of the Optimized CD-MCHS

To further validate the optimized configurations obtained through the ANN-NSGA-II-TOPSIS framework, an exergetic performance assessment was carried out using the Exergy Destruction Ratio (EDR) and exergy efficiency (η_{ex}). While the preceding analyses focused on heat-transfer enhancement and entropy-generation characteristics, exergy analysis provides a more rigorous second-law evaluation by quantifying the quality of energy utilization and the extent of thermodynamic irreversibilities within the system. Consequently, this assessment serves as a cross-validation tool to determine whether the configurations identified as optimal from hydrothermal and entropy-generation perspectives also exhibit favorable exergetic behavior. The comparative evaluation of the reference, Pareto-optimal, and TOPSIS-selected designs therefore provides additional

insight into the overall thermodynamic reliability of the proposed CD-MCHS configurations.

Table 5.9: Exergetic performance comparison of reference, Pareto-optimal, and TOPSIS-selected configurations for the baseline CD-MCHS

Design Configuration	EDR	Relative EDR	η_{ex}
Ref Study	11.47 %	-	88.53 %
Case-01	33.54 %	192.36 % ↑	66.46 %
Case-02	17.70 %	54.31 % ↑	82.30 %
Case-03 (TOPSIS-Optimised Design)	8.53 %	25.62 % ↓	91.47 %

Table 5.9 compares the exergetic performance of the reference configuration, the representative Pareto-optimal solutions, and the TOPSIS-selected design. The reference microchannel exhibits an EDR of 11.47% and an exergy efficiency of 88.53%, which serve as the benchmark for evaluating the optimized configurations.

Among the Pareto-optimal solutions, Case-01 achieves the highest heat-transfer enhancement; however, this improvement is accompanied by a substantial increase in thermodynamic irreversibility. The EDR increases to 33.54%, representing a 192.36% rise relative to the baseline, while the exergy efficiency decreases to 66.46%. This behavior indicates that the aggressive thermal enhancement achieved by this configuration comes at the expense of significant useful-energy destruction.

Case-02 exhibits a comparatively moderate exergetic response, with an EDR of 17.70% and an exergy efficiency of 82.30%. Although the irreversibility remains higher than that of the baseline configuration, the deterioration in exergetic performance is considerably lower than that observed for Case-01, reflecting a more balanced compromise between thermal enhancement and thermodynamic losses.

In contrast, the TOPSIS-selected design (Case-03) demonstrates the most favorable exergetic performance among all investigated configurations. The EDR decreases to 8.53%, corresponding to a 25.62% reduction relative to the reference design, while the exergy efficiency increases to 91.47%, representing the highest value among the evaluated cases. These results indicate that the selected configuration not only improves heat-transfer performance but also reduces thermodynamic irreversibilities, thereby enhancing the overall utilization of available energy.

Overall, the exergetic assessment confirms the effectiveness of the integrated ANN–NSGA-II–TOPSIS optimization framework in identifying a thermally and thermodynamically superior CD-MCHS configuration. The TOPSIS-selected design simultaneously achieves enhanced heat-transfer performance, reduced entropy generation, lower exergy destruction, and higher exergy efficiency, thereby establishing it as the most balanced and reliable configuration among the investigated alternatives. Consequently, this optimized CD-MCHS design was adopted as the baseline configuration for the subsequent enhancement studies. Building upon this optimized geometry, the following section investigates the influence of micro-pillars on the hydrothermal and exergetic performance of the convergent-divergent microchannel heat sink.

5.2 Performance Enhancement of Baseline CD MCHS via Micro Pillar Integration

The preceding section established the baseline optimization framework for the convergent-divergent microchannel heat sink and identified an optimized channel geometry through the integrated ANN-NSGA-II-TOPSIS methodology. Building upon this optimized platform, the present section investigates the incorporation of micro-pillars within the flow domain as a passive enhancement technique. Unlike the baseline configuration, where performance improvement was achieved solely through channel-shape optimization, the introduction of micro-pillars promotes flow redistribution, boundary-layer interruption, and localized mixing, thereby creating additional mechanisms for heat-transfer enhancement. The objective of the present investigation is therefore to evaluate the combined influence of pillar geometry, pillar arrangement, and nanofluid concentration on the hydrothermal and exergetic behavior of the optimized CD-MCHS using the same multi-objective optimization framework established in Section 5.1.

5.2.1 Design Variables and Optimization Objectives

The optimized baseline CD-MCHS identified in Section 5.1 serves as the reference configuration for the present investigation. To further enhance its thermal performance, micro-pillars were introduced within the convergent-divergent flow passages. Unlike geometric optimization alone, the incorporation of micro-pillars provides additional heat-transfer enhancement mechanisms through boundary-layer interruption, flow acceleration around pillar surfaces, wake formation, and localized fluid mixing. These mechanisms

modify the transport characteristics of the coolant and significantly influence the thermo-hydraulic behavior of the microchannel heat sink.

To systematically evaluate the influence of micro-pillar integration, four independent design variables were selected for optimization: pillar design (P_d), nanoparticle volume fraction (ϕ), pillar count (P_c), and pillar offset (P_o). These parameters collectively govern the extent of flow obstruction, mixing intensity, thermal boundary-layer redevelopment, and effective heat-transfer area within the microchannel. While increasing the number of pillars or nanoparticle concentration may enhance thermal transport, such modifications can also increase hydraulic resistance and thermodynamic irreversibility. Similarly, variations in pillar geometry and arrangement alter the local flow structure, thereby affecting both heat-transfer enhancement and pressure-loss characteristics.

The performance of the micro-pillar-enhanced CD-MCHS was evaluated using two objective functions: the average Nusselt number (Nu) and total entropy generation (S_{gen}). The Nusselt number represents the heat-transfer capability of the system, whereas entropy generation provides a thermodynamic measure of irreversibility arising from heat transfer and fluid friction. Consequently, maximizing Nu and minimizing S_{gen} constitute inherently conflicting objectives, requiring a balanced optimization strategy.

The optimization problem was therefore formulated within the ANN-NSGA-II-TOPSIS framework established in Section 5.1. By simultaneously considering thermal enhancement and thermodynamic efficiency, the adopted methodology enables the identification of micro-pillar configurations capable of delivering superior cooling performance without incurring excessive irreversibility. The detailed optimization results and the associated transport mechanisms are discussed in the following sections.

5.2.2 Exploration of Design Space and Initial CFD Database

To establish a representative optimization database for the micro-pillar-enhanced CD-MCHS, the design space defined by the four optimization variables was sampled using the Latin Hypercube Sampling (LHS) technique. The LHS approach ensures a uniform distribution of sample points throughout the feasible design domain, enabling efficient exploration of the combined effects of pillar geometry, nanoparticle concentration, pillar count, and pillar offset using a limited number of numerical simulations.

Based on the prescribed variable ranges, a total of 30 design configurations were generated through the LHS procedure and subsequently evaluated using three-dimensional

numerical simulations. For each design point, the average Nusselt number and total entropy generation were determined to quantify the thermal and thermodynamic performance of the micro-pillar-enhanced configuration. The resulting CFD database forms the foundation for the development of ANN surrogate models and the subsequent multi-objective optimization process.

Table 5.10: LHS-generated design variables and corresponding CFD responses for the micro-pillar enhanced CD-MCHS

S. No.	Design variable (Generated with LHS)				Corresponding results	
	Pillar Design	Nanofluid Concentration	Pillar Count	Pillar Offset	Nusselt Number	Entropy Generation
1	2	1	64	10	64.61	0.001266
2	3	1	48	5	63.68	0.001263
3	1	3	48	10	65.70	0.001096
4	3	1	32	15	64.30	0.001265
5	3	1	80	15	66.78	0.001275
6	2	0	48	0	62.13	0.001360
7	2	1	64	5	63.99	0.001264
8	4	0	64	5	65.54	0.001377
9	3	2	32	10	63.83	0.001173
10	3	2	48	10	64.45	0.001178
11	4	2	48	15	66.47	0.001180
12	2	1	48	5	63.06	0.001261
13	4	0	80	5	66.63	0.001382
14	3	3	80	0	65.85	0.001097
15	3	3	64	15	66.94	0.001099
16	2	2	32	5	62.75	0.001170
17	3	1	32	10	63.53	0.001272
18	2	3	32	10	64.14	0.001093
19	2	1	80	5	64.92	0.001268
20	2	1	80	10	65.39	0.001273
21	4	2	64	10	67.10	0.001182
22	1	0	48	5	63.52	0.001367

Cont....

23	2	0	64	15	65.57	0.001373
24	1	2	48	0	64.31	0.001171
25	3	2	48	5	64.95	0.001172
26	1	2	64	5	65.88	0.001175
27	4	2	48	10	66.51	0.001177
28	2	2	64	0	64.48	0.001171
29	1	3	64	10	67.14	0.001097
30	3	1	64	0	64.63	0.001263
Ref:	Re:400, α :0.70, β :0.65, γ :0.70, δ :0.70, N ₁ :60, N ₂ :08				44.45	0.001429

Table 5.10 summarizes the generated design configurations together with their corresponding objective-function values. The results reveal substantial variations in both Nusselt number and entropy generation across the sampled design space, indicating that the selected micro-pillar parameters exert a pronounced influence on the transport characteristics of the system. Such variability confirms the sensitivity of the hydrothermal performance to pillar geometry, pillar arrangement, and nanoparticle loading, while simultaneously demonstrating the effectiveness of the selected design variables in controlling the overall cooling behavior.

The observed response variations can be attributed to the complex interaction between flow obstruction, boundary-layer redevelopment, and enhanced thermal transport within the microchannel. Configurations promoting stronger flow mixing and repeated thermal boundary-layer disruption generally exhibit improved heat-transfer performance, whereas excessive flow obstruction may increase frictional losses and thermodynamic irreversibilities. These observations highlight the inherently coupled nature of the thermal and hydraulic transport mechanisms governing the performance of the micro-pillar-enhanced CD-MCHS.

Overall, the generated CFD database provides a comprehensive representation of the feasible design space and adequately captures the influence of the selected optimization variables on the objective functions. Consequently, the dataset serves as a reliable basis for the development and validation of ANN surrogate models, which are discussed in the subsequent section.

5.2.3 Development and Validation of ANN Surrogate Models

The CFD database generated from the Latin Hypercube Sampling strategy was subsequently employed to develop ANN surrogate models for predicting the average Nusselt number and total entropy generation of the micro-pillar-enhanced CD-MCHS. In contrast to the baseline optimization presented in Section 5.1, the present models establish relationships between the hydrothermal responses and four design variables, namely pillar geometry (P_d), nanoparticle volume fraction (ϕ), pillar count (P_c), and pillar offset (P_o). The ANN models were developed to replace computationally intensive CFD evaluations during the optimization stage while maintaining high predictive accuracy.

Prior to training, the response data were normalized to improve numerical stability and enhance learning efficiency. The available dataset was then divided into training (70%), validation (15%), and testing (15%) subsets to ensure reliable assessment of model generalization capability.

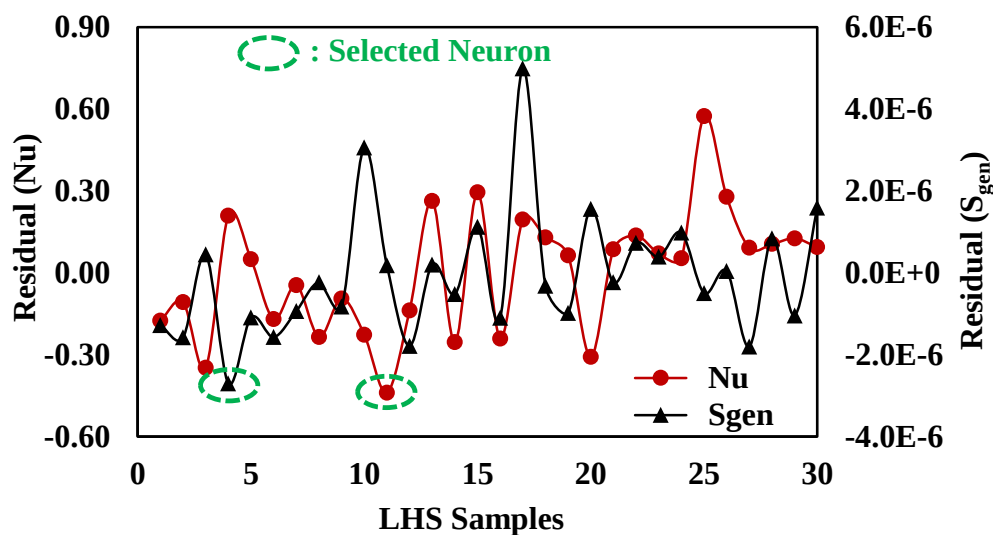


Figure 5.11: Neuron independence analysis for ANN development of the micro-pillar enhanced CD-MCHS

Figure 5.11 presents the neuron independence analysis performed to determine the optimal ANN architecture for the micro-pillar-enhanced CD-MCHS. Different hidden-layer configurations were systematically examined, and the corresponding residual errors were monitored. The analysis indicated that the optimum architecture for predicting the average Nusselt number consists of two hidden layers with six neurons each, whereas the entropy-generation model achieved the best performance using two hidden layers with seven neurons each. These architectures provided the lowest prediction errors and stable convergence characteristics.

Following architecture selection, the networks were trained using the Levenberg-Marquardt backpropagation algorithm. The training process demonstrated rapid convergence and consistently low prediction errors, indicating successful learning of the nonlinear relationships between the micro-pillar design variables and the objective functions.

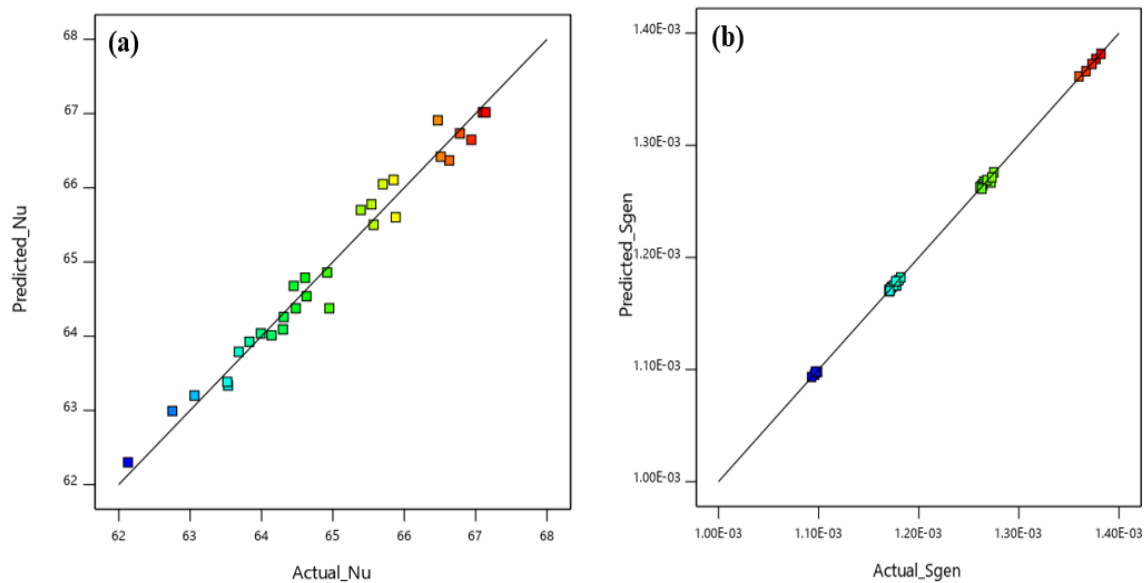


Figure 5.12: Parity plots comparing CFD-generated and ANN-predicted responses for the micro-pillar-enhanced CD-MCHS: (a) Nusselt number and (b) entropy generation

The predictive capability of the developed ANN models was first assessed through parity-plot analysis. As shown in the Figures 5.12, the predicted responses closely follow the corresponding CFD data and remain concentrated around the line of perfect agreement, demonstrating excellent consistency between numerical simulations and ANN predictions throughout the investigated design space.

To further quantify model accuracy, several statistical indicators including the correlation coefficient (R), coefficient of determination (R^2), root mean square error (RMSE), mean absolute error (MAE), and mean absolute percentage error (MAPE) were evaluated. The corresponding statistical performance metrics for the developed ANN models are summarized in Table 5.11.

The obtained statistical indicators confirm the excellent predictive capability of both ANN models, characterized by high correlation coefficients and low prediction errors. These results demonstrate that the surrogate models accurately reproduce the CFD-generated responses and are therefore suitable for multi-objective optimization.

Table 5.11: Statistical validation metrics of ANN surrogate models for the micro-pillar enhanced CD-MCHS

S. No.	Performance metrics	Nusselt number	Entropy generation
01	Pearson's Correlation Coefficient	0.9861	0.9998
02	Coefficient of determination	0.9724	0.9997
03	Mean Absolute Error	0.1867	1.17×10^{-6}
04	Root Mean Squared Error	0.2226	1.62×10^{-6}
05	Mean Absolute Percentage Error	0.2869 %	0.0946 %

Figure 5.13 presents the externally studentized residuals obtained for the developed ANN models. The residuals are randomly distributed around zero without any discernible trend, indicating the absence of systematic prediction bias and confirming that the developed models satisfy the assumptions of statistical adequacy. Furthermore, all residuals remain within acceptable confidence limits, providing additional evidence of model reliability.

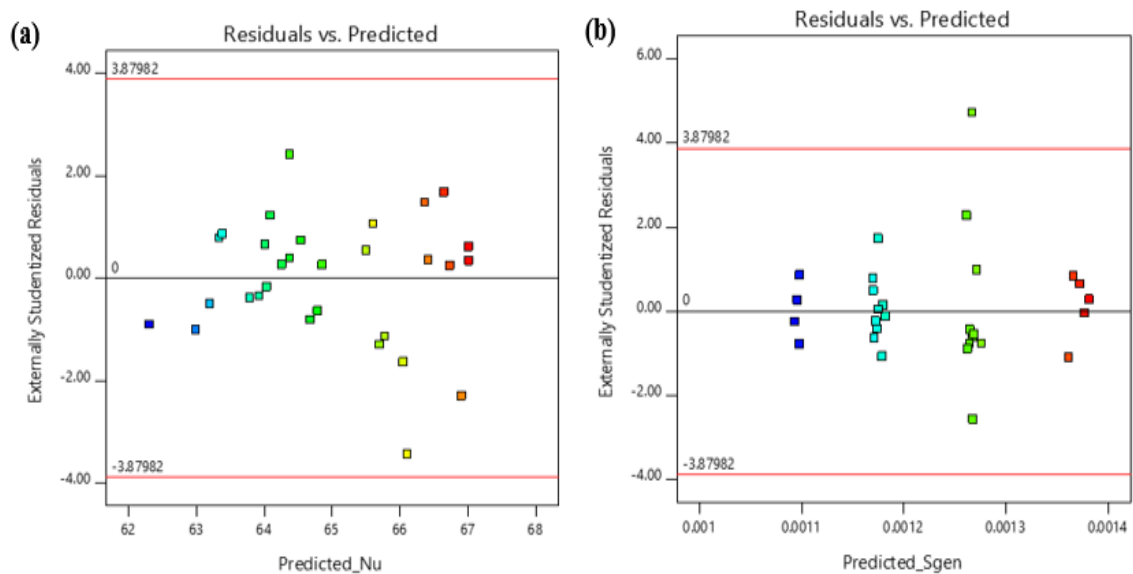


Figure 5.13: Externally studentized residual analysis for ANN validation of the micro-pillar enhanced CD-MCHS: (a) Nusselt number and (b) entropy generation

To provide physical insight into the influence of the governing design variables, three-dimensional response surfaces and corresponding contour plots were generated using the trained ANN models. The variations of the average Nusselt number and total entropy generation with the governing design variables are illustrated in Figures 5.14 and 5.15, respectively. These visualizations illustrate the combined effects of pillar geometry,

nanoparticle concentration, pillar count, and pillar offset on the thermal and thermodynamic responses. The response surfaces reveal strong nonlinear interactions among the design variables and further confirm the capability of the ANN models to capture the complex behavior of the micro-pillar-enhanced CD-MCHS.

