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Intelligent Algorithm-Driven Optimization of Water-Cooled Plate Structures for Enhanced Thermal Performance

Ethan L. Norwick [1], Adrian T. Caldwell [2], Vincent M. Roemer [3] and Felix J. Hargrove [4,*]

[1] Department of Mechanical Engineering, South Dakota School of Mines and Technology, Rapid City, SD, USA
[2] School of Engineering, University of North Texas, Denton, TX, USA
[3] Department of Thermal and Fluid Sciences, University of Idaho, Moscow, ID, USA
[4] Department of Mechanical and Aerospace Engineering, New Mexico Institute of Mining and Technology, Socorro, NM, USA
* Correspondence: Felix J. Hargrove, Department of Mechanical and Aerospace Engineering, New Mexico Institute of Mining and Technology, Socorro, NM, USA

Abstract: The study presents a systematic approach to optimizing heat sink performance in high-heat flux applications through topology optimization (TO). A computational framework was developed that combines computational fluid dynamics (CFD) simulations with a simplified two-dimensional thermo-fluidic model to reduce computational complexity while maintaining accuracy. The design domain was constructed to minimize pressure drop under specific thermal constraints, with material properties interpolated using a rational approximation of material properties (RAMP) method to ensure a smooth transition between fluid and solid regions during optimization. Validation through three-dimensional numerical simulations in ANSYS Fluent confirmed the reliability of the two-dimensional model, with turbulence modeling and mesh refinement ensuring high accuracy in capturing critical flow and thermal characteristics. The results indicate that the topology-optimized designs achieved significant improvements over conventional straight-channel heat sinks, including a 25% reduction in thermal resistance and up to a 30% increase in heat transfer efficiency under varying flow rates. Moreover, the study demonstrates the feasibility of integrating artificial intelligence algorithms to streamline design optimization processes and enhance adaptability to complex performance requirements. These findings offer valuable insights for advancing heat management solutions in high-performance electronics and related applications.

Keywords: water-cooled plate; thermal management; topology optimization; CFD; AI-based optimization; numerical simulation

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1. Introduction

As global reliance on digital infrastructure grows, managing the energy demands of data centers has become increasingly important for ensuring long-term sustainability. By 2022, data centers worldwide consumed 200 TWh of electricity, accounting for about 1% of global electricity use. Among this, cooling systems contributed 20% to 40% of the total energy consumption [1]. As demand for high-performance computing and cloud services continues to rise, designing efficient cooling systems is essential to reduce energy use and improve the economic and environmental performance of data centers. Traditional cooling methods, including air-cooled and liquid-cooled systems, often rely on numerical simulation approaches such as finite element analysis (FEM) and computational fluid dynamics (CFD). These methods have successfully improved flow channel designs and enhanced cooling efficiency. A CFD-based approach was used to optimize radiator flow paths, resulting in a 12% reduction in thermal resistance and approximately 7% energy savings [2,3]. However, such methods often suffer from high computational costs, requiring long simulation times to explore complex design spaces, which limits the potential for global optimization.

In recent years, the integration of AI-driven optimization techniques has provided new avenues for improving cooling efficiency. Topology optimization combined with genetic algorithms was applied to enhance microchannel radiator designs, achieving a 15% increase in cooling performance and a 30% reduction in design time [4,5]. Similarly, Deep neural networks (DNNs) were employed to develop a thermal-flow prediction model, reducing simulation time from 12 hours to 6 hours while maintaining accuracy [6,7]. These advancements highlight AI's potential in radiator design, particularly in accelerating optimization processes and reducing computational overhead [8]. Emerging AI-based methodologies, such as generative adversarial networks (GANs) and reinforcement learning (RL), have introduced novel approaches to radiator optimization [9]. Generative adversarial networks (GANs) were applied to generate 1,000 radiator designs, with 30% outperforming traditional counterparts and achieving a maximum thermal resistance reduction of 18% [10]. Reinforcement learning (RL) was utilized to optimize flow paths, resulting in a 20% decrease in fluid pressure losses [11]. These findings underscore AI's capability to improve cooling performance while expanding design possibilities. Multi-objective optimization has also been explored to balance competing factors such as cooling efficiency, structural integrity, and manufacturing costs [12]. A composite material modeling approach was proposed, enhancing cooling efficiency by 8% while reducing material consumption by 10% [13]. However, large-scale parameter optimization remains challenging due to slow convergence rates and intricate constraints.

The study aims to integrate deep learning with multi-objective optimization to develop a data-driven design methodology for water-cooled plate structures. By leveraging generative models within an optimization framework, the goal is to enhance cooling efficiency by 15%-20% while achieving a 10%-15% reduction in energy consumption. The proposed approach contributes to the advancement of sustainable, high-performance thermal management solutions for next-generation data centers and electronic systems.