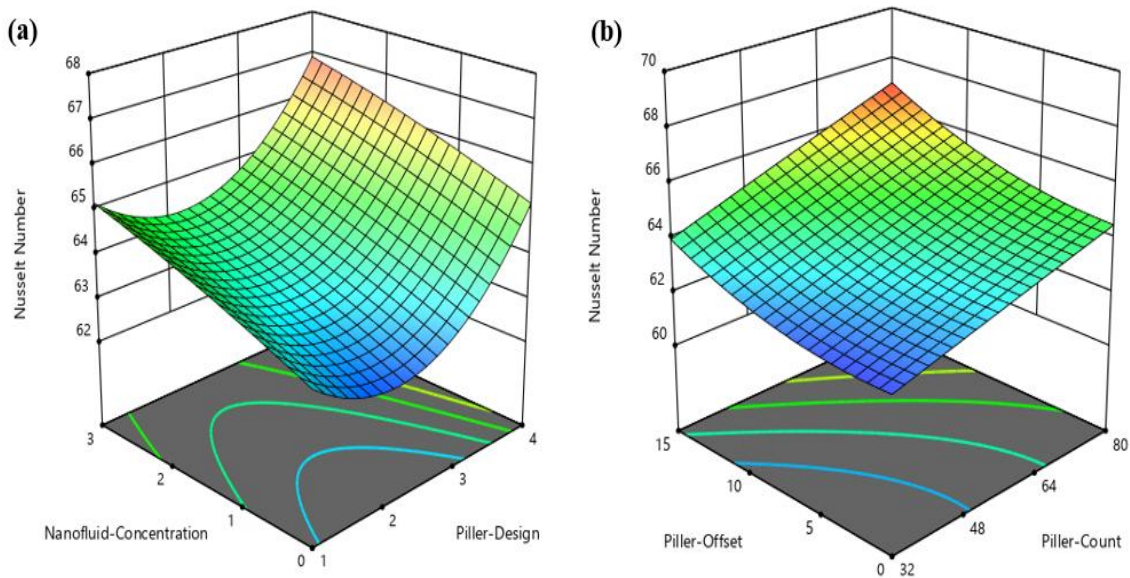


Figure 5.14: Three-dimensional ANN response surfaces for Nusselt number of the micro-pillar enhanced CD-MCHS (a) P_d - ϕ at $P_c = 48$ and $P_o = 05$, and (b) P_c - P_o at $P_d = 02$ and $\phi = 01\%$

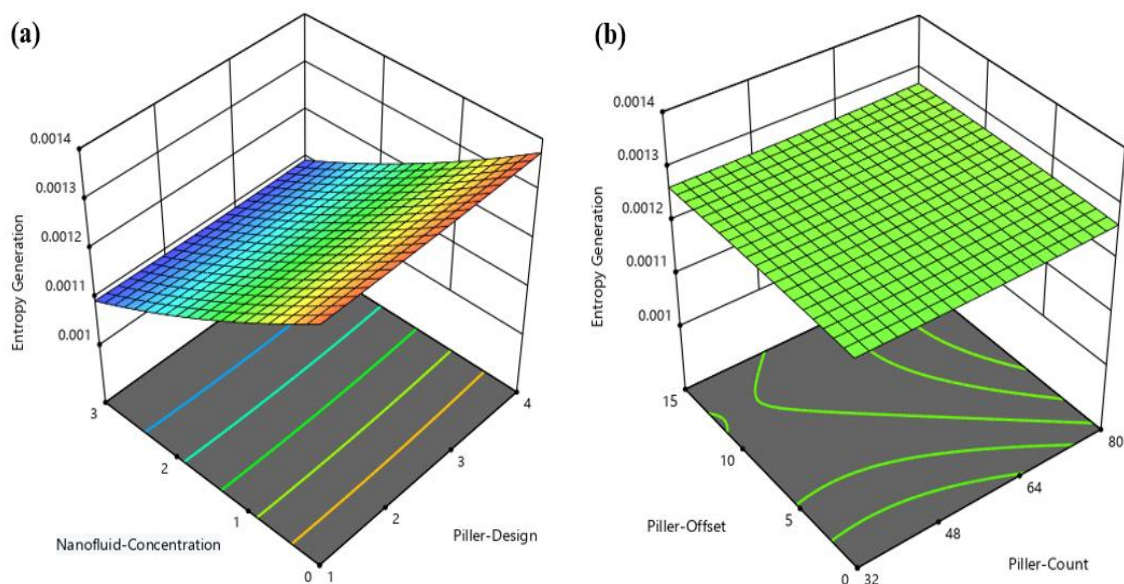


Figure 5.15: Three-dimensional ANN response surfaces for entropy generation of the micro-pillar enhanced CD-MCHS: (a) P_d - ϕ at $P_c = 48$ and $P_o = 05$, and (b) P_c - P_o at $P_d = 02$ and $\phi = 01\%$

Based on the trained ANN model, an explicit surrogate relationship for predicting the average Nusselt number was obtained and is expressed by Equation (5.4).

$$\mathbf{Nu} = 61.55 - 2.33 X_1 + 0.94 X_2 + 0.07 X_3 + 0.06 X_4 - 0.006 X_1 X_2 - 0.009 X_1 X_3 - 0.06 X_1 X_4 - 0.003 X_2 X_3 - 0.01 X_2 X_4 + 0.001 X_3 X_4 + 0.73 X_1^2 - 0.04 X_2^2 - 0.0003 X_3^2 + 0.009 X_4^2. \quad (5.4)$$

Similarly, the ANN-derived surrogate model for total entropy generation is represented by Equation (5.5).

$$\mathbf{S_{gen}} = 1.37 \times 10^{-3} - 4.63 \times 10^{-6} X_1 - 1.09 \times 10^{-4} X_2 - 3.62 \times 10^{-7} X_3 + 8.61 \times 10^{-7} X_4 - 9.72 \times 10^{-7} X_1 X_2 + 2.64 \times 10^{-8} X_1 X_3 + 1.97 \times 10^{-7} X_1 X_4 + 2.04 \times 10^{-8} X_2 X_3 - 1.54 \times 10^{-7} X_2 X_4 + 1.42 \times 10^{-9} X_3 X_4 + 1.03 \times 10^{-6} X_1^2 + 6.54 \times 10^{-6} X_2^2 + 3.71 \times 10^{-9} X_3^2 - 4.82 \times 10^{-8} X_4^2. \quad (5.5)$$

Where, $X_1 = \text{Pillar Design}$

$X_2 = \text{Nanofluid Concentration}$

$X_3 = \text{Pillar Counts}$

$X_4 = \text{Pillar Offset}$

The validated ANN models provide an efficient and computationally robust platform for rapid response prediction and were subsequently integrated with the NSGA-II algorithm to identify Pareto-optimal micro-pillar configurations, as discussed in the following section.

5.2.4 Selection of NSGA-II Parameters

The performance of the NSGA-II algorithm depends strongly on the selection of appropriate evolutionary parameters, particularly the population size and the number of generations. Therefore, a sensitivity analysis similar to that performed for the baseline CD-MCHS was conducted to ensure adequate convergence and diversity of the Pareto-optimal solutions for the micro-pillar enhanced configuration.

5.2.4.1 Population Size Analysis

To investigate the influence of population size, NSGA-II simulations were performed using different population values while maintaining identical optimization settings. The resulting Pareto fronts are presented in Figure 5.16.

As shown in Figure 5.16, increasing the population size improves the distribution and continuity of the Pareto-optimal solutions by enabling a more comprehensive exploration

of the design space. Smaller populations generate relatively sparse solution sets, whereas larger populations provide improved coverage of the objective space. Beyond a population size of 100, only marginal improvements in Pareto-front quality were observed. Therefore, a population size of 100 was selected for subsequent optimization studies.

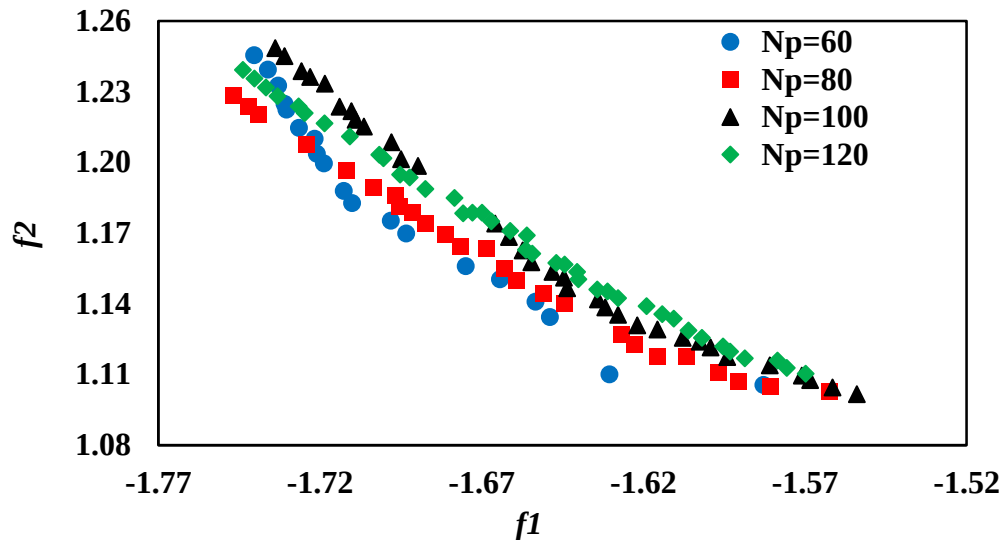


Figure 5.16: Influence of population size on Pareto-front development for the micro-pillar enhanced CD-MCHS

5.2.4.2 Generation Number Analysis

The influence of generation number on optimization convergence was subsequently evaluated using the selected population size. The Pareto fronts obtained at different generation numbers are illustrated in Figure 5.17.

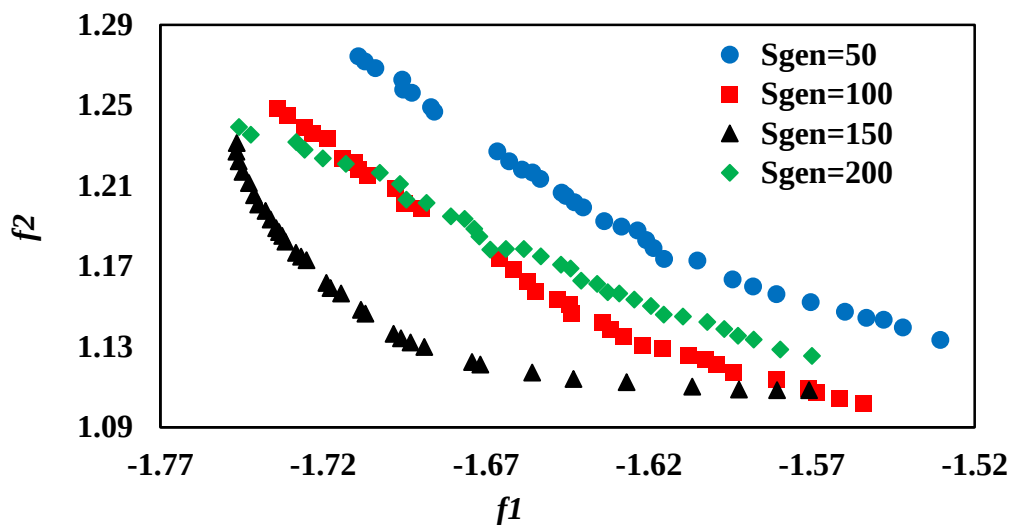


Figure 5.17: Influence of generation number on Pareto-front convergence for the micro-pillar enhanced CD-MCHS

The results indicate progressive improvement in Pareto-front development with increasing generations. At lower generation numbers, the solution set remains relatively scattered, whereas higher generations produce a smoother and more converged Pareto front. Beyond 150 generations, negligible changes were observed in the Pareto-front distribution, indicating that convergence had been achieved. Consequently, 150 generations were adopted for all subsequent optimization analyses.

5.2.4.3 Final NSGA-II Parameters

Based on the population-size and generation-number investigations, the final NSGA-II parameters employed for the micro-pillar enhanced CD-MCHS are summarized in Table 5.12.

Table 5.12: Final NSGA-II control parameters adopted for the micro-pillar enhanced CD-MCHS

Parameter		Parameter Value
Population (N_p)		100
Maximum Generation (Gen)		150
Reproduction / Selection	Tournament Selection (Rank and Crowding Distance)	
Pareto Fraction	0.35	
Crossover Rate	0.80	
Mutation Rate	0.10	

The selected parameter set provided a stable and well-converged optimization framework capable of generating a diverse set of non-dominated solutions while maintaining computational efficiency. The validated ANN surrogate models and optimized NSGA-II settings were subsequently utilized to establish the Pareto-optimal design set discussed in the following section.

5.2.5 Characterization of the Optimal Pareto Front

Following the establishment of the optimal NSGA-II settings, the trained ANN surrogate models were coupled with the optimization algorithm to generate a set of Pareto-optimal micro-pillar configurations. The resulting Pareto front represents the best achievable trade-offs between maximizing the average Nusselt number and minimizing total entropy

generation. The complete set of Pareto-optimal solutions obtained for the micro-pillar-enhanced CD-MCHS is presented in Table 5.13.

Table 5.13: Pareto-optimal design variables and corresponding responses for the micro-pillar enhanced CD-MCHS

S. No.	Pareto design variable (150 th Generation)				Corresponding results	
	Pillar Design	Nanofluid Concentration	Pillar Count	Pillar Offset	Nusselt Number	Entropy Generation
1	1	3	56	12	64.124	0.001095
2	1	0	32	6	62.483	0.001367
3	1	1.5	32	6	63.549	0.001217
4	2	2.5	40	15	65.239	0.001130
5	3	0.5	56	9	64.121	0.001320
6	2	2	48	9	64.240	0.001173
7	4	0	48	12	65.442	0.001381
8	4	2.5	32	9	66.049	0.001135
9	4	1	32	15	65.673	0.001273
10	1	1.5	40	6	64.044	0.001216
11	1	1.5	48	3	64.150	0.001215
12	1	1.5	48	6	64.535	0.001217
13	1	2.5	64	9	66.587	0.001135
14	3	1.5	64	9	65.059	0.001222
15	3	3	72	0	65.864	0.001095
16	3	2	56	0	64.850	0.001169
17	2	0.5	72	3	63.966	0.001315
18	3	2	32	3	63.770	0.001170
19	2	2	72	6	65.074	0.001177
20	1	2.5	80	6	66.901	0.001139
21	1	2	40	6	64.341	0.001173
22	1	2.5	48	6	65.080	0.001133
23	4	0.5	40	6	65.186	0.001320
24	2	1.5	32	15	64.259	0.001216
25	2	2	32	15	64.519	0.001171

Cont....

26	2	1	56	15	65.524	0.001266
27	1	2	64	12	67.149	0.001175
28	1	3	32	3	67.036	0.001096
29	1	0.5	32	12	64.118	0.001315
30	4	1	72	9	66.776	0.001277
31	4	3	64	6	67.335	0.001100
32	1	1	80	6	66.204	0.001269
33	2	1.5	32	3	62.602	0.001214
34	1	2	64	3	65.338	0.001174
35	1	1	48	6	64.229	0.001263

The distribution of the Pareto-optimal solutions indicates a well-converged and diverse solution set, confirming the effectiveness of the adopted ANN-NSGA-II framework in exploring the feasible design space. A noticeable clustering of solutions is observed in specific regions of the Pareto front, suggesting the emergence of robust configurations that simultaneously provide enhanced heat-transfer performance and acceptable thermodynamic behavior. At the same time, the presence of dispersed solutions demonstrates that the optimization process maintained sufficient diversity and avoided premature convergence, thereby enabling a comprehensive exploration of the design domain.

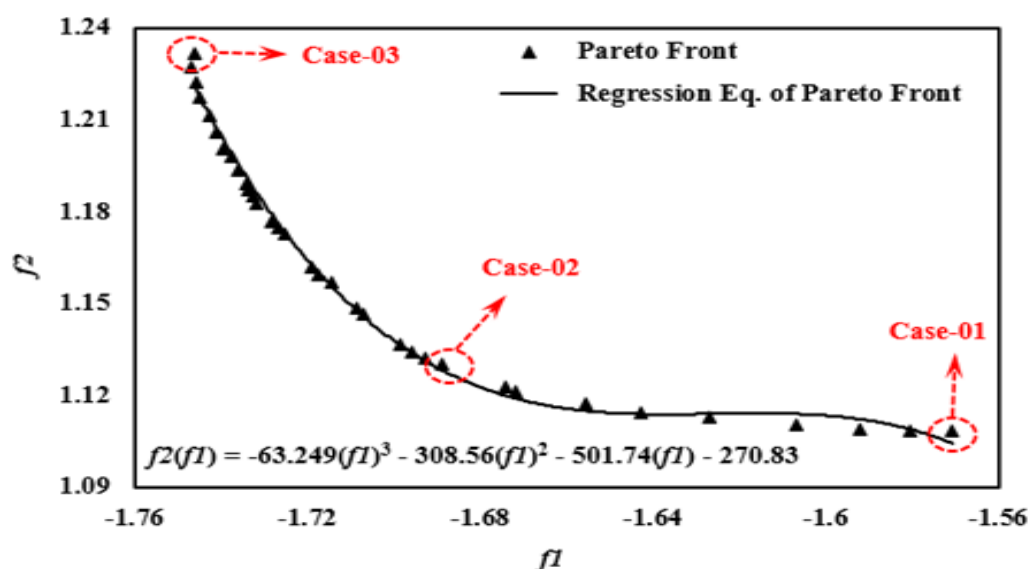


Figure 5.18: Representative solutions selected from the optimal Pareto front for the micro-pillar enhanced CD-MCHS

To facilitate the physical interpretation of the optimization results, three representative Pareto-optimal solutions were selected from different regions of the Pareto front, as illustrated in Figure 5.18. These solutions correspond to distinct hydrothermal performance priorities and represent a low-entropy-generation design (Case-01), an intermediate compromise design (Case-02), and a high-heat-transfer design (Case-03). Their relative performance with respect to the reference CD-MCHS configuration is summarized in Table 5.14.

Table 5.14: Relative performance of selected Pareto-optimal solutions for the micro-pillar configuration with respect to the optimized baseline CD-MCHS

Reference Study (Without Pillar)	Nu ($f_1 = -1$)	S_{gen} ($f_2 = 1$)
Case – 01: ($P_d:1$, $\phi:01\%$, $P_c:48$, $P_o:06$)	57.10 % ↑	10.80 % ↑
Case – 02: ($P_d:2$, $\phi:01\%$, $P_c:56$, $P_o:15$)	68.90 % ↑	12.90 % ↑
Case – 03: ($P_d:1$, $\phi:03\%$, $P_c:56$, $P_o:12$)	74.60 % ↑	23.10 % ↑

As illustrated in Figure 5.18, Case-01 corresponds to a configuration that prioritizes thermodynamic performance while maintaining substantial heat-transfer enhancement. This design achieves a 57.10% increase in the average Nusselt number, accompanied by only a 10.80% increase in entropy generation relative to the reference configuration. The comparatively low entropy penalty indicates that effective cooling enhancement can be achieved without introducing excessive thermodynamic irreversibilities.

Case-02 is located within the intermediate region of the Pareto front and represents a balanced hydrothermal compromise. Relative to the reference design, this configuration provides a 68.90% enhancement in Nusselt number while increasing entropy generation by 12.90%. The simultaneous improvement in heat-transfer performance and moderate entropy penalty demonstrates a favorable balance between thermal enhancement and thermodynamic efficiency.

Case-03 is positioned toward the heat-transfer-dominant end of the Pareto front and exhibits the highest thermal performance among the selected solutions. This configuration achieves a 74.60% increase in the average Nusselt number, accompanied by a 23.10% increase in entropy generation. Although the intensified flow disruption generated by the micro-pillars significantly enhances convective heat transfer, it also increases fluid friction and associated irreversibilities, resulting in higher entropy production. Nevertheless, such

a configuration may be desirable in applications where maximum cooling capability is the primary design requirement.

Overall, the selected Pareto-optimal solutions clearly demonstrate the inherent trade-off between heat-transfer enhancement and entropy-generation minimization in micro-pillar-enhanced convergent-divergent microchannels. While aggressive thermal augmentation yields superior cooling performance, it is generally accompanied by increased thermodynamic irreversibility. Consequently, the final selection of the most appropriate design requires a compromise-based decision-making approach capable of simultaneously considering both objectives. For this purpose, the TOPSIS method was employed to identify the most balanced solution from the obtained Pareto set, as discussed in the subsequent section.

5.2.6 TOPSIS-Based Selection of the Optimal Micro-Pillar Configuration

Although the Pareto front provides a set of equally optimal non-dominated solutions, practical implementation requires the identification of a single design that offers the most favorable balance between heat-transfer enhancement and entropy-generation minimization. Therefore, the TOPSIS method was employed to rank the Pareto-optimal solutions according to their relative closeness to the ideal solution.

To evaluate the robustness of the decision-making process, a sensitivity analysis was performed by varying the weighting combinations assigned to the average Nusselt number and entropy generation from (0.4, 0.6) to (0.8, 0.2). The resulting rankings are presented in Table 5.15.

Table 5.15: Sensitivity analysis of TOPSIS rankings to variations in objective weighting for the micro-pillar enhanced CD-MCHS

TOPSIS	W₁ (0.4;0.6)		W₂ (0.5;0.5)		W₃ (0.6;0.4)		W₄ (0.7;0.3)		W₅ (0.8;0.2)	
Ranking	(C_i)₁	DoE	(C_i)₂	DoE	(C_i)₃	DoE	(C_i)₄	DoE	(C_i)₅	DoE
01	0.7715	26	0.7497	24	0.7462	22	0.7815	22	0.8397	22
02	0.7699	25	0.7486	22	0.7452	21	0.7810	18	0.8384	19
03	0.7680	27	0.7482	23	0.7396	19	0.7762	15	0.8382	12
04	0.7658	28	0.7425	26	0.7395	20	0.7762	16	0.8380	11
05	0.7645	22	0.7297	22	0.7394	23	0.7760	17	0.8371	15

The results indicate that DoE-22 consistently remains among the highest-ranked solutions across all weighting scenarios. It attains Rank-5 under the entropy-dominant weighting condition (0.4, 0.6), improves to Rank-2 for the balanced weighting condition (0.5, 0.5), and achieves Rank-1 when greater emphasis is placed on heat-transfer enhancement through the weighting combinations (0.6, 0.4), (0.7, 0.3), and (0.8, 0.2). This consistent ranking behaviour demonstrates the robustness of DoE-22 against variations in decision-maker preference and identifies it as a reliable compromise solution for micro-pillar-enhanced CD-MCHS applications.

To further assess the stability of the selected solution, the variation of the relative closeness index (C_i) for DoE-22 under different weighting combinations was evaluated and is summarized in Table 5.16.

Table 5.16: Stability of relative closeness for the selected TOPSIS design under different weighting distributions for the micro-pillar configuration

S. No.	Weight (Nu, Sgen)	Relative Closeness (C_i)	
1	W_1 (0.4;0.6)	0.7645	
2	W_2 (0.5;0.5)	0.7486	
3	W_3 (0.6;0.4)	0.7462	Selected
4	W_4 (0.7;0.3)	0.7815	
5	W_5 (0.8;0.2)	0.8397	
Coefficient of variation (CV)		4.93 %	

The relative closeness values exhibit a low coefficient of variation of 4.93%, indicating limited sensitivity to changes in weighting preference. Among the investigated weighting combinations, the distribution (0.6, 0.4) provides a balanced emphasis on thermal enhancement and entropy-generation minimization and was therefore adopted as the reference weighting strategy for final design selection. Under this condition, the distribution of relative closeness values for the Pareto-optimal solutions is illustrated in Figure 5.19.

As shown in Figure 5.19, DoE-22 exhibits the highest relative closeness among the Pareto-optimal solutions and is therefore identified as the best compromise design. The TOPSIS-selected configuration corresponds to $P_d = 1$, $\phi = 2.5\%$, $P_c = 48$, and $P_o = 06 \mu\text{m}$, representing an elliptical micro-pillar configuration with a 2.5% nanoparticle concentration, 48 micro-pillars, and a 6 μm lateral offset from the channel centerline. The

pillars are arranged alternately about the centerline, forming a zig-zag pattern along the flow direction. This overall configuration provides the most favorable compromise between heat-transfer enhancement and entropy-generation minimization among the Pareto-optimal solutions and was therefore selected as the optimal design for subsequent hydrothermal and exergetic analyses.

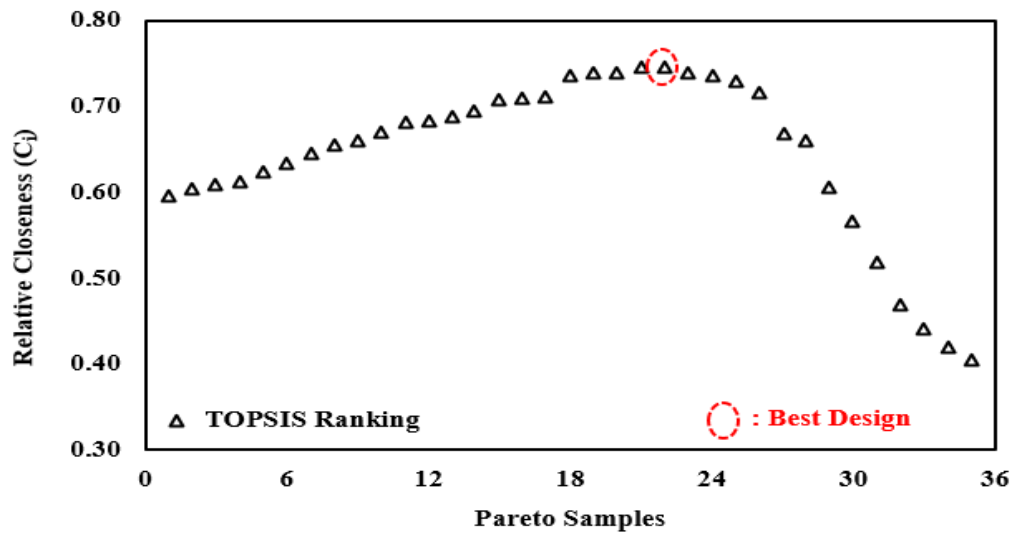


Figure 5.19: TOPSIS-based ranking of Pareto-optimal solutions for the micro-pillar enhanced CD-MCHS

To further assess the effectiveness of the selected TOPSIS design, its thermo-hydraulic performance was compared with the representative Pareto-optimal configurations selected from the Pareto front of the present micro-pillar optimization study as well as the optimized baseline CD-MCHS configuration obtained from the design optimization study presented in Section 5.1. The comparison provides insight into the relative advantages of the selected micro-pillar configuration in terms of heat-transfer enhancement and entropy-generation characteristics. The corresponding results are summarized in Table 5.17.

Table 5.17: Comparative performance of the TOPSIS-selected micro-pillar configuration with representative Pareto-optimal designs and the baseline CD-MCHS

TOPSIS : ($P_d:1$, $\phi:2.5\%$, $P_c:48$, $P_o:06$)	Nu (f_1)	S_{gen} (f_2)
Case – 01: ($P_d:1$, $\phi:01\%$, $P_c:48$, $P_o:06$)	9.13 % ↑	4.37 % ↑
Case – 02: ($P_d:2$, $\phi:01\%$, $P_c:56$, $P_o:15$)	1.51 % ↑	2.43 % ↑
Case – 03: ($P_d:1$, $\phi:3\%$, $P_c:56$, $P_o:12$)	1.81 % ↓	6.06 % ↓
Reference Study (Without Pillar)	71.45 % ↑	15.64 % ↑

The comparison confirms that the TOPSIS-selected configuration provides the most balanced thermo-hydraulic performance among the Pareto-optimal solutions. Relative to Case-01 and Case-02, the selected design achieves higher heat-transfer enhancement, with increases of 9.13% and 1.51% in the average Nusselt number, respectively. These improvements are accompanied by moderate increases in entropy generation of 4.37% and 2.43%, indicating that the additional thermal benefit is obtained at a relatively small thermodynamic penalty.

In contrast, Relative to Case-03, the TOPSIS-selected configuration exhibits only a 1.81% reduction in the average Nusselt number, while simultaneously achieving a 6.06% reduction in entropy generation. This indicates that a relatively small sacrifice in heat-transfer enhancement results in a considerably larger improvement in thermodynamic performance. Consequently, the TOPSIS design provides a more favorable balance between cooling effectiveness and irreversibility minimization than the heat-transfer-dominant Pareto solution.

Furthermore, relative to the optimized baseline CD-MCHS without micro-pillars, the selected configuration provides a substantial 71.45% enhancement in the average Nusselt number with a 15.64% increase in entropy generation, demonstrating the effectiveness of micro-pillar integration for improving overall cooling performance while maintaining acceptable thermodynamic irreversibility.

Accordingly, the TOPSIS-selected configuration was adopted as the optimal micro-pillar-enhanced CD-MCHS design for the subsequent flow-field and exergetic analyses.

5.2.7 Hydrothermal Characteristics of the Selected TOPSIS Design

To further understand the physical mechanisms responsible for the improved thermo-hydraulic performance, the temperature, velocity, and pressure contours of the reference configuration (without pillars) and the TOPSIS-selected micro-pillar configuration were compared, as shown in Figure 5.20.

As illustrated in Figure 5.20, the incorporation of micro-pillars significantly modifies the flow and thermal fields within the convergent-divergent microchannel. The reference configuration exhibits a continuous temperature rise along the flow direction, reaching a maximum temperature of approximately 311.8 K. In contrast, the TOPSIS-selected design limits the maximum temperature to approximately 308.3 K, corresponding to a reduction of nearly 3.5 K. This behavior indicates enhanced convective heat transfer resulting from

increased flow disturbance and boundary-layer disruption induced by the micro-pillar array.

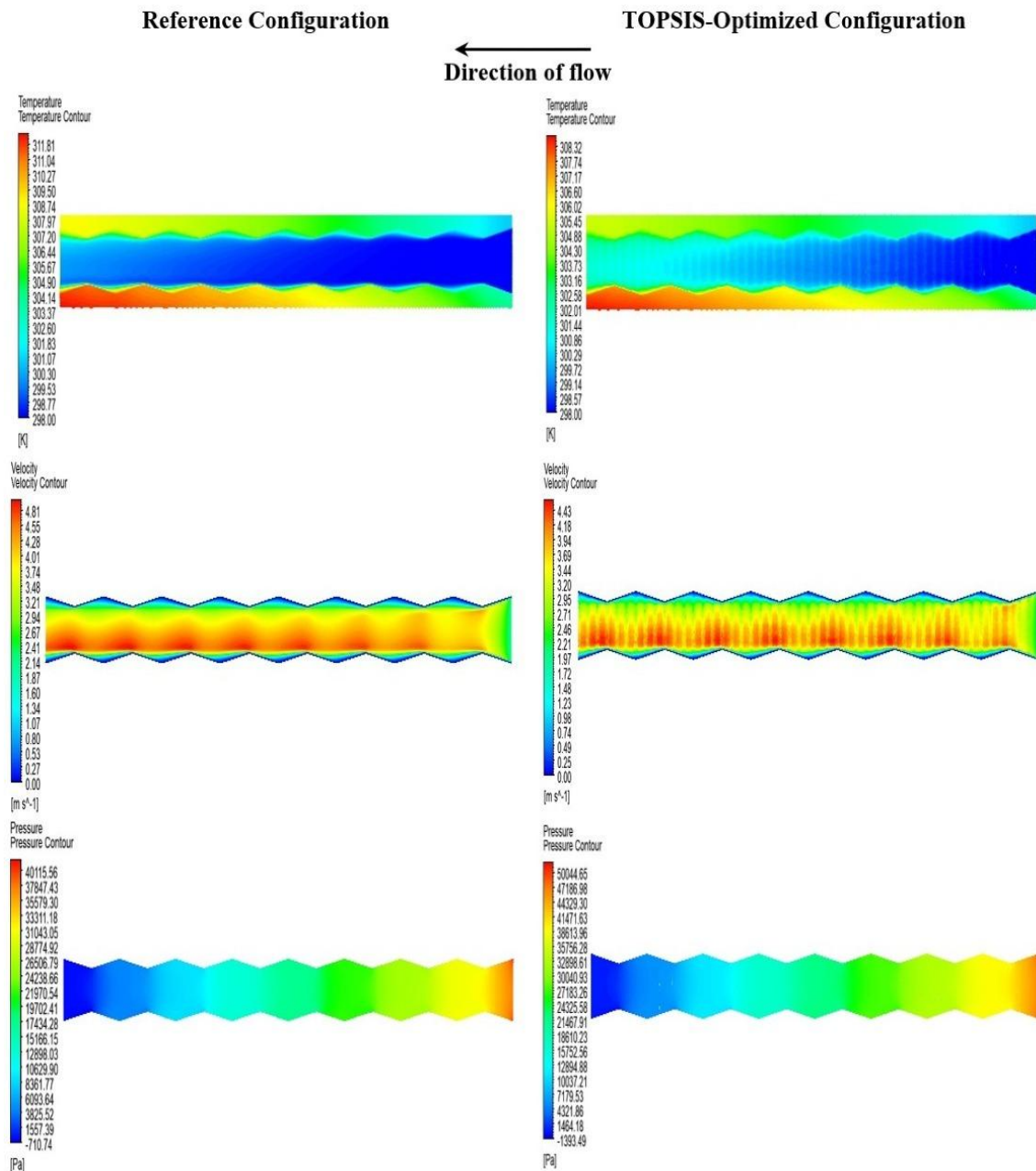


Figure 5.20: Comparison of temperature, velocity, and pressure contours for the reference and TOPSIS-optimized micro-pillar configurations

The velocity contours reveal a redistribution of the flow field in the optimized configuration. Unlike the reference channel, where the fluid primarily follows a relatively uniform path, the presence of staggered micro-pillars promotes local acceleration and enhanced momentum exchange around the pillar surfaces. Consequently, improved

mixing between the core and near-wall fluid regions contributes to more effective heat removal.

The pressure contours indicate an increase in flow resistance due to the obstruction introduced by the micro-pillars. The maximum pressure rises from approximately 4×10^4 Pa in the reference configuration to nearly 5×10^4 Pa in the optimized design. Although this increase reflects an additional hydrodynamic penalty, the corresponding thermal enhancement obtained through intensified mixing and boundary-layer redevelopment outweighs the increase in pressure loss.

Overall, the contour analysis confirms that the selected micro-pillar configuration improves heat-transfer performance through enhanced flow redistribution and thermal mixing while maintaining an acceptable pressure-drop penalty. These observations are consistent with its identification as the most balanced solution from the Pareto-optimal design set.

5.2.8 Exergetic Performance Evaluation

Although the optimization process was performed using the Nusselt number and entropy generation as objective functions, an additional exergetic assessment was carried out to verify the thermodynamic suitability of the selected designs. The analysis was performed using the Exergy Destruction Ratio (EDR) and exergy efficiency (η_{ex}), which provide a second-law measure of system irreversibility and useful energy utilization. The comparison among the reference configuration, representative Pareto-optimal solutions, and the TOPSIS-selected design is summarized in Table 5.18.

Table 5.18: Exergetic performance comparison of reference, Pareto-optimal, and TOPSIS-selected micro-pillar configurations

Design Configuration	EDR	Relative EDR	η_{ex}
Reference Study (Without Pillar)	8.53 %	-	91.47 %
Case-01: (P_d :1, ϕ :1%, P_c :48, P_o :6)	19.55 %	129.19 % $\uparrow$	80.45 %
Case-02: (P_d :2, ϕ :1%, P_c :56, P_o :15)	21.54 %	152.52 % $\uparrow$	80.08 %
Case-03: (P_d :1, ϕ :3%, P_c :56, P_o :12)	23.49 %	175.38 % $\uparrow$	76.51 %
TOPSIS Design: (P_d :1, ϕ :2.5%, P_c :48, P_o :6)	22.06 %	158.61 % $\uparrow$	77.94 %

The reference configuration exhibits the lowest irreversibility, with an EDR of 8.53% and an exergy efficiency of 91.47%, owing to the absence of flow obstructions and the

resulting lower viscous dissipation. The introduction of micro-pillars enhances heat transfer by promoting secondary-flow formation, boundary-layer disruption, and near-wall mixing; however, these mechanisms also increase frictional losses and exergy destruction.

Among the representative Pareto-optimal solutions, Case-01 shows the lowest EDR (19.55%) and the highest exergy efficiency (80.45%), whereas Case-03 exhibits the highest EDR (23.49%) and the lowest exergy efficiency (76.51%), indicating greater thermodynamic irreversibility. Case-02 demonstrates an intermediate exergetic response. The TOPSIS-selected configuration yields an EDR of 22.06% and an exergy efficiency of 77.94%, positioning it within a favorable region of the Pareto front.

Although the TOPSIS design does not correspond to the minimum exergy destruction, it successfully avoids excessive thermodynamic losses while preserving substantial heat-transfer enhancement. This behavior confirms that the selected elliptical micro-pillar arrangement provides an effective balance between thermal augmentation and thermodynamic efficiency. Consequently, the exergetic assessment further validates the suitability of the TOPSIS-selected configuration as the final optimized micro-pillar design for high-performance electronic thermal management applications.

5.3 Performance Enhancement of baseline CD-MCHS using Hybrid Nanofluids

The results presented in Sections 5.1 and 5.2 demonstrated that substantial improvements in the hydrothermal performance of the convergent-divergent microchannel heat sink can be achieved through geometric optimization and micro-pillar integration. These passive enhancement techniques improve heat transfer primarily by promoting flow redistribution, boundary-layer redevelopment, and fluid mixing within the microchannel. However, despite these modifications, the thermal transport capability of the working fluid remains unchanged and may ultimately limit further enhancement of the cooling performance.

An alternative approach for improving thermal management is the utilization of advanced coolants with superior thermophysical properties. Among the various techniques available, nanofluids have emerged as promising working fluids for high-heat-flux applications owing to their enhanced thermal conductivity and improved energy transport characteristics. More recently, tri-hybrid nanofluids have attracted considerable attention because they combine the favorable properties of multiple nanoparticle species within a single base fluid, thereby offering greater flexibility in tailoring thermal performance.

Accordingly, the present section investigates the hydrothermal and thermodynamic performance of a CuO-Al₂O₃-Ag/water tri-hybrid nanofluid flowing through the optimized CD-MCHS configuration. The objective is to identify an optimal nanoparticle composition capable of maximizing heat-transfer enhancement while simultaneously minimizing thermodynamic irreversibilities. For this purpose, the ANN-NSGA-II-TOPSIS optimization framework established in the previous sections was employed to systematically explore the design space and determine the most effective tri-hybrid nanofluid formulation.

5.3.1 Design Variables and Optimization Objectives

The optimized CD-MCHS configuration obtained from Section 5.1 was adopted as the baseline geometry for the present investigation. To evaluate the influence of tri-hybrid nanofluid composition on system performance, four independent design variables were selected: the total nanoparticle volume concentration (Φ_T), the CuO nanoparticle fraction (f_{CuO}), the Al₂O₃ nanoparticle fraction ($f_{Al_2O_3}$), and the Ag nanoparticle fraction (f_{Ag}). These variables govern the effective thermophysical properties of the coolant and therefore directly affect the heat-transfer, flow, and entropy-generation characteristics of the microchannel heat sink.

The total nanoparticle concentration controls the overall magnitude of thermal conductivity enhancement and viscosity variation, whereas the relative fractions of CuO, Al₂O₃, and Ag determine the contribution of each nanoparticle species to the effective properties of the tri-hybrid suspension. Consequently, different nanoparticle combinations can produce significantly different hydrothermal and thermodynamic responses even at the same total concentration.

The performance of the system was evaluated using two objective functions: the average Nusselt number and the total entropy generation. The Nusselt number represents the heat-transfer capability of the nanofluid-cooled CD-MCHS, whereas entropy generation provides a measure of the thermodynamic irreversibilities associated with heat transfer and fluid friction. Similar to the previous optimization studies, these objectives exhibit conflicting behavior because conditions that promote stronger heat-transfer enhancement may also increase viscous effects and entropy production.

Therefore, a multi-objective optimization framework was adopted to simultaneously maximize the average Nusselt number and minimize total entropy generation. The

resulting optimization problem forms the basis for the subsequent exploration of the design space and development of the CFD database.

5.3.2 Exploration of Design Space and Initial CFD Database

To establish a representative optimization database, the design space defined by the total nanoparticle concentration and the relative fractions of CuO, Al₂O₃, and Ag nanoparticles was systematically sampled using the Latin Hypercube Sampling (LHS) technique. The LHS approach ensures an efficient distribution of sample points throughout the feasible design domain, enabling the effects of both nanoparticle concentration and composition on system performance to be accurately captured using a limited number of numerical simulations.

Based on the prescribed ranges of the design variables, a total of 30 design configurations were generated using the LHS approach. Each configuration was subsequently evaluated through three-dimensional CFD simulations to determine the corresponding values of the average Nusselt number and total entropy generation. The resulting database forms the foundation for the development of ANN surrogate models and the subsequent multi-objective optimization process.

Table 5.19: LHS-generated design variables and corresponding CFD responses for the tri-hybrid nanofluid enhanced CD-MCHS

S. No.	Design variable (Generated with LHS)				Corresponding Results	
	Φ_{Total} (%)	f_{CuO} (%)	$f_{\text{Al}_2\text{O}_3}$ (%)	f_{Ag} (%)	Nu_{avg}	S_{gen}
1	1.00	55	25	20	46.90	0.001565
2	2.00	55	30	15	47.12	0.001572
3	0.50	55	20	25	47.23	0.001576
4	2.00	50	35	15	46.67	0.001558
5	2.00	60	20	20	48.45	0.001615
6	1.50	50	30	20	47.01	0.001568
7	1.00	60	20	20	47.34	0.001579
8	2.00	55	25	20	48.01	0.001601
9	1.00	50	30	20	46.45	0.001550
10	1.50	50	20	30	48.78	0.001625
11	2.00	50	20	30	49.34	0.001643

Cont....

12	1.00	55	20	25	47.78	0.001593
13	0.50	60	20	20	46.78	0.001561
14	1.00	55	30	15	46.01	0.001536
15	0.50	50	30	20	45.90	0.001533
16	1.50	60	25	15	46.56	0.001554
17	0.50	50	35	15	45.01	0.001504
18	2.00	55	20	25	48.90	0.001629
19	0.50	55	30	15	45.45	0.001518
20	1.50	50	35	15	46.12	0.001540
21	2.00	65	20	15	48.12	0.001604
22	0.50	60	25	15	45.78	0.001529
23	1.00	50	25	25	47.90	0.001597
24	0.50	50	25	25	46.23	0.001543
25	0.50	50	20	30	47.67	0.001590
26	1.50	65	20	15	47.45	0.001582
27	2.00	50	30	20	47.56	0.001586
28	0.50	65	20	15	46.34	0.001547
29	0.50	55	25	20	45.67	0.001525
30	1.50	55	20	25	48.34	0.001611
Ref:	Re:400, α :0.70, β :0.65, γ :0.70, δ :0.70, N ₁ :60, N ₂ :08				44.45	0.001429

Table 5.19 summarizes the generated tri-hybrid nanofluid compositions together with the corresponding values of the average Nusselt number and total entropy generation. The sampled configurations provide a comprehensive representation of the feasible design space and capture the combined influence of nanoparticle loading and constituent fractions on the thermal and thermodynamic behavior of the optimized CD-MCHS.

The CFD results reveal noticeable variations in both objective functions across the sampled designs. The average Nusselt number varies from approximately 45.01 to 49.34, while the corresponding entropy generation ranges between 1.504×10^{-3} and 1.643×10^{-3} W/K, indicating a clear sensitivity of system performance to the selected nanofluid composition. In general, increasing nanoparticle concentration tends to enhance heat-transfer performance owing to improved effective thermal conductivity; however, this enhancement is often accompanied by a corresponding increase in entropy generation due

to higher viscous and thermal irreversibilities. Furthermore, the relative fractions of CuO, Al₂O₃, and Ag nanoparticles significantly influence this trade-off by modifying the effective thermophysical properties of the suspension.

The observed variability in the response dataset confirms the suitability of the selected design variables for optimization and provides sufficient information for developing reliable ANN surrogate models. Consequently, the generated CFD database serves as the foundation for the ANN training, validation, and subsequent multi-objective optimization presented in the following sections.

5.3.3 Development and Validation of ANN Surrogate Models

The CFD database generated through the LHS sampling procedure was subsequently employed to develop ANN surrogate models capable of predicting the average Nusselt number and total entropy generation as functions of the tri-hybrid nanofluid-enhanced CD-MCHS. The total nanoparticle concentration (Φ_T) together with the relative fractions of CuO, Al₂O₃, and Ag nanoparticles were used as the input parameters, while Nu and S_{gen} were considered as the output responses.

The available dataset was divided into training, validation, and testing datasets using a 70:15:15 ratio, and the network training was performed using the Levenberg-Marquardt backpropagation algorithm.

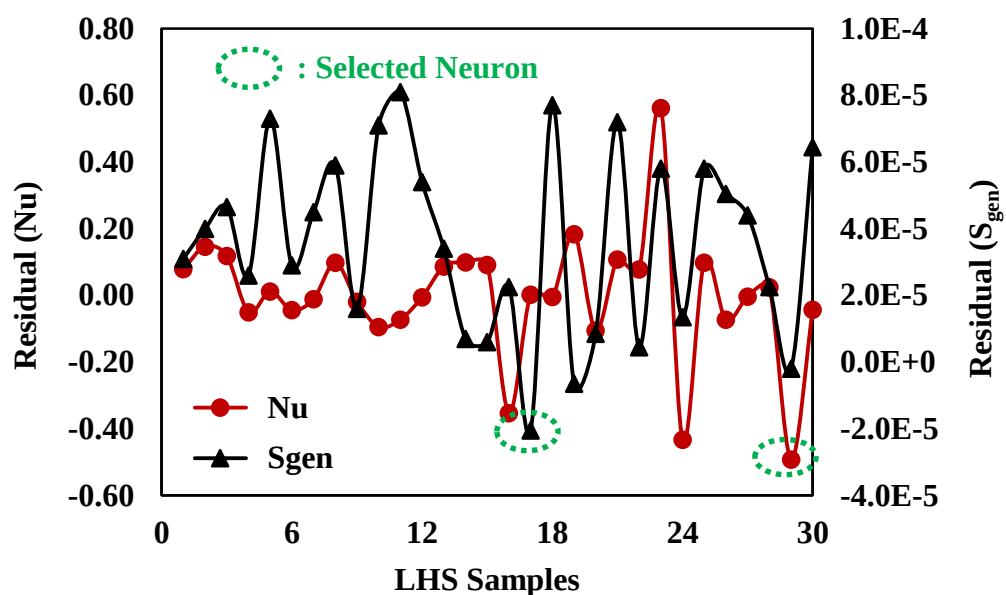


Figure 5.21: Neuron independence analysis for ANN development of the tri-hybrid nanofluid-enhanced CD-MCHS

A neuron-independence study was conducted to identify the most suitable ANN architecture for each objective function. Different hidden-layer configurations were examined, and the prediction accuracy was evaluated using the residual error. The corresponding results are presented in Figure 5.21.

Based on the neuron study, the optimal ANN architecture for the Nusselt number consisted of two hidden layers containing six neurons each, whereas the entropy-generation model employed two hidden layers with seven neurons each. These architectures provided the best balance between prediction accuracy and model generalization.

The predictive capability of the developed ANN models was evaluated through parity analysis by comparing ANN predictions against the corresponding CFD results. As illustrated in Figure 5.22, the predicted values closely follow the line of perfect agreement for both objective functions, indicating excellent consistency between the surrogate models and the numerical database.