2. Materials and Methods

2.1. Design Domain and Optimization Objectives

The study adopts the design domain from Benam [14], the domain measures 45 mm in length and 2 mm in width, with water entering at 25°C and a bottom heat flux of q_{bt} = 25 W/cm², simulating high-heat-flux chip cooling requirements. The primary objective is to minimize the pressure drop (ΔP) while ensuring the average bottom surface temperature ($T_{bt,ave}$) remains below a predefined threshold (T_{con}). The optimization framework incorporates multi-objective criteria, balancing thermal resistance, pressure loss, and manufacturing constraints. The material distribution is interpolated using the RAMP function, which allows a smooth transition between solid and fluid regions, ensuring numerical stability and improving the design feasibility [15]. The optimization goal is to minimize the pressure drop (ΔP) while keeping the average bottom surface temperature ($T_{bt,ave}$) below the specified threshold (T_{con}).

$$\text{Minimize: } \Delta P$$
$$\text{Subject to: } T_{bt,ave} \leq T_{con},\ 0 \leq \gamma(x) \leq 1$$

Here, γ(x) represents the material distribution variable ranging from 0 (solid) to 1 (fluid). AI was introduced to assist in evaluating objectives and predicting optimized results.

2.2. Computational Framework and AI Model Integration

A 2D three-layer thermal-fluid model was employed to optimize computational efficiency while preserving accuracy. The model is divided into three sections: the fluid-fin layer, the fin-base layer, and the bottom layer, which together simulate mass, momentum, and energy conservation. Mesh refinement and turbulence modeling were applied to improve numerical stability. AI-assisted optimization was incorporated to accelerate design iterations and enhance performance prediction accuracy. A deep learning model, trained on 5000 design parameter sets with a learning rate of 0.001 and batch size of 64, was integrated to predict optimal configurations. The AI system analyzed thermal-fluid interactions and adjusted topology parameters to generate high-performance designs [16].

Mass Conservation:

$$\nabla \cdot \vec{u} = 0$$

Momentum Conservation:

$$\rho_{fl}(\vec{u} \cdot \nabla)\vec{u} = -\nabla P + \mu\nabla^2\vec{u} - \alpha(\gamma)\vec{u}$$

Energy Conservation:

$$\rho_{fl}c_{fl}\left(\vec{u} \cdot \nabla T_{ff}\right) = \nabla \cdot \left(k(\gamma)\nabla T_{ff}\right) + h(\gamma)\left(T_{fb} - T_{ff}\right)H_{fin}$$

To further improve speed and accuracy, a deep learning model was developed to predict thermal-fluid performance by learning the relationships between design parameters and performance indicators.

2.3. Optimization Strategy and Comparative Methods

The optimization framework considers multiple objectives with assigned weights: thermal resistance (30%), pressure drop (30%), material cost (20%), and manufacturing feasibility (20%). Various operating conditions were analyzed, including low (50 mL/min) and high (500 mL/min) flow rates, as well as different heat flux conditions (10 W/cm² vs. 100 W/cm²). The study also compares AI-driven methodologies with traditional CFD-based approaches. GANs were utilized to explore non-intuitive design variations, while reinforcement learning was tested against gradient-based optimization techniques to evaluate convergence speed and design efficiency [17]. The topology-optimized designs were validated through 3D simulations in ANSYS Fluent, ensuring consistency between the optimized structures and their predicted performance.

2.4. Integration of AI and Traditional Methods

AI played a key role in the optimization process, including parameter tuning, high-dimensional solution exploration, and automated post-processing [18]. AI models analyzed simulation data to adjust design parameters, used reinforcement learning to explore multi-objective solutions, and automatically generated manufacturable topology structures [19]. This integration improved the overall efficiency and effectiveness of the optimization process.

3. Results and Discussion

3.1. Numerical Validation and Model Performance

To verify the accuracy of the proposed two-dimensional optimization framework, three-dimensional numerical simulations were conducted. The computational model was developed using ANSYS Fluent, incorporating a detailed turbulence model to enhance predictive accuracy [20]. Water enters the cooling channel at a controlled velocity of 50 mL/min to 500 mL/min, with the outlet maintained at atmospheric pressure. A uniform heat flux of 10 W/cm² to 100 W/cm² is applied to the heated surface to replicate high-power dissipation scenarios. Boundary conditions were carefully adjusted to reflect realistic operating conditions, and mesh independence tests were performed to ensure numerical stability [21]. For turbulence modeling, the RNG k-ε model with enhanced wall treatment was adopted. The SIMPLEC algorithm facilitated pressure-velocity coupling, while higher-order discretization schemes were utilized for momentum, energy, and turbulence equations. A parametric study confirmed mesh convergence at approximately 5.6 million elements, ensuring accurate heat transfer and pressure drop predictions. Comparisons with experimental benchmarks validated the numerical approach, with deviations in junction temperature and pressure drop remaining below 0.8°C and 4%, respectively.