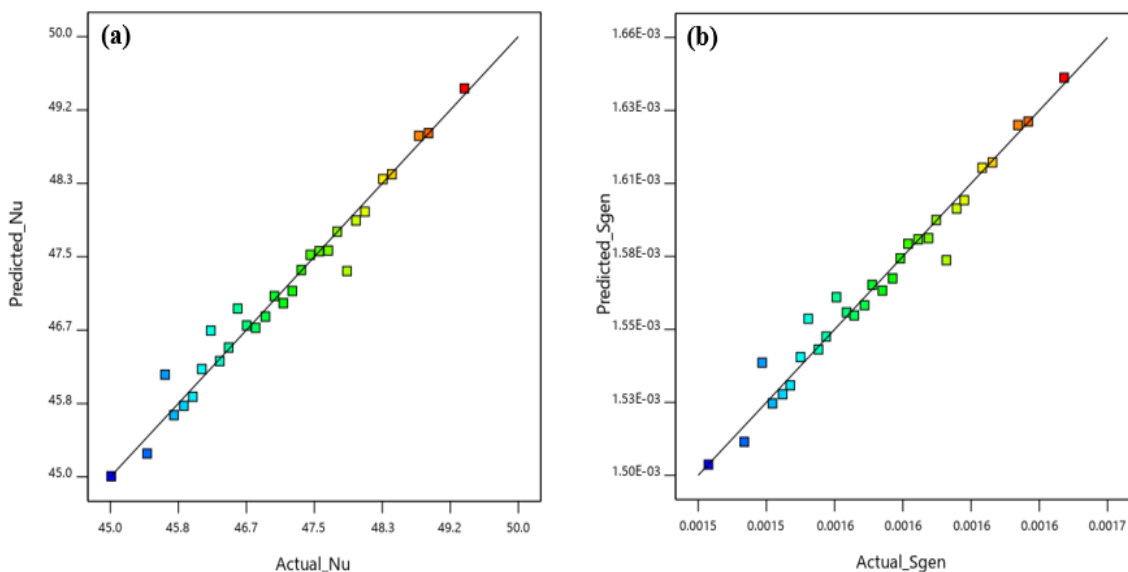


Figure 5.22: Parity plot between CFD and ANN predictions for the tri-hybrid nanofluid-enhanced CD-MCHS: (a) Nusselt number and (b) entropy generation

To further quantify the prediction accuracy, several statistical indicators including the correlation coefficient (R), coefficient of determination (R^2), root mean square error (RMSE), mean absolute error (MAE), and mean absolute percentage error (MAPE) were evaluated. The corresponding validation metrics are summarized in Table 5.20.

The obtained statistical results demonstrate excellent predictive capability for both ANN models, characterized by correlation coefficients approaching unity and very low

prediction errors. These findings confirm that the developed surrogate models accurately reproduce the CFD-generated responses and are suitable for subsequent optimization.

Table 5.20: Statistical validation metrics of ANN models for the tri-hybrid nanofluid-enhanced CD-MCHS

S. No.	Performance Metrics	Nusselt Number	Entropy Generation
01	Pearson's Correlation Coefficient	0.9851	0.9677
02	Coefficient of determination	0.9724	0.9428
03	Mean Absolute Error	0.1190	3.80×10^{-5}
04	Root Mean Squared Error	0.1859	4.51×10^{-5}
05	Mean Absolute Percentage Error	0.25 %	2.39 %

To further examine the influence of the nanofluid design variables, ANN-based response surfaces were generated for the Nusselt number and entropy generation, as shown in Figures 5.23 and 5.24, respectively.

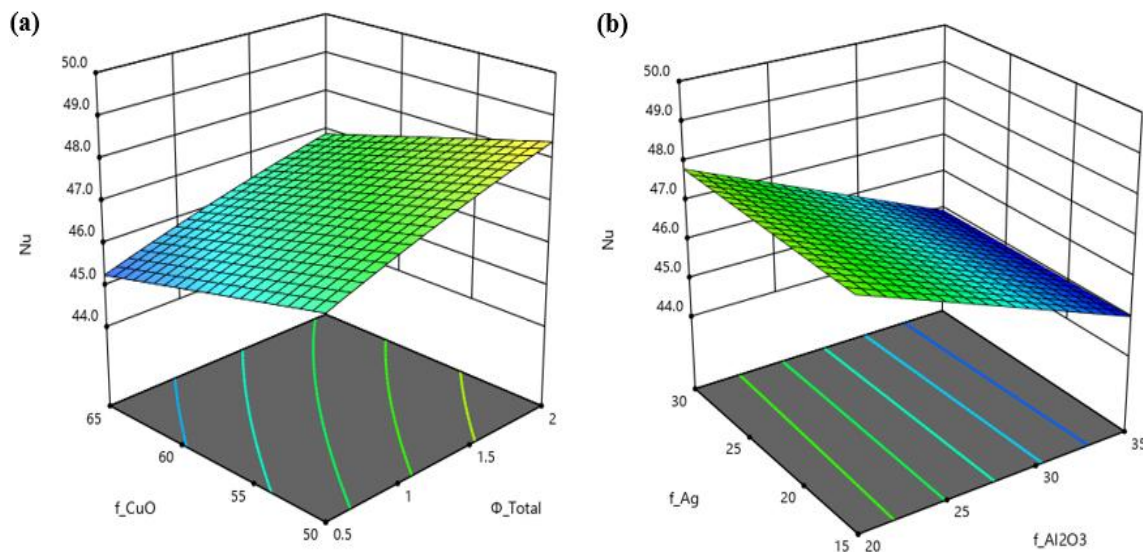


Figure 5.23: Three-dimensional ANN response surfaces for Nusselt number of the tri-hybrid nanofluid-enhanced CD-MCHS (a) Φ_T - f_{CuO} at $f_{Al2O3} = 25\%$ and $f_{Ag} = 20\%$, and (b) f_{Al2O3} - f_{Ag} at $\Phi_T = 01\%$ and $f_{CuO} = 55\%$

The response surfaces indicate that the average Nusselt number generally increases with increasing total nanoparticle concentration owing to the enhancement of the effective thermal conductivity of the tri-hybrid nanofluid. However, the magnitude of improvement is also influenced by the relative fractions of CuO, Al₂O₃, and Ag nanoparticles, demonstrating the existence of strong interaction effects among the constituent particles.

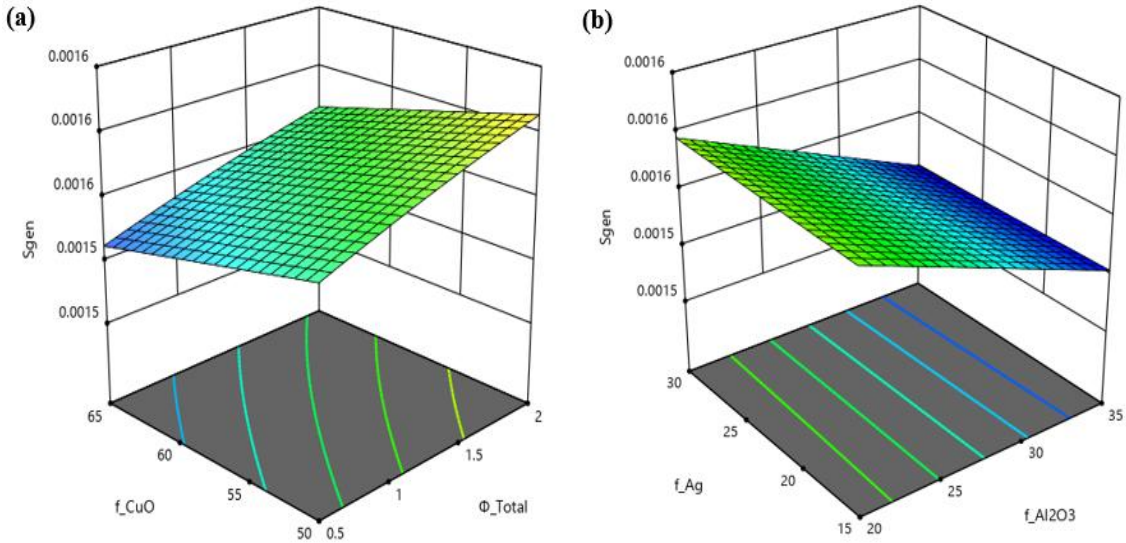


Figure 5.24: Three-dimensional ANN response surfaces for entropy generation of the tri-hybrid nanofluid-enhanced CD-MCHS (a) Φ_T - f_{CuO} at $f_{Al2O3} = 25\%$ and $f_{Ag} = 20\%$, and (b) f_{Al2O3} - f_{Ag} at $\Phi_T = 01\%$ and $f_{CuO} = 55\%$

A similar dependence is observed for entropy generation. Increasing nanoparticle concentration enhances heat-transfer capability but simultaneously modifies the flow and thermal characteristics of the coolant, resulting in variations in thermodynamic irreversibility. The response surfaces therefore highlight the competing influence of concentration and nanoparticle composition on the thermo-hydraulic behavior of the system and justify the need for multi-objective optimization.

Following validation, the trained ANN networks were transformed into explicit surrogate equations to facilitate rapid objective-function evaluation during the optimization stage.

$$\begin{aligned} \mathbf{Nu} = & 45.47 + 4.91 \times 10^{-4} X_1 - 1.30 \times 10^{-5} X_2 - 1.10 \times 10^{-5} X_3 + 2.40 \times 10^{-5} X_4 + \\ & 1.40 \times 10^{-2} X_1 X_2 + 1.47 \times 10^{-2} X_1 X_3 + 2.04 \times 10^{-2} X_1 X_4 - 2.42 \times 10^{-3} X_2 X_3 + 6.83 \times 10^{-4} X_2 X_4 + \\ & 6.47 \times 10^{-4} X_3 X_4 - 1.51 \times 10^{-1} X_1^2 + 4.51 \times 10^{-4} X_2^2 + 6.80 \times 10^{-4} X_3^2 + 1.05 \times 10^{-3} X_4^2. \end{aligned} \quad (5.5)$$

$$\begin{aligned} \mathbf{S}_{gen} = & 1.518 \times 10^{-3} + 2.10 \times 10^{-7} X_1 + 1.35 \times 10^{-7} X_2 + 9.80 \times 10^{-8} X_3 + 1.60 \times 10^{-7} X_4 + \\ & 8.40 \times 10^{-7} X_1 X_2 + 6.90 \times 10^{-7} X_1 X_3 + 1.00 \times 10^{-6} X_1 X_4 + 4.30 \times 10^{-7} X_2 X_3 + 3.80 \times 10^{-7} X_2 X_4 + \\ & 3.10 \times 10^{-7} X_3 X_4 - 4.00 \times 10^{-6} X_1^2 + 6.50 \times 10^{-7} X_2^2 + 5.20 \times 10^{-7} X_3^2 + 7.10 \times 10^{-7} X_4^2. \end{aligned} \quad (5.6)$$

Where, X_1 = Total nanoparticle volume fraction (%)

X_2 = Volume fraction of CuO nanoparticles (%)

X_3 = Volume fraction of Al_2O_3 nanoparticles (%)

X_4 = Volume fraction of Ag nanoparticles (%)

The developed surrogate equations provide computationally efficient representations of the CFD database and eliminate the need for repeated numerical simulations during optimization. Consequently, the validated ANN models were integrated with the NSGA-II algorithm to identify Pareto-optimal tri-hybrid nanofluid compositions that simultaneously maximize heat-transfer enhancement and minimize entropy generation. The optimization results are presented in the following section.

5.3.4 Selection of NSGA-II Parameters

The quality and convergence behavior of the NSGA-II algorithm are primarily influenced by the selected population size and generation number. Therefore, a sensitivity analysis was performed to identify suitable optimization parameters for the tri-hybrid nanofluid optimization problem.

5.3.4.1 Population Size Analysis

The influence of population size on the development of the Pareto front is illustrated in Figure 5.25.

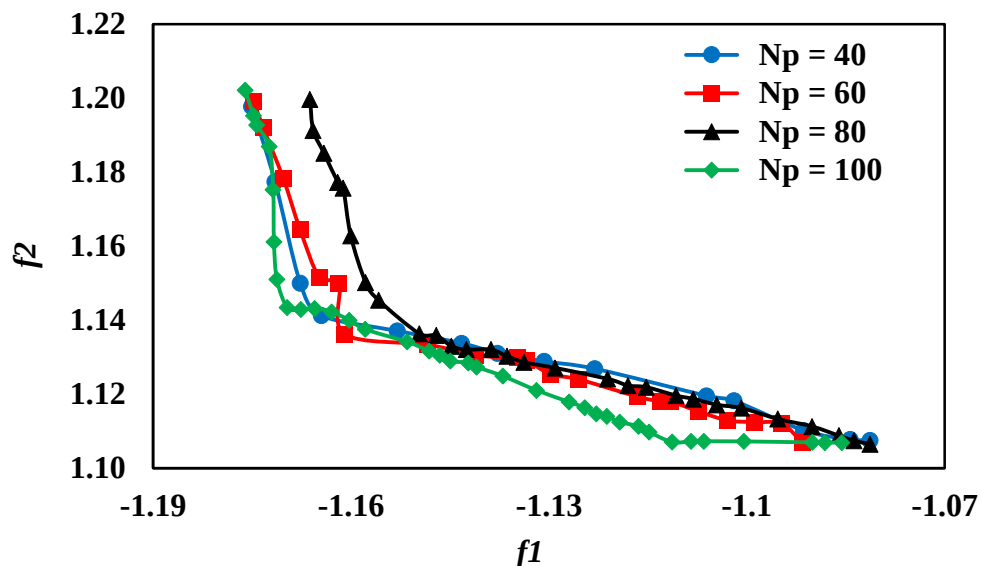


Figure 5.25: Influence of population size on Pareto-front development for the tri-hybrid nanofluid-enhanced CD-MCHS

As the population size increases, the Pareto front becomes progressively denser and more uniformly distributed, indicating improved exploration of the design space. Smaller populations generate relatively sparse solution sets and fail to adequately capture the

trade-off between heat-transfer enhancement and entropy generation. However, only marginal improvement in Pareto-front quality is observed beyond a population size of 80. Therefore, a population size of 80 was selected as an appropriate balance between solution diversity and computational efficiency.

5.3.4.2 Generation Number Analysis

The effect of generation number on Pareto-front convergence is presented in Figure 5.26.

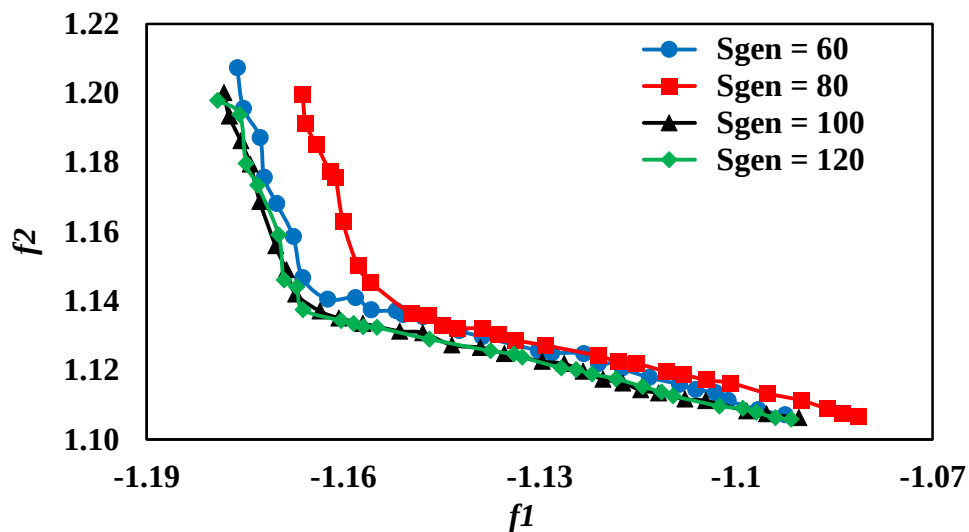


Figure 5.26: Influence of generation number on Pareto-front convergence for the tri-hybrid nanofluid-enhanced CD-MCHS

The results demonstrate that the Pareto front gradually evolves toward a stable and well-defined trade-off region with increasing generations. At lower generation numbers, the solutions remain scattered and do not fully represent the objective space. As the optimization progresses, the Pareto front becomes smoother and more uniformly distributed, indicating improved convergence. Beyond 100 generations, negligible changes are observed in the Pareto-front distribution, suggesting that further iterations provide limited additional benefit. Consequently, 100 generations were adopted for all subsequent optimization studies.

5.3.4.3 Final NSGA-II Parameters

Based on the population size and generation number investigations, the final NSGA-II parameters employed for the tri-hybrid nanofluid enhanced CD M CHS are summarized in Table 5.30

Table 5.21: Final NSGA-II control parameters adopted for the tri-hybrid nanofluid enhanced CD-MCHS

Parameter	Parameter Value
Population (N_p)	80
Maximum Generation (Gen)	100
Reproduction / Selection	Tournament Selection (Rank and Crowding Distance)
Pareto Fraction	0.35
Crossover Rate	0.85
Mutation Rate	0.10

The selected parameter set provided stable convergence and sufficient Pareto-front diversity while maintaining computational efficiency. The validated ANN surrogate models together with the optimized NSGA-II settings were subsequently utilized to identify the Pareto-optimal tri-hybrid nanofluid compositions discussed in the following section.

5.3.5 Characterization of the Optimal Pareto Front

Following the establishment of the optimal NSGA-II settings, the validated ANN surrogate models were coupled with the optimization algorithm to generate the Pareto-optimal tri-hybrid nanofluid compositions. The resulting Pareto front represents the best achievable trade-offs between maximizing the average Nusselt number and minimizing entropy generation for the optimized CD-MCHS. The complete set of Pareto-optimal solutions is presented in Table 5.22.

Table 5.22: Pareto-optimal design variables and corresponding responses for the tri-hybrid nanofluid enhanced CD-MCHS

S. No.	Pareto Design Variable (100th Generation)				Corresponding Results	
	Φ_{Total} (%)	f_{CuO} (%)	$f_{\text{Al}_2\text{O}_3}$ (%)	f_{Ag} (%)	Nu_{avg}	S_{gen}
1	2.00	56.50	21.0	22.50	52.37	0.001715
2	2.00	57.50	22.0	20.50	52.34	0.001705
3	2.00	58.50	23.0	18.50	52.26	0.001695
4	2.00	59.50	24.0	16.50	52.19	0.001685
5	1.75	57.00	22.5	20.50	52.13	0.001670

Cont....

6	1.75	58.50	24.5	17.00	52.02	0.001652
7	1.75	58.00	23.5	18.50	51.95	0.001642
8	1.75	56.00	21.5	22.50	51.88	0.001632
9	1.75	55.00	20.5	24.50	51.72	0.001625
10	1.50	56.50	22.0	21.50	51.59	0.001622
11	1.50	59.50	25.0	15.50	51.43	0.001620
12	1.50	57.50	23.0	19.50	51.18	0.001617
13	1.50	58.50	24.0	17.50	51.02	0.001616
14	1.50	55.50	21.0	23.50	50.82	0.001611
15	1.25	55.00	21.0	24.00	50.63	0.001610
16	1.25	59.00	25.0	16.00	50.47	0.001607
17	1.25	57.00	23.0	20.00	50.21	0.001604
18	1.25	56.00	22.0	22.00	50.06	0.001603
19	1.00	59.50	24.5	16.00	49.93	0.001600
20	1.00	57.50	22.5	20.00	49.80	0.001597
21	1.00	55.50	20.5	24.00	49.66	0.001595
22	1.00	58.50	23.5	18.00	49.54	0.001592
23	1.00	56.50	21.5	22.00	49.42	0.001591
24	0.50	58.00	23.0	19.00	49.24	0.001588
25	0.50	56.00	21.0	23.00	49.10	0.001588
26	0.50	59.00	24.0	17.00	48.82	0.001584
27	0.50	57.00	22.0	21.00	48.69	0.001582
28	1.75	55.00	20.0	25.00	48.47	0.001581

To further visualize the trade-off characteristics of the optimization process, the obtained Pareto front is presented in Figure 5.27.

As illustrated in Figure 5.27, the Pareto front exhibits the expected conflicting relationship between heat-transfer enhancement and entropy-generation minimization. Each point on the Pareto front represents a non-dominated solution for which improvement in one objective can only be achieved at the expense of the other. The continuous distribution of solutions confirms the existence of multiple feasible nanofluid compositions capable of delivering different thermo-hydraulic trade-offs.

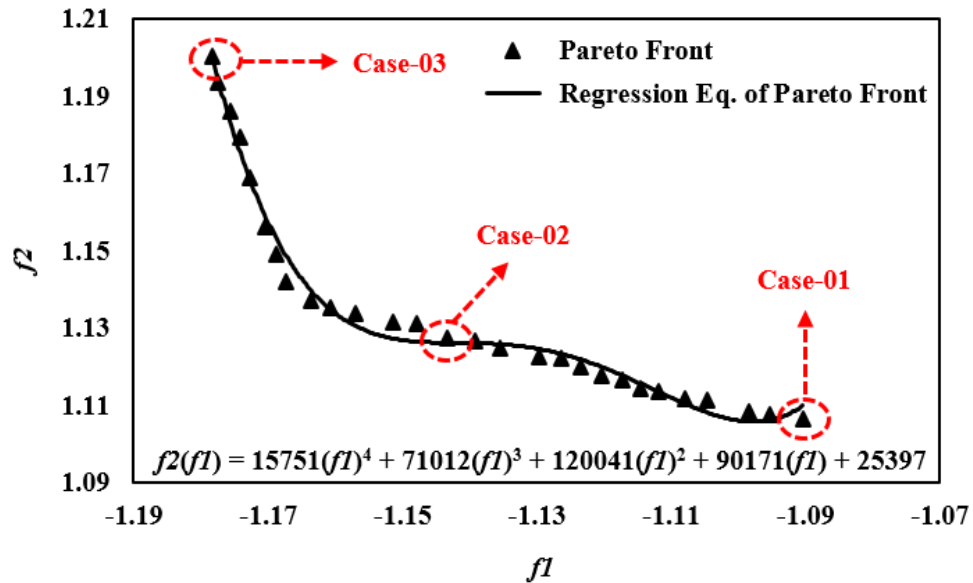


Figure 5.27: Representative solutions selected from the optimal Pareto front for the tri-hybrid nanofluid enhanced CD-MCHS

To facilitate physical interpretation of the optimization results, three representative Pareto-optimal solutions were selected from different regions of the Pareto front, corresponding to distinct performance priorities. These include a low-entropy-generation design (Case-01), an intermediate compromise design (Case-02), and a high-heat-transfer design (Case-03). Their relative performance with respect to the optimized baseline CD-MCHS is summarized in Table 5.23.

Table 5.23: Relative performance of selected Pareto-optimal tri-hybrid nanofluid configurations with respect to the optimized baseline CD-MCHS

Reference Study (Without Nanofluid)	Nu ($f_1 = -1$)	S_{gen} ($f_2 = 1$)
Case – 01: (Φ_T :2.0%, f_{CuO} :56.5%, $f_{Al_2O_3}$:21.0%, f_{Ag} :22.5%)	9.04 % ↑	10.63 % ↑
Case – 02: (Φ_T :1.50%, f_{CuO} :55.5%, $f_{Al_2O_3}$:21.0%, f_{Ag} :23.5%)	14.34 % ↑	12.72 % ↑
Case – 03: (Φ_T :1.75%, f_{CuO} :55.0%, $f_{Al_2O_3}$:20.0%, f_{Ag} :25.0%)	17.82 % ↑	20.01 % ↑

Case-01 (Φ_T :2.0%, f_{CuO} :56.5%, $f_{Al_2O_3}$:21.0%, f_{Ag} :22.5%) achieves a 9.04% increase in the average Nusselt number with a corresponding 10.63% rise in entropy generation relative to the baseline configuration. The moderate entropy penalty associated with the thermal enhancement indicates a thermodynamically favorable improvement in cooling performance. Case-02 (Φ_T :1.50%, f_{CuO} :55.5%, $f_{Al_2O_3}$:21.0%, f_{Ag} :23.5%) provides a more balanced hydrothermal response, yielding a 14.34% enhancement in the Nusselt number

while increasing entropy generation by 12.72%. This configuration therefore represents an effective compromise between heat-transfer augmentation and thermodynamic irreversibility.

Case-03 (Φ_T :1.75%, f_{CuO} :55.0%, $f_{Al_2O_3}$:20.0%, f_{Ag} :25.0%) is located toward the high-performance end of the Pareto front and delivers the largest thermal enhancement among the selected solutions. Compared with the baseline configuration, the average Nusselt number increases by 17.82%, accompanied by a 20.01% increase in entropy generation. Although this solution provides superior cooling capability, the higher entropy penalty reflects the thermodynamic cost associated with maximizing heat-transfer performance. Overall, the representative Pareto solutions clearly demonstrate the inherent trade-off between thermal enhancement and entropy-generation minimization in tri-hybrid nanofluid-assisted cooling. While higher nanoparticle loading and favorable constituent fractions can significantly improve heat-transfer performance, they also tend to increase thermodynamic irreversibilities. Consequently, the final design selection cannot be based solely on either objective and requires a compromise-based decision-making approach. Therefore, the Pareto-optimal solution set was further evaluated using the TOPSIS method to identify the most balanced tri-hybrid nanofluid composition, as discussed in the following section.

5.3.6 TOPSIS-Based Selection of the Optimal Tri-Hybrid Nanofluid Composition

Although the NSGA-II optimization identifies a set of Pareto-optimal solutions, practical implementation requires the selection of a single design that provides the most desirable compromise between enhanced heat-transfer performance and minimized thermodynamic irreversibility. Therefore, the TOPSIS method was employed to rank the Pareto-optimal solutions according to their relative closeness to the ideal solution.

To evaluate the influence of decision-maker preference, a weight-sensitivity analysis was performed by systematically varying the weighting combinations assigned to the average Nusselt number and entropy generation, ranging from entropy-dominant conditions (0.4, 0.6) to heat-transfer-dominant conditions (0.8, 0.2). The resulting TOPSIS rankings are summarized in Table 5.24.

The ranking results show that DoE-09 maintains a consistently high ranking across all weighting scenarios and achieves the highest rank under the selected weighting

combination (0.6, 0.4). This behavior confirms the robustness of the solution and supports its selection for further analysis.

Table 5.24: Sensitivity analysis of TOPSIS rankings to variations in objective weighting for the tri-hybrid nanofluid enhanced CD-MCHS

TOPSIS	W ₁ (0.4;0.6)		W ₂ (0.5;0.5)		W ₃ (0.6;0.4)		W ₄ (0.7;0.3)		W ₅ (0.8;0.2)	
Ranking	(C _i) ₁	DoE	(C _i) ₂	DoE	(C _i) ₃	DoE	(C _i) ₄	DoE	(C _i) ₅	DoE
01	0.7228	11	0.7394	10	0.7695	9	0.8160	8	0.8470	7
02	0.7224	12	0.7386	9	0.7660	8	0.7979	9	0.8467	8
03	0.7216	9	0.7317	11	0.7604	10	0.7972	7	0.8454	6
04	0.7205	10	0.7200	8	0.7413	11	0.7829	6	0.8328	5
05	0.7135	13	0.7151	12	0.7394	7	0.7789	10	0.8188	9

To further verify the robustness of the decision-making outcome, the variation of the TOPSIS relative closeness index (C_i) for DoE-09 was examined under different weighting combinations. The corresponding results are presented in Table 5.25.

Table 5.25: Stability of relative closeness for the selected TOPSIS tri-hybrid nanofluid composition under different weighting distributions

S. No.	Weight (Nu, S _{gen})	Relative Closeness (C _i)
1	W ₁ (0.4;0.6)	0.7216
2	W ₂ (0.5;0.5)	0.7386
3	W ₃ (0.6;0.4)	0.7695 Selected
4	W ₄ (0.7;0.3)	0.7979
5	W ₅ (0.8;0.2)	0.8188
Mean (μ)		0.7693
Std. Dev. (σ)		0.041
Coefficient of variation (CV)		5.24 %

The relative closeness values of DoE-09 exhibit only minor variation across the investigated weighting schemes, yielding a mean value of 0.7693 and a coefficient of variation of 5.24%. This low variability confirms the stability of the selected solution and demonstrates that its ranking is largely insensitive to changes in weighting preference. Accordingly, the weighting combination (Nu:0.6, S_{gen}:0.4) was adopted for the subsequent analysis.

The corresponding TOPSIS ranking distribution of the Pareto-optimal solutions is presented in Figure 5.28, where higher relative closeness values indicate a more favorable compromise between heat-transfer enhancement and entropy-generation minimization.

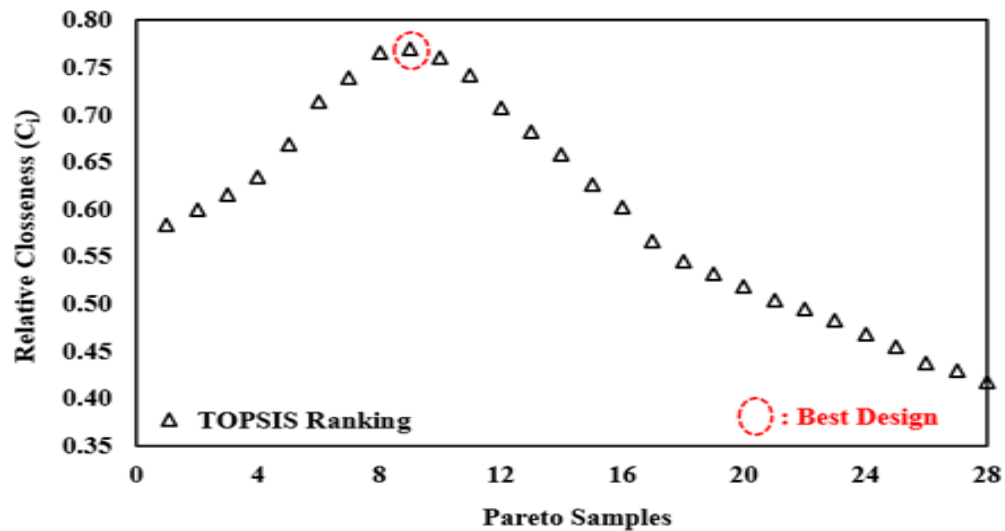


Figure 5.28: TOPSIS-based ranking of Pareto-optimal solutions for the tri-hybrid nanofluid enhanced CD-MCHS

Figure 5.28 shows that DoE-09 achieves the highest relative closeness value among all Pareto-optimal solutions. Therefore, this configuration was identified as the most balanced design and selected for subsequent thermo-hydraulic and exergetic evaluations. The selected TOPSIS configuration corresponds to: Φ_T :1.75%, f_{CuO} :55.0%, $f_{Al_2O_3}$:20.5%, f_{Ag} :24.5%. This composition represents a moderate nanoparticle loading with a balanced distribution of CuO, Al_2O_3 , and Ag nanoparticles, providing an effective compromise between heat-transfer enhancement and entropy-generation control.

A comparative assessment of the selected design with representative Pareto-optimal solutions and the reference case without nanofluid is presented in Table 5.26.

Table 5.26: Comparative performance of the TOPSIS-selected tri-hybrid nanofluid configuration with representative Pareto-optimal designs and the baseline CD-MCHS

TOPSIS : (Φ_T :1.75%, f_{CuO} :55.0%, $f_{Al_2O_3}$:20.5%, f_{Ag} :24.5%)	Nu (f_1)	S _{gen} (f_2)
Case – 01: (Φ_T :2.0%, f_{CuO} :56.5%, $f_{Al_2O_3}$:21.0%, f_{Ag} :22.5%)	6.71 % ↑	2.78 % ↑
Case – 02: (Φ_T :1.5%, f_{CuO} :55.5%, $f_{Al_2O_3}$:21.0%, f_{Ag} :23.5%)	1.76 % ↑	0.88 % ↑
Case – 03: (Φ_T :1.75%, f_{CuO} :55.0%, $f_{Al_2O_3}$:20.0%, f_{Ag} :25.0%)	1.24 % ↓	5.25 % ↓
Reference Study (Without Nanofluid)	16.36 % ↑	13.71 % ↑

The TOPSIS-selected configuration demonstrates a balanced thermo-hydraulic response among the competing Pareto solutions. Relative to Case-01 and Case-02, the selected design increases the average Nusselt number by 6.71% and 1.76%, respectively, accompanied by only moderate increases in entropy generation of 2.78% and 0.88%. Compared with Case-03, a marginal reduction of 1.24% in heat-transfer performance is observed; however, this is compensated by a 5.25% decrease in entropy generation, indicating improved thermodynamic behavior. More importantly, when benchmarked against the reference configuration without nanofluid, the selected composition enhances the Nusselt number by 16.36%, while the corresponding increase in entropy generation is limited to 13.71%.

Overall, the TOPSIS-ranked configuration achieves the most desirable balance between heat-transfer augmentation and thermodynamic irreversibility among the Pareto-optimal solutions, thereby validating its selection as the final optimized tri-hybrid nanofluid composition for the present study.

5.3.7 Hydrothermal Characteristics of the Selected TOPSIS Design

To further examine the flow and thermal behavior of the optimized tri-hybrid nanofluid configuration, the temperature, velocity, and pressure contours of the selected TOPSIS design were compared with those of the reference configuration. The corresponding contour distributions are presented in Figure 5.29.

As illustrated in Figure 5.29, the reference configuration exhibits a gradual increase in fluid temperature along the flow direction, reaching a maximum temperature of approximately 311.81 K. In contrast, the TOPSIS-selected nanofluid configuration restricts the peak temperature to about 309.92 K, corresponding to a reduction of nearly 1.89 K. This reduction indicates improved convective heat transport and enhanced thermal diffusion resulting from the optimized tri-hybrid nanofluid composition.

The velocity contours reveal a slight decrease in the peak velocity from 4.81 m/s in the reference case to 4.23 m/s for the TOPSIS-selected configuration. This behavior suggests improved flow redistribution and more uniform momentum transport within the microchannel rather than localized flow acceleration. Conversely, the pressure contours indicate an increase in the maximum pressure from approximately 40.12 kPa to 50.31 kPa, reflecting the additional hydraulic resistance associated with the modified thermo-physical properties of the nanofluid and the intensified flow-surface interactions.

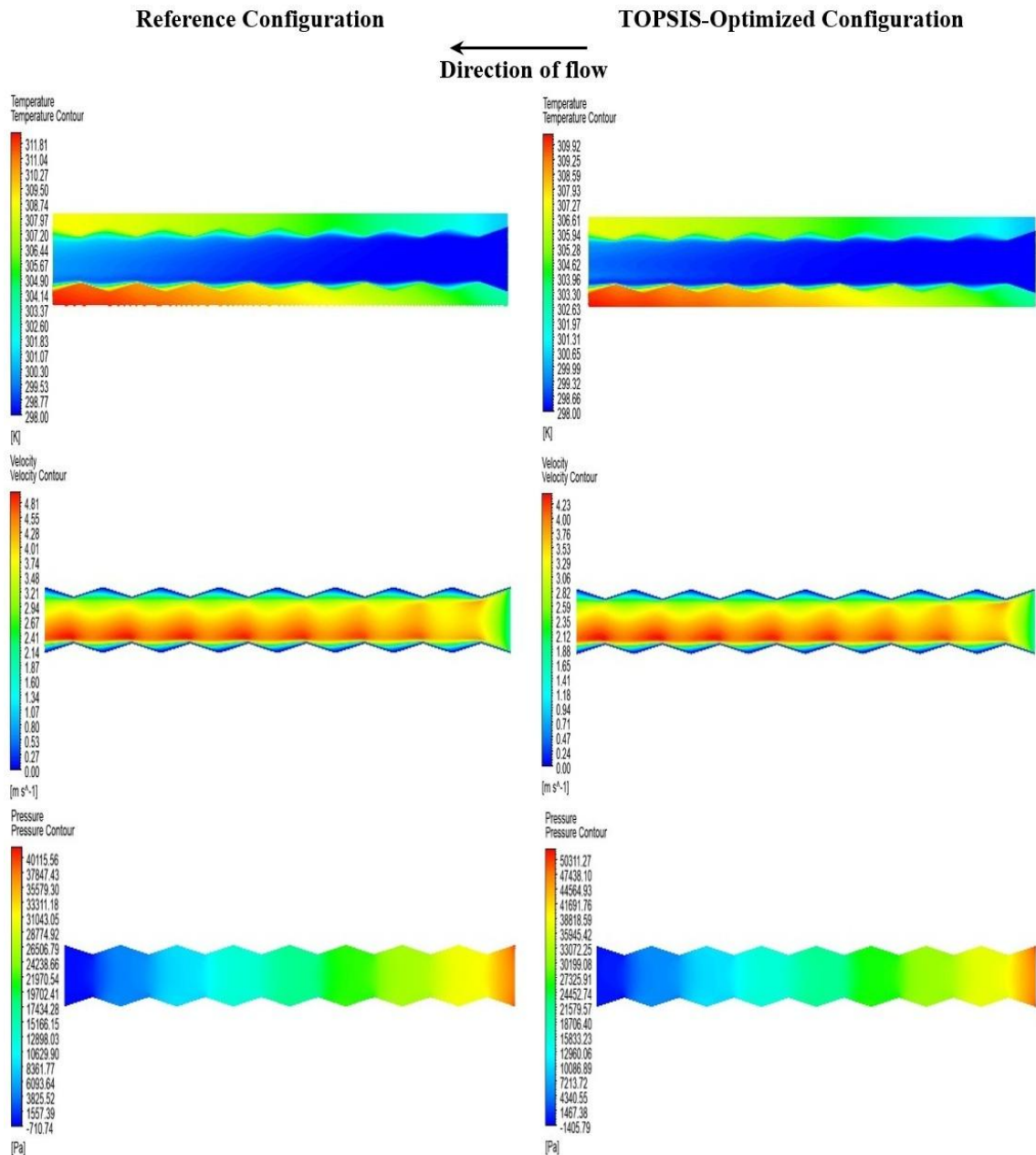


Figure 5.29: Comparison of temperature, velocity, and pressure contours for the reference and TOPSIS-selected tri-hybrid nanofluid configurations

Overall, the contour analysis confirms that the selected tri-hybrid nanofluid configuration enhances heat-transfer performance and reduces the maximum fluid temperature while maintaining an acceptable pressure-drop penalty. These observations further support the suitability of the TOPSIS-selected composition as a balanced thermo-hydraulic solution for advanced electronic cooling applications.

5.3.8 Exergetic Performance Evaluation

To further evaluate the thermodynamic suitability of the selected tri-hybrid nanofluid configuration, an exergetic performance assessment was performed using the Exergy Destruction Ratio (EDR) and exergy efficiency (η_{ex}). These parameters provide insight into the irreversibility characteristics of the system and enable validation of the optimized designs from a second-law perspective. The exergetic performance of the reference configuration, representative Pareto-optimal solutions, and the TOPSIS-selected composition is summarized in Table 5.27.

Table 5.27: Comparative exergetic performance assessment of the reference, Pareto-optimal, and TOPSIS-selected tri-hybrid nanofluid configurations

Design Configuration	EDR	Relative EDR	η_{ex}
Reference Study (Without Nanofluids)	8.53 %	-	91.47 %
Case-01: (Φ_T :2.0%, f_{CuO} :56.5%, $f_{Al_2O_3}$:21.0%, f_{Ag} :22.5%)	18.74 %	119.69 % ↑	81.26 %
Case-02: (Φ_T :1.5%, f_{CuO} :55.5%, $f_{Al_2O_3}$:21.0%, f_{Ag} :23.5%)	19.10 %	123.92 % ↑	80.90 %
Case-03: (Φ_T :1.75%, f_{CuO} :55.0%, $f_{Al_2O_3}$:20.0%, f_{Ag} :25.0%)	20.32 %	138.22 % ↑	79.68 %
TOPSIS: (Φ_T :1.75%, f_{CuO} :55.0%, $f_{Al_2O_3}$:20.5%, f_{Ag} :24.5%)	19.26 %	125.79 % ↑	80.74 %

The reference configuration without nanofluids exhibits the lowest exergy destruction ratio (EDR = 8.53%) and the highest exergy efficiency ($\eta_{ex} = 91.47\%$), indicating the lowest thermodynamic irreversibility among the evaluated cases. The incorporation of tri-hybrid nanoparticles improves heat-transfer performance but results in a corresponding increase in exergy destruction.

Among the representative Pareto-optimal solutions, Case-01 achieves the lowest EDR (18.74%) and highest exergy efficiency (81.26%), whereas Case-03 exhibits the highest EDR (20.32%) and lowest exergy efficiency (79.68%). Case-02 provides intermediate exergetic performance with an EDR of 19.10% and an exergy efficiency of 80.90%, reflecting the progressive increase in thermodynamic irreversibility associated with greater thermal enhancement.

The TOPSIS-selected composition yields an EDR of 19.26% and an exergy efficiency of 80.74%, positioning it between the extreme Pareto solutions. Although it does not correspond to the minimum exergy destruction, it maintains favorable exergetic performance while delivering enhanced heat-transfer capability, thereby reinforcing its selection as the most balanced design.

Overall, the exergetic assessment confirms that the optimized tri-hybrid nanofluid composition achieves improved cooling performance while maintaining acceptable thermodynamic efficiency, highlighting its suitability for high-performance electronic cooling applications.

5.4 Performance Enhancement of Baseline CD-MCHS using Porous Media

Building upon the optimized baseline CD-MCHS developed in Section 5.1, porous media were introduced as a passive enhancement strategy to further improve the hydrothermal and thermodynamic performance of the cooling system. The incorporation of a porous matrix modifies the flow and heat-transfer characteristics within the microchannel by increasing the fluid-solid interaction area and enhancing thermal transport through the porous region. However, the resulting improvement in heat-transfer performance is often accompanied by changes in flow resistance and thermodynamic irreversibility. Therefore, a systematic optimization framework is required to identify porous-media configurations capable of delivering maximum thermal enhancement while maintaining favorable thermodynamic performance.

Accordingly, a surrogate-assisted multi-objective optimization methodology based on CFD simulations, Artificial Neural Networks (ANN), Non-Dominated Sorting Genetic Algorithm-II (NSGA-II), and TOPSIS was employed to determine the optimal porous-media configuration. The optimization was performed by simultaneously maximizing the average Nusselt number and minimizing total entropy generation, thereby ensuring an effective balance between heat-transfer enhancement and thermodynamic efficiency.

5.4.1 Design Variables and Optimization Objectives

To further enhance the performance of the optimized CD-MCHS, porous media were incorporated within the channel and optimized using three key design variables: porosity (ϵ), pore diameter (d_p), and porous material (M_c). These parameters govern the permeability, effective thermal conductivity, and fluid-solid interaction characteristics of the porous region, thereby directly influencing both heat-transfer enhancement and thermodynamic irreversibility.

Porosity controls the balance between coolant flow and solid matrix volume, while pore diameter affects the characteristic flow pathways and hydraulic resistance within the porous structure. The porous material influences heat conduction through the solid matrix

and consequently plays a significant role in thermal transport. Through their combined effect, these parameters determine the overall thermo-hydraulic behavior of the porous-media-enhanced CD-MCHS.

The optimization was formulated as a multi-objective problem with the objective of maximizing the average Nusselt number and minimizing the total entropy generation rate. These objectives were selected to simultaneously evaluate heat-transfer enhancement and thermodynamic performance, thereby enabling the identification of porous configurations capable of delivering superior cooling effectiveness with reduced irreversibility.

5.4.2 Exploration of Design Space and Initial CFD Database

To investigate the combined influence of porosity, pore diameter, and porous substrate material on the performance of the optimized CD-MCHS, the design space was systematically explored using the Latin Hypercube Sampling (LHS) technique. Twenty-five porous configurations were generated and analyzed through three-dimensional CFD simulations, yielding the corresponding values of the average Nusselt number and total entropy generation. The resulting dataset captures the response of the porous-media-enhanced microchannel over the feasible design domain and provides the foundation for ANN-based surrogate modeling and subsequent multi-objective optimization. The generated LHS design matrix together with the corresponding CFD responses is summarized in Table 5.28.

Table 5.28: Initial LHS design matrix and corresponding CFD responses for the porous-media-enhanced CD-MCHS

S. No.	Design Variable (Generated with LHS)			Corresponding Results	
	Porosity	Pore Diameter	Coded-Material	Nusselt Number	Entropy Generation
1	0.70	24	4	129.25	0.1004
2	0.55	16	2	159.71	0.6773
3	0.40	32	2	165.83	0.9416
4	0.70	16	3	103.81	0.1782
5	0.70	24	2	144.71	0.1004
6	0.40	08	4	158.70	9.2455
7	0.85	16	3	86.27	0.0395

Cont....

8	0.55	32	2	159.59	0.2405
9	0.70	16	2	144.81	0.1781
10	0.85	16	1	134.54	0.0393
11	0.55	24	4	147.94	0.3641
12	0.40	08	3	135.87	9.2456
13	0.70	32	2	144.58	0.0686
14	0.55	08	2	159.84	2.1434
15	0.85	24	1	134.15	0.0242
16	0.55	08	3	123.79	2.1435
17	0.70	24	3	103.57	0.1005
18	0.55	24	3	123.56	0.3641
19	0.55	16	1	181.07	0.6773
20	0.85	24	3	72.56	0.0244
21	0.40	24	3	135.73	1.4588
22	0.70	32	1	160.42	0.0686
23	0.40	16	4	158.57	2.7977
24	0.85	08	3	74.15	0.1008
25	0.55	32	4	147.88	0.2405
Ref:	0.85	32	3	80.85	0.4759

The CFD results presented in Table 5.28 demonstrate that the porous-medium parameters exert a significant influence on both the heat-transfer and thermodynamic performance of the optimized CD-MCHS. Noticeable variations in the Nusselt number and entropy generation are observed across the sampled configurations, indicating that the combined effects of porosity, pore diameter, and porous substrate material substantially alter the thermal transport and flow characteristics within the porous region. These variations highlight the existence of multiple competing design trade-offs and confirm the suitability of the selected parameters for multi-objective optimization.

The generated CFD database establishes the relationship between the porous-medium parameters and the corresponding thermo-hydraulic responses over the explored design space. This dataset was subsequently utilized for the development and validation of ANN surrogate models, enabling efficient prediction of the objective functions during the optimization process.

5.4.3 Development and Validation of ANN Surrogate Models

The CFD database generated from the Latin Hypercube Sampling strategy was subsequently employed to develop ANN surrogate models for predicting the average Nusselt number and total entropy generation of the porous-media-enhanced CD-MCHS. The models establish nonlinear relationships between the porous-medium design variables, namely porosity (ϵ), pore diameter (d_p), and porous substrate material (M_c), and the corresponding objective functions. The developed ANN models serve as computationally efficient surrogate representations of the CFD simulations and were subsequently integrated with the multi-objective optimization framework.