3.2. Influence of Flow Conditions on Cooling Efficiency

A systematic investigation of thermodynamic and fluidic performance was conducted under varying operating conditions. The study examined flow rates ranging from 50mL/min to 500 mL/min, revealing that at higher flow rates, convective cooling effects significantly enhanced heat transfer, reducing the thermal resistance by 15%-25% compared to conventional straight-channel designs. At lower flow rates, optimized secondary flow patterns contributed to more uniform temperature distributions, mitigating localized hotspots [22,23]. The optimized structure exhibited a thermal resistance of 0.12K/W at 500 mL/min, compared to 0.16K/W in traditional designs, demonstrating a measurable improvement. The influence of fin spacing was also assessed, with configurations of 2 mm and 4 mm examined under identical thermal conditions. The 2mm fin spacing exhibited superior heat dissipation at high flow rates, attributed to intensified fluid disturbances, reducing average surface temperatures by 4.5°C. Conversely, the 4 mm fin spacing demonstrated lower pressure drop and improved efficiency in low-flow scenarios, with a 30% decrease in pump power requirements compared to denser fin arrangements. These findings emphasize the necessity of application-specific design considerations when optimizing water-cooled structures.

3.3. AI-Driven Optimization vs. Conventional CFD Design

A comparative analysis was conducted to assess the effectiveness of AI-driven optimization relative to traditional CFD-based design approaches. The study integrated Generative Adversarial Networks (GANs) to explore unconventional flow channel geometries, evaluating whether AI-generated designs exhibited superior performance characteristics. The GAN-based topology optimization yielded channel structures with 18% higher heat transfer efficiency, improving local convective coefficients while reducing overall thermal resistance. Additionally, AI-designed structures demonstrated a 25% reduction in overall thermal gradients, ensuring more uniform temperature distributions across the heat sink. Additionally, reinforcement learning (RL) methodologies were employed to optimize flow path configurations [24]. The RL-based approach was benchmarked against conventional gradient-based optimization, demonstrating 30% faster convergence and a broader exploration of high-performance design alternatives. The AI-enhanced framework reduced optimization time by 30%, while delivering designs with up to 20% lower pressure drop and 15% higher heat transfer efficiency compared to conventional methods. The RL-optimized designs exhibited a pressure drop of 18kPa, which is significantly lower than the 23 kPa recorded for traditional CFD-based optimization techniques.

3.4. Optimization Criteria and Weighting Scheme

The multi-objective optimization framework incorporated weighted criteria to balance thermal performance, hydraulic resistance, and manufacturability [25,26]. The selected weight distribution was as follows: Thermal resistance: 30%, Pressure drop: 30%, Material cost: 20%, Manufacturing feasibility: 20%. This weighting scheme ensured that the final optimized structures maintained a practical balance between energy efficiency and production viability [27-30]. The results highlight the necessity of a holistic optimization approach when designing high-performance cooling solutions. The GAN-generated designs demonstrated improved manufacturability, achieving 10% material cost savings due to optimized topology structures.

4. Conclusion

This study systematically explored the optimization of water-cooled plate structures by integrating CFD, FEM, and AI-driven methodologies to enhance thermal performance and energy efficiency. The research demonstrated that topology-optimized designs significantly reduce thermal resistance (by 15%-25%), lower pressure drop (by up to 20%), and improve heat transfer efficiency (by 15%) compared to conventional straight-channel heat sinks. Furthermore, AI-driven approaches, including GANs and RL-based optimizations, were found to be particularly effective in accelerating convergence (by 30%) while generating innovative cooling structures that maintain manufacturing feasibility. The study highlighted the role of AI in enhancing cooling performance, showing that AI-generated designs achieve more uniform temperature distributions and improved material utilization (by 10%), reducing unnecessary complexity in fabrication. Additionally, design variations, such as fin spacing adjustments (2 mm vs. 4 mm), were shown to significantly impact energy consumption, with optimal configurations providing a 30% reduction in pump power requirements in low-flow conditions. Overall, this work contributes to the advancement of next-generation thermal management solutions, emphasizing the necessity of adaptive design strategies for varying operational conditions. Future research will extend this methodology to include multi-material integration and dynamic cooling environments, further optimizing the performance and sustainability of advanced cooling systems.

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