Prior to training, the response data were normalized to improve numerical stability and learning efficiency. The available dataset was divided into training (70%), validation (15%), and testing (15%) subsets to ensure reliable assessment of model accuracy and generalization capability. Network training was performed using the Levenberg-Marquardt backpropagation algorithm, which is widely recognized for its rapid convergence and suitability for nonlinear regression problems.

A neuron-independence study was conducted to identify the optimal ANN architecture for each objective function. Different hidden-layer configurations were examined and the corresponding residual errors were monitored. The obtained results are presented in Figure 5.30.

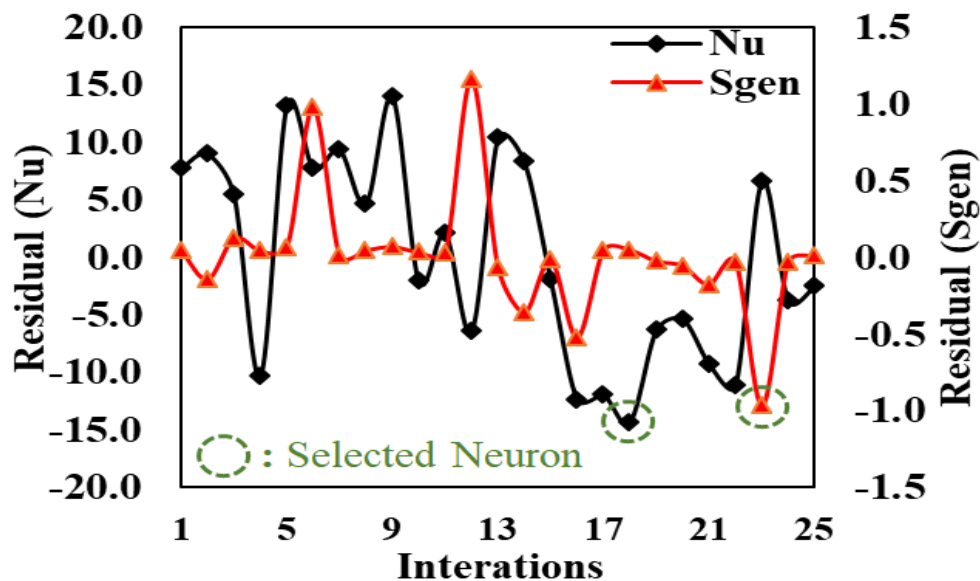


Figure 5.30: Neuron independence analysis for ANN development of the porous-media-enhanced CD-MCHS

The neuron study revealed that the optimum ANN architecture for predicting the average Nusselt number consists of two hidden layers with three neurons each, whereas the entropy-generation model achieved the best performance using two hidden layers with six neurons each. These architectures provided the lowest prediction errors while maintaining stable convergence and satisfactory generalization capability. Accordingly, the selected network structures were adopted for subsequent model validation and surrogate-model development.

The predictive capability of the developed ANN models was first assessed through parity-plot analysis by comparing ANN predictions with the corresponding CFD-generated responses. The resulting parity plots are presented in Figure 5.31.

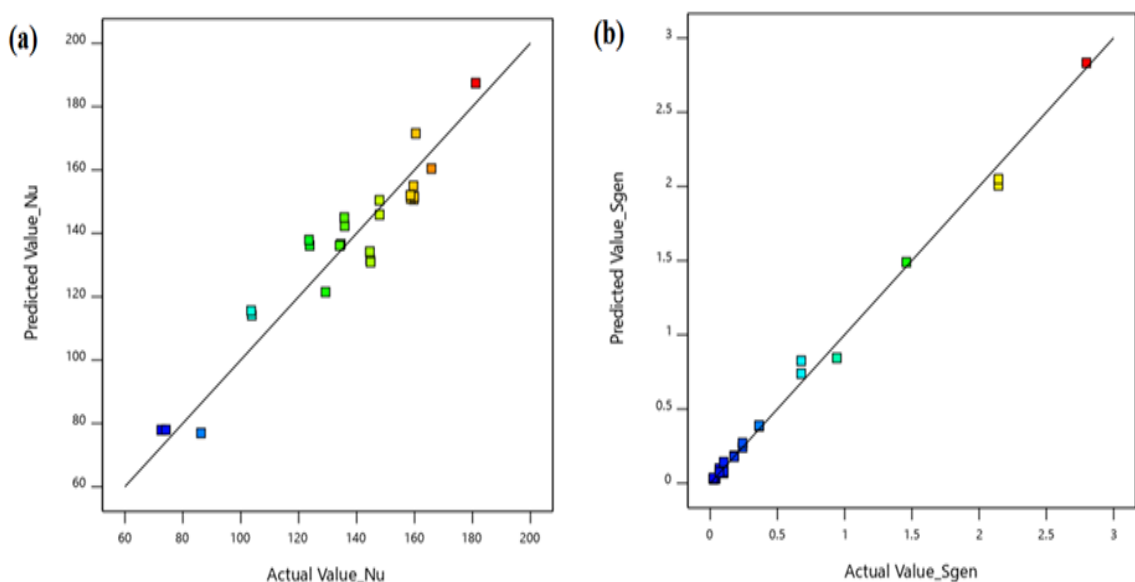


Figure 5.31: Parity plot between CFD and ANN predictions for the porous-media-enhanced CD-MCHS: (a) Nusselt number and (b) entropy generation

As shown in Figure 5.31, the predicted responses closely follow the line of perfect agreement for both objective functions, indicating excellent consistency between the ANN models and the CFD database. The close clustering of the data around the parity line demonstrates that the developed surrogate models accurately capture the nonlinear influence of the porous-medium parameters on the hydrothermal and thermodynamic responses of the optimized CD-MCHS.

To further quantify the prediction accuracy, several statistical indicators including the correlation coefficient (R), coefficient of determination (R^2), root mean square error

(RMSE), mean absolute error (MAE), and mean absolute percentage error (MAPE) were evaluated. The corresponding validation metrics are summarized in Table 5.29.

Table 5.29: Statistical validation metrics of ANN models for the porous-media-enhanced CD-MCHS

S. No.	Performance Metrics	Nusselt Number	Entropy Generation
01	Pearson's Correlation Coefficient	0.951	0.991
02	Coefficient of determination	0.903	0.982
03	Mean Absolute Error	7.839	0.337
04	Root Mean Squared Error	8.680	1.071
05	Mean Absolute Percentage Error	6.1 %	9.2 %

The obtained statistical indicators confirm the excellent predictive capability of both ANN models, characterized by correlation coefficients approaching unity and very low prediction errors. These results demonstrate that the developed surrogate models accurately reproduce the CFD-generated responses and are therefore suitable for subsequent multi-objective optimization.

To further examine the influence of the porous-medium parameters on system performance, ANN-based response surfaces were generated for the Nusselt number and entropy generation, as illustrated in Figures 5.32 and 5.33, respectively.

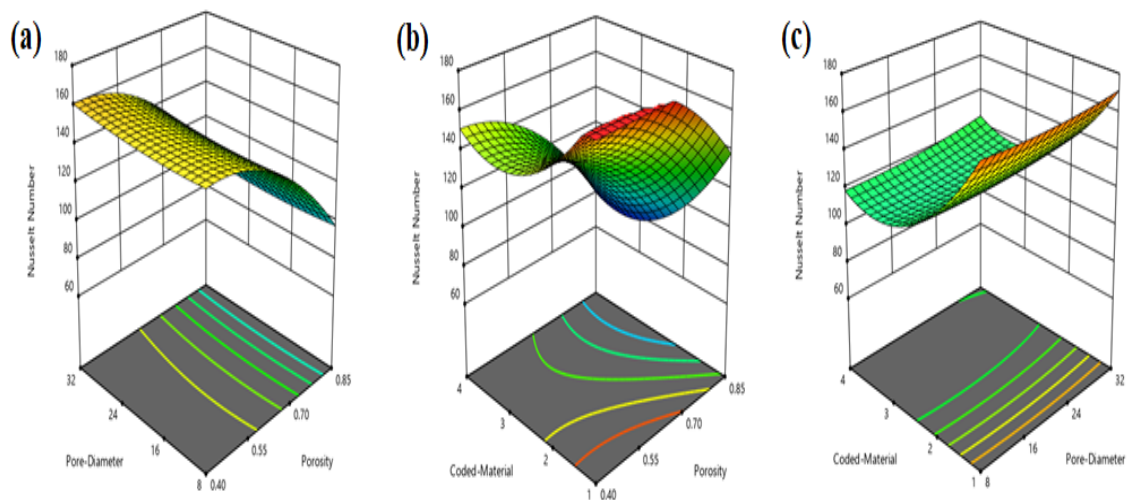


Figure 5.32: ANN-based response surface for Nusselt number of the porous-media-enhanced CD-MCHS: (a) ϵ - d_p at $M_c=02$, (b) ϵ - M_c at $d_p=08$, and (c) M_c - d_p at $\epsilon=0.7$

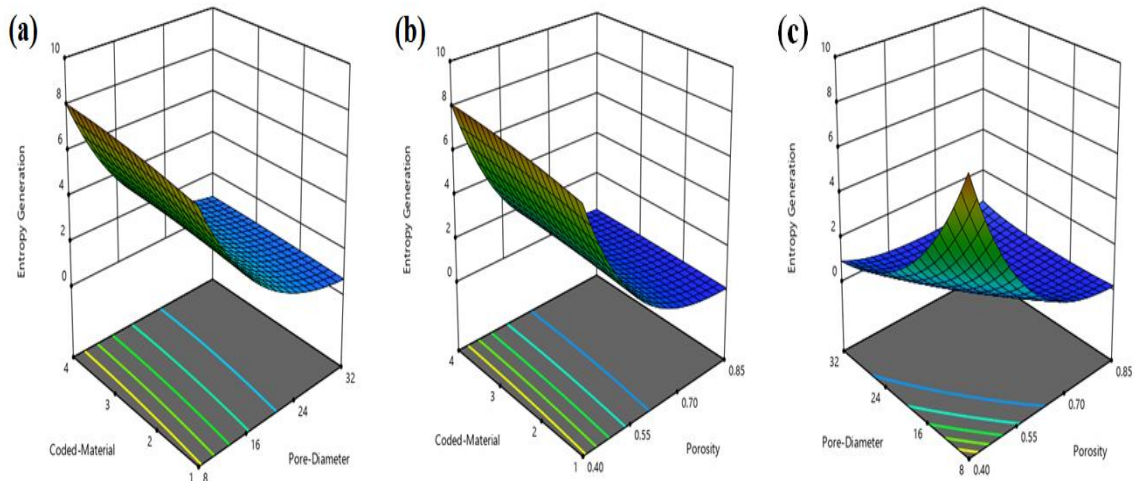


Figure 5.33: ANN-based response surface for entropy generation of the porous-media-enhanced CD-MCHS: (a) ϵ - d_p at $M_c=02$, (b) ϵ - M_c at $d_p=08$, and (c) M_c - d_p at $\epsilon=0.7$

The response surfaces reveal the strong dependence of both objective functions on the selected porous-medium parameters and further confirm the highly nonlinear nature of the design space. The generated surfaces provide additional physical insight into the interaction between porosity, pore diameter, and porous substrate material, while simultaneously demonstrating the capability of the ANN models to represent the underlying CFD responses throughout the investigated design domain.

The final ANN surrogate equations developed for predicting the Nusselt number and entropy generation are presented below and were subsequently employed during the NSGA-II optimization process.

$$Nu = 196.816 + (287.475 * X_1) - (1.061 * X_2) - (64.766 * X_3) - (0.057 * X_1 X_2) - (11.384 * X_1 * X_3) + (0.262 * X_2 * X_3) - (318.934 * X_1^2) + (0.016 * X_2^2) + (10.089 * X_3^2) \quad (5.7)$$

$$\sqrt{S_{gen}} = 6.995 - (12.131 * X_1) - (0.173 * X_2) + (0.132 * X_3) + (0.129 * X_1 * X_2) - (0.089 * X_1 * X_3) + (0.001 * X_2 * X_3) + (5.601 * X_1^2) + (0.002 X_2^2) - (0.014 X_3^2) \quad (5.8)$$

Where, $X_1 = Porosity$

$X_2 = Pore Diameter$

$X_3 = Coded Material$

The validated ANN surrogate models therefore provide an accurate and computationally efficient representation of the porous-media-enhanced CD-MCHS. These models were

subsequently integrated with the NSGA-II algorithm to identify Pareto-optimal solutions and explore the trade-off between heat-transfer enhancement and entropy-generation minimization, as discussed in the following section.

5.4.4 Selection of NSGA-II Parameters

The effectiveness of the NSGA-II algorithm depends strongly on the selection of appropriate evolutionary parameters, particularly the population size and the number of generations. These parameters govern the exploration capability, convergence behavior, and diversity of the Pareto-optimal solutions. Therefore, a sensitivity analysis was conducted to identify suitable NSGA-II settings for the porous-media-enhanced CD-MCHS optimization problem.

5.4.4.1 Population Size Analysis

The influence of population size on the development of the Pareto front is illustrated in Figure 5.34.

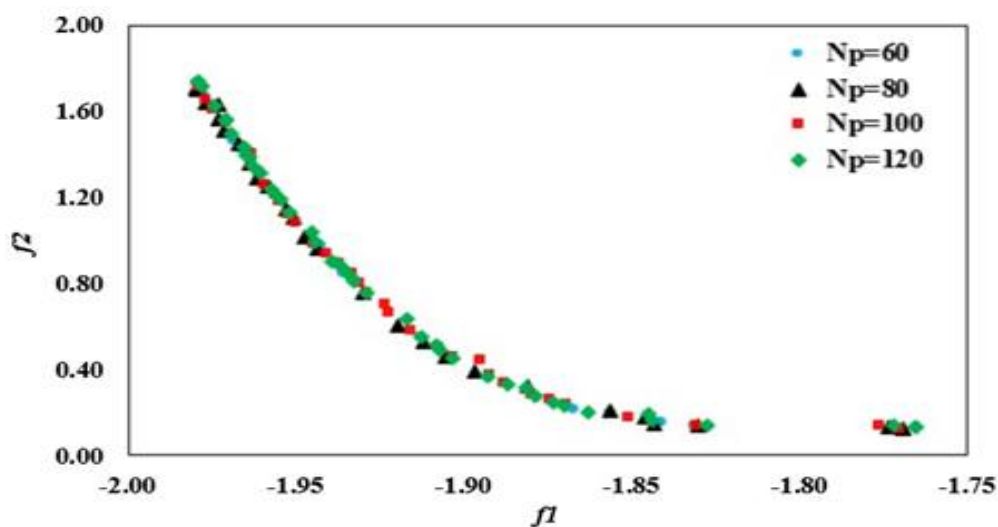


Figure 5.34: Influence of population size on Pareto-front development for the porous-media-enhanced CD-MCHS

As illustrated in Figure 5.34, increasing the population size improves the density and distribution of Pareto-optimal solutions. Smaller populations generate relatively sparse solution sets and provide limited coverage of the objective space. In contrast, larger populations enhance the exploration capability of the optimization algorithm and produce a more uniformly distributed Pareto front. However, only marginal improvement in

Pareto-front quality is observed beyond a population size of 80. Therefore, a population size of 80 was selected as an appropriate compromise between solution diversity and computational efficiency.

5.4.4.2 Generation Number Analysis

The influence of generation number on Pareto-front convergence is presented in Figure 5.35.

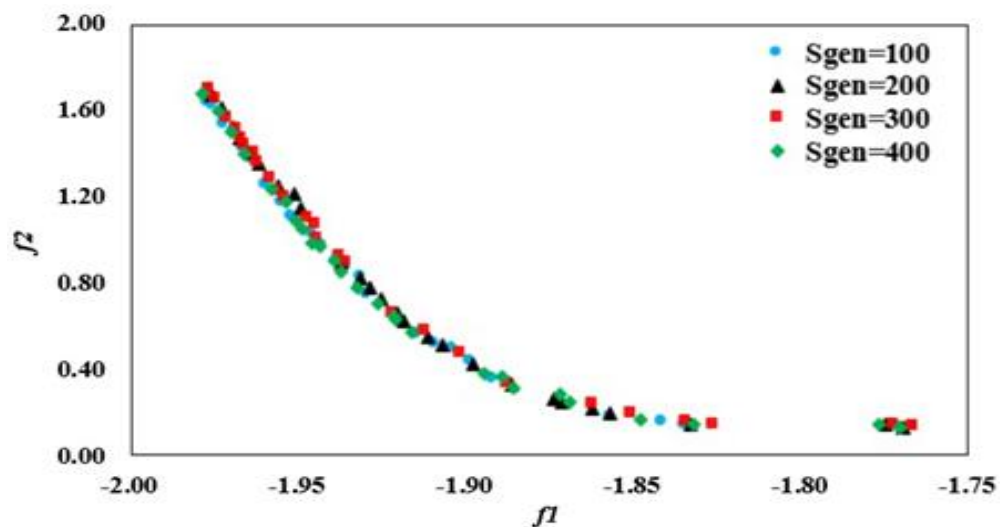


Figure 5.35: Influence of generation number on Pareto-front convergence for the porous-media-enhanced CD-MCHS

The results demonstrate that the Pareto front progressively evolves toward a stable trade-off region with increasing generations. At lower generation numbers, the solutions remain relatively scattered and do not adequately represent the objective space. As the optimization progresses, the Pareto front becomes smoother and more uniformly distributed, indicating improved convergence characteristics. Beyond 200 generations, negligible changes are observed in the Pareto-front distribution, suggesting that convergence has been achieved and additional generations provide limited benefit. Consequently, 200 generations were adopted for all subsequent optimization studies.

5.4.4.3 Final NSGA-II Parameters

Based on the population-size and generation-number investigations, the final NSGA-II parameters employed for the porous-media-enhanced CD-MCHS are summarized in Table 5.30.

Table 5.30: Final NSGA-II control parameters adopted for the porous-media-enhanced CD-MCHS

Parameter	Parameter Value
Population (N_p)	80
Maximum Generation (Gen)	200
Reproduction / Selection	Tournament Selection (Rank and Crowding Distance)
Pareto Fraction	0.35
Crossover Rate	0.80
Mutation Rate	0.10

The selected parameter set provided stable convergence and sufficient Pareto-front diversity while maintaining computational efficiency. The validated ANN surrogate models together with the optimized NSGA-II settings were subsequently utilized to identify the Pareto-optimal porous-media configurations discussed in the following section.

5.4.5 Characterization of the Optimal Pareto Front

Following the establishment of the optimal NSGA-II settings, the validated ANN surrogate models were integrated with the NSGA-II algorithm to generate a set of Pareto-optimal porous-media configurations for the CD-MCHS. The resulting Pareto front represents the best achievable trade-offs between maximizing the average Nusselt number and minimizing entropy generation. The complete set of Pareto-optimal solutions obtained for the porous-media-enhanced CD-MCHS is presented in Table 5.31.

Table 5.31: Pareto-optimal design variables and corresponding responses for the porous-media-enhanced CD-MCHS

S. No.	Pareto design variable (200 th Generation)			Corresponding Results	
	Porosity	Pore Diameter	Coded-Material	Nusselt Number	Entropy Generation
1	0.74	16	1	162.51	0.0906
2	0.83	15	1	142.55	0.0382
3	0.81	14	4	88.27	0.0513
4	0.41	32	4	160.29	0.8742

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Cont....

5	0.73	27	4	116.24	0.0509
6	0.51	27	4	150.36	0.4610
7	0.79	19	4	96.05	0.0301
8	0.61	28	4	139.53	0.1595
9	0.51	20	4	145.29	0.8117
10	0.83	15	1	142.55	0.0382
11	0.53	24	4	146.17	0.4679
12	0.68	29	2	137.17	0.0825
13	0.64	26	4	133.12	0.1233
14	0.63	30	4	138.22	0.1315
15	0.46	25	4	152.19	0.8433
16	0.47	30	4	155.91	0.5714
17	0.46	31	4	157.43	0.5987
18	0.53	22	4	144.76	0.5556
19	0.80	19	4	93.39	0.0263
20	0.48	31	4	156.24	0.5030
21	0.42	31	4	159.05	0.8394
22	0.56	25	3	137.67	0.3229
23	0.55	30	4	149.11	0.2740
24	0.46	26	4	152.98	0.7857
25	0.52	20	2	154.23	0.7043
26	0.51	27	4	150.36	0.4610
27	0.48	31	4	156.24	0.5030
28	0.41	32	4	160.29	0.8742

The Pareto front demonstrates the inherent conflict between thermal enhancement and thermodynamic irreversibility. Configurations that promote stronger heat-transfer augmentation generally require lower porosity and smaller pore diameters, which intensify fluid-solid interaction and improve convective transport within the porous matrix. However, these conditions simultaneously increase flow resistance and viscous dissipation, leading to higher entropy generation. Conversely, configurations characterized by higher porosity and larger pore diameters reduce flow resistance and entropy production but provide comparatively lower heat-transfer enhancement.

Consequently, no single configuration simultaneously maximizes the Nusselt number and minimizes entropy generation, resulting in a non-dominated Pareto solution set.

To facilitate a physical interpretation of the Pareto-optimal solutions, three representative configurations were selected from distinct regions of the Pareto front, namely the low-entropy-generation region (Case-01), the intermediate compromise region (Case-02), and the high-heat-transfer region (Case-03). The locations of these representative points on the Pareto front are illustrated in Figure 5.36. These solutions provide insight into the influence of porous-medium characteristics on the competing objectives of heat-transfer enhancement and entropy-generation minimization.

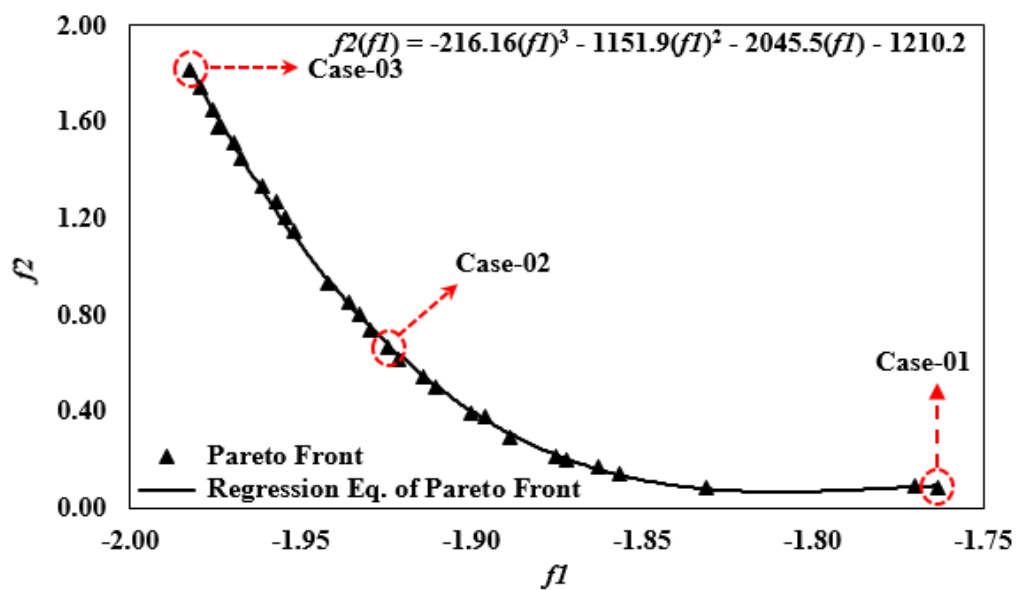


Figure 5.36: Representative solutions selected from the optimal Pareto front for the porous-media-enhanced CD-MCHS

The progression from Case-01 to Case-03 reflects a gradual shift in design priority from thermodynamic efficiency toward maximum thermal performance. Case-01 is characterized by comparatively higher porosity and larger pore diameter, which reduce flow resistance and suppress frictional irreversibility within the porous matrix. Consequently, entropy generation remains relatively low, although the attainable heat-transfer enhancement is moderate. In contrast, Case-03 corresponds to a more thermally aggressive configuration characterized by lower porosity and smaller pore diameter. These porous characteristics intensify fluid-solid interactions, strengthen local velocity gradients, and promote repeated disruption of the thermal boundary layer within the convergent-divergent channel. As a result, convective heat transfer is significantly

enhanced; however, the associated increase in flow resistance leads to higher entropy generation. Case-02 occupies an intermediate position between these two extremes and represents a balanced hydrothermal design in which substantial heat-transfer enhancement is achieved without a proportional increase in thermodynamic irreversibility. These observations confirm that porous-medium morphology governs the trade-off between thermal augmentation and entropy generation through its simultaneous influence on permeability, conductive heat spreading, and viscous dissipation.

For a quantitative assessment, the hydrothermal performances of the selected Pareto-optimal configurations relative to the optimized baseline CD-MCHS are summarized in Table 5.32.

Table 5.32: Comparative performance of the TOPSIS-selected porous media configuration with representative Pareto-optimal designs and the reference study

Ref Study : (ϵ :0.85, d_p :32, M_c :03)	Nu ($f_1 = -1$)	S _{gen} ($f_2 = 1$)
Case – 01: (ϵ :0.83, d_p :15, M_c :01)	76.34 % ↑	91.35 % ↓
Case – 02: (ϵ :0.64, d_p :26, M_c :04)	92.45 % ↑	33.58 % ↓
Case – 03: (ϵ :0.41, d_p :32, M_c :04)	98.25 % ↑	81.54 % ↑

Case-01 (ϵ :0.83, d_p :15, M_c :01) achieves a 76.34% increase in the average Nusselt number while simultaneously reducing entropy generation by 91.35% relative to the reference configuration. Although the heat-transfer enhancement is comparatively lower than the other selected solutions, the substantial reduction in entropy generation highlights its strong thermodynamic performance.

Case-02 (ϵ :0.64, d_p :26, M_c :04) provides a more balanced hydrothermal response, yielding a 92.45% enhancement in the Nusselt number together with a 33.58% reduction in entropy generation. This configuration therefore represents an effective compromise between thermal enhancement and thermodynamic efficiency.

Case-03 (ϵ :0.41, d_p :32, M_c :04) delivers the highest thermal performance among the selected solutions, achieving a 98.25% increase in the average Nusselt number. However, this improvement is accompanied by an 81.54% increase in entropy generation, indicating the thermodynamic cost associated with maximizing heat-transfer enhancement.

Overall, the selected Pareto-optimal solutions clearly demonstrate the competing relationship between thermal enhancement and entropy generation. While Case-01 favors thermodynamic efficiency and Case-03 prioritizes maximum cooling performance, Case-

02 occupies an intermediate position and provides a balanced compromise between the two objectives. Consequently, a systematic decision-making procedure is required to identify the most suitable design from the Pareto-optimal set. Therefore, the TOPSIS method was subsequently employed to determine the final optimal porous-media configuration.

5.4.6 TOPSIS-Based Selection of the Optimal Porous-Media Configuration

To identify the most balanced solution from the Pareto-optimal set, the TOPSIS method was employed to rank the candidate configurations according to their relative closeness to the ideal solution. Since thermal enhancement is the primary objective in electronic cooling applications, greater emphasis was assigned to the average Nusselt number while simultaneously accounting for entropy-generation minimization.

To evaluate the robustness of the decision-making process, a sensitivity analysis was performed by varying the weighting distributions between the Nusselt number and entropy generation. The corresponding ranking results are summarized in Table 5.33.

Table 5.33: Sensitivity of TOPSIS rankings to different weighting distributions for the porous-media-enhanced CD-MCHS

TOPSIS	W ₁ (0.4;0.6)		W ₂ (0.5;0.5)		W ₃ (0.6;0.4)		W ₄ (0.7;0.3)		W ₅ (0.8;0.2)	
Ranking	(C _i) ₁	DoE	(C _i) ₂	DoE	(C _i) ₃	DoE	(C _i) ₄	DoE	(C _i) ₅	DoE
01	0.9460	02	0.9278	01	0.9316	01	0.9391	01	0.9531	01
02	0.9460	10	0.9234	02	0.8930	02	0.8523	02	0.8012	02
03	0.9258	01	0.9234	10	0.8930	10	0.8523	10	0.8012	10
04	0.9073	12	0.8849	12	0.8517	12	0.8047	12	0.7705	23
05	0.8813	05	0.8492	14	0.8262	14	0.7901	14	0.7440	12

The ranking results indicate that **DoE-01** consistently remains among the highest-ranked Pareto solutions across all weighting scenarios and attains the first rank for four of the five investigated weighting combinations. This stable ranking behavior confirms that the selection of DoE-01 is not strongly dependent on a particular decision preference and demonstrates the robustness of the identified optimum solution.

The stability of the TOPSIS decision was further assessed through the variation of the relative closeness index (C_i) for DoE-01 under different weighting combinations. The corresponding results are summarized in Table 5.34.

The relative closeness values vary only marginally across the investigated weighting schemes, yielding a mean value of **0.9355** and a coefficient of variation of only **1.10%**. The low dispersion confirms the stability of the TOPSIS decision and demonstrates that the selected solution remains largely insensitive to variations in decision-maker preference. Among the investigated weighting combinations, the (Nu:0.6, S_{gen} :0.4) criterion was adopted for the final decision-making analysis.

Table 5.34: Stability of relative closeness for the selected TOPSIS porous-media configuration under different weighting distributions

S. No.	Weight (Nu, S_{gen})	Relative Closeness (C_i)
1	$W_1(0.4;0.6)$	0.9258
2	$W_2(0.5;0.5)$	0.9278
3	$W_3(0.6;0.4)$	0.9316 Selected
4	$W_4(0.7;0.3)$	0.9391
5	$W_5(0.8;0.2)$	0.9531
Mean (μ)		0.9355
Std. Dev. (σ)		0.01
Coefficient of variation (CV)		1.10%

The distribution of the relative closeness values for the Pareto-optimal solutions under the selected weighting combination is illustrated in Figure 5.37.

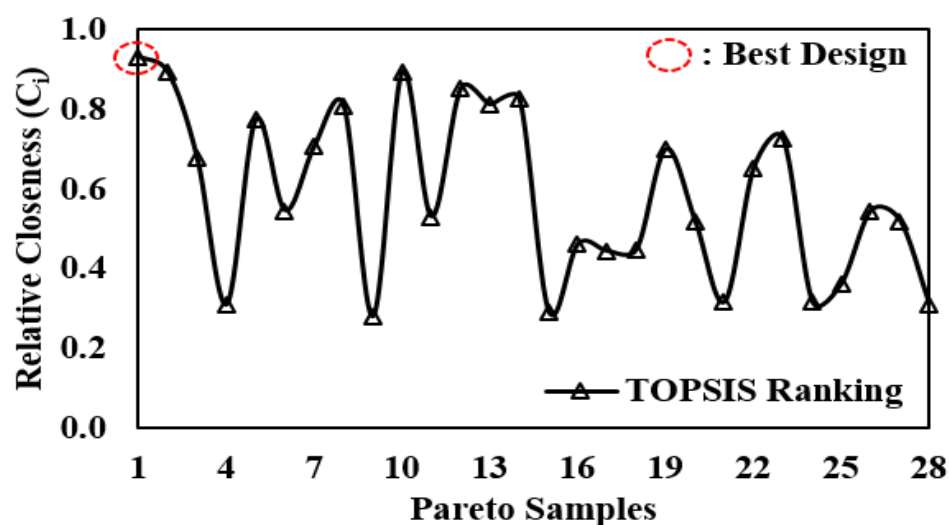


Figure 5.37: TOPSIS-based ranking of the optimal Pareto front solutions for the porous-media-enhanced CD-MCHS

As shown in Figure 5.37, DoE-01 exhibits the highest relative closeness value among all Pareto-optimal solutions, confirming its superiority as the most balanced compromise between heat-transfer enhancement and entropy-generation control. Accordingly, DoE-01 was selected as the final optimized porous-media configuration for subsequent analysis. The TOPSIS-selected optimum corresponds to a porous structure with $\varepsilon = 0.74$, $d_p = 16 \mu\text{m}$, and a copper substrate ($M_c = 01$). This configuration was identified as the most balanced Pareto-optimal solution, offering a favorable trade-off between thermal enhancement and thermodynamic performance.

To further evaluate the effectiveness of the selected design, its performance was compared with the representative Pareto-optimal solutions discussed in the previous section, the porous-media reference configuration, and the non-porous (clear) channel. The corresponding results are summarized in Table 5.35.

Table 5.35: Performance comparison of the TOPSIS-selected porous-media configuration with representative Pareto-optimal solutions, reference configurations and baseline CD-MCHS

TOPSIS : (ε:0.74, d_p:16, M_c:01)	Nu (f_1)	S_{gen} (f_2)
Case – 01: (ε :0.83, d_p :15, M_c :01)	13.99 % ↑	120.10 % ↑
Case – 02: (ε :0.64, d_p :26, M_c :04)	4.44 % ↑	71.29 % ↓
Case – 03: (ε :0.41, d_p :32, M_c :04)	1.39 % ↑	89.48 % ↓
Ref Study : (ε:0.85, d_p:32, M_c:03)	101.0 % ↑	80.96 % ↓
Non-Porous (Clear) Channel	265.65 ↑	534.66 ↑

Compared with Case-01, the TOPSIS-selected configuration increases the average Nusselt number by 13.99%, although this improvement is accompanied by a corresponding 120.10% increase in entropy generation. Relative to Case-02, the selected design provides a 4.44% enhancement in heat-transfer performance while simultaneously reducing entropy generation by 71.29%, indicating a superior balance between thermal enhancement and thermodynamic irreversibility. In comparison with Case-03, the selected configuration achieves a comparable thermal response with a marginal 1.39% increase in the Nusselt number while reducing entropy generation by 89.48%.

More importantly, when compared with the porous-media reference configuration, the TOPSIS-selected design enhances the average Nusselt number by 101.0% while reducing entropy generation by 80.96%. Relative to the non-porous clear channel, the

corresponding improvements reach 265.65% and 534.66%, respectively. These results clearly demonstrate the substantial thermal and thermodynamic benefits achieved through the optimized porous-medium design.

Overall, the TOPSIS-selected configuration provides the most favorable compromise between heat-transfer enhancement and entropy-generation minimization among the Pareto-optimal solutions. The identified optimum design was therefore adopted for the subsequent flow-field and thermal-field analysis presented in the following section.

5.4.7 Hydrothermal Characteristics of the Selected TOPSIS Design

To further elucidate the mechanisms responsible for the superior performance of the TOPSIS-selected porous configuration, the temperature, velocity, and pressure distributions were compared with those of the non-porous (clear) channel. The corresponding contours are presented in Figure 5.38.

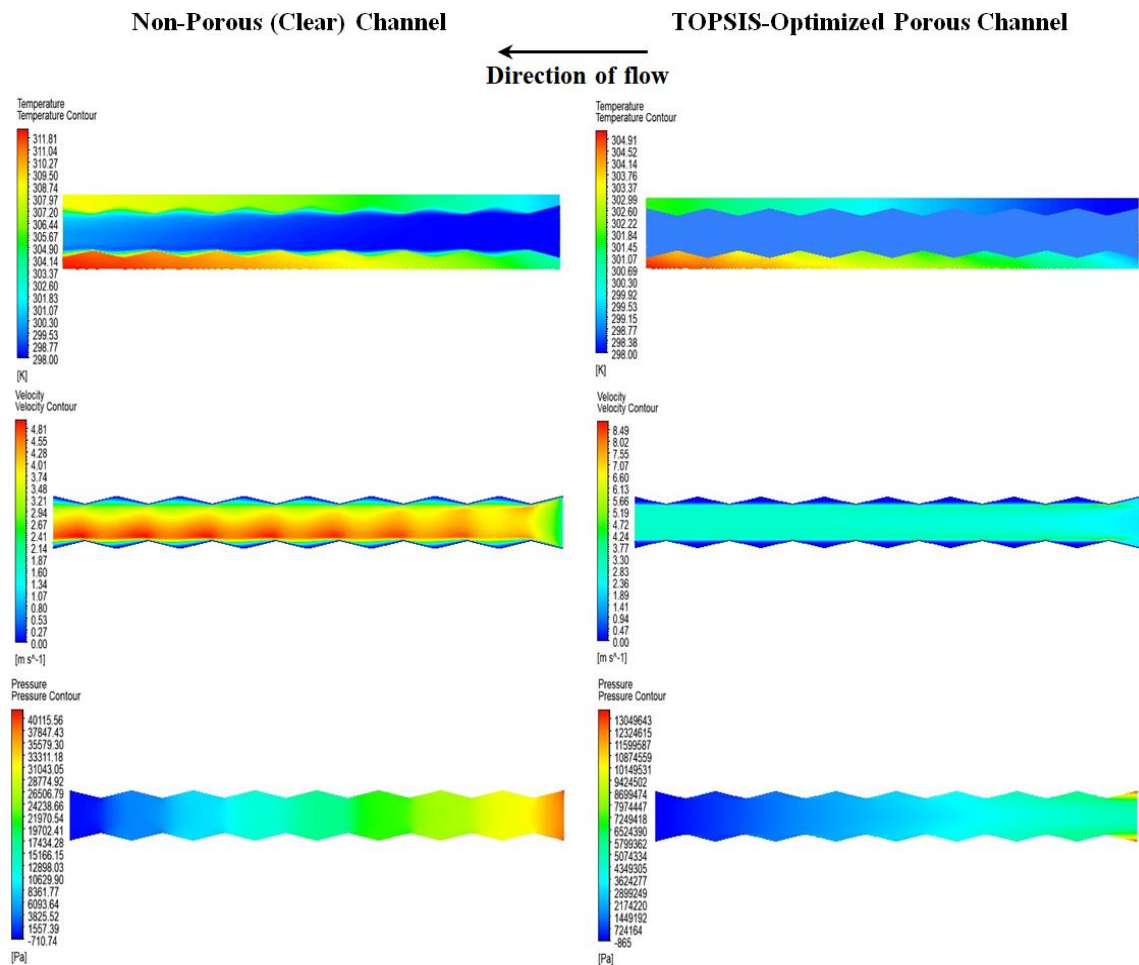


Figure 5.38: Comparison of temperature, velocity, and pressure contours for the reference and the TOPSIS-optimized porous configuration

As shown in Figure 5.xx, the optimized porous channel exhibits a substantially lower temperature level throughout the flow domain compared with the clear channel. While the non-porous configuration reaches a maximum temperature of approximately 311.8 K, the corresponding temperature in the porous channel is limited to about 304.9 K, representing a reduction of nearly 7 K. This behavior indicates significantly improved heat extraction from the heated walls and explains the remarkable enhancement in the Nusselt number observed for the optimized porous configuration.

The velocity contours further demonstrate the influence of the porous matrix on the flow field. In the clear channel, the peak velocity remains approximately 4.8 m/s, whereas the restricted flow passages within the porous structure accelerate the coolant to nearly 8.5 m/s. The resulting increase in local momentum transport strengthens fluid-solid interaction and enhances convective heat transfer throughout the channel.

This intensified flow behavior is accompanied by a substantial increase in pressure drop, as evident from the pressure contours. The porous matrix generates strong local pressure gradients due to flow constriction and increased hydraulic resistance, resulting in significantly larger pressure losses than those observed in the clear channel. Although this increases the pumping requirement, the enhanced thermal transport achieved through the porous structure outweighs the associated hydraulic penalty.

Overall, the contour analysis confirms that the optimized porous configuration promotes more effective heat removal through the combined effects of enhanced fluid-solid interaction, increased local flow acceleration, and improved thermal transport within the porous matrix. These mechanisms are directly responsible for the substantial hydrothermal enhancement achieved by the TOPSIS-selected design.

5.4.8 Exergetic Performance Evaluation

To further assess the thermodynamic suitability of the selected porous-media configurations, an exergetic performance evaluation was conducted using the exergy destruction ratio (EDR) and exergy efficiency (η_{ex}). These parameters provide a second-law perspective of system performance by quantifying the irreversibilities associated with heat transfer and fluid flow within the porous-media-enhanced CD-MCHS. The exergetic performances of the reference configuration, representative Pareto-optimal solutions, TOPSIS-selected design, and non-porous channel are summarized in Table 5.36.

Table 5.36: Exergetic performance comparison of the reference, Pareto-optimal, TOPSIS-selected, and non-porous configurations

Design Configuration	EDR	Relative EDR	η_{ex}
Ref Study : (ϵ :0.85, d_p :32, M_c :3)	98.26 %	-	1.74 %
Case-01: (ϵ :0.83, d_p :15, M_c :1)	81.96 %	16.58 % ↓	18.04 %
Case-02: (ϵ :0.64, d_p :26, M_c :4)	93.61 %	4.73 % ↓	6.39 %
Case-03: (ϵ :0.41, d_p :32, M_c :4)	99.05 %	0.804 % ↑	0.95 %
TOPSIS Design: (ϵ :0.74, d_p :16, M_c :1)	83.51 %	15.01 % ↓	16.49 %
Non-Porous (Clear) Channel	8.53%	91.31 % ↓	91.47 %

The reference porous configuration exhibits a high exergy destruction ratio (EDR = 98.26%) and a low exergy efficiency ($\eta_{ex} = 1.74\%$), indicating that thermodynamic losses are dominated by flow resistance within the porous matrix. Among the representative Pareto-optimal solutions, Case-01 achieves the most favorable exergetic performance with an EDR of 81.96% and an exergy efficiency of 18.04%, whereas Case-03 exhibits the highest exergy destruction (EDR = 99.05%) and the lowest exergy efficiency ($\eta_{ex} = 0.95\%$). Case-02 provides intermediate performance with an EDR of 93.61% and an exergy efficiency of 6.39%, reflecting a moderate balance between thermal enhancement and thermodynamic irreversibility.

The TOPSIS-selected configuration yields an EDR of 83.51% and an exergy efficiency of 16.49%, positioning it close to the best-performing Pareto solution from an exergetic perspective. Although it does not correspond to the minimum exergy destruction, it maintains favorable thermodynamic performance while simultaneously delivering substantial heat-transfer enhancement. This behavior further supports its selection as the most balanced porous-media configuration identified through the multi-objective optimization process.

For comparison, the non-porous channel exhibits a very low EDR of 8.53% and a high exergy efficiency of 91.47%, owing to the absence of porous-induced flow resistance. However, this thermodynamic advantage is accompanied by significantly lower heat-transfer capability than the optimized porous configurations.

Overall, the exergetic assessment confirms that the optimized porous-media designs achieve enhanced thermal performance at the expense of additional thermodynamic losses. Among the investigated configurations, the TOPSIS-selected design provides the

most favorable compromise between heat-transfer enhancement and exergy destruction, thereby reinforcing its suitability for high-performance electronic cooling applications.

5.5 Comparative Performance Analysis of Passive Enhancement Techniques in CD-MCHS

A comprehensive comparison was performed among the three passive enhancement strategies investigated in the present study, namely micro-pillar integration, hybrid nanofluid utilization, and porous-media incorporation, in order to identify the most suitable approach for advanced electronic cooling applications. The comparison was conducted using the optimized configurations obtained from the ANN-NSGA-II-TOPSIS framework, considering thermal performance, entropy generation, and exergetic behavior simultaneously. The corresponding results are summarized in Table 5.37.

Table 5.37: Comparative performance analysis of passive enhancement techniques in CD-MCHS

Performance Matrices	CD-MCHS (Ref)	Micro Pillar	Change (%)	Hybrid Nanofluid	Change (%)	Porous Media	Change (%)
$T_{\max}$ (K)	311.81	308.32	3.49 ↓	309.92	1.89 ↓	304.91	6.90 ↓
Nu	39.85	68.32	71.45 ↑	46.37	16.36 ↑	145.73	265.65 ↑
S_{gen} (W/K)	0.000716	0.000828	15.64 ↑	0.000814	13.71 ↑	0.00454	534.66 ↑
EDR (%)	8.53	22.06	158.61 ↑	19.26	125.79 ↑	83.51	879.01 ↑
η_{ex} (%)	91.47	77.94	14.79 ↓	80.74	11.73 ↓	16.49	81.97 ↓

The results demonstrate that all passive enhancement techniques improve the thermal performance of the baseline CD-MCHS; however, the magnitude of enhancement and the associated thermodynamic penalties differ considerably. Among the investigated configurations, the porous-media-enhanced CD-MCHS exhibits the highest cooling capability, reducing the maximum wall temperature by 6.90 K and increasing the average Nusselt number by 265.65% relative to the baseline configuration. Nevertheless, this substantial thermal enhancement is accompanied by the largest increase in entropy generation (534.66%) and a significant reduction in exergy efficiency (81.97%), indicating considerable flow resistance and irreversibility within the porous matrix.

In contrast, the hybrid nanofluid-enhanced CD-MCHS exhibits the most conservative thermodynamic behavior. The optimized tri-hybrid nanofluid reduces the maximum temperature by 1.89 K and enhances the Nusselt number by 16.36%, while limiting the increase in entropy generation to 13.71%. Consequently, it experiences the smallest

reduction in exergy efficiency (11.73%) among all enhancement techniques, indicating relatively stable hydrothermal performance with minimal thermodynamic penalties.

The micro-pillar-enhanced CD-MCHS exhibits intermediate behavior between these two extremes. The optimized micro-pillar configuration reduces the maximum wall temperature by 3.49 K and improves the Nusselt number by 71.45%, while the corresponding increase in entropy generation (15.64%) remains significantly lower than that observed for porous media. Although exergy efficiency (14.79%) decreases relative to the baseline configuration, the associated thermodynamic penalty remains moderate compared with the substantial improvement in cooling performance.

From an overall thermo-hydraulic perspective, the enhancement techniques can be ranked according to cooling capability as:

Porous Media > Micro-Pillar > Hybrid Nanofluid

Whereas, their thermodynamic behavior follows the opposite trend:

Hybrid Nanofluid > Micro-Pillar > Porous Media

This opposing behavior highlights the inherent conflict between maximizing heat-transfer enhancement and minimizing thermodynamic irreversibility.

5.5.1 Scientific Insight

The comparative assessment reveals that the optimal passive enhancement strategy depends not only on the achievable heat-transfer augmentation but also on the thermodynamic cost required to obtain it. Although porous media delivers the highest cooling performance, the associated increase in entropy generation and exergy destruction indicates a substantial hydraulic and energetic penalty. Conversely, hybrid nanofluids maintain favorable thermodynamic characteristics but provide comparatively limited thermal enhancement. The micro-pillar configuration effectively bridges these two extremes by combining significant heat-transfer augmentation with moderate entropy-generation and exergetic penalties. Therefore, among the passive enhancement techniques investigated in the present study, the micro-pillar-enhanced CD-MCHS emerges as the most balanced solution for high-performance electronic cooling and thermal management applications, offering the most favorable compromise between cooling effectiveness, pumping-power requirements, and thermodynamic efficiency.

CHAPTER 6

CONCLUSIONS

The present research investigated the hydrothermal and thermodynamic performance of convergent-divergent microchannel heat sinks (CD-MCHS) for advanced electronic cooling applications. An integrated optimization framework combining Computational Fluid Dynamics (CFD), Artificial Neural Networks (ANN), Non-dominated Sorting Genetic Algorithm-II (NSGA-II), and the Technique for Order Preference by Similarity to Ideal Solution (TOPSIS) was developed to identify optimal designs under competing objectives of maximizing heat-transfer enhancement and minimizing thermodynamic irreversibility. Three passive enhancement strategies, namely micro-pillar integration, tri-hybrid nanofluid utilization, and porous-media incorporation, were systematically evaluated and compared. The major conclusions drawn from the present investigation are summarized as follows.

6.1 Numerical Analysis of Convergent-Divergent Microchannel Heat Sink without and with Pillars. (Objective-1)

Baseline CD-MCHS (without Pillar)

- The ANN-NSGA-II-TOPSIS framework successfully identified an optimized convergent-divergent CD-MCHS configuration characterized by $Re = 400$, $\alpha = 0.70$, $\beta = 0.65$, $\gamma = 0.70$, $\delta = 0.70$, $N_1 = 60$, and $N_2 = 08$.
- The TOPSIS-selected CD-MCHS design showed a 20.1% improvement in heat transfer and a 38.1% drop in entropy generation with respect to straight MCHS configuration, highlights the trade-off and confirming its balanced performance.
- Compared to the straight MCHS configuration, the TOPSIS-optimized trapezoidal CD-MCHS enhances mixing and disrupts the thermal boundary layer, reducing outlet temperature by ~ 8 K.
- TOPSIS-selected design achieves the lowest exergy destruction (8.53%) and highest exergy efficiency (91.47%), indicating superior performance with minimized irreversibilities.

Micro-Pillar-Enhanced CD-MCHS

- The ANN-NSGA-II-TOPSIS framework successfully identified an optimized micro-pillar configuration corresponding to $P_d = 1$ (Elliptical), $\phi = 2.5\%$, $P_c = 48$, and $P_o = 6 \mu\text{m}$.
- TOPSIS-selected elliptical-micro-pillar configuration achieves 71.45% heat transfer enhancement with only 15.64% rise in entropy generation, representing the most balanced solution.
- The TOPSIS-selected micro-pillar configuration reduced the maximum wall temperature by ~ 3.5 K relative to the optimized baseline CD-MCH, indicating enhanced heat-removal capability.
- The TOPSIS-selected micro-pillar configuration maintained balanced exergetic performance (EDR: 22.06%, η_{ex} : 77.94%), confirming practical suitability.

6.2 To Investigate the Hydrodynamic and Heat Transfer Characteristics of Convergent-Divergent Microchannel Heat Sink with Nanofluids. (Objective-2)

- The ANN-NSGA-II-TOPSIS framework successfully identified an optimized tri-hybrid nanofluid composition corresponding to a total nanoparticle concentration of $\Phi_T = 1.75\%$, comprising 55.0% CuO, 20.5% Al_2O_3 , and 24.5% Ag nanoparticles.
- TOPSIS-selected tri-hybrid nanofluid composition achieves a 16.36% increase in heat transfer relative to the reference study, with a 13.71% rise in entropy generation, representing the most balanced solution.
- The TOPSIS-selected tri-hybrid nanofluid composition reduced the maximum wall temperature by ~ 1.89 K relative to the optimized baseline CD-MCHS.
- The TOPSIS-selected tri-hybrid nanofluid composition maintained favorable exergetic performance (EDR: 19.26%, η_{ex} : 80.74%), indicating improved thermodynamic behavior

6.3 To Investigate the Hydrodynamic and Heat Transfer Characteristics of Convergent-Divergent Microchannel Heat Sink with Porous Media. (Objective-3)

- The ANN-NSGA-II-TOPSIS framework successfully identified an optimized porous-media configuration characterized by a porosity of $\varepsilon = 0.74$, a pore diameter of $d_p = 16 \mu\text{m}$, and a copper porous substrate ($M_c = 01$).
- TOPSIS-selected porous-media configuration achieves 101% heat transfer enhancement with 80.96% reduction in entropy generation compared to the reference case, representing the best overall performance.
- Compared to the non-porous configuration, the TOPSIS-selected design achieves a 265.65% increase in heat transfer, accompanied by a 534.66% rise in entropy generation.
- Compared with the non-porous channel, the TOPSIS-optimized porous configuration reduced the maximum wall temperature by $\sim 7 \text{ K}$, confirming its enhanced cooling performance.
- The TOPSIS-selected porous configuration exhibited relatively high exergy destruction (EDR: 83.51%) and low exergy efficiency (η_{ex} : 16.49%) due to porous-induced flow resistance.

6.4 Comparative Assessment of Passive Enhancement Techniques. (Objective-4)

- The results demonstrate that the optimum passive enhancement strategy cannot be determined solely on the basis of heat-transfer enhancement, but must be evaluated through a combined thermo-hydraulic and thermodynamic perspective.
- Porous media delivered the maximum cooling performance, whereas the tri-hybrid nanofluid incurred the lowest thermodynamic penalty. These enhancement strategies therefore represent two contrasting performance extremes, prioritizing thermal augmentation and thermodynamic efficiency, respectively.
- Among the investigated techniques, the micro-pillar-enhanced CD-MCHS provided the most favorable overall compromise between cooling effectiveness, thermodynamic efficiency, and implementation practicality, making it the preferred passive enhancement strategy for advanced electronic thermal-management applications.

CHAPTER 7

LIMITATIONS, FUTURE SCOPE, AND ENGINEERING SIGNIFICANCE

7.1 Limitations of the Present Study

❖ Numerical Modeling and Optimization

- The ANN surrogate models were developed using a finite CFD dataset; therefore, certain complex microscale flow and heat-transfer interactions may not be fully captured.
- The optimization was restricted to predefined design-variable ranges, and global optimum solutions beyond the selected design space may remain unexplored.

❖ Modeling Assumptions and Physical Simplifications

- The numerical simulations were performed under idealized conditions, neglecting manufacturing imperfections, surface roughness, fouling, and long-term performance degradation.
- The nanofluid model assumes homogeneous nanoparticle dispersion and employs effective-property correlations without explicitly considering agglomeration, sedimentation, or particle-level interactions.

❖ Practical and Manufacturing Constraints

- Fabrication complexity, manufacturing cost, and large-scale implementation considerations were not incorporated into the present optimization framework.
- Geometric scaling constraints limited the feasible design space, with pore diameters maintained at least two orders of magnitude smaller than the channel hydraulic diameter and micro-pillar dimensions kept substantially smaller than the channel dimensions.

❖ Scope of Investigation

- The study was limited to steady-state, single-phase numerical simulations within the selected operating conditions for electronic cooling applications.

- Experimental analysis of the optimized configurations was not conducted; therefore, the reported improvements are limited to the numerical framework employed in the present investigation.

7.2 Recommendations for Future Studies

- ❖ Extend the present investigation to transient operating conditions, non-uniform heat loads, and multiphase cooling mechanisms for more realistic electronic-cooling applications.
- ❖ Explore hybrid passive enhancement strategies combining micro-pillars, porous media, and advanced nanofluids to further improve thermo-hydraulic performance.
- ❖ Develop advanced machine-learning and optimization frameworks to achieve more robust and computationally efficient thermal-system design.
- ❖ Perform experimental validation of the optimized configurations and investigate long-term effects such as fouling, nanoparticle stability, and porous-media degradation.
- ❖ Incorporate manufacturing constraints, fabrication tolerances, and economic considerations to facilitate practical implementation of the proposed designs.
- ❖ Extend the proposed framework to multi-scale thermal management, including hotspot cooling, electronic packaging, and integrated chip-to-system thermal design.
- ❖ Apply the developed optimization methodology to emerging applications such as artificial-intelligence hardware, data centers, electric vehicles, and renewable-energy systems.

7.3 Engineering Significance and Societal Impact

❖ Energy Efficiency and Sustainability

- The passive enhancement strategies investigated in this work improve thermal performance without requiring external energy input, supporting the development of energy-efficient cooling technologies.
- Enhanced cooling efficiency can reduce the energy footprint of advanced electronic systems, contributing to long-term sustainability and energy conservation.

- The incorporation of entropy-generation minimization and exergy-based evaluation promotes thermodynamically sustainable thermal-management solutions through improved utilization of available energy resources.

❖ **Advanced Electronic Cooling and Industrial Applications**

- The optimized CD-MCHS configurations provide effective cooling solutions for high-heat-flux electronics, including processors, GPUs, power electronics, and data-center systems.
- Enhanced heat-removal capability and lower operating temperatures can improve device reliability, stability, and service life.
- The proposed optimization framework provides practical guidance for the development of compact, high-performance cooling technologies across multiple industrial sectors.

❖ **Healthcare and Societal Benefits**

- The growing complexity of advanced medical and biomedical devices demands compact and reliable thermal-management solutions to ensure safe and stable operation.
- The passive cooling concepts investigated in this work can support the development of compact and reliable thermal solutions for advanced diagnostic, monitoring, and medical-electronic systems.
- Improved thermal performance and enhanced device reliability contribute indirectly to societal well-being through more dependable technological infrastructure and reduced operational costs.

❖ **Research, Innovation, and Technological Advancement**

- The present work demonstrates the successful integration of computational fluid dynamics, machine learning, and multi-objective optimization for advanced thermal-system design.
- The developed ANN-NSGA-II-TOPSIS framework provides a versatile platform for future investigations involving novel microchannel geometries, nanofluids and hybrid cooling technologies.
- The outcomes contribute to the advancement of intelligent, optimization-driven thermal-management methodologies for emerging engineering applications.

❖ **Environmental and Resource Conservation Impact**

- Improved thermal-management performance can reduce cooling-related energy consumption, thereby lowering associated greenhouse-gas emissions and environmental impacts.
- Enhanced thermodynamic efficiency minimizes unnecessary energy dissipation and promotes more effective utilization of available resources.
- Longer operational lifetimes of electronic devices may contribute to reduced material consumption and mitigation of electronic-waste generation.

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APPENDIX

❖ Algorithm A1: MATLAB code for LHS sample generation for baseline CD-MCHS.

```
% Define the number of runs and variables
nRuns = 45; % Total number of runs
nVars = 7; % Number of variables (Re,  $\alpha$ ,  $\beta$ ,  $\gamma$ ,  $\delta$ , N1, N2)
% Define the reference study values for one specific run
referenceStudy = [300, 1.0, 0.5, 0.5, 1, 50, 6];
% Define the ranges and step sizes for each variable
ranges = [
    100, 500, 100; % Re (Reynolds number) range and step size
    0.5, 1.5, 0.25; %  $\alpha$  range and step size
    0.4, 0.8, 0.10; %  $\beta$  range and step size
    0.4, 0.8, 0.10; %  $\gamma$  range and step size
    0.2, 1.0, 0.20; %  $\delta$  range and step size
    30, 70, 10; % N1 range and step size
    4, 12, 2; % N2 range and step size
];
% Generate Latin Hypercube Sample for 39 runs (excluding the reference study)
lhsSample = lhsdesign(nRuns-1, nVars);
% Scale the sample to the ranges of each variable and round to nearest step
scaledSample = zeros(nRuns-1, nVars);
for i = 1:nVars
    minVal = ranges(i, 1);
    maxVal = ranges(i, 2);
    stepSize = ranges(i, 3);
    % Scale the sample and round to the nearest step
    scaledSample(:,i) = round((lhsSample(:,i) * (maxVal - minVal) + minVal) / stepSize) *
stepSize;
end
% Insert the reference study values as the first run
fullSample = [referenceStudy; scaledSample];
% Display the Latin Hypercube Sample with reference study as the first run
```

```
fprintf('Run | Re |  $\alpha$  |  $\beta$  |  $\gamma$  |  $\delta$  | N1 | N2 \n');
fprintf('-----\n');
for i = 1:nRuns
    fprintf('%-5d | %-5d | %-4.2f | %-4.2f | %-4.2f | %-4.2f | %-4d | %-4d\n', i,
fullSample(i,:));
end
```

❖ Algorithm A2: MATLAB code for LHS sample generation for micro-pillar-assisted CD-MCHS.

```
%% =====
% Latin Hypercube Sampling (LHS)
% Micro-Pillar CD-MCHS Optimization
% Design Variables:
% Pd,  $\phi$ , Pc, Po
%% =====
clc;
clear;
close all;
%% Number of Runs and Variables
nRuns = 30;
nVars = 4;
%% Reference Configuration
Reference_Case = [2 1 48 5];
%% Design Space Definition
% [Lower Bound Upper Bound Step Size]
Ranges = [
    1 4 1;    % Pd
    0 3 1;    %  $\phi$ 
    32 80 16; % Pc
    0 15 5    % Po
];
%% Generate LHS Samples
```

```

lhsSample = lhsdesign(nRuns-1,nVars,'criterion','maximin','iterations',100);
%% Scale Samples to Actual Design Space
scaledSample = zeros(nRuns-1,nVars);
for i = 1:nVars
    minVal = Ranges(i,1);
    maxVal = Ranges(i,2);
    stepVal = Ranges(i,3);
    scaledSample(:,i) = round((lhsSample(:,i)*(maxVal-
minVal)+minVal)/stepVal)*stepVal;
end
%% Insert Reference Case
DesignMatrix = [Reference_Case; scaledSample];
%% Remove Duplicate Rows
DesignMatrix = unique(DesignMatrix,'rows','stable');
%% Display Design Matrix
fprintf('\n');
fprintf('-----\n');
fprintf('Run\tPd\tPhi\tPc\tPo\n');
fprintf('-----\n');
for i = 1:size(DesignMatrix,1)
    fprintf('%2d\t%d\t%d\t%d\t%d\n',...
        i,...
        DesignMatrix(i,1),...
        DesignMatrix(i,2),...
        DesignMatrix(i,3),...
        DesignMatrix(i,4));
end
%% Save Sample Matrix
VariableNames = {'Pd','Phi','Pc','Po'};
LHS_Table = array2table(DesignMatrix,'VariableNames',VariableNames);
writetable(LHS_Table,'LHS_Micro_Pillar_CD_MCHS.xlsx');
disp(' ');
disp('LHS sampling completed successfully.');
```

❖ Algorithm A3: MATLAB code for LHS sample generation for hybrid nanofluid integrated CD-MCHS.

```
%% LHS for hybrid nanofluid with mixture constraint
rng(1); % reproducibility
nRuns = 30;
% Define levels
phi_total_levels = 0.5:0.5:2.0; % overall vol%
f_CuO_levels = 50:5:65; % %
f_Al2O3_levels = 20:5:35; % %
f_Ag_levels = 15:5:30; % %
% Filter candidates satisfying mixture sum = 100%
candidates = [];
for phi = phi_total_levels
    for CuO = f_CuO_levels
        for Al = f_Al2O3_levels
            for Ag = f_Ag_levels
                if CuO + Al + Ag == 100
                    candidates = [candidates; phi, CuO, Al, Ag];
                end
            end
        end
    end
end
% Check how many candidates exist
nCandidates = size(candidates,1);
fprintf('Total feasible candidates: %d\n', nCandidates);
if nCandidates < nRuns
    error('Not enough feasible candidates (%d) for %d runs. Adjust ranges/steps.',
nCandidates, nRuns);
end
% Randomly select nRuns from feasible candidates (LHS-like spread)
```

```

idx = randperm(nCandidates, nRuns);
sample = candidates(idx,:);
% Compute absolute volume fractions
phi_total = sample(:,1);
f_CuO = sample(:,2);
f_Al2O3 = sample(:,3);
f_Ag = sample(:,4);
phi_CuO = phi_total .* (f_CuO / 100);
phi_Al2O3 = phi_total .* (f_Al2O3 / 100);
phi_Ag = phi_total .* (f_Ag / 100);
% Display table
fprintf('Run | phi_total | f_CuO | f_Al2O3 | f_Ag | phi_CuO | phi_Al2O3 | phi_Ag\n');
fprintf('-----\n');
for i = 1:nRuns
    fprintf('%2d | %4.2f | %3d | %3d | %3d | %6.3f | %6.3f | %6.3f\n', ...
        i, phi_total(i), f_CuO(i), f_Al2O3(i), f_Ag(i), phi_CuO(i), phi_Al2O3(i),
        phi_Ag(i));
end

```

❖ Algorithm A4: MATLAB code for LHS sample generation of porous-media-assisted CD-MCHS

```

%% =====
% Latin Hypercube Sampling (LHS)
% Porous-Media-Assisted CD-MCHS Optimization
% Design Variables:
% ε, dp, Mc
%% =====

clc;
clear;
close all;

%% Number of Runs and Variables
nRuns = 25;
nVars = 3;

```

```

%% Design Space Definition
% [Lower Bound Upper Bound Step Size]
Ranges = [
    0.40 0.85 0.15; % ε
    8    32    8;    % dp (μm)
    1    4    1      % Mc
];
%% Generate LHS Samples
lhsSample = lhsdesign(nRuns,nVars,...
    'criterion','maximin',...
    'iterations',100);
%% Scale Samples to Actual Design Space
scaledSample = zeros(nRuns,nVars);
for i = 1:nVars
    minVal = Ranges(i,1);
    maxVal = Ranges(i,2);
    stepVal = Ranges(i,3);
    tempVals = lhsSample(:,i)*(maxVal-minVal) + minVal;
    scaledSample(:,i) = ...
        round((tempVals-minVal)/stepVal)*stepVal + minVal;
    scaledSample(:,i) = ...
        min(max(scaledSample(:,i),minVal),maxVal);
end
%% Display Design Matrix
fprintf('\n');
fprintf('-----\n');
fprintf('Run\tε\ttdp\tMc\n');
fprintf('-----\n');
for i = 1:nRuns
    fprintf('%2d\t%.2f\t%d\t%d\n',...
        i,...
        scaledSample(i,1),...
        round(scaledSample(i,2)),...

```

```

        round(scaledSample(i,3)));
    end
%% Save Sample Matrix
VariableNames = {'Porosity','dp','Mc'};
LHS_Table = array2table(scaledSample,...
                        'VariableNames',VariableNames);
writetable(LHS_Table,'LHS_Porous_Media_CD_MCHS.xlsx');
disp(' ');
disp('LHS sampling completed successfully.');
```

List of Publications

Paper publication details (International journals papers)				
S. No.	Publisher	Paper title name	Paper journal name	Status
1.	Elsevier	Multi-objective optimization of hydrothermal performance of a porous minichannel heat sink using RSM and NSGA-II algorithm.	International Journal of Heat and Fluid Flow. [SCIE index, IF-4.8].	Paper Published
2.	Elsevier	Multi-objective optimization of the hydrothermal and exergetic performance of a convergent-divergent microchannel heat sink using ANN, NSGA-II, and TOPSIS algorithms.	Thermal Science and Engineering Progress. [SCIE index, IF-5.6].	Paper Published
3.	Elsevier	Multi-objective optimization of porous medium characteristics for enhanced hydrothermal and exergetic performance in a convergent-divergent microchannel heat sink.	International Communications in Heat and Mass Transfer. [SCIE index, IF-6.2].	Paper Published
4	Elsevier	Multi objective optimization of micro-pillar configurations for enhanced thermo hydraulic and exergetic performance in convergent-divergent microchannel heat sinks.	Applied Thermal Engineering. [SCIE index, IF-7.5].	Paper Published

5	YTU	Numerical investigation of hydrothermal performances of minichannel heat sink using porous media.	Journal of Thermal Engineering. [ESCI index, IF-1.1].	Paper Published
6	ASME	Multi-Objective Optimization of Tri-Hybrid Nanofluid Composition for Enhanced Thermo-Hydraulic and Exergetic Performance in Convergent-Divergent Microchannel Heat Sinks	Journal of Thermal Science and Engineering Applications. [SCIE index, IF-1.4].	Under Review

Paper publication details (International Conference papers)				
S. No.	Publisher	Paper title name	Paper journal name	Status
1.	Springer Nature	Numerical Analysis of Heat Transfer and Entropy Generation in Minichannel Heat Sinks with Fe ₃ O ₄ /Water Nanofluids.	Lecture Notes in Mechanical Engineering.	Accepted
2.	Springer Nature	Advancements in Hydrothermal Performance of Minichannel Heat Sinks with Bronze Porous Media: A Numerical Analysis.	Lecture Notes in Mechanical Engineering.	Accepted

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Multi-objective optimization of hydrothermal performance of a porous minichannel heat sink using RSM and NSGA-II algorithm

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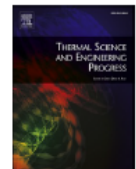
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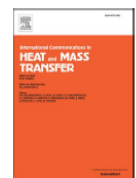
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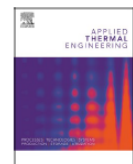
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Research Article

Numerical investigation of hydrothermal performances of minichannel heat sink using porous media

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Rajesh Kumar is a doctoral research scholar in the Department of Mechanical Engineering at Delhi Technological University (formerly Delhi College of Engineering), Delhi, where he has been pursuing his Ph.D. since August 2021 with a specialization in advanced thermal management and optimization of microchannel heat sinks for high-performance electronic cooling applications.

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- Microchannel Heat Sinks
- Computational Fluid Dynamics
- Heat Transfer and Fluid Flow
- Exergy and Entropy Generation Analysis
- Machine Learning Applications in Thermal Engineering
- Multi-Objective Optimization
- Porous Media and Hybrid Nanofluids

During his doctoral research, he has published four SCIE-indexed journal articles, two Scopus-indexed journal articles, and one ESCI-indexed journal article, while an additional SCIE journal paper is currently under review. His research contributions focus on developing intelligent optimization frameworks for improving the performance, reliability, and sustainability of advanced thermal-management systems.

He believes that the future of electronic cooling lies in the integration of advanced thermal-design concepts with intelligent optimization techniques capable of simultaneously addressing thermal performance, hydraulic losses, and thermodynamic efficiency. In his view, the combination of computational modeling, machine learning, and multi-objective optimization provides a powerful pathway for developing next-generation cooling technologies that are both energy-efficient and practically deployable. His research philosophy emphasizes achieving meaningful thermal-performance enhancement while maintaining a balanced consideration of engineering feasibility, energy utilization, and long-term sustainability.

